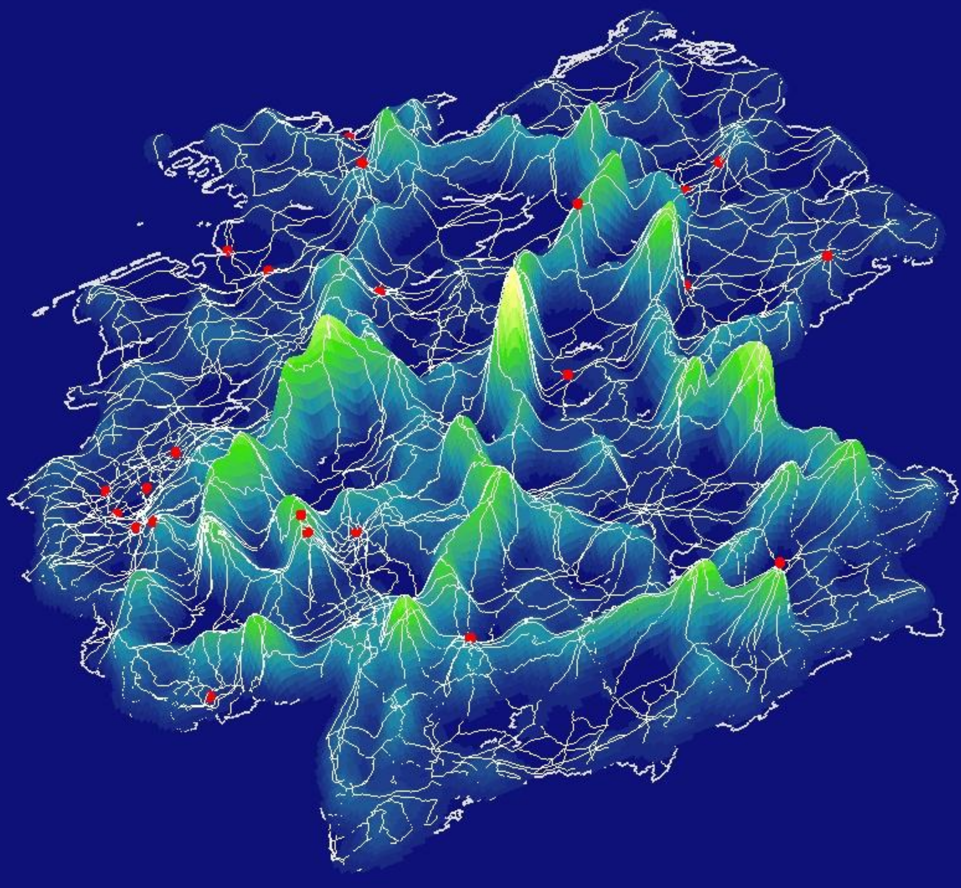
# Regional Labour Markets in Germany

## Statistical Analysis of Spatio-Temporal Disparities and Network Structures



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VRIJE UNIVERSITEIT

# Regional Labour Markets in Germany: Statistical Analysis of Spatio-Temporal Disparities and Network Structures

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door

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geboren te Ravenna, Italië

promotoren: prof.dr. P. Nijkamp
prof.dr. A. Reggiani

# Contents

# Acknowledgements

It has been quite a journey that finally brought me to the completion of this manuscript. My first experience of research was in 2001, immediately after my Bachelor's degree, when I first visited the VU, on a scholarship from the University of Bologna, for a few months. Fittingly, after a few years of what my girlfriend refers to as 'nomadism', the circle now closes in the very same place. I consider this a blessing and a sign of how important it is to build on established professional relationships.

It is not easy to summarize in a few lines or a few names the number of people who contributed to my personal and professional development (though this is still a work-in-progress). Some contributed from an academic point of view, while others provided support without any discussion whatsoever about research. Ultimately, all were precious.

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Of course, I am in debt not only to colleagues, but also to personal friends, who – because of the distance that often separates us – represent my ‘virtual’ support network. In particular, I feel I have to mention: Alberta, Cinzia, Emanuele, Giorgia, Luca, Mete and Sandra. My SVU Volleybal teammates (Edwin, Jens (both), Jore, Kees, Mark, Rense and Wouter) contributed to my mental equilibrium as well in the past year.

My final – and most personal – thanks go to my family. Like most researchers, I struggle to explain to my parents, Lidia and Sergio, what I do, for how long I will be doing it, and why I do it, so I hope this manuscript will make it slightly clearer (although I am not so sure it will). Like my parents, my sister, uncle and aunt, cousins and nephews had to share my limited time in Italy, but I promise it will be easier in the future.

Last, but of course not least, I will try to express my gratitude to my long-time girlfriend, Carlotta. Whoever knows me indirectly knows her, since she is my preferred topic of discussion, whether I am making fun of her or listing her qualities. She has been very patient over the past few years, supporting my choices and tolerating the geographical distance between us (in other words, my constant absence). I do not know enough words to thank her for being on my side all the time. Our trying times are coming to an end and I see a bright future ahead of us. In the meantime, I dedicate this manuscript to her.

# PART A

# REGIONAL LABOUR MARKET ISSUES: GENERAL

Chapter 1

# Introduction: Theoretical and Policy Aspects

## 1.1 Motivation for the Study

In recent years researchers and policy makers have become increasingly interested in the study and interpretation of socio-economic processes at the meso- or regional level. At the present time, the region is often considered to be the 'place of action', where micro-behaviour and macro-outcomes come together. From a scientific point of view, what used to be the major focus of mainstream economists – the analysis of larger areas such as nations – now increasingly gives way to the study of regional-economic systems. Although empirical studies are carried out at different geographic/political scales, ranging, for example, from the larger US states to the smaller EU regions, down to the municipality level, regions are attractive units of analysis to researchers for a number of reasons. While nations – with some partial exceptions due to trade agreements or more complex relationships such as the EU – can be seen as relatively closed economic systems, regions can easily be interpreted as small open economic systems (see, for instance, Blanchard 1991). They are often administrative areas with a certain competence for economic policy and planning. As such, regions may show high levels of heterogeneity and interaction with each other, based on local characteristics, mobility of production factors, common institutions and regulations and lack of trade barriers. These factors make for fascinating research questions, which are not strictly related to economic issues, but also allow (or, one might say, require) us to delve into spatial/regional economics, by taking into account – in an interdisciplinary perspective – geography, land use planning and resource management, and so on. In this context, the recent development of extensive data sets allows the application of sophisticated approximation and forecasting techniques.

From a policy viewpoint, it is straightforward to understand the implications of a deeper knowledge of regional economic processes. Most national governments implement increasingly local policies to answer the populations' diverse needs and characteristics. Similar concerns can be imagined, for example, for large firms, with regard to the localized demand for the goods and services they produce (Armstrong and Taylor 2000).

In this framework, the analysis of regional labour markets is also of great importance for their financial and socio-economic implications. Localized top-to-bottom labour policies may address more efficiently the specific problems of single regions or areas. Moreover, the funding for unemployment benefits or employment programmes is distributed, in countries such as Germany, on a regional basis. Being able to effectively forecast labour market aggregates, such as unemployment levels, is therefore critical.

These aspects assume even greater relevance if we consider the wide disparities in the performance of regional labour markets that many countries experience (see, for instance, Elhorst 2003; Bayer and Juessen 2007). We can think of the differences between the northern and southern areas in Italy and between West and East Germany, or between urbanized and rural areas. Regional disparities are a conspicuous cost for the national economy: for instance, because of the welfare policies necessary to support underperforming areas, and because the phenomenon of long-term unemployment – frequent in high-unemployment areas – is often associated with problematic socio-political aspects (for example, criminality or political sclerosis), which add up to the aforementioned costs (see, for instance, Gilles 1998). Regional disparities may also slow down the economic performance of the country as a whole, because of the consequent inefficient allocation of resources. And, finally, a high heterogeneity among regions makes it difficult to provide accurate estimates of their reactions to national trends or shocks (Blanchard 2003). In such a scenario, the analysis of the evolution of regional disparities, in particular in the short run, is problematic, as many factors which may determine heterogeneity deserve thorough consideration. Just a few examples are: the concentration of capital due to positive agglomeration externalities; constraints in land use regulations; varying quality of infrastructure.

In neoclassical economics, disparities among regions (for example, in per capita income) are expected to decline in the long run, as capital and labour tend to move towards lower- and higher-wage regions, respectively, until the equalization of the two factors' productivity in all regions is reached (Armstrong and Taylor 2000). In addition, underperforming regions have the possibility of catching up with the richer ones in technology. However, in the short run, regional disparities do seem rather persistent (see, for example, Elhorst 2003).

The present study is concerned with the statistical analysis of the economic indicators underlying the aforementioned disparities. Employing disaggregated data sets on German regions for our case studies, we analyse and model the heterogeneity in regional labour markets. In this context, the relevance of the space-time components is taken into account according to different methodological approaches. In addition, we examine regional labour mobility – by means of network theory – in order to better interpret the dynamic patterns of the dominant and marginal areas.

The theoretical-methodological framework – and the related empirical research questions – supporting the above research agenda are outlined in the next sections.

## 1.2 Labour Markets and Economic Output

The performance of labour markets depends on a number of factors (characteristics of the labour force, efficiency of the labour demand/supply match, mobility of labour and capital, and so on). Microeconomic processes based on individual utility functions, preferences and constraints (such as residential location and mobility choices or employment regulations) have been – and still are – widely studied from different perspectives (see, for example, White 1977; Boyce et al. 1988; van Ommeren et al. 1999a,b, 2000). These micro-mechanisms determine the single individual's choices and are at the basis of the aggregate economic results that we observe at the regional (and national) level (such as employment levels or commuting flows). The analysis of such phenomena is undoubtedly a sine qua non for understanding the inner functioning of labour markets (see, for instance, Fischer and Nijkamp 1987; Topel 1994). On the other hand, the statistical modelling – let alone forecasting – of this type of economic process requires extensive data.

Therefore, we may also look at aggregate labour market outcomes (such as regional (un)employment) from an alternative – yet complementary – perspective. In the 1960s, Arthur Okun described and interpreted a recurring empirical finding, according to which changes in unemployment are related to the growth of the GDP. In other words, this relationship, which is now known as Okun's law (Okun 1970; Prachowny 1993),[1] links economic output and unemployment. In more detail, it is suggested that the growth rate of per capita GDP is negatively correlated with simultaneous variations in unemployment. The actual extent to which GDP affects unemployment has been widely discussed in the literature (Paldam 1987; Prachowny 1993). Not only unemployment, but also employment variations are related to the aforementioned relationship. In fact, an increase in production levels corresponds – in the short run – to an increase in labour demand. This increase leads to higher employment levels and to a consequent decrease in the unemployment rate, since, assuming a conventional labour/capital production function, firms adjust to the need for increased production by hiring more personnel.

The short-run increase of the labour factor in production is expected, because the additional adjustments to increased production need are long-run phenomena. Over a longer period, however, improvements in labour productivity are sought, by augmenting the share of capital in the production factors. With regard to labour, adjustments to increased demand may ultimately generate migration phenomena (depending on the efficiency of the real estate market). These medium- to long-term effects are not analysed in this study, as additional data, theories and analytical tools would be needed.

We choose therefore to focus on short-term economic adjustments. At the national level, these adjustments – the effect of economic output variations on the labour market – may be

[1] Prachowny (1993) actually elevates Okun's 'law' to the level of 'theory', providing extended theoretical discussion and empirical tests on the validity of Okun's hypotheses.

influenced by the business cycle, together with demographic and institutional factors (Kosfeld and Dreger 2006). The need for additional employees can then be absorbed not only by the unemployed, but also, for instance, by an increase in participation rates, as discouraged workers resume their search for a job. Similarly, in a scenario of a growing labour force, the decrease in the unemployment rate might be less than the related increase in employment.

At the regional level, the above relations are further complicated by spatial matters. As regions are small open economies, they are not self-contained (which is most likely the case of nations), but are highly interactive. The aforementioned demographic phenomena seen for the national case are still relevant, but with the additional element of the interaction between regions. In this framework, one of the effects of an increase in labour demand in a single region is the increased mobility – towards that region – of the (potential) workers residing in neighbouring regions (that is, increased incoming commuting). Similarly, in a downward period, workers who are laid off may seek work opportunities in neighbouring regions.

Additionally, regions may show consistently different levels (or growth rates) of economic output. These regional differentials in output are – following Okun's law –reflected in the regional labour market aggregates; that is, employment and unemployment. On the basis of the above discussion, we can stress that the observation of such aggregates provides us 'with a signal of where the [regional] economy stands' (Blanchard 2003, p. 29). In other words, changes in regional labour markets, such as an increase in unemployment rates, can be interpreted as an indication (a *proxy*) of the changes in the levels of regional economic activity (for example, per capita regional GDP). Evidence of the existence of the relationship between per capita regional GDP and unemployment rates can found in the literature (see, for example, European Commission 1996). On the other hand, others are more critical of the consistency of this relationship over time, because of concerns about the stationarity of the series observed (Elhorst 2003). These concerns are, however, related to full employment conditions implicit in Okun's law and can be considered to be particularly relevant in an unemployment/regional GDP regression framework and in the medium to long run.

## 1.3 Regional Interactions and Persistence of Heterogeneity

As mentioned above, in the short run the main adjustments to changes in the level of economic activity arise in labour demand. These changes in output levels are due to increased/decreased demand for the goods and services produced in the area concerned. A distinction should be made at this point, as to what is the final destination of the output. It is safe to assume that a share – the extent of which varies from case to case – of the production is consumed within the domestic market, while the remaining quantity of goods/services produced is destined for export.

Setting aside the internal consumption of goods, which depends largely on population size and income levels, we can consider two examples of the trade of goods and services. At the national level, the exchange of output will happen over country boundaries. The extent of the cross-country trade and, in particular, the finding of a positive or negative balance show whether a country is an importer or an exporter or resources. For instance, the USA has had a negative international trade balance for more than two decades, while smaller countries such as the Netherlands tend to have a positive trade balance (CBS 2007). More generally, with some notable exceptions such as the USA, richer countries will have positive trade balances, and poorer countries will have negative ones. In principle, the same can be expected on a regional basis. On the other hand, the analysis of regional trade poses additional obstacles than in the case of nations, the major one being the lack of official statistics measuring the flows of goods and services between regions (Armstrong and Taylor 2000; Polenske and Hewings 2004). The relevance of this aspect appears to be greater if we consider that regions are more open systems than nations. In open systems, interregional trade can be expected to absorb a larger share of the total output; more generally, interactions between regions have a greater role in the socio-economic development of each single region. It has been observed that only geographically small countries, such as the Netherlands, rely on trade as much as single regions within a larger country, such as the UK.

The nature and extent of the economic flows between regions is important in our context for two main reasons:

(a) The aforementioned Okun's law refers to closed economic systems (Okun 1970; Prachowny 1993), where the increased demand for labour is absorbed internally. This is – for the most part – the case of nations, though one might argue that rather small countries like San Marino or Luxembourg rely on the open nature of their economies. The assumptions of fixed endowment of production factors – one being labour – and of constant returns of scale, which are key assumptions of conventional trade models such as Heckscher-Ohlin's (Ohlin 1933), are increasingly undermined by the abatement of capital and labour mobility barriers (we can think of free-trade areas and the Schengen agreement). Such assumptions also seem to be restrictive when considering small open systems such as regions, where an increased demand for labour in a particular region may not be sufficiently satisfied internally and is complemented by intensified labour mobility (that is, incoming commuting from the neighbouring areas). As a consequence, the difference between closed and open systems – in particular with regard to regional labour markets – deserves further investigation for its implications on the Okun framework described in the previous section.

(b) A second reason for interest in regional trade is related to regional convergence (Barro and Sala-i-Martin 1991, 1992). The concept of convergence refers to the economic process by which poorer regions tend to catch up over time – for example in per capita income – with the richer ones. Though the data employed in the present study do not

> allow us to verify long-term adjustments and trends (see Chapter 3), it is still possible to investigate medium-range (5–10 years) tendencies to regional convergence. In this regard, the investigation of convergence in the economic output of regions would require knowledge of the interregional exchange of goods and services (flows of resources). In particular, because such data, as stated above, are not available at the required level of detail, it is not possible to shed light on the network of economic interrelations that would favour convergence between regions. An alternative approach is therefore necessary.

In light of the above discussion, we can again exploit and reinterpret the framework provided by Okun's law. In the preceding section we argued that labour market aggregates, such as unemployment rates, provide information on where the economy stands. Likewise, we now argue that the daily flows of workers across regions (interregional commuting) are a *proxy* for (a direct and indirect consequence of) the flows of economic resources between regions. Following our speculation, regions with a prevailing outward movement of resources will show high rates of incoming workers from the neighbouring regions. Accordingly, regions which mainly 'import' resources will be providers of labour force.[2] In other words, the degree of interdependence among regions is expected to be determined by commuting flows.

The significance of labour mobility (often comprising migration phenomena) as an indicator of interregional flows, in particular as an implication of open systems with regard to regional convergence, is discussed in the recent literature. Magrini (2004) discusses interregional interactions in terms of both trade and labour mobility. In an analysis of the Chicago metropolitan area, Hewings et al. (2001) come to a conclusion which also seems to support the above approach. The authors find that journey-to-work flows, rather than regional trade, generate a closer interdependence among regions. The level of interdependence among regions is crucial in determining the extent and duration of differentials among them (in terms of economic performance). As Arbia et al. (2002, p. 25) stress, in the presence of strong regional interdependence, 'a region experiencing growth propagates positive effects onto the neighbouring regions thus producing an acceleration of the convergence process'. Further, on the basis of their experiments concerning Italian regions, the authors find that, by taking into consideration – by means of spatial econometric techniques – the levels of regional interdependence, a significantly higher degree of convergence is found.

If the extent of the aforementioned regional interdependencies may be an indicator of the interaction externalities, the distribution and persistence over time of these interregional liaisons are also important, since they show the direction towards convergence or divergence. In view of the commuting flows analogy described above, the distribution of labour mobility

[2] The existence of more specific phenomena such as the 'dormitory districts' can instead be attributed to distortions caused by zoning/land-use policies, real estate prices and so on.

can tell rather different stories: Do regions which are already economically advanced tend to receive increasing or decreasing shares of mobility over time? Do regions evolve from being providers of resources to being attractors of resources? Do mobility patterns which are stable over time imply a lack of convergence?

The evolution of the mobility network caused by economic activity can provide a dynamic outlook on this convergence process (or on the lack of it). Its study, together with the analysis and interpretation of regional differentials in labour markets, may allow the questions listed above to be answered.

Finally, it should be remarked that, while the theoretical links between labour markets and economic output outlined here, as well as those made in the preceding section, are at the basis of the motivations for the present study, our aim is *not* to test or prove the validity of Okun's law or other economic theories. We limit our scope to the statistical description and interpretation of the labour market-related variables discussed above.

## 1.4 Objectives of the Study

The aim of the present study is the statistical analysis of regional labour market developments and disparities in Germany. In particular, our analysis is carried out following two distinct – but interrelated – research questions.

The first research question concerns the statistical analysis and forecast of the key variables that characterize the functioning of regional labour markets, notably employment and unemployment. In particular, we are interested in selecting and applying appropriate novel methodological tools in order to take into account the complex spatio-temporal relationships among regions. Hence, as well as using conventional analytical tools such as spatial econometrics, we pay considerable attention to neural networks (NNs) and spatial filtering techniques. The NN approach provides advantages over conventional statistical techniques, in that NNs are nonlinear methodologies which are able to autonomously learn – from the data – functional relationships between the variables employed. We aim to integrate in a forecasting framework – through the internal complex interactions of the NN paradigm – the various forces that drive regional labour market developments. A further step is taken with the use of spatial filtering techniques. This approach allows us to take explicitly into account the spatial dependence among regions and to generate more appropriate estimates for the labour market variables studied.

The second research question is concerned with the spatial mobility associated with regional labour market developments addressed in the first empirical task. By studying commuting flows between regions and their evolution over time, we aim to integrate evidence from conventional spatial interaction and urban-economic approaches with statistical methods emanating from recently developed network analysis frameworks, such as those related to scale-free networks and the concept of 'hubs'. The integration of such approaches allows us to further investigate patterns of regional disparity. In particular, we explore the emergence and the stability of 'hubs' of mobility and, consequently, of regional development. In light of our findings, a discussion of the mechanisms which drive regional change is offered.

Together, the experiments related to our two research questions aim to provide novel approaches to regional labour market forecasting and modelling. The two-step approach of geography-based econometrics and spatial network modelling offers tools for both observing/analysing spatial correlation between regional labour markets and interpreting the underlying workers' mobility levels as an indicator of regional interaction.

## 1.5 Structure of the Study

The present dissertation gathers a number of empirical studies, which provide a progressively closer and in-depth analysis of regional disparities in the labour market (see Figure 1.1). In the context of the theoretical framework and of the research questions outlined in the previous sections, we employ a varied set of methodologies which are described briefly in Chapter 2. As a background specific to the case study of this thesis – the German regional labour markets – Chapter 3 provides a concise overview of the recent (post-reunification) economic history of Germany, as well as of the research carried out with regard to the aforementioned German regional disparities, before finally describing in detail the data employed in the study. The first three chapters of this study form Part A of the thesis.

The empirical studies contained in the dissertation can be divided in two main parts. The first empirical part (Part B) is concerned with the first research question outlined in the previous section, and involves the utilization of novel econometric approaches for forecasting and modelling regional labour market changes. We first deal with regional labour market forecasts by means of neural networks, while subsequently employing spatial filtering techniques in order to accommodate spatial heterogeneity in regional labour market aggregates. The second and last empirical part of the thesis (Part C) is concerned with our second research question, and deals with the integration of recently developed network theories with conventional spatial interaction modelling.

Part B of the dissertation includes the first four empirical chapters. In the first three of these chapters (4–6) we discuss and test the use of neural network (NN) techniques for the forecast of variations in regional labour markets. Several factors make NNs a desirable approach in this matter, such as: (a) the imbalance emerging from the availability of data which are wider horizontally (that is, the geographical disaggregation) than vertically (that is, number of observations in time); and (b) the specification constraints and assumptions typical of several conventional econometric techniques and further issues such as model identification and multicollinearity. NNs offer an alternative approach, since they bypass all the above problems, offering a data-driven, unstructured and nonlinear tool. Using German data at the NUTS-3 level of disaggregation[3] and full-time employment as a dependent variable, Chapter 4 introduces and tests NNs as a forecasting tool, its specific application to panel (space-time) data, and the results obtained for a set of basic NN models.

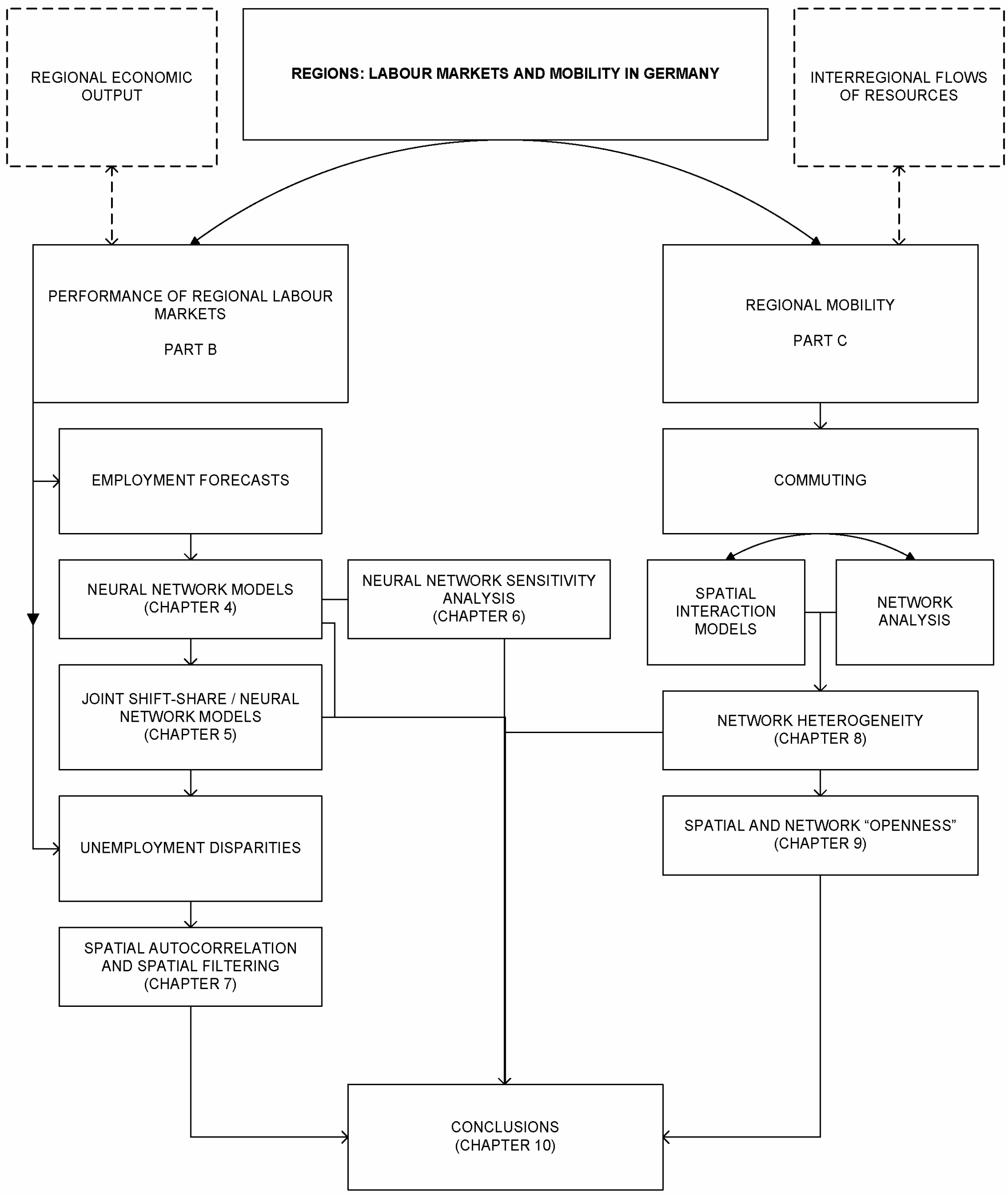


Figure 1.1 – Structure of the study

Chapter 5 enriches the preceding analyses by introducing additional NN models, which aim to improve the understanding of the causes of regional variations in economic entities. In particular, a mixed NN-shift-share analysis (NN-SS) approach is presented and tested.

[3] For a description of the data employed in the thesis, see Chapter 3.

Components derived from different shift-share analysis paradigms are introduced in the models, and these comprise a recently developed 'spatial' extension of shift-share analysis. As a further level of analysis, Chapter 6 presents a sensitivity analysis, testing the robustness of NN models with regard to varying computing parameters.

In the remainder of Part B, we start off from the analyses of the three preceding chapters, and then extend the spatial connotation of our analyses, which was hinted at with the use of the spatial shift-share decomposition, in order to take into account the persistent disparities observed for the German regional labour markets. These spatial disparities have been recently studied employing spatial econometric techniques. In this framework, convergence (or the lack of it) between German regions has also been investigated in recent years. We propose the use of a novel technique: namely, spatial filtering, in order to investigate time-invariant spatial patterns of economic variables, such as unemployment and wages. Subsequently, common spatial patterns can be recognized and utilized in an econometric framework. Using German regional data on unemployment rates, Chapter 7 presents the computation, description and interpretation of time-invariant regional geographic patterns (namely, spatial filters). Subsequently, we select new spatial filters, based on the introduction of additional socio-economic variables (full-time employees, average daily wages and working-age population), in order to estimate a simple unemployment model and to compare its statistical results and estimates with those emerging from conventional spatial econometric techniques.

Part C of the dissertation aims to complete the empirical tasks previously carried out, by providing a novel integration with spatial interaction analyses. As mentioned in Section 1.3, regional interactions are relevant for understanding differences between regions. In particular, commuting flows can provide a picture of the exchanges, across administrative boundaries, of the labour factor. Journey-to-work trips have long been modelled by means of spatial interaction models. We propose the integration of this established approach with novel developments emerging from network theory, in order to find the most suitable indicators of tendencies towards regional heterogeneity. In this framework, Chapter 8 investigates the distributional properties of commuting flows between regions and attempts an interpretation of such flows according to spatial interaction functions. Finally, Chapter 9 presents statistical results related to the two above approaches – involving space and networks – and analyses them in an integrated and systematic fashion. As a final step, we attempt to assess the relevance of network effects for identifying regional 'hubs' of economic activity.

Lastly, Chapter 10 summarizes the empirical applications and the related findings pertaining to our research questions, and offers suggestions for future research.

Chapter 2

# Methodological Background

## 2.1 Introduction: Progressively Accounting for Spatial and Time Disparities

The main aim of this study is to offer an in-depth statistical analysis of regional labour markets in Germany. The emphasis is not on the development of new theory, but on the use of advanced and modern statistical tools for analysing the actual evolution of these labour markets. Thus, the main idea is: 'let the facts speak for themselves'. Hence, the present study is mainly exploratory in nature and not based on a deductive economic methodology.

We have already outlined the main motivations for the present study in Chapter 1. The main objective of the study – the statistical empirical analysis of disparities in regional labour markets – is addressed, over the course of the applied chapters of the thesis (Chapters 4–9), following the research questions stated in Section 1.4. These research questions outline the importance of analysing spatio-temporal processes and the consequent emerging patterns, such as network structures.

In particular, the focus – in our experiments – on space and time is highlighted by the utilization of three main analytical approaches – *neural network forecasting techniques*, *spatial econometrics*, and *network theories*. We intend to analyse the evidence of spatial correlation and networks in regional labour markets and their performance indicators. The choice of the methodologies adopted – and the order in which they are presented in the study – is motivated as follows:

(a) Step 1: *Neural networks* (NNs) are recently developed computation techniques which aim to overcome the limitations of conventional (linear and nonlinear) methods by means of a data-driven approach. As such, they represent a fascinating tool for analysing or forecasting complex functional relationships like those that can be expected for the case of a large set of small, contiguous regions.

(b) Step 2: *Spatial econometrics* explicitly acknowledges the influence of geographical proximity on the value of (georeferenced) variables. The use of contiguity matrices allows us to extend conventional econometric models, while the computation of statistics such as Moran's $I$ or the Geary ratio provides synthetic indicators of the extent of spatial autocorrelation (SAC) in the data. In this framework, *spatial filtering* techniques, such as the one employed in this study, aim to discern map patterns in georeferenced data and account for large- and small-scale spatial effects.

(c) Step 3: *Network analysis* is employed in the study of regional commuting flows. Examining home-to-work trips from a conventional 'spatial interaction' perspective, and from the novel perspective provided by recently developed network theories allows us to investigate complementary aspects of labour mobility and to reinterpret the spatial relationships between regions and the different performances of their labour markets.

The remainder of this chapter briefly describes these three methodological approaches and discuss the added value of each of them for our analyses and the research questions investigated.

## 2.2 Neural Networks

### *2.2.1 Forecasting Regional Employment with Neural Networks*

The need for accurate forecasts of modern socio-economic (regional and national) systems has been growing in recent years (for a discussion of the importance of forecasting, see, among others, Daub 1984). Most economic interventions, such as the distribution of federal or EU funds to less favoured regions, require adequate policy preparation and analysis, usually made well in advance, and, often, at a disaggregated level. In this context, an emerging problem is the increasing level of disaggregation for which economic data are collected, and, hence, the imbalance between the number of disaggregated (regional) figures to be forecasted, and the quantity of observations (usually years) available. Although conventional econometric techniques can be useful in this respect (see, for example, Bade 2006), it is well known that, in addition to the many constraints and hypotheses that these econometric models have to cope with, such as the use of fixed regressors, the choice of the model specification – and, most important, of the explanatory variables to be used – is crucial. These econometric tools all have their own merits, and have contributed to significant progress in the understanding of complex labour market dynamics. However, the great abundance of data that has emerged in the recent years has presented new challenges to both researchers and policy makers. Researchers have to be selective regarding the choice of a method that is suitable for analysis and forecasting, while policy makers have to be alert to the results – and in particular the robustness – of predictions offered to them.

A new approach to this problem of large data sets in complex spatial economic systems that is able to overcome some of the aforementioned limitations of conventional econometrics – especially in the framework of short-term forecasts – is provided by neural networks (NNs), a family of nonlinear statistical optimization methods, which can override such restrictions (see, for example, Cheng and Titterington 1994). The NNs' capacity to learn from the data, and to find functional relationships among variables, makes it possible to forgo strict statistical assumptions and specification problems, and to process data by means of a flexible statistical tool. The present use of complex forecasting models is made possible by the dramatically increased computational power of computers, which can now handle large data sets.

Chapters 4–6 of the present study are concerned with the use of NNs in order to forecast regional employment change. Employment data are necessary in economic and regional policy analysis. Pension systems, social security reforms and annual policy-making tasks, such as the establishment of budget allocations, require detailed employment forecasts. Focusing on the evolution of labour markets in Germany, our NN experiments focus on short-term employment forecasts.

The aim of our experiments is not to validate the use of an NN in itself (nowadays NNs are widely used in different research fields in many disciplines), but to explore an NN's ability to forecast changes in economic variables in a panel data framework, with particular attention to regional labour markets. This is, however, not a straightforward procedure: applications of NNs to time series data – or to other pattern recognition settings – are rather frequent, while contributions on NNs dealing with panel data are very limited. The high number of cross-sections in panel data such as the ones employed in our study and the limited number of years for which the information is available are a problematic issue for conventional econometric techniques. Here lies the rationale underlying our methodological choice of NN techniques.

### *2.2.2 Neural Forecasting*

Forecasting is one of the main functions of NNs (see, for example, Werbos 1974; Lapedes and Farber 1987; Weigend et al. 1990). With regard to economics, several reviews of the use of NNs in business/financial applications can be found (we refer, for example, to Herbrich et al. 1999; Vellido et al. 1999), while a wider look at neural forecasting is provided by, amongst others, Zhang et al. (1998). For a historical review of the NN methodology we refer to, amongst others, Taylor (1997).

Neural forecasting is attractive to researchers and practitioners in economics for a number of reasons, one being the weaknesses of both linear methods (which are meant to forecast future values which are linearly related to previous observations) and nonlinear methods (which can indeed incorporate richer data information but were developed for specific problems: for example, logit models are used for discrete choice problems). The nature of the data-generating process is indeed a critical issue, in particular concerning whether it has linear or nonlinear characteristics, which defines which statistical (forecasting) tool is most suitable (see Chapter 4). Additional issues pushing towards the utilization of NNs in forecasting relate to data quality. Multicollinearity (in a panel data framework) and noise in the data can invalidate the results of conventional regression analyses.

A wide literature is available that examines the (possible) advantages of NNs and draws comparisons with conventional statistical methods (see, amongst others, Cheng and Titterington 1994; Swanson and White 1997a,b; Baker and Richards 1999; Sargent 2001). For example, Nijkamp et al. (2004) compared NNs with logit and probit models in an analysis of multimodal freight transport choice. The evaluation of the effectiveness of NNs shows quite some variety in the literature: with respect, for example, to variables such as employment, industrial production, or corporate profits, as different authors have either made positive observations (Swanson and White 1997b; Adya and Collopy 1998) or have come to negative conclusions (Stock and Watson 1998). Stock and Watson (1998) concluded that NNs, and nonlinear methods in general, mainly perform worse than linear methods. On the other hand, Swanson and White (1997b, p. 459) suggest that it could be possible to improve macroeconomic forecasts ‘using flexible specification econometric models’, whose specification ‘is allowed to vary over time, as new information becomes available’. Finally, Adya and Collopy (1998) found that, most of the time, NNs seem to provide better forecasts than the models with which they are compared. Examining a string of studies which developed NNs for business forecasting, they find that, of the studies correctly validating and implementing the NN models, 88 per cent show that the NNs have a superior performance.

NNs have been extensively used in economic fields, as well as elsewhere, ranging from pattern recognition to transportation (Himanen et al. 1998; Reggiani et al. 2000). In the labour field, NNs have been employed in the study of labour productivity (Sonmez and Rowings 1998; Lu et al. 2000), or in the analysis of market segmentation (Gaubert and Cottrell 1999). Longhi et al. (2005a,b) have studied the application of NNs in a panel and cross-sectional data framework.

### *2.2.3 The Neural Network Method*

NNs are solid statistical validation tools, even though they are often referred to as a ‘black box’ approach. Though they are regarded as such particularly in the social sciences, because of their no-theory modelling characteristics, NNs are not an obscure tool. The internal functions that process the information inputs, as well as the algorithms that determine the direction and the degree of interaction of the factors, can be clearly explained formally and mathematically. On top of this, they can be proven to be consistent with standard goodness-of-fit conditions (see, for example, Schintler and Olurotimi 1998). The main characteristic of NNs is their ability to find numerical solutions when the relationships between the variables are not fully known. Thus, they are particularly useful when one has a limited knowledge of the phenomenon examined.

NNs originate from the scientists' interest in the development of techniques that could replicate the type of simultaneous information processing and data-driven learning seen in biological networks. Since Rosenblatt's first introduction of an artificial NN (Rosenblatt 1958) and the works of Werbos (1974), who provided a proper mathematical framework, and those of Rumelhart and McClelland (1986), who developed the most commonly used error-correction algorithm (backpropagation – see Chapter 4), many developments have been made in the NN framework.

Similarly to what happens in the human brain, calculation in NNs is distributed over a number of processing units (neurons), which work in parallel. These units are distributed in 'layers' and are internally connected through a set of weights. The layers are made up of units which represent the input variables, the output variables, or intermediate (hidden) computational units. In feedforward NNs, the most popular family of NN methods, the units of each layer are unidirectionally connected and transfer information only to units of the succeeding layer.

Following Fischer (2001b, p. 23), we define the generic processing unit $u_{i,n}$ as:

$$u_{i,n} = \varphi(\mathbf{u}_{n-1}) = \Im[f(\mathbf{u}_{n-1})], \tag{2.1}$$

where $\mathbf{u}_{n-1} = \{u_{1,n-1}, \ldots, u_{k,n-1}\}$ is the preceding layer of units, and the transfer function $\varphi$ can be decomposed into two separate functions: the activation function $\Im$, and the integrator function $f$. The integrator function is used to aggregate the data entering the processing unit $u_{i,n}$ into a single input. The integrator function is a weighted sum:

$$v_{i,n} = f(\mathbf{u}_{n-1}) = \sum_j w_{ij,n-1} u_{j,n-1}, \tag{2.2}$$

where $u_{j,n-1}$ is the $j$th unit connected to unit $u_{i,n}$, and $w_{ij,n-1}$ is the weight connecting the two units (Fischer 2001a). The activation function – most often a sigmoid/logistic function – computes the unit's output and can be represented as (Fischer 2001b, p. 24):

$$\Im(v_{i,n}) = \frac{1}{1 + \exp(-\beta v_{i,n})}, \tag{2.3}$$

where $\beta$ defines the slope of the curve. The value of $\beta$ can be selected a priori or, for example, by means of sensitivity analysis. It is worth noting that, in NNs, all the input variables are rescaled to the (0, 1) interval. Accordingly, the outputs of the algorithm – as suggested, for example, by the use of sigmoid functions – are also in the same interval. These are subsequently rescaled to the output numerical interval observed in the sample data.

A recursive modification of the weights employed in Equation (2.2) guides the 'learning' process (see Chapter 4 or, for instance, Rumelhart and McClelland 1986) of an NN. This recursive weight computation is often carried out by means of the backpropagation algorithm (BPA). The BPA – as does every other 'supervised' NN algorithm – uses input examples and their corresponding outputs (provided by the analyst) in order to map out and replicate the data-underlying behaviour. Two parameters – 'learning rate' and 'momentum', which are discussed later in the study – define, respectively, the extent and the duration (in terms of iterations) of the corrections.

For our experiments concerning regional employment forecasts, we employ conventional feedforward NNs. Chapters 4–6 detail the particular settings used (for example, for the calculation of the NN weights) and the implementation of the NN models for our case study. Additional methods (instrumental to NNs), such as genetic algorithms or shift-share analysis, are also described.

## 2.3 Spatial Econometrics and Spatial Filtering

### *2.3.1 Spatial Econometrics for Regional Labour Market Analysis*

The neural network (NN) method outlined in Section 2.2 is employed in our study as a tool to forecast the development of regional labour markets. Although NNs provide a nonlinear response to the different stimuli that influence the performance of the single regions, they do not take into explicit consideration the fact that noise and shocks in regional labour markets are not symmetrically distributed in space. Similarly, small open systems such as regions can be expected – as stated in Chapter 1 – to have a great level of interaction between them and, consequently, to influence each other's economic performance (for example, regional spillovers). Correlation 'in space' among regions is evident, for example, in Germany, most evidently in its still-existing East/West economic divide. Although in Chapter 5 we attempt to (partially) answer the need to consider the above effects by enhancing NN models with (spatial) shift-share analysis components, the issue remains an open one, which conventional econometric techniques also cannot resolve.

A systematic detection of these spatial structures in the data and their inclusion in econometric models is necessary in order to correctly assess economic relationships: for example (as observed in our case study), the one between unemployment rates and a set of explanatory variables. We are therefore interested in the application of a set of techniques and models known as 'spatial econometrics' (see, for example, Anselin 1988). These methods take into account within econometric models – by means of a geographic weights matrix – the proximity relations of regions, with regard to both the variable being analysed and the explanatory variables.

Spatial econometric techniques appear to be of particular use, for example, with respect to the case of unemployment, for which a persistence of regional disparities has been observed (see, for example, Suedekum 2005). Persistent regional differentials contradict the idea that residential and labour mobility act as a balancing device until the disparities themselves become less. Differentials in unemployment can therefore be associated with, for example, the level of amenities of the regions, which generate, as economic compensation, higher/lower wages and lower/higher unemployment for disadvantaged/advantaged locations (Elhorst 2003).

More generally, it is a demanding task to include in an econometric model all the factors that may determine regional unemployment differentials and the observed spatial patterns. These factors may be socio-economic or locational: spillover effects, and rigidities in the labour markets (highly unionized workers) or in mobility (high real estate prices). Consequently, in modelling labour market dynamics the analyst may choose to focus on a few main explanatory variables relating to labour demand and supply, such as employment, population, or wages, in order to explain – as in our case study – unemployment variations. The effects of the remaining (excluded) factors – in particular if related to location – might identify a set of spatial structures. We propose the use of spatial filtering techniques: namely, the ones developed by Griffith (1996, 2000, 2003), in order to account for spatial structures due to unobserved/omitted variables. The inclusion of what is called a 'spatial filter' in an econometric model aims to provide correct estimates of the functional relationships between the dependent variable (unemployment) and its identified covariates.

### *2.3.2 Spatial Econometrics and the Spatial Filtering Method*

It is common to refer to the extent of the aforementioned spatial structures in the data as a problem of 'spatial autocorrelation' (SAC). SAC is defined as the correlation, amongst the values of a georeferenced variable; that is attributable to the proximity of the objects to which the values are attached. Consequently, positive autocorrelation implies that the geographical proximity of two objects tends to produce similar values of the variable examined for the two (Cliff and Ord 1981). This phenomenon is often observed in reality, especially in economics. On the contrary, negative spatial autocorrelation is seldom observed and studied, though a renewed interest in this particular phenomenon emerged recently (see, for example, Griffith 2006). The most common indicator of spatial autocorrelation is the Moran statistic (Moran's $I$, hereafter abbreviated to MI). This is calculated as follows:

$$I = \frac{N \sum_i \sum_j w_{i,j} (x_i - \overline{x})(x_j - \overline{x})}{(\sum_i \sum_j w_{i,j}) \sum_i (x_i - \overline{x})^2}, \qquad (2.4)$$

where, in the case of a set of $N$ regions analysed, $x_i$ is the value assumed by the generic variable $x$ in region $i$, and $w_{i,j}$ is the cell $(i, j)$ of a geographic weights matrix $\mathbf{W}$, indicating the proximity of each pair of regions $i$ and $j$. Proximity is often defined by means of a geographic connectivity matrix $\mathbf{W}$, of dimension $N$ x $N$. Binary matrices are often used, containing only 1 and 0 values, depending on whether the regions to which each cell is associated are, or are not, neighbours. Different types of matrices are available in the literature, based on different standardization procedures. Chapter 7 briefly discusses possible modifications of geographic weights matrices.

From a statistical analysis point of view, the spatial structures highlighted by the spatial autocorrelation measures are problematic, since they make standard statistics, such as correlation coefficients or ordinary least squares (OLS) estimates, potentially inappropriate (see Chapter 7).

Among the variety of spatial econometric techniques for the statistical analysis of georeferenced data, spatial autoregression (see, amongst others, Anselin 1988) is commonly employed. Recent examples of its application to the case of Germany are, amongst others, Elhorst et al. 2002; Niebuhr 2003; Longhi and Nijkamp 2006. Spatial autoregressive techniques take into account spatial effects using geographic weights matrices. These matrices measure the spatial linkages (dependence) between the values of a georeferenced variable. A general notation of the spatial autoregressive model, which is known as a Cliff-Ord-type model, has been proposed by Anselin (1988):

$$\begin{aligned} &y = \rho\mathbf{W}_1 y + \mathbf{X}\beta + u, \\ &u = \lambda\mathbf{W}_2 u + \varepsilon, \\ &\varepsilon \sim (0, \Omega). \end{aligned} \tag{2.5}$$

Models of this type can be estimated either by (quasi-) maximum likelihood (ML), as described in Anselin (1988, 2001) and Lee (2004), or by the generalized method of moments (GMM, also known as 2SLS, 3SLS or IV estimation; Kelejian and Prucha 1998, 1999; Anselin 2001). These estimators assume that the autocorrelation pattern can be combined/concentrated in one or two parameters and that the spatial weights matrix $\mathbf{W}$ describes the spatial interdependence adequately.

An alternative approach to spatial autoregression is the use of spatial filtering techniques, such as the ones described in Getis (1995) or Griffith (2003). The main advantage of these filtering procedures is that the studied variables (which are – initially – spatially correlated) are split into spatial and non-spatial components. These components can then be employed in an OLS modelling framework. In addition, filtering out spatially autocorrelated patterns enables one to reduce the stochastic noise normally found in the residuals of standard statistical tools such as OLS. This conversion procedure requires the computation of 'spatial filters'.

Applications of spatial filtering techniques, using the one developed by Griffith (2003), have recently been carried out by Kosfeld, Dreger and Eckey (Kosfeld and Dreger 2006; Kosfeld et al. 2006a) for the case of Germany. These contributions deal with German regional labour markets, exploiting the spatial filters in order to improve understanding of different phenomena, such as the Beveridge curve or (un)employment thresholds. Applications applying Getis's (1995) approach can be found as well in Badinger and Url (2002), who analysed the Austrian regional labour markets, and in Mayor and López (2006) for the case of Spain.

For the experiments presented in this study, relating to regional labour markets, the approach developed by Griffith is to be preferred to the one by Getis, which requires variables with a natural origin and positive value. Consequently, rates, percentage changes, and so on, can not be used in the Getis approach.

To compute the spatial part of variables, spatial filtering techniques rely on the computational formula of the MI. The methodology uses eigenvector decomposition techniques, which extract *orthogonal* and *uncorrelated* numerical components from a geographic weights matrix of dimension $N$ x $N$. Details on the computation of the spatial filter components are provided in Chapter 7. This approach may be compared to that of principal components analysis (PCA), as in fact both methodologies generate orthogonal and uncorrelated new 'variables' that can be employed in a regression analysis framework. However, while the PCA components may have an economic interpretation (eigenvectors are used to construct linear combinations of attribute variables), spatial filters are linear combinations of the eigenvectors themselves and represent the latent SAC (or redundant information due to spatial interdependencies) of a georeferenced variable, found according to the given geographic weights matrix. Moreover, the single eigenvectors can be observed to represent specific spatial patterns tied to administrative/economic/social factors.

When employed as additional regressors in an otherwise non-spatial regression equation, the computed eigenvectors (usually a subset of the whole set) may function as proxies for missing explanatory variables, and account for the residual spatial correlation in the data. Notably, the top two eigenvectors that are computed often identify map patterns along the cardinal points, that is, major North-South and East-West patterns (for example, the German East/West divide), while the subsequent eigenvectors display map patterns at a smaller scale. In this framework, the advantage implied by the orthogonality of the eigenvectors is that partial correlations and multicollinearity issues do not arise. Each eigenvector selected for inclusion is considered to be part of a 'spatial filter' for the dependent variable. If this is regressed on its own spatial filter, the regression residuals constitute the *spatially filtered* part of the variable. Additionally, a (presumably) smaller set of eigenvectors can be computed, including further covariates in the analysis. In this case, the selected eigenvectors will account for the SAC in the dependent variable *and* in the covariates. This approach would allow non-spatial regression models (either linear or nonlinear) to be implemented by incorporating the appropriate spatial filter computed.

## 2.4 Network Analysis

### *2.4.1 Investigating Labour Mobility Networks*

We have pointed out in the preceding sections that spatial econometrics and the spatial filtering methodology outlined above do provide a systematic way of including – in an econometric framework – spatial relations between regions. In particular, spatial filtering allows us to observe what the main spatial patterns underlying georeferenced data are. The map patterns visualized through the spatial filter components are a useful tool for econometric computation (for example, they do not require complex estimation methods) and can be interpreted visually.

However, spatial econometrics cannot guide the analyst beyond the observations and acknowledgement of such spatial structures inherent in data. The further step which is required in the analysis of the evolution in space and time of these spatial patterns is their *interpretation*. Even if new theories or empirical regularities are not investigated, being able to 'read the data' more in-depth is essential to a successful spatial economic analysis. Our case study on regional labour markets in Germany is no exception to this rule. Consequently, we need to inspect the regional labour dynamics more thoroughly.

In Chapter 1 we stated that interactions between regions contribute to generating spatial associations and, more generally, patterns of development (whatever the economic variable observed), as shown by spatial econometrics. We then stressed that commuting flows can be employed as a proxy for the levels of regional interaction. If we analyse regional labour mobility (in time and space), we can observe that the aggregate flows of workers between their place of residence and their place of work underlie to a (mobility) network. Spatial interaction theories (Wilson 1967; Sen and Smith 1995) have long been employed in explaining such patterns of mobility, including by means of established analytical tools such as the four-step transport model. Recent theoretical and empirical developments link mobility and employment in general to further phenomena, such as agglomeration (see, for example, Fujita et al. 1999; Fujita and Thisse 2002) or spatial mismatch (Brueckner and Zenou 2003).

In particular, a growing literature is available that studies commuting in a spatial or network framework. Spatial job-matching processes have been widely studied in a social network framework (Montgomery 1991), while job mobility has been investigated in both an urban and a regional network context (for example, see Thorsen et al. 1999; van Nuffel and Saey 2005; Russo et al. 2007). Russo et al. (2007) use commuting flows in Germany to identify 'entrepreneurial cities' in Germany. Van der Laan (1998) and van Nuffel and Saey

(2005) investigate – on the basis of commuting flows – the emergence of local and regional multi-nodality for the Netherlands and the Flanders area, respectively.

On the basis of the aforementioned developments, we propose the use of network theories[4] in order to assess the relevance of the connectivity and topology of the German commuting network, in addition to the economic variables that influence the volume and distribution of these flows. The reason for studying commuting in a network perspective is the idea that the network distribution of mobility can help to explain other relevant economic phenomena, such as variations in key labour market indicators or production levels. It is also possible to observe how the network topology – and its changes over time – affects the dynamic trajectory of the geographic commuting network and its hierarchies.

For this aim we employ recently developed network theories, which emerged in the works by Barabási and Albert (1999). The following section briefly describes recent contributions to complex network theory.

### *2.4.2 Network Theory and Scale-free Networks*

This section briefly reviews the main issues related to recent network theories in the social sciences, and in particular their implications for commuting and transportation networks. Networks have had considerable attention in the past years in regional and spatial science (for a review, see, for example, Casti 1979; Batten et al. 1995; Nijkamp and Reggiani 1998). In graph theory, research had been carried out some 40 years ago by Erdös and Renyi (1960), whose major assumption was an underlying random network structure. However, because of insufficient computational power and suitable data, for most of the 20th century, these random theories formed the basis for the most common methods of network simulation in social sciences, although they were not adequately challenged (Barabási 2001). Recently, Albert and Barabási (2002) offered stronger foundations and applications to network theory in the social sciences, by developing the new framework of 'scale-free networks',[5] in contrast to random networks (in this regard, see also Jackson and Rogers 2007). In particular, these authors found that several (large) networks were behaving according to three main characteristics:

(1) Short average path length;
(2) High level of clustering;
(3) Power-law and exponential degree distributions.

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4 A network can be defined as 'an ordered connectivity structure … which is characterized by the existence of main nodes which act as receivers or senders (push and pull centres) and which are connected by means of corridors or edges' (Nijkamp and Reggiani 1998, p. 132).

5 Scale-free networks are characterized by the presence of a few nodes (the 'hubs') with a high number of links (a high 'degree'), while the remaining nodes have only a limited (and fast-decreasing) number of links.

In detail, 'short average-path length' indicates that any two nodes on a network can be reached with a limited number of hops. High clustering, on the other hand, occurs because of nodes locating topologically close to each other in cliques that are well connected to each other. This property had been formalized by Watts and Strogatz (1998). Finally, the frequency distributions of node density (or, more generally, number of connections) are called 'degrees' and can follow power-law and exponential distributions. This third property implies connections that cut across the graph, directly linking different clusters of vertices. These direct links between clusters bring an increased level of efficiency – in terms of number of hops – to the network. This result shows the limits of the Erdös and Renyi models, in which the exponential decay of the degree distribution does not imply a higher number of connections available to the most important nodes. The novelty in the Barabási-Albert approach is incorporating an additional component: network growth. Consequently, not only can the number of nodes in the network increase but new nodes are found to have a higher probability of connecting to other nodes that are already well-connected (preferential attachment).

A certain amount of literature is now available on the analysis of transportation networks – even though not on commuting – in terms of network theory (Reggiani and Schintler 2005). Because of their short average path length, airline networks have been considered by Amaral et al. (2000) as a 'small-world' network,[6] referring to the model presented by Watts and Strogatz (1998). On the other hand, the same authors note that the structural limitation of airline networks, such as the limited space available in the airports, may hinder the emergence of scale-free properties. Other authors have found similar results. This could also be thought to be the case for commuting networks, as the number of nodes in the networks (the regions) and the transport infrastructure are not subject to dramatic changes. In other transport-related studies, Latora and Marchiori (2002) analysed the Boston subway network, while Schintler and Kulkarni (2000) observed congested road networks. Both articles found small-world network properties in the analysed networks. The suitability of transport networks for an evolution in time towards a scale-free structure, as well as the implications of such networks, are discussed in Chapter 9.

The experiments carried out on German labour mobility test the relevance of the above network theories for our case study. We investigate the importance of connectivity in identifying the most 'active' and 'mobile' regions in Germany, and in explaining the regional hierarchies observed and – most importantly – their evolution.

A description of the data sets employed in our empirical analyses, as well as a brief discussion of the socio-economic context in Germany, is presented in the next chapter.

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6 Small-world networks can be described as rewired and highly clustered networks, which also exhibit small average shortest-paths.

Chapter 3

# Context and Data Description

## 3.1 Post-Reunification Germany

Germany is the largest economy in Europe. Because of its economic size, local shocks in Germany are likely to have repercussions for the entire European Union (EU), and in particular for those countries which share borders or have strong commercial liaisons with Germany. In this framework, the most relevant – and we might say 'exogenous' – socio-economic shock in the last decades has been the reunification of the formerly separate West and East Germany.

The economic reunification of Germany occurred on 30 June 1990, shortly before the actual political/administrative reunification, which took place on 3 October of the same year. With the economic merger of the West and the East, free movement of capital and labour, as well as of goods, was introduced. The German reunification process can be considered, from many perspectives, a successful operation, as the East has effectively restructured its legal system, preserved its cultural heritage, and adjusted its standards to the Western ones in terms of attention to the environment and to higher education (Berg 2005).

