Location changes of jobs and people

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Analyses of population–employment interactions and impacts of gender and geography

The research reported in this book was conducted at the Faculty of Spatial Sciences at the University of Groningen and is part of the programme of the Urban and Regional Studies Institute (URSI).

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For Marloes, Saskia and Tobias

Preface

The book in front of you is the culmination of my PhD research at the Faculty of Spatial Sciences of the University of Groningen. The idea of doing this research was suggested to me by Prof. dr. Paulus Huigen (who had supervised my master's thesis in Human Geography). He informed me of a PhD vacancy at the Department of Economic Geography that involved "*performing an empirical analysis of small area employment growth in the Northern Netherlands by using spatial econometric modelling techniques and Geographical Information Systems*". With apparently few people applying for the job (the strong emphasis on statistics and methodologies must have scared geographers off), I fancied my chances to start modelling and studying to be a doctor, and thanks to Prof. dr. Jouke van Dijk and Prof. dr. Piet Pellenbarg I was given the opportunity.

Initially, my activities centred on collecting, extensively checking and analysing data from the Establishment and Employment registers of Fryslân, Groningen and Drenthe. In this period I did several firm-demographic analyses [on the employment effects of firm start-ups, shutdowns, expansions, contractions, and relocations] that offer some important insights into the employment dynamics of the Northern Netherlands, but which ultimately have not been included in this book. For readers interested in a more detailed picture of the employment changes studied in chapters 3, 4 and 5, I gladly refer to Hoogstra (2005, 2007) and Hoogstra and Van Dijk (2004).

Later, Prof. Dr. Raymond Florax agreed to join Prof. dr. Jouke van Dijk as one of my supervisors and the focus shifted from only analysing local employment patterns to also analysing local population patterns. It was also Raymond Florax who introduced me the Carlino–Mills model and who made me notice the possibilities of meta-analysis for research synthesis. Back then (and still now) meta-analysis was rarely used in geographic research, and the Carlino–Mills model had yet to achieve the status it has today. Importantly, with the focus on the Carlino–Mills model the interactions between population and employment location changes ("do jobs follow people or do people follow jobs") became the focal point of my research.

In the end, completing this book took longer than anticipated, partly because I mostly worked part-time, but mainly because I found it difficult to finish things off. For me, the joy was always thinking about research designs, collecting and preparing the necessary data and subsequently, preferably by new methodologies, digging nuggets of interesting information out of these data –not the prospect of writing a book or getting a PhD degree. Now that I have not only completed my analyses, but also the not-so-small matter of writing things down, I am very pleased that I have managed to meet expectations and obligations.

Through the years, I have received lots of help with my research. First of all, this research would not have been possible without the data collection efforts and kind cooperation of many organisations: the provinces of Fryslân, Groningen and Drenthe,

the municipality of Groningen, CAB Groningen, ETIN Consultants, the former Regional Employment Office (now the Centre for Work and Income) of Drenthe, Statistics Netherlands, the Social and Cultural Planning Office of the Netherlands and the former Netherlands Institute for Spatial Research (now the Netherlands Environmental Assessment Agency).

My supervisor Jouke van Dijk has been instrumental in guiding me through the PhD journey. Without him, it would definitely have been a less rewarding journey, as he really gave me the opportunity to stimulate my own ideas, was always available to provide practical solutions and thought-provoking comments and, overall, enabled me to work under the best possible conditions. I am very thankful for his enthusiasm, his constant belief in my abilities, and for his never-ending support in me completing my PhD. My second supervisor Raymond Florax brought in some great ideas and taught me some important lessons about scientific thoroughness. I truly enjoyed learning those lessons, which have greatly improved the quality of my work, and would like to thank Raymond for all his dedication, support and hospitality at the Free University of Amsterdam.

I thank Daniel Griffith, former editor of the *Geographical Analysis*, and reviewers for their valuable feedback on previous versions of the papers presented in Chapters 3 and 5. Also, I am greatly indebted to Guyslain Ngeleza for his help with computer codes used in these chapters and Giles Stacey for editing the English of Chapters 1 and 6. For their willingness to serve on the reading committee of this thesis, I would like to express my gratitude to Henk Folmer, Jos van Ommeren and Frank van Oort.

I thoroughly enjoyed my time at the faculty of spatial sciences. Therefore, a sincere thanks to all my (former) colleagues and then specifically Cees-Jan Pen and Sierd-Jan Koster whom I had the pleasure to share an office with for a number of years. A special thanks also to Ad van den Boom and Jaco Blokker for showing an interest in what I have been doing these past few years and for willing to act as paranymphs during the defence of my thesis.

My father, mother and sister have always been very supportive to me, and I owe them a lot. For them, and for my grandparents who have always taken a special interest in my research activities, I am particularly pleased to can say that I “got it done”.

Finally, I reserve my warmest thanks to the three most important people in my life, without whom this research would possibly not have succeeded. I am forever grateful for their love and inspiration, and it is to them that I dedicate this book.

Gerke Hoogstra
Stiens, January 2013

Contents

1. Introduction

The restless urban landscape[1]

Viewing the earth from above, the legacy of man is no better reflected than in the patterns of the land used for human activities. The most striking feature of these patterns is the uneven distribution of these activities which, when viewed over time, reveal a remarkable consistency. It seems that these spatial patterns do not change easily; rather, they show signs of a cumulative process in which a concentration of human activity attracts further activity.

