Growth, Specialisation, and Economic Integration in Europe

by

Mercedes Vera-Martin, London School of Economics

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Abstract

This thesis contributes to the understanding of the economic effects of European integration, on both the pattern of industrial specialisation in European regions and openness and income for countries of the European Economic Community (EEC).

Chapter 2 provides a descriptive analysis of the evolution of the patterns of specialisation across European regions during 1975-1995. We find that regions are more specialised than countries. Over time, countries and regions have increased specialisation, although at a slow pace. When analysing specialisation dynamics, mobility within the pattern of specialisation changes notably at the regional level. We also find significant cross-country and within-country differences in specialisation.

Chapter 3 studies production patterns in 45 European regions since 1975. We estimate a structural equation derived directly from the Heckscher-Ohlin theory, which relates an industry's share of a region's GDP to factor endowments and relative prices. Factor endowments are found to play a significant and quantitatively important role. The explanation is most successful for aggregate industries, and works less well for disaggregated industries within the manufacturing sector. We find no evidence that increasing European integration has weakened or stengthened the relation between factor endowments and production patterns.

Chapter 4 adds economic geography considerations into the analysis of patterns of specialisation in manufacturing industries across regions in seven European countries since 1985. We estimate an equation that relates an industry's share of GDP to factor endowments, industry characteristics, and economic geography variables. Both factor endowments and economic geography are found to be significant in explaining specialisation. Among economic geography variables, cost linkages are more important than demand linkages. There is no evidence that increasing integration has weakened or stengthened the relationship between factor endowments, economic geography, and production patterns within countries.

Chapter 5 explores how European economic integration has affected openness and income. We test for permanent effects of EEC membership on openness, income, and income convergence at the time of accession. Results indicate EEC membership improves permanently openness within the EEC and income, but has neither an effect on income growth nor on convergence. Second, we investigate the differential effect of EEC membership by applying a differences in differences specification which controls for common time series shock. Openness, income, and convergence among the EEC countries were improved significantly.

Chapter 1 presents an overview of the thesis with a summary of conclusions and contributions. Chapter 6 summarises the main findings of the thesis.

Contents

[1] As certified at the beginning of the thesis, this chapter is based on a co-joint research with my supervisor, Dr. Stephen Redding from the London School of Economics.

List of Tables

List of Figures

Certification of Co-joint Work

Chapter 3 "Factor Endowments and Production in European Regions" is based on a co-joint endeavor with my supervisor, Dr. Stephen Redding from the London School of Economics. In this regard, I was involved as a full co-author in the paper on which this chapter is based, including the formulation of theoretical hypotheses to be tested, the development of the empirical strategy, the construction of the dataset, the econometric estimation, and the interpretation of the empirical results. The joint research is published as a Centre for Economic Policy and Research discussion paper, no. 3755 (January 2003), London.

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A mis padres, Juan y Mercedes

Chapter 1

An Overview of the Thesis

1.1 Introduction

The global economy has integrated rapidly, driven by widespread general deregulation, the dismantling of barriers to trade and capital flows, vastly improved global communications. In some regions, integration has advanced at an even more rapid path; with Europe's economic and monetary union being perhaps the most impressive example.

Economic integration in Europe was institutionalized in 1957 with the creation of the European Economic Community (EEC). One of the critical elements on the process of integration was the creation of an internal market within the Community, aiming at the free movements of goods, labour, and capital. The creation of the internal free and competitive market had important implications for the location of economic activity in Europe. Regions have been able to realise benefits from comparative advantage, and industries have been able to locate to their benefits, exploiting economies of scale and benefiting from the decline in transport costs.

This thesis attempts to analyse developments and determinants of these production patterns in European regions. Moreover, it aims at examining macroeconomic effects of economic integration on trade and income. In so doing, the thesis contributes not only to a better understanding of the impact of economic integration in Europe, but also to draw lessons that could be useful for understanding and fostering similar processes of economic integration, both in developed and developing countries.

1.2 Historical Background: Steps towards European Integration

Post-war European economic integration started with the formation of the International Committee of the Movements for European Integration in 1947. Several delegates from 16 countries initiated a debate and supported the creation of an European assembly and an European court. The idea of some form of common market gathered strength by the mid-1950s. It culminated with the treaty of Rome in 1957, which envisaged the creation of the European Economic Community (EEC). The treaty was ratified by six European countries (Belgium, France, Luxembourg, Italy, Netherlands, and West Germany) in March 1958. The Treaty of Rome outlined the objectives of the new Community as follows, "*by establishing a Common Market and progressively approximating the economic policies of Member States,*" the EEC will "*promote throughout the Community a harmonious development of economic activities, a continuous and balanced expansion, and increase in stability, and accelerated raising of the standard of living, and closer relations between the States belonging to it*". The new organisation aimed to end economic restrictions such as price fixing, limiting production, dumping, and all elements of protective government aid (subsidies) so as to ensure free and fair competition. The EEC was also expected to coordinate economic and monetary policies and to help harmonise fiscal and social policies.

Broadly speaking, transformation into a common market was to evolve over 12 and 15 years. Movements towards a common market were somewhat limited until the 1992 program. Tariffs and trade restrictions were to be reduced only gradually, so as to allow the EEC to agree with the world organisation, General Agreement on Tariffs and Trade (GATT), the predecessor to the World Trade Organisation (WTO). During the first years of operation, there was good progress towards some of the economic goals. By 1961, internal tariff barriers had been substantially reduced, and quota restrictions on industrial products had been largely eliminated. Trade within the EEC expanded at a rate double that of trade with non-members, and the EEC became the world's largest trading power (Crafts abd Toniolo, 1996). A customs unions was declared operational in 1968, with a single external customs duty and the abolition of all internal tariffs. The common external tariff was based on an average of the existing duties levied by the member states at their national borders, though with some downward adjustment. The common agricultural policy (CAP) also started in 1968.

It was clear from the onset that the EEC was not a limited club, and other European countries soon expressed interest in EEC membership. Greece enjoyed associate status from July 1961 and became full member in 1981. The association helped to provide for a sequence of transitional adjustments of Greek tariffs to bring them into line with EEC standards, with the promise of full membership within 22 years. 1961 saw Ireland, Denmark, and the United Kingdom formally applying for EEC membership, followed by negotiations with Norway.[1] During the 1960s, France vetoed UK's application until 1969, when a summit agreed on the principles for enlargement. Discussions then re-opened with these countries and Norway. Treaties were signed in 1972, and after Norway rejected membership in a referendum, the other three countries joined in 1973.

Until 1969, the Community's development benefited from monetary stability as a pretext for policy coordination. However, turbulences in the international monetary system led to readjustments in some European currencies, forcing the EEC to introduce, among other things, the notion of green currencies in order to maintain a common price structure for the CAP. The project of economic and monetary union (EMU) corresponded with the desire to extend the customs union and was considered central to European development. Monetary union was the most fundamental policy required for a true economic community. In early 1971, three decisions were taken towards EMU: to increase the coordination of short-term policies, to improve coordination between central banks, and to develop a means of providing medium-term financial aid. But the plans were severely affected by the international climate, particularly the fall of the Bretton Woods system in 1973. Within the EEC, the first post-enlargement period culminated with the decision in 1978 to establish a European Monetary System with three major elements: the exchange rate mechanism (ERM), the European Currency Union (ECU), and the European Monetary Compensation Fund.

In the 1980s, the EEC approved the accession of three southern European countries. Greece signed the Treaty of Accession in May 1979 and entered in January 1981. Greece

[1] These countries, together with Austria, Portugal, Sweden, and Switzerland, were members of the European Free Trade Association (EFTA, 1960). EFTA's immediate economic aim was to work for the reduction and eventual elimination of tariffs on most industrial goods among its members. EFTA established an industrial free trade area in 1970. With the defection of three of its member countries, the remaining EFTA countries reconsidered their positions, and asked for special associate arrangements with the EEC.

would be granted a five-year transitional period, with two additional years for the elimination of tariffs on some agricultural products and for the full implementation of the free movement of labour. Spain and Portugal formally became members in January 1986 with similar transitional periods as Greece. Finally, Sweden, Austria, and Finland joined in January 1995, completing the EEC of the 15 countries that still exists nowadays.

Progress on monetary and economic union led to the Single European Act of 1987 aimed at eliminating all remaining barriers to trade within Europe and to establish a genuinely efficient and competitive single market by the end of 1992. The Maastricht Treaty (1992) laid down convergence conditions, established a European Monetary Institute in 1994 to precede the European Central Bank, and targeted 1999 as the start date for EMU. The new currency was called the euro, and was first used for interbank and other wholesale purposes with notes and coins following in January 2002. The objective of EMU was to secure a range of benefits, such as price transparency leading to more competition, a logical completion towards a single competitive market, savings in foreign currency transactions, and fostering more efficient capital markets.

Waiting to join the European Union (EU) in 2004, and some time later EMU, are 10 Eastern European countries: the Czech Republic, Cyprus, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Slovakia, and Slovenia.

1.3 Economic Integration and the Location of Industry

The European Union has chosen deeper economic integration as the path for an ever-closer union. This thesis studies the location of industry in Europe, investigates the roles of factor endowments and economic geography variables in determining the location of industry, and analyses the locational effects of integration economic, mainly whether further European integration will increase the incentives for regional specialisation of economic activity. The discussion in this section is based on Midelfart-Knarvik and Overman (2002).

Two relevant sources of potential gains from deeper EU integration in the location of industry can be identified. First, economic integration may lead to a more efficient allocation of resources. Integration may also promote the buildup of further resources (Baldwin, 1994). In order to analyse these first effects, determining industrial location, and how economic integration would have an effect on location, need to be taking into consideration. Two forces operate in defining the location of industry: (i) agglomeration (*centripetal*) forces, encouraging firms to concentrate geographically as firms exploit localized external economies of scale; and (ii) dispersion (*centrifugal*) forces, encouraging economic activity to spread out because of natural resources and other immobile factors of production. Both, agglomeration and dispersion forces may work within a certain industry and across industries.

Agglomeration and dispersion forces interact to determine the location of industry, and their strength will depend on the mobility of goods and factors of production. If factors are immobile, and there are barriers preventing trade, then production occurs locally, regardless of factor prices differentials or potential gains from agglomeration. Production will be located according to the spatial distribution of factors. On the other hand, if goods and/or factors of production are somewhat mobile, forces for dispersion and agglomeration come into play having both an effect on the location of industry. Furthermore, absolute mobility is important, particularly for agglomeration, but relative mobility may be more important. If labour and other factors of production are less mobile than goods and services, the initial geographical distribution of factors will serve as an anchor effectively preventing geographic concentration. Trade will induce geographic specialisation, possibly in the form of specialised industrial agglomerations, but no more. If, however, factors of production are more mobile than goods and services, overall geographic concentration cannot be ruled out.

Economic integration will affect the location of production through changes in good and factor mobility, changes in trade costs, and changes in market structures. However, these forces are not exogenous to the integration process, and their absolute and relative strength will be affected by integration. For example, if integration has a larger effect on trade costs than on mobility, the geographical distribution of factors will work as a force of dispersion (see Norman and Venables, 1995), providing a limitation to the extent of geographical industrial concentration that integration may promote. The incentives to agglomerate or disperse are probably also limited by the degree of market competition. Relocation of production may be more likely to occur only under high market competition. Competition and mobility in Europe has increased dramatically as the process of economic integration has progressed, for example, as the result of deregulation, liberalisation of capital movements, and integration of European markets. In this regard, integration of European product markets and deregulation of national markets break up traditional market structures. As national monopolies are dismantled, restriction are lifted, and trading opportunities arise, firm and market structures change rapidly through international networking and cross-border mergers and acquisitions which may transform national industries into European ones.

Following Norman (2000), various outcomes of closer integration can be established with respect to the location of economic activity as a function of the gains from agglomeration and improved factor mobility. The degrees of factor mobility may be classified as low factor mobility; low labour mobility but high firm and capital mobility; and finally, high mobility for all factors. Benefits from agglomeration can be defined according to its intensity in small; large but restricted to the industry level; and finally, large and across industries. As mentioned above, economic integration will have an effect on both the agglomeration forces and on factor mobility. Our discussion of how the different forces interact suggests three different scenarios for the future economic geography of Europe, depending on the mobility of factors of production, and on the strength of latent agglomeration forces.

- If factor endowments are immobile, economic integration would lead to industrial specialisation, and economic location will be defined by comparative advantage, irrespective of whether or not there are gains from agglomeration. There can be no reallocation of production under any circumstances.

- If all factors are mobile, then the extent of agglomeration would reflect the nature of linkages. When gains from agglomeration are small, we might still get specialisation. However, if linkages are strong within sectors, but weak between sectors, then concentration of specific industries would arise. If linkages are strong across sectors then we would expect one large agglomeration in the core region.

- When firms and capital are mobile but labour is relatively immobile, if there are modest gains from agglomeration, and these are stronger within industries than between industries, European integration will lead to increased competition and greater specialisation– both at the level of firms and industries. This will induce relocation of companies and to the formation of industrial agglomeration, but it will not lead to greater overall geographic concentration. By exploiting local comparative advantage and developing specialised industrial agglomerations, the regions of Europe will converge in terms of factor price equalisation, making geographic diversity robust. With strong linkages within sectors and large gains from agglomeration, we expect the same tendency towards industrial concentration as with mobile labour. However, some countries may see larger gains if particular industry concentration deliver greater returns than others. We would expect high-productivity industries to agglomerate, and because critical factors of production are mobile, there will be few counteracting forces preventing overall geographic concentration.. If firm linkages are strong across sectors, it is possible to observe overall geographical agglomeration of industrial activity.

1.4 Description of Thesis

This thesis aims at contributing to the understanding of the economic impact of European integration, with respect to both (i) the pattern of industrial specialisation in European regions and (ii) openness and income for member countries of the European Economic Community (EEC).

The second chapter analyses the evolution of economic activity in 45 European regions for the period 1975-95, comparing the pattern of specialisation at the country and regional levels. First, we assemble a series of summary statistics that give an overview of the patterns of specialisation at the country and regional levels. We study the dispersion in the patterns of specialisation by computing coefficients of variation at the industry level. Then, we explore the similarity of the patterns of specialisation across the manufacturing industries by computing pairwise correlations and bilateral differences with respect to the rest of Europe. Second, we investigate the nature of a country's changes in the degree of specialisation at the industry level. Through an accounting decomposition, we explore whether changes in specialisation at the country level are due to changes in regional specialisation or to changes in the relative importance of regions in the country's GDP. Third, the dynamics of the entire distribution of the pattern of specialisation is estimated using a statistical model of distribution dynamics. This enables us to explore the observed changes in the external shape of the distribution as well as mobility and persistence in the pattern of specialisation. We also test for cross-country and within-country differences in specialisation dynamics.

In the third chapter, we study patterns of production across 14 industries in 45 regions from seven European countries since 1975. This chapter examines the ability of the Heckscher-Ohlin (HO) model to explain production patterns at the regional level in Europe, using a newly constructed panel dataset on output in 14 industries and endowments of five factors of production for 45 NUTS-1 regions from seven European countries since 1975.[2] The use of regional data enables us to abstract from many of the reasons advanced for the poor performance of the HO model at the country-level. For example, both measurement error and technology differences are likely to be smaller across regions within Europe than for a cross-section of developed and developing countries. The ongoing process of economic integration within the European Union provides an interesting context within which to explore the relationship between production and factor endowments. We control for exogenous variation in relative prices induced by European integration and examine whether this process of integration has strengthened or weakened the relationship between production and factor endowments across regions within countries.

Chapter 4 then analyses the role of economic geography and factor endowments in explaining the patterns of specialisation for eight manufacturing industries from 1985-95. The analysis builds on a theoretical model that integrates both factor endowments and economic geography considerations. We consider a measure of specialisation derived from theory and consistent with the measure used in the previous chapter, the GDP share of industry j in region z. The model establishes a relationship between the share of an industry's value added in GDP, factor endowments and economic geography variables. The model estimated in Chapter 4 is broader than the one used in Chapter 3, as we explicitly analyse factor endowments, industry intensities, and economic geography factors in the location of production in European regions. We also control for exogenous variation induced by European integration and examine whether this process of integration has strengthened or weakened the relationship between production, factor endowments, and economic geography across regions.

Chapter 5 takes a more macroeconomic approach to investigate the impact of economic integration in Europe. The chapter analyses the impact of trade on income and income growth based on the predictions from endogenous growth models. Openness could have an effect on innovation and growth through improved knowledge spillovers, international competition, or enlargement of markets. We first explore whether economic integration, defined as membership to the EEC, has a permanent effect on openness, income, and income growth at the country level. Our analysis tries to link entry into the EEC to permanent

[2]NUTS stands for Nomenclature of Statistical Territorial Units. NUTS-1 regions are the first-tier of subnational geographical units for which Eurostat collects data on the EU member countries.

changes in the time series of these variables. We define a time interval related to the accession date and perform a sequential structural break test that endogenously defines the time of the break. While informative, a problem with the tests for structural breaks with univariate time-series is that there may be other time-series shocks which affect countries at the same time as their entry into the EEC. To help address this concern, we use EEC membership as an experiment to shed further light on its effect on openness, income, and income convergence in Europe by considering a differences-in-differences specification which controls for common time series shocks affecting both EEC members and non-members. In our specification, we use the timing of membership (pre- and post-accession) to identify the effects of trade liberalisation. We therefore explore for differential time-series cross-section effects as a result of EEC membership.

1.5 Results and Contributions

The primary motivation of this thesis is to understand the economic effects of European integration, with respect to both the pattern of industrial specialisation in European regions, and openness and income.

The descriptive analysis in the second chapter provides a panoramic view of patterns of specialisation at the country and regional levels. The chapter contributes to the existing literature in the following ways. The analysis suggests, first, that regional GDP shares vary markedly. Variation is higher across regions than across countries, indicating that regions are more specialised than countries. Second, there is evidence of some variation across regions, but no evidence of major changes in the industrial structure of countries and regions over the sample period. Pairwise correlations indicate that, in general, country's patterns of specialisation are becoming more dissimilar over time, with more heterogeneity in the degree of similarity of the patterns of specialisation at the regional level. Analysing specialisation relative to Europe, countries and regions show slight increasing specialisation in manufacturing industries.

An accounting decomposition indicates that changes in specialisation at the country level are mainly due to changes in specialisation at the regional level. There is no evidence of significant between-region changes, and the relative importance of regions seems to remain fairly constant over the sample period. The results show that *within-region* changes in specialisation are more important in accounting for changes in specialisation at the country level than changes in the shares of regions in a country's overall economic activity. Regions are changing their pattern of specialisation more than countries, as the *within-region* change is typically higher in value than the total change. Changes in regional shares of GDP do play a small role in explaining changes in specialisation at the country level for the disaggregated manufacturing industries.

Finally, there is no evidence of an increase in the overall degree of specialisation over time, but of significant mobility. Mobility suggests significant changes in the patterns of specialisation. In general, regions display higher mobility in their patterns of specialisation. Comparing the initial and the ergodic distribution, there is a general pattern of polarisation toward the three lowest quintiles of the distribution at the country and regional levels. We find evidence of within-country differences in the evolution of the patterns of specialisation. Out of 45 of the regions, 31 follow a dynamic process that is statistically significantly different from the one at the country level.

Chapters 3 and 4 analyse the determinants of specialisation. Chapter 3 considers solely the role of factor endowments in explaining the patterns of specialisation at the regional level in Europe. Our main empirical findings are as follows:

- First, the HO model provides an incomplete explanation of patterns of production across European regions and is rejected against more general neoclassical alternatives.
- Second, although the HO model is rejected, factor endowments remain statistically significant and quantitatively important in explaining production structure within different neoclassical alternatives. Individual factor endowments are highly statistically significant and including information on factor endowments reduces the model's within-sample average absolute prediction error by a factor of around three in Manufacturing.
- Third, the pattern of estimated coefficients on factor endowments across industries is generally consistent with economic priors regarding factor intensity. For example, physical capital endowments are positively correlated with the share of Manufacturing in GDP and negatively correlated with the shares of Agriculture and Services.
- Fourth, factor endowments are more successful in explaining patterns of production at the aggregate level in Agriculture, Manufacturing and Services (where we have

three industries and either three or five factor endowments) than in disaggregated manufacturing industries (where we have 11 industries and either three or five factor endowments). Within-sample average absolute prediction errors are typically far larger in the disaggregated manufacturing industries, and this is exactly as theory would predict. In the HO model with identical prices and technology and with no joint production, patterns of production are only determinate if there are at least as many factors of production as goods.

- Finally, we find no evidence that the process of increasing economic integration in Europe has weakened or strengthened the relationship between patterns of production and factor endowments across regions within countries.

As factor endowments alone were not very successful in explaining patterns of specialisation for the disaggregated manufacturing industries, Chapter 4 incorporates economic geography into the analysis of the determinants of specialisation in the manufacturing sector across European regions. The empirical findings yield the following conclusions.

- First, both factor endowments and economic geography are statistically significant in explaining specialisation patterns in manufacturing industries in European regions.

- Second, the estimation results are in line with economic priors. Other things being equal, regions with high education endowments would be more specialised in skill-intensive industries. Among the economic geography variables, the interaction of access to suppliers and intermediate intensity is statistically significant in explaining specialisation at the one percent level. Regions with good access to intermediate goods attract industries that are more intensive in intermediate goods. Cost linkages are more important than demand linkages.

- Third, our model performs well in explaining patterns of specialisation across European regions. The model's average prediction error across all disaggregated manufacturing industries, regions, and time is 13 percent, and ranges from 8 percent to 20 percent in individual manufacturing industries. Average prediction errors compare positively with those reported in Chapter 3, where the average prediction error for the same eight manufacturing industries was 58 percent from 1985-95.

- Finally, prediction errors remain stable over time, not only within countries, but also across industries in our sample.

Having found that economic integration has not changed the relationship between patterns of specialisation and its determinants over time, Chapter 5 uses a more macroeconomic approach to analyse the effects of EEC membership. The analysis is divided in two sections.

First, we investigate permanent effects of EEC membership. A sequential structural break analysis indicates that EEC membership improves openness within the EEC permanently. As there is no evidence of permanent effects on overall openness, it appears that EEC membership has a smaller effect on trade flows, and these effects could be obscured by changes in other variables, which is consistent with some trade diversion. The empirical evidence supports the existence of level effects on income, but not of scale effects on income growth nor of effects on income convergence as a result of economic integration. While informative, a problem with the tests for structural breaks with univariate time-series is that there may be other time-series shocks which affect countries at the same time as their entry into the EEC. To help address this concern, we use EEC membership as an experiment to shed further light on its effect on openness, income, and income convergence in Europe by considering a differences in differences specification which controls for common time series shocks affecting both EEC members and non-members.

In the second section of the chapter, we explore the differential effects of EEC membership with a difference-in-difference analysis. In contrast with the structural break analysis, the differences-in-differences analysis controls for common time-series shocks affecting members and non-members. When differencing out the common time-series effects and focusing on the differential effects of EEC membership across countries relative to non-members, openness among the EEC countries improved significantly as a result of new countries entering the EEC, in line with the results from the structural breaks. We also find level effects on income as a result of countries joining the EEC. GDP and per-capita GDP also improve significantly as countries joined the EEC. Finally, results also support the idea that joining the EEC improves the convergence process. The coefficient estimate associated to relative income reports the expected (negative) sign indicating a decrease in income dispersion relative to Germany, the leading economy, and it is statistically significant.

On the whole, this thesis makes a contribution to our understanding of the determinants of specialisation patterns at the regional level in Europe, as well as of the impact of economic integration on openness, income, and income growth. It also offers some ideas for future research.

Chapter 2

Industrial Specialisation in European Regions

2.1 Introduction

Interest in the location of production and economic activity has been revived, both in academic circles and among policymakers, especially since international trade theory has been combined with insights from industrial economics and economic geography. Contributing to this interest, a number of empirical studies on the location of economic activity have been developed in recent years.

Moreover, because of continued economic integration, trade theories predict increasing concentration of economic activity and higher industrial specialisation in countries/regions at least for a certain range of trade costs (Krugman and Venables, 1995). This integration has over time involved the removal of trade barriers, the reduction of non-tariff barriers through harmonising product standards, and the simplification of government formalities. Higher industrial specialisation may be the result of regions, either exploiting more efficiently their comparative advantage, their economies of scale in production, or taking advantage of commercial linkages. In the neoclassical model, factor endowments and factor intensities determine the structure of international trade, as countries/regions specialise according to their relative comparative advantage. This is due to the assumption of immobility of factors across countries. New trade theories show that each country/region would produce less product varieties within an industry so as to take advantage of increasing returns to scale

(Krugman, 1981 and Ethier, 1984).[1] Regional specialisation would also arise as firms take advantage of increasing returns to scale (Krugman, 1991b).

In models of economic geography, industrial concentration arises from backward and forward linkages. These linkages stem from a combination of increasing returns to scale, trade costs and the fact that industries are linked via their input-output structures (see Fujita et al., 1999). Under a certain range of trade costs, economic linkages among industries yield to a non-monotonous relationship between the location of economic activity and trade costs (Krugman and Venables, 1990 and Venables, 1996). Forslid et al. (2002) simulate the effects of gradual economic integration on the location of industrial production. Industries with large-scale elasticities display a non-monotonous relationship between trade liberalisation and concentration, with maximum concentration of industries for intermediate trade costs. Industries driven by comparative advantage become monotonously more concentrated as trade costs fall. On the aggregate level, their results reveal an (inverted) U-shaped relation between trade costs and concentration.

However, counteracting forces for the dispersion of economic activity are also present, such as factor immobility, congestion externalities, and the intrinsic diversity of demand preferences. Demand considerations could result in firms being located somehow in proportion to demand, working against the agglomeration of economic activity.[2] Factor-market competition may well lead to a higher relative price of factors if industries located in one country/region, an element which works also against agglomeration. Moreover, changes in specialisation may not necessarily be observed if economic integration encourages intra-industry trade rather than inter-industry trade. In general, increase in industrial specialisation would depend on whether, as trade costs fall, forces of agglomeration would increase or decrease relative to forces for dispersion.[3]

This chapter analyses the evolution of specialisation in Europe at the country and regional

[1] The impact of an increase in specialisation in this case might not be observable at high levels of aggregation of data. As explained later, this paper considers two levels of aggregation, the sectoral level and individual manufacturing industries.

[2] Models of economic geography however exhibit a "home-market effect" or "magnification effect" where increases in demand lead to more than proportionate increases in production, and therefore more concentration of economic activity in locations with higher demand.

[3] Measurement issues may also hinder the analysis on changes in specialisation and agglomeration. In this sense, the definition of locational units (regions) and of industrial aggregation may not necessarily capture the change in specialisation predicted by trade theories. Recent literature has analysed the location of production using microgeographic data (see next section for a description of these studies).

level. The study has implications regarding the likelihood of asymmetric shocks in Europe, especially within the framework of a monetary union. The effect of shocks depends on the nature of the shock, how different the shock is across country/region, the production structure in each country/region, and the degree of similarity of the pattern of specialisation across regions. Higher specialisation will increase the vulnerability of countries/regions to asymmetric shocks. Midelfart-Knarvik et al. (2003) finds evidence of modest increases in specialisation across European Union countries, as the results of increasing product market integration. This may somehow explain results from other studies[4] showing that, although convergence is occurring at the country level in Europe, regional incomes are diverging over time. Analysing patterns of specialisation at the regional level may help to understand this divergence. The monetary union is likely to lead to further increases in trade volumes among the EU members and hence in specialisation as firms take advantage of comparative advantage and clustering. There may also be major implications for regional policies, as new mechanisms may need to be put in place to lessen the impact of these shocks.

With all these ideas as motivation, this chapter reveals the key facts related to patterns of specialisation in seven European countries and regions over the 20-year period from 1975-95, combining the rich variation existing at the country and regional levels. The choice of countries is dictated by availability of the data. We use a theory-consistent measure of specialisation derived from the Neoclassical theory of trade —the GDP share of an industry in a country/region at a point in time. Trade theory yields implications for the distribution of GDP shares across industries (localisation) and regions (specialisation). In this chapter, both dimensions are examined, and therefore we will make statements about specialisation of a particular geographical unit (region), as well as about localisation of a particular economic activity (industry).[5] In particular, the following questions will be addressed: Are regions more (less) specialised than countries? Is regional specialisation evolving as a reflection of the country-level specialisation? How are specialisation patterns evolving over time at the country and regional levels? How concentrated are industries in regions relative to countries? By itself, the analysis does not lead to policy implications, as no analysis on the economic determinants behind the patterns of specialisation (or of market failures) are considered in

[4]See, for example, Rodriguez-Pose (1999), Magrini (1999), Puga (2001), and Giannetti (2002).

[5]For a more detailed discussion about specialisation versus localisation, see Haaland et al. (1999) and Overman et al. (2001).

this chapter.

Thus, the chapter focuses on three major issues. First, we describe the degree of regional specialisation in Europe using our measure of specialisation derived from the neoclassical model. We analyse whether regions are becoming more similar over time by using a series of summary statistics and taking into account the cross-section variation and the evolution over time of the pattern of specialisation. The analysis also addresses the localisation of industries, as the degree of concentration of economic activity at the industry level is also studied. Second, we discern how much of these changes in specialisation at the country level can be explained by changes in the regional pattern of specialisation (*within-region effect*) and by changes in the relative importance of regions within each country (*between-region effect*).

Finally, we analyse the dynamics of the pattern of specialisation in EU regions within manufacturing industries. In contrast with the summary statistics analysis, using distribution dynamics has the advantage of evaluating the evolution of the entire distribution of GDP shares in a country/region across industries. As countries or regions increasingly specialise in one set of industries and reduce specialisation in others, an increase in specialisation over time will be reflected in a polarization of the distribution of GDP towards extreme values. In the extreme, a bimodal distribution will emerge, and countries/regions will display increasing specialisation over time. Furthermore, the analysis also addresses issues of intra-distribution dynamics, such as the mobility and persistence in the pattern of specialisation.

The analysis is undertaken at two different levels of activity. First, we consider the aggregate sectors of the economy (Agriculture, Manufacturing and Services). We then concentrate the analysis to the evolution of specialisation within the manufacturing sector for which we have eleven industries.

The rest of the chapter is structured as follows. In Section 2, we place the study within the existing literature. In Section 3, we derive our theory-consistent measure of specialisation, which is the GDP share of industry j. Section 4 briefly describes the statistical model of distribution dynamics. Section 5 describes the data and the sample. Section 6 presents the summary statistics analysis with respect to the degree of specialisation across industries at the country and regional levels. Section 7 studies the nature of the changes in specialisation at the country level using an accounting decomposition. Section 8 presents the analysis of the distribution dynamics and the degree of mobility and persistence in specialisation dynamics.

Finally, Section 9 concludes the analysis.

2.2 Related Literature

This chapter relates closely to a number of descriptive studies on the evolution of specialisation and localisation in Europe. Combes and Overman (2003) review extensively this literature. Some stylised facts are listed in their study: (i) despite increasing disparities, they can identify a group of countries with similar production structures; (ii) European regions show a much more diverse pattern than countries with small changes in specialisation; and (iii) the extent of industrial concentration varies widely by industry.

Most studies conclude that countries have become increasingly specialised since the mid-1980s as economic integration proceeded, although on average, these increases are small.[6] Molle (1997) computes differences in production structure with Krugman indices for 96 European regions from 1950 to 1990, and identifies 3 groups of regions. The majority of regions report decreasing specialisation; a smaller group reports a small rise at the beginning of the sample, with decreasing specialisation thereafter. Finally, one group of regions reports no change in specialisation. Brülhart (1998), computing rank correlations between Gini indices of spatial concentration, finds evidence of increased localisation in E.U. industry in the 1980s. Amiti (1999) computes Gini indices of both employment and production to find increasing geographical concentration for 65 manufacturing industries in five European countries between 1976 and 1989. Haaland et al. (1999) find significant differences across industries regarding the extent to which they are geographically concentrated during the period 1985-92 in Europe, although most industries have become increasingly concentrated. Hallet (2000) finds that, between 1980 and 1995, only 34 out of 119 regions in Europe became more specialised, while the rest became less specialised. Midelfart-Knarvik et al. (2000a), using data on gross production for country members of the EU, also find increasing specialisation at the country level from the mid-1980s onwards, although the changes are not particularly large. Computing bilateral differences by using Krugman indices, Midelfart-Knarvik et al. (2000a) show that countries are also becoming more dissimilar to one another in their production structures. Industrial localisation experiences are diverse with some

[6] For studies on the U.S., see Kim (1995).

industries localising and others dispersing. Midelfart-Knarvik and Overman (2002) find a more mixed picture at the regional level, with 53 percent of the regions becoming more specialised.

A number of these papers extend these descriptive exercises further by constructing measures of industry characteristics and running regressions of localisation coefficients on these characteristics. The studies find support for the new trade theories and economic geography models. Brülhart (1998) finds that industries characterised by strong internal scale economies are localised at the E.U. core, while labour-intensive industries are found to be dispersed. Amiti (1999) finds evidence that increasing geographical concentration is linked to industries characterised by high-scale economies and large levels of intermediate goods in production. Haaland et al. (1999) shows that concentration on the demand side is the most important factor for relative and absolute concentration of activity.

These empirical exercises, while informative, are only loosely linked to theory. A vast theoretical literature emphasises the important role of factor accumulation as a determinant of the evolution of specialisation (see, for example, Findlay, 1970, Deardoff, 1974, Eaton 1987, and Davis and Reeve, 1997). An extensive empirical literature investigates the economic forces driving specialisation and the location of economic activity. At the international level, David and Weinstein (1999, 2001) identify home market effects in manufacturing industries for OECD countries. Middlefart-Knarvik et al. (2000b) estimate a model showing that economic geography and comparative advantage are joint determinants for the location of industry in Europe at the country level. At the regional level, Redding and Vera-Martin (2003) analyse the role of factor endowments in the pattern of production in Europe, finding a statistically significant relationship between factor endowments and specialisation. Chapter 3 builds on this joint work and analyses the role of factor endowments in explaining the pattern of specialisation in European regions. Although factor endowments explain a sizable proportion of the variation in patterns of specialisation, there remains substantial unexplained variation, especially for the disaggregated industries within manufacturing, suggesting a role for other considerations such as those emphasised in the new economic geography literature. Chapter 4 of this thesis extends the analysis of Chapter 3 by incorporating considerations of economic geography, alongside those of factor endowments and factor intensities to explain the pattern of specialisation within manufacturing industries in European regions.

Over time, countries may reverse or reinforce their specialisation patterns, depending on how they accumulate factor endowments. On a theoretical level, Grossman and Helpman (1991a) show that both international knowledge spillovers and cross-country differences in the productivity of R&D or rates of learning by doing provide reasons why initial patterns of specialisation may be reversed over time. In the absence of international knowledge spillover effects, models of endogenous investments in R&D predict that initial patterns of specialisation will become locked-in over time (Grossman and Helpman, 1991a, chapter 7, Krugman, 1987). Redding (2002) estimates specialisation dynamics for seven OECD countries since 1970. The analysis finds no evidence of increasing specialisation at the country level, but of substantial mobility within the patterns of specialisation. Over five-year periods, mobility can be explained by common forces across countries; while changes in factor endowments become more important for longer horizon periods.

Finally, a recent literature on the location of production has used micro-geographic data. Ellison and Glaeser (1997) define a measure of localisation relative to the industry activity as a whole and relative to a random location of the industry's plants. When computing this index for 459 industries across all 50 U.S. states in 1987, 446 out of the 459 industries are more localised compared to a random allocation of activity, although many are only slightly localised. They also find evidence of concentration across different industries (co-agglomeration) within both 3 and two digits. Co-agglomeration is more intensive in industries with strong forward and backward linkages. Following a similar approach, Dereveux et al. (1999) and Maurel and Sedillot (1999) analyse the geographic distribution of production activity in the United Kingdom and in France, respectively. The studies find a significant degree of geographic concentration in some industries, with evidence of interdependence of firm's location choice and of highly localised industries. Concentration is explained by factor proximity, persistence in the location of activity, or knowledge spillovers. Duranton and Overman (2002) extend Ellison and Glaeser's study by defining distance-based tests of industrial localisation. Their approach permits assessing the statistical significance of departures from randomness. Using data for four-digit industries for the U.K., localisation occurs in 51 percent industries at the 5 percent confidence interval, mostly at scales below 50 kilometres with a very skewed distribution.

This chapter analyses the evolution of specialisation in Europe. It informs the subsequent analysis of econometric determinants of regional specialisation in Chapters 3 and 4. The chapter contributes to the existing literature in the following main ways. First, it combines country and regional-level data to provide a detailed analysis of the evolution of patterns of specialisation in European countries. We analyse the extent to which regions within a country are similar to one another and similar to the country's overall pattern of specialisation, using the rich regional variation underlying observed country-level patterns of specialisation. Second, in contrast with many existing studies, we use a theory-consistent measure derived directly from the neoclassical trade theory. Third, an important feature of the analysis is that the country/region's pattern of specialisation is thought of as a distribution across different sectors. In addition to some summary statistics, the dynamics of the entire distribution of the pattern of specialisation is estimated using a statistical model of distribution dynamics. This enables us to explore the observed changes in the external shape of the distribution as well as mobility and persistence in the degree of specialisation.

2.3 A Measure of Specialisation from the Neoclassical Theory

We consider the neoclassical model as expounded by Dixit and Norman (1980) and Woodland (1982). Regions are indexed by $z \in \{1, ..., Z\}$, goods by $j \in \{1, ..., N\}$ and factors of production by $i \in \{1, ..., M\}$. Time is indexed by t. Denote the vector of factors of production in region z at time t by v_{zt}. Production of each good occurs under conditions of perfect competition and constant returns to scale. The neoclassical model allows for regional differences in factor endowments as well as region-industry differences in technology and relative prices.

General equilibrium in production may be represented using the revenue function $r_z(p_{zt}, v_{zt})$, where p_{zt} denotes a region's vector of relative prices and v_{zt} is its vector of factor endowments. Under the assumption that the revenue function is twice continuously differentiable, we obtain determinate predictions for a region's vector of profit-maximizing net outputs $y_z(p_{zt}, v_{zt})$ which equals the gradient of $r_z(p_{zt}, v_{zt})$ with respect to p_{zt}. The revenue function will be twice continuously differentiable if there are at least as many factors as goods $(M \geq N)$. In the HO model where relative prices and technology are identical, production levels may still be determinant when $N > M$ if there is joint production. More generally, differences in technology and relative prices may also yield defined production patterns when $N > M$.[7] We allow for Hicks-neutral region-industry-time technology differences so that the production technology takes the form $y_{zjt} = \theta_{zjt} F_j(v_{zjt})$, where θ_{zjt} parameterizes technology or productivity in industry j of region z at time t.[8] In this case, the revenue function takes the form $r_z(p_{zt}, v_{zt}) = r_z(\theta_{zt} p_{zt}, v_{zt})$, where θ_{zt} is an $N \times N$ diagonal matrix of the technology parameters θ_{zjt}.[9] Changes in technology in industry j of region z have analogous effects on revenue to changes in industry j prices.

We follow Harrigan (1997) and Kohli (1991) in assuming a translog revenue function. This flexible functional form provides an arbitrarily close local approximation to the true underlying revenue function:

$$\begin{aligned} \ln r(\theta_{zt} p_{zt}, v_{zt}) = \beta_{00} + \textstyle\sum_j \beta_{0j} \ln \theta_{zjt} p_{zjt} + \frac{1}{2} \sum_j \sum_k \beta_{jk} \ln(\theta_{zjt} p_{zjt}) \ln(\theta_{zkt} p_{zkt}) \\ + \textstyle\sum_i \delta_{0i} \ln v_{zit} + \frac{1}{2} \sum_i \sum_h \delta_{ih} \ln v_{zit} \ln v_{zht} \qquad (2.1) \\ + \textstyle\sum_j \sum_i \gamma_{ji} \ln(\theta_{zjt} p_{zjt}) \ln(v_{zit}), \end{aligned}$$

where $j, k \in \{1, .., N\}$ index goods and $i, h \in \{1, .., M\}$ index factors. Under symmetry of the cross effects, the following equalities apply:

$$\beta_{jk} = \beta_{kj} \qquad \textit{and} \qquad \delta_{ih} = \delta_{hi} \qquad \forall j, k, i, h. \tag{2.2}$$

Linear homogeneity of degree 1 in v and p requires,

$$\sum_j \beta_{0j} = 1, \qquad \sum_i \delta_{0i} = 1, \qquad \sum_j \beta_{jk} = 0, \qquad \sum_i \delta_{ih} = 0, \qquad \sum_i \gamma_{ji} = 0. \tag{2.3}$$

[7] Chapter 3 of this thesis addresses the potential for production indeterminancy in the neoclassical model in more detail.

[8] The technology differences may vary across industries but are Hicks-neutral in the sense that they raise the productivity of all factors of production in industry j of region z by the same proportion. It is also possible to examine factor augmenting technology differences, as discussed further in Dixit and Norman (1980).

[9] See Dixit and Norman (1980), pages 137-9.

Differentiating the revenue function with respect to the price of good j, we obtain,

$$s_{zjt} \equiv \frac{p_{zjt}y_{zjt}(p_{zt}, v_{zt})}{r\left(p_{zt}, v_{zt}\right)} = \beta_{0j} + \sum_k \beta_{jk} \ln p_{zkt} + \sum_i \gamma_{ji} \ln v_{zit}, \tag{2.4}$$

Thus, a sector's share of a region's GDP, s_{zjt}, provides a natural and theory-consistent measure of specialisation in a particular industry. Equation (2.4) constitutes a general equilibrium relationship between the share of a sector in GDP, relative prices, and factor endowments that must hold under the assumptions of the neoclassical model.

This is the measure of specialisation used in our analysis, which is divided into three sections. First, we analyse the degree of specialisation across countries and regions within industries, and across industries within countries and regions using a series of summary statistics. Second, we investigate the nature of a country's changes in the degree of specialisation at the industry level. Through an accounting decomposition, we explore whether changes in specialisation at the country level are due to changes in regional specialisation or to changes in the relative importance of regions in the country's GDP. Finally, we analyse specialisation dynamics by considering the entire distribution of GDP shares across manufacturing industries. Results are reported through Section 1.5 and Section 1.7. We outline the empirical model of specialisation dynamics in the next section.

2.4 Empirical Modelling of Specialisation Dynamics

This section introduces the model of distribution dynamics. We employ a statistical model of distribution dynamics that has been widely used in the cross-country growth literature (Quah, 1993, 1996a, 1996b). Proudman and Redding (1998, 2000) and Redding (2002) employ distribution dynamics to analyse the evolution of international patterns of specialisation at the country level.

Conceptually, a region's pattern of specialisation corresponds to a distribution across sectors of GDP shares (our measure of specialisation). On the basis of this distribution, we can define a probability measure λ_{rt}, describing the probability density function for the GDP shares across industries j in region r at time t. In Figure 2.1, we show this density function for a region in which most GDP shares concentrate at intermediate values and there are few industries with very small/high values.

<**Figure 1.1 about here**>

In order to study the dynamic process, the evolution of the cross-section distribution is modeled as a stochastic process of order one:

$$\lambda_{rt} = M_r^* \left(\lambda_{r(t-1)}, u_t\right), \qquad \text{interger } t \tag{2.5}$$

where M_r^* is an operator mapping disturbances (u_t) and probability measures, into probability measures. Assuming that the mapping is time invariant and including the disturbance into the operator definition, we have:

$$\begin{aligned} \lambda_{rt} &= M_r^* \left(\lambda_{r(t-1)}\right) = M_r^* \left(M_r^* \left(\lambda_{r(t-2)}\right)\right) \\ &= M_r^* \left(M_r^* \left(M_r^* ... \left(M_r^* \left(\lambda_{rt-\tau}\right)\right)\right)\right) = \left(M_r^*\right)^{\tau} \lambda_{rt}. \end{aligned} \tag{2.6}$$

Dividing the space of possible values for GDP shares into a number of discrete cells N, the operator becomes a transition probability matrix,

$$\lambda_{r(t+1)} = M_r^* . \lambda_{rt} \qquad M_r^* \equiv \begin{bmatrix} m_r^{11} & m_r^{12} & \cdots & m_r^{1N} \\ m_r^{21} & m_r^{22} & \cdots & m_r^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ m_r^{N1} & m_r^{N2} & \cdots & m_r^{NN} \end{bmatrix} \tag{2.7}$$

The transition probability matrix gives information about the degree of mobility and persistence in patterns of specialisation. High values of the diagonal elements imply a high probability of staying in the same grid cell, and therefore, high persistence. High values in the off-diagonal elements of the matrix imply a high probability of moving to another cell, and hence, higher mobility in the pattern of specialisation.

In order to make the information encoded in the transition probability matrix more accessible to comparison, we compute two different indices of mobility. The first of the indices (M_1, following Shorrocks, 1978, and Quah, 1996c) evaluates the trace, *tr*, of the transition probability matrix. The second follows Shorrocks (1978) and Geweke et al. (1986) and evaluates the determinant, *det*, of the transition probability matrix,

$$M_1 = \frac{n - tr\left[M_r^*\right]}{N-1}, \qquad M_2 = 1 - \left|\det(M_r^*)\right| \tag{2.8}$$

In addition, we also study the ergodic or stationary distribution by taking the limit $\pi \to \infty$.[10] The ergodic distribution is the limiting distribution to which the dynamic process evolves. It gives information about the external shape of the distribution of the GDP shares. By computation, it is the eigenvector associated with the highest eigenvalue of the transition probability matrix. Two different scenarios could arise: Figure 2.2 shows the case in which the distribution evolves towards a distribution with increasing specialisation, since there is a bimodal concentration of the values of the GDP shares. In Figure 2.3, we observe higher concentration of GDP shares in the centre of the distribution over time, and therefore, a decrease in the degree of specialisation.

<Figures 2.2-2.3 about here>

Finally, using results from Anderson and Goodman (1957), we perform hypothesis testing on the estimated transition probabilities. The null hypothesis is $p^{nl} = q^{nl}$, where p^{nl} refers to the estimated transition probabilities, and q^{nl} are the probabilities of transition under the (known) null. The transition probabilities for each state n have an asymptotic distribution χ^2,

$$\sum_{l=1}^{N} I^n . \frac{(p^{nl} - q^{nl})^2}{q^{nl}} \sim \chi^2 (N-1) \qquad I^n \equiv \sum_{t=0}^{T-1} I^n (t) \tag{2.9}$$

where $I^n(t)$ denotes the number of industries in cell n at time t. This test statistic holds for each state $n = 1, ...N$. Since the transition probabilities are independently distributed across states, we may sum over states, and the resulting test statistic is asymptotically distributed $\chi^2 (N (N-1))$.

2.5 Data Description

The main source of data is the Regio dataset compiled by the European Statistics Office (Eurostat). We analyse patterns of production across 14 industries in 45 NUTS-1 regions

[10] Our analysis here is robust to the arguments presented in Kremer, et al. (2001) about estimation of transition probability matrices and ergodic distributions. We estimate transition probabilities over five-year intervals rather than annual intervals, and compare the ergodic distribution with those implied by the initial distribution.

from seven European countries since 1975.[11] The choice of countries reflects the availability of data, and includes Belgium, France, Italy, Luxembourg, Netherlands, Spain, and the United Kingdom.[12] This chapter, therefore, characterises patterns of specialisation across regions of the seven countries since 1975. As it will be shown below, this is a group of countries among which there is substantial heterogeneity in patterns of production. The sample includes several countries close to the "core" of Europe (e.g. Belgium and France) and others located further towards the "periphery" (e.g. Italy and Spain).

The number and size of NUTS-1 regions varies across European countries. In some European countries, such as Italy, the NUTS-1 regions correspond to the main regional political units. In the U.K., they comprise geographical areas such as the North, Southeast, and Southwest. A full list of NUTS-1 regions in each country is given in Appendix 2.A. We show below that there is also substantial variation in specialisation across NUTS-1 regions within a country, for example, from the North of Italy to Sicily.

Patterns of production are analysed at two alternative levels of aggregation. First, we consider the three aggregate (one-digit) industries: Agriculture, Manufacturing, and Services. Second, we exploit more disaggregated information on individual industries within Manufacturing. These are mainly two-digit industries, and include, for example, Textiles/Clothing and Chemicals. Again, full details are given in Appendix 2.A.

The Regio dataset provides information on industry value-added and GDP by region, from which we compute the share of each sector in GDP. The length of the time-series available varies with the level of industrial aggregation. In order to exploit all of the information available, we consider two samples. First, at the level of the three aggregate industries, we have an unbalanced panel of approximately 811 observations per industry on the 45 regions during the period 1975-95 (Sample A). Second, for the disaggregated manufacturing industries, we have an unbalanced panel per industry from approximately 1980 onwards (Sample B). Full details of the composition of each sample are given in Appendix 2.A.