However, the considerable progress experienced in East German society in recent years has not been matched by a similar degree of economic progress. The economic reunification of West and East Germany has in fact been highly problematic from the very first moments, when the newly unified markets for consumption goods generated, almost immediately, a demand crisis and a consequent rise of unemployment rates in East Germany. The growing desire for Western-produced goods and the more efficient production standards of the West represented a huge problem for the East German firms, of which only 8 per cent were able to competitively adjust to the new reality (Akerlof et al. 1991). Evidence of such decay in Eastern production levels is provided by the employment figures for the area (see Figure 3.1: ratio between the employment levels of 2004 and 1993). The strong migration towards the West of the country, as well as the more-than-proportional counterurbanization[7] (and loss of

[7] 'Counterurbanization' is defined as a trend of population movement from urban towards rural areas (Berry and Cohen 1973).

employment) of the agglomerated areas (Kiehl and Panebianco 2002) are further indicators of the reduced economic opportunities of East Germany.

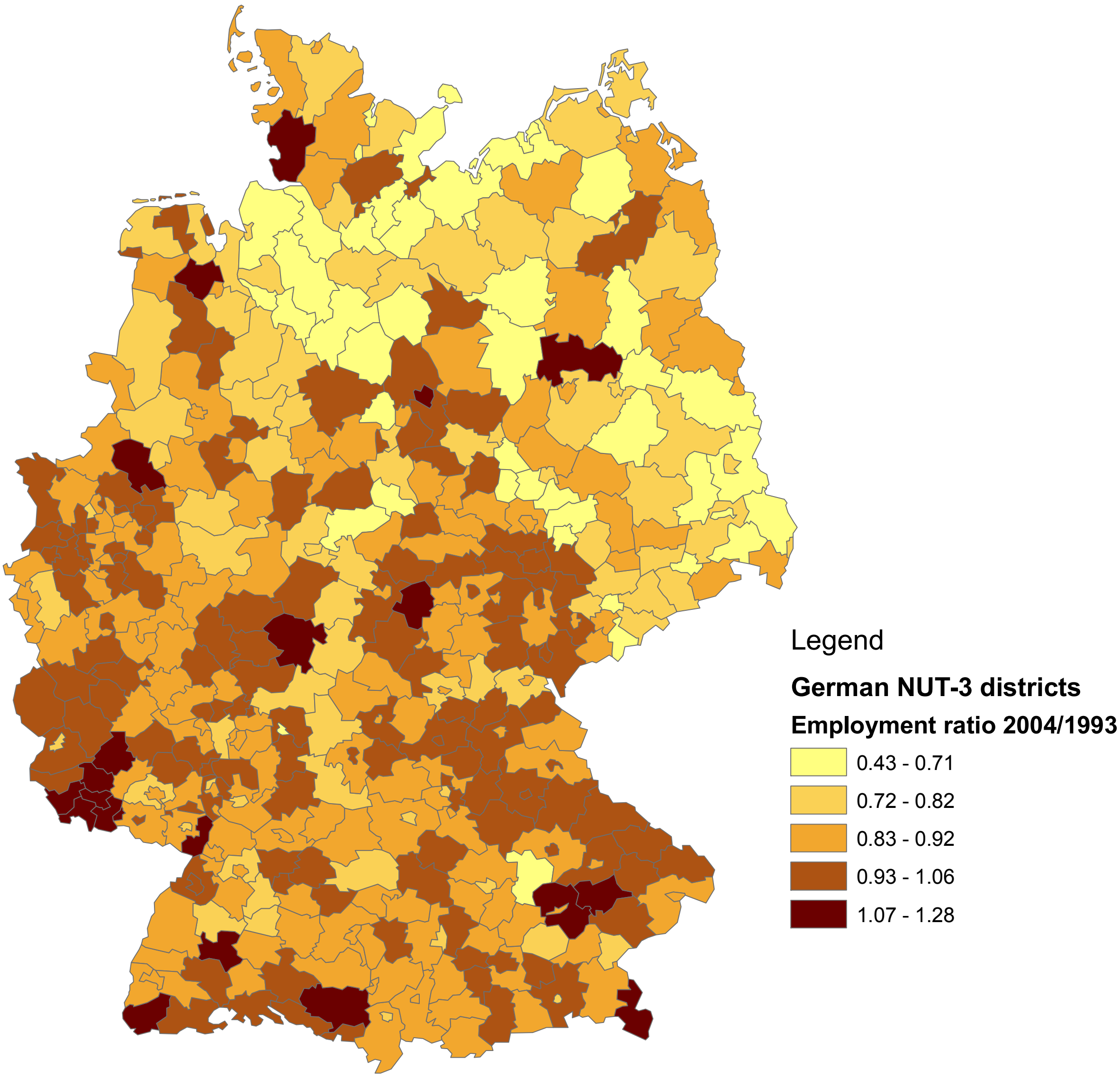



Figure 3.1 – Full-time employment trends in Germany, 1993–2004 (ratio of 2004 and 1993 employment levels)

As a result of the reunification process, Germany experienced – in the 1990s – low economic growth and high unemployment rates, while other countries such as the US showed (under the Clinton administrations) high development rates. On the one hand, this difference in performance can be attributed to the more rigid German labour regulations and institutional and policy structures. On the other hand, attempts to introduce the New Economy (a transition from a manufacturing-based economy to a service economy: see, for example, Stiglitz 2004) in East Germany were not entirely successful (Bonin and Zimmermann 2000). Although the number of individuals employed in research-and-development (R&D) increased greatly, and evidence has been found, for the 1990s, of a positive correlation between economic growth and start-up rates (Audretsch and Fritsch 2003), this happened for the most part in the Western areas of the country.

In recent times (the 2000s), the employment statistics have shown an overall decline in employment for Germany in 2002 and 2003. Confident hopes for a trend turn were fuelled in 2004 by a positive spike, only to be shattered by a negative result for 2005. Accordingly, the long-term unemployment rates – which could be interpreted as an indicator of labour market rigidity – were found in 2005 to be even higher than in countries such as Italy. In the meantime, the quality of jobs has also changed: in 2005, part-time employment represented about 25 per cent of the total employment (40 per cent for women), showing a growth in its share – over five years – of more than 4 per cent. However, the number of working hours per person decreased by 2.2 per cent in the corresponding period (European Commission 2006).

After more than 15 years since the reunification, the East is still struggling economically (Wunsch 2005). Local employment rates are low, intense migration to the West – in particular by highly skilled and educated workers – is observed, as well as a lack of medium-size businesses and entrepreneurship initiatives (Berg 2005). Unemployment in East Germany has risen from 10 per cent (in 1991) to 20 per cent (in 2004) (Wunsch 2005) and the employment gap between the East and the West has widened still further (Kiehl and Panebianco 2002).

In addition to these disappointing results for the East, the reunification process brought severe difficulties for the West as well. Nowadays, solidarity transfers to the East amount to €70–80 billion per year, with an estimated total cost of the reunification around €1.5 trillion. As the reunification costs amount to about 4 per cent of the annual German GDP, and the rate of economic growth is considerably below 4 per cent, it has been underlined in government-related documents how the economic base of Germany is being undermined by this process. Visible effects can also be observed with regard to West Germany, which is also experiencing levels of high and persistent unemployment.[8] The next section contains a brief discussion of the German-wide regional differentials and persistent patterns of unemployment.

## 3.2 Regional Labour Market Disparities

Regional (economic and labour market) disparities are not a phenomenon unique to Germany. Plenty of examples of regional differentials can be found all over Europe. These have been extensively studied at an intermediate aggregation scale (NUTS-2: see Section 3.3.2), in particular with regard to the effects of the massive structural funds provided by the EU in favour of disadvantaged regions. This topic became even more critical with the recent entry of less-developed countries in the enlarged EU. But, even on a single-country scale, wide

[8] It should be pointed out that generally higher unemployment rates have been observed in the same years in most of Europe, therefore making a case for a possible upward shift of the equilibrium unemployment rates (Taylor and Bradley 1997).

disparities can still be observed. For example, Italy had, in 2006, the widest differential in employment rates between regions. With regard to our case study, while these differentials have been reducing in Italy, they have been increasing in Germany (European Commission 2006).

This is particularly relevant in the light of the German Constitution (Basic Law for the Federal Republic of Germany, Article 72), which states the equity principle of 'equal living conditions throughout the federal territory' (see also Eckey et al. 2007). It is therefore considered a crucial policy objective to alleviate regional disparities, in particular with regard to the East-West (EW) differentials. While the debate continues on whether or not an actual economic convergence process has started between the German regions and is the subject of several studies (see, for example, Niebuhr 2001; Juessen 2005; Kosfeld et al. 2006a; Eckey et al. 2007), disadvantaged regions in Germany still benefit from the EU structural funds and from the joint task 'Improving Regional Economic Structures' (*Gemeinschaftsafgabe Verbesserung der regionalen Wirtschaftsstruktur*, GRW). Nevertheless, despite the subsidies aimed at pushing the East German economy towards the standards of West Germany, wide differences still exist, and not only on the East-West axis (see, in particular, Chapter 7 of the present study).[9]

In September 2004, German regional unemployment rates varied from 4 to 27 per cent (Blien et al. 2005). Bonin and Zimmermann (2000) attribute the high unemployment rates observed in the East mainly to labour supply. The authors point out that the employment levels of the East have actually converged to almost those of the West, but, in the context of a different demand structure; that is, the East has not developed into a service economy (as pointed out in the preceding section). The continuing out-migration of educated workers to the West contributes to the shortage of part-time, service and independent jobs. A summary of the labour market characteristics of different German areas is provided by Blien et al. (2005, Table 4).

More generally, in Taylor and Bradley (1997) additional causes for spatial differentials amongst regions can be:

(a) the periodic cycles in regional production levels;
(b) real wages in excess of the corresponding productivity levels (unemployment can be expected to be lower in highly productive regions);
(c) an unfavourable regional production mix. For example, northern regions such as Niedersachsen and Schleswig-Holstein and generally East Germany have suffered from the decline of their heavy manufacturing industry, while, conversely, Baden-Wurttemberg and Bayern have benefited from the composition of their industrial mix;

9 For a discussion of the determinants of high unemployment rates and regional differentials, see, for example, Taylor and Bradley (1997) and Elhorst (2003).

(d) the mix of urban and rural areas. It is expensive for firms to operate and expand in congested areas (see, for example, McCann 2001). Consequently, small- and medium-sized firms tend to experience faster growth in less urbanized areas, and foreign direct investment (FDI) for new production plants tends to concentrate in Greenfield sites.[10]

Accordingly, with reference to the latter point, agricultural regions in Germany tend to have lower unemployment rates. Unemployment is positively correlated with job density, while it is negatively correlated with the size of the labour market (in terms of number of jobs); that is, larger agglomerations offer more work opportunities, therefore shortening the job search time (Taylor and Bradley 1997).

Still, the former EW divide is the most relevant spatial structure in defining regional inequalities. With regard to per capita GDP, in 1992 all eastern districts but three (Berlin being one) appear in the lower third of the full distribution of German regional GDP. In 2001 80 per cent of East German districts (compared with 97 per cent in 1992) were still in the poorest group (Colavecchio et al. 2005).

While these data imply a certain catching-up of the East German districts – in particular with the emergence of a few higher-income districts – a case could be made about the persistence of the (low) economic status of most eastern districts. However, evidence of economic convergence in Germany is also presented by Juessen (2005) for the period 1992–2002 (the income convergence process being driven mostly by the catching-up Eastern regions) and by Kosfeld et al. (2006b) for the years 1992–2000. They find, for 133 labour market areas, convergence in income and productivity. On the other hand, other authors struggle to identify the economic/modelling explanations for East Germany's low productivity levels (Smolny 2003), while Eckey et al. (2007) suggest – as a possible solution – the computation of local/regional (beta)-convergence parameters.[11]

The aforementioned analysis hints that an ongoing convergence pattern for the eastern regions might be supported with regard to the recent EU enlargement. Regions with shared boundaries with new or recent EU members, such as Poland, might benefit from cost advantages in trading – because of spatial proximity. This view may be supported, for example, in the new economic geography (NEG) framework, in which such regions could become more attractive to businesses, thereby pushing agglomeration – and the consequent economic growth – towards the bordering areas (Niebuhr and Stiller 2004).

Despite the above discussion and results, long-run forecasts by Juessen (2005) and Eckey et al. (2007) suggest that the differences between regions and in particular a significant gap between the North and the South of Germany – with Bavaria being the most prosperous area –

[10] A greenfield site is an area previously used (if at all) for agricultural purposes.
[11] See Section 1.3 in Chapter 1.

will persist.[12] In view of this, highly disaggregated labour market data, for the entire German territory, are employed in the empirical analyses of the present study. The next section discusses the choice of the data disaggregation level and details the characteristics of the data.

## 3.3 Data and Geographical Disaggregation

### *3.3.1 Data Disaggregation*

The data available for the experiments carried out in the present study concern district units in the former West Germany and East Germany. All data employed (described in detail in Section 3.3.2) are at the same geographically disaggregated level; that is, NUTS-3.[13] This disaggregation level corresponds, in Germany, to administrative units, the *kreise*, which can be classified in-between the *Länder* (the German states, NUTS-1) and the municipalities (NUTS-4, now renamed LAU-1).

The choice of our disaggregation level involves a multitude of aspects that should be considered for any economic analysis. In addition to aforementioned administrative units such as NUTS-1, NUTS-3 and LAU-1, further geographic aggregation levels may be employed, such as NUTS-2 (an aggregation of NUTS-3 districts which does not correspond to official regional boundaries) or functional areas.[14] In particular, local labour markets (LLMs) – an aggregation compatible with *Länder* (upwards) and *kreise* (downwards)[15] – are employed by the Ministry of the Economy within the Federal government as the official unit for distributing funds. On the other hand, as they are not formal administrative areas, the LLMs do not manage these financial resources, which are instead redistributed locally at the administrative level (NUTS-3). This observation/redistribution asymmetry causes policy analysis concerns, as socio-economic directions are driven by elected representatives in administrative areas (Panebianco 2005). Further, LLMs are redefined every four years on the basis of current policy objectives, which further complicates the construction of a data set of time-space analyses.

More generally, the use of the larger (aggregated) analysis areas may tend to blur the variability between them (see, for example, Colavecchio et al. 2005) or bring ecological fallacy problems (Ertur and Le Gallo 2003). On the other hand, data concerning purely

[12] At present, only a limited number of studies have analysed convergence for *all* German regions, while most contributions focus on the convergence between the East and the West, or – and this is the most general case – only employ data on West Germany.

[13] NUTS stands for 'Nomenclature of Territorial Units for Statistics', which is a coding standard, developed by the European Union, for referencing geographically-referenced variables within countries. The reference number in NUTS-1, 2 or 3 refers to the level of (increasing) geographical disaggregation considered (see http://europa.eu.int/comm/eurostat/ /ramon/nuts/home_regions_en.html).

[14] For a comprehensive discussion of different administrative and functional areas in Germany and their comparability, see OECD (2002).

[15] Note that the German city-states of Berlin, Hamburg and Bremen have a particular aggregation, as they stand alone, being simultaneously states, LLMs (for more particularities in this case, see OECD 2002) and *kreise*.

administrative areas such as NUTS-3 could be biased (for example, in terms of spatial autocorrelation patterns; Eckey et al. 2007) by the type and degree of urbanization and agglomeration, and could therefore generate spurious results, because of the subdivision of otherwise homogeneous areas (Ertur and Le Gallo 2003). We can consider, for example, the impact of the choice of the aggregation level on the analysis of commuting flows, which tend to be observed mainly within metropolitan areas. Therefore, any subdivision of these areas into smaller ones would generate different patterns of mobility, whose cause should be acknowledged.

However, the most frequent criterion for the choice of a data disaggregation level is data availability. In most cases, in fact, appropriate data are only available at formal aggregation levels, such as NUTS-3, and extensive data set construction would be necessary in the case of aggregation to, for example, functional areas such as LLMs. Consequently, administrative areas are often used for labour market analysis (Cörvers and Hensen 2003). Therefore, we choose to employ, for the analyses carried out in the present study, data disaggregated at the NUTS-3 level. These are described in the subsequent section.

### *3.3.2 The Data Employed*

The analyses presented in this study employ different types of data, all aggregated at the NUTS-3 level; that is, the equivalent of the German districts (*kreise*). The data cover the entire German territory and are concerned with various aspects of the labour markets. The number of districts under analysis is 326 for West Germany and 113 for East Germany, providing a total of 439 districts.

The variables employed in our case study and the time periods covered are summarized here:

- Employment: 1987–2004 for West Germany and 1993–2004 for East Germany;
- Unemployment: 1996–2002;
- Working-age population (age 15–65): 1987–2005;
- Wages: 1987–2004 for West Germany and 1993–2003 for East Germany;
- Journey-to-work flows: 1995, 2004 and 2005;[16]
- Type of district urbanization/agglomeration: 9-point index.

In the author's view, the above data provide a time-consistent overview of the evolution of German regional labour markets and represent a solid basis for the analyses presented in this study. A more detailed description of the data set follows.

[16] Additional data on journey-to-work flows for the year 2002, kindly provided by Prof. Gunter Haag (STASA, Stuttgart, Germany), are employed in Chapters 5 and 7.

The main variables employed in the empirical analyses presented in Chapters 4–6 (with regard to neural network forecasts) concern employment and wages. As shown above, these data are not available for the same time period for West Germany (1987–2003/4) and East Germany (1993–2003/4), since East German data only became available after the reunification. In practical terms, we have two data sets, organized as panels of regions, which are more extensive horizontally (regional disaggregation) than vertically (time disaggregation). However, the length of the data sets – in particular for West Germany, considering the richness of the regional information – can be considered to be acceptable. All data are collected for social security purposes by the (German) Federal Employment Services (*Bundesanstalt für Arbeit*, BA). As these data, provided by the German Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung*, IAB), are directly collected for administrative purposes and at the single-firm level, they are expected to have rather low and non-systematic measurement errors. The panel data set on employment is drawn from quarterly statistics and includes information on the number of full-time workers employed every year on 30 June. The wages information refers to the average (regional) daily wages earned by full-time workers. In particular, the data on the number of employees are subdivided into nine economic sectors, obtained by aggregating 12 industries:[17]

(1) primary sector;
(2) industry goods;
(3) consumer goods;
(4) food manufacturing;
(5) construction;
(6) distributive services;
(7) financial services;
(8) household services;
(9) public services.

In addition to employment, data on unemployment and working-age population (that is, of age 15–65) are used in the empirical analyses (concerning spatial econometrics) presented in Chapter 7. The unemployment panel data set – available for the period 1996–2002 – contains yearly information on the number of unemployed individuals and the relative (regional) unemployment rates. These data were also collected by the (German) Federal Employment Services (BA). The information on working-age population is instead available for the years 1987–2005. Both variables were provided by the IAB.

[17] It should be noted that, because of a recent change in the sectoral classification of firms, a percentage of employees cannot now be allocated to a specific industry classification. The missing data amount to about 2 per cent of the total in 2003, and to about 3–4 per cent in 2004. A study aiming to find a solution to this problem is currently in progress within the German Ministry of Labour.

In Chapters 8 and 9, which study commuting networks, we employ data on regional journeys to work, that is, information on the employees' place of residence and of work, on a district-to-district basis. As a result, we have an origin-destination (O-D) matrix, of size 439 x 439, which contains, for each cell (*i*, *j*), the number of workers residing in district *i* and working in district *j*. The journey-to-work data are available for the years 1995, 2004 and 2005, and they were provided by Prof. Franz-Josef Bade (University of Dortmund, Dortmund, Germany). The data (collected in this detail since 1993) cover approximately 75–80 per cent of the total working population. Government officials, public servants, the self-employed, insignificant employees and family workers are not included, as they do not require social security (Papanikolaou 2006). It should also be noted that, while in the years 1995 and 2004 – the years used in Chapter 8 – Berlin is included as two separate districts (along the former West and East Berlin border), the city is included in the data set for 2005 as a single all-comprehensive district. A similar *caveat* should be made about the Hannover area, where the main city district and its surrounding region are kept separate in the 1995–2004 data set, although they are joint as one district in the 2005 data. As a consequence, the number of districts considered in 1995 and 2004 is 441, against the 439 considered in 2005. In Chapter 9, we employ 1995 and 2005 data, where the year 1995 is readjusted for the district merges as well.

Finally, a classification variable, concerning the type of urbanization and agglomeration of the German NUTS-3 districts, is now available and is employed in both our neural network forecast experiments and in the study of commuting networks. This district classification by the *Bundesanstalt für Bauwesen und Raumordnung* (BBR) (Böltgen and Irmen 1997) subdivides the NUTS-3 districts as follows:

(1) Central cities in regions with urban agglomerations;
(2) Highly urbanized districts in regions with urban agglomerations;
(3) Urbanized districts in regions with urban agglomerations;
(4) Rural districts in regions with urban agglomerations;
(5) Central cities in regions with tendencies towards agglomeration;
(6) Highly urbanized districts in regions with tendencies towards agglomeration;
(7) Rural districts in regions with tendencies towards agglomeration;
(8) Urbanized districts in regions with rural features;
(9) Rural districts in regions with rural features.

The variables described in the present section are the basis for the empirical applications that follow. Part B of this study starts off in Chapter 4 by presenting an application of neural network techniques for forecasting regional employment variations.

# PART B
# STATISTICAL MODELLING OF REGIONAL LABOUR MARKETS IN GERMANY

Chapter 4

# Neural Networks for Forecasting Regional Employment

## 4.1 Introduction[18]

Key economic variables such as (un)employment have always been considered important indicators of the performance of labour markets, at both the local and the national level (see, for example, Longhi 2005). Shocks to labour demand, which eventually lead to permanent changes in employment, are likely to be region- rather than country-specific (see, for instance, the theoretical models by Krugman, 1998, and the empirical evidence by Blanchard and Katz, 1992, and by Decressin and Fatás, 1995). To allow policy makers to allocate public expenditures efficiently among regions, labour market forecasts at the regional level are a necessary complement to forecasts at the national level. Their performance is the result of a complex (multi)-regional force field, while their functioning is decisive for a balanced growth of a regional system.

Accordingly, the first research question of the present study, stated in Chapter 1, revolves around the statistical analysis *and forecast* of key labour market variables. Therefore, the first step we take in this regard – in the present and the subsequent chapter – is to introduce a set of forecasting models, which we develop for the estimation of short-term regional employment variations. The particularity of the models presented here is that they employ a non-conventional forecasting technique – that is, neural networks (NNs) – rather than standard time series or panel approaches. The present chapter describes the practical issues in developing such NN models and presents the main statistical results obtained. Subsequently, in Chapter 5 we introduce further NN forecasting models based on the use of shift-share analysis techniques. In addition, a sensitivity analysis concerned with testing varying NN configurations is offered in Chapter 6.

With the development of NN forecasting models in the regional labour market context, we aim to take into account (that is, include in our models) the socio-economic complexity involved in regional/spatial systems. This is made possible by the peculiar characteristics of

[18] The present chapter is based on Patuelli et al. (2007a), forthcoming in *Environment & Planning B*.

NNs, which are statistical approximation techniques able to 'learn from the data'. The increased computational power of current computers allows multiple experiments to be carried out with such tools. The 'good old days' of statistics and econometrics, which were for researchers a 'serious play to estimate one model a day' using standard ordinary least squares techniques, have long gone. The range of model specifications that we can now estimate, under different background conditions, with a large set of sensitivity tests and with the help of different aggregation levels of endogenous variables is illustrated, for example, by the title of an article by Sala-i-Martin (1997): 'I Just Ran Two Million Regressions'. Such advancements in forecasting techniques – and the emergence of the NN techniques – are of particular value in our case study.

Most econometric methods commonly used at present to compute forecasts require the availability of long time series of (national) aggregates. However, when forecasts at a highly disaggregated regional level are needed, the data available for the analysis are likely to include – as in the case of the German labour market – a high number of cross-sections and a small number of time periods. In addition to this, regional data are often characterized by spatial heterogeneity. As underlined in Section 3.2, Germany is a clear example of significant disparities among regional labour markets. Such disparities are visible not only between regions located in the former West Germany and those in the former East Germany, but also within each of the two parts of the country. For example, the southern part of West Germany is developing faster than the rest of the country (see, for instance, Bade 2006; Bayer and Juessen 2007). The availability of panel data allows us to correctly identify similarities and differences across regions and obtain more reliable regional employment forecasts.

In this regard, the adoption of a suitable functional form is also critical. The choice between models that impose linear behaviour and models that allow for nonlinear behaviour of the relevant variables is extensively discussed in the forecasting literature, though mostly in the context of time-series analysis. Linear methods have been extensively used over the years because of their easy implementation and interpretation, although many empirical problems involve nonlinear behaviour (Granger and Teräsvirta 1993), in particular when longer forecasting periods are concerned (Zhang 2001). A number of authors (for instance, Swanson and White 1997a,b and Stock and Watson 1998) have compared the performance of linear and nonlinear methods – time-series regression versus NNs, genetic algorithms, or fuzzy logic – in forecasting variables such as national employment, industrial production or corporate profits, and have come to various conclusions (see Section 2.2.2).

Attempts to compute labour market forecasts for German regions using linear techniques have been made by several authors, amongst others, Blien and Tassinopoulos (2001) and Bade (2006). Blien and Tassinopoulos compute short-term employment forecasts for West German regions by combining a top-down and a bottom-up approach. Their forecasts take into account regional autonomous trends that are then combined with expectations about the development of single industrial sectors by means of an entropy-optimizing procedure. Bade forecasts the long-term development of regional shares in national employment by means of an extended ARIMA approach. Both methodologies require a number of constraints and economic, as well as econometric, assumptions. A nonlinear non-conventional approach may help to overcome such constraints, in particular if the nonlinear nature of the data represents a problem.[19]

In the present chapter, starting from previous research by Longhi et al. (2005a,b), we propose statistical techniques that exploit the panel nature of the data. By means of NN models, we compute short-term forecasts (2-years ahead) of employment at the regional level (all the 439 German NUTS-3 regions), for East and West Germany. We assume an autoregressive relationship, in which future developments of employment are the result of its past developments. We further exploit the panel nature of the data by modelling region-specific characteristics.

Modelling panel data in the context of NNs is not straightforward. Nevertheless, NNs have some advantages over conventional techniques. For example, the asynchronic nature of the regions' business cycles may make conventional econometric models rather complicated, imposing constraints that would limit the scope of the analysis. The advantage of NNs is their flexibility and the absence of strong underlying modelling hypotheses; this makes them suitable for our empirical purposes. On the other hand, their no-modelling hypothesis could be considered a drawback, because of the lack of theoretical economic (or behavioural) interpretation, which forces the analyst to accept the data-driven results of the NN models 'as they are'. However, the limited possibilities of interpretation of the results are less relevant when the aim is, as in our case, to produce forecasts, rather than to explain the relationships between the driving factors. In fact, our aim is not to validate the use of NNs *per se* – in fact, nowadays, they are employed in a wide range of disciplines – but to evaluate the NNs' ability to forecast regional labour market change in a panel data framework.

The remainder of the chapter is structured as follows. Section 4.2 briefly illustrates the main characteristics of the NN method and issues related to what is called 'neural forecasting'. Section 4.3 describes the further optimization of NNs by means of genetic algorithms. Section 4.4 describes the empirical application carried out – that is, the practical steps involved in formulating NN models – while Section 4.5 presents the results obtained. Section 4.6 provides some final remarks and conclusions.

[19] Linearity tests in the univariate case (time series) have been developed in the literature (see, for example, Granger and Teräsvirta 1993). However, tests for panel data are still recent and difficult to implement. Consequently, at this stage, we consider random walk and ordinary least squares (OLS) as naïve linear extrapolation models. The statistical performance of the (nonlinear) NN models is then compared with that of these (linear) models. Future research will then address the use of panel linearity tests, such as the one recently developed by Hjellvik et al. (2004).

## 4.2 Neural Network Models

### *4.2.1 The Neural Network Framework*

As outlined in Section 2.2.3, NNs are algorithms which are able to find goodness-of-fit solutions to empirical problems when the information on the (dependent/independent) variable interactions is limited or unknown. While traditional statistical models require an identification process for the set of regressors employed, as well as a specification of the relationship between dependent and independent variables, these steps are not necessary in NNs, therefore bypassing the aforementioned issues, which are so familiar in conventional econometrics. In addition, NNs are also more robust against statistical noise, since they store redundant information. Because of their relatively simple application, NNs are attractive in various fields of socio-economic application. It could be generally underlined that NNs enjoy great scalability properties, as they can be applied to problem-solving related to practically any application area. Reviews of NNs used in several fields can easily be found in the literature. Many examples could be listed, as well as academic journals entirely dedicated to NN-related studies. A very concise and non-exhaustive selection of these is shown in Table 4.1.

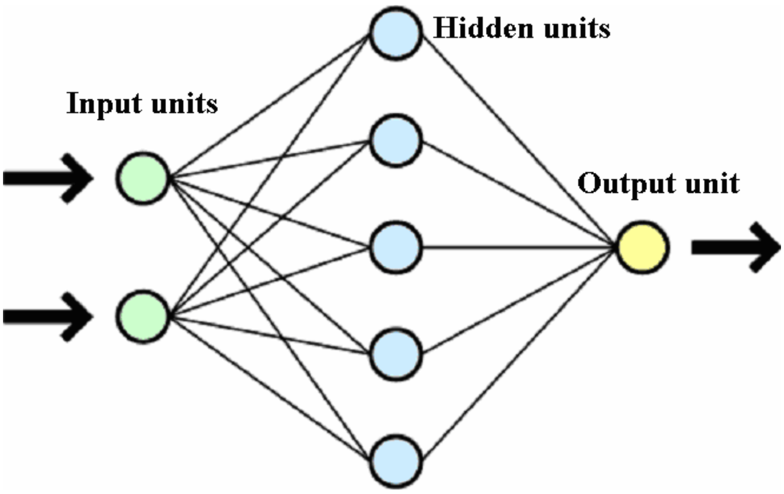
Table 4.1 – Some illustrative reviews of NN applications in different fields, and in various NN journals

| Field | Authors |
|---|---|
| Atmospheric sciences | Gardner and Dorling 1998 |
| Business and finance | Wong et al. 1997; Wong and Selvi 1998; Chatterjee et al. 2000 |
| Classification of medical data | Dreiseitl and Ohno-Machado 2002 |
| Economics | Herbrich et al. 1999 |
| Environmental modelling | Maier and Dandy 2000; Shiva Nagendra and Khare 2002 |
| Medical imaging and signal processing | Miller et al. 1992 |
| Transportation | Himanen et al. 1998 |
| *IEEE Transactions on Neural Networks* | – |
| *Neural Computing & Applications* | – |
| *Neural Computing Surveys* | – |
| *Neural Networks* | – |
| *Neural Processing Letters* | – |

The NN typology used in our empirical analysis – namely, 'supervised' NNs – aims at iteratively maximizing the fit between example cases of input and output variables provided by the analyst. The obtained NN parameters may then be employed for out-of-sample estimations (that is, cases for which the output variable was not provided). As described in

Section 2.3.3, structurally, NNs are organized in layers of processing units (the 'neurons'). The input layer contains as many units as the input variables. Likewise, the output layer refers to the output variable(s). Intermediate ('hidden') processing layers are also often used. Sets of 'weights' connect the units in each layer to all units of the succeeding layer, while units belonging to the same layer process information in parallel. In feedforward NNs (see Figure 4.1), the transfer of information between layers is unidirectional (that is, from the input layer towards the output layer), as opposed to what happens in recurrent neural networks, where the connections between units and layers form a directed circle (for example, see Hagan et al. 1996).

With regard to the number of layers used, if no hidden layers are present, input and output units are directly linked, and the NN can be referred to as a 'linear NN' or as a 1-layer NN (see, for example, Chandrasekaran and Manry 1999), since no computation is carried out at the input layer level. Similarly, an NN with one hidden layer is called a 2-layer NN. More generally, an *N*-layer NN implies the computation of *N* sets of weights between the layers.




*Source:* The image licence is held by Creative Commons (http://creativecommons.org/ /licenses/by/1.0).
Figure 4.1 – A graphical illustration of a feedforward neural network

In Section 2.2.3, we defined the generic processing unit $u_{i,n}$ as:

$$u_{i,n} = \varphi(\mathbf{u}_{n-1}) = \Im[f(\mathbf{u}_{n-1})]; \tag{4.1}$$

that is, a function of the preceding layer of units $\mathbf{u}_{n-1} = \{u_{1,n-1}, ..., u_{k,n-1}\}$, given the transfer function $\varphi$, resulting from the activation function $\Im$ and the integrator function *f*. In particular, the integrator function *f* aggregates the data entering the processing unit $u_{i,n}$. The weights *w* employed in this function, which can be written as:

$$v_{i,n} = f(\mathbf{u}_{n-1}) = \sum_j w_{ij,n-1} u_{j,n-1}, \tag{4.2}$$

have a critical role in the 'learning process' of the NN. The backpropagation algorithm (BPA: see Rumelhart and McClelland 1986) is a commonly used method for driving the iterative modification of the above-mentioned weights. The BPA requires the analyst to provide input examples and their correct – and known – outputs (from this comes the term 'supervised'). The sample data allow the NN to identify the behaviour underlying the data and to replicate it. The actual learning process is given by the comparison of the output generated from the current weight configuration[20] with the correct output, by means of a backward propagation of the obtained error through the network. The error term is often computed as the mean of the single units' squared errors. In our experiments, the error is computed as:

$$e_j = y_j(1 - y_j)(d_j - y_j), \tag{4.3}$$

where the error term $e_j$ is a function of the actual output $y_j$, and of the difference between the expected and the actual output of the model, $d_j$.[21] This process is repeated for each record of the sample, with a consequent readjustment of the weights, which are defined, for the generic $w_{ij,n}$, as:

$$w_{ij,n} = w^{*}_{ij,n} + (1 - \mathrm{m})\mathrm{lr} \cdot e_j \cdot x_{i,n} + \mathrm{m}(w^{*}_{ij,n} - w^{**}_{ij,n}). \tag{4.4}$$

In this equation, lr and m are an NN's learning and momentum (see Chapter 6); $x_{i,n}$ is the input value of the computational unit concerned; and $w^{*}_{ij,n}$ and $w^{**}_{ij,n}$ are the previous values of the same weight (one and two steps before, respectively).

The cycle's stopping condition can be decided by the analyst on the basis of, for example, computing time, error level or number of iterations. A number of drawbacks of the BPA have been outlined in the literature: for example, McCollum (1998) noted that the algorithm 'will never exactly learn the ideal function, but rather it will asymptotically approach the ideal function'. In addition, local-minima problems can arise.[22] The BPA is governed by the values

[20] The starting set of weights is usually randomly defined, so that a large error is generated at first (Cooper 1999). On the other hand, Ripley (1993, p. 50) points out that the initial values 'should be chosen close to the optimal values, so as to seek the correct values are used'. Since, in our case, the optimal value of the weights is unknown, a set of random weights is used.

[21] Note that in NN computation, all inputs are converted to the (0, 1) interval. Outputs belong to the same range, but are subsequently rescaled as a final step.

[22] In detail, a shortcoming of the BPA is that the algorithm is only expected to reach a stationary error, which can indeed be the result of a non-global (local) minimum (Ripley 1993). On the other hand, Fahlmann (1992, as reported in Ripley 1993) stresses that, although NNs do fall into local minima, these are often the ones that the analyst wants to reach. He also points out that, in some cases, local minima are blamed for problems which are in fact the result of other causes.

of two parameters: namely, the learning rate and momentum. NNs have been shown to be sensitive to changes in such values, as well as to the choice of the activation function used (Klimasauskas 1991; Hagan et al. 1996).

In this chapter, with regard to our NN models, which employ a BPA, the learning rate and momentum parameters are set to 0.9 and 1, respectively, and, for reasons of comparison, are kept fixed during the iterative process. A sigmoid/logistic activation function is used. An in-depth discussion and empirical testing of adaptive learning rates, multiple learning parameter values and activation functions can be found in Chapter 6.

A further noteworthy aspect of NN models concerns the balance between network simplicity and complexity (in terms of the number of layers and computational units). An overly simple NN will not learn the relationship between the input and output variables, and therefore it will generate large errors (Fischer 2001a). On the other hand, an NN that is too complex will lead to generalization problems (overfitting), causing high variance and unreliable forecasts. For a discussion of the model selection problem with NNs, see, for instance, Fischer (2000). Many techniques have been proposed to tackle the problem of overfitting. Here we use one of the most common methods: namely, 'early stopping' (see Sarle 1997), which consists of stopping the learning process (iterations) when the performance indices (the error computed) start to worsen. The NN model concerned then runs for the number of iterations previously selected by means of the early stopping method.

Additional issues regarding the application of NNs to forecasting should be discussed, such as the inclusion of time or the nature of the data-generating process. These are discussed in the next section, together with recent developments in neural forecasting.

### *4.2.2 Neural Forecasting Issues*

This section provides a brief discussion of three issues of particularly interest in the framework of forecasting with NNs: (a) the nature of the data-generating process; (b) the size of the data set used; and (c) the inclusion of time in NNs. These aspects of neural forecasting deserve consideration in the perspective of the originality of the NN experiments carried out here; that is, the use of panel data.

As previously pointed out in Section 2.2, the nature of the data-generating process, in particular whether this has linear or nonlinear characteristics, is of critical relevance for the case of NNs in the motivation itself for employing neural techniques. However, NNs can also be suitable tools in the presence of underlying linear processes. Zhang (2001, p. 1199) analyses the suitability of NNs for approximating linear data-generating processes and finds that NNs 'have the competitive ability for linear time-series modeling and forecasting'. Furthermore, (non)-linearity tests are only developed for specific functional forms, and it is therefore difficult to test multiple possible nonlinear relations. NNs allow us to bypass the process of choosing the functional form of the model. This is particularly true when sufficiently long series of data are employed. In this case, as shown by Balkin and Ord (2000), NNs are able to detect possible nonlinearity in the data and to outperform linear methods.

On the other hand, for the case of linear processes, NNs could be thought to overcomplicate forecasting. However, if we consider – in a (highly disaggregated) panel data forecasting problem such as ours – the number of specific characteristics of single regions, we can expect these diverse characteristics to show up in economic data as outliers, which deviate from the average national trend. Furthermore, NNs have been found to provide a comparatively better performance than linear time-series models when the data show more statistical noise or when specification/multicollinearity problems occur (Markham and Rakes 1998, in Zhang 2001). Though this finding was obtained in a comparison based on time-series data, we should consider it to be particularly valuable with regard to the objectives of the present study, which is concerned with highly disaggregated regional forecasts.

In addition to the nature and distributional properties of the data, a further aspect should be considered when discussing neural forecasting; that is, the extension of the data sets employed and the forecasting horizon. Balkin and Ord (2000) suggest that a long-enough data series must be available in order for NNs to outperform simpler methods. Unfortunately, the authors do not provide additional information supporting this claim. However, Tkacz (2001) also suggests that NNs are more useful for larger data sets. Furthermore, the author stresses, on the basis of multiple time-series-based experiments, that NNs provide a forecasting accuracy advantage when forecasts are carried out for longer time horizons (the author tested a single-quarter and a four-quarter forecast horizon).

This discussion has shown that NNs are particularly helpful, as a forecasting technique, when complex and large data sets are employed. A further issue to be addressed here is the inclusion of time (serial correlation) in NNs. Van Veelen et al. (2000) review the different solutions applicable to NNs dealing with time-series data. The authors present two main approaches to the inclusion of time information in NNs: (1) explicit representation of time (which is used in the present study); and (2) dynamic NN models. The latter NN paradigms – we refer, for example, to time-delay neural networks (TDNNs) – have been extensively applied to time-series forecasting, though, according to van Veelen et al. (2000, p. 4), ‘they lost some attention in the last few years’. The authors also stress that such models are not free of problems. TDNNs, for example, make it challenging to employ a BPA, and are found to have poor heuristic properties. Other dynamic NN methods (for a review, see Hagan et al. 1996) resort to the ‘recurrent’ NN paradigm, starting with the introduction of the Hopfield neuron (Hopfield 1982).

The alternative approach of explicitly including time information has also been criticized (see van Veelen et al. 2000), since it does not include a dynamic framework. This shortcoming may possibly result in the incapacity of NNs to locate hidden time trends. But it should be pointed out that, in most cases, trends or temporary shocks can be accounted for by including one or more counters or a periodic variable in an NN. This type of approach is adopted in our experiments, in which multiple observations per year are processed by the NN, and recognizing specific temporal shocks appears to be critical for maximizing the generalization power of the NNs. However, this approach does not account for serial correlation between single region observations, which is instead included in the models by means of lagged variables. The operationalization of the approach discussed above is described in detail in Section 4.4.1.

## 4.3 Implementation of Genetic Algorithms in Neural Networks

The previous discussion has highlighted, among other issues, the difficulty of finding the best NN structure. The high number of choices that have to be made in order to obtain the final forecast generally requires the supervision of an expert analyst. In this chapter, we test whether automatic procedures, such as genetic algorithms (GAs), can be a suitable substitute for 'manual' – and therefore subjective – techniques used to identify the best NN structure. GAs are used here as optimization procedures to choose the best NN structure and parameters; we should then expect GAs to provide better generalization properties and to reduce the time and work needed in the fine-tuning of NN models.

GAs are optimization tools belonging to the class of evolutionary algorithms. They mimic natural biological evolution dynamics (of the 'survival-of-the-fittest' type: see Holland 1975) and are nowadays widely adopted in the scientific literature for various purposes (see, for example, Fischer and Leung 1998; Reggiani et al. 2000, 2001). Formally, GAs are stochastic search methods, which aim to solve an optimization problem that can be expressed as follows (Fischer and Leung 1998; Nag and Mitra 2002):

$$\max\left\{g\left(\mathbf{s}\right)\middle|\mathbf{s}\in\Omega\right\}, \tag{4.5}$$

where $g$ is a fitness function and $\mathbf{s}$ is a single 'individual' (candidate solution to the optimization problem) belonging to a 'population' $\Omega$ of $d$-dimensional binary vectors called 'strings'. These strings are used to represent nature's genotypes, which contain the genetic information (referred to as the 'structure') of an individual.

In our empirical application, the fitness function is an objective function to be minimized on the training set.[23] The strings include two types of information: (a) the NN learning parameters (learning rate, momentum and input noise – a small, randomly distributed disturbance effect); and (b) the NN configuration. The NN configuration string contains the total number of layers and the number of computational units in each hidden layer. In detail, the algorithm tests NN structures with up to two hidden layers, comprising a default

[23] Fischer and Leung (1998) show how an objective function can be recoded into a fitness function.

maximum of 30 and 10 units in the first and second hidden layer, respectively. A larger number of units per layer can be considered to be superfluous – if not harmful – for NN generalization.[24]

Figure 4.2 shows the functioning of a GA (Fischer and Leung 1998; Riechmann 2001). The GA starts from an initial – randomly chosen – set of NN structures, $\overline{m}_0$. Each structure is evaluated by means of the fitness function. Here we use the mean square error (MSE) computed over the input/output examples set. Genetic operators (namely, 'selection' and 'recombination/crossover'; for more details, see Rumelhart and McClelland 1986; Riechmann 2001) subsequently generate a new structure, leading to the successive 'generation' of NN structures. Lastly, a final operator ('mutation', see Fischer and Leung 1998) introduces an exogenous, stochastic change in the structures.

| | |
|---|---|
| $t := 0$ | |
| Creation of First Population $\overline{m}_0$ | |
| Evaluation of $\overline{m}_0$ | |
| **while** Stopping Condition not Met | |
| | $t := t + 1$ |
| | Selection from $\overline{m}_{t-1}$ and Reproduction into $\overline{m}_t$ |
| | Recombination on $\overline{m}_t$ |
| | Mutation on $\overline{m}_t$ |
| | Evaluation of $\overline{m}_t$ |
| End | |

*Source:* Riechmann (2001).
Figure 4.2 – Structure of a standard GA

In our experiments, all the structures tested are selected for reproduction/recombination, so as to generate new sets of parameters. Here the mutation operator is limited to 10 per cent of the structures for each generation. Once the newly generated structures $\overline{m}_t$ have been computed, they are substituted for the old ones ($\overline{m}_0$), and their fitness is computed. The process continues until a stopping condition is met. In the present chapter, the stopping condition is set at ten iterations. At the end of this process, the best-fitting structure obtained in the last iteration is adopted as the NN architecture. At each iteration three structures were generated and evaluated, resulting in three final 'optimized' NN configurations to choose from. Although three structures and ten iterations might at first seem insufficient, they nevertheless seem to be enough for our empirical analysis. A combination of 100 iterations

[24] As an implicit rule, the second hidden layer will always contain a smaller number of units than, or an equal number of units to, the first hidden layer.

and a population size of 100 structures did not improve our results, while greatly increasing computation time.

## 4.4 Empirical Analysis: Forecasting Regional Employment in West and East Germany

### *4.4.1 The Neural Network Models Developed*

In this and the subsequent sections we propose, on the basis of the methodologies described above, a number of NN models that can be used for our forecasting purposes. The data employed in our experiments are listed below, though they were more extensively described in Section 3.3.2. The aim of our experiments is to compute short-term forecasts (2-years ahead) of employment at the regional level for East and West Germany, for the years 2001–04.[25] The independent variable in all our NN models is the biannual (between $t - 2$ and $t$) growth rate of regional full-time employment observed in each district. Because of the different span of the data for West Germany (1987–2004) and East Germany (1993–2004), we develop separate NN models for the two areas.

To exploit the panel structure of our data, we use what we indicate as a 'time' variable. This can be done in two different ways. The first consists of using a periodic variable identifying the year to which the data refer. The variable is rescaled to the interval (0, 1) and might resemble a trend variable in a time-series model.[26] The second way to include time consists of adding a set of dummy variables (one dummy per year). The use of dummy variables to identify time periods might be compared to a 'time fixed effects' approach in a conventional panel modelling framework (Longhi et al. 2005b). Both approaches allow us to identify a year-specific mean (common to all the districts) for the output variable.

A second group of variables can be added to capture the correlation across the observations belonging to the same – or a similar – district. First, a counter ranging from 1 to 326 in West Germany and from 1 to 113 in East Germany is added to model district-specific characteristics. The variable is substituted for the more commonly used – when working with panel data – regional dummies (fixed effects), which would require the computation of an overly large number of weights. In panel data modelling, such an 'incidental parameter problem' can be avoided by using the 'within transformation' (see, for example, Hsiao 2003).

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[25] In order to provide forecasts more years ahead, there are two possibilities: (1) recursively feeding, for example, the results of a ($t$, $t + 2$) NN forecast in a new NN model in order to obtain forecasts for ($t + 2$, $t + 4$). This aspect might be investigated in the future, but goes beyond the objectives of the present study; and (2) increasing the forecasting period (for example, ($t$, $t + 4$)). However, this approach is not desirable, given the relatively short time span of the data sets, in particular in the case of East Germany. It is therefore not considered.

[26] The commercial software used for carrying out our experiments, Neuralyst, enables non-numeric (string) input and output variables to be used. The software processes such variables by associating their values with numeric values between 0 and 1. The interpretation and mapping of the relationship between the numeric and non-numeric variables are automatically taken care of by a built-in algorithm.

However, this solution does not seem appropriate in our case, since the most important input – sectoral employment – is added as growth rates. We call this variable the ‘district identifier’.

Alternatively, we may assume that regions with a similar degree of urbanization or agglomeration behave in similar ways, ceteris paribus. Consequently, the variable ‘type of district’ (also described in Section 3.3.2) can be added to the independent variables either as a counter, ranging from 1 to 9, or as a set of nine dummy variables. Similarly to the time dummies, the type-of-district dummies identify – for each district type – a different mean (common to all years).

Finally, selected models are enhanced with a further input variable: the lagged biannual growth rate of average daily wages earned by full-time workers. The rationale for the inclusion of this variable is the possible relationship between wages and employment.

In total, we compute nine different NN models, whose equation can be generically represented by the following relationship:

$$\Delta e_{i,t+2} = f[T, district, \Delta e_{i,1,t}, ..., \Delta e_{i,9,t}, \Delta w_{i,t}], \tag{4.6}$$

where $\Delta e_{i,t+2}$, the percentage variation of employment in region $i$ in the period $(t, t+2)$, is a function of: (1) the time variable $T$; (2) *district* characteristics (either the district identifier or urbanization/agglomeration types); (3) lagged employment variations in the nine economic sectors ($\Delta e_{i,1,t}, \ldots, \Delta e_{i,9,t}$); and (4) lagged variation in average daily wages, $\Delta w_{i,t}$.

The models can then be grouped according to the input variables used (see also Tables 4.A1 and 4.A2 in Annex 4.A):

- Model A and all subsequent models starting with the letter A include sectoral employment and time as dummy variables (time fixed effects).
- Model B and all subsequent models starting with the letter B include sectoral employment and time as a periodic ordinal (trend) variable.
- The following models were developed, on the basis of Model A and Model B, as follows:
    - Model AC also includes the variable ‘district identifier’, to capture region-specific characteristics, while
    - Model AD and Model AE also include the variable ‘type of district’ as a counter (Model AD) or as dummy variables (Model AE), in order to capture differences across districts with different urbanization/agglomeration characteristics.
    - Model BD also includes the variable ‘type of district’, similarly to Model AD.
- Finally, Models AW, ADW and BW (ending with the letter W) use average daily wages as a further input. These models may be seen as extensions of Models A, AD and B, respectively.

The next section describes the validation process followed for all models, as well as the introduction of genetic algorithm-enhanced NN models (NNGA).

### *4.4.2 The Validating and Testing Procedure*

#### 4.4.2.1 The validation phase

As mentioned above, our NN models use the employment growth rates for the time period ($t - 2$, $t$) in order to forecast the growth rates for the period ($t$, $t + 2$). Since the data for West and East Germany start from 1987 and 1993, respectively, the first available forecasting periods are 1989–91 and 1995–97. In the remainder of the chapter we refer to the generic ($t$, $t + 2$) interval using the end year of the period (for example, 1989–91 is referred to as 1991).

The first test phase of our NN experiments – referred to as the model validation phase – is summarized in Table 4.2. This phase is concerned with the evaluation of a set of alternative NN configurations (see, for instance, Fischer 1998) and the selection – for each NN model – of the most suitable architecture and training threshold. For this phase, we employed data for up to and including the year 2000. The NN models concerning West Germany were validated on the basis of their performance for the years 1999 and 2000. The NN models for East Germany were instead validated using the year 2000 only, because of the shorter time span of the data set used. The use of a double validation set for the NN models for West Germany – and the consequent computation of average statistical results – is expected to provide a more reliable validation of the NN models, as their performance tends not to be uniform across test sets, and to reduce the effect of time-specific shocks on the model validation.

Table 4.2 – Data utilization in the model validation phase

| Models | Training | Validating |
|---|---|---|
| West Germany | 1991–98 | 1999–2000 |
| East Germany | 1997–99 | 2000 |

In the validation phase, for every NN model we tested five configurations. First, a 1-layer NN was tested, and then three 2-layer models containing 5, 10 and 15 hidden units, respectively (in one hidden layer). Finally, a 3-layer model was tested, using 5 units in each of the two hidden layers.[27]

[27] The rationale for proceeding in ‘jumps’ of a few computational units in validating NN structures is in the lengthy testing process, and is supported in the empirical literature on NNs. Future experiments may address the behaviour of NNs for intermediate structures (for instance, using 4 or 7 hidden computational units), and will focus on 2-layer NN structures, since empirical evidence has proven that an NN with one hidden layer (that is, a 2-layer NN) can approximate nearly any type of function (Cheng and Titterington 1994; Kuan and White 1994).

The NN models, trained as described above, were evaluated by means of two statistical indicators: MSE and MAE.[28] Given the panel structure of the data, these indicators have been calculated on the basis of the *ex post* forecasts computed by district. Hence, contrary to their usual time-series interpretation, these indicators summarize the error of the forecasts across districts, rather than over time. On the basis of the above indicators, the best-performing structure of the validation phase was selected for each model, and was then employed in the subsequent test phase. The statistical performance of each NN structure was tested for an increasing number of iterations (training epochs), in order to find the optimal training period (after which the performance of the algorithm tends to deteriorate or to reach a plateau).

Subsequently, an additional NN structure, obtained by means of a GA optimizer (see Section 4.3), was selected for each model previously developed. In addition to varying architectures, each of these models – which we call NNGA – also employs an alternative set of learning parameters (learning rate, momentum, and an additional input noise component), which have a constant and equal value in the manually-developed NN models (see Section 4.2.1). Tables 4.A1 and 4.A2 in Annex 4.A summarize the input and network structure of the models developed for West and East Germany, respectively. All NNGA models are identified, in the remainder of the chapter, by the GA suffix.

#### 4.4.2.2 The test phase

The present section describes the test phase for our NN models. Generally, we can define a set of basic rules for the test and comparison of NNs. The following requirements are derived from Collopy et al. (1994):

- Comparison with widely-accepted 'conventional' models. Forecasts from the NN models should be at least as accurate as those generated by a naïve extrapolation, such as a random walk.

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[28] The statistical indicators employed in the validation of the NN models – and more in general in the forecasting literature – are commonly used for the evaluation of both time-series and NN forecasts (see, for example, Zhang et al. 1998) and are computed as follows:

Mean Square Error: $\mathrm{MSE} = 1/N * \left[\sum_i (y_i - y_i^f)^2\right]$;

Mean Absolute Error: $\mathrm{MAE} = 1/N * \left[\sum_i \left|y_i - y_i^f\right|\right]$;

Mean Absolute Percentage Error: $\mathrm{MAPE} = 1/N * \left[\sum_i \left|y_i - y_i^f\right| * 100 / y_i\right]$,

where $y_i$ is the observed value (target); $y_i^f$ is the forecast of the model adopted (NN); and $N$ is the number of observations. The MAPE is used in place of the MAE in the statistical evaluation of the *ex post* forecasts, since the forecasting error is computed, in this case, with the employment levels resulting from the estimated growth rates.

Different and non-symmetrical statistical indicators (or, more generally, cost functions) might be considered for the evaluation of the NN models' performance. However, it might be argued that over- and under-estimation of regional employment levels – which are used by governments for fund allocation – would generate similar problems: on the one hand, scarcity of resources; on the other hand, inefficient allocation of funds that were needed elsewhere.

- Test of the models' out-of-sample performance. The results of out-of-sample forecasts should be used in comparing different methodologies.
- Use of an adequate sample size. The size of the sample has to allow for statistical inference.

The above rules are respected in our experiments (see the present and the subsequent section). Additional rules may also apply with regard to the actual implementation of NN models. These requirements define the correct execution of NN modelling experiments, and the presentation of their results. Here, we refer to the requirements formulated by Adya and Collopy (1998):

- Provision of the in-sample performance of the models. Sample data provide the basis for the learning process (see Section 4.2.1), and are a benchmark for the evaluation of the generalization properties of the NN models.
- Generalization. The level of similarity between in- and out-of-sample performance provides an indication of the generalization potential of the models. In this regard, a generalization estimator has been proposed and computed by Patuelli et al. (2003).
- Stability. Similar performance over different data sets allows the stability of the forecasting tool, and its reliability, to be assessed.

On the basis of the above criteria, in our test phase, the evaluation of the structures selected in the validation phase was provided by out-of-sample, *ex post* forecasts carried out for the years 2001–04, in order to assess the statistical performance of the NN models developed above.[29] This involves computing forecasts for four different years separately.[30] Table 4.3 summarizes the data which were used at this stage. In this phase, the weights were reset to random initial values (between 0 and 0.1) for each out-of-sample forecasting year, and the models were retrained, for each forecasting year, until the preceding year (that is, training until 2000 if 2001 is the *ex post* forecasting year, until 2001 for 2002, and so on).