Everyday observations of the human landscape, such as those above, clearly expose an inert, path-dependent and self-reinforcing system. Yet, while the tendency in this system appears univocally to be towards a clustering of human activities, relatively recent evidence suggests that this pattern of spatial clustering may not be stable, or only partially so. In the United States (US), for example, at least three radical changes in the location of human activities are known to have taken place over the last fifty years or so, away from existing spatial concentrations: the *frostbelt–sunbelt* movement saw a shift of activities from the Northeast to the South and West; *suburbanisation* saw a move from central to suburban locations within metropolitan areas; and, finally, *counter-urbanisation* saw a shift from metropolitan to non-metropolitan areas (Carlino and Mills 1987). The impact of these movements has been a dramatic change in the hierarchy of cities, the landscape's most prominent features of spatial concentration. For example, only four of today's ten most populated US cities were on the equivalent 1950 list, while only one (New York) has held its position (as the nation's largest city). In the Netherlands, the landscape has undergone similar changes albeit not as dramatic as in the US. No less than eight of the top ten Dutch cities in 1950 are also on today's list, with the top four remaining Amsterdam, Rotterdam, The Hague and Utrecht, and still in that order. Nonetheless, at the regional level, there has been a clear movement of activities from the densely populated Randstad area in the west of the county to the provinces in the adjoining intermediate zone (see, for example, Van Dam et al. 2006). Also, as with suburbanisation and counter-urbanisation in the US, some radical changes have taken place in and near Dutch agglomerations, with human activities moving away from urban centres towards peri-urban and rural locations (see, for example, Bontje 2001). The examples from the US and the Netherlands make clear that the landscape of human activities is more changeable and thus more interesting than it first appears. However, why should one bother to study this landscape and its changes in the first

[1] The title is taken from Knox (1991) who refers to a passage by Harvey (1985, p. 150) referring to "the restless formation and reformation of geographical landscapes".

place? Basically, there are three reasons for doing so, and these broadly coincide with the academic, public and policy interests shown in these issues.

A first reason, and one which mainly explains the intellectual interest, is innate curiosity about such things and a wish to understand them. Naturally, the clear clustering of human activities gives rise to questions about the reasons why, similarly the opposing deconcentration tendencies do stir the mind as to what has changed. Also, spatial patterns reveal some interesting information, for example about the way human activities are organised or carried out, thus making these patterns much more than merely geographically interesting. Importantly, spatial changes do not stand alone but originate from, and reflect, broader (i.e., social, cultural, economic and technological) trends in society. Yet, while these changes may tell us much about the times in which they occur, they may not necessarily be easily understood as the complex relationships among societal developments make it difficult to determine what is really behind such changes. Naturally, these driving forces can be easiest identified when the spatial changes have a clear and definite direction. For instance, in the case of counter-urbanisation, explanations have been sought and found in several global societal restructuring processes, coined “megatrends” by Naisbitt (1984). According to Bowler et al. (1992) these trends have deeply transformed urbanised societies by bringing: (i) new needs; (ii) increased time-space compression; and (iii) economic restructuring.

The “new needs” are reflected in a change in values and lifestyles in favour of so-called quality of life factors or amenities. In other words, people’s locational preferences are driven less by economic opportunities and more by aspects that influence one’s mental or physical wellbeing, or simply by greater consumption (Partridge 2010). Megatrends that are supposed to be behind these value changes are rising incomes and increasing spare time (such as through early retirement or part-time working).

Next, the “increased space-time compression” refers to the fact that the impact of space, as a barrier, has significantly changed. Thanks to major advancements in personal mobility (through increased car ownership, better infrastructure etc.) and information and communication technologies (ICTs), it now takes ever less time for people, goods and information to cover geographical distance. An important consequence of this is that people are more able to act upon their locational preferences. More specifically, people have become increasingly free to do their activities in a range of locations as the necessity to co-locate these activities has somewhat disappeared. Given the significant rise in commuting distances between home and work, which has become a common feature of everyday life, there can be little doubt that the space-time compression has been instrumental in shaping urban form.

Finally, with regard to “economic restructuring”, Bowler et al. (1992) highlight an increase in the locational freedom of production activities similar to that for people’s residential activities. This restructuring is usually explained in terms of a change towards a “post-industrial”, “knowledge” or “information” society, reflecting an economic transition from a manufacturing-based economy to a service-based one in which knowledge and information are key. Behind this transformation are the interlocking effects of globalisation, liberalisation, increased competition (leading to more volatile markets and downsizing of many production processes) and, again notably, advancements in ICT. Specifically, the new forms of communication are widely credited with offering the possibility of economic transactions that are free from traditional space and time constraints. Combined with the new production requirements (for knowledge and information), economic activity is said to have become increasingly "abstract", that is, disconnected from land, manual labour and physical capital (machines and industrial infrastructure), thereby increasing the spatial flexibility of firms. However, opposing such suggestions that developments in ICT are driving us towards a flat world (Friedman 2006), there are also suggestions that the world remains uneven or curved (McCann 2008): that density and spatial proximity remain important for innovation, productivity and economic growth. However, the effect is probably not unlimited as congestion may halt and even reverse the positive effects of agglomeration (see, for example, Broersma and Van Dijk 2008).

In brief, spatial changes are clearly closely linked to other changes in society, and this guarantees an interesting topic for research. Further, the insights generated by such research are beneficial in view of the real-life implications of these changes. Given these implications, which are further discussed below, there is also a strong non-academic impetus for such research.

While spatial changes do not occur alone (as outlined above) they also do not occur without having wider effects. Another reason for studying these changes, and which explains most of the public interest, is a concern over some of the ramifications. For example, much is often made about the impact of urban sprawl, ranging from increased traffic congestion and the loss of culture and identity, to the disappearance of open space and damaging effects on the natural environment (see, for example, Beauregard 2006). Ironically, public interest may also be stirred by the lack or loss of activities because of the consequences of this on the overall liveability of places and the opportunities open to residents. Specifically, the propensity of human activities to be self-reinforcing (see also the opening statement of this section) means that places can easily get trapped in a vicious circle of decline (see, for example, Haartsen and Venhorst 2010). Being simultaneously a symptom and a cause of the decline, the loss of activities is naturally a focal point of public interest.