[11] NUTS stands for Nomenclature of Statistical Territorial Units. NUTS-1 regions are the first-tier of subnational geographical units for which Eurostat collects data on the E.U. member countries. See Appendix 2.A for more details concerning the data used.

[12] Data for other European countries are very incomplete. Where information is available, it is for a very short time period. Data constraints are not such an issue when estimating the neoclassical model in Chapter 3. However, it becomes more relevant when introducing issues of economic geography in the analysis (as in Chapter 4). We incorporate additional information from the rest of Europe which is available at the aggregate (regional) level in the econometric estimation of Chapter 4.

Table 2.1 presents information on the share of the 3 aggregate industries in each region's GDP in 1975, 1985, and 1995. We find substantial variation in patterns of production across regions at any one point in time, even at the level of the 3 aggregate industries. For example, the share of Agriculture in GDP in 1985 varies from 0.03 percent in Be1 (Brussels) to 11.86 percent in Esp4 (Centre), while the share of Services in GDP in 1985 varies from 81.61 percent in Be1 (Brussels) to 49.57 percent in Esp2 (North East). There are also marked changes in patterns of specialisation over time. The share of Agriculture in GDP in Esp4 (Centre) falls from 14.72 percent in 1980 to 5.39 percent in 1995, while the share of Services in GDP in Fra3 (Nord-Pas-de-Calais) rises from 46.68 percent in 1975 to 67.00 percent in 1995.

<Table 2.1 about here>

Table 2.2 displays the evolution of the shares of the disaggregated manufacturing industries in GDP. For brevity, only the data for France and Spain are reported. Again, we observe substantial variation in patterns of production across regions at any one point in time. This is true both within and between countries. For example, the share of Metal Products and Machinery (Machine) in GDP in Fra7 (Centre-East) in 1985 is almost three times larger than that in Fra8 (Mediterranean) and almost six times larger than that in Esp6 (South). There are also changes in production patterns over time. The share of Chemicals in GDP in Esp6 (South) falls by 45 percent between 1980 and 1994, while the share of Paper in Fra3 (Nord-Pas-de-Calais) rises by 24 percent over the same period.

<Table 2.2 about here>

2.6 Localisation and Specialisation in Europe: Some Summary Statistics

We analyse first localisation in Europe by studying the distribution of GDP shares across countries/regions for each industry. The analysis is done at two levels: for the sectoral level (Agriculture, Manufacturing, and Services) and for eleven manufacturing industries. Then, the pattern of specialisation of countries/regions is considered by analyzing the distribution of the GDP shares across industries for each of the geographical unit. In both cases, we do so by computing a number of summary statistics used in the literature. We first examine the variation in GDP shares across regions for each industry. The higher the variation is, the more the industry would differ in its location distribution, and the more localised it will be. We then explore the similarity in specialisation of geographical units by computing pairwise correlations of GDP shares across all manufacturing industries at different points in time. An increase in the correlation over time would imply that countries/regions are becoming more similar to one another in their production structure. We also evaluate differences in production structures by computing the Krugman indices across countries/regions. The index compares the specialisation of a country/region to a defined benchmark. An increase in the index would imply that countries/regions are becoming more specialised.

2.6.1 Industry Localisation in Europe

We analyse the variation in GDP shares for a particular industry across countries, across regions, and across regions within a country. Specialisation would be reflected in high variation. An increase in variation over time would imply that regions or countries are becoming more dissimilar in their production mix. Countries and regions would then be more vulnerable to the occurrence of asymmetric shocks.

We compute the coefficient of variation for four different years (1980, 1985, 1990, and 1995) across countries, across all regions, and across regions within a country. The coefficient of variation is a measure of dispersion, where the standard variation is normalised by the mean to take account for different means of the GDP shares by industry. We also compute the relative coefficient of variation, defined as the ratio of the coefficient of variation for an individual industry to its average value across sectors/industries at a point in time. The relative coefficient of variation yields information about the degree of dispersion in an industry across the different geographical units relative to the average dispersion across all industries.[13]

Industries are more localised at the regional level. The coefficient of variation reports higher dispersion at the regional level than at the country level (Table 2.3). At the sectoral level, manufacturing is becoming more localised (higher variation) while Agriculture and Services show decreasing variation both at the country and regional levels. Variation in

[13]In this part of the analysis, we drop the United Kingdom from our sample and begin in 1980 so that we have a balanced panel of observations across regions and over time. We do not report tables for the relative coefficient of variation for brevity.

manufacturing is increasing in all regions within each country, except for the Dutch regions. Production structures across regions in a country are becoming more distinct.

<Table 2.3 about here>

Within the manufacturing industries, industries are more localised at the regional level (Tables 2.4-2.6). The coefficient of variation is higher at the regional level than at the country level for each of the manufacturing industries. Within countries, we observe differences across industries. In the categories of Machine and Other, the industry is more localised across regions within a country than across countries. For other industries, variation differs depending on the country and the industry considered. There are also marked differences in localisation when considering regions within a country. For example, Food is more localised across regions in France than across countries; while it is less localised across Spanish, Dutch or Belgian regions. Over time, industries show different paths in the evolution of dispersion. The Transport industry shows increasing localisation at the country and regional levels in general, but it is becoming less localised in regions within Belgium, Italy, and the Netherlands.

<Table 2.4-2.6 about here>

The analysis of the relative coefficient of variation yields similar conclusions. Industries are more localised at the regional level than at the country level, with marked differences in localisation across regions within a country. Manufacturing is becoming more localised, although at a slow pace. Services is the least concentrated sector relative to the overall dispersion across industries, and its variation is decreasing over time. Across manufacturing industries, Fuel, Metal, Transports, and Textile are the more localised industries both at the country and regional levels.

2.6.2 Specialisation across Europe

In this section, we analyse the similarities of the pattern of specialisation in manufacturing industries across countries and regions in Europe, by computing first the correlation of the whole cross-section distribution of shares across two countries/regions at a point in time. Then, we compute the Krugman index, that compares the pattern of specialisation of a country/region with respect to a benchmark. Our results show evidence of higher diversity in specialisation at the regional level, as the correlations across regions are lower than across countries. The Krugman indices indicate increasing specialisation over time in manufacturing industries.

Correlations in the Patterns of Specialisation

We examine pairwise correlations of the GDP shares across the manufacturing industries among countries/regions. At the country level, Belgium, Spain, France and Italy have become more dissimilar pairwise over time, while Luxembourg, Netherlands and the U.K. report increasing correlation (Table 2.7). Luxembourg displays a pattern of specialisation in the manufacturing industries that is extremely diverse with respect to the rest of the European countries, although becoming more similar over time to the rest of the countries. Despite Belgium and Spain being the most similar countries in 1980 and in 1995, countries have changed their degree of similarity over time.[14]

<Table 2.7 about here>

At the regional level, Tables 2.8A-F display the correlation of the pattern of specialisation at the regional level within each country, and that of each region with its country's patterns of specialisation. The correlations indicate higher heterogeneity in the degree of similarity in specialisation. Within a country, pairwise correlations across regions differ significantly. For example, in Italy, the correlation between regions *ita1 (Northwest)* and *it2 (Lombardia)* is 0.86 in 1980 while between regions *it1 (Northwest)* and *ita (Sicily)* it is only 0.16, pointing to substantial north-south differences in specialisation. Over time, there are also significant changes in the degree of correlation. In Belgium, correlations in 1995 are all lower than in 1980, indicating that regions are somewhat diverging in their specialisation pattern. In Spain, we can however observe that all regions have increased their correlation coefficients, specifically after its EU membership (1986). For instance, the correlation doubled between regions *esp1 (Northwest)* and *esp5 (East)* in the period 1985-90. In other countries, the evolution of the correlation is not so homogenous across regions. In France, the correlation

[14]The high correlation between Belgium and Spain in their manufacturing structures is contradictory with other results in the literature. However, similar results were found when we sequentially excluded each industry from the sample and when we considered different years to the ones reported here. Further analysis leads to the following conclusions: (i) that the countries have very similar average GDP share for the manufacturing sector as a whole, over the sample period (0.32 for Belgium and 0.35 for Spain), (ii) that the countries display very similar pattern of specialisation across the two-digit industries, (iii) that the GDP shares of Fuel (FP), Chemicals (CHE), Transport (TRP), and Building (BUI) do not display significant correlation over time, while the rest of the industries display very high and significant correlation, (iv) that the evolution of the GDP shares at the two-digit industries is very similar at the country and regional levels.

between *fra1 (Ile-de-France)* and *fra8 (Mediterranean)* has been increasing during the sample period as the result of a transition away from industrialisation and towards Services. These regions report significant increases in Services over the sample period, and they are the most specialised regions in Services in France. Regions *fra3 (North-Pas-de-Calais)* and *fra4 (East)* display decreasing correlations: *fra3* is becoming less specialised (a more flat profile of GDP shares in manufacturing industries), while *fra4* is more specialised in Machine and Transports. The country showing the largest cross-region differences is Italy. *It3 (Northeast)* is the region with a production structure most similar to other Italian regions, while *it5 (Centre)* is a very distinct region, sharing significant similarities only with one other region (*it1, Northwest*).

Correlations in specialisation between a country and its regions are very high for most of the regions (ranging from 60 to 98 percent when statistically significant). However, we observe substantial differences in their evolution over time. In France, for example, *fra3* correlation with the country's pattern drops from 84 percent to 67 percent, while *fra8* increases it from 75 percent to 82 percent. Only 7 out of 45 regions show statistically significant differences in the pattern of specialisation: *esp2 (Northeast)* in Spain (1980), *ita (Sicily)* and *itb (Sardinia)* in Italy in all years, *ndl4 (South)* in Netherlands (1980, 1985), and *ukb (Northern Ireland)* in 1980, and *uk4 (East Anglia)*, *uk6 (Southwest), uk7 (West Midlands)*, and *ukb (Northern Ireland)* in 1985.

<Table 2.8A-F about here>

Finally, given that Spain and Belgium were found to be the countries with the most similar industrial structures, Table 2.9 displays the correlation matrices of the pattern of specialisation for the Belgian and Spanish regions. We investigate now whether that similarity translates into high correlations across all regions in those countries, or whether it is only due to high correlation between some regions in those countries.[15] We observe lower correlations as regions are more diverse in their production structure. Over time, regions evolve in different ways: *esp7 (Canary Islands)* evolves more unlike Belgian regions while *esp2 (Northeast)* becomes more similar to Belgian regions over the sample period.

<Table 2.9 about here>

[15] We do not report other correlation matrices across other different regions for reasons of brevity.

Krugman Specialisation Indices

In the section above, we analysed pairwise similarities in the pattern of specialisation across countries and regions within a country. Here, we compare the industrial structure of a country/region relative to a defined benchmark that exploits information from the whole sample. For each country/region, the benchmark is defined as the average GDP share in industry j in the rest of the sample.[16] For each country/region, denote δ_{jt} the share of the same sector or industry in the production of the rest of the sample at the country/regional levels respectively. We then measure the difference between the industrial structure of country/region i and all other countries/regions in our sample by taking the absolute values of the difference between our measure of specialisation (s_{ijt}) and δ_{jt}, summed over all sectors or industries. Formally, the Krugman index is defined as follows:

$$K_{it} = \sum_j abs\left(s_{ijt} - \delta_{jt}\right) \tag{2.10}$$

where i refers to country/region, and j is the industry index.

The Krugman index takes any value between zero and two. If zero, the country/region has an industrial structure that is identical to that of the benchmark, i.e., the rest of the countries/regions. If it takes the value of two, the country/region has no industries in common with the rest of the E.U. Given the level of industry aggregation in the sample, this is not going to be the case in our sample since all regions and countries produce in all the sectors and industries specified.

Table 2.10 displays five-year averages of Krugman indices computed for the three sectors at the country, regional, and within-country levels. The Krugman indices take values close to zero at this level of aggregation, indicating that countries and regions in Europe are not really specialised. Krugman indices, however, usually double in value when computed at the regional level, supporting our previous conclusion that regions are more specialised than countries. Over time, we observe a decrease in the Krugman indices across countries, across regions, and across regions within a country. Countries and regions are becoming more similar over time to the average, in line with our previous results of increasing correlations

[16] In this part of the analysis, we again drop United Kingdom from our sample and start in 1980 so that we have a balanced panel of observations across regions and over time. This makes the indices comparable over time.

over time. The secular trend of countries and regions decreasing their share of Agriculture and Manufacturing, while increasing specialisation in Services may underlie these results.

<Table 2.10 about here>

Table 2.11 reports the results for the disaggregated manufacturing industries. At this more disaggregated level, we observe more variation. At the country level, we find an increase in specialisation over the sample period in line with Amiti (1999) and Midelfart-Knarvik et al. (2000a). Luxembourg is the only country reporting a decrease in specialisation, although it is the most specialised country in the sample. At the regional level, we also find increasing specialisation, although evolving at a slow pace. Over the entire sample, Krugman indices display only a 5 percent growth for regions, although higher than at the country level (3 percent).

<Table 2.11 about here>

2.7 Changes in Specialisation at the Country Level: A Decomposition

In the next step, we investigate the nature of changes in the evolution of the pattern of specialisation at the country level. We discern whether the country-level changes in GDP shares are mainly due to changes in the GDP shares at the regional level (*within-region*) or to changes in the regional shares of GDP (*between-region*). In the first case, changes in specialisation at the country level will be related to regional changes in specialisation. Regions will be changing their pattern of specialisation in line with some of the trade theories mentioned in the first section. Regions would take advantage of either comparative advantage, economies of scale, or commercial linkages. In the second case, changes in the country's pattern of specialisation would be due to changes in the relative importance of the region in its country. Changes in the latter could possibly be due to, for example, mobility of factors or region-specific productivity growth. In this regard, comparative advantage would typically lead over time to between region reallocations of industrial activity, if factors of production are mobile. If the analysis indicates that changes in specialisation at the country level are related to within-region changes, then the analysis of specialisation at the regional is, in itself, meaningful. Otherwise, the analysis will indicate that the interest would need to shift to the relative importance of regions within a country, and the underlinning forces directing changes in the relative relevance of regions.

Using our measure of specialisation, and performing simple computations, we can express the country's GDP share of industry j as a weighted sum of the regional GDP shares of industry j:

$$s_{cjt} = \sum_{r \in c} (s_{rjt}\ \omega_{rt})$$

where s_{cjt} is the country's GDP share of industry j; s_{rjt} is the regional GDP share of industry j in region r; and ω_{rt} is the ratio of region r's GDP to its country's total GDP. Considering differences in the expression over time, we arrive at the following expression:

$$\Delta s_{cjt} = \sum_{r \in c} (\Delta s_{rjt}\ \omega_{rt}) + \sum_{r \in c} (s_{rjt}\ \Delta\omega_{rt}), \tag{2.11}$$

where the first term of the summation is the *within-region* effect and the second term is the *between-region* effect. Equation 2.11 expresses changes in GDP shares at the country level as the sum of changes in GDP shares at the regional level *(within-region)* and changes in the relative importance of each region in the country *(between-region).* As an accounting decomposition, the analysis does not in itself yield to any conclusions regarding causality or economic determinants for specialisation at the country level.

Table 2.12 reports annualised averages of the total, the within-region, and the between-region changes in GDP shares for the one-digit sectors. Total changes confirm that all countries are reducing specialisation in Agriculture and Manufacturing while increasing specialisation in Services. This is as expected due to the secular decline in Agriculture and Manufacturing in Europe over the sample period. European countries are decreasing their Manufacturing shares between 0.3 and 0.6 percent every year, while increasing their shares in Services at an average rate of around 0.5 percent per year. *Within-region* changes are driving the changes in the pattern of specialisation at the country level. The magnitude of the country's changes are usually smaller than that of *within-region* changes. *Between-region* changes are very small and generally of the opposite direction.

<Table 2.12 about here>

Changes in GDP shares within manufacturing at the country level are also mainly due to changes in GDP shares at the regional level. Tables 2.13-2.14 report the decomposition for the each of the disaggregated manufacturing industries, with the percentage contribution of the within- and between-region changes. The Netherlands, for instance, has reduced its Electronics share in total GDP by 0.07 percent every year, of which 113 percent would be explained by changes in GDP shares at the regional level, and minus 13 percent by the relative weight of the regions in total output. However, in contrast to the results for aggregate industries, some of the between-region changes are of the same direction as the within-region change. For example, in Chemicals, the United Kingdom is decreasing its share by 0.01 percent every year, of which 75 percent can be explained by changes in specialisation at the regional level, and 25 percent by changes in the regional shares of GDP.

<Tables 2.13-2.14 about here>

These results show that *within-region* changes in specialisation are more important in accounting for changes in specialisation at the country level than changes in the shares of regions in a country's overall economic activity. Regions are changing their pattern of specialisation more than countries, as the *within-region* change is typically higher in value than the total change. Changes in regional shares of GDP do play a small role in explaining changes in specialisation at the country level.

2.8 Dynamics of Patterns of Specialisation

In the sections above, we condensed information about specialisation in a number of summary statistics (coefficient of variation, correlations, Krugman indices), and we accounted for changes in specialisation at the country level. In this section, we explore how the entire pattern of specialisation evolves over time. We analyse specialisation dynamics across manufacturing industries over time, addressing issues related to intra-distribution dynamics (mobility and persistence) as well as to the evolution of the external shape of the distribution of GDP shares.[17] By computing transition probability matrices, we are able to compare the external shape of the distribution for countries/regions. We also study whether regions display higher (lower) mobility in specialisation.

For each geographical unit, we divide the space of possible values of GDP shares into

[17]We do not undertake the analysis for the aggregate industries (Agriculture, Manufacturing, and Services) because of the high level of aggregation and small number of observations involved.

five discrete cells and estimate the transition probability matrix over five-year periods. The upper-point of each cell is computed such that industry-year observations are divided roughly equally between the cells. Each cell corresponds to approximately one quintile of the distribution of GDP shares across industries and time.

Tables 2.15-2.20 report the estimated transition probability matrix for each country and their corresponding regions.[18] The interpretation of the transition probability matrix goes as follows. The first column describes the number of industry-time observations placed in each cell across all time periods. The first numerical row describes the upper-point of each grid cell. Thereafter, each row describes the probability of passing from one state into another. Estimated probabilities in the diagonal give information about the degree of persistence in the pattern of specialisation. Off-diagonal elements inform about the probability of passing to another state and, therefore, about mobility. The final two rows give the initial distribution of industry-time observations across grid cells and the ergodic distribution implied by the estimated transition probability matrix.

<Tables 2.15-2.20 about here>

We find evidence of substantial mobility in patterns of specialisation at the country and regional levels, suggesting that there are interesting changes in patterns of specialisation in Europe. In general, the estimated probability of moving out of a quintile of the distribution after a five-year period ranges from 0.04 to 0.65 at the country level. At the regional level, the same probability increases from 0.04 to 0.79. In general, regions display higher mobility in their patterns of specialisation, although differences can be found depending on the regions and countries considered. Mobility is higher in the middle quintiles, with higher persistence in the extreme quintiles. Comparing the initial and the ergodic distribution, there is a general pattern of polarisation towards the three lowest quintiles of the distribution at the country and regional levels. This may reflect two different issues: First, the general decline in the size of manufacturing industries in Europe over the sample period, and second, the relative changes in the position of industries with respect to each other, due to different rates of growth and decline— resulting in changes in the relative position within the distribution of GDP shares.

[18] The entire estimation is undertaken using Professor Danny Quah's TSRF econometrics package, which is available at http://econ.lse.ac.uk/stajj/dquah/tsrf/html. Responsibility for any results and errors is the author's alone.

In order to ensure that the mobility found in the patterns of specialisation is not due just to the general decline of manufacturing, we undertake the following robustness test. We compute the *relative* GDP share in an individual industry at time t (rs_{ijt}) by normalising the GDP share by the average share of all manufacturing industries in the country/region's GDP at time t. The normalisation completely removes the country/region specific decline in the average GDP shares of manufacturing industries. The analysis now captures specialisation *within manufacturing*. Transition probability matrices are then estimated with the relative GDP shares. The estimated transition probabilities capture the changes in the relative position of industries within the distribution of GDP shares. Table 2.21 reports the estimation results at the country level.[19] We find evidence of mobility of the relative position of industries within the distribution. The probability of moving out of a quintile of the distribution ranges from 0.04 to 0.62 (in line with those reported for the GDP shares).

<Table 2.21 about here>

Having concluded that the mobility in the patterns of specialisation is due to the changes in the relative size of individual industries in Manufacturing, we proceed now to compare country and regional patterns of specialisation using the GDP shares (s_{ijt}). Regions do not always display higher mobility/persistence in the pattern of specialisation. For instance, while all Belgian and French regions display higher mobility with respect to the pattern of specialisation than the country, Dutch regions display lower mobility. For Belgium, the average probability of moving out of a quintile of the distribution is 0.19 while for the regions it ranges from 0.29 to 0.33. For France, the average probability of moving out of a quintile of the distribution is 0.21, while for the regions it ranges from 0.22 to 0.47. On average, the probability of moving out of a quintile of the distribution is 0.40 for Netherlands while it varies from 0.19 to 0.35 at the regional level. In Spain, most of the regions display lower mobility in their pattern of specialisation than the country.

Mobility indices yield similar conclusions. Table 2.22 uses indices of mobility at the regional level relative to the corresponding country level, to evaluate the overall degree of mobility in patterns of specialisation at the regional level. A value above one implies that the region displays higher mobility than the country. Overall, regions display higher mobility: in 27 out of the 45 regions, relative mobility indices were higher than one.

[19] Similar results were reported at the regional level, but they are not shown here for reasons of brevity. Results are available in an appendix upon request from the author.

<Table 2.22 about here>

Analysing the ergodic distribution, we can study the external shape which the distribution is evolving to. There is no evidence of the emergence of a bimodal distribution. A comparison of the initial and ergodic distributions provides evidence of the general decline in the size of the manufacturing industries during the sample period. The trend is towards a decrease in mass in the upper quartiles and an increase in mass in the lower quintiles, with evidence of polarisation of GDP shares towards the bottom quintiles of the distribution. Exceptions are Luxembourg and *ita1*, which report an increase in mass in the upper quintiles.

There are cases of complete polarisation. For example, at the country level, Belgium displays an ergodic distribution leading to complete polarisation to the lower quintile of the distribution. In Spain, the results indicate complete polarisation for four of the regions (*esp1*, *esp3*, *esp4*, and *esp6*). Furthermore, there are significant differences between country and regional data. For example, Italy's ergodic distribution is characterised by partial polarisation towards the lower quintiles of the distribution. At the regional level, however, regions show a very diverse pattern of specialisation. While *ita1* reports polarisation towards the upper quintiles of the distribution, *ita7* evolves towards convergence on the degree of specialisation for the industries under consideration (most of the mass is concentrating in the central quintiles of the distribution), and *itaa,* and *itab* evolve towards complete polarisation (all the distribution concentrates in the lowest quintile). Finally, there are cases, although exceptional, in which two ergodic distribution were reported (*fra7*, *it6*), signalling that the dynamic process is not fully determined. Given the regional differences regarding intra-distribution dynamics and the ergodic distribution, the results seem to suggest that analysing specialisation dynamics at the regional level can bring further insights about how specialisation evolves over time.

Next, we explore the cross-country and within-country differences in the dynamic process. Table 2.23 examines the statistical significance of the cross-country differences. The null hypothesis is that the Data Generating Process (DGP) is equal to the transition probability matrix that was estimated for France. France is the largest country in our sample, and by location, it is at the core of our sample. We test whether the estimated transition probability matrix for each of the other countries is statistically significantly different from this known null. The null hypothesis is rejected at the 1 percent level for Belgium, Luxembourg and Netherlands (the small countries), but it is not rejected for Italy, Spain and United Kingdom.

Results are somehow surprising as we might expect that Belgium and Netherlands display a similar dynamic process according to which the industrial structures evolves to that of France, as they are commonly thought as being at the core of Europe and distinct from the periphery.

<Table 2.23 about here>

Table 2.24 reports the statistics on the within-country differences with respect to the dynamic process. The null hypothesis is that a region's Data Generating Process (DGP) equals the transition probability matrix estimated for the corresponding country. Overall, we find evidence of within-country differences in the evolution of the patterns of specialisation. We are unable to reject the null hypothesis in only 14 out of 45 regions. However, conclusions differ depending on the country considered. In Belgium and Italy, none of the regions show statistically significant differences in the evolution of the patterns of specialisation to the null hypothesis. For France, Spain and United Kingdom, most of the regions rejected the null hypothesis, reflecting statistically significant differences in the evolution of the patterns of specialisation at the regional level.

These results suggest that specialisation dynamics at the regional level should be taken into account in addition to specialisation dynamics at the country level. Regions show more mobility in the degree of specialisation and significant differences to countries in the dynamic process. These results complement the analysis of the patterns of specialisation across manufacturing industries presented above, regarding the evolution of the pairwise correlation. The summary statistics analysis relate to the external shape rather than to the intra-distribution dynamics, and therefore, some information is lost from not considering the evolution of the entire distribution. The estimation of the transition probability matrices gives additional insights about the dynamic process. Substantial within-country differences are revealed through the transition probability matrices, that we were unable to uncover with the use of summary statistics.

<Table 2.24 about here>

Finally, we perform a series of independent robustness tests. The analysis above made a series of assumptions, all of them testable by using eq.2.9. We have assumed that the operator M_r^* was time invariant. We test this assumption as well as whether there exist significant differences when we consider other lengths of the transition period or a different number of grid cells.

Our results are robust to each of these tests. First, in the estimation above, we assume the stationarity of the dynamic process for the estimation of the transition probability matrices. We then test for this assumption by eliminating the last five years of each sample, and reestimating the transition probability matrices. We test for the null hypothesis that the data generating processes are the same under the two samples. The null hypothesis can not be rejected for any country or region except for Bel (Brussels). Second, when estimating transition probabilities matrices, boundaries between grid cells were chosen such that observations were allocated roughly equally across cells. We are therefore always concerned with movements of industries between quintiles of the GDP shares distribution. Now, we consider the space of GDP share values to be divided in four grid cells instead of five and transition probability matrices were reestimated over five-year periods. We again find evidence of mobility in the patterns of specialisation at the country and regional levels, with similar mobility indices reported. Finally, we estimate the transition probability matrices by choosing three-year transitions instead of five-year transitions. The estimated transition probability matrices yield very similar results at the country and regional levels.

2.9 Conclusions

This chapter has analysed the evolution of specialisation in European countries and regions, combining the rich variation existing at the country and regional levels over the period 1975-95. We use a theory-consistent measure of specialisation, the GDP share of an industry at a point in time, which is derived from the neoclassical theory of trade. The analysis concentrates on uncovering the key facts concerning the evolution of patterns of specialisation in European countries. Subsequent chapters analyse the econometric determinants of evolving patterns of specialisation at the regional level.

The analysis above suggests the following conclusions. In the first part of the analysis, we use summary statistics to study the patterns of specialisation at the country and regional levels. Regional GDP shares vary markedly. Variation is higher across regions than across countries, indicating that regions are more specialised than countries. There are notable changes over time, and regions within countries show different patterns in the evolution of variation over time. Pairwise correlations indicate that, in general, countries' patterns of specialisation are becoming more dissimilar over time. When comparing a region's pattern of specialisation with that of its country, we find high heterogeneity in the degree of similarity in specialisation. When analysing specialisation relative to Europe, countries and regions also show increasing specialisation in the manufacturing industries, although at a slow pace.

When studying the nature of the changes in specialisation at the country level, an accounting decomposition indicates that changes in specialisation at the country level are mainly due to changes in specialisation at the regional level. There is no evidence of significant *between-region* changes in terms of shares of a country's GDP, and the relative importance of regions seem to remain fairly constant over the sample period.

Because the summary statistics condensed information about specialisation, we also explore how the entire pattern of specialisation evolves over time. We analyse specialisation dynamics across manufacturing industries over time, addressing issues related to intra-distribution dynamics (mobility and persistence) as well as to the evolution of the external shape of the distribution of GDP shares. By computing transition probability matrices, we are able to compare the external shape of the distribution for countries/regions. We also study whether regions display higher (lower) mobility in specialisation. The analysis of the evolution of the entire distribution of GDP shares reveals that no evidence of an increase in the overall degree of specialisation over time, but of significant mobility. The sample period is characterised by a decline in the average share of manufacturing in GDP. This is reflected in a polarisation of the distribution of GDP shares towards the bottom two quintiles of the distribution for most of the countries and regions under analysis. We find evidence of substantial mobility in patterns of specialisation at the country and regional levels. This mobility suggests that there are significant changes in the patterns of specialisation. In general, regions display higher mobility in their patterns of specialisation, although differences can be found depending on the regions and countries considered. Also, there is evidence of higher mobility in the middle quintiles and higher persistence in the extreme quintiles at the regional level. Comparing the initial and the ergodic distribution, there is a general pattern of polarisation toward the three lowest quintiles of the distribution at the country and regional levels. We find evidence of within-country differences in the evolution of the patterns of specialisation: 31 out of 45 of the regions follow a dynamic process that is statistically significantly different to that of their country.

Having found significant variation in specialisation at the regional level, the two following chapters will investigate the role of factor endowments and economic geography in explaining the variation in the patterns of specialisation at the regional level in Europe. Chapter 3 analyses the role of factor endowments. Although factor endowments explain a sizable proportion of the variation in patterns of specialisation, there remains substantial unexplained variation, especially for the disaggregated industries within manufacturing, suggesting a role for other considerations such as those emphasised in the new economic geography literature. Chapter 4 of this thesis extends further the analysis of the determinants of specialisation by incorporating considerations of economic geography alongside those of factor endowments and factor intensities to explain the pattern of specialisation within manufacturing industries in European regions.

Table 2.1: Shares of Agriculture, Manufacturing, and Services in GDP (percent)

Region	Year	Agric	Manuf	Serv	Region	Year	Agric	Manuf	Serv
Be1	1975	0.01	28.58	71.42	Fra7	1975	4.30	46.46	49.24
	1985	0.03	18.35	81.61		1985	3.11	36.85	60.04
	1995	0.02	15.75	84.23		1995	2.43	32.17	65.40
Be2	1975	3.64	42.45	53.92	Fra8	1975	5.98	32.96	61.06
	1985	2.64	37.39	59.96		1985	4.27	25.21	70.52
	1995	1.52	34.27	64.21		1995	3.24	20.26	76.51
Be3	1975	3.91	39.93	56.16	It1	1975	4.46	48.20	47.34
	1985	3.00	32.24	64.76		1985	3.12	41.17	55.71
	1995	1.76	27.36	70.88		1995	2.42	36.87	60.71
Esp1	1980	9.35	39.22	51.43	It2	1975	2.87	55.18	41.95
	1985	8.07	39.29	52.64		1985	2.05	45.49	52.45
	1995	4.82	34.45	60.73		1995	1.56	41.21	57.23
Esp2	1980	5.93	48.12	45.95	It3	1975	6.03	45.82	48.15
	1985	4.59	45.84	49.57		1985	4.38	40.96	54.66
	1995	2.25	42.12	55.63		1995	3.13	36.71	60.17
Esp3	1980	0.55	30.58	68.86	It4	1975	8.72	47.13	44.15
	1985	0.32	28.61	71.08		1985	5.75	40.87	53.38
	1995	0.17	25.26	74.57		1995	3.70	36.94	59.36
Esp4	1980	14.72	34.61	50.67	It5	1975	5.32	45.34	49.34
	1985	11.86	36.10	52.04		1985	3.36	41.09	55.55
	1995	5.39	34.50	60.11		1995	2.64	34.62	62.75
Esp5	1980	4.24	42.19	53.56	It6	1975	4.40	26.02	69.57
	1985	3.00	39.44	57.56		1985	2.59	25.09	72.32
	1995	1.57	34.55	63.87		1995	1.62	21.24	77.14
Esp6	1980	10.91	33.13	55.97	It7	1975	10.70	39.19	50.11
	1985	10.84	29.25	59.91		1985	6.72	34.32	58.95
	1995	6.15	27.91	65.95		1995	4.53	32.04	63.43
Esp7	1980	8.25	21.38	70.37	It8	1975	10.26	31.29	58.45
	1985	4.80	18.41	76.79		1985	5.38	27.71	66.91
	1995	2.06	18.56	79.38		1995	3.33	24.30	72.36
Fra1	1975	0.68	34.87	64.45	It9	1975	14.17	31.02	54.81
	1985	0.40	29.50	70.10		1985	9.42	27.81	62.77
	1995	0.18	22.54	77.28		1995	6.49	24.49	69.02
Fra2	1975	8.73	43.58	47.69	Ita	1975	12.56	29.54	57.90
	1985	7.41	36.07	56.52		1985	9.36	28.33	62.32
	1995	4.27	32.69	63.04		1995	5.73	21.47	72.80
Fra3	1975	4.04	49.28	46.68	Itab	1975	9.09	36.40	54.51
	1985	2.62	35.80	61.58		1985	5.96	33.64	60.39
	1995	1.35	31.66	67.00		1995	4.11	27.37	68.52
Fra4	1975	4.45	47.50	48.05	Lux	1975	3.24	39.18	57.57
	1985	3.71	37.48	58.81		1985	2.36	34.04	63.60
	1995	2.60	34.66	62.74		1995	1.21	31.61	67.19
Fra5	1975	11.38	37.48	51.14	Nld1	1975	7.55	36.91	55.54
	1985	7.98	29.24	62.78		1985	4.33	35.08	60.58
	1995	5.24	27.08	67.69		1995	4.45	38.53	57.02
Fra6	1975	8.57	37.15	54.28	Nld2	1975	7.24	35.21	57.55
	1985	6.67	30.56	62.77		1985	6.12	29.77	64.11
	1995	4.41	24.37	71.22		1995	4.19	27.24	68.58

Table 2.1 (cont): Shares of Agriculture, Manufacturing, and Services in GDP (percent)

Region	Year	Agric	Manuf	Serv	Region	Year	Agric	Manuf	Serv
Nld3	1975	3.73	32.48	63.80	Uk6	1975	3.27	36.86	59.87
	1985	3.29	28.23	68.48		1980	3.23	35.60	61.17
	1995	2.71	23.64	73.65		1985	2.16	34.36	63.48
Nld4	1975	4.70	43.21	52.09	Uk7	1975	1.51	48.94	49.55
	1985	5.48	37.25	57.27		1980	1.71	46.34	51.94
	1995	3.55	32.62	63.83		1985	1.23	43.64	55.13
Uk1	1975	2.04	50.04	47.93	Uk8	1975	0.87	45.53	53.60
	1980	1.58	47.29	51.12		1980	0.70	45.46	53.84
	1985	1.37	41.37	57.25		1985	0.53	44.32	55.15
Uk2	1975	2.31	46.46	51.23	Uk9	1975	2.81	45.57	51.61
	1980	1.92	44.88	53.21		1980	2.88	45.14	51.98
	1985	1.43	41.40	57.17		1985	2.48	45.93	51.59
Uk3	1975	2.76	48.36	48.88	Uka	1975	2.98	43.73	53.28
	1980	2.76	46.45	50.79		1980	2.39	42.17	55.44
	1985	1.59	44.29	54.11		1985	1.69	38.82	59.49
Uk4	1975	6.56	36.12	57.32	Ukb	1975	3.40	43.37	53.23
	1980	5.78	35.93	58.29		1980	3.30	37.21	59.49
	1985	3.07	36.02	60.91		1985	2.89	36.00	61.11
Uk5	1975	0.82	32.14	67.03					
	1980	0.85	32.51	66.65					
	1985	0.48	29.46	70.06					

Notes: [a] Figures may not sum to exactly 100 due to rounding.

Table 2.2: Shares of the Disaggregated Manufacturing Industries in GDP in France and Spain (percent)

Region	Year	Fuel	Metal	Mineral	Chem	Machine	Transp
Esp1	1980	7.47	5.61	2.13	1.34	3.49	2.82
	1985	9.56	4.98	2.18	1.69	2.62	2.90
	1994	7.84	2.63	1.92	0.79	2.34	2.19
Esp2	1980	4.52	5.14	2.12	1.96	12.65	3.01
	1985	5.77	4.29	1.72	1.98	10.15	3.35
	1994	7.00	2.11	1.69	1.10	8.82	3.28
Esp3	1980	1.14	0.60	1.21	2.71	7.27	2.54
	1985	2.27	0.24	0.89	2.76	6.00	2.09
	1994	2.41	0.16	0.77	1.75	4.28	1.76
Esp4	1980	6.16	0.41	2.06	1.41	2.30	3.74
	1985	9.86	0.33	1.87	1.67	1.97	2.78
	1994	9.50	0.17	1.80	1.10	1.88	2.11
Esp5	1980	3.41	0.61	2.37	3.41	6.09	2.72
	1985	4.83	0.42	2.22	3.47	5.58	2.05
	1994	4.80	0.21	1.86	2.67	4.53	1.75
Esp6	1980	5.69	1.14	2.61	1.39	1.89	1.71
	1985	4.80	1.41	1.38	2.24	1.68	1.45
	1994	6.04	0.61	1.14	0.77	1.34	1.09
Esp7	1980	3.36	0.00	1.08	0.38	0.53	0.18
	1985	4.18	0.01	0.86	0.24	0.63	0.31
	1994	5.12	0.03	0.79	0.13	0.42	0.29
Fra1	1980	4.48	0.87	0.64	2.52	7.88	4.47
	1985	5.56	0.70	0.55	2.52	7.11	2.49
	1994	5.06	0.28	0.49	2.01	4.78	1.87
Fra2	1980	3.89	1.42	1.57	2.81	9.96	3.93
	1985	5.47	1.09	1.18	2.26	8.07	2.20
	1994	4.57	0.88	1.14	2.46	7.62	2.68
Fra3	1980	5.47	4.00	2.36	2.80	7.38	3.77
	1985	4.69	2.59	1.99	1.73	5.47	2.35
	1994	3.06	2.55	1.65	2.49	4.41	2.29
Fra4	1980	3.65	3.86	1.77	2.52	9.27	5.48
	1985	3.34	2.41	1.55	1.98	8.28	4.26
	1994	2.71	1.39	1.18	1.65	7.81	5.24
Fra5	1980	3.22	0.38	1.31	.75	6.34	4.17
	1985	2.85	0.34	0.95	0.73	5.40	2.50
	1994	2.46	0.20	0.95	0.68	5.34	2.57
Fra6	1980	6.99	0.63	1.50	2.36	4.61	2.93
	1985	6.94	0.56	1.09	1.30	4.16	2.33
	1994	3.74	0.21	1.02	1.15	4.05	2.47
Fra7	1980	3.57	1.55	1.29	2.64	12.06	2.96
	1985	4.18	1.09	1.05	2.39	9.83	1.61
	1994	4.02	1.00	.87	2.16	8.86	1.43
Fra8	1980	4.41	1.85	1.41	1.90	3.32	1.59
	1985	5.42	1.51	1.14	1.31	3.53	1.28
	1994	4.22	0.86	.89	1.55	2.80	0.99

[a] See Appendix 1.A for industry definitions.

Table 2.2 (cont): Shares of the Disaggregated Manufacturing Industries in GDP in France and Spain (percent)

		Food	Textile	Paper	Other	Constr
Esp1	1980	4.20	0.74	0.54	1.69	9.19
	1985	4.87	0.88	0.75	1.34	7.53
	1994	4.53	0.69	0.51	1.08	9.06
Esp2	1980	5.00	1.55	2.01	4.11	6.05
	1985	5.64	1.64	1.97	3.63	5.70
	1994	4.59	0.95	1.45	2.52	6.83
Esp3	1980	2.67	1.32	1.32	1.66	7.72
	1985	3.08	1.54	2.11	1.57	6.06
	1994	2.09	0.78	2.01	1.04	8.14
Esp4	1980	5.11	1.57	0.58	2.29	8.98
	1985	5.65	1.80	0.74	1.92	7.50
	1994	4.76	1.21	0.52	1.54	9.85
Esp5	1980	4.35	6.49	1.50	3.24	8.01
	1985	4.99	5.54	1.52	2.88	5.94
	1994	3.97	3.39	1.38	2.34	6.94
Esp6	1980	5.94	1.32	0.56	1.07	9.81
	1985	6.65	1.33	0.62	0.88	6.80
	1994	5.07	0.79	0.46	0.73	8.67
Esp7	1980	4.63	0.09	0.72	0.53	9.89
	1985	3.05	0.31	0.59	0.70	7.53
	1994	3.10	0.17	0.49	0.40	7.36
Fra1	1980	2.26	1.08	1.80	1.16	5.61
	1985	1.63	0.95	2.21	1.03	4.73
	1994	1.41	0.70	2.36	0.72	4.04
Fra2	1980	6.08	2.05	1.31	2.82	6.73
	1985	4.68	1.79	1.46	2.51	5.35
	1994	3.59	1.16	1.46	2.62	4.99
Fra3	1980	5.43	5.34	1.46	1.31	6.82
	1985	4.10	4.71	1.67	1.23	5.28
	1994	4.23	2.54	1.81	1.48	4.58
Fra4	1980	4.71	2.66	1.49	2.45	6.62
	1985	4.03	2.44	1.67	2.48	5.04
	1994	3.78	1.35	1.76	2.58	4.98
Fra5	1980	6.73	2.25	1.09	2.42	8.71
	1985	4.99	1.94	1.22	2.46	5.85
	1994	5.04	1.19	1.30	2.49	5.34
Fra6	1980	4.09	2.39	1.31	1.85	7.52
	1985	3.27	1.98	1.35	1.64	5.93
	1994	3.35	0.99	1.24	1.76	5.16
Fra7	1980	3.60	2.96	1.44	4.00	7.43
	1985	2.94	2.46	1.37	3.69	6.22
	1994	2.69	1.83	1.27	3.27	5.41
Fra8	1980	3.70	0.82	0.68	0.92	9.12
	1985	2.36	0.59	0.78	0.88	6.42
	1994	2.17	0.37	0.75	0.83	5.35

[a] See Appendix 1.A for industry definitions.

Table 2.3: Evolution of the Coefficient of Variation for the One-Digit Sectors, at the Country and Regional Levels

		Years	Agriculture	Manufacture	Services
Across Countries		1980	0.427	0.061	0.062
		1985	0.338	0.058	0.047
		1990	0.344	0.063	0.035
		1995	0.373	0.076	0.036
Across all EU regions		1980	0.618	0.212	0.145
		1985	0.596	0.239	0.141
		1990	0.575	0.205	0.111
		1995	0.559	0.224	0.104
Across all regions within a country	Bel	1980	0.860	0.261	0.156
		1985	0.857	0.336	0.165
		1990	0.872	0.321	0.146
		1995	0.861	0.363	0.139
	Esp	1980	0.601	0.243	0.165
		1985	0.678	0.269	0.172
		1990	0.667	0.201	0.127
		1995	0.699	0.249	0.128
	Fra	1980	0.550	0.153	0.116
		1985	0.581	0.139	0.080
		1990	0.592	0.165	0.084
		1995	0.567	0.190	0.082
	It	1980	0.466	0.219	0.128
		1985	0.477	0.202	0.103
		1990	0.383	0.231	0.110
		1995	0.440	0.232	0.099
	Ndl	1980	0.226	0.309	0.216
		1985	0.261	0.384	0.264
		1990	0.244	0.222	0.222
		1995	0.208	0.213	0.108

Note: The table reports the coefficient of variation, a measure of dispersion, computed as the standard variation at the industry level normalised by the mean.

Table 2.4: Evolution of the Coefficient of Variation for the Manufacturing Industries, at the Country and Regional Levels

		Years	Fuel	Metal	Mineral	Chem	Machine
Across Countries		1980	0.559	1.389	0.313	0.344	0.341
		1985	0.631	1.421	0.299	0.408	0.286
		1990	0.386	1.276	0.474	0.470	0.201
		1995	0.350	0.902	0.509	0.525	0.223
Across all EU regions		1980	1.134	1.362	0.501	0.452	0.579
		1985	1.052	1.440	0.468	0.510	0.554
		1990	0.812	1.249	0.475	0.538	0.553
		1995	0.655	1.010	0.512	0.548	0.564
Across all regions within a country	Bel	1980	0.144	1.053	0.952	0.507	0.327
		1985	0.358	0.992	1.019	0.667	0.283
		1990	0.407	0.933	0.891	0.842	0.312
		1995	0.363	0.977	0.987	0.736	0.341
	Esp	1980	0.465	1.272	0.296	0.556	0.851
		1985	0.478	1.250	0.355	0.501	0.817
		1990	0.380	1.252	0.348	0.585	0.843
		1995	0.377	1.303	0.354	0.689	0.849
	Fra	1980	0.278	0.764	0.328	0.300	0.376
		1985	0.278	0.648	0.357	0.352	0.338
		1990	0.268	0.720	0.356	0.319	0.341
		1995	0.227	1.014	0.319	0.389	0.390
	It	1980	0.506	0.688	0.459	0.486	0.642
		1985	0.554	0.653	0.437	0.494	0.614
		1990	0.474	0.649	0.384	0.436	0.637
		1995	0.471	0.730	0.434	0.492	0.612
	Ndl	1980	1.333	0.847	0.518	0.437	0.490
		1985	1.353	0.604	0.406	0.383	0.451
		1990	1.222	0.572	0.479	0.323	0.483
		1995	1.006	0.588	0.524	0.246	0.452

Note: The table reports the coefficient of variation, a measure of dispersion, computed as the standard variation at the industry level normalised by the mean.

Table 2.5: (cont) Evolution of the Coefficient of Variation for the Manufacturing Industries, at the Country and Regional Levels

			Transp	Food	Textile	Paper	Other	Constr
Across Countries		1980	0.603	0.227	0.714	0.274	0.333	0.067
		1985	0.544	0.283	0.767	0.274	0.422	0.148
		1990	0.538	0.250	0.721	0.272	0.417	0.207
		1995	0.626	0.283	0.805	0.233	0.328	0.338
Across Regions		1980	0.671	0.351	0.940	0.425	0.572	0.254
		1985	0.635	0.381	0.982	0.461	0.559	0.277
		1990	0.681	0.381	0.940	0.488	0.568	0.270
		1995	0.709	0.436	1.029	0.483	0.577	0.299
Across Regions within a country	Be	1980	0.668	0.225	0.741	0.232	0.953	0.228
		1985	0.304	0.216	0.827	0.115	0.948	0.237
		1990	0.346	0.189	0.695	0.181	0.820	0.190
		1995	0.367	0.291	0.819	0.144	0.877	0.236
	Esp	1980	0.480	0.222	1.128	0.604	0.597	0.161
		1985	0.480	0.278	0.913	0.561	0.577	0.122
		1990	0.430	0.248	0.924	0.629	0.606	0.178
		1995	0.529	0.274	0.928	0.613	0.598	0.136
	Fra	1980	0.320	0.320	0.566	0.247	0.484	0.157
		1985	0.369	0.331	0.589	0.281	0.483	0.106
		1990	0.527	0.345	0.524	0.274	0.450	0.088
		1995	0.610	0.360	0.555	0.320	0.467	0.103
	Italy	1980	0.872	0.337	0.764	0.506	0.571	0.314
		1985	0.883	0.402	0.828	0.597	0.572	0.290
		1990	0.864	0.407	0.748	0.633	0.562	0.194
		1995	0.621	0.397	0.752	0.623	0.547	0.173
	Ndl	1980	0.311	0.151	0.814	0.144	0.466	0.146
		1985	0.353	0.174	0.871	0.105	0.413	0.060
		1990	0.389	0.316	0.761	0.179	0.242	0.118
		1995	0.265	0.368	0.761	0.142	0.348	0.116

Note: The table reports the coefficient of variation, a measure of dispersion, computed as the standard variation at the industry level normalised by the mean.