Table 4.3 – Data utilization for the test phase

| *Models* | *Training* | *Testing* |
|---|---|---|
| West Germany | 1991–2000/2003 | 2001/2004 |
| East Germany | 1997–2000/2003 | 2001/2004 |

[29] The in-sample performance of the NN models is not reported here, but can be found, for selected years, in Patuelli et al. (2006a,b),

[30] Longhi (2005) suggests the use of a 'rolling' training data set, which would eliminate the first year of data employed when data for a new year become available or are utilized. In our case, when switching from 2001 to 2002–03–04 *ex post* forecasts, the first years of our data sets would exit the NN training sample. This practice deserves future testing because of its clear computational advantages, and for the diminishing influence that early years have on economic variables as years go by.

The comparison of the 2001–04 *ex post* forecasts with the actual data allows us to statistically evaluate the models' generalization properties. The statistical performance of the models is summarized and compared by means of the MSE and MAPE indicators (see Footnote 27). Further, the models can be compared – pairwise – by using forecast equality tests,[31] in particular, the Morgan-Granger-Newbold (MGN) test (Granger and Newbold 1977) and the sign test (ST) (Lehmann 1998).

Following Diebold and Mariano (1995), we compute the MGN test as:

$$\mathrm{MGN} = \hat{\rho} \Big/ \sqrt{(1-\hat{\rho})/(N-1)}\,, \tag{4.7}$$

where $\hat{\rho}$ is the estimated correlation between the sum S and the difference D of the forecast error vectors ($N$ x 1) of the two models compared; and $N$ is the number of districts for which forecasts are carried out. The null hypothesis is that of equally accurate forecasts (no correlation between $S$ and $D$) and follows a Student's-$t$ distribution with ($N$ – 1) degrees of freedom. The MGN test relies on the assumption of absence of serial correlation and of deviations from normality in the forecasting errors, both of which have been shown to significantly influence the reliability of the test (Tkacz 2001). At this stage, we consider the assumption of no serial correlation to be feasible. In fact, in our panel forecast experiments, forecasts are not carried out over time, with a series of time-progressive (autoregressive) forecasts, but over regions instead. The assumption of the MGN test would imply, in our case, horizontal correlation; that is, pairwise correlation between (the forecasts for) region 1 and region 2, regions 2 and 3, 3 and 4, and so on. On the contrary, what we attempt to capture with the NNs developed in the present chapter is the specificity of each single region.

Alternatively, the ST is based on the following idea: if two models, 1 and 2, are equally accurate, the number of forecasts of Model 2 which have a bigger error than that of Model 1 will be expected to be 50 per cent of the total number of forecasts obtained. Consequently, Model 1 will be considered superior to Model 2 if Model 2 has higher forecasting errors (than Model 1) in more than 50 per cent of the cases. The test statistic is then computed as:

$$\mathrm{ST} = \frac{C - N/2}{1/2\sqrt{N}}\,, \tag{4.8}$$

[31] It may be argued that an assessment of the models' performance should ideally be carried out by means of resampling techniques, or Monte Carlo simulations. In our case, the focus is on forecasting German employment variations for all districts and for the most recent years available. Consequently, resampling experiments – in particular in a jackknife context – are the most appropriate solution, implying the repeated selection of data subsamples for testing. However, such an approach involves the development of repeated subsample-selection-and-NN-estimation procedures. This task may be explored in future research. With regard to the case study concerned, the forecast equality tests allow us to infer findings from the statistical results found, and we can therefore consider them an acceptable compromise.

where $C$ is the number of times in which Model 2 shows higher errors than Model 1, and $N$ is, again, the number of forecasts carried out (in our case, the same as the number of districts concerned). The ST statistic follows a normal distribution $N(0, 1)$.

Finally, as benchmarks to our NN models, we present two random walk (RW) models and an OLS model. These are illustrated in the subsequent section.

### *4.4.3 Benchmark Forecasting Models*

For comparison purposes, we propose random walk (RW) models and OLS panel regression. These techniques were chosen for their easy and fast implementation. Also, a comparison with RW models is the first step in the evaluation of any proposed econometric technique (Collopy et al. 1994); that is, a proposed methodology should be at least as accurate as a naïve extrapolation. On the other hand, RW models clearly have shortcomings: for example, they do not exploit the potential explanatory power of covariates. In our work, we employed two types of RW models, which are defined as follows:

(a) Random Walk Nat.: this model assumes that the number of employees in each district in year $(t + 2)$ is equal to the number of employees in year $t$. For example, the forecast for 2001 equals the number of employees in 1999, and the regional growth rates are equal to zero.
(b) Random Walk G.R.: this model assumes, for the period $(t, t + 2)$, the same regional growth rates recorded (district-by-district) for the period $(t – 2, t)$. Consequently, the regional growth rates of employment between 1999 and 2001 will be equal to those recorded between 1997 and 1999.

In addition to the RW models, we propose OLS regression models as additional benchmarks for the NNs. As for the NN models presented in Section 4.4.1, we developed separate regression models for West and East Germany, employing the same basic variables as those in the NN models; that is, the lagged $(t – 2, t)$ biannual growth rates of regional full-time employment observed in nine economic sectors. Additionally, time fixed effects (dummies) are added to account for year-specific shocks that affect all districts. No intercept was estimated, for comparability purposes. Because of the above settings and specification, the OLS models are particularly comparable to Model A. Following from Equation (4.6), the model estimated can be written as follows:

$$\Delta e_{i,t+2} = b_1 \Delta e_{i,1,t} + \ldots + b_9 \Delta e_{i,9,t} + b_{10} v_t, \tag{4.9}$$

where $v_t$ represents the dummy variable for year $t$. Additional regression models could be carried out in a similar fashion, for direct comparability with each NN model. In particular, one might argue that the best possible model – or the current standard – should be employed as a benchmark. While such as approach is highly desirable and should be explored in-depth in the future, we limit our present comparative analysis to the above models because of practical space limitations.

The next sections present our empirical findings with regard to both the NN and the NNGA models. First, Sections 4.5.1 and 4.5.2 show the results obtained for the former West and East Germany, respectively. Subsequently, Section 4.5.3 concludes the discussion of our empirical experiments, focussing on the differences in the statistical performance of NN and NNGA models.

## 4.5 Regional Employment Forecasts for West and East Germany

### *4.5.1 Estimation of West German Employment*

As indicated in the previous sections, nine NN models were developed and tested for each data set (West and East Germany). On the basis of the NN structures selected (as described in Section 4.4.2.1), we obtained *ex post* forecasts for the years 2001–04. The pooled statistical indicators emerging from these experiments (see Section 4.4.2.2), and computed on the forecasts of full-time employment for each West German district, are presented in Table 4.4.

Table 4.4 – Pooled statistical error of the NN models; West Germany, years 2001–04

| West | MSE | MAPE | MGN: Model BW | ST: Model BW |
|---|---|---|---|---|
| Model A | 23920356 (7) | 4.6679 (8) | *** | *** |
| Model AC | 20475032 (5) | 4.0083 (4) | ** | *** |
| Model AD | 25353851 (9) | 4.6487 (6) | *** | *** |
| Model ADW | 20322345 (4) | 4.6525 (7) | *** | *** |
| Model AE | 20746758 (6) | 4.3881 (5) | *** | *** |
| Model AW | 24543855 (8) | 4.8889 (9) | * | *** |
| Model B | 6772694 (2) | 2.7517 (3) | | *** |
| Model BD | 7806311 (3) | 2.7580 (2) | *** | *** |
| Model BW | 6069135 (1) | 2.6472 (1) | – | – |
| RW Nat. | 15756094 | 3.5188 | *** | ** |
| RW G.R. | 59799512 | 3.6069 | *** | *** |
| OLS (Model A) | 18885393 | 3.7585 | *** | * |

*Note:* The ranking of the NN models is shown in brackets.
*** Rejection of forecast equivalence at the 99 per cent level.
** Rejection of forecast equivalence at the 95 per cent level.
* Rejection of forecast equivalence at the 90 per cent level.

The statistical results shown in Table 4.4 can be read as follows. The main result is that the models of type ‘B’ outperform the models of type ‘A’, as *all* of the top results are obtained by the former class of models In particular, Model BW appears to be the best-performing one for the four years examined. A second finding is that the inclusion of information on the district classification (D- and E-models) or wages (W-models) does not seem to significantly (or uniformly) improve the forecasting potential of the models: for example, while the introduction of wages improves the performance of Model B, it does not do so for Model A. Similarly, the D-models do not improve on their respective basic models' performance. Such evidence suggests a predominance of the autoregressive effect in determining employment growth rates.

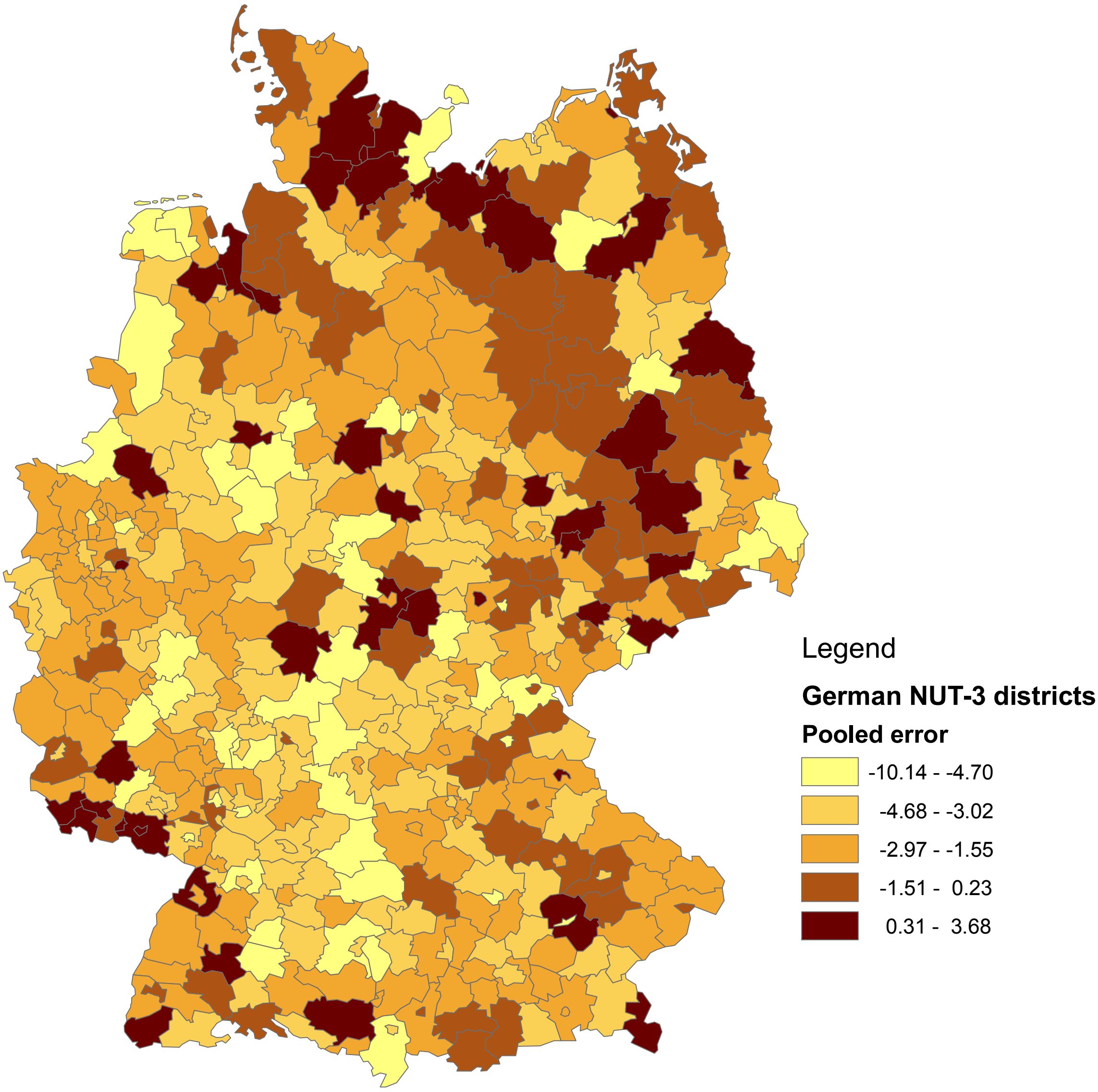



Figure 4.3 – Pooled growth rate estimation error of the three B-type NN models, 2001–04

In addition to providing the pooled statistical results, Table 4.4 also provides summary results of the forecast equivalence tests, carried out to investigate whether the winning model

– Model BW – is significantly more accurate than the competing models. The tests confirm the dominance of the model, as most tests are highly significant. Therefore, the inclusion in the model of the wages variable appears to be critical in the special case of forecasting West German employment. Overall, the 'B-type' models appear to also outperform the benchmark models (RW models and OLS panel regression), which, however, can be preferred, in this context, to the 'A-type' models. Note that the OLS regression is directly comparable only to Model A.

Because of the statistical variability of the results of the NN models shown in Table 4.4, we also considered, as a main performance indicator, the error generated by the pooled (averaged) forecast of our 'B-type' NN models, as suggested in Granger and Newbold (1986).[32] A map visualization of these results – which also includes the error levels found for the subsequent East Germany analysis – is presented in Figure 4.3 above. The map shows a general tendency towards an overestimation of employment growth rates, while underestimation seems to be more frequent for the case of East Germany. Further investigation of the average NN error, which suggests an overestimation around 2 per cent, will be considered in future research.

### *4.5.2 Estimation of East German Employment*

The data set for East German employment contains information on the number of employees in 113 districts, for the period between 1993 and 2004. The data set has a smaller number of districts and is six years shorter than the one for West Germany. Consequently, only four years could be used for training and validating the models. One year, 2000, was used for the test (see Table 4.2, Section 4.4.2.1).

The selected NN models were subsequently trained, similarly to the West German case, employing the years 2001–04 as *ex post* testing periods, while the years up to these aforementioned years acted as training periods (for example, 1997–2000 is the training period for the 2001 *ex post* forecasts; see Table 4.3). Table 4.5 contains the pooled results of the aforementioned 2001–04 out-of-sample forecasts, in addition to the results concerning the benchmark models and the forecast equivalence tests.

Table 4.5 confirms the results found for the West German NN models (see preceding section). The 'B-type' models again outperform both the 'A-type' models and the benchmark models. However, differently from the case of West Germany, Model BW is *not* the best performer. Model B and Model BD provide lower error levels, though it is not clear, from the above results, which model should be preferred between the two. While the use of the pooled results of the B-BD Models could be a suitable solution, here the forecast equivalence tests introduced in Section 4.4.2.2 are used again, in order to distinguish between the two

[32] It should be noted that Granger and Newbold originally referred to experiments based on time series data.

competing models. Table 4.5 shows that Model B significantly dominates – if compared pairwise – all the other NN and benchmarking models (although the results of the MGN test are less conclusive). The present finding is confirmed by inverse testing (Model BD versus the other models; not reported here), which shows an insignificant result in comparison with Model B and generally lower significance levels. Overall, the limited relevance of the inclusion – in all models – of socio-economic variables also confirms the initial intuition of a general dominance of the autoregressive temporal component in the data employed. The pooled errors for the NN models of type B are shown in Figure 4.3 above.

Table 4.5 – Pooled statistical error of the NN models; East Germany, years 2001–04

| East | MSE | MAPE | MGN: Model B | ST: Model B |
|---|---|---|---|---|
| Model A | 7746408 (4) | 3.7744 (5) | | *** |
| Model AC | 14073715 (6) | 3.9274 (7) | | *** |
| Model AD | 18843351 (9) | 5.2501 (9) | | *** |
| Model ADW | 17263920 (7) | 4.2827 (8) | | *** |
| Model AE | 12706553 (5) | 3.7889 (6) | | *** |
| Model AW | 18546697 (8) | 3.6246 (4) | | ** |
| Model B | 6971273 (2) | 3.0883 (1) | – | – |
| Model BD | 5315250 (1) | 3.2494 (2) | *** | *** |
| Model BW | 7685641 (3) | 3.3986 (3) | *** | *** |
| RW Nat. | 26400993 | 7.2101 | | *** |
| RW G.R. | 11347151 | 4.6095 | *** | *** |
| OLS (Model A) | 27612412 | 7.1411 | | *** |

*Note:* The ranking of the NN models is shown in brackets.
*** Rejection of forecast equivalence at the 99 per cent level.
** Rejection of forecast equivalence at the 95 per cent level.
* Rejection of forecast equivalence at the 90 per cent level.

The NN models presented in this and the preceding section were subsequently compared with GA-enhanced otherwise-identical NN models. The next subsection summarizes the results obtained.

### *4.5.3 NN Models vs NNGA Models*

In this section we present a summary of the results obtained by enhancing our NN models with a GA-based structure and parameter optimization (NNGA models: see Section 4.3). The experiments discussed here refer only to the year 2001. Therefore, the extent of the analyses is in this case limited. However, the focus here is on 'within-model' comparison (an NN model against itself) rather than on the reliability of a model over time. Table 4.6 summarizes our findings.

Table 4.6 – Comparative statistical performances of NN and NNGA models: *ex post* forecasts for the year 2001

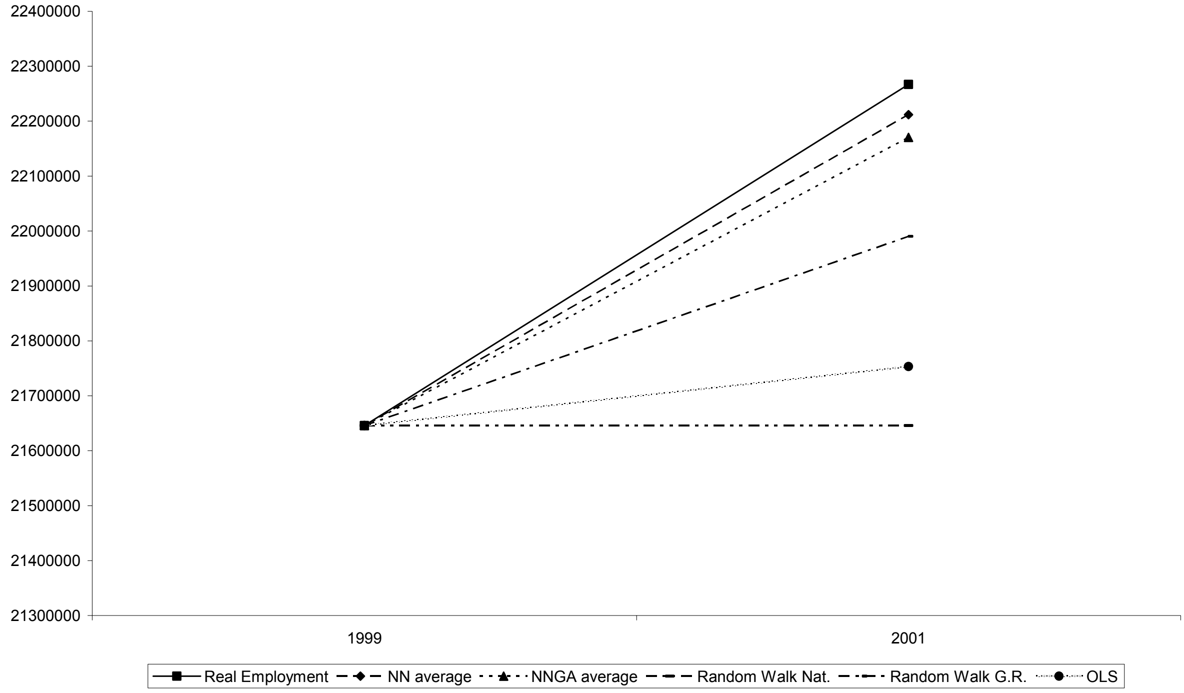
| | Model A | Model AC | Model AD | Model ADW | Model AE | Model AW | Model B | Model BD | Model BW |
|---|---|---|---|---|---|---|---|---|---|
| *West Germany* | | | | | | | | | |
| MSE | Y | N | N | N | Y | N | N | N | N |
| MAPE | Y | N | N | Y | Y | Y | N | N | N |
| MGN | *** | | | | | | | ** | |
| ST | *** | | | ** | | * | | | |
| *East Germany* | | | | | | | | | |
| MSE | Y | N | N | Y | Y | Y | N | N | N |
| MAPE | N | Y | Y | N | N | N | Y | Y | Y |
| MGN | ** | | | | *** | | | | |
| ST | | *** | *** | | | | *** | *** | *** |

Y: NNGA model has lower error than corresponding NN model.
N: NNGA model has higher error than corresponding NN model.
*** Rejection of forecast equivalence at the 99 per cent level.
** Rejection of forecast equivalence at the 95 per cent level.
* Rejection of forecast equivalence at the 90 per cent level.

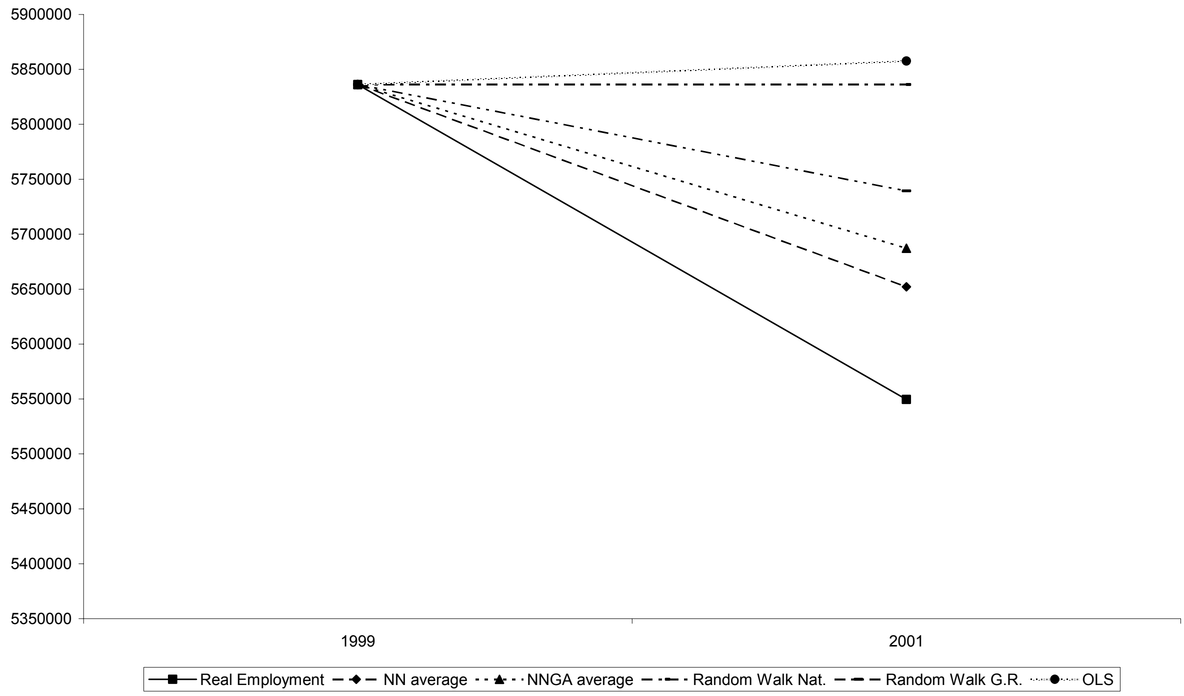
To compare these additional models with the previously-developed NN models, Table 4.6 first identifies which NNGA models show lower MSE or MAPE than their corresponding NN model. For each NNGA model, we test the equivalence of the 'new' (NNGA) and 'old' (NN) forecasts by means, again, of the MGN and sign (ST) tests.

The comparison of NN and NNGA models shows that, for the year 2001, the NNGA models perform ambiguously compared with the conventional NN models. Only one model (model AGA, for West Germany) improves the statistical reliability of its baseline model for both statistical indicators, while the average error levels of the NNGA models are greater than those of conventional NN models. The MGN and sign tests – comparing each NNGA model with its baseline NN model – confirm the above result, since only a limited number of tests were statistically significant. These tendencies are also visible at an aggregate level (for a graphical visualization of the average NN and NNGA aggregate forecasts for the year 2001, see Figures 4.4 and 4.5), which suggests that the inclusion of GA in the NN model-setting process does not lead – in our case study – to conclusive statistical results.

Trying to explain the above differences between NN and NNGA models is indeed the most difficult part. Nevertheless, we can make a number of hypotheses on the basis of our results. First, the stochastic nature of the choice of the NNGA structures might play a role in determining a higher variance in the models' performance. The GA-enhanced models develop more heterogeneous structures than the simpler NN models, which were set by means of a manual procedure (see Section 4.4.2.1). The settings chosen for the NNGA models may be expected to provide improved performance, because of the optimization procedure that generates them. This automated process also relieves the analyst from the lengthy process of manual choice of the network parameters and configuration.




*Note:* The graph does not suggest employment levels for the year 2000 to be a linear interpolation of the years 1999 and 2001.
Figure 4.4 – West Germany's *ex post* forecasts for the year 2001




*Note:* The graph does not suggest employment levels for the year 2000 to be a linear interpolation of the years 1999 and 2001.
Figure 4.5 – East Germany's *ex post* forecasts for the year 2001

Secondly, it might be seen as beneficial to allow the GA to go through a greater number of iterations than are used in the present chapter, in order to have a wider set of alternatives examined by the software (this issue was briefly discussed in Section 4.3). On the other hand, a shortcoming of the NNGA approach is that computing time increases significantly, in particular for wide data sets such as ours.

A balance between the optimization and the computational time aspects of GAs should then be sought, in particular when database size becomes relevant.

## 4.6 Conclusions

The aim of this chapter was to produce 2-years-ahead forecasts of the number of individuals employed in the 439 (NUTS-3) districts in Germany. Several models based on neural network (NN) and genetic algorithm (GA) techniques were developed. Because of data availability, the East and West German districts were analysed separately, and comparable sets of neural models were applied to Eastern and Western districts. The models were developed and configured both manually (NN models) and by means of GAs (NNGA models). The results of *ex post* forecasts for the years 2001–04 (2001 only for NNGA models) were evaluated by means of MSE, MAPE, and of forecast equivalence tests: namely, the Morgan-Granger-Newbold (MGN) test and the sign test (ST).

From the empirical point of view, we observed varying levels of statistical error, for both the West and East Germany models. The variability in the results can be mostly attributed to the different performance of the ‘A’-type models, which use time dummies for temporal correlation, and of the ‘B’-type models, which use a unique rescaled time variable. The ‘B’ family of models obtains the lowest error levels in all cases, and therefore outperforms the ‘A’-type family. Our first conclusion is, therefore, that, with regard to our NN forecasting framework for regional unemployment, a time correlation approach by means of dummy variables is not suitable. A second conclusion that can be drawn from the results presented in Tables 4.4 and 4.5 is that the inclusion of additional socio-economic variables does not seem to carry improved statistical explanatory power. The exception is the case of Model BW for West Germany. The results of the forecast equivalence tests carried out for the winning NN models (Model BW for the West and Model B for the East) reinforce the above findings and indicate the clear dominance of the analysed models over the remaining models. The ability to actually choose *one* NN model over the others should be considered – because of its relevance for policy purposes – as a value added of our analysis.

From a methodological viewpoint, the enhancement of the NN models with GAs (Table 4.7) did not seem to significantly improve the NNs’ performance, showing mixed results in our case study of labour market forecasting. Increased iterations subsequently carried out did not bring any better results, suggesting that the NN structure and – in particular – the learning parameters (that is, the settings which are modified by the GA) deserve further investigation to facilitate the optimization of our NN models’ performance.

Finally, concerning the policy issue of generalization, because the West German data set is much wider, both spatially and temporally, than the East German, the results obtained for the former might be considered to be more reliable and suitable for benchmarking considerations.

In conclusion, our experiments show that NN (and NNGA) models for forecasting regional German employment have different levels of reliability, depending on the data sets used and the socio-economic background. This is certainly caused by the different time spans of the data sets for West and East Germany. It should also be remarked that our empirical analysis has been based on two main explanatory variables (employment and wages), and thus it cannot be comprehensive with regard to the many variables that may come into play when employment and social conditions are involved. Further, in order to assess the relative advantage of the NN models, these should be ideally compared – one-by-one – with benchmark models utilizing the same set of variables, while the OLS regressions used here can be directly associated only with Model A. The next chapter aims to fill one of the gaps indicated here – the lack of additional socio-economic explanatory variables – by modelling regional and industry specificities in NNs. This is done by introducing shift-share analysis in a joint modelling framework with NNs. Subsequently, in Chapter 6, we test the robustness of NN models to changes in the learning parameters (as suggested above), so as to finally provide a more comprehensive overview of the improvement limits of the models developed here.

## Annex 4.A Details of Model Experiments

The NN models used in the present chapter were computed using the network parameters shown in the table below.

Table 4.A1 – Parameter values of the NN models adopted: the case of West Germany

| Models | Inputs | IU | HU | Epochs | LR | M | IN |
|---|---|---|---|---|---|---|---|
| | | | *NN Models* | | | | |
| Model A | Employment (GR), time (dummies) | 22 | 10 | 900 | 0.9 | 1 | 0 |
| Model AC | Employment (GR), time (dummies), district identifier | 23 | 5 | 600 | 0.9 | 1 | 0 |
| Model AD | Employment (GR), time (dummies), district type (ordinal) | 23 | 10 | 600 | 0.9 | 1 | 0 |
| Model AE | Employment (GR), time (dummies), district type (dummies) | 31 | 10 | 200 | 0.9 | 1 | 0 |
| Model AW | Employment (GR), time (dummies), wage (GR) | 23 | 5 | 750 | 0.9 | 1 | 0 |
| Model ADW | Employment (GR), time (dummies), district type (ordinal), wage (GR) | 24 | 15 | 900 | 0.9 | 1 | 0 |
| Model B | Employment (GR), time (periodic) | 10 | 5(1$^{st}$L), 5(2$^{nd}$L) | 650 | 0.9 | 1 | 0 |
| Model BD | Employment (GR), time (periodic), district type (ordinal) | 11 | 10 | 300 | 0.9 | 1 | 0 |
| Model BW | Employment (GR), time (periodic), wage (GR) | 11 | 5(1$^{st}$L), 5(2$^{nd}$L) | 1600 | 0.9 | 1 | 0 |
| | | | *NNGA Models* | | | | |
| Model AGA | Employment (GR), time (dummies) | 22 | 24(1$^{st}$L), 5(2$^{nd}$L) | 250 | 0.8279 | 0.2252 | 0.0071 |
| Model ACGA | Employment (GR), time (dummies), district identifier | 23 | 29 | 350 | 0.9492 | 0.1246 | 0.0101 |
| Model ADGA | Employment (GR), time (dummies), district type (ordinal) | 23 | 27 | 600 | 0.9575 | 0.5977 | 0.0175 |
| Model AEGA | Employment (GR), time (dummies), district type (dummies) | 31 | 24(1$^{st}$L), 8(2$^{nd}$L) | 200 | 0.6892 | 0.0515 | 0.0198 |
| Model AWGA | Employment (GR), time (dummies), wage (GR) | 23 | 29(1$^{st}$L), 9(2$^{nd}$L) | 350 | 0.6002 | 0.4409 | 0.0028 |
| Model ADWGA | Employment (GR), time (dummies), district type (ordinal), wage (GR) | 24 | 24(1$^{st}$L), 10(2$^{nd}$L) | 300 | 0.8294 | 0.1348 | 0.0076 |
| Model BGA | Employment (GR), time (periodic) | 10 | 0 | 400 | 0.9013 | 0.3330 | 0.0118 |
| Model BDGA | Employment (GR), time (periodic), district type (ordinal) | 11 | 0 | 500 | 0.7982 | 0.2698 | 0.0164 |
| Model BWGA | Employment (GR), time (periodic), wage (GR) | 11 | 0 | 1800 | 0.8416 | 0.2774 | 0.0187 |

*Notes:* IU = input units; HU = hidden units; GR = growth rates; 1$^{st}$L = first hidden layer; 2$^{nd}$L = second hidden layer; LR = learning rate; M = momentum; IN = input noise. All models have only 1 output unit; the activation function is always a sigmoid.

Table 4.A2 – Parameter values of the NN models adopted: the case of East Germany

| Models | Inputs | IU | HU | Epochs | LR | M | IN |
|---|---|---|---|---|---|---|---|
| | | | *NN Models* | | | | |
| Model A | Employment (GR), time (dummies) | 16 | 10 | 100 | 0.9 | 1 | 0 |
| Model AC | Employment (GR), time (dummies), district identifier | 17 | 10 | 300 | 0.9 | 1 | 0 |
| Model AD | Employment (GR), time (dummies), district type (ordinal) | 17 | 5 | 300 | 0.9 | 1 | 0 |
| Model AE | Employment (GR), time (dummies), district type (dummies) | 25 | 15 | 300 | 0.9 | 1 | 0 |
| Model AW | Employment (GR), time (dummies), wage (GR) | 17 | 5(1stL), 5(2ndL) | 200 | 0.9 | 1 | 0 |
| Model ADW | Employment (GR), time (dummies), district type (ordinal), wage (GR) | 18 | 5(1stL), 5(2ndL) | 200 | 0.9 | 1 | 0 |
| Model B | Employment (GR), time (trend) | 10 | 5(1stL), 5(2ndL) | 900 | 0.9 | 1 | 0 |
| Model BD | Employment (GR), time (trend), district type (ordinal) | 11 | 15 | 1100 | 0.9 | 1 | 0 |
| Model BW | Employment (GR), time (trend), wage (GR) | 11 | 5 | 1000 | 0.9 | 1 | 0 |
| | | | *NNGA Models* | | | | |
| Model AGA | Employment (GR), time (dummies) | 16 | 26(1stL), 8(2ndL) | 300 | 0.5685 | 0.799 | 0.0022 |
| Model ACGA | Employment (GR), time (dummies), district identifier | 17 | 14 | 200 | 0.6385 | 0.0994 | 0.0019 |
| Model ADGA | Employment (GR), time (dummies), district type (ordinal) | 17 | 16 | 200 | 0.9573 | 0.1433 | 0.0129 |
| Model AEGA | Employment (GR), time (dummies), district type (dummies) | 25 | 16 | 100 | 0.9443 | 0.0666 | 0.0061 |
| Model AWGA | Employment (GR), time (dummies), wage (GR) | 17 | 8 | 200 | 0.5705 | 0.0272 | 0.0170 |
| Model ADWGA | Employment (GR), time (dummies), district type (ordinal), wage (GR) | 18 | 6 | 100 | 0.8544 | 0.0764 | 0.0034 |
| Model BGA | Employment (GR), time (periodic) | 10 | 19 | 1700 | 0.6878 | 0.3651 | 0.0230 |
| Model BDGA | Employment (GR), time (periodic), district type (ordinal) | 11 | 29 | 1000 | 0.7201 | 0.4295 | 0.0196 |
| Model BWGA | Employment (GR), time (periodic), wage (GR) | 11 | 13 | 200 | 0.6973 | 0.4033 | 0.0004 |

*Notes:* IU = input units; HU = hidden units; GR = growth rates; 1stL = first hidden layer; 2ndL = second hidden layer; LR = learning rate; M = momentum; IN = input noise. All models have only 1 output unit; the activation function is always a sigmoid.

Chapter 5

# Joint Shift-Share and Neural Network Approaches for Regional Employment Forecasting

## 5.1 Introduction[33]

The preceding chapter presented a series of statistical procedures – and the resulting empirical findings – aimed at forecasting, by means of neural network (NN) models, regional variations in German employment. The novel aspect of carrying out such forecasts is in that out-of-sample estimates are obtained in a panel data framework (rather than in a time-series framework); that is, we forecast the development of all concerned regions at a given time, by fully exploiting the full temporal depth of the data set.

The results presented in Chapter 4 for several NN models showed that the main factor in determining their statistical performance is the treatment of the time-specific shocks: in econometric terms, of the time fixed effects. The inclusion of socio-economic variables concerning district urbanization or wages did not appear to provide a consistent improvement to the NN models.

Consequently, the objective of the present chapter is to evaluate possible alternative economic variables in order to enrich the data set information and, consequently, to improve the fit between the dependent and the independent variables. In this regard, we propose the incorporation of shift-share analysis (SSA) in NN models. We introduce several variants of SSA, including some recent specifications, known as spatial shift-share and shift-share regression (SSR). This class of methods is integrated with the NN methodology previously employed, ideally providing a balance between a data-driven technique like NNs and a solid well-known research method like SSA. *Ex post* forecasts are used – with regard to our objective – to evaluate the statistical performance of the new NN models.

The present chapter is organized as follows. Section 5.2 introduces various classes of shift-share techniques. Section 5.3 first recalls the main steps in the implementation of the NN models, illustrates the new additional ones, and, subsequently, reviews the statistical results of

[33] The present chapter is based on Patuelli et al. (2006b), published in *Spatial Economic Analysis*. The original publication is available at www.springerlink.com.

the empirical application, which aims to estimate employment variations in the former West and East Germany for the years 2001–04. A contribution to NN analysis is offered by embedding SSA components. The results of these newly developed NN models are evaluated – in comparison with the winning models found in Chapter 4 – by means of appropriate statistical indicators, forecast equivalence tests, and map visualizations. Finally, Section 5.4 offers some conclusions and sets future research directions.

## 5.2 Shift-Share Analysis for Regional Growth Analysis

### *5.2.1 The Conventional Shift-Share Analysis Identities*

Shift-share analysis (SSA) has, since its inception in the 1960s, been a popular analytical tool among regional scientists, and not only for improving the understanding of changes in economic variables, such as employment or GDP, at the regional level. SSA can be usually employed in four ways: (a) in forecasting; (b) in strategic planning (that is, observing the weight of the effects); (c) in policy evaluation (before-and-after analysis); and (d) in decision making (Dinc et al. 1998; Loveridge and Selting 1998).

SSA was first introduced by Dunn (1960), and subsequently formalized by Fuschs (1962) and Ashby (1964). In SSA, the growth shown by economic variables is decomposed into several components. Using employment as an example, the conventional shift-share decomposition can be written as:

$$\Delta e_{ir} = [G + (G_i - G) + (g_{ir} - G_i)]e_{ir}, \tag{5.1}$$

where $e_{ir}$ is the employment observed in region $r$ for sector $i$; $G$ is the overall national employment growth rate; $G_i$ is the national growth rate of sector $i$; and $g_i$ is the growth rate of region $r$ in sector $i$. The employment growth rate $\Delta e_{ir}$ is therefore decomposed into three components:

(1) the ‘national effect’ $G$;
(2) the ‘sectoral effect’, given by the difference between the sectoral and overall national growth rates, $G_i$ and $G$;
(3) the ‘competitive effect’, given by the difference between the local and nationwide sectoral growth rates, $g_i$ and $G_i$.

Each of the three components can be calculated for each region, over all the sectors, and nationwide. In particular, when summed nationwide, the sectoral and competitive effects sum to zero. This property is usually referred to as the ‘zero national deviation’ (ZND) property.

The above SSA identity has been studied and modified by several authors over the years. Alternative formulations of SSA also include, for instance, an industry-structure approach where, in place of growth rates, industrial structures are compared (Ray 1990).

However, perhaps the most popular SSA extension is the one developed by Esteban-Marquillas (E-M) (1972):

$$\Delta e_{ir} = Ge_{ir} + (G_i - G)e_{ir} + (g_{ir} - G_i)e_{ir}^h + (g_{ir} - G_i)(e_{ir} - e_{ir}^h). \tag{5.2}$$

In this SSA formulation, $e_{ir}^h$ is the homothetic employment of sector *i* in region *r*. Homothetic employment is calculated as $e_{ir}^h = eE_{ir}/E$, that is, region *r*'s employment in sector *i*, as it would be if the sector had the same structure as the nation. The homothetic competitive effect (third component) measures 'a region's comparative advantage/disadvantage in [sector] *i* relative to the nation' (Esteban-Marquillas 1972, p. 43). The fourth and last component is called the 'allocation effect', as it is the product of the expected employment and the differential which measures a region's competitive advantage in sector *i*. The claim of this model is that it isolates the competitive effect from its relationship with the sectoral effect. Critiques of the E-M model can be found in Stokes (1974) and in Haynes and Machunda (1987). The E-M extension is not considered in our experiments, since the competitive effect is computed in the same way as in conventional SSA, the only difference being that it is multiplied by the homothetic employment.

More generally, according to Loveridge and Selting (1998), the main criticisms of SSA concern:

- its lack of theoretical content. In order to fill this gap, there have been attempts to link SSA to neoclassical microeconomics and factor demand for labour;
- aggregation problems. Finer categories increase the weight of the sectoral effect and shrink the competitive effect. On the other hand, it has to be remembered that other techniques are also sensitive to aggregation issues;
- weighting bias. It is not clear whether it is more convenient to use the base or the terminal year. Alternatively, the average of the two or a middle year could be used, or a 'dynamic shift-share' formulation (see Wilson 2000);
- instability of the competitive effect. This instability makes employment projections by means of SSA somewhat precarious. On the other hand, this issue does not exclude the use of SSA in forecasting, particularly in the framework of NNs;
- interdependence of the sectoral and competitive effects.

A number of new SSA specifications have been developed over the years,[34] on the basis of the first technical advances described above, often focusing on the elimination of dependence among shift-share components, or trying to solve other deficiencies of SSA. However, the application of newer methodologies has often deprived the models of their contribution to understanding local phenomena (Loveridge and Selting 1998). While all types of decomposition can be obtained by adding and subtracting variables, all of them can be shown to be rooted in the simple SSA decomposition (Nazara and Hewings 2004). Consequently, the basic models and a few other modifications, widely accepted as standards, are still preferred by most analysts, because of their intuitive and simple specifications.

Despite the above considerations, the development of new SSA extensions still goes on. One of the most recent developments in this matter is the extension proposed by Nazara and Hewings (2004), also called 'spatial shift-share' by the authors, and described in the next subsection.

### *5.2.2 Spatial Shift-Share*

The development of the recent shift-share extension termed 'spatial shift-share' is justified by the fact that spatial issues, such as spillovers and spatial competition, have not been considered in the application of SSA. There is, therefore, a need for the introduction of an element that accounts for the spatial structure of a particular region. If we consider that regions are – as seems logical – interdependent and they influence each other, we note, in fact, that horizontal-influence relationships (that is, region to region: we refer to such relationships in particular in Chapter 9) are not enclosed in the traditional SSA formulation, while only hierarchical ones are accounted for (that is, nation to region).

Starting from this consideration, Nazara and Hewings modified the conventional shift-share identity in:

$$\Delta e_{ir} = [G + (\vec{g}_{ir} - G) + (g_{ir} - \vec{g}_{ir})]e_{ir}, \tag{5.3}$$

where $\vec{g}_{ir}$ is sector $i$'s growth rate in the regions that are neighbours to region $r$, and is formulated, for a generic $(t, t+n)$ period, as:

$$\vec{g}_{ir} = \frac{\sum_{s=1}^{N} \widetilde{w}_{rs} e_{is}^{t+n} - \sum_{s=1}^{N} \widetilde{w}_{rs} e_{is}^{t}}{\sum_{s=1}^{N} \widetilde{w}_{rs} e_{is}^{t}}, \tag{5.4}$$

[34] For a review of SSA identities, see Loveridge and Selting (1998), and Dinc et al. (1998).

where $N$ is the number of regions, and the employment levels of the neighbouring regions are weighted according to a row-standardized weight matrix $\tilde{\mathbf{W}}$, which defines the intensity of the neighbours' interaction with region $r$. This interaction can be defined in many ways: for instance, on the basis of geographical contiguity or economic flows. A simplified version of the weight matrix is employed in this chapter, where the neighbours of a given region are empirically defined as the three regions that provide the highest number of individuals commuting towards the region considered.[35] In practical terms, the weight matrix employed here is an asymmetric matrix with only three identical values differing from 0 for each region considered (that is, for each row or column of the matrix). The overall employment growth rate of the neighbours is subsequently computed.

As a consequence of the new variable presented in Equation (5.3), the sectoral and the competitive components change in meaning. In detail:

- The sectoral component now identifies the difference between the growth rate of region $r$'s neighbours in sector $i$ and the national all-sector growth.
- The competitive component is the difference between sector $i$'s growth rate in region $r$ and in its neighbouring regions.

This recent decomposition is already the subject of further study and expansion. Mayor Fernández and López Menéndez (2005) developed a mixed Nazara-Hewings/E-M model, which employs both homothetic employment and the spatial connotation given by a geographic connectivity matrix. The interest in the SSA framework also goes beyond its deterministic nature. The next section describes a stochastic shift-share approach termed 'shift-share regression'.

### *5.2.3 Shift-Share Regression*

One of the main critiques of SSA is the lack of hypothesis testing, which is due to shift-share's deterministic nature. A stochastic approach, based on regression techniques equivalent to shift-share, has been developed by Patterson (1991), and subsequently used by, amongst others, Möller and Tassinopoulos (2000), Blien and Wolf (2002), and Suedekum et al. (2006) in the analysis of employment patterns in Eastern Germany.

The model proposed by Patterson is rather simple, and strictly related to the conventional SSA approach:

$$\Delta e_{irt} = \alpha_i + \lambda_t + k_r + \varepsilon_{irt}, \tag{5.5}$$

[35] The data on commuting flows used in Model SSN were kindly provided by Günter Haag (STASA, Stuttgart, Germany), and refer to the year 2002. Future research would ideally also look at changes in the commuting patterns, so as to also have a 'dynamic' definition of 'neighbours'.

where $\Delta e_{irt}$ is the regional employment growth rate in sector $i$ during period ($t$, $t + 1$); $\alpha_i$ is the effect of sector $i$; $\lambda_t$ incorporates time period $t$ (period effect); $k_r$ is a locational effect specific to region $r$; and $\varepsilon_{irt}$ is stochastic noise. The aforementioned authors proposed extensions of this specification, incorporating additional variables, such as structural adjustment, region-type indicators and qualification level of employees. Equation (5.5) suffers from perfect multicollinearity, and is therefore estimated by introducing a set of constraints (see Blien and Wolf 2002). A Weighted Least Squares (WLS) estimation procedure is suggested in order to reduce the impact of outliers.

This Shift-Share Regression (SSR) approach is replicated, in this chapter, in a simplified version. We are interested in introducing shift-share components in NNs in order to forecast overall regional employment. Therefore, we only employ the locational effects regressors, which are region-specific, as explanatory variables in NN models. In our case, the dependent variable is $\Delta e_{rt}$, that is, the overall employment change of region $r$. Equation (5.5) is therefore simplified as follows:

$$\Delta e_{rt} = a + k_r + \varepsilon_{rt}. \tag{5.6}$$

In Equation (5.6), $a$ is the intercept, while $\varepsilon_{rt}$ is the stochastic noise for region $r$ at time $t$. In this case, the locational effects variable is computed as the competitive effects used in conventional SSA. Consequently, there is a set of locational effects regressors: one for each sector. The model was estimated, by means of WLS,[36] for each 2-year period. We found most of the locational effect variables to be statistically significant (for details, see Tables 5.A1 and 5.A2 in Annex 5.A). The multiple per-year estimations seem logical in the NN forecasting framework. The estimation of a single regression coefficient per sector would only change the scale of the independent variables introduced in an NN model, as they are multiplied by the corresponding regression coefficients. Computing a regression for each 2-year period enables what could be seen as a 'fine tuning' of the locational/competitive effect variables, the regression coefficient being different for each year. However, the correctness of this procedure – from a methodological viewpoint – will certainly have to be examined more in-depth.

On the basis of the considerations of this and of the preceding sections, several mixed NN-SSA (which hereafter we refer to as NN-SS) models were developed, using conventional and 'spatial' SSA formulations, as well as SSR. The next section provides details of the NN models developed and their results.

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[36] The weights are computed, in our case, as the ratio between the regional and the national overall employment levels, in a base year.

## 5.3 Introduction of Shift-Share Analysis in Neural Network Models

### *5.3.1 Forecasting Employment by Means of Neural Networks*

This section focuses on the description of the new NN models developed in this chapter for our forecasting purposes and employing SSA components. As explained in more detail in Chapter 4, the main inputs of our models are the growth rates of the number of workers regionally employed in the nine economic sectors. The aim of the models is to produce 2-years-ahead ($t$, $t + 2$) *ex post* employment forecasts for the German regional labour markets (at the NUTS-3 level).

In our previously developed NN models, a ‘time’ variable – inserted in order to exploit the panel nature of the data – was identified in the models in two different ways: (1) as a set of dummy variables (‘A-type’ models), resembling ‘time fixed effects’ in panel econometric models (Longhi et al. 2005b); and (2) as a periodic ordinal (trend) variable (‘B-type’ models). On the basis of the conclusions reached in our previous analysis (see Section 4.6), in this chapter, we rule out the time dummies approach (that is, the A-models), focusing on the winning family of B-type models.

We refer to the NN models employing SSA-computed variables as NN-SS models. They use Model B as a basis (Section 4.4.1), and they are otherwise specified as follows:

- Model BSS: this NN model contains nine additional explanatory variables, which are the competitive effect coefficients calculated, for each sector, in the framework of a conventional SSA. As a result, for each German district and each year, we have nine coefficients expressing regional competitiveness.
- Model BSSN: similarly, this model employs the competitive effect coefficients, this time deriving from the Nazara and Hewings spatial shift-share extension.
- Model BSSR: the present model embeds variables computed in the SSR framework. The variables employed are the multiplicative product of the competitive effect variables used in Model BSS and their regression coefficients, as found in the analysis explained in Section 5.2.3 (for details on the coefficient values, see Tables 5.A1 and 5.A2 in Annex 5.A).

The three previously developed NN-SS models of the ‘B-type’ family are employed in the next sections for purposes of comparison: (1) Model B; (2) Model BD – has the same inputs as Model B, plus the variable ‘type of district’ as a counter; and (3) Model BW – also has the same inputs as Model B, with the inclusion of average daily wages as an input variable. The characteristics of all the models presented are summarized in Annex 5.B.

All the models adopted use, as input variables, the regional growth rates of sectoral employment. The data used in our NN-SS models started from 1991 (1989–91) for West

Germany and from 1997 (1995–97) for East Germany. The data set available for West Germany is six years longer and allows for longer training and testing periods. Consequently, we formulate separate West and East German NN-SS models.

The models were developed (validated and tested) following the procedure in Section 4.4.2. In summary, the data set years concerned are:

(a) Validation phase: for West Germany, 1991–2000; for East Germany, 1997–2000.
(b) Test phase: for West Germany, 1991–2004; for East Germany, 1997–2004.

The objective of this procedure was to obtain *ex post*, out-of-sample forecasts for the years 2001–04 (year-by-year) that could be compared with the actual data, in order to evaluate the models' generalization properties.

The next sections explain and discuss the empirical findings from our experiments. First, the results obtained for West Germany are shown and examined (Section 5.3.2), followed by those found for East Germany (Section 5.3.3).

### *5.3.2 Estimation of West German Employment*

As indicated in the previous section, three NN-SS models were developed and tested for each data set. Here the NN-SS models are compared with the three winning NN models of Chapter 4 (with Model BW having been the winner in our previous more comprehensive analysis). The statistical indicators emerging from these experiments for the case of West Germany are presented in Table 5.1. These results assess the statistical performance of the NN and NN-SS models.

Table 5.1 – Statistical performances of the *ex post* forecasts for the years 2001–04: the case of West Germany

| West | MSE | MAPE | MGN: Model BSS | ST: Model BSS |
|---|---|---|---|---|
| | | *NN Models* | | |
| Model B | 6772694 (4) | 2.7517 (5) | *** | *** |
| Model BD | 7806311 (6) | 2.7580 (6) | *** | *** |
| Model BW | 6069135 (1) | 2.6472 (3) | *** | *** |
| | | *NN-SS Models* | | |
| Model BSS | 6446501 (2) | 2.5465 (1) | – | – |
| Model BSSN | 6709151 (3) | 2.6812 (4) | *** | *** |
| Model BSSR | 6993894 (5) | 2.6370 (2) | | |

*Note:* The ranking of the NN models is shown in brackets.
*** Rejection of forecast equivalence at the 99 per cent level.
** Rejection of forecast equivalence at the 95 per cent level.
* Rejection of forecast equivalence at the 90 per cent level.

The results presented in Table 5.1 show that the new (NN-SS) models seem to provide promising results, improving on the performance of the simpler Model B (on which they are based). Moreover, Model BSS seems to challenge the dominance, seen in Chapter 4, of Model BW. Forecast equivalence tests carried out for Model BSS confirm the preliminary observation of Table 5.1. We find that Model BSS significantly outperforms – and is therefore preferable to – all three NN models (B, BD and BW) and Model BSSN. Inverse testing on Model BW returns non-significant results in the comparison with the NN-SS models (that is, Model BW does not outperform the NN-SS models).

### *5.3.3 Estimation of East German Employment*

The analysis presented in the preceding section is repeated here for the NN and NN-SS models carried out for East Germany. The corresponding statistical results – for the 2001–04 *ex post* forecasts – are presented in Table 5.2.

Table 5.2 – Statistical performances of the *ex post* forecasts for the years 2001–04: the case of East Germany

| West | MSE | MAPE | MGN: Model BSS | ST: Model BSS |
|---|---|---|---|---|
| | | *NN Models* | | |
| Model B | 6971273 (4) | 3.0883 (1) | *** | |
| Model BD | 5315250 (1) | 3.2494 (5) | *** | *** |
| Model BW | 7685641 (6) | 3.3986 (6) | *** | *** |
| | | *NN-SS Models* | | |
| Model BSS | 6696829 (3) | 3.0950 (2) | – | – |
| Model BSSN | 6460406 (2) | 3.1101 (3) | | *** |
| Model BSSR | 7464860 (5) | 3.1174 (4) | ** | *** |

*Note:* The ranking of the NN models is shown in brackets.
*** Rejection of forecast equivalence at the 99 per cent level.
** Rejection of forecast equivalence at the 95 per cent level.
* Rejection of forecast equivalence at the 90 per cent level.

The results shown in Table 5.2 are fairly consistent with the ones obtained for the West German NN and NN-SS models, presented in Table 5.1. The NN-SS models, particularly Model BSS, suggest an enhanced generalization power compared with the benchmark models used (the NN models). The NN models that were winning in our previous analysis of Chapter 4 still win in this case, but the NN-SS models provide most of the best estimates, ranking amongst the top models with respect to both statistical indicators. Usual forecast equivalence tests were carried out in order to investigate a possible significant preference between Model B and Model BSS. Neither of the two models consistently outperforms the other, as the only significant result comes from the MGN test (on the dominance of Model BSS on Model B). While this finding suggests a general equivalence between the two models, we observed that

Model BSS actually increases generally the levels of significance of the tests; that is, it outperforms the remaining models to a greater extent.

The consistent results between the West/East German NN and NN-SS models lead to interesting considerations. Our main finding is that the inclusion of SSA components (spatial or non-spatial, and, to a lesser degree, shift-share regression) in NN models clearly increases their forecasting reliability. A second finding is that Model BSS (employing components from conventional SSA) emerges in the analysis for both West Germany and East Germany as the winning model. The above results confirm the importance of including region-specific information, but also the problem of which region-specific information is relevant. In the case of the NN-SS models, it is sector/region/year-specific information.

## 5.4 Conclusions

In the present chapter, we presented an empirical analysis of the performance of NN models developed for regional employment forecasting. We extended the analyses first presented in the preceding chapter, by evaluating a joint shift-share analysis/NN approach. We developed three new NN models (NN-SS), utilizing components from different SSA approaches as inputs, and we carried out *ex post* forecasts for four out-of-sample time periods (2001–04).