Many of the issues that are important to people also originate in the fact that the various activities do not move in the same direction. Earlier, the increased separation of home and work, and its effect on the daily journey between these places, was mentioned. However, this spatial discrepancy may also result in a situation in which the desired activities are too far apart to be overcome by travelling. Following Kain (1968), there has been huge interest in the idea that the mismatch between places of residence and places of jobs (because of job deconcentration, housing segregation, discrimination and/or a lack of spatial mobility) could be key to explaining the labour market outcomes for particular subgroups (such as blacks and women) and the concentrations of unemployment, low wages and poverty in particular locations (such as in the inner areas of US cities; see Kain 2004 for further discussion). Clearly, the implications of spatial changes are very serious in real-life, which makes the analysis of these changes much more than just of academic interest.

Finally, and closely following the previous argument, there may be a strong policy interest in these matters, not necessarily because of the wish to understand past, current or future dynamics per se but mainly to aid decision-making with regard to a number of issues. For example, authorities are expected to facilitate the spatial changes taking place (through the provision of infrastructure, public services etc.). In addition, based on efficiency and/or equity considerations, authorities may want to take an active role in channelling these changes, and hence the existence of many development programmes. Besides the obvious equity considerations, with residents of different regions facing unequal opportunities, these programmes may equally originate from efficiency considerations given that the allocation of activities directly influences the use of resources such as labour and land. These considerations may also play such roles at the local level, with a particular distribution of activities within a region being viewed as non-optimal due to environmental or economic costs (such as those linked to congestion), or unfair to residents of places that lack access to these activities. Accordingly, from policy considerations, there is clearly a pressing need to understand the spatial distributions of human activities and changes therein.

The locations of jobs and people: the issue of interaction

Having thus far talked about human activities in rather abstract terms, the relevance of studying spatial patterns and changes therein is arguably better understood if these activities are accurately delimited. For most readers, the first reflection will have been, and rightly so, that the discussion above is primarily about the residential and employment activities of people. Among the many possible activities, these are clearly the most elemental: they absorb most of our time and also have the greatest spatial impact. Unsurprisingly given these considerations, it is also these activities that are best covered in the data collected on human activities and that attract most of the interest from scientists analysing spatial patterns.

Especially interesting with regard to residential and employment activities, aside from them representing the most salient features of urban form, is the existence of a clear spatial relationship between them that largely explains why spatial concentrations dominate the landscape. That is, space and time constraints dictate that these activities take place in close proximity to each other, or as Haig (1926) observed: "*The great bulk of population […] must work and must consume most of what they earn where they earn it. With them consumption and production is practically a simultaneous process and* *must be carried on for the most part in the same place*" (pp. 185–186). Further, in reference to the statement at the beginning of this chapter, it is this very relationship that seems to explain why existing patterns tend to remain and usually strengthen over time as the need to co-locate naturally results in a cumulative and self-reinforcing process. As Marshall (1890) put it: "*Employers are apt to resort to any place where they are likely to find a good choice of workers with the special skill which they require; while men seeking employment naturally go to places where there are many employers who need such skills as theirs and where therefore it is likely to find a good market*" (p. 225). Similarly, the interaction may occur through consumption as Papageorgiou and Thisse (1985) note: "*households are attracted by places where the density of firms is high because opportunities are more numerous [...] firms are attracted to places where the density of consumers is high because there the expected volume of business is large*" (p. 20). Simply put, for whatever reason, firms will tend to locate near people and people will tend to locate near firms, thereby creating a feedback mechanism that is key in shaping the urban form.

To further highlight the critical role of circular causation, which results from the location decisions of firms and of households sustaining each other, it is useful to introduce the long-standing distinction between "first nature" and "second nature" geography (see, for example, Ottaviano and Thisse 2005). Clearly, some of the spatial variation in human activity can be attributed to variations in exogenously given, eternal location features, labelled as *first nature*, such as access to natural transportation networks, the climate and the presence of raw materials. However, in trying to ease first-nature constraints, people have developed spatial distributions that, in many cases, are largely independent of natural advantages (Ottaviano and Thisse 2005). Essentially, second nature is distinct from first nature in that it concerns features that are dependent on existing spatial structures and previous developments rather than being intrinsic to the location itself. Regarding the uneven distribution of human activities across space, second-nature explanations argue that people themselves have a strong incentive to cluster their activities, with the advantages gained from spatial proximity at the heart of these explanations. In terms of the interest shown in the natural (first nature) as against the human (second nature) aspects of geography, it is the latter that are generally found to be more intriguing as their endogeneity makes them relatively difficult to pin down. Furthermore, the former are mainly held accountable for the initial concentrations of activities in particular places, whereas the latter are mostly credited for the further development of these concentrations (see, for example, Roos 2005). Accordingly, it is also primarily these second nature forces that need to be understood in order to foresee future spatial changes and to possibly control these changes in the light of efficiency and/or equity considerations. Finally, modern regional economic growth theories, such as the much debated "New Economic Geography" (NEG) developed by Nobel laureate Paul Krugman and others, almost exclusively focus on second nature explanations. Essential to these theories are the cumulative interactions among economic agents, notably firms and households (see also Fujita and Thisse 2009 for a summary of NEG and related theories).

