Innovation, Competitiveness, and Structural Change

Essays in Empirical Economics

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Contents

Introduction

Innovation and technological change is one of the leading paradigms in modern economics (Antonelli, 2003, Freeman, 1990). After a slow start initiated by the seminal work of Schumpeter (1934, 1942), innovation economics has become increasingly popular since the 1970s, promoted amongst others by Freeman (1974) and Dosi et al. (1988). Today, research on innovation and technology is established as part of "mainstream" economics, both as independent disciplines in micro- and macroeconomics and as research topics in, for instance, environmental (Jaffe et al. 2004), financial (Carlin and Mayer, 2003), or health economics (Cutler, 2007).

In macroeconomic theory, technological change is viewed as the main driver of growth. In search of the explanations for long-term economic growth, which neoclassical theories could not fully explain, a breakthrough was made by Solow (1957) who described the residual factor (TFP) as technological change. In the following period, a large number of models have been developed to describe the mechanisms linking technological progress and economic growth (Romer, 1990, Aghion and Howitt, 1992, and Barro and Sala-i-Martin, 1997), but also illustrating the process of technological change in terms of innovation and technology diffusion (e.g. Grossman and Helpman, 1991). The speed of the process depends on the innovative capabilities of the society, which is argued to be the reason for growth differentials between countries (Fagerberg, 1994, Nelson, 2005). But economic development is not only about growth. Along with technological change and growth go changes in the production and innovation systems, consumption patterns and industry structure (as described by Sundbo, 1998, p. 109). As both countries and industries evolve over time, complex processes of structural change take place, leading to ever new and changing patterns of emergence and decline of industries, industrial specialization and re-orientation, catching-up and falling-behind of countries (see e.g. Fagerberg, 1988, Patel and Pavitt, 1995).

Microeconomic research has made large efforts investigating the sources and effects of innovation over the last decades. The understanding of innovation here is limited to industrial innovation, being the introduction of new products or production processes to the market (which dates back to Schumpeter, 1934). The basic is that firms will seek to economically exploit technological opportunities and devote resources to the generation of new products and production processes, which is mainly (but not exclusively) reached by research and development (R&D). From these innovations firms gain competitive advantage as production costs decrease, product quality or diversity rises or new markets are opened up (Dosi, 1988). But as technological knowledge can be kept secret only partly, so that other companies imitate the new products or processes, building on the innovator's efforts, and the innovators competitive advantage drops. Thus, these knowledge spillover-effects decrease the incentive to innovate (Jaffe, 1986), but at the same time lead to technological progress of the economy as a whole. Based on these principal mechanisms a broad spectrum of questions arise, such as: Why are some firms more engaged in innovation than others, subject to, for instance, market structure (Dasgupta and Stiglitz, 1980 a, b) or firm size (Scherer, 1965, Acs and Audretsch, 1988, Cohen and Klepper, 1996)? Why do some firms perform better in producing and exploiting innovations? This question relates to the organization of R&D (Aghion and Tirole, 1994) as well as to technological opportunities, path-dependencies and uncertainty (Nelson and Winter, 1982). What are the benefits of innovation, relating to indicators like profits (Geroski et al., 1993), productivity (Griliches, 1979), or firm growth (Audretsch, 1995)? What determines knowledge spillovers (Jaffe, 1986, Cohen and Levinthal, 1990), and how do these spillovers affect the firms' behavior, regarding e.g. the location near and the cooperation with other firms (Audretsch and Feldman, 1996, Cassiman and Veugelers, 2002)? And finally: Which role should public policy play given the importance of innovation combined with the risk of market failures (Martin and Scott, 2000)? Policymakers must balance the trade-off between intellectual property protection and social welfare, promote innovation without producing free-rider effects, and consider applications on research projects estimating their scientific and commercial potentials while the outcome of innovation is "per se" uncertain.

Within this wide spectrum of innovation, competitiveness and structural change, the present analysis highlights four specific questions spanning from firm-level mechanisms of innovation to the role of technological change for the development of European countries. Each of the four chapters presented in the following is a self-contained article.

Chapter 1 deals with the generation of innovations, empirically analyzing the R&D activities of German manufacturing firms. Based on representative survey data drawn from the Mannheim Innovation Panel (MIP), the German part of the European Community Innovation Survey, it examines if external R&D, i.e. R&D contracting and R&D cooperation, is a complement or rather a substitute for internal R&D. For this, in addition to the correlation of internal and external R&D conditional on a set of variables affecting the firms' innovation behavior the role of internal and external R&D for innovation output (patents and market novelties) is analyzed, using Logit and Tobit models, respectively. In the literature, there is evidence for complementarities in innovation activities, but the analysis of the innovation performance of German firms confirms these findings only partly: Internal R&D and R&D cooperation can be seen as complements while internal and contracted R&D do not significantly affect each other. The study was published under the title "Complementarities of Innovation Activities: An empirical analysis of the German manufacturing sector" in Research Policy (2008, Vol. 37(9), p. 1492-1503). Earlier versions have been presented at the Spring Meeting of Young Economists (SMYE) 2007 in Hamburg and the Conference of the European Association for Research in Industrial Economics (EARIE) 2008 in Toulouse.

Chapter 2 treats of the effect of innovation on firms' competitiveness with a focus on the relationship between innovation and export activities. It extends the general question if innovating companies have a higher propensity to export with regard to the catching-up of East German firms after German reunification in 1990. For the panel estimations of export status and export shares of German manufacturing companies in the period 1993-2003 again firm-level data drawn from the Mannheim Innovation Panel (MIP) is used. The findings indicate a strong link between innovation and export performance as well as structural differences between East and West German firms: Innovating firms and firms in West Germany are more likely to export. Moreover, West German medium technology firms are comparable in their export behavior to high tech companies while in East Germany these firms are more similar to the low technology sector. Also, labor productivity turns out to be more important in East Germany. These results are interpreted as a specialization of West German firms towards technologically driven high quality markets, whereas East German companies are faced with higher sunk costs and seem to operate more often in less dynamic, price-sensitive markets. The article is co-authored with Matthias Kirbach from the University of Ulm. It is published under the title "Innovation and Export Performance. Adjustment and remaining differences in East and West German manufacturing" in Economics of Innovation and New Technology (2008, Vol. 17/5, p. 435-457). The results have been presented at several conferences such as the Annual Meeting of the Austrian Economic Association (NOEG) 2006 in Vienna and the Conference of the EARIE 2006 in Amsterdam.

In chapter 3 the focus is on policy in the context of innovation and regional competitiveness, in special consideration on (innovation) cluster policy. Given market failures such as spillover-effects and the importance of innovation and technology, innovation policy is a frequent and - at least in principle - justified policy instrument. But the design is persistently debated, cluster policy being one possible form of it. In order to decide, however, if a policy instrument had the desired impact, empirical analyses are required, which is a difficult task in particular in the case of cluster policy. These challenges as well as the range of evaluation methods appropriate to cluster policy are discussed in chapter 3. The methodological discussion spans a wide range of techniques, from project reporting, to qualitative and quantitative impact analysis, such as econometric methods, social network analysis and input-output-analysis, to comprehensive cost-related approaches, giving advice on how to choose the appropriate evaluation method according to requirements and resources. The (single-authored) article has not been published elsewhere yet.

Chapter 4 finally shifts from the firm- to the country-level. It analyzes the development of economic structures of European Countries over the period 1970-2005, which theory considers as being considerably influenced by technological change. Building on the three-sector-hypothesis, the New Theory of Trade, and the New Economic Geography, the investigation tests for structural convergence and divergence thereby integrating inter- and intrasectoral perspectives. The results point towards significant intersectoral convergence as countries shift from agrarian and industrialized to service economies. In contrast, the results regarding intrasectoral convergence are mixed: Increasing spatial concentration in production is dominant in technology-intensive manufacturing industries which are characterized by economies of scale and path-dependency, whereas convergence is found in mature, less technology-intensive industries. In most service branches, country-specific differences do not change to a significant extent with the exception of transport and storage services which exhibit significant convergence. The article is co-authored with Nicole Höhenberger from the Karl-Franzens-University Graz. An early version of the article is published in the working paper series of the University of Göttingen with the title "Structural Convergence of European Countries" as cege discussion paper no. 75. In a revised version it is available as Graz Schumpeter Working Paper No. 4-2008. It has been presented at the conference of the European Association for Evolutionary Political Economy (EAEPE) 2008 in Rome, the Workshop for International Economic Relations 2008 in Göttingen, and the International Conference on Developments in Economic Theory and Policy 2008 in Bilbao.

Taken together, these contributions draw a picture of a steadily innovating and developing world. They are at the intersection of several schools of thought such as Industrial Organization, Innovation Economics, New Economic Geography, New Trade Theory, Evolutionary Theory, and Political Economics, treating the issues innovation, competitiveness, and structural change from different perspectives.

Chapter 1

Complementarities of Innovation Activities

An empirical analysis of the German manufacturing sector*

Abstract:
Innovation strategies in manufacturing often involve internal R&D activities as well as external partnerships. Thereby it is not clear if internal and external activities are complements or substitutes. This paper tests for complementarity of different innovation activities, i.e. internal R&D, R&D contracting, and R&D cooperation. The empirical analysis of cross-sectional firm level data of the German manufacturing sector comprises both indirect and direct complementarity tests; it is based on data from the German part of the Community Innovation Survey (CIS 3). The results provide evidence for significant complementarities between internal R&D and R&D cooperation, but cast doubt on the complementarity of internal and contracted R&D, since a productivity effect on firms' patenting probability or sales with new products cannot be found.

Keywords: Complementarities, Innovation, R&D Cooperation
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1.1 Introduction

Innovation persistently attracts the attention of both economists and politicians as a driver of competitiveness and firm performance (Lachenmaier 2007). The importance of innovation is reflected by considerably increasing innovation expenditures, observed across countries and industries: in Germany, for instance, total business R&D expenditure has risen by 54.5% in the period 1995-2004 (Stifterverband 2006); in the European Union the annual increase in this period was 3% (OECD 2007). R&D is not a perfect indicator for innovation given the existence of innovation activities other than R&D, but a large part of innovation is based on R&D (Crepon et al. 1998). However, R&D can be organized in different ways, be it in-house R&D activities, subcontracting of R&D projects or R&D cooperation with scientific institutes or other companies. Thus, innovation strategies are highly firm-specific and complex, often including both internal innovation activities and the involvement of external R&D partners (Nooteboom 1999). Policy support (e.g. European Commission 2005) is currently given in particular to partnerships in R&D due to their assumed advantages like efficiency gains due to the division of labor (Fritsch 2004), cost and risk sharing (Love and Roper 2004), the access to external knowledge or as well the control of outflowing knowledge (Cassiman and Veugelers 2002).[1] However, internal and external R&D activities are not independent from each other; they could be used as substitutes or complements in the innovation process. Both potential relationships have been investigated empirically, but conclusions are not clear cut (see literature review below).

Building upon the existing literature, this paper presents empirical evidence for complementarity of internal and external innovation activities in German manufacturing. It employs a twofold strategy, as used similarly by Cassiman and Veugelers (2002b, 2006), which comprises the search for correlation as well as for a direct productivity effect, using representative data drawn from the German part of the community innovation survey (CIS 3) in 2000. Both R&D contracting and R&D cooperation and their complementarity to internal R&D are included in order to depict a comprehensive picture of the firms' innovation strategies. To my knowledge, regarding German manufacturing only complementarities between internal R&D and R&D cooperation have been investigated substantially (Becker and Peters 2000, Love and Roper 2001), whereas the relationship of internal and contracted R&D has been tested in detail so far only on the basis of Belgian data (Cassiman and Veugelers 2002b, 2006). The case of multiple complementarities, i.e. between internal, contracted and collaborative R&D, is not considered in the analysis.

[1] The role of internal and external R&D for innovation output has been investigated comprehensively; Faems et al. (2005) e.g. examine a sample of Belgian manufacturing firms and find a positive relationship between external R&D sourcing and innovative performance, confirming prior related studies (e.g. Stuart 2000, François et al. 2002, Becker and Dietz 2002, Chang 2003, Rogers 2004, Belderbos et al. 2004). Also the link between internal R&D and innovation output is well documented (Mansfield 1981, Romijn and Albaladejo 2002, Bhattacharya and Bloch 2004).

The paper is structured as follows: After a review on the existing empirical literature and an explanation of the conceptual framework and the mechanisms that drive complementarities in R&D in the following section, the methodology to measure complementarities is explained in chapter 4. In section 5, an overview of the used data from the Mannheim Innovation Panel and the implemented variables is given. Section 6 presents and discusses the empirical results, and Section 7 finally summarizes and relates the results to prior research.

1.2 Empirical literature on complementarities

If and to what extent the complementarities assumed by economic theory exist has been discussed in the literature since the nineties. But empirical research has not come to a clear conclusion yet: A large part of the literature concentrates on the relation of internal and external R&D as input factors to innovation. In particular the influence of internal R&D on R&D cooperation has been investigated at length. So, e.g. Abramovsky et al. (2005) find a positive impact of internal R&D on the probability of R&D cooperation for four European countries, confirming prior empirical results. Arora and Gambardella (1994) analyze pharmaceutical firms in the US, Colombo (1995) the number cooperation agreements of firms in IT industries; both studies present a significant correlation between internal R&D and R&D cooperation. Similar results are reported also by Cassiman and Veugelers (2002) for Belgium, Bönte and Keilbach (2004) and Schmidt (2005) for Germany, Colombo et al. (2006) for high-tech startups in Italy, and López (2008) for Spanish manufacturing. Similarly the dependence of R&D contracting on internal R&D has been studied (e.g. Nakamura and Odagiri 2005, Dhont-Peltrault and Pfister 2007), as well as the opposite direction of causality, i.e. the influence of external linkages on internal R&D intensity (Veugelers 1997, Harabi 2002). Some authors refer to complementarity when explaining the link between internal and external R&D; however, the positive correlation between internal and external R&D does not necessarily imply complementarity of these activities.

Thus, to analyze the relationship in detail, more elaborate methods are used by a number of researchers: Analyzing data of 1,300 UK manufacturing plants, Love and Roper (1999) implement a three-step procedure which includes both the adoption of internal and external innovation activities, an endogeneity test for the input factors and the analysis of innovation output subject to innovation activities. Their results regarding the adoption of activities suggest that internal and external R&D are substitutes rather than complements, whereby they do not differentiate between R&D cooperation and sub-contracting. In addition, they show that both external R&D and the existence of a R&D department have a significant positive impact on innovation output. Conclusions on the effect of joint implementation of internal and external R&D, however, cannot be drawn from their analysis. In a later investigation, Love and Roper (2001) confirm these results for the UK and Ireland, without finding a clear substitute or complementary relationship in Germany, though. When directly testing the impact of joint implementation of internal and external R&D activities, however, R&D cooperation does not seem to have any influence on innovation output (measured as sales of new products) at all. Beneito (2006) focuses on R&D contracting, using a panel of Spanish manufacturing firms in the period 1990-1996. The results reveal a positive effect of contracted R&D when combined with internal R&D, pointing out the role of absorptive capacity. Based on the distinction between innovation types measured by patents and utility models, Beneito stresses a particular aspect of complementarity concluding that internal R&D produces rather significant innovation while contracted R&D is used for incremental innovation. Becker and Peters (2000) test the impact of university cooperations both on innovation input and output. They find a positive and significant influence of university cooperation on the intensity of in-house innovation activities as well as a complementarity effect of university cooperation and the regular conduction of R&D on patent production. R&D cooperation between firms and contracted R&D are not included in their investigation, though. Jirjahn and Kraft (2006) analyze if a firm's R&D intensity and its research cooperations are complementary regarding the production of product and process innovations and patents. They interpret their findings as a hint towards a rather substitutive relationship. Cassiman and Veugelers (2006) focus on the acquisition of external knowledge in comparison to inhouse R&D activities and find complementarities between internal R&D and R&D contracting using data from 269 Belgian manufacturing firms. They analyze both the adoption of innovation activities and the impact of the (joint) implementation of the activities on innovation output. R&D cooperation is not considered in the investigation, however.

1.3 Main sources of complementarity in R&D

According to transaction cost theory firms are confronted with a make-or-buy decision regarding R&D activities, i.e. externally available technologies are regarded as a substitute for internal R&D (Pisano 1990). Outsourcing R&D while giving up own research is argued to be a reasonable decision in order to exploit the partners' specialized knowledge and the economies of scale associated with specialization (Veugelers and Cassiman 1999). On the other hand, high transaction costs due to the complexity, specificity, and uncertainty of R&D as well as monitoring costs in order to deter leakage of knowledge might reduce the outsourcing potential of R&D activities (Brockhoff 1992). Transaction cost based literature on R&D outsourcing is quite frequent (e.g. Oerlemans and Meeus 2001, Odagiri 2003), but since the mid-90s the concurring concept of complementarity between internal and external R&D has been gaining more and more attention. A number of reasons for complementarity between different kinds of R&D activities have been mentioned in economic literature (e.g. Cassiman and Veugelers 2002b). In the context of this paper, three factors are of particular interest, which will be explicated in the following paragraphs.

A rather prominent factor is absorptive capacity, which was defined by Cohen and Levinthal (1990) as the ability to "recognize the value of new, external information, assimilate it and apply it to commercial ends" (p. 128). Their argumentation stresses learning as the second important function of R&D in addition to the (direct) production of R&D outcome (Cohen and Levinthal 1989).[2] By innovating, the involved individuals as well as the entire organization gain experience with technologies and research methods which again enables them to understand the research results produced by others. Absorptive capacity has two main implications in the context of external R&D: On the one hand, it facilitates the search for appropriate cooperation partners or R&D suppliers because it permits to appraise the potential partners' quality more easily (Nicholls-Nixon 1995, Tyler and Steensma 1998). On the other hand, absorptive capacity raises the expected outcome of external R&D projects because firms will choose more profitable R&D projects if external R&D is conducted to supplement internal R&D, i.e. to fill specific gaps regarding the existing knowledge (Haour 1992, Arora and Gambardella 1994). In addition, as absorptive capacity improves communication and coordination between internal and external R&D the firms will be more likely to complete cooperative projects successfully (Bougrain and Haudeville 2002).

As to the mechanisms of economies of scope in R&D, substantial theoretical literature exists (for an overview see e.g. Henderson and Cockburn 1996). Economies of scope are defined to exist when a single firm can produce an aggregate output at lower cost than could several firms each one specialized in one part of the output (Baumol et al. 1982). The reasons for economies of scope are sharable inputs (as shown by Panzar and Willig 1981), which may arise if research infrastructure and personnel can be used for several innovation activities. Economies of scope in R&D are in particular due to knowledge spillovers between research groups (as defined by Klette 1996), i.e. knowledge is here seen as the sharable input: Cross-fertilization between R&D projects or spillovers from one project to others might enhance the productivity of R&D. Thereby, interfirm spillovers are not limited to research groups in close contact so that also between completely independent R&D projects (Jovanovic 1993) and even across industry categories (Scott and Pascoe 1987) spillovers might occur. By assuming furthermore the possibility of intertemporal spillovers, i.e. the influence of past R&D projects on actual R&D productivity (as Klette

[2] Certainly, R&D is not the only determinant of absorptive capacity; further factors such as the qualification of the staff involved are essential, as has been pointed out e.g. by Cohen and Levinthal (1990) and Gray (2006). For an overview on the concept of absorptive capacity see Zahra and George (2002).

1996, Griliches 1979 do) the concept of economies of scope can still be broadened. The argumentation on economies of scope is valid also for multiple internal R&D projects, which have been empirically investigated by a number of studies (e.g. Henderson and Cockburn 1996, Helfat 1997, Kim et al. 2005, Miravete and Pernias 2006). But in case of the combination of internal and external R&D the spillover effect might be even stronger due to the larger pool of knowledge.

The third aspect matters only regarding R&D cooperation: Internal R&D activities may improve the attractiveness of a firm as a cooperation partner (Veugelers and Cassiman 1999, Colombo et al. 2006). In contrast to contracted R&D, which can be seen as a "normal" market transaction, R&D cooperation establishes a reciprocal relationship between the cooperating partners (Oxley 1997). A reason for the creation of R&D cooperations is the (expected) complementarity of assets, be it expected bidirectional knowledge transfer or e.g. the bargain technology vs. commercialization (Teece 1986).

Summing up these points, both types of external R&D are expected to be complementary to internal R&D, but complementarity between internal R&D and R&D cooperation should be stronger than between internal and contracted R&D.

1.4 Measuring complementarity

The concept of complementarity implies that the implementation of one activity pays off more if the complementary activity is present, too. Thus, internal and external R&D being complements means that the performance of externally sourced R&D is higher if the firm conducts internal R&D at the same time and vice versa. Complementarity can be formally expressed via supermodularity, a concept introduced by Topkis (e.g. 1998 for a recent and comprehensive version) and put forward later by Milgrom and Roberts (1995).

From this concept, a number of different empirical testing procedures can be derived (for an overview see Athey and Stern 1998). The analysis in this paper consists of two steps: First, the adoption approach based on the correlation of R&D activities, and second, the productivity approach which directly measures the innovation output respective to the innovation activities. This testing procedure has been implemented in various specifications before (e.g. Arora and Gambardella 1990, Leiponen 2005, Cassiman and Veugelers 2006).[3]

The adoption approach (step 1) is based on revealed preferences, i.e. the assumption that rationally behaving (profit maximizing) firms will adopt either both complementary activities or none of them, which implies a positive correlation between the adoption of the activities. But common unobserved factors

[3]Supermodularity can be used for analyzing multiple complementarities as well (e.g. Mohnen and Röller 2005, Belderbos et al. 2006), implying a different testing method though.

may influence the correlation so that two activities may be positively correlated without being complements or the (essentially existing) correlation may be hidden (Athey and Stern 1998). Therefore, controlling for exogenous factors that have an influence on the correlation is necessary, although the problem of further unobserved heterogeneity or measurement errors still remains.[4] The adoption of the respective innovation activities is regressed conditionally on controlling factors, given by the vector Zi:

$$R\&D\_int_i = \alpha_1' Z_i + \varepsilon_{int,i}, \quad (1.1)$$
$$R\&D\_ext_i = \alpha_2' Z_i + \varepsilon_{ext,i}, \quad (1.2)$$
$$R\&D\_coop_i = \alpha_3' Z_i + \varepsilon_{coop,i}. \quad (1.3)$$

$R\&D\_int$, $R\&D\_ext$, and $R\&D\_coop$ stand for the firm's decision to adopt internal or contracted R&D or R&D cooperation, respectively. The error terms ε_i are assumed to be jointly normally distributed with mean zero and the variance-covariance-matrix Σ.[5]

Positive pair-wise correlation between the error terms of the regressions would imply a complementary relationship. Note that we are interested only in correlation between internal and contracted R&D and between internal R&D and R&D cooperation.

The productivity approach (step 2) is a direct test for supermodularity via the regression of innovation output on internal and external R&D. The following estimation equations are implemented (separately):

$$Inno_i = \alpha_{10}\, R\&D\_int_i + \alpha_{01}\, R\&D\_ext_i + \alpha_{11}\, (R\&D\_int_i R\&D\_ext_i) + \beta' Z_i + \varepsilon_i, \quad (1.4)$$
$$Inno_i = \alpha_{10}\, R\&D\_int_i + \alpha_{01}\, R\&D\_coop_i + \alpha_{11}\, (R\&D\_int_i R\&D\_coop_i) + \beta' Z_i + \varepsilon_i (1.5)$$

The innovation output of a firm i ($Inno_i$) depends on its own innovation input, $R\&D\_int_i$ and external R&D activities ($R\&D\_ext_i$ and $R\&D\_coop_i$, respectively). The vector Z_i includes other firm and industry specific factors as control variables. Complementarity here is expressed by the interaction term of both variables ($R\&D\_int_i R\&D\_ext_i$). The usage of interaction terms is equivalent to the construction of exclusive dummies for implementing one or both innovation activities, which can be found in the literature frequently (e.g. Leiponen 2005, Cassiman and Veugelers 2006). For approving the complementarity condition, the coefficient of the interaction term has to be significantly larger than zero. A significant and negative coefficient would be a sign for submodularity and thus for the two innovation activities being substitutes.

[4] A model which accounts for unobservable heterogeneity has been developed by Miravete and Pernías (2006).

[5] Variances in Σ equal one; the focus of the complementarity test is on the covariances σ_{12}, σ_{13}, neglecting σ_{23}, since complementarity between R&D contracting and R&D cooperation is not considered.

1.5 Data and model

The analysis presented in this paper makes use of data from the Mannheim Innovation Panel (MIP), a representative survey of the German manufacturing and service sectors targeting companies with five or more employees. The MIP regularly is the German part of the European "Community Innovation Survey" (CIS), which focuses on firms' innovation behavior according to the OECD recommendations published in the OSLO Manual (OECD/Eurostat 2005, Janz et al. 2001). The survey is conducted annually since 1993 comprising data on about 3000 companies each year. As firms' cooperation activities are not reported in all years, in this study only the 2001 survey is used, which for the manufacturing sector comprises data on about 2000 companies. It provides information on the firms' innovation activities during three years preceding the survey, i.e. during the period 1998-2000. For our analysis the sample is restricted to innovating firms, i.e. firms that have a R&D budget or stated to have performed activities in order to develop new products or processes in the three years preceding the survey. If innovation activities have been successful does not matter. After excluding further observations due to missing data a sample of 689 innovating companies remains in the dataset.

Innovation is represented in the data set by several variables, including both input and output measures. According to the OSLO-Manual, innovation is defined as "implemented technologically new products and processes and significant technological improvements in products and processes" (p. 31), excluding organizational changes as well as minor or aesthetic improvements. Innovation input is measured by R&D personnel and R&D expenditures of innovating firms as well as by variables specifying the firms' innovation activities (e.g. R&D cooperation, having a R&D department). Three of these variables are used in the first step of the analysis to examine correlations regarding the adoption of innovation activities; in the second step they are included as explanatory variables. Firms were asked in the survey about their innovation expenditures in the preceding two years and about the type of innovation activities. The answers were used to construct the binary variables (internal R&D, contracted R&D and R&D cooperation) which indicate if a firm performed internal, cooperative or contracted R&D, respectively. These variables have some drawbacks: On the one hand, data is only available on the firm instead of project level so that R&D activities might be jointly observed in multi-project companies without being necessarily complementary (Veugelers and Cassiman 1999). On the other hand, the use of binary variables allows only for a rough distinction of R&D activities without considering the scale of the activities. Alternative variables such as the number of cooperation agreements or R&D expenditures have been used in the empirical literature, too (e.g. Arora and Gambardella 1990, Colombo and Garrone 1996). But assuming differences between e.g. cooperating and non-cooperating firms to be more important than marginal changes in expenditures, a binary distinction seems adequate. Taking into account this binary structure, for the regression of innovation activities on common controlling factors as described in equations (1.1)-(1.3) a Logit model is implemented; i.e. a (logistically distributed) latent variable RD^* is estimated, which can be interpreted as the propensity to implement a specific innovation activity in our case, and from this the observable binary choice on the activity RD is derived:[6]

$$RD_i^* = \beta' Z_i + \varepsilon_i,$$
$$RD_i = \begin{cases} 1 \; if \; RD_i^* > 0, \\ 0 \; if \; RD_i^* \leq 0. \end{cases}$$

The estimations are run for each of the three innovation activities, i.e. RD stands for *internal R&D*, *contracted R&D* and *R&D cooperation*, respectively. Estimating the three equations separately will lead to inefficient (though consistent) estimates if the adoption of R&D activities is not independent from each other. Therefore, a multivariate Logit model is used which accounts for the correlation of error terms. The correlation of the error terms of these estimations (i.e. the conditional correlation) is interpreted as a hint towards complementarity of the innovation activities.

The control variables regarding the firms' innovation behavior (i.e. the variables contained in vector Z_i in the equation above) are displayed in table 1.1, which indicates also in which step of the investigation (1 = adoption approach, 2 = productivity approach) the respective variables are included.

The first group of control variables concerns information sources used for innovation. In the survey, the firms were asked to indicate the importance of twelve potential information sources on a Likert scale. The variable *market information* contains the rating of customers, suppliers and competitors as information sources, while *scientific information* includes universities and scientific institutes. To construct the composed variables the values of the information sources were added and the scores rescaled to a number between 0 and 1. The rating of information sources provides an indicator of the importance of incoming spillovers, which are expected to increase the probability of external R&D strategies (Cassiman and Veugelers 2002).

The variables on mechanisms to protect intellectual property, *legal protection* and *strategic protection*, are used to capture the appropriability conditions. Firms were asked to rate the importance of seven measures to protect intellectual property, but only if they used the respective measure. The answers to the two groups of protection mechanisms are added and normalized. In contrast to strategic protection mechanisms which are assumed to depend on the firms' assets and management, legal and market characteristics which affect appropriability are expected to be rather industry specific; therefore, industry averages of legal protection are used in the estimations. In general, good appropriability conditions are expected to have a positive impact on the firms' innovation activities, since they enable the firms to exploit the returns to R&D investments (Spence 1984).

The two variables on barriers to innovation are derived from the companies' ratings as well: The surveyed firms had to rate the importance of nine factors as barriers to innovation on a Likert scale. These ratings were combined to three barriers to innovation: The factors "excessive perceived risk", "too high innovation cost" and "lack

[6] For a more detailed description of the estimation models see e.g. Greene (2003), p. 666 (Logit) and p. 764ff (Tobit).