We found that the NN-SS models further improve the statistical performance of the basic ‘B’-type model. Overall, Model BSS, employing conventional SSA components, proved to be the most reliable and was shown to outperform the remaining models. This finding shows the effectiveness of a simple deterministic tool such as SSA, moving in the direction of integrating linear and nonlinear methods and, in the case of Model BSSN, spatial information. In this particular regard, the incorporation in the NNs of information on the performance of the ‘neighbours’ allows us to fill – or start filling – one of the gaps of conventional SSA, and maybe of NNs, that is, that they do not include information regarding the spatial characteristics of the data.

In this regard, spatial econometrics methods, such as spatial filtering (Griffith 2003), are discussed in the last chapter of Part B. Future research should ideally study the implementation of spatial NN models, potentially employing – as input – spatial econometric output, in order to alleviate the weakness of the NN algorithms in such matter. Grounds for additional improvement should also be sought in the experimentation of NN parameters alternative to the ones used until now in this study. This task is carried out in the next chapter.

## Annex 5.A Details of Shift-Share Regression Parameter Estimates

Tables 5.A1 and 5.A2 present the regression coefficients found when regressing the districts' overall growth rates on the competitive effect variable seen in Equation (5.1), for West and East Germany, respectively. A competitive effect variable was used for each of the nine industry sectors. WLS regressions were carried out for each year (that is, for each 2-year period).

Table 5.A1 – Shift-share regression parameters for the competitive effect variables: the case of West Germany

| Sector | 87–89 | 88–90 | 89–91 | 90–92 | 91–93 | 92–94 | 93–95 | 94–96 | 95–97 | 96–98 | 97–99 | 98–00 | 99–01 | 00–02 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Primary sector | 0.060*** | 0.109*** | 0.087*** | 0.051*** | 0.042*** | 0.061*** | 0.022*** | 0.012*** | 0.012* | 0.015*** | 0.028*** | 0.028*** | 0.018*** | 0.021*** |
| Industry goods | 0.246*** | 0.195*** | 0.195*** | 0.269*** | 0.295*** | 0.244*** | 0.231*** | 0.211*** | 0.221*** | 0.197*** | 0.242*** | 0.256*** | 0.265*** | 0.195*** |
| Consumer goods | 0.038*** | 0.049*** | 0.053*** | 0.074*** | 0.085*** | 0.072*** | 0.058*** | 0.053*** | 0.032*** | 0.054*** | 0.053*** | 0.057*** | 0.038*** | 0.036*** |
| Food manufacturing | 0.030** | 0.019 | 0.061*** | 0.033*** | 0.031*** | –0.021 | 0.025*** | 0.024*** | 0.015** | 0.018*** | 0.000 | 0.020* | 0.017 | 0.001 |
| Construction | 0.044** | 0.073*** | 0.039** | 0.043** | 0.038* | 0.099*** | 0.096*** | 0.067*** | 0.046*** | 0.004 | 0.002 | –0.022 | –0.001 | 0.058*** |
| Distributive services | 0.156*** | 0.146*** | 0.109*** | 0.090*** | 0.135*** | 0.140*** | 0.107*** | 0.137*** | 0.115*** | 0.152*** | 0.167*** | 0.093*** | 0.197*** | 0.186*** |
| Financial services | 0.060*** | 0.075*** | 0.056*** | 0.066*** | 0.052*** | 0.033* | 0.068*** | 0.099*** | 0.100*** | 0.105*** | 0.097*** | 0.075*** | 0.117*** | 0.112*** |
| Household services | 0.029*** | 0.058*** | 0.116*** | 0.057*** | 0.052*** | 0.042** | 0.045*** | 0.043*** | 0.060*** | 0.084*** | 0.074*** | 0.090*** | 0.058*** | 0.077*** |
| Public services | 0.161*** | 0.106*** | 0.139*** | 0.188*** | 0.080*** | 0.110*** | 0.127*** | 0.092*** | 0.164*** | 0.181*** | 0.093*** | 0.097*** | 0.155*** | 0.209*** |

*** Rejection of forecast equivalence at the 99 per cent level.
** Rejection of forecast equivalence at the 95 per cent level.
* Rejection of forecast equivalence at the 90 per cent level.

Table 5.A2 – Shift-share regression parameters for the competitive effect variables: the case of East Germany

| Sector | 93–95 | 94–96 | 95–97 | 96–98 | 97–99 | 98–00 | 99–01 | 00–02 |
|---|---|---|---|---|---|---|---|---|
| Primary sector | 0.077*** | 0.097*** | 0.073*** | 0.056*** | 0.056*** | 0.054*** | 0.011 | 0.035*** |
| Industry goods | 0.150*** | 0.103*** | 0.096*** | 0.135*** | 0.135*** | 0.114*** | 0.157*** | 0.139*** |
| Consumer goods | 0.008 | 0.002 | 0.011 | –0.011 | –0.011 | 0.035** | 0.040*** | 0.035** |
| Food manufacturing | 0.035** | 0.017 | 0.009 | 0.009 | 0.009 | 0.013 | 0.035*** | 0.015 |
| Construction | 0.151*** | 0.144*** | 0.187*** | 0.210*** | 0.210*** | 0.158*** | 0.172*** | 0.076*** |
| Distributive services | 0.181*** | 0.211*** | 0.123*** | 0.139*** | 0.139*** | 0.115*** | 0.191*** | 0.195*** |
| Financial services | 0.043*** | 0.089*** | 0.091*** | 0.101*** | 0.101*** | 0.126*** | 0.176*** | 0.166*** |
| Household services | 0.004 | –0.027 | 0.055** | –0.002 | –0.002 | 0.140*** | 0.098*** | 0.086*** |
| Public services | 0.208*** | 0.175*** | 0.306*** | 0.288*** | 0.288*** | 0.267*** | 0.302*** | 0.275*** |

*** Rejection of forecast equivalence at the 99 per cent level.
** Rejection of forecast equivalence at the 95 per cent level.
* Rejection of forecast equivalence at the 90 per cent level.

## Annex 5.B Details of Model Experiments

The NN models used in the present chapter were computed using the network parameters shown in the table below. In addition, the following parameters were used: LR: 0.9; momentum: 1; input noise: 0.

Table 5.B1 – Parameter values of the NN models adopted; the case of West Germany

| Models | Inputs | IU | HU | Epochs |
|---|---|---|---|---|
| | *NN Models* | | | |
| Model B | Employment (GR), time (periodic) | 10 | 5(1$^{st}$L), 5(2$^{nd}$L) | 650 |
| Model BD | Employment (GR), time (periodic), district type (ordinal) | 11 | 10 | 300 |
| Model BW | Employment (GR), time (periodic), wage (GR) | 11 | 5(1$^{st}$L), 5(2$^{nd}$L) | 1600 |
| | *NN-SS Models* | | | |
| Model BSS | Employment (GR), time (periodic), SSA regional component | 19 | 15 | 100 |
| Model BSSN | Employment (GR), time (periodic), SSA spatial regional component | 19 | 5 | 400 |
| Model BSSR | Employment (GR), time (periodic), SSA modified competitive effect | 19 | 5 | 900 |

*Notes:* IU = input units; HU = hidden units; GR = growth rates; 1$^{st}$L = first hidden layer; 2$^{nd}$L = second hidden layer. All models have only 1 output unit; the activation function is always a sigmoid.

Table 5.B2 – Parameter values of the NN models adopted; the case of East Germany

| Models | Inputs | IU | HU | Epochs |
|---|---|---|---|---|
| | *NN Models* | | | |
| Model B | Employment (GR), time (periodic) | 10 | 5(1$^{st}$L), 5(2$^{nd}$L) | 900 |
| Model BD | Employment (GR), time (periodic), district type (ordinal) | 11 | 15 | 1100 |
| Model BW | Employment (GR), time (periodic), wage (GR) | 11 | 5 | 1000 |
| | *NN-SS Models* | | | |
| Model BSS | Employment (GR), time (periodic), SSA regional component | 19 | 5(1$^{st}$L), 5(2$^{nd}$L) | 200 |
| Model BSSN | Employment (GR), time (periodic), SSA spatial regional component | 19 | 5(1$^{st}$L), 5(2$^{nd}$L) | 300 |
| Model BSSR | Employment (GR), time (periodic), SSA modified competitive effect | 19 | 5(1$^{st}$L), 5(2$^{nd}$L) | 300 |

*Notes:* IU = input units; HU = hidden units; GR = growth rates; 1$^{st}$L = first hidden layer; 2$^{nd}$L = second hidden layer. All models have only 1 output unit; the activation function is always a sigmoid.

Chapter 6

# Sensitivity Analysis of Neural Network Models for Regional Employment Forecasting

## 6.1 Introduction[37]

In the preceding chapters we presented methodological and empirical approaches aimed at the development of neural forecasting models, with the particular objective of estimating short-term regional variations in German employment. On the one hand, we have shown that the inclusion of proper economic variables improves the forecasting power of the NN models, in particular with the implementation of the shift-share-analysis-enhanced 'NN-SS' models (see Chapter 5). On the other hand, the experiments on 'NNGA' models carried out in Chapter 4 showed that the genetic algorithm-enhancement of the NN models did not provide added statistical reliability, which prompts us to carry out a thorough investigation of the sensitivity of our models to varying parameters of the NN algorithm. This analysis appears to be particularly useful and necessary, since NNs have been shown to be sensitive to the choice of the parameters implemented within the algorithms used (see, for example, Hagan et al. 1996).

Therefore, the objective of the present chapter is to investigate the sensitivity of the NN models to different model specifications and to changing parameter values, with the final aim being to maximize the forecasting potential of the models under consideration. The statistical performance of the NN models is evaluated by means of *ex post* forecasts and appropriate statistical indicators, in line with the analyses of the preceding chapters.

The present chapter is organized as follows. Section 6.2 presents the sensitivity analysis that was carried out. We test different combinations of learning parameters and internal functional forms. We then review the changes in the performance of the NN models, after the findings of the sensitivity analysis are implemented. Subsequently, Section 6.3 provides conclusions and future research directions in the light of both the experiments presented in this chapter and, more generally, of Part B of the present study.

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[37] The present chapter is based on Patuelli et al. (2006c).

## 6.2 Sensitivity Analysis

### *6.2.1 Preface*

This section is concerned with describing – and testing – the main parameters and functions that are used internally in NNs. We do not repeat here a general description of the NN methodology, nor the specification details of the NN models used. This information can be traced, with regard to the NN paradigm and the basic models used, in Chapter 4, and, with regard to the NN-SS models, in Chapter 5. We focus on the discussion of NN setting parameters. It is relevant to deal with concepts such as learning rate or activation function, since they greatly influence the performance of NN models (see, for example, Hagan et al. 1996). In our case, the objective is to find the optimal combination of parameters in order to increase the forecasting potential of our models.

Sensitivity analyses of NN learning parameters or activation functions have been carried out previously. Srinivasan et al. (1994) experimented with different activation functions (symmetrical and non-symmetrical) and learning parameters, in the context of electrical load forecasting. However, no detailed results which emerge from their analysis are presented. Gorr et al. (1994) used a grid search procedure for choosing learning rate values (jointly with the number of iterations), but did not test the suitability of alternative activation functions; neither do Sharda and Patil (1992). Generally, more attention is focused on the choice of NN learning parameters, rather than on the choice of the activation function.

The sensitivity analysis illustrated in the following sections aims to evaluate the use both of different combinations of learning parameters (Section 6.2.2) and of varying activation functions (Section 6.2.3), so as to provide a more complete overview of NN setting issues. Model B, first presented in Chapter 4 of this study, is used hereafter as a baseline model for the analysis.

### *6.2.2 Learning Rate and Momentum*

#### 6.2.2.1 Description

The backpropagation algorithm (BPA) (see Section 4.2.1) can be seen as a gradient steepest descent method, an optimization method based on the search for local minima of functions (Zhang et al. 1998; see also Weisstein 2006). In order to use a gradient descent algorithm, a step size – that is, a scaling parameter – is necessary. In NNs, this is called the 'learning rate' (LR), which, together with the 'momentum' parameter, is crucial in determining the NN learning curve in terms of potential, stability, and computing time. Different combinations of the values given to the two parameters can generate significantly different results. Simply put, an NN's LR determines the magnitude of the correction that is applied, during the learning phase, when adjusting the weights of the computational units; and the momentum defines how long the corrections applied will last; that is, for how many iterations they will survive.

Learning rates take positive values, which range from 0 to 1. On the one hand, large values imply that the NN learns quickly. On the other hand, values that are too large may cause the NN to be unstable, by nullifying the learning carried out at previous iterations. Generally, unstable behaviour can be avoided for LR values smaller than 0.25. The drawback of using such small LR values is the longer computing time required for training.

The tricky nature of the LR parameter calls for empirical testing. In fact, the BPA is known to suffer from slow convergence, inefficiency and lack of robustness (Zhang et al. 1998). Furthermore, it can be very sensitive to the choice of the LR. Ideally, one should experiment with different values of LR, in order to find the most suitable one for the data at hand. Amongst others, Gorr et al. (1994) propose using a search grid in order to test different LR values. Although automated optimization procedures can be used in this regard (we refer, for example, to the discussion of adaptive LR in Section 6.2.2.3), a more conservative approach may be to manually adjust the LR values, starting from low values, which can be increased if the learning process is slow.

The performance of the BPA can be improved by including an additional parameter, viz. momentum. The momentum parameter determines the lifespan of the corrections made to the NN weights during the training process. Its aim is to allow for greater values of the LR, therefore speeding up convergence, while reducing the fluctuations of the BPA. The momentum parameter takes values greater than (or equal to) 0, but smaller than 1.[38] On the one hand, momentum values that are close to 1 will increase the influence that previous corrections to the weights have on the current corrections. On the other hand, an NN with a momentum close to 0 will mainly (or 'only', in the case of a value of 0) rely on the current corrective term, at each stage of the training. For example, a momentum value set at 0.5 means that 50 per cent of the weight adjustment, at each stage, will be on the basis of the current error, while the remaining 50 per cent will be due to the adjustment applied in the previous iteration. As a result, any weight adjustment will have a continuing effect, following an exponential decay.

The 'smoothing out' effect of this process is the main benefit of the momentum parameter, since it prevents outliers from forcing learning in an undesirable direction. By using momentum, weight changes in the training of the NN are channelled in the same direction as the preceding iteration. This is particularly true when higher momentum values are used. In such a case, high momentum tends to accelerate convergence, giving it, as the word suggests, 'momentum' (Hagan et al. 1996). Alternatively, lower momentum values may be suitable for

[38] The momentum parameter cannot assume the value of exactly 1. The reason for this *caveat* is easily shown by an example. If the momentum was set at 1, 100 per cent of the previous error adjustment would be used at each stage of the training. Because no previous adjustments are present at the very first training iteration, the first weight adjustment would be 0. But the same adjustment (0) would be repeated at each iteration, since the current error is not considered, resulting in no training whatsoever.

data which are more regular or smoother, or when the functional relationships to be learned are relatively simple. In general, experimenting with different values of momentum might be necessary, as in the case of LR, in order to find the appropriate value for the problem concerned, unless more sophisticated methods are employed in order to determine the right momentum value (see, for example, Yu et al. 1995). These methods can also be linked to the use of adaptive LRs.

#### 6.2.2.2 Sensitivity analysis

When testing for values of LR and momentum, an exhaustive search of the (0, 1) interval for both parameters, including all their possible combinations, would be rather time-consuming. Sharda and Patil (1992) suggest a simpler strategy, based on the use of three values (0.1, 0.5, 0.9) for each parameter. The resulting nine combinations can be tested separately, with no excessive computation, while covering most of the spectrum of possible values.

The same approach was followed in our experiments. The sensitivity of the NNs to different LRs and momentums was tested for the above nine combinations of values. Model B (see Chapter 4) was chosen as a basic model for testing, because of its simple application and the stable performance previously observed. For all NN models, the ideal training time was identified by means of early stopping (see Section 4.2.1). Table 6.1 shows the results obtained, in our preliminary analysis, for 2004. Statistical errors may be computed as MSE and MAPE.

In Table 6.1, the stochastic variability that is inherent to NNs generates different degrees of statistical performance for the West and East German NN models, and for the two error indicators used. However, upper-right combinations of LR and momentum (0.9, 0.1) seem to provide a consistently low statistical error (second-best in all cases).

Our finding is that a high LR, matched with a low momentum, leads to better performance for the case of regional employment forecasts. A NN model employing such parameters is expected to show greater weight corrections – and a potentially faster convergence – between iterations. This higher volatility of the NN would be offset by the low momentum, due to which the corrections computed would not have a lasting effect through the course of the iterations. The utility of a low momentum is greater when the NN meets outliers or falls into local minima.

Table 6.1 – Sensitivity analysis for learning rate and momentum: Model B, West and East Germany, year 2004

| West Germany | | | | | | | |
|---|---|---|---|---|---|---|---|
| MSE | | | | MAPE | | | |
| Learning rate | 0.1 | 0.5 | 0.9 | Learning rate | 0.1 | 0.5 | 0.9 |
| Momentum | | | | Momentum | | | |
| 0.1 | 2347490 (7) | 2079652 (1) | 2080340 (2) | 0.1 | 1.9126 (7) | 1.8249 (4) | 1.8102 (2) |
| 0.5 | 2138962 (5) | 2111147 (4) | 2095362 (3) | 0.5 | 1.8250 (5) | 1.8145 (3) | 1.7825 (1) |
| 0.9 | 2416247 (8) | 4227822 (9) | 2216129 (6) | 0.9 | 1.9118 (6) | 2.4695 (9) | 1.9573 (8) |
| *East Germany* | | | | | | | |
| MSE | | | | MAPE | | | |
| Learning rate | 0.1 | 0.5 | 0.9 | Learning rate | 0.1 | 0.5 | 0.9 |
| Momentum | | | | Momentum | | | |
| 0.1 | 1156742 (9) | 1107711 (5) | 1099063 (2) | 0.1 | 2.6847 (8) | 2.6600 (6) | 2.6519 (2) |
| 0.5 | 1124816 (7) | 1096330 (1) | 1102930 (4) | 0.5 | 2.6703 (7) | 2.6582 (5) | 2.6557 (3) |
| 0.9 | 1142501 (8) | 1111843 (6) | 1102913 (3) | 0.9 | 2.7043 (9) | 2.6570 (4) | 2.6470 (1) |

*Note:* The ranking of the NN models is shown in brackets.

Our results can be compared with the ones by Tang et al. (1991), who found that high LRs are adequate for use with less complex data, while lower values (and higher momentum) are appropriate for more complex data. Whether or not our findings accord with these considerations relies on whether our data should be considered 'complex'. Generally, Tang and Fishwick (1993) state that, for each series of data, a set of NN parameters can be found which performs significantly better than the rest. This consideration stresses once again the crucial role played by the learning parameters in the performance of NNs. The inconsistent results in the literature regarding the search for ideal values of the learning parameters (see, for example, Chakraborty et al. 1992; Sharda and Patil 1992) are blamed by Zhang et al. (1998) on the (minimum) search inefficiencies of the BPA.

#### 6.2.2.3 Adaptive learning rate

We pointed out in Section 4.2.1 that the BPA has flaws, that is, it can have slow convergence (if any) (Kuan and Hornik 1991) and, most importantly, can get trapped in local minima. Several techniques have been developed in order to solve the problem of slow convergence. In addition to this, the BPA is also sensitive to the initial conditions chosen and can show oscillations in the computational units' output (Sarkar 1995). While the momentum parameter can be seen as – and mostly is – a regulator of the oscillations and of the local minima problems (and involving the LR parameter), its value is chosen a priori, and is therefore not tied to the actual progress of the NN iterations.

In order to overcome these limitations, the use of the adaptive learning rate (ALR) has been proposed. In the 'bold driver' method (Vogl et al. 1988), the LR – as defined in Section 6.2.2.1 – is augmented by a factor $\rho$ when the error computed at iteration $i$ is greater than the one previously found at iteration $i - 1$. Otherwise, the LR is diminished by a factor $\sigma$ when the error decreases.[39] A further step in the application of ALR techniques is the implementation of NNs that have *multiple* ALRs. In the 'SAB' method (self-adaptive backpropagation), each weight can have its own LR, which is computed as the partial derivative of the learning error estimator. The method is based on the idea that the same LR may not be appropriate for all the weights of the NN. Moreover, in the 'SuperSAB' method, it is suggested that the $\rho$ and $\sigma$ factors that modify the multiple LRs should be also different in value, and that the decrease in the LR caused by the $\sigma$ factor should be greater (see Jacobs 1988; Tollenaere 1990). Tollenaere concludes that the SuperSAB algorithm considerably speeds up learning.

The ALR approaches listed above provide a somehow faster learning for NNs. On the other hand, Park et al. (2000) advise that these methods can not completely avoid the

[39] The momentum parameter can also be modified: that is, it can be forced to 0 when the error increases and brought back to its value in the opposite case (Hagan et al. 1996). In addition, Yu et al. (1995) propose a dynamically adaptive method for the optimization of the LR, which employs derivative information. Moreover, Plagianakos (1999) suggests an acceptability criterion for the modification of the LR, based on the previous $M$ computed errors. This approach seems to speed up the convergence of the NNs and to make them more robust against oscillations.

algorithm from stalling in slow convergence plateaus. This is because this class of methods uses the same search direction that is used in the conventional BPA. Consequently, we want to test the statistical performance of the ALR algorithm, in comparison with the NNs using a fixed LR. We consider two NN models, based on Model B, for 2004: the first model employs an LR of 0.9, while the second model uses the ALR algorithm. Both models have a momentum of 0.1, as found in Section 6.2.2.2.

With regard to the implementation of the ALR, this is implemented as follows:

- The LR is modified at this training iteration. The extent of its recalculation is based on the error computed at the previous iteration.
- If the error decreases as a result of the last iteration, the LR drops in proportion to the error decrease. If the error increases, the LR also increases proportionally.
- The training of the NN models ends once the stopping condition is satisfied.

Our first question is whether the ALR algorithm provides, in our case, a faster convergence, which requires us to observe the evolution of the training error. When plotting the error against the number of training epochs, the NNs with an ALR seem to reach a stable training error (converge) faster than the ones with a fixed LR. This 'informal' result is consistent with the literature. The subsequent question is, therefore, whether the algorithm can improve the statistical performance of the models. Table 6.2 reports the error of the conventional fixed LR models, as well as of the ALR models.

Table 6.2 – Sensitivity analysis for the adaptive learning rate: Model B, West and East Germany, year 2004

| | West Germany | | East Germany | |
|---|---|---|---|---|
| | MSE | MAPE | MSE | MAPE |
| Fixed LR (0.9) | 2080340 (2) | 1.8102 (1) | 1124118 (2) | 2.6624 (2) |
| Adaptive LR | 2078876 (1) | 1.8232 (2) | 1102830 (1) | 2.6494 (1) |

Note: The ranking of the NN models is shown between brackets.

Table 6.2 shows a rather similar statistical performance for the fixed and adaptive LR models compared. This result is found for both data sets – West and East German – and the differences in the statistical error can be considered of limited relevance when compared with the variability shown in the LR/momentum and activation function analyses.

On the basis of the analyses carried out in this section, we can conclude that, in our forecasting experiments, ALR did not provide relevant approximation advantages, but only a faster convergence of the algorithm, consistent with the literature. It should be pointed out that such a result may be greatly relevant when computational issues arise.

### 6.2.3 Activation Function

#### 6.2.3.1 Description

The greater benefit of using NNs is their nonlinear behaviour, which allows them to approximate nearly every type of function. The nonlinearity is introduced in NNs by means of the activation function. Ideally, any differentiable function can be used as an activation function. Practically, only a few nonlinear functions are usually considered for NNs; that is:

- sigmoid (logistic) functions;
- augmented ratio functions;
- Gaussian functions; and
- hyperbolic (tangent) functions.

As a special case, we also consider:

- linear functions,

whose use is sometimes suggested in NNs (see below). The sigmoid function is, in fact, the most widely used activation function. It is a smooth function, which returns nearly proportional outputs for intermediate values, while smoothing out values at the extremes of the spectrum. The augmented ratio function and the hyperbolic function are mostly similar to the sigmoid function, but, in the augmented ratio function, small values are rounded to 0, while the hyperbolic function is negatively oriented, tending to force extreme values of the distribution to either 1 or –1. The Gaussian function forces small values to 1, and extreme values to 0. The augmented ratio function looks like an inverted Gaussian function. Differently from the functions described above, a linear function proportionally rescales the values within the (0, 1) interval.

While any of the described functions can be implemented in NNs, there are no clear rules on how to select the most appropriate activation function. Some heuristic rules have been proposed in the literature in order to select a suitable function, such as in Klimasauskas (1991). The author suggests the use of sigmoid functions for classification problems (for example, with binary outputs) and of hyperbolic functions for forecasting problems; that is, when learning about deviations from the average is involved. A different function can ideally be used for each computational unit in the NN (for example, Wong, 1991, uses both linear and sigmoid functions). While the usual NN models found in the literature employ the same activation function for all units, examples can also be found of NNs in which a different function is selected for the output units. Sigmoid functions are mostly used in the input and hidden layers, while there is no agreement on what activation function should be employed for the output units. In this latter regard, Zhang et al. (1998) and Rumelhart et al. (1995)

suggest the use of linear functions. Zhang et al. cite a set of studies following the same procedure (see, for example, Srinivasan et al. 1994; Kuan and Liu 1995), which, according to the authors, provide no clear results on whether linear or nonlinear activation functions should be preferred for the implementation in the output units.

#### 6.2.3.2 Sensitivity analysis

A sensitivity analysis of the performance of NNs with different activation functions would ideally require a full exploration of the possibilities available, and also of the mixed approaches discussed above. In the present study, we are limited to testing NNs employing the same activation function for all layers of units.[40]

The activation functions that are tested here are: (1) sigmoid; (2) augmented ratio; (3) Gaussian; (4) hyperbolic; and (5) linear, as outlined in the previous section. While we pointed out above that the linear function is normally used only in the output layer, our experiments aim to test its implementation in a whole NN. All models are based on Model B and carried out for the year 2004. Table 6.3 presents the results obtained for both the West and the East German models. The statistical error is computed as MSE and MAPE.

Table 6.3 – Sensitivity analysis for activation functions: Model B, West and East Germany, year 2004

| West Germany | Sigmoid | Aug. Ratio | Gaussian | Hyperbolic | Linear |
|---|---|---|---|---|---|
| MSE | 2080340 (2) | 2597494 (5) | 2493604 (4) | 2166504 (3) | 2038430 (1) |
| MAPE | 1.8102 (3) | 1.9628 (5) | 1.9018 (4) | 1.7984 (2) | 1.7927 (1) |
| **East Germany** | **Sigmoid** | **Aug. Ratio** | **Gaussian** | **Hyperbolic** | **Linear** |
| MSE | 1124118 (2) | 1121622 (1) | 1224547 (3) | 1483758 (4) | 1569152 (5) |
| MAPE | 2.6624 (2) | 2.7024 (3) | 2.6540 (1) | 2.7754 (4) | 2.8157 (5) |

Note: The ranking of the NN models is shown between brackets.

The statistical results shown in Table 6.3 generally confirm the results found in the literature. The NN models employing a sigmoid activation function show a stable and good statistical performance, for both West and East Germany. This finding is in line with the general consensus on the use of the sigmoid function, and confirms our initial choice of activation function (see Chapter 4). However, more in-depth explorations should be carried out in the framework of alternative multi-function NN specifications and, in particular, with regard to the relative performance of the hyperbolic function. It should be noted that the linear activation function provides the best statistical result for West Germany, while its results for East Germany are not satisfactory. This finding suggests that the West German data have a tendency towards linearity. The full reasons for the differences in the performance of the linear function should be further investigated, in order to better grasp the relationship between data complexity and the ideal (linear or nonlinear) approximation function to use. As for our

[40] The software used for our experiments does not allow multiple simultaneous functions to be selected.

case study, as linearity tests were not carried out here, it might be suggested, on the basis of our result, that ideally experiments should be made with both the sigmoid and the linear function.

The statistical results of the sensitivity analysis carried out above call for further testing. In particular, we are interested in verifying which changes can be observed in the performance of the models employed in Chapter 5 once the new NN settings are in place. Therefore, the next section presents a numerical comparison of NN and NN-SS models developed before and after the sensitivity analysis.

### *6.2.4 Evaluation of the Sensitivity Analysis Empirical Findings*

In light of the findings of the sensitivity analysis carried out in the preceding sections, we want to evaluate how the use of a different NN specification influences the results obtained in Chapter 5. As a preliminary comparison, Table 6.4 presents the statistical results computed, for all models, in 2004 (that is, the 2002–04 forecasting period). The word 'Old' identifies the NN models carried out before the sensitivity analysis, where the LR is 1, and the momentum is 0.9. The word 'New' identifies the NN models carried out according to the findings emerging from the sensitivity analysis, where the LR is 0.9, and the momentum is 0.1. All models employ sigmoid (logistic) activation functions.

The statistical performance of the models, shown in Table 6.4, suggests the following results. Concerning the West German NN models: (a) amongst the 'New' models, carried out after the sensitivity analysis, Models B and BD seem to slightly improve their performance, while the other models do not show similar or consistent results; (b) in terms of the ranking of the models, Model B moves from fourth to first. On the other hand, it should be noted that the newly obtained Model B does not outperform the previous best results (pre-sensitivity analysis), which were obtained by Model BSSN.

Concerning the East German models, our results are less clear. It appears that the new learning parameters implemented did not bring a uniformly better performance for any NN model.

In summary, the statistical results of Table 6.4 suggest that more investigation is needed with regard to the influence of the new set of parameters on our NN models. In particular, attention should be focused on whether the models employ more or less rich data and specifications. It should also be pointed out that the findings presented above are related to a sensitivity analysis carried out for Model B only. It could be argued that, in order to improve the performance of alternative models, such as Model BSS (which exploits a richer data set), additional sensitivity analyses should be carried out, which might lead to different conclusions. The extension of the sensitivity analysis to the entire time spectrum considered in Chapters 4 and 5, though time-consuming, is also desirable, in order to strengthen the reliability of our results.

Table 6.4 – Comparison of statistical error of pre- and post-sensitivity analysis NN models, West and East Germany, year 2004

| West Germany | MSE | | MAPE | | East Germany | MSE | | MAPE | |
|---|---|---|---|---|---|---|---|---|---|
| | Old | New | Old | New | | Old | New | Old | New |
| *NN Models* | | | | | | | | | |
| Model B | 2213570 (4) | <u>*2080340 (1)*</u> | 1.8947 (4) | <u>*1.8102 (1)*</u> | Model B | 1081583 (2) | 1099063 (2) | 2.6044 (2) | 2.6519 (4) |
| Model BD | 2612326 (5) | 2696335 (4) | 1.9818 (5) | <u>*1.9386 (4)*</u> | Model BD | 1632222 (5) | 2130699 (6) | 2.7859 (9) | <u>*2.5356 (1)*</u> |
| Model BW | 1797892 (1) | 2274200 (3) | 1.7910 (2) | 1.8587 (2) | Model BW | 1702475 (6) | 1862681 (5) | 2.6605 (6) | 2.9366 (6) |
| *NN-SS Models* | | | | | | | | | |
| Model BSS | 2194846 (3) | 3744141 (5) | 1.8677 (3) | 2.1739 (5) | Model BSS | 1171623 (3) | <u>*1142492 (3)*</u> | 2.5831 (1) | 2.6026 (2) |
| Model BSSN | 2001280 (2) | 2250801 (2) | 1.7842 (1) | 1.8714 (3) | Model BSSN | 1218817 (4) | 1584560 (4) | 2.6894 (5) | 2.8061 (5) |
| Model BSSR | 4802468 (6) | 6641354 (6) | 2.3349 (6) | 2.5849 (6) | Model BSSR | 1067005 (1) | 1078266 (1) | 2.6312 (3) | <u>*2.6261 (3)*</u> |

*Note:* Models with improved performance are in italics and underlined. The ranking of the NN models is shown between brackets.

## 6.3 Conclusions

In the present chapter, we extended the experiments on neural forecasting of regional employment, previously carried out in Chapters 4 and 5. We carried out a sensitivity analysis, investigating the effect of varying learning parameters and functional forms on the NN models' forecasts. The performance of our NN and NN-SS models (see Chapter 5) was then re-evaluated in the light of the sensitivity analysis findings.

Our analyses showed that, in the specific case of Model B, a particular combination of learning parameters (high LR values and low momentum) tends to improve the forecasts of the model. We also found that the sigmoid (logistic) function used is appropriate for the forecasting problem concerned, even if a linear activation function seems to be more suitable for the case of West Germany (in 2004). This result calls for much needed testing on the linearity of the employment data. In our final undertaking, a comparative analysis of the findings of the sensitivity analysis showed that a statistical performance improvement is indeed achieved to some degree, while more sensitivity tests, concerning the type of data used in NN models, should be undertaken.

The analyses illustrated in the present and preceding chapters can be expanded by carrying out further research in several directions. From an empirical viewpoint, a longer (and more up-to-date) data span (for example, comprising data for 2005 and 2006) would allow us to increase the years of testing of the NNs and, consequently, the reliability of the average (pooled) statistical results. The development of further NN models, utilizing new variables (such as unemployment or migration) could also be desirable, as well as a comparison of the accuracy of forecasts for the $(t + 1)$ and $(t + 2)$ periods. Finally, the sensitivity analysis carried out in the present chapter would benefit from being extended to more out-of-sample testing periods (as seen in Section 5.3), as well as to more model specifications.

From a methodological viewpoint, it might be desirable to carry out more elaborate NN models, such as time-delay NNs (Waibel et al. 1989), or multi-function NNs. In particular, the testing of linear functions integrated within NNs should be a main objective. Fulfilling such a task would make it possible to combine the benefits of both families of methods in a more complete approach to labour market analysis. This could, therefore, be exploited in the NN forecasting.

A further conclusion, pertaining to the first research objective of the present study, should be made. The NN-SS models developed in Chapter 5 have highlighted the importance of understanding the 'complexity' involved in regional forecasting. The introduction of SSA allowed us to take a first step in this direction. Further, a more in-depth analysis of the spatial interactions among districts might help to better understand the regional phenomena. While district (*kreise*) interactions are discussed in Part C of this study with regard to commuting, the incorporation, in Model BSSN, of information on the (employment) performance of the 'neighbours' was a preliminary attempt at modelling the interactions of small open systems such as the German *kreise* districts. A further step in this direction is exploiting the potential of spatial econometric methods for the analysis of developing spatial/regional variables. In particular, the application of 'spatial filtering' methods (Griffith 2003) will be examined. The next chapter is devoted to this task.

Chapter 7

# Spatial Filtering and Eigenvector Stability: The Space-Time Structure of German Unemployment Data

## 7.1 Introduction[41]

The preceding chapters (4–6) provided an assessment of the suitability of neural network models for forecasting regional employment variations. In this regard, one of the main conclusions reached was that it is desirable to include, in our modelling efforts, additional aspects, pertaining to the relevance of space/geography and regional interaction. In order to widen the analyses concerning our first research question – concerning the statistical analysis of key regional labour market variables – the present chapter focuses on the spatial aspect (regional interactions are treated in-depth in Chapters 8 and 9). We propose the use of spatial econometric techniques: namely, spatial filtering, in order to capture spatial (and temporal) variations in regional unemployment patterns.

Spatial matters are of critical importance when considering socio-economic (and other) phenomena (see, for example, Bockstael 1996; Weinhold 2002), partly because of their implications for policy making (Lacombe 2004). To account for the presence of spatial structures that influence (positively or negatively) observable economic entities, such as unemployment or trade, requires a rigorous and systematic assessment of their impact and extent. The concept of 'spatial autocorrelation' (SAC) (Cliff and Ord 1981) is commonly used to represent the correlation – in space – between the values of a single georeferenced variable. Phenomena of SAC are often observed in socio-economic data, particularly for the case of positive SAC; that is, a positive association between georeferenced values. The phenomenon of negative SAC is, in fact, more limited (see, for example, Griffith 2006).

The introduction of the SAC concept was a departure from the classical assumption of independence of the observations constituting a single variable. SAC also complements the concept of temporal autocorrelation, which has been extensively studied and dealt with in

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[41] The present chapter is based on Patuelli et al. (2006d,e).

time-series econometrics. SAC measures, such as Moran's *I* or Geary's ratio, are used to quantify the nature and degree of the spatial correlation within a variable, or to test the assumption of independence or randomness.

From a statistical analysis viewpoint, spatial correlation patterns are problematic, since they make standard statistics, such as correlation coefficients or ordinary least squares (OLS) estimates, potentially inappropriate. In particular, spatially correlated values of a variable make the estimator of the error variance – in an OLS framework – biased. This is the case when we analyse regional labour market variables such as unemployment. The persistent differentials of regional unemployment observed in Germany (see for example, Taylor and Bradley 1997; Bayer and Juessen 2007) may be caused by spatial effects that concern the variable itself. As a result, a linear, non-spatial model, such as OLS, that studies German unemployment (as a dependent variable) would have biased regression parameters. In spatial econometrics, 'spatial lag' models are used to accommodate this problem (we employ such a modelling framework later in the chapter for purposes of comparison). If spatial effects were to be related to significant unobserved variables – thus causing SAC in the model's error term – the test statistics of the coefficients would be invalid. In this case, a 'spatial error' model can be employed. A more general spatial econometric specification is the Cliff-Ord-type model, presented in Equation (2.5), Chapter 2 (for a taxonomy of spatial econometric models, see, for example, Anselin 1988).

This chapter aims to provide an assessment of how important spatial effects are in explaining unemployment levels in Germany, and, in particular, to show that these (or, more precisely, a subset of these) patterns are consistent over time. The definition of stable and recognizable spatial patterns enables systematic differences in regional unemployment to be observed. Such findings can have implications for policy evaluation and strategic planning. As an alternative to conventional spatial econometric modelling, this chapter presents analyses carried out by means of a semi-parametric 'spatial filtering' technique (described in Griffith 2003), which is based on the decomposition of geographic weights matrices. In our analysis, these matrices are defined, for 439 German districts (*kreise*), according to both topological and distance-based criteria – such as shared boundaries or centroid distance – and economic flows. In this regard, journey-to-work flows are employed as a proxy for economic linkages.

At present, only a limited number of applications of the spatial filtering techniques to regional labour markets can be found. Badinger and Url (2002) apply spatial filtering to the study of Austrian regional unemployment. Kosfeld and Dreger (2006) and Kosfeld et al. (2006a) investigate – by means of the same spatial filtering method proposed here (Griffith 2000) – the spatial patterns of German regional labour markets, for periods ranging from 1992 to 2004. However, their approach involves computing spatial filters for each year within the framework of a spatial seemingly unrelated regression (SUR) model. Our approach differs from theirs in that we focus on the search for a set of spatial filters that are significant and consistent over time, and can therefore be employed for the entire time period considered (that is, 1996–2002). Moreover, we employ data at a finer level of disaggregation (439 districts versus 180 regions), which enables a more detailed analysis of the underlying spatial patterns.

The remainder of the chapter is structured as follows. Section 7.2 provides a brief overview of the spatial filtering method, as well as a discussion of the possible coding schemes for geographic weights matrices. Section 7.3 illustrates the spatial filtering analysis of unemployment rates. Section 7.4 presents additional results based on the introduction of socio-economic covariates in the spatial filtering framework. Finally, Section 7.5 offers some summary information and concluding remarks, which also concern the present research objective.

## 7.2 Spatial Filtering: An Overview

### *7.2.1 Preface*

As outlined in the preceding section, a wide array of methods, as well as several dedicated 'spatial' econometric procedures (see, for example, Anselin et al. 2004) for the statistical analysis of georeferenced data are available in the literature. These techniques are useful when analysing regional unemployment data, as in our case study, and, particularly, when the final aim is to develop forecasting models for some regional scale. Of the conventional spatial econometric methods, spatial autoregression (see, amongst others, Anselin 1988; Griffith 1988) is a powerful method commonly employed. In order to take spatial effects into account, spatial autoregressive techniques use geographic weights matrices that provide measures of the spatial linkages (dependence) between the values of georeferenced variables. Because of the aforementioned regression bias issues, statistical efficiency concerns and the normality assumption, ordinary least squares (OLS) should not be carried out with such data. Furthermore, maximum likelihood (ML) or generalized method of moments (GMM) estimators of spatial regression models (such as those by Kelejian and Prucha 1998, 1999) are based on restrictive assumptions.

An alternative approach to spatial autoregression is the use of spatial filtering techniques, such as the ones described in Griffith (1981), Haining (1991), Getis and Griffith (2002), and Tiefelsdorf and Griffith (2007). The advantage of these filtering procedures is that the variables studied (which, initially, are spatially correlated) are split into spatial and non-spatial components, which can be employed in an OLS modelling framework. Filtering out spatially autocorrelated patterns also makes it possible to reduce the stochastic noise in the residuals of conventional statistical methods such as OLS. This conversion procedure requires the computation of 'spatial filters'. The approach developed by Griffith (1996, 2000) is briefly described here. This approach is preferred in our case study to the one by Getis (1990, 1995) which requires variables with a natural origin. This constraint would not allow us to analyse patterns in employment growth rates, which will be the subject of future research.

The spatial filtering technique introduced by Griffith is based on the computational formula of Moran's *I* (MI) statistic. This coefficient is the most common, and oldest, indicator of SAC. It is calculated as:

$$I = \frac{N \sum_i \sum_j w_{i,j}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_i \sum_j w_{i,j}) \sum_i (x_i - \bar{x})^2}, \tag{7.1}$$

where $N$ is the number of cases; $x_i$ is the value of the variable $X$ at location $i$; and $w_{i,j}$ is the cell ($i$, $j$) value of the geographic weights matrix $\mathbf{W}$ (see Section 7.2.2). Positive SAC $(I > -(N-1)^{-1})$ implies that geographical proximity tends to produce similar values of the variable examined. This is a phenomenon that is often observed in reality, especially in economics. On the other hand, negative SAC $(I < -(N-1)^{-1})$ is a much rarer phenomenon.

The spatial filtering methodology employed here exploits eigenvector decomposition techniques, which extract *orthogonal* and *uncorrelated* numerical components from an $N$ x $N$ matrix (Tiefelsdorf and Boots 1995). In this regard, this method is often compared to principal components analysis (PCA), since both methodologies generate orthogonal and uncorrelated new 'variables' that can be employed in regression analyses. However, the components derived in PCA have an economic interpretation, since the PCA eigenvectors are used to construct linear combinations of attribute variables. On the other hand, a spatial filter is a linear combination of the eigenvectors themselves, and as such it should be regarded mostly as a pattern of independent spatial dimensions. Accordingly, the single eigenvectors can be seen as independent map patterns, and represent the latent SAC of the georeferenced variable concerned, according to the given geographic weights matrix. They also can be interpreted as redundant information due to spatial interdependence, in the framework of standard regression equations.

Formally, these orthogonal components are the computed eigenvectors of the modified geographic weights matrix:

$$(\mathbf{I} - \mathbf{1}\mathbf{1}^{\mathrm{T}}/N)\mathbf{W}(\mathbf{I} - \mathbf{1}\mathbf{1}^{\mathrm{T}}/N), \tag{7.2}$$

where $\mathbf{W}$ is the given geographic weights matrix; $\mathbf{I}$ is an identity matrix of dimension $N$ x $N$; and $\mathbf{1}$ is an $N$ x 1 vector containing 1's. The eigenvectors of the modified matrix are extracted in sequence, so as to maximize the sequential residual MI values. The first computed eigenvector, $E_1$, is, therefore, the one whose numerical values generate the largest MI value amongst all eigenvectors (of the modified matrix). Similarly, the second eigenvector, $E_2$, is the set of numerical values that, again, maximize the MI value, while being uncorrelated with

$E_1$. The eigenvector extraction process continues until *N* eigenvectors have been computed. This is the complete set of all possible (mutually) orthogonal and uncorrelated map patterns (Getis and Griffith 2002). When employed as regressors, these eigenvectors may function as proxies for missing explanatory variables.

However, employing all *N* eigenvectors in a regression framework is not desirable for reasons of model parsimony and statistical significance, and is altogether impossible in a cross-sectional framework, since the number of explanatory variables would be equal to or greater than the number of observations. A smaller set of 'candidate' eigenvectors can then be selected from the *N* eigenvectors, on the basis of their MI values. A pre-specified threshold value can be used in this regard. Since the eigenvectors are both orthogonal and uncorrelated, a stepwise (linear) regression can be used to achieve this end. In this framework, the advantage implied by the orthogonality of the eigenvectors is the absence of partial correlations and, therefore, of multicollinearity issues.

The residuals obtained with the stepwise regression constitute the *spatially filtered* component of the georeferenced variable examined. Each eigenvector selected for inclusion is considered to be part of a 'spatial filter' for the dependent variable. The top two eigenvectors computed ($E_1$ and $E_2$) have a special role, since they often identify map patterns along the cardinal points; that is, major North-South and East-West patterns. Eigenvectors with intermediate values of MI tend to display regional map patterns, whereas eigenvectors with smaller values of MI display local map patterns. A linear combination of the above eigenvectors can be defined as *the* spatial filter for the variable examined.

Also relevant to the use of the eigenvector decomposition process is the choice of the geographic weights matrix to be used, in particular with regard to: (a) the definition of proximity; (b) the variable chosen (if any) to indicate proximity; and (c) the coding scheme employed in the calculation of the matrix. While points (a) and (b) are discussed later in the chapter, the latter point is just briefly addressed in the subsequent section.

### *7.2.2 Coding of Geographic Weights Matrices*

The spatial filters presented in the previous section are computed on the basis of a modified geographic weights matrix. Formally, a geographic weights matrix is a (squared) *N* x *N* matrix containing, most often, binary values (0 and 1). A value of 1 for the generic cell $(i, j)$ implies that the two georeferenced objects (for example, regions) *i* and *j* are neighbours. The opposite applies for the value 0. It is straightforward that the choice of the matrix to be used is critical in defining the set of spatial filters. Many coding techniques for geographic weights matrices can be found in the literature (Tiefelsdorf et al. 1999; Getis and Aldstadt 2004). The main factor that discriminates between the different schemes is the way in which each scheme treats the spatial links between georeferenced objects.

Generally speaking, we can define a *family* of coding schemes based on the following expression (Tiefelsdorf and Griffith 2007, with details in Chun et al. 2005):

$$\mathbf{V}_{[q]} = \frac{N}{\sum_{i=1}^{N} d_i^{q+1}} \cdot \mathbf{D}^q \cdot \mathbf{W}, \tag{7.3}$$

where **W** is a binary geographic weights matrix, and $\mathbf{D}^q$ is a diagonal matrix that contains the $d_i^q$ components ($d_1^q,...,d_N^q$), belonging to vector $\mathbf{d} = \mathbf{W} \cdot \mathbf{1}$, and representing the degree of 'linkage' of the spatial object *i*. Different coding schemes are obtained by varying the *q* parameter. In particular, the following schemes can be obtained:

- $q = 0$: *C-coding* (globally standardized). This scheme is commonly used in spatial statistics, and tends to emphasize spatial objects with a greater degree of linkage. The C-coded matrix is symmetrical.
- $q = –0.5$: *S-coding* (variance stabilized). This scheme tends to even out the variation levels of weights assigned to spatial objects.
- $q = –1$: *W-coding* (row-sum standardized). This scheme is mostly used in autoregressive response and simultaneous spatial autoregressive model specifications, and, contrary to the C-coding scheme, tends to emphasize the weight of objects with small spatial linkages. The scheme produces an arithmetic average of the neighbouring values in the original **W** matrix.

Different spatial patterns may well result from the calculation of the eigenvectors of the above coded matrices. For instance, a W-coded matrix can be expected to show more 'extreme' values along the edges of a study area, while, on the other hand, a C-coded matrix is expected to present stronger patterns in the inner study area. Figure 7.1 presents an illustrative example, for the case of German unemployment, of the first two eigenvectors generated from the adjacency matrix coded in the different coding schemes.

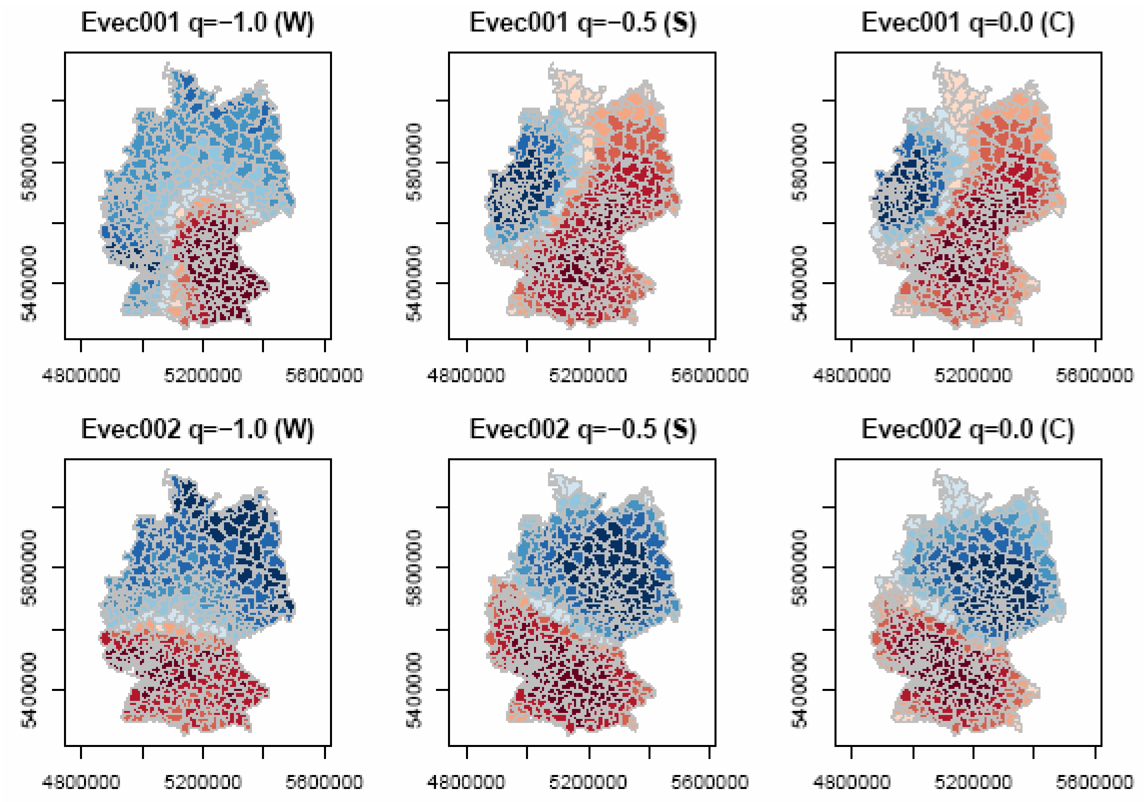



Figure 7.1 – Eigenvector variation for different coding schemes, the case of German unemployment

The choice of coding scheme, and therefore of the geographic weights matrix, not only determines the set of eigenvectors out of which the spatial filters are selected, but is also a factor from the perspective of the utilization of its results in a spatial econometric or spatial statistics framework. With regard to the empirical application presented in this chapter, both W-coding and C-coding are employed in Section 7.3. A single coding scheme (C-coding) is then selected for further analyses, presented in Section 7.4. The results of a correlation analysis of the geographic weights matrices used are also presented, in order to compare the different approaches.

## 7.3 Computation and Choice of Spatial Filters for German Unemployment

### *7.3.1 Preface*

The above spatial filtering techniques are now illustrated empirically. This chapter presents results based on the analysis of German unemployment data (unemployment rates). The data set, described more fully in Chapter 3, consists of a panel of 439 German districts (*kreise*), for which the years from 1996 to 2002 are available, while the level of aggregation of the data set is NUTS-3. In particular, the NUTS-3 aggregation level enables a more detailed examination of 'local' unemployment patterns. In fact, data at the NUTS-2 level would only have 41 regions (*Regierungsbezirke*). Alternatively, an intermediate approach is proposed by Kosfeld and Dreger (2006), who carry out a spatial filtering analysis of German regional labour market data, using 180 regional labour market areas (Eckey 2001).

Additionally, in Section 7.4, we employ information at the same aggregation level on: (a) regional daily wages of full-time workers; (b) number of full-time employees; and (c) working-age population. For the analysis presented in this chapter, we employ these three variables over the period of 1994 up to and including 2001 (see Chapter 3 for a complete description of the variables used).

A further spatial relationship matrix, concerning German commuting flows, is employed in our analysis. For each pair $(i, j)$ of NUTS-3 origin and destination (O-D), the data consist of the number of employees who are residents of district $i$ and work in district $j$. We can treat these flows as home-to-work trips. The data used in this chapter refer to the year 2002, and are employed in the computation of an 'economic flows' geographic weights matrix (see Section 7.3.2). Commuting data for one year only are employed in our analysis, since varying commuting data would generate different geographic weights matrices, and, consequently, different sets of eigenvectors. Furthermore, we can assume some spatio-temporal persistence with respect to the local commuting patterns. The daily commuting flows between two districts are transformed to satisfy the statistical symmetry requirement of spatial weights matrices. Consequently, this transformation models the daily to-work and back-home flows.

### *7.3.2 Geographic Weights Matrices: The Different Approaches Used*

As mentioned above, the spatial filtering methods employed in this analysis are based on the decomposition of a geographic weights matrix. Therefore, it is important to carefully consider, in addition to matrix computation methods (see Section 7.2.2), the concept of proximity that is used and its consequences.

In our case study, we present a set of different definitions of the geographic weights matrix:

- *economic flows*: based on patterns of commuting flows;
- *shared boundaries*: based on geographical contiguity, which by definition is symmetric;
- *distance*: based on symmetric distances separating district centroids.

The definitions highlighted here enable us to observe the influence of different operational definitions of proximity on the final results. First, commuting flows are employed as a proxy for the economic interdependence between districts (as outlined in Section 1.3). Second, shared boundaries utilize the topology of NUTS-3 administrative boundaries (*kreise*) in defining proximity. Third, distance-based matrices calculated using the centroids of the same districts define proximity in terms of geographical distance-decay relationships.

A total of five geographic weights matrices are employed in this chapter. The matrices are as follows:

a) A journey-to-work flows matrix, computed according to the $q = -1$ coding scheme (W-coding). This matrix is based on the location-to-location commuting data described above.[42]
b) Two matrices based upon shared boundaries, constructed by defining contiguity according to the 'rook' rule, and then computed according to the C- and W-coding schemes. Results from the application of a 'queen' contiguity rule (which also considers contiguity on vertices) are not considered here, since the two specifications of adjacency differ only by 25 neighbour links.
c) Two distance-based matrices derived from a spatial interaction model (SIM);[43] the variables used for the estimation of the model are district full-time employment data and the distance (as the crow flies) between the centroids of each district:
    a. First, a distance-decay (deterrence) exponent of –2.7 is obtained from the estimated SIM and then converted into the W-coding scheme.
    b. Second, this distance-decay (deterrence) exponent is increased to –6.3 in order to obtain the same number of candidate eigenvectors that are obtained with the shared boundaries W-coding scheme.

The unconstrained SIM that follows was used to describe the journey-to-work flows and to estimate the deterrence parameters:

$$T_{ij} = KO_i^{\alpha} D_j^{\beta} e^{-\gamma d_{ij}} + \varepsilon_{ij}, \tag{7.4}$$

where $T_{ij}$ is the quantity of flows between the areal units $i$ and $j$; $O_i$ is the number of workers residing in the origin areal unit $i$; $D_j$ is the number of jobs located in the destination (place of work) $j$; K, α, β and γ are parameters; and $\varepsilon_{ij}$ is a random error associated with the flows between the origin $i$ and the destination $j$.

The estimated deterrence parameter, $\hat{\gamma}$, was used, in order to define the W-coding scheme, as follows:

---

[42] On the one hand, the journey-to-work matrix might be closely related to the different levels of urbanization of the districts. On the other hand, it might be argued that endogeneity should be considered as a potential issue, in particular if covariates are added to the current autoregression approach.