Table 2.6: Matrix of Correlation of the Pattern of Specilisation across Countries, Manufacturing Industries

Year=1980	Be	Esp	Fra	It	Lux	Ndl
Esp	**0.97***	1.00				
Fra	0.89*	0.90*	1.00			
It	0.73*	0.78*	0.82*	1.00		
Lux	0.27	0.19	0.08	0.11	1.00	
Ndl	0.86*	0.77*	0.72*	0.44	0.07	1.00
UK	0.76*	0.68*	0.77*	0.45	-0.06	0.93*
Year=1985	Be	Esp	Fra	Ita	Lux	Ndl
Esp	0.93*	1.00				
Fra	0.90*	0.87*	1.00			
It	0.67*	0.68*	0.83*	1.00		
Lux	0.09	-0.03	-0.02	-0.02	1.00	
Ndl	0.78*	0.76*	0.74*	0.36	-0.05	1.00
UK	0.84*	0.84*	0.85*	0.49	-0.10	**0.97***
Year=1990	Be	Esp	Fra	Ita	Lux	Ndl
Esp	0.90*	1.00				
Fra	**0.91***	0.80*	1.00			
It	0.76*	0.72*	0.86*	1.00		
Lux	0.38	0.34	0.27	0.32	1.00	
Ndl	0.88*	0.80*	0.83*	0.59	0.13	1.00
Year=1995	Be	Esp	Fra	Ita	Lux	Ndl
Esp	**0.91***	1.00				
Fra	0.88*	0.78*	1.00			
It	0.68*	0.66*	0.80*	1.00		
Lux	0.63*	0.74*	0.54	0.64*	1.00	
Ndl	0.90*	0.83*	0.83*	0.57	0.48	1.0000

Notes: The table reports the pairwise correlations of the GDP shares across the manufacturing industries between geographical units. Bold figures refer to the highest pairwise correlation in the year under analysis.* refers to the correlation being statistically significant different from zero at the 5 percent significance level.

Table 2.7: Correlation Matrices of the Pattern of Specialisation for the Regions within the same Country

Table 2.8.A: Belgium

Year=1980	Be	Lux	Be1	Be2
Lux	0.27	1.00		
Be1	0.91*	0.02	1.00	
Be2	0.97*	0.14	**0.88***	1.00
Be3	0.89*	0.52	0.71*	0.75*
Year=1985	Be	Lux	Be1	Be2
Lux	0.09			
Be1	0.83*	-0.14	1.00	
Be2	0.96*	-0.02	**0.75***	1.00
Be3	0.81*	0.44	0.61*	0.64*
Year=1990	Be	Lux	Be1	Be2
Lux	0.38			
Be1	0.84*	0.19	1.00	
Be2	0.96*	0.23	**0.77***	1.00
Be3	0.81*	0.68*	0.62*	0.65*
Year=1995	Be	Lux	Be1	Be2
Lux	0.63*			
Be1	0.86*	0.59	1.00	
Be2	0.97*	0.47	**0.80***	1.00
Be3	0.81*	0.86*	0.65*	0.66*

Notes: The table reports the pairwise correlations of the GDP shares across the manufacturing industries between geographical units. Bold figures refer to the highest pairwise correlation in the year under analysis.* refers to the correlation being statistically significant different from zero at the 5 percent significance level.

Table 2.8.B: Netherlands

Year=1980	Ndl	Ndl1	Ndl2	Ndl3
Ndl1	0.83*	1.00		
Ndl2	0.73*	0.26	1.00	
Ndl3	0.88*	0.56	0.77*	1.00
Ndl4	0.59	0.12	**0.87***	0.68*
Year=1985	Ndl	Ndl1	Ndl2	Ndl3
Ndl1	0.94*	1.00		
Ndl2	0.60*	0.33	1.00	
Ndl3	0.79*	0.59	0.73*	1.00
Ndl4	0.37	0.08	**0.83***	0.60
Year=1990	Ndl	Ndl1	Ndl2	Ndl3
Ndl1	0.72*	1.00		
Ndl2	0.79*	0.18	1.00	
Ndl3	0.97*	0.69*	0.74*	1.00
Ndl4	0.67*	0.04	**0.90***	0.59
Year=1995	Ndl	Ndl1	Ndl2	Ndl3
Ndl1	0.84*	1.00		
Ndl2	0.80*	0.34	1.00	
Ndl3	0.97*	0.92*	0.64*	1.00
Ndl4	0.64*	0.16	**0.93***	0.42

Notes: The table reports the pairwise correlations of the GDP shares across the manufacturing industries between geographical units. Bold figures refer to the highest pairwise correlation in the year under analysis.* refers to the correlation being statistically significant different from zero at the 5 percent significance level.

Table 2.8.C: Spain

Year=1980	Es	Es1	Es2	Es3	Es4	Es5	Es6
Es1	0.74*	1.00					
Es2	0.60	0.41	1.00				
Es3	0.83*	0.39	0.70*	1.00			
Es4	0.85*	0.79*	0.23	0.52	1.00		
Es5	0.83*	0.32	0.39	0.74*	0.59	1.00	
Es6	0.86*	0.83*	0.23	0.51	0.95*	0.58	1.00
Es7	0.84*	0.77*	0.20	0.57	0.91*	0.59	**0.97***
Year=1985	Es	Es1	Es2	Es3	Es4	Es5	Es6
Es1	0.75*	1.00					
Es2	0.69*	0.47	1.00				
Es3	0.76*	0.27	0.71*	1.00			
Es4	0.86*	0.87*	0.38	0.40	1.00		
Es5	0.83*	0.32	0.49	0.72*	0.60	1.00	
Es6	0.87*	0.76*	0.40	0.52	0.84*	0.61*	1.00
Es7	0.85*	0.78*	0.35	0.58	0.86*	0.58	**0.88***
Year=1990	Es	Es1	Es2	Es3	Es4	Es5	Es6
Es1	0.89*	1.00					
Es2	0.71*	0.55	1.00				
Es3	0.88*	0.65*	0.74*	1.00			
Es4	0.92*	0.94*	0.53	0.65*	1.00		
Es5	0.92*	0.68*	0.65*	0.85*	0.79*	1.00	
Es6	0.93*	0.93*	0.46	0.75*	0.91*	0.80*	1.00
Es7	0.93*	0.94*	0.46	0.74*	0.94*	0.79*	**0.99***
Year=1995	Es	Es1	Es2	Es3	Es4	Es5	Es6
Es1	0.92*	1.00					
Es2	0.81*	0.72*	1.00				
Es3	0.88*	0.72*	0.71*	1.00			
Es4	0.95*	0.96*	0.69*	0.73*	1.00		
Es5	0.94*	0.75*	0.75*	0.86*	0.83*	1.00	
Es6	0.96*	0.96*	0.66*	0.78*	0.97*	0.84*	1.00
Es7	0.95*	0.96*	0.63*	0.79*	0.97*	0.82*	**0.99***

Notes: The table reports the pairwise correlations of the GDP shares across the manufacturing industries between geographical units. Bold figures refer to the highest pairwise correlation in the year under analysis.* refers to the correlation being statistically significant different from zero at the 5 percent significance level.

Table 2.8.D: France

Year=1980	Fra	Fra1	Fra2	Fra3	Fra4	Fra5	Fra6	Fra7
Fra1	0.93*	1.00						
Fra2	0.96*	0.87*	1.00					
Fra3	0.84*	0.72*	0.78*	1.00				
Fra4	0.93*	0.88*	0.92*	0.81*	1.00			
Fra5	0.89*	0.71*	0.86*	0.75*	0.78*	1.00		
Fra6	0.81*	0.73*	0.68*	0.74*	0.58	0.78*	1.00	
Fra7	0.91*	0.86*	**0.93***	0.72*	0.89*	0.72*	0.58	1.00
Fra8	0.75*	0.60	0.61*	0.69*	0.57	0.79*	0.87*	0.52
Year=1985	Fra	Fra1	Fra2	Fra3	Fra4	Fra5	Fra6	Fra7
Fra1	0.94*	1.00						
Fra2	0.98*	0.89*	1.00					
Fra3	0.80*	0.66*	0.77*	1.00				
Fra4	0.87*	0.79*	0.88*	0.70*	1.00			
Fra5	0.85*	0.65*	0.86*	0.74*	0.82*	1.00		
Fra6	0.86*	0.80*	0.80*	0.76*	0.57	0.73*	1.00	
Fra7	0.92*	0.85*	0.92*	0.70*	0.89*	0.79*	0.64*	1.00
Fra8	0.84*	0.77*	0.75*	0.72*	0.55	0.70*	**0.93***	0.64*
Year=1990	Fra	Fra1	Fra2	Fra3	Fra4	Fra5	Fra6	Fra7
Fra1	0.93*	1.00						
Fra2	0.97*	0.86*	1.00					
Fra3	0.88*	0.73*	0.84*	1.00				
Fra4	0.84*	0.70*	0.86*	0.75*	1.00			
Fra5	0.86*	0.64*	0.88*	0.82*	0.78*	1.00		
Fra6	0.93*	0.85*	0.86*	0.83*	0.72*	0.89*	1.00	
Fra7	0.94*	0.85*	**0.96***	0.83*	0.81*	0.78*	0.78*	1.00
Fra8	0.80*	0.76*	0.70*	0.76*	0.45	0.69*	0.88*	0.65*
Year=1995	Fra	Fra1	Fra2	Fra3	Fra4	Fra5	Fra6	Fra7
Fra1	0.90*	1.00						
Fra2	0.98*	0.85*	1.00					
Fra3	0.67*	0.49	0.62*	1.00				
Fra4	0.82*	0.62*	0.85*	0.53	1.00			
Fra5	0.85*	0.59	0.82*	0.67*	0.81*	1.00		
Fra6	0.92*	0.80*	0.84*	0.65*	0.70*	0.90*	1.00	
Fra7	0.90*	0.73*	**0.93***	0.57	0.76*	0.77*	0.72*	1.00
Fra8	0.82*	0.82*	0.72*	0.68*	0.45	0.66*	0.90*	0.61*

Notes: The table reports the pairwise correlations of the GDP shares across the manufacturing industries between geographical units. Bold figures refer to the highest pairwise correlation in the year under analysis.* refers to the correlation being statistically significant different from zero at the 5 percent significance level.

Table 2.8.E: Italy

Year=1980	It	It1	It2	It3	It4	It5	It6	It7	It8	It9	Ita
It1	0.82*	1.00									
It2	0.89*	0.86*	1.00								
It3	0.95*	0.70*	0.82*	1.00							
It4	0.90*	0.76*	0.83*	0.84*	1.00						
It5	0.65*	0.35	0.49	0.70*	0.46	1.00					
It6	0.85*	0.54	0.64*	0.80*	0.76	0.41	1.00				
It7	0.69*	0.30	0.31	0.64*	0.57	0.48	0.87*	1.00			
It8	0.92*	0.69*	0.67*	0.84*	0.81	0.60*	0.89*	0.87*	1.00		
It9	0.69*	0.32	0.32	0.64*	0.56	0.44	0.86*	0.95*	0.88*	1.00	
Ita	0.54	0.16	0.19	0.48	0.42	0.31	0.80*	0.96*	0.75*	0.90*	1.00
Itb	0.58	0.19	0.21	0.54	0.46	0.33	0.84*	0.96*	0.80*	**0.97***	0.95*
Year=1985	It	It1	It2	It3	It4	It5	It6	It7	It8	It9	Ita
It1	0.79*	1.00									
It2	0.89*	0.81*	1.00								
It3	0.94*	0.66*	0.83*	1.00							
It4	0.87*	0.76*	0.87*	0.82*	1.00						
It5	0.62*	0.30	0.49	0.71*	0.44	1.00					
It6	0.84*	0.55	0.64*	0.75*	0.65*	0.29	1.00				
It7	0.77*	0.46	0.43	0.65*	0.54	0.41	0.89*	1.00			
It8	0.83*	0.57	0.54	0.74*	0.59	0.40	0.91*	0.93*	1.00		
It9	0.66*	0.29	0.30	0.60	0.40	0.35	0.81*	0.91*	0.94*	1.00	
Ita	0.53	0.22	0.20	0.39	0.27	0.19	0.78*	0.91*	0.78*	0.83*	1.00
Itb	0.52	0.16	0.19	0.39	0.23	0.15	0.79*	0.89*	0.82*	0.89*	**0.97***
Year=1990	It	It1	It2	It3	It4	It5	It6	It7	It8	It9	Ita
It1	0.79*	1.00									
It2	0.90*	0.79*	1.00								
It3	0.94*	0.64*	0.85*	1.00							
It4	0.90*	0.78*	0.90*	0.85*	1.00						
It5	0.66*	0.27	0.55	0.78*	0.51	1.00					
It6	0.77*	0.53	0.57	0.60*	0.58	0.26	1.00				
It7	0.85*	0.57	0.55	0.74*	0.65*	0.52	0.89*	1.00			
It8	0.79*	0.58	0.47	0.67*	0.56	0.46	0.86*	**0.97***	1.00		
It9	0.72*	0.35	0.38	0.66*	0.51	0.52	0.80*	0.94*	0.94*	1.00	
Ita	0.55	0.28	0.20	0.40	0.30	0.27	0.81*	0.86*	0.84*	0.88*	1.00
Itb	0.50	0.17	0.18	0.35	0.25	0.23	0.81*	0.79*	0.79*	0.87*	0.96*
Year=1995	It	It1	It2	It3	It4	It5	It6	It7	It8	It9	Ita
It1	0.89*	1.00									
It2	0.91*	0.84*	1.00								
It3	0.93*	0.75*	0.86*	1.00							
It4	0.88*	0.84*	0.85*	0.82*	1.00						
It5	0.73*	0.47	0.67*	0.83*	0.54	1.00					
It6	0.73*	0.61*	0.55	0.56	0.56	0.25	1.00				
It7	0.81*	0.66*	0.55	0.66*	0.58	0.58	0.82*	1.00			
It8	0.85*	0.75*	0.58	0.73*	0.67*	0.54	0.81*	0.90*	1.00		
It9	0.73*	0.61*	0.44	0.62*	0.48	0.48	0.74*	0.86*	0.92*	1.00	
Ita	0.48	0.38	0.17	0.27	0.22	0.21	0.75*	0.85*	0.72*	0.80*	1.00
Itb	0.46	0.29	0.17	0.28	0.19	0.20	0.79*	0.77*	0.72*	0.82*	**0.94***

Notes: The table reports the pairwise correlations of the GDP shares across the manufacturing industries between geographical units. Bold figures refer to the highest pairwise correlation in the year under analysis.* refers to the correlation being statistically significant different from zero at the 5 percent significance level.

Table 2.8.F: United Kingdom

Year=1980	uk	uk1	uk2	uk3	uk4	uk5	uk6	uk7	uk8	uk9	uka
uk1	0.93*	1.00									
uk2	0.95*	0.88*	1.00								
uk3	0.88*	0.83*	0.91*	1.00							
uk4	0.65*	0.73*	0.53	0.66*	1.00						
uk5	0.87*	0.87*	0.77*	0.80*	0.84*	1.00					
uk6	0.71*	0.74*	0.59	0.70*	**0.97***	0.82*	1.00				
uk7	0.61*	0.61*	0.57	0.66*	0.68*	0.78*	0.69*	1.00			
uk8	0.90*	0.93*	0.81*	0.87*	0.80*	0.88*	0.84*	0.67*	1.00		
uk9	0.89*	0.76*	0.89*	0.68*	0.27	0.62*	0.37	0.32	0.64*	1.00	
uka	0.79*	0.82*	0.71*	0.75*	0.87*	0.74*	0.91*	0.47	0.86*	0.54	1.00
ukb	0.48	0.50	0.41	0.49	0.66*	0.35	0.73*	0.09	0.59	0.29	0.88*
year=1985	uk	uk1	uk2	uk3	uk4	uk5	uk6	uk7	uk8	uk9	uka
uk1	0.78*	1.00									
uk2	0.97*	0.75*	1.00								
uk3	0.66*	0.59	0.69*	1.00							
uk4	0.51	0.67*	0.47	0.76*	1.00						
uk5	0.77*	0.79*	0.67*	0.64*	0.80*	1.00					
uk6	0.58	0.58	0.52	0.79*	**0.93***	0.80*	1.00				
uk7	0.54	0.64*	0.43	0.59	0.66*	0.80*	0.72*	1.00			
uk8	0.85*	0.75*	0.81*	0.81*	0.73*	0.69*	0.77*	0.49	1.00		
uk9	0.88*	0.56	0.89*	0.32	0.09	0.43	0.18	0.22	0.60	1.00	
uka	0.72*	0.69*	0.72*	0.89*	0.90*	0.77*	0.93*	0.62*	0.89*	0.39	1.00
ukb	0.33	0.23	0.39	0.70*	0.66*	0.25	0.70*	0.10	0.70*	0.11	0.78*

Notes: The table reports the pairwise correlations of the GDP shares across the manufacturing industries between geographical units. Bold figures refer to the highest pairwise correlation in the year under analysis.* refers to the correlation being statistically significant different from zero at the 5 percent significance level.

Table 2.8: Correlation Matrices of the Pattern of Specialisation for the Belgian and Spanish Regions

Year=1980	Be1	Be2	Be3
Esp1	0.73*	0.74*	0.77*
Esp2	0.50	0.55	0.71*
Esp3	0.70*	0.76*	0.77*
Esp4	0.85*	**0.85***	0.58
Esp5	0.61*	0.77*	0.55
Esp6	0.84*	0.81*	0.67*
Esp7	0.82*	0.78*	0.68*
Year=1985	Be1	Be2	Be3
Esp1	0.56	0.59	**0.85***
Esp2	0.70*	0.72*	0.63*
Esp3	0.83*	0.76*	0.57
Esp4	0.69*	0.67*	0.65*
Esp5	0.69*	0.76*	0.36
Esp6	0.81*	0.65*	0.67*
Esp7	0.73*	0.59	0.76*
Year=1990	Be1	Be2	Be3
Esp1	0.66*	0.62*	**0.93***
Esp2	0.77*	0.80*	0.65*
Esp3	0.87*	0.80*	0.73*
Esp4	0.67*	0.66*	0.80*
Esp5	0.81*	0.79*	0.64*
Esp6	0.74*	0.60	0.84*
Esp7	0.69*	0.59	0.85*
Year=1995	Be1	Be2	Be3
Esp1	0.77*	0.69*	**0.87***
Esp2	0.84*	0.81*	0.69*
Esp3	0.83*	0.73*	0.81*
Esp4	0.78*	0.74*	0.79*
Esp5	0.84*	0.84*	0.69*
Esp6	0.84*	0.71*	0.81*
Esp7	0.80*	0.68*	0.82*

Notes: The table reports the pairwise correlations of the GDP shares across the manufacturing industries between geographical units. Bold figures refer to the highest pairwise correlation in the year under analysis.* refers to the correlation being statistically significant different from zero at the 5 percent significance level.

Table 2.9: Krugman Indices for the Aggregated Industries, 1980-95

Country	Period	Country Level	Regional Level	Within Country[1]
Belgium	1980-85	0.098	0.176	0.195
	1985-90	0.070	0.180	0.220
	1990-95	0.053	0.170	0.216
Spain	1980-85	0.052	0.187	0.200
	1985-90	0.071	0.174	0.178
	1990-95	0.052	0.152	0.159
France	1980-85	0.073	0.110	0.129
	1985-90	0.084	0.109	0.122
	1990-95	0.074	0.106	0.121
Italy	1980-85	0.099	0.146	0.154
	1985-90	0.083	0.143	0.155
	1990-95	0.071	0.133	0.140
Luxembourg	1980-85	0.080	0.081	.[2]
	1985-90	0.048	0.048	.[2]
	1990-95	0.038	0.036	.[2]
Netherlands	1980-85	0.047	0.204	0.267
	1985-90	0.044	0.160	0.210
	1990-95	0.043	0.131	0.171
Whole Sample	1980-85	0.075	0.154	0.170
	1985-90	0.067	0.144	0.160
	1990-95	0.055	0.131	0.146

Notes: Krugman indices are defined as the $K_{it} = \sum_j abs\,(s_{ijt} - \delta_{jt})$, where s_{ijt} refers to the GDP share of industry j in country/region i at time t; and δ_{jt} refers to the average GDP share of industry j at time t computed among all geographical units, excluding country/region i. [1] In this case, the Krugman indices are computed among the regions that are part of the country. [2] Luxembourg is formed by only one region and we can therefore not differentiate between within and between effects in the changes of specialisation.

Table 2.10: Krugman Indices for the Disaggregated Manufacturing Industries

Country	Period	Country Level	Regional Level	Within Country[1]
Belgium	1980-85	0.663	0.692	0.697
	1985-90	0.680	0.719	0.719
	1990-95	0.699	0.736	0.735
Spain	1980-85	0.633	0.659	0.669
	1985-90	0.648	0.665	0.673
	1990-95	0.673	0.684	0.691
France	1980-85	0.658	0.645	0.646
	1985-90	0.690	0.682	0.682
	1990-95	0.712	0.702	0.702
Italy	1980-85	0.609	0.642	0.641
	1985-90	0.638	0.667	0.666
	1990-95	0.666	0.689	0.687
Luxembourg	1980-85	0.827	0.824	.[2]
	1985-90	0.795	0.801	.[2]
	1990-95	0.742	0.749	.[2]
Netherlands	1980-85	0.657	0.734	0.723
	1985-90	0.682	0.721	0.720
	1990-95	0.708	0.725	0.715
Whole Sample	1980-85	0.674	0.667	0.644
	1985-90	0.689	0.685	0.663
	1990-95	0.700	0.701	0.679

Notes: Krugman indices are defined as the $K_{it} = \sum_j abs\left(s_{ijt} - \delta_{jt}\right)$, where s_{ijt} refers to the GDP share of industry j in country/region i at time t; and δ_{jt} refers to the average GDP share of industry j at time t computed among all geographical units, excluding country/region i. [1] In this case, the Krugman indices are computed among the regions that are part of the country. [2] Luxembourg is formed by only one region and we can therefore not differentiate between within and between effects in the changes of specialisation.

Table 2.11: Annual Averages for Total Change, and, Actual Within- and Between-Region Changes in Specialisation for the Aggregated Industries, 1975-94 (in percentage)

		Agriculture	Manufacturing	Services
Be	Total Change	**-0.091**	**-0.516**	**0.595**
	Within	-0.079	-0.526	0.605
	Between	-0.012	0.010	-0.010
Esp(1)	Total Change	**-0.229**	**-0.353**	**0.777**
	Within	-0.232	-0.403	0.635
	Between	0.003	0.050	0.142
Fra	Total Change	**-0.135**	**-0.594**	**0.732**
	Within	-0.139	-0.598	0.737
	Between	0.004	0.004	-0.005
It	Total Change	**-0.172**	**-0.492**	**0.672**
	Within	-0.180	-0.500	0.680
	Between	0.008	0.008	-0.008
Lux(2)	Total Change	**-0.096**	**-0.377**	**0.472**
Ndl	Total Change	**-0.114**	**-0.475**	**0.546**
	Within	-0.073	-0.495	0.568
	Between	-0.041	0.020	-0.022
UK(3)	Total Change	**-0.039**	**-0.336**	**0.380**
	Within	-0.042	-0.359	0.402
	Between	0.003	0.023	-0.022

Notes: The table reports annual average changes in the GDP share at the country level, which are decomposed as $\Delta s_{cjt} = \sum_{r\in c}(\Delta s_{rjt}\ \omega_{rt}) + \sum_{r\in c}(s_{rjt}\ \Delta\omega_{rt})$,where the first term of the summation is the *within-region* effect and the second term is the *between-region* effect. The table reports actual within and between contributions. (1) Spain computations are for the period 1980-94. (2) Luxembourg is formed by only one region and we can therefore not differentiate between within and between effects in the changes of specialisation. (3)U.K. computations are for the period 1975-86.

Table 2.12: Total Change (in percentage), and Proportional Within- and Between-Region Changes for the Disaggregated Manufacturing Industries, 1980-1995
(1)

		Fuel	Metal	Mineral	Chem	Machine
Be	Total Change	**-0.077**	**-0.060**	**-0.017**	**0.015**	**-0.134**
	Within	104.364	102.683	98.300	65.584	101.677
	Between	-4.364	-2.683	1.700	34.416	-1.677
Esp(2)	Total Change	**0.127**	**-0.077**	**-0.026**	**-0.038**	**-0.108**
	Within	101.656	96.974	107.970	114.176	109.481
	Between	-1.656	3.026	-7.970	-14.176	-9.481
Fra	Total Change	**-0.036**	**-0.056**	**-0.029**	**-0.043**	**-0.142**
	Within	111.387	95.530	93.152	101.384	97.304
	Between	-11.387	4.470	6.848	-1.384	2.696
It	Total Change	**0.046**	**-0.050**	**-0.055**	**-0.028**	**-0.210**
	Within	100.882	94.991	102.291	95.915	95.399
	Between	-0.882	5.009	-2.291	4.085	4.611
Ndl	Total Change	**-0.114**	**-0.023**	**-0.011**	**-0.009**	**-0.068**
	Within	72.698	100.088	111.491	162.506	113.079
	Between	27.302	-0.088	-11.491	-62.506	-13.079
UK(3)	Total Change	**-0.153**	**-0.046**	**-0.041**	**-0.008**	**-0.261**
	Within	97.571	93.409	98.349	75.081	97.435
	Between	2.429	6.591	1.651	24.919	2.565

Table 2.13: (cont.) Total Change (in percentage) and Proportional Within and Between-Region Changes for the Manufacturing Industries, 1980-1995
(1)

		Transp	Food	Textile	Paper	Other	Constr
Be	Total Change	**0.023**	**-0.047**	**-0.039**	**-0.010**	**-0.027**	**-0.131**
	Within	86.931	101.586	107.088	101.955	113.553	100.804
	Between	13.069	-1.586	-7.088	-1.955	-13.553	-0.804
Esp(2)	Total Change	**-0.052**	**-0.014**	**-0.096**	**-0.004**	**-0.056**	**-0.062**
	Within	104.483	143.643	105.943	196.087	106.197	125.927
	Between	-4.483	-43.643	-5.943	-96.087	-6.197	-25.927
Fra	Total Change	**-0.103**	**-0.087**	**-0.072**	**0.015**	**-0.016**	**-0.146**
	Within	98.474	93.581	95.358	91.181	82.350	99.186
	Between	1.526	6.419	4.642	8.819	17.650	0.814
It	Total Change	**-0.063**	**-0.041**	**-0.103**	**-0.027**	**-0.059**	**-0.144**
	Within	88.228	102.185	98.348	100.174	101.604	103.689
	Between	11.772	-2.185	1.652	-0.174	-1.604	-3.689
Ndl	Total Change	**-0.039**	**0.020**	**-0.027**	**-0.001**	**-0.032**	**-0.140**
	Within	101.797	77.911	107.609	144.198	100.455	101.582
	Between	-1.797	22.089	-7.609	-44.198	-0.455	-1.582
UK(3)	Total Change	**-0.106**	**-0.043**	**-0.108**	**-0.008**	**-0.061**	**0.041**
	Within	96.709	107.446	99.902	106.557	98.924	94.196
	Between	3.291	-7.446	0.098	-6.557	1.076	5.804

Notes: The table reports annual average changes in the GDP share at the country level, which are decomposed as $\Delta s_{cjt} = \sum_{r \in c}(\Delta s_{rjt}\ \omega_{rt}) + \sum_{r \in c}(s_{rjt}\ \Delta\omega_{rt})$,where the first term of the summation is the *within-region* effect and the second term is the *between-region* effect. The table reports within and between contributions in percentage. (1) Spain computations are for the period 1980-94. (2) Luxembourg is formed by only one region and we can therefore not differentiate between within and between effects in the changes of specialisation. (3)U.K. computations are for the period 1975-86.

Table 2.14: Transition Probabilities Matrices for Belgium, Shares of GDP 5-year transitions

Belgium

s_{cjt}	Upper Endpoint (% GDP)				
Number	(1.5)	(2.0)	(3.0)	(4.5)	(8.0)
(21)	1.00	0.00	0.00	0.00	0.00
(27)	0.15	0.63	0.22	0.00	0.00
(24)	0.08	0.17	0.62	0.12	0.00
(22)	0.00	0.00	0.27	0.73	0.00
(27)	0.00	0.00	0.00	0.37	0.63
Initial	0.17	0.22	0.20	0.18	0.22
Ergodic	1.00	0.00	0.00	0.00	0.00

Be1

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.3)	(0.9)	(1.6)	(3.5)	(5.8)
(23)	0.87	0.13	0.00	0.00	0.00
(24)	0.33	0.62	0.04	0.00	0.00
(26)	0.00	0.19	0.73	0.08	0.00
(21)	0.00	0.00	0.19	0.76	0.05
(27)	0.00	0.00	0.00	0.44	0.56
Initial	0.19	0.20	0.21	0.17	0.22
Ergodic	0.66	0.26	0.06	0.02	0.00

Be2

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.6)	(2.7)	(3.7)	(5.1)	(8.0)
(21)	0.95	0.05	0.00	0.00	0.00
(25)	0.24	0.72	0.04	0.00	0.00
(27)	0.00	0.26	0.56	0.19	0.00
(23)	0.00	0.00	0.26	0.52	0.22
(25)	0.00	0.00	0.00	0.36	0.64
Initial	0.17	0.21	0.22	0.19	0.21
Ergodic	0.79	0.16	0.02	0.02	0.01

Be3

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.2)	(2.1)	(2.7)	(4.2)	(9.3)
(0.21)	0.60	0.40	0.00	0.00	0.00
(0.18)	0.27	0.59	0.14	0.00	0.00
(0.21)	0.00	0.24	0.76	0.00	0.00
(0.18)	0.00	0.00	0.27	0.64	0.09
(0.22)	0.00	0.00	0.04	0.41	0.56
Initial	0.21	0.18	0.21	0.18	0.22
Ergodic	0.30	0.44	0.25	0.00	0.00

Notes: initial is the distribution of industries across grid cells in 1975. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.15: Transition Probabilities Matrices for Spain, Shares of GDP 5-year transitions

Spain

s_{cjt}	Upper Endpoint (% GDP)				
Number	(1.6)	(2.0)	(3.3)	(4.8)	(8.0)
(15)	1.00	0.00	0.00	0.00	0.00
(12)	0.50	0.50	0.00	0.00	0.00
(31)	0.10	0.55	0.35	0.23	0.00
(21)	0.00	0.00	0.10	0.76	0.05
(20)	0.00	0.00	0.00	0.15	0.85
Initial	0.15	0.12	0.31	0.21	0.20
Ergodic	1.00	0.00	0.00	0.00	0.00

Esp1

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.9)	(2.1)	(2.7)	(5.1)	(10.2)
(18)	1.00	0.00	0.00	0.00	0.00
(21)	0.14	0.71	0.14	0.00	0.00
(16)	0.00	0.19	0.81	0.00	0.00
(24)	0.00	0.00	0.46	0.54	0.00
(20)	0.00	0.00	0.00	0.10	0.90
Initial	0.18	0.21	0.16	0.24	0.20
Ergodic	1.00	0.00	0.00	0.00	0.00

Esp2

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.8)	(2.7)	(4.2)	(6.0)	(12.9)
(13)	0.85	0.15	0.00	0.00	0.00
(23)	0.61	0.39	0.00	0.00	0.00
(21)	0.00	0.29	0.71	0.00	0.00
(26)	0.00	0.00	0.27	0.38	0.35
(16)	0.00	0.00	0.00	0.19	0.81
Initial	0.13	0.23	0.21	0.26	0.16
Ergodic	0.80	0.20	0.00	0.00	0.00

Esp3

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.0)	(1.8)	(2.3)	(3.1)	(8.9)
(16)	1.00	0.00	0.00	0.00	0.00
(11)	0.36	0.55	0.00	0.09	0.00
(17)	0.00	0.12	0.47	0.41	0.00
(24)	0.00	0.08	0.54	0.38	0.00
(20)	0.00	0.00	0.00	0.10	0.90
Initial	0.18	0.13	0.19	0.27	0.23
Ergodic	1.00	0.00	0.00	0.00	0.00

Esp4

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.1)	(1.8)	(2.2)	(5.5)	(10.4)
(18)	1.00	0.00	0.00	0.00	0.00
(18)	0.17	0.83	0.00	0.00	0.00
(20)	0.00	0.30	0.50	0.20	0.00
(23)	0.00	0.00	0.48	0.48	0.04
(20)	0.00	0.00	0.00	0.10	0.90
Initial	0.18	0.18	0.20	0.23	0.20
Ergodic	1.00	0.00	0.00	0.00	0.00

Esp5

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.7)	(2.7)	(4.1)	(5.1)	(8.2)
(20)	0.90	0.10	0.00	0.00	0.00
(15)	0.20	0.80	0.00	0.00	0.00
(20)	0.00	0.40	0.55	0.05	0.00
(20)	0.00	0.00	0.30	0.70	0.00
(24)	0.00	0.00	0.08	0.29	0.62
Initial	0.20	0.15	0.20	0.20	0.24
Ergodic	0.67	0.33	0.00	0.00	0.00

Esp6

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.8)	(1.2)	(1.6)	(5.6)	(12.0)
(10)	1.00	0.00	0.00	0.00	0.00
(21)	0.52	0.48	0.00	0.00	0.00
(22)	0.14	0.36	0.32	0.18	0.00
(25)	0.08	0.08	0.48	0.24	0.12
(21)	0.00	0.00	0.00	0.29	0.71
Initial	0.10	0.21	0.22	0.25	0.21
Ergodic	1.00	0.00	0.00	0.00	0.00

Esp7

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.2)	(0.4)	(0.8)	(3.5)	(11.4)
(18)	0.50	0.44	0.06	0.00	0.00
(19)	0.42	0.37	0.21	0.00	0.00
(21)	0.00	0.29	0.71	0.00	0.00
(21)	0.00	0.05	0.14	0.62	0.19
(20)	0.00	0.00	0.00	0.20	0.80
Initial	0.18	0.19	0.21	0.21	0.20
Ergodic	0.31	0.36	0.33	0.00	0.00

Notes: initial is the distribution of industries across grid cells in 1980. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.16: Transition Probabilities Matrices for France, Shares of GDP 5-year transitions

France

s_{cjt}	Upper Endpoint (% GDP)				
Number	(1.4)	(1.9)	(2.7)	(4.8)	(8.1)
(24)	0.92	0.08	0.00	0.00	0.00
(26)	0.27	0.62	0.12	0.00	0.00
(29)	0.00	0.34	0.66	0.00	0.00
(28)	0.00	0.00	0.14	0.82	0.04
(25)	0.00	0.00	0.00	0.04	0.96
Initial	0.18	0.20	0.22	0.21	0.19
Ergodic	0.71	0.22	0.07	0.00	0.00

Fra1

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.8)	(1.5)	(2.4)	(4.9)	(8.3)
(23)	1.00	0.00	0.00	0.00	0.00
(28)	0.21	0.79	0.00	0.00	0.00
(24)	0.00	0.21	0.71	0.08	0.00
(30)	0.00	0.00	0.30	0.57	0.13
(27)	0.00	0.00	0.00	0.30	0.70
Initial	0.17	0.21	0.18	0.23	0.20
Ergodic	1.00	0.00	0.00	0.00	0.00

Fra2

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.4)	(2.4)	(2.9)	(5.4)	(10.4)
(24)	0.79	0.21	0.00	0.00	0.00
(30)	0.40	0.47	0.13	0.00	0.00
(26)	0.00	0.15	0.81	0.04	0.00
(25)	0.00	0.04	0.12	0.80	0.04
(27)	0.00	0.00	0.00	0.26	0.74
Initial	0.18	0.23	0.20	0.19	0.20
Ergodic	0.48	0.25	0.21	0.05	0.01

Fra3

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.8)	(2.4)	(4.0)	(5.3)	(7.7)
(27)	0.67	0.33	0.00	0.00	0.00
(22)	0.27	0.55	0.18	0.00	0.00
(23)	0.13	0.43	0.39	0.04	0.00
(30)	0.00	0.07	0.50	0.40	0.03
(30)	0.00	0.00	0.03	0.50	0.47
Initial	0.20	0.17	0.17	0.23	0.23
Ergodic	0.41	0.44	0.14	0.01	0.00

Fra4

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.7)	(2.5)	(3.5)	(5.3)	(9.6)
(22)	0.82	0.18	0.00	0.00	0.00
(27)	0.44	0.41	0.15	0.00	0.00
(29)	0.03	0.38	0.59	0.00	0.00
(28)	0.00	0.07	0.18	0.57	0.18
(26)	0.00	0.00	0.00	0.38	0.62
Initial	0.17	0.20	0.22	0.21	0.20
Ergodic	0.65	0.26	0.09	0.00	0.00

Fra5

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.0)	(1.8)	(2.7)	(5.3)	(9.0)
(25)	0.96	0.04	0.00	0.00	0.00
(26)	0.15	0.85	0.00	0.00	0.00
(25)	0.00	0.20	0.68	0.12	0.00
(30)	0.00	0.00	0.37	0.53	0.10
(26)	0.00	0.00	0.00	0.31	0.69
Initial	0.19	0.20	0.19	0.23	0.20
Ergodic	0.79	0.21	0.00	0.00	0.00

Fra6

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.3)	(1.7)	(2.8)	(4.4)	(9.0)
(19)	1.00	0.00	0.00	0.00	0.00
(32)	0.38	0.47	0.16	0.00	0.00
(29)	0.07	0.41	0.48	0.03	0.00
(24)	0.00	0.00	0.12	0.79	0.08
(29)	0.00	0.00	0.00	0.32	0.68
Initial	0.14	0.24	0.22	0.18	0.21
Ergodic	1.00	0.00	0.00	0.00	0.00

Fra7

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.4)	(2.3)	(3.2)	(4.8)	(12.2)
(24)	0.92	0.08	0.00	0.00	0.00
(23)	0.35	0.65	0.00	0.00	0.00
(32)	0.00	0.41	0.56	0.03	0.00
(29)	0.00	0.00	0.21	0.76	0.03
(24)	0.00	0.00	0.00	0.00	1.00
Initial	0.18	0.17	0.24	0.22	0.18
Ergodic	0.81	0.19	0.00	0.00	0.00
Ergodic	0.00	0.00	0.00	0.00	1.00

Fra8

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.9)	(1.2)	(1.9)	(3.7)	(9.2)
(24)	0.92	0.08	0.00	0.00	0.00
(23)	0.22	0.74	0.04	0.00	0.00
(32)	0.06	0.38	0.47	0.00	0.00
(28)	0.00	0.00	0.25	0.71	0.04
(25)	0.00	0.00	0.00	0.08	0.92
Initial	0.18	0.17	0.24	0.21	0.19
Ergodic	0.70	0.26	0.03	0.01	0.00

Notes: initial is the distribution of industries across grid cells in 1975. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.17: Transition Probabilities Matrices for Italy, Shares of GDP 5-year transitions

Italy

s_{cjt}	Upper Endpoint (% GDP)				
Number	(1.6)	(2.2)	(2.8)	(4.7)	(9.3)
(18)	0.89	0.11	0.00	0.00	0.00
(22)	0.27	0.45	0.23	0.05	0.00
(24)	0.04	0.42	0.42	0.12	0.00
(23)	0.00	0.00	0.35	0.65	0.00
(23)	0.00	0.00	0.00	0.13	0.87
Initial	0.16	0.20	0.22	0.21	0.21
Ergodic	0.58	0.22	0.13	0.07	0.00

It1

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.7)	(2.2)	(3.2)	(5.5)	(12.5)
(23)	0.78	0.17	0.04	0.00	0.00
(21)	0.05	0.67	0.29	0.00	0.00
(23)	0.00	0.22	0.61	0.17	0.00
(19)	0.00	0.00	0.11	0.63	0.26
(24)	0.00	0.00	0.00	0.38	0.62
Initial	0.21	0.19	0.21	0.17	0.22
Ergodic	0.03	0.16	0.21	0.35	0.25

It2

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.8)	(2.5)	(3.6)	(5.8)	(15.2)
(19)	0.89	0.11	0.00	0.00	0.00
(27)	0.33	0.37	0.30	0.00	0.00
(18)	0.00	0.22	0.72	0.06	0.00
(21)	0.00	0.00	0.24	0.67	0.10
(25)	0.00	0.00	0.00	0.36	0.64
Initial	0.17	0.25	0.16	0.19	0.23
Ergodic	0.54	0.17	0.23	0.05	0.01

It3

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.4)	(1.9)	(2.9)	(6.0)	(9.4)
(21)	0.95	0.05	0.00	0.00	0.00
(19)	0.05	0.63	0.32	0.00	0.00
(24)	0.04	0.42	0.54	0.00	0.00
(23)	0.00	0.00	0.17	0.74	0.09
(23)	0.00	0.00	0.00	0.13	0.87
Initial	0.19	0.17	0.22	0.21	0.21
Ergodic	0.50	0.29	0.20	0.00	0.00

It4

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.3)	(2.2)	(3.4)	(5.4)	(12.6)
(18)	0.83	0.17	0.00	0.00	0.00
(25)	0.32	0.60	0.08	0.00	0.00
(20)	0.00	0.20	0.80	0.00	0.00
(24)	0.00	0.00	0.25	0.67	0.08
(23)	0.00	0.00	0.00	0.13	0.87
Initial	0.16	0.23	0.18	0.22	0.21
Ergodic	0.58	0.30	0.12	0.00	0.00

It5

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.5)	(2.0)	(3.4)	(5.3)	(12.1)
(18)	0.78	0.22	0.00	0.00	0.00
(23)	0.48	0.26	0.26	0.00	0.00
(23)	0.00	0.48	0.43	0.09	0.00
(23)	0.00	0.00	0.22	0.78	0.00
(23)	0.00	0.00	0.00	0.13	0.87
Initial	0.16	0.21	0.21	0.21	0.21
Ergodic	0.55	0.26	0.14	0.06	0.00

It6

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.1)	(1.4)	(2.1)	(3.1)	(6.8)
(16)	0.88	0.12	0.00	0.00	0.00
(21)	0.43	0.57	0.00	0.00	0.00
(32)	0.09	0.41	0.22	0.28	0.00
(21)	0.00	0.00	0.1	0.76	0.14
(20)	0.00	0.00	0.00	0.00	1.00
Initial	0.15	0.19	0.29	0.19	0.18
Ergodic	0.00	0.00	0.00	0.00	1.00
Ergodic	0.77	0.23	0.00	0.00	0.00

It7

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.5)	(1.9)	(2.9)	(4.3)	(12.1)
(25)	0.64	0.32	0.04	0.00	0.00
(16)	0.19	0.56	0.25	0.00	0.00
(22)	0.00	0.36	0.45	0.18	0.00
(27)	0.00	0.00	0.33	0.37	0.30
(20)	0.00	0.00	0.00	0.35	0.65
Initial	0.23	0.15	0.20	0.25	0.18
Ergodic	0.17	0.33	0.25	0.14	0.11

It8

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.1)	(1.7)	(2.0)	(2.9)	(10.3)
(23)	0.78	0.17	0.00	0.04	0.00
(20)	0.25	0.50	0.25	0.00	0.00
(24)	0.00	0.29	0.46	0.25	0.00
(20)	0.00	0.00	0.35	0.60	0.05
(23)	0.00	0.00	0.04	0.09	0.87
Initial	0.21	0.18	0.22	0.18	0.21
Ergodic	0.27	0.23	0.24	0.19	0.07

It9

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.0)	(1.5)	(2.0)	(2.9)	(12.8)
(21)	0.76	0.24	0.00	0.00	0.00
(19)	0.32	0.32	0.32	0.05	0.00
(24)	0.00	0.42	0.46	0.12	0.00
(28)	0.00	0.04	0.25	0.43	0.29
(18)	0.00	0.00	0.00	0.17	0.83
Initial	0.19	0.17	0.22	0.25	0.16
Ergodic	0.28	0.22	0.18	0.12	0.20

Notes: initial is the distribution of industries across grid cells in 1975. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.18 (cont.): Transition Probabilities Matrices for Italy, Shares of GDP 5-year transitions

Ita

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.7)	(1.1)	(1.4)	(2.3)	(11.2)
(20)	1.00	0.00	0.00	0.00	0.00
(14)	0.14	0.79	0.07	0.00	0.00
(30)	0.00	0.53	0.30	0.17	0.00
(23)	0.04	0.09	0.22	0.65	0.00
(23)	0.00	0.00	0.00	0.13	0.87
Initial	0.18	0.13	0.27	0.21	0.21
Ergodic	1.00	0.00	0.00	0.00	0.00

Itb

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.5)	(1.3)	(2.2)	(3.4)	(15.2)
(15)	1.00	0.00	0.00	0.00	0.00
(26)	0.50	0.42	0.08	0.00	0.00
(24)	0.00	0.33	0.33	0.29	0.04
(22)	0.00	0.00	0.55	0.36	0.09
(23)	0.00	0.00	0.00	0.13	0.87
Initial	0.14	0.24	0.22	0.20	0.21
Ergodic	1.00	0.00	0.00	0.00	0.00

Notes: initial is the distribution of industries across grid cells in 1975. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.18: Transition Probabilities Matrices for Luxembourg and Netherlands, Shares of GDP 5-year transitions

Luxembourg

s_{cjt}	Upper Endpoint (% GDP)				
Number	(0.7)	(1.8)	(2.7)	(5.1)	(15.3)
(28)	0.68	0.32	0.00	0.00	0.00
(25)	0.24	0.60	0.08	0.08	0.00
(29)	0.00	0.14	0.76	0.10	0.00
(27)	0.00	0.00	0.07	0.63	0.3
(23)	0.00	0.00	0.00	0.26	0.74
Initial	0.21	0.19	0.22	0.20	0.17
Ergodic	0.09	0.12	0.13	0.31	0.35

Netherlands

s_{cjt}	Upper Endpoint (% GDP)				
Number	(0.9)	(1.1)	(2.8)	(5.3)	(12.1)
(23)	0.70	0.30	0.00	0.00	0.00
(32)	0.50	0.50	0.00	0.00	0.00
(33)	0.00	0.21	0.58	0.21	0.00
(24)	0.00	0.00	0.17	0.67	0.17
(31)	0.00	0.00	0.00	0.29	0.71
Initial	0.16	0.22	0.23	0.17	0.22
Ergodic	0.62	0.38	0.00	0.00	0.00

Ndl1

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.8)	(1.3)	(2.4)	(4.7)	(35.8)
(28)	0.93	0.07	0.00	0.00	0.00
(29)	0.10	0.76	0.14	0.00	0.00
(28)	0.00	0.21	0.54	0.25	0.00
(27)	0.00	0.00	0.30	0.59	0.11
(31)	0.00	0.00	0.00	0.26	0.74
Initial	0.20	0.20	0.20	0.19	0.21
Ergodic	0.37	0.26	0.17	0.14	0.06

Ndl2

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.1)	(1.6)	(2.8)	(3.8)	(8.8)
(26)	1.00	0.00	0.00	0.00	0.00
(29)	0.14	0.66	0.07	0.14	0.00
(31)	0.00	0.39	0.32	0.29	0.00
(31)	0.00	0.00	0.42	0.52	0.06
(26)	0.00	0.00	0.00	0.00	1.00
Initial	0.18	0.20	0.22	0.22	0.18
Ergodic	1.00	0.00	0.00	0.00	0.00
	0.00	0.00	0.00	0.00	1.00

Ndl3

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.6)	(1.2)	(2.7)	(4.3)	(6.9)
(26)	1.00	0.00	0.00	0.00	0.00
(29)	0.14	0.79	0.07	0.00	0.00
(27)	0.00	0.37	0.63	0.00	0.00
(33)	0.00	0.00	0.18	0.76	0.06
(28)	0.00	0.00	0.07	0.00	0.93
Initial	0.18	0.20	0.19	0.23	0.20
Ergodic	1.00	0.00	0.00	0.00	0.00

Ndl4

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.4)	(1.8)	(2.6)	(5.5)	(11.6)
(22)	0.86	0.14	0.00	0.00	0.00
(30)	0.30	0.53	0.17	0.00	0.00
(33)	0.12	0.36	0.45	0.06	0.00
(32)	0.00	0.06	0.09	0.62	0.22
(26)	0.00	0.00	0.00	0.19	0.81
Initial	0.15	0.21	0.23	0.22	0.18
Ergodic	0.61	0.25	0.08	0.03	0.04

Notes: initial is the distribution of industries across grid cells in 1975. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.19: Transition Probabilities Matrices for United Kingdom, Shares of GDP 5-year transitions

United Kingdom

s_{cjt}	Upper Endpoint (% GDP)				
Number	(1.6)	(2.1)	(3.2)	(6.9)	(11.9)
(11)	0.91	0.09	0.00	0.00	0.00
(15)	0.40	0.40	0.20	0.00	0.00
(14)	0.07	0.36	0.57	0.00	0.00
(14)	0.00	0.00	0.14	0.86	0.00
(12)	0.00	0.00	0.00	0.08	0.92
Initial	0.17	0.23	0.21	0.21	0.18
Ergodic	0.77	0.16	0.07	0.00	0.00

Uk1

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.7)	(2.1)	(5.4)	(7.4)	(11.9)
(13)	0.62	0.31	0.08	0.00	0.00
(14)	0.29	0.5	0.21	0.00	0.00
(12)	0.25	0.08	0.50	0.17	0.00
(13)	0.00	0.00	0.46	0.54	0.00
(14)	0.00	0.00	0.00	0.36	0.64
Initial	0.20	0.21	0.18	0.20	0.21
Ergodic	0.37	0.27	0.26	0.10	0.00