Table 1.1: Variable definitions

Variable	Definition	Step
internal R&D	binary: 1 if a firm performed internal R&D activities	1, 2
contracted R&D	binary: 1 if a firm performed contracted R&D activities	1, 2
R&D cooperation	binary: 1 if a firm participated in a R&D cooperation	1, 2
patent	binary: 1 if a firm applied for a patent in the period 1998-2000	2
newprod	Sales share of new products (in relation to total turnover)	2
market info	Importance of information from other companies (customers, suppliers, or competitors)	1
scientific info	Importance of information from scientific research	1
legal protection	Importance of legal mechanisms to protect intellectual property (e.g. patents) – industry level variable	1
strategic protection	Importance of strategic mechanisms to protect intellectual property (e.g. secrecy)	1
financial barriers	Importance of financial barriers to innovation (high innovation costs, lack of financial resources, high risk)	1
organizational barriers	Importance of lack of qualified personnel, organizational difficulties, internal resistance as barriers to innovation	1
external barriers	Importance of external barriers to innovation (legal, market demand)	1
high-skilled staff	Share of employees holding a university degree (in relation to total employment)	1, 2
size-s, *size-m*, *size-l*	Size classes according to firm employment: size-s 5-49 employees, size-m 50-249 employees, size-l 250 employees and more	1, 2
low tech, medium-low tech, medium-high tech, high tech	Technology classes according to OECD industry ranking (see table A.1 in the Appendix)	1, 2
East Germany	binary: 1 if a firm is located in East Germany	2
export intensity	Export share in relation to total turnover	2
industry	13 industry dummies (2-digit-NACE-classification)	2

of appropriate resources of finance" have been combined to the variable *financial barriers*, whereas the variable *organizational barriers* combines the factors "organizational problems within the firm", "lack of skilled personnel", "lack of information on technology", and "lack of information on markets". Legal factors ("legislation, norms, regulations, standards, taxation") and the statement "customers unresponsive to new products and processes" have been combined to the factor *external barriers*. The values have been added up and normalized to the interval [0; 1]. Several studies using CIS data include variables on barriers to innovation, classifying them in differing ways, though (e.g. Cassiman and Veugelers 2006, Love and Roper 1999, Peeters and van Pottelsberghe de la Potterie 2006). The three composite variables control for differences in the innovativeness of firms, and shed light on the motives of R&D activities: Financial barriers may increase the probability to adopt external R&D due to the motive of cost and risk sharing; in contrast, organizational and external barriers to innovation are expected to lower the probability of conducting either type of R&D.

As an indicator of absorptive capacity the variable *high-skilled staff* is included that measures the share of employees holding a university degree. The underlying assumption is that academic staff is required for R&D activities, in particular in case of external R&D; high-skilled workers might be more able e.g. to cooperate with scientific institutes due to lesser cognitive distance (Nooteboom et al. 2007). In addition, the share of academic personnel can be considered as a hint regarding the technological level of the firms' innovation activities.

Basic control variables used in both steps of the investigation are firm size and industry. Economic sectors are included according to the two-digit NACE classification. Besides, industries are classified according to their technology intensity based on the OECD industry ranking on sector average R&D expenditures between 1991 and 1999 (OECD 2003). In high-tech sectors both a higher probability of adopting either innovation activity and a higher innovation output (in particular regarding patenting) is expected; according to the short product lifecycle in some industries, such as telecommunications and IT, also the percentage of revenue realized with innovative products is expected to vary across sectors. An overview on the industries included as well as the technology classification is given in table A.1 in the Appendix.

To control for firm size, size classes are included, which differentiate between small firms with less than 50 employees, medium large firms with 50-249 employees and large companies with 250 and more employees. The interrelation of firm size and innovation output has long been discussed (e.g. Cohen and Klepper 1996): often it is found that R&D spending increases with size, while R&D productivity tends to decrease. R&D productivity is not the focus here, but still size differences regarding the innovation output are likely: For larger firms the probability to have at least one patent is expected to be higher. In contrast, the smaller a firm's product range the more likely is a high sales share of a new product; as the product range tends to grow with firm size a higher sales share of market novelties might be found rather in case of small than large innovators.

Regarding the second step of the analysis which measures the impact of innovation activities on innovation output, two innovation indicators are used as dependent variables. In the dataset, information is available regarding patent applications and the turnover generated with new products.

The binary variable on patent applications (*patent*) does not count the number of patents of a company but only indicates if it applied for patents at all, since differences between patenting and not patenting firms might be more important than marginal effects of additional patents. The use of patent data has some drawbacks: The variable does not specify the technological value of the patents as long as no additional information such as the number of patent citations is included (Lanjouw and Schankerman 2004). Patenting is not equivalent to innovating: Minor inventions might be patented whereas firms may use other strategies to protect intellectual property, e.g. secrecy instead of patenting, so that even high-value inventions might not be patented. The extent of patenting activities is industry-specific (Arora 1997), and in particular depends of the firms' individual innovation strategies (Peeters and van Pottelsberghe de la Potterie 2006). Furthermore, it is objected that patents should not be seen as innovation output but rather as input factor to innovation (Faems et al. 2005). Nevertheless the use of patent data is a generally accepted proxy for innovative activities (Kleinknecht et al. 2002, Griliches 1990, Acs and Audretsch 1989). As the patenting variable is binary, for the estimations a standard Logit model is implemented, similar to the model illustrated above.

The economic value of innovations is captured by the variable *newprod* which measures the revenue generated by new products in relation to total turnover. New products are defined here as market novelties, i.e. products which are totally new to the respective market. The rating if a product is new to the market has to be made by the companies in the questionnaire, so that a certain degree of subjectivity cannot be ruled out. Instead of new products sales, often the share of turnover generated with innovative (i.e. technologically new or improved) products is used (e.g. Faems et al. 2005, Mohnen and Röller 2005, Mairesse and Mohnen 2002), which can be seen as a related, but less strict version of sales of market novelties, though. As many companies do not have market novelties and hence report no new products sales the variable is evidently censored at zero. To account for this a Tobit model is estimated, which considers both the distinction between firms with and without new products and the economic success of the new products given by their sales shares.

$$
\begin{aligned}
newprod_i^* &= \beta' \, Z_i + \varepsilon_i, \\
newprod_i &= \begin{cases} newprod_i^* & if\ newprod_i^* \geq 0, \\ 0 & if\ newprod_i^* < 0. \end{cases}
\end{aligned}
$$

Central independent variables in the second step are the firms' innovation activities (*internal R&D*, *contracted R&D* and *R&D cooperation*) which have been used also in the first step of the analysis (see above). For the complementarity test, the interaction terms of internal R&D with contracted R&D and R&D cooperation, respectively, are included.

Control variables in the second step should account for firm specific differences regarding innovation output given the innovation activities. This is in particular the share of *high-skilled staff* which is included also in the first step of the analysis, and the firm's export orientation, measured as *export intensity* (in relation to total turnover). As before, the share of academic personnel is regarded as a hint on the firms' technological level, so that a higher share should imply a higher patenting probability. The positive impact of exports on innovation output, however, may be due to international spillovers as exporting firms get access to foreign knowledge sources (Castellani and Zanfei 2007). Furthermore, the larger market of exporting firms implies both greater opportunities to exploit innovation profits and a higher imitation potential which should both lead to higher patenting activity (Peeters and van Pottelsberghe de la Potterie 2006).

Besides, differences between East and West Germany are taken into account. One decade after the German Reunification it can still be expected that firms in East and West Germany might behave differently regarding their innovation activities,

Table 1.2: Descriptive statistics

Variable	**sample mean**	**s.d.**
internal R&D	0.735	-
contracted R&D	0.355	-
R&D cooperation	0.330	-
patent	0.369	-
newprod[1]	0.112	0.169
Importance of information sources:[2]		
market information	0.573	0.228
scientific information	0.240	0.271
Importance of protection mechanisms:[2]		
legal IP protection	0.188	0.233
strategic IP protection	0.375	0.336
Barriers to innovation activities:[2]		
financial barriers	0.587	0.275
organizational barriers	0.386	0.230
external barriers	0.333	0.259
East Germany	0.324	-
large firms	0.279	-
medium-sized firms	0.368	-
small firms	0.354	-
high tech sector	0.307	-
medium-high tech sector	0.308	-
medium-low tech sector	0.176	-
low tech sector	0.209	-
Total observations	689	

[1] *in relation to total turnover;* [2] *0 = not important, 1 = very important.* *Source: MIP 2001*

East German firms achieving less innovation output. In the 90s, East German firms started from a rather low technological level (e.g. Smolny 2004) and as building up innovative capabilities takes time (Henderson and Cockburn 1994) they may not yet have reached the West German standards. Thus, a dummy variable *East Germany* indicating firms located in East Germany is included in the regression.

An overview of the sample distribution of the variables is given in table 1.2. As only innovating companies are included in the sample, the high percentage of firms with internal R&D activities is not surprising. Also external R&D activities are rather common: 35.5% of the observed firms report contracted R&D, 33% R&D cooperation. 36.9% of the companies applied for a patent in the observed period. The revenue share generated with new products is on average 11.2% of the total turnover, with a rather high standard deviation, since a considerable number of companies do not have any products totally new to the market.

Barriers to innovation are rated moderately important, factors related to cost and

Table 1.3: (Conditional) correlation between internal and external R&D

	internal R&D	*internal R&D* (conditional)
contracted R&D	0.313 ***	
R&D cooperation	0.253 ***	
contracted R&D (conditional)		0.173 ***
R&D cooperation (conditional)		0.121 ***

**** significant at 1%.*

risk of innovation being most important. Regarding the importance of information sources for innovation, the higher value of other companies compared to scientific institutions is remarkable. Notable as well is the more important role of strategic protection mechanisms in contrast to legal methods such as patenting. This finding, which is in line with previous studies (e.g. Schmidt 2005), reveals again the challenge of finding the right innovation indicator, since companies might avoid patent applications for strategic reasons. As to the distribution on size and technology classes, the sample seems balanced, the majority of firms belonging to high or medium-high technology industries, which should be due to the focus on innovating companies.

1.6 Empirical results

Table 1.3 presents the pair-wise correlation of the adoption of R&D activities (i.e. correlation between the variables internal R&D, contracted R&D and R&D cooperation) as well as the conditional correlation of the residuals obtained from regressions on control variables like firm size, information sources and barriers to innovation. The estimation results of these control regressions are shown in table 1.4 below.

It can be seen from table 1.3 that a significant correlation between internal and external R&D exists. The correlation is smaller when introducing control variables (see the conditional correlation in the right column of table 1.3), but still remains at a significant level. Interestingly, the internal R&D and R&D contracting are correlated more closely than internal R&D and R&D cooperation. This is opposite to the hypothesis mentioned above that R&D cooperation is more complementary to internal R&D than R&D contracting. However, as has been explained above, correlation is only a first hint towards complementarity.

In table 1.4 the impact of the control variables on the adoption of the three innovation activities is shown. Differences between internal R&D, contracted R&D and R&D cooperation exist, but as expected many variables have a similar impact on either of the R&D activities. All in all, the results are in line with related studies on the adoption of R&D activities (e.g. Cassiman and Veugelers 2002, Bönte and Keilbach 2004, Nakamura and Odagiri 2005, Lopez 2008).

Significant and positive coefficients are found regarding the importance of information from universities and research institutes, influencing both internal R&D, R&D contracting and R&D cooperation, the coefficient being notably higher in case of

Table 1.4: Regression results for the choice of innovation activities

dep. var.	*internal R&D*		*contracted R&D*		*R&D cooperation*	
scientific information	1.445	***	2.578	***	2.955	***
	(0.536)		*(0.389)*		*(0.390)*	
market information	0.552		-0.352		-0.525	
	(0.484)		*(0.455)*		*(0.444)*	
legal IP protection	10.707	**	-0.280		5.632	
	(4.886)		*(4.595)*		*(4.430)*	
strategic IP protection	1.680	***	0.939	***	1.395	***
	(0.346)		*(0.305)*		*(0.295)*	
financial barriers	0.549		-0.050		1.045	***
	(0.439)		*(0.405)*		*(0.390)*	
Organizational barriers	-0.079		0.328		-0.897	**
	(0.502)		*(0.485)*		*(0.445)*	
external barriers	-0.037		0.266		-0.040	
	(0.430)		*(0.416)*		*(0.394)*	
high-skilled staff	0.154	***	0.175	***	0.171	***
	(0.059)		*(0.054)*		*(0.054)*	
size-m	0.214		0.765	***	0.667	***
	(0.227)		*(0.240)*		*(0.226)*	
size-l	0.576	**	1.566	***	0.721	***
	(0.293)		*(0.271)*		*(0.259)*	
medium-low tech	0.171		0.307		-0.010	
	(0.297)		*(0.338)*		*(0.346)*	
medium-high tech	-0.308		0.121		-0.132	
	(0.566)		*(0.608)*		*(0.592)*	
high tech	-0.391		0.431		-0.235	
	(0.672)		*(0.659)*		*(0.637)*	
intercept	-2.644	***	-3.237	***	-4.071	***
	(0.606)		*(0.595)*		*(0.583)*	
Observations	689		689		689	
Log likelihood	-315.69		-337.46		-361.85	
LR chi^2 (13)	148.23	***	189.93	***	241.67	***
Pseudo R^2	0.190		0.220		0.250	

**** (**, *) significant at 1% (5%, 10%); s.e. in parentheses.*

the external R&D activities. In contrast, the importance of other companies, i.e. suppliers, customers and competitors, as information sources does not change the probability of internal or external R&D. In general, the variables on information sources are interpreted as the degree of incoming spillovers (e.g. Cassiman and Veugelers 2002, Lopez 2008), but from the difference between the two variables a further aspect becomes evident: Firms relying on scientific information can be seen as specialized in technologically advanced topics; in these fields it is more important for firms to conduct either type of R&D, and in particular external R&D.

As information from universities and scientific institutes is more basic and technology oriented relying on scientific information can be seen as a hint on technological opportunities and the firms' absorptive capacities. Thus, firms specialized in technologically advanced topics and firms with high absorptive capacities will be more likely to conduct either type of R&D, and in particular external R&D.

As regards appropriability a positive impact is found: The importance of *legal IP protection* has a significant and positive impact on internal R&D, whereas *strategic IP protection* significantly increases the probability of all R&D activities. This is in line with prior studies (e.g. Cassiman and Veugelers 2002, Nakamura and Odagiri 2005, Lopez 2008) and confirms the importance of appropriability conditions on the decision to innovate.

The variables on barriers to innovation are not significant regarding internal and contracted R&D. Only the probability of R&D cooperation is significantly influenced by *financial* and *organizational barriers*, the former having a positive, the latter a negative impact. This confirms the hypothesis of cost and risk sharing as reasons for R&D cooperation (Lopez 2008), and on the other hand it shows that internal organizational capacities must be adequate to allow firms to cooperate.

The share of *high-skilled staff* significantly increases the probability of R&D. This confirms that the workers' qualifications are crucial for the firm's ability to conduct R&D (François et al. 2002). In addition, human capital is important for the firm's absorptive capacity which in turn will increase the probability of external R&D activities.

Finally, the basic control variables: Firm size is significant and positive as expected, whereas technology classes do not prove significant. This finding points out that the innovation strategy a firm adopts does not depend on the industry-level of technology intensity but rather on firm-specific characteristics which affect the incentives and ability to innovate.

The results of the second step of the investigation, i.e. the productivity approach are presented in the following. Tables 1.5 and 1.6 show the results of the complementarity test, both for R&D contracting (1) and R&D cooperation (2) in connection with internal R&D. Table 1.5 displays estimations which use the patent dummy as endogenous variable, whereas in the regression shown in table 1.6 the sales share realized with new products is used as dependent variable.

Regarding innovation output measured by firms' patenting activities, no complementarity between internal and contracted R&D is found. Performing internal or

Table 1.5: Regression results for innovation output (patents)

dep. var.: *patent* (0/1)	(1)			(2)		
internal R&D	0.639	**	*(0.287)*	0.513	*	*(0.276)*
contracted R&D	1.091	**	*(0.543)*			
R&D cooperation				0.277		*(0.532)*
internal & contracted R&D	0.137		*(0.576)*			
internal R&D & R&D cooperation				1.071	*	*(0.570)*
size-m	0.490	**	*(0.228)*	0.407	*	*(0.226)*
size-l	1.408	***	*(0.260)*	1.561	***	*(0.253)*
medium-low tech	1.094		*(0.697)*	1.260		*(0.765)*
medium-high tech	1.536	**	*(0.756)*	1.450	**	*(0.707)*
high tech	2.169	***	*(0.719)*	2.058	***	*(0.713)*
export intensity	1.024	***	*(0.370)*	0.992	***	*(0.372)*
high-skilled staff	0.136	**	*(0.055)*	0.094	*	*(0.055)*
East Germany	-0.473	**	*(0.209)*	-0.439	**	*(0.210)*
intercept	-4.257	***	*(0.704)*	-3.913	***	*(0.686)*
industry dummies	incl.			incl.		
Observations	689			689		
Log likelihood	-387.00			-390.71		
LR chi^2 (13)	280.30	***		280.47	***	
Pseudo R^2	0.266			0.264		

**** (**, *) significant at 1% (5%, 10%); s.e. in parentheses.*

contracted R&D significantly raises patenting probability, as evident by the significant coefficients of *internal R&D* and *contracted R&D*, but joint implementation (*internal & contracted R&D*) does not have any significant additional impact.

In contrast, internal R&D and R&D cooperation seem to be complementary as the significant and positive interaction term (*internal R&D & R&D cooperation*) shows. Doing only *internal R&D* is significant as before, but noticeably the coefficient of the interaction term is twice as big as the coefficient of *internal R&D* (alone). *R&D cooperation* (alone) is insignificant, which is in line with the hypotheses mentioned in section 3. But this coefficient should be interpreted with care since in the sample the number of firms having R&D cooperations without internal R&D is small (see table A.2 in the Appendix).

Coefficients of the control variables are similar in both regressions: Size and technology classes are significant, showing that large firms and firms in more technology intensive industries are more likely to apply for a patent. Also the hypotheses regarding export intensity and high-skilled staff are confirmed; the higher a firms export intensity and the higher the share of academic personnel, the higher is its patenting probability (similar e.g. to Jirjahn and Kraft 2006). As well, the dummy *East Germany* is significant, having the expected negative sign.

Compared to the patenting probability regressions, the estimations of the share of

Table 1.6: Regression results for innovation output (sales of new products)

dep. var.: *newprod* (0/1)	(1)			(2)		
internal R&D	1.975	***	*(0.425)*	2.162	***	*(0.425)*
contracted R&D	0.738		*(0.999)*			
R&D cooperation				0.061		*(0.895)*
internal & contracted R&D	-0.081		*(1.033)*			
internal R&D & R&D cooperation				-0.012		*(0.946)*
size-m	-0.298		*(0.349)*	-0.180		*(0.347)*
size-l	-0.870	**	*(0.408)*	-0.653		*(0.397)*
medium-low tech	-1.860	**	*(0.729)*	-1.750	**	*(0.733)*
medium-high tech	0.302		*(0.760)*	-1.571	*	*(0.915)*
high tech	0.116		*(0.796)*	0.096		*(0.800)*
export intensity	1.300	**	*(0.612)*	1.500	**	*(0.613)*
high-skilled staff	0.220	***	*(0.083)*	0.261	***	*(0.084)*
East Germany	-1.022	***	*(0.327)*	-1.008	***	*(0.327)*
intercept	-0.968		*(0.680)*	-1.168	*	*(0.693)*
industry dummies	incl.			incl.		
Observations	689			689		
Log likelihood	-1273.04			-1294.23		
LR chi^2 (13)	140.62	***		133.92	***	
Pseudo R^2	0.052			0.049		

**** (**, *) significant at 1% (5%, 10%); s.e. in parentheses.*

revenue generated with new products, which are presented in table 1.6, are quite different: The only R&D activity which significantly affects innovation output is *internal R&D*, while both *contracted R&D* and *R&D cooperation* are not significant. Furthermore, the complementarity between internal R&D and R&D cooperation found in table 1.5 is not confirmed.

Results regarding the control variables are similar in both regressions and do not differ largely from the above mentioned findings. They point out the impact of export intensity and high-skilled personnel on innovation output, but interestingly, size differences and technology classes do not show the expected pattern; firms in high-tech industries do not realize a significantly larger share of sales with new products than in low-tech industries. In contrast, companies in medium-low technology industries have a significantly lower share of new products sales. The negative and significant coefficient regarding East Germany again shows the differences between East and West Germany.

1.7 Conclusion

The ongoing debate if internal and external R&D activities are complementary production factors in the innovation process reveals the difficulties to provide unambiguous evidence for the existence of complementarities. Empirical findings are inconsistent, depending on the data base and the research method employed. This paper adds to the existing literature on this topic by presenting results of the analysis of data from 689 German manufacturing firms, drawn from the Mannheim Innovation Panel (MIP), the German part of the Community Innovation Survey (CIS 3) in 2000. A standard approach is implemented which includes a correlation test regarding the adoption of internal and external R&D activities as well as the analysis of productivity effects of the joint implementation measured by the interaction terms of the respective R&D activities.

The results of the analysis are twofold: A complementary relationship between internal R&D and R&D cooperation can be confirmed, since both tests yield positive results. The two innovation activities are positively correlated (even after controlling for common influencing factors) and the productivity of each activity increases if the other one is performed, too. The latter finding is significant regarding the probability of patenting, but not for the share of revenue which is realized with new products.

This is in line with the literature: Becker and Peters (2000) obtain results similar to the present ones; they report complementarity between internal R&D and R&D cooperation when focusing patenting behavior, but regarding sales shares of new products the existence of complementarities is not confirmed. Also Cassiman and Veugelers (2002b) reject the complementarity hypothesis based on the analysis of sales shares generated by new products. And Love and Roper (2001) do not find any influence of external (both contracted and collaborative) R&D on innovation success when analyzing the sales shares of new products in UK, Ireland and Germany. Sales shares of new products do not seem to be a comprehensive indicator of innovation output; however, differentiating respective to the cooperation partner (as e.g. Belderbos et al. 2004 and Roper et al. 2006 do) might lead to interesting results also with respect to complementarities.

As regards the relationship between internal and contracted R&D, the evidence for complementarity is rather weak – and contrasts prior findings reported in the literature. A significant and positive correlation is found, but the productivity effects of the joint implementation are insignificant. This means, firms which conduct internal R&D are more likely to contract R&D, and vice versa, but doing the one type of R&D does not make the other more valuable. So, instead of complementarity other (unobserved) underlying factors may cause the correlation.

The insignificant results on internal and contracted R&D are in contrast to Cassiman and Veugelers (2006) who find a clear complementary relationship between "make" and "buy" in innovation. As they use a similar methodology and comparable data (with focus on Belgium instead of Germany), this difference is remarkable. A reason for it could be found in country-specific conditions which affect the firms' innovative behavior. The organization of production in Germany is little flexible and innovation strategies are oriented rather towards continual, incremental innovation (e.g. Culpepper 1999, Love and Roper 2004), which might lead to a less market responsive focus of external innovation strategies (Roper 1997).

Summing up, a straightforward conclusion cannot be drawn. What is more, the differences between the results of existing studies cast some doubt on the robustness of empirical findings on complementarity highlighting their sensitivity to model specification and measurement. Hence, future research could concentrate on a more appropriate and precise measurement of innovation input and output; as well project level investigations or analyses of the country-specific conditions of innovation could be promising.

Chapter 2

Innovation and Export Performance

Adjustment and remaining differences in East and West German manufacturing*

Abstract:
The economic situation in Germany 16 years after reunification is marked by the fading out of the adjustment process between East and West. This paper refers to this context analyzing the export behavior comparing firms in West and East Germany. Our estimates confirm a strong relationship between innovations and export performance as well as structural differences between East and West German firms. East German firms are less likely to export than firms in the West. Besides, West German medium technology firms are comparable in their export behavior to high tech firms while East German firms are more similar to the low technology sector. Labor productivity turns out to be more important in East Germany. We interpret these findings as a specialization of West German firms towards technologically driven high quality markets, whereas East German companies are faced with higher sunk costs and seem to operate more often in less dynamic, price-sensitive markets.

Keywords: Innovation, Export, Manufacturing firms, Microeconometrics
JEL-No.: C21, F14, O12, O31

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2.1 Introduction

In order to understand economic differences between East and West Germany, the situation and the development over the last sixteen years have to be considered. After reunification in 1990, the convergence process seemed to be a great success. Starting from a rather low level, the East German economy developed dynamically. But in the mid-nineties the catching-up process has come to a standstill, leaving an unfavorable economic situation: Unemployment is higher, productivity is lower than in West Germany, and East German firms' weak export performance suggests a shortcoming of competitiveness compared to the West German economy.

One of the currently most popular credos in economics and economic policy bears on the crucial role of innovation on competitiveness, progress and economic prosperity of firms and regions. The argumentation runs as follows: First, firms can create a specific competitive advantage through innovation because of the cumulative nature of innovation and innovatory capabilities. Innovating companies generate and accumulate knowledge and increase their capabilities, both regarding their innovative assets and their human capital. Second, innovations have a long-term impact on spillover effects. Third, in the case of process innovations there are benefits in terms of cost reduction which in turn make firm price competitive. Innovation, like the introduction of new products, generates potential monopoly rents and reveals in case of product innovations. Wakelin (1997) states: "Innovation is considered as a characteristic which fundamentally changes the firm and its performance, including the firm's export performance." The logical extension is to consider the relationship between innovation and export performance.

Our paper refers to these aspects in the convergence discussion of East and West Germany. We analyze the importance of innovations on export behavior of manufacturing firms in Germany and their development during the last decade. We explore the impact of innovation on trade performance of German firms from an empirical perspective. Therefore, our contribution is twofold: On the one hand, we focus on the general question how firms' export behavior depends on their innovative attitude, or to put it differently, whether more innovative firms are more likely to export or exhibit higher export shares. On the other hand, we study the catching-up process of the East German industry and the assimilation of East and West Germany with respect to the companies' export activities. For the empirical analysis we use data of German manufacturing from 1993 to 2003 from the Mannheim Innovation Panel (MIP) which are provided by the Center for European Economic Research (ZEW).

The paper is structured as follows: Section 2 illustrates the theoretical framework of the determinants of export activity and briefly overviews the existing literature on innovation and exports. Section 3 develops the economic model and its econometric implementation and presents descriptive statistics of export behavior in East and West Germany. Section 4 presents the results of Probit and Tobit estimations. Section 5 summarizes and concludes.

2.2 Conceptual framework

2.2.1 Determinants of export activities

In order to analyze the impact of innovation activities on export performance at the firm level, a differentiated view of innovation activities is essential. Firms innovate in order to reduce costs or to increase demand. The first point is straightforward in that a drop in production costs means an advantage in price competition. The second aspect is that innovation permits a differentiation strategy, which provides an innovator with a competitive advantage regarding product features or product quality. Hence, the company will realize monopoly profits until its competitors catch up by innovating or imitating. Assuming that conditions for operating profitably on international markets are harder than on the home market, the effects influence the export behavior of a company. On the one hand, cost competitiveness is of special interest on international markets where an exporting company has to bear sunk costs and variable costs, like transport costs. Consequently, only the more productive and more innovative firms are able to overcome these costs and make profits in the export markets (Roberts and Tybout 1997). On the other hand, product quality competition is not hindered by national borders so that a company's competitive edge also exists on international markets enhancing its export performance. The two aspects of innovation can roughly be assigned to these two types of innovation: Cost reduction is achieved by using process innovations, while differentiation is realized via product innovations. Yet, typically product and process innovations are linked to each other, since a newly developed product often requires new production technologies, which in turn may or may not change production costs.

Apart from this reasoning, several comprehensive international trade theories including innovation as an explaining factor exist: Starting from Posner's (1961) technological gap theories, product lifecycle models by Vernon (1966), and the North-South-model by Krugman (1979), the neo-technology-approach characterizes innovations as the main reason for international trade. As innovations diffuse more rapidly within the economy than internationally, firms are able to keep their competitive advantage in foreign trade rather than on national markets. Therefore, innovators tend to be engaged internationally in order to exploit the monopoly rents stemming from innovation. The lifecycle concept cannot only be applied to products, but also to product groups and especially to industrial sectors. From this consideration the industry lifecycle illustrates the development of sectors over stages of rise, maturity and decline that industries pass through. Product innovations combined with strong efforts in R&D are of major importance in young and rising industries (Cassiman and Martinez-Ros 2004), whereas process innovations and productivity gain weight in later stages with dominant price competition. Industrialized countries with high wages and a skilled labor force have competitive advantages in emerging industries rather than in mature sectors' price competition. Consequently, product innovations and R&D are more important in developed countries, or to put it more generally, in regions which are specialized in high technology sectors, whereas productivity and process innovations prevail in less developed regions.

This is the connecting factor to differences between East and West Germany. Soon after reunification, the former German Democratic Republic was less developed than West Germany regarding both technological and economic aspects. In the following years the adjustment process has abated the differences, but has not eliminated them completely to this day. Differences in technology should be visible with respect to East and West German companies' export activities, too. After the economic breakdown at the beginning of the nineties in East Germany, export activities were low for a number of reasons: On the one hand, the former trade partners in Eastern Europe had broken away, and international networks and brand awareness had not been established yet. On the other hand, East German manufacturing lagged behind technologically, while having higher unit labor costs and lower productivity, which rendered the products hardly competitive. The catch-up process changed the situation significantly, but still the economic structures of East and West Germany differ: East German companies tend to be smaller, younger and more specialized in different branches than West German firms. Furthermore, the average productivity of firms located in East Germany is still lower than in West Germany, which might explain their weak export performance. The geographic location in relation to Western Europe as Germany's main trading partner, is less favorable for East German firms.