Given the strong interdependencies between the location decisions of households and of firms, employment and population changes across space have a tendency to go hand in hand, and are often seen as being part of one and the same process. Broadly, at the regional level or beyond, the geographies of jobs and people largely overlap and it is not by coincidence that concepts such as suburbanisation and counter-urbanisation have been used interchangeably in describing both population and employment dynamics. However, as the discussion in the previous section clearly illustrates, it remains important to separate population and employment in the analysis of location changes. First and foremost because their relationship is not as clear-cut as it once was, as shown by data on commuting and by detailed local analyses of these changes which show that places of residence have become increasingly disconnected from places of work. This is due to the growing number of people outside the labour force (such as retirees that do not make employment location decisions), two-worker households (that need to balance the place of residence between two often-divergent job locations), and advancements in spatial mobility and ICT, with especially these latter playing a crucial role in what Renkow (2003) describes as "the continuing de-linking of the residential and employment location decisions". As outlined in the previous section, it is also this de-linking that attracts considerable public and policy interest (considering the effects on travelling and associated space claims, the effects on unemployment when employment changes fail to match population changes, etc.). Finally, the fact that location choices made by firms and households have increasingly become self-governing makes it particularly interesting to disentangle these choices in order to determine which comes first, and so getting to the root of the second-nature forces of spatial change. In other words, one can address the chicken-or-egg question as to whether "people follow jobs" or "jobs follow people". This question first received widespread attention in the 1960s and 1970s, when profound changes in the landscapes of jobs and people prompted researchers to analyse the mechanisms behind these changes in more detail. The changes at that time in favour of amenity-rich residential areas suggested that people were led by factors other than employment, thereby questioning the then prevailing ideas on the direction of causality. Until then, the dominant view had been that spatial changes were first and foremost employment-driven (i.e., "people follow jobs"). Accordingly, in intra-urban models, population was simply assumed to be endogenous to employment but not the other way around.

Over the past twenty-five years or so, the debate as to whether "people follow jobs or jobs follow people" has been reignited. At least four factors explain this upsurge of interest, which has seen population–employment interaction become one of most important topics in regional science and urban economics.

First, on a practical note, methodological advancements and more sophisticated computer systems mean that the possibilities of studying spatial changes have been greatly enhanced. The major methodological breakthrough, which has proved to be a starting point for much of the research, came in the late 1980s thanks to Carlino and Mills (1987). In their study on US county growth, which became the most-cited publication of its year in regional science (Isserman 2004), they introduced a now classic framework in which the impact of both exogenous first nature and endogenous second nature features (and then specifically the nature of population–employment interaction) could be assessed in a fairly straightforward manner. Since then, a whole new literature has emerged centred around the so-called “Carlino–Mills model”. This received a fresh impetus in the 1990s when Boarnet (1992, 1994a, b) integrated spatial econometric techniques. In addition to the necessary analytical tools now being available, researchers have clearly made good use of improvements in the collection and accessibility of georeferenced, or spatial, data. Over the years, the population and employment data required for these sorts of analyses have become increasingly detailed and available, not only in spatial terms, but also in terms of their non-spatial characteristics. Mainly because of the richness of the data, the literature has seen a rapid increase in studies focusing on population–employment interaction in different regions, over different time periods, for different groups of jobs and/or people, and on various spatial scales.

Second, the societal changes taking place, that bring about the spatial changes, are currently believed to be the most enduring of our time, with speculation rife that the landscapes of jobs and people are about to radically change. According to Florida (2002), we are now in the midst of a fundamental economic revolution, larger than the change from an agricultural to an industrial society. Also, to quote Knox (1991): “*The changes underway […] add up to the most pronounced restlessness in urban landscapes since the late 19th century when street cars and elevators turned cities inside out and upside down*” (p. ix). A crucial role in these changes is generally ascribed to ICT, whose impact is likened by many to the massive revolutions in transport and other technologies in the late 19th and early 20th centuries. At that time, Marshall (1890) was drawing attention to the battle of centrifugal and centripetal forces shaping the landscape and noted that “*every cheapening of the means of communication […] alters the action of forces that tend to localise industries*” (p. 227). Speculation is rife that the centrifugal forces will come to predominate, with distance-shrinking technologies rendering the need for spatial clustering obsolete. Some researchers have gone as far as to claim the “death of distance”, the “end of geography”, or the “world to become flat” and foresee the very existence of cities as being under threat (see, for example, Cairncross 1997; Friedman 2006).

Amid the speculation on where the urban landscape is heading, much of the interest has focused on a possible change in the relationship between jobs and people. Back in the 1980s, Toffler (1980) was already hinting at a revolutionary impact of ICT on the residential and employment location decisions of people, predicting that the “second wave of industrialisation” (which had seen commuting become an integral part of our lives) would be overtaken by a third wave in which work would be brought back to the home setting. The argument was that ICT enables people to work from essentially anywhere, thereby loosening the ties that traditionally bind residential and employment location decisions. Similarly, for firms, the replacement of geographic proximity with virtual connectivity will render them more footloose and allow them to make a location decision independent of the residential location decisions of current and prospective employees.

An alternative view on the societal changes taking place, and shaping the urban landscape, was put forward by Richard Florida (2002). In *The Rise of the Creative Class*, Florida discusses one of the most important emerging trends in the early 21st century which he argues is behind a host of seemingly unrelated societal changes: the growing importance attributed to creativity. In his view, the rise of human creativity is the key factor in our economy, and society as a whole, and the main force driving spatial changes. He goes as far as to allude to the “creative economy” being much more important than the much heralded “information” or “knowledge” economy. Human creativity, he argues, is valued more highly and cultivated more intensely than ever before because of the rise of individuality, self-expression, changing attitudes, expressions and behaviour, which have all been building for decades. With regard to spatial outcomes, Florida clearly does not share the end of the city view that some ICT proponents are predicting, but rather sees a change in the existing urban hierarchy. Specifically, he foresees that the thriving cities of tomorrow will be what he calls “creative centres”, places that actively foster the three “T’s”: technology, talent and tolerance. A particularly interesting aspect of his argument is that the success or failure of cities will essentially hinge on their ability to attract and retain talented people belonging to the creative class. Florida crucially suggests that, for these people, jobs are not all that matters when making a decision on where to live. Rather, the overall quality of the life they may live, and the experiences they may consume, which validate their identities as creative people, will be of overriding importance. As such, they will be looking for places that are primarily diverse, tolerant and full of opportunities for intense, high quality and multidimensional experiences. Further, while suggesting a decline in the influence of jobs on the residential location decision, Florida conversely presumes a growing influence of the population distribution on the location decisions of firms. Specifically, regardless of the increased locational flexibility that comes from the advancements in ICT, firms will have a strong incentive to locate near to the creative class, with creativity becoming the scarce commodity and main production requirement. In brief, Florida offers the strongest arguments so far that, today, population changes are driving employment changes, and not the other way around.