Uk2

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.7)	(2.3)	(4.2)	(6.2)	(12.6)
(15)	0.60	0.33	0.07	0.00	0.00
(12)	0.33	0.50	0.17	0.00	0.00
(13)	0.00	0.23	0.77	0.00	0.00
(13)	0.00	0.08	0.00	0.85	0.08
(13)	0.00	0.00	0.08	0.23	0.69
Initial	0.23	0.18	0.20	0.20	0.20
Ergodic	0.30	0.36	0.34	0.00	0.00

Uk3

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.9)	(2.1)	(5.5)	(7.5)	(10.7)
(14)	0.57	0.43	0.00	0.00	0.00
(13)	0.31	0.38	0.31	0.00	0.00
(13)	0.23	0.23	0.31	0.15	0.08
(15)	0.00	0.00	0.33	0.53	0.13
(11)	0.00	0.00	0.09	0.09	0.82
Initial	0.21	0.20	0.20	0.23	0.17
Ergodic	0.30	0.28	0.19	0.09	0.14

Uk4

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.1)	(2.1)	(2.8)	(7.1)	(9.8)
(14)	0.64	0.36	0.00	0.00	0.00
(15)	0.27	0.33	0.13	0.27	0.00
(13)	0.00	0.15	0.69	0.15	0.00
(11)	0.00	0.09	0.18	0.64	0.09
(13)	0.00	0.00	0.00	0.31	0.69
Initial	0.21	0.23	0.20	0.17	0.20
Ergodic	0.13	0.18	0.27	0.32	0.10

Uk5

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.7)	(1.9)	(3.0)	(5.5)	(7.9)
(12)	0.92	0.08	0.00	0.00	0.00
(15)	0.33	0.53	0.13	0.00	0.00
(12)	0.00	0.25	0.58	0.17	0.00
(16)	0.00	0.00	0.38	0.44	0.19
(11)	0.00	0.00	0.00	0.09	0.91
Initial	0.18	0.23	0.18	0.24	0.17
Ergodic	0.64	0.16	0.09	0.04	0.08

Uk6

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.1)	(1.9)	(3.3)	(6.6)	(7.8)
(13)	0.54	0.46	0.00	0.00	0.00
(12)	0.5	0.42	0.08	0.00	0.00
(16)	0.00	0.31	0.50	0.19	0.00
(12)	0.00	0.00	0.25	0.5	0.25
(13)	0.00	0.00	0.00	0.54	0.46
Initial	0.20	0.18	0.24	0.18	0.20
Ergodic	0.41	0.38	0.10	0.08	0.04

Uk7

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.3)	(2.5)	(3.9)	(5.7)	(16.3)
(16)	0.69	0.31	0.00	0.00	0.00
(9)	0.00	1.00	0.00	0.00	0.00
(15)	0.00	0.13	0.73	0.13	0.00
(13)	0.00	0.15	0.08	0.69	0.08
(13)	0.00	0.08	0.00	0.31	0.62
Initial	0.24	0.14	0.23	0.20	0.20
Ergodic	0.00	1.00	0.00	0.00	0.00

Notes: initial is the distribution of industries across grid cells in 1975. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.20(cont.): Transition Probabilities Matrices for United Kingdom, Shares of GDP 5-year transitions

Uk8

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.9)	(2.7)	(4.5)	(7.1)	(9.4)
(12)	1.00	0.00	0.00	0.00	0.00
(13)	0.23	0.77	0.00	0.00	0.00
(15)	0.00	0.33	0.67	0.00	0.00
(15)	0.00	0.00	0.13	0.47	0.40
(11)	0.00	0.00	0.00	0.36	0.64
Initial	0.18	0.20	0.23	0.23	0.17
Ergodic	1.00	0.00	0.00	0.00	0.00

Uk9

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.3)	(2.1)	(3.3)	(6.0)	(21.1)
(12)	0.92	0.08	0.00	0.00	0.00
(13)	0.31	0.46	0.23	0.00	0.00
(19)	0.00	0.42	0.21	0.37	0.00
(7)	0.00	0.00	0.29	0.71	0.00
(15)	0.00	0.00	0.00	0.53	0.47
Initial	0.18	0.20	0.29	0.11	0.23
Ergodic	0.62	0.17	0.09	0.12	0.00

Uka

s_{rjt}	Upper Endpoint (% GDP)				
Number	(1.1)	(1.8)	(2.5)	(7.3)	(11.7)
(12)	1.00	0.00	0.00	0.00	0.00
(14)	0.21	0.71	0.07	0.00	0.00
(14)	0.00	0.14	0.86	0.00	0.00
(13)	0.00	0.15	0.00	0.69	0.15
(13)	0.00	0.00	0.00	0.46	0.54
Initial	0.18	0.21	0.21	0.20	0.20
Ergodic	1.00	0.00	0.00	0.00	0.00

Ukb

s_{rjt}	Upper Endpoint (% GDP)				
Number	(0.9)	(1.5)	(2.8)	(5.9)	(15.1)
(15)	0.53	0.40	0.07	0.00	0.00
(10)	0.20	0.50	0.30	0.00	0.00
(12)	0.25	0.42	0.33	0.00	0.00
(16)	0.00	0.00	0.44	0.56	0.00
(13)	0.00	0.00	0.08	0.15	0.77
Initial	0.23	0.15	0.18	0.24	0.20
Ergodic	0.31	0.45	0.23	0.00	0.00

Notes: initial is the distribution of industries across grid cells in 1975. Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.20: Transition Probabilities, Relative Shares of GDP 5-year transitions, Country Level Analysis

Belgium

rs_{ijt}	Upper Endpoint (% GDP)				
Number	(0.54)	(0.72)	(1.12)	(1.56)	(2.45)
(23)	0.96	0.04	0.00	0.00	0.00
(27)	0.11	0.56	0.33	0.00	0.00
(24)	0.04	0.12	0.58	0.25	0.00
(24)	0.00	0.00	0.17	0.62	0.21
(23)	0.00	0.00	0.00	0.35	0.65
Initial	0.19	0.22	0.20	0.20	0.19
Ergodic	0.37	0.08	0.16	0.24	0.15

Spain

rs_{ijt}	Upper Endpoint (% GDP)				
Number	(0.53)	(0.63)	(0.77)	(1.54)	(2.99)
(17)	1.00	0.00	0.00	0.00	0.00
(12)	0.25	0.67	0.08	0.00	0.00
(29)	0.07	0.52	0.34	0.07	0.00
(21)	0.00	0.14	0.10	0.71	0.05
(20)	0.00	0.00	0.00	0.15	0.85
Initial	0.17	0.12	0.29	0.21	0.20
Ergodic	1.00	0.00	0.00	0.00	0.00

France

s_{cjt}	Upper Endpoint (% GDP)				
Number	(0.44)	(0.65)	(0.94)	(1.69)	(2.44)
(27)	0.85	0.15	0.00	0.00	0.00
(29)	0.07	0.72	0.21	0.00	0.00
(23)	0.00	0.00	0.96	0.04	0.00
(28)	0.00	0.00	0.18	0.79	0.04
(25)	0.00	0.00	0.00	0.04	0.96
Initial	0.20	0.22	0.17	0.21	0.19
Ergodic	0.00	0.00	0.69	0.16	0.15

Italy

s_{cjt}	Upper Endpoint (% GDP)				
Number	(0.52)	(0.67)	(0.86)	(1.36)	(2.54)
(21)	0.95	0.05	0.00	0.00	0.00
(25)	0.08	0.68	0.20	0.04	0.00
(23)	0.00	0.00	0.74	0.26	0.00
(18)	0.00	0.00	0.06	0.83	0.11
(23)	0.00	0.00	0.00	0.13	0.87
Initial	0.19	0.23	0.21	0.16	0.21
Ergodic	0.00	0.00	0.10	0.48	0.42

Luxembourg

rs_{ijt}	Upper Endpoint (% GDP)				
Number	(0.22)	(0.59)	(0.91)	(1.80)	(4.47)
(28)	0.71	0.29	0.00	0.00	0.00
(25)	0.20	0.68	0.04	0.08	0.00
(29)	0.00	0.10	0.76	0.14	0.00
(29)	0.00	0.00	0.00	0.62	0.28
(21)	0.00	0.00	0.00	0.19	0.81
Initial	0.21	0.19	0.22	0.22	0.16
Ergodic	0.08	0.12	0.14	0.27	0.39

Netherlands

rs_{ijt}	Upper Endpoint (% GDP)				
Number	(0.29)	(0.38)	(1.04)	(1.89)	(3.79)
(28)	0.68	0.32	0.00	0.00	0.00
(29)	0.31	0.62	0.07	0.00	0.00
(33)	0.03	0.12	0.58	0.27	0.00
(27)	0.00	0.00	0.15	0.59	0.26
(26)	0.00	0.00	0.00	0.19	0.81
Initial	0.20	0.20	0.23	0.19	0.18
Ergodic	0.23	0.22	0.10	0.19	0.25

United Kingdom

rs_{ijt}	Upper Endpoint (% GDP)				
Number	(0.43)	(0.55)	(0.84)	(1.87)	(3.21)
(11)	0.91	0.09	0.00	0.00	0.00
(16)	0.38	0.38	0.25	0.00	0.00
(13)	0.08	0.31	0.62	0.00	0.00
(14)	0.00	0.00	0.14	0.86	0.00
(12)	0.00	0.00	0.00	0.08	0.92
Initial	0.17	0.24	0.20	0.21	0.18
Ergodic	0.74	0.16	0.10	0.00	0.00

Notes: initial is the distribution of industries across grid cells in the 1975 (1980 for Spain). Ergodic is the stationary distribution implied by the estimated transition probability matrix.

Table 2.21: Regional Mobility Indices Relative to Corresponding Country Indices, 5-year transitions

Region	M_1	M_2	Region	M_1	M_2
Be1	1.05	1.01	It6	0.91	0.97
Be2	1.16	1.09	It7	1.35	1.03
Be3	1.33	1.11	It8	1.04	1.01
Esp1	0.68	0.83	It9	1.28	1.02
Esp2	1.21	1.08	Ita	0.81	0.94
Esp3	1.10	1.10	Itb	1.17	1.01
Esp4	0.84	1.01	Lux[1]	1.14	1.07
Esp5	0.93	0.95	Nld1	0.78	0.94
Esp6	1.46	1.12	Nld2	0.82	1.01
Esp7	1.30	1.11	Nld3	0.48	0.70
Fra1	1.21	1.09	Nld4	0.94	0.98
Fra2	1.36	1.17	Uk1	1.20	1.02
Fra3	2.47	1.33	Uk2	0.86	0.97
Fra4	1.95	1.30	Uk3	1.30	1.04
Fra5	1.26	1.13	Uk4	1.09	1.02
Fra6	1.55	1.23	Uk5	0.88	0.98
Fra7	1.09	1.02	Uk6	1.40	1.05
Fra8	1.22	1.10	Uk7	0.69	0.84
It1	0.98	0.96	Uk8	0.79	0.96
It2	0.99	0.97	Uk9	1.21	1.02
It3	0.74	0.91	Uka	0.65	0.86
It4	0.72	0.83	Ukb	1.26	1.04
It5	1.09	0.99			

Note: This table reports the ratio of region's mobility indices to its corresponding country's index. M_1evaluates the trace, *tr*, of the transition probability matrix ($M_1 = \frac{n-tr[M_r^*]}{N-1}$) M_2 evaluates the determinant, *det*, of the transition probability matrix, $M_2 = 1 - |\det(M_r^*)|$. [1] Relative to the mobility index of Belgium (country-level).

Table 2.22: Cross-country Differences in Specialisation Dynamics, 5-year transitions

Country	χ
Belgium	87.94***
	(Reject)
Spain	20.60
	(Accept)
Italy	19.84
	(Accept)
Luxembourg	102.95***
	(Reject)
Netherlands	89.35***
	(Reject)
United Kingdom	4.20
	(Accept)

Note: Null Hypothesis is that the Data Generating Process equals the matrix of transition probabilities estimated for France. We test whether the matrices estimated for the other countries are statistically significantly different from this null. Test statistic is distributed $\chi^2(20)$. The *** indicates significance level at 1 percent.

Table 2.23: Within-country Differences in Specialisation Dynamics, 5-year transitions

Region	χ	Region	χ	Region	χ
Be1	13.20 *(Accept)*	Fra6	64.74*** *(Reject)*	Ndl2	54.75*** *(Reject)*
Be2	11.52 *(Accept)*	Fra7	6.50 *(Accept)*	Ndl3	45.41*** *(Reject)*
Be3	13.89 *(Accept)*	Fra8	7.75 *(Accept)*	Ndl4	16.23 *(Accept)*
Esp1	58.96*** *(Reject)*	It1	30.43 *(Accept)*	Uk1	43.21*** *(Reject)*
Esp2	75.92*** *(Reject)*	It2	21.93 *(Accept)*	Uk2	20.34 *(Accept)*
Esp3	61.31*** *(Reject)*	It3	13.28 *(Accept)*	Uk3	33.63* *(Reject)*
Esp4	51.72*** *(Reject)*	It4	18.92 *(Accept)*	Uk4	26.57 *(Accept)*
Esp5	26.43 *(Accept)*	It5	12.07 *(Accept)*	Uk5	12.32 *(Accept)*
Esp6	52.66*** *(Reject)*	It6	27.57 *(Accept)*	Uk6	64.50*** *(Reject)*
Esp7	27.87 *(Accept)*	It7	27.04 *(Accept)*	Uk7	37.52** *(Reject)*
Fra1	69.70*** *(Reject)*	It8	8.00 *(Accept)*	Uk8	24.91 *(Accept)*
Fra2	46.26*** *(Reject)*	It9	9.37 *(Accept)*	Uk9	48.87*** *(Reject)*
Fra3	227.35*** *(Reject)*	Ita	14.03 *(Accept)*	Uka	39.69*** *(Reject)*
Fra4	102.80*** *(Reject)*	Itb	23.87 *(Accept)*	Ukb	40.11*** *(Reject)*
Fra5	75.20*** *(Reject)*	Ndl1	24.19 *(Accept)*		

Note: Null hypothesis is that the data generating process equals the matrix of transition probabilities of the corresponding country. We test whether the matrices estimated for the regions are statistically significantly different from the null. Test statistic is distributed as $\chi^2(20)$. The ** and *** indicate significance levels at the 2.5 and 1 percent significance level, respectively.

Figure 2-1: Specialisation at a Point in Time

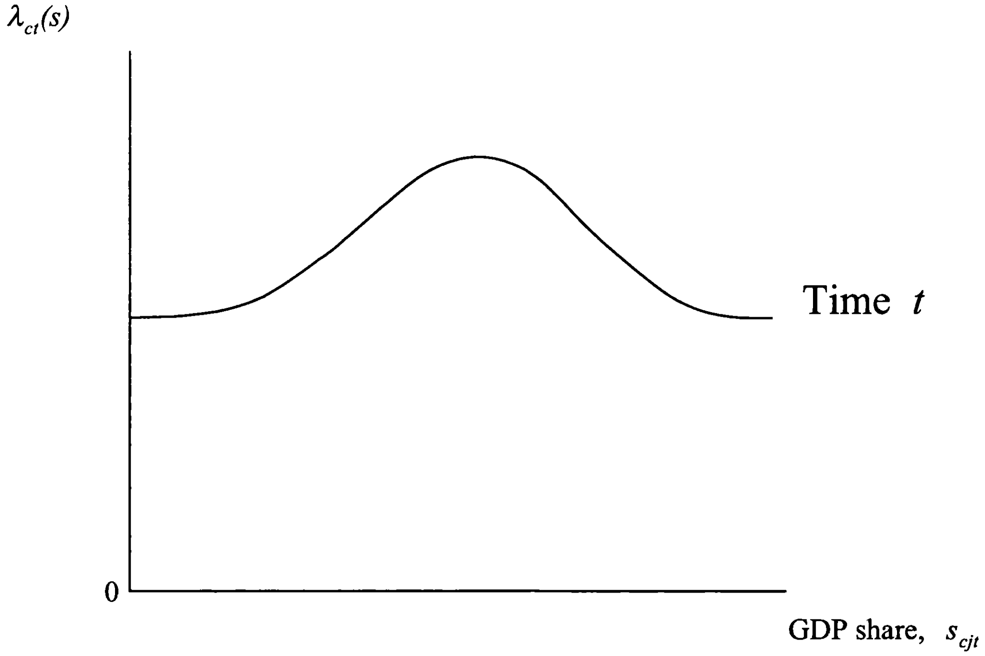


Figure 2-2: Specialisation Dynamics 1, Increased Specialisation

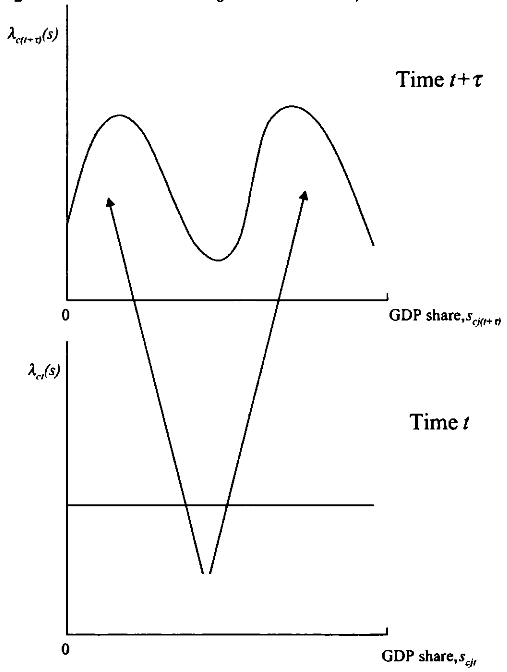
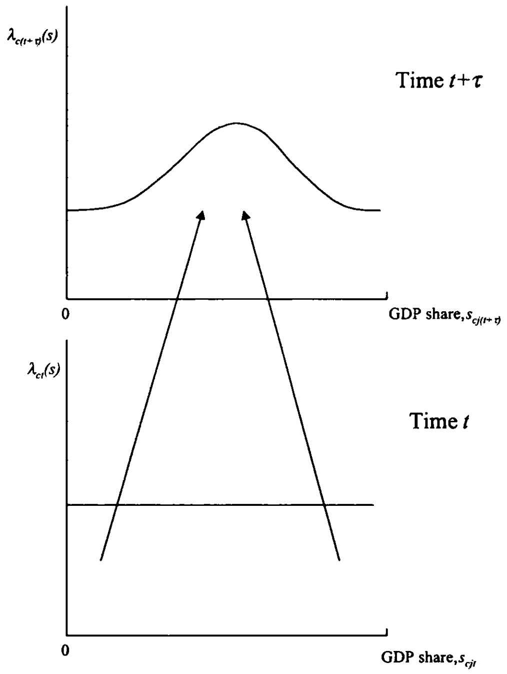


Figure 2-3: Specialisation Dynamics 2, Decreased Specialisation



2.10 Appendix 2A

Table 2.24: Sample Composition

Country	Sample A	Sample B	Number of NUTS-1 regions
Belgium	1975-95	1979-95	3 (be1-be3)
Spain	1980-95	1980-94	7 (esp1- esp7)
France	1975-95	1977-94	8 (fra1-fra8)
Italy	1975-95	1980-95	11 (ita1-ita9, itaa/b)
Luxembourg	1975-95	1979-90	1 (lux)
Netherlands	1975-95	1977-95	4 (ndl1-ndl4)
United Kingdom	1975-86	1975-86	11 (uk1-uk9, uka/b)

Table 2.25: Industry Composition

Code	Industry Description
Aggregate Industries	
1	Agricultural Sector: Food, Forestry and Fishery Products **(Agric)**
2	Manufacturing Sector **(Manuf)**
3	Services Sector: Market Services **(Serv)**
Disaggregated Manufacturing Industries	
4	Fuel And Power Products **(Fuel)**
5	Ferrous And Non-Ferrous Ores And Metals, Other Than Radioactive **(Metal)**
6	Non-Metallic Minerals And Mineral Products **(Mineral)**
7	Chemical Products **(Chem)**
8	Metal Products, Machinery, Equipment And Electrical Goods **(Machine)**
9	Transport Equipment **(Transp)**
11	Food, Beverages And Tobacco **(Food)**
12	Textiles And Clothing, Leather And Footwear **(Textile)**
13	Paper And Printing Products **(Paper)**
14	Products Of Various Industries **(Other)**
15	Building And Construction **(Constr)**

Table 2.26: Regions Included in the Sample

Code	Description	Code	Description
Belgium		**Luxembourg**	
Be1	Brussels	Lux	Luxembourg (Grand-Duche)
Be2	Vlaams Gewest		
Be3	Region Wallonne	**Netherlands**	
Spain		Nld1	North-Netherland
Esp1	Northwest (E)	Nld2	East-Netherland
Esp2	Northeast (E)	Nld3	West-Netherland
Esp3	Madrid	Nld4	South-Netherland
Esp4	Centre (E)	**United Kingdom**	
Esp5	East (E)	UK1	North (UK)
Esp6	South (E)	UK2	Yorkshire And Humberside
Esp7	Canaries	UK3	East Midlands
France		UK4	East Anglia
Fra1	Ile-De-France	UK5	Southeast (UK)
Fra2	Bassin Parisien	UK6	Southwest (UK)
Fra3	Nord-Pas-de-Calais	UK7	West Midlands
Fra4	East (F)	UK8	Northwest (UK)
Fra5	West (F)	UK9	Wales
Fra6	Southwest (F)	UKA	Scotland
Fra7	Centre-East (F)	UKB	Northern Ireland
Fra8	Mediterranean		
Italy			
Ita1	Northwest (I)		
Ita2	Lombardia		
Ita3	Nordeast (I)		
Ita4	Emilia-Romagna		
Ita5	Centre (I)		
Ita6	Lazio		
Ita7	Abruzzo-Molise		
Ita8	Campania		
Ita9	South (I)		
Itaa	Sicily		
Itab	Sardinia		

Chapter 3

Factor Endowments and Production in European Regions

3.1 Introduction[1]

> "One of the best ways to understand how the international economy works is to start looking at what happens inside nations... The data will be better and pose fewer problems of compatibility, and the underlying economic forces will be less distorted by government policies."[2]

One of the most influential conceptual frameworks for theoretical and empirical work in international trade is the Heckscher-Ohlin (HO) model. A key attraction is the model's ability to yield precisely formulated theoretical predictions which are amenable to direct empirical testing. However, a number of cross-country studies have called into question its empirical validity. For example, using data on cross-country trade in factor services, Bowen et al. (1987), Trefler (1995) and Davis and Weinstein (2001) reject the HO model's assumptions of identical and homothetic preferences, identical technologies, and no barriers to trade against a variety of more general alternatives.[3] Similarly, when examining the cross-country relationship between industry-level production and factor endowments, Harrigan (1995) finds large within-sample prediction errors, while Harrigan (1997) provides evidence

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[1] **As certified at the beginning of the thesis, this chapter is based on a co-joint research with my supervisor, Dr. Stephen Redding from the London School of Economics.**

[2] Paul Krugman (1991b, page 3), cited in Bernstein and Weinstein (2002).

[3] These more general alternatives allow, among other things, for cross-country differences in technology, non-factor price equalization, trade costs and measurement error. See also Davis *et al.* (1997) and Gabaix (1997).

that non-neutral technology differences play an important role in explaining cross-country variation in production structure.

This chapter examines the ability of the HO model to explain production patterns at the regional level in Europe using a newly constructed panel dataset on output in 14 industries and endowments of five factors of production for 45 NUTS-1 regions from 7 European countries since 1975.[4] The use of regional data enables us to abstract from many of the reasons advanced for the poor performance of the HO model at the country-level. For example, both measurement error and technology differences are likely to be much smaller across regions within Europe than for a cross-section of developed and developing countries. The ongoing process of economic integration within the European Union means that it is an interesting context within which to explore the relationship between production and factor endowments. We control for exogenous variation in relative prices induced by European integration and examine whether this process of international integration has strengthened or weakened the relationship between production and factor endowments across regions within countries.

Much existing empirical work on the international location of production has, for reasons of data availability, been concerned with the manufacturing sector. This paper explicitly considers both manufacturing and non-manufacturing, where the latter accounts for more than 70 percent of GDP in many NUTS-1 regions. We analyze production structure at two alternative levels of industrial aggregation. First, we consider the three aggregate industries of Agriculture, Manufacturing and Services. Second, we break out Manufacturing into 11 more disaggregated industries. We consider endowments of five factors of production: high-education, medium-education, and low education individuals, physical capital, and land area. The analysis focuses on patterns of production rather than trade, because the central predictions of the HO model are for producer equilibrium and, in so doing, we abstract from any violations of the model's assumptions concerning consumer behaviour.[5]

The paper derives a general equilibrium relationship between production structure and factor endowments that holds under the null hypothesis of the HO model with its assumptions of identical prices and technologies. We compare this with the relationship that holds under the more general alternative hypothesis of the neoclassical model of trade which allows for regional variation in both relative prices and technology. We are able to explicitly test for

[4]NUTS stands for Nomenclature of Statistical Territorial Units. NUTS-1 regions are the first-tier of sub-national geographical units for which Eurostat collects data on the EU member countries. See Appendix A for more details concerning the data used.

[5]Three of the HO model's four key theorems - the Rybczynski, Stolper-Samuelson, and Factor Price Equalization Theorems - require no assumptions about consumer preferences.

European regions whether the HO null is rejected against neoclassical alternatives, and use our framework to examine the quantitative importance of factor endowments relative to other considerations in explaining regional variation in production patterns.

While the use of regional data has many advantages, it means that the standard trade assumption that endowments of factors of production are exogenous and perfectly immobile across locations is less likely to apply. We show that the general equilibrium relationship between production structure and factor endowments under the null hypothesis and the corresponding relationship under the alternative hypothesis hold irrespective of whether factors of production are perfectly immobile or perfectly mobile across locations [6]

Factor mobility does, however, change the interpretation of these relationships. If factor endowments are exogenous and perfectly immobile across locations, the general equilibrium relationship between production structure and factor endowments has a *supply-side* interpretation. Changes in factor endowments cause changes in production structure (production moves in response to factor endowments). If factor endowments are mobile across locations, they become potentially endogenous to production structure. In addition to the *supply-side* interpretation given above, there is also a *demand-side* interpretation whereby changes in production structure cause factor endowments to move across regions (factor endowments move in response to production structure). Irrespective of whether the relationships we estimate are demand-side, supply-side or a combination of both, we are able to test the HO model's predictions for the relationship between production and endowments against those of the more general neoclassical model. Similarly, irrespective of which interpretation applies, we can take the more general neoclassical model and examine the respective contributions of factor endowments and other considerations in statistically explaining variation in production structure across European regions.

Our main empirical findings are as follows. First, the HO model provides an incomplete explanation of patterns of production across European regions and is rejected against more general neoclassical alternatives. Second, although the HO model is rejected, factor endowments remain statistically significant and quantitatively important in explaining production structure within these neoclassical alternatives. Individual factor endowments are highly statistically significant and including information on factor endowments reduces the model's within-sample average absolute prediction error by a factor of around three in Manufacturing.

[6] In practice, a wide range of evidence suggests that factor mobility across European regions is relatively low. This is particularly true across countries, where language and cultural differences act as barriers to labour mobility. However even within European countries, there is evidence that labour mobility is relatively low: see for example McCormick (1997) and Cameron and Muellbauer (1999) for evidence on the U.K.

Third, the pattern of estimated coefficients on factor endowments across industries is generally consistent with economic priors regarding factor intensity. For example, physical capital endowments are positively correlated with the share of Manufacturing in GDP and negatively correlated with the shares of Agriculture and Services. Higher numbers of medium education individuals relative to low education individuals are associated with a lower share of Agriculture in GDP and a higher share of Manufacturing. Higher numbers of high education individuals relative to medium education individuals are associated with a lower share of Manufacturing in GDP and a higher share of Services.

Fourth, factor endowments are more successful in explaining patterns of production at the aggregate level in Agriculture, Manufacturing and Services (where we have three industries and either three or 5 factor endowments) than in disaggregated manufacturing industries (where we have 11 industries and either three or 5 factor endowments). Within-sample average absolute prediction errors are typically far larger in the disaggregated manufacturing industries, and this is exactly as theory would predict. In the HO model with identical prices and technology and with no joint production, patterns of production are only determinate if there are at least as many factors of production as goods. Therefore, production indeterminacy provides one explanation for larger average absolute prediction errors in disaggregated manufacturing industries. Another explanation, again consistent with the theory, is that regional price and technology differences not controlled for in the right-hand side variables are particularly large in individual manufacturing industries.

Fifth, we find no evidence that the process of increasing economic integration in Europe has weakened or stengthened the relationship between patterns of production and factor endowments across regions within countries. Our baseline econometric specification includes country-year dummies so that the coefficients on factor endowments' are identified solely from variation across regions within countries. Examining within-sample prediction errors for this specification reveals no systematic trend over time for either the three aggregate industries or the 11 disaggregated industries within manufacturing.

The remainder of the chapter is organized as follows. Section 2 relates the chapter to the existing literature. Section 3 introduces the theoretical framework and derives predictions for production patterns under the HO null and the neoclassical alternative. Section 4 describes the European regional production and factor endowments data. Section 5 discusses the econometric specification. Section 6 presents the estimation results. Section 7 concludes.

3.2 Related Literature

A number of papers, including Leamer (1984), Bowen et al. (1987), Trefler (1995), Davis et al. (1997), Gabaix (1997), and Davis and Weinstein (2001); have considered the relationship between factor endowments and international trade in factor services at the country-level. As discussed above, this literature typically finds that the HO model is rejected against more general alternatives. Davis and Weinstein (2001) argue that, with a few plausible amendments, including cross-country differences in technology and a more flexible specification of preferences, the HO model is consistent with international data on trade in factor services. Although, the model is no longer Heckscher-Ohlin as traditionally conceived or strictly interpreted. The first paper to examine the empirical predictions of the HO model for the location of production was Harrigan (1995), which used data on 10 manufacturing industries in 20 OECD countries during 1970-85. Factor endowments were found to account for much of the variation in output, although average prediction errors, expressed as a percentage of actual production were around 40 percent. Physical capital was found to be an important determinant of manufacturing output, although the effects of endowments of skilled and unskilled labour were more ambiguous. Harrigan (1997) and Harrigan and Zakrajsek (2000) use country-level data to estimate the neoclassical model of trade, which generalizes the HO model to allow cross-country differences in technology and preferences. Harrigan (1997) finds that both relative technology levels and factor endowments are important determinants of patterns of production. Redding (2002) uses the neoclassical model to analyze the dynamics of countries' production patterns, while Nickell et al. (2001) use a newly constructed and disaggregated dataset on educational attainment in the OECD at the country level to analyze the relationship between changing levels of educational attainment and production patterns.

An emerging empirical literature has recently begun to examine the predictions of the HO model using regional-data. Davis et al. (1997) analyze trade in factor services using both country-level and Japanese regional data. The data on production in Japanese regions are found to be consistent with factor price equalization. When the model is applied to data on regional rather than country-level data on trade in factor services, the empirical results are much more favourable. Bernstein and Weinstein (2002) use more disaggregated Japanese regional data to examine the relationship between factor endowments and the location of production. The data are again consistent with factor price equalization. However, there are substantial within-sample prediction errors, which Bernstein and Weinstein (2002) interpret as evidence of production indeterminacy. Hanson and Slaughter (2002) use data on immigration in US States to test a generalization of the Rybczynski Theorem, which predicts that regions will accommodate immigrant inflows by changes in output mix rather than changes in relative factor prices.[7] Changes in state output mix are found to broadly match changes in state endowments. Moreover, the variation in factor intensities across US States is found to be consistent with relative factor price equalization. Assuming that each US State is small, the latter is a sufficient condition for changes in endowments to be accommodated by changes in output mix.

A body of empirical work has sought to characterize the nature and evolution over time of specialisation in Europe using country-level data: see, for example, Amiti (1999), Brülhart (2000), Midelfart-Knarvik, Overman, Redding, and Venables (2000) and Proudman and Redding (1998, 2000). Amiti (1999) finds evidence of increasing specialisation in Europe using production and employment data, while Brülhart (2000) finds that specialisation has increased in employment terms but remained roughly unchanged in export terms. Using export data and statistical techniques for modelling the evolution of entire distributions, Proudman and Redding (1998, 2000) find evidence of substantial changes in patterns of specialisation over time. In contrast to all of these papers, which employ country-level data, Chapter 2 characterizes specialisation at the regional-level in Europe for the same sample considered here. We refer to chapter 2 for related work on specialisation at the regional level in Europe (see Combes and Overman, 2003, for an extensive review).

Finally, the chapter relates to a recent empirical literature on economic geography (see Overman et al. 2002, for a survey on this literature). Davis and Weinstein (1999, 2003) use data on Japanese regions and on a cross-section of countries, respectively, to test for a 'home market' or 'magnification' effect. That is, in models of economic geography, the presence of increasing returns to scale and transport costs means that an increase in expenditure on a good has a more than proportionate effect on domestic production of the good. The same is not true in the constant returns to scale world of HO, and this provides the basis for an identifying restriction. Using country-level data on OECD manufacturing industries, Davis and Weinstein (2003) investigate the existence of home market effects from idiosyncratic demand on the pattern of production with a framework that nests a conventional Heckscher-Ohlin model (based on comparative advantage) with a model of economic geography. They find evidence suggesting that home market effects are important for a broad segment of OECD manufacturing. The analysis of regional-level data on Japanese manufacturing industries in Davis and Weinstein (1999) also reveals evidence of economic geography effects in eight out

[7]See Gandal, Hanson, and Slaughter (2002) for a related analysis of immigration in Israel.

of 19 industries, and these effects are shown to be quantitatively important. Brülhart and Torstensson (1996) consider the effects of increasing integration on the location of increasing returns to scale industries and the pattern of international trade. Data on 11 European countries provide some empirical support for the predictions of an economic geography model: employment in increasing returns to scale industries tends to be concentrated at the centre of the EU and intra-industry trade is relatively low in these industries. Midelfart-Knarvik, Overman, and Venables (2000b) employ European country-level data to analyze the determinants of specialisation in manufacturing industries during 1970-97. A role is found for both the considerations of traditional trade theory (e.g., factor endowments and factor intensities) and those emphasized by the economic geography literature (e.g., geographical proximity and forward/backward linkages).

3.3 Theoretical Framework

The theoretical framework is provided by the neoclassical theory of trade and production (see, in particular, the exposition in Dixit and Norman, 1980). Regions are indexed by $z \in \{1, ..., Z\}$; goods by $j \in \{1, ..., N\}$; factors of production by $i \in \{1, ..., M\}$; and time by t. Production is assumed to occur under conditions of perfect competition and constant returns to scale.[8] The neoclassical model allows for regional differences in factor endowments as well as region-industry differences in technology and relative prices. The HO model corresponds to a special case where all regions have identical relative prices and technology, and is therefore nested by the neoclassical model.

General equilibrium in production may be represented using the revenue function $r_z(p_{zt}, v_{zt})$, where p_{zt} denotes a region's vector of relative prices and v_{zt} is its vector of factor endowments. Under the assumption that the revenue function is twice continuously differentiable, we obtain determinate predictions for a region's vector of profit-maximizing net outputs $y_z(p_{zt}, v_{zt})$ which equals the gradient of $r_z(p_{zt}, v_{zt})$ with respect to p_{zt}.[9] We allow for Hicks-neutral

[8] While analysis of the neclassical model typically focuses on the perfectly competitive case, it is also possible to analyze imperfect competition as discussed in Helpman (1984).

[9] A sufficient condition for the revenue function to be twice continuously differentiable and production patterns to be determinate is that there are at least as many factors as goods: $M \geq N$. In the HO model where relative prices and technology are identical, production levels may still be determinant when $N > M$ if there is joint production. More generally in the neoclassical model, differences in technology and relative prices may render production determinant when $N > M$. The potential existence of production indeterminacy is really an empirical issue which we investigate below for alternative numbers of goods and factors. If production indeterminacy exists, the equation that we derive under the null linking production and factor endowments will be relatively unsuccessful in explaining regions' production patterns, in terms of having statistically insignificant right-hand side variables, low explanatory power and large within-sample

region-industry-time technology differences so that the production technology takes the form $y_{zjt} = \theta_{zjt} F_j(v_{zjt})$, where θ_{zjt} parameterizes technology or productivity in industry j of region z at time t.[10] In this case, the revenue function takes the form $r_z(p_{zt}, v_{zt}) = r(\theta_{zt} p_{zt}, v_{zt})$, where θ_{zt} is an $N \times N$ diagonal matrix of the technology parameters θ_{zjt}.[11] Changes in technology in industry j of region z have analogous effects on revenue to changes in industry j prices.

We follow Harrigan (1997) and Kohli (1991) in assuming a translog revenue function. This flexible functional form provides an arbitrarily close local approximation to the true underlying revenue function:

$$\begin{aligned}\ln r(\theta_{zt} p_{zt}, v_{zt}) = \beta_{00} &+ \textstyle\sum_j \beta_{0j} \ln \theta_{zjt} p_{zjt} + \frac{1}{2} \sum_j \sum_k \beta_{jk} \ln(\theta_{zjt} p_{zjt}) \ln(\theta_{zkt} p_{zkt}) \\ &+ \textstyle\sum_i \delta_{0i} \ln v_{zit} + \frac{1}{2} \sum_i \sum_h \delta_{ih} \ln v_{zit} \ln v_{zht} \\ &+ \textstyle\sum_j \sum_i \gamma_{ji} \ln(\theta_{zjt} p_{zjt}) \ln(v_{zit}),\end{aligned} \tag{3.1}$$

where $j, k \in \{1, .., N\}$ index goods and $i, h \in \{1, .., M\}$ index factors. Symmetry of the cross effects implies: $\beta_{jk} = \beta_{kj}$ and $\delta_{ih} = \delta_{hi}$ for all j, k, i, h. Linear homogeneity of degree 1 in v and p requires: $\sum_j \beta_{0j} = 1$, $\sum_i \delta_{0i} = 1$, $\sum_j \beta_{jk} = 0$, $\sum_i \delta_{ih} = 0$, and $\sum_i \gamma_{ji} = 0$. Differentiating the revenue function with respect to p_j, we obtain the following equation for the share of industry j in region z's GDP at time t:

$$s_{zjt} \equiv \frac{p_{zjt} y_{zjt}(p_{zt}, v_{zt})}{r(p_{zt}, v_{zt})} = \beta_{0j} + \sum_k \beta_{jk} \ln p_{zkt} + \sum_k \beta_{jk} \ln \theta_{zkt} + \sum_i \gamma_{ji} \ln v_{zit}. \tag{3.2}$$

Thus, the share of an industry in GDP (s_{zjt}) provides a natural and theory-consistent measure of a region's extent of specialisation in an industry. Under the assumptions of the neoclassical model, this theory-consistent measure is related in general equilibrium to the region's vectors of relative prices, technology levels, and factor endowments according to equation (3.2). The translog specification implies coefficients on these variables that are constant across regions and over time. This is true even without factor price equalization and,

prediction errors.

[10]The technology differences may vary across industries but are Hicks-neutral in the sense that they raise the productivity of all factors of production in industry j of region z by the same proportion. It is also possible to examine factor augmenting technology differences, as discussed further in Dixit and Norman (1980).

[11]See Dixit and Norman (1980), pages 137-9.

with regional differences in prices and technology, factor price equalization will typically not be observed. The effect of regional differences in relative prices and technology on patterns of production is directly controlled for by the presence of the second and third terms on the right-hand side of the equation.

The analysis so far makes no assumptions about whether regions are large or small, and allows for both tradeable and non-tradeable goods. If regions are small and all goods are tradeable, relative prices will be exogenously determined on world markets. More generally, relative prices will themselves be endogenous. Factors of production may be either perfectly immobile or exhibit a degree of mobility across regions. In either case, the relationship in equation (3.2) must hold in general equilibrium.

Under the assumptions of the HO model, relative prices and technology are identical across regions. In this case, the terms for relative prices and technology on the right hand-side of equation (3.2) may be replaced by a set of time dummies. These time dummies have industry-specific coefficients (the coefficients β_{jk} vary across industries j), reflecting the fact that changes in relative prices and technology have different effects in different industries. Substituting for relative prices and technology, we obtain our *null hypothesis*:

$$\textbf{(NULL)} \qquad s_{zjt} = \sum_t \phi_{jt} d_t + \sum_i \gamma_{ji} \ln v_{zit} + \varepsilon_{zjt}, \tag{3.3}$$

where d_t are $\{0, 1\}$ dummies for time periods; ϕ_{jt} are the industry-specific coefficients on the time dummies; ε_{zjt} is a stochastic error; and the constant β_{0j} from equation (3.2) has been absorbed in the industry-specific coefficients on the time dummies. Since all coefficients in equation (3.3) vary across industries j, this relationship may be estimated separately for each industry, pooling observations across regions and over time.

Under the *alternative hypothesis* of the neoclassical model, relative prices and technology may vary across regions, industries and time. Unfortunately, region-industry-time specific data on prices are not available for European regions, and it is not therefore possible to construct direct measures of relative prices and technical efficiency. Therefore, we follow Harrigan (1997) in modelling relative prices and technology as being drawn from an estimable probability distribution. We consider a series of progressively more general models of relative prices and technology, each of which when substituted in equation (3.2) provides a progressively more general alternative to the HO null. First, we model differences in relative prices and technology with a country-industry fixed effect (η_{cj}), industry-time dummies

$(\mu_{jt} d_t)$, and a stochastic error (u_{zjt}):

$$\sum_k \beta_{jk} \ln p_{zkt} + \sum_k \beta_{jk} \ln \theta_{zkt} = \eta_{cj} + \sum_t \mu_{jt} d_t + u_{zjt}, \tag{3.4}$$

which yields our first alternative hypothesis:

$$\textbf{(ALT1)} \qquad s_{zjt} = \eta_{cj} + \sum_t \zeta_{jt} d_t + \sum_i \gamma_{ji} \ln v_{zit} + \omega_{zjt}, \tag{3.5}$$

where the constant β_{0j} has again been absorbed in other coefficients. This specification differs from the null hypothesis through the inclusion of the country-industry fixed effect which allows for permanent cross-country differences in relative prices and technology that are non-neutral across industries.

Second, we generalize the model of relative prices and technology to allow for country-specific trends in relative prices and technology over time. We capture these by including country-time dummies, which again have industry-specific coefficients reflecting the fact that changes in relative prices impact differentially across industries:

$$\sum_k \beta_{jk} \ln p_{zkt} + \sum_k \beta_{jk} \ln \theta_{zkt} = \sum_c \sum_t \mu_{cjt} d_{ct} + u_{zjt}, \tag{3.6}$$

where d_{ct} are $\{0,1\}$ country-time dummies and μ_{cjt} are the industry-specific coefficients on these country-time dummies. This yields our second alternative hypothesis:

$$\textbf{(ALT2)} \qquad s_{zjt} = \sum_c \sum_t \zeta_{cjt} d_{ct} + \sum_i \gamma_{ji} \ln v_{zit} + \omega_{zjt}, \tag{3.7}$$

where the constant β_{0j} has again been absorbed in other coefficients, and this specification differs from the null hypothesis because the effects of the time dummies now vary across both countries and industries.

Equation **(ALT2)** allows for cross-country differences in relative prices and technology that are both non-neutral across industries and time-varying. It is consistent with empirical evidence from the literature on productivity measurement, which typically finds cross-country productivity differences with these properties.[12] It is also substantially more general than many existing studies in the empirical trade literature, which often focus on technology differences that are neutral across industries, and it allows European integration to have

[12]See, for example, Bernard and Jones (1996b) and Griffith et al. (2000).

different effects on relative prices across countries.

Third, we extend the model of relative prices and technology further to allow for permanent region-industry specific differences in relative prices and technology (η_{zj}), country-specific trends in relative prices and technology over time (d_{ct}) and a stochastic error (u_{zjt}):

$$\sum_k \beta_{jk} \ln p_{zkt} + \sum_k \beta_{jk} \ln \theta_{zkt} = \eta_{zj} + \sum_c \sum_t \mu_{cjt} d_{ct} + u_{zjt}, \tag{3.8}$$

which yields our third alternative hypothesis:

$$\textbf{(ALT3)} \qquad s_{zjt} = \eta_{zj} + \sum_c \sum_t \zeta_{cjt} d_{ct} + \sum_i \gamma_{ji} \ln v_{zit} + \omega_{zjt}, \tag{3.9}$$

where the constant β_{0j} has again been absorbed in other coefficients. This specification differs from the null hypothesis, because of both coefficients on the time dummies that vary across countries and industries, and because of the inclusion of a region-industry fixed effect.

The null hypothesis is derived directly from the HO model with its assumption of identical relative prices and technology. Similarly, each of the alternative hypotheses is derived directly from the neoclassical model and involves making progressively more general assumptions about relative prices and technology. Both variable choice and functional form are shaped by the underlying theory. Hence, under the assumptions of the null hypothesis or a particular alternative hypothesis, the relevant relationship may be given an economic interpretation.

In particular, *under the assumptions of the null hypothesis*, the coefficients on factor endowments (γ_{ji}) in **(NULL)** are directly related to the *Rybczynksi derivatives* of HO theory - the general equilibrium relationship between production and factor endowments holding constant relative prices and technology.[13] As discussed above, if factor endowments exhibit a degree of mobility across regions, the Rybczynski derivatives capture a relationship between output and factor endowments that must hold in general equilibrium, but that may be given either a demand-side or supply-side interpretation. In relating the coefficients γ_{ji} to the Rybczynksi derivatives, we are *not* asserting the existence of a causal relationship between exogenous changes in factor endowments and endogenous changes in production, but are instead examining a relationship that holds in equilibrium (examining the equilibrium value of the derivatives).

The factor intensities of industries are directly captured in our analysis by the estimated

[13]Formally, the *Rybczynski derivatives* are $\partial y_j(p,v)/\partial v_i = \partial^2 r(p,v)/\partial p_j \partial v_i = \partial^2 r(p,v)/\partial v_i \partial p_j$ for all j, i. Differentiating with respect to v_i in equation **(NULL)** and rearranging, $\partial^2 \ln(r(p,v))/\partial p_j \partial v_i = \gamma_{ji}/(p_j v_i)$ so that the *Rybczynski derivatives* take the same sign as the γ_{ji}.

coefficients (γ_{ji}) on factor endowments. With large numbers of factors (M) and goods (N), many conventional definitions of factor intensity (such as the ratio of use of one factor of production to another) are problematic. Nevertheless, the fact that in our approach the estimated coefficients on factor endowments are directly linked to the Rybczynski derivatives of HO theory means that they can be related to natural measures of factor intensity.

For example, with $M = N$, a positive value of a Rybczynski derivative for factor i and good j implies that, if the price of factor i increases by one unit and all other factor prices are adjusted to keep other goods' unit costs unchanged, the unit costs of production for good j must rise. In this sense, good j is intensive in the use of factor i relative to the economy as a whole when $\partial^2 r(p,v)/\partial p_j \partial v_i$ and hence γ_{ji} is positive . With $M \geq N$, there will generally be more than one set of values for other factor prices that leave other goods' unit costs unchanged. Nonetheless, a natural measure of factor intensity still exists based on the Rybczynski derivatives themselves, whereby good j is said to be relatively more intensive in factor i than the average if $\partial^2 r(p,v)/\partial p_j \partial v_i$ and hence γ_{ji} is positive.[14]

Intuitively, we do not try to construct conventional measures of factor intensity which are often problematic with large numbers of factors and goods, but instead directly estimate the relationship between production and factor endowments. Under the HO null, factor intensities are captured in the estimated coefficients on factor endowments. The fact that natural measures of factor intensity are defined relative to the whole structure of general equilibrium when there are large numbers of factors (M) and goods (N) is directly related to the way in which the theorems of the $2\times2\times2$ HO model now hold in a weakened form as averages and correlations.[15]

Note that the estimated coefficients on factor endowments (γ_{ji}) in **(NULL)** only correspond to Rybczynski derivatives if the assumptions of the HO null are satisfied. *Under the alternative hypothesis* of the more general neoclassical model, **(NULL)** is mis-specified because it omits terms capturing regional variation in relative prices and technology. In general, these terms will be correlated with factor endowments and their omission will give rise to omitted variables bias and inconsistent estimates of the γ_{ji}. Only by including these additional terms, as for example in **(ALT2)**, can consistent estimates of the γ_{ji} be obtained.

We investigate the importance of regional variation in relative prices and technology by comparing the results of estimating **(NULL)** to those from estimating the three alternative specifications **(ALT1)-(ALT3)**. We compare the specifications along four main dimensions.

[14] See Dixit and Norman (1980), pages 53-9.