The latter point, location, plays an important role for export performance for various reasons: First, a firm's location determines its transportation costs, so that companies located near the main foreign markets or in regions with developed railway and road networks are more likely to export (Ebling and Janz 1999). Second, location counts for regional spillovers which foster knowledge and technology diffusion as well as export activities. Knowledge spilling over from neighboring companies increases a firm's capabilities to innovate, thus firms which are part of regional innovation clusters are expected to be more competitive. Exports of clustered firms might be enhanced by greater innovation efforts due to technology spillovers, but also by network and branding effects. Acting in an export-oriented geographical area allows firms to get in touch with foreign trade partners easily, for example through regional cooperation partners or local trade fairs. Consequently, it is not surprising that East German firms have disadvantages in entering international markets.

2.2.2 Empirical evidence

Substantial studies analyzing the relationship between export and innovation have been published in recent years. One of the first contributions stems from Hirsch and Bijaoui (1985) who observed that the intensity of research and development positively influences changes in export performance, using data of 111 R&D conducting companies in Israel. Later studies mainly supported their findings of a positive relationship between export and innovation, for example Brouwer and Kleinknecht (1996) for the Netherlands, Zhao and Li (1997) for China, and Gourlay and Seaton (2004) for Great Britain. In addition, Brouwer and Kleinknecht (1996) emphasize that product innovation, in contrast to process innovation, is relevant for trade performance. Schlegelmilch and Crook (1988), and Landesmann and Pfaffermayr (1997) do not report positive results regarding the relationship of R&D and export performance. Wakelin (1998), and Verspagen and Wakelin (1997) even find negative effects of research and development activities on export behavior in certain sectors, such as small enterprises and some high technology sectors.

Considering these seemingly contradictory results, it is argued that indicators such as R&D expenditure, which was used as measure in most studies, do not capture innovation efforts properly. Thus, several authors started using more sophisticated innovation variables. Lefebvre and Bourgault (1998) do not report positive effects of R&D intensity on export activities while some other indicators like the share of scientific employees or external R&D cooperation proved to be significant. Bernard and Jensen (2004) analyzed 13,550 US-American firms and found that larger and more productive companies exhibit a higher probability of exporting and that the introduction of a new product increases export performance. Furthermore, Castellani and Zanfei (2007) state differences between exporters and non-exporters regarding productivity as well as R&D intensity and innovation performance.

Export and innovation in Germany have been discussed in several studies. Arnold and Hussinger (2005) focus on the influence of productivity, but on R&D expenditure and on the market share of new products as well. They find a positive relationship between exports and innovation activity. Roper and Love (2001), comparing German and British firms, report a strong positive impact of product innovations both on the probability to export and export shares, but a negative relationship between R&D intensity and the probability to export for the sample of German firms. Lachenmaier and WÄo$\frac{1}{4}$mann (2006) analyze the effects of promoting or impeding export activities using data of 981 companies in 2002. Their results support the hypothesis that larger and more innovative firms tend to export more. However, although these studies took into account the structural differences between East andWest Germany, mostly via dummy variables, none of them focused on the question why East German firms perform worse than West German companies.

2.3 Data and empirical specification

2.3.1 Empirical model and variables

Testing the effect of innovation activities on export success, we use a common empirical model that defines the export behavior of a firm as a function of its innovation activity, a vector of firm characteristics, and its location in East Germany:

$$Export = f(Innovation, Characteristics, East)$$

Several measures of export activity have been tested in empirical studies. Our investigation uses two different variables: First we implement a dummy variable that equals one if a firm exported in the observed period, to get an idea about what determines the *probability of exporting*. Second, we use *export intensity*, which is measured as the ratio of exports to the total revenue, in order to test the robustness of our results and to get differentiated insights into the firms' export behavior. For the purpose of analyzing firms entering export markets we construct a third variable (*starters*) which indicates if a firm starts exporting in the observed period. This reduces the number of observations drastically because we include only firms which took part in the survey at least in two consecutive years. The binary variable equals one if a firm exports in period t but did not export in the previous period $t - 1$. In contrast, starters takes the value zero if a firm does not export either in year t or in year $t - 1$. Firms that export in both years are excluded from this sample.

As we focus on the role of innovation efforts, we include indicators measuring both input and output of the innovation process that are assumed to perform differently. According to the OSLO-Manual (see OECD and Eurostat 1997), a firm is defined as innovating if it implements technologically new products and processes or significant technological improvements in products and processes. Products do not have to be novelties on the market, which means imitative development activities are included in this classification of innovation, too. We use two dummy variables $InProd$ and $InProc$ to indicate if a firm implemented new or improved products or processes, respectively, during the last three years. Product innovations are seen as more important and are thus expected to have a stronger influence on export than process innovations. Regarding differences between East and West Germany, we expect process innovation to be more and product innovation to be less important for East German than forWest German firms. Our assumption is that firms inWest Germany operate mainly in high technology sectors and provide technologically developed products, while East German firms more often serve low quality markets with fierce price competition. Thus, higher coefficients of product innovations are expected for the West rather than for the East German sample and vice versa for process innovations.

A shortcoming of dummy variables on innovation activities is that the quality and the technological level of innovations are not considered. Taking this into account, we include an additional variable $R\&D$ measuring the intensity of research and development activities, expressed as the ratio of R&D expenditures on total sales. We expect $R\&D$ positively to correlate with both export probability and export intensity. As innovation activities are costly, they may produce financial constraints that may lead to a trade-off between innovation and export activities (see Roper and Love 2001). Which effect prevails depends on the level of R&D conducted. To account for this, the squared term of R&D intensity, $R\&D^2$ is used, which allows for a nonlinear relationship between export and R&D.

Besides innovation and technology, firm size is generally expected to be one of the main factors driving export activities (see Lefebvre and Lefebvre 2001), since larger companies have easier access both to internal and external financial resources as well as adequate organizational capacities required for international success. Economies of scale, lowering export costs of larger companies, may play an important role as well. Controlling for firm size, we classified small $(size-s)$, medium $(size-m)$ and large $(size-l)$ companies, which have less than 50, from 50 to 249, and 250 and more employees, respectively. In particular, small East German firms might face large difficulties entering foreign markets, as they are less linked to international networks and have less trade experience.

Regarding firms' competitiveness, productivity seems to be crucial for export success. Exporting implicates additional costs such as sunk costs for the market entry, transaction costs etc. Consequently, a firm will be more likely to come up with these costs, the higher its productivity and thus the lower its production costs are. The relationship between productivity and exports is shown by a range of empirical studies. (For an overview see Arnold and Hussinger, 2005.) Controlling for differences in productivity, we include a variable of labor productivity (LP) which is expected to have a positive effect on exports, in particular in the East German sample. As productivity may be influenced by several factors such as technological progress, inflation, market concentration, the direct measure (turnover per employee) cannot be used. Assuming that differences between branches exist, we prefer a transformation of this variable: we measure labor productivity relative to the average in industry and year. This method does not require any deflation and accounts for structural differences between industries. The interpretation of the variable is straightforward: A value close to one means that the firm's productivity is equal to the industry average in the observed year; values higher or lower than one indicate a higher or lower labor productivity, respectively.

Both innovation and export behavior varies between sectors, thus dummy variables controlling for sectors are included. In addition, we use a technology-based classification which refers to the OECD industry ranking based on sector average R&D expenditures between 1991 and 1999 (see OECD 2003, and Hatzichronoglou 1997). Higher ranked industries exhibit higher R&D expenditures per value added and higher R&D expenditures per production. With respect to this heterogeneity, we divided industries into four technology classes: The high technology sector (*high tech*) contains branches like electronics, and communications engineering, chemical and pharmaceutical industry. The medium high technology sector (*med-high tech*) includes branches like machinery, motor vehicles and aeronautical engineering as well as rubber and plastics products. In the medium-low technology class (med-low tech) non-metallic mineral and glass industries are included. Finally, food, beverages, tobacco, textiles, wood and paper industries are classified as low technology branches (*low tech*); low technology firms were used as the reference value. For a description of branches and technology classification see Appendix, table B.1.

Analyzing the development of East and West German firms in comparison we use a panel technique of pooled cross-sectional data. We present estimations both for the whole sample and for East and West Germany separately, analyzing the period from 1993 to 2003. Within the convergence process after reunification, the differences between East and West Germany are assumed to decrease, i.e. both the coefficient of the dummy variable East, indicating if a company is located in the Eastern or Western part of Germany, and the differences between the separate estimations for East and West Germany should be smaller in 2003 than in the previous years.

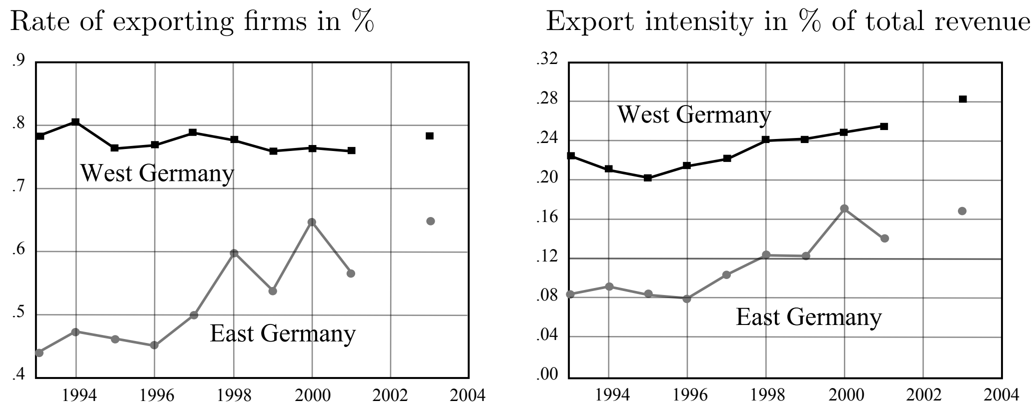
Regarding the causality between innovations and exporting, both directions have been discussed by economic theory: One might argue that experience in foreign trade enables a company to conduct more research and development and to draw greater benefits from it (learning-by-exporting). On the other hand, firms increase their innovation efforts in order to enter foreign markets, and only excellent companies in terms of innovativeness and technological level have the ability to succeed in international trade. By focusing on innovation output during a certain period before the observed year, we test the hypothesis that innovating makes a firm more able to export, not vice versa. But the problem of endogeneity still persists. One common way to correct this bias of endogeneity is the use of a two-stage instrumental variables procedure. However, as it is well known, it seems difficult to create an effective set of instruments. This procedure requires the availability of variables which affect the endogenous variables without directly affecting exports. The lack of credible instruments renders the results very sensitive to the choice of the variables, which casts some doubts on the usefulness and efficiency of this approach. In our opinion, the importance and influence of the potential biases by endogeneity should be seen in relation to the estimation problems stemming from the instrumental variable method.

The problem of heteroskedasticity occurs in empirical analyses as well. The coefficients are consistent, but the standard errors are biased. Therefore, we present heteroskedasticity consistent estimates by Huber and White.

2.3.2 Descriptive statistics

Our analysis uses micro data from the Mannheim Innovation Panel (MIP), a representative survey of the German manufacturing sector provided by the ZEW (Center for European Economic Research). The MIP is the German part of the European "Community Innovation Survey" (CIS), which focuses on firms' innovation behavior according to the OECD recommendations published in the OSLO-Manual (see Janz, Ebling, Gottschalk, and Peters 2002). Starting in 1993, the survey is conducted annually, though the panel is unbalanced, i.e. there is some variation due to companies' closing down and the integration of newly founded firms. Moreover, the questionnaire changes from time to time so that not all variables are available for each year. For the survey, up to 11,000 companies are contacted, the response rate being about 20-25%. The data set used in this paper covers about 12,500 observations for a period of 11 years, 1993-2003, which corresponds to the years 1992-2002. For the analysis, an unbalanced panel of about 8,700 manufacturing firms in West and about 3,900 firms in East Germany is used. Firms from Berlin are excluded.

Figure 2.1: Export behavior of firms in West and East Germany



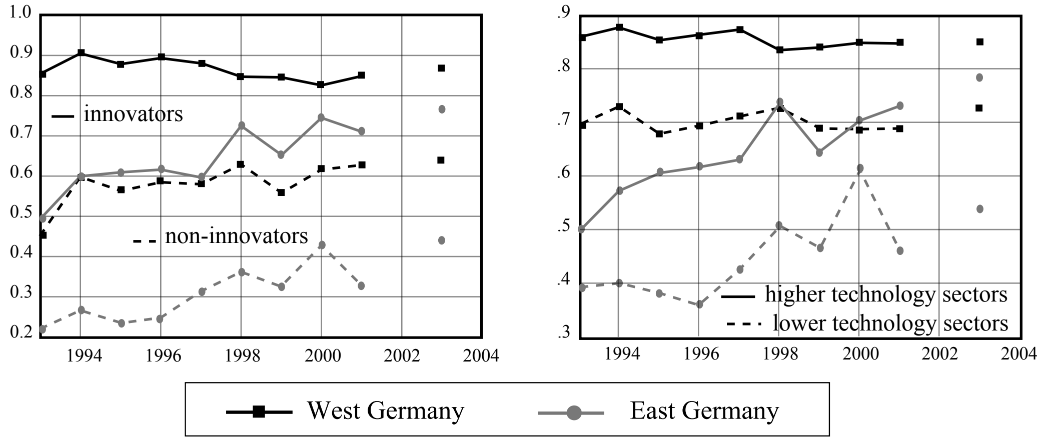
Source: MIP 1993-2003
Data for 2002 is not available.

As the left graph in figure 2.1 indicates, the share of exporting firms in West Germany remains roughly constant over time. The development of East German companies' export behavior describes a contrary picture: In 1993 only 45% of the companies exported their goods to international markets. Over the observed period the share of exporters rose from 45 to 65 percent in 2003, leaving a gap to West German firms' export activities of which export amounts to nearly 79 percent. This increase confirms the rising international competitiveness of East German firms. The right graph of figure 2.1 describes the development of export intensity (share of exports in relation to the total revenue) of firms in East and West Germany over the observed period. Export intensity depicts a similar structure. For both East and West an increase in exports is visible, and as expected, the development is stronger for the East German sample. Thus, a stable convergence process from East towards the high Western export level is visible for the whole period.

Export behavior of innovators and non-innovators is shown in the left panel of figure 2.2. Structures are similar in both parts of Germany: Innovators are more orientated towards foreign markets than non-innovators, though relative participation of the latter in exporting has been rising since 1997. This is a first hint towards innovation activities influencing export probability and performance of a firm. In the East German sample, differences between innovators and non-innovators are slightly larger. In particular, East German innovators show a higher export share than West German non-innovators. So, innovating seems to pay off for East German firms.

Figure 2.2: Innovativeness and export behavior

Innovator vs. Non-Innovator Technology classes



Rate of exporting firms in percent

Source: MIP 1993-2003

Data for 2002 is not available.

Industry structure in East and West differs as West Germany is dominated by firms operating in high tech branches whereas East Germany is characterized by a more or less equal distribution of the branches regarding their technological level (see table 2.1). As the right panel of figure 2.2 shows, firms in high technology sectors are more often engaged in foreign markets than lower technology industries.[1] The strong international orientation of higher technology sectors of western firms is visible as well as the increasing export

[1]For a better illustration higher (high tech and medium-high tech industries) and lower (low and medium-low) technology classes are differentiated in this figure.

Table 2.1: Characteristics of firms in East and West Germany

Variable	**West**			**East**		
	1993	1997	2003	1993	1997	2003
Exporter (yes/no)	0.80	0.85	0.79	0.45	0.57	0.65
Export intensity (if exporter)	0.23	0.23	0.28	0.09	0.11	0.17
Innovator (yes/no)	0.84	0.72	0.65	0.81	0.69	0.64
Product innovator (yes/no)	0.80	0.69	0.57	0.74	0.65	0.59
Process innovator (yes/no)	0.67	0.59	0.38	0.66	0.52	0.39
Innovation intensity (if innovator)	0.07	0.03	0.04	0.15	0.04	0.05
R&D expenditure	0.02	0.02	0.02	0.03	0.02	0.03
Labor productivity (turnover/employee)	0.26	0.29	0.30	0.13	0.20	0.22
Sales in m Euro	396.0	237.3	198.2	48.6	34.7	25.3
Low tech in %	18.8	21.8	25.3	24.7	28.5	24.5
Medium-low tech in %	17.9	19.8	19.5	22.5	26.0	23.4
Medium-high tech in %	37.3	34.7	29.3	32.8	26.0	25.8
High tech in %	26.1	23.6	25.8	20.1	19.5	26.3
Small size firms in %	30.6	32.8	40.1	45.6	50.5	53.0
Medium size firms in %	27.7	33.6	30.7	39.7	40.0	35.2
Large firms in %	41.7	33.6	29.2	14.7	9.6	11.7

Source: MIP 1993-2003, own calculations

behavior of higher technology firms in the East: In 1993 about 50 percent of these firms exported, whereas in 2003 more than 78 percent did so. This supports our hypothesis regarding export advantages of the German high tech industry. Whereas the gap of lower technology sectors between East and West German firms still persists at a high level. Considering the hypothesis that larger firms and firms operating in high tech sectors are more likely to export, the described differences of East and West German industry structures should explain at least partly Eastern companies' backlog regarding their export activities.

Table 2.1 summarizes some further characteristics of firms in East and West Germany. Labor productivity is higher in West than in East German firms. Obviously, there is an upward motion in both parts of Germany, as well as an adjustment between East and West. In 2003, the average revenue per employee is about 300,000 Euro for West German companies, and 220,000 e for East German firms. But as the convergence process faded out in the mid-nineties, the productivity gap persists. Moreover, firm size structure between East and West Germany differs: Firms in the West are larger. In 2003, about one third of the West German firms employ 250 and more people, whereas in East Germany large firms amount only to about 12 percent.

Finally, the high innovation intensity (measured as the share of innovation expenditures in relation to the revenue) of firms in East Germany at the beginning of the observed period is notable. This reflects the high investments for catching-up in the first years after reunification when East German firms were marked by outdated technology. In this context, massive subsidies and transfers from the federal government have flowed into the East German economy.

2.4 Empirical results

At first, we model the decision to export and firms' export intensity analyzing the determinants of export behavior in Germany. Second, we separate our sample into two sub samples, regarding East andWest Germany in order to focus on the question why East German firms perform worse. In a third step, we take into account that a firm's export activities probably depend on its prior export experiences. We restrict our sample on firms which started exporting in the observed period - with regard to differences between East and West Germany. In order to test for significant differences between East and West German firms, we run Wald tests.

Results regarding the (binary) export decision are shown in table 2.2, including both coefficients and marginal effects for each model. We present two versions of the model: First, with respect to the heterogeneity of the different branches, we estimate a regression including all industries (rows (1) and (2)). Second, to test the comparative advantages of higher technology industries on export and for a more generalized view, we use four technology classes (rows (3) and (4)).

Interesting differences between product and process innovation are visible in the regression results (see columns (1) and (2)). As expected, product innovation has a significant impact on the probability to export, which indicates that firms with new or improved products are more able to succeed in international competition. The impact of process innovations is negative and not significant. The low significance stems from multicollinearity between product and process innovations, since the production of new products often requires changes in production processes. If the product innovation dummy is excluded from the regression, process innovations gain significance though remaining negative. R&D expenditures have a significantly positive effect on export probability which points out the comparative advantage of technologically developed firms. $R\&D^2$ has the expected negative sign and is strongly significant as well.

Firm size variables show that larger firms are more likely to export. Especially the coefficients of small firms (with less than 50 employees) show a lower export probability in comparison to the reference group (-19.2% compared to medium sized firms). This is in line with the hypothesis that a minimum size is required to enter foreign markets. Furthermore, labor productivity increases the probability to export significantly. If a firm rises its labor productivity

Table 2.2: Panel estimations for Germany 1993-2003, Probit

endogenous variable: export probability (0/1)

	(1) coeff.		(2) marg. eff.		(3) coeff.		(4) marg. eff.	
constant	**0.359**	(0.073)			**0.235**	(0.071)		
InProd	**0.334**	(0.038)	**0.093**	(0.011)	**0.329**	(0.038)	**0.092**	(0.011)
InProc	-0.210	(0.035)	-0.005	(0.009)	-0.008	(0.035)	-0.002	(0.009)
R&D	**22.323**	(1.445)	**5.759**	(0.365)	**21.928**	(1.434)	**5.685**	(0.364)
R&D^2	**-131.275**	(10.055)	**-33.870**	(2.547)	**-128.091**	(9.979)	**-33.208**	(2.541)
size-s	**-0.684**	(0.317)	**-0.192**	(0.010)	**-0.674**	(0.031)	**-0.190**	(0.010)
size-l	**0.361**	(0.043)	**0.087**	(0.010)	**0.344**	(0.043)	**0.083**	(0.009)
LP	**0.210**	(0.026)	**0.054**	(0.007)	**0.199**	(0.025)	**0.052**	(0.007)
med-low tech					0.036	(0.039)	0.009	(0.010)
med-high tech					**0.422**	(0.039)	**0.102**	(0.009)
high tech					**0.253**	(0.043)	**0.062**	(0.010)
sector 2	**-0.139**	(0.049)	**-0.038**	(0.014)				
sector 3	**-0.136**	(0.054)	**-0.037**	(0.015)				
sector 4	0.098	(0.067)	0.024	(0.016)				
sector 5	**0.404**	(0.060)	**0.088**	(0.011)				
sector 6	**-0.373**	(0.065)	**-0.111**	(0.021)				
sector 8	**0.273**	(0.051)	**0.065**	(0.011)				
sector 9	0.015	(0.060)	0.004	(0.015)				
sector 10	**0.251**	(0.066)	**0.058**	(0.014)				
sector 11	0.106	(0.073)	0.026	(0.017)				
East 1993	**-0.842**	(0.074)	**-0.282**	(0.029)	**-0.854**	(0.074)	**-0.288**	(0.029)
East 1994	**-0.928**	(0.087)	**-0.317**	(0.034)	**-0.935**	(0.086)	**-0.321**	(0.034)
East 1995	**-0.726**	(0.091)	**-0.239**	(0.035)	**-0.725**	(0.091)	**-0.240**	(0.035)
East 1996	**-1.041**	(0.142)	**-0.365**	(0.056)	**-1.035**	(0.140)	**-0.363**	(0.055)
East 1997	**-0.712**	(0.080)	**-0.234**	(0.030)	**-0.721**	(0.079)	**-0.238**	(0.030)
East 1999	**-0.532**	(0.073)	**-0.166**	(0.026)	**-0.537**	(0.073)	**-0.168**	(0.026)
East 2000	-0.208	(0.138)	-0.059	(0.042)	-0.223†	(0.137)	-0.063y	(0.043)
East 2001	**-0.519**	(0.082)	**-0.162**	(0.029)	**-0.516**	(0.081)	**-0.161**	(0.029)
East 2003	**-0.321**	(0.078)	**-0.094**	(0.025)	**-0.329**	(0.077)	**-0.097**	(0.025)
Time dummies	**incl.**		**incl.**		**incl.**		**incl.**	
Mean dep var	0.825		0.825		0.823		0.823	
Observations	12,569		12,569		12,569		12,569	
Log likelihood	-5,233.06		-5,233.06		-5,261.47		-5,261.47	

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

by one percent, the average marginal effect reaches 5.4%. Controlling for the different branches, the coefficients confirm the heterogeneity with respect to export probability. The stable and consistent effect of technology classes is remarkable (see columns (3) and (4)): firms operating in the lower technology sectors exhibit a lower probability to export than firms in higher technology classes. Surprisingly, medium-high tech industries show a higher export probability than firms in the high tech sector. This reflects the particular strength of the German economy regarding branches like machinery and aircraft industries, which seem to be more competitive and export-orientated than the high technology sector.

The strong negative but decreasing coefficients for East Germany over the observed period are noticeable, indicating that firms in East Germany are less likely to export than firms in West Germany. These differences were expected, as well as the decreasing disadvantages of being located in East Germany. In the year 2003, the marginal effect takes the value of 9.4%, so East German firms still seem to have problems keeping up with West German companies.[2] The convergence regarding the export probability is still in progress.

As a robustness check of our estimations we ran Tobit estimations in order to analyze the impact of innovation on export intensity (see table B.2). All in all, the results confirm our findings. There is a strong positive influence of R&D and product innovation, firm size and productivity. Industries also seem to differ regarding their export intensity, those in medium high tech sectors exporting the most. The export gap between East and West German firms, which we observed in the Probit estimations, is visible for export intensity, too.

A more detailed picture regarding differences between East and West Germany is drawn in tables 2.3 and 2.4, where we report results for East and West sub samples.[3] As corporate with the results for the whole sample, the constant is lower for East Germany. The basic probability to export (expressed by the constant) is significant and strongly positive for firms situated in West Germany, while the coefficient in the East German sample is significant and negative. In other words, the probability of being an exporter is significantly lower for East than for West German companies.

Looking at table 2.3, product innovation has a clear positive impact on the probability to export in both samples, being more important in East than in West Germany. Differences also exist regarding process innovation although due to multicollinearity with product innovation the coefficients are insignificant in the presented tables. We interpret these findings as a sign that East

[2] The coefficients and marginal effects of the even years should be interpreted with care, as only a few numbers of observations are available.

[3] We ran Wald-Tests in order to test the disparity between East and West Germany (see table B.2 and B.3 in the Appendix). The results show that although coefficients converge, equality is not reached yet.

Table 2.3: Panel estimations for East and West Germany 1993-2003, Probit
endogenous variable: export probability (0/1)

	(West 1)		(West 2)		(East 1)		(East 2)	
	coeff.		marg. eff.		coeff.		marg. eff.	
constant	**0.346**	(0.082)			**-0.772**	(0.092)		
InProd	**0.297**	(0.049)	**0.061**	(0.011)	**0.388**	(0.062)	**0.151**	(0.024)
InProc	-0.054	(0.046)	-0.010	(0.008)	0.037	(0.054)	0.014	(0.021)
R&D	**24.542**	(2.129)	**4.594**	(0.380)	**20.431**	(1.973)	**7.861**	(0.757)
R&D^2	**-154.460**	(15.032)	**-28.916**	(2.703)	**-112.783**	(13.473)	**-43.395**	(5.172)
size-s	**-0.718**	(0.042)	**-0.159**	(0.011)	**-0.627**	(0.047)	**-0.239**	(0.018)
size-l	**0.346**	(0.052)	**0.061**	(0.009)	**0.306**	(0.078)	**0.113**	(0.027)
LP	**0.154**	(0.031)	**0.029**	(0.006)	**0.301**	(0.046)	**0.116**	(0.018)
med-low tech	0.087†	(0.052)	0.016†	(0.009)	-0.015	(0.062)	-0.006	(0.024)
med-high tech	**0.443**	(0.050)	**0.077**	(0.008)	**0.397**	(0.062)	**0.148**	(0.023)
high tech	**0.227**	(0.055)	**0.040**	(0.009)	**0.307**	(0.067)	**0.115**	(0.024)
time dummies	**incl.**		**incl.**		**incl.**		**incl.**	
Mean dep var	0.891		0.891		0.606		0.606	
Observations	8,666		8,666		3,903		3,903	
Log likelihood	-3,053.29		-3,053.29		-2,193.13		-2,193.13	

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

German companies can improve their international standing through innovation more than West German firms, i.e. by innovating they can recoup disadvantages and gain on their West German counterparts. The strong and positive influence of R&D expenditure on export activities is significantly higher in East than in West Germany. The higher impact of R&D on exports in East Germany may indicate large differences between technologically advanced firms with high R&D expenditures, which are likely to export, and firms on a lower technological level which are not. In contrast, West German business strategies and main characteristics of R&D intense and non-R&D conducting firms seem to be more similar.

Also, the impact of firm size is stronger in East than in West Germany. Both the export advantage of large firms and the small firms' lag are larger in the East German sample. Firms with less than 50 employees have a 23.9 percent lower probability to export whereas in West Germany the difference is only 15.9 percent. These results point out the strong position of West German small and medium companies on international markets. The size differentials which are more distinct for the East German sample are also remarkable. This is a further hint towards the higher entry costs that East German firms might face, caused for example by the lack of international networks, a less favorable regional location or poor international business experience.

The results regarding labor productivity are similar, seeing that it is found to increase the probability to export. Export activities of West German firms are in- fluenced to a lesser degree by labor productivity than those of East German firms. Having a look at the wave-specific estimates in table B.3 and B.4, we can analyze the development of this variable over the observed period. Labor productivity of West German firms is insignificant and negative for the first years, but positive and significant since 1997. In the East German sample the coefficients are positively significant over the whole period and higher throughout than for West German firms. One explanation might be that East German firms are faced by higher costs, like transport costs due to less favorable location or transaction costs due to lower integration into Western European markets. Particularly sunk costs, e.g. costs for market testing, should play a major role for East German companies. In order to bear these additional costs, low production costs and thus higher productivity are essential. Besides, the result points towards West German firms having particular strengths in branding and quality competition, which East German companies seem to lack.