Third, and arguably even more than because the discussions about causality have stirred an interest, research has blossomed because the findings from empirical studies that reveal the nature of population–employment interaction are believed to be extremely conflicting and equivocal. As a result, the issue of how population and employment interact is now generally thought of as an enigma, a puzzle which, like most chicken-or-egg dilemmas, is fascinating in itself, and not necessarily because the outcome would have practical relevance. On the one hand, the apparent lack of consensus has prompted researchers to conduct their own studies on the nature of population–employment interaction, rather than drawing on the findings of previous studies. On the other hand, it has motivated researchers to vary with different techniques, variables and data to provide insights that may explain the variations in these earlier findings.

Finally, as a distinct argument, it is worth emphasising that the population–employment interaction would not have been so intensively studied if it was not for its sheer relevance, a point which brings us to the academic and policy ramifications of the question. With regard to the academic interest, the relevance finds its origins in two contrasting schools of thought on the spatial changes taking place (see, for example, Bierens and Kontuly 2008). First, there is the so-called *regional restructuring* perspective, which postulates that these changes primarily result from households adjusting their locations to those of firms (i.e., people follow jobs). Specifically, proponents of this view claim that suburbanisation, counter-urbanisation and similar trends have occurred mainly because of economic restructuring that has radically altered the preferences for industrial locations and the need to react to these preferences. Second, there is the so-called *dispersion* or *deconcentration* perspective, which leans towards highlighting changing residential needs and lifestyles as the driving forces behind these changes. Hence, according to this view, of which Florida is a notable proponent, consumption-related motives have gained the upper hand over employment-related motives in residential relocation, with jobs being tied to the location preferences of households (i.e., jobs follow people).

Alongside the socio-geographical contemplations about the role of various megatrends, the discussion on the mechanisms behind spatial change also plays a prominent, and arguably more formal, role in the economic debate. Researchers in this field basically draw from two classes of theories to explain the economic growth of regions. Those that conform to the idea that "jobs follow people" assume that growth is *supply-driven* (as in the neo-classical growth theory) and those that back the "people follow jobs" hypothesis assume that this is *demand-driven* (as in the export-base theory). Crucially, and reflecting these opposing theories, there are a range of models which focus either on labour demand or labour supply, and which respectively assume the interaction to be running from population to employment or from employment to population, but never in both directions. For instance, a line starting with the classic monocentric city model developed by Alonso (1964) assumes population to be endogenous to employment (and employment to be exogenous to population), and produces an urban literature in which the idea that "people follow jobs" is strongly rooted. However, as Boarnet (1994b), among others, points out, models that are based on such assumption are inappropriate and result in misleading conclusions where such an interaction is counter-directional. In other words, the validity of models that do not at least consider the possibility of dual causality, or two-way interactions, should be questioned as long as the debate on causality remains unsettled.

Finally, in drawing possibly misleading interferences, the implications may not be limited to a misunderstanding of the spatial changes taking place, but may also have wider implications. Specifically, with this issue lying at heart of many challenges confronting policymakers, a true insight into the direction of causality becomes of paramount importance in successfully implementing measures that aim to address inefficiency and/or inequity claims. Accordingly, the answers provided by researchers are also likely to be greeted with much interest beyond the academic world.

The practical relevance of the chicken-or-egg question whether "jobs follow people or people follow jobs" is perhaps best illustrated by the different strategies local and regional authorities can choose between when striving to stimulate their economies. Essentially, authorities need to make a decision on whether to invest in the residential amenities of places or to adopt an employment-directed approach. The latter approach, which may involve industrial recruitment and interfering in the business climate as well as improving the employability and mobility of people, appears to be the obvious strategy if one believes growth is labour-demand-driven (i.e., "people follow jobs"). If, however, growth is in reality supply-driven (i.e., "jobs follow people"), these fairly conventional economic interventions to enhance the development of places will not be effective and may even be counterproductive. That is, if the residential or "quality of life" aspects are more important to people than job opportunities, and the former are threatened by government interventions, this will likely lead to population losses and, since employment is driven by labour supply in this scenario, eventually also to employment losses. Similarly, the opposite route of trying to attract households first, by boosting the residential qualities of a place, in the belief that firms and jobs will automatically follow, i.e., a population-directed approach, will only work if jobs do indeed follow people and not the other way around (for further discussion see, for example, Henry et al. 1997 and Freeman 2001).

Objectives, research questions and methodologies

Motivated by the growing interest in population and employment location changes, this study aims to enhance the understanding of population–employment interaction by addressing the following research questions:

1. *What do research findings on population–employment interactions indicate about whether "jobs follow people" or "people follow jobs"?*

2. *Why do research findings on population–employment interactions differ, and what are the sources of this variation: are they empirical, intrinsically related to*

variations in the nature of population–employment interactions over time, or space or between subgroups of jobs and people; or methodological, related to the way in which the issue is investigated?

3. *What are the spatial dimensions of population–employment interactions: how far do they stretch, and how quickly do they fall away with distance?*

4. *What is the impact of gender on the location changes of jobs and people: is there a difference between men's and women's employment in the strength, direction and spatial range of population–employment interactions, interactions within employment groups, and interactions between employment groups?*

In addressing the first two research questions, this study will synthesise, for the first time, the substantial body of research on population–employment interactions conducted in recent years. As outlined in the previous section, there is a compelling need to do this since, in spite of all the research endeavours, the issue of whether "jobs follow people" or "people follow jobs" appears to be as unclear, if not even more so, as when it was first brought up some thirty years ago. To date, convincing insights into the nature of population–employment interactions that would allow predictions and the design of effective policy measures are still lacking. Crucially, it seems that the controversy surrounding the population–employment interaction has actually deepened *because* of these past endeavours. Rather than de-mystifying the enigma of population–employment interaction, the literature appears to be going around in circles, with every new research contribution raising as many questions as it answers, and further adding to the confusion. The question that needs to be asked, or rather answered, is *why* the empirical findings on population–employment interactions are *what they are* and whether they are indeed as inconsistent as conventional wisdom suggests, and what an initial simple comparison would probably indicate. At present, one can only speculate on the possible impact of studying different datasets, and which of these would signal real-world variations in population–employment interaction, or on the impact of using alternative methodologies, and which could explain the variations in the results from various studies as a scientific artefact.