[43] For details about the estimation of spatial interaction models, see, amongst others, Sen and Smith (1995), and Haynes and Fotheringham (1984).

$$w_{ij} = \frac{e^{-\hat{\gamma} d_{ij}}}{\sum_{j=1}^{N} e^{-\hat{\gamma} d_{ij}}}, \tag{7.5}$$

where $w_{ij}$ is the value of the generic cell $(i, j)$ of the geographic weights matrix $\mathbf{W}$.

Next, $\hat{\gamma}$ was incrementally increased until the matrix $(\mathbf{W}^{\mathrm{T}} + \mathbf{W})/2$ yielded the same number of prominent eigenvectors that were obtained with the $(\mathbf{W}^{\mathrm{T}} + \mathbf{W})/2$ matrix constructed as the row-standardized version of the (topological-based) binary contiguity matrix. Note that the eigenvectors for all W-coding schemes are extracted from $(\mathbf{W}^{\mathrm{T}} + \mathbf{W})/2$ in order to convert the matrix from an asymmetric to a symmetric one.

On the basis of the geographic weights matrices described above, the next section describes the spatial filter selection process followed.

### *7.3.3 Computation and Selection of the Spatial Filters over Time*

The first step in the construction of a spatial filter to be applied to the variable of study (in this case, German regional unemployment rates) is the computation of the eigenvectors of the geographic weights matrix, followed by the choice of a set of candidate eigenvectors from which a selection is made. Eigenvectors are selected for inclusion on the basis of their MI values and their correlation with our georeferenced data. A minimum MI/max(MI) value of 0.25 has been used, in our case, to identify the candidate set. The results of this process, carried out for the matrices presented in the preceding section, are presented in Table 7.1.

Table 7.1 – Candidate eigenvectors selected and maximum MI values

| Geographic weights matrix | Number of candidate eigenvectors | max(MI) |
|---|---|---|
| Journey-to-work flows matrix | 78 | 2.92 |
| Rook matrix (S-coding) | 130 | 1.07 |
| Rook matrix (C-coding) | 98 | 1.24 |
| Distance-based matrix ($\beta = -2.7$) | 36 | 0.97 |
| Distance-based matrix ($\beta = -6.3$) | 97 | 1.02 |

Once the five sets of ‘candidate’ eigenvectors shown in Table 7.1 have been selected, the statistical significance of each set as an explanatory variable for regional unemployment rates has to be established. This process was carried out by means of a stepwise logistic regression analysis. The stopping condition employed is a 10% level of significance for inclusion and retention of the eigenvectors. In addition to the stepwise regression analysis, a further manual backward elimination of regressors was carried out through the sequential estimation of a generalized linear model coupled with a binomial distribution. A marginal eigenvector was excluded if its $\chi^2$ value remained non-significant.

This process was repeated for all available years of unemployment data – from 1996 to 2002 – and for each geographic weights matrix. As a result, seven sets of 'significant' eigenvectors (one set for each year) were selected, for each of the employed matrices. These are the 'spatial filters' uncovered for each year and matrix.

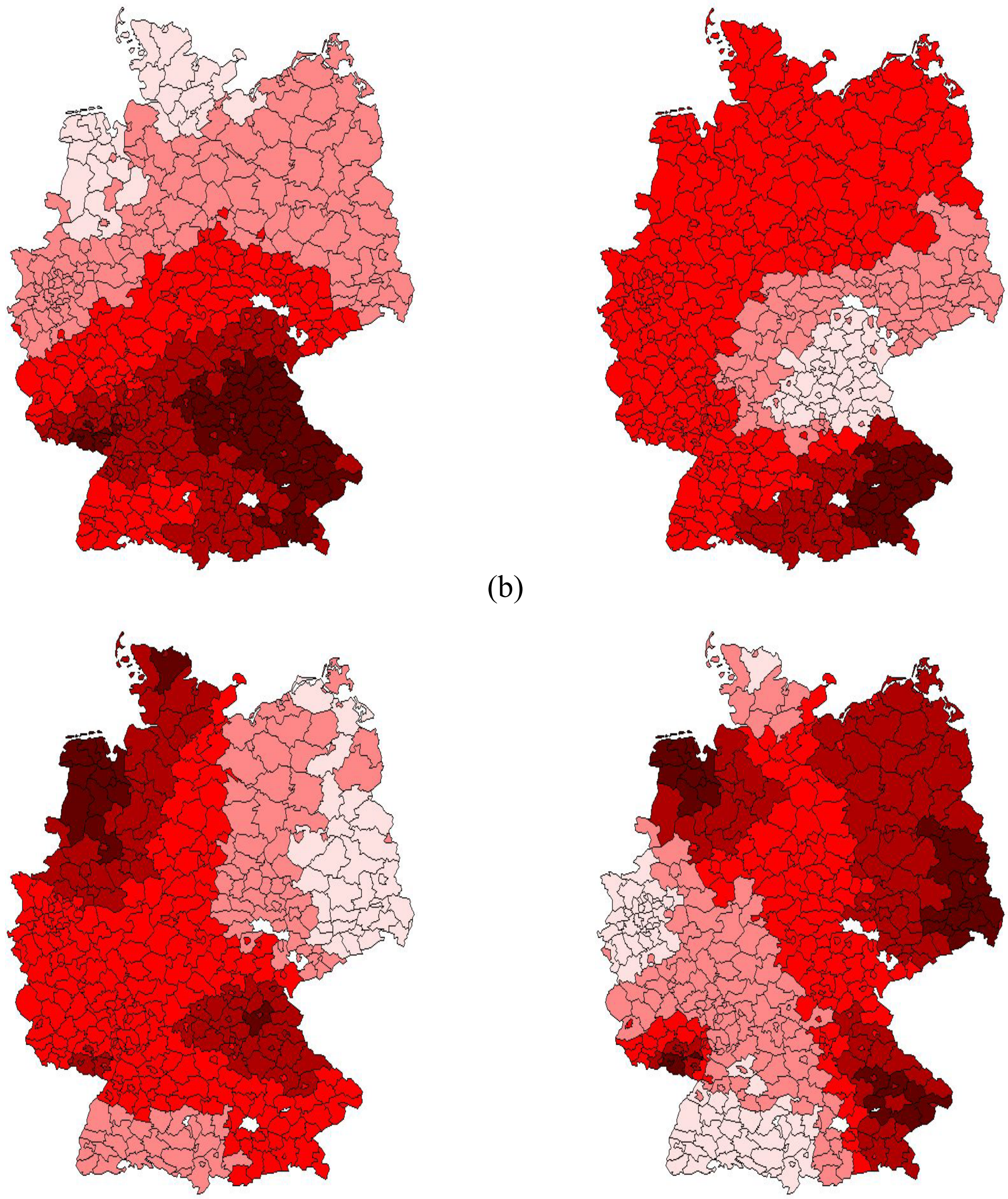
Next, for each geographic weights matrix, we aim to pinpoint a subset of eigenvectors that is common to all the years (1996–2002). The results of the analyses described above are summarized in Table 7.2. Details about the eigenvectors selected in each context and year are shown in the Table 7.A1, Annex 7.A. Of particular note, in Table 7.A1, is that the sum-of-squared prediction error (SSPE) divided by the mean squared error (MSE) in all cases is roughly 1 (that is, $\sqrt{\mathrm{SSPE}/\mathrm{MSE}}$); in other words, a jackknife type of cross-validation assessment of the selected eigenvectors yields a prediction error that is almost identical to the OLS error minimization results. This validates the constructed spatial filters.

Table 7.2 – Amount of variance explained by the selected eigenvectors, and the number of common eigenvectors, 1996–2002

| Geographic weights matrix | Common eigenvectors | Pseudo-$\bar{R}^2$ 1996 | Pseudo-$\bar{R}^2$ 1997 | Pseudo-$\bar{R}^2$ 1998 | Pseudo-$\bar{R}^2$ 1999 | Pseudo-$\bar{R}^2$ 2000 | Pseudo-$\bar{R}^2$ 2001 | Pseudo-$\bar{R}^2$ 2002 |
|---|---|---|---|---|---|---|---|---|
| Journey-to-work flows matrix | 14 | 0.3004 | 0.2911 | 0.3305 | 0.3142 | 0.3379 | 0.3453 | 0.3285 |
| Rook matrix (S-coding) | 17 | 0.6477 | 0.6821 | 0.7293 | 0.7453 | 0.7945 | 0.8022 | 0.7909 |
| Rook matrix (C-coding) | 15 | 0.5929 | 0.6425 | 0.6846 | 0.7068 | 0.7483 | 0.7683 | 0.7549 |
| Distance-based matrix (β = –2.7) | 6 | 0.6215 | 0.5968 | 0.6519 | 0.6930 | 0.7296 | 0.7448 | 0.7382 |
| Distance-based matrix (β = –6.3) | 11 | 0.6233 | 0.6067 | 0.6501 | 0.6818 | 0.7247 | 0.7442 | 0.7331 |

The results summarized in Table 7.2 show that we found sets of eigenvectors (that is, spatial filters) that are statistically significant, as explanatory variables of German regional unemployment, over the entire time period considered. Of note here is that all the proposed contiguity approaches (that is, economic flows, shared boundaries, and distance) enable us to define sets of common spatial filters.

In terms of statistical relevance, the amount of variance explained by the spatial filtering regressors is fairly consistent over the years (reasonably, unemployment patterns do not change much from year to year), and at comparable levels, for all the *geographical* contexts (that is, shared boundaries and distance). The adjusted pseudo-$R^2$ values found for these analyses are around 0.60–0.80, with the S-coded rook matrix approach being the most significant. The results obtained for the commuting flows matrix approach are, however, not as encouraging. The amount of variance explained by the model, in this case, is only in the 0.29–0.35 range.



(a) (b) (c) (d)

Figure 7.2 – Spatial filters computed for the rook matrix (S-coding): (a) = $E_2$; (b) = $E_3$; (c) = $E_5$; and (d) = $E_6$ (see Table 7.A1, Annex 7.A)

As mentioned in Section 7.2, the constructed spatial filters can be interpreted not only as potential explanatory variables substituting for missing ones but also as map patterns. A graphical visualization of the spatial filters uncovered by our analysis provides an example of the map features embedded in the eigenvectors' values. Figure 7.2 above shows the four eigenvectors with the largest MI values computed for the rook adjacency matrix S-coding scheme, and that are also common to all the years examined.

As noted previously, the first two eigenvectors for adjacency matrices usually show East-West and North-South patterns. Spatial filter component (a) ($E_2$) in Figure 7.2 seems, in fact, to be characterized by a North-South pattern. When we observe the subsequent spatial filter components (b, c and d), the geographic patterns mapped relate to characteristics of smaller geographic scale, showing patterns that can be categorized first as 'regional', then as 'local'. Although they may contain some common map patterns (for example, North-South and East-West patterns), spatial filters computed with different geographic weights matrices will vary to some degree. Meanwhile, an assessment of the statistical significance of the spatial filters (shown in Table 7.2) enables us to assess the utility of the different proximity approaches employed.

### *7.3.4 Discussion of the Results of Different Proximity Approaches*

The preceding section reveals that all the definitions employed in this chapter in order to operationalize proximity have been found to generate sets of eigenvectors (whose linear combinations are spatial filters) that are statistically significant for all the years examined. Consequently, our focus is on observing similarities and differences in the statistical performance of the different definitions used.

In order to understand the descriptive performance associated with different geographic weights matrices, we need to compare the matrices themselves. Therefore, a correlation analysis of the matrices employed here has been carried out. The results of this analysis appear in Table 7.3 (for details on the computation of matrix correlation, see Oden 1984, and Tiefelsdorf 2000).

Several features of Table 7.3 are noteworthy. The most conspicuous result pertains to the correlations between the journey-to-work flows matrix and the remaining matrices (that is, of the shared-boundaries and distance-based types). The low correlation values found are plausible and, to a certain degree, to be expected. The flows matrix differs from the other matrices in that it is not based on topology, but is a proxy for the economic links between the German districts. These links are, in fact, not fully limited by geographical contiguity, and they embrace hierarchical components of the geographical landscape as well. With regard to the remaining matrices, they all seem to have fairly high correlations, which would be consistent with the similarities we observed in the statistical performance of their spatial filters (see Table 7.2). Also of note is that:

- Matrices based on more similar definitions tend to be more strongly correlated with each other than with those based on less similar definitions.

- The correlation between the two rook adjacency-based matrices is higher than that between the two distance-based matrices, in spite of the different coding schemes employed.
- Both distance-based matrices, which have been constructed with the W-coding scheme, seem to be more strongly correlated with the S-coded than with the C-coded rook matrix.

Table 7.3 – Correlations of geographic weights matrices

| | Journey-to-work flows matrix | Rook matrix (S-coding) | Rook Matrix (C-coding) | Distance-based matrix ($\beta = -2.7$) | Distance-based matrix ($\beta = -6.3$) |
|---|---|---|---|---|---|
| Journey-to-work flows matrix | 1.0000 | 0.5641 | 0.5102 | 0.4919 | 0.5949 |
| Rook matrix (S-coding) | 0.5641 | 1.0000 | 0.9152 | 0.6892 | 0.7923 |
| Rook matrix (C-coding) | 0.5102 | 0.9152 | 1.0000 | 0.6533 | 0.6879 |
| Distance-based matrix ($\beta = -2.7$) | 0.4919 | 0.6892 | 0.6533 | 1.0000 | 0.8775 |
| Distance-based matrix ($\beta = -6.3$) | 0.5949 | 0.7923 | 0.6879 | 0.8775 | 1.0000 |

These findings call for a more in-depth analysis of the issues related to the choice of a coding scheme, particularly in view of the type of data patterns that a spatial analyst wants to emphasize (different coding schemes accentuate different kind of patterns). The discussion of such problems goes beyond the scope of this chapter; however, an interesting treatment can be found in Tiefelsdorf et al. (1999).

### *7.3.5 A Spatial Autoregressive Panel Model for German Unemployment*

The preceding sections focused on computing and selecting, for different geographic weights matrices, sets of eigenvectors that are commonly significant for all the years examined (1996–2002). In this section, we exploit these findings by estimating a spatial autoregressive panel model in order to evaluate the explanatory power of a time-invariant spatial filter. We employ a generalized linear mixed model (GLMM), which we develop for the case of the rook geographic weights matrix using the C-coding scheme.[44] The 15 common selected

[44] Clearly, any of the geographic weights matrices developed in the preceding sections could be employed. However, aside from the case of the journey-to-work flows matrix, which showed less reliable statistical results, we might expect rather similar results from the remaining matrices, as suggested by the close values of Table 7.2, and by the high correlation levels shown in Table 7.3.

eigenvectors (see Section 7.3.3) were entered as regressors in a generalized linear model (GLM) with a binomial distribution for the response variable, together with a normal-distributed random effects intercept variable, in order to handle temporal correlation. In a GLMM, the intercept will be a geographically-varying random variable, which accounts for the serial correlation in short time series such as that employed in our case study. This random effects intercept also supports inferences beyond the surface partitioning and the set of points in time concerned.

Table 7.4 presents summary results regarding the spatial autocorrelation accounted for by this model.

Table 7.4 – Spatial autocorrelation measures for German unemployment, based upon the rook (C-coding) geographic weights matrix

| Year | Fitted values | | | Spatial filter residuals | |
|---|---|---|---|---|---|
| | MI | $z_I$ | Geary ratio | MI | Geary ratio |
| 1996 | 0.6651 | 21.9 | 0.3213 | 0.2107 | 0.6161 |
| 1997 | 0.7320 | 24.1 | 0.3268 | 0.2004 | 0.6627 |
| 1998 | 0.7596 | 25.0 | 0.2869 | 0.1999 | 0.6389 |
| 1999 | 0.7854 | 25.8 | 0.2492 | 0.2057 | 0.6128 |
| 2000 | 0.8324 | 27.4 | 0.2222 | 0.2454 | 0.5862 |
| 2001 | 0.8537 | 28.1 | 0.2088 | 0.2653 | 0.5701 |
| 2002 | 0.8500 | 28.0 | 0.2140 | 0.2713 | 0.5632 |
| Spatial filter | 1.1358 | – | 0.1459 | – | – |

*Note*: $z_I$ denotes the *z*-score for MI.

The statistical results presented in Table 7.4 show that the spatial filter (linear combination of the common set of eigenvectors employed) accounts for a large share of SAC, though not all of it (a perfectly random map pattern, free of SAC, has an MI of –0.0023 and a Geary ratio of 1). A graphical visualization of the spatial filter appears in Figure 7.3. In terms of goodness-of-fit, the model has an adjusted pseudo-$R^2$ of 0.9425, and all the eigenvectors employed are significant. We can note that, while the model fits the data fairly well, this is true, in particular, when information on the previous years is fed into the model.

While the estimation described above provides comforting results, a further level of analysis is necessary in order to carry out more detailed experiments on the dynamics of unemployment patterns. In this regard, the limitation of the experiments presented earlier is that they refer to an unemployment autoregression. Therefore, we propose the utilization of additional explanatory variables in the model.

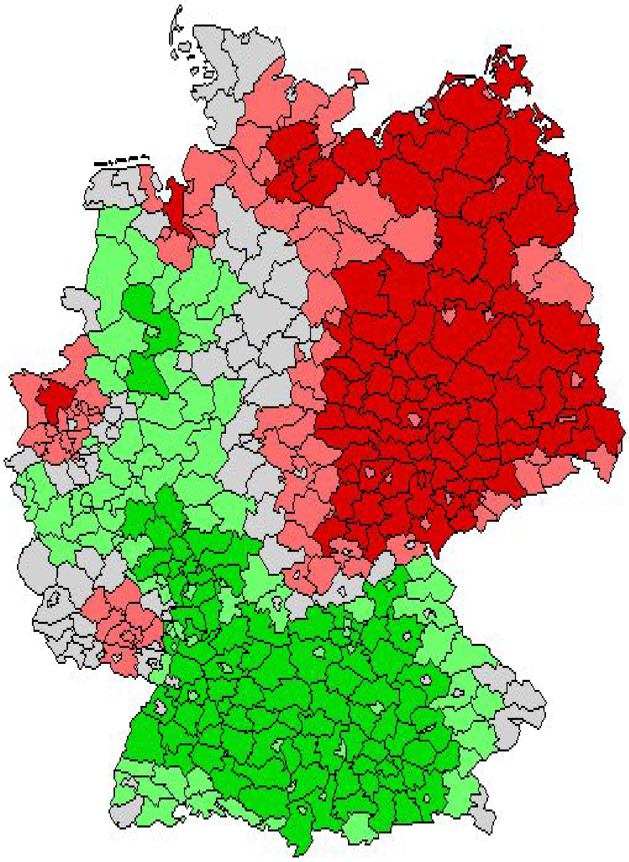


Figure 7.3 – Graphical visualization of the spatial filter obtained in the case of the rook geographic weights matrix (C-coding)

The joint employment of spatial filters and socio-economic explanatory variables involves further attention to the mechanics of spatial filtering. Eigenvectors that are significant both to the explained and to the explanatory variable(s) also imply filtering of the latter. This issue is addressed in the next section.

## 7.4 Inclusion of Explanatory Variables in Spatial Filtering

### *7.4.1 Selection of the Spatial Filters for the Unemployment Models*

The next step in our analysis is to further the autoregressive analysis presented above by including covariates with clear socio-economic meaning. By doing so, we fulfil two main objectives: (a) we go beyond the limit of the previous analyses, which accounted only for the purely geographical distribution of the variable concerned (German unemployment rates); and (b) we exploit fully the potential of spatial filtering, as we compute new (reduced) spatial filters. This procedure allows us to obtain non-distortionary estimates of the regression parameters relating to the real covariates employed.

With this objective in mind, we include in our analysis three explanatory variables: (a) the number of full-time employed individuals; (b) average daily wages of full-time employees; and (c) working age population (age 15-65). All data are available for all German regions and at the same level of disaggregation as the dependent variable (that is, NUTS-3). As outlined earlier in Section 2.3.1, we develop a simple three-variable unemployment model rather than a more exhaustive one employing a large number of covariates. In fact, the focus is not on testing a particular theory or model, but rather on exploring the impact and potential of the spatial filtering technique discussed above in the case where covariates are included. The model estimated is therefore:

$$unempl_{it} = \Delta wage_{i,t-1} + \Delta empl_{i,t-1} + \Delta pop_{i,t-1} + \varepsilon_{it}, \tag{7.6}$$

where $unempl_{it}$ is the unemployment rate of region $i$ at time $t$; $\Delta wage_{i,t-1}$ is the variation of wages in the same region in the period ($t-2$, $t-1$); $\Delta empl_{i,t-1}$ and $\Delta pop_{i,t-1}$ are the corresponding variations in full-time employment and working-age population for the same period; and $\varepsilon_{it}$ is the error term. Longer lags, in particular with regard to population variations, could ideally be used (see, for example, Carlino and Mills 1987), but are not considered in our experiments because of the limited period of data availability.

In our model, the wages and employment variables refer to the labour demand factors that influence unemployment. On the other hand, the population variable can be seen as an indicator of both labour supply and demand factors, as it aims to account for several aspects, such as migration and changes in the age structure of the pool of workers. The expected signs for the covariates are positive for wages and negative for employment. The case of population is less straightforward in terms of sign, because of its ambivalent aspects.

Clearly, the model could be estimated in terms of unemployment rate *variations*. Although this solution would make more sense in economic terms (relating variations in the explanatory variables to variations in the dependent variable), we choose to proceed, as in Section 7.3, with the analysis of (static) unemployment rates. As a result, the spatial filters obtained for this model specification are comparable to the ones found in the autoregressive case of Section 7.3. The differences between the new and the old spatial filters may be caused by the inclusion in the model of the covariates, for which the spatial filters previously selected were a surrogate. With the inclusion of spatial filter components (eigenvectors of the modified geographic weights matrix), Equation (7.6) becomes:

$$unempl_{it} = \Delta wage_{i,t-1} + \Delta empl_{i,t-1} + \Delta pop_{i,t-1} + sf_i + \varepsilon_{it}, \tag{7.7}$$

where $sf_i$ is the linear combination – for region $i$ – of the selected spatial filter components.

The first step in estimating Equation (7.7) is therefore to find the appropriate spatial filters for this empirical case. Again, we employ the C-coded rook geographic weights matrix selected in Section 7.3.5. We start from the set of 98 candidate eigenvectors previously presented in Table 7.1 and follow a spatial filter selection procedure similar to that employed above. We employ a forward stepwise logistic regression of Equation (7.7), where the socio-economic covariates are the initial regressors included (and therefore cannot be dropped), and the subsequent inclusion of single eigenvectors as additional regressors is decided on the basis of the model's Akaike information criterion (AIC).[45] The stepwise selection concludes when the current model has the lowest AIC score (no further regressor included).

For each year (1996–2002), we compute the spatial filter concerning jointly the dependent and the independent variables. As shown in Table 7.5, we find spatial filters comprising between 23 and 30 eigenvectors each. The adjusted $R^2$ values of the models are significantly higher than those found in Section 7.3.3: they range from 0.78 to 0.87. The improved statistical power of the analysis (with respect to the autoregression range: 0.59–0.76) is a reasonable finding, since we introduced 'real' explanatory variables. With regard to the spatial filters, the set of eigenvectors common to all years that we find is smaller (10 eigenvectors) than that previously found (15 components), as the inclusion of the covariates 'eats up' a share of the variance to be accounted for in the data. A map visualization of the four common eigenvectors with the largest MI values is shown in Figure 7.4.

With regard to the covariates employed (wages/employment/population), we observe, in Table 7.6, that:

- The related regression parameters are mostly significant. While a comparison model comprising *only* the covariates showed just three non-significant parameters, the significance levels of the spatial filter model are still satisfactory, as they generally confirm the relevance of the variables.
- The signs of the wages and employment covariates are as expected, and constant over the years (aside from one case). However, the stable result of a negative parameter for the population growth variable deserves further investigation in order to be fully interpreted in this context.

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[45] The Akaike information criterion (AIC) was proposed by Akaike (1974) and is a goodness-of-fit measure based on the concept of entropy. The AIC takes into account the trade-off between model complexity and model fit. It is calculated as:

$AIC = 2k - 2\ln(L)$,

where $k$ is the number of estimated parameters and $L$ is the likelihood function of the estimated model.

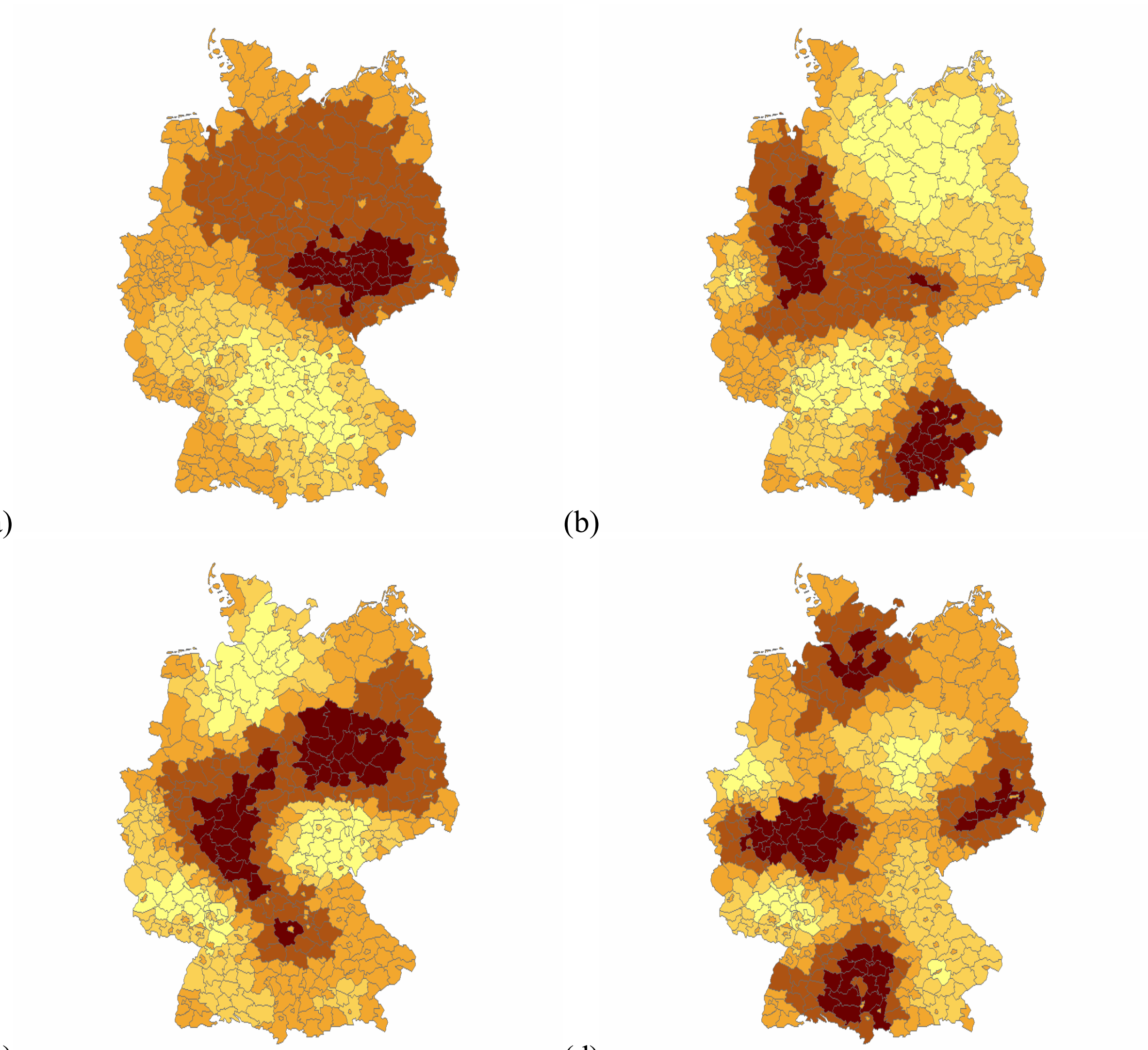
Table 7.5 – Common and year-specific eigenvectors selected in the case of the rook geographic weights matrix (C-coding), years 1996–2002

| Year | Number of eigenvectors | Year-specific eigenvectors | | | Common eigenvectors | | | Pseudo-$\bar{R}^2$ | MSE |
|---|---|---|---|---|---|---|---|---|---|
| | | Global | Regional | Local | Global | Regional | Local | | |
| 1996 | 24 | E5 | E17, E19, E21, E25, E26, E28, E30, E33, E34, E41, E51 | E68, E81 | E2 | E6, E9, E11, E15, E16, E18, E24, E39 | E74 | 0.7774 | 3.8648 |
| 1997 | 23 | E3, E4 | E7, E8, E17, E19, E25, E26, E28, E30, E34, E42, E52, E54, E60, E65 | E81 | | | | 0.8169 | 4.2103 |
| 1998 | 30 | E3, E4, E5 | E7, E8, E13, E17, E20, E21, E25, E26, E28, E30, E34, E38, E42, E51, E52, E65 | E81 | | | | 0.8064 | 4.5847 |
| 1999 | 30 | E3, E4 | E7, E8, E10, E17, E20, E21, E25, E26, E28, E30, E34, E38, E42, E52, E55, E60, E65 | E81 | | | | 0.8179 | 4.4606 |
| 2000 | 30 | E3, E4 | E7, E8, E10, E17, E20, E21, E25, E26, E28, E30, E34, E38, E42, E44, E52, E60, E65 | E81 | | | | 0.8342 | 4.4916 |
| 2001 | 25 | | E8, E10, E17, E20, E23, E26, E33, E34, E38, E40, E42, E44, E65 | E76 | | | | 0.8675 | 4.0981 |
| 2002 | 23 | | E7, E8, E10, E20, E23, E31, E38, E42, E44, E54, E55, E60 | E87 | | | | 0.8636 | 4.3005 |

Table 7.6 – Sign and statistical significance of the socio-economic covariates, 1996–2002

| | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| Wages | +*** | +*** | +** | + | + | + | –** |
| Employment | –*** | –* | – | –*** | – | –*** | –*** |
| Population | – | –*** | –*** | –*** | –*** | –*** | –*** |

*** Significant at the 99 per cent level.
** Significant at the 95 per cent level.
* Significant at the 90 per cent level.



(a) (b)

(c) (d)

Figure 7.4 – Spatial filters computed for the rook matrix (C-coding): (a) = $E_2$; (b) = $E_6$; (c) = $E_9$; and (d) = $E_{11}$ (see Table 7.5)

The results presented in Tables 7.5 and 7.6 assess the statistical power of our spatial filter-enhanced models. We next present the results of the models with regard to SAC. We analyse the SAC of the models' residuals, in order to evaluate to what extent the spatial filters – both the single-year filters and the filter common to all years – account for the residual (unexplained) spatial patterns in unemployment rates. Table 7.7 summarizes our empirical findings. In the table, we can note that, if our naïve unemployment model is carried out *without* including the spatial filter components, the regression residuals obtained (by OLS or logistic regression) for each year range between 0.28 and 0.71, therefore implying rather high SAC. The re-computation of the models *with* the inclusion of the spatial filters decreases SAC, in the range from –0.02 to 0.13. Further, if we re-run our logistic regression models by including, together with the covariates, only the set of common eigenvectors for 1996–2002, we find residual SAC varying between 0.20 and 0.31, implying a loss in the SAC abatement power of about 0.20 between the full yearly spatial filters and the time-invariant spatial filter.

This is, therefore, the compromise we accept by selecting a common spatial filter for the entire data set.

Table 7.7 – Spatial autocorrelation of model residuals, 1996–2002

| | 1996 | | 1997 | | 1998 | | 1999 | | 2000 | | 2001 | | 2002 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | MI | Pr | MI | Pr | MI | Pr | MI | Pr | MI | Pr | MI | Pr | MI | Pr |
| OLS | 0.5628 | 0.0000 | 0.5206 | 0.0000 | 0.5345 | 0.0000 | 0.5993 | 0.0000 | 0.7093 | 0.0000 | 0.3990 | 0.0000 | 0.3340 | 0.0000 |
| GLM | 0.5472 | 0.0000 | 0.5082 | 0.0000 | 0.5316 | 0.0000 | 0.5980 | 0.0000 | 0.6863 | 0.0000 | 0.3577 | 0.0000 | 0.2806 | 0.0000 |
| GLM-SF | 0.1316 | 0.0000 | 0.0921 | 0.0000 | 0.0155 | 0.0160 | 0.0061 | 0.0370 | 0.0058 | 0.0380 | –0.0150 | 0.2023 | 0.0292 | 0.0226 |
| GLM-SF(red) | 0.3141 | 0.0000 | 0.2801 | 0.0000 | 0.2977 | 0.0000 | 0.2762 | 0.0000 | 0.2782 | 0.0000 | 0.2094 | 0.0000 | 0.1985 | 0.0000 |

*Notes:*
OLS and GLM (logistic regression) use only the three economic covariates.
GLM-SF uses the economic covariates and the selected eigenvectors.
GLM-SF(red) uses the economic covariates and the set of eigenvectors common to the seven years.

Given the above results, the next necessary step is to exploit the time-invariant spatial filter found in Table 7.5 in a ‘dynamic’ modelling framework. The results emerging from this task are presented in the next subsection.

### *7.4.2 A Spatial Filtering Panel Model for German Unemployment*

The analyses carried out on the joint inclusion, in a logistic regression framework, of our socio-economic explanatory variables and the spatial filter components showed that acceptably low levels of SAC can be reached by narrowing down the spatial filters separately computed for each year to one spatial filter common to all years. The advantage of employing this reduced set of eigenvectors (see Table 7.5) is that it can be employed in the generalized linear mixed model (GLMM) framework previously outlined in Section 7.3.5.

As in our first GLMM approach, the German regional unemployment rates are the dependent variable, while our three economic covariates (wages, employment and population), as well as the spatial filter selected in the preceding section, serve as explanatory variables. The results of our new GLMM estimation are presented in Table 7.8, while a graphical visualization of the emerging spatial filter can be seen in Figure 7.5.

Not surprisingly, the map visualization of the spatial filter emerging from our GLMM estimation outlines a clear contrast between the former West and East Germany. This finding was to be expected, since our analysis is concerned with the levels of regional unemployment, rather than with variations in it. As a result, the spatial filter takes into account the stock of unemployment that is not explained by recent labour market trends (that is, it is acquired prior to the period examined).

Table 7.8 – GLMM parameter estimates, 1996–2002

| Parameter | Estimate | $t$ | Value |
|---|---|---|---|
| $b_0$ | 3.0336 | 3.72 | 0.0002 |
| logsig | −1.5078 | −31.45 | 0.0000 |
| Wages | 1.2965 | 3.97 | 0.0000 |
| Employment | −2.3272 | −10.42 | 0.0000 |
| Population | −4.2187 | −4.84 | 0.0000 |
| $E_2$ | 7.1327 | 27.34 | 0.0000 |
| $E_6$ | −2.2255 | −8.53 | 0.0000 |
| $E_9$ | 1.5373 | 6.08 | 0.0000 |
| $E_{11}$ | −0.8196 | −3.18 | 0.0016 |
| $E_{15}$ | −1.9668 | −7.69 | 0.0000 |
| $E_{16}$ | 0.8015 | 3.17 | 0.0016 |
| $E_{18}$ | 1.0849 | 4.23 | 0.0000 |
| $E_{24}$ | −0.9567 | −3.76 | 0.0002 |
| $E_{39}$ | 0.9020 | 3.55 | 0.0004 |
| $E_{74}$ | −0.5897 | −2.32 | 0.0210 |

*Notes:* $\alpha = 0.0036$; p(S-W) = 0.0043; and logsig = $\ln(\sigma_\alpha) = -1.5078$.

With regard to the estimation of the model parameters, Table 7.8 shows that the employed covariates are statistically significant, with regard to both the economic variables and the spatial filter components. The signs of the former are as expected and consistent with the findings of the separate year-by-year analyses. Again, the negative sign for the population growth variable requires further investigation in order to be correctly interpreted. The share of variance explained by the GLMM in each year can be read, by means of the adjusted $R^2$, in Table 7.9.

Table 7.9 – GLMM fitting, 1996–2002

| Year | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| Pseudo-$\bar{R}^2$ | 0.9219 | 0.9574 | 0.9592 | 0.9656 | 0.9647 | 0.9272 | 0.9536 |

The results found for the GLMM estimation can now be compared with those of benchmark models. For purposes of comparison, we carry out three alternative models, each employing, as explanatory variables, the growth rates of wages, employment and population:

- a simple OLS regression;
- a spatial lag panel model;
- a spatial lag panel model with time fixed effects.

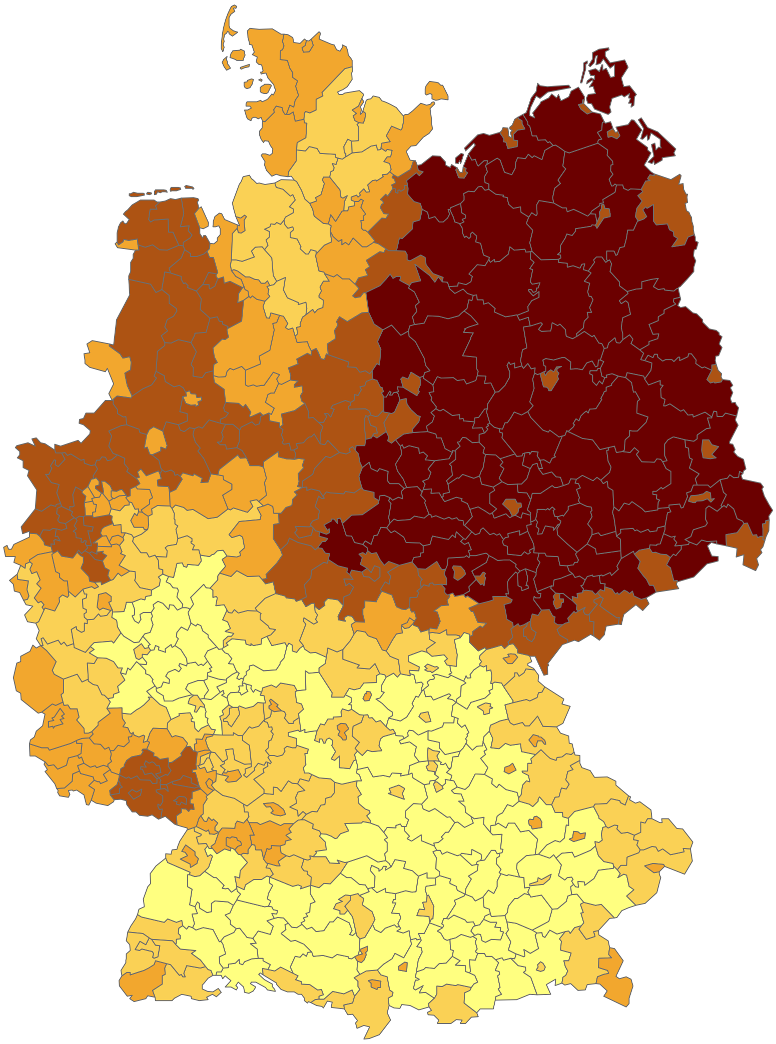


Figure 7.5 – Graphical visualization of the spatial filter obtained in the case of the rook geographic weights matrix (C-coding) with the inclusion of covariates

A spatial lag model is computed as follows:

$$\begin{aligned} y &= \rho \mathbf{W} y + \mathbf{X}\beta + u, \\ u &\sim (0, \Omega), \end{aligned} \tag{7.8}$$

where the values assumed by the dependent variable $y$ are explained by spatial autoregressive values defined according to a row-standardized geographic weights matrix **W**, and by the values of the covariates. We choose to compute a spatial lag panel model on the basis of a set of specification tests (see, for example, Anselin 1988), carried out year-by-year,[46] a summary of which is presented in Table 7.B1, in Annex 7.B. The spatial-lag time-fixed-effects specification is an expansion of the spatial lag model illustrated above, in that it also employs year dummies to take into account temporal shocks. The three models provided the following results, shown in Table 7.10.

Table 7.10 – Statistical results of benchmark models, 1996–2002

| Model | (Pseudo-) $\bar{R}^2$ | Lag coefficient |
|---|---|---|
| OLS | 0.3276 | – |
| Spatial lag | 0.7528 | $0.57^{***}$ |
| Spatial lag w/ time fixed effects | 0.7934 | $0.57^{***}$ |

$^{***}$ 99 per cent significant.

It is easy to note, in Table 7.10, that the fitting levels of the models above are lower than those found for the GLMM estimation (which has an average adjusted $R^2$ of 0.95). The signs of the covariates were found to be consistent with those previously observed (see Tables 7.6 and 7.8).

Given the above results, we can conclude that the GLMM estimation provides a satisfactory statistical performance, showing higher fitting than the benchmark models and providing parameter estimates consistent with the literature. However, it would be possible to implement better comparison models, which mirror the serial correlation captured by the GLMM, as well as the geographically-varying effect of the GLMM intercept. This need for further computations is reflected in the conclusions to this chapter.

## 7.5 Conclusions

In this chapter, we have presented an analysis of German regional unemployment by means of 'spatial filtering' techniques. The analysis presented in Section 7.3 enabled us to uncover spatial structures underlying the georeferenced unemployment data by selecting sets of 'spatial filters' that significantly explain geographic variations in the data (unemployment rates). In addition, we have observed subsets of spatial filters that (partially) define the spatial structures of the data over time. The spatial filters selected in this case are the ones that were common to the analyses carried out for each year in the 1996–2002 period.

Several definitions of the geographic weights matrix have been employed to operationalize spatial linkages according to contiguity and non-contiguity criteria. All of these definitions have yielded sets of time-invariant spatial filters, though at different levels of statistical significance. In the shared boundaries- and distance-based approaches, the spatial

[46] Single specification tests could ideally be carried out for the entire time range. We resorted to cross-sectional diagnostics, since the software employed (Geoda, http://www.geoda.uiuc.edu) did not provide such a possibility.

filters computed explain 60 to 80 per cent of the total variance when employed as the sole regressors of unemployment rates in a generalized linear regression model. But the 'economic flows' approach, based on a journey-to-work flows matrix, failed to produce the same encouraging results. This finding might be caused by the artificial nature of the data used (logical connections between districts) and by the lack of a more suitable measure of regional economic proximity. A correlation analysis of the geographic weights matrices showed that the journey-to-work matrix seems to be much less correlated with the topological-based matrices than the other matrices are correlated with each other. This result is consistent with the varying statistical performance of the spatial filters computed.

If shown as graphical visualizations, the spatial filters found in our analyses provide certain indications of the geographical distribution of unemployment trends. Using Figure 7.2 as an example, map (a) can be interpreted as the visualization of a North-South divide, while map (b) seems to distinguish Southern Bavaria from the rest of the country. Maps (c) and (d) both suggest differences between East and West Germany. Additional eigenvectors (not shown here) show smaller scale patterns of the regional/local spatial dependency structure.

The analysis illustrated above was then repeated, in Section 7.4, by introducing in the autoregression framework three explanatory variables with socio-economic meaning: namely, wages, employment and population. Taking a single matrix specification as an example, we selected new sets of spatial filters, which, in this case, are the result not only of the analysis of the dependent variable, but also of the covariates. We showed that in this case also, it is possible to select a time-invariant spatial filter subset which accounts for spatial structures in all the years of data analysed. Subsequently, a generalized linear mixed model (GLMM) was used in order to model unemployment rates by means of the covariates and the spatial filter components jointly. We showed that the GLMM estimation provides a high level of statistical reliability, as well as parameter estimates consistent with the literature.

With regard to the research objective pursued in Part B of the present study, the analyses presented in this chapter have highlighted the relevance – and most importantly the persistence – of spatial structures in German regional unemployment rates (and, we could generalize, in the corresponding labour markets). Our finding of common spatial filters for different years is a reflection of this general stability. The spatial filtering technique employed here is therefore one of several useful tools that can be deployed in the analysis of regional disparities.

However, further research along these lines is needed. On the empirical side, a better proxy for economic proximity than commuting flows should be employed. In addition, the analysis of unemployment levels should be more formally concerned with the joint analysis of factors pertaining to labour supply and demand. While the introduction in the analysis of our three covariates is a first step, future investigations need to address this issue. A full spatial filter analysis of the covariates proposed is also desirable, for comparison reasons.

On the methodological side, a comparison of the performance of the spatial autoregressive approach with more sophisticated spatial econometrics methods than those used, as well as with nonlinear approaches, such as neural networks, is desirable. Mixed neural networks/spatial filtering approaches also should be tested, as a continuation and final integration of the two methodological approaches that have been followed in Part B of the study.

Finally, from a policy perspective, a more thorough examination of the spatially-filtered residuals resulting from the analysis should be carried out, in order to fully grasp the benefits of the methodology applied.

## Annex 7.A  Details of Selected Eigenvectors

Table 7.A1 – Common and year-specific eigenvectors selected, years 1996–2002

| Year | Number of eigenvectors | Year-specific eigenvectors | | | Common eigenvectors | | | Scale | Pseudo-$\bar{R}^2$ | $\sqrt{SSPE/SSE}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Global | Regional | Local | Global | Regional | Local | | | |
| Eigenvectors extracted from the journey-to-work flows matrix (78 candidate eigenvectors) | | | | | | | | | | |
| 1996 | 20 | | E10 | E35, E52, E62, E63, E69 | E1 | E4, E5, E7 | E13, E18, E19, E25, E38, E44, E48, E50, E54, E77 | 26.67 | 0.3004 | 1.0438 |
| 1997 | 18 | | | E31, E62, E63, E78 | | | | 31.32 | 0.2911 | 1.0407 |
| 1998 | 22 | | E10 | E31, E62, E63, E68, E70, E71, E78 | | | | 31.05 | 0.3305 | 1.0550 |
| 1999 | 20 | | E10 | E31, E62, E63, E71, E78 | | | | 32.20 | 0.3142 | 1.0442 |
| 2000 | 21 | | E10 | E31, E62, E63, E69, E71, E78 | | | | 35.25 | 0.3379 | 1.0487 |
| 2001 | 21 | | E10 | E31, E62, E63, E69, E70, E78 | | | | 37.91 | 0.3453 | 1.0507 |
| 2002 | 19 | | E10 | E31, E68, E71, E78 | | | | 37.91 | 0.3285 | 1.0411 |

| Year | Number of eigenvectors | Year-specific eigenvectors | | | Common eigenvectors | | | Scale | Pseudo-$\bar{R}^2$ | $\sqrt{SSPE/SSE}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Global | Regional | Local | Global | Regional | Local | | | |
| Eigenvectors extracted from the rook matrix (S-coding) (130 candidate eigenvectors) | | | | | | | | | | |
| 1996 | 23 | E1 | E24, E25, E60 | E113, E124 | E2, E3, E5, E6, E7, E8, E9, E10, E11 | E15, E16, E22, E39, E41, E52, E71 | E130 | 20.88 | 0.647662 | 1.0226 |
| 1997 | 24 | | E17, E25, E28, E70, E82, E97 | E113 | | | | 23.32 | 0.682067 | 1.0395 |
| 1998 | 20 | | E14, E25, E28, E36, E60, E70, E82 | E113, E129 | | | | 22.07 | 0.729332 | 1.0476 |
| 1999 | 26 | | E14, E23, E36, E38, E70, E82 | E113, E115, E129 | | | | 22.06 | 0.745331 | 1.0438 |
| 2000 | 31 | | E14, E25, E28, E33, E36, E38, E40, E50, E70, E82, E85 | E113, E115, E129 | | | | 22.00 | 0.794492 | 1.0702 |
| 2001 | 28 | | E14, E18, E23, E32, E36, E38, E40, E82 | E110, E115, E129 | | | | 23.87 | 0.802178 | 1.0489 |
| 2002 | 25 | | E14, E23, E36, E38, E40, E82 | E115, E129 | | | | 24.81 | 0.790917 | 1.0387 |

| Year | Number of eigenvectors | Year-specific eigenvectors | | | Common eigenvectors | | | Scale | Pseudo-$\bar{R}^2$ | $\sqrt{SSPE/SSE}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Global | Regional | Local | Global | Regional | Local | | | |
| Eigenvectors extracted from the rook matrix (C-coding) (98 candidate eigenvectors) | | | | | | | | | | |
| 1996 | 24 | | E9, E16, E21, E25, E41, E52, E53, E64 | E89 | E2, E3, E4, E5 | E6, E7, E8, E11, E18, E24, E28, E30, E39, E60 | E74 | 21.98 | 0.5929 | 1.0232 |
| 1997 | 23 | E1 | E15, E19, E21, E34, E38, E64 | E93 | | | | 24.38 | 0.6425 | 1.0412 |
| 1998 | 27 | | E13, E15, E16, E19, E21, E34, E38, E42, E52, E66 | E68, E93 | | | | 23.52 | 0.6846 | 1.0438 |
| 1999 | 27 | | E9, E13, E15, E16, E19, E21, E34, E38, E42, E52, E66 | E93 | | | | 23.25 | 0.7068 | 1.0364 |
| 2000 | 30 | | E9, E13, E15, E16, E19, E21, E25, E34, E38, E42, E51, E52, E66 | E93, E97 | | | | 23.83 | 0.7483 | 1.0507 |
| 2001 | 30 | | E9, E12, E13, E15, E16, E19, E34, E42, E52, E56, E65, E66 | E68, E93, E97 | | | | 25.18 | 0.7683 | 1.0489 |
| 2002 | 29 | E1 | E9, E12, E13, E15, E16, E19, E20, E25, E38, E42, E52, E65, E66 | | | | | 26.08 | 0.7549 | 1.0459 |

| Year | Number of eigenvectors | Year-specific eigenvectors | | | Common eigenvectors | | | Scale | Pseudo-$\bar{R}^2$ | $\sqrt{SSPE/SSE}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Global | Regional | Local | Global | Regional | Local | | | |
| Eigenvectors extracted from the distance-based matrix (β = –2.7) (36 candidate eigenvectors) | | | | | | | | | | |
| 1996 | 18 | | E7, E11, E12, E14 | E26, E29, E30, E32, E34 | E1, E2, E3 | E5, E6, E16, E23 | | 21.59 | 0.6215 | 1.0018 |
| 1997 | 13 | | E7, E12, E14, E17 | E31, E32 | | | | 25.65 | 0.5968 | 1.0063 |
| 1998 | 14 | | E11, E12, E17, E21 | E26, E31, E32 | | | | 24.88 | 0.6519 | 1.0079 |
| 1999 | 14 | | E11, E14, E17, E21 | E26, E30, E31 | | | | 24.41 | 0.6930 | 1.0040 |
| 2000 | 15 | | E11, E14, E17, E21 | E26, E30, E31, E32 | | | | 25.54 | 0.7296 | 1.0092 |
| 2001 | 14 | | E11, E17, E20, E21 | E26, E30, E31 | | | | 26.68 | 0.7448 | 1.0087 |
| 2002 | 13 | | E11, E17, E20, E21 | E26, E30 | | | | 26.87 | 0.7382 | 1.0101 |

| Year | Number of eigenvectors | Year-specific eigenvectors | | | Common eigenvectors | | | Scale | Pseudo-$\bar{R}^2$ | $\sqrt{SSPE/SSE}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Global | Regional | Local | Global | Regional | Local | | | |
| Eigenvectors extracted from the distance-based matrix (β = –6.3) (97 candidate eigenvectors) | | | | | | | | | | |
| 1996 | 24 | | E13, E17, E26, E27, E29, E31, E34, E35, E39, E52 | E90, E96 | E1, E2, E3, E5, E6, E8 | E15, E32, E55, E64 | E91 | 20.75 | 0.6233 | 1.0460 |
| 1997 | 20 | E7 | E13, E17, E20, E23, E34, E35 | E79, E96 | | | | 24.66 | 0.6067 | 1.0334 |
| 1998 | 21 | | E13, E17, E20, E23, E24, E26, E31, E34 | E79, E96 | | | | 24.29 | 0.6501 | 1.0424 |
| 1999 | 19 | | E13, E20, E23, E26, E39, E63 | E79, E96 | | | | 24.09 | 0.6818 | 1.0248 |
| 2000 | 24 | | E13, E17, E20, E23, E24, E26, E29, E39, E40, E63 | E71, E79, E96 | | | | 24.69 | 0.7247 | 1.0371 |
| 2001 | 23 | | E13, E17, E20, E23, E24, E25, E26, E39, E40, E63 | E79, E96 | | | | 26.03 | 0.7442 | 1.0392 |
| 2002 | 21 | | E17, E20, E23, E25, E26, E27, E39, E40, E63 | E79 | | | | 26.98 | 0.7331 | 1.1589 |

## Annex 7.B  Summary of Specification Tests

Table 7.B1 – Year-by-year specification tests, 1996–2002

| | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| LM-lag | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| LM-error | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust LM-lag | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Robust LM-error | No | No | No | No | Yes (95%) | No | No |
| Suggested model | Spatial lag | Spatial lag | Spatial lag | Spatial lag | ?? | Spatial lag | Spatial lag |

*Notes:*
Yes: $H_0$ rejected (significant at the 99 per cent level).
No: $H_0$ not rejected.

# PART C
# SPATIAL INTERACTIONS AND NETWORKS FOR COMMUTING

Chapter 8

# Network Exploration of German Commuting Patterns

## 8.1 Introduction[47]

The willingness to travel further and longer has led to complex commuting patterns which have extended in geographic scale over the past decades. As a consequence, home-to-work trips have adopted multi-regional network configurations and have thus led to complex interactive networks. We have stressed in Section 1.3 that labour mobility patterns can be seen as an important cause of interdependences between regions (see, for example, Hewings et al. 2001). The extent of such regional interdependences is at the basis of the existence (and persistence) of regional disparities. In Part B of the present study, we proposed – with regard to our first research objective – empirical approaches aimed at coping, in statistical analyses and forecasts, with the relevance of (persistent) regional differentials in labour markets. We showed that neural forecasting models may benefit from the inclusion of region-specific information, and that, by means of spatial filtering methods, a stable spatial configuration of regions can be identified.

Given the above results, the present and subsequent chapter (Part C of this study) focus on our second research objective, originally stated in Chapter 1, which deals with the "spatial mobility associated with [the] regional labour market developments" previously analysed. Here, our intent is to integrate the conventional spatial interaction approach to commuting with novel network analysis approaches, the final aim being to further investigate regional disparity patterns. In particular, this chapter (Chapter 8) provides a first exploration – in a network perspective – of German regional commuting data, as well as of the results of differently specified spatial interaction modelling (SIM) approaches. Subsequently, Chapter 9 offers a more comprehensive analysis of commuting patterns, according to spatial and network perspectives.

[47] The present chapter is based on Patuelli et al. (2007c), forthcoming in *Networks and Spatial Economics*. The original publication is available at www.springerlink.com.

The focus on commuting, in this part of the study, is justified by the rising relevance of this phenomenon, also in the light of its implications for economic interactions between regions (see Chapter 1). Labour mobility has become an important field of study in geography, transportation science and regional science (see, for instance, Rouwendal and Nijkamp 2004). However, commuting has long been studied, particularly in terms of forecasting and approximating flows (see, amongst others, White 1977; Fotheringham 1983; White 1986). Recent works include the application of models such as the one developed at STASA (Haag et al. 2001). A growing literature is available that studies commuting in a 'spatial' framework. Rouwendal (2004) introduces search theory and spatial behaviour in commuting choice modelling, while Ma and Banister (2005) analyse the relationship between urban spatial structure decentralization and average commuting distance. Commuting has been investigated in both an urban and a regional network context (for example, see Thorsen et al. 1999; van Nuffel and Saey 2005; Russo et al. 2007), and it has been used in order to study functional relationships between regions (Cörvers and Hensen 2003).