For the analysis of industry-specific differences, we included the technology sector classification that has been introduced and compared to industry dummies above. The estimations reveal the traditional strength ofWest German firms in the medium-high technology sector. A different result arises for East Germany: Differences are by far lower than in the West German sample, showing two clear cut groups. Firms in low and medium-low technology sectors have the same probability to export, and firms in the two upper technology classes feature nearly the same export probability.

¿From this point of view, it seems that East German companies are more able to exploit their competitive advantages in high-tech industries resulting e.g. from a technological lead position, branding or cluster effects. The traditional strength in medium high tech industries, which is found for West Germany, is less distinct.

The results of our Tobit estimations confirm our findings drawn from the Probit estimations (see table 2.4). The lower impact of product innovations in East as compared to West Germany attracts attention. In order to increase export probability, product innovations are more important in East Germany, but once exporting, West German firms profit more from product innovations than East German companies. In contrast, R&D expenditure is more important for export intensity in East than in West Germany. This finding leads to our conclusion that the quality of innovation in East and West Germany differs, as East German firms might be more often engaged in imitating product innovations while West German firms rather develop new products.

The final step of our analysis reduces the data set to firms which started exporting during the observed period. Therefore, only companies which participated in the survey at least twice in two consecutive years are included in order to assess which factors influence the entry to international markets. The results

Table 2.4: Panel estimations for East and West Germany 1993-2003, Tobit
endogenous variable: export intensity

	(West)		(East)	
constant	-0.008	(0.013)	**-0.197**	(0.021)
InProd	**0.079**	(0.008)	**0.067**	(0.014)
InProc	-0.009	(0.007)	-0.015	(0.012)
R&D	**3.513**	(0.258)	**4.110**	(0.409)
R&D^2	**-18.240**	(1.895)	**-19.486**	(2.758)
size-s	**-0.147**	(0.007)	**-0.142**	(0.011)
size-l	**0.070**	(0.007)	**0.095**	(0.015)
LP	**0.057**	(0.005)	**0.099**	(0.010)
med-low tech	**0.026**	(0.009)	**-0.004**	(0.015)
med-high tech	**0.104**	(0.008)	**0.080**	(0.014)
high tech	**0.051**	(0.009)	**0.083**	(0.015)
time dummies	**incl.**		**incl.**	
Observations	8,666		3,903	
Log likelihood	-1,448.60		-1,268.03	

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

are shown in table 2.5, where we report coefficients for the whole sample as well as for East and West Germany separately.

The lack of impact of both product and process innovation is remarkable: If a firm introduced new products or processes in the preceding years, it does not influence its exporting decision, at least in West Germany; for East Germany we find a positive effect of product innovation. R&D expenditure, on the other hand, has a significant effect in the whole as well as in the two sub-samples. We see two possible interpretations of this result: On the one hand, the time lag between the observed innovation and the export decision is too short, so that in period $t+1$ an effect of innovation on export could be visible. On the other hand, the dummy variables do not reflect the quality of an innovation which is accounted for by R&D intensity. So one may argue that only technologically advanced firms enter international markets. Also size and technology classes are partly significant. Small firms exhibit a lower probability to enter export markets, probably due to entry barriers such as sunk costs, which require a minimum size. Regarding companies with more than 250 employees, no significant effect is found, which could result from the low number of large firms starting export activities.

What conclusion can be drawn from these results of export-starters for the analysis regarding the German adjustment process? The dummies indicating East German firms (in the entire sample) are mostly insignificant with changing sign. That means that for a not-exporting company located in East Germany, the probability to start exporting is the same as for a similar West German

Table 2.5: Panel estimations for export-starters, 1993-2003, Probit
endogenous variable: export probability (0/1)

	(Germany)		(West)		(East)	
constant	**-1.152**	(0.244)	-0.704	(0.412)	**-1.564**	(0.321)
InProd	0.107	(0.138)	0.054	(0.199)	**0.305**	(0.203)
InProc	-0.102	(0.131)	-0.111	(0.197)	-0.118	(0.178)
R&D	**15.797**	(5.120)	**24.916**	(8.896)	11.226†	(6.392)
R&D^2	**-94.193**	(36.155)	**-159.018**	(62.904)	-64.227	(44.901)
size-s	**-0.319**	(0.112)	**-0.271**	(0.176)	**-0.380**	(0.149)
size-l	-0.103	(0.193)	-0.049	(0.270)	-0.210	(0.290)
LP	**0.240**	(0.010)	0.133	(0.138)	**0.390**	(0.147)
med-low tech	-0.207	(0.144)	-0.083	(0.212)	0.297	(0.201)
med-high tech	**0.505**	(0.133)	**0.424**	(0.189)	**0.586**	(0.190)
high tech	0.069	(0.156)	0.100	(0.241)	0.230	(0.210)
East 1994	-0.458†	(0.241)				
East 1995	-0.026	(0.286)				
East 1996	**-1.433**	(0.465)				
East 1997	0.069	(0.211)				
East 1999	-0.156	(0.252)				
East 2000	0.128	(0.313)				
East 2001	-0.277	(0.310)				
time dummies	**incl.**		**incl.**		**incl.**	
Mean dep var	0.128		0.153		0.102	
Observations	1,053		461		592	
Log likelihood	-404.61		-192.07		-208.94	

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

firm. This can be seen as an indicator that for East German firms entry barriers are not higher than for West German companies. However, for catching up, the entry rate would have to be higher in East than in West Germany, which is the case only in the beginning of the observation period. A drawback of our estimation is the low number of observations in each year (varying from 46 to 112), as well as the restriction of the sample to only those firms which participated twice or more times in the survey, which should be taken into account when interpreting the values.

2.5 Conclusion

Analyzing export behavior of German manufacturing in the decade after reunification, we find significant differences between innovating and non-innovating companies. Innovating firms are more likely to export and tend to realize a larger share of their revenue on international markets. The results suggest a strong impact of product innovations both on the decision to export and export intensity, while process innovations did not prove significant. We find a strong positive, nonlinear relationship between R&D and both export probability and export share. Similarly, there is a positive correlation between the technological level of the sector which a firm is operating in and the firm's export success. Firms in higher technology sectors, such as chemical, automotive and optical industries, exhibit higher export intensity, while in low tech industries like food, tobacco and textile production, export shares are significantly lower. Moreover, firm size has a strong impact both on the probability of exporting and export intensity, as well as labor productivity.

Comparing East and West German firms, we find significant differences regarding firms' characteristics and their impact on firms' export behavior - although disparities have been getting smaller over time. East German companies are less likely to export and tend to realize smaller shares of their total turnover abroad. This can partly be explained through East Germany's economic structure which is dominated by small firms without a distinct focus on highly competitive sectors. One of the main factors hindering East German companies from further export success seems to be the low labor productivity and the lower propensity to innovate products. East German firms are faced by higher sunk costs.

Our results show that innovative activities are more important for East than for West German firms, which we interpret as a sign for greater differences in East Germany between competitive innovating firms on the one hand, and on the other hand firms who lack dynamics regarding both their innovative attitude and their export behavior. From these findings we draw two conclusions: first in both parts of Germany firms have to face sharper price competition, and second East German companies tend to be specialized towards low price markets, whereas West German firms rather operate in high price markets.

Finally, a number of questions remain unanswered, regarding both regional aspects and a more detailed specification of innovation activities. In order to get deeper insights into the role of innovations for export performance subject to the industry lifecycle, firm strategy and technical opportunities, more specific information on the quality of innovation output is needed. Moreover, strong regional disparities within East and West Germany can be observed, so that further research on the influence of regional networks and spillovers might be promising.

Chapter 3

Evaluation of Cluster Policy

A methodological overview

Abstract:
Cluster policy is becoming more and more part of many governments' economic policy strategies. At the same time, evidence-based policy making is gaining importance, bringing about the call for policy evaluation. The quality of the evaluation results, however, depends highly on the method used, since data, assumptions, and techniques must be adequate for the specific evaluation question. This holds for cluster policy evaluation in particular, given the complexity and indirect nature of cluster policy interventions. This paper provides an overview on evaluation methods suited for the ex-post analysis of cluster policy, covering both micro- and macroeconomic approaches.

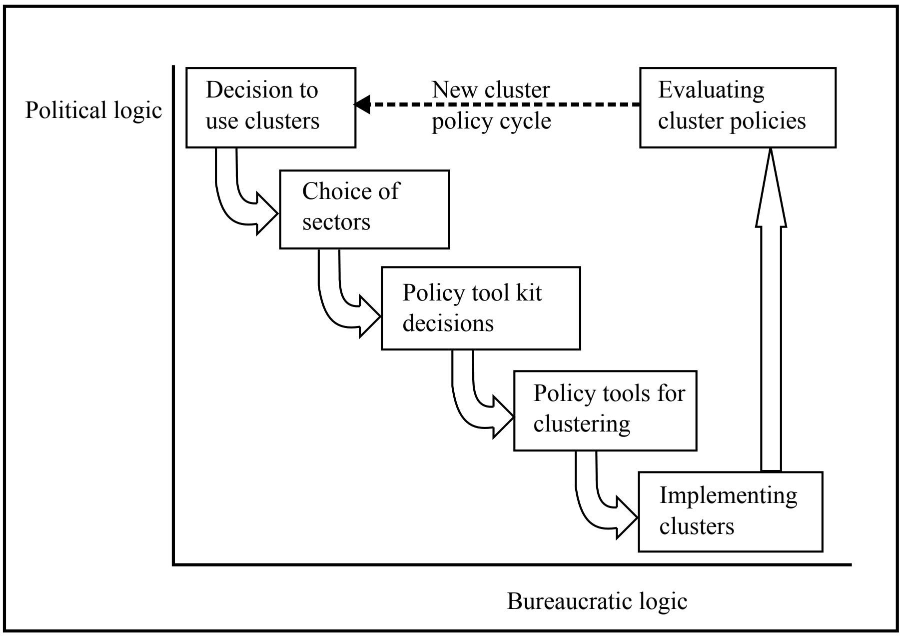
Keywords: Policy Evaluation, Innovation Clusters, Regional Policy
JEL-No.: H43, H54, O22, R58

3.1 Introduction

To the concept of regional industry clusters is paid increasing attention (see e.g. Lagendijk (1999) for the development of the concept). Since the 1990s, promoted in particular by the seminal work of Porter (1990), it has become popular as a lever to increase the competitiveness of regions, not only in industrialized countries (see OECD 1999, Bachtler et al., 2005), but also in lagging countries and regions (Schmitz and Nadvi 1999, Camagni 1995, Rosenfeld, 2002). The definition of the characteristics and constituting elements of clusters exhibit considerable variation (Gordon and McCann, 2000, Martin and Sunley, 2003, Benneworth et al., 2003, for an overview on cluster definitions see Lublinski, 2002), and the lines between cluster policy and traditional industry, innovation, and regional policy are blurry (Raines, 2002, Boekholt and Thuriaux 1999). For the present discussion, a cluster is defined as a group of proximate firms "interlinked by input/output, knowledge and other flows that may give rise to agglomerative advantages" (Lublinski, 2003, p. 454). This definition emphasizes the difference between clustering and co-location of firms, meaning that firms join a cluster intentionally in order to profit from spatial proximity, while co-location may be a result of external factors or contingent historic developments. The advantages of agglomeration are stated in the literature (an overview is given e.g. by OECD, 2007), including in particular the existence of specialized suppliers and labor pools (Florida, 2002, Marshall, 1920), low transportation costs (Krugman, 1991), and knowledge spillovers (Krugman, 1991, Malmberg and Maskell, 2002). From these factors, the competitive advantage of clusters is derived, which in some cases may deserve an initial impulse from policy, though. Based on these considerations, cluster policy is regarded as a promising approach to strengthen the innovative, or in a more general expression: the response capacities of the regional system, leading to greater competitiveness of the region and its actors. Applying the hierarchical cluster concept (Litzenberger and Sternberg, 2005), cluster policy means upgrading the cluster from the mere agglomeration to a regional innovation system with its beneficial implications for the clustered firms (see European Commission, 2002). How such policies are implemented has been shown in a number of case studies (e.g. Styria (Hartmann, 2002), Basque Country (Aranguren et al., 2006)) and manuals (DTI, 2004, GTZ, 2007). On the other hand, as Formica (2003) argues, an interventionist cluster policy is not necessarily beneficial, due to the high potential of political institutions to bureaucracy, patronage systems and unresponsiveness which increase transaction and compliance costs and potential inefficiencies. Besides, cluster policy can adopt a wide range of measures (as listed e.g. by Pfähler and Lublinski, 2003), while it is not definite which form of cluster policy is most effective. Hence, if and to what extent the measures actually are fruitful remains to be proven - cluster policy requires evaluation.[1]

[1]The function of evaluation as an integral part of the cluster policy cycle is shown in figure 3.1.

Figure 3.1: Cluster policy cycle



Source: Benneworth and Charles, 2001.

From the comprehensive literature on policy evaluation [2] (for an overview, see e.g. Georghiou and Roessner, 2000, Hansen, 2005) the reasons for evaluation as well as a basic methodological understanding are given. The key evaluation question is: "Does the policy program work?" In times of financial constraints in public households a careful selection of where to spend the money is essential, and decision makers are more and more held accountable. Hence, the function of evaluation is twofold: First, it legitimates policy actions by proving their effectiveness, and second, it deepens the understanding on the mechanisms of the measures supporting future decision making (Guy, 2003). Regarding evaluation techniques, a large variety of tools is available, which differ in terms of their rationale, complexity, data requirements and underlying assumptions; hence, evaluators face the task to choose the appropriate method for a specific evaluation study (Foss-Hansen, 2005).

In general, these considerations hold for cluster policy evaluation alike; but the complexity and the indirect nature of the interventions in the cluster policy approach pose some particular difficulties and require adequate analytical methods in order to validly attribute effects. And while a body of literature exists which develops and proposes evaluation methods in general, a distinct evaluation concept or toolkit with focus on cluster policy has not been made available yet. There is some literature on cluster policy evaluation with focus on special topics like participatory evaluation (Angeles Diez and Esteban,

[2] Throughout this paper, the terminus evaluation is used according to the definition of the UK Cabinet Office (Spencer et al. 2003) which distinguishes (ex-post) evaluation from (ex-ante) appraisal (see also Rip 2003).

2000) or performance indicators (Arthurs et al., 2007). A different strand of literature (e.g. Learmonth et al., 2003, and Fromhold-Eisebith and Eisebith, 2008) develops specific evaluation models. Raines (2002b) presents a comprehensive evaluation model for cluster policy covering the multiple dimensions of policy effects, but without going into methodological details. The purpose of the present paper is, hence, filling this gap by providing an overview on existing cluster policy evaluation methods. Due to the broad perspective, this overview is limited in depth, the focus being on how the presented methods can be applied to cluster policy evaluation. Hints on further methodological discussions as well as implementation manuals are given below.

The paper is structured as follows: In the next section particularities of cluster policy evaluation as compared to other policy areas are discussed. Section 3 presents evaluation methods, classified in five categories. Section 4 summarizes and concludes.

3.2 Challenges of cluster policy evaluation

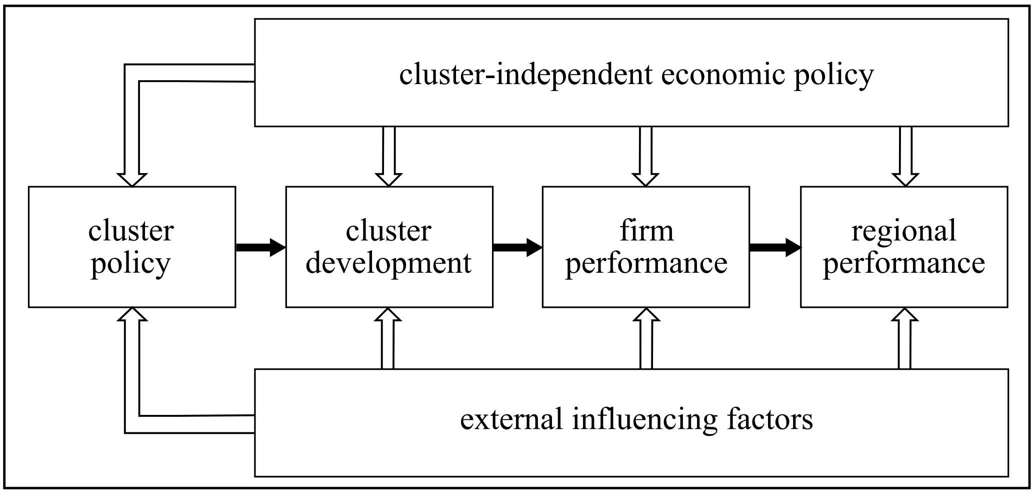
The main challenges of evaluation, regarding for instance the definition of a control group, the identification and measurement of effects and side effects, and the calculation of overall program costs, are independent from the type of policy to be evaluated. But according to the hybrid character of cluster policy which combines elements of various policy areas (Raines, 2002b), but also due to the multi-dimensional, systemic concept of clusters, evaluation of cluster policy programs faces particular challenges, which are discussed in the following.

3.2.1 Defining performance

The indirect nature of cluster policy interventions has been stressed before (see Guinet, 2003, p.158): The primary objective of cluster policy is not cluster formation but the assumed benefits of clustered firms or more generally the region, e.g. increasing returns to scale and comparative advantages (see Buendia, 2005). This is illustrated by figure 3.2.

Therefore the question arises which should be the policy outcome in focus. Evaluation could investigate the development of the cluster, e.g. the growth of the cluster or the number and intensity of interfirm connections, or on the region of the cluster concentrating on macroeconomic factors (e.g. employment rates); alternatively the focus could be on the individual firm whose performance should be strengthened by the development of the cluster. In addition, a distinction can be made between genuine economic indicators such as profit growth, productivity or (regional) GDP growth and technological (i.e. rather intermediate) indicators like R&D expenditure, patenting activities, collabo-

Figure 3.2: Factors affecting economic performance of firms and regions



rative agreements etc. Which indicator is considered from which perspective may crucially influence the evaluation result.

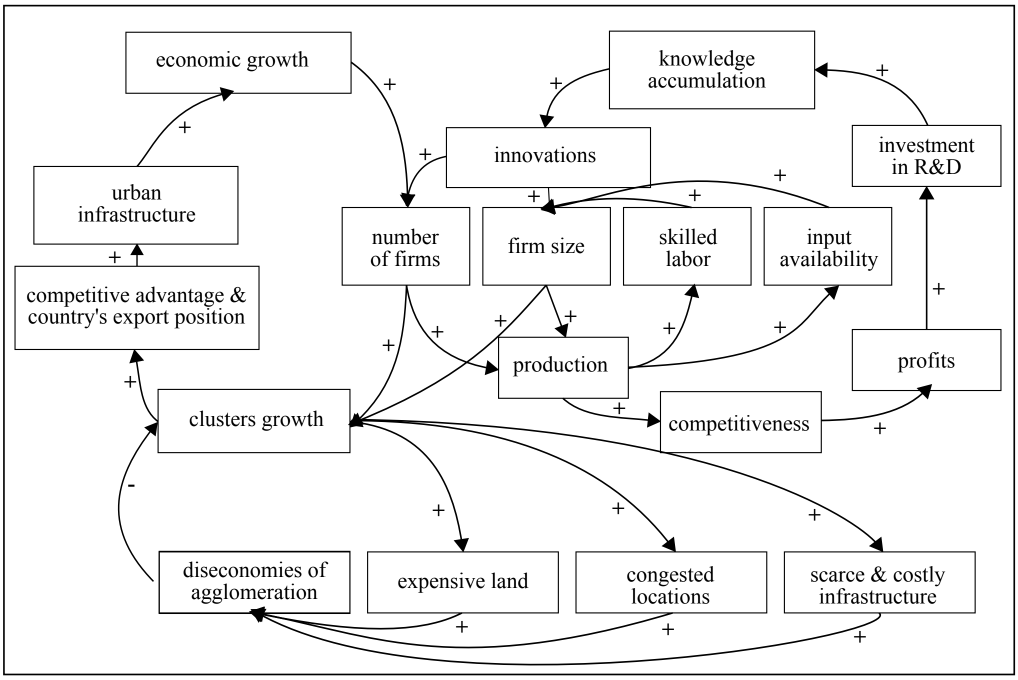
A further difficulty in this context is the definition of the cluster (see Raines, 2002b). It is characteristic for clusters that they integrate multiple industries and link different players, so that typically neither general industry classifications nor administrative regions are adequate to capture the boundaries of a cluster. As well, geographic proximity of the members, which is seen as a central feature of a cluster (Davies et al., 2006), entails considerable difficulties regarding definition and measurement (Litzenberger and Sternberg, 2005). The drawbacks of a measurement based on secondary data have been highlighted by Lublinski (2003). He shows that a multitude of indicators must be used to define the boundaries of the cluster, which still remain to a certain extent blurry, though. Besides, the boundaries might be evolving so that an evaluation based on a too rigid cluster definition might overlook a part of the development. Finally, as clustering is more than co-location, the evaluation must not be limited to measurements of firm density, industry-specific regional economic growth or the like; rather it should encompass the strength of agglomeration advantages to capture how the program has changed the quality of the cluster.

3.2.2 Attributing impacts

Cluster policy is mainly indirect (i.e. facilitative instead of pushing, according to Porter, 1998) and system oriented instead of targeted to single projects or firms (Rip, 2003). What's more, a large number of different interventions are often combined, which increases the complexity of the policy approach (Boekholt, 2003, p. 257). For evaluation this poses particular difficulties.

Buendia (2005) has captured the complexity of influencing factors and the mutual causality links in the context of cluster policy and performance (see figure 3.3). The development of clusters is affected by a large number of (often unobservable) factors which are in many cases beyond the reach of cluster policy. Besides, cluster policy is embedded in a particular socio-economic and institutional context, which must be taken into account (Angeles Diez and Esteban, 2000). Also non-cluster policy instruments may influence the development of the cluster or the behavior of the clustered firms, e.g. through unintended effects of technology policy (Sternberg, 2003, p.359). On the other hand, a policy intervention is likely to have several outcomes, both intended effects and unforeseen secondary actions (Schmidt, 1999). The effects may crop up only after a while (van der Linde, 2005, p. 29), so that the lag between policy intervention and policy impact may hide the causal link. Finally, cluster policy may not only affect the clustered firms but (e.g. via knowledge spillovers) also firms outside the cluster. Taken together, these factors lead to an attribution problem (Boekholt, 2003, p.257), which requires adequate analytical (econometric) techniques and reliable data to detect causal relations which can be interpreted as actual impacts of policy tools.

Figure 3.3: The evolution of industrial clusters



Source: Buendia, 2005.

3.2.3 Data availability

A third group of challenges relates to data restrictions which influence the choice of evaluation techniques. Particular limitations regarding cluster policy evaluation arise both due to the difficulties of measuring innovation and the regionally bounded perspective. On the one hand, the typical dimensions of clusters make macroeconomic modeling difficult, on the other hand applications of microeconomic methods are confronted with small numbers of observations (if comparing e.g. similar clusters) and/or insufficient data quality. Data on innovation and network activities can be measured only partly, using often criticized indicators such as patent statistics, R&D expenditure or number of linkages (for an overview on innovation indicators, see e.g. Arthurs et al., 2007). To be applied in the cluster context, the data must contain detailed information on both industry and region of the firms and, for instance, their cooperation partners, which is not always the case in official statistics. Thus, evaluation must rely on imperfect data, which restricts the use of some methods.

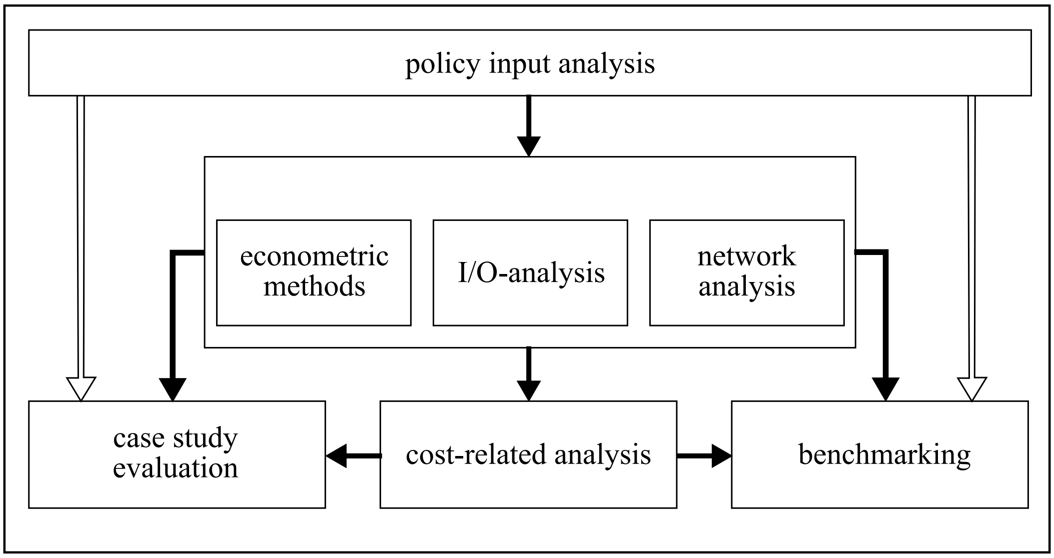
Besides, the fundamental difficulty of analyzing clusters in comparison to each other must be considered: Innovation clusters seem hardly comparable to each other, due to path dependencies and the cumulativeness of knowledge, but also as to the uniqueness of cluster structure, which makes the cluster to a "singularity in economic space" (Guinet, 2003, p. 154). As cluster policy seeks to focus on high-potential clusters, i.e. "picking winners" instead of spreading equally over all regions or even supporting lagging regions (see Cheshire, 2003) for the promoted clusters even greater peculiarities are likely. If cluster policy is well targeted its effects will only add on the above-average development that would be expected without the policy intervention. Hence, evaluation must identify the additional effect of the intervention separate from the clusters innate potential, whereby comparisons to other clusters tend to have only limited analytical power.

3.3 Evaluation methods

In the following a range of evaluation methods is presented. The discussion proceeds from rather simple, intuitive approaches to more complex and comprehensive methods. Figure 3.4 gives an overview of the methods and illustrates possible combinations of tools constituting an evaluation model similar to the evaluation model proposed by Raines (2002b).

A complete evaluation would encompass a qualitative and quantitative analysis of policy input, output and outcome on firm, cluster and regional level. But for the value of evaluation to stand in relation to cost and effort, only parts of this process will be realized. In practice, most evaluation studies rely on single methods, accepting thereby that results will be selective depending on the

Figure 3.4: Evaluation methods



focus and the method applied. Accordingly, choosing the optimal evaluation method is critical. The following discussion describes the possibilities and limitations of the methods included in figure 3.4.

3.3.1 Policy input oriented/reporting methods

Policy input oriented methods, or as they will be called in the following: Reporting methods, though rarely mentioned in the academic literature, are frequently applied in various policy contexts, for instance education (e.g. U.S. Department of Education, 1999), social (e.g. TMSFG, 2008) or science and technology policy (e.g. European Commission, 2004). An example of cluster policy evaluation of this type is given by Aranguren et al. (2006). Instead of analyzing policy impacts they report on the execution of the program, including e.g. the chronological progress, faced difficulties and procedural failures (Jans, 2007 p. 34) as well as subjective perceptions of participating parties. Their main objective, hence, is accountability and transparency (see Rip, 2003) rather than enhancing the understanding of if and how the measures work.

Reporting methods can be based both on quantitative and qualitative data; often a combination of qualitative and quantitative information is used. Reporting is related to performance auditing, which starts with the question on the financial implementation of the program, i.e. the correct and efficient commitment of funds (as defined e.g. in Council Regulation (EC) No 1260/1999, Art. 38). In addition to financial data, information on the structure and the components of the program are reported, such as the timeframe of activities, description of operations as well as indicators like the number of beneficiaries, handling time e.g. when considering applications. For a more comprehensive investigation an implementation analysis is included. It focuses on what was done when executing the program, taking into account also qualitative information on how the measures were executed. For this purpose, official (quantitative) data is gathered as a documentation of the implementation process, e.g. operations and activities (Nagarajan and Vanheukelen, 1997). Surveys and interviews for additional qualitative data can be targeted at customers (e.g. for customer satisfaction, as applied in Buchinger and Wagner, 2003) and beneficiaries as well as at the staff involved in the implementation of the program.

The appeal of reporting methods obviously lies in their practicability: attribution problems due to hidden causalities or inadequate control groups are unlikely. In addition, requirements regarding the evaluator's methodological capabilities and resources are moderate compared to output oriented techniques and, at least as regards auditing, data can be made available easily from the public accounting system. Also, reporting can provide immediate evidence (see Corbett and Lennon, 2003) by which it enables early intervention in case of a clear failure of the policy measures or their implementation. But again, reporting methods are not able to provide any information on the effectiveness of the program, but should be seen rather as a supporting tool. A number of criteria for the evaluation of cluster policy initiatives are discussed by Jappe-Heinze et al. (2008), who also show the value of a preparing policy input oriented analysis.