One aim of this study is to make sense of what is currently known about population–employment interaction following several years of research. Another aim is to add to this knowledge by filling some of the gaps in the existing literature. As outlined in Research Questions 3 and 4, this study focuses on two specific issues that have been largely ignored. The first issue concerns the spatial dimensions of population–employment interactions, which is today especially relevant in light of the distance-negating impacts of modern ICT systems (for example, by enabling teleworking) and the overall loosening of the ties between residential and employment location decisions. Here, of particular interest is the scope of the interactions, as this will reveal the impact of events occurring in one place on those occurring elsewhere. Clearly, such insights are crucial for policy (for example, by indicating whether regional strategies will be more effective than local strategies). In addition, the answer to Research Question 3 may provide some useful insights for studies that aim to spatially delineate labour markets, daily urban systems or functional economic areas, or which focus on spatial accessibility.

The second issue, which somewhat surprisingly (considering the many studies investigating possible group effects) has yet to be investigated, concerns the role of gender in location changes and population–employment interactions. Given that labour markets are clearly still segmented along gender lines (as, for example, shown by gender differences in labour participation, occupations and commuting), one can reasonably assume that gender plays a crucial role. Given the increasing number of two-worker households and women increasingly contributing to regional employment growth, the role of gender is a relevant topic for research. For reasons of equity (emancipation) and efficiency (economic growth), there is also a strong public and policy interest in information about the functioning of the labour market for women.

To answer the questions outlined above, this study makes use of a number of rather novel methodologies, and this makes it distinct from other studies in its field. Specifically, Research Questions 1 and 2 are answered through a quantitative literature review technique known as "meta-analysis", an approach which thus far has been rarely used in urban and regional studies. The application of this technique to investigate the findings of a simultaneous equations model is somewhat of a novelty, as is the application of a quasi-experimental meta-analysis which is specifically employed here to address Research Question 2. A key element to both these approaches is the use of statistical techniques to determine the variation among research findings and the appropriate combination of factors that explain this variation. Both approaches allow a rigorous assessment of the alleged inconsistencies in population–employment interaction findings, and an evaluation of the impact of substantive study features related to data sampling and impact of methodological study features. They differ in that the data input for the fairly routine, literature-based, meta-analysis comes from the primary data analyses already completed in other studies. In the quasi-experimental analysis, which is more akin to a robustness analysis, the data are generated in a series of one's own experiments. Here, the meta-analysis will focus on a group of existing "Carlino–Mills studies" that individually do not tell us much in relation to Research Questions 1 and 2 but, collectively, are considered to be sufficiently rich to provide answers. In the quasi-experimental meta-analysis, a similar model to those used in these Carlino–Mills studies will be repeatedly estimated, while systematically changing its design (as if it were different studies). The freedom to decide these experiments for oneself allows an assessment to be made of the impacts of particular study features that, for whatever reason, cannot be properly determined from existing studies, but which hold potentially important information for future research. For example, here, the experiments will be designed such that the outcomes will have a direct relevance for a spatial econometric simultaneous equations analysis that will be performed later in this study. There, questions will again be asked about how various aspects such as model specification and estimation techniques might shape estimation results. Similarly, the experiments can anticipate future analyses by making considered choices about the data to be investigated. For example, here, these experiments will have the later analyses required for answering Research Questions 3 and 4 in mind, and examine population–employment interactions in a region that will also be studied in Chapters 4 and 5. Similarly, the experiments will focus on spatial units of similar size to those that will be observed later in the study.

In addition to the statistical techniques used to further analyse previous statistical analyses, this study also capitalises on recent advancements in the analysis of spatial, data. Unlike non-spatial data, the data used in a spatial analysis are typically interdependent. The explanation for this is rooted in the so-called "First Law of Geography" coined by Tobler (1970) which states that "*everything is related to everything else, but near things are more related than distant things*" (p. 236). Crucially, when one assumes that data are not independent, and that things are further complicated by the dependence probably working in more than one direction (unlike the dependence between time-series observations) and possibly taking on different forms, conventional statistical analysis techniques are no longer appropriate. Fortuitously, starting in the 1980s, but not exactly widespread until recently, spatial econometric techniques have come available that can be used when addressing the peculiarities of spatial data. Further, computer routines have also become available, both integrated in regular statistical programs and as freestanding programs such as *SpaceStat* and *GeoDa* (see Anselin 2010), which have significantly eased the application of spatial econometric techniques. Since Boarnet (1992), studies on population–employment interaction have increasingly recognised the need for, and the potential of, these techniques. Also in this study they will be extensively used, with the analyses including two different, yet complementary, types of spatial data analysis: an Exploratory Spatial Data Analysis (ESDA) and a Confirmatory Spatial Data Analysis (CSDA). The former will be used to investigate *bivariate* spatial association among two variables (that reflect local employment and local population growth), rather than the usual investigation of *univariate* spatial association of a single variable (in addressing Research Question 3). Subsequently, these local population and employment changes will be formally explained using a CSDA. This involves the application of a spatial econometric Carlino–Mills model to jointly investigate the role of space (Research Question 3) and gender (Research Question 4). By including all the potential forms of spatial dependence, the selected model reflects the most advanced form of a spatial econometric simultaneous equations system, as formally categorised by Rey and Boarnet (2004). This study is one of the first to use this model that has only recently been possible to solve due to the previous lack of a proper estimation technique.