[15] See, for example, Dixit and Norman (1980), Chapter 4 of this thesis, and Ethier (1984), Sections 6 & 7.

First, since the null is nested by each of the alternatives, a test of the statistical significance of the additional terms capturing regional variation in relative prices and technology provides a formal test of the null against each of the more general alternatives. Second, we investigate the importance of the omitted variables bias by considering how the estimated coefficients on factor endowments change as we move to progressively more general models of relative prices and technology. Third, we examine the quantitative importance of factor endowments relative to other considerations in explaining regional variation in production structure. Fourth, we evaluate the empirical performance of the null and alternative hypotheses using a number of model specification tests.

Finally, it is worth noting that factor mobility does, however, change the interpretation of these relationships. If factor endowments are exogenous and perfectly immobile across locations, the general equilibrium relationship between production structure and factor endowments has a *supply-side* interpretation. Changes in factor endowments cause changes in production structure (production moves in response to factor endowments). If factor endowments are mobile across locations, they become potentially endogenous to production structure. In addition to the *supply-side* interpretation given above, there is also a *demand-side* interpretation whereby changes in production structure cause factor endowments to move across regions (factor endowments move in response to production structure). Irrespective of whether the relationships we estimate are demand-side, supply-side or a combination of both, we are able to test the HO model's predictions for the relationship between production and endowments against those of the more general neoclassical model. Similarly, irrespective of which interpretation applies, we can take the more general neoclassical model and examine the respective contributions of factor endowments and other considerations in statistically explaining variation in production structure across European regions.

3.4 Data Description

As discussed in Chapter 2, the main source of data is the Regio dataset compiled by the European Statistics Office (Eurostat). We analyze patterns of production across 14 industries in 45 NUTS-1 regions from 7 European countries since 1975. The number and size of NUTS-1 regions varies across European countries. This is perfectly consistent with our model, and the variation in size will be exploited in tests of the linear homogeneity restrictions implied by theory.

Patterns of production are analyzed at two alternative levels of aggregation. First, we consider three aggregate (one-digit) industries: Agriculture, Manufacturing and Services. Second, we exploit more disaggregated information on individual industries within Manufacturing. These are mainly two-digit industries and include, for example, Textiles & Clothing and Chemicals. Again, full details are given in Appendix 3A.

The Regio dataset provides information on industry value-added and GDP by region, from which we compute the share of each sector in GDP. It also provides information on three broad factor endowments: total population, physical capital and land area.[16] These data are merged with information on educational attainment at the regional level from individual country labour force surveys. This enables us to disaggregate the population endowment into low, medium and high education. The definitions we employ are standard in the labour market literature (see, for example, Nickell and Bell, 1996, and Machin and Van Reenen, 1998). 'Low education' corresponds to no or primary qualifications, 'medium education' denotes secondary and/or vocational qualifications, and 'high education' is college degree or equivalent.[17]

The length of the time-series available varies with the level of industrial aggregation, whether or not we use the information on educational attainment, and with the country considered. In order to exploit all of the information available, we consider two estimation samples. First, at the level of the three aggregate industries and for the three factor endowments (population, physical capital and land area), we have an unbalanced panel of 811 observations per industry on the 45 regions during approximately 1975-95 (Sample A). Second, for the disaggregated manufacturing industries and for the 5 factor endowments (low education, medium education, high education, physical capital and land area), we have an unbalanced panel of 696 observations per industry from approximately 1980 onwards (Sample B). Full details of the composition of each sample are given in Appendix A.

Table 3.1 examines variation in the three broad factor endowments (Population, Capital and Land) across regions at a point in time and within regions over time. The sample includes both UK5 (with a population of more than 16 million in 1985) and Luxembourg (with a population of just over 350,000 in 1985). Land area varies from around 16,000 hectares in Be1 (Brussels) to 21 million hectares in Es4 (Centre). While population declined in some regions, such as UK1 (North), it rose in others, such as UK6 (South-West). All regions exhibit an increase in the real stock of physical capital over time, although the rate of increase varies across regions.

[16]We also experiment with using data on arable land area to control for variation in land quality.

[17]See Appendix 3A for further information concerning the data used.

<**Table 3.1 about here**>

In Table 3.2 we report regional educational attainment as a percentage of the population for the years 1985 and 1995. It is well known from the labour market literature that the sample period was one of rising educational attainment in European countries (see, for example, Nickell and Bell 1996 and Machin and Van Reenen 1998). With the exception of Bel (Brussels), all regions in Table 3.2 experience a rise in the share of the population with high education. However the rate of increase varies substantially, even across regions even within a country. For example, in Esp2 (North-East) the high education share rises by over 70 percent, while in the neighbouring region of Esp1 (North-West) the proportional rate of increase is approximately 40 percent. Multiplying the percentage shares in Table 3.2 by the population levels reported in Table 3.1, we obtain regions' endowments of low, medium and high education individuals.

<**Table 3.2 about here**>

3.5 Econometric Specification

Our null and alternative specifications are derived directly from the structure of the theoretical model, as explained above, and are reproduced below:

$$
\begin{array}{llcl}
\textbf{(NULL)} & s_{zjt} & = & \sum_t \phi_{jt} d_t + \sum_i \gamma_{ji} \ln v_{zit} + \varepsilon_{zjt}, \\
\textbf{(ALT1)} & s_{zjt} & = & \eta_{cj} + \sum_t \zeta_{jt} d_t + \sum_i \gamma_{ji} \ln v_{zit} + \omega_{zjt}, \\
\textbf{(ALT2)} & s_{zjt} & = & \sum_c \sum_t \zeta_{cjt} d_{ct} + \sum_i \gamma_{ji} \ln v_{zit} + \omega_{zjt}, \\
\textbf{(ALT3)} & s_{zjt} & = & \eta_{zj} + \sum_c \sum_t \zeta_{cjt} d_{ct} + \sum_i \gamma_{ji} \ln v_{zit} + \omega_{zjt}.
\end{array}
$$

Since all coefficients vary across industries, specifications are estimated separately for each industry, pooling observations across regions and over time.

As we move from the null to each of the alternative specifications, we change the source of variation in the data used to identify the coefficients on factor endowments (γ_{ji}). For example, in **(NULL)**, the inclusion of time dummies in each industry regression means that we abstract from any common trend in factor endowments over time across all regions, and the γ_{ji} are identified from variation across regions at a point in time and differential variation within regions over time. In **(ALT2)**, the inclusion of country-time dummies means that we abstract from any common trend in factor endowments across all regions within a country, and the γ_{ji} are identified from variation across regions within a country at a point in time and differential variation within regions over time. If the assumptions of the HO model are satisfied, the additional terms included in specifications **(ALT1)-(ALT3)** should be statistically insignificant, and the estimated γ_{ji} should remain unchanged, as we move to progressively more general models of relative prices and technology and exploit different sources of variation in the data.

However, as we move from **(ALT2)** to **(ALT3)**, the within groups transformation due to the inclusion of the regional fixed effect (η_{zj}) can greatly exacerbate any attenuation bias from measurement error in the independent variables (see, in particular, Griliches and Hausman 1986). Intuitively, the extent of 'within' or time-series variation in factor endowments due to true variation in the independent variables may be small relative to the variation due to measurement error. This is likely to be a particular problem in the present application because the extent of time-series variation in some of our factor endowments (in particular land area and, to a lesser extent, population) is limited.

We address this problem in two ways. First, we exploit disaggregated data on the educational attainment of the population and on arable land area. The resulting measures of factor endowments control for variation in levels of skills and land quality, and exhibit greater differential variation over time within regions. Second, following Griliches and Hausman (1986), we consider the use of first-difference estimators. The longer the interval of time over which we difference the data, the greater the amount of true variation in factor endowments relative to that due to measurement error. Hence, the attenuation bias due to measurement error should be smaller using longer differences, and we analyze the results of 10-year difference estimators. We thus obtain a fourth alternative specification:

$$\textbf{(ALT4)} \qquad \triangle_{10} s_{zjt} = \sum_t \zeta_{jt} d_t + \sum_i \gamma_{ji} \triangle_{10} \ln v_{zit} + \psi_{zjt},$$

where differencing eliminates the regional fixed effect (η_{zj}). In taking long differences, we substantially reduce the sample size and, therefore, we concentrate on a specification with only industry-specific coefficients on the time dummies.

In comparing the results of estimating the null and alternative specifications, we also make use of two model specification tests. The first of these focuses on the time-series properties of the model. By construction, the share of sector j in GDP (s_{zjt}) is bounded between 0 and 100 per cent, and is therefore I(0). However, in any finite sample, GDP shares may be I(1).

This is particularly true of our sample period (1975-95) which, in general, is characterized by a secular decline in the GDP shares of Agriculture and Manufacturing combined with a secular rise in the share of Services. Similarly, a region's population and physical capital endowments may be I(1). In this case, the static levels regressions **(NULL)-(ALT3)** should be interpreted as cointegrating relationships between a sector's share of GDP and factor endowments. Under this interpretation, the residuals should be I(0) if the assumptions underlying a particular specification are satisfied. Therefore, we make use of the panel data unit root test of Maddala and Wu (1999) to test for the stationarity of the residuals.[18]

Second, neoclassical trade theory assumes that the production technology is constant returns to scale and hence that the revenue function in equation (3.1) is homogeneous of degree one in factor endowments. Therefore, a test of the null hypothesis that the sum of the estimated coefficients on factor endowments is equal to zero provides another model specification test ($\sum_i \gamma_{ji} = 0$).

3.6 Empirical Results

We begin in Column (1) of Tables 3.3-3.5 by reporting the results of estimating the HO specification **(NULL)** for the aggregate industries (Agriculture, Manufacturing and Services) using our three broad measures of factor endowments (population, physical capital and land area). We find a statistically significant relationship between regional patterns of production and factor endowments and, from the regression R^2, the HO specification explains some 30-45 percent of the variation in production patterns across European regions.[19] We also find statistically significant effects of the year dummies, consistent with an important role for common changes in relative prices and technology.

<Tables 3.3-3.5 about here>

In Column (2) of Tables 3.3-3.5, we relax the assumption of identical relative prices and technology in the first alternative specification **(ALT1)**. The country fixed effects are highly statistically significant, as shown in the first of the F-statistics reported in Column (2). The R^2 of the regression rises substantially, and by more than one third in both Agriculture and

[18]The Maddala and Wu or Fisher test statistic is based on the sum of the p-values from conventional Augmented Dickey Fuller (ADF) tests on the residuals for each cross-section unit $z \in Z$. It can be shown that $-2\sum_z \ln P_z$ has a χ^2 distribution with $2Z$ degrees of freedom. This test statistic has a direct intuitive interpretation, is valid for unbalanced panels and has attractive small sample properties (Maddala and Wu 1999). Other analyses of unit roots and cointegration in a panel data context include Im et al. (2003), Levin and Lin (1992), Pedroni (1999), Pesaran et al. (1998) and Quah (1994).

[19]Except where otherwise indicated, statements about statistical significance refer to the 5% level.

Manufacturing. The pattern of estimated coefficients on factor endowments also changes and moves more in line with economic priors concerning factor intensity. For example, in Agriculture the coefficient on physical capital switches from being positive and statistically significant to negative and statistically significant, while in Manufacturing the coefficients on physical capital and population increase by an order of magnitude. The statistical significance of the country fixed effects rejects the null hypothesis of the HO model; the rise in R^2 suggests that the additional terms capturing variation in relative prices and technology are quantitatively important; and the change in the estimated pattern of coefficients suggests the importance of including these controls in identifying the relationship between production patterns and factor endowments.

In Column (3) of Tables 3.3-3.5, we generalize the model of relative prices and technology further and consider specification **(ALT2)** which allows for different cross-country trends in relative prices and technology over time. In the HO specification **(NULL)**, each industry regression includes a set of time dummies. In moving from **(NULL)** to **(ALT2)**, we retain these time dummies (which will capture effects for the omitted country) and augment the regression specification with country-time dummies for all countries except one. The first of the F-statistics in this column of the tables reports the results of a test whether the coefficients on the additional country-year dummies are statistically significantly different from zero. In all industries, the country-year dummies are highly statistically significant, and the HO specification **(NULL)** is again rejected against the more general alternative.

Comparing Columns (2) and (3), the pattern of estimated coefficients on factor endowments remains stable between specifications **(ALT1)** and **(ALT2)**. This suggests that controlling for different cross-country trends in relative prices and technology does not substantially alter the relationship between factor endowments and regional production patterns, and that it is far more important to control for permanent cross-country differences in relative prices and technology (the move from **(NULL)** to **(ALT1)**).

The values of the estimated coefficients on factor endowments in **(ALT2)** are generally consistent with economic priors. Population endowments are positively correlated with specialisation in Services and negatively correlated with specialisation in Manufacturing. Greater endowments of physical capital are associated with a higher share of Manufacturing in GDP and a lower share of Agriculture and Services. Land area is positively related to specialisation in Agriculture and Manufacturing and negatively related to specialisation in Services. With the exception of the coefficient on population in the regression for Agriculture, all estimated coefficients are statistically significant at the 5 percent level.

Column (4) of Tables 3.3-3.5 reports the results of extending the model of relative prices and technology further to include a region-industry fixed effect in specification **(ALT3)**. Here, the pattern of estimated coefficients changes substantially and no longer has a plausible economic interpretation. For example, land area is negatively correlated with the share of Agriculture in GDP, while endowments of physical capital are positively and statistically significantly correlated with specialisation in Agriculture. Since there is almost no time-series variation in land area (see Table 3.2), it is unclear how appropriate or meaningful this econometric specification is. The parameters of interest are being identified from deviations from time means for individual regions, which in all cases are extremely small and in many cases are literally zero. It is plausible that the change in the estimated coefficients between **(ALT2)** and **(ALT3)** is largely driven by measurement error (Griliches and Hausman 1986). We investigate this possibility further below, where we disaggregate factor endowments (thereby introducing more time-series variation) and explore the results of long differences estimation.

Tables 3.3-3.5 also report the sum of the estimated coefficients on factor endowments in each industry and the results of a test whether the revenue function is linearly homogenous of degree one in factor endowments (a test of the null hypothesis that $\sum_i \gamma_{ji} = 0$). Although the sum of the estimated coefficients is close to zero (in several cases, the order of magnitude is 10^{-2}), the null hypothesis is frequently rejected at conventional levels of statistical significance. There is some evidence of increasing returns to scale in Manufacturing, where the sum of the estimated coefficients is strictly greater than zero in all specifications.

Our other model specification test examines the stationarity of the residuals using the unit root tests of Maddala and Wu (1999). In Agriculture we are able to reject the null hypothesis of a unit root in the residuals in all specifications, while in Services and Manufacturing we are unable to reject the null hypothesis in half the specifications. Taken together, these results provide some evidence of model mis-specification. Two possible explanations for the non-stationarity of the residuals are the omission of information on relevant factor endowments or time-varying regional price and technology differences that have not been controlled for (both of which will be included in the error term).

Table 3.6 investigates the first of these possibilities by introducing information on educational attainment and land quality. The availability of the educational attainment data reduces the sample size to 696 observations per industry (Sample B).[20] In the interests of

[20]The model in Tables 3.3-3.5 was re-estimated for the reduced sample; this yields very similar results to those reported in the paper.

brevity, we only report the results for specifications **(ALT2)** and **(ALT3)**. In both cases, as shown in the first F-statistic reported in the table, we reject the HO null against the more general neoclassical alternative, and we begin by considering the estimation results for specification **(ALT2)**.

<Table 3.6 about here>

The estimated coefficients on physical capital are very similar to before, while the arable land coefficients closely resemble those on total land area. In addition, we find highly statistically significant effects of education endowments. Greater endowments of low-education labour are positively and statistically significantly correlated with specialisation in Agriculture, while endowments of medium-education labour are negatively and statistically significantly correlated with the share of Agriculture in GDP. There is a positive and statistically significant relationship between endowments of medium-education labour and Manufacturing's share of GDP, while the relationship with endowments of high-education labour is negative and statistically significant. Endowments of high-education labour are positively and statistically significantly linked with specialisation in Services, while endowments of medium-education labour are negatively and statistically significantly linked with the share of Services in GDP. This pattern of results is consistent with the idea that Services is skilled-labour intensive relative to Agriculture and Manufacturing.

The introduction of more disaggregated measures of factor endowments increases the regression R^2, which in Manufacturing rises from 0.42 in Column (3) of Table 3.4 to 0.50 in Column (2) of Table 3.6. Furthermore, we are now able to reject the null hypothesis of a unit root in the residuals at the 5 percent level in all three industries. This is consistent with the idea that the non-stationarity of the residuals in the specification with population, physical capital and land area was due to the omission of information on relevant factor endowments. The sum of the estimated coefficients on factor endowments in all three industries is again close to zero, although the null hypothesis that the revenue function is linearly homogenous of degree one is typically rejected at the 5 percent level. The sum of the estimated coefficients in Manufacturing remains strictly greater than zero, again providing some evidence of increasing returns to scale.

The introduction of the region-industry fixed effects in **(ALT3)** again leads to a change in the estimated pattern of coefficients which often no longer have a plausible economic interpretation. For example, increases in arable land area are negatively (though not statistically significantly) related to specialisation in Agriculture. Again, it is plausible that these results are driven by measurement error - the extent of true time-series variation in factor endowments within regions still remains small relative to that due to measurement error, and this is particularly the case for arable land area.[21]

Table 3.7 investigates this possibility further using the results of long differences estimation over a 10-year time period **(ALT4)**. The long differences estimator enables us to control for unobserved heterogeneity at the regional level, while reducing the magnitude of any attenuation bias induced by measurement error. The pattern of estimated coefficients in Table 3.8 is similar to that reported for **(ALT2)** in Table 3.5. For example, arable land area is positively and statistically significantly correlated with the share of Agriculture in GDP and negatively and statistically significantly correlated with the share of Services. The main exception is for the low education endowment where one of the estimated coefficients changes sign.

<Table 3.7 about here>

The constancy of the estimated parameters as one moves from **(ALT1)** to **(ALT2)** in Tables 3.3-3.5, the fact that **(ALT2)** is explicitly concerned with variation across regions within countries, and the support provided by the long differences estimation lead us to select **(ALT2)** as our preferred specification. Throughout the remainder on the paper, we concentrate on the results using the more disaggregated data on factor endowments that control for educational attainment and land quality.

The analysis so far has established that the HO model's assumptions of identical relative prices and technology are rejected against more general alternatives consistent with the neoclassical model of trade. The additional terms capturing regional variation in relative prices and technology are not only highly statistically significant but also quantitatively important. In Manufacturing the regression R^2 rises from 0.29 in **(NULL)** to 0.42 in our preferred alternative specification **(ALT2)**, while in Services the R^2 rises from 0.45 to 0.55. Taken together, the results provide evidence that HO is an incomplete model of patterns of production across European regions.

Nonetheless, factor endowments remain highly statistically significant within each of the alternative specifications, and Table 3.8 examines their quantitative importance in explaining patterns of production within our preferred alternative specification. The first row of each panel of the table reports the average share of a sector in GDP for the whole sample and for individual countries. The remaining rows of each panel report within sample average absolute prediction errors. These are defined in proportional terms as $\left|s_{zjt} - \hat{s}_{zjt}\right| / s_{zjt}$, where a hat

[21] The time-series variation in arable land area, though larger than that in total land area, remains small.

above a variable indicates a predicted value.[22] The prediction errors reported in the table differ in terms of how predicted shares of GDP are calculated. The first and simplest measure uses the fitted values from **(ALT2)**, and provides an overall indication of the model's within-sample predictive ability. The second measure takes the parameter estimates from **(ALT2)** but only uses the country-year dummies to predict shares of sectors in GDP. Comparing the second and first measures reveals the contribution of factor endowments to reducing the model's within-sample prediction error. The third measure takes the parameter estimates from **(ALT2)** but only uses the 5 factor endowments to predict shares of sectors in GDP. Comparing the third and first measures reveals the contribution of the terms capturing relative prices and technology to reducing the model's within-sample prediction error.

<Table 3.8 about here>

The model's overall average prediction error across regions and years in Manufacturing is 13 percent, which compares favorably with the average prediction error across disaggregated manufacturing industries in Harrigan (1995) using country-level data (38 percent) and the average prediction errors reported using regional data in Bernstein and Weinstein (2002). For individual countries, the average prediction error within Manufacturing varies from 6 percent in Belgium to 18 percent in the Netherlands. Looking across industries, the model is most successful at explaining European regional production patterns in Services and Manufacturing. For the whole sample and all countries except the Netherlands, we find the same ranking of industries in terms of (increasing) average prediction errors: from Services, through Manufacturing, to Agriculture.

Factor endowments are quantitatively important in explaining variation in production patterns across European regions over time. The model's average prediction error rises by a factor of more than three in Manufacturing and more than doubles in Services if information on factor endowments is excluded. In Agriculture and Manufacturing, excluding the country-year dummies has a roughly similar effect to excluding factor endowments, suggesting that these two sets of considerations make roughly equal contributions towards explaining variation in specialisation patterns. In Services, the country-year dummies are much more important. In general equilibrium, variation in relative prices affects the share of all sectors in GDP (the country-year dummies are important in all sectors), but the finding of the largest effects in Services is consistent with this sector being the least tradeable.

One of the features that makes our sample period interesting is that it is characterized

[22]The model's predictions for output levels can be obtained by multiplying predicted GDP shares by actual GDP. Proportional prediction errors for output are therefore exactly the same as for shares of sectors in GDP (one is multiplying both the numerator and denominator of the formula in the text by actual GDP).

by increasing European integration. In Table 3.9, we examine the model's average absolute prediction errors over time. Has the process of closer integration weakened the relationship between regions' patterns of production and their factor endowments, so that we observe an increase in average prediction errors over time? Since the country-year dummies in **(ALT2)** control for any country-specific changes in patterns of production over time, we are explicitly concerned here with how increasing integration has affected the relationship between production and endowments across regions *within countries.* From Table 3.10, we find no systematic increase or decrease in average prediction errors over time. Across all regions and years, the average prediction error falls in Services and remains broadly constant in Manufacturing and Agriculture.

<Table 3.9 about here>

Finally, it is frequently asserted that factor endowments explain specialisation and trade at the aggregate level in industries such as Agriculture, Manufacturing and Services, while other considerations, including imperfect competition and increasing returns to scale, are more important for specialisation and trade within these aggregate industries. This hypothesis is implicit in the construction of theoretical models of inter and intra-industry trade, such as Helpman and Krugman (1985). The same assumption is made in empirical work by Davis and Weinstein (1999), (2002). The present dataset and empirical framework may be used to shed light on whether this hypothesis holds for European regions. In addition to the aggregate industries considered above, we also estimate the model for disaggregated industries within the manufacturing sector, and the results are reported in Tables 3.14 and 3.15 of Appendix 3C.

Factor endowments are again found to play a statistically significant role in explaining production structure in European regions. For example, physical capital is positively and statistically significantly related to the share of Chemicals, Machinery and Transport Equipment in a region's GDP. Medium education is positively and statistically significantly correlated with specialisation in Metals, Machinery and Transport Equipment. However, in all industries, the HO specification **(NULL)** is rejected against the more general neoclassical alternative **(ALT2)** at the 5 percent level of statistical significance

Tables 3.10-3.11 examines average absolute prediction errors at the disaggregated level. In 10 of the 11 manufacturing industries and for every 5-year period considered, average prediction errors across regions and time are higher than those reported for manufacturing as a whole in Table 3.10 (the exception is the Construction industry). Considering all 11 disaggregated industries together, the average prediction error across regions during 1985-

90 was 47 percent, compared with an average prediction error across the three aggregated industries in Tables 3.10-3.11 of 31 percent during the same period. This provides evidence that factor endowments are indeed more successful at explaining patterns production at the aggregate level (Agriculture, Manufacturing and Services) than in disaggregated industries within the manufacturing sector.

<Tables 3.10- 3.11 about here>

These findings concerning the model's predictive ability are consistent with our theoretical approach. At the aggregate level, there are at least as many factors of production as the number of goods ($M \geq N$), which we noted earlier is a condition for the revenue function to be twice continuously differentiable. Whereas for the 11 disaggregated manufacturing industries, there are more goods than factors of production ($N > M$). One theory-consistent explanation for the larger disaggregated prediction errors is, therefore, that there is a degree of indeterminacy in the production of individual manufacturing industries at the regional level. Another theory-consistent explanation is that there are larger price and technology differences across regions within individual disaggregated manufacturing industries that are not being captured in the right-hand side variables.

At the disaggregated level, we also find no systematic trend in the average absolute prediction errors over time, so that there is again no evidence that increasing European integration has weakened or stregthened the relationship between factor endowments and production across regions within countries.

3.7 Conclusions

This paper has analyzed the relationship between production patterns and factor endowments using data on a panel of 14 industries in 45 regions from 7 European countries since 1975. Under the assumptions of the Heckscher-Ohlin (HO) model of identical relative prices and technology, we derived a general equilibrium relationship between the share of a sector in GDP and factor endowments. The HO model is a special case of the more general neoclassical model of trade, which allows for regional variation in relative prices and technology. We compared the empirical performance of the HO null against a series of alternative specifications derived from the neoclassical model and including progressively more general models of relative prices and technology.

The use of European regional data enables us to abstract from many of the considerations that have been proposed as explanations for the disappointing empirical performance of HO theory at the country-level. For example, both measurement error and technology differences are likely to be much smaller across regions within Europe than for a cross-section of developed and developing countries. If factor endowments are mobile across regions, the general equilibrium relationships that we estimate have both a demand-side and a supply-side interpretation. Irrespective of whether the relationships are demand-side, supply-side or a combination of both, we are able to test between the null and alternative specifications, and we are able to examine the respective contributions of factor endowments and other considerations to explaining patterns of production.

For both aggregate industries (Agriculture, Manufacturing and Services) and disaggregated manufacturing industries, the HO null is rejected against more general neoclassical alternatives that allow for regional variation in relative prices and technology. Nevertheless, within each of the alternative specifications considered, factor endowments remain highly statistically significant and make an important contribution to explaining patterns of production. Excluding information on factor endowments in our preferred alternative specification increases within-sample prediction errors for Manufacturing by a factor of more than three. The pattern of estimated coefficients across industries accords with economic priors. For example, endowments of physical capital are positively correlated with the share of Manufacturing in GDP and negatively correlated with the share of Agriculture and Services.

Factor endowments are more successful at explaining production structure at the aggregate level (Agriculture, Manufacturing and Services) than in disaggregated industries within manufacturing, a finding that is consistent with the predictions of theory. The large number of disaggregated manufacturing industries relative to the number of factor endowments suggests the possibility of production indeterminacy, and regional differences in relative prices and technology may be particularly large in individual manufacturing industries. At both the aggregate and disaggregate level, we find no evidence that the process of increasing European integration has weakened or strengthened the relationship between factor endowments and production across regions within countries.

Table 3.1: Factor Endowments in 1975, 1985, and 1995[a]

Region	Year	Pop	Cap	Land	Region	Year	Pop	Cap	Land
Bel	1975	967.38	6721.539	16.2	Fra7	1975	5884.79	87949.34	7113.6
	1985	961.1	7945.636	16.1		1985	6388.3	131157.8	7113.6
	1995	944.9	9068.479	16.1		1995	6765.8	154844.7	7113.6
Be2	1975	5400.21	11579.08	1351.1	Fra8	1975	5240.18	57037.51	6828.2
	1985	5646.7	21646.15	1351.2		1985	5627.4	96296.46	6828.2
	1995	5852	37943.63	1351.2		1995	6775.3	124957.2	6828.2
Be3	1975	3160.45	6758.029	1684.8	Ital	1975	6431.26	65155.07	3407.6
	1985	3197.8	9619.443	1684.4		1985	6199	101068	3407.7
	1995	3307.9	14563.69	1684.4		1995	5978.6	131306.6	3407.9
Espl	1975	4210.96	27446.6	4528.8	Ita2	1975	8665.99	94042.59	2385.03
	1985	4443	39729.87	4532.8		1985	8752.7	154774.1	2385.7
	1995	4298	54444.34	4536.2		1995	8786.7	202913.6	2387.3
Esp2	1975	3855.28	34242.75	7037.4	Ita3	1975	6229.93	67239.92	3982.47
	1985	4088.35	44469.33	7038.6		1985	6344.9	109107.3	3983.1
	1995	3993.6	63817.2	7034.3		1995	6407.3	147813.5	3982.7
Esp3	1975	4345.41	31732.97	799.5	Ita4	1975	3864.12	38671.77	2212.3
	1985	4824.05	39215.81	799.5		1985	3893.2	65189.58	2212.3
	1995	5040.40	65441.33	802.8		1995	3866.7	82760.49	2212.3
Esp4	1975	4947.70	33809.81	21492.3	Ita5	1975	5642.75	53216.01	4114.13
	1985	5217.08	54417.75	21483.5		1985	5750.3	88498.08	4114.2
	1995	5170.5	74640.4	21483.6		1995	5714	105956	4114.2
Esp5	1975	9490.14	83441.64	6020.5	Ita6	1975	4823.32	37194.79	1720.3
	1985	10169.84	108768.1	6013.4		1985	5008.7	70660.65	1720.3
	1995	10594.5	169036.2	6014.8		1995	5099.1	115990.2	1720.3
Esp6	1975	6667.77	38905.89	9858.5	Ita7	1975	1494.95	16654.18	1523.2
	1985	7449.77	59331.64	9858.7		1985	1555.7	26232.84	1523.2
	1995	8197.3	93269.52	9867.6		1995	1579.2	30796.81	1523.2
Esp7	1975	1229.36	7540.541	746.6	Ita8	1975	5147.29	31031.16	1359.5
	1985	1389.59	11781.26	750		1985	5557.1	59298.32	1359.5
	1995	1521.4	20202.67	748		1995	5687.1	74722.96	1359.5
Fral	1975	9899.95	177317.3	1196.5	Ita9	1975	6255.12	44407.48	4442
	1985	10345.2	272393.2	1196.5		1985	6620.9	75853.26	4442
	1995	10703.7	396078.6	1196.5		1995	6654.6	91471.69	4442
Fra2	1975	8877.92	147434.4	14659.9	Itaa	1975	4739.18	28564.2	2570.8
	1985	9452.4	206561.2	14659.9		1985	4973	54135.88	2570.8
	1995	9888.5	231949.6	14659.9		1995	5000.3	67786.23	2570.9
Fra3	1975	3854.59	40983.74	1245.1	Itab	1975	1504.68	14526.73	2409
	1985	3910.9	61957.58	1245.1		1985	1607.2	24124.79	2409
	1995	3821.9	73979.1	1245.1		1995	1639.9	30440.95	2409
Fra4	1975	4694.08	77341.84	4830.9	Lux	1975	351.73	5928.26	258.6
	1985	4670.8	108023.8	4830.9		1985	355.9	8309.376	258.6
	1995	4858.4	123198	4830.9		1995	402.5	13997.32	256.8
Fra5	1975	6465.02	83522.45	8585.6	Nld1	1975	1465.86	18254.55	904.5
	1985	6927.4	124273	8585.6		1985	1553.87	29099.54	1070
	1995	7589.1	148911.2	8585.6		1995	1593.9	37060.6	1138.8
Fra6	1975	5014.20	75540.89	10449	Nld2	1975	2579.9	26835.04	1021.1
	1985	5607.2	108094.2	10449		1985	2877.51	45296.34	1020.1
	1995	5932.9	120266	10449		1995	3129.4	61913.82	1097.6

[a] See Appendix 3A for further details concerning the factor endowments used.

Table 3.1 (cont.): Factor Endowments in 1975, 1985, and 1995[a]

Region	Year	Pop	Cap	Land	Region	Year	Pop	Cap	Land
Nld3	1975	6351.84	75012.2	1037.8	Uk6	1975	4162.70	16877.93	2383
	1985	6597.38	125395.7	1123.5		1985	4407.4	28854.15	2385
	1995	7099.5	167428.8	1187.1		1995	4711.5	37562.04	2385
Nld4	1975	2925.58	33294.7	731.4	Uk7	1975	5133.62	15359.96	1301.3
	1985	3124.39	53328.02	731.5		1985	5127.5	27263.04	1301.3
	1995	3350.2	74382.43	729.1		1995	5231.8	39124.63	1301.3
Ukl	1975	3125.56	13258.54	1540.03	Uk8	1975	6498.89	21552.36	731.43
	1985	3051.7	21612.87	1540.1		1985	6305.7	35511.66	733.1
	1995	3055.2	27599.95	1542.1		1995	6323.1	48322.58	734.4
Uk2	1975	4876.12	20716	1541.8	Uk9	1975	2764.09	6902.181	2076.6
	1985	4845.4	32875.4	1542		1985	2777.3	13993.15	2076.8
	1995	4959.2	41394.54	1542.1		1995	2868.2	22284.25	2076.6
Uk3	1975	3728.18	14490.71	1561	Uka	1975	5122.10	21536.84	7877.13
	1985	3851.7	24247.27	1563		1985	5052.3	33158.39	7878.3
	1995	4063.6	34597.66	1563		1995	5051	43721.04	7878.3
Uk4	1975	1763.64	11419.7	1256.57	Ukb	1975	1519.85	6602.664	1412.07
	1985	1934.1	17298.85	1257.3		1985	1535.1	10267.07	1412
	1995	2092	19389.3	1257.3		1995	1598.8	13058.63	1412.2
Uk5	1975	16688.35	87776.61	2722.27		1975			
	1985	16880.9	134179.3	2722.2		1985			
	1995	17570.2	155221.4	2722.7		1995			

[a] See Appendix 3A for further details concerning the factor endowments used.

Table 3.2: Educational Attainment by Region in 1985 and 1995 (percentage of total population)
(a)

Region	Year	Low	Med	High	Region	Year	Low	Med	High
Be1	1985	53.35	41.55	5.10	Ita6	1985	60.43	29.38	9.41
	1995	35.97	59.68	4.35		1995	46.34	39.99	13.67
Be2	1985	50.97	45.35	3.67	Ita7	1985	71.65	21.99	6.30
	1995	41.90	52.51	5.59		1995	56.26	34.15	9.59
Be3	1985	51.07	45.27	3.66	Ita8	1985	73.40	19.98	6.71
	1995	37.49	57.20	5.31		1995	57.98	31.73	10.29
Esp1	1985	65.31	28.52	6.18	Ita9	1985	73.91	20.45	5.72
	1995	44.46	46.94	8.60		1995	60.67	29.67	9.67
Esp2	1985	59.83	32.45	7.72	Itaa	1985	70.94	21.73	7.26
	1995	38.35	48.30	13.34		1995	59.83	30.07	10.10
Esp3	1985	47.22	40.70	12.08	Itab	1985	77.40	17.16	5.79
	1995	33.51	50.17	16.32		1995	65.70	27.35	6.96
Esp4	1985	67.42	26.44	6.14	Lux	1985	51.07	45.27	3.66
	1995	48.11	42.43	9.46		1990	37.49	57.20	5.31
Esp5	1985	67.42	30.49	6.13	Nld1	1985	29.75	62.33	9.03
	1995	39.36	50.94	9.71		1995	14.86	68.53	16.79
Esp6	1985	70.07	24.53	5.39	Nld2	1985	27.76	62.77	9.33
	1995	49.28	43.28	7.45		1995	14.53	68.48	16.95
Esp7	1985	65.39	28.19	6.42	Nld3	1985	28.33	58.68	12.02
	1995	43.66	46.23	10.11		1995	14.80	62.88	22.12
Fra1	1985	46.13	34.18	19.44	Nld4	1985	29.06	61.16	9.47
	1994	36.50	40.50	23.00		1995	15.08	67.58	17.08
Fra2	1985	61.95	35.98	9.36	Uk1	1985	40.48	44.32	3.18
	1994	40.00	38.50	21.50		1994	25.51	68.37	5.80
Fra3	1985	65.91	35.08	7.92	Uk2	1985	38.39	46.85	3.56
	1994	49.00	38.50	12.50		1994	24.42	68.10	7.14
Fra4	1985	55.36	38.68	10.80	Uk3	1985	34.89	47.15	4.43
	1994	40.50	44.00	15.50		1994	24.81	67.38	7.60
Fra5	1985	55.36	38.68	10.08	Uk4	1985	36.31	48.60	4.66
	1994	40.00	45.00	15.00		1994	21.79	70.63	7.49
Fra6	1985	48.77	40.48	12.96	Uk5	1985	27.98	53.17	7.41
	1994	35.50	46.00	18.50		1994	19.44	68.50	11.71
Fra7	1985	50.09	39.58	13.68	Uk6	1985	41.86	40.71	4.06
	1994	36.32	44.28	19.40		1994	20.90	70.24	8.63
Fra8	1985	56.68	36.88	12.24	Uk7	1985	34.77	47.92	4.14
	1994	41.79	41.29	16.92		1994	27.67	64.79	7.07
Ita1	1985	73.54	21.43	5.06	Uk8	1985	37.25	47.46	4.26
	1995	56.55	34.64	8.81		1994	25.09	66.89	7.77
Ita2	1985	74.03	20.84	5.21	Uk9	1985	43.44	43.44	5.10
	1995	54.46	35.32	10.22		1994	26.15	66.20	7.54
Ita3	1985	77.29	18.46	4.54	Uka	1985	55.00	39.80	3.81
	1995	56.92	35.54	7.54		1994	20.30	70.60	8.86
Ita4	1985	71.98	22.00	5.97	Ukb	1985	55.62	39.18	3.97
	1995	54.89	35.79	9.33		1994	35.40	56.13	8.05
Ita5	1985	73.19	21.36	5.47					
	1995	56.84	34.02	9.14					

Notes: [a] Figures may not sum to exactly 100 due to rounding. See Appendix 3A for further details concerning the data used.

Table 3.3: Factor Endowments and Specialisation in Agriculture

s_{zjt}	(2)	(3)	(4)	(5)
Obs	811	811	811	811
Years	1975-95	1975-95	1975-95	1975-95
Capital_{zt}	0.004**	-0.022**	-0.019**	0.011**
	(0.0013)	*(0.0035)*	*(0.0038)*	*(0.0040)*
Population_{zt}	-0.021**	0.002	-0.002	-0.129**
	(0.0018)	*(0.0040)*	*(0.0042)*	*(0.0153)*
Land_{zt}	0.017**	0.016**	0.016**	-0.055**
	(0.0008)	*(0.0009)*	*(0.0009)*	*(0.0159)*
Sample	A	A	A	A
Specification	**(NULL)**	**(ALT1)**	**(ALT2)**	**(ALT3)**
Year dummies	yes	yes		
Country effects		yes		
Cty-year dummies			yes	yes
Region effects				yes
Prob>F(NULL-ALT)	N/A	0.0000	0.0000	0.0000
Prob>F(ALL)	0.0000	0.0000	0.0000	0.0000
R-squared	0.40	0.63	0.65	0.96
Sum of Coeff.	0.0003	-0.0046	-0.050	-0.1730
Linear Homog	*(0.8061)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
(p-value)	Accept	Reject	Reject	Reject
Maddala-Wu	*(0.0188)*	*(0.0389)*	*(0.0263)*	*(0.0002)*
(p-value)	Reject	Reject	Reject	Reject

Notes: Prob>F(NULL-ALT) is the p-value for an F-test of the null hypothesis that the coefficients on the variables excluded from specification (NULL) but included in the alternative specification are equal to 0. Prob>F(ALL) is the p-value for the conventional F-test that the coefficients on all independent variables are equal to zero. Sum of Coeff. is the sum of the estimated coefficients on factor endowments. Linear Homog. is the p-value for a test of the null hypothesis that the sum of the estimated coefficients on factor endowments is equal to zero. Maddala-Wu is the p-value for the Maddala and Wu (1999) panel data test of the null hypothesis that the residuals have a unit root. Huber-White heteroscedasticity robust standard errors in parentheses. ** denotes significance at the 5 percent level, * denotes significance at the 10 percent level.

Table 3.4: Factor Endowments and Specialisation in Manufacturing

s_{zjt}	(2)	(3)	(4)	(5)
Obs	811	811	811	811
Years	1975-95	1975-95	1975-95	1975-95
Capital_{zt}	-0.005	0.071**	0.073**	0.043**
	(0.0040)	*(0.0116)*	*(0.0133)*	*(0.0082)*
Population_{zt}	-0.008	-0.079**	-0.082**	0.205**
	(0.0058)	*(0.0124)*	*(0.0140)*	*(0.0322)*
Land_{zt}	0.021**	0.032**	0.033**	-0.130*
	(0.0023)	*(0.0027)*	*(0.0029)*	*(0.0739)*
Sample	A	A	A	A
Specification	**(NULL)**	**(ALT1)**	**(ALT2)**	**(ALT3)**
Year dummies	yes	yes		
Country effects		yes		
Cty-year dummies			yes	yes
Region effects				yes
Prob>F(NULL-ALT)	N/A	0.0000	0.0000	0.0000
Prob>F(ALL)	0.0000	0.0000	0.0000	0.0000
R-squared	0.29	0.40	0.42	0.97
Sum of Coeff.	0.0082	0.0239	0.0240	0.1180
Linear Homog	*(0.0133)*	*(0.0000)*	*(0.0000)*	*(0.1625)*
(p-value)	Reject	Reject	Reject	Accept
Maddala-Wu	*(0.0040)*	*(0.0020)*	*(0.1949)*	*(0.1779)*
(p-value)	Reject	Reject	Accept	Accept

Notes: Prob>F(NULL-ALT) is the p-value for an F-test of the null hypothesis that the coefficients on the variables excluded from specification (NULL) but included in the alternative specification are equal to 0. Prob>F(ALL) is the p-value for the conventional F-test that the coefficients on all independent variables are equal to zero. Sum of Coeff. is the sum of the estimated coefficients on factor endowments. Linear Homog. is the p-value for a test of the null hypothesis that the sum of the estimated coefficients on factor endowments is equal to zero. Maddala-Wu is the p-value for the Maddala and Wu (1999) panel data test of the null hypothesis that the residuals have a unit root. Huber-White heteroscedasticity robust standard errors in parentheses. ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 3.5: Factor Endowments and Specialisation in Services

s_{zjt}	(2)	(3)	(4)	(5)
Obs	811	811	811	811
Years	1975-95	1975-95	1975-95	1975-95
Capital_{zt}	0.0006	-0.049**	-0.054**	-0.054**
	(0.0039)	*(0.0100)*	*(0.0113)*	*(0.0094)*
Population_{zt}	0.029**	0.078**	0.083**	-0.076**
	(0.0057)	*(0.0106)*	*(0.0119)*	*(0.0296)*
Land_{zt}	-0.038**	-0.048**	-0.048**	0.185**
	(0.0021)	*(0.0025)*	*(0.0027)*	*(0.0656)*
Sample	A	A	A	A
Specification	**(NULL)**	**(ALT1)**	**(ALT2)**	**(ALT3)**
Year dummies	yes	yes		
Country effects		yes		
Cty-year dummies			yes	yes
Region effects				yes
Prob>F(NULL-ALT)	N/A	0.0000	0.0000	0.0000
Prob>F(ALL)	0.0000	0.0000	0.0000	0.0000
R-squared	0.45	0.53	0.55	0.98
Sum of Coeff.	-0.0085	-0.0192	-0.019	0.055
Linear Homog	*(0.0091)*	*(0.0001)*	*(0.0002)*	*(0.4556)*
(p-value)	Reject	Reject	Reject	Accept
Maddala-Wu	*(0.1705)*	*(0.2460)*	*(0.0464)*	*(0.4115)*
(p-value)	Accept	Accept	Reject	Accept

Notes: Prob>F(NULL-ALT) is the p-value for an F-test of the null hypothesis that the coefficients on the variables excluded from specification (NULL) but included in the alternative specification are equal to 0. Prob>F(ALL) is the p-value for the conventional F-test that the coefficients on all independent variables are equal to zero. Sum of Coeff. is the sum of the estimated coefficients on factor endowments. Linear Homog. is the p-value for a test of the null hypothesis that the sum of the estimated coefficients on factor endowments is equal to zero. Maddala-Wu is the p-value for the Maddala and Wu (1999) panel data test of the null hypothesis that the residuals have a unit root. Huber-White heteroscedasticity robust standard errors in parentheses. ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 3.6: Factor Endowments and Specialisation at the Aggregate Level

s_{zjt}	(1)	(2)	(3)	(4)	(5)	(6)
Obs	696	696	696	696	696	696
Years	1975-95	1975-95	1975-95	1975-95	1975-95	1975-95
Capital_{zt}	-0.016**	0.083**	-0.067**	0.012**	0.059**	-0.071**
	(0.0036)	*(0.0142)*	*(0.0129)*	*(0.0049)*	*(0.0116)*	*(0.0110)*
Low Educ_{zt}	0.028**	-0.035*	0.007	-0.040**	0.015	0.024*
	(0.0049)	*(0.0181)*	*(0.0161)*	*(0.0066)*	*(0.0160)*	*(0.0148)*
Med Educ_{zt}	-0.030**	0.077**	-0.048**	-0.014**	0.021**	-0.07
	(0.0046)	*(0.0188)*	*(0.0182)*	*(0.0028)*	*(0.0063)*	*(0.0053)*
High Educ_{zt}	-0.001	-0.130**	0.131**	-0.011**	0.015*	-0.004
	(0.0033)	*(0.0160)*	*(0.0155)*	*(0.0031)*	*(0.0073)*	*(0.0058)*
Arable land_{zt}	0.012**	0.020**	-0.032**	-0.001	0.017	-0.016
	(0.0008)	*(0.0025)*	*(0.0022)*	*(0.0021)*	*(0.0108)*	*(0.0111)*
Industry	Agric	Manuf	Serv	Agric	Manuf	Serv
Sample	B	B	B	B	B	B
Specification	**(ALT2)**	**(ALT2)**	**(ALT2)**	**(ALT3)**	**(ALT3)**	**(ALT3)**
Regional effects				yes	yes	yes
Cty-year dummies	yes	yes	yes	yes	yes	yes
Prob>F(NULL-ALT)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.67	0.50	0.62	0.96	0.97	0.98
Sum of Coeff.	-0.0067	0.1541	-0.0087	-0.0541	0.1267	-0.0727
Linear Homog	*(0.0000)*	*(0.0102)*	*(0.1273)*	*(0.0000)*	*(0.0000)*	*(0.0114)*
(p-value)	Reject	Reject	Accept	Reject	Reject	Reject
Maddala-Wu	*(0.0002)*	*(0.0106)*	*(0.0041)*	*(0.0000)*	*(0.2084)*	*(0.0092)*
(p-value)	Reject	Reject	Reject	Reject	Accept	Reject

Notes: Prob>F(NULL-ALT) is the p-value for an F-test of the null hypothesis that the coefficients on the variables excluded from specification (NULL) but included in the alternative specification are equal to 0. Prob>F(ALL) is the p-value for the conventional F-test that the coefficients on all independent variables are equal to zero. Sum of Coeff. is the sum of the estimated coefficients on factor endowments. Linear Homog. is the p-value for a test of the null hypothesis that the sum of the estimated coefficients on factor endowments is equal to zero. Maddala-Wu is the p-value for the Maddala and Wu (1999) panel data test of the null hypothesis that the residuals have a unit root. Huber-White heteroscedasticity robust standard errors in parentheses. ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 3.7: Factor Endowments and Specialisation at the Aggregate Level (Long Differences)

Δs_{zjt}	(1)	(2)	(3)
Obs	341	341	341
Years	1975-95	1975-95	1975-95
ΔCapital$_{zt}$	-0.006	0.062**	-0.057**
	(0.0043)	*(0.0104)*	*(0.0112)*
ΔLow Educ$_{zt}$	-0.035**	-0.009	0.044**
	(0.0043)	*(0.0185)*	*(0.0187)*
ΔMed Educ$_{zt}$	-0.031**	0.023**	0.008
	(0.0038)	*(0.0082)*	*(0.0081)*
ΔHigh Educ$_{zt}$	-0.010**	-0.002	0.012**
	(0.0017)	*(0.0042)*	*(0.0044)*
ΔArable Land$_{zt}$	0.013**	0.018*	-0.031**
	(0.0035)	*(0.0108)*	*(0.0122)*
Industry	Agric	Manuf	Serv
Sample	B	B	B
Specification	**(ALT4)**	**(ALT4)**	**(ALT4)**
Year dummies	yes	yes	yes
Difference period	10 years	10 years	10 years
Prob>F	0.0000	0.0000	0.0000
R-squared	0.46	0.21	0.19
Sum of Coeff.	-0.0685	0.0915	-0.0229
Linear Homog	*(0.0000)*	*(0.0016)*	*(0.4466)*
(p-value)	Reject	Reject	Accept

Notes: Sum of Coeff. is the sum of the estimated coefficients on factor endowments. Linear Homog. is the p-value for a test of the null hypothesis that the sum of the estimated coefficients on factor endowments is equal to zero. Huber-White heteroscedasticity robust standard errors in parentheses. ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 3.8: Average Shares of Sectors in GDP and Within-sample Average Absolute Prediction Errors

		(1)	(2)	(3)
		Agric	Manuf	Serv
All countries[a]	GDP share	0.042	0.354	0.604
	Prediction Error 1 **(ALT2)**	0.582	0.133	0.068
	Prediction Error 2 **(ALT2 only cty-yr)**	6.316	0.499	0.159
	Prediction Error 3 **(ALT2 only endow.)**	6.985	0.501	1.099
Belgium[a]	GDP share	0.026	0.337	0.637
	Prediction Error 1 **(ALT2)**	0.519	0.056	0.038
	Prediction Error 2 **(ALT2 only cty-yr)**	5.151	0.572	0.107
	Prediction Error 3 **(ALT2 only endow.)**	5.632	0.476	1.099
Spain	GDP share	0.057	0.334	0.609
	Prediction Error 1 **(ALT2)**	1.529	0.170	0.072
	Prediction Error 2 **(ALT2 only cty-yr)**	10.603	0.439	0.159
	Prediction Error 3 **(ALT2 only endow.)**	10.277	0.524	1.095
France	GDP share	0.043	0.337	0.620
	Prediction Error 1 **(ALT2)**	0.677	0.118	0.046
	Prediction Error 2 **(ALT2 only cty-yr)**	8.700	0.526	0.124
	Prediction Error 3 **(ALT2 only endow.)**	9.267	0.461	1.104
Italy	GDP share	0.048	0.339	0.613
	Prediction Error 1 **(ALT2)**	0.280	0.121	0.053
	Prediction Error 2 **(ALT2 only cty-yr)**	2.940	0.502	0.151
	Prediction Error 3 **(ALT2 only endow.)**	3.822	0.471	1.133
Luxembourg	GDP share	0.024	0.342	0.634
	Prediction Error 1 **(ALT2)**	0[c]	0[c]	0[c]
	Prediction Error 2 **(ALT2 only cty-yr)**	5.003	0.897	0.301
	Prediction Error 3 **(ALT2 only endow.)**	6.003	0.104	1.301
Netherlands	GDP share	0.047	0.353	0.600
	Prediction Error 1 **(ALT2)**	0.125	0.177	0.114
	Prediction Error 2 **(ALT2 only cty-yr)**	3.875	0.526	0.156
	Prediction Error 3 **(ALT2 only endow.)**	4.858	0.426	1.058
UK	GDP share	0.025	0.415	0.561
	Prediction Error 1 **(ALT2)**	0.462	0.145	0.098
	Prediction Error 2 **(ALT2 only cty-yr)**	6.634	0.444	0.213
	Prediction Error 3 **(ALT2 only endow.)**	7.755	0.650	1.057
	Sample	B	B	B

Notes: Table reports mean values for the whole sample and individual countries. Absolute proportional prediction errors are calculated as |s - s(P)| / s, where a capital P indicates a predicted value. Prediction error (ALT2) is based on the fitted values from specification (ALT2) using the disaggregated data on 5 factor endowments, and parameter estimates for this specification are reported in Table 3.5; Prediction error (ALT2, only cty-year) indicates that predicted values use the parameter estimates from specification (ALT2) but only the country-year dummies are used to construct predicted shares of GDP. Prediction error (ALT2, only endowments) indicates that predicted values use the parameter estimates from specification (ALT2) but only the 5 factor endowments are used to construct predicted shares of GDP.