However, fewer efforts have been made in studying the network properties of commuting patterns. Network concepts have received remarkable attention in spatial economics in recent decades. Examples are the well-known ideas of the network economy (Shapiro and Varian 1999) and the knowledge economy (Cooke 2001). Networks are based on the existence of interactions – at multiple levels/layers – between agents operating in a network, giving rise to synergy effects. Clearly, interactions between regions can be seen in such a context. The effects of these interactions are often investigated and modelled by considering, amongst other things, network externalities or spillover effects (Yilmaz et al. 2002), although without the study of a real 'network'.[48] The labour market literature is no exception to this trend: for instance, spatial job matching processes have been widely studied in a social network framework (Montgomery 1991). Similarly, there have been a number of experiments employing network-modelling approaches to the analysis of commuting flows. Thorsen et al. (1999) examined the effects of transportation infrastructure and spatial structure on commuting flows in a network of cities. Russo et al. (2007) used commuting flows in Germany to identify 'entrepreneurial cities' in Germany. Van der Laan (1998) and van Nuffel and Saey (2005) investigated – on the basis of commuting flows – the emergence of local and regional multi-nodality for the Netherlands and the Flanders area, respectively. Further examples include the studies by Sheffi (1985) and Sohn (2005), who investigate commuting at the urban level, and by Binder et al. (2003), who propose a graph theory approach.

In the present chapter, we propose the use of novel network approaches, mainly formulated by Barabási and Albert (1999), in addition to conventional spatial-economic approaches, as an analytical framework for investigating the heterogeneity/homogeneity of German commuting patterns. Here, our objective is to investigate the changes that occur over

[48] See Section 2.4.1 for a definition of 'network'.

time (1995–2004) in the commuting network, as well as the associated relationships with the underlying network configuration. This is done by considering commuting networks as graphs, where flows of commuters between two locations (seen as nodes in the network) represent a logical link between them. Our purpose is to compare the network models of Barabási and Albert with conventional SIMs and with the observed (real) flows. In addition to the above analysis, we also propose an analysis of the main German road network, by means of a shortest-path algorithm, and subsequently compare the structural properties found – for the road network – with those found for the real data and the simulation models.

The chapter unfolds as follows. Section 8.2 briefly describes recent developments in network analysis, on which the subsequent empirical analyses are based. In Section 8.3, we discuss two SIM formulations employed in the chapter, as well as their interpretation in terms of preferential attachment. Section 8.4 describes the empirical application that was carried out. First, in Section 8.4.1, the statistical properties of the German commuting network are analysed in a graph theory perspective. Secondly, in Section 8.4.2, we analyse the network structure of commuting flows in Germany from the viewpoint of network spatial interaction. In this context, in Section 8.4.3 we try to identify the appropriate deterrence form inherent to spatial interaction modelling, by carrying out two functional specifications concerning an unconstrained SIM: (a) a power-law function; (b) an exponential function. Finally, in Section 8.5, a discussion of these findings with respect to the ones obtained by an analysis of the physical German road network is presented. Lastly, in Section 8.6, we draw some conclusions on the basis of our findings.

## 8.2 New Network Analysis Perspectives

This section briefly discusses recent developments related to the analysis of networks and, in particular, their implications for regional networks. We focus on recent discoveries by Albert and Barabási (2000, 2002). Their approach radically changed the pre-existing frameworks of analysis of (large) networks, with the introduction of the concept of 'scale-free (SF) networks', which revisits the 'small-world network' approach conceived by Watts and Strogatz (1998).

The novelty in the approach of Albert and Barabási (2002) is the hypothesis that connections between the nodes are *not* random. In this context, SF networks are characterized by the presence of a few nodes (the 'hubs') with a high number of connecting links (a high 'degree' – see Section 2.4.2), while the remaining nodes have only a limited (fast-decreasing) number of links (the term 'scale-free' refers to this property). These hubs emerge because nodes tend to connect to well-connected nodes. As a result of this process, the probability distribution of the nodes' degree $x$ for SF networks tends to decay following a power function, of the type:

$$\Pr(X = x) \sim x^{-a}, \tag{8.1}$$

where a value of the exponent $a$ between 2 and 3 implies a 'hierarchy of hubs' (Barabási and Oltvai 2004), while $a = 2$ suggests the existence of a hub-and-spoke network, centralized on a major super-connected node (see, for example, O'Kelly 1998).

According to Adamic (2000), a direct relation follows, from Equation (8.1), between the power law and Zipf's law (1932), a distribution relating the degree of the nodes to their rank (in the full list of nodes sorted by their degree). According to Zipf, the relation between these two variables is as follows:

$$x \sim r^{-b}, \tag{8.2}$$

where $r$ is the rank of the node concerned. The exponent $b$ is expected to be equal to 1. Again, in Adamic (2000), Equation (8.2) will have the same exponent as a Pareto distribution, which explains the rank $r$ by means of the degree $x$; that is, the axes are inverted, if $b = 1$. Following from the mathematical relation of the Pareto and power-law distributions, any process having a Zipf's distribution will have a power-law density function. In this context, Adamic shows that the relation between Equations (8.1) and (8.2) is given by:

$$a = 1 + 1/b. \tag{8.3}$$

On the basis of the above considerations, we consider and apply – in our empirical experiments – Equations (8.2) and (8.3).

In addition to the aforementioned properties, SF networks are also characterized by high clustering (related to the concept of small-world networks) and short average-path lengths, as the hubs in the networks allow for direct links between clusters. In the SF framework, the structural importance of a randomly selected node is likely to be rather limited, while the few 'hubs' of the network are critical for its functioning. These characteristics lead to higher network efficiency, for which the emergence of SF networks is to be preferred in many cases.

In contrast to Barabási's work, it is worth mentioning long-established random network (RN) theories originally developed by Erdös and Renyi (1960). In an RN, connections (links) between agents (nodes) of the network are supposed to arise randomly. As a result, the distribution of the number of links per node (the degree) follows a Poisson distribution, that is, most of the nodes have a similar number of links (close to the average degree) and, consequently, a similar importance. The probability distribution of the degree decays exponentially for a large-enough number of nodes.

In our empirical applications we test whether our commuting network shows SF or random network characteristics. In order to be consistent with Equation (8.2), in the case of

RN patterns we adopt the exponential Equation (8.4), where $x$ is the degree distribution sorted in decreasing order and $r$ is the rank of each node:

$$x \sim e^{-\beta r}. \tag{8.4}$$

As briefly discussed in Section 2.4.2, in recent years great interest has arisen for the analysis of transportation networks in the framework of the recent developments discussed here. Case studies have been carried out by Amaral et al. (2000) for airline networks, as well as by Latora and Marchiori (2002) for the Boston subway, and by Schintler and Kulkarni (2000) with regard to congested road networks. However, generally, it might be argued that transportation networks are less prone to evolve into an SF structure over time, given the fact that they tend to be planar. In these networks, the maximum number of connections for a single node can be limited by the physical space available (to connect it to other nodes), therefore making it difficult to obtain the large number of connections needed for finding SF properties.

SF networks have many implications, but a far-reaching consequence of their unique hub structure is that they are very fault tolerant and – at the same time – also susceptible to attack (Albert et al. 2000). Specifically, an SF network remains connected even when up to the 80 per cent of nodes are randomly removed from the network. On the other hand, when the most connected nodes are removed, the average path length of the network increases rapidly, doubling up when the top 5 per cent of nodes are removed (Albert et al. 2000).

Starting from the considerations made above, the next section presents the SIMs that were modelled as approximations of preferential attachment, in order to compare them – in the framework of spatial mobility – with an SF model inspired by the theories described above.

## 8.3 Spatial Interaction Models as an Approximation of Preferential Attachment

### *8.3.1 Spatial Interaction Models for Identifying Commuter Flows in the German Labour Market Network*

Spatial interaction models (SIMs) are arguably one of the most common methods employed and studied for estimating commuting flows (see, recently, Thorsen and Gitlesen 1998; Johansson et al. 2003; Jörnsten et al. 2004). Generally, SIMs have long been a popular technique for describing and explaining behavioural, demographic and economic phenomena in space (Reggiani et al. 2006; for an extensive presentation of the family of methods, see Sen and Smith 1995).[49] The main reason for the widespread utilization of SIMs is their simple mathematical form, in addition to the intuitive assumptions underlying the approach.

The common form of an SIM (here presented as double-constrained) is as follows:

$$T_{ij} = KA_iB_jO_iD_jf(\beta, c_{ij}), \quad \text{for } i = 1,\ldots,I; j = 1,\ldots,J, \tag{8.5}$$

where:

$$A_i = 1\Big/\sum_j B_jD_jf(\beta, c_{ij}), \text{ and} \tag{8.6}$$

$$B_j = 1\Big/\sum_i A_iO_if(\beta, c_{ij}). \tag{8.7}$$

$T_{ij}$ measures the flow of interaction between the origin $i$ and the destination $j$, depending on the stock variables $O_i$ and $D_j$, as well as on the deterrence function $f(\beta, c_{ij})$, on the balancing factors $A_i$ and $B_j$ (see Reggiani 2004) and a scaling factor $K$. $A_i$ and $B_i$ correspond, in a Poisson estimation framework, to the coefficients of the origin and the destination dummy variables, respectively (see, for example, Flowerdew and Aitkin 1982).

The deterrence function in Equation (8.5) depends on the deterrence factor β and the interaction costs $c_{ij}$. The variable $c_{ij}$ might also be considered as generalized costs. In our experiment, distances were used as a proxy for the interaction costs (such as congestion), because of the analysis's geographic scale (German NUTS-3 level, *kreise*). The functional form of the deterrence function is also a relevant issue. While in its first formulations the distance deterrence function was shaped as a power-law function – as used in the Newtonian formula – Kulldorf (1955) showed that an exponential deterrence function seemed to better fit migration phenomena. Subsequently, the exponential deterrence form emerged mathematically from the entropy maximization approach developed by Wilson (1967).

In our analysis, both the power-law and exponential specifications were used, in order to draw a parallel with the network distributional properties illustrated in Section 8.2. We aim to investigate the network properties resulting from the two SIM specifications. We expect the power-law form to show a larger number of flows – compared with the exponential form – in the presence of long distances or travel times. In addition to the shape of the deterrence

[49] The most common specification of SIM has its origins in an analogy with Isaac Newton's law of universal gravitation. The idea of utilizing models derived from this theory had already been introduced, in the 19th century, in the field of social sciences by Carey (1858) and Ravenstein (1885), and subsequently mathematically formalized by Stewart (1941). Remarkably, SIMs have been shown to have theoretical justification in entropy theory and in utility maximization/cost minimization (see, for example, Nijkamp 1975; Nijkamp and Reggiani 1992). While Isard (1960) first suggested the use of SIMs in regional science, the entropy root of SIMs introduced by Wilson (1967, 1970) and, subsequently, the micro-economic derivation introduced by McFadden (1974, 1979) contributed to make SIMs more suitable to interpret spatial-economic phenomena.

function, the value of the β deterrence factor was researched for both specifications (see Section 8.4.3). In detail, we adopted two unconstrained[50] SIM forms, specified as follows:

$$T_{ij} = KE_i E_j d_{ij}^{\beta}; \tag{8.8}$$

$$T_{ij} = KE_i E_j e^{\beta d_{ij}}. \tag{8.9}$$

In Equations (8.8) and (8.9), the flows $T_{ij}$ are the employees commuting from the origin district $i$ to the destination district $j$. They are a function of the number of persons $E_i$ and $E_j$ employed[51] in the two districts, as well as of the distance $d_{ij}$ between the two. The models that we propose are, of course, overly simple. For example, $E_i$ and $E_j$ should have exponents, so as to indicate their proportionality to the flows $T_{ij}$. However, what is most relevant for our experiments is not the exact estimation of the German commuting flows, but the structure of the network that underlies the numerical data (see Section 8.4.2).

When employing an SIM for estimating inter-urban commuting flows, additional issues should be cited. One of them is the treatment of internal commuting: in particular, the distance between the working and living areas, by definition, is counted as null (although travel time or costs would not necessarily be). This issue is sometimes solved by assigning an arbitrary value to the distance for internal commuting. Alternatively, the flows assigned to internal commuting can be omitted in the analyses. A number of additional ways to treat internal commuting are available in the literature. The method suggested by Thorsen and Gitlesen (1998) starts from the consideration that intra-commuting might imply different transportation means, such as biking or walking. The authors suggest an additional component to be added to the deterrence function exponent. This component would represent – depending on the case – either a start-up (generalized) cost for commuting between different zones, or a premium, expressing the benefit of intra-commuting. An example model with these characteristics, reminiscent of the Champernowne deterrence function (see Sen and Smith 1995), is presented by Thorsen and Gitlesen (1998, p. 279) for a double-constrained specification. Alternatively, the authors suggest that labour market characteristics might be used to influence the elements on the diagonal of the O-D matrix.

In our case, the elements of the diagonal are omitted from the analysis. This choice was taken mainly as a result of our network approach to commuting. As we analyse the properties of the German commuting network, the measure of the number of commuters within a certain

[50] We are aware that a doubly-constrained model would be a more suitable specification of Equations (8.8) and (8.9). However, we used it as a simple, naïve approximation in our experiments, since the focus is not on forecasting the exact flows, but rather on the network properties deriving from the fitted values. Future research will contemplate the use of the doubly-constrained SIM.

[51] It should be noted that the use of $E_j$ is formally correct according to spatial interaction theory, since it is proportional to the inflows $D_j$. Concerning the outflows $O_i$, the use of the variable $E_i$ is a necessary approximation due to data availability. Endogeneity implications should be considered in future applications, if no proper outflows variable is employed.

district would not add additional information about the network, apart from the 'socio/economic weight' of a certain node, and it would create 'loops' – that is, links revolving on the same node – which represent added complications from a network perspective. On the other hand, the total number of employees in each district already embraces this aspect.

### *8.3.2 Interpretation of Spatial Interaction Behaviour as Preferential Attachment*

The usual practice in the use of SIMs, when dealing with commuting flows, is to employ the models in forecasting future flows, given certain conditions. In our experiments, we propose the utilization of the simple power-law-specified SIM shown in Equation (8.8) as a tool for approximating the connectivity and structural properties of a commuting network, as opposed to the more mainstream and studied exponential specification (Equation 8.9). In particular, we want to verify if an SIM can allow for preferential attachment behaviour. In the models introduced by Barabási and Albert, nodes have a higher probability of connecting to other nodes that are already well-connected. The hypothesis that we test in the next section is that commuting networks follow a similar preferential attachment-based behaviour in terms of connectivity and structure. They would not be the first transportation network to be referred to in these terms. In fact, hub-and-spoke networks operated by airlines are a well-known example of preferential attachment behaviour (see, for example, Bowen 2002, and, most importantly, Wojahn 2001).

An additional reason for the consideration of commuting networks in such a framework can be found if we think of preferential attachment as a maximization of utility levels. The idea is that utility is maximized by connecting to the most-connected nodes of the network. If so, this hypothesis would be consistent with the theoretical basis of utility maximization that justifies the use of SIMs. In particular, the hub-and-spoke network might – conceptually – be interpreted as a network tree consistent with a nested logit/hierarchical SIM structure (for the compatibility between the nested-logit and double-constrained SIM, see Nijkamp and Reggiani 1992).

Given these premises, the next three sections present the empirical application undertaken in this chapter. We first carry out a statistical exploration of the data (Section 8.4.1). This is followed, in Section 8.4.2, by a network analysis of the commuting data and the SIM results. Finally, an analysis of the results of the SIMs is presented in Section 8.4.3.

## 8.4 Empirical Analysis: Commuting Networks over Time

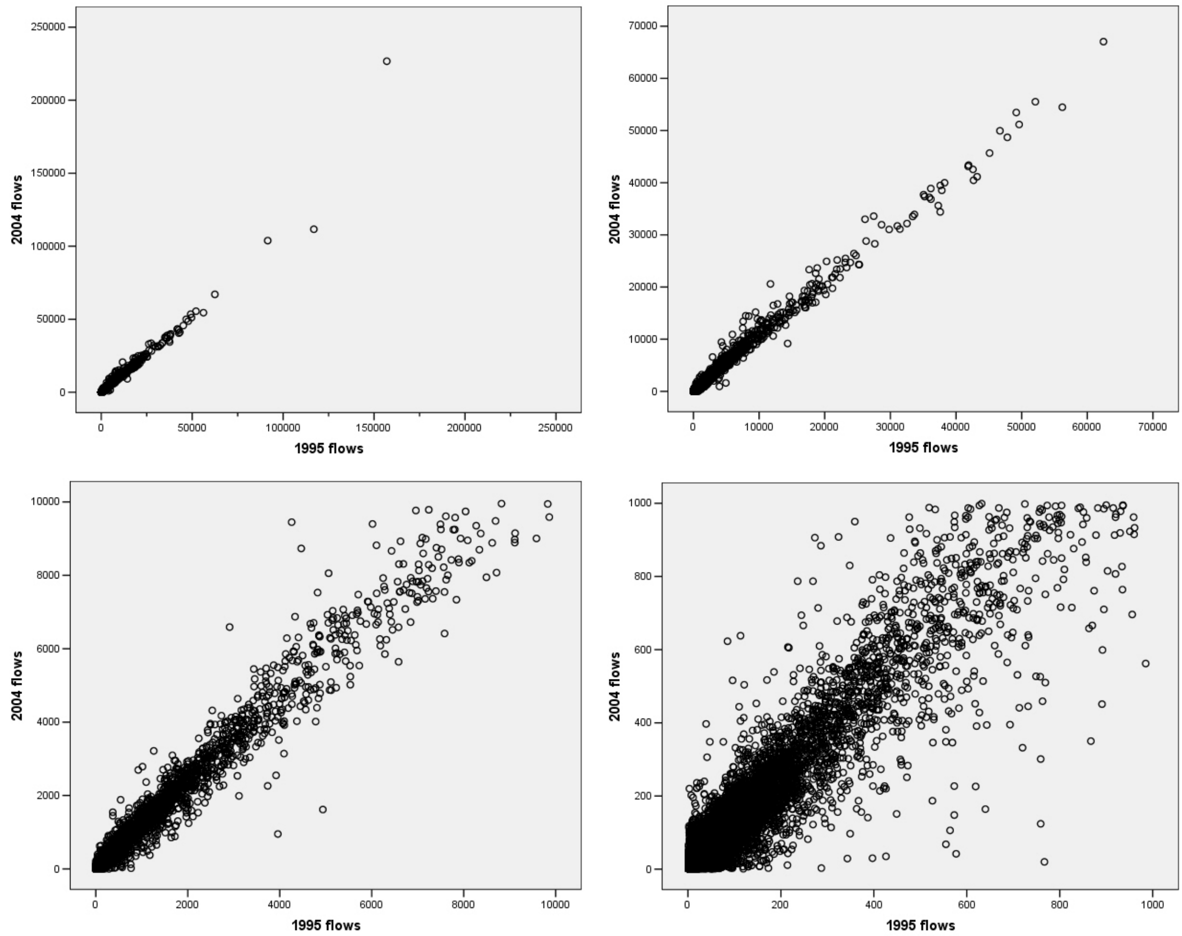
### *8.4.1 A Statistical Comparison of Commuting Flows for 1995 and 2004*

The primary data employed in the analyses presented below consist of information on German commuting flows between NUTS-3 districts. While the data are described more in detail in Section 3.3.2, they can now be briefly described, for each origin-destination (O-D) pair $(i,j)$, as the number of workers commuting to district $j$. As stated above, internal commuters are not included in our analyses. The home-to-work data employed in this chapter refer to the years 1995 and 2004.

A first step in our network analysis is to statistically explore the commuting data available. In particular, we focus our attention on the statistical comparison of the observations collected for the first and the last year of the data set.

The four graphs in Figure 8.1 show the distribution of the commuter flows, for both 1995 and 2004, at different scales. While the top-left graph shows the entire range of the flows, the remaining graphs reduce the visualization to flows less than 70,000, 10,000 and 1,000 commuters (bottom-right), respectively. A high correlation between the observations for the two years can be observed. This result might imply a certain stability in the relationships between centres, or the absence of dramatic changes in transport infrastructure over the period considered, which are amongst the prime determinants of variations in commuting patterns. However, as we observe the smallest ranges of commuters, more spreading starts to be seen. The $R^2$ obtained by regressing the data for the year 2004 on those for 1995 decreases from 0.975 to 0.898, when considering the whole range of flows or only those with fewer than 1,000 commuters.

In the top-left graph of Figure 8.1, the most visible outlier, which has the highest number of commuters, represents the commuting flows between the two formerly-separate East and West Berlins. Workers who live and work on opposite 'sides' of Berlin seem to have increased in the 9-year period, which seems to be a reasonable and somehow expected finding, considering that the data for the first year considered, 1995, were collected only five years after reunification. Therefore, it makes sense to expect a gradual redistribution of residential and business location choices on both sides of Berlin, This might be particularly true for relocations into the formerly-Soviet side of the city, where rents are, or were, supposedly cheaper (see, for example, Kemper 1998). As explained in Section 3.3.2, the two Berlin districts are kept separate in this data set. On the one hand, it could be considered unrealistic to separately analyse areas that, as a matter of fact, belong to the same city; further, by doing so, we reintroduce, for the case of Berlin, intra-district commuting flows that have been excluded by the analysis for all the other districts. On the other hand, this allows us to observe the huge amount of mobility that has been generated, within the city, since reunification.




*Note:* Overall $R^2$ (top left) = 0.975; $R^2$ for flows below 1,000 (bottom right) = 0.898.
Figure 8.1 – Scatterplot of commuting flows in 1995 and 2004, at different scales

Following our previous remarks (see Section 3.3.1), a more general observation can be made here with regard to the spatial demarcation of the districts used in our analysis, in that our results are influenced by the level of geographic aggregation used (NUTS-3). For instance, a different distribution of the flows – most likely eliminating the major outliers in our data – could be obtained if we employed labour market areas (LLM), which minimize commuting within major metropolitan areas. The investigation of the effects of geographic scale on our results is a possible direction for future research.

In addition to the above considerations, a more in-depth exploration of the data is necessary. Table 8.1 summarizes the statistical results obtained for the two data sets. The summary statistics show the change in the commuting flows over the years. Consequently, the total number of commuters also increased, by 15.41 per cent. The average number of commuters per O-D pair increases from about 108 to about 119. However, the large increase in the commuting flows within Berlin suggests that the 15.41 per cent increase may not be distributed uniformly over the network. In particular, the difference between the mean and the median of the ratio statistics for the two data sets – they stand at 1.67 (mean) and 1.21 (median) – seems to suggest a Poisson distribution.

Table 8.1 – Statistical exploration of the commuting flows data sets, for 1995 and 2004

| Year | Maximum value | Sum | Mean | Mean 2004/1995 ratio | Median 2004/1995 ratio |
|---|---|---|---|---|---|
| 1995 flows | 156999 | 8616362 | 107.59 | 1.670 | 1.214 |
| 2004 flows | 226700 | 9944326 | 118.53 | | |

Having statistically explored the data, the next section examines, from a network perspective, the implications and properties of the logical links derived from the data set analysed.

### *8.4.2 Network Analysis: The Results*

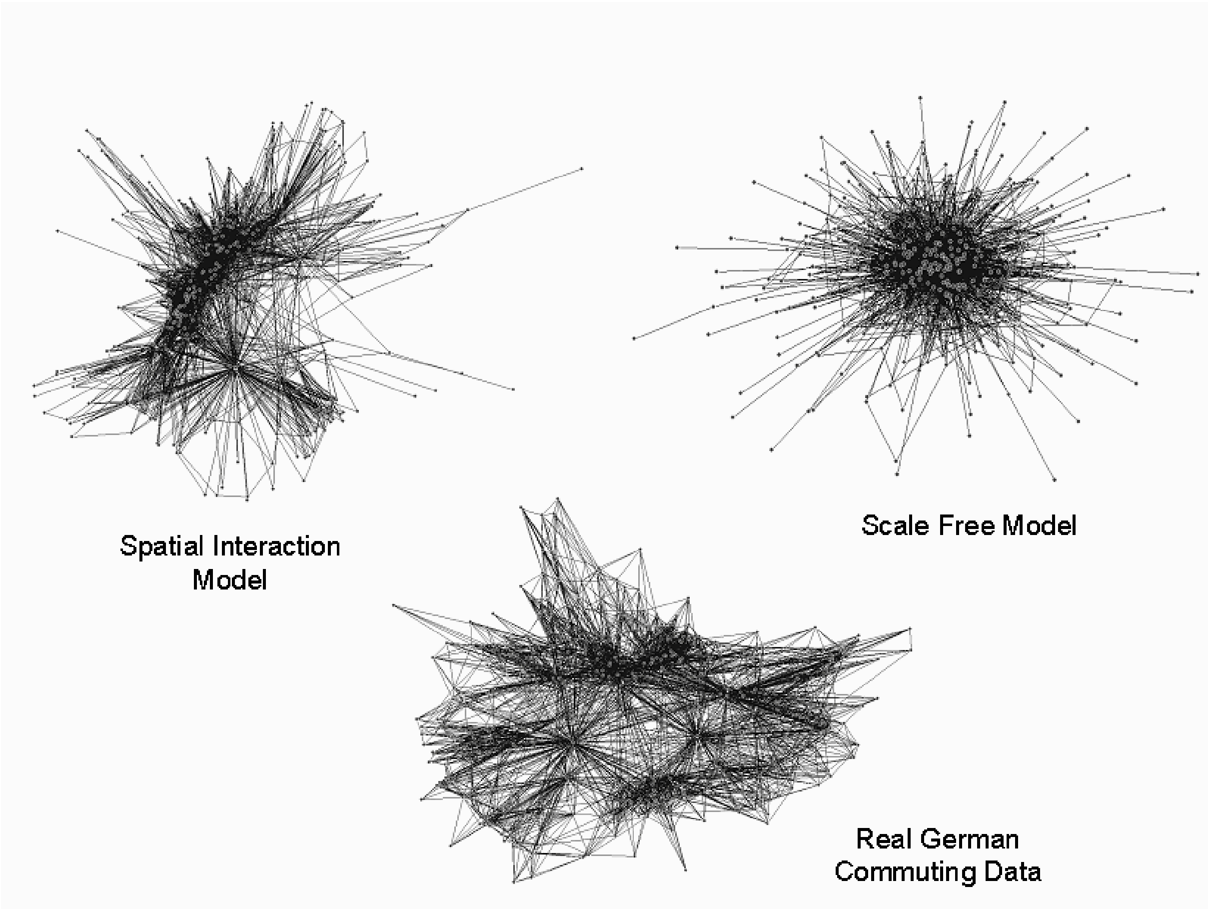
As stated in Section 8.1, we want to examine the network structure underlying the commuting flows data. In order to do so, we may consider each O-D pair $(i,j)$ as a link between nodes $i$ and $j$, within our commuting network. The nodes of the network are, therefore, the districts the commuters travel to and from on the network.

The commuting flows are translated into a network structure by means of a simple procedure. Each O-D pair that has at least a given number of commuters (for example, 1) contributes to generate a vertex index, which is a counter of the number of links that attach to one or another node of the network. The final product of this operation is a ranked list of the nodes (districts) in the network, ordered according to the number of connections they enjoy. For example, the presence of commuters on the link between Munich and Rostock increases by 1 the number of connections (the 'degree') of both districts. The threshold for the minimum number of flows to be observed on each link in order to be valid is, of course, subjective. The higher the threshold, the fewer the long-distance routes identified will be, therefore emphasizing the relevance of local mobility (sub-)networks. Once the vertex list is complete, a graph software such as Pajek[52] can visualize the resulting network. Figure 8.2 shows the graphs obtained, in preliminary research, for commuting flows observed in the year 2002, as well as for a simulated SF model and for the power-specified SIM shown in Equation (8.8). In this case, a threshold of at least 100 commuters per O-D pair was set for computational reasons.

While the SIM in Figure 8.2 was formalized as described in Section 8.3.1, the SF model created for comparison was based on a network having a 0.3 connectivity probability, an alpha parameter also of 0.3, and an initial three districts to connect to. The relative position of the nodes (the districts) in the graph is not based on geographic coordinates, but on their topological role; that is, on how central or peripheral they are to the network. From a visual inspection of the three networks, the SIM comes closest to replicating the German commuting network, though lacking the same level of interconnectivity seen in the real data. The SF

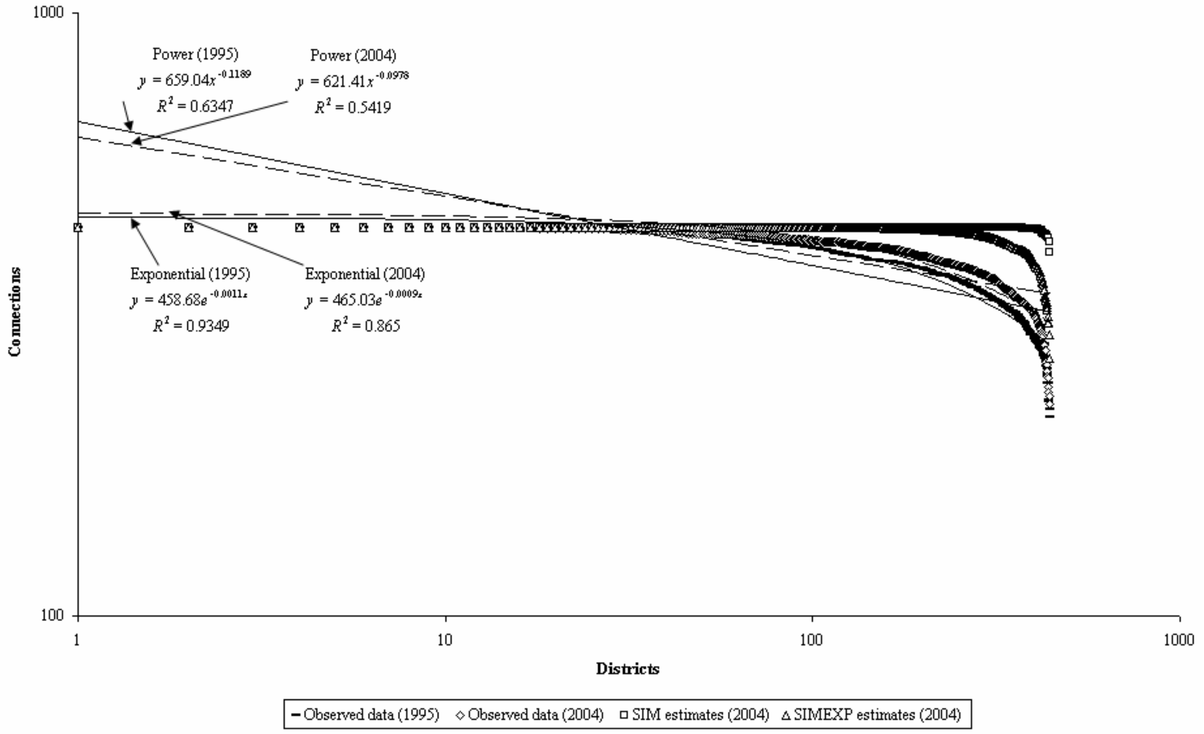
[52] Pajek is publicly available at http://vlado.fmf.uni-lj.si/pub/networks/pajek.

model shows even less interconnectivity, since most connections go directly to the hubs rather than being found between the spokes – as seen in the data.




*Source:* Gorman et al. (2007, p. 177).
Figure 8.2 – Network Visualization of the Network BA Model, Spatial Interaction Network Model, and German Commuting Network

The topology of networks can also be investigated by examining their distributional properties; that is, by means of a ranked plot of the number of connections (degree) by district. Figure 8.3 is the plot of the degree distribution concerning the 1995 and 2004 data, as well as of the values fitted – for 2004 – by means of our SIMs (for both the power and the exponential specifications). The degree decay of both the data and the SIM-estimated values seems to be better interpolated by an exponential distribution, rather than a power law. A large number of nodes seem to enjoy connections to all other nodes in the network (that is, they are fully connected). If we consider a list of the most- and the least-connected districts for the two years (see Annex 8.A, Table 8.A1), and if we follow the BBR district classification (Böltgen and Irmen 1997) previously employed in Chapter 4, we see that most of the districts with the highest number of connections belong to type 1; that is, they are 'central cities in regions with urban agglomerations'. Conversely, the least connected districts are mostly classified as types 8 or 9, which refer to regions with rural features. However, the connections are still quite high even in the rural regions, showing a rather good connectivity structure over the entire network. The high value of the connectivity shows that we are indeed dealing with more general connectivity rather than just daily commuting.




*Notes:* $R^2$ values refer to the exponential and power functions fitted to the observed data.
SIM: power-law SIM.
SIMEXP: exponential SIM.
Figure 8.3 – Log-log plot of the connections of German districts, for observed (1995 and 2004) and estimated data (2004)

The findings presented here – a high number of fully-connected districts and a slow decay of the number of connections – can be explained by the limited number of nodes (districts) in the network, and by one of the conditions considered in the Barabási and Albert framework: network growth. In our case, no new node can be added to the network over time, unless new districts are introduced.

The network analyses presented in this and the preceding section showed the distribution of the commuting data from two points of view: numerical and structure-wise. It is also interesting, at this point, to explore the network's characteristics (that is, homogeneity of the network) from the perspective of the deterrence function in the commuting flows. In other words, it is worth examining, by means of appropriate models, like SIMs, whether the network under analysis shows – in its deterrence function – an exponential function, reflecting a homogeneous network, or alternatively a power function – reflecting a hub structure. Therefore, the next section investigates how the SIMs introduced earlier fit the data and, most importantly, which specification (power or exponential) is more suitable to approximate the deterrence form of the commuting network.

### 8.4.3 Spatial Interaction Models: The Results

The last steps in our analysis are: (a) the calibration of the SIMs for 2004; and (b) the test of the distributional properties of the commuting network in Germany, in the light of its impedance function. Concerning the calibration phase, it should be recalled that the SIMs were calibrated in the unconstrained specification, in their log-linear form. The zero-flows in the O-D matrix were excluded, as they represent an almost unresolvable econometric problem in the estimation procedure. Additionally, if no flow threshold is used – as in our case – the O-D matrix is far from sparse (zero-flows represent only about 30 per cent of the matrix), and includes, for the most part, values close to 0.[53] A value of –1.658 was estimated for the β deterrence factor of the power-law specification (Equation 8.8), while a value of –0.006 was computed for the exponential specification (Equation 8.9). The results of the power-law SIM calibration are consistent with the findings of Olsson (1980) for Sweden. From this first analysis, the power-law coefficient seems more appropriate than the exponential coefficient, since the latter suggests a rather low propensity towards mobility in the German commuting network.

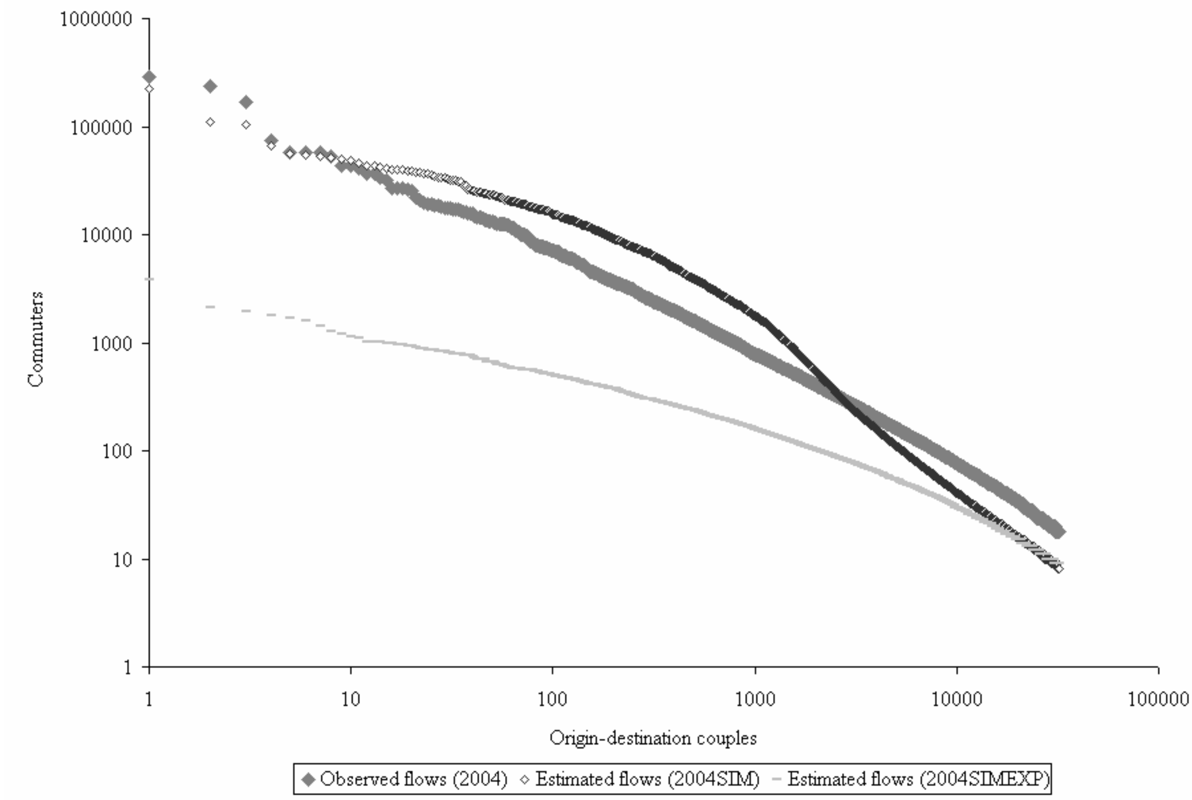
Concerning the test phase, we are interested in comparing the connectivity structure emerging from the real data with the results of the SIMs from the O-D perspective. This is achieved by first ranking the observed and estimated data in decreasing order of commuters per O-D pair. We can now analyse the decay of the flows and fit a curve to the data. Table 8.2 shows the results obtained when fitting both a power-law and an exponential distribution to the data, while Figure 8.4 provides a 'partial' visualization of the distribution of the two data sets and models, on a log-log scale.

Table 8.2 – Fitting exponential and power-law distributions to commuting flows observed and estimated for 2004

| Distributions | $R^2$ | Parameter estimates | |
|---|---|---|---|
| | | Constant | $b_1$ |
| | | Observed flows | |
| Power | 0.972 | 97636479.740$^{***}$ | –1.589$^{***}$ |
| Exponential | 0.839 | 92.631$^{***}$ | –0.00006$^{***}$ |
| | | Estimated flows (power-law-specified SIM) | |
| Power | 0.934 | 28033260.494$^{***}$ | –1.405$^{***}$ |
| Exponential | 0.908 | 123.979$^{***}$ | –0.00005$^{***}$ |
| | | Estimated flows (exponential-specified SIM) | |
| Power | 0.901 | 1290073.530$^{***}$ | –1.176$^{***}$ |
| Exponential | 0.941 | 47.716$^{***}$ | –0.00004$^{***}$ |

*Note:* All parameters are significant at the 99 per cent level ($^{***}$).

[53] A number of solutions have been suggested in the literature for dealing with zero-flows, such as adding 0.5 to all cells of the O-D matrix. Since the discussion of this issue is beyond the scope of our experiments, which represent a preliminary exploration, we refer to Sen and Smith (1995) and Fotheringham and O'Kelly (1989).




*Notes:* Visualization limited to the top 32,000 observations of the data sets, according to a decreasing rank order of the number of commuters per O-D pair.
SIM: power-law SIM.
SIMEXP: exponential SIM.
Figure 8.4 – A partial visualization of the observed and the estimated commuting flows for the year 2004

According to the results shown in Table 8.2, the distribution of the observed flows fits a power-law distribution better than an exponential distribution, from both a statistical and spatial-economic viewpoint. However, from a purely statistical viewpoint, both functions could be suitable. In this context, refinements of these two functions might be adopted, for example, by means of a Box-Cox transformation (Box and Cox 1964) and other functional forms (see, for example, de Vries et al. 2004). The two SIMs specified earlier – Equations (8.8) and (8.9) – seem to better fit the respective functions (power-law and exponential) at the basis of their computation, although with lower $R^2$ values. Two considerations may be made regarding the SIMs. On the one hand, the modelling results tend to be smoothed out in comparison with the observed data. The model data show a lower $R^2$ and a lower exponent for the power-law function, although its implications are not straightforward (for a discussion of power-law exponent values, see, for example, Albert and Barabási 2002). On the other hand, fitting a power-law function implies aiming at a more-than-proportional concentration of commuting flows over a few routes, with the number of commuters for the other O-D pairs decreasing rapidly afterwards. This does not seem to happen with the real data.[54]

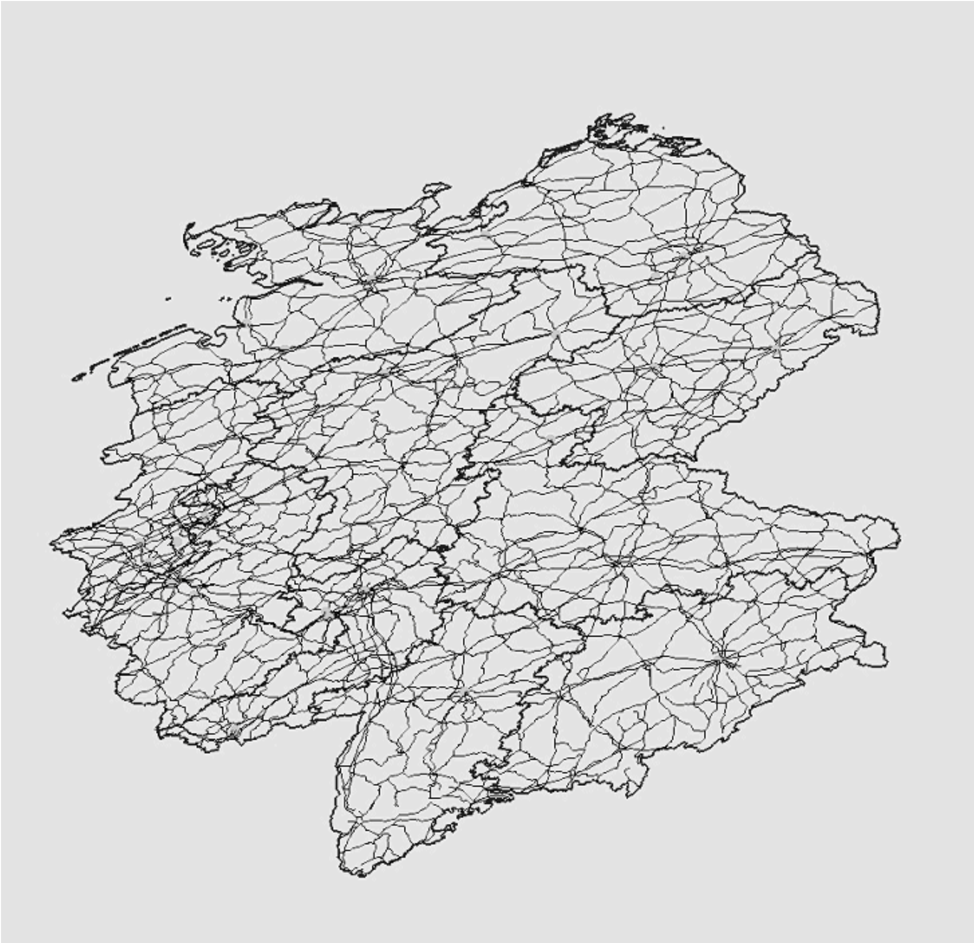
Next, by ranking the number of connections (degree) per district emerging from the SIMs (Figure 8.3), it can be seen that the exponential-specified SIM better approximates the commuting network's connectivity structure, as it shows a cut-off, for the less-connected districts, that is more similar to the one of the observed data. This can be explained by the fact that the data themselves fit an exponential distribution better (see also Russo et al. 2007). Further, our finding of a slow decay of connections can also be considered to be a consequence of trends, more or less recent, due to the overcrowding of the main cities, such as the tendency to suburbanization, which causes an increase in commuting.

## 8.5 Structural Analysis of the Physical Commuting Network by Means of a Shortest-Path Algorithm

In addition to studying the flows of commuters between cities, it is also possible to study the structure of the infrastructure they utilize. The economic flows of commuters and the physical links of infrastructure are intrinsically connected, but belong to two very different network structures. Commuting flows belong to logical networks, which are non-planar in nature, since the fact that two links intersect does not mean a node actually exists at their intersection. A flow in the commuter network could therefore be between Frankfurt and Munich with only two nodes and one link, even though the physical path goes through Stuttgart. The physical network, on the other hand, is planar; the intersection of two links creates a navigable intersection. In order to travel from Munich to Frankfurt, several intermediate nodes have to be traversed. Commuting data represent the flows across the physical network, but the two networks are quite different in nature and structure.

As an exploratory analysis in the direction of addressing the relationship and differences of these networks, we analysed, in preliminary research (Gorman et al. 2007), the physical road network of Germany. Unlike the commuting flow network, it is straightforward to visualize what the road network looks like with a simple map. Figure 8.5 provides a map of the German road network.

[54] We can visualize the distribution of the flows estimated by the power-law SIM by plotting them against the data observed for the year 2004 (see Figure 8.B1 in Annex 8.B, the scales are the same as in Figure 8.1). It is evident that, although the data employed refer to the same year, the clear correlation patterns found in Figure 8.1 are not matched in these new plots. It can be noted, in the top-left graph, that three observations in particular are wrongly estimated by the SIM. The model underestimates the commuting flows between Hannover and its surrounding region, while it again overestimates the flows between the cities of Munich and Bamberg and their respective surrounding districts. Overall, the $R^2$ obtained by regressing the observed data on the SIM results is 0.415. Similarly to the discussion above for the years 1995 and 2004, the $R^2$ decreases (to 0.405) when only observations with less than 1,000 commuters are considered. The bottom-right plot of Figure 8.B1 confirms the wide spread of the data. Generally, a more marked tendency to underestimation can be seen for mid-range flows (bottom-left graph).



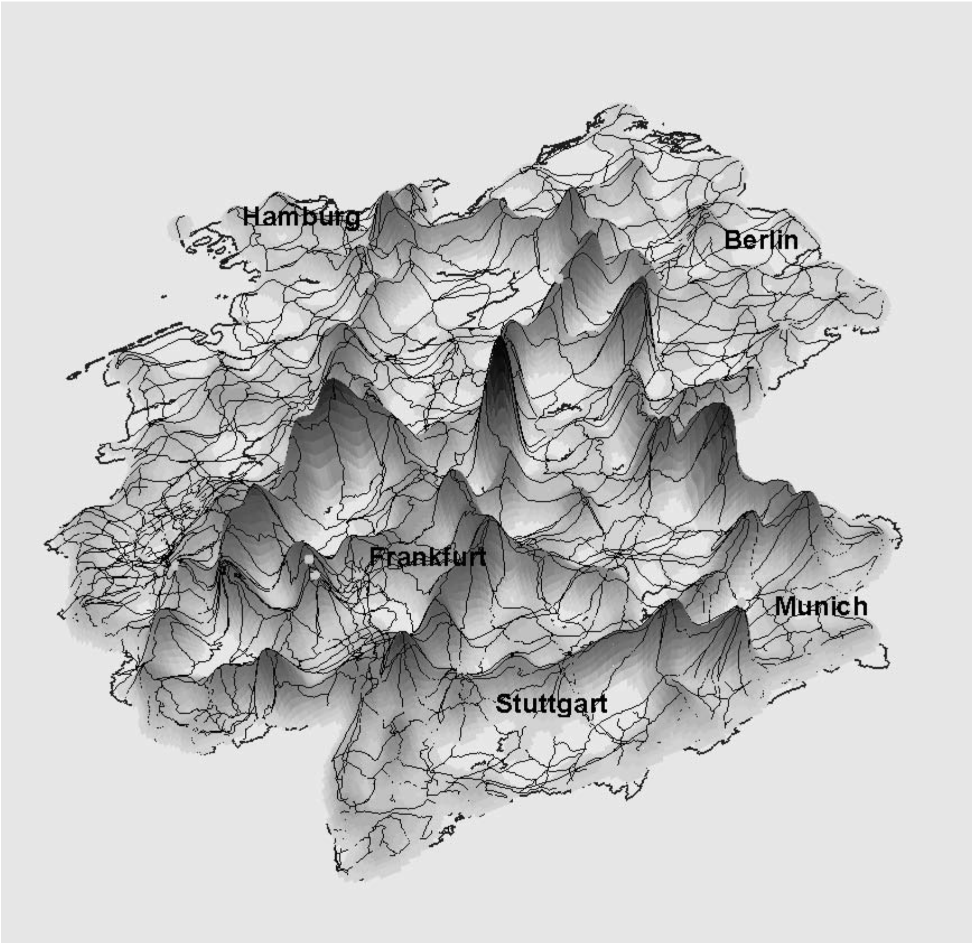
*Source:* Gorman et al. (2007).
Figure 8.5 – The German road network

While the map visualized in Figure 8.5 does illustrate the layout of the road network, it does not give much insight into its structural properties. In order to gain some perspective on the structure of the road network, a routing frequency analysis was performed.[55] The road network was first partitioned into nodes and links, and then shortest paths were calculated to and from all nodes in the network. Links were then assigned a frequency count, based on the number of times the link was utilized in all possible link combinations. This provided a structural analysis of which links, in the German road network, are potentially most critical and heavily utilized in all possible travel combinations. To visualize these results Figure 8.6 was constructed.

In Figure 8.6, the height and colour (lighter to darker) of the peaks is determined by the number of routes that use a particular link in the road network. The higher the frequency of routes, the higher the peak. The routes that connect through the middle of the country are particularly utilized, especially the routes that appear to connect Berlin to Frankfurt and

[55] An additional way to explore the network properties of the road infrastructure involves the use of a contiguity matrix (see Chapter 7). In particular, the principal eigenvector of the geographical contiguity matrix contains information on the topological accessibility of the network nodes. This approach – in combination with recent network analysis developments described above – will be explored in future research.

Stuttgart. The routes connecting Berlin to Munich and Hamburg are also prevalent. In general, it can be noted that the routes in Western Germany have a higher frequency than the ones in Eastern Germany.




*Source:* Gorman et al. (2007).
Figure 8.6 – German road network route frequency analysis

In spite of the results obtained, it should, however, be remarked that this analysis was simply based on shortest-path frequency and, consequently, does not take into account socio-economic dimensions such as population or employment levels. Therefore, we cannot address – at this stage – questions such as: Are the highest flows of commuters also utilizing the main structural links? How well does the physical structure of the network match the economic flows across it? In this regard, a desirable further development of the present analysis is the implementation of a multi-layered GIS approach, which would allow us to merge: (a) the road network; (b) the regional boundaries; and (c) the commuting flows information.

## 8.6 Conclusions

The present chapter has provided an overview of the network properties found for home-to-work commuting patterns in Germany. We analysed flows between German districts (*kreise*) at what is called the NUTS-3 geographic aggregation level. First, an exploration of the commuting data was carried out, showing a significant increase of flows on the network, with a tendency to a more pronounced skewness. Second, a network analysis was considered in order to investigate the connectivity properties of the network. The analysis highlighted, by means of an investigation of the distributional properties of the number of connections per district (degree) (Figure 8.3), a rather slow decay in the degree of the districts. Over the period considered (1995–2004), the number of average connections per district increased, showing a denser net of reciprocal connections between cities. A tendency towards somewhat of a hub process – with reference to the connectivity aspect – is inhibited by the constrained-growth condition of the network (the number of nodes in the network is fixed), which hinders significant topological changes (this was also evident from the graph visualization of Figure 8.2). In this regard, not only does the number of districts not grow: it actually decreases, since a few districts have been amalgamated over time (this is the case of the Hannover and Berlin areas).[56] The general conclusion that can be drawn from our analysis is that the German transportation network can be compared to a rather homogeneous network. As a consequence, the least-connected districts also still enjoy connections to the majority of the nodes in the network (see Annex 8.A, Table 8.A1). Consequently, the increase in commuting over the years can be attributed to a better efficiency of the transportation network already in place.

In addition to the network analysis, two SIMs (alternatively using a power-law and an exponential deterrence function) were utilized in order to detect the network structure underlying the flows. While the SIM modelling results for the flow variables were quite ambiguous (see Footnote 54), most probably because of the simplicity of the models employed (unconstrained SIMs), the network connectivity structures generated by the two SIMs seem to favour the use of the exponential specification of Equation (8.9), highlighting the homogeneity of the observed data.

An additional analysis was subsequently presented, concerning the German physical road network. This analysis of the road infrastructure visually showed which points, according to a shortest-path routing algorithm, are (theoretical) critical points in the German road network; that is, central to the routes calculated over the network.

Further research should investigate the network properties of commuting by employing better specified, doubly-constrained SIMs, which would fully account for the total flows on the network, using a more suitable proxy for the travel opportunity cost than distance (for example, travel time or cost). In addition, it is desirable to go beyond the purely logical

[56] At this stage, however, these mergers are not considered in our analysis. They are, however, indeed considered in the analyses presented in the next chapter.

analysis of connections carried out here, by considering the real routes that, in the case of surface transportation, commuters have to follow. This could be done by expanding the implementation of the road-network shortest-path analysis presented in Section 8.5, by weighting the network with the commuting flows. Alternatively, rail routes could be observed. From an empirical viewpoint, a careful consideration of the level of spatial aggregation used should also be pursued. In fact, a recombination of smaller districts into 'macro-districts' might significantly influence the network structure found in this chapter. A final interesting analysis, from a policy viewpoint, might be the investigation of pre- and post-reunification mobility patterns, as well as the effects of the occasional merging of districts.

Given the above finding of a homogeneous pattern of the German infrastructure network, it is worthwhile analysing whether specific economic variables may highlight more diversified patterns and trends in the commuting flows. In this framework, a suitable variable can be the 'openness' of the German districts; that is, the potential mobility of each district. This is the focus of Chapter 9, which analyses that aspect from both a conventional (spatial) perspective and a network perspective. Here, more up-to-date data are employed, with the final aim to identify the most 'open' and 'connected' German regions.