Thesis outline

The rest of this thesis comprises four major chapters that address the research questions in chronological order, followed by a summary and conclusions. The thesis is structured keeping the end in mind, meaning that if it is read from beginning to end the chapters will fit together and the reader will be led through the process. However, there is no strict chronology that has to be followed, and the thesis does not have to be read in its entirety to understand the separate contributions. That is, each chapter is sufficiently self-contained to be read in isolation. All the chapters start with an introduction and end with conclusions (alongside possible implications that are picked up in later chapters). Further, cross-references to passages elsewhere are included throughout to provide further explanation.

Chapter 2 presents a meta-analysis of the population–employment interaction literature inspired by Carlino and Mills (1987), thereby addressing Research Questions 1 and 2. Following a brief introduction to meta-analysis as a quantitative technique for research synthesis, it discusses the features that are essential for a Carlino–Mills model specification, and the subsequent identification of relevant studies. Next, it summarises study results of population–employment interactions, and categorises the various study features that may explain the variation in these results. Finally, it discusses the outcomes of a meta-regression analysis in which the impacts of several selected study features on the population–employment interaction findings are verified.

Chapter 3 presents a quasi-experimental meta-analysis of empirical results based on settlement data from the Dutch province of Fryslân and adds to the findings previously obtained in Chapter 2 that relate to Research Question 2. It starts with a discussion on how a quasi-experimental meta-analysis may complement a conventional, i.e., literature-based, meta-analysis. Subsequently, it describes the econometric model and data used, the design of the experiments, i.e., which study features to vary, and eventually the results of a regression analysis that assesses the impact of these features on the population–employment interactions found. In terms of selecting study features, the quasi-experimental meta-analysis draws on suggestions found in the literature review presented in Chapter 2. Among these features are different specifications and estimations of a spatial econometric model that will again be used in Chapter 5.

Being the first of two chapters that explicitly focus on postcode-level population and employment growth in the Northern Netherlands, Chapter 4 presents an Exploratory Spatial Data Analysis (ESDA) used to investigate the spatial dimensions of population–employment interactions (Research Question 3). It begins with a review of the assumptions made and the empirical evidence found in previous studies on the deterrence effect of distance. Next, it discusses various ways to measure population and employment growth, and the use of statistical techniques to detect bivariate spatial association. This is followed by a discussion of the results that assess the spatial range and the decay with distance of population–employment interactions in the study region. Finally, as preparation for Chapter 5, where postcode-level growth patterns will be formally explained, it is investigated how the observed patterns of spatial association are influenced by spatial policies that shape local population growth.

Following the Exploratory Spatial Data Analysis of Chapter 4, Chapter 5 presents a spatial econometric analysis of postcode-level population and employment growth in the Northern Netherlands that addresses Research Questions 3 and 4. This chapter starts with a literature review on the role of gender in population and employment growth patterns. Following this, it describes a spatial simultaneous equations model that distinguishes between population- and gender-specific employment groups, and that further includes both autoregressive and cross-regressive spatial lags to detect relationships both within and among these groups at various distance intervals. Following a description of the selected postcode-level data from the north of the country, and a reflection on specification and estimation issues, a discussion of the model's estimation results completes the chapter.

Finally, Chapter 6 presents a summary and draws conclusions from this study. First, it recaps on the reasons and relevance of this study, followed by a summary of the research questions posed, the methodologies used, and the findings obtained in response to these questions. It ends with a discussion of the implications for policy and with suggestions for future research.

2.
Do “jobs follow people” or “people follow jobs”? A meta-analysis of Carlino–Mills studies[2]

Introduction

Recently, regional science, urban economics and related disciplines have seen the emergence of a significant body of research interested in the location patterns of jobs and people. Among the main reasons for this interest is the controversy surrounding the issue of population–employment interaction, which is echoed in the classic phrase “do people follow jobs or do jobs follow people?” (Steinnes 1982). According to popular view and narrative descriptions of the literature (see, e.g., Sohn and Hewings 2000; Bollinger and Ihlanfeldt 2001), research findings for this chicken-or-egg question are extremely varied and confusing. Not surprisingly, questions have been asked about the reasons behind this variation. For example, Carruthers and Vias (2003) have claimed that “*the character of the process* [i.e., population–employment interaction] *probably varies from region to region and maybe even from time period to time period*” (p. 4). Alternatively, it has been suggested that the alleged wide divergence in findings represents a scientific artefact, stemming from methodological study differences (see, for example, Boarnet et al. 2002).

To date, there has been little effort put into making a precise statement about the variation in research findings on the direction of causality in the jobs–people relationship. Arguably, the supposed wide variation in these findings is viewed as a stylised fact that needs no further validation. Alternatively, researchers may have refrained from comparing the research findings from different studies because of the considerable heterogeneity in terms of data and methodologies used. In other words, the research findings of individual studies appear unique and not amenable to summarising. Whatever the reason, this absence of a comprehensive literature review is not helpful when considering future research. Most importantly, it is still unknown which factors are responsible for the alleged variation in research findings and, consequently, whether the ambiguity surrounding the population–employment interaction would disappear if these factors were accounted for. Without understanding *why* the research findings are *what they are* the literature is likely to maintain its questionable tag of being very elusive. Moreover, with no clear answers provided to guide policy, and apparently yielding unending calls for further research, the literature ultimately runs the risk of being viewed as trivial.

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[2] The content of this chapter has also appeared in a paper presented at the 45th Congress of the European Regional Science Association (see Hoogstra et al. 2005).

This study is the first to systematically review and synthesize the research literature in which the "people follow jobs" and "jobs follow people" hypotheses have been verified. The objective is to obtain increased understanding of the nature of population–employment interaction by exploring the reasons for the variation in research findings. To this end, a relatively new, but increasingly popular quantitative literature review technique known as "meta-analysis" is adopted. Meta-analysis goes beyond a conventional narrative state of the art literature review. It constitutes the application of statistical techniques to collections of empirical findings from previous studies for the purpose of integrating, synthesising, and making sense of them (Glass 1976). Among the most powerful of these statistical techniques is a meta-regression analysis, which thrives on the variation among studies that make up a literature and which is particularly suited to clarify seeming inconsistencies in research findings across a literature.[3] In a meta-regression model, research findings are directly linked to data sampling, methodologies, and other features of the studies under investigation. Through the assessment of the marginal effects of study features insights can be obtained in the robustness of research findings and study characteristics that explain most of the variation. Such insights not only help to understand an existing body of research, but also provide important suggestions for future studies.