3.3.2 Case studies

Case study evaluation is a research strategy, rather than a method (Yin, 2003, p. 14). Being a rather open and flexible approach (see Ruegg and Feller, 2003, pp. 34 ff.), case studies can involve several techniques both of qualitative and quantitative nature ("triangulation", Jick, 1979). *Qualitative/descriptive case studies* try to trace the historical process, i.e. the development of the analyzed case, by the description, explanation, and interpretation of data drawn from multiple information sources (see Ghauri, 2004). For cluster policy evaluation, the focus can be either on single participants of the program or on the development of the entire cluster. Similarly to qualitative case studies, *benefit-cost-case studies* are based on multiple data sources. But in addition to the context analysis, the monetary effects and costs are to be estimated. For the quantification of costs financial business analysis methods are applied (which goes back to Mansfield et al., 1977), including measures such as benefit-cost ratio, net present value and rate of return (see Pelsoci, 2005). But in contrast to a full cost-benefit-evaluation, benefit-cost-case study evaluation only analyzes some exemplary cases from which conclusions on cost drivers and efficiency of the measure are derived.

Case studies are at the same time quite popular and highly controversial (see e.g. Flyvbjerg, 2004). Their appeal certainly lies in the intuitive understanding and plasticity of the results (see Ruegg and Feller, 2003, p. 34) as well as in the fact that case studies provide a comprehensive in-depth analysis of the subject in its context (Ghauri, 2004). In addition, due to its openness to qualitative information case study evaluation can take into account also aspects which cannot be expressed in quantitative or monetary terms (Ruegg, 2006).

On the other hand, the lack of objectivity, validity and generalizability are criticized (Flyvbjerg, 2004). One main objection regarding case studies is that analyzing only the participants of the policy program does not allow for conclusions on causality. This argument is based on the counterfactual definition of causality which as evidence that A being a cause of B requires two conditions: A and B coincide, and B would not have happened without the occurrence of A (Mohr, 1999). To examine the counterfactual case, i.e. to check whether B would have occurred if A had not happened, a control group is necessary. Case studies which compare participants and non-participants (e.g. clusters with and without political support or institutions within and outside the cluster) rely on this concept of causality. But if only participants are analyzed, an alternative definition is required: Corresponding approaches have been developed, like the modus operandi (Scriven, 1976), process tracing (George and Bennett, 2005), and pattern matching (Campbell, 1966) which take as evidence for causality the existence of a “signature” (Mohr, 1999) which links the cause with the result. In this manner, the case study must rule out concurring plausible causes and step by step show the “characteristic value chain” (Scriven, 1976, p. 105), i.e. the mechanism how the cause A lead to the effect B. In social sciences the physical causes for an event are often intangible and thus difficult to detect, but nevertheless this method can produce (internally) valid results (Mohr, 1999).[3] However, the more indirect a policy instrument is, the more difficult is it to track the mechanisms.

A second objection is related to the degree to which these results can be generalized: The smaller the sample, the higher is the risk that the observed subjects are (positive or negative) particular cases (Mohr, 1999).[4] This implies the necessity to document the circumstances of the cases to gain explanatory power; but then case studies, which target at the understanding of the causal process, may even have an advantage over large sample econometric studies, as Mohr (1999) argues. In the context of cluster policy evaluation, where cases can be focused for instance on single players and their linkages as well as on specific projects of the program, generalization issues are demanding: Not only the circumstances of the cluster development must be taken into account, but

[3]In contrast to its controversial status in the field of evaluation, this kind of causal inference is used widely in other disciplines such as medical diagnosis, history or engineering (Scriven 1976).

[4]From an epistemological viewpoint, the difference between case studies and large sample observational studies is only secondary: From single observations - regardless of their number - one cannot derive universal conclusions, so both types of empirical evidence are subject to the “problem of induction” (Popper 2002, p. 3).

also particularities of the analyzed players and their position and function in the cluster.

Hence, for case study evaluation the first step appears to be crucial, the choice of the case or cases. They should give insights in the functioning of the program and enable learning instead of only illustrating success stories in the manner of "cherry-picking". (In particular also the analysis of unsuccessful projects, for instance, can be instructive, according to Shipp et al., 2005). Then, it seems to be a suitable approach capable to take into account both the idiosyncrasies of clusters and the complexity of cluster policy. In fact, a considerable number of case studies have been conducted for evaluation purposes (e.g. Fromhold-Eisebith and Eisebith, 2008).

3.3.3 Econometric models

In contrast to case study analysis, (micro-) econometric impact analysis is based on the above mentioned counterfactual definition of causality (White et al., 2006). It has been gaining attention over the last years as a set of elaborate and informative techniques (see Augurzky and Kluve, 2004, Heckman, 2004), its strength lying in the distinction between significant policy impacts and concomitant circumstances independent of the policy measures (White et al., 2006). But, as the analysis is focused on the clustered firms (instead of the entire cluster), rather than the policy impact on the cluster the indirect effects on the members of the cluster are captured. Therefore, the indirect (i.e. through cluster development) effects of cluster policy on firm performance must be taken into account explicitly in the underlying theoretical model. Accordingly, indicators must be found which adequately represent the effects of the policy measure on firm performance. As companies benefit from innovation clusters in various ways - be it knowledge flows, a specialized labor pool or specialized suppliers - intermediate indicators such as innovation performance can be taken as well as success measures like profits, firm growth, or entrepreneurship (for an overview on indicators see Arthurs et al., 2007). The choice of indicators is not trivial, since all of them are criticized for having their deficiencies: Input indicators such as R&D spending are criticized as being little informative regarding firm performance. If using output indicators like patents, profits or firm growth, on the other hand, due to the large number of potential influencing factors and the time lag between the intervention and measurable impact a clear attribution of policy impacts is difficult (as discussed above). In addition, quantitative indicators capture reality only incompletely; measuring e.g. linkages within the cluster by the number of cooperative agreements does not consider the intensity, quality or the success of the cooperations (Ahuja, 2000).

Quantitative (microeconomic) evaluation explicitly aims at answering the question: "what would have happened without the intervention?" This question has been formalized in the "Potential Outcome Model" (POM, see Holland, 1986). The policy impact can be written as the difference between the case of policy intervention $Y_i(1)$ and the case without intervention $Y_i(0)$:

$$\Delta Y_i = Y_i(1) - Y_i(0)$$

Where Y can be any indicator as described above, and i is the observed unit respective to the aggregation level, e.g. a firm or household. The analysis can be based on a sample of $i = 1, 2, \ldots, N$ units as well as on one element in $i = 1, 2, \ldots, T$ different points in time. The value of ΔY_i, as formulated above, is not observable, since for each i only one of the cases has actually materialized, while the second case is an unobserved counterfactual situation.

Instead of on individual level effects, evaluation typically focuses on the average treatment effect on the treated (see Keilbach, 2005), assuming that the intervention does not have any impact on not participating elements (White et al., 2006). These average treatment effects result from the (hypothetical) comparison of the "treated" elements, which have undergone the intervention (i.e. $M = 1$), with the counterfactual case that these elements would not have participated in the program:

$$\tau = E\{\Delta Y|M = 1\} = E\{Y(1)|M = 1\} - E\{Y(0)|M = 1\}$$

Still, the counterfactual $E\{Y(0)|M = 0\}$ cannot be observed, so the counterfactual average must be substituted by an alternative, observable average. This is done by constructing a control group (outside the policy program); according to the type of control group a number of approaches can be distinguished.

The *before/after-comparison* focuses only the treated elements, but at two different moments so that the performance of the treated units previous to the intervention ($t = 0$) can be used for comparison with the performance during or after the program ($t = 1$).

$$\tau = E\{Y_{t=1}(1)|X, M = 1\} - E\{Y_{t=0}(0)|X, M = 1\}$$

The main underlying assumption here is that (while controlling for observable factors X) unobserved factors remain constant over time, both regarding environmental conditions and unobserved properties of the elements like management talent of firms (Grossman, 1994). In particular, strategic behavior of program participants, e.g. postponing eligible investments to the program period, cannot be detected, which leads to overestimation of the policy impact (see Ashenfelter, 1978). Considering cluster policy evaluation as field of application, an additional bias of before-after comparisons might arise from the fact that a linear development of clusters independent of business cycle influences and path-dependencies cannot be assumed. Thus, the before/after-estimator which compares each clustered firm to itself attributes also the effects of changed unobservable characteristics to the cluster.

The *with/without-comparison* contrasts participants with non-participants:

$$\tau = E\{Y(1)|X, M = 1\} - E\{Y(0)|X, M = 0\}$$

That implies that the participants would have performed similarly to the non-participants if they had not been subject to the intervention, conditional to additional observable characteristics (X). But if program participation is not random - which can be assumed for cluster policy, which is explicitly targeted at high-potential clusters - the with/without-comparison is vulnerable to self-selection bias, since factors leading to program participation might also influence the performance of the participants irrespective of the intervention. In addition, the comparison might be biased by exogenous factors which influence the control group in a different way than the participant group (see Blundell und Costa Dias, 2000).

The *difference-in-difference estimator* can be seen as a combination of the two above mentioned approaches as it compares the development of the performance of both participates and non-participants.

$$\tau = E\{Y_{t=1}(1) - Y_{t=0}(1)|X, M = 1\} - E\{Y_{t=1}(0) - Y_{t=0}(0)|X, M = 0\}$$

However, bias due to self-selection and strategic behavior of the participants persist also in this method, even if controlling for observable characteristics (see Heckman and Smith, 1999). Besides, panel data on both participates and non-participates is required.

Thus, also if these control group methods captivate by their intuitive understanding and more or less simple implementation, they are likely to be biased by neglecting unobservable factors. Nevertheless both approaches can produce very informative and reliable results provided that an adequate control group is chosen to simulate a natural experiment. Opportunities for a simple control group comparison arise often in case of a structural break, e.g. due to changes in policy conditions or regional differences. In these cases, neither selection bias nor strategic behavior interferes with the identification assumption.

Alternatively, *selection models* can be applied which explicitly consider the participation decision and thus eliminate potential selection bias. The first type, *instrumental variables estimation* is based on the assumption that some variables (Z) explain the participation status, but are uncorrelated with unobservable characteristics affecting the outcome Y. Then, the treatment variable M can be regressed on Z, so that the coefficient of the resulting instrument $\hat{M}$ can be interpreted as the treatment effect. The choice of instruments, however, is difficult, since both weak instruments and the correlation with omitted variables will lead to inconsistent estimation results (Angrist and Krueger, 2001). As a second type, the *Heckman Selection Correction* (Heckman, 1979) takes into account both observable and unobservable factors when modeling the participation selection. In a two-stage approach, a (binary) participation estimation is specified which is subsequently used for the outcome regression (in form of the inverse Mills ratio). By this, the estimated effect of the expected participation status conditional on observable and unobservable characteristics is interpreted as the treatment effect. But, as has been shown by LaLonde (1986), the results may be biased due to specification errors, regarding both the choice of control variables and the distribution of the error term.

In contrast, *matching* as a quasi-simulation approach tries to overcome the shortcomings of observational data by building "twin" pairs of treated and non-treated elements, i.e. assigning to each participant a non-participant with similar observable characteristics. After the matching procedure the sub-samples of treated and not-treated elements should be comparable so that the average treatment effect on the treated can be estimated:

$$\tau = E\{Y(1)|X, M = 1\} - E\{Y(0)|X, M = 0\}$$

As finding a perfectly identical twin is difficult (and impossible in case of continuous control variables as argued by González and Pazó, 2008) and requires large data sets, a certain degree of dissimilarity between the matched elements is allowed; for instance, in nearest neighbor or radius matching from the variables X a propensity score (Rosenbaum and Rubin, 1983) is estimated which is used as matching criterion afterwards (see Becker and Ichino, 2002).

The matching method relies on two assumptions:

- The unconfoundedness assumption $\{Y(0), Y(1)\} \perp M|X$
  means that treatment and potential outcomes are independent, conditional on the observed variables X (Rosenbaum and Rubin, 1983).
- Overlap: $0 < p(M = 1|X) < 1$.
  This condition ensures that statistical twins can be found, since the propensity score of both treated and treated firms lies within the same interval $[0; 1]$ (Imbens, 2004).

Unlike two-stage-estimation methods, matching permits an intuitive understanding and direct interpretation of the results (Dar and Gill, 1998). On the other hand, matching is sensitive to the choice of control variables as well as unobservable characteristics. In particular, the plausibility of the unconfoundedness assumption is doubted (Imbens, 2004). Furthermore, all methods alike face the difficulty of identifying not treated firms, which should be part of a comparable cluster, but not participate in any (cluster) policy program;

otherwise the analysis would overstate the treatment effect by confounding agglomeration advantages and policy impact if the firms in the treated cluster were compared to not treated and not clustered firms.

Apart from the econometric pitfalls of all the mentioned methods their explanatory power of econometric methods depends on the data available (Schmidt, 1999). The applications are based on micro-level data focusing firms, households or persons for which data on a large number of comparable observations is available.[5] A systemic view on the entire cluster, however, seems hardly compatible with these econometric models; and by only comparing treated and not treated firms the whole process of cluster policy and development is seen as a black box. Thus, these approaches are likely to miss the core aspect of cluster development of a collective action (Raines, 2002b). Furthermore, also if applied on the firm-level, the quantitative precision of the results produced by econometric methods may in some cases be misplaced (Corley, 2007) and create an overstated impression of objectivity. After all, the results depend on the specification so that even small changes regarding method or variables alter the measured treatment effects. This has to be born in mind as well if comparing evaluation studies on different programs.

3.3.4 Systemic approaches

As an alternative to the microeconomic level analysis, also a number of quantitative methods taking a systemic point of view are at hand. These tools provide a static descriptive view on the cluster, so that for evaluation the analysis must include two or more points in time to investigate how the cluster has developed regarding its size and structure. Insofar, this can be seen as a before/after-comparison, but without being able to attribute the changes to the policy program via significance tests.

Input-output-models study the relations between industries and spatial units on the basis of commodity flows (see Schaffer, 1999). Based on regional input-output-tables, linkages between industries and the importance of industries on the economic development of the region can be approximated. This method is commonly used to identify clusters (e.g. Larreina, 2007), but also for cluster policy evaluation (Learmonth et al., 2003).

Input-output-models can be implemented at any regional level, so that the aggregation can to a certain degree be adapted to the dimensions of the cluster. But full input-output tables on small regional scale are rarely available and difficult to construct, in particular if the analysis focuses single sectors on a disaggregated level (see Gabriel (2001) for Hamburg and Larreina (2007) for the Rioja region). To determine the regional level of the model, assumptions on

[5]In fact, the bulk of contributions can be found in the literature on firm R&D subsidies (e.g. Gabriele et al. 2006, Autio et al., 2008) and labor market programs (e.g. Heckman et al., 1997, Ichino et al. 2008).

the geographical boundaries of the cluster are necessary; if the cluster is spread over administrative borders a realistic delimitation is difficult. Similarly, the sectoral delineation of the cluster is problematic as typically the clustered firms belong to more than one industry, so that the results given by input-output analysis are somewhat arbitrary (Lublinski, 2001). Furthermore, input-output models only consider commodity flows whereas immaterial linkages such as flows of (both codified and tacit) knowledge are not captured (Lublinski, 2001). Hence, input-output analysis will produce - at best - an incomplete picture of the linkages within the cluster so that in the majority of cases additional investigations will be necessary, be it network analysis (as proposed e.g. by van den Hove et al., 1998) or microeconomic methods.

Network analysis explicitly takes a systemic perspective as well, but instead of value-added chains it relies on communication and interaction linkages between the players within the cluster (Dybe and Kujath, 2001). In network analysis, the cluster as a social system is represented by a network of vertices and edges which represent the actors within the cluster and the ties between the actors, respectively. It is based on an interaction matrix (possible matrix types are similarity or distance matrices, see Hawe et al., 2004) containing data on the relationships between the members of the network.[6] The required data can be drawn from surveys asking the actors about their relations with other actors (for a description of survey methods and difficulties see Marsden, 2005); also communication flows measured by e-mail traffic (e.g. Gloor et al., 2008), coauthorship in the academia (e.g. Newman, 2004) or collaborations between firms (e.g. Breschi and Cusmano, 2002) can used to identify the existence and strength of ties between the members of the network.

Depending on the research question and the scale of the network, three (distinct, but partly complementary) types of analysis can be used: Graphical visualizing is predominantly used as a tool for explorative analysis; it can give intuitive insights in network structure, though its analytical power is limited to small networks (Newman, 2003, p.169-171). Quantitative analysis applies a number of (descriptive) statistical metrics on network properties, such as density, connectivity, clustering, resilience or community structure (see Wassermann and Faust, 2005). Similarly, the position of single actors within the network can be studied, considering e.g. their centrality, hierarchical position, and structural holes.

Cluster development - which is focused for evaluation - can be defined as network growth, i.e. the addition of vertices and/or edges, as well as changes in the properties of the cluster as measured by indicators like resilience and transitivity or regarding the simulated performance of the network. A number of models also take into account dynamic network evolution explicitly (for an

[6]Social network analysis studies typically use complete network data instead of random samples (see Breiger, 2004), which increases the efforts to be made for data collection as compared to empirical analyses on individuals. Apart from that, for data collection the same methods are applied as for individual level studies (see Hawe et al., 2004).

overview see Snijders, 2004). By setting network development in a relationship to the cluster policy measures, the analysis can give insights - though without statistical significance - on how the policy influenced the cluster.

As cluster policy explicitly focuses the interaction of players, network analysis seems to be an adequate tool, at least for exploratory analysis on cluster development. However, the value of a cluster is determined not only by network size and strength, but by the economic value the firms draw from these relationships (Raines, 2002b). Thus, by relying only on network analysis, the evaluation remains limited to intermediate outputs, but cannot draw conclusions on the real economic benefits of the policy.

Benchmarking can be used if cluster policy is spread over a number of clusters, so that the success of the single projects can be evaluated in comparison to each other. This can help to detect success factors and give insights in why certain measures did (not) work by putting successful interventions side by side to failed concepts; similarly, the implementation of one specific measure in several clusters can be analyzed by benchmarking cluster development. It should be kept in mind, though, that the results are sensitive to contextual factors which should be taken into account (Gebel, 2006). As multiple indicators, both of qualitative and quantitative nature, can be included, a detailed picture can be drawn (Schütz et al., 1998), depending on the quality of performance indicators (Gebel, 2006). In particular, indicators can be drawn from preceding evaluation steps, combining for instance network indicators or policy input measures in one benchmarking study. An overview on indicators for cluster analyses is given e.g. by Koschatzky and Lo (2007).

In short, the benchmarking process contains the following steps (Tornatzky, 2003, Schütz et al., 1998, Gebel, 2006): (1) finding a benchmarking group, (2) defining dimensions and indicators of performance, (3) identifying "best-in-class" organizations or programs, (4) determining the performance gap, and (5) describing best practices.

For the measurement of the performance gap a number of methods have been proposed (Jones, 2004). If a combination of indicators is used, they can be integrated in a Radar-chart analysis, which reduces complexity and thus permits an intuitive analysis (Schütz et al., 1998). Starting from a graphical representation of the indicators (normalized to the interval $[0;1]$)in a radial chart, the SMOP[7] (Surface Measure of Overall Performance) can be calculated for each cluster:

$$SMOP = \Big((x_1\,x_2) + (x_2\,x_3) + (x_3\,x_4) + \ldots + (x_n\,x_1)\Big)\sin\frac{(360/n)}{2},$$

Where $x_1, \ldots, x_n$ are the distances of the respective corner to the center of the chart, corresponding to the value of the respective indicator. The higher

[7]An application of SMOP not on cluster policy, but for benchmarking clusters can be found in Pfähler and Lublinski (2003).

the SMOP-value, the better is the performance of the respective project, so that projects can be ranked according to their performance. The graphical analysis, in addition, can be used to find strength and weaknesses of measures and to identify trade-offs between policy targets (Schütz et al., 1998). To find the reasons for the different performance, however, a further analysis of best practices is required.

3.3.5 Cost-related approaches

So far, evaluation methods have been presented which take into account only the impact of the policy measure. But for a full assessment of the success of an intervention, also the cost side should be considered (Dar and Gill, 1998), in order to assess if the effect of the program is worth the expenditure. That is, instead of effectiveness of the policy measure, cost-oriented methods investigate efficiency (Schmidt, 1999). Insofar, these approaches are an extension of the presented methods, of which they make use for the estimation of impacts and to which they add the calculation of costs. This implies, however, that the drawbacks of the methods applied to capture program impacts persist, so the quality of the results depends centrally on the underlying "pure" impact analysis (e.g. econometric methods or network analysis).

A number of methods are available which differ in the way they capture policy impacts: *Cost-benefit analysis* expresses the estimated impact in monetary terms in order to measure the net benefit or the rate of return of an intervention (Levin and McEwan, 2000). To set lagged impacts into relation to immediate expenditure values are discounted over time. This point is of particular importance if long-term effects of programs are studied (as is the case in cluster policy). But the social discount rate, being a key parameter in the cost-benefit analysis, is difficult to define (Spackman, 2007). Moreover, in many cases the quantification of benefits in monetary values is questionable, particularly if "soft" effects like communication flows in a firm network are measured (Levin and McEwan, 2000). For a full financial appraisal of benefits, both direct and indirect beneficiaries as well as unintended side effects (Stufflebeam, 1999) and also negative effects of the program such as potential displacement effects, i.e. the shifting of economic activity from other regions, must be considered (Dar and Gill, 1998).

In contrast, *cost-effectiveness analysis* directly sets the effects in relation to costs by building cost-per-unit ratios (e.g. based on regression coefficients of the preceding impact analysis). By this, assumptions on valuation and discount rates can be avoided, and any outcome indicator can be used. But the intuitive and simple character of the analysis vanishes as soon as more than one policy outcome is analyzed. This compound of effects can be expected for most cluster policies which typically combine of a range of measures (Raines, 2002b). Furthermore, these calculated values do not allow for conclusions on the efficiency of a program, as long as they are not contrasted to another (comparable!) intervention (Levin and McEwan, 2000).

The calculation of costs is identical for both methods, bearing difficulties similar to the estimation of financial benefits: First, the evaluator must be sure to have included all relevant costs, being direct implementation costs of the program as well as social costs and opportunity costs (Schmidt, 1999). Again the proper discount rate must be defined, giving rise to over- or underestimation. Besides, as many of the required values (e.g. opportunity costs) can only be approximated, the calculation relies on strong or even dubious (Stufflebeam, 1999, p.21) assumptions.

Applications of all named approaches can be found in various policy areas (illustrative examples on education are listed by Levin and McEwan, 2000).[8] However, the use of cost-related methods is limited by their complexity and high data requirements, in particular in policy areas with intricate structures. Accordingly, cluster policy is rarely evaluated using cost-oriented approaches mainly due to the complexity of the field; as determining impacts is quite difficult, most evaluations are limited to this task, avoiding additional time and effort for financial quantification of benefits and costs.

3.4 Summary: Choosing evaluation methods

In the preceding discussion, a range of methods has been presented which can be applied for cluster policy evaluation. It has been shown that these approaches are different in their focus and the underlying assumptions, building on different theoretical models and taking different perspectives. Which method is appropriate depends on the purpose of the evaluation and the structure and scope of the program, but also on limitations regarding time, financial resources and methodological capacities. In table 3.1 an overview on relevant characteristics of the techniques is given, according to the criteria guiding the decision on the actual evaluation design in a specific case. The first group of criteria regards the basic conditions of the evaluation and gives clear guidance: If short-term evaluation is requested, the analysis is limited to policy input reporting, while for learning purposes qualitative studies including case studies are advisable. Besides, a good match between the policy strategy and the evaluation method is important in order to produce informative evaluation results. For instance, if the program primarily pursues a branding strategy, an I/O-analysis on commodity flows will be off target. In the second group of criteria data requirements are summarized. Data availability has been spotted as one of the central problems in evaluation of cluster policy, so that a thorough appraisal of existing data, information sources and options of collecting data

[8] In particular cost-benefit-analysis is used not only for (ex-post) evaluation, but also for ex-ante appraisal (see e.g. European Commission, 2006).

must precede the evaluation design. Data limitations, which preclude the application of corresponding methods, may arise if resources required for the data collection are lacking, data (e.g. financial data for cost-related approaches) is not made available by the program coordinators and participants, or the sample size (e.g. the number of firms in the cluster) is too small. The third group of criteria shows what can be expected of the methods. Certainly, the more complex methods have the higher explanatory power, but on the other hand if the results are difficult to understand or do not allow for practical conclusions the impact of the evaluation on policy makers will be low. Thus, resource requirements, explanatory power and practical value of the evaluation method should be balanced and adapted to the target group.

Table 3.1: Characteristics of evaluation methods

Approach / Criterion	Reporting	Case studies	Econometric methods	Systemic approaches: I/O-analysis	Systemic approaches: Network analysis	Systemic approaches: Benchmarking	Cost-related approaches
1. Evaluation conditions							
Time horizon	short	medium/long	medium/long	medium/long	medium/long	medium/long	medium/long
Type of cluster policy	all types	combination of multiple instruments	clearly defined policy targets (with focus on firm performance)	focus on buyer-supplier-relationships	network oriented policy strategy	all; in particular for programs targeting several clusters	depending on type of impact analysis
Purpose of evaluation	preparing further evaluation steps; transparency	learning	legitimating and efficiency control	legitimating and efficiency control	legitimating and efficiency control	learning	decision support; legitimating and efficiency control
Target group	tax payers; policy makers	policy makers	economic research; policy makers	economic research; policy makers	economic research; policy makers	policy makers	economic research; tax payers; policy makers
2. Data requirements							
Collect own data	not necessarily: use of official project reports and statistics	yes: detailed and specific information on the cases required	not necessarily: use of existing firm level databases	yes: I/O-tables on cluster-level usually not available	yes: complete data on all network participants required	not necessarily: use of official statistical data	not necessarily, depending on type of impact analysis
Indicators	a) information from project reports, e.g. activities, financial resources b) opinions of participants	multiple indicators (qualitative and quantitative)	(quantitative) firm level indicators: productivity, firm growth, etc.	regional commodity flows (from regional I/O-tables)	firm level data, e.g. patents, communication flows, collaboration links	multiple (quantitative) indicators	unit-costs, net benefit; complete cost accounting, estimation of opportunity costs
Sample size	a) no sample b) only participants (interviews, surveys)	small sample	large sample: comparison group outside the cluster and/or observation over time	aggregate (regionalized) data	large sample required: complete representation of the network	information on several clusters needed	depending on type of impact analysis
3. Evaluation results							
Perspective	policy input	single aspects, of e.g. firms' benefits, program execution	impact on firm performance	impact on cluster performance; impact on territorial performance	impact on cluster performance	impact on cluster performance; impact on territorial performance	depending on type of impact analysis
Explanatory power	low: no impact measurement	exploratory, conclusions on best practices	statistical significance of impacts; cluster treated as a black box	only information on commodity flows, no significance test if changes are caused by policy	descriptive results on network behavior, no significance test on policy impacts, no conclusions on economic impact	comparisons of measures/programs; conclusions on best practices	information on both impacts and costs; statistical significance only in combination with econometric methods
Interpretation of results	shows shortcomings in program execution	illustrative, concrete examples	abstract, needs explanation	abstract, needs explanation	graphical illustration possible	graphical illustration possible	clear interpretation of indicators

Chapter 4

Structural Convergence of European Countries[‡]

Abstract:
Building on the three-sector-hypothesis, the New Theory of Trade, and the New Economic Geography, we investigate the development of economic structures of European countries over the last three decades using employment data. We test for structural convergence which we analyze on the aggregate level as well as specifically for manufacturing and service industries. For this we implement both time series and panel data methods. Our results indicate overall structural convergence between Western European countries over time. This is mainly due to strong intersectoral convergence patterns as countries shift from industrialized to service economies. In contrast, the results regarding intrasectoral convergence are mixed: Increasing spatial concentration in production is dominant in technology-intensive manufacturing industries which are characterized by economies of scale and path-dependency, whereas convergence is found in mature, less technology-intensive industries. In most service branches, country-specific differences do not change to a significant extent with the exception of transport and storage services.

Keywords: Structural Convergence, European Integration, Economic Development
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4.1 Introduction

The European Union has strongly fostered economic integration between its Member states since the 1980s. Milestones of this policy are the Single European Act, the establishment of the Single Market, and the introduction of a common currency (for a historical overview see Watts, 2008). According to economic theory, deeper integration should have initiated a reallocation of economic production due to diminishing trading costs. Two adjustment processes are possible: On the one hand, the ability to exploit economies of scale and comparative advantages is expected to amplify the structural differences between countries over time, as production is moved to the economic centers at the cost of periphery regions (Krugman 1991a, Haaland et al. 1998). The better access to suppliers and other complementary activities moreover ought to favor production in larger countries (Venables 1996, Fujita et al. 1999). On the other hand, lower transaction costs could lead to a lower importance for the proximity of producers and suppliers, which then results in de-concentration of economic activities as the competitive disadvantages of peripheries diminish (Rossi-Hansberg 2005, Murata and Thisse 2005).

There is also a gap between theoretical predictions and European reality due to the following reasons: The structural and cohesion policy of the European Union aims to foster convergence between the member states (art. 158 and 160 of the treaty establishing the European Community). Furthermore, labor is still a highly immobile production factor and consumers have made use of the new consumption possibilities to a lesser extent than expected. Additionally, international technology diffusion fosters catch-up processes and might lead not only to income convergence but also to structural convergence across Europe (Pigliaru 2003). Another point is that, the ongoing globalization makes all European countries lose competitiveness in labor-intensive, low-skill, and low-technology industries in favor of low-cost countries outside Europe, and forces all European countries to shift production towards high-technology, high-skill and capital-intensive industries. Altogether, the verdict is inconclusive, suggesting extensive branch-specific differences with regard to their convergence potential.