## Annex 8.A Most- and Least-Connected Districts

Table 8.A1 – Classification of most- and least-connected districts, years 1995 and 2004

| 1995 | | | 2004 | | |
|---|---|---|---|---|---|
| District | District type | Degree | District | District type | Degree |
| Most connected districts | | | | | |
| Hamburg, Freie und Hansestadt (W) | 1 | 440 | Hamburg, Freie und Hansestadt (W) | 1 | 440 |
| Hannover, Stadt (W) | 1 | 440 | Hannover, Stadt (W) | 1 | 440 |
| Cologne, Stadt (W) | 1 | 440 | Düsseldorf, Stadt (W) | 1 | 440 |
| Frankfurt am Main, Stadt (W) | 1 | 440 | Bonn, Stadt (W) | 1 | 440 |
| Stuttgart (W) | 1 | 440 | Cologne, Stadt (W) | 1 | 440 |
| Munich, Stadt (W) | 1 | 440 | Frankfurt am Main, Stadt (W) | 1 | 440 |
| West Berlin, Stadt (E) | 1 | 440 | Offenbach (W) | 2 | 440 |
| East Berlin, Stadt (E) | 1 | 440 | Stuttgart (W) | 1 | 440 |
| Dresden, Stadt (E) | 1 | 440 | Esslingen (W) | 2 | 440 |
| Düsseldorf, Stadt (W) | 1 | 439 | Karlsruhe (W) | 1 | 440 |
| Offenbach (W) | 2 | 439 | Mannheim (W) | 1 | 440 |
| Esslingen (W) | 2 | 439 | Munich, Stadt (W) | 1 | 440 |
| Bremen, Stadt (W) | 1 | 438 | Munich (W) | 2 | 440 |
| Munich (W) | 2 | 438 | Nuremberg, Stadt (W) | 1 | 440 |
| Nuremberg, Stadt (W) | 1 | 438 | West Berlin, Stadt (E) | 1 | 440 |
| Main-Kinzig-Kreis (W) | 3 | 437 | East Berlin, Stadt (E) | 1 | 440 |
| Leipzig, Stadt (E) | 1 | 437 | Dresden, Stadt (E) | 1 | 440 |
| … | | | | | |
| Least connected districts | | | | | |
| Sonneberg (E) | 8 | 259 | Regen (W) | 9 | 263 |
| Straubing, Stadt (W) | 9 | 257 | Stralsund (E) | 9 | 261 |
| Kaufbeuren, Stadt (W) | 9 | 252 | Kaufbeuren, Stadt (W) | 9 | 254 |
| Regen (W) | 9 | 251 | Emden, Stadt (W) | 8 | 249 |
| Emden, Stadt (W) | 8 | 243 | Kusel (W) | 7 | 249 |
| Pirmasens, Stadt (W) | 6 | 243 | Pirmasens, Stadt (W) | 6 | 248 |
| Lüchow-Dannenberg (W) | 9 | 228 | Freyung-Grafenau (W) | 9 | 240 |
| Freyung-Grafenau (W) | 9 | 227 | Zweibrücken, Stadt (W) | 6 | 235 |
| Zweibrücken, Stadt (W) | 6 | 220 | Wismar (E) | 8 | 231 |
| Wismar (E) | 8 | 214 | Lüchow-Dannenberg (W) | 9 | 225 |

## Annex 8.B Comparison of Observed and Estimated Commuting Flows

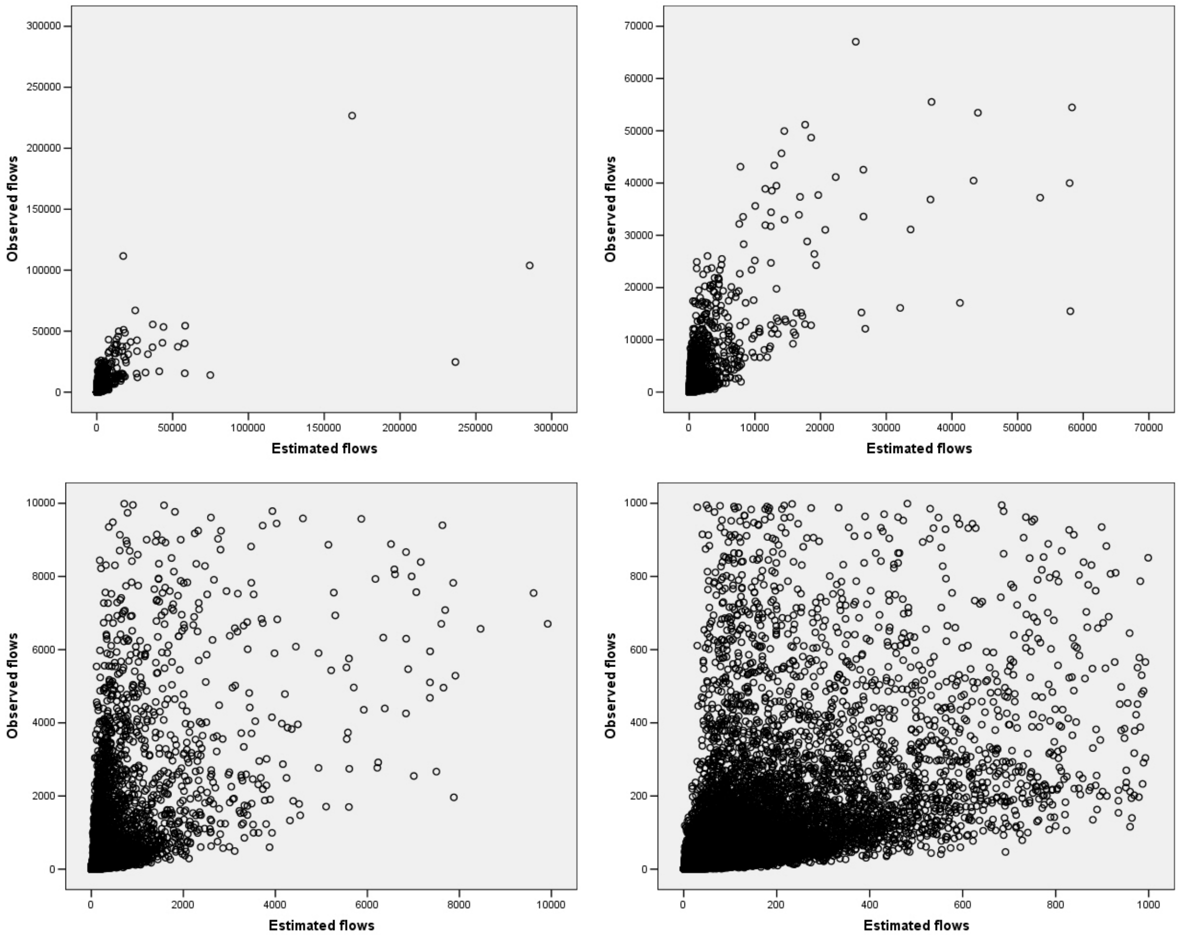



Figure 8.B1 – Scatterplot of observed and estimated (power-law SIM) commuting flows, year 2004, at different scales

Chapter 9

# Network Evolution and Spatial Dynamics of German Commuting

## 9.1 Introduction[57]

The preceding chapter offered a first exploration of a data set concerning home-to-work mobility in Germany. Until now, we have focused on the total flows observed over all origin-destination (O-D) pairs (say, for example, Berlin-Munich), irrespective of the direction of the flows. The implications of such flows were considered from a network viewpoint. We found the (logical) commuting network to be rather homogeneous and stable, within a general picture of increased interconnection levels between the German NUTS-3 districts.

In the present chapter, also in the light of the second research objective of this study, we further deepen our analysis of German commuting, by focusing on the directionality of mobility. Consequently, our attention shifts to the analysis of the hierarchies of the regions, in terms of the extent to which they are capable of attracting or pushing commuters. Similarly to Chapter 8, we analyse the network structure underlying the commuting flows, but here we match the network framework with the conventional spatial iteration framework.

When considering the direction of commuting flows, clear implications with regard to urban shape and regional network of cities arise. Commuting has for a long time been studied in these perspectives, in particular concerning locational/development trends leading to either of the following: (a) the monocentric (central) city; and (b) the polycentric city (for a more extensive review of urban economic theories, see Button 2000; Hall and Pain 2006). The latter perspective has been developed by observing the various deconcentration trends observed in many major cities (for example, see Fujita et al. 1999; Bar-El and Parr 2003). These trends are now increasingly found at a larger spatial scale leading, for example, to the idea of 'network cities' (Batten 1995). In this context, horizontal relations between cities tend to emerge (Wiberg 1993; van der Laan 1998). This also results from the improvements in transportation systems and accessibility, which diminish the importance of distance. Remarkably, Papanikolaou (2006) suggests that spatial structure alone does not strongly

[57] The present chapter is based on Patuelli et al. (2007b).

account for different commuting distances. As a result of the ongoing process described above, local hierarchies – originally consistent with monocentric theories – are subject to constant change and exhibit more decentralized urban regions (examples are the Randstad area in the Netherlands – see Clark and Kuijpers-Linde 1994 – or the emergence of edge urban areas (edge cities) – see Phelps and Parsons 2003). In particular, van der Laan finds that more horizontal (non-hierarchical) relations emerge for regions with modern manufacturing systems, while the (hierarchical) status quo is preserved for peripheral, less advanced regions.

On the basis of the aforementioned developments, in the present chapter we aim to assess how network topology – and its changes over time – affects the dynamic trajectory of the geographic commuting network and its hierarchies. The reason for studying the commuting network in a connectivity perspective is inspired by the idea that the network distribution of mobility can help explain other relevant economic phenomena, such as variations in key labour market indicators or production levels, and is therefore relevant with regard to the objectives of the present study. The remaining parts of the chapter are structured in the following way. Section 9.2 illustrates a spatial analysis of commuting flows in Germany, while Section 9.3 presents the results of the network modelling experiment undertaken. Section 9.4 then presents a comparative multicriteria analysis that addresses the change in hierarchies in the main German districts. Finally, Section 9.5 concludes the chapter with some final remarks and suggestions for future research, as well as with a number of considerations concerning the research objective followed in Part C of this study.

## 9.2 Dynamics of Commuting: Spatial Data Exploration

In the preceding chapter (Section 8.2) we illustrated recent developments in the analysis of networks. These tools, in particular with reference to the work of Barabási (2002), are, again, amongst the central ones considered in our study for exploring changes in the characteristics of the German commuting network topology. Before analysing the network properties of spatial commuting patterns, we present the German database from a regional/spatial perspective.

The data employed in our analysis refer to the residence and workplace of all dependent workers in Germany, and are the same as the ones employed in Chapter 8, except for two aspects: (a) the years considered here are 1995 and 2005 (instead of 2004); and (b) the number of NUTS-3 districts decreases from 441 to 439, because of the Berlin and Hannover areal unit mergers described in Section 3.3.2. Consequently, we have an origin-destination (O-D) matrix of dimension 439 x 439 containing in each cell the number of home-to-work trips. Here, we also employ a district classification by the BBR (*Bundesanstalt für Bauwesen und Raumordnung*) (Böltgen and Irmen 1997) regarding levels of urbanization and agglomeration (again, see Section 3.3.2).

In order to show the propensity to mobility of the districts, we employ indicators of incoming and outgoing mobility, which we refer to, adapting from van der Laan (1998), as inward and outward 'openness'. The 'inward openness' of a district indicates to what extent it attracts workers from outside, and is computed as the percentage of local jobs absorbed by non-residents of the given district.[58] Similarly, the 'outward openness' can be defined as the percentage of residents who commute outside of their district. Finally, as a synthetic indicator of mobility (openness), we compute the average of inward and outward openness. Figure 9.1a,b and Figure 9.2a,b present a visualization of the change of district inward and outward openness, respectively, within Germany between 1995 and 2005.

Concerning the inward mobility, for both 1995 and 2005, greater inward openness tends to be observed for the central cities (of types 1 or 5). These are overrepresented among the most open districts. While the districts of types 1 or 5 are only 72 out of 439 (16 per cent of the total), they account for 46 per cent of the districts when considering an inward openness greater than 0.50. Therefore, central cities appear to truly function as small regional open systems. This result could be accentuated by the limited area of such districts. In fact, the German *kreise* (NUTS-3) classification has rather small districts for the main cities, whereas larger districts surround them (for example, districts of type 2). The above findings are consistent with what is conventional in regional and urban economics and spatial interaction modelling. Overall, though not a central city, the district – of type 2 – surrounding Munich (*Landkreis München*) emerges as the most open (inwards), as workers residing outside the district take up 70 (1995) to 76 (2005) per cent of the local jobs considered. As seen from these shares, the trend is towards a further accentuation of this peculiarity. A particular case, however, is that of Berlin, which, because of its economic and population size, generates large flows in absolute terms, both inwards and outwards, but, on the other hand, has rather low inward openness (11 per cent in 1995 and 20 per cent in 2005).

As far as the evolution of the indicators is concerned, we can observe, over the ten years of the data set, a generalized increase in mobility. In particular, the area surrounding Berlin seems to attract, in 2005, a higher share of commuters than in 1995. As the first year of our data set (1995) is only a few years after the German reunification, we might consider the higher propensity to mobility in 2005 to be the result of the reintegration of Berlin as the capital of Germany, from which a number of positive economic (economic/employment) externalities can be assumed (the German parliament and government restarted operations in Berlin in 1999) (see, for example, Burda and Hunt 2001).

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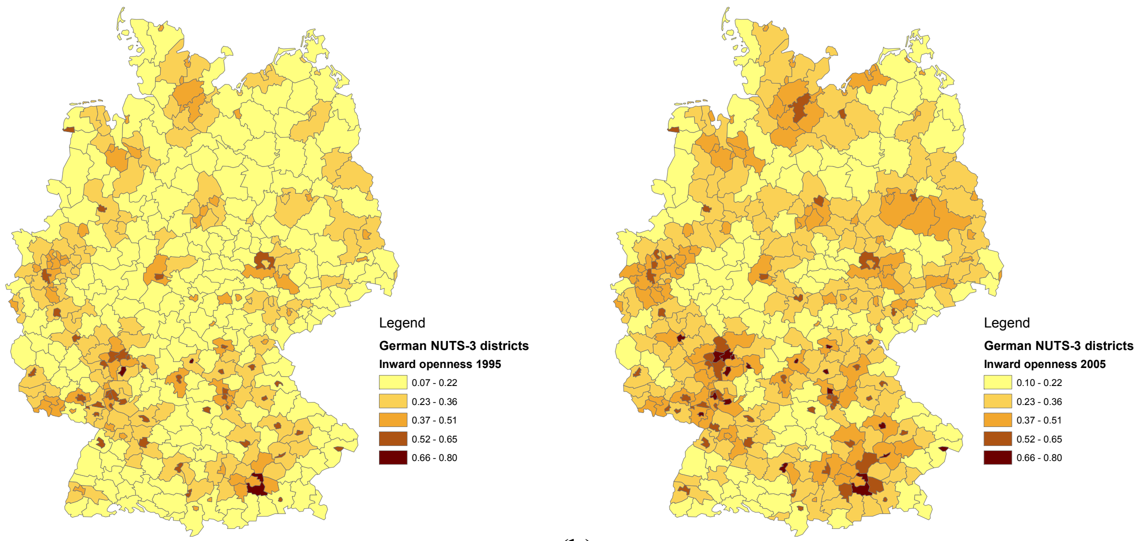
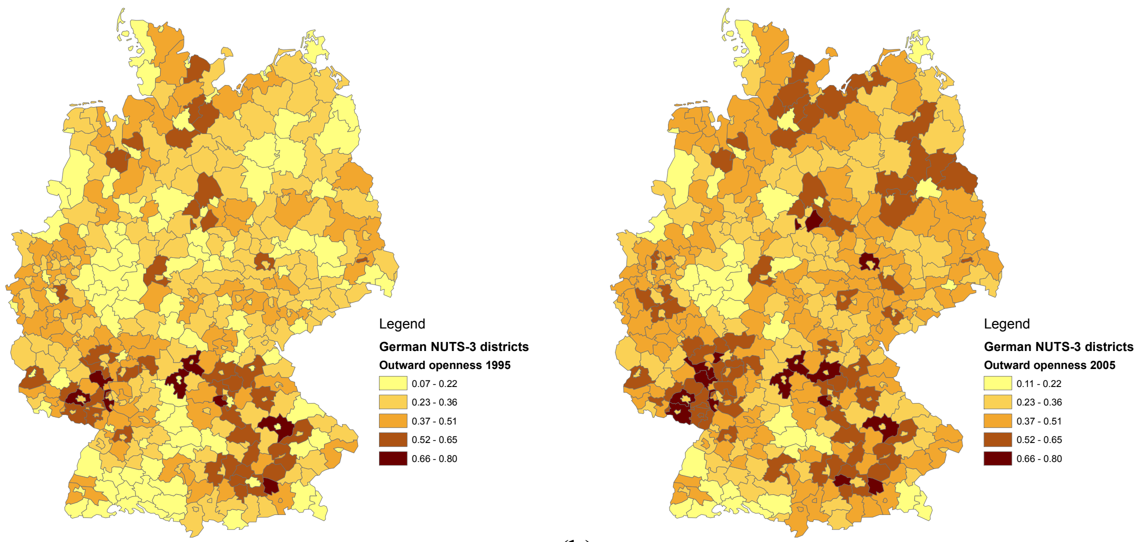
[58] The inward openness is computed, for a generic district *j*, as the ratio between the number of employees of the district *j* residing in other districts and the total number of employees of the district. If $e_{ij}$ is the number of individuals living in *i* and working in *j*, the inward openness of district *j* is equal to: $\sum_{i \neq j} e_{ij} \Big/ \sum_{i} e_{ij}$. Similarly, the outward openness of district *i* is equal to: $\sum_{j \neq i} e_{ij} \Big/ \sum_{j} e_{ij}$.




(a) (b)

Figure 9.1 – Maps of inward openness per district, 1995 and 2005




(a) (b)

Figure 9.2 – Maps of outward openness per district, 1995 and 2005

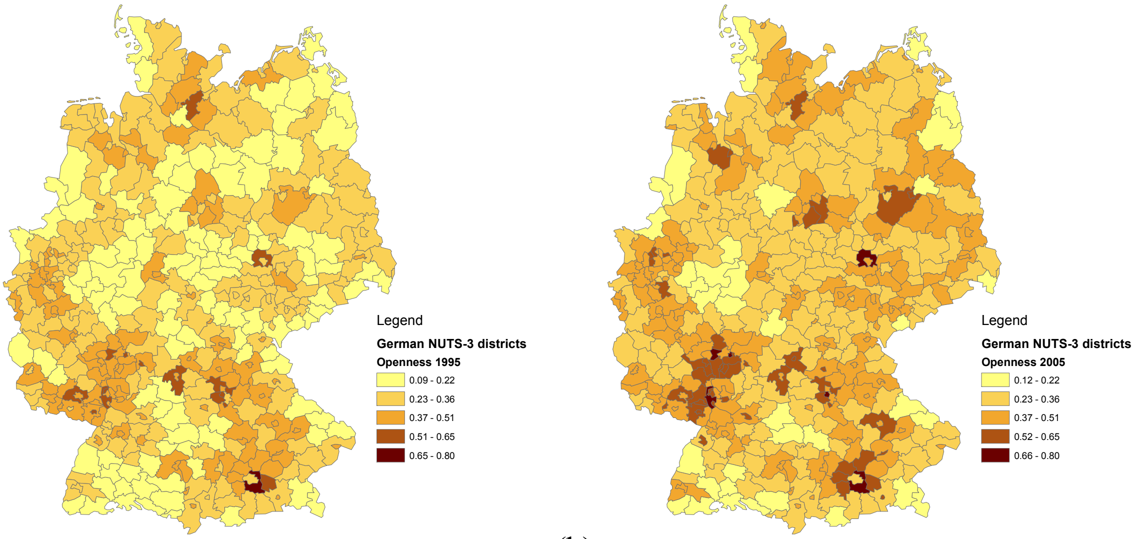
The evolution of openness can also be grasped in Table 9.1, which shows the openness of the nine types of districts. The overall dominance of the central city districts as regional mobility poles is also exemplified here. Central cities (of types 1 and 5) appear to have great inward mobility (ranging from 37 to 53 per cent in 1995 and 2005, respectively) compared with their surrounding districts of types 6 and 2 (22 to 37 per cent). This hierarchy is reversed when considering outgoing commuters. Highly urbanized districts (of type 2) show the greatest share of commuters leaving their districts for work (39 to 45 per cent in 1995 and 2005, respectively), followed by the urbanized districts of type 3 (38 to 45 per cent in 1995 and 2005). In summary, the central cities show a 'pull' effect, while the urbanized districts display a 'push' effect (see also Figures 9.1 and 9.2), in agreement with the transport economic generation/attraction models. The remaining typologies of districts show intermediate values, within a general increase – over the years – in the levels of mobility.

Table 9.1 – Inward, outward and total openness by type of district urbanization

| District Urbanization* | Inward | | Outward | | Openness | |
|---|---|---|---|---|---|---|
| | 1995 | 2005 | 1995 | 2005 | 1995 | 2005 |
| Central cities in regions with urban agglomerations (1) | 37.4 | 45.6 | 20.1 | 27.4 | 28.8 | 36.5 |
| Central cities in regions with tendencies towards agglomeration (5) | 44.2 | 53.3 | 22.2 | 30.0 | 33.2 | 41.7 |
| Highly urbanized districts in regions with urban agglomerations (2) | 29.9 | 37.4 | 38.7 | 44.6 | 34.3 | 41.0 |
| Highly urbanized districts in regions with tendencies towards agglomeration (6) | 22.4 | 28.2 | 33.6 | 40.0 | 28.0 | 34.1 |
| Urbanized districts in regions with urban agglomerations (3) | 25.1 | 32.5 | 38.2 | 45.2 | 31.6 | 38.9 |
| Urbanized districts in regions with rural features (8) | 27.0 | 33.9 | 30.0 | 36.8 | 28.5 | 35.4 |
| Rural districts in regions with urban agglomerations (4) | 23.1 | 31.5 | 37.4 | 48.7 | 30.3 | 40.1 |
| Rural districts in regions with tendencies towards agglomeration (7) | 18.9 | 24.7 | 29.3 | 36.8 | 24.1 | 30.7 |
| Rural districts in regions with rural features (9) | 18.1 | 23.9 | 25.9 | 33.1 | 22.0 | 28.5 |
| Totals | 29.8 | 37.1 | 29.8 | 37.1 | 29.8 | 37.1 |

* See Böltgen and Irmen (1997).

After observing the distribution of inward and outward openness, we can use – as an indicator of the overall 'openness' of the districts – the average of the two above indicators. This synthetic openness measure represents the capacity of a district to be 'mobile' and, consequently, 'active'. Van der Laan (1998, p. 238) identifies high values of openness as possible signs of a 'multi-nodal urban region'. In Figure 9.3, which maps the openness values, a specific group of cities emerges as the most 'active' in both years. These are mainly central cities (of type 1) and highly urbanized districts (of type 2), with the Munich *Landkreis* resulting in both 1995 and 2005 as the most 'open'. Their higher concentration of population and economic activities (located within, or in the surroundings of, the city) – or even the characteristics of a mobile population exploring new opportunities instead of the conventional jobs – might explain this result (van Oort 2002). Exceptions with rather low openness values, such as Berlin and the city district of Munich (a separate entity from the aforementioned surrounding *Landkreis*), should be noted. The reason for these exceptions should be sought in the fact that the districts to which these cities belong are larger than other central city districts, but still have a high density. Consequently, commuting (for example, from the city periphery to the CBD) seems to be carried out within the district boundaries. Over the 10-year period we observe a generalized increase in the propensity to mobility, while a more than proportional variation can be found for the area surrounding Berlin. In this context, it could be interesting to explore whether the most ‘open’ cities seen above are also connected together in a city-network pattern.




(a) (b)

Figure 9.3 – Maps of openness of districts, 1995 and 2005

In summary, given the mobility characteristics of the districts, it might be relevant to explore how these patterns are affected by the underlying connectivity networks, taking into account the findings on multi-nodality[59] presented by van Nuffel and Saey (2005) for the case of the Flanders region, and by Batten (1995) for the Netherlands and Japan. This aspect is investigated in the next section.

## 9.3 Dynamics of Commuting: Network Data Exploration

### *9.3.1 Preface*

The following sections present a set of analyses carried out from a network connectivity viewpoint, in order to investigate the distributional properties of German commuting. Section 9.3.2 aims to show how incoming and outgoing flows per district – and district-to-district connections – are allocated over the country. Subsequently, Section 9.3.3 presents aggregate indices concerning the commuting network, while indicating its centralization (dispersion) and interconnectivity.

[59] Van Nuffel and Saey (2005) find indications of ‘multi-nodality’ (defined as van der Laan’s integration of commuting systems with a high intensity of local ‘non-nodal’ horizontal relations) for the area of Ghent-Hasselt. Batten (1995) discusses the existence of ‘network cities’, of which local and regional multi-nodality (van Nuffel and Saey 2005) can be considered as special cases.

### *9.3.2 Connectivity Distribution*

An initial analysis of the network underlying the commuting activities can be carried out by considering – as previously done in Chapter 8 – the statistical distribution of the mobility observed between districts. We concentrate on inward and outward commuting separately, in order to identify the attractiveness and propensity to mobility of the districts, respectively. Two exploratory approaches are adopted here. First, following the formulation of Zipf's law – see Equation (8.2) – the number of inward connections per district (referred to hereafter as 'indegree'; see de Nooy et al. 2005) is examined; that is, from how many districts commuters come. From this viewpoint, it is relevant *if* there is commuting between two districts $i$ and $j$ (whatever its extent). We are therefore looking at logical topology.[60] Secondly, we examine the inward openness of the districts (as defined in Section 9.2). In this case we consider the weights tied to the links; that is, the inflows. In detail, the total inflows of each district are standardized by the number of jobs available there. The distributions of incoming connections and inward openness, for 1995 and 2005, are plotted in Figures 9.A1 and 9.A2, Annex 9.A.

We next interpolate the related data for 1995 and 2005 with two types of nonlinear functions: a power and an exponential function (see Section 9.2, Equations (9.2) and (9.4)). The resulting $R^2$ coefficients, as well as the values of the exponents of the functions, are shown in Table 9.2.

Table 9.2 – $R^2$ values and exponents for power and exponential interpolations of incoming connections (indegree) and inward openness, 1995 and 2005

| Year | Indegree | | Inward openness | |
|---|---|---|---|---|
| | Power-law | Exponential | Power-law | Exponential |
| 1995 | 0.7002 | 0.9739 | 0.8027 | 0.9871 |
| (exponent) | (0.2442) | (0.0022) | (0.4623) | (0.0039) |
| 2005 | 0.6046 | 0.9316 | 0.7820 | 0.9859 |
| (exponent) | (0.2589) | (0.0025) | (0.4000) | (0.0034) |

For the case of the indegree distribution (incoming connections per district), it is easily observable that an exponential distribution fits the degree decay rather well, an exception being a sharp cut-off at the end. The $R^2$ for the exponential function decreases slightly over time, from 0.97 to 0.93. The $R^2$ for the power function is lower – around 0.70 – and is also decreasing over time (to about 0.60). If we follow Adamic's (2000) suggestion and transform the indegree power-law coefficient according to Equation (9.3), we can see that we obtain coefficients much greater than 3, thus suggesting random network characteristics (homogeneous pattern). Overall, these findings suggest the existence of a highly interconnected commuting network, with a few districts that can be considered more

[60] Logical topology is the (virtual) network configuration emerging from the O-D matrix. When the (real) physical infrastructure network is considered, we talk about physical topology.

peripheral in network terms. However, these ambiguous results between exponential and power-law suggest that no clear agglomeration-pattern can be inferred in the case of the indegree distribution.

As in the case of the indegree distribution, the results for the distribution of the inward openness in the two years remain fairly stable. As observed for the indegree distribution, the exponential function better interpolates the data (the $R^2$ being 0.99). However, the power function also has a high $R^2$ of 0.78–0.80. In addition, the exponent values for the power interpolation are now higher (0.40–0.46). In this case also, the transformed power-law coefficients are greater than 3. Overall, this preliminary data exploration shows that the exponential function is a better fit to both the indegree and the inward openness distributions, suggesting an equilibrated network for these variables. The reason for these results with regard to the indegree coefficients could be attributed to the lack of network growth and rewiring, two critical factors in pushing the emergence of scale-free properties in networks. On the other hand, the results for the inward openness distribution could be attributed to the constrained values assumed by the variable analysed (between 0 and 1) after standardization. The results for the non-standardized inflows values can be found in Table 9.5.

### *9.3.3 Network Indices*

After exploring the data and their distribution, we provide a set of synthetic indices, which describe three principal aspects in order to explore the dominance of nodes under different perspectives, which are: (a) centralization; (b) clustering; and (c) variety/dispersion. The first of these indices, 'network centralization', is an aggregate assessment of the centrality of each node belonging to the network. The centrality of a node can be defined as a measure of its structural importance (the relative importance of a node within a graph). Various centrality indices have been developed over the years (see, for example, Sabidussi 1966; Freeman 1977), which take into consideration different aspects of centrality. The centrality index presented here can be called 'indegree centralization', and is based on the concept of the relative degree centrality of nodes. This measure deals with the 'visibility' of a node (in our case, a district). Visibility can be linked to the 'hub' concept (Latora and Marchiori 2004), since the most visible node can be considered as a hub. The particularity of this index, compared with other indices described in the literature, is that it only considers direct connections (indirect connections cannot be considered in our case study of commuting, unless the transportation infrastructure is included in the analysis). In our case, only inward connections are considered (hence, the denomination 'indegree centralization'), in order to show the nodes' attractiveness for outside workers. The indegree of a node is seen, in social network analysis, as a measure of 'prestige'. In our case, it can be considered as a dominance index. Relative indegree centrality ($ric_i$) is computed, for each node $i$, as the ratio between the observed and the maximum possible number of connections of a node ($N - 1$), where $N$ is the total number of nodes:

$$ric_i = \text{indegree}_i /(N-1), \tag{9.1}$$

while the aggregate network indegree centralization (*NIC*) index is computed, similarly to Freeman (1979), as:

$$NIC = \sum_{i \in N} (ric^* - ric_i) \Big/ (N-2), \tag{9.2}$$

where $ric^*$ is $\max_i (ric_i)$.

The second index computed refers to 'network clustering'. Network clustering coefficients have previously been used by Watts and Strogatz (1998) in order to search for small-world networks (see Section 8.2). We consider clustering coefficients in order to determine the level of interconnectedness of the network. In order to compute a clustering coefficient for a node, we need to define its neighbourhood. The neighbours are identified – if first-order relations are considered – by the nodes directly connected to the node concerned. Consequently, a first-order clustering coefficient for node $i$ is computed as the ratio of the number of links existing between the nodes of its neighbours and the maximum number of links that may exist between the same nodes:

$$c_i = l_i \big/ l_i^*, \tag{9.3}$$

where $l_i$ and $l_i^*$ are the actual and possible number of links in node $i$'s neighbourhood, respectively. In a fully connected network – where each node is connected to each of the other nodes – all nodes will have a clustering coefficient of 1. A synthetic network clustering coefficient is then computed as the average of the single nodes' coefficients. Clearly, if $k$-order neighbours are considered, a node's neighbourhood is represented by all the nodes that can be reached in $k$ hops. Consequently, a clustering coefficient of $k$-order will be computed. In this latter case, the observation of a high level of clustering suggests a highly interconnected network.

As a final index for describing, from the viewpoint of the 'variety/dispersal' of centres, the network's connectivity, we use the entropy formulation. Entropy is a concept originally derived from information theory (Shannon 1948) and widely used in spatial-economic science, thanks to Wilson's (1967, 1970) studies from a statistical perspective. Entropy has recently been applied by several authors in order to identify 'hidden' order in urban sprawl (Sun et al. 2007), in urban traffic (Haynes et al. 2006), and in industrial economics (Frenken

2006). In our context, entropy is employed as an indicator of the probability that the flows observed are generated by a ‘stochastic spatial allocation process’ (Nijkamp and Reggiani 1992, p. 18). The higher the entropy, the more dispersed the flows are over the network. The indicator is computed as:

$$E = -\sum_{ij} p_{ij} \ln p_{ij}, \tag{9.4}$$

where

$$p_{ij} = t_{ij} / O_i . \tag{9.5}$$

In Equation (9.5), $t_{ij}$ is the number of commuters between districts $i$ and $j$, while $O_i$ represents the outflows of district $i$.

The results computed for the German commuting network, according to the three indices described above, are presented in Table 9.3. Years 1995 and 2005 are again taken into consideration. Although no dramatic changes seem to occur over the ten years, the network shows two distinct trends. On the one hand, the centralization of the network decreases – at least as far as inward connections are concerned – and the entropy increases. These results imply a more distributed structure of the network. On the other hand, the clustering coefficient of the network grows, suggesting a tendency towards greater interconnectivity. These results seem to confirm the findings emerging in our spatial analysis (Section 9.2), highlighting the network’s tendency towards a multi-nodal structure (van der Laan 1998).

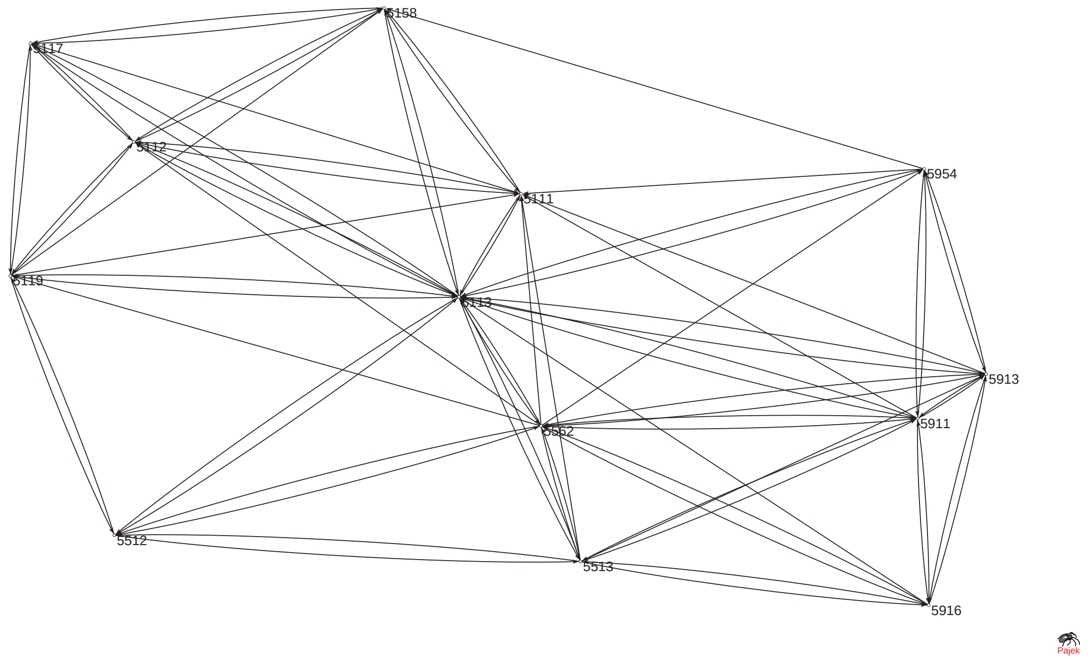
Table 9.3 – Descriptive indices for the German commuting network, 1995 and 2005

| Indices | 1995 | 2005 |
|---|---|---|
| Indegree centralization | 0.33 | 0.31 |
| Clustering | 0.59 | 0.63 |
| Entropy | 8.23 | 8.38 |

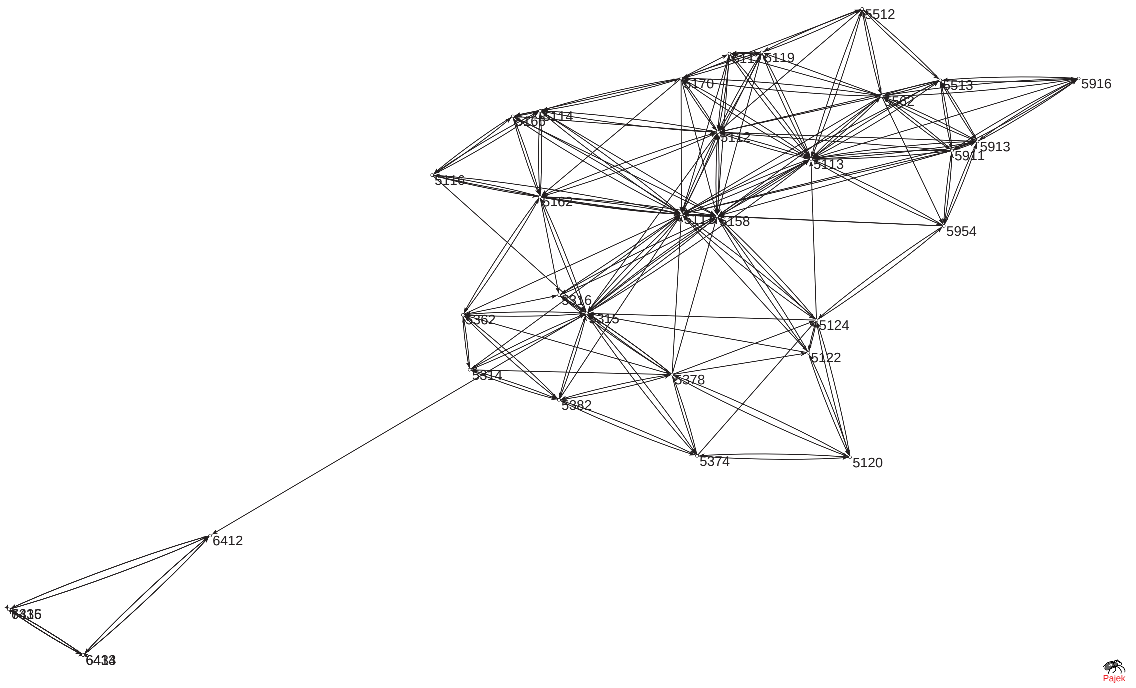
A graphical representation of the multi-polar tendency in the commuting network structure – in our case, from an ‘inward connections’ viewpoint – can be obtained, for 1995 and 2005, on the basis of the ‘*k*-core’ concept (Figure 9.4a,b). [61] A *k*-core is a subgraph (or more than one) in which each included node has a minimal degree (in our case, indegree) of *k*; that is, each node in the *k*-core has direct connections with at least *k* other nodes in the same subgraph (Holme 2005). For a more meaningful computation and a readable graph, we have selected a subsample of the data consisting only of those commuting flows above an arbitrary

[61] Core computations have been carried out by means of the freely available software Pajek (http://vlado.fmf.uni-lj.si/pub/networks/pajek).

threshold of 1,000 individuals. We find – for both 1995 and 2005 – *k*-cores of level 4 (4-cores), comprising 13 and 33 districts, respectively.




(a)




(b)

Figure 9.4 – '4-cores' in the commuting network: (a) 1995; (b) 2005

For the year 1995, we find a small core of 13 districts, identifying a heavily interconnected – and local – network headed by Düsseldorf and Dortmund. Each node (district) appearing in our 4-core receives at least 1,000 commuters from at least 4 other nodes in the same core, showing in this case intense horizontal (local) relations. The fact that other districts do not appear in the 4-core does not mean that they do not have reciprocal flows of commuters with the core districts. Simply, these other nodes do not feature the minimal levels of interconnectedness and number of commuters of the core nodes, although they can show several district-to-district flows greater than 1,000 individuals. Frankfurt is the most evident example. This city was not selected for the 1995 core, but when the year 2005 is considered, a larger and denser graph is found, composed of 33 districts. While the Düsseldorf/Dortmund cluster increases and is still the main body of the core, it is noteworthy to cite the function of Frankfurt (code 6412), which is now included in the 4-core and acts as a hub, connecting a local cluster of its own to the main Düsseldorf/Dortmund cluster. Of course, as these are logical topology results, here it is not implied that Frankfurt is physically implicated in interconnecting nodes belonging to the two parts of the core cluster.

The results of the network analysis carried out in the present section seem to confirm the multi-nodality structure of the German commuting network (especially at the local level), while also suggesting increased connectivity between the major centres (Berlin, Stuttgart, Munich, and so on) – centrality decreases over time – and, consequently, a tendency towards two layers of multi-nodality: (a) at the local level (see, for example, the Düsseldorf/Dortmund cluster); and (b) at the regional level (city-network level). As also seen by van Nuffel and Saey (2005, p. 326) and by van der Laan (1998, p. 244), these relations between the main centres do not overshadow local links (which still carry most of the mobility) but complement them.

As a next step of this research endeavour, it is worthwhile to map – within this multi-nodality structure – the hierarchies of the districts and their persistence over time, in order to identify the main relevant centres from both a spatial and a network viewpoint. In order to offer a 'synthetic' measure of the multiple spatial and connectivity dimensions – with reference to the dynamics of the districts under analysis – we use a multidimensional method, well-known in the spatial-economic literature, called 'multicriteria analysis'. This method may serve to identify the most prominent configurations in Germany.

## 9.4 Multidimensional Assessment: Application of Multicriteria Analysis

### *9.4.1 The Network of the 'Open' and Connected Districts*

The present section aims to provide a synthetic assessment of the district characteristics observed – by means of both a spatial and a connectivity approach – in Sections 9.2 and 9.3, for the purpose of defining a dominance ranking of the main districts concerned. We are also interested in investigating changes in this ranking over the period 1995–2005.

The subsample of districts ('alternatives') employed in our multicriteria analysis (MCA) is selected on the basis of a synthetic connections-flows (CF) index, computed as follows for each district $i$:

$$(CF)_i = [C_i/\max_i(C_i)]*[F_i/\max_i(F_i)], \tag{9.6}$$

where $C_i$ and $F_i$ are the number of incoming connections (the indegree) and the inward openness of district $i$, respectively. The index is the product of the two normalized indicators $C_i$ and $F_i$, and it ranges from 0 to 1. It aims to provide a balanced assessment of the openness and connectedness of the districts, that is, from a conventional spatial interaction perspective and a network perspective, respectively. On the basis of the CF index, we were able to select 26 districts, which are common to the top 30 districts for both 1995 and 2005. Such a stable group of 'open' districts (26 of 30) over a 10-year period suggests an overall stability between the upper tier and the rest of the districts. If we consider the 'district urbanization' index shown in Table 9.1, we find that the districts, with only a few exceptions, are urban districts – that is, central cities of types 1 and 5.

The MCA is carried out on the basis of two aggregate assessment criteria (macro-criteria):[62] spatial mobility (comprising inward and outward openness – see Footnote 58) and connectivity (comprising relative indegree centrality and clustering coefficients – see Equations (9.1) and (9.3)). We now proceed in two steps: first, by carrying out an MCA for each macro-criterion (consisting of the single criteria described above); and, second, by carrying out a final MCA which synthesizes the two previous analyses.

With respect to the MCA based on spatial-economic indicators, the results show that – out of the main cities included – Munich (*Landkreis*) persistently occupies the first position (Table 9.4). Moreover, the ranking of the top districts is rather stable over the two years concerned. It is noteworthy that further well-known cities such as Frankfurt, Stuttgart and Düsseldorf do not perform as well as Munich. The results of the second MCA, based on connectivity criteria, provide – in 1995 – a rather different ranking. In the connectivity ranking the main cities are dominant. As seen in Section 9.3.3 for the *k*-core results, Düsseldorf emerges as important from a network perspective. Other large cities such as Frankfurt, Stuttgart and Munich follow. It is interesting to observe that in 2005 some centres, most notably Wiesbaden (a district in the Frankfurt metropolitan area and capital of the state of Hesse) and Karlsruhe, attain higher positions in the ranking. We can also note that, with the exception of Munich, the districts that headed the spatial MCA rankings only perform at an intermediate level in the connectivity MCA.

[62] The regime multicriteria method (and software) was used (Hinloopen and Nijkamp 1990). In particular, three scenarios were considered at all stages: (a) equal weights to all criteria; (b) ascending weights; and (c) descending weights. A further MCA of the resulting rankings provides the final results.

Table 9.4 – Multicriteria analysis for the ‘open’ and connected districts: resulting rankings for 1995 and 2005

| Districts | Spatial results[a] | | Districts | Connectivity results[b] | | Districts | Final results[c] | |
|---|---|---|---|---|---|---|---|---|
| | 1995 | 2005 | | 1995 | 2005 | | 1995 | 2005 |
| 09184 Munich, Land. | 1 | 1 | 05111 Düsseldorf, Stadt | 1 | 1 | 09184 Munich, Land. | 1 | 1 |
| 06436 Main-Taunus-Kreis | 2 | 2 | 06412 Frankfurt am Main, Stadt | 2 | 2 | 06436 Main-Taunus-Kreis | 2 | 4 |
| 09661 Aschaffenburg, Stadt | 3 | 4 | 08111 Stuttgart | 3 | 4 | 06411 Darmstadt, Stadt | 3 | 3 |
| 06413 Offenbach am Main, Stadt | 4 | 3 | 09184 Munich, Land. | 4 | 7 | 07315 Mainz, Stadt | 4 | 5 |
| 06411 Darmstadt, Stadt | 5 | 5 | 09564 Nuremberg, Stadt | 5 | 8 | 08221 Heidelberg | 5 | 9 |
| 07314 Ludwigshafen am Rhein, Stadt | 6 | 6 | 05314 Bonn, Stadt | 6 | 9 | 05314 Bonn, Stadt | 6 | 7 |
| 08221 Heidelberg | 7 | 8 | 08222 Mannheim | 7 | 6 | 06414 Wiesbaden, Land. | 7 | 2 |
| 07315 Mainz, Stadt | 8 | 7 | 06414 Wiesbaden, Land. | 8 | 3 | 09562 Erlangen, Stadt | 8 | 15 |
| 09662 Schweinfurt, Stadt | 9 | 15 | 06436 Main-Taunus-Kreis | 9 | 11 | 08121 Heilbronn | 9 | 16 |
| 08121 Heilbronn | 10 | 9 | 08212 Karlsruhe | 10 | 5 | 07314 Ludwigshafen am Rhein, Stadt | 10 | 18 |
| 09461 Bamberg, Stadt | 11 | 12 | 06411 Darmstadt, Stadt | 11 | 10 | 08421 Ulm | 11 | 12 |
| 08421 Ulm | 12 | 11 | 07315 Mainz, Stadt | 12 | 13 | 06412 Frankfurt am Main, Stadt | 12 | 8 |
| 09562 Erlangen, Stadt | 13 | 10 | 09562 Erlangen, Stadt | 13 | 12 | 06413 Offenbach am Main, Stadt | 13 | 10 |
| 06611 Kassel, Stadt | 14 | 16 | 08221 Heidelberg | 14 | 15 | 08222 Mannheim | 14 | 6 |
| 07111 Koblenz, Stadt | 15 | 13 | 08421 Ulm | 15 | 14 | 08111 Stuttgart | 15 | 11 |
| 06414 Wiesbaden, Land. | 16 | 14 | 08121 Heilbronn | 16 | 20 | 06611 Kassel, Stadt | 16 | 17 |
| 05314 Bonn, Stadt | 17 | 17 | 09663 Wuerzburg, Stadt | 17 | 22 | 09661 Aschaffenburg, Stadt | 17 | 20 |
| 09362 Regensburg, Stadt | 18 | 20 | 07314 Ludwigshafen am Rhein, Stadt | 18 | 21 | 05111 Düsseldorf, Stadt | 18 | 13 |
| 09161 Ingolstadt, Stadt | 19 | 24 | 06413 Offenbach am Main, Stadt | 19 | 16 | 09663 Wuerzburg, Stadt | 19 | 24 |
| 09663 Wuerzburg, Stadt | 20 | 19 | 06611 Kassel, Stadt | 20 | 17 | 07111 Koblenz, Stadt | 20 | 22 |
| 08222 Mannheim | 21 | 18 | 09161 Ingolstadt, Stadt | 21 | 18 | 08212 Karlsruhe | 21 | 14 |
| 06412 Frankfurt am Main, Stadt | 22 | 22 | 09362 Regensburg, Stadt | 22 | 19 | 09564 Nuremberg, Stadt | 22 | 19 |
| 08111 Stuttgart | 23 | 21 | 07111 Koblenz, Stadt | 23 | 24 | 09461 Bamberg, Stadt | 23 | 25 |
| 05111 Düsseldorf, Stadt | 24 | 25 | 09661 Aschaffenburg, Stadt | 24 | 23 | 09161 Ingolstadt, Stadt | 24 | 23 |
| 08212 Karlsruhe | 25 | 26 | 09461 Bamberg, Stadt | 25 | 25 | 09362 Regensburg, Stadt | 25 | 21 |
| 09564 Nuremberg, Stadt | 26 | 23 | 09662 Schweinfurt, Stadt | 26 | 26 | 09662 Schweinfurt, Stadt | 26 | 26 |

[a] Spatial criteria: inward and outward openness.
[b] Connectivity criteria: relative indegree centrality and clustering coefficient.
[c] Final MCA: uses as criteria the spatial and connectivity results.

The final results, which synthesize the two preceding analyses by employing the results of the spatial and connectivity macro-criteria, can be summarized as follows. The district of Munich (*Landkreis*) emerges as the most dominant for both 1995 and 2005, while a reshuffling in the ranking of the districts can be observed over the 10-year period. Some dynamic districts seem to emerge. In particular, these are: Wiesbaden (from 7th to 2nd), Mannheim (14th to 6th), Frankfurt (12th to 8th), Stuttgart (15th to 11th), Düsseldorf (18th to 13th) and Karlsruhe (21st to 14th). The observed progress of such districts is mainly due to the connectivity macro-criterion. Clearly, their high clustering coefficients show that the above districts are oriented towards agglomeration patterns, in addition to their openness.

The districts emerging in the above analysis are the most 'open' and 'active', but they still cannot be considered as the main 'attractors'. If we want to explore this characteristic, we then have to use – in the CF index computation of Equation (9.6) – other variables (such as actual inflows or workplaces) which can detect the relevance of the destination, as the well-known attraction models in transport literature suggest. The result of this further analysis (again utilizing MCA) is illustrated in next section.

### *9.4.2 The Network of the 'Attraction' and Connected Districts*

The preceding section illustrated the results for the MCA that investigated the group of the most open and connected districts. However, in the light of the transport economics literature, this group of cities cannot be identified as the most attracting ones (and hence, according to Barabási's work, the 'preferential nodes'; that is, the 'hubs'). On the basis of the 'attraction-model' formulation in the conventional four-step transportation model, the 'attraction variable' is conventionally identified as the total inflows per district (or another variable that detects the relevance of destinations, such as workplaces). Consequently, we repeat our last analysis by substituting – in the CF index – the previously employed inward openness with the total inflows per district, which can be seen as a measure of the importance of the destinations.

As inflows are not normalized by city-size, they have, of course, a different distribution with respect to the inward openness, the characteristics of which are reported in Table 9.5 and plotted in Figure 9.A3, Annex 9.A. While the distribution of the inward openness was found to fit – to a large extent – an exponential function (see Section 9.2), the distribution of the inflows according to Equation (8.2) is best interpolated, in this case, by the power function (an $R^2$ of 0.94 versus an $R^2$ of 0.92 for the exponential case). Also, the value of the power function exponent of about 0.89 is more interesting than the value of 0.46 (see Table 9.2) observed for the inward openness. In fact, the transformed coefficient would be about 2.1, which suggests the emergence of hub patterns (in particular, Munich, Frankfurt and Hamburg mainly seem to emerge as principal attraction-hub nodes).

Table 9.5 – $R^2$ values and exponents for power and exponential interpolations of incoming connections (indegree) and inflows, 1995 and 2005

| Year | Indegree | | Inflows | |
|---|---|---|---|---|
| | Power-law | Exponential | Power-law | Exponential |
| 1995 | 0.7002 | 0.9739 | 0.9447 | 0.9163 |
| (exponent) | (0.2442) | (0.0022) | (0.8962) | (0.0068) |
| 2005 | 0.6046 | 0.9316 | 0.9411 | 0.9162 |
| (exponent) | (0.2589) | (0.0025) | (0.8841) | (0.0067) |

Having observed the variation in the distributional results obtained by employing inflows, we modify the CF index (see Equation (9.6)) so as to include – in place of the inward openness – the total inflows. Employing the same selection process illustrated above, we then obtain a new group of districts; that is, 29 'alternatives' to be analysed in a further MCA. The same methodology followed in the preceding section applies. This new group is evaluated by means of the same criteria employed in Section 9.4.1 in order to classify the attraction districts on the basis of their openness and connectedness. The results of the spatial and connectivity MCAs, as well as the final MCA results, are summarized in Table 9.6, showing a hierarchy of attraction nodes which are also open and active.

This concluding analysis shows that again Munich (*Landkreis*) emerges on the top of the rankings for the spatial MCA. The connectivity MCA, instead, favours the most important German cities, such as Hamburg, the Düsseldorf/Cologne agglomeration and Frankfurt, with Munich and Berlin following closely. The results from the final MCA, a synthesis of the two preceding MCAs, show that the 1995 hierarchy – which in principle matches the main German cities – changes in 2005, because of the emergence of new districts, such as Mettmann (from 5th to 1st), Weisbaden (9th to 2nd), Darmstadt (16th to 8th), and Karlsruhe (15th to 9th). As a consequence, the main cities decline in the ranking, most notably: Munich (from 1st to 3rd), Frankfurt (2nd to 5th), Stuttgart (3rd to 4th) and Düsseldorf (4th to 6th). Once again, this reshuffling can mostly be attributed to the high clustering coefficient values attached to the above-mentioned emerging districts.

Clearly, the selection of the 29 districts analysed emerges from the choice of the inflows variable in the CF index, as an indicator for the attraction nodes (Equation (9.6)). If, on the other hand, we wish to consider in this index the 'strength' of the connection (in other words, inflows and outflows, by means of, for example, spatial interaction models) instead of the attraction only (the inflows), we may expect to be more likely to detect the 'hub' cluster, since a hub – in a strict sense – not only attracts flows, but also distributes them (hub-and-spoke). In this context, it should be noted that preliminary analyses showed that, had inflows *and* outflows been employed as criteria for the spatial MCA, a ranking similar to the one of the connectivity MCA would have emerged.

Table 9.6 – Multicriteria analysis for the 'attraction' and connected districts: resulting rankings for 1995 and 2005

| Districts | Spatial results[a] | | Districts | Connectivity results[b] | | Districts | Final results[c] | |
|---|---|---|---|---|---|---|---|---|
| | 1995 | 2005 | | 1995 | 2005 | | 1995 | 2005 |
| 09184 Munich, Land. | 1 | 1 | 02000 Hamburg, Freie und Hansestadt | 1 | 1 | 09184 Munich, Land. | 1 | 3 |
| 06411 Darmstadt, Stadt | 2 | 2 | 03241 Region Hannover | 2 | 15 | 06412 Frankfurt am Main, Stadt | 2 | 5 |
| 07314 Ludwigshafen am Rhein, Stadt | 3 | 3 | 05111 Düsseldorf, Stadt | 3 | 2 | 08111 Stuttgart, Land. | 3 | 4 |
| 07315 Mainz, Stadt | 4 | 4 | 05315 Cologne, Stadt | 4 | 4 | 05111 Düsseldorf, Stadt | 4 | 6 |
| 05158 Mettmann | 5 | 5 | 06412 Frankfurt am Main, Stadt | 5 | 5 | 05158 Mettmann | 5 | 1 |
| 06414 Wiesbaden, Land. | 6 | 6 | 08111 Stuttgart, Land. | 6 | 7 | 08222 Mannheim, Universitätsstadt | 6 | 7 |
| 05314 Bonn, Stadt | 7 | 7 | 09162 Munich, Stadt | 7 | 11 | 05314 Bonn, Stadt | 7 | 10 |
| 08222 Mannheim, Universitätsstadt | 8 | 8 | 11000 Berlin | 8 | 14 | 09564 Nuremberg, Stadt | 8 | 14 |
| 05911 Bochum, Stadt | 9 | 11 | 08116 Esslingen | 9 | 16 | 06414 Wiesbaden, Land. | 9 | 2 |
| 08111 Stuttgart, Land. | 10 | 10 | 09184 Munich, Land. | 10 | 12 | 05315 Cologne, Stadt | 10 | 12 |
| 06412 Frankfurt am Main, Stadt | 11 | 12 | 09564 Nuremberg, Stadt | 11 | 13 | 08116 Esslingen | 11 | 16 |
| 05112 Duisburg, Stadt | 12 | 9 | 14365 Leipzig, Stadt | 12 | 26 | 05113 Essen, Stadt | 12 | 19 |
| 09761 Augsburg, Stadt | 13 | 13 | 14262 Dresden, Stadt | 13 | 28 | 07315 Mainz, Stadt | 13 | 18 |
| 05111 Düsseldorf, Stadt | 14 | 14 | 04011 Bremen, Stadt | 14 | 20 | 09162 Munich, Stadt | 14 | 17 |
| 05113 Essen, Stadt | 15 | 15 | 08222 Mannheim, Universitätsstadt | 15 | 10 | 08212 Karlsruhe, Stadt | 15 | 9 |
| 08212 Karlsruhe, Stadt | 16 | 16 | 05158 Mettmann | 16 | 3 | 06411 Darmstadt, Stadt | 16 | 8 |
| 08115 Böblingen | 17 | 17 | 05314 Bonn, Stadt | 17 | 17 | 09761 Augsburg, Stadt | 17 | 13 |
| 09564 Nuremberg, Stadt | 18 | 19 | 06414 Wiesbaden, Land. | 18 | 6 | 02000 Hamburg, Freie und Hansestadt | 18 | 20 |
| 05913 Dortmund, Stadt | 19 | 18 | 05113 Essen, Stadt | 19 | 22 | 08115 Böblingen | 19 | 11 |
| 05515 Munster, Stadt | 20 | 22 | 08212 Karlsruhe, Stadt | 20 | 9 | 04011 Bremen, Stadt | 20 | 25 |
| 08116 Esslingen | 21 | 20 | 08115 Böblingen | 21 | 8 | 14365 Leipzig, Stadt | 21 | 28 |
| 05315 Cologne, Stadt | 22 | 21 | 05913 Dortmund, Stadt | 22 | 21 | 03241 Region Hannover | 22 | 24 |
| 09162 Munich, Stadt | 23 | 23 | 09761 Augsburg, Stadt | 23 | 19 | 05911 Bochum, Stadt | 23 | 21 |
| 04011 Bremen, Stadt | 24 | 26 | 07315 Mainz, Stadt | 24 | 25 | 05112 Duisburg, Stadt | 24 | 15 |
| 14365 Leipzig, Stadt | 25 | 24 | 06411 Darmstadt, Stadt | 25 | 18 | 05913 Dortmund, Stadt | 25 | 22 |
| 14262 Dresden, Stadt | 26 | 25 | 05112 Duisburg, Stadt | 26 | 23 | 14262 Dresden, Stadt | 26 | 29 |
| 02000 Hamburg, Freie und Hansestadt | 27 | 27 | 05911 Bochum, Stadt | 27 | 24 | 07314 Ludwigshafen am Rhein, Stadt | 27 | 23 |
| 03241 Region Hannover | 28 | 28 | 05515 Munster, Stadt | 28 | 27 | 11000 Berlin | 28 | 27 |
| 11000 Berlin | 29 | 29 | 07314 Ludwigshafen am Rhein, Stadt | 29 | 29 | 05515 Munster, Stadt | 29 | 26 |

[a] Spatial criteria: inward and outward openness.
[b] Connectivity criteria: relative indegree centrality and clustering coefficient.
[c] Final MCA: uses as criteria the spatial and connectivity results.