[a] Reported prediction errors exclude region Bel (Brussels). Brussels is a capital city, and the share of Agriculture in this region is a clear outlier. As a robustness test, we re-estimated the model excluding this region; this produced very similar estimated coefficients to those reported earlier. (b) Luxembourg has only one NUTS-1 region. The fitted values for shares of sectors in GDP in the specification with country-year dummies are therefore exactly equal to the actual values (we estimate as many country-year coefficients as there are observations for Luxembourg). We experimented with treating Luxembourg as a region of Belgium; again this yielded very similar estimated coefficients to those reported earlier.

Table 3.9: Within-sample Average Absolute Prediction Errors over Time

		Period	(1)	(2)	(3)
All countries[a]	Prediction Error **(ALT2)**	1980-85	0.568	0.132	0.070
	Prediction Error **(ALT2)**	1985-90	0.735	0.130	0.062
	Prediction Error **(ALT2)**	1990-95	0.566	0.131	0.054
Belgium[a]	Prediction Error **(ALT2)**	1980-85	0.403	0.031	0.029
	Prediction Error **(ALT2)**	1985-90	0.421	0.064	0.040
	Prediction Error **(ALT2)**	1990-95	0.708	0.078	0.048
Spain	Prediction Error **(ALT2)**	1980-85	1.195	0.191	0.083
	Prediction Error **(ALT2)**	1985-90	1.983	0.157	0.068
	Prediction Error **(ALT2)**	1990-95	1.513	0.164	0.064
France	Prediction Error **(ALT2)**	1980-85	0.724	0.111	0.042
	Prediction Error **(ALT2)**	1985-90	0.721	0.126	0.043
	Prediction Error **(ALT2)**	1990-94	0.565	0.117	0.043
Italy	Prediction Error **(ALT2)**	1980-85	0.340	0.107	0.047
	Prediction Error **(ALT2)**	1985-90	0.283	0.126	0.059
	Prediction Error **(ALT2)**	1990-95	0.213	0.129	0.053
Luxembourg	Prediction Error **(ALT2)**	1980-85	0[b]	0[b]	0[b]
	Prediction Error **(ALT2)**	1985-90	0[b]	0[b]	0[b]
Netherlands	Prediction Error **(ALT2)**	1980-85	0.174	0.224	0.170
	Prediction Error **(ALT2)**	1985-90	0.114	0.172	0.103
	Prediction Error **(ALT2)**	1990-95	0.083	0.141	0.065
UK	Prediction Error **(ALT2)**	1975-80	0.328	0.165	0.117
	Prediction Error **(ALT2)**	1980-85	0.501	0.129	0.082
	Sample		B	B	B

Notes: Table reports mean values for the whole sample and individual countries. Absolute proportional prediction errors are calculated as |s - s(P)| / s, where a capital P indicates a predicted value. Prediction error (ALT2) is based on the fitted values from specification (ALT2) using the disaggregated data on 5 factor endowments, and parameter estimates for this specification are reported in Table 3.6. (a) Reported prediction errors exclude region Bel (Brussels). Brussels is a capital city, and the share of Agriculture in this region is a clear outlier. As a robustness test, we re-estimated the model excluding this region; this produced very similar estimated coefficients to those reported earlier. (b) Luxembourg has only one NUTS-1 region. The fitted values for shares of sectors in GDP in the specification with country-year dummies are therefore exactly equal to the actual values (we estimate as many country-year coefficients as there are observations for Luxembourg). We experimented with treating Luxembourg as a region of Belgium; again this yielded very similar estimated coefficients to those reported earlier.

Table 3.10: Within-sample Average Absolute Prediction Errors (PE (ALT2)) in the Disaggregated Manufacturing Industries over Time

		(1)	(2)	(3)	(4)	(5)	(6)
Country	**Period**	**Fuel**	**Ferrous**	**Minerals**	**Chemical**	**Machine**	**Transport**
All countries[(a),(b)]	1980-85	0.579	2.467	0.286	0.457	0.486	0.575
	1985-90	0.542	1.455	0.279	0.350	0.496	0.512
	1990-95	0.536	1.246	0.286	0.389	0.551	0.550
Belgium[(a)]	1980-85	0.402	0.357	0.583	0.252	0.266	1.011
	1985-90	0.271	0.246	0.542	0.213	0.167	0.156
	1990-95	0.123	0.320	0.480	0.209	0.193	0.136
Spain[(b)]	1980-85	0.569	1.953	0.211	0.741	1.235	1.217
	1985-90	0.378	2.289	0.259	0.497	1.155	0.649
	1990-94	0.339	1.958	0.274	0.548	1.247	0.833
France	1980-85	0.325	0.886	0.216	0.318	0.283	0.288
	1985-90	0.341	0.922	0.209	0.339	0.259	0.371
	1990-94	0.421	1.146	0.175	0.342	0.274	0.371
Italy	1980-85	0.396	1.263	0.289	0.330	0.488	0.605
	1985-90	0.399	1.218	0.271	0.307	0.415	0.714
	1990-95	0.378	1.215	0.282	0.435	0.483	0.634
Luxembourg	1980-85	0[(c)]	0[(c)]	0[(c)]	0[(c)]	0[(c)]	0[(c)]
	1985-90	0[(c)]	0[(c)]	0[(c)]	0[(c)]	0[(c)]	0[(c)]
Netherlands	1980-85	1.442	0.473	0.363	0.330	0.439	0.366
	1985-90	1.561	0.420	0.392	0.213	0.415	0.428
	1990-95	1.578	0.789	0.414	0.198	0.388	0.436
UK	1975-80	0.654	3.720	0.529	0.548	0.319	0.492
	1980-85	0.722	6.731	0.324	0.579	0.257	0.395
	Sample	B	B	B	B	B	B

Notes: Table reports mean values for the whole sample and individual countries. For full industry names, see Appendix A. Absolute proportional prediction errors are calculated as |s - s(P)| / s, where a capital P indicates a predicted value. Prediction error (ALT2) is based on the fitted values from specification (ALT2) using the disaggregated data on 5 factor endowments, and parameter estimates for this specification are reported in Table 3.6. (a) The reported prediction errors exclude region Be1 (Brussels). Brussels is a capital city, and the shares of some disaggregated manufacturing industries in this region are clear outliers. As a robustness test, we re-estimated the model excluding this region; this produced very similar estimated coefficients to those reported earlier.

Table 3.11: Within-sample Average Absolute Prediction Errors (PE (ALT2)) in the Disaggregated Manufacturing Industries over Time

		(1)	(2)	(3)	(4)	(5)
Country	**Period**	**Food**	**Textile**	**Paper**	**Other**	**Construction**
All countries	1980-85	0.239	0.784	0.296	0.334	0.127
	1985-90	0.240	0.730	0.395	0.351	0.125
	1990-95	0.242	0.813	0.469	0.390	0.093
Belgium[a]	1980-85	0.288	0.189	0.331	0.374	0.064
	1985-90	0.245	0.249	0.256	0.217	0.075
	1990-95	0.324	0.174	0.292	0.171	0.022
Spain[b]	1980-85	0.198	1.050	0.402	0.454	0.134
	1985-90	0.185	0.756	0.490	0.539	0.133
	1990-95	0.152	0.916	0.552	0.586	0.112
France	1980-85	0.146	0.476	0.195	0.314	0.089
	1985-90	0.115	0.499	0.196	0.346	0.068
	1990-94	0.142	0.489	0.229	0.403	0.063
Italy	1980-85	0.252	0.628	0.481	0.328	0.199
	1985-90	0.283	0.801	0.698	0.294	0.179
	1990-95	0.345	1.065	0.723	0.341	0.104
Luxembourg	1980-85	0[c]	0[c]	0[c]	0[c]	0[c]
	1985-90	0[c]	0[c]	0[c]	0[c]	0[c]
Netherlands	1980-85	0.213	1.691	0.147	0.427	0.109
	1985-90	0.324	1.279	0.153	0.370	0.138
	1990-95	0.225	0.862	0.157	0.340	0.126
UK	1975-80	0.418	1.111	0.282	0.264	0.083
	1980-85	0.345	0.845	0.191	0.269	0.110
	Sample	B	B	B	B	B

Notes: Table reports mean values for the whole sample and individual countries. For full industry names, see Appendix 3A. Absolute proportional prediction errors are calculated as |s - s(P)| / s, where a capital P indicates a predicted value. Prediction error (ALT2) is based on the fitted values from specification (ALT2) using the disaggregated data on 5 factor endowments, and parameter estimates for this specification are reported in Table 3.6. (a) The reported prediction errors exclude region Be1 (Brussels). Brussels is a capital city, and the shares of some disaggregated manufacturing industries in this region are clear outliers. As a robustness test, we re-estimated the model excluding this region; this produced very similar estimated coefficients to those reported earlier.

3.8 Appendix 3A

Table 3.12: Sample Composition

Country	Sample A	Sample B	Number of NUTS-1 regions[1/]
Belgium	1975-95	1979-95	3 (bel-be3)
Spain	1980-95	1980-94	7 (espl- esp7)
France	1975-95	1977-94	8 (fral-fra8)
Italy	1975-95	1980-95	11 (ital-ita9, itaa/b)
Luxembourg	1975-95	1979-90	1 (lux)
Netherlands	1975-95	1977-95	4 (ndl1-ndl4)
United Kingdom	1975-86	1975-86	11 (ukl-uk9, uka/b)

[1/] For a description of the NUTS-1 regions, see Appendix 2A in Chapter 2.

Table 3.13: Industry Composition

Code	Industry Description
Aggregate Industries	
1	Agricultural Sector: Food, Forestry and Fishery Products **(Agric)**
2	Manufacturing Sector **(Manu)**
3	Services Sector: Market Services **(Serv)**
Disaggregated Manufacturing Industries	
4	Fuel And Power Products **(Fuel)**
5	Ferrous And Non-Ferrous Ores And Metals, Other Than Radioactive **(Metal)**
6	Non-Metallic Minerals And Mineral Products **(Mineral)**
7	Chemical Products **(Chem)**
8	Metal Products, Machinery, Equipment And Electrical Goods **(Machine)**
9	Transport Equipment **(Transp)**
11	Food, Beverages And Tobacco **(Food)**
12	Textiles And Clothing, Leather And Footwear **(Textile)**
13	Paper And Printing Products **(Paper)**
14	Products Of Various Industries **(Other)**
15	Building And Construction **(Constr)**

3.9 Appendix 3B

3.9.1 B1. Regional-level Data on Production and Endowments

1. Value Added: current price value-added, millions of ECUs, from Regio dataset, Eurostat.

2. GDP: current price, millions of ECUs, from Regio dataset, Eurostat.

3. Population: total population, thousands of people, from Regio dataset, Eurostat.

4. Land: total land area, thousands of hectares, from Regio dataset, Eurostat.

5. Arable Land: total arable land area, thousands of hectares, from Regio dataset, Eurostat.

6. Capital Stock: constructed by the perpetual inventory method (see, for example, Barro and Sala-i-Martin, 1995) using regional-level investment data (Gross Fixed Capital Formation), constant 1990 prices, millions of ECUs. The main source for the investment data is the Regio dataset, Eurostat. Current price investment was converted into constant prices using price deflators from the Penn World Tables, 5.6. For some countries, regional current price investment data were extended backwards in time using country-level information from the IMF International Financial Statistics.

B2. Summary of Educational Attainment Data Sources

Following the labour market literature (see, for example, Nickell and Bell, 1996, and Machin and Van Reenen, 1998), educational attainment is grouped into three categories: low, medium and high. 'Low education' is no or primary education, while 'high education' is College degree or equivalent. 'Medium education' corresponds to all intermediate levels of educational attainment, including secondary school and vocational qualifications. Using individual country labour force surveys, we compute the percentage of the population with each level of educational attainment. The endowment variables included in the regressions are these percentages multiplied by the population data from Regio, Eurostat.

1. Belgium: regional data on educational attainment from *Annuaire de Statistiques Regionales.* Years available are 1970, 1977, 1981 and 1991. Linear interpolation of the data.

2. Spain: educational attainment data from Spanish Labour Force, *Instituto Nacional de Estadistica.* Years available are 1977, 1979, 1981, and 1983-94. Linear interpolation of the data when required.

3. Italy: educational attainment data from 1986-97 is from *Forze di Lavoro* and *Rilevazione delle forze di Lavore*, ISTAT. For years prior to 1986, the regional data is extended backwards in time using country-level information from Nickell et al. (2000).

4. France: educational attainment data from *Key data on Education*, DG for Education and Culture, European Commission. Years available are 1993 and 1995. Linear interpolation of the data for 1994. The regional data are extended backwards in time country-level information from Nickell et al. (2000).

5. Netherlands: Data from *National Statistical Office*, years 1992-98. The regional data are extended backwards in time using country-level information from Nickell et al. (2000).

6. Luxembourg: Data are from Belgian region closest to Luxembourg (be3, Region Wallone).

7. United Kingdom: Data from the Labour Force Survey, years 1977, 1979, 1981, and 1983-94. Linear interpolation of the data when required. Bibliographic citation: Office for National Statistics Labour Market Statistics Group, Department of Finance and Personnel (Northern Ireland), Central Survey Unit, Quarterly Labour Force Survey. Data distributed by the Data Archive, Colchester, Essex. Data disclaimer: although all efforts are made to ensure the quality of the materials, neither the copyright holder, the original data producer, the relevant funding agency, The Data Archive, bear any responsibility for the accuracy or comprehensiveness of these materials.

3.10 Appendix 3C

Table 3.14: Factor Endowments and Specialisation at the Disaggregate Level

GDP share	(1)	(2)	(3)	(4)	(5)	(6)
Obs	696	689	689	696	696	693
Years	1975-95	1975-95	1975-95	1975-95	1975-95	1975-95
Capital	0.006	-0.008**	-0.001	0.007**	0.036**	0.001
	(0.0069)	*(0.0017)*	*(0.0009)*	*(0.0014)*	*(0.0047)*	*(0.0002)*
Low Educ	-0.035**	0.009**	0.002**	-0.001	-0.017**	0.004**
	(0.0076)	*(0.0015)*	*(0.0007)*	*(0.0012)*	*(0.0030)*	*(0.0011)*
Med Educ	0.001	0.004	-0.002**	0.005**	0.038**	0.010***
	(0.0056)	*(0.0029)*	*(0.0008)*	*(0.0019)*	*(0.0056)*	*(0.0021)*
High Educ	-0.001	-0.004**	-0.003**	-0.004**	-0.040**	-0.008**
	(0.0050)	*(0.0017)*	*(0.0008)*	*(0.0018)*	*(0.0049)*	*(0.0020)*
Arable Land	0.010**	0.001**	0.003**	-0.001	-0.001	-0.001**
	(0.0016)	*(0.0004)*	*(0.0002)*	*(0.0004)*	*(0.0007)*	*(0.0003)*
Industry	Fuel	Metal	Mineral	Chem	Machine	Transp
Sample	B	B	B	B	B	B
Specification	**(ALT2)**	**(ALT2)**	**(ALT2)**	**(ALT2)**	**(ALT2)**	**(ALT2)**
Cty-year dummies	yes	yes	yes	yes	yes	yes
Prob>F(NULL-ALT2)	XXX	XXX	XXX	XXX	XXX	XXX
Prob>F(ALL)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.25	0.64	0.47	0.31	0.35	0.34
Sum of Coeff.	0.0710	0.0020	-0.0010	0.0060	0.0160	0.0060
Linear Homog	*(0.0000)*	*(0.0016)*	*(0.0135)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
(p-value)	Accept	Accept	Accept	Accept	Accept	Accept
Maddala-Wu						
(p-value)						

Notes: for full industry names, see Appendix A. Prob>F(NULL-ALT) is the p-value for an F-test of the null hypothesis that the coefficients on the variables excluded from specification (NULL) but included in the alternative specification are equal to 0. Prob>F(ALL) is the p-value for the conventional F-test that the coefficients on all independent variables are equal to zero. Sum of Coeff. is the sum of the estimated coefficients on factor endowments. Linear Homog. is the p-value for a test of the null hypothesis that the sum of the estimated coefficients on factor endowments is equal to zero. Maddala-Wu is the p-value for the Maddala and Wu (1999) panel data test of the null hypothesis that the residuals have a unit root. Huber-White heteroscedasticity robust standard errors in parentheses. ** denotes significance at the 5% level, * denotes significance at the 10% level.

Table 3.15: Factor Endowments and Specialisation at the Disaggregate Level

GDP share	(1)	(2)	(3)	(4)	(5)
Obs	696	696	696	696	696
Years	1975-95	1975-95	1975-95	1975-95	1975-95
Capital	0.013***	0.021***	0.008***	0.014***	-0.010***
	(0.0021)	*(0.0024)*	*(0.0008)*	*(0.0014)*	*(0.0017)*
Low Educ	-0.003*	0.008***	-0.008***	0.003***	0.005***
	(0.0017)	*(0.0015)*	*(0.0005)*	*(0.0009)*	*(0.0012)*
Med Educ	0.001	0.008***	0.009***	0.005***	-0.021***
	(0.0030)	*(0.0022)*	*(0.0007)*	*(0.0013)*	*(0.0020)*
High Educ	-0.022***	-0.029***	-0.005***	-0.017***	0.013***
	(0.0026)	*(0.0028)*	*(0.0008)*	*(0.0014)*	*(0.0019)*
Arable Land	0.004***	0.001***	-0.001***	0.002***	0.005***
	(0.0005)	*(0.0004)*	*(0.0002)*	*(0.0002)*	*(0.0004)*
Industry	Food	Textile	Paper	Other	Construction
Sample	B	B	B	B	B
Specification	**(ALT2)**	**(ALT2)**	**(ALT2)**	**(ALT2)**	**(ALT2)**
Cty-year dummies	yes	yes	yes	yes	yes
Prob>F(NULL-ALT2)	XXX	XXX	XXX	XXX	XXX
Prob>F(ALL)	0.0000	0.0000	0.0000	0.0000	0.0000
R-squared	0.54	0.42	0.56	0.47	0.64
Sum of Coeff.	-0.0070	0.0090	0.0030	0.0070	-0.0080
Linear Homog	*(0.0001)*	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
(p-value)	Accept	Accept	Accept	Accept	Accept
Maddala-Wu					
(p-value)					

Notes: for full industry names, see Appendix A. Prob>F(NULL-ALT) is the p-value for an F-test of the null hypothesis that the coefficients on the variables excluded from specification (NULL) but included in the alternative specification are equal to 0. Prob>F(ALL) is the p-value for the conventional F-test that the coefficients on all independent variables are equal to zero. Sum of Coeff. is the sum of the estimated coefficients on factor endowments. Linear Homog. is the p-value for a test of the null hypothesis that the sum of the estimated coefficients on factor endowments is equal to zero. Maddala-Wu is the p-value for the Maddala and Wu (1999) panel data test of the null hypothesis that the residuals have a unit root. Huber-White heteroscedasticity robust standard errors in parentheses. ** denotes significance at the 5% level, * denotes significance at the 10% level.

Chapter 4

Factor Endowments, Economic Geography, and Specialisation in European Regions

4.1 Introduction

In the two previous chapters, we analysed the evolution of specialisation in European regions and countries, and the role of factor endowments in determining the pattern of production in European regions. In particular, Chapter 3 considered the neoclassical model of trade of which the Heckscher-Ohlin model is a special case. Under the assumptions of the Heckscher-Ohlin model, we derived an equation relating specialisation (measured as the share of an industry's value-added in GDP) to relative prices and factor endowments. Across a wide range of econometric specifications, there is a statistically significant and quantitatively important relationship between factor endowments and patterns of production. Factor endowments are most successful in explaining production patterns at the aggregate level. In particular, among the 3 aggregate industries considered, factor endowments are most successful at explaining regional specialisation in Services and Manufacturing. We found no evidence that the process of increasing economic integration in Europe has weakened the relationship between patterns of production and factor endowments within countries over time.

While the Neoclassical model was reasonably successful in explaining patterns of production at the aggregate level, the econometric specifications were less successful in explaining specialisation within manufacturing industries. In this case, the average prediction error across regions from 1985-90 was 47 percent, compared with an average prediction error across the three aggregated industries of 31 percent during the same period. As set forth in the last chapter, one theory-consistent explanation for the larger prediction errors for disaggregated industries is indeterminacy in the production of individual manufacturing industries at the regional level. Another explanation is that the analysis in Chapter 3 neglected economic geography considerations. A large theoretical literature has emphasised the role of transport costs and increasing returns to scale in determining the location of production. Given the size of the prediction errors, we could expect that economic geography effects operate most strongly in disaggregated manufacturing industries. Intuitively, increasing returns to scale imply that firms would like to concentrate in a single location, while the existence of transport costs implies that, other things equal, this concentration will occur close to large markets and sources of supply. Other things being equal, industries will locate in regions with good market access and sources of supply of intermediate goods.

Economic geography models incorporate the role of location of agents relative to one another in physical space into the analysis. The model may have multiple equilibria, some unstable, and other with agglomeration (see for example, Krugman, 1991a and 1991b). If trade is perfectly free (no transport cost), comparative advantage (as driven by technology and factor endowments) determines the structure of production in each region. However, if transport costs are also present in the analysis, then both supply and demand matters for the location of economic activity, and industries would want to be relatively close to suppliers and consumers (benefiting from backward and forward linkages). These linkages are important in creating and sustaining spatial concentration of economic activity, as firms exploit their economies of scale. If transport costs depend on distance, then geographical factors play a role determining the location of production in each region. In practice, both factor endowments and economic geography are important. Moreover, given the process of integration that has taken place in Europe since the Second World War, there are reasons for thinking that economic geography may have a particularly important role to play in Europe. This chapter reviews a general theoretical model that incorporates both sets of considerations before presenting empirical evidence on the relative importance of each using European regional data.

The analysis is the first of its kind using European regional data. We extend the analysis of the previous chapter by incorporating considerations of economic geography alongside those of factor endowments and factor intensities to explain specialisation at the regional level in Europe, in line with the approach developed by Midelfart-Knarvik et al. (2000b). We derive an equation relating an industry's value-added share in GDP to factor endowments and the location of supply and demand, factors determining the location of production in conjunction with industry characteristics, such as factor intensities and transport costs. We focus on the manufacturing industries, as the analysis in the previous chapter found the largest prediction errors in disaggregated manufacturing.

We find that both factor endowments and economic geography are relevant forces in explaining specialisation in the manufacturing sector across European regions. Parameter estimates are statistically significant and constant across different specifications that account for different sources of unobserved heterogeneity in the data. Other things being equal, regions with high skill endowments would be more specialised in skill-intensive industries. Among the economic geography variables, the interaction term of access to suppliers and intermediate demand intensity is always statistically significant in explaining specialisation at the one percent level. Regions with good access to intermediate goods attract industries using intermediate goods more intensively, and become more specialised in those industries over time. Location with respect to supply is more relevant for specialisation than the location of demand.

Our model performs well in explaining patterns of specialisation across European regions. The model's average prediction error across all disaggregated manufacturing industries, regions, and time is 13 percent, and ranges from 8 percent to 20 percent in individual manufacturing industries. Hence, average prediction errors compare positively with those reported in Chapter 3. The average prediction error for the eight manufacturing industries was 58 percent during 1985-95 when considering only the role of factor endowments. Furthermore, when using the estimated coefficients to evaluate predicted shares of GDP excluding information on factor endowments, economic geography and industry characteristics; the average prediction error in manufacturing industries across all countries, industries, and years rises to 120 percent. Over time, prediction errors remain stable, not only across countries, but also across industries in our sample.

4.2 Related Literature

Although this chapter relates to the empirical literature on both the role of factor endowments and the role of economic geography in determining the location of production, this section focuses on the existing empirical work in economic geography.[1] A large theoretical literature has emphasised the role of transport costs and increasing returns to scale in determining the location of production (see Fujita, Krugman, and Venables, 1999). Increasing returns to scale imply that firms would like to concentrate production in a single location, while the existence of transport costs implies that, other things equal, this concentration will occur close to large markets and sources of supply. The geographical structure of trade costs mean that some locations will be attractive to industry because of good market access and also because of good intermediate supplier access.

[1]For a review of the recent empirical literature on the role of factor endowments, see Section 3.2 on related literature in Chapter 3.

Based on this theoretical literature, a number of studies have described how specialisation and concentration have evolved, as reviewed in Chapter 2. A smaller number of studies have analysed the underlying economic determinants of the location of activity. The studies find support for the new trade theories and economic geography models. In general, two related dimensions are considered in these studies: how localised a certain economic activity is, and how specialised a certain geographical unit is. A series of studies find evidence of increasing localisation and specialisation within countries or a group of countries. Kim (1995) found evidence of a non-monotonic evolution of specialisation and localisation across the states within the United States during the period 1860-1987. States became more specialised until 1930, when the process was reversed — specialisation is lower today that it was in 1860. In the European Union, these kind of studies have found increasing specialisation and localisation as European integration proceeds. Amiti (1999) and Midelfart-Knarvik et al. (2000a) both found increasing specialisation across European countries from the mid-1980 onwards, the first study using data on employment and production and the second, using data on gross output. However, although these studies describe well the evolution of specialisation and localisation, they devote relatively little attention to determining the underlying forces of the process. Evidence of increasing specialisation and localisation by itself does not discriminate between comparative advantage and economic geography.

Consequently, a number of studies in the literature have tried to identify the underlying forces shaping specialisation and localisation. Two different approaches have been adopted at the international level. One approach has tried to identify home market effects, or an increase in demand for a good reflects in a more than proportionate increase in production of the good. Davis and Weinstein (1998, 2003) use this home market effect for testing between models of imperfect competition/increasing returns to scale and perfect competition/constant return to scale. Davis and Weinstein (1998) consider a nested specification where factor endowments are assumed to determine production at the three-digit industry level, while economic geography effects operate in disaggregated industries. Using data for 13 OECD countries, they first construct measures of idiosyncratic demand for each four-digit industry based on demand in the country and its trading partners. Estimating the impact of this demand variable on production in a pooled sample across countries and all four-digit industries, they find evidence of a strong home market effect. Disaggregating and running separate regressions for each three-digit industry with a sample of countries and four-digit sub-industries, they also find evidence of a home market effect in a majority of industries. Head and Ries (2001) find a weak home market effect when looking at the United States and Canada trade at the three-digit level during the period 1990-95. Feenstra, Markusen and Rose (2001) identify a home market effect in estimating a gravity model separately for differentiated products, reference-priced exports, and homogeneous goods. Another approach tries to combine comparative advantage and economic geography to investigate the relative contribution of the forces underlying localisation and specialisation. Midelfart-Knarvik et al. (2000b) develop a model where both elements explain the location of production in Europe. They find endowments of skilled and scientific labour as well as forward and backward linkages to be important determinants of industrial structure over the sample period 1980-92 at the country level. Also, economic geography effects are becoming econometrically more relevant over time, which could be attributable to the process of economic integration.

At the subnational level, the empirical literature addresses issues such as of the existence and determination of clustering. Hanson (1998) examines the spatial distribution of economic activity within the United States, and finds significant demand linkages across regions. Estimating the structural parameters of the Krugman (1991a) model of economic geography, he finds small but significant scale economies. Geographic concentration is found to be a stable feature of the spatial distribution of economic activity. Demand linkages are strong across regions and are growing over time, although limited in geographic scope. Davis and Weinstein (1999), in a specification similar to the study mentioned above, find significant home market effects when considering 29 sectors and 47 Japanese perfectures in 1985. These effects are quantitatively important: for the eight sectors with statistically significant home market effects, a one standard deviation movement in idiosyncratic demand is found to move production by half a standard deviation on average. Ellison and Glaeser (1999) consider the extent at which localisation can be explained by natural advantage, studying the shares of U.S. states in different industries as a function of the interaction between industry and state characteristics. Their results suggest that between 50 percent and 80 percent of localisation at the state level is left unexplained by natural advantage. Different lines of research have tried to explain this residual excess localisation, either by assessing the importance of localisation versus urbanisation economies (see Henderson, 1999 for a discussion of these issues), or by analysing the effect of the scale or density of economic activity on productivity levels (Ciccone and Hall, 1996, and Davis and Weinstein, 2001). However, these subnational studies have focused on determining either the role of comparative advantage or of economic geography in the pattern of localisation/specialisation independently.[2] None of the studies are done at the subnational European level, which represents an interesting context given the process of economic integration during the post-war period.

This chapter analyses how economic geography and factor endowments jointly determine the

[2] Duranton and Overman (2001) looks within the U.K. using microgeographic data.

pattern of specialisation in European regions. The analysis builds on a theoretical background that integrates both factor endowments and economic geography considerations. The study is the first of its kind using regional data in Europe. We consider a measure of specialisation derived from theory and consistent with the measure used in the previous chapter—the GDP share of industry j in region z. In describing the model, we are able to establish a relationship between the share of an industry's value added in GDP, factor endowments, and economic geography variables. We concentrate on industries within the manufacturing sector across 45 European regions. The model estimated here is broader than the one used in the previous chapter, as we explicitly analyse both factor endowments/industry intensities and economic geography factors in the location of production in European regions.

The rest of the chapter is structured as follows. Section 3 outlines the model and the equation relating our measure of specialisation to factor endowments and economic geography variables. Section 4 describes the data. Section 5 discusses the econometric estimation, and Section 6 concludes.

4.3 The model

In this section, we outline a canonical model relating economic geography factors to the structure of production. We follow Midelfart-Knarvik et al. (2000b) and Overman, Redding and Venables (2001). The model considers a number of regions (locations) despicted by the subscript z and a number of industries, indexed by j. Denote y_{zjt} as the level of production in region z of industry j at time t.[3] The demand side of the model takes a CES form, with the price index for each of the industries given by:

$$P_{aj} = \left[\sum_{z} n_{zj} \left(p_{zj} t_{zaj} \right)^{1-\sigma_j} \right]^{\frac{1}{1-\sigma_j}}, \tag{4.1}$$

where n_{zj} is the number of varieties of industry j products produced in region z, p_{zj} refers to its fob prices, and t_{zaj} refers to the iceberg cost $(t_{zaj} - 1)$ incurred on trading industry j products from region z to region a. σ_j is the elasticity of substitution between varieties, assumed from now to be equal for all industries $(\sigma_j = \sigma)$.

Define E_{aj} as the total expenditure on industry j products in region a. Then, sales of a single industry j variety produced in region z and sold in a in given by

$$y_{zaj} = \left(p_{zj} \right)^{-\sigma} \left(t_{zaj} \right)^{1-\sigma} E_{aj} \left(P_{aj} \right)^{\sigma-1}, \tag{4.2}$$

[3]To simplify notation, we suppress the time sub-script except where important.

derived using Shepard's lemma on the price index. Summing over all markets and over all varieties of industry j produced in region a, the total value of industry j output produced in region z, x_{zj}, is defined as

$$x_{zj} = n_{zj} p_{zj} y_{zj} = n_{zj} \left(p_{zj}\right)^{1-\sigma} \sum_a \left(t_{zaj}\right)^{1-\sigma} E_{aj} \left(P_{aj}\right)^{\sigma-1}, \tag{4.3}$$

where

$$y_{zj} = \sum_a y_{zaj}, \tag{4.4}$$

Prices are set proportional to marginal costs on the production side,

$$p_{zj} = \Phi_j c_j \left(w_z, G_z\right), \tag{4.5}$$

where $\Phi_j = 1$ in perfectly competitive industries, and greater than one if firms mark up price over marginal costs (in imperfectly competitive industries). $c_j \left(w_z, G_z\right)$ refers to marginal cost, being a function of primary factor prices in location z (w_z), and prices of intermediates $\left(G_z\right)$.

Consider our measure of specialisation to be the GDP share of industry j in total regional production, defined as

$$s_{zj} = \frac{x_{zj}}{\sum_j x_{zj}}. \tag{4.6}$$

Equation 4.3 can be rewritten as follows

$$s_{zj} = \left(c_j \left(w_z, G_z\right)\right)^{1-\sigma} \sum_a \left(t_{zaj}\right)^{1-\sigma} E_{aj} \left(P_{aj}\right)^{\sigma-1} \tag{4.7}$$

where we assume all industries are perfectly competitive and that the number of varieties in each industry is exogenously determined and proportional to the size of the region, $n_z = \sum_j x_{zj}$. This assumption departs from the one in Midelfart-Knarvik et al. (2000b) in which the number of varieties in each industry is assumed to be proportional to the size of the industry and to the size of the region. Under our assumption, the number of varieties within each region-industry depends solely on the size of the region. The assumption here allows us to focus on specialisation, measured by the GDP share of industry j. This is exactly the measure of specialisation used in previous chapters. By doing so, the analysis here is directly comparable with the analysis in Chapter 3. With perfect competition, the production technology must have either constant returns to scale or external increasing returns to scale (Euler's Theorem). If the industry was monopolistically competitive, the scale of output of each variety would be fixed by the zero profit condition, and the value of n_z would be determined endogenously by the free entry condition.

The term in the summation of equation 4.3 refers to demand linkages or market potential for industry j in region z. Denote

$$m(\Upsilon_j : z) = \sum_a (t_{azj})^{1-\sigma} E_{aj} (P_{aj})^{\sigma-1}, \tag{4.8}$$

where Υ_j refers to the industry characteristics that interact with the spatial distribution of demand. Equation 4.7 then becomes:

$$s_{zj} = (c_j (w_z, G_z))^{1-\sigma} m(\Upsilon_j : z) \, exp(\epsilon_{zj}), \tag{4.9}$$

where ϵ_{zj} is a stochastic error. The equation indicates that both cost and demand factors determine specialisation. Input price variation is captured in the unit cost function, while demand variation is captured by the market potential of industry j in region z. On the cost side, input prices include factor prices and a price of the composite intermediate good. For primary factors, we consider factor endowments as factor prices are endogenous. Geography enters the model through trade costs, which vary systematically with distance and other geographical forces, and across industries. The geographical structure of trade costs mean that some locations will be attractive to industry because of good market access, and also because of good intermediate supplier access. In equilibrium, this will show up through the spatial variation in the prices of immobile factors, which will be bid up in regions with good market and supplier access. Another manifestation will be through the location of activity, as some types of industry will be particularly drawn to these locations.

Linearization of the model around a reference value[4] gives a sum of interactions between regional characteristics and industry characteristics. The estimating equation takes the following form:

$$\ln(s_{zj}) = \mu + \sum_h \beta_h (\varphi_z [h] - \varphi [h]) (\zeta_j [h] - \zeta [h]) + \varepsilon_{zj}, \tag{4.10}$$

where $\varphi_z [h]$ refers to regional characteristics while $\zeta_j [h]$ refers to industry characteristics. $\varphi [h]$ and $\zeta [h]$ refer to the reference values. Index h runs across the set of interactions. The equation shows how regional characteristics (such as factor endowments and location of supply and demand) interact with industry features (factor intensities or transport cost) to determine the production structure. Specialisation in each region is a function of both economic geography and comparative advantage. For example, the first inner product gives regions' input prices times industries' input shares. The second gives, for example, industries' characteristics times elasticities of countries'

[4]For more details on this point, see Midelfart et al. (2000b).

market potential with respect to those characteristics. The interpretation of the equation could be seen by thinking about the interaction, for example, of land endowment and agricultural intensity. Countries whose land abundance exceeds some reference level ($\varphi_z[h] > \varphi[h]$) will have high production in industries with agricultural intensity (above a reference level ($\zeta_j[h] > \zeta[h]$)), and vice-versa, which describes a Rybzcynski effect.

This model makes specific assumptions about demand (Dixit-Stiglitz preferences) and production (Dixit-Stiglitz intermediate inputs). This enables the derivation of an equation that, although different in form from the previous chapter, incorporates the role of both factor endowments and economic geography considerations. Thus, making more specific assumptions about demand and production enables one to derive a more general specification that encompasses both sets of considerations. We use five interactions in our econometric specification, which are specified in the next section.

4.4 Data Description

In this chapter, we analyse patterns of production across eight manufacturing industries in 45 NUTS-1 regions from seven European countries between 1985 and 1995. The sample period is smaller compared to the previous chapter due to data availability. The number of industries considered is also restricted by the availability of data on industry characteristics (see Appendix 3A for more details). We consider the same countries as in Chapter 3: Belgium, France, Italy, Netherlands, Luxembourg, Spain, and the United Kingdom. We build on the data used in Chapter 3, as the main source of data is the Regio dataset compiled by the European Statistics Office (Eurostat).

4.4.1 Regional Characteristics

Factor endowments were described in the previous chapter. For the analysis in this chapter, we use the following factor endowment variables. First, we consider arable land as our measure of agricultural endowment. Second, we consider population endowment, classified in three levels according to educational attainment (low, medium and high).[5] See Appendix 3B for information on data sources.

We extend the dataset by two economic geography variables, which are supply access and the elasticity of market potential with respect to transport cost. Market potential is computed at

[5] We do not consider capital endowments in the analysis on the grounds that is internationally mobile and has the same price throughout the European Union.

the NUTS2 level of disaggregation in order to exploit more disaggregated information.[6] First, we compute market potential for each of the NUTS2 regions in Europe.[7] As discussed in the Overman et al (2203) survey, the standard measure of market potential is defined as a weighted sum of the purchasing power of all other regions a with the weights being a declining function of distance ($dist$). Market potential is therefore defined as follows:

$$mkp_z = \sum_a \left(\frac{GDP_a}{dist_{za}} \right)^{\rho}, \tag{4.11}$$

where ρ represents the elasticity of market potential with respect to transport cost, and $dist_{za}$ is the circular distance between the two major centres in NUTS2 regions z and a. Major centres are defined as the main town/city in the region. $dist_{aa}$ is assumed to be equal to one indicating that access to the demand within the region is perfect.[8] The elasticity of market potential with respect to the elasticity of transport costs is computed by analysing the relative variation of market potential with respect to relative variation in ρ. We evaluate market potential for two values of ρ, $\rho_1 = 0.7$ and $\rho_2 = 1.6$. Therefore, the elasticity of market potential with respect to transport cost for region z is defined as:

$$emp_z = -\frac{\left(\frac{mkp_{z2} - mkp_{z1}}{mkp_{z1}} \right)}{\left(\frac{\rho_2 - \rho_1}{\rho_1} \right)}, \tag{4.12}$$

where mkp_{z1} and mkp_{z2} refer to market potential evaluated at ρ_1 and ρ_2, respectively. Once the elasticity of market potential is computed at the NUTS2 level, we compute the elasticity of market potential for the NUTS-1 regions in our sample as a weighted average of the elasticity of market potential of the NUTS2 regions within the same NUTS-1 region. As there are no theoretical priors on the weights to use, we consider three different alternatives (population share, production share, and output share).[9]

[6] NUTS2 refers to the second tier of subnational units for which Eurostat collects data on the EU member countries. By computing market potential at the NUTS2 level, we are able to exploit more dissaggregated information, enabling us to compute a more accurate measure of market potential.

[7] Market potential is computed by considering access to all other regions in Europe (not just the regions from the countries considered in our empirical analysis). The computational analysis here includes NUTS2 regions in REGIO (a total of 179 regions, including all EU15 countries except for Austria, Finland, and Sweden, for which data in Regio is available). For practical reasons, we restrict the attention to European regions rather than all regions in the world as a good approximation of the market and supplier access of a region.

[8] As the inclusion of the own region in the right hand side variable could generate endogeneity in the empirical analysis, we re-estimate the model with a measure of market potential that excludes the region itself. The estimation results did not change our conclusions.

[9] In the econometric estimation, we report the results with respect to the production share (GDP weighted). Results do not change significantly when considering other measures.

Supply access gives an indication on how well positioned a region is with respect to intermediate demand. Upstream industries will locate in countries in which the market potential from intermediate sales is high relative to the market potential from final sales. We compute supply access as a market potential measure based on intermediate expenditures,

$$supply_z = \sum_j \tau_j \left(\sum_a \left(\frac{x_{aj}}{dist_{za}} \right) \right), \tag{4.13}$$

where τ_j is the intermediate share of costs for industry j, x_{aj} is the level of production in industry j of region a ; and $dist_{za}$ is the circular distance between the two major economic centres in regions z and a, assuming the internal distance to be equal to one.[10] τ_j is computed as the share of sales to aggregate manufacturing industry as share of gross output for each industry, and is computed with information from the input-output matrix at the country level.[11] Lack of input-output tables at the regional level for the regions in our sample hinders the analysis at the regional level, although we get some regional variation from the expression in the brackets. Implicitly, we assume that the share of sales to aggregate manufacturing as a share of gross output is the same across regions within a country (see next subsection for further discussion on industry characteristics). The term in brackets gives, for each region and industry, a distance weighted measure of proximity to production in the industry. The τ_j weighted average of these gives each region's proximity to suppliers of the production that goes into the composite intermediate, which is an overall measure of the supplier access of a region. Contrary to market potential, supply access is computed only at the NUTS-1 level and within the 45 regions in our sample. This reflects data availability. Data on value added for manufacturing is very incomplete at the regional level.[12]

The specification of market potential and supply access follows Midelfart-Knarvik et al. (2000b) in order to make our results comparable to those reported in their study, which covers Europe although at the country level.

4.4.2 Industry Characteristics

The industry characteristics used in the analysis are agricultural intensity, skill intensities, transport costs, and intermediate intensity. Agricultural intensity is computed as the share of agricultural

[10] We assume the elasticity with respect to distance to be equal to -1, in line with estimates from gravity models of trade.

[11] Data from Midelfart-Knarvik et al. (2000b). See Appendix 3B for further details.

[12] Parallel to market potential, the inclusion of the own region in the right hand side variable could create endogeneity problems. We re-estimate the model with a measure of supply access that excludes the region itself. The estimation results did not change significantly our conclusions.

inputs (including fishery and forestry) in the gross value of output. Skill intensities are computed as the product of the share of (low/medium/high)-skilled employment in total employment times the ratio of the wage bill to total costs.[13] Transport cost intensity are defined as the share of transport costs in fob priced sales within the European Union. Intermediate intensity is the share of intermediate use in the gross value of output. Most industry variables are taken from Midelfart-Knarvik et al. (2000b), with the OECD as the main source. See Appendix 3B for a description of the data at the industry level.[14]

Lack of comparable data on input-output tables at the regional level hinders the computation of industry characteristics at the regional level. Therefore, industry characteristics are defined at the country level, which implicitly assumes that regions within the same country face the same technology. If technologies are identical and factor price equalisation occurs within countries, this implies factor intensities will be the same for the regions within the country. Empirical evidence from Bernstein and Weinstein (2002) and Davis et al. (1997) provides support for the assumptions made here. In the former study, the authors confirm that Japanese regions employ the same production techniques. Davis et al. (1997) find evidence that countries with similar per capita income produce within the same cone of diversification (identical technology), and the results are much stronger for regional than international data. Therefore, the underlying assumption of identical techniques across regions within a country is supported by previous empirical evidence.[15]

4.4.3 Region-Industry Interactions

With the data compiled, we are able to specify six different interactions in our econometric analysis as illustrated below. The first four interactions are related to the notion of comparative advantage, while the last two are to economic geography.

[13] Data on skill level at the industry level are from Machin and Van Reenen (1998). Data are available only for France and the United Kingdom in our sample, from which we compute the average for each of the industries. A more accurate measure could be computed with the wage bill by educational attaintment, but data are not available at the industry level.

[14] See Appendix 3B in this chapter for an explanation of data sources and construction of the variables. Industry characteristics are constant over time and are taken from Table A1 in Appendix A5 in Midelfart-Knarvik et al. (2000b). Although they reported a higher level of disaggregation, we are able to consolidate their information for eight of the two-digit manufacturing industries in REGIO.

[15] However, we are aware that this relationship could fail to hold up as a result of increasing returns to scale, industry-region technical differences, fewer goods than factors, or any other reason that would cause factor price equalisation to fail. Empirical evidence of technological differences at the regional level is in Europe is left for future research. In the empirical analysis, we account for technical differences at the regional level by controlling for further variation in the data.

	Regional Characteristic	Industry Characteristic
Factor Endowments Interactions		
$h = 1$	Agricultural endowment (log)	Agricultural intensity (elast)
$h = 2$	Low Skill endowment (log)	$Skill_L$ intensity (elast)
$h = 3$	Medium Skill endowment (log)	$Skill_M$ intensity (elast)
$h = 4$	High Skill endowment (log)	$Skill_H$ intensity (elast)
Economic Geography Interactions		
$h = 5$	Elasticity of market potential wrt elasticity of transport cost (elast)	Transport cost (log)
$h = 6$	Supply access (log)	Intermediate intensity (elast)

We would expect a positive estimated coefficient on each of these interaction terms. The first four interactions represent a linear approximation to the way in which factor intensities and factor endowments interact to determine production. We would expect factor-abundant regions to have high production in industries in which the share of this particular factor is large, and low production in industries where it is low. The fifth interaction incorporates demand considerations in our equation through the interaction between industry characteristics and the elasticity of market potential to transport cost. The last interaction takes into account the role of forward linkages into the analysis. If transport costs exist, then the prices of intermediate goods vary across regions. The model assumes a single composite intermediate good where variation in the price of this good interacts with the cross-industry variation in intermediate input shares to determine output. We would expect that industries with high intermediate shares are driven into locations with good access to supply of intermediates, and vice versa.