Until recently, research on this topic has not received much attention: Whereas the empirical research on income convergence has flourished, studies on structural convergence are rare. Some work has been done regarding regional convergence (e.g. Cuadrado-Roura et al. 1999, Guerrieri and Iammarino 2003, Longhi and Musolesi 2007); others investigate the interrelationship between structural convergence and income convergence (Wacziarg 2001, Imbs and Wacziarg 2003), productivity convergence (Fagerberg 2000, Gugler and Pfaffermayr 2004), and monetary integration (Brülhart 1998). Still others focus on the economic catch-up and structural assimilation of countries, e.g. Landesmann (2000) for the movement of Central and Eastern Countries towards the Western European countries and Abegaz (2002) for the convergence between industrialized, newly industrialized and least-industrialized country groups. With a focus similar to the present paper, Midelfart-Knarvik et al. (2000) investigate structural convergence between European countries. However, they analyze the reasons for the concentration of industries, and for the choice of countries industries actually settle, but hardly analyze the convergence of industries development over time. Hence, the impact of economic integration and globalization on the evolution of individual industries within Europe over the last decades remains to be explored.

Our analysis fills these gaps in the literature: First, we provide a comprehensive view on both intersectoral and intrasectoral convergence. For that purpose we use data for the three aggregate sectors (agriculture, manufacturing, and services) as well as for nineteen manufacturing and ten service industries, covering fourteen European countries over the period from 1970 to 2004 and 2005, respectively. We are thus able to show that the bulk of convergence across European countries in the last decades was owed to intersectoral rather than intrasectoral convergence. For this, we define a heterogeneity index which permits a decomposition into inter- and intrasectoral heterogeneity. Second, we analyze the dynamics of employment structures not only in manufacturing but also in service industries, which so far have been mostly neglected in the literature. Third, we provide evidence of industry-specific convergence (or divergence) patterns and establish a procedure to distinguish between two forms of divergence: General divergence, where some countries win employment shares in the respective industry at the expense of other countries, and concentration processes driven by one-country specialization, where employment shares of all but one country remain stable and only one country strongly increases its employment share. We do not, however, provide evidence on the causalities underlying the convergence and divergence trends, nor do we explicitly analyze the role of European economic policy on industry development.

The paper is structured as follows: Section 2 discusses relevant theoretical concepts including the main driving forces of convergence and divergence. In Section 3 we present our approach to the implementation of empirical convergence tests, followed by information on the employment data used in section 4. Section 5 reports descriptive statistics as well as the results of σ- and β-convergence tests, and section 6 concludes.

4.2 Theoretical framework and literature

For the discussion of structural convergence, we have to distinguish between two types of structural change have to be distinguished: inter- and intrasectoral change. The former refers to variations of employment shares between the aggregate sectors[1] of an economy, and hence focuses on the transition from

[1] We investigate the three aggregate sectors agriculture, manufacturing and services. In recent years the impact of industries associated with information and communication technologies (ICT)

the agrarian to the industrial and finally to the service economy. The latter relates to changes of production structures within one of the aggregate sectors, for instance a change in the share of the textile industry on total manufacturing employment.

Arguments for intersectoral convergence can be derived from the three-sector-hypothesis and the convergence hypothesis of Chenery (1960), which both assume that there is a strong correlation between the production structure of a country and its per-capita income level. According to these hypotheses, intersectoral convergence is expected to occur whenever poorer countries are able to close the income gap, since consumption patterns then converge towards those of richer countries (Fisher 1939, 1952). Rising incomes therefore lead to a decline in the consumption of basic goods and a rise in the consumption of luxury goods. When the production side adapts to these changes in demand, employment in agriculture declines, whereas employment shares rise first in manufacturing; similarly, in later stages, manufacturing declines, whereas service industries increase. The three-sector hypothesis also stresses supply-side convergence potentials: Knowledge transfer enables technologically lagging countries to increase labor productivity and catch up to technologically leading countries (Clark 1940, Fourastié 1949). This process of productivity growth reduces employment in the agricultural and (in a later stage) the manufacturing sector and increases the share of the service sector. Thus, convergence of income levels and labor productivity is expected to lead to structural convergence (as stressed by Pigliaru 2003).

For our investigation of European countries we therefore expect to find that an intersectoral convergence process has taken place since the 1970s. Countries which were characterized by a disproportionately high employment share in agriculture and relatively low labor productivity at the beginning of the investigation period should have undergone a period of extensive catch-up and transition towards industrialized and service economies. Moreover, as the incomes of poorer countries have risen, demand patterns should have converged to those of richer countries, which implies a shift in consumption from manufacturing goods to services.

A certain degree of heterogeneity between countries will remain, however, due to differences in natural resources, country size, institutional frameworks, and

has risen dramatically, and the degree of heterogeneity between "classical" services such as banking and knowledge-producing branches within the service sector has increased. Therefore it has been argued that the three-sector-hypothesis should be complemented by a forth sector (Porat 1976 and OECD 2005). But a classification of which industries belong to one which of the four sectors is difficult, since consequently activities associated with services which are in the manufacturing sector ought to be counted for the service sector; so we decided not to introduce a separate ICT based sector and stick to the more traditional division of sectors. Moreover, our data are too highly aggregated to allow for a forth sector. As a consequence we decided to work with three aggregate sectors and included ICT branches in the manufacturing and service sectors respectively. Hence, we study the impact of the diffusion of information and communication technologies in the economy only through intrasectoral convergence.

cultural backgrounds (Chenery 1960). Whereas the importance of the latter two factors is diminishing as a consequence of the ongoing process of European integration, the impact of differences in country size on divergence processes should not be underestimated, as is suggested by models of the New Economic Geography (Krugman 1991a, 1991b, Puga 1999).

Regarding intrasectoral convergence and divergence, the direction of development is less clear-cut and highly dependent on the characteristics of each individual industry, but also on trading costs, trading barriers, and the natural endowments of European countries. On the one hand, the ongoing process of globalization and the decline in trade costs have affected the comparative advantages of European countries similarly. The competitiveness in labor-intensive and low-skill industries has decreased compared to low-cost countries. This should have lead to a massive reallocation of labor within Europe, as low-technology and labor-intensive industries have been outsourced whilst the shares of technology-, skill-, and capital-intensive industries have risen. Structural change has been most dramatic in countries with a disproportionately high share of low-skill industries at the beginning of this process. Besides, the vanishing of trade barriers enhances the diffusion of knowledge so that new technologies become available to a large group of countries and enable technologically lagging countries to catch-up to technological leaders (de la Fuente 1997; Pigliaru 2003). One important precondition for this catch-up is that lagging countries have a sufficient base of "social and technological capabilities" (Nelson 2005) in order to absorb new knowledge and to use new high-class technologies (Fagerberg 1994). Within Europe, these capabilities ought to be present in all countries - whereas this is not necessarily the case for newly industrialized countries. For this reason, the diffusion of knowledge is expected to cause convergence in medium and high-technology industries. In emerging high-tech industries, however, divergence is possible, as technologically leading European countries may specialize in high-technology industries to maintain their competitive edge.

The effect of European integration, on the other hand, is ambiguous: Lower transaction costs due to European integration imply on the one hand a lower importance for the proximity of producers and suppliers, and on the other hand better access of firms located at peripheries to markets, which result in de-concentration of economic activities (Rossi-Hansberg 2005). Therefore, convergence of regions and countries becomes more probable the fiercer the competition of agglomerated firms, the higher the (productivity-adjusted) wages, rents and congestion costs at economic centers compared to the peripheries are (Krugman and Venables 1995, Murata and Thisse 2005).

Yet, this implication is somehow in contrast with the thesis of the New Economic Geography (Krugman 1980, Krugman 1991a) that both specialization and concentration exhibit a U-shape relationship with transport and trade costs, in that for a decrease in transaction costs from very high to intermediate levels, specialization and concentration increase, since they enhance the opportunities of firms to exploit economies of scale, reduce production costs and make it less necessary to be close to immobile consumers. Economic integration and trade liberalization therefore are expected to facilitate the international division of labor and contribute to the persistence or even the broadening of structural differences between countries. When, however, transaction costs get very low, centripetal forces outweigh centrifugal forces and thereby drive de-concentration and de-specialization processes.

Intrasectoral divergence may be promoted by European integration particularly in the following cases: Industries which exhibit increasing returns to scale are likely to concentrate production in larger countries, as large domestic markets can more easily attract firms and workers than smaller domestic markets (Krugman 1980, Midelfart et al. 2003). Similarly, a large number of up- and downstream linkages in imperfectly competitive industries leads to a high level of concentration (or clustering) of economic activities, such as in the case in the automobile industry (Fujita et al. 1999): firms benefit from locating close to upstream firms, because intermediate products can be purchased at lower prices, transport costs are saved, and a greater number of differentiated inputs becomes available, which further enhances competitiveness.

Further driving forces for intrasectoral divergence are the existence of pecuniary or technological externalities (Krugman and Venables 1995) because industries are likely to be spatially concentrated in order to minimize production costs, benefit from a common pool of knowledge and infrastructure and take advantage of the path-dependency in the creation and accumulation of knowledge in the presence of such externalities. In addition, the divergence of production structures is due to path-dependent developments (Venables 1996). This is especially true for high-skill and high-technology industries, which are likely to show strong patterns of path dependency, since the creation and accumulation of knowledge are characterized by path-dependencies. Moreover, countries are expected to specialize in those branches where they originally have comparative advantages (Ohlin 1933). In our case however, the argumentation of comparative advantages is of limited value since European countries, though they show similar factor endowments and use similar technologies, still exhibit quite different production structures, which cannot be explained by traditional trade theory.

A central point in the argumentation of New Economic Geography models is the mobility of labor (Krugman 1991a, Puga 1998). Only in case of high intersectoral and/or interregional mobility of labor there can be considerable agglomeration of economic activities, as only then firms at economic centers are able to attract workers from other regions by paying higher real wages. This leads to even greater markets, lower production costs and a greater attractiveness of production at economic centers. In European reality, however, migration and labor mobility are rather low, therefore economic activity ought to be spread more unevenly across space, as captured by Tabuchi and Thisse (2002) who account for individual preferences to live in a country (region) even though other regions would pay higher wages.

From these arguments (as summarized in table 4.1) we derive the hypothesis that the impact of globalization has been particularly strong on mature, labor-intensive, and low-technology industries. Hence, we expect convergence in these industries, as employment there should shrink in all observed countries due to outsourcing processes to mainly slowly-imitating countries (Krugman 1979). Moreover, there should not be "technological gaps" within Europe in these branches, making specialization almost impossible, as there are hardly any innovations which are not imitated within very short periods of time (Posner 1961). Secondly, we expect convergence for low and medium technology industries due to technology diffusion across European countries. Industries which exhibit economies of scale and are technology- and knowledge-intensive can be expected to exhibit divergence ought to occur, since in these industries path-dependencies are likely to exist. They will be located in countries with large home markets and good access to skilled labor and infrastructure.

Table 4.1: Driving forces of convergence and divergence

Convergence	**Divergence**
Supply side effects	
- Increases in labor productivity in lagging countries, i.e. technological catch-up, imitation of new techniques - Cost-differential in production between core and periphery (i.e. high wages and rents in the center) letting firms spread to the periphery at very low costs of trade - Outsourcing of production from Europe to other countries, i.e. increase in trade with low-wage countries (leading to a decline of labor intensive industries across Europe)	- Technological gap (differences in productivity), implying comparative advantages of advanced countries in high-tech industries - Externalities (technological or pecuniary) and input-output-linkages, leading to concentration of production at the center - High spatial concentration of one specific input factor (natural resources, special skills) - High labor mobility
Demand side effects	
- Convergence in demand structures leading to convergence in production, especially in the service sector	- Home market effects, i.e. more sales in big markets where demand is large
European integration	
- Structural funds for lagging countries by the EU fostering firm localization in the periphery	- Economic integration, leading to lower transaction costs and better possibilities to exploit economies of scale

Industries in the service sector are expected to show slow development - if any - because they are characterized by a high degree of immobility. Conversely, manufacturing goods are more easily tradable. European integration as well as globalization therefore is assumed to have a greater impact on manufacturing than on the service sector. At the same time, we expect to observe differences between locally oriented branches and globalizing industries.

4.3 Methodological issues

In order to detect structural convergence (or divergence, respectively) we implement the classical approaches of σ- and β-convergence that were initially introduced by Barro and Sala-i-Martin (1992, 1995) in the context of income convergence.

4.3.1 σ-convergence

For empirical tests on structural σ-convergence, a measure of heterogeneity is required, since increasing (decreasing) heterogeneity is interpreted as divergence (convergence). A number of indices developed for this purpose can be found in the literature (e.g. Krugman 1991a, Cuadrado-Roura 1999, Landesmann 2000, Aiginger and Davies 2004, Brülhart and Traeger 2005). The major drawback of all of these indices is that they are not able to distinguish between inter- and intrasectoral developments, and to account for size differences of sectors when calculating intrasectoral convergence. This might lead to misleading conclusions about the structural economic development within Europe. We construct an index which captures the total heterogeneity of economic structures between N countries, the *Index of Structural Heterogeneity* (SHE^N).[2] It is based on the industry-specific SHE_s^N, i.e. the N countries' heterogeneity in each industry s (similar to Krugman 1991a), calculated as the sum of the countries' deviations b_s^n from the average employment share of industry s from total employment over all countries $\overline{b_s}$:

$$SHE_s^N = \frac{1}{N}\sum_{n=1}^{N}\left|b_s^n - \overline{b_s}\right|. \tag{4.6}$$

[2]With this index we do not overcome the fundamental shortcomings of aggregate national-level indices which do not account for localization, i.e. the role of firm clustering and concentration effects on country specialization. In addition, these indices do not enable us to see which countries (de-)specialize in which industries. For these aspects, a more detailed analysis based on regional or firm-level data would be required (see Duranton and Overman, 2005), which is beyond the scope of this paper. However, in contrast to the existing indices SHE^N permits the decomposition into inter- and intrasectoral parts, conforming to the emphasis of the present analysis. We use absolute deviation instead of variance in order to maintain the intuitive interpretation of the index as the employment share which would have to be relocated to achieve the European average.

Summing the index over all industries yields the aggregate index of structural heterogeneity, which indicates the overall heterogeneity of all countries' industry structures. This index is then divided by the number of industries being analyzed, so for S industries and N countries this is:

$$SHE^N = \frac{1}{N}\frac{1}{S}\sum_{s=1}^{S}\sum_{n=1}^{N}\left|b_s^n - \overline{b_s}\right|. \tag{4.7}$$

Using this index we are able to measure absolute concentration, that is, to what degree the production structures of individual countries differ from the average production structure in Europe. We do not, however, measure relative concentration, such as whether country A - being twice as large as country B - produces twice as much as country B in industry s.

So far, we have not distinguished between inter- and intrasectoral heterogeneity, meaning that the index can be used for all aggregation levels alike. Taking the shares of the three aggregate sectors, (agriculture, manufacturing, and services), makes it possible to test for intersectoral change and thereby for the validity of the three-sector-hypothesis; similarly we could focus on only one of these sectors, measuring for example the shares of individual manufacturing industries on total manufacturing, and analyze intrasectoral convergence instead. For a comprehensive analysis, we combine the different aggregation levels and test to which extent they contribute to overall convergence across countries. For this purpose, we have to put the respective heterogeneity index values into relation. We calculate SHE^N for N countries and assume K aggregate sectors, each consisting of S_k industries; the employment shares b are calculated relative to total employment of the aggregate sector (marked by the subscript k) or employment of the entire economy (subscript E). It is easy to show that the following equality holds:

$$\underbrace{\frac{1}{N}\frac{1}{S}\sum_{n=1}^{N}\sum_{s=1}^{S}\left|b_{s,E}^n - \overline{b_{s,E}}\right|}_{total\ SHE^N} = \underbrace{\frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{K}\frac{1}{s_k}\left|b_{k,E}^n - \overline{b_{k,E}}\right|}_{intersectoral\ SHE^N} + \underbrace{\frac{1}{N}\sum_{n=1}^{N}\sum_{k=1}^{K}\frac{1}{s_k}b_{k,E}^n\sum_{s=1}^{S_k}\left|b_{s,k}^n - \overline{b_{s,k}}\right|}_{intrasectoral\ SHE^N} \tag{4.8}$$

Equation (4.8) implies that heterogeneity - and hence convergence or divergence - can be formally decomposed into an intersectoral and an intrasectoral part (given by the first and the second terms on the right-hand side, respectively), the latter being scaled by the average share of the respective sector k. The smaller a sector (i.e. the smaller its employment share $\overline{b_{k,E}}$), the smaller is the impact of intrasectoral heterogeneity within this sector on the aggregate index of structural heterogeneity. This means for instance that while the service sector has been growing, intrasectoral heterogeneity in the service sector contributes more to the total SHE^N in 2005 than in 1970, even if the actual degree of intrasectoral heterogeneity had not changed at all.

In order to test for σ-convergence we calculate SHE^N for each year in the observation period 1970-2005 (1970-2004 for manufacturing industries) and analyze the development of the index over time using the time series methods described below. A growing SHE^N is interpreted as a sign of divergence, while a decreasing SHE^N points towards convergence. We model the development of heterogeneity as an autoregressive integrated moving average process ($ARIMA(p, d, q)$) with $d = 1$ according to the following (general) equation:

$$\Delta lnSHE_t = \phi+\mu_1\Delta lnSHE_{t-1}+...+\mu_p\Delta lnSHE_{t-p}+\varepsilon_t+\theta_1\varepsilon_{t-1}+...+\theta_q\varepsilon_{t-q}. \quad (4.9)$$

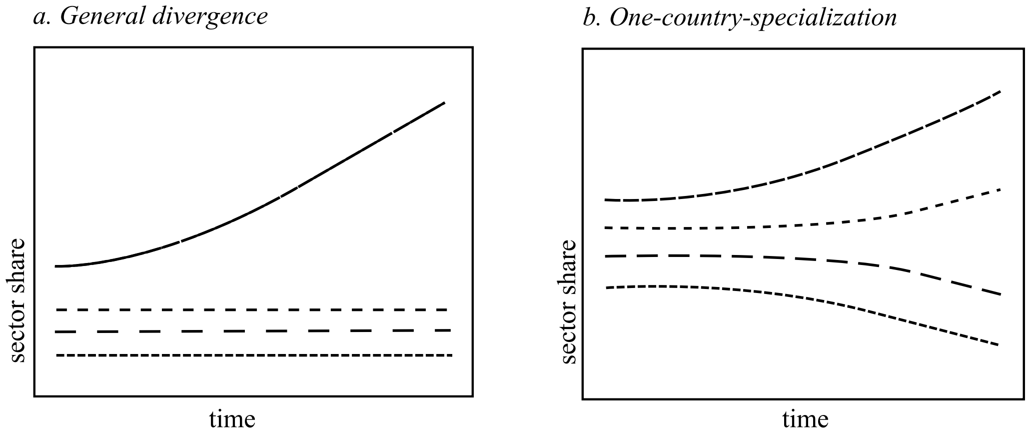
To achieve stationarity of variances and covariances we use the logarithm of the values. First differences have been taken in all cases, since the hypothesis of (trend-)stationarity was rejected for all time series. Using the Augmented Dickey-Fuller test we cannot reject the hypothesis of a unit root for all time series, but we find stationarity of the first differences for nearly all sectors/industries; for the results of the ADF see tables C.2 and C.3 in the appendix. The estimation result we are most interested in is the constant ϕ which in the case of $d = 1$ indicates the (deterministic) time trend of the time series.[3] A value of ϕ significantly greater than zero is interpreted as a sign that heterogeneity increases over time implying divergence, whereas a significant and negative ϕ indicates a decrease of SHE and thus convergence.

In contrast to the existing literature, we distinguish between general divergence (convergence) in an industry and one-country specialization (catch-up). Though this distinction is relevant for economic policy, it has not yet been accounted for in the literature. Particularly in the case of divergence the difference between one-country-specialization and a general dispersion trend would be notable: Whenever economic integration causes all countries to drift apart gradually, this is likely due to the possibility of some countries to enhance their competitive advantage at the cost of other countries. This might be the case if larger countries gain from economic integration at the cost of smaller countries, as larger countries can then better exploit input-output linkages and their availability of skilled workers. On the other hand, one-country-specialization presumably takes place in emerging industries and highly path-dependent industries, in which case only one (or very few) countries gains leadership and can perpetuate and even increase their competitiveness over time. Figure 4.1 illustrates both divergence types in a simplified form.

As the lines between one-country-specialization and general divergence can be blurry, an exact differentiation between general dispersion and one-country-specialization is difficult. As an approximate solution we calculate SHE^N, SHE^{N-1} for the country group without the country deviating the most, and the employment share of the most deviating country in relation to the European average (*max deviation*).

[3] Lag orders were specified for each time series separately in order to achieve a good fit of the model. However, we are not interested in the values of the AR- and MA-characteristics of the series. Therefore the complete results of the $ARIMA$ regressions are reported only in the appendix (see tables C.4-C.9).

Figure 4.1: Divergence types



The development of these three variables over time can be used to identify the different convergence/divergence types: One-country-specialization is present instead of general divergence either in the following two cases: First, if the time trend of the maximum deviation is significant and positive, and second if the time trend of SHE^N is insignificant or positive and the time trend of SHE^{N-1} of the remaining countries is significant and negative, insignificant, or significantly smaller than SHE^N. As to convergence, a similar distinction is possible for the case that the most specialized country gives up its position. We should expect a negative and significant time trend of the maximum deviation, together with an insignificant time trend of SHE^{N-1}. To validate the result in case of one-country-specialization, we must rule out the possibility that the role of the most deviating country devolves from one country to the other from one year to the next. For general divergence, a change in the most deviating country is irrelevant. In our data, we find changes regarding the role of the most deviating country only for general convergence or divergence - or to be more precise, in cases where no country is highly specialized.

Table 4.2: Identification of convergence/divergence types

	SHE^N	SHE^{N-1}	$max\ deviation$
General divergence	> 0	> 0	≥ 0
One-country-specialization	≥ 0	$< SHE^N$	> 0
General convergence	< 0	< 0	≤ 0
One-country-despecialization	≤ 0	$> SHE^N$	< 0

4.3.2 β-convergence

The second approach to measure convergence/divergence is the β-convergence test. We test for unconditional convergence, which implies that all countries tend to converge until all countries have the same employment shares in all respective industries.

Therefore, countries whose industrial structure deviates the most from the average structure have to undergo the largest transition and adaptation process. Although this approach has been criticized in the literature (Quah 1993), β-convergence is still a commonly used concept, based on the appealingly simple idea that if the initial value of the variable (in the case of structural convergence this is the industries' employment shares) has a significant and negative impact on the growth of the variable over the investigation period $0 - T$, then the countries are considered to converge:

$$\Delta e_T^{i,s} = \alpha^s + \beta^s e_0^{i,s} + \varepsilon^{i,s}, \tag{4.10}$$

where $\Delta e_T^{i,s} = e_T^{i,s} - e_0^{i,s}$ and $e_t^{i,s}$ is the deviation of country i's employment share in industry s relative to the average European employment share of this industry at time t. We use the deviation from the average instead of normal employment shares to control for structural change which affects all countries similarly, thereby causing a bias on the convergence estimation. In order to fully exploit our cross-sectional time series data, we depart from the aforementioned basic model and estimate the following equation:

$$\Delta e_t^{i,s} = \alpha^s + \beta^s e_{t-1}^{i,s} + \varepsilon_t^{i,s}. \tag{4.11}$$

Here, $\Delta e_t^{i,s}$ is the annual change of country i's deviation of the employment share in industry s at time t from the European average, i.e. we test the hypothesis that there is a negative (or in the case of divergence, positive) link between the deviation from the European average in the previous year and the growth of the employment share in relation to the European average. For the analysis of β-convergence, we use a linear[4]random effects estimator, since we don't want to attribute the changes in employment shares to specific (fixed) country effects.[5] Each industry has been analyzed separately in order to distinguish between diverging and converging branches, instead of making generalizations across industries.

4.4 Data

Our empirical analysis is based on macro data of 14 EU member states (EU 15 without Luxembourg), covering the observation period of 1970-2004/2005. The data is drawn from the KLEMS data base (see Timmer et al. 2007), which provides data collected from the EU countries' national accounts, and additionally from the public Eurostat data base.

Above we presented a method of detecting convergence and divergence, respectively. For the implementation of these concepts, we use a classification of three aggregate sectors (agriculture, manufacturing, and services), nineteen manufacturing indus-

[4]One could argue that a linear model does not take into account that our dependent variable, the deviations from employment shares, is limited between -1 and 1 by definition. Since we do not expect any observations near the boundaries however, the OLS model is a reasonable choice, mainly due to its robustness to heteroscedasticity and non-normality.

[5]The adequacy of the random effects model has been confirmed by Hausman tests.

tries and ten service branches, according to the NACE classification.[6] The agricultural sector is not further differentiated, since we do not expect substantial intrasectoral structural change within this sector, which contains only three industries. Instead of establishing ICT as a forth aggregate sector, we integrate the ICT-related industries in the manufacturing and service sectors, respectively, since the high aggregation level of our industry classification precludes a precise distinction of ICT and non-ICT industries, like for example in the case of post and telecommunication.

Some industries are not included in the analysis: Data for utilities (electricity, gas and water supply), public administration and community services, like public waste disposal or cultural activities, is partly missing or available only at a highly aggregated level. Furthermore, we exclude the construction sector, due to its high sensitivity to business cycles and public spending.

The main variable used is employment, captured in total yearly hours worked by employed persons, which is the most comprehensive and (for our purpose) robust measure of sector (industry) shares available. Total hours worked per year are preferable to the number of employees, which can be biased by national and intertemporal differences in working hours and the share of part-time workers. A drawback of employment data is a productivity bias: Countries with particular low productivities in an industry appear more specialized in this industry if focusing employment data than regarding output data. This could lead to an underestimation of specialization as high productivity and specialization may be correlated. To overcome this problem, output-oriented indicators such as value added or exports could be used, but these bear the risk of being biased by inflation, exchange rates, world market influences (e.g. the prices of intermediate inputs), variation due to the business cycle and outsourcing. Besides, the calculation methods used for the national accounts have been standardized only in 1995, so that measurement errors may occur in particular at the beginning of the observation period.

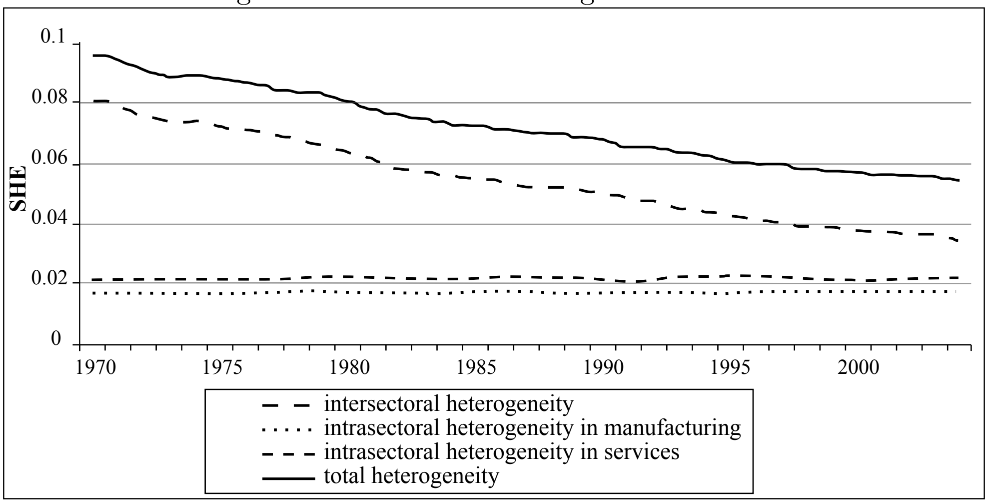
Although employment data is less problematic than value added, some drawbacks of the long observation period remain: At the beginning of our observation period, the European Community was made up of only the six founding member states. Since then, the European Union has been continuously enlarged and from 1995 on comprises all countries investigated over the observation period. We therefore analyze member and (still) non-member states together, without accounting for potential differences due to membership. A second question is how to treat Germany before and after reunification in 1990: On the one hand, comparability is affected if we switch between West and unified Germany; on the other hand, excluding Eastern Germany after Unification and thus including only West Germany in the analysis for the whole period would result in a biased picture of the German industry structure. Therefore, we use the extrapolated values for Germany at its present size for 1970-1990, which are included in the KLEMS database.

[6]A description of the industry classification can be found in table C.1 in the appendix.

4.5 Empirical results

Overall and considering both intersectoral and intrasectoral aspects, we clearly find convergence between European countries: Total structural heterogeneity decreases steadily from 1970 to 2004 (from 0.096 to 0.054). As can be seen from figure 4.2[7], the driver of convergence is intersectoral change due to industrialization and tertiarization processes occurring in all countries, especially in countries which were characterized by a relatively large agricultural sector in the 1970s. These results corroborate the three-sector-hypothesis.[8] On the intrasectoral level, in contrast, we find slight divergence. This is not unexpected, since the industries aggregated in these two sectors may not develop in identical directions. Some industries may diverge due to path-dependencies and economies of scale, whereas in other industries congestion costs and high labor costs at production centers may lead to convergence. As these (simultaneous) opposing trends may cancel each other out in the aggregate view, an analysis on the industry level is necessary to detect the convergence and divergence tendencies within the manufacturing and service sector respectively.