## 9.5 Conclusions

This chapter has presented a dual analysis of commuting trends in Germany, from both a spatial and a network perspective. We have analysed data for home-to-work trips for 439 German districts, for the years 1995 and 2005.

With regard to the spatial perspective, we considered the distribution of commuting inflows and outflows per district, in our case normalized by jobs and residents, respectively (Section 9.2). Our analyses showed that – as expected – mobility revolves around the major metropolitan areas, and that the districts identified as central cities (of types 1 and 5 – see Table 9.1) have the larger shares of inward labour mobility. When considering inward and outward mobility in a synthetic indicator ('openness'), the *Landkreis* district of Munich (which surrounds the city of Munich itself, an independent district) emerges as the most mobile centre, most likely because of its role revolving around the city.

With regard to the network perspective, we have considered first the distribution of the inward openness and of the number of incoming connections (which we call the 'indegree') per district (Section 9.3.2). Our results show that the distribution of the districts' inward openness is slightly more heterogeneous than that of the number of incoming connections (the indegree). In addition, if we consider the distribution of the inflows, further heterogeneity is found, implying possible hub patterns. We have then computed aggregate indicators showing the evolution of the commuting network (Section 9.3.3). In particular, in addition to a local multi-nodal commuting network (between nearby cities), a regional network is also present to some extent, which, however, does not overshadow well-defined local relations (see, for example, the results of the *k*-core analysis).[63]

Accordingly, the MCAs carried out in Section 9.4 suggest that the German districts are rather stable – in the 10-year period examined – at the spatial level, with regard to the hierarchies between the districts. In particular, the *Landkreis* district of Munich emerges as the most mobile/connected district over the ten years. In addition, we may note, from the results of the connectivity-based MCAs, that network connectivity appears to be influenced by the clustering coefficient indicator, as suggested in the works of Watts and Strogatz (1998). In this context, new districts, such as Mettmann and Wiesbaden, seem to emerge – together with Munich – as the most attracting, open and connected. This final result mainly depends on the values of the clustering coefficients – which emphasize the network agglomerations related to the main dominant districts – in the connectivity criteria. For example, Mettmann is connected to Düsseldorf and Wiesbaden to Frankfurt. This 'hub' clustering effect might also be taken into account in future research concerned with the

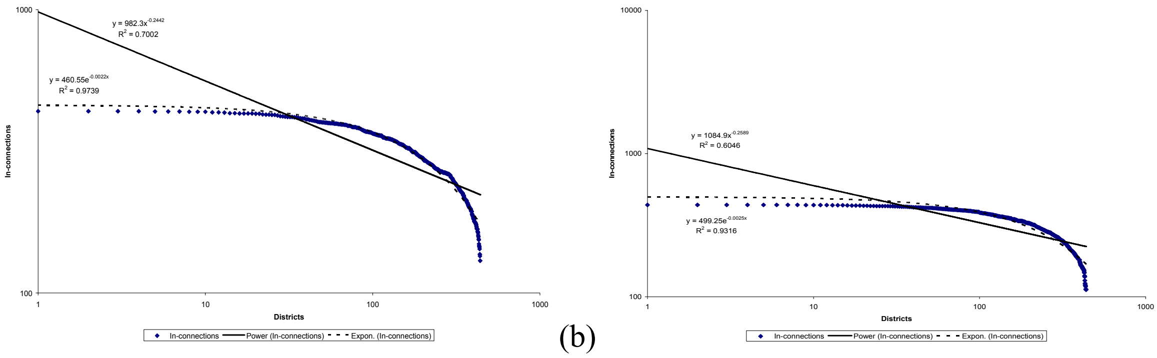
[63] If, in addition to finding high clustering, well-connected nodes are also found to be connected to each other, then highly interconnected clusters can emerge, which, according to Holme (2005), can possibly lead to a core-periphery network structure (Chung and Lu 2002). In particular, Holme finds that transportation networks (or, more generically, geographically-embedded networks) show these characteristics at some level.

identification of network hubs, since they appear to be the engine of these new cluster agglomerations.

A few general conclusions may be drawn in this regard, in particular relating to the research objective pursued in Part C of this study. First, we can consider the stability of German commuting patterns found in Chapters 8 and 9. This general stability, even over a medium-range period like ten years, can be related to the findings of Part B of the study, where by means of spatial filtering techniques we analysed the (again) stability of regional patterns of unemployment and other socio-economic variables. Our findings appear to be consistent, since we might expect, on the basis of the regional interaction interpretation given in Chapter 1, that regional change would be driven by phenomena such as labour mobility. Therefore, our finding of relatively stable commuting patterns contributes to justify the stickiness of regional labour market aggregates observed in Chapter 7. A second conclusion may be drawn with regard to the hierarchies observed in our MCAs. We observed, particularly in our second MCA, that West German centres in Bavaria (Munich) and in the Düsseldorf/Stuttgart/Frankfurt area emerge as the most active, mobile and connected. It is worth noting that these areas have also been shown, in our preceding analyses, to be the ones which have well-performing regional labour markets. Similarly, East German districts, in addition to having underperforming labour markets, also show rather low levels of labour mobility and connectivity. In this regard, we might draw attention to East Germany's different sectoral distribution, which influences the type of labour demand in the regions, as well as at the lower level of the East's infrastructure, which hinders higher levels of mobility, especially for longer distances.

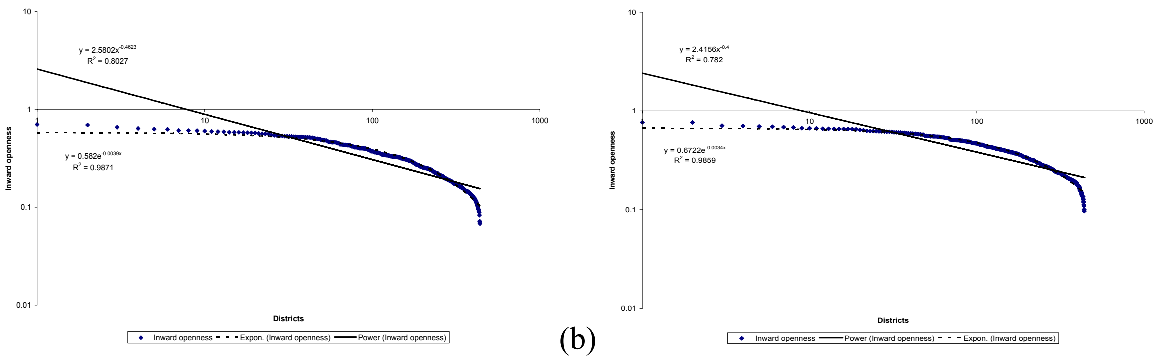
Further future research should fruitfully address, from a theoretical viewpoint, the behavioural/economic implications of our findings, in particular with regard to the role of distance/travel time and accessibility (wasteful commuting could be an issue), as well as of labour market characteristics, in the genesis of commuting. Moreover, the direction of causality between the regional labour market trends and the network findings observed here deserves investigation. From a methodological viewpoint, a joint network/physical infrastructure analysis is desirable (this research task is described in more detail in the conclusions of Chapter 8), while, from an empirical viewpoint, the study of pre- and post-unification networks in Germany might provide relevant information on the evolution of its commuting patterns. Finally, it would be useful to experiment with alternative spatial disaggregation levels (for example, community levels or functional areas), in order to analyse the consistency of our findings.

## Annex 9.A Plots of Various Distributions



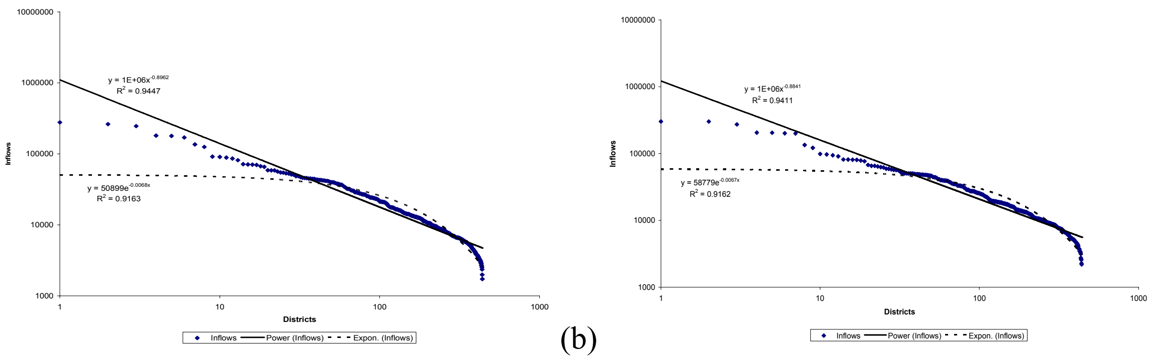

(a) (b)

Figure 9.A1 – Log-log distributions of input degree: (a) 1995; (b) 2005. Interpolating functions are power-law (continuous line) and exponential (broken line)




(a) (b)

Figure 9.A2 – Log-log distributions of inward openness: (a) 1995; (b) 2005. Interpolating functions are power-law (continuous line) and exponential (broken line)




(a) (b)

Figure 9.A3 – Log-log distributions of inflows: (a) 1995; (b) 2005. Interpolating functions are power-law (continuous line) and exponential (broken line)

# PART D
# RETROSPECT AND PROSPECT

Chapter 10

# Conclusions

## 10.1 Content of the Study

The present study has offered a set of statistical analyses concerning regional labour markets in Germany. The objective of this dissertation was to analyse, from a statistical perspective, their development and the associated spatial disparities observed for the case of Germany. The emphasis is less on policy, but rather on patterns in the evolution of labour markets in Germany. The motivation for the study has been rooted in the increased importance, which has emerged in recent years, of ‘regions’ as a focal level of analysis, both in academia and in applied policy contexts. Economic aggregates for regions of varying size (depending on country size or on the level of spatial disaggregation) are an essential tool for developing ‘micro-policies’, since, in particular for the case of actual administrative areas, that is where public funding is redistributed. Also, given their different characteristics with respect to nations (that is, regions can be considered as much more open systems than nations), regions show greater socio-economic heterogeneity. As stated earlier in Chapter 1, this aspect and the reduced geographic scale, which allows us to apply interdisciplinary approaches (mixing, for example, urban economics, geography or land use) and new methodological frameworks, call for challenging research questions and interesting empirical investigations. In particular, Germany, with its high number of small geographic units (NUTS-3 districts) and complex socio-economic scenario emerging from the reunification of 1990, is a textbook case for such spatial-economic analyses.

The present study focused on two aspects of German regional labour markets and two related research questions:

- Key labour market indicators, such as employment or unemployment, can be seen as a proxy for the levels of economic activity. Consequently, the *first research objective* of this dissertation concerned the spatio-temporal analysis of regional labour market aggregates. We focused on two main issues: (a) the forecast of regional employment variations; and (b) the analysis of unemployment differentials in the presence of spatial autocorrelation.

- Likewise, commuting can be interpreted as a proxy for the economic interactions between regions, for which actual data are rarely available. The *second research objective* of the present study concerned the analysis of the diversification of journey-to-work trips (which are implicitly associated with regional labour markets). In particular, we focused on the investigation of the commuting flows' distribution (in terms of heterogeneity/homogeneity) and of the related level of 'openness' of regions.

As underlined in Chapter 1, this study did not aim to test or prove established theoretical foundations, but concentrated on the statistical analysis of regional labour markets. As a result of the dual research objective outlined above, the empirical applications carried out in this thesis were subdivided into two main parts: Part B of the thesis addressed the first research question, while Part C was dedicated to the second research question. The remainder of this chapter discusses the analyses carried out (Section 10.2), the main findings obtained (Section 10.3), and the directions for future research (Section 10.4).

## 10.2 Empirical Applications

### *10.2.1 Statistical Modelling of Regional Labour Markets in Germany*

Part B of the present study was concerned with the statistical analysis and forecast of key labour market indicators. In detail, Chapters 4–6 were concerned with carrying out regional labour market forecasts. Neural network (NN) techniques were employed as a novel statistical approach for estimating regional employment variations. Subsequently, Chapter 7 was concerned with the analysis of regional unemployment rates. We employed spatial filtering techniques in order to accommodate spatial heterogeneity in the data.

With regard to our NN applications, our main objective was to develop NN models in order to provide short-term forecasts (in our case, 2-years-ahead) of variations in the number of German full-time employees by region. Chapter 4 provided a discussion of the main technical issues involved in developing NN forecasting models, particularly with regard to the panel nature of the labour market data employed. Several models, based on NN and genetic algorithm (GA) techniques, were developed, which computed estimates for a range of out-of-sample forecasting periods (2001–04), for all 439 NUTS-3 districts (*kreise*) in Germany. Because of the different length of the data sets, NN models for East and West Germany were developed separately. We presented the results for both conventional models (NN models) and for GA-specified models (NNGA models); that is, NN models which used an internal (GA)-optimization algorithm for the choice of the specification. The results of *ex post* forecasts were evaluated by means of statistical indicators and of forecast equivalence tests: namely, the Morgan-Granger-Newbold (MGN) test and the sign test (ST).

In Chapter 5, we extended the aforementioned analyses by proposing a joint shift-share analysis/NN approach, in order to catch regional specificities related to each region's sectoral performance. We developed additional NN models (NN-SS), which include – as inputs – components from several SSA approaches (that is, conventional deterministic shift-share, spatial shift-share and shift-share regression). These new NN-SS models were then statistically evaluated using the predefined out-of-sample periods, and compared with the winning models of Chapter 4.

In Chapter 6, we focused on the settings of the particular NN algorithm employed. We carried out a sensitivity analysis in order to investigate how the NN models' forecasting performance varied in the presence of changing learning parameters and functional forms. A subsequent re-evaluation – in the light of the sensitivity analysis findings – of the NN and NN-SS models developed in Chapters 4 and 5 was offered. Final considerations on the importance of considering region-specific aspects (such as in the case of the spatial shift-share NN model) prompted us to a more thorough analysis of spatial issues.

Consequently, in Chapter 7, our objective was to analyse space-time patterns in German regional unemployment rates. We presented an analysis based on 'spatial filtering' techniques, and aimed at uncovering spatial structures underlying regional unemployment data. Using varying definitions of the contiguity concept, we computed and selected sets of year-specific 'spatial filters', in order to explain the geographic variations in the unemployment rates, as well as subsets of these spatial filters that defined time-invariant spatial structures. These analyses were then repeated, with the introduction of explanatory variables that have socio-economic meaning (wages, employment and population). The value added of the new analyses is that the use of covariates in a simple unemployment model allowed us to identify spatial structures, that is, spatial filters, which are the result of the analysis not only of the dependent variable but also of the covariates. Once the underlying spatial structures have been accounted for, a clearer estimation of the regression parameters in the unemployment model (that is, the relationship between unemployment and the socio-economic explanatory variables) is possible.

### *10.2.2 Spatial Interactions and Networks for Commuting*

Part C of the present study was concerned with the description and analysis of the regional labour mobility pattern in Germany. In particular, we aimed to integrate the conventional spatial interaction framework – usually used to describe commuting flows – with novel approaches emerging from network theory, so as to better understand the mechanisms leading to, and evidence of, regional disparities. In this framework, network analyses were used to study the heterogeneity of commuting flows.

In Chapter 8, we provided an overview of the network properties found for German commuting patterns. We analysed flows between NUTS-3 districts (*kreise*), by first exploring their distribution over origin-destination (O-D) pairs. Second, we performed a network analysis, with the aim to investigate the connectivity properties of the network; that is, the number of connections per district ('degree'). In addition to the above analyses, we developed two spatial interaction models (SIMs) – employing different functional forms – in order to simulate the network structure underlying the commuting flows, and we compared the results emerging from the estimations.

Expanding the set of analyses outlined above, Chapter 9 further investigated the evolution of commuting flows in Germany, focusing on the relative mobility levels of the districts; that is, their 'openness'. In this context, we analysed the flows' spatial and network distributions, for all the 439 German districts, with reference to the years 1995 and 2005. From the spatial perspective, we investigated the distribution of regional inflows and outflows. From the network perspective, we again considered the distributional properties of the network – but this time from the incoming flows viewpoint – and we subsequently computed aggregate network indicators showing the evolution of commuting patterns. Finally, multicriteria analyses (MCAs) were employed to systematically assess the overall change in the hierarchies of the German most 'open' and 'connected' regions.

The results and findings that emerge from the empirical applications outlined in this section are summarized next.

## 10.3 Analysis of the Findings

### *10.3.1 Statistical Modelling of Regional Labour Markets in Germany*

The first set of analyses presented in Part B of the dissertation concerned neural forecasting experiments, aimed at providing short-term forecasts of regional employment variations. In Chapter 4, NN models were developed for this task, based on varying sets of explanatory variables and two different approaches with regard to the inclusion of the 'time' variable.

The NN models showed, from the empirical point of view, a range of statistical error levels. In particular, we attributed the variability in the results to the differences in the specification of the NN models, in that the typology of inclusion of time correlation determines the provision of lower error levels. A second finding was that the inclusion of the additional socio-economic variables (such as wages or urbanization/agglomeration levels) did not result in a uniform improvement of the models, with the exception of the inclusion in NNs of shift-share analysis (SSA) components (see Chapter 5). In particular, a new NN model employing components derived from a conventional SSA approach (Model BSS) proved to be the most reliable, and was shown to outperform the remaining models. Consequently, we were able to select Model BSS as *the* winning NN model, to be employed in the future for benchmarking and policy purposes. This finding demonstrated the effectiveness of the integration of a nonlinear tool such as NNs and of long-established deterministic (or linear) tools (such as SSA). Furthermore, the incorporation in NN models of spatial information (see Model BSSN) represented a first step towards a joint NN/spatial econometrics approach, which could be considered to be desirable, since, at present, NNs require further research into the incorporation and processing of cross-sectional and panel information. From a methodological viewpoint, we found that our experiments on the joint application of NNs and GAs did not improved the models' forecasting power, which called for an in-depth investigation of the NN learning parameters. The sensitivity analysis of NN models carried out in Chapter 6 showed that, in the specific case analysed, a particular combination of learning parameters was able to provide improved forecasting power, which was also demonstrated by the subsequent comparative analysis carried out.

In summary, our neural forecasting experiments showed the importance of understanding the 'complexity' involved in regional labour market forecasting. Our NN models had different levels of reliability, depending on the data sets used and the socio-economic background. While this is certainly caused by the different time spans of the data sets, and by the fact that our empirical analyses were based on just a few main explanatory variables, the results emerging from the aforementioned NN-SS models nevertheless provide preliminary evidence with regard to the most promising direction in which further research steps should be made.

A step in this direction is, indeed, the direct consideration of 'space' in our analyses. The spatial filtering experiments on German unemployment rates, which were presented in Chapter 7, aimed to do this, by identifying space-time structures (that is, time-invariant 'spatial filters') inherent to the data, for future inclusion in econometric modelling. We experimented with different definitions of space and contiguity, both geographical and non-geographical. The results emerging from the two types of approach suggested that the non-geographical approach – based on the idea of commuting flows as a proxy for economic interdependence between regions – did not provide a level of statistical reliability comparable to that of the geographical approaches. The reason for this finding could be found in the nature of the data used, which concerned only logical connections between districts, or, most importantly, in the lack of more suitable measures of regional economic interactions. In summary, we showed that it is possible to identify time-stable spatial structures in unemployment data, both when only unemployment is considered and when socio-economic covariates are included. In the latter case, we obtained improved statistical reliability and consistent parameter estimates, in the framework of a simple unemployment model estimation.

With regard to the research objective pursued in Part B of the present study, the statistical analyses presented in Chapter 7 appear consistent with our neural forecasting experiments, which benefited from the inclusion of the SSA paradigm. Furthermore, we highlighted the relevance and the persistence of spatial structures and local specificities in German regional labour markets. The existence of spatial filters which are common to different years is a reflection of this general stability. The spatial filtering technique employed here should therefore be considered as one of several useful tools that can be deployed in the analysis of regional disparities.

### *10.3.2 Spatial Interactions and Networks for Commuting*

Following the analyses of Part B, which were centred on the analysis of labour market aggregates (employment and unemployment), Part C of the dissertation concerned the study of a variable which is associated with labour market accessibility patterns: that is, commuting. We jointly employed the conventional spatial interaction framework and novel network approaches in order to identify patterns of heterogeneity in journey-to-work trips.

From these two perspectives, we first provided – in Chapter 8 – a preliminary investigation of German district-to-district commuting trips. By means of a network analysis, we demonstrated that the German commuting (transportation) network has rather homogeneous characteristics, in terms of the number of interconnections between districts, which were also shown to increase over the period considered (1995–2004). In this network, we observed that even the least-connected districts (with fewer connections to other districts) still reach a major share of the network nodes. This finding was confirmed, with regard to spatial interaction modelling, by the empirical evidence suggesting that the use of an exponential deterrence function (see Equation (8.9)) better interpolates the real data from the connectivity viewpoint.

The above analyses were subsequently extended by focusing on the direction of the flows and, in particular, on the 'openness' of the German districts; that is, their potential mobility (see Chapter 9). In this perspective, the analysis of the commuting flows indicated that, spatially, mobility is concentrated around the major metropolitan areas (the urban centres attract larger shares of incoming commuting) and, overall, districts in agglomerated areas tend to be the most 'mobile'. From the network perspective, we showed that network heterogeneity –which may suggest the possible emergence of 'hubs' – is found only when considering raw commuting (in)flows, rather than relative indicators of openness or connectedness. Accordingly, the multicriteria analyses (MCAs) carried out in order to identify the most 'open' and 'connected' German districts suggest that, while there is a certain stability – during the period examined – at the spatial level, it is with regard to the clustering of destinations that new districts (such as Mettmann and Wiesbaden) emerge.

With regard to the research objective pursued in Part C of this study, we can relate this general medium-term stability of the German commuting patterns to the spatial filtering findings, which revealed stable spatial structures underlying regional labour markets. Since we stated in Chapter 1 that regional change (convergence or divergence) may be driven by interaction phenomena such as commuting, the finding of stable hierarchies with regard to journey-to-work patterns contributes to justifying the time-invariance of regional labour market aggregate patterns. In this context, the emergence, in our MCAs, of leading West

German centres in Bavaria (Munich) and in the Düsseldorf/Stuttgart/Frankfurt area, and the depression of East Germany, is a consistent and corroborating result.

In synthesis, the results of the present study drew a fairly consistent picture of German regional labour markets – with regard to employment and unemployment – and their hierarchies. We showed that they exhibit spatial heterogeneity that is persistent in time and can be explained only in part by recent socio-economic trends (such as, for example, demographic changes) or by regional interactions (in our case, commuting flows). In the presence of persistent spatial (heterogeneity) structures such as the ones observed, the methodological tools proposed here should be considered as a novel contribution to the existing literature – also in the light of possible application to other contexts – in the following terms:

- We developed a neural network framework for computing labour market forecasts at the regional level.
- We proposed an approach for the study of time-invariant spatial structures in georeferenced data, particularly in the presence of explanatory factors.
- We developed a multidimensional framework for the evaluation of the degree and level of heterogeneity of regional interactions (such as commuting).

Applications of the methodological approaches outlined above in a policy-making context can be proposed, for example, for decision making at a meso- or micro-level, which often requires fast thinking and may be based on limited information. In this context, the analyses carried out here offer potential support for better decision making.

## 10.4 Directions for Future Research

This dissertation has showcased the statistical potential of the application of novel methods for the space-time analysis of regional labour markets, with regard to forecasting and heterogeneity. However, our empirical applications can be considered neither exhaustive nor complete, and call for further research to be carried out. The following is a shortlist of desirable future developments within the general framework outlined in this study, and in the perspective of a future integration of the methodological approaches proposed.

Research directions should first be specified with regard to the methodologies employed in the dissertation. The experiments carried out in Chapters 4–6 showed that NNs can be a useful tool for regional labour market forecasting. However, we obtained the greatest gain in statistical reliability when information regarding regional specificities was introduced (that is, shift-share analysis), which, in our opinion, highlighted the major direction of research to be followed, with regard to regional neural forecasting: that is, the introduction of ‘space’ in NNs. While the introduction of a ‘spatial shift-share’ extension in NNs moved us one step closer to filling this gap, further joint approaches should be tested, in particular with regard to the integration of the two techniques employed in Part B of this study: namely, NNs and spatial filtering (see Chapter 7). In this framework, in order to fully exploit the method's potential, additional spatial filtering experiments are needed, such as a more in-depth empirical investigation of the proposed economic variables. In addition, the development of a more suitable economic-proximity matrix is desirable. The results emerging from the analyses carried out in Chapters 8 and 9 (Part C) could be used in this regard. The investigation of the German commuting patterns has highlighted that, in this case too, improvements could be sought in several directions, such as the use of more sophisticated spatial interaction models or the integration of the logical network and the spatial flows associated with it.

In particular, challenging research can be foreseen in the direction of the joint application of the methodologies showcased in this dissertation. In addition to the aforementioned integration of spatial filtering and NN techniques, additional novel methods, which apply (spatial) econometrics to spatial interaction (see, for example, LeSage and Pace 2005; Fischer et al. 2006) should be investigated, as well as recent developments that relate spatial filtering and spatial interaction (Fischer and Griffith 2006). These recent approaches may allow us to fruitfully mix the economic modelling contribution of spatial interaction techniques and the empirical advantages of spatial econometrics.

In addition, again from the viewpoint of the integration of methodologies and the enrichment of established ones, wider economic modelling frameworks, such as general spatial equilibrium models, might benefit from the incorporation of techniques such as NNs, spatial filtering or network analysis. From this perspective, the amalgamation of such methodologies in a different but complementary research framework would represent a significant added value, and appears to be a fascinating scenario that could profitably be explored in the future.

Finally, further research should also address policy perspectives more extensively. For instance, many labour market policies have been implemented in Germany during the period considered in our case study. From this perspective, a profitable use of the methodological approaches proposed in the study could be in the statistical impact analysis of the policies applied to labour markets (for example, unemployment benefits, firm subsidies, and so on). In addition, the approaches developed here may also be applied to alternative regional contexts, in order to carry out comparative analyses in the light of common European policies.

In conclusion, our study demonstrated that regional labour markets are a very fruitful research area, which may lead to challenging questions and fascinating empirical findings, in the light also of ever-evolving socio-economic and political systems. These will most likely be the subject of further innovative research in the coming years.

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Nederlandse Samenvatting (Summary in Dutch)

# Regionale Arbeidsmarkten in Duitsland: Statistische Analyse van Tijd-Ruimte Verschillen en Netwerkstructuren

**Inhoud van de Studie**

Deze dissertatie presenteert diverse moderne statistische analyses van regionale markten in Duitsland. De doelstelling van deze studie is een kwantitatieve analyse van de ontwikkelingen op deze markten en van de daarmee samenhangende ruimtelijke verschillen vanuit statistisch perspectief. De nadruk ligt daarbij niet zo zeer op beleidsanalyse als wel op de ontwikkelingspatronen van de arbeidsmarkten in Duitsland. De motieven voor de studie vloeien voort uit het toegenomen belang van 'de regio' als focus voor sociaal-economische analyse. Informatie over relevante economische kerngrootheden voor regio's van verschillende omvang, positie en structuur vormt een onmisbaar instrument voor het ontwikkelen van gericht beleid. Dit geldt in het bijzonder voor Duitsland waar de regio's het ruimtelijk relevante aggregatieniveau vormen voor de verdeling van werkloosheidsuitkeringen. Belangrijk is bovendien dat regio's een grotere sociaal-economische diversiteit vertonen dan landen, omdat, gegeven hun verschillende kenmerken, regio's als een veel opener sociaal-economisch systeem kunnen worden beschouwd. Zoals beargumenteerd in Hoofdstuk 1, leidt dit gegeven – tezamen met het lagere geografische schaalniveau dat ons mede in staat stelt om een interdisciplinaire aanpak te volgen en nieuwe methodologische kaders toe te passen – tot uitdagende onderzoeksvragen en boeiend empirisch onderzoek. Daarbij geldt Duitsland als een schoolvoorbeeld voor vernieuwende ruimtelijk-economische analyses, vanwege haar grote aantal kleine geografisch-administratieve regio's (NUTS-3 regio's) en de complexe sociaal-economische context die voortkomt uit de hereniging van Oost- en West-Duitsland in 1990.

Tegen deze achtergrond, richt dit proefschrift zich op twee kernaspecten van de Duitse regionale arbeidsmarkt en op twee daaraan gerelateerde onderzoeksvragen:

- Belangrijke arbeidsmarktindicatoren, zoals werkgelegenheid of werkloosheid, kunnen worden gezien als indicatoren voor het niveau van economische activiteit. Daarom richt de *eerste onderzoeksdoelstelling* van deze dissertatie zich op de ruimtelijk-temporele analyse van regionale-arbeidsmarkt kerngrootheden. We richten ons daarbij op twee hoofdissues: (a) het voorspellen van variaties in regionale werkgelegenheid; en (b) de analyse van verschillen in werkloosheid in geval van ruimtelijke autocorrelatie.
- Op vergelijkbare wijze kan men woon-werkverkeer interpreteren als een indicator (proxy) voor de omvang van economische interactie tussen regio's. De *tweede onderzoeksdoelstelling* van deze studie betreft daarom het analyseren van de diversificatie in woon-werkverkeer (dat impliciet verbonden is met de regionale arbeidsmarkten). We richten ons daarbij vooral op het onderzoek naar de verdeling in woon-werkverkeer (in termen van heterogeniteit/homogeniteit) en van het daarmee samenhangende niveau van 'openheid' van de regio's.

Het dient vermeld te worden dat deze studie niet als doelstelling heeft om gevestigde theoretische onderbouwingen te testen of bewijzen, maar de zoeker te richten op de statistische analyse van regionale arbeidsmarkten op basis van moderne statistische methoden (zoals neurale netwerkanalyse). Deel 1 van deze studie biedt daarom een bredere methodologische introductie. In lijn met de twee hierboven uiteengezette onderzoeksdoelstellingen, zijn de empirische toepassingen die in dit proefschrift zijn uitgevoerd onderverdeeld in twee hoofdonderdelen: Deel B van het proefschrift richt zich op de eerste onderzoeksvraag; Deel C is gewijd aan de tweede onderzoeksvraag.

**Methodologische Aanpak van Arbeidsmarktgegevens in Duitsland**

*Statistische Modellering van Regionale Arbeidsmarkten in Duitsland*

Deel B van deze studie behelt de statistische analyse en voorspelling van kerngrootheden voor de arbeidsmarkt. Meer specifiek houden Hoofdstukken 4–6 zich bezig met het uitvoeren van regionale arbeidsmarktvoorspellingen. Neurale netwerk (NN) technieken worden benut als een statistische noviteit om regionale variaties in werkgelegenheid te schatten. Vervolgens richt Hoofdstuk 7 zich op de analyse van regionale werkloosheidspercentages. We hebben recent ontwikkelde, zgn. ruimtelijke filtertechnieken benut om recht te doen aan ruimtelijke heterogeniteit in de data.

Wat onze NN toepassingen betreft, is het hoofddoel om NN modellen te ontwikkelen om daarmee korte-termijn voorspellingen (2 jaar vooruit) te genereren van variaties in het aantal Duitse voltijdwerkers per regio. Hoofdstuk 4 behandelt daarom de voornaamste technische vragen die optreden bij het ontwikkelen van NN voorspellingsmodellen, in het bijzonder betreffende de paneldata structuur van de gebruikte arbeidsmarktgegevens. Verscheidene modellen gebaseerd op NN en genetisch algoritme (GA) technieken zijn recentelijk ontwikkeld, waarmee we schattingen hebben gemaakt van een aantal 'out-of-sample' voorspellingsperioden (2001–04), voor alle 439 NUTS-3 districten (*Kreise*) in Duitsland. Vanwege de verschillen in de tijdsspanne van de data, hebben we de NN modellen apart ontwikkeld voor Oost- en West-Duitsland. We presenteren de resultaten voor zowel de gangbare modellen (NN modellen), als voor GA-gespecificeerde modellen (NNGA modellen). De laatste categorie betreft NN modellen die een interne (GA-) optimaliseringsalgoritme gebruiken voor het bepalen van de specificatiekeuze. De resultaten van *ex post* voorspellingen zijn geëvalueerd door middel van passende statistische indicatoren en testen voor voorspellingsequivalentie, te weten de Morgan-Granger-Newbold (MGN) test en de teken test (sign test: ST).

In Hoofdstuk 5 breiden we de bovengenoemde analyses uit door een gecombineerde 'shift-share'-analyse/NN aanpak voor te stellen, om op die manier regio-specifieke aspecten die gerelateerd zijn aan de sectorale prestaties van iedere in de analyse te betrekken regio te omvatten. Daartoe ontwikkelen we additionele NN modellen (NN-SS), die als inputs de componenten uit diverse SSA methoden bevatten (dat wil zeggen, uit conventionele deterministische 'shift-share', ruimtelijke 'shift-share' en 'shift-share' regressie analyse). Vervolgens evalueren we deze nieuwe NN-SS modellen statistisch voor de hierboven gedefinieerde 'out-of-sample' perioden en vergelijken we de resultaten met de winnende modellen uit Hoofdstuk 4.

In Hoofdstuk 6 leggen we de nadruk op de eigenschappen van het specifieke NN algoritme dat gebruikt is. We voeren een gevoeligheidsanalyse uit om te bepalen hoe de voorspelprestaties van de NN modellen verschillen onder diverse veronderstellingen van andere leer-parameters en functionele specificaties. Een herevaluatie – in het licht van de uitkomsten van de gevoeligheidsanalyse – van de NN en NN-SS modellen die ontwikkeld zijn in Hoofdstukken 4 en 5 is vervolgens uitgevoerd. De uiteindelijke overwegingen over het belang van het in ogenschouw nemen van regio-specifieke aspecten (zoals in het geval van het ruimtelijke 'shift-share' NN model) brengen ons daarbij tot een meer diepgaande analyse van ruimtelijke vraagstukken.

Tenslotte is onze doelstelling in Hoofdstuk 7 om ruimte-tijd patronen in de regionale Duitse werkloosheidspercentages te analyseren. We presenteren daartoe een analyse die gebaseerd is op ruimtelijke filteringstechnieken, met als doel om ruimtelijke structuren die ten grondslag liggen aan de regionale werkloosheidscijfers te identificeren. Gebruikmakend van verschillende definities van het nabijheidsconcept, berekenen en selecteren we jaar-specifieke verzamelingen van 'ruimtelijke filters', om daarmee de geografische variatie in werkloosheidspercentages te verklaren. Bovendien bepalen we deelverzamelingen van deze ruimtelijke filters die tijdsonafhankelijke ruimtelijke structuren weergeven. Vervolgens worden deze analyses herhaald, na introductie van verklarende variabelen die een duidelijke sociaal-economische betekenis hebben (lonen, werkgelegenheid en bevolkingsomvang). De toegevoegde waarde van deze nieuwe analyses is dat het gebruik van verklarende variabelen in een eenvoudig model ter verklaring van werkloosheid ons in staat stelt om ruimtelijke structuren (dat wil zeggen: ruimtelijke filters) te identificeren die niet alleen het resultaat zijn van het analyseren van de afhankelijke variabele, maar ook van deze verklarende variabelen. Als de onderliggende ruimtelijke structuren eenmaal in acht zijn genomen, is het mogelijk om de regressieparameters in het werkloosheidsmodel (te weten: de verbanden tussen werkloosheid en de sociaal-economische verklarende variabelen) meer eenduidig te schatten.

*Ruimtelijke Interactie en Netwerken in Woonwerkverkeer*

Deel C van het proefschrift beschrijft en analyseert de patronen van regionale arbeidsmobiliteit in Duitsland. De doelstelling is in het bijzonder om het gangbare analyse-raamwerk van ruimtelijke interactie patronen – gewoonlijk gebruikt om woon-werkverkeer te beschrijven – te integreren met de vernieuwende aanpak die uit de moderne netwerktheorie voortkomt, zodat we de mechanismen die leiden tot regionale ongelijkheden beter kunnen begrijpen.

In Hoofdstuk 8 geven we een overzicht van de netwerkeigenschappen in het Duitse woon-werkverkeer. We onderzoeken de stromen tussen NUTS-3 regio's (*Kreise*) door allereerst de verdeling over oorsprong-bestemmings (origin-destination: O-D) paren te verkennen. Vervolgens voeren we een netwerkanalyse uit met als doel om de verbindingseigenschappen van het netwerk te onderzoeken, ofwel: het aantal verbindingen per district ('degree'). Ter uitbreiding van deze analyses ontwikkelen we twee ruimtelijke interactiemodellen (spatial interaction models: SIMs), om de netwerkstructuur die ten grondslag ligt aan de woon-werkverkeersstromen te simuleren. We vergelijken vervolgens de resultaten die uit de schattingen voortkomen.

Voortbouwend op de hierboven uiteengezette analyses onderzoekt Hoofdstuk 9 de evolutie van het woon-werkverkeer in Duitsland verder, met nadruk op de relatieve mobiliteitsniveau's van de districten, ofwel: hun 'openheid'. In deze context worden de ruimtelijke- en netwerkverdeling van de stromen voor alle 439 Duitse districten geanalyseerd, voor de jaren 1995 en 2005. Vanuit een ruimtelijke perspectief, onderzoeken we de verdeling van de regio-specifieke instroom en uitstroom. Vanuit een netwerkperspectief, beschouwen we opnieuw de verdelingseigenschappen van het netwerk – echter, ditmaal vanuit het perspectief van de inkomende stromen – en berekenen we vervolgens geaggregeerde netwerkindicatoren die de ontwikkeling in de patronen van woon-werkverkeer weergeven. Tenslotte gebruiken we als evaluatie-instrument multicriteria analyses (MCAs) om de algehele verandering in de hiërarchie van de meest 'open' en 'verbonden' regio's van Duitsland systematisch te toetsen en weer te geven. De resultaten en vindingen die voortkomen uit de empirische toepassingen zoals in deze sectie zijn uiteengezet, worden hierna kort samengevat.

**Analyse van de Resultaten**

*Statistische Modellering van Regionale Arbeidsmarkten in Duitsland*

De eerste reeks analyses, gepresenteerd in Deel B van de dissertatie, houdt zich bezig met neurale voorspellingsexperimenten, gericht op het verkrijgen van kortetermijnprognoses met betrekking tot de variatie in regionale werkgelegenheid. In Hoofdstuk 4 zijn hiertoe NN-modellen ontwikkeld, gebaseerd op wisselende verzamelingen van verklarende variabelen en twee verschillende benaderingen met betrekking tot het opnemen van de tijdsvariabele.

Vanuit een empirisch gezichtspunt bezien, laten de NN-modellen een 'range' van statistische foutenniveaus zien. In het bijzonder schrijven we de variabiliteit van de resultaten toe aan de verschillen in de specificatie van de NN-modellen, in die zin dat de typologie van het opnemen van temporele correlatie de oplevering van lagere foutenmarges bepaalt. Een tweede bevinding is dat het opnemen van additionele sociaal-economische variabelen (zoals loon of stedelijkheids- /agglomeratiegraad) geen uniforme verbetering van de modellen tot gevolg heeft, met uitzondering van het opnemen in neurale netwerken van componenten van shift-share analyse (SSA) (zie Hoofdstuk 5). In het bijzonder blijkt dat een vernieuwend NN-model, dat gebruik maakt van componenten die afgeleid zijn van een conventionele SSA-benadering (Model BSS), het meest betrouwbaar is en beter presteert dan de overige modellen. Als gevolg hiervan kunnen we Model BSS beschouwen als het meest succesvolle NN-model, in het vervolg te gebruiken voor benchmarking- en beleidsdoeleinden. Deze constatering toont de effectiviteit aan van de integratie van een niet-linair instrument als neurale netwerken met deterministische (of lineaire) instrumenten (zoals SSA). Bovendien vertegenwoordigt het opnemen van ruimtelijke informatie (zie Model BSSN) binnen NN-modellen een eerste stap in de richting van een gezamenlijke NN/ruimtelijke econometrische benadering, hetgeen zeer wenselijk is gezien het feit dat vervolgonderzoek vereist is naar het opnemen en verwerken van cross-sectiedata en paneldata bij neurale netwerken. Vanuit een methodologisch gezichtspunt bezien, constateren we dat onze experimenten met betrekking tot de gecombineerde toepassing van neurale netwerken en GA's niet leidt tot een verbetering van de voorspelkracht van de modellen, hetgeen vraagt om een diepgaand onderzoek naar de NN-leerparameters. De gevoeligheidsanalyse van NN-modellen, uitgevoerd in Hoofdstuk 6, toont aan dat, in het specifieke onderzochte geval, een zekere combinatie van 'learning parameters' een verbetering van de voorspelkracht mogelijk maakt, hetgeen tevens aangetoond wordt via de daaropvolgende uitgevoerde vergelijkende analyse.

Samenvattend tonen onze neurale voorspellingexperimenten het belang aan van het verkrijgen van meer inzicht in de 'complexiteit' die regionale arbeidsmarktprognoses met zich meebrengen. Onze NN-modellen hebben, afhankelijk van de gebruikte datasets en de sociaal-economische achtergrond, verschillende betrouwbaarheidsniveau's. Hoewel dit met zekerheid wordt veroorzaakt door de verschillende tijdsspannen van de datasets, en door het feit dat onze empirische analyses gebaseerd zijn op slechts enkele belangrijke verklarende variabelen, leveren de resultaten die voortkomen uit de hiervoorgenoemde NN-SS-modellen toch voorlopige aanwijzingen op met betrekking tot de meest veelbelovende richting waarin vervolgonderzoek zich zou dienen te ontwikkelen.

Een stap in deze richting wordt inderdaad genomen door in onze analyses direct rekening te houden met 'ruimte'. De ruimtelijke filterexperimenten, uitgevoerd op Duitse werkloosheidspercentages, die in Hoofdstuk 7 zijn gepresenteerd, streven dit na door ruimte-tijdstructuren (i.e. tijdsinvariante 'spatial filters') te identificeren voor de gebruikte data, teneinde deze in toekomstige econometrische modellen op te nemen. We experimenteren met verschillende, zowel geografische als niet-geografische, definities van ruimte en nabijheid. De resultaten die op basis van de twee typen benaderingen naar voren komen, suggereren dat een niet-geografische benadering – gebaseerd op de idee dat woon-werkverkeersstromen als proxy-variabele voor economische interactie tussen regio's beschouwd kunnen worden – geen statistisch betrouwbaarheidsniveau oplevert dat vergelijkbaar is met dat van geografische benaderingen. De oorzaak van deze vinding kan gevonden worden in de aard van de gebruikte data, die alleen logische verbindingen tussen districten betreffen, of, belangrijker, in het ontbreken van beter geschikte maatstaven van regionale economische interactie. Samenvattend tonen we aan dat het mogelijk is om in werkloosheidsdata temporeel stabiele ruimtelijke structuren te identificeren, zowel in het geval waarbij alleen rekening wordt gehouden met werkloosheid als in het geval waarbij ook sociaal-economische covariaten worden opgenomen. In het laatste geval worden, binnen het kader van een schatting van een eenvoudig werkloosheidsmodel, een hogere statistische betrouwbaarheid en consistente parameterschattingen verkregen.

Met betrekking tot de onderzoeksdoelstelling nagestreefd in deel B van deze studie, lijken de statistische analyses die in Hoofdstuk 7 werden gepresenteerd consistent te zijn met onze neurale voorspellingsexperimenten, die het voordeel hadden van het opnemen van het SSA paradigma.

### *Ruimtelijke Interactie en Netwerken voor Woonwerkverkeer*

Deel C van de dissertatie houdt zich vervolgens bezig met het bestuderen van een variabele die samenhangt met toegankelijkheidspatronen van arbeidsmarkten, namelijk woonwerkverkeer. Wij hanteren het gebruikelijke ruimtelijke interactiekader in combinatie met nieuwe netwerkbenaderingen, met als doel het identificeren van patronen van heterogeniteit in woonwerkverplaatsingen.

Vanuit deze twee perspectieven, voeren we eerst – in Hoofdstuk 8 – een voorlopig onderzoek uit naar woonwerkmobiliteit tussen Duitse arbeidsdistricten. Met behulp van een netwerkanalyse tonen we aan dat het Duitse netwerk van woonwerkverkeer tamelijk homogene kenmerken vertoont met betrekking tot het aantal verbindingen tussen districten, welke gedurende de bestudeerde periode (1995–2004) bovendien in aantal bleken toe te nemen. Binnen dit netwerk zien we dat zelfs de slechtst verbonden districten (die met minder verbindingen dan andere districten) nog altijd een belangrijk deel van de netwerkknooppunten bereiken.

Bovenstaande analyses worden vervolgens uitgebreid door de richting van de vervoerstromen te bezien en, in het bijzonder, de 'openheid' van de Duitse districten, dat wil zeggen, hun potentiële mobiliteit (zie Hoofdstuk 9). In dit opzicht wijst de analyse van de woonwerkvervoerstromen erop dat, in ruimtelijke zin, mobiliteit geconcentreerd is rond de belangrijkste stedelijke gebieden (de stedelijke centra trekken een grotere aandeel van de ingaande woonwerkverkeerstromen aan) en dat, in algemene zin, districten in agglomeratiegebieden het meest 'mobiel' zijn. Vanuit een netwerkperspectief bezien, wordt netwerkheterogeniteit – wat kan wijzen op de mogelijke opkomst van 'hubs' – slechts aangetroffen wanneer ruwe data met betrekking tot woonwerkverkeerstromen in beschouwing worden genomen, in plaats van relatieve indicatoren van openheid of verbondenheid. Overeenkomstig deze bevindingen wijst de multicriteria-analyse (MCA), die is uitgevoerd met als doel om de meest 'open' en 'verbonden' Duitse districten te identificeren, erop dat, ondanks een zekere stabiliteit – gedurende de bestudeerde periode – op ruimtelijk niveau, nieuwe districten (zoals Mettmann en Wiesbaden) opkomen.

Met betrekking tot de onderzoeksdoelstelling nagestreefd in deel C van deze studie kunnen we deze algemene middellangetermijn-stabiliteit van de Duitse woonwerkverkeerpatronen relateren aan de resultaten van de 'spatial filtering' experimenten, die met betrekking tot regionale arbeidsmarkten stabiele onderliggende ruimtelijke structuren aantonen. Regionale verandering (convergentie of divergentie) wordt mede aangestuurd door interactie-gerelateerde verschijnselen zoals woonwerkverkeer, en zo draagt de constatering van stabiele hiërarchieën met betrekking tot woonwerk-verplaatsingen bij aan het begrijpen van de stabiliteit van patronen van geaggregeerde regionale arbeidsmarkten. In deze context is de opkomst van toonaangevende Westduitse centra in Beieren (München) en in het gebied Düsseldorf/Stuttgart/Frankfurt, alsmede de depressie in Oostduitsland, een consistent en ondersteunend resultaat.

Samengevoegd geven de resultaten van deze studie een tamelijk consistent beeld van Duitse regionale arbeidsmarkten – met betrekking tot werkgelegenheid en werkloosheid – en hun hiërarchieën. Deze markten vertonen ruimtelijke heterogeniteit, die hardnekkig is in de tijd en die slechts gedeeltelijk verklaard kan worden vanuit recente sociaal-economische interacties (in dit geval, woonwerk-verkeerstromen). De door ons gehanteerde methodologische instrumenten dienen te worden beschouwd als een vernieuwende bijdrage aan de bestaande literatuur – mede in het licht van toepassingsmogelijkheden in andere contexten – in de volgende opzichten:

- We hebben een neuraal netwerk-kader ontwikkeld voor het berekenen van arbeidsmarktprognoses op regionaal niveau.
- We hebben een benadering getoetst voor het bestuderen van temporeel invariante ruimtelijke structuren in geografisch gerefereerde data, in het bijzonder in de aanwezigheid van verklarende factoren daarbij.
- We hebben een multidimensioneel kader ontwikkeld voor het evalueren van de mate en het niveau van heterogeniteit van regionale interacties (waaronder woonwerk-verkeer)

**Aanbevelingen voor Vervolgonderzoek**

Deze dissertatie heeft een demonstratie gegeven van de statistische potentie van de toepassing van nieuwe methoden voor de ruimte-tijd analyse van regionale arbeidsmarkten, vanuit de optiek van prognose en heterogeniteit. Onze empirische toepassingen kunnen echter noch als uitputtend noch als compleet beschouwd worden, en vereisen het verrichten van vervolgonderzoek. Hierna volgt een shortlist van wenselijke toekomstige ontwikkelingen binnen het algemene kader dat in deze studie is geschetst, vanuit het perspectief van een toekomstige integratie van de voorgedragen methodologische benaderingen.

Onderzoeksrichtingen dienen eerst nader te worden gespecificeerd met betrekking tot de in deze dissertatie gebruikte methodologieën. De in Hoofdstuk 4-6 uitgevoerde experimenten tonen aan dat neurale netwerken een bruikbaar instrument kunnen zijn voor het maken van regionale arbeidsmarktprognoses. De grootste toename in statistische betrouwbaarheid wordt echter verkregen door de introductie van informatie met betrekking tot specifieke regionale kenmerken (shift-share analysis), hetgeen volgens ons de belangrijkste vervolgonderzoeksrichting met betrekking tot regionale neurale voorspellingen suggereert, namelijk, de introductie van ‘ruimte’ in neurale netwerken. Hoewel de introductie van een ‘ruimtelijke shift-share’ uitbreiding in neurale netwerken ons een stap dichter bij het opvullen van dit hiaat heeft gebracht, dienen verdere gecombineerde benaderingen getest te worden, met name met betrekking tot het de integratie van de twee in deel B van deze studie gehanteerde technieken, namelijk: neurale netwerken en ‘spatial filtering’ (zie Hoofdstuk 7). Teneinde zo volledig mogelijk het potentieel van de methode te benutten, is er binnen dit kader behoefte aan aanvullende ruimtelijke filterexperimenten, zoals een diepgaand empirisch onderzoek naar de beschouwde economische variabelen. Bovendien is de ontwikkeling van een beter geschikte ‘economic-proximity matrix’ wenselijk. Hierbij kan gebruik worden gemaakt van de resultaten van de in Hoofdstuk 8 en 9 uitgevoerde analyse (deel C). Het onderzoeken van de patronen van het Duitse woonwerk verkeer heeft benadrukt dat, ook in dit specifieke geval, verbeteringen in diverse richtingen kunnen worden gezocht, zoals het gebruik van meer geavanceerde ruimtelijke interactiemodellen of de integratie van logistieke netwerken en de bijbehorende ruimtelijke stromen.

Uitdagende onderzoeksmogelijkheden mogen met name worden verwacht in de richting van de gecombineerde toepassing van de in deze dissertatie belichte methodologieën. Naast de genoemde integratie van 'spatial filtering' en NN-technieken, zouden aanvullende nieuwe methodes die (ruimtelijke) econometrie op ruimtelijke interactie toepassen onderzocht dienen te worden. Dit geldt tevens voor recente ontwikkelingen waarbij 'spatial filtering' en ruimtelijke interactie aan elkaar worden gerelateerd. Deze recente benaderingen zouden ons in staat kunnen stellen om de economische modelleringsaspecten van ruimtelijke interactietechnieken op succesvolle wijze te kunnen combineren met de empirische voordelen van de ruimtelijke econometrie.

Verder kunnen bredere economische modelkaders, zoals ruimtelijke evenwichtsmodellen, profijt hebben van het opnemen van technieken zoals neurale netwerken, 'spatial filtering' of netwerkanalyse. In dit opzicht zou de combinatie van dergelijke methodologieën binnen een ander, complementair onderzoekskader een significante toevoegende waarde hebben en een fascinerend researchscenario kunnen zijn dat in de toekomst onderzocht zou kunnen worden.

Tenslotte dient vervolgonderzoek ook ruimere aandacht te besteden aan beleidsperspectieven. Veel beleidslijnen op het gebied van arbeidsmarkten in Duitsland zijn bijvoorbeeld geïmplementeerd tijdens de periode die onze case studie beslaat. Vanuit dit perspectief bezien zou een vruchtbaar gebruik van de in deze studie gehanteerde methodologische benaderingen gevormd kunnen worden door een statistische impactanalyse van het op de arbeidsmarkt toegepaste beleid (bijvoorbeeld werkloosheidsuitkeringen, bedrijvensubsidies enzovoorts). Verder zouden de hier ontwikkelde benaderingen ook toegepast kunnen worden op alternatieve regionale contexten, teneinde vergelijkende analyses uit te voeren in het licht van het gemeenschappelijk Europees beleid.

Concluderend toont onze studie aan dat regionale arbeidsmarkten een erg vruchtbaar onderzoeksterrein vormen, dat kan leiden tot uitdagende onderzoeksvragen en fascinerende empirische bevindingen, mede in het licht van continu evoluerende sociaal-economische en politieke beleidssystemen. Deze zullen de komende jaren hoogstwaarschijnlijk het onderwerp vormen van innovatief vervolgonderzoek.

In recent years, researchers and policy makers have shown a rising interest in the study and interpretation of socio-economic processes at the meso- or regional level. From that perspective, the region is often considered to be the ‘place of action’, where micro-behaviour and macro-outcomes come together.

The present study offers a novel statistical analysis of the development of regional labour markets in Germany. The objective of the dissertation is to analyse their patterns and evolution, as well as the associated spatial disparities. In particular, Germany – with its large number of small geographical units (NUTS-3 districts in EU terminology) and complex socio-economic ramifications emerging from the reunification of 1990 – is a textbook case for such spatial-economic analyses.

The first empirical part of the study concerns the spatio-temporal analysis of regional labour market aggregates. The focus is on two main issues: (a) the forecast of regional employment variations; and (b) the analysis of unemployment differentials in the presence of spatial autocorrelation. The second empirical part concerns the analysis of the diversification of journey-to-work trips. In particular, we focus on the investigation of the commuting flows’ heterogeneity/homogeneity and of the related level of ‘openness’ of regions. The results draw a fairly consistent picture of German regional labour markets and their hierarchies, in which spatial heterogeneity is persistent in time, and can be explained only in part by recent socio-economic trends or regional interactions.

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