It is worth mentioning that the estimation approach with respect to factor endowments differs from that in the previous chapter. In Chapter 3, we estimated Rybczinski derivatives directly by running industry-level regressions of output on factor endowments and obtaining an industry-specific estimated coefficient of the general equilibrium effect of factor endowments on production of a particular good. With equal numbers of goods and factors, these Rybczinski derivatives have an interpretation in terms of factor intensities. In this chapter, however, we consider interaction terms between factor intensities and factor endowments. The interaction places restrictions on how the coefficient on factor endowments varies across industries. With the approach here, we are parameterizing the relationship between endowments and production using observed factor intensities.

4.5 Empirical Results

4.5.1 Estimation Results

Our main econometric equation is directly derived from the model in Section 3, and it takes the form,

$$\ln(s_{zjt}) = \mu + \sum_h \beta_h \left(\varphi_{zt}[h] - \varphi[h]\right)\left(\zeta_j[h] - \zeta[h]\right) + \varepsilon_{zjt}, \tag{4.14}$$

Equation 4.14 is first estimated by ordinary least squares assuming that the error is independently and identically distributed across regions, industries, and years. We relax this assumption below by considering a more general error components structure. The equation is first estimated by pooling observations across regions, industries, and years. Results are reported in the first column of Table 4.1, with robust standard errors in parentheses.

In the error term, we consider year dummies (d_t) to control for common trends in GDP shares of regions over time, and also for common macroeconomic shocks across regions and across industries that may have occurred at the European level.[16]

In addition to common macroeconomic shocks across regions, one might want to allow for a common error component across regions and time within a country or across time within individual regions. We expand the error component structure of the residual in different specifications in which we introduce country dummies and regional dummies. These control for unobserved heterogeneity in the determinants of patterns of specialisation across countries and regions.

Finally, we generalise the approach by also allowing for country-time dummies in equation 4.14. The country-time dummies control for a country-specific level and trend in relative prices and other variables over time. This specification allows us to abstract from cross-country variation and focus on the ability of the model to explain regional variation in patterns of production within countries. The analysis allows European integration to have different effects on relative prices in individual

[16]This approach differs from Midelfart-Knarvik et al. (2000b), where the model was estimated separately for different cross-sections. We did replicate the approach by running three different cross sections. As our sample expands over the period 1985-95, we considered a division of the sample in three periods (1985-88, 1989-92, and 1992-95). We averaged variables within each period in order to remove business cycle variability. Parameter estimates were reasonably constant over time, and the significance of the variables remained unchanged over the different cross sections. The constancy of the parameters supports our approach of pooling the data across time. Results are not reported in the interests of brevity.

countries. The parameters of interest are now identified from variation in factor endowments and economic geography variables across regions and industries within a country. This includes both cross-section variation (across regions within a country at a point in time) and differential time-series variation (in individual regions within a country over time).

Factor mobility does, however, change the interpretation of these relationships. If factor endowments are exogenous and perfectly immobile across locations, the general equilibrium relationship between production structure and factor endowments has a *supply-side* interpretation. Changes in factor endowments cause changes in production structure (production moves in response to factor endowments). If factor endowments are mobile across locations, they become potentially endogenous to production structure. In addition to the *supply-side* interpretation given above, there is also a *demand-side* interpretation whereby changes in production structure cause factor endowments to move across regions (factor endowments move in response to production structure). Irrespective of whether the relationships we estimate are demand-side, supply-side or a combination of both, we are able to test the model's predictions for the relationship between production, factor endowments and economic geography.

It is worth mentioning that the source of variation that identifies the relationship between specialisation and factor endowments and economic geography varies as we move between the different specifications. For example, in the first specification, parameter estimates are computed from variation in factor endowment and economic geography variables across countries, regions, industries and time. In the specification with regional dummies, the parameter estimates are identified from variation over time within individual regions and industries.

Finally, we report standardised coefficients by conditioning on the standard deviation of the underlying variables in order to compare coefficients across explanatory variables. The parameter estimates therefore indicate the elasticity of GDP shares with respect to a region (industry) characteristic for an industry (region) with a corresponding industry (region) characteristic one standard deviation above its average value. Our parameters of interest are those associated with the interaction variables. Theory predicts a positive significant relationship between specialisation and these interactions.

Results are summarised in Tables 4.1-4.2. Estimation results show that both factor endowments and economic geography variables are relevant in explaining the pattern of specialisation in the manufacturing sector across European regions. Parameter estimates are reasonably constant across different specifications, maintaining also the level of significance. When considering estimation results with country and regional dummies, industry characteristics' estimates remain fairly constant, with significance levels being unchanged, providing some support for our assumption that regions within a country share the same technology. If this was not the case, we would expect to observe changes in how the industry characteristics relate to specialisation when moving across these two specifications. With respect to factor endowments, all variables are statistically significant and show the expected sign across most specifications. The coefficient estimate is highest for unskilled education endowment (followed by high-skilled education endowment) —changes in the factor are associated with larger changes in production shares. Note that once regional dummies are included, the agricultural endowment becomes insignificant for explaining specialisation across European regions, probably due to the little time-series variation in the arable land series within regions.

<Tables 4.1-4.2 about here>

Considering the economic geography variables, the interaction associated with supplier access has the expected sign and is statistically significant at the one percent level in explaining specialisation across European regions. The interaction associated with the location of demand shows the wrong sign, and it is not significant. This outcome is difficult to interpret, although the magnitude of the parameter estimate indicates that it is not very important. The parameter estimate associated with supply access is much higher than any of the ones associated with factor endowments, indicating that the former is highly relevant in explaining production patterns across European regions within the manufacturing industries. Hence, cost linkages are stronger than demand linkages. The results are consistent with those reported by Midelfart-Knarvik et al. (2000b), where market potential also had the wrong sign and was not significant, although the magnitude of the parameter estimate associated with supply access in our results is larger than the one reported by Midelfart-Knarvik et al. (2000b).

Before proceeding with the analysis of the prediction errors of the model, we analyse the robustness of the empirical results by considering two approaches: first, we control for measurement error in the industry characteristics, and then, we report the estimation results accounting for the clustering of observations across groups, since some of the explanatory variables are defined at a more aggregated level than the dependent variable.

First, we analyse the robustness of our specification to mismeasurement of the industry characteristics. If the latter were the case, the measurement errors would translate into fixed effects for the industry concerned. We include a set of industry dummies and re-estimate equation 4.14 dropping the industry level variables. The results of the interaction variables are reported in Table 4.3. The first column reports the parameter estimates when performing OLS regression, while the second column shows the fixed-effect panel data results. Our results on the interaction terms are robust to the inclusion of industry fixed effects. The explanatory power of the estimation is increased,

as would be expected, with the R-squared rising from 0.47 to 0.52 when considering pooled OLS estimation results, while the changes in the parameter estimates on the interactions are negligible.
<Table 4.3 about here>

Second, our explanatory variable data in the regressions are drawn from a population with a grouped structure. In this case, it may be the case that regression errors are correlated within groups (Moulton, 1986). Therefore, as a further robustnests test, we report standard errors adjusted for the clustering of standard errors on groups. The fact that some of the explanatory variables are defined at a more aggregated level (country) than the region-industry-time units may indicate that the conventional, although robust, standard errors are too small. This is especially the case when the regressors include a variable with repeated values within groups, which is the situation here with respect to the industry characteristics. In such cases, the downward bias in OLS standard errors can be large. We experiment with clustering the standard errors in different ways (industry, region, and industry-region). Table 4.4 reports the OLS results for the specification in which we allow all the region-industry-time variation in the data (Column 1, no dummies), and the specification in which we consider country-year dummies, clustering observations within industry-regions.[17] Most parameter estimates remain significant when clustering observations within industry-region. Only agricultural and medium skill endowments lose their significance.
<Table 4.4 about here>

4.5.2 Prediction Errors

In line with the analysis presented in Chapter 3, we evaluate the model in terms of the magnitude of the prediction errors. Table 4.5 reports mean proportional prediction errors across regions, industries, and time for each country. The mean prediction errors correspond to the mean across regions, industries and time for the absolute value of actual minus predicted shares of sectors in GDP, divided by the actual share $(\mid s_{zjt} - \hat{s}_{zjt} \mid / s_{zjt})$. Predicted shares are computed in two ways. First, we evaluate the fitted values from the regression reported in Column (1) of Table 4.2; these are indicated by the superscript 1 in Table 4.5.[18] Second, we compute predicted shares from the remaining terms after excluding factor endowment and economic geography variables (i.e. from the country-year dummies). These are indicated as superscript 2.

[17]Results regarding significance of the parameter estimates did not change when clustering observations across countries, regions, or industries.

[18]The constancy of the estimated parameters as we move across different specifications in Tables 4.1-4.2, and the fact that when introducing country-year dummies, we are concerned with the variation in factor endowments and economic geography across regions within a country make this our preferred specification.

<**Table 4.5 about here**>

Considering all manufacturing industries together, the first column in Table 4.5 reports average prediction errors for the entire sample period. The model's average prediction error in the manufacturing industries across all countries, industries, and time is 13 percent, and varies from 8 percent in France to 27 percent in Luxembourg. Factor endowments and economic geography make a substantial contribution to explaining patterns of specialisation across regions within countries. If we use the estimated coefficients to evaluate predicted shares of GDP excluding information on factor endowments and economic geography, the average prediction error in the manufacturing industries across all countries, industries, and years rises to 120 percent. The average prediction error across all countries, disaggregated manufacturing industries, and time compares favorably with the average prediction errors using the approach based on considerations of traditional trade theory only. Following this last approach, Harrigan (1995) reported prediction errors of 38 percent using OECD country-level data. Prediction errors also compare positively with those reported in Chapter 3, where only the role of factor endowments was considered as determinant of the location of economic activity in European regions. The average prediction error for the eight manufacturing industries was 58 percent during 1985-95 when considering only the role of factor endowments and using regional data (see Tables 3.11 and 3.12). The results confirm our prior belief that economic geography helps to explain the location of economic activity at a more disaggregated level, in line with findings in Davis and Weinstein (1999).

As mentioned in the previous chapter, our sample period is characterised by increasing European integration. In Table 4.5, columns (2) and (3) report prediction errors for two sub-samples so that we can evaluate how the model performs over time. Since the country-year dummies control for any country-specific changes in patterns of production over time, the analysis is explicitly concerned with how increasing integration affects the relationship between specialisation and factor endowments and economic geography within countries. Prediction errors remain fairly constant over time across countries and industries. We do not find any systematic increase or decrease in average prediction errors over time. The results are in line with those for the manufacturing industries in the previous chapter (Tables 3.11 and 3.12), where the relation between factor endowments and specialisation does not show any specific trend over time with increasing economic integration.

Finally, we investigate prediction errors for each of the industries in our sample and over time (Tables 4.6 and 4.7). Average within-sample prediction errors are similar across all industries in general and constant over time. Our specification performs best in explaining specialisation in Minerals (9 percent average prediction error), and worst in explaining Metals (with average prediction errors of 20 percent). The within-sample prediction errors exhibit no systematic trend and are relatively constant over time. In each individual manufacturing industry, we find no evidence that the process of increasing European integration has weakened or strengthened the relationship between factor endowments, economic geography, and patterns of production within countries.

<Tables 4.6-4.7 about here>

4.6 Conclusions

This chapter investigated the roles of comparative advantage and economic geography in determining the pattern of specialisation at the regional level in Europe. We derive an equation relating an industry's share of GDP to factor endowments, the locations of supply and of demand, and industry characteristics such as transport costs.

The estimation yields the following conclusions. Both factor endowments and economic geography are relevant in explaining specialisation in the manufacturing sector across European regions. Parameter estimates are statistically significant and constant over different specifications that account for different sources of unobserved heterogeneity in the data. Other things being equal, regions with high skill endowments will tend to be more specialised in skill-intensive industries. Among the economic geography variables, access to suppliers is always statistically significant in explaining specialisation at the one percent level. Location of demand is not significant in explaining specialisation patterns for European regions. Hence, cost linkages are more relevant than demand linkages.

Our model performs well in explaining patterns of specialisation across European regions. The model's average prediction error in Manufacturing across all countries, industries, and time is 13 percent, and ranges from 8 percent to 20 percent for specific industries. If we use the estimated coefficients to evaluate predicted shares of GDP excluding information on factor endowments, industry characteristics, and economic geography, the average prediction error in manufacturing industries across all countries, industries, and years rises to 120 percent. Average prediction errors compare positively with those reported in Chapter 3. The average prediction error for the eight manufacturing industries was 58 percent during 1985-95 when considering only the role of factor endowments. Over time, prediction errors remain relatively stable, not only across regions and industries for each country but also across industries.

Table 4.1: OLS Regression Results, pooled observations, all manuf. industries

Dependent Variable : $lsmp_{zjt}$	1985-95	1985-95	1985-95
Regional Characteristics ($-\beta_h y[h]$)			
Agricultural Endowment	0.1943***	0.1979***	0.1489***
	(0.0322)	*(0.0321)*	*(0.0314)*
Low Education Endow.	-0.8116***	-0.8503***	-0.9258***
	(0.0805)	*(0.0795)*	*(0.0960)*
Medium Education Endow.	-0.0432	-0.0496	-0.1117
	(0.0612)	*(0.0616)*	*(0.0958)*
High Education Endow.	-0.4734***	-0.4437***	-0.3953***
	(0.0434)	*(0.0446)*	*(0.0717)*
Supplier Access	-1.2965***	-1.2859***	-1.2087***
	(0.2186)	*(0.2184)*	*(0.2136)*
Market Potential Elasticity	-0.0583	-0.0569	-0.0945
	(0.0666)	*(0.0673)*	*(0.0671)*
Industry Characteristics ($-\beta_h x[h]$)			
Agricultural Intensity	2.7846***	2.7849***	2.7848***
	(0.1397)	*(0.1377)*	*(0.1340)*
$Skill_L$ intensity	-1.1063***	-1.1088***	-1.1039***
	(0.2703)	*(0.2705)*	*(0.2603)*
$Skill_M$ intensity	0.1582	0.1508	0.1592
	(0.3223)	*(0.3233)*	*(0.2936)*
$Skill_H$ intensity	-0.3538*	-0.3513*	-0.3547*
	(0.2100)	*(0.2092)*	*(0.2053)*
Intermediate Intensity	-8.8680***	-8.8848***	-8.8682***
	(1.0615)	*(1.0612)*	*(1.0381)*
Transport costs	-6.5445***	-6.5749***	-6.5452***
	(1.5613)	*(1.5674)*	*(1.5456)*
Share of output to industry	1.7619***	1.7631***	1.7619***
	(0.1087)	*(0.1073)*	*(0.1050)*
Interactions (β_h)			
Agric Endow*Agric inputs	0.1359*	0.1367*	0.1359*
	(0.0796)	*(0.0789)*	*(0.0799)*
Low Educ Endow* $Skill_L$	2.5627***	2.5655***	2.5604***
	(0.2799)	*(0.2803)*	*(0.2712)*
Med Educ Endow* $Skill_M$	0.6206**	0.6285**	0.6196**
	(0.3132)	*(0.3143)*	*(0.2827)*
High Educ Endow* $Skill_H$	1.0377***	1.0350***	1.0386***
	(0.2060)	*(0.2052)*	*(0.2011)*
Supplier access* Intermed. int	8.2799***	8.2959***	8.2804***
	(1.0836)	*(1.0833)*	*(1.0610)*
Market pot. elasticity * Transport c.	-0.0460	-0.0472	-0.0461
	(0.0736)	*(0.0741)*	*(0.0739)*
Year dummies		yes	yes
Country dummies			yes
Number of observations	3930	3930	3930
F-statistic	273.14	182.40	174.61
Prob>F	*0.0000*	*0.0000*	*0.0000*
R-sqed	0.52	0.52	0.53

Notes: Robust standard errors in parenthesis. The ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table 4.2: (cont) OLS Regression Results, pooled observations, all manuf. industries

Dependent Variable : $lsmp_{zjt}$	1985-95	1985-95	1985-95
Regional Characteristics			
Agricultural Endowment	0.1526***	-0.2215	0.1531
	(0.0316)	*(0.0760)*	*(0.4942)*
Low Education Endow.	-0.7713***	-0.9453***	-0.8199***
	(0.1024)	*(0.1426)*	*(0.2211)*
Medium Education Endow.	-0.1845*	-0.3767***	-0.1712
	(0.1040)	*(0.1203)*	*(0.2144)*
High Education Endow.	-0.4724***	-0.1075	-0.0768
	(0.0746)	*(0.1113)*	*(0.1189)*
Supplier Access	-1.1904***	-1.8733***	-1.7765***
	(0.2145)	*(0.2213)*	*(0.2279)*
Market Potential Elasticity	-0.0653	-0.2357	0.3237
	(0.0684)	*(0.1710)*	*(0.4124)*
Industry Characteristics			
Agricultural Intensity	2.7819***	2.7791***	2.7782***
	(0.1330)	*(0.1322)*	*(0.1318)*
$Skill_L$ intensity	-1.0910***	-1.0824***	-1.0769***
	(0.2571)	*(0.2425)*	*(0.2407)*
$Skill_M$ intensity	0.1772	0.2217	0.2287
	(0.2920)	*(0.2849)*	*(0.2832)*
$Skill_H$ intensity	-0.3578*	-0.3768**	-0.3775**
	(0.2049)	*(0.1979)*	*(0.1980)*
Intermediate Intensity	-8.8128***	-8.6791***	-8.6585***
	(1.0429)	*(1.0042)*	*(1.0130)*
Transport costs	-6.4310***	-6.1222***	-6.0830***
	(1.5775)	*(1.5958)*	*(1.5969)*
Share of output to industry	1.7564***	1.7438***	1.7422***
	(0.1041)	*(0.0988)*	*(0.0983)*
Interactions			
Agric Endow*Agric inputs	0.1335***	0.1264	0.1256
	(0.0791)	*(0.0828)*	*(0.0828)*
Low Educ Endow* $Skill_L$	2.5458***	2.5337***	2.5277***
	(0.2681)	*(0.2530)*	*(0.2511)*
Med Educ Endow* $Skill_M$	0.6002**	0.5503 **	0.5431**
	(0.2816)	*(0.2771)*	*(0.2755)*
High Educ Endow* $Skill_H$	1.0422***	1.0630***	1.0638***
	(0.2008)	*(0.1941)*	*(0.1940)*
Supplier access* Intermed. int	8.2288***	8.1018***	8.0827***
	(1.0658)	*(1.0257)*	*(1.0348)*
Market pot. elasticity * transport c.	-0.0416	-0.0281	-0.0266
	(0.0755)	*(0.0760)*	*(0.0761)*
Country-year dummies	yes		yes
Regional Dummies		yes	yes
No. of Observations	3930	3930	3930
F statistic	65.07	114.82	55.39
Prob>F	*0.0000*	*0.0000*	*0.0000*
R-sqred	0.55	0.58	0.58

Notes: Robust standard errors in parenthesis. The ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table 4.3: Robustness Analysis with Industry Dummies, All Manuf. Industries

Dependent Variable : $lsmp_{zjt}$	1985-95	1985-95
	(OLS)	*(FE)*
Interactions (β_h)		
Agric Endow*Agric intensity	0.1367*	0.1264**
	(0.0789)	*(0.0530)*
Low Educ Endow*$Skill_L$	2.5655***	2.5337***
	(0.2803)	*(0.1865)*
MedEduc Endow*$Skill_M$	0.6285**	0.5503**
	(0.3143)	*(0.2397)*
High Educ Endow*$Skill_H$	1.0350***	1.0630***
	(0.2051)	*(0.1505)*
Supplier Access*Intermed. int.	8.2959***	8.1018***
	(1.0834)	*(0.7410)*
Mkt potential elasticity*tc	-0.0472	-0.0281
	(0.0741)	*(0.0966)*
Industry dummies	yes	yes
Country-year dummies	yes	yes
No. of Observations	3930	3930
F-statistic	182.40	181.29
Prob>F	*0.0000*	*0.0000*
R-sqed	0.52	0.47

Notes: Robust standard errors in parenthesis. The ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table 4.4: Robustness Analysis by Clustering Observations, All Manuf. Industries

Dependent Variable : $lsmp_{zjt}$	1985-95	1985-95
	(1)	(2)
Interactions (β_h)		
Agric Endow*Agric intensity	0.1359	0.1335
	(0.2405)	*(0.2461)*
Low Educ Endow*$Skill_L$	2.5627***	2.5458***
	(0.8556)	*(0.8256)*
MedEduc Endow*$Skill_M$	0.6206	0.6002
	(0.9829)	*(0.8823)*
High Educ Endow*$Skill_H$	1.0377*	1.0422*
	(0.6297)	*(0.6186)*
Supplier Access*Intermed. int.	8.2799***	8.2288***
	(3.3437)	*(3.2952)*
Mkt potential elasticity*tc	-0.0460	-0.0416
	(0.2325)	*(0.2410)*
Country-year dummies		yes
No. of Observations	3930	3930
F-statistic	57.96	27.57
Prob>F	*0.0000*	*0.0000*
R-sqed	0.52	0.55

Notes: Robust standard errors in parenthesis. The ***, **, and * denotes significance at the 1, 5, and 10 percent levels, respectively.

Table 4.5: Average Within-sample Prediction Errors Over Time, all Manuf. Industries

		1985-95	1985-90	1985-90
All countries	GDP Share	0.026	0.026	0.026
	Prediction Error 1	0.1258	0.1225	0.1289
	Prediction Error 2 (only cty-year)	1.2192	1.2294	1.2050
Belgium	GDP Share	0.021	0.022	0.020
	Prediction Error 1	0.1285	0.1302	0.1259
	Prediction Error 2 (only cty-year)	1.1215	1.1563	1.0891
Spain	GDP Share	0.021	0.023	0.019
	Prediction Error 1	0.1358	0.13671	0.1350
	Prediction Error 2 (only cty-year)	1.2158	1.2477	1.1809
France	GDP Share	0.024	0.025	0.023
	Prediction Error 1	0.0765	0.0785	0.0746
	Prediction Error 2 (only cty-year)	1.2072	1.2236	1.1907
Italy	GDP Share	0.024	0.026	0.023
	Prediction Error 1	0.1197	0.1200	0.1193
	Prediction Error 2 (only cty-year)	1.2175	1.2545	1.1774
Luxembourg	GDP Share	0.026	0.027	0.024
	Prediction Error 1	0.2760	0.2877	0.2647
	Prediction Error 2 (only cty-year)	1.0416	1.0450	1.0313
Netherlands	GDP Share	0.023	0.024	0.022
	Prediction Error 1	0.1143	0.1152	0.1125
	Prediction Error 2 (only cty-year)	1.2165	1.2315	1.1757
United Kingdom	GDP Share	0.036	0.033	0.030
	Prediction Error 1	0.1522	0.13349	0.1707
	Prediction Error 2 (only cty-year)	1.2776	1.2330	1.3230
Country-year dummies		yes	yes	yes

Notes: table reports mean values for the whole sample and individual countries. For full industry names, see Appendix A. Absolute proportional prediction errors are calculated as $|s - s(P)|/s$, where a capital P indicates a predicted value and s is the GDP share (in natural log), our dependent variable. Prediction error is based on the fitted values from specification reported in Column 1 of Table 2 using the disaggregated data on regional factor endowments, country characteristics, and country-year dummies. Parameter estimates for this specification are reported in Table 2. Prediction error 2 (only cty-year) indicates that predicted values use the parameter estimates from the same specification but only the country-year dummies are used to construct predicted shares of GDP.

Table 4.6: Average Within-sample Prediction Errors Over Time, by Industry

			(1)	(2)	(3)	(4)
			Metal	Mineral	Chemical	Machine
All countries	Prediction Error 1	1985-95	0.2052	0.0906	0.1088	0.1174
	Prediction Error 1	1985-90	0.2069	0.0842	0.1027	0.1183
	Prediction Error 1	1990-95	0.2030	0.0979	0.1145	0.1159
Belgium	Prediction Error 1	1985-95	0.3304	0.1523	0.1234	0.0717
	Prediction Error 1	1985-90	0.3313	0.1588	0.1192	0.0748
	Prediction Error 1	1990-95	0.3293	0.1445	0.1262	0.0709
Spain	Prediction Error 1	1985-95	0.2285	0.0713	0.1023	0.1787
	Prediction Error 1	1985-90	0.2510	0.0635	0.0881	0.1870
	Prediction Error 1	1990-95	0.2065	0.0828	0.1167	0.1711
France	Prediction Error 1	1985-95	0.1317	0.0453	0.0709	0.0779
	Prediction Error 1	1985-90	0.1341	0.0508	0.0738	0.0811
	Prediction Error 1	1990-95	0.1287	0.0402	0.0675	0.0738
Italy	Prediction Error 1	1985-95	0.1108	0.1134	0.1021	0.1091
	Prediction Error 1	1985-90	0.1218	0.1067	0.1025	0.1107
	Prediction Error 1	1990-95	0.0977	0.1213	0.1013	0.1076
Luxembourg	Prediction Error 1	1985-95	0.9270	0.2333	0.1989	0.2332
	Prediction Error 1	1985-90	1.1198	0.1859	0.1442	0.2079
	Prediction Error 1	1990-95	0.7350	0.2846	0.2523	0.2584
Netherlands	Prediction Error 1	1985-95	0.1101	0.0749	0.1560	0.1339
	Prediction Error 1	1985-90	0.0993	0.0741	0.1768	0.1374
	Prediction Error 1	1990-95	0.1218	0.0760	0.1349	0.1279
United Kingdom	Prediction Error 1	1985-95	0.2767	0.0890	0.1180	0.1113
	Prediction Error 1	1985-90	0.2394	0.0733	0.0980	0.1059
	Prediction Error 1	1990-95	0.3171	0.1045	0.1374	0.1147
Country-year dummies			yes	yes	yes	yes

Notes: Table reports mean values for the whole sample and individual countries. For full industry names, see Appendix A. Absolute proportional prediction errors are calculated as $|s - s(P)|/s$, where a capital P indicates a predicted value and s is the GDP share (in natural log), our dependent variable. Prediction error is based on the fitted values from specification reported in Column 1 of Table 2 using the disaggregated data on regional factor endowments, country characteristics, and country-year dummies. Parameter estimates for this specification are reported in Table 2.

Table 4.7: Average Within-sample Prediction Errors Over Time, by Industry

			(1)	(2)	(3)	(4)
			Transport	Food	Textile	Paper
All countries	Prediction Error 1	1985-95	0.1116	0.1405	0.1333	0.1004
	Prediction Error 1	1985-90	0.1103	0.1346	0.1301	0.0933
	Prediction Error 1	1990-95	0.1132	0.1452	0.1354	0.1073
Belgium	Prediction Error 1	1985-95	0.1279	0.0776	0.0771	0.0674
	Prediction Error 1	1985-90	0.1122	0.0858	0.0869	0.0723
	Prediction Error 1	1990-95	0.1429	0.0689	0.0647	0.0601
Spain	Prediction Error 1	1985-95	0.0949	0.2076	0.0951	0.1082
	Prediction Error 1	1985-90	0.0916	0.2058	0.1013	0.1054
	Prediction Error 1	1990-95	0.0957	0.2079	0.0891	0.1103
France	Prediction Error 1	1985-95	0.0937	0.0545	0.0887	0.0496
	Prediction Error 1	1985-90	0.0912	0.0516	0.0964	0.0493
	Prediction Error 1	1990-95	0.0984	0.0588	0.0801	0.0494
Italy	Prediction Error 1	1985-95	0.1363	0.1060	0.1677	0.1121
	Prediction Error 1	1985-90	0.1472	0.1076	0.1536	0.1101
	Prediction Error 1	1990-95	0.1276	0.1050	0.1795	0.1145
Luxembourg	Prediction Error 1	1985-95	0.2035	0.3172	0.0513	0.0437
	Prediction Error 1	1985-90	0.2148	0.3068	0.0784	0.0434
	Prediction Error 1	1990-95	0.1922	0.3325	0.0208	0.0420
Netherlands	Prediction Error 1	1985-95	0.0697	0.0672	0.1303	0.1725
	Prediction Error 1	1985-90	0.0654	0.0747	0.1378	0.1563
	Prediction Error 1	1990-95	0.0720	0.0566	0.1224	0.1880
United Kingdom	Prediction Error 1	1985-95	0.1130	0.2276	0.1818	0.1085
	Prediction Error 1	1985-90	0.1055	0.1980	0.1635	0.0880
	Prediction Error 1	1990-95	0.1218	0.2543	0.2016	0.1296
Country-year dummies			yes	yes	yes	yes

Notes: table reports mean values for the whole sample and individual countries. For full industry names, see Appendix A. Absolute proportional prediction errors are calculated as $|s - s(P)|/s$, where a capital P indicates a predicted value and s is the GDP share (in natural log), our dependent variable. Prediction error is based on the fitted values from specification reported in Column 1 of Table 2 using the disaggregated data on regional factor endowments, country characteristics, and country-year dummies. Parameter estimates for this specification are reported in Table 2.

4.7 Appendix A

Table 4.8: Sample Composition

Country	Sample	Number of NUTS-1 regions[1/]
Belgium	1985-95	3 (be1-be3)
Spain	1985-95	7 (esp1- esp7)
France	1985-95	8 (fra1-fra8)
Italy	1985-95	11 (ita1-ita9, itaa/b)
Luxembourg	1985-95	1 (lux)
Netherlands	1985-95	4 (ndl1-ndl4)
United Kingdom	1985-95	11 (uk1-uk9, uka, ukb)

[1/] For a description of the NUTS-1 regions, see Appendix 2A in Chapter 2.

Table 4.9: Industry Composition

Code	Industry Description: Disaggregated Manufacturing Industries
5	Ferrous And Non-Ferrous Ores And Metals, Other Than Radioactive **(Metal)**
6	Non-Metallic Minerals And Mineral Products **(Mineral)**
7	Chemical Products **(Chem)**
8	Metal Products, Machinery, Equipment And Electrical Goods **(Machine)**
9	Transport Equipment **(Transp)**
11	Food, Beverages And Tobacco **(Food)**
12	Textiles And Clothing, Leather And Footwear **(Textile)**
13	Paper And Printing Products **(Paper)**

4.8 Appendix B

4.8.1 B1. Regional-level Data on Production and Endowments

1. Value Added: current price value-added, millions of ECUs, from Regio dataset, Eurostat.

2. GDP: current price, millions of ECUs, from Regio dataset, Eurostat.

3. Arable Land: total arable land area, thousands of hectares, from Regio dataset, Eurostat.

4. Population: total population, thousands of people, from Regio dataset, Eurostat.

5. Education Attaintment: Educational attainment is grouped into 3 categories: low, medium and high. 'Low education' is no or primary education, while 'high education' is College degree or equivalent. 'Medium education' corresponds to all intermediate levels of educational attainment, including secondary school and vocational qualifications. Using individual country labour force surveys, we compute the percentage of the population with each level of educational attainment. The endowment variables included in the regressions are these percentages multiplied by the population data from Regio, Eurostat. See Appendix 3B in Chapter 3 for further details.

4.8.2 B2. Industry Characteristics

1. Labour compensation: Defined as a share of total costs, from Midelfart-Knarvik et al. (2000b), Table A1 in Appendix A5.

2. Skill intensities: Data on education attaintment at the industry level is from Machin and Van Reenen (1998). Data is only available for France and the United Kingdom. We compute simple averages at the industry level. Skill intensity for industry j is computed as follows

$$Skill\ intensity_{ij} = \frac{employment\ with\ skill\ i_j}{total\ employment_j} \cdot \frac{wage\ bill_j}{Total\ Cost_j},$$

where $i = low, medium, high$, and wage bill refers to labour compensation. Data constraints hinder the computation of a more accurate measure of skill intensity in which wage bill would be broken down by the level of education of employment.

3. Agricultural input share: Use of agricultural inputs (including fishery and forestry) as a share of gross value of output, from Midelfart-Knarvik et al. (2000b), Table A1 in Appendix A5.

4. Transport costs intensity: Transport costs as share of fob price sales within the EU, from Midelfart-Knarvik et al. (2000b), Table A1 in Appendix A5.

5. Use of intermediate: Total use of intermediates as a share of gross value of output, from Midelfart-Knarvik et al. (2000b), Table A1 in Appendix A5.

Table 4.10: Industry Characteristics

Industries	Share of low education workers in work-force	Share of medium education workers in work-force
Metals	0.56	0.39
Mineral	0.45	0.45
Chemical	0.46	0.38
Machine	0.44	0.41
Transport	0.45	0.46
Food	0.62	0.34
Textile	0.71	0.26
Paper	0.50	0.40

Table 4.11: Industry Characteristics (cont.)

Industries	Share of high education workers in work-force	Labour compensation (share of costs)
Metals	0.06	0.185
Mineral	0.09	0.285
Chemical	0.16	0.242
Machine	0.15	0.301
Transport	0.08	0.336
Food	0.04	0.123
Textile	0.03	0.248
Paper	0.10	0.262

Table 4.12: Industry Characteristics (cont.)

Industries	Input of agriculture (share of costs)	Transport costs (share of fob shipped)	Use of intermediate (share of costs)
Metals	0.0001	0.540	0.746
Mineral	0.003	0.114	0.567
Chemical	0.005	0.068	0.639
Machine	0.0001	0.040	0.606
Transport	0.0001	0.033	0.636
Food	0.266	0.042	0.708
Textile	0.158	0.053	0.643
Paper	0.005	0.043	0.614

Chapter 5

Membership in European Economic Community, Openness, and Growth

5.1 Introduction

In previous chapters, we analysed the evolution of industrial specialisation and investigated the determinants of specialisation in European regions. In Chapter 2, we found that regions are more specialised than countries; that specialisation has increased since the 1980s, although at a slow pace; and that regions have higher mobility in the patterns of specialisation than countries, with the majority of them showing a dynamic process that is statistically significant from that of the corresponding country. Chapter 3 estimated an equation derived from the Heckscher-Ohlin theory that relates an industry's share of a region's GDP to factor endowments and relative prices. Factor endowments were found to have a statistically significant and quantitatively important role in explaining production patterns. The explanation was most successful for aggregate industries, and works less well for disaggregated industries within manufacturing. Next, Chapter 4 analysed patterns of specialisation across eight manufacturing industries from seven European countries since 1985 incorporating economic geography considerations together with factor endowments as determinants of specialisation. Both factor endowments and economic geography were found to be significant in explaining specialisation in the manufacturing sector. However, in both chapters on the determinants of specialisation, we found no evidence that increasing European integration has weakened the relationship between factor endowments, economic geography, and production patterns within countries.

This chapter takes a more macroeconomic approach to investigate the impact of economic integration in Europe. We explore whether economic integration, defined as joining the European Economic Community (EEC), has a permanent effect on openness, income, and income growth at the country level. We also evaluate whether economic integration changes openness and convergence in the onset of EEC membership for country members of the EEC. We begin by presenting results that exploit only time-series variation (compare an individual country's performance before and after the data of EEC entry). We then present results that exploit both time-series and cross-section vvariation in a differences in differences specification (the first difference is before and after date of accession, the second difference is between EEC members and non-members). In this second specification, the effects of EEC membership are identified from differential changes in performance pre- and post-dates of EEC entry for members and non-members.

The notion that openness is an important determinant for growth has become increasingly accepted by policymakers. Casual observation seems to suggest that outward oriented economies have performed better than inward-oriented, protectionist economies with high tariffs to international trade and capital controls. As regards the EEC, it also appears that growth prospects for countries joining the EEC were enhanced by a freer trade regime. Ben-David (1993), for example, provides evidence of a strong link between the timing of trade reform (freer trade among European countries) and income convergence among countries. Furthermore, income convergence is achieved by raising the income of poor countries rather than by lowering that of rich countries.

Nonetheless, the question of whether openness enhances growth remains controversial in trade economics. Economists have offered the following argument: other things equal, countries that liberalise their external sector and reduce impediments to international trade should outperform those that failed to do so. First, trade liberalisation tends to increase exports and imports (and thus, GDP) via changes in specialisation and realisation of gains from trade. Second, the interaction with international markets enhances the flows of ideas, such that total factor productivity improves (and hence the country's income). The increase in market size, increased competition, and increased specialisation should have an impact on a country's income. A number of authors have expressed skepticism, however, about the theoretical and empirical validity of this proposition.[1] It has also been argued that the theoretical validity of a link between openness and income are weak. While static gains from trade are uncontroversial, the existence of dynamic gains for growth remains the subject of a lively debate.

The more recent debate on the relationship between trade and income has been enriched by

[1]See, for example, Grossman and Helpman (1991a), Edwards (1998), Prichett (1996), Rodriguez and Rodrik (1999), and Harrison and Hanson (1999). A more detailed analysis of these studies is presented in the next section.

the endogenous growth theory. Grossman and Helpman (1991a) present a model with international trade in goods and services, foreign direct investment (FDI), and international exchange of information and dissemination of knowledge. A country's productivity level depends on its own R&D as well as on the R&D of trade partners. Countries become more productive as they take advantage of technological advances in the rest of the world. Based on these theoretical underpinnings, Coe and Helpman (1995) provide empirical evidence that a country's total factor productivity depends not only on domestic R&D but also on foreign R&D. Foreign R&D has beneficial effects on domestic productivity, and the effect is increasing with the openness of the economy. Lichtenberg and van Pottelsberghe de la Potterie (2001) investigate the role of foreign direct investment on technology transfers across borders. Their results confirm that more open economies are more likely to benefit from foreign outward R&D. New growth theories do not predict that trade would unambiguously raise economic growth. Increased competition could discourage innovation by lowering firms' expected returns. Keller (1997) questions the role of international trade in driving R&D international spillovers as suggested by Coe and Helpman (1995). Using randomly created trade partners, he finds international R&D spillover estimates that are often larger and explain more of the variation in productivity across countries than those found when considering real trading partners.

This chapter contributes to the debate by investigating long-run effects on trade and income as a result of economic integration. It does so using the example of the European countries joining the EEC after its foundation in 1957. The EEC provides the scenario of a controlled experiment where the process of economic integration can be established in a timely manner. The analysis uses a policy-based measure of economic integration (entrance date into the EEC), and explores its link to openness (ratio of exports and imports to GDP), and on income and income growth. Thus, this approach exploits a natural experiment to investigate the relationship between openness and growth. First, we search for permanent changes in the time series of openness during a time interval that is related to EEC membership. We then explore whether there is a corresponding permanent change in the time series of income and income growth. While informative, a problem with the tests for structural breaks with univariate time-series is that there may be other time-series shocks which affect countries at the same time as their entry into the EEC. To help address this concern, the empirical analysis considers a differences-in-differences specification which controls for common time series shocks affecting both EEC members and non-members. We take also advantage of the cross-section dimension so as to account for the differential effect on trade and income as the result of these countries joining the EEC. We study the differential effect of EEC membership among member and non-member countries on openness, income, and income convergence.

The empirical analysis takes into account two definitions of openness. First, we consider overall openness, defined as the ratio of exports and imports to GDP, and we refer to this concept as overall openness in the chapter. Then, we also consider EEC openness, defined as the GDP share of exports and imports within the twelve European countries members of the EEC by 1986. We also refer to this concept as EEC-trade.

The empirical analysis comes to the following conclusions. First, from the analysis of individual time-series, EEC membership improves openness within the EEC permanently, but not overall openness for the countries joining the EEC after the first (1973) and second (1986) enlargements. Trade flows seem to increase within the EEC, however, there is less evidence of an increase in overall trade. This may reflect trade diversion or offsetting changes in other variables affecting non-EEC trade. The effect on openness is not reflected in permanent changes on income levels or income growth. The results do not support the existence of scale effects on growth nor of improved convergence as a result of economic integration. Second, analysing the differential effect of EEC membership for members and non-members pre- and post-entry, we get similar conclusions with respect to openness. Openness with EEC countries improves significantly following entry into the EEC. We also find evidence of improved income levels for EEC country members as countries joined the EEC. Contrary to the analysis of individual time-series, the empirical results here also give support to the idea that joining the EEC improves income convergence, reflected in a decrease in income dispersion. This may reflect the ability of the differences in differences analysis to control for time-series shocks coincident with dates of entry to the EEC that are common to members and non-members.

The structure of the chapter is as follows. In the next section, we briefly describe the steps towards economic integration in Europe. In section 3, we overview the related empirical literature. Section 4 presents a theoretical model illustrating the relationship between trade and income. Section 5 presents the econometric modelling structure using structural break tests on individual time-series, and discusses the results of this analysis. Sections 6 discusses the difference in difference analysis. Section 7 concludes.

5.2 Steps to European Integration: Some Historical Background

The European Economic Community (EEC) was established by the Rome Treaties, signed first by six member states in 1957.[2] The EEC Treaty's immediate objectives were the establishment of a

[2] Belgium, France, Italy, Luxembourg, Netherlands, and West Germany.

customs union with free movement of goods between Member States, the dismantling of quotas and barriers to trade, and the free movement of persons, services, and capital. All these customs duties were to be abolished gradually according to a timetable outlined in the EEC Treaty. As regards trade with the rest of the world, a common external customs tariff was gradually established. The first cut in customs duties in trade between the Member States was on 1 January 1959.

Other European countries soon showed interest in joining the Community. In July 1961, the EEC and Greece signed an association agreement to promote economic cooperation between Greece and the Community, with a view to subsequent accession. In July and August 1961, Ireland, Denmark and the United Kingdom submitted applications for membership. In 1962, Spain and Portugal asked for negotiations for Community association. That year the Council also decided to accelerate the reduction of customs duties within the common market.

In 1964, the GATT multilateral trade negotiations resulted in a substantial cut in international customs duties. The Community's external tariff was reduced by between 35 percent and 40 percent, depending on the product (and excluding agricultural products). In 1979, the European Council endorsed the results of subsequent GATT trade negotiations, and a further cut in customs duties (by about one-third) took place in 1980.

The negotiations for the accession of Denmark, Ireland, Norway and the United Kingdom began in 1970. In 1972 the treaties of accession were signed and rapidly ratified by the Member States, (except for Norway, where a narrow majority in a referendum rejected accession). The new Community of Nine started on 1 January 1973. In 1975, Greece submitted its application for accession to the Community. Portugal and Spain followed in 1977. Greece signed the Treaty of Accession in May 1979, becoming a full member from January 1981. Greek accession would take place over a five-year transitional period during which the Greek economy was supposed to gradually converge to the higher economic levels of the Community.

In 1982, the EEC presented 80 proposals for measures to remove barriers to trade so that the business world could take full advantage of the European dimension. The Community also began work on devising a new strategy to modernise European industry. Two years later, the Community proposed a program for consolidating the internal market covering the abolition of customs barriers, harmonisation of business law, the free movement of capital and people, and freedom to provide services, as well as the liberalisation of agricultural, taxation, and transport policies.

In July 1985, the Treaty of Accession of Portugal and Spain was signed, and these countries became member states on January 1986. Spain was characterised by a relatively low degree of openness in its economy. On the eve of EEC membership, Spain still had a low degree of openness when compared with other European economies, and even with new or recent entrants like Portugal and Greece. While imports plus exports were only 33 percent of GDP in Spain, they were 61 percent in the EC12 countries, 44 percent in Greece, and 64 percent in Portugal.

All the three Mediterranean countries (Greece, Portugal, and Spain) reduced external protection significantly after accession with a gradual tariff rate reduction process going to zero for the other EEC countries, and to the lower Common External Tariff rate (approximately at 4-5 percent). The process lasted for eight years with an average tariff reduction of 12.5 percent per year. Quantitative restrictions were eliminated by 1990 for Portugal and Spain.

Progress on monetary and economic union led to the Single European Act of 1987 aimed at eliminating all remaining barriers to trade within Europe and to establish a genuinely efficient and competitive single market by the end of 1992. The Maastricht Treaty (1992) laid down convergence conditions, established a European Monetary Institute in 1994 to precede the European Central Bank, and targeted 1999 as the start date for EMU. The new currency was called the euro, and was first used for interbank and other wholesale purposes with notes and coins following in January 2002. The objective of EMU was to secure a range of benefits, such as price transparency leading to more competition, a logical completion towards a single competitive market, savings in foreign currency transactions, and fostering more efficient capital markets.

5.3 Related Literature

The chapter relates to an extensive empirical literature that addresses the relationship between openness and income (see Edwards, 1998, Harrison, 1996, and Rodriguez and Rodrik, 1999, for surveys). The analysis has struggled with several limitations, the most important being the difficulty to construct a satisfactory and convincing measure of openness. Among the most frequently used measures are the trade ratios (imports and/or exports over GDP) and the elaborate indicators of Dollar (1992) and of Sachs and Warner (1995). Dollar (1992) constructs a measure of the degree of outward orientation of an economy and finds a positive relationship between openness and growth. This measure is based on the level of protection, measured by real exchange rate distortion and the degree of variability in the real exchange rate. Rodriguez and Rodrik (1999) show that the empirical relationship found in Dollar (1992) is not robust to the inclusion of standard control variables, the use of more recent data, and other changes in the sample period. Also, the relation between Dollar's measure of openness and trade protection holds only under very restrictive conditions that are unlikely to apply in practice. Sachs and Warner (1995) construct a composite indicator that combines five different criteria of a quantitative and qualitative nature.[3] They also find a positive relationship between openness and growth. However, the relationship between this indicator and the degree of openness has been questioned in several studies. Harrison and Hanson (1999) show that Sachs and Warner's measure of openness fails to establish a robust link between more open trade policies and long-run growth because the measure captures many other aspects of openness than pure trade policy. By decomposing the measure into its five components, only one element (market structure of the economy) is reported to have a significant impact on growth. Moreover, Rodrik and Rodriguez (1999) show that the two variables the most closely related to trade policy (tariffs and non-tariff barriers) play an insignificant role. Sachs and Warner's indicator seems to serve as a proxy for a wide range of policy and institutional differences, yielding to an overestimation of the effects of trade restrictions on growth.

As the issue on the appropriateness of an openness measure has not been resolved, the empirical literature has focused on analysing the robustness of different openness indicators. Pritchett (1996) questions the ability to capture trade policy of different openness indicators used in the literature. Pairwise correlations between these indicators are low. Ranking analysis yields entirely different country orderings that are actively different to one another with respect to the degree of openness. Moreover, the analysis does not yield any preferred openness indicator. Harrison (1996) gathers many openness measures available for a cross-section of less developed countries over time, and tests whether these measures yield the same conclusions about the relationship between trade and growth. Using panel data techniques, the results suggest that the choice of the time period is critical for whether a positive significant impact is found. Whereas only one of the measures yields a positive effect on growth in the cross section, six are statistically significant when exploiting the time dimension. Edwards (1998) performs a cross-country analysis using nine openness indicators previously suggested in the literature. Analysing the effect of openness on total factor productivity (TFP), the study shows that only five out of nine indicators are statistically significant and yield the expected sign.

The cross-country regression results have also been questioned because they suffer from endogeneity in the regressors. Some authors have followed an instrumental variable approach to overcome endogeneity. Frankel and Romer (1999) instrument trade shares using predictions for bilateral trade derived from a gravity equation. They argue that geography variables, describ-

[3] They define an economy as closed if it satisfies at least one of the following conditions: (i) tariffs in the mid-1970s were 40 percent or more; (ii) quotas in the mid-1980s were 40 percent or more; (iii) the black market premium was 20 percent or higher either in the 1970s or 1980s; (iv) the economy has a state economy on main exports; and finally, (v) the country has a socialist economic system.

ing a country's size and its proximity to other countries, are valid instruments for trade shares, since geography variables would unlikely affect average income other than through their influence on international trade. The results confirm a positive relationship between openness and growth. Brunner (2003) extends Frankel and Romer's analysis to a panel data setting and finds that openness has a permanent effect on income, but it does not have such an effect on income growth. Brunner allows for time varying coefficients on geography variables to capture a changing impact on trade over time. The only time-varying instrument is population, which may just capture demand factors. Furthermore, the instruments only capture that part of trade policy that is related to geography. Irwin and Tervio (2000) show that once a country's distance to the equator is included as a regressor, trade has no effect on average labour productivity.

Rodriguez and Rodrik (1999) critically review the empirical literature on the link between trade policy and growth in great detail. After pointing out various methodological problems in the empirical analysis, they argue that some of the openness indicators used are poor measures of trade barriers, or have little explanatory power as they are highly correlated with other sources of economic performance. The link between trade and growth established in theoretical models does not stand up to the empirical investigation: empirical results are often neither robust to the sample definition, to the sample period, nor to the methodology applied. In this regard, Alcalá and Ciccone (2001) develop a model where productivity gains from international trade arise due to increasing return to specialisation. The study argues that standard measures of openness may not capture the effect of trade on productivity growth, and the authors suggest a measure of *real* openness (imports and exports in exchange rate U.S. dollars relative to gross domestic product in purchasing power parity (PPP) U.S. dollars). Real openness is capable to explain a greater amount of variation in cross-country productivity than *nominal* openness. Their analysis is robust to the inclusion of institutional quality, expropriation risk, and geography controls.