Figure 4.2: Structural convergence over time



Source: EU KLEMS Database, March 2007

A first overview of the data is given in tables 4.3 and 4.4, which list the values of the intrasectoral heterogeneity indices SHE^N of manufacturing and service industries at the beginning and the end of the observation period. Table 4.3 shows that both the degree of (country-) heterogeneity and the rate and direction of the development of heterogeneity vary widely between industries: In some cases, like for example in the

[7]The lines depicting inter- and intrasectoral heterogeneity in this figure do not add up to total heterogeneity, because the total SHE contains intrasectoral heterogeneity weighted by the respective sector share (see equation (4.8)). Figure 4.2 depicts the intrasectoral SHE in its unweighted form to abstract from changes in the size of the sector, which would bias the SHE in manufacturing towards convergence and in services towards divergence.

[8]We do not go into detail on aggregate basic sectors which have been investigated in some detail in previous work (see e.g. Chenery and Syrquin 1989).

Table 4.3: Heterogeneity in manufacturing industries

Industry	SHE^N 1970	SHE^N 2004	$SHE^N/branch\ size$ 1970	$SHE^N/branch\ size$ 2004
Food, Drink & Tobacco (FDT)	0.5681	0.3976	0.0523	0.0301
Textile	0.6410	0.8927	0.0401	0.1066
Leather	0.1298	0.2021	0.0539	0.1295
Wood	0.2686	0.1934	0.0856	0.0565
Paper	0.1828	0.1473	0.0704	0.0609
Printing & Publishing	0.1861	0.2134	0.0442	0.0364
Coke & Fuel	0.0464	0.0431	0.0685	0.0847
Chemicals	0.1803	0.2679	0.0344	0.0502
Rubber & Plastic	0.0758	0.1447	0.0260	0.0305
Non-metal Mineral Products	0.1586	0.1691	0.0308	0.0353
Basic Metals	0.3402	0.1710	0.0689	0.0545
Fabricated Metals	0.2518	0.1848	0.0267	0.0166
Machinery	0.4260	0.4591	0.0420	0.0442
Accounting & Computing Machines	0.0462	0.0893	0.0914	0.1641
Electrical Engineering	0.1853	0.1603	0.0457	0.0365
Communications Equipment	0.1458	0.1687	0.0606	0.0709
Precision Instruments	0.1734	0.1920	0.0652	0.0646
Transport Equipment	0.3232	0.4571	0.0405	0.0527
Recycling	0.1902	0.2507	0.0407	0.0409

Source: EU KLEMS Database, March 2007

Table 4.4: Heterogeneity in service industries

Industry	SHE^N 1970	SHE^N 2005	$SHE^N/branch\ size$ 1970	$SHE^N/branch\ size$ 2005
Domestic Services	0.2828	0.3035	0.1130	0.0943
Hotels & Restaurants	0.4250	0.4721	0.0504	0.0533
Wholesale & Retail Trade	0.3853	0.4511	0.0104	0.0173
Transport & Storage	0.2609	0.1326	0.0214	0.0159
Post & Telecommunication	0.1080	0.0795	0.0277	0.0336
Financial Intermediation	0.1467	0.1551	0.0288	0.0317
Real Estate	0.0773	0.0884	0.0651	0.0513
Business Services	0.4407	0.5788	0.0476	0.0283
Education	0.1966	0.1813	0.0223	0.0197
Health & Social Work	0.4778	0.6133	0.0414	0.0414

Source: EU KLEMS Database, March 2007

wood and paper branches, countries are more similar in 2004 as compared to 1970, while in others, such as in the textile and leather industries, heterogeneity in 2004 is higher than in 1970. Note that heterogeneity tends to be higher in large industries, since we measure absolute deviations from the average employment share.

Similar differences in the degree and development of heterogeneity can be found in service industries (see table 4.4). Interestingly, most of the service industries are more heterogeneous in 2005 as compared to 1970, with the exception of transport/storage and post/telecommunication services.

4.5.1 Estimation results - manufacturing sector

Building on the descriptive statistics, we analyze intrasectoral convergence and divergence using time-series and panel data methods (for σ- and β-convergence tests, respectively), starting with the manufacturing sector.

As table 4.5 shows, we find both σ-convergence and σ-divergence in the manufacturing sector. Significant convergence over the entire observation period is found for the food, drink and tobacco (FDT) industry, the manufacturing of wood products and the fabricated metal industry. In the former two branches, convergence seems to result from the de-specialization of one country, as the low coefficient of SHE^{N-1} shows: Ireland and Finland, which in the 1970s had particularly high shares in the FDT and wood industries, respectively, shifted towards the emerging ICT-industries over time. This finding confirms the results of Midelfart-Knarvik et al. (2000) who discuss the outstanding phenomenon of structural change in Finland and Ireland at length. It is remarkable that the paper industry, though it resembles the wood industry and is also dominated by the Scandinavian countries in the 1970s, does not significantly converge over time.

Regarding divergence, our hypothesis on the role of economies of scale is confirmed: the chemical, rubber and plastics, and transport equipment industries significantly diverge over the observation period, which we attribute to economies of scale and strong forward-backward-linkages. The influence of these factors can be seen as an explanation also for the significant divergence of textile, leather and footwear production as well as of the manufacturing of non-metal mineral products, though regarding the latter only from the mid 1980s on. Additional specific factors may play a role in most of these industries, as discussed in our theoretical argumentation; e.g. the specialization of South European countries on textiles may be driven by the lower wage level, whereas in the transport equipment industry a path-dependent development based on traditional industrial orientations can be assumed to prevail.

We expected divergence also in emerging industries, in particular in the ICT-related branches, but here specifically one-country-specialization. In four industries (recycling, accounting and computing machines, communications equipment, and precision instruments) the results can be interpreted in this way, given the insignificant or slightly positive time trends of the SHE^N combined with significant and positive coefficients of the *max deviation*. The countries which specialize in these emerging industries are Ireland for accounting and computing machines and precision instru-

Table 4.5: σ-convergence in manufacturing industries

Industry	**time trend** $ln\ SHE_s^N$		**time trend** $ln\ SHE_s^{N-1}$		**time trend** *max deviation*	
Food, Drink & Tobacco (FDT)	-0.0110 **	*(0.0052)*	-0.0087	*(0.0071)*	-0.0193 **	*(0.0091)*
Textile	0.0097 ***	*(0.0030)*	0.0105 **	*(0.0041)*	0.0075	*(0.0050)*
Leather	0.0135 **	*(0.0059)*	0.0122 **	*(0.0061)*	0.0187 *	*(0.0106)*
Wood	-0.0097 **	*(0.0047)*	-0.0072 *	*(0.0044)*	-0.195 *	*(0.0112)*
Paper	-0.0065	*(0.0062)*	-0.0047	*(0.0069)*	-0.0083	*(0.0105)*
Printing & Publishing[1]	0.0160 *** -0.0215 ***	*(0.0051)* *(0.0081)*	0.0203 *** -0.0194 *	*(0.0067)* *(0.0114)*	-0.0057	*(0.0106)*
Coke & Fuel	0.0001	*(0.0119)*	-0.0025	*(0.0158)*	0.0062	*(0.0193)*
Chemicals	0.0116 **	*(0.0059)*	0.0067 *	*(0.0037)*	0.0373 ***	*(0.0115)*
Rubber & Plastic	0.0192 ***	*(0.0056)*	0.0212 ***	*(0.0058)*	0.0056	*(0.0101)*
Non-metal Mineral Products[2]	-0.0221 * 0.0188 **	*(0.0122)* *(0.0086)*	-0.198 0.0213 **	*(0.0215)* *(0.0089)*	-0.0080	*(0.0138)*
Basic Metals[5]	-0.0044	*(0.0027)*	-0.0036	*(0.0023)*	-0.0235 ***	*(0.0088)*
Fabricated Metals	-0.0091 *	*(0.0052)*	-0.0106 *	*(0.0057)*	0.0052	*(0.0244)*
Machinery	0.0022	*(0.0031)*	0.0016	*(0.0035)*	0.0109	*(0.0073)*
Accounting & Computing Machines	0.0194	*(0.0163)*	0.0029	*(0.0132)*	0.0387 *	*(0.0198)*
Electrical Engineering	-0.0050	*(0.0035)*	-0.0065 *	*(0.0037)*	0.0078	*(0.0068)*
Communications Equipment[3]	0.0050	*(0.0141)*	-0.0028	*(0.0158)*	-0.0099 0.1145 *	*(0.0103)* *(0.0614)*
Precision Instruments[4]	0.0033	*(0.0047)*	-0.0035	*(0.0031)*	-0.0057 0.0830 **	*(0.0107)* *(0.0344)*
Transport Equipment	0.0110 *	*(0.0061)*	0.0109 *	*(0.0064)*	0.0103	*(0.0113)*
Recycling	0.0081 *	*(0.0046)*	0.0019	*(0.0043)*	0.0188 **	*(0.0089)*

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

[1] *structural break in 1993/1994;* [2] *structural break in 1984/1985;* [3] *structural break in 1994/1995;* [4] *structural break in 1991/1992. In all cases, the first sub-period is in the upper line.* [5] *no logarithm.*

ments, Finland for communications equipment and the Netherlands for the recycling industry. We attribute this phenomenon to the existence of first-mover advantages in combination with economies of scale and technological externalities. Interestingly, the specialization in precision instruments as well as in communications equipment only started in the 1990s, which is in line with the technological development in these branches.

A number of industries do not significantly change over time, which can be interpreted in several ways. In the case of machinery, electrical engineering, and basic metals, linkages to other branches like transport equipment might influence the location of firms so that divergence in transport equipment should cause divergence also in machinery; but if the respective industry is linked to several other branches, as should be the case for these generic industries, the result will be neither convergence nor divergence. In contrast, in the coke and fuels industry opposing forces may play a role, such as a changing endowment with natural resources (e.g. due to pipeline projects), influences of economic policy, or productivity differences which may level each other out and preclude a clear development.

The estimations of β-convergence in general confirm the results of the σ-convergence test (see table 4.6). If necessary, the observation period was divided into sub-periods to account for a structural break; this was the case in 12 of the 19 manufacturing industries, while the others exhibit a steady development over time. When comparing the sub-periods across industries it can be seen that the timing of the structural breaks is industry-specific rather than linked to European and worldwide economic integration, respectively.

Going into detail, the findings again show convergence of mature industries with high labor-, energy- and (natural) resource-intensities such as FDT, wood, paper, basic and fabricated metals. The significant convergence of the paper and basic metals industries is not unexpected in respect of our hypotheses, but yet notable given the insignificant σ-coefficients.

Divergence of industries with economies of scale is found as well, but is significant mainly in later intervals of the observation period (e.g. in rubber/plastics and transport equipment, as well as recycling and precision instruments). Only the chemical industry significantly diverges over the entire period.

The results regarding the ICT-industries (i.e. communications equipment, and accounting and computing machines) are remarkable: We expected divergence in the early stages of emerging industries when single countries lead the development, followed by convergence when countries catch up. This pattern is found in both cases, with significance being high both for divergence and convergence.

The development of textile and leather manufacturing is also surprising since both industries significantly diverge until the mid 1990s and significantly converge afterwards. This pattern can be analyzed from two different perspectives: On the one hand, both industries are characterized by high labor-intensities and the existence of economies of scale. The first attribute would imply the outsourcing of production to low-cost countries and thus convergence across European countries while the second should favor industry concentration and thus divergence. Our findings could indicate that the second force prevailed in the beginning of the observation period before later on the first force gained more importance in the course of globalization. On the other hand, both branches are dominated by South European countries, which have a long tradition in textile and leather production, especially Italy, Spain, and Portugal. Compared to North European countries structural change in these economies took place more slowly, because - due to low wage levels - the Mediterranean countries could maintain their cost-competitiveness in labor-intensive industries longer, and at the same time had less social and technological capabilities to shift to more skill- and technology-intensive branches. This holds in particular for Portugal, which started abandoning the textile and leather industries only in the mid-1990s. From

Table 4.6: β-convergence in manufacturing industries

Industry	**period**	β	**wald** χ^2	**period**	β	**wald** χ^2
Food, Drink & Tobacco (FDT)	1970-2004	-0.0082 ** *(0.0048)*	2.87	-		
Textile	1970-1993	0.0122 *** *(0.0031)*	15.42	1994-2004	-0.0086 ** *(0.0043)*	3.97
Leather	1970-1994	0.0201 *** *(0.0049)*	17.00	1995-2004	-0.0159 *** *(0.0056)*	8.03
Wood	1970-2004	-0.0172 *** *(0.0039)*	19.42	-		
Paper	1970-2004	-0.0094 *** *(0.0025)*	14.21	-		
Printing & Publishing	1970-1993	0.0044 *(0.0072)*	0.37	1994-2004	-0.0317 ** *(0.0129)*	5.99
Coke & Fuel	1970-2000	-0.0119 ** *(0.0061)*	3.86	2001-2004	0.0395 ** *(0.0190)*	4.30
Chemicals	1970-2004	0.0138 ** *(0.0058)*	5.65	-		
Rubber & Plastic	1970-1983	-0.0116 *(0.0137)*	0.73	1984-2004	0.0124 * *(0.0074)*	2.78
Non-metal Mineral Products	1970-1984	-0.018 ** *(0.0078)*	5.30	1985-2004	0.0029 *(0.0083)*	0.12
Basic Metals	1970-2004	-0.0219 *** *(0.0042)*	27.50	-		
Fabricated Metals	1970-1987	-0.0117 * *(0.0069)*	2.91	1988-2004	-0.0043 *(0.0084)*	0.26
Machinery	1970-2004	-0.0010 *(0.0043)*	0.05	-		
Accounting & Computing Machines	1970-2001	0.0475 *** *(0.0054)*	76.08	2002-2004	-0.1136 *** *(0.0278)*	16.66
Electrical Engineering	1970-2004	-0.0017 *(0.0051)*	0.11	-		
Communications Equipment	1970-2000	0.0552 *** *(0.0098)*	31.64	2001-2004	-0.0605 ** *(0.0253)*	5.73
Precision Instruments	1970-2000	0.0082 *(0.0069)*	1.41	2001-2004	0.0596 *** *(0.0166)*	12.85
Transport Equipment	1970-1993	-0.0027 *(0.0082)*	0.11	1994-2004	0.0174 ** *(0.0081)*	4.64
Recycling	1970-1980	0.0111 *(0.0110)*	1.02	1981-2004	0.0122 ** *(0.0060)*	4.14

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

this point of view, the β-coefficients could be interpreted as a sequence of divergence and convergence between North and South Europe. The question of whether the development of the textile and leather branches mirrors the influence of economies of scale or rather the structural development of South European countries remains open.

Regarding the printing and publishing industry, which exhibits an interesting development as well, the limitations of our data become evident. We find weak σ-convergence until 1984 and both σ- and β-divergence in later sub-periods. The convergence trend may be caused by the structural change in Scandinavia, since the printing industry is closely linked to forestry and the wood and paper industries. In contrast, for the later divergence tendency, several factors may play a role: On the one hand, digitalization may have created economies of scale both in printing, publishing, and media reproduction; on the other hand divergence may have occurred prevalently in the publishing industry which at the same time has gained importance in relation to printing over time. However, for the analysis on which subdivisions of the industry drive divergence, more disaggregated data would be required.

4.5.2 Estimation results - service sector

In the service sector our expectation that convergence or divergence should be low (as pointed out in chapter 2), is largely confirmed by the σ-convergence test. The time trends of the heterogeneity index are not significant in most industries, as shown in table 4.7. Significant trends of the SHE are found only in transport/storage, post and telecommunications services, and financial intermediation. The transport/storage branch significantly converges over the observation period, while the latter two industries show a divergence trend in the second sub-period, which appears to be mainly caused by the specialization of Ireland. Notable is the highly significant convergence of post and telecommunication services until 1988, which we attribute to technological and organizational developments resulting in productivity convergence across European countries.

The remaining service branches do not show significant changes in heterogeneity over time. In the first three branches, which are mainly consumer-oriented (i.e. domestic services, hotels and restaurants, and trade), the reason may be local boundedness, which restrains both (path dependent) specialization within Europe and outsourcing to low-cost countries outside Europe. The results for education as well as for health and social work might mirror the differences in the social systems of the European countries. Interestingly, no significant divergence is found for business services, which we expected to be characterized by economies of scale and a strong dependence on the manufacturing industries. A reason for this could be the heterogeneity of business services subsumed in this branch so that convergence and divergence trends within the business services industry may level each other out.

Applying the β-convergence test on service industries, we find convergence in several branches, but no case of divergence (see table 4.8). Divergence has not been expected except for business services and financial intermediation, since concentra-

Table 4.7: σ-convergence in service industries

Industry	**time trend** $ln\ SHE_s^N$		**time trend** $ln\ SHE_s^{N-1}$		**time trend** *max deviation*	
Domestic Services[1]	-0.0168	*(0.0138)*	0.0072	*(0.0052)*	-0.0423 **	*(0.0170)*
	0.0096	*(0.0068)*			0.0279	*(0.0253)*
Hotels & Restaurants	0.0025	*(0.0022)*	0.0044	*(0.0068)*	-0.0061	*(0.0173)*
Wholesale & Retail Trade	0.0042	*(0.0074)*	0.0004	*(0.0078)*	0.0162	*(0.0120)*
Transport & Storage	-0.0191 **	*(0.0089)*	-0.0116 *	*(0.0060)*	-0.0331	*(0.0225)*
Post &	-0.0236 ***	*(0.0052)*	-0.0260 **	*(0.0098)*	-0.0132	*(0.0227)*
Telecommunication[2]	0.0105 *	*(0.0060)*	0.0056	*(0.0074)*	0.0233 *	*(0.0123)*
Financial	-0.0058	*(0.0163)*	0.0012	*(0.0209)*	-0.0112	*(0.0183)*
Intermediation[3]	0.0160 **	*(0.0072)*	0.0023	*(0.0108)*	0.0839 ***	*(0.0321)*
Real Estate	0.0038	*(0.0074)*	0.0052	*(0.0114)*	0.0007	*(0.0156)*
Business Services	0.0086	*(0.0087)*	0.0090	*(0.0093)*	0.0042	*(0.0168)*
Education	-0.0023	*(0.0097)*	-0.0068	*(0.0173)*	0.0091	*(0.0063)*
Health & Social Work	0.0073	*(0.0058)*	0.0082	*(0.0065)*	0.0030	*(0.0063)*

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

[1] *structural break in 1981/1982 for* SHE^N*, in 1990/1991 for maxdeviation;* [2] *structural break in 1988/1989;* [3] *structural break in 1993/1994; In all cases, the first sub-period is in the upper line.*

tion potential of service branches is regarded as low. But it is surprising that six out of ten service industries significantly converge, albeit not necessarily over the entire observation period. We interpret this as a result of income convergence leading to more and more similar consumption patterns.

Interestingly, the results of the β-convergence test concur with the σ-convergence regressions only to a certain degree. Indeed, convergence of transport and storage is significant in both tests, and also the insignificant β in the case of domestic services, business services, and health and social services is in line with the σ-convergence regressions. But in the other branches, the results differ from the σ-regressions: On the one hand, for hotels/restaurants, trade, real estate, and education the results tentatively point towards convergence, contrarily to the insignificant time trend in the $ARIMA$-regressions; since significance of the β is rather low and/or restricted to single sub-periods, the contrast might be caused by the lower power of the time series regressions. On the other hand, in the case of post and telecommunication services, we were not able to reproduce the significant convergence and divergence trends found in the σ-convergence test.

A surprisingly sharp discrepancy between β and σ is found in financial intermediation, where we find significant σ-divergence from the 1990s on in contrast to the highly significant β-convergence in the same sub-period. The reason for this is that all countries converge, with exception of Ireland which rapidly specializes in financial intermediation; in the σ-convergence test, we identify this phenomenon as one-country-specialization while the β-convergence test is not able to take this effect

Table 4.8: β-convergence in service industries

Industry	**period**	β	**wald** χ^2	**period**	β	**wald** χ^2
Domestic Services	1970-2004	-0.0024 *(0.0086)*	0.08	-		
Hotels & Restaurants	1970-1987	0.0058 *(0.0043)*	1.83	1988-2005	-0.0140 * *(0.0078)*	3.17
Wholesale & Retail Trade	1970-2005	-0.0140* *(0.0081)*	3.00	-		
Transport & Storage	1970-2005	-0.0214*** *(0.0046)*	21.33	-		
Post & Telecommunication	1970-2005	-0.0035 *(0.0082)*	0.18	-		
Financial Intermediation	1970-1990	0.0020 *(0.0069)*	0.08	1991-2005	-0.0532*** *(0.0175)*	9.21
Real Estate	1970-1988	-0.0256*** *(0.0073)*	12.33	1989-2005	-0.0106 *(0.0122)*	0.75
Business Services	1970-2005	0.0009 *(0.0055)*	0.03	-		
Education	1970-1990	-0.0145* *(0.0080)*	3.30	1991-2005	-0.0023 *(0.0089)*	0.06
Health & Social Work	1970-2005	0.0001 *(0.0039)*	0.00	-		

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

into account. This confirms our view that a combination of both tests is required in order to reach a reliable and comprehensive analysis.

4.6 Conclusion

Structural convergence between industrialized countries is a topic which has not been paid a great deal of attention in the literature. We fill this gap by providing a comprehensive investigation of the convergence of 14 European countries over the period from 1970 to 2004/2005. Our analysis is based on employment data drawn from national accounts, which is provided by the EU KLEMS database. We take into account both intersectoral and intrasectoral convergence, focusing first on shifts between agriculture, manufacturing and services, and second on nineteen manufacturing and ten service industries, respectively. Relying on the two common convergence tests, σ- and β-convergence, we consider also industry specific differences, i.e. that some branches might converge and others diverge (instead of drawing generalizing conclusions for all manufacturing or service industries).

We find significant and rapid intersectoral convergence, accompanied by a mixed picture with regard to intrasectoral convergence. In total, European countries do not become more similar regarding the sector composition within the industry and service sectors, respectively; rather some industries are found to converge over time, whereas others diverge or do not change at all. In particular, mature, labor intensive industries show convergence tendencies, while emerging technology- and knowledge-intensive branches tend to diverge. We explain this by the changes in the preponderance of the existing antagonistic forces over the industry life cycle: In emerging industries (with high-technology or knowledge intensity) concentration-favoring influences prevail, such as knowledge spillovers and the existence of a specialized labor force. With increasing maturity, these effects diminish, and industries disperse over the other countries, as long as economies of scale do not outweigh the technology diffusion effect. Our results on manufacturing industries confirm these hypotheses, showing a distinct divergence-convergence pattern over time. Service branches, in contrast, converge or diverge less dynamically, which might be due to the low mobility of services and the importance of local markets. We find significant convergence in both tests only in transport and storage services, which might be related to the growing traffic flows all across Europe. A more disaggregated branch classification would be required in order to detect country specialization effects like that of the UK in investment banking.

Overall, the results presented in this paper draw a comprehensive picture of the complex interplay between the European countries, varying from industry to industry. For future research, we see two promising possibilities: First, research could combine the overall view on European countries with a finer focus on regional convergence in order to distinguish between international and intra-national convergence and shed light on the role of regional industry concentration. In this respect it will be interesting to test to what degree the higher factor mobility between regions has an effect on overall concentration and specialization patterns and whether the ongoing European integration has favored the concentration of economic activity in metropolitan areas at the expense of peripheral regions. Second, it would be interesting to investigate the adjustment process of the Central and Eastern European countries towards the economies of Western Europe; catch-up in terms of income and nominal convergence has been substantial, and one might expect the same to hold for structural convergence as well.

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List of Tables

List of Figures

A Appendix to Chapter 1

Table A.1: Industry definition & technology classification

Technology Class	**Classification of Manufacturing Industries**	**NACE**	**MIP**
Low technology	Food and beverages, tobacco	15, 16	2
	Textiles, leather, footwear	17-19	3
	Wood, paper, paper products	20, 21	4
	Furniture	22	13
Medium-low technology	Non-metallic mineral products	26	7
	Metals products	27, 28	8
Medium-high technology	Rubber and plastics products	25	6
	Machinery and equipment, n.e.c.	29	9
	Motor vehicles, aircraft and spacecraft	34, 35	12
High technology	Coke, refined petroleum, chemical industry	23, 24	5
	Electrical apparatus, computing machines, communications equipment	30-32	10
	Medical, precision and optical instruments	33	11

The data includes firms in the manufacturing sector, according to the NACE-Rev.1 classification and the MIP-classification; data on natural resources based activities such as mining and utilities as well as the construction sector are excluded. Industry classification is according to OECD (2003).

Table A.2: Descriptive statistics of innovation activities

	internal R&D	*no internal R&D*
contracted R&D	224	21
R&D cooperation	208	19
Observations	182	507

B Appendix to Chapter 2

Table B.1: Definition of technology classes

technology class	manufacturing industries*	NACE	MIP
low-tech	Food products and beverages	15	2
	Tobacco products	16	2
	Textiles, textile products, leather and footwear	17-19	2
	Wood, paper, furniture	20-22	3
medium-low tech	Non-Metallic mineral products	26	6
	Basic metals products	27	7
	Fabricated metal products	28	7
medium-high tech	Rubber and plastics products	25	5
	Machinery and equipment, n.e.c.	29	8
	Motor vehicles, aircraft and spacecraft	34,35	11
high-tech	Coke, refined petroleum products, chemical industry	23,24	4
	Office, accounting and computing machinery	30	9
	Radio, TV and communications equipment	31,32	9
	Medical, precision and optical instruments	33	10

** The data includes firms in the manufacturing sector, as defined by NACE-Rev.1 classification and according to the MIP-classification; data on natural resources based activities such as agriculture, fishing, mining and utilities like the construction sector are excluded. The industry classification is according to Eurostat/OECD.*

Table B.2: Panel estimations for Germany 1993-2003, Tobit

endogenous variable: export intensity

	(1)		(2)	
constant	**-0.003**	(0.012)	**-0.018**	(0.012)
InProd	**0.073**	(0.007)	**0.075**	(0.007)
InProc	-0.006	(0.006)	-0.010†	(0.006)
R&D	**3.258**	(0.215)	**3.527**	(0.216)
R&D^2	**-16.001**	(1.526)	**-17.308**	(1.530)
size-s	**-0.142**	(0.006)	**-0.144**	(0.006)
size-l	**0.078**	(0.006)	**0.076**	(0.006)
LP	**0.066**	(0.004)	**0.065**	(0.004)
med-low tech			**0.016**	(0.008)
med-high tech			**0.098**	(0.007)
high tech			**0.058**	(0.008)
sector 2	-0.022†	(0.009)		
sector 3	**-0.018**	(0.010)		
sector 4	**0.029**	(0.011)		
sector 5	**0.023**	(0.010)		
sector 6	-0.015	(0.013)		
sector 8	**0.117**	(0.008)		
sector 9	**0.024**	(0.010)		
sector 10	**0.078**	(0.011)		
sector 11	**0.044**	(0.012)		
time dummies	**incl.**		**incl.**	
Observations	12,569		12,569	
Log likelihood	-2,686.59		-2,754.26	

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

Table B.3: Wave-specific estimates for West Germany, Probit

endogenous variable: export probability (0/1)

	1993	1995	1997	1999	2001	2003
constant	**0.419**	**1.088**	**0.867**	**0.570**	**0.562**	**0.451**
	(0.206)	(0.320)	(0.184)	(0.157)	(0.176)	(0.168)
InProd	**0.516**	0.106	0.259†	**0.339**	0.229†	**0.307**
	(0.145)	(0.195)	(0.157)	(0.137)	(0.127)	(0.125)
InProc	-0.003	-0.149	-0.095	-0.156	0.011	-0.131
	(0.112)	(0.177)	(0.153)	(0.134)	(0.124)	(0.122)
R&D	**26.356**	**25.439**	**32.559**	**31.338**	**18.664**	**11.564**
	(5.116)	(6.029)	(7.243)	(5.897)	(6.864)	(5.757)
R&D^2	**-175.595**	**-174.804**	**-200.531**	**-166.624**	**-116.899**	**-51.378**
	(35.944)	(43.093)	(51.562)	(44.177)	(50.064)	(39.973)
size-small	**-0.603**	**-0.704**	**-0.828**	**-0.870**	**-0.689**	**-0.736**
	(0.117)	(0.144)	(0.120)	(0.104)	(0.113)	(0.112)
size-large	**0.386**	**0.442**	0.275†	0.208†	**0.661**	**0.386**
	(0.127)	(0.150)	(0.157)	(0.132)	(0.179)	(0.154)
LP	-0.047	-0.039	**0.202**	**0.180**	**0.333**	**0.430**
	(0.062)	(0.105)	(0.096)	(0.078)	(0.093)	(0.090)
sector 2	-0.020	**-0.560**	-0.334†	-0.208	-0.265†	-0.097
	(0.193)	(0.217)	(0.186)	(0.147)	(0.170)	(0.159)
sector 3	-0.020	-0.031	-0.043	**-0.410**	**-0.510**	**-0.468**
	(0.188)	(0.227)	(0.180)	(0.174)	(0.200)	(0.181)
sector 4	0.258	0.033	-0.202	-0.152	-0.091	-0.222
	(0.210)	(0.267)	(0.240)	(0.211)	(0.255)	(0.221)
sector 5	**0.444**	0.345	0.387†	**0.380**	0.147	0.396†
	(0.220)	(0.276)	(0.222)	(0.196)	(0.210)	(0.210)
sector 6	-0.368	-0.392	**-0.472**	**-0.452**	**-0.621**	-0.427†
	(0.256)	(0.301)	(0.226)	(0.207)	(0.238)	(0.231)
sector 8	0.276†	0.164	0.201	0.252	0.166	0.162
	(0.159)	(0.216)	(0.185)	(0.166)	(0.195)	(0.176)
sector 9	0.108	-0.264	-0.603	-0.198	-0.108	0.473†
	(0.201)	(0.241)	(0.218)	(0.195)	(0.223)	(0.244)
sector 10	0.004	**0.823**	0.189	0.184	0.521†	-0.037
	(0.215)	(0.377)	(0.270)	(0.251)	(0.316)	(0.206)
sector 11	0.039	0.050	0.110	0.039	-0.305	0.082
	(0.233)	(0.007)	(0.280)	(0.229)	(0.283)	(0.297)
Observations	1,278	951	1,128	1,257	949	1,118
Log likelihood	-429.27	-274.88	-388.47	-529.46	-401.48	-453.17