As the empirical studies on the relationship between trade and economic performance have not been conclusive, another part of the literature has investigated whether openness relates to income convergence among countries, with mixed conclusions. Ben-David (1993) analyses the effect of trade policies on income by asking whether trade liberalisation leads to a reduction in the dispersion of income levels among liberalising countries. Considering the EEC as a controlled experiment, Ben-David shows that (i) a decrease in the dispersion of income among European countries coincides with economic integration, and (ii) convergence among EEC countries is achieved by raising the income of the poorer countries and is the result of trade liberalisation. Ben-David (1996) compares two groups of countries (trading partners and random partners) and finds significant per capita income convergence among trading partners, relative to the convergence patterns of randomly grouped countries. Bernard and Jones (1996b) show that cross-country productivity levels for individual manufacturing industries since 1970 have either not converged or even diverged. They conclude that international trade may be causing the divergence. Slaughter (2001) undertakes a difference-in-difference analysis to compare convergence patterns among liberalising countries before and after liberalisation, using randomly chosen control countries before and after liberalisation. In contrast with Ben-David (1996), Slaughter (2001) takes also into account the convergence pattern during earlier periods, i.e. periods in which the countries do not trade extensively. The results indicate that trade liberalisation does not accelerate the convergence process. The analysis here also considers a difference-in-differences approach but focuses on the EEC as a natural experiment.

As regards its methodology, the chapter also relates to the empirical literature on structural breaks in time series. Ben-David and Papell (1995) use sequential trend break tests to identify the primary structural break in 120-year long growth paths of OECD countries since 1870. They find that most countries exhibit fairly steady growth for a period lasting several decades, terminated by a significant drop in GDP levels. After the break, per capita output continues to grow at roughly double their pre-break rates, and even after original growth paths were surpassed. Ben-David et al. (2003) extend the analysis to a two-break unit root test. While half the countries exhibit slowdowns in growth following postwar breaks, the majority of them exhibit faster growth after their second break. Ben-David and Papell (1997) study structural breaks in the paths of export-GDP and import-GDP ratios for 48 countries since the Second World War. Performing the structural break test from Vogelsang (1997), structural breaks exist in the time paths of trade ratios for most of the economies. The structural breaks are associated with an increase in trade, with none of the shifts occurring prior to the implementation of the Kennedy Round of the GATT.

Searching for scale effects, Ben-David and Papell (1998) perform structural break tests on the economic growth series for a large sample of countries at different states of development. The majority of countries report significant structural breaks in their postwar growth rates, which is usually followed by a growth slowdown. The slowdown is associated with the first oil crisis in 1973 for developed countries and with the debt crisis of the 1980s for developing countries. Testing for endogenous growth effects, Jones (1995), in contrast, finds little evidence of permanent changes in growth despite reporting permanent changes in investment rates and in R&D rates for the OECD countries. Permanent changes in certain policy variables do not seem to be reflected in permanent changes on the rate of economic growth.

The chapter contributes to the literature in the following ways. First, we exploit the exogenous variation created by the natural experiment of European integration, to search for permanent changes in openness and in income. We analyse whether any systematic pattern exists between the timing of the breaks (where they exist) and the timing of EEC entry. We perform a sequential structural break test (Vogelsang, 1997) that endogenously searches for permanent shifts in the time series. The timing of the break is determined endogenously but is restricted to be within a 10 year interval related to the accession date to the EEC. The methodology explores univariate time-series properties and compares the timing of any breaks with the known timing of policy-based integration. Second, we use a differences in differences methodology to identify the differential impact on trade and on income convergence of accession to the EEC for members relative to non-members, after the first and second enlargements (1973 and 1986, respectively).

5.4 The model

The model presented in this section should be considered as an illustration, aiming at sketching the impact of trade on income and income growth. In this regard, the model constitutes an example of a wider set of models in which total factor productivity growth benefits from technological transfers resulting from trade. In these models, trade has an effect on innovation and growth through improved knowledge spillovers, international competition, or enlargement of markets (Grossman and Helpman, 1991a).

We consider the growth model described in Bernard and Jones (1996a) and extended by Cameron, Proudman and Redding (1998, 2003) to include the role of international openness on growth. Consider two economies $i = (B, F)$, each producing any of a fixed number of manufacturing products $j = 1, 2, ...n$. Each of the manufacturing goods is produced according to the following production function:

$$Y_{ij} = A_{ij} F_j \left(L_{ij}, K_{ij} \right), \tag{5.1}$$

where A, L, K refer to the level of total factor productivity, labour, and capital respectively. Economy F is defined to be the frontier economy (with the highest level of TFP)[4] while economy B is behind the technology frontier, and benefits from technological transfer. Following Bernard and Jones (1996a), we assume that total factor productivity in economy B for each sector may grow as a result of domestic innovation and of technological transfer from the frontier economy:

$$\ln \left[\frac{A_{ij(t)}}{A_{ij(t-1)}} \right] = \gamma_{ij} + \lambda_j \ln \left[\frac{\omega_{ij} A_{Fj(t-1)}}{A_{ij(t-1)}} \right], \tag{5.2}$$

where $i = B, F$ *and* $\gamma_i, \lambda \geq 0 \quad \omega_i \in (0, 1)$. γ_{ij} is the country-specific innovation growth rate,

[4]For simplicity, we assume F is the frontier in all industries,. We could allow one country to be the frontier in one industry, and country B to be the frontier in the other industry.

λ_j denotes the rate at which the technology transfer occurs in industry j, and ω_{ij} is the fraction of technology in the frontier economy that may potentially be transferred to economy B. Since economy F is in possession of the latest technology, there is no potential for technology transfers we assume no technology transfers $\left(w_F = 1,\ and\ ln\left(\frac{\omega_{ij}A_{Fj(t-1)}}{A_{ij(t-1)}}\right) = 0,\ if\ i = F\right)$. The fact that technology transfer exists implies that productivity growth in economy B is a function of the technological gap. Combining equation 5.2 for both economies, the evolution of relative TFP is:

$$\ln\left[\frac{A_{Bj(t)}}{A_{Fj(t-1)}}\right] = (\gamma_{Bj} - \gamma_{Fj}) + \lambda_j \ln \omega_{Bj} + (1-\lambda_j)\ln\left[\frac{A_{Fj(t-1)}}{A_{Bj(t-1)}}\right]. \tag{5.3}$$

We can solve for the steady-state level of relative TFP in each industry j:

$$\ln\left[\frac{A_{Bj}}{A_{Fj}}\right]^* = \frac{(\gamma_{Bj} - \gamma_{Fj})}{\lambda_j} + \ln \omega_{Bj}, \tag{5.4}$$

where a sufficient condition for the initially backward economy to remain so in steady state rate, is $\gamma_{Fj} > \gamma_{Bj}$. In steady state, the non-frontier country iis an equilibrium distance behind the frontier such that the model implies that TFP in both economies will grow at the same rate γ_{Fj} in sector j.

We can think of several channels through which openness could have an effect on the rate of productivity growth in the economy below the technological frontier. First, an increase in trade may improve the amount of technological knowledge in the frontier economy that can be transferred to its less advanced counterpart (ω_{Bj}). Second, an increase in trade may change the rate at which knowledge may be transferred to economy B (λ_j). Through each of these channels, increases in openness might raise TFP growth in country B. In this model, trade has a permanent effect on income levels, but growth is only affected during the transition. Over the long term, openness has no effect on the steady-state growth rate if the rate of innovation in the frontier (γ_{Fj}) remains unchanged.

However, openness could affect long-run growth if it raises the rate of innovation in the frontier economy. Countries that trade in world markets invariably learn a great deal about innovative products and about methods that are being used to produce goods. Therefore, cross-country knowledge flows could promote faster growth. If economy F could benefit from trade (through, for example, R&D spillovers), then both economies could grow permanently at a higher growth rate over the long run. By assumption, country F is the frontier. However, openness might affect growth in the frontier through for example specialisation, market size, or competition effects. In this case, trade would exert a scale effect on growth. In the basic form of the model, however, economic integration improves openness and income, but not income growth, which is only affected during the transition (Figure 5.1). If there is a permanent effect on income growth, one would also find scale effects (Figure 5.2).[5]

<Figures 5.1 and 5.2 about here>

In the next section, we proceed to the empirical analysis of these effects.

5.5 Permanent Effects of EEC Membership

In this section, we investigate the existence of permanent effects in the series of openness, income and income growth as the result of economic integration. We perform the sequential structural break test as described by Vogelsang (1997), which has the advantage of endogenously determining the time of the structural break.

Although the time of the break is defined endogenously, we restrict the structural break to be within a 10-year interval of the date in which a country entered the EEC. For example, the interval in which we search for structural breaks in the case of Spain is 1981-91, since the country joined in 1986. However, within this interval, the breakpoint is endogenously determined. The restriction allows us to relate the breakpoint to the date of EEC accession. The 10-year interval aims at taking into account how expectations could have an effect on the countries before/after joining the EEC. The negotiations toward accession took several years. The removal of internal trade barriers was defined to take another five to seven years. The benefits of economic integration could start either as soon as positive expectations of entering the EEC took hold, or, alternatively, after the full removal of the trade barriers.

Our sample is based on the EEC members in 1986. The member countries in 1986 were Belgium, Denmark, France, Germany, Greece, Italy, Ireland, Luxembourg, Netherlands, Portugal, Spain, and United Kingdom. We refer to this group of countries as EU12 in our discussion. For the structural break analysis, we consider those countries that entered the EEC after its foundation (Denmark, Ireland and the U.K. in 1973, Greece in 1981, and Spain and Portugal in 1986).[6] Two measures of openness are analysed: overall openness and EEC openness. Overall openness is measured as the ratio of exports plus imports to GDP, and with data from the IMF's International Financial

[5] See Jones (1999) for a detailed discussion on the existence of scale effects in endogenous growth theory.

[6] We do not consider the initial members of the EEC owing to data restrictions. The analysis of structural breaks requires a certain degree of sample trimming. The power of structural break tests is low when breaks are at the extremes of the sample period. Given that the EEC was constituted in 1957, the power of the test would be low, as the data generally starts in 1950. By the same way of reasoning, we do not take into account countries that joined the EEC after 1986.

Statistics (IFS). The sample period extends from 1950-2000, except for Spain (1954-2000) due to data availability. EEC openness is measured as the ratio of exports and imports to the 12 country members that were part of the EEC in 1986. EEC exports and imports were constructed from bilateral trade flows as reported in the Direction of Trade dataset (also from the IMF), for 1954-2000. As measures of income, we use GDP level, per capita GDP, and relative GDP per capita. Relative GDP per capita is defined as income relative to Germany, the leading economy in Europe. Income growth rates are defined in terms of GDP levels. Table 5.1 summarises the data and variables.

<Table 5.1 about here>

Although the specification of the Vogelsang test is independent of the integration properties of the time series, the critical values depend on whether the series is stationary or contains a unit root. Therefore, our first step is to analyse the stationary properties of the time series for each of the variables considered. We perform the Zivot and Andrews (1992) test on the null hypothesis of a unit root, under the alternative hypothesis of a structural break at an unknown date. This test is an extension to the Perron (1989) test, with the improvement that the unit root test endogenises the date of the break. Specifically, the null hypothesis is a unit root process with a drift and no structural break:

$$H_o : y_t = \mu + y_{t-1} + e_t. \tag{5.5}$$

Under the alternative hypothesis, we allow for a structural change in the intercept,

$$H_1^1 : y_t = \mu + \theta DU_t(\lambda) + \beta t + \alpha y_{t-1} + \sum_{j=1}^{k} c_j \Delta y_{t-j} + e_t, \tag{5.6}$$

where $DU_t(\lambda) = 1$ if $t > \lambda T$, 0 otherwise.

The test statistic of the Zivot and Andrews test depends on the degree of autocorrelation in the error term. In this regard, there is considerable evidence suggesting that data dependent methods are superior to making an *a priori* choice of a fixed degree of autoregression. We follow Campbell and Perron (1991), and Ng and Perron (1995) by setting an upper bound of $k_{\max}$ on k and apply a general-to-specific recursive procedure. $k_{\max}$ is set at 8. If the last lag is significant at the 10 percent level, the choice of k is $k_{\max}$; if that is not the case, k is reduced by one. Ultimately, k could shrink to zero.

After establishing the stationarity properties of the series under analysis, we search for breaks in the time series by performing the Vogelsang (1997) test. The test has the advantage of endogenously defining the breakpoint. Vogelsang defines statistics for detecting a break at an unknown date in the trend function of a dynamic univariate time series,[7] allowing for serial correlation in the error term. The trend function is modeled as a polynomial in time, with a time trend. As we search for changes in the intercept, our equation of interest is:

$$y_t = \mu + \theta DU_t + \beta t + \alpha y_{t-1} + \sum_{j=1}^{k} c_j y_{t-j} + \varepsilon_t, \tag{5.7}$$

where y_t refers to the variable under consideration. T_B is the year at which the break in the trend occurs. The variable related to the break in the intercept is defined as $DU_t = 1$ if $t > T_B$, 0 otherwise.

The method to select the time of the break, T_B, is endogenous. The test computes Wald Statistics for a break in the intercept over a range of possible break dates and takes the supremum of the statistics. Following Zivot and Andrews (1992), Banerjee, Lumsdaine and Stock (1992) and Perron (1990, 1997), we consider the procedure by which T_B is selected as the value, over all possible break points, which minimizes the t-statistic for testing $\alpha = 1$ in the appropriate autoregression. The length of the autoregressive process is selected as described above. $SupF_t$ is the maximum of the standard F-statistic for testing $\theta = 0$. As mentioned above, Vogelsang tabulates critical values for both stationary and unit root series, which we evaluate in line with the results of the Zivot & Andrews test. We compare the value of the supremum statistic to the tabulated critical values reported by Vogelsang (1997).[8]

There is evidence of structural breaks in the series of EEC openness but not in the series of overall openness (Tables 5.2 and 5.3). Although most of the structural breaks in the series of overall openness report the expected sign, only the United Kingdom has a significant permanent change. The breaks in EEC openness occur at a date close to membership. Countries joining the EEC in its first enlargement (1973) and Greece (1981) report a shift in the intercept at the year when their Accession Treaties were signed, in 1972 and 1979 respectively. Spain has the shift at the date of EEC membership, in 1986. EEC permanently improves EEC openness in four out of the six countries, Greece, Ireland, Spain and the U.K. Denmark has a positive shift at the date of its Accession Treaty, but it is not statistically significant. Portugal, in contrast, displays a

[7] Recent research has sought to test for structural breaks in a multivariate setting. This remains an active area of research: see, for example, Hendry and Mizon (1998) and Hendry (1999).

[8] We also compare the value of the supremum statistics to the critical values reported for a 15 percent of sample trimming ($\lambda = 0.15$). By trimming, we drop 15 percent of the observations at the tails of the period. The power of the test is greater to detect breaks near the middle of the sample. Although the trimming in our sample period could be different from 15 percent, critical values of the supremum statistic do not depend heavily on the amount of trimming (see Volgesang, 1997 for further details on this point).

negative impact at a date after entry. It is difficult to interpret this result, but it may relate to the fact that Portugal entered the EEC while in recession. The lack of significance in the breaks for overall openness may reflect some trade diversion or off-setting changes in third variables affecting non-EEC trade.

<Tables 5.2-5.3 about here>

Some evidence is found of effects on income (Tables 5.4-5.5). Only 3 out of the six countries have a statistically significant structural break on income levels. Ireland and the United Kingdom display positive effects in GDP levels at a date of the signature of the accession treaties in 1972. Portugal has a negative break in GDP at the entry date, in line with the fall in trade flows. Furthermore, there is no evidence of structural breaks in per capita income.

<Tables 5.4-5.5 about here>

Finally, there is no evidence of scale effects. Only two countries have permanent changes in the growth rate (Spain and Portugal), although not with the expected sign (Table 5.6). Furthermore, the results show no evidence of convergence (Table 5.7). When analysing the results from relative GDP, we would expect a negative sign associated with the parameter estimate of the structural break dummy (DU_t), indicative of a decrease in income dispersion. Only two countries (Ireland and Portugal) show a significant change in the intercept, but have structural breaks with an unexpected sign. For example, the structural break for Ireland shows a positive sign (divergence), while reporting positive structural breaks for the series of EEC openness and GDP. The structural break reported for Portugal also goes against prior beliefs: the structural break for income growth is negative (indicative of convergence), and the country reported negative breaks for the series for EEC openness and GDP.

<Tables 5.6-5.7 about here>

To summarise, the sequential structural break analysis indicates that EEC membership improves openness to other EEC countries permanently. Although overall openness reports breaks with the right sign, they are not significant. There is some evidence of permanent effects in the series of income, with three out of six countries reporting a significant permanent change in the series of GDP in line with those in the openness series. However, the empirical results do not support permanent changes in per-capita income. Permanent changes in openness however are not reflected on permanent changes in income growth.

This could be the result of other elements affecting income in the opposite direction from openness (for example, if it was the case of weak productivity growth at the time of the break). Three of the countries analysed joined the EEC at the time of the first oil crisis in the first half of the 1970s that severely hit Western Europe. The empirical evidence does neither point to scale effects on income growth nor on income convergence as a result of economic integration. While informative, a problem with the tests for structural breaks with univariate time-series is that there may be other time-series shocks which affect countries at the same time as their entry into the EEC. To help address this concern, the next section considers a differences in differences specification which controls for common time series shocks affecting both EEC members and non-members.

5.6 Differential Effects of EEC Membership

The strategy in this section is to use EEC membership as an experiment to shed further light on its effect on openness, income and income convergence in Europe. In our specification, we use the timing of membership (pre- and post-accession) to identify the effects of trade liberalisation, by employing the differences in differences approach.[9] We include all countries in the EEC by the time Portugal and Spain joined the community in 1986 (i.e., EU12). The difference-in-difference analysis allows us to identify the differential effect of joining the EEC on openness and income. Therefore, our econometric specification takes the following form:

$$y_{it}^{c} = \alpha + \alpha_1 d_t + \alpha_2 d_c + \beta DEU_t^c + \varepsilon_{ij}^{c}, \tag{5.8}$$

where y_{it}^{c} refers to an economic outcome of interest (e.g. openness or income convergence), d_t and d_c are vectors of year- and country-dummies respectively. DEU_t^c is a dummy equal to 1 if the country is an EEC member at time t; 0 otherwise. The inclusion of the country fixed-effect d_c allows for unobserved heterogeneity in the determinants of economic performance that is specific to individual countries and that may be correlated with the right-hand side variables. The year dummies d_t control for changes in economic performance over time. They, therefore, capture the overall effect of EEC membership across countries, as well as controlling for common macroeconomic shocks. Equation 5.8 is therefore a "difference-in-difference" specification because we difference out both the common trend over time for countries (captured in the year dummies) and the time-mean for individual countries (the country fixed effect).

The effect of EEC membership is measured by β, our parameter of interest. In this specification, β is identified from differential changes in the outcome of interest pre and post dates of EEC entry for members and non-members.[10] The presence of country fixed effects and time dummies

[9] As mentioned in the previous section, the member countries in 1986 were Belgium, Denmark, France, Germany, Greece, Italy, Ireland, Luxembourg, Netherlands, Portugal, Spain, and United Kingdom. We refer to this group of countries as EU12 in our discussion.

[10] To ensure comparability with the univariate time-series analysis earlier, we restrict the sample to the

means that this coefficient captures the differential change in economic performance across countries between the pre- and post-accession periods. The theoretical model predicts that β should be positive (negative) and statistically significant when considering openness and income levels (income dispersion), implying that openness (income dispersion) increases (decreases) by more in the post-accession period in countries that went through the trade liberalisation.

In this context, we impose the time of the effect to come into place at the time of accession. This is consistent with the evidence found in the previous section, as permanent changes in EEC openness occurred at the time of the signature of Accession Treaty. In the previous section, we argued that EEC membership marked a dramatic change in the environment in which countries operated and provided evidence that openness display clear and large changes at the time of accession. However, there remains the econometric concern that there are other unobserved variables that change at the same time as accession and that influence economic outcomes. The difference-in-difference analysis specification used in this section means that these unobserved must not only change over time and influence economic outcomes, but must also be correlated in a particular way with pre-accession to openness, income, and income dispersion.

We first analyse the effect of EEC membership on overall openness and EU12 openness. We would expect the sign associated with EEC openness to be positive as countries entering into EEC would have liberalised trade within the other countries in the union (removal of internal trade barriers). A positive sign of β when considering *overall* openness would indicate trade creation (with the impact on EEC trade flows being transferred to overall trade flows). we then analyse whether EEC membership has an effect on income of the member countries. In line with the previous section, our economic outcome of interest would be GDP and per-capita GDP levles (in log terms). We would expect a positive parameter estimate indicating that EEC membership improves income levels for all countries within the EEC. Finally, we consider the effect of EEC membership on the convergence process. Following the previous section, our measure of relative income is defined as the difference (in absolute terms) of each country's per-capita income level and that of Germany, where income levels are in natural log terms. β would then identify the differential effect in the convergence (divergence) process after those countries joined the EEC, i.e. it is negative (positive) to the extent the process of convergence accelerated (decelerated) as a result of countries joining the EEC. In this analysis of convergence, we focus on the catch-up effect of other member countries to Germany, without taking into account any income level effect on the leading economy (i.e. relative

12 countries who became EEC members by 1986. Identification, therefore, comes from those countries that transit from being non-members to members in the period leading up to this date. It would be interesting to expand the sample to a wider group of control countries.

income for Germany is always zero).

Openness among the EEC countries was improved significantly as a result of new countries entering the EEC (Table 5.8). Both openness measures report the expected sign, although only openness within the EEC countries is statistically significant. Openness among the EEC country members increases with the onset of membership, in line with our previous result from the structural break analysis. EEC membership also improves income levels for the country members. GDP and per-capita GDP report the expected (positive) sign although the estimate is statistically significant only for per-capita GDP. Finally, results also support the idea that joining the EEC improves the convergence process. The coefficient estimate associated with relative income reports the expected (negative) sign and it is statistically significant.[11]

<Table 5.8 about here>

Finally, we also report the difference-in-difference analysis when excluding the countries that joined the EEC in 1973 (Denmark, Ireland, and United Kingdom) for robustness purposes. These countries joined the EEC in a period of worldwide recession, and although we control for country and year effects, it may be the case that these countries were affected especially severely by the recession.[12] The results (Table 5.9) support the idea that trade flows within the EEC members were improved strongly, that income levels were increased for all country members, and that joining the EEC after 1973 (Greece, Portugal, Spain) is associated with income convergence. Our results support the idea that trade liberalisation associated with economic integration displays the expected effect on overall openness, although not statistically significant. The β coefficient associated with EU openness is again positive and statistically significant. Furthermore, we find stronger evidence of improved income levels, and of convergence, as the β coefficient estimates associated with the corresponding measures report a higher magnitude.

<Table 5.9 about here>

The results on income convergence differ from those in the previous section: there, we did not find evidence of convergence, here we do. This may be due to the different structures of the emprical models. In the structural break analysis, the timing of the break is endogenously determined, but we are unable to control for common and/or country-specific shocks. In some cases, this may introduce "spurious" breaks, i.e., breaks that are related to global macroeconomic shocks such as

[11]For robustness purposes, we analysed convergence when considering relative income with respect to the average income in the sample (again, relative income is defined as the difference in absolute values of a country's per-capita income with respect to the average income). Evidence of convergence was also found in this case.

[12]We believe these countries were especially affected by the external economic situation. Britain, Denmark, and Ireland left the monetary snake almost at the moment when it began to operate, and decided to float their currencies without any EEC restrictions.

the oil crisis rather than EEC accession. In contrast, in the difference-in-difference analysis, we are able to account for common shocks. We pay for the greater richness in model specification, however, by having to give up some of the flexibility that the nonparametric structural break analysis permits: we need to pre-specify the timing of the break in the series for the variable of interest (the year of EEC accession), rather than having it endogenously determined by the data.[13]

5.7 Conclusions

This chapter examined the impact of economic integration at a more macroeconomic level. It has investigated the existence of a permanent effect of EEC membership on openness, income, and income growth in Europe. This analysis could draw important lessons for countries joining the European Union in the future, as well as for other emerging economies seeking further economic integration with the formation of regional blocks.

First, the chapter analysed whether countries entering the EEC after its foundation permanently increased openness as the result of the economic integration process. Then, we investigated whether the impact was reflected in a permanent change in income and income growth. In the empirical analysis, we first applied a sequential structural break analysis to investigate whether these economic variables display permanent breaks at a time related to the country's date of entry into the EEC. Thus, the analysis allows us to exploit a controlled experiment of the effects of economic integration at specific times.

The sequential structural break analysis indicated that EEC membership improved openness within the EEC countries permanently. Although structural breaks in the series of overall openness are reported and showed the right sign, they are not statistically significant. The lack of significance may reflect some trade diversion or off-setting changes in third variables affecting non-EEC trade. There is some evidence of permanent effects in the series of income, with three out of six countries reporting a significant permanent change in the series of GDP in line with those in the openness series. However, the empirical results do not support permanent changes in per-capita income. Permanent changes in openness however are not reflected on permanent changes in income growth. This could be the result of other elements affecting income in the opposite direction from openness (for example, if it was the case of weak productivity growth at the time of the break). Three of the countries analysed joined the EEC at the time of the first oil crisis in the first half of the 1970s

[13]Further empirical analysis in the direction of searching for structural breaks endogenously and at the same time imposing some structure to control for common shocks would be welcome, but lies beyond the scope of this chapter.

that severely hit Western Europe. The empirical evidence does neither point to scale effects on income growth nor on income convergence as a result of economic integration. While informative, a problem with the tests for structural breaks with univariate time-series is that there may be other time-series shocks which affect countries at the same time as their entry into the EEC. To help address this concern, the next section considers a differences in differences specification which controls for common time series shocks affecting both EEC members and non-members.

Next, we investigated the differential effect of EEC membership on openness, income, and convergence for all countries within the EEC. In contrast with the structural break analysis, the differences in differences analysis controls for common time-series shocks affecting members and non-members. The difference-in-difference analysis yields similar conclusions with respect to openness. Openness among the EEC countries was improved significantly as a result of new countries entering the EEC. Both openness measures showed the expected sign, although only openness within the EEC countries was statistically significant. Openness among the EEC country members was increased with onset of membership, in line with the structural breaks results. We then study the effect of EEC membership on income levels. We find evidence of improved income for EEC countries as countries joined the EEC. Finally, we analyse whether EEC membership has an effect on the convergence process. The empirical analysis supports the idea that joining the EEC improves the convergence process, as there is a decrease in dispersion in income. Convergence to Germany, the leading economy, accelerated as a result of countries joining the EEC. The coefficient estimates associated with relative income reports the expected (negative) sign and it is statistically significant.

Table 5.1: EEC Membership

Countries	Accession Treaty	EEC membership	Break Interval	Sample Period
Denmark	January, 1972	1973	1968-78	1950-2000
Greece	May, 1979	1981	1968-78	1950-2000
Ireland	January, 1972	1973	1976-86	1950-2000
Portugal	June, 1985	1986	1981-91	1950-2000
Spain	June, 1985	1986	1981-91	1954-2000
United Kingdom	January, 1972	1973	1968-78	1950-2000

Table 5.2: Change in the Intercept in the Series of Overall Openness

Country	Z&A test[1]	T_B	$SupF_t$	k	DU_t
Denmark	-3.582	1972	2.352	3	1.118
$(t-stat)$					*(1.5336)*
Greece	-5.227**	1975	2.046	1	2.309
$(t-stat)$					*(1.4303)*
Ireland	-4.083	1972	6.374	1	9.194
$(t-stat)$					*(2.5248)*
Portugal	-4.289	1984	5.493	5	-6.478
$(t-stat)$					*(-2.3437)*
Spain	-2.541	1987	1.940	2	1.254
$(t-stat)$					*(1.3927)*
United Kingdom	-4.893**	1972	16.205***	1	4.630
$(t-stat)$					*(4.0255)*

Note: Overall Openness is defined as the ratio of total imports and exports to GDP. The ***, **, and * indicate significance levels at the 1, 5, or 10 percent respectively. t-statistics are reported in parenthesis. T_B, k, and $SupF_t$ refer to the year of the break, the degree of autocorrelation, and the Wald statistics for the sequential structural break test (Vogelsang, 1997). DU_t is the variable related to the break in the intercept, defined as $DU_t = 1$ if $t > T_B$, 0 otherwise. [1]Zivot and Andrews (1992) statistic for the unit root test versus the alternative hypothesis that the series is stationary with a structural break.

Table 5.3: Change in the Intercept in the Series of EEC Openness

Country	Z&A test[1]	T_B	$SupF_t$	k	DU_t
Denmark	-3.237	1972	6.156	5	1.699
$(t-stat)$					*(2.4811)*
Greece	-4.580*	1979	7.335*	1	2.392
$(t-stat)$					*(2.7084)*
Ireland	-3.273	1972	19.728*	3	11.204
$(t-stat)$					*(4.4416)*
Portugal	-4.932**	1990	15.522***	7	-5.921
$(t-stat)$					*(-3.9398)*
Spain	-4.935**	1986	8.841*	8	1.784
$(t-stat)$					*(2.9734)*
United Kingdom	-4.712*	1972	10.899**	6	2.881
$(t-stat)$					*(3.3014)*

Note: EEC Openness is defined as the ratio of imports and exports to the twelve countries that were members of the EEC by 1986. The ***, **, and * indicate significance levels at the 1, 5, or 10 percent respectively. t-statistics are reported in parenthesis. T_B, k, and $SupF_t$ refer to the year of the break, the degree of autocorrelation, and the Wald statistics for the sequential structural break test (Vogelsang, 1997). DU_t is the variable related to the break in the intercept, defined as $DU_t = 1$ if $t > T_B$, 0 otherwise. [1]Zivot and Andrews (1992) statistic for the unit root test versus the alternative hypothesis that the series is stationary with a structural break.

Table 5.4: Change in the Intercept in the Series of GDP (log)

Country	Z&A test[1]	T_B	$SupF_t$	k	DU_t
Denmark	-2.192	1976	3.218	4	-0.026
					(-1.7940)
Greece	-3.143	1975	3.609	3	0.070
					(1.9001)
Ireland	-4.825**	1967	8.621*	2	0.069
					(2.9360)
Portugal	-4.025	1986	23.893***	4	-0.127
					(-4.8880)
Spain	-2.854	1987	5.250	3	-0.045
					(-2.2910)
United Kingdom	-4.768*	1969	13.348***	7	0.056
					(3.6535)

Note: The ***, **, and * indicate significance levels at the 1, 5, or 10 percent respectively. t-statistics are reported in parenthesis. T_B, k, and $SupF_t$ refer to the year of the break, the degree of autocorrelation, and the Wald statistics for the sequential structural break test (Vogelsang, 1997). DU_t is the variable related to the break in the intercept, defined as $DU_t = 1$ if $t > T_B$, 0 otherwise. [1]Zivot and Andrews (1992) statistic for the unit root test versus the alternative hypothesis that the series is stationary with a structural break.

Table 5.5: Change in the Intercept in the Series of Per-Capita GDP (log)

Country	Z&A test[1]	T_B	$SupF_t$	k	DU_t
Denmark	-2.274	1976	3.021	4	-0.025
					(-1.7381)
Greece	-3.393	1975	3.362	3.	0.067
					(1.8334)
Ireland	-4.540	1967	9.811	2.	0.070
					(3.1323)
Portugal	-4.738*	1986	18.011**	4	-0.125
					(-4.2439)
Spain	-1.792	1987	5.135	3	-0.044
					(-2.2660)
United Kingdom	-3.654	1969	13.144	7	0.057
					(3.6255)

Note: The ***, **, and * indicate significance levels at the 1, 5, or 10 percent respectively. t-statistics are reported in parenthesis. T_B, k, and $SupF_t$ refer to the year of the break, the degree of autocorrelation, and the Wald statistics for the sequential structural break test (Vogelsang, 1997). DU_t is the variable related to the break in the intercept, defined as $DU_t = 1$ if $t > T_B$, 0 otherwise. [1]Zivot and Andrews (1992) statistic for the unit root test versus the alternative hypothesis that the series is stationary with a structural break.

Table 5.6: Change in the Intercept in the Series of GDP Growth Rates

Country	Z&A test[1]	T_B	$SupF_t$	k	DU_t
Denmark	-5.649***	1976	6.649	3	-1.912
					(-2.5786)
Greece	-5.571***	1985	0.536	3	-1.481
					(-0.7323)
Ireland	-6.229***	1967	4.619	1	3.524
					(2.1493)
Portugal	-4.835**	1986	9.873**	3	-5.173
					(-3.1422)
Spain	-4.794*	1983.	9.889**	8	-4.466
					(-3.1446)
United Kingdom	-4.755*	1975	2.740	6	-1.614
					(-1.6553)

Note: The ***, **, and * indicate significance levels at the 1, 5, or 10 percent respectively. t-statistics are reported in parenthesis. T_B, k, and $SupF_t$ refer to the year of the break, the degree of autocorrelation, and the Wald statistics for the sequential structural break test (Vogelsang, 1997). DU_t is the variable related to the break in the intercept, defined as $DU_t = 1$ if $t > T_B$, 0 otherwise. [1]Zivot and Andrews (1992) statistic for the unit root test versus the alternative hypothesis that the series is stationary with a structural break.

Table 5.7: Change in the Intercept in the Series of Relative GDP

Country	Z&A test[1]	T_B	$SupF_t$	k	DU_t
Denmark	-5.372***	1974	3.347	1	0.026
					(1.8295)
Greece	-5.586***	1985	2.851	2	-0.041
					(-1.6880)
Ireland	-1.515	1976	11.576**	7	0.1060
					(3.4020)
Portugal	-6.281***	1987	10.176**	2	-0.151
					(-3.1899)
Spain	-10.627***	1991	5.986	7	-0.104
					(-2.4467)
United Kingdom	-4.314	1967	3.386	2	0.048
					(1.8401)

Notes: The ***, **, and * indicate significance levels at the 1, 5, or 10 percent respectively. t-statistics are reported in parenthesis. T_B, k, and $SupF_t$ refer to the year of the break, the degree of autocorrelation, and the Wald statistics for the sequential structural break test (Vogelsang, 1997). DU_t is the variable related to the break in the intercept, defined as $DU_t = 1$ if $t > T_B$, 0 otherwise. [1]Zivot and Andrews (1992) statistic for the unit root test versus the alternative hypothesis that the series is stationary with a structural break.

Table 5.8: Differences in Differences Analysis: EEC Countries

Variable	Openness	EEC Openness	GDP	Per-capita GDP	Relative GDP
DEU_t	2.438	6.019***	0.056	0.065*	-0.068**
	(1.6216)	*(0.8080)*	*(0.0376)*	*(0.0375)*	*(0.0285)*
R^2	0.90	0.92	0.99	0.99	0.99
F-Stat	138.07	74.39	5034.13	6539.82	2268.84
Prob>F	*(0.0000)*	*(0.0000)*	0.0000	*(0.0000)*	*(0.0000)*
No. Obs.	608	608	608	608	608

Notes: DEU_t^c is a dummy equal to 1 if the country is an EEC member at time t; 0 otherwise. The differential effect of EEC membership is measured by the parameter associated to DEU_t^c, identified from differential changes in the outcome of interest pre and post dates of EEC entry for members and non-members. EEC countries refers to the 12 European countries that were members of the EEC by 1986. The ***, **, and * indicate significance levels at the 1, 5, or 10 percent respectively. Robust standard errors in parenthesis. Openness and EEC openness are defined as the ratio of overall import and exports to GDP, and ratio of EU12 imports and exports to GDP, respectively. GDP and Per-Capita GDP are defined in log terms. Relative GDP is defined as the absolute difference of the natural log of per-capita income of a country and Germany (the leading economy). Country and year dummies are included in all specifications.

Table 5.9: Differences in Differences Analysis: EEC12 Countries except those joining in 1973 (Denmark, Ireland and UK)

	Openness	EEC Openness	GDP	Per-Capita	Relative GDP
DEU_t	1.728	7.210***	0.159***	0.150**	-0.186***
	(2.1909)	*(1.0277)*	*(0.0607)*	*(0.0620)*	*(0.0328)*
R^2	0.91	0.81	0.99	0.99	0.99
F-Stat	134.34	20.97	3041.91	3400.50	2484.30
Prob>F	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*	*(0.0000)*
No. Obs.	400	400	400	400	400

Notes: DEU_t^c is a dummy equal to 1 if the country is an EEC member at time t; 0 otherwise. The differential effect of EEC membership is measured by the parameter associated to DEU_t^c, identified from differential changes in the outcome of interest pre and post dates of EEC entry for members and non-members. EEC countries refers to the 12 European countries that were members of the EEC by 1986. The ***, **, and * indicate significance levels at the 1, 5, or 10 percent respectively. Robust standard errors in parenthesis. Openness and EEC openness are defined as the ratio of overall import and exports to GDP, and ratio of EU12 imports and exports to GDP, respectively. GDP and Per-Capita GDP are defined in log terms.. Relative GDP is defined as the absolute difference of the natural log of per-capita income of a country and Germany (the leading economy). Country and year dummies are included in all specifications.

Figure 5-1: Structural Break with no Scale Effect

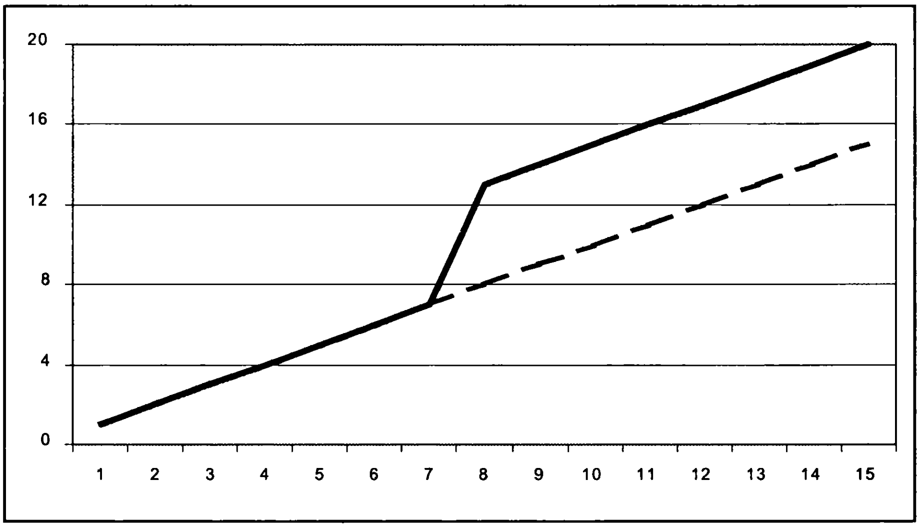
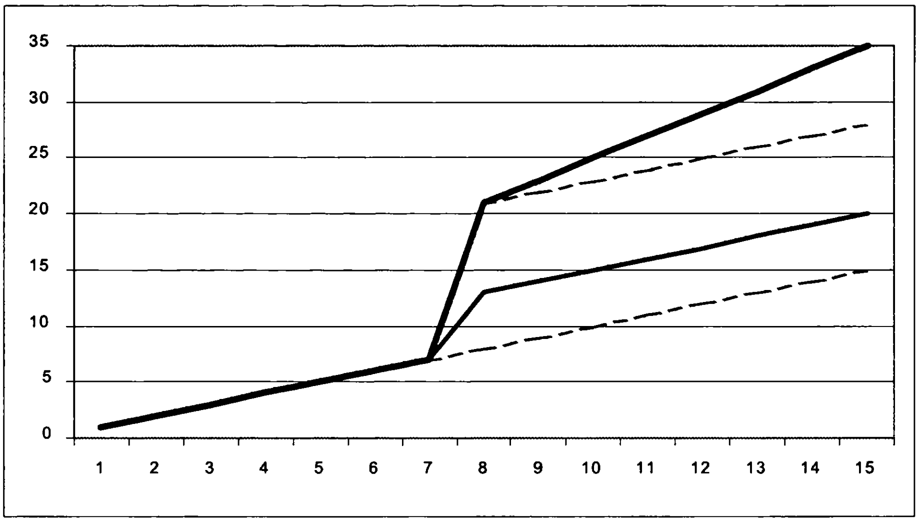


Figure 5-2: Structural Break with Scale Effects



Chapter 6

Conclusions

The primary motivation of this thesis is to understand the economic effects of European integration, with respect to both the pattern of industrial specialisation in European regions, and openness and income.

The descriptive analysis in the second chapter provides a panoramic view of patterns of specialisation at the country and regional levels. The chapter contributes to the existing literature in the following ways. First, it combines country and regional-level data to provide a detailed analysis of the evolution of patterns of specialisation in European countries. Second, in contrast to the majority of the existing literature, it uses a theory-consistent measure derived directly from the neoclassical trade theory as the basis of the analysis. Third, the dynamics of the entire distribution of the pattern of specialisation is estimated using a statistical model of distribution dynamics.

The analysis suggests, first, that regional GDP shares vary markedly. Variation is higher across regions than across countries, indicating that regions are more specialised than countries. Second, there is evidence of some variation across regions, but no evidence of major changes in the industrial structure of countries and regions over the sample period. Pairwise correlations indicate that, in general, country's patterns of specialisation are becoming more dissimilar over time, with substantial heterogeneity in the degree of similarity in specialisation at the regional level. Analysing specialisation relative to Europe, countries and regions show increasing specialisation in manufacturing industries, although specialisation patterns progress at a slow pace.

An accounting decomposition indicates that changes in specialisation at the country level are mainly due to changes in specialisation at the regional level. There is no evidence of significant between-region changes, and the relative importance of regions seems to remain fairly constant over the sample period. The results show that *within-region* changes in specialisation are more important in accounting for changes in specialisation at the country level than changes in the shares of regions in a country's overall economic activity. Regions are changing their pattern of specialisation more than countries, as the *within-region* change is typically higher in value than the total change. Changes in regional shares of GDP do play a small role in explaining changes in specialisation at the country level for the disaggregated manufacturing industries.

Finally, there is no evidence of an increase in the overall degree of specialisation over time, but of significant mobility. The analysis of the distribution dynamics indicate certain polarisation of the distribution of GDP shares towards the bottom two quintiles for most of the countries and regions under analysis. We find evidence of substantial mobility in patterns of specialisation at the country and regional levels. Mobility suggests significant changes in the patterns of specialisation. In general, regions display higher mobility in their patterns of specialisation, although differences can be found, depending on the regions and countries considered. Also, there is evidence of higher mobility in the middle quintiles and higher persistence in the extreme quintiles of the distribution at the regional level. Comparing the initial and the ergodic distribution, there is a general pattern of polarisation toward the three lowest quintiles of the distribution at the country and regional levels. Additionally, we find evidence of within-country differences in the evolution of the patterns of specialisation. Out of 45 of the regions, 31 follow a dynamic process that is statistically significantly different from the one at the country level.

Chapters 3 and 4 analyse the determinants of specialisation. Chapter 3 considers solely the role of factor endowments in explaining the patterns of specialisation at the regional level in Europe. Our main empirical findings are as follows. First, the HO model provides an incomplete explanation of patterns of production across European regions and is rejected against more general neoclassical alternatives. Second, although the HO model is rejected, factor endowments remain statistically significant and quantitatively important in explaining production structure within different neoclassical alternatives. Individual factor endowments are highly statistically significant and including information on factor endowments reduces the model's within-sample average absolute prediction error by a factor of around three in Manufacturing.

Third, the pattern of estimated coefficients on factor endowments across industries is generally consistent with economic priors regarding factor intensity. For example, physical capital endowments are positively correlated with the share of Manufacturing in GDP and negatively correlated with the shares of Agriculture and Services. Higher numbers of medium education individuals relative to low education individuals are associated with a lower share of Agriculture in GDP and a higher share of Manufacturing. Higher numbers of high education individuals relative to medium education individuals are associated with a lower share of Manufacturing in GDP and a higher share of Services.

Fourth, factor endowments are more successful in explaining patterns of production at the aggregate level in Agriculture, Manufacturing and Services (where we have three industries and either three or five factor endowments) than in disaggregated manufacturing industries (where we have 11 industries and either three or five factor endowments). Within-sample average absolute prediction errors are typically far larger in the disaggregated manufacturing industries, and this is exactly as theory would predict. In the HO model with identical prices and technology and with no joint production, patterns of production are only determinate if there are at least as many factors of production as goods. Therefore, production indeterminacy provides one explanation for larger average absolute prediction errors in disaggregated manufacturing industries. Another explanation, again consistent with the theory, could be that regional price and technology differences not controlled for in the right-hand side variables are particularly large in individual manufacturing industries. Also, economic geography considerations are not controlled for in the analysis.

Finally, we find no evidence that the process of increasing economic integration in Europe has weakened the relationship between patterns of production and factor endowments across regions within countries. Examining within-sample prediction errors for this specification reveals no systematic trend over time for either the three aggregate industries or the 11 disaggregated industries within manufacturing.

As factor endowments alone were not very successful in explaining patterns of specialisation for the disaggregated manufacturing industries, Chapter 4 incorporates economic geography into the analysis of the determinants of specialisation in the manufacturing sector across European regions. The empirical findings yield the following conclusions. First, both factor endowments and economic geography are statistically significant in explaining specialisation patterns in manufacturing industries in European regions. Parameter estimates are relatively constant across different specifications that take into account different sources of unobserved heterogeneity. Second, the estimation results are in line with economic priors. Other things being equal, regions with high education endowments would be more specialised in skill-intensive industries. Among the economic geography variables, the interaction of access to suppliers and intermediate intensity is statistically significant in explaining specialisation at the one percent level. Regions with good access to intermediate goods attract industries that are more intensive in intermediate goods. Cost linkages are more important than demand linkages. Third, our model performs well in explaining patterns of specialisation across European regions. The model's average prediction error across all disaggregated manufacturing industries, regions, and time is 13 percent, and ranges from 8 percent to 20 percent in individual manufacturing industries. Average prediction errors compare positively with those reported in Chapter 3, where the average prediction error for the same eight manufacturing industries was 58 percent from 1985-95. Furthermore, when using the estimated coefficients to evaluate predicted shares of GDP excluding information on factor endowments, economic geography, and industry characteristics; the average prediction error in manufacturing industries rises to 120 percent. Finally, prediction errors remain stable over time, not only within countries, but also across industries in our sample.

Having found that economic integration has not changed the relationship between patterns of specialisation and its determinants over time, Chapter 5 uses a more macroeconomic approach to analyse the effects of EEC membership. The analysis is divided in two sections. First, we investigate permanent effects of EEC membership. A sequential structural break analysis indicates that EEC membership improves openness within the EEC permanently. As there is no evidence of permanent effects on overall openness, it appears that EEC membership has a smaller effect on trade flows, and these effects could be obscured by changes in other variables, which is consistent with some trade diversion. There is some evidence of permanent effects on income, with three out of six countries showing a significant permanent change in the series of GDP in line with openness. Permanent changes in openness are, however, not reflected in permanent changes in income growth. This could be the result of other elements affecting income in the opposite direction from openness, e.g., if weak productivity growth were the case at the time of the break. Three of the countries analysed joined the EEC at the time of the first oil crisis, which severely affected Western Europe in the first half of the 1970s. The empirical evidence supports the existence of level effects on income, but not of scale effects on income growth nor of effects on income convergence as a result of economic integration. While informative, a problem with the tests for structural breaks with univariate time-series is that there may be other time-series shocks which affect countries at the same time as their entry into the EEC. To help address this concern, we use EEC membership as an experiment to shed further light on its effect on openness, income, and income convergence in Europe by considering a differences in differences specification which controls for common time series shocks affecting both EEC members and non-members. Therefore, in the second section, we explore the differential effects of EEC membership with a difference-in-difference analysis. In contrast with the structural break analysis, the differences in differences analysis is controlling for common time-series shocks affecting members and non-members. When differencing out the common time-series effects and focusing on the differential effects of EEC membership across countries relative to non-members, openness among the EEC countries improved significantly as a result of new countries entering the EEC, in line with the results from the structural breaks. We also find level effects on income as a result of countries joining the EEC. GDP and per-capita GDP improve significantly as countries joined the EEC. Finally, results also support the idea that joining the EEC improves the convergence process. The coefficient estimate associated to relative income reports the expected (negative) sign indicating a decrease in income dispersion relative to Germany, the leading economy, and it is statistically significant.

On the whole, we believe that this thesis makes a contribution to our understanding of the determinants of specialisation patterns at the regional level in Europe, as well as of the impact of economic integration on openness, income, and income growth. It also offers some ideas for future research.

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