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

Table B.4: Wave-specific estimates for East Germany, Probit

endogenous variable: export probability (0/1)

	1993	**1995**	**1997**	**1999**	**2001**	**2003**
constant	-0.315	-0.274	-0.369†	**-0.594**	**-0.547**	-0.041
	(0.241)	(0.322)	(0.203)	(0.199)	(0.208)	(0.209)
InProd	0.026	0.174	0.189	**0.439**	**0.339**	**0.629**
	(0.180)	(0.237)	(0.176)	(0.189)	(0.160)	(0.164)
InProc	-0.033	0.037	0.180	0.001	0.233	-0.241†
	(0.134)	(0.195)	(0.162)	(0.174)	(0.153)	(0.155)
R&D	**20.230**	**13.179**	**26.676**	**23.901**	**32.830**	**22.786**
	(4.735)	(5.707)	(5.953)	(5.883)	(7.468)	(6.522)
R&D^2	**-117.764**	**-66.250**†	**-154.972**	**-132.462**	**-172.725**	**-127.956**
	(32.734)	(38.938)	(42.458)	(40.033)	(51.574)	(42.609)
size-small	**-0.712**	**-0.716**	**-0.553**	**-0.629**	**-0.630**	**-0.799**
	(0.121)	(0.154)	(0.134)	(0.130)	(0.150)	(0.149)
size-large	**0.698**	**0.507**	0.194	0.278	0.088	-0.017
	(0.181)	(0.247)	(0.247)	(0.233)	(0.273)	(0.240)
LP	0.026	0.211	**0.347**	**0.579**	**0.485**	**0.422**
	(0.107)	(0.174)	(0.125)	(0.127)	(0.131)	(0.139)
sector 2	-0.051	0.118	-0.163	-0.219	0.184	0.114
	(0.208)	(0.242)	(0.210)	(0.198)	(0.214)	(0.206)
sector 3	-0.047	-0.085	0.394	-0.190	-0.248	**-0.531**
	(0.208)	(0.269)	(0.247)	(0.258)	(0.273)	(0.255)
sector 4	0.491†	0.634†	0.308	-0.161	-0.117	0.292
	(0.308)	(0.337)	(0.304)	(0.293)	(0.317)	(0.331)
sector 5	0.385†	0.501†	0.352	0.407†	0.289	0.600†
	(0.237)	(0.285)	(0.259)	(0.255)	(0.281)	(0.311)
sector 6	-0.039	-0.287	**-0.594**	-0.467†	0.051	-0.169
	(0.266)	(0.304)	(0.249)	(0.259)	(0.300)	(0.289)
sector 8	0.095	**0.500**	0.362†	0.266	**0.561**	0.289
	(0.193)	(0.242)	(0.233)	(0.238)	(0.261)	(0.235)
sector 9	-0.005	0.334	0.313	0.120	0.187	0.433
	(0.234)	(0.284)	(0.292)	(0.251)	(0.284)	(0.295)
sector 10	0.037	**0.919**	0.526†	0.164	0.231	0.255
	(0.240)	(0.340)	(0.293)	(0.267)	(0.307)	(0.245)
sector 11	-0.102	0.448	-0.042	0.242	0.520	0.093
	(0.260)	(0.500)	(0.335)	(0.290)	(0.395)	(0.298)
Observations	609	397	492	548	459	529
Log likelihood	-349.97	-222.49	-276.20	-292.90	-235.64	-260.67

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

Table B.5: Wave-specific estimates for West Germany, Tobit

endogenous variable: export intensity

	1993	**1995**	**1997**	**1999**	**2001**	**2003**
constant	0.050	0.008	0.008	0.031	0.046	-0.012
	(0.036)	(0.048)	(0.034)	(0.034)	(0.037)	(0.037)
InProd	**0.080**	**0.089**	**0.071**	**0.100**	**0.056**	**0.059**
	(0.045)	(0.031)	(0.024)	(0.026)	(0.022)	(0.022)
InProc	-0.003	0.019	-0.008	**-0.046**	0.015	-0.009
	(0.017)	(0.022)	(0.022)	(0.023)	(0.020)	(0.020)
R&D	**3.272**	**2.205**	**3.339**	**3.652**	**3.403**	**3.234**
	(0.593)	(0.669)	(0.794)	(0.777)	(0.938)	(0.845)
R&D^2	**-18.243**	**-12.714**	**-15.443**	**-16.734**	**-19.645**	**-14.771**
	(4.357)	(5.043)	(5.940)	(5.640)	(6.874)	(5.929)
size-small	**-0.129**	**-0.105**	**-0.116**	**-0.183**	**-0.157**	**-0.168**
	(0.019)	(0.022)	(0.022)	(0.020)	(0.021)	(0.021)
size-large	**0.069**	**0.067**	**0.075**	**0.069**	**0.117**	**0.069**
	(0.016)	(0.017)	(0.019)	(0.020)	(0.023)	(0.022)
LP	0.006	**0.029**	**0.068**	**0.074**	**0.096**	**0.150**
	(0.009)	(0.015)	(0.015)	(0.014)	(0.016)	(0.016)
sector 2	-0.006	-0.065†	-0.043	-0.044	-0.017	0.009
	(0.030)	(0.034)	(0.032)	(0.029)	(0.032)	(0.030)
sector 3	-0.006	0.001	-0.011	**-0.092**	**-0.110**	-0.097
	(0.030)	(0.033)	(0.030)	(0.036)	(0.039)	(0.037)
sector 4	0.030	0.014	0.005	-0.016	0.020	0.035
	(0.028)	(0.035)	(0.035)	(0.036)	(0.041)	(0.038)
sector 5	-0.009	0.012	0.010	0.008	-0.003	0.041
	(0.030)	(0.034)	(0.032)	(0.034)	(0.036)	(0.036)
sector 6	-0.036	0.002	0.027	-0.011	-0.072	-0.075†
	(0.041)	(0.046)	(0.039)	(0.042)	(0.048)	(0.047)
sector 8	**0.133**	**0.146**	**0.093**	**0.102**	0.060†	0.112
	(0.023)	(0.028)	(0.027)	(0.029)	(0.032)	(0.030)
sector 9	0.004	0.015	0.009	-0.047	-0.036	0.061†
	(0.028)	(0.033)	(0.035)	(0.034)	(0.037)	(0.036)
sector 10	0.019	**0.104**	0.034	0.028	**0.119**	**0.130**
	(0.031)	(0.036)	(0.036)	(0.040)	(0.045)	(0.037)
sector 11	0.062†	**0.102**	0.074†	0.024	0.017	0.046
	(0.032)	(0.035)	(0.040)	(0.039)	(0.049)	(0.046)
Observations	1,278	951	1,128	1,257	949	1,118
Log likelihood	-429.27	-274.88	-388.47	-529.46	-401.48	-453.17

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

Table B.6: Wave-specific estimates for East Germany, Tobit

endogenous variable: export intensity

	1993	**1995**	**1997**	**1999**	**2001**	**2003**
constant	**-0.136**	**-0.104**	**-0.200**	**-0.248**	**-0.264**	**-0.160**
	(0.062)	(0.071)	(0.055)	(0.055)	(0.064)	(0.055)
InProd	0.071†	0.014	0.004	0.075†	0.059†	**0.103**
	(0.045)	(0.050)	(0.040)	(0.044)	(0.036)	(0.035)
InProc	-0.041	-0.059	0.038	-0.016	0.036	-0.014
	(0.031)	(0.040)	(0.035)	(0.038)	(0.033)	(0.030)
R&D	**4.211**	1.857†	**5.460**	**4.941**	**4.130**	**2.666**
	(1.034)	(1.101)	(1.174)	(1.207)	(1.395)	(1.231)
R&D^2	**-21.439**	-5.030	**-26.075**	**-23.463**	**-20.084**	-11.100
	(7.095)	(7.439)	(8.338)	(8.132)	(9.497)	(7.960)
size-small	**-0.161**	**-0.141**	**-0.118**	**-0.136**	**-0.150**	**-0.132**
	(0.029)	(0.032)	(0.029)	(0.029)	(0.034)	(0.031)
size-large	**0.151**	**0.090**	0.093†	0.063	0.056	0.069†
	(0.035)	(0.041)	(0.048)	(0.044)	(0.053)	(0.043)
LP	0.010	0.060†	**0.142**	**0.164**	**0.157**	**0.122**
	(0.025)	(0.034)	(0.028)	(0.028)	(0.029)	(0.027)
sector 2	-0.004	0.052	-0.027	-0.039	-0.015	0.061
	(0.050)	(0.052)	(0.050)	(0.046)	(0.052)	(0.047)
sector 3	0.058	0.088	0.031	0.042	-0.029	-0.101†
	(0.049)	(0.058)	(0.056)	(0.061)	(0.070)	(0.063)
sector 4	0.112†	**0.149**	0.087	-0.011	0.016	**0.170**
	(0.064)	(0.063)	(0.063)	(0.064)	(0.070)	(0.064)
sector 5	0.067	0.090	-0.045	0.036	0.085	0.071
	(0.055)	(0.059)	(0.060)	(0.055)	(0.062)	(0.063)
sector 6	0.012	0.027	-0.052	-0.043	0.081	0.030
	(0.062)	(0.067)	(0.057)	(0.061)	(0.071)	(0.068)
sector 8	0.066	**0.187**	0.096†	**0.108**	**0.165**	**0.164**
	(0.043)	(0.047)	(0.050)	(0.050)	(0.056)	(0.049)
sector 9	0.017	**0.133**	0.040	0.087†	0.116†	**0.128**
	(0.053)	(0.057)	(0.062)	(0.055)	(0.061)	(0.055)
sector 10	0.013	**0.232**	0.069	0.091†	**0.136**	**0.141**
	(0.056)	(0.062)	(0.061)	(0.058)	(0.064)	(0.052)
sector 11	-0.014	0.038	-0.049	0.021	0.040	0.066
	(0.062)	(0.085)	(0.074)	(0.062)	(0.085)	(0.062)
Observations	609	397	492	548	459	529
Log likelihood	-195.31	-101.69	-157.00	-173.98	-155.00	-167.00

coefficients printed in bold: 5%, †: 10% significance level; standard error in parantheses

C Appendix to Chapter 4

Table C.1: Industry classification

Sectors	**Classification of Industries**	**NACE**
Agriculture	Agriculture, hunting, forestry and fishing	01, 02
Manufacturing	Food, drink and tobacco (FDT)	15, 16
	Textiles and textile products	17-18
	Leather and footwear	19
	Wood, wood products and furniture	20
	Pulp, paper and paper products	21
	Printing, publishing and reproduction of recorded media	22
	Coke, refined petroleum, and nuclear fuel	23
	Chemical industry	24
	Rubber and plastics products	25
	Non-metallic mineral products (glass, ceramics, plaster)	26
	Basic metals products	27
	Fabricated metal products	28
	Machinery and equipment, n.e.c.	29
	Office, accounting and computing machines	30
	Electrical machinery and apparatus, n.e.c.	31
	Radio, TV, communication equipment	32
	Medical, precision and optical instruments	33
	Transport equipment: motor vehicles, aircraft and spacecraft	34, 35
	Recycling; manufacturing n.e.c.	36, 37
Services	Domestic services	95
	Hotels and restaurants	55
	Wholesale and retail trade	50-52
	Transport and storage	60-63
	Post and telecommunication	64
	Financial intermediation	65-67
	Real estate	70
	Business services	71-74
	Education	80
	Health and social work	85

Table C.2: Augmented Dickey-Fuller test for manufacturing industries

Industry	*ln SHE*^{N}		*ln SHE*$^{N-1}$		*ln max deviation*	
	$d=0$	$d=1$	$d=0$	$d=1$	$d=0$	$d=1$
Food, Drink & Tobacco (FDT)	-0.852	-4.742	-1.835	-4.891	0.461	-3.874
Textile	-2.922	-4.417	-2.398	-5.114	-2.023	-5.273
Leather	-2.759	-3.737	-3.036	-3.822	-1.189	-4.311
Wood	-1.608	-4.089	-1.427	-5.148	-1.655	-5.000
Paper	-1.037	-3.995	-1.779	-5.359	-0.645	-5.443
Printing & Publishing	-1.632	-4.102	-1.741	-3.988	-0.597	-6.090
Coke & Fuel	-0.512	-3.569	-0.241	-4.042	-1.543	-5.394
Chemicals	-1.371	-7.161	-1.231	-7.235	-2.022	-5.239
Rubber & Plastic	-1.330	-3.826	-1.641	-3.599	0.580	-6.157
Non-metal Mineral Products	-1.446	-3.703	-1.469	-4.049	-2.661	-4.587
Basic Metals	-0.468	-5.101	-1.245	-5.067	-1.644	-3.884
Fabricated Metals	0.179	-6.200	0.279	-6.321	-1.376	-5.110
Machinery	-1.078	-5.279	-1.548	-5.951	-2.070	-3.725
Accounting & Computing Machines	-1.194	-2.187	-1.203	-2.638	0.498	-4.009
Electrical Engineering	-0.250	-4.309	-2.055	-5.396	2.606	-2.523
Communications Equipment	-0.468	-4.127	-0.980	-4.354	-0.194	-5.227
Precision Instruments	0.111	-4.599	-1.512	-4.688	-0.073	-3.518
Transport Equipment	-0.394	-4.791	-0.879	-4.728	-1.414	-5.388
Recycling	-0.636	-5.024	-1.046	-4.753	-0.557	-5.515

1%/5%/10% critical values: -3.689/-2.975/-2.619 (d=0); -3.696/-2.978/-2.620 (d=1).

Table C.3: Augmented Dickey-Fuller test for service industries

Industry	*ln SHE*^{N}		*ln SHE*$^{N-1}$		*ln max deviation*	
	$d=0$	$d=1$	$d=0$	$d=1$	$d=0$	$d=1$
Domestic Services	-0.596	-5.630	0.006	-5.767	-2.270	-6.041
Hotels & Restaurants	-2.383	-9.826	-1.249	-8.087	-1.597	-4.606
Wholesale & Retail Trade	-2.034	-5.449	-1.359	-4.634	-2.539	-8.004
Transport & Storage	1.348	-5.279	0.302	-6.338	0.852	-5.894
Post & Telecommunication	-1.711	-5.457	-1.899	-6.065	-1.174	-5.468
Financial Intermediation	-1.461	-7.091	-1.027	-8.038	-0.056	-4.895
Real Estate	-2.380	-4.946	-2.684	-5.253	-1.207	-3.365
Business Services	-0.636	-4.032	-0.548	-4.187	-1.577	-2.769
Education	-1.323	-4.517	-1.242	-4.330	-1.844	-4.99
Health & Social Work	-2.629	-4.347	-2.529	-4.391	-1.926	-4.83

1%/5%/10% critical values: -3.682/-2.972/-2.618 (d=0); -3.689/-2.975/-2.619 (d=1).

Table C.4: ARIMA results: SHE^N in manufacturing industries

Industry	**constant**	**AR(1)**	**AR(2)**	**AR(3)**	**MA(1)**	**MA(2)**
Food, Drink & Tobacco (FDT)	-0.0110 ** *(0.0052)*	-0.8182 *** *(0.2410)*	-	-	1.1116 *** *(0.2637)*	0.4358 ** *(0.2050)*
Textile	0.0097 *** *(0.0030)*	-	-	-	-	-
Leather	0.0135 ** *(0.0059)*	-0.0095 *(0.3936)*	-	-	0.4636 *(0.3502)*	-
Wood	-0.0097 ** *(0.0047)*	-	-	-	-	-
Paper	-0.0065 *(0.0062)*	0.3044 *(0.1353)*	-	-	-	-
Printing & Publishing (structural break 1993/1994)	0.0160 *** *(0.0051)*	-	-	-	-0.0876 *(0.2328)*	-
	-0.0215 *** *(0.0081)*	0.4501 *(0.3335)*	-0.5169 *(0.4687)*	-	-	-
Coke & Fuel	0.0001 *(0.0119)*	0.3259 *(0.2650)*	-	-	-	-
Chemicals	0.0116 ** *(0.0059)*	-	-	-	-	-
Rubber & Plastic	0.0192 *** *(0.0056)*	-0.9524 *(0.6912)*	-0.4422 *(0.7513)*	-0.2954 *(0.2134)*	0.8789 *(0.6797)*	0.2001 *(0.6706)*
Non-metal Mineral Products (structural break 1984/1985)	-0.0221 * *(0.0122)*	-	-	-	-	-
	0.0188 ** *(0.0086)*	-0.8893 *** *(0.2022)*	-	-	0.9905 *** *(0.2780)*	0.2930 *(0.2785)*
Basic Metals	-0.0044 *(0.0027)*	0.3004 * *(0.1700)*	0.2937 *(0.2602)*	-	-	-
Fabricated Metals	-0.0091 * *(0.0052)*	-	-	-	-	-
Machinery	0.0022 *(0.0031)*	-	-	-	-	-
Accounting & Computing Machines	0.0194 *(0.0163)*	-	-	-	0.1121 *(0.2353)*	-
Electrical Engineering	-0.0050 *(0.0035)*	-	-	-	-0.4579 *** *(0.1535)*	-
Communications Equipment	-0.0050 *(0.0141)*	-	-	-	-0.6350 *** *(0.1182)*	-
Precision Instruments	0.0033 *(0.0047)*	-	-	-	0.3229 * *(0.1805)*	-0.2331 *(0.1842)*
Transport Equipment	0.0110 * *(0.0061)*	0.3072 *(0.1942)*	-	-	-	-
Recycling	0.0081 * *(0.0046)*	0.9357 * *(0.4903)*	-0.3041 *(0.2303)*	-	-0.7709 * *(0.4308)*	-

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

Table C.5: ARIMA results: SHE^{N-1} in manufacturing industries

Industry	**constant**	**AR(1)**	**AR(2)**	**AR(3)**	**MA(1)**	**MA(2)**
Food, Drink &	-0.0087	-0.8331 ***	-	-	1.4896 ***	0.9194 ***
Tobacco (FDT)	*(0.0071)*	*(0.1297)*			*(0.1895)*	*(0.2205)*
Textile	0.0105 **	-	-	-	-	-
	(0.0041)					
Leather	0.0122 **	-0.0332	-	-	0.5102 *	-
	(0.0061)	*(0.3298)*			*(0.3030)*	
Wood	-0.0072 *	-0.0875	-0.0080	-	-	-
	(0.0044)	*(0.2778)*	*(0.2899)*			
Paper	-0.0047	0.0180	-	-	-	-
	(0.0069)	*(0.1698)*				
Printing &	0.0203 ***	-	-	-	-	-
Publishing	*(0.0067)*					
(structural break	-0.0194 *	0.7412	-0.6332 ***	-	-	-
1993/1994)	*(0.0114)*	*(0.4637)*	*(0.1964)*			
Coke & Fuel	-0.0025	-0.2329	-	-	0.5736	0.3112
	(0.0158)	*(0.7247)*			*(0.6588)*	*(0.2927)*
Chemicals	-0.0067 *	-	-	-	-0.3843 **	-0.1182
	(0.0037)				*(0.1701)*	*(0.2140)*
Rubber & Plastic	0.0212 ***	-0.0544	-0.2461	-	-0.0892	-
	(0.0058)	*(0.8166)*	*(0.2472)*		*(0.7846)*	
Non-metal Mineral	-0.1980	0.4498 *	-	-	-	-
Products	*(0.0215)*	*(0.2586)*				
(structural break	0.0213 **	-0.9459 **	-	-	0.9244	0.1017
1984/1985)	*(0.0089)*	*(0.3776)*			*(0.5650)*	*(0.3010)*
Basic Metals	-0.0036	0.3003 **	0.1411	-	-	-
	(0.0023)	*(0.1374)*	*(0.1498)*			
Fabricated Metals	-0.0106 *	-	-	-	-	-
	(0.0057)					
Machinery	0.0016	-	-	-	-	-
	(0.0035)					
Accounting &	0.0029	-0.6367 *	-	-	0.8203 ***	-
Computing Machines	*(0.0132)*	*(0.3442)*			*(0.3116)*	
Electrical Engineering	-0.0065 *	-	-	-	-0.4693 ***	-
	(0.0037)				*(0.1497)*	
Communications	-0.0028	-	-	-	-0.9047 ***	-
Equipment	*(0.0158)*				*(0.0824)*	
Precision Instruments	0.0035	-	-	-	0.1267 *	-0.4917 ***
	(0.0031)				*(0.1662)*	*(0.1702)*
Transport Equipment	0.0109 *	0.2703	-	-	-	-
	(0.0064)	*(0.2067)*				
Recycling	0.0019	1.4622 ***	-0.8896 ***	-	-1.5698 ***	0.8202 ***
	(0.0043)	*(0.1409)*	*(0.1570)*		*(0.2733)*	*(0.2549)*

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

Table C.6: ARIMA results: *max deviation* in manufacturing industries

Industry	**constant**	**AR(1)**	**AR(2)**	**MA(1)**	**MA(2)**	**MA(3)**
Food, Drink & Tobacco (FDT)	-0.0193 ** *(0.0091)*	-	-	0.3448 *** *(0.1055)*	-	-
Textile	0.0075 *(0.0050)*	-	-	-	-	-
Leather	0.0187 * *(0.0106)*	-	-	0.1941 *(0.1504)*	-	-
Wood	-0.0195 * *0.0112*	0.1217 *(0.1721)*	-0.3774 * *(0.2226)*	-	-	-
Paper	-0.0083 *(0.0105)*	-	-	0.2091 *(0.1643)*	-0.0570 *(0.1972)*	0.4099 ** *(0.2004)*
Printing & Publishing	-0.0057 *(0.0106)*	-0.0687 *(0.1755)*	0.1400 *(0.2090)*	-	-	-
Coke & Fuel	0.0062 *(0.0193)*	-0.5194 * *(0.2741)*	-	0.8919 *** *(0.1433)*	-	-
Chemicals	0.0373 *** *(0.0115)*	-	-	0.4547 *** *(0.1651)*	-	-
Rubber & Plastic	0.0056 *(0.0101)*	-	-	-	-	-
Non-metal Mineral Products	-0.0080 *(0.0138)*	-	-	-	-	-
Basic Metals	-0.0235 *** *(0.0088)*	-	-	-	-	-
Fabricated Metals	0.0052 *(0.0244)*	-	-	0.5850 *** *(0.2206)*	0.4892 *** *(0.1645)*	-
Machinery	0.0109 *(0.0073)*	-0.7674 *** *(0.1822)*	-0.7130 *** *(0.1770)*	1.2787 *** *(0.2243)*	0.5794 ** *(0.2509)*	-
Accounting & Computing Machines	0.0387 * *(0.0198)*	-	-	-	-	-
Electrical Engineering	0.0078 *(0.0068)*	0.0835 *(0.1704)*	-0.2185 *(0.1275)*	-	-	-
Communications Equipment (structural break 1994/1995)	-0.0099 *(0.0103)*	-	-	0.0946 *(0.2067)*	-	-
	0.1145 * *(0.0614)*	-	-	-	-	-
Precision Instruments (structural break 1991/1992)	-0.0057 *(0.0107)*	-	-	0.0562 *(0.2829)*	-	-
	0.0830 ** *(0.0344)*	-	-	-	-	-
Transport Equipment	0.0103 *(0.0113)*	-0.6154 * *(0.3182)*	-	0.8133 *** *(0.2562)*	-	-
Recycling	0.0188 ** *(0.0089)*	0.4145 *** *(0.1518)*	-	-	-	-

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

Table C.7: ARIMA results: SHE^N in service industries

Industry	constant	AR(1)	AR(2)	AR(3)	MA(1)
Domestic Services	-0.0168	0.5568 *	-	-	-
(structural break	*(0.0138)*	*(0.2983)*			
1981/1982)	0.0096	-	-	-	-
	(0.0068)				
Hotels &	0.0025	-0.1322	-	-	-0.4863 **
Restaurants	*(0.0022)*	*(0.2436)*			*(0.2158)*
Wholesale &	0.0042	-0.6853	0.0820	0.1968	0.7845 *
Retail Trade	*(0.0074)*	*(0.462)*	*(0.2907)*	*(0.2445)*	*(0.4383)*
Transport & Storage	-0.0191 **	0.0529	0.2380	-	-
	(0.0089)	*(0.1975)*	*(0.2155)*		
Post & Telecommunication	-0.0236 ***	-	-	-	-0.4013 *
(structural break	*(0.0052)*				*(0.2251)*
1988/1989)	0.0105 *	-0.5492	-0.4022	-	-
	(0.0060)	*(0.3920)*	*(0.4116)*		
Financial Intermediation	-0.0058	-	-	-	-
(structural break	*(0.0163)*				
1993/1994)	0.0160 **	-	-	-	-0.1536
	(0.0072)				*(0.3831)*
Real Estate	0.0038	-	-	-	-
	(0.0074)				
Business Services	0.0086	-	-	-	0.4059 ***
	(0.0087)				*(0.1538)*
Education	-0.0023	-	-	-	-
	(0.0097)				
Health & Social Work	0.0073	0.2431	-	-	-
	(0.0058)	*(0.1822)*			

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

Table C.8: ARIMA results: SHE^{N-1} in service industries

Industry	**constant**	**AR(1)**	**AR(2)**	**MA(1)**
Domestic Services	0.0072	-	-	-
	(0.0052)			
Hotels & Restaurants	0.0044	-0.9343 ***	-	0.7923 **
	(0.0068)	*(0.1487)*		*(0.3482)*
Wholesale & Retail Trade	0.0004	0.2420	-	-
	(0.0078)	*(0.1945)*		
Transport & Storage	-0.0116 *	-0.1660	-0.2183	0.0531
	(0.0060)	*(0.7663)*	*(0.2317)*	*(0.8739)*
Post & Telecommunication	-0.0260 **	-	-	-
(structural break	*(0.0098)*			
1988/1989)	0.0056	-0.4213	-	-
	(0.0074)	*(0.2708)*		
Financial Intermediation	0.0012	-	-	0.6706 **
(structural break	*(0.0209)*			*(0.3112)*
1993/1994)	0.0023	0.2854	-	-
	(0.0108)	*(0.4288)*		
Real Estate	0.0052	-	-	0.2596 *
	(0.0114)			*(0.1495)*
Business Services	0.009	-	-	0.4015 ***
	(0.0093)			*(0.1465)*
Education	-0.0068	0.2492	-	-
	(0.0173)	*(0.3009)*		
Health & Social Work	0.0082	-	-	0.2338
	(0.0065)			*(0.1614)*

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*

Table C.9: ARIMA results: *max deviation* in service industries

Industry	**constant**	**AR(1)**	**AR(2)**	**MA(1)**	**MA(2)**
Domestic Services (structural break 1990/1991)	-0.0423 ** (0.0170)	-	-	-	-
	0.0279 (0.0253)	-0.0192 (0.4432)	-	-	-
Hotels & Restaurants	-0.0061 (0.0173)	-	-	0.1506 (0.1725)	-0.3205 (0.2143)
Wholesale & Retail Trade	0.0162 (0.0120)	-0.3245 ** (0.1342)	-	-	-
Transport & Storage	-0.0331 (0.0225)	0.0083 (0.2103)	0.3359 (0.2614)	-	-
Post & Telecommunication (structural break 1988/1989)	-0.0132 (0.0227)	0.3067 (0.3823)	-	-	-
	0.0233 * (0.0123)	-0.3459 * (0.1879)	-	-	-
Financial Intermediation (structural break 1993/1994)	-0.0112 (0.0183)	-	-	0.6312 ** (0.2569)	-
	0.0839 *** (0.0321)	-0.2533 (0.5193)	-0.7490 ** (0.3383)	-	-
Real Estate	0.0007 (0.0156)	0.1674 (0.4171)	-	0.2643 (0.3625)	0.4720 *** (0.1574)
Business Services	0.0042 (0.0168)	-	-	0.6331 *** (0.1943)	-
Education	0.0091 (0.0063)	-	-	-	-
Health & Social Work	0.0030 (0.0063)	-	-	-	-

*s.d. in parantheses; ***/**/* significant at 1/5/10%.*