The research synthesis carried out here concentrates on studies inspired by Carlino and Mills (1987). The simultaneous equations model with adjustment lags that they introduced has become the standard methodology for population–employment interaction studies. Over a period of more than twenty-five years, the widespread use of this model has resulted in a wealth of so-called "Carlino–Mills studies". These studies differ on a plethora of research dimensions, and this makes them suitable for attempting to draw inferences about the impact of various aspects of data sampling and methodologies on empirical findings of the nature of population–employment interaction.

The outline of this study is as follows. The next section discusses meta-analysis as a tool for research synthesis, which is followed by a description of the econometric framework that underlies the Carlino–Mills studies. The successive sections confer the selection of Carlino–Mills studies, variation in study results within and across these studies, and variation in study factors that possibly influence these results. Subsequently, the results of a meta-regression analysis are presented in which the impacts of these factors are formally verified. The final section recapitulates the main findings of the analysis and discusses some avenues for future research.

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[3] While differing data and methodologies are often viewed as a major drawback or reason to even refrain from summarising research findings across a literature, they also give the opportunity to conduct a systematic analysis of the relationships between these characteristics and study results, which is one of the most attractive aspects of research synthesis (Cooper et al. 2009). In fact, a certain degree of variation among the studies that make up a literature is a prerequisite for meta-regression analysis.

Meta-analysis for research synthesis

The research literature is growing at an exponential rate. As research results accumulate, it becomes increasingly complicated to make sense of the flood of information. Researchers normally do not aspire to replicate or re-analyse. Rather, they typically pursue the new, the novel or at the least attempt to extend what is considered to be the current state of knowledge.[4] With no two studies being exactly alike, it is difficult to determine whether the variation in study outcomes can be attributed to methodological, contextual, or substantive variations in the research studies by using informal methods of narrative review techniques (Rudner et al. 2002).

Meta-analysis is a quantitative literature review technique that is tailor-made to compare research findings of different studies. Introduced by Glass (1976) in the mid-1970s, meta-analysis can be best seen as a statistical approach towards reviewing and summarising the literature (Stanley 2001). It complements the casual, narrative discussions of research studies that typify traditional attempts to make sense of the rapidly expanding research literature. Although ordinary literature reviews are valuable in their own right, there are a number of disadvantages in solely relying on such surveys (Dalhuisen et al. 2003). For instance, they can usually be criticised for a lack of objectivity in the selection of studies, which makes the comparison of study results largely arbitrary (Van den Bergh et al. 1997). Although alternative methods of research synthesis are not necessarily free from subjectivity either, the selection procedure followed in a meta-analysis has to be explicit and is therefore more transparent (Florax et al. 2002).

Next, qualitative literature surveys generally rely on some sort of vote-counting procedure, which is not very powerful in coming up with the right conclusion. Hedges and Olkin (1980) have shown that this technique, which essentially boils down to simply tallying significant results of a specific sign and non-zero results, has a basic flaw in that it tends to make the wrong interference when the number of studies increases.[5] In addition, the crudity of vote counting by looking solely at the sign-effects leaves much to be desired. Statistical significance alone is insufficient to determine whether the results of different studies agree (Hedges 1997). The most fundamental problem associated with qualitative review techniques, however, is that they are not equipped to cope with the complexity of a literature, in which many factors are interconnected to each other through relationships that can only be identified in a mathematical framework. In words of Rudner et al. (2002): "*Confronted with the results*

[4] In the terminology of Smith and Pattanayak (2002) it is the "competition of ideas" (p. 272) instead of replication that triggers creativity in economic research. To illustrate, the editorial board of *Labour Economics* announced in its June 1997 issue a policy to actively encourage replication and re-analysis studies by giving a conditional guarantee for publication, but abandoned this policy shortly afterwards due to a lack of responses.

[5] This is because the Type-II errors (i.e., failing to detect a true effect) in the original studies do not cancel (see also Hedges and Olkin 1985).

of 20 similar studies, the mind copes only with great difficulty. Confronted with 200, the mind reels. Yet that is exactly the scope of the problem faced by a researcher attempting to integrate the results from a large number of studies" (p. 2). In a meta-analysis, hundreds of research studies can be coded and interpreted using statistical methods similar to those applied in an individual empirically designed study. The quantitative approach implies that studies are compared in a systematic way that is more objective and exact than a narrative review. Moreover, given its statistical nature, meta-analysis furnishes more insight and greater explanatory power than the mere listing of studies and research findings (Rudner et al. 2002).

As for the use of statistical techniques, meta-analysis is not unlike primary and secondary analysis. However, it differs with regard to the data that are investigated. Whereas primary and secondary analysis can be referred to as an original and an extended examination of a single dataset, respectively, meta-analysis uses aggregate data from existing studies and thus exploits a number of datasets (Glass 1976). Consequently, it may arrive at conclusions that are not available to primary or secondary analysis. For instance, individual studies usually provide relatively good estimates of the sampling uncertainty of results, but generally rather poor estimates of the impacts of non-sampling issues, such as research design, model specification, and estimation technique (Hedges 1997). Meta-analysis opens the possibility of investigating these non-sampling issues, which are usually constant within studies, in a multivariate framework that allows the assessment of marginal effects (Florax et al. 2002).

Over the years, meta-analysis has become a conventional practice for research synthesis, originally mainly in the experimental sciences (education, psychology, and medicine), but later also in economics and then especially environmental economics, transport economics, labour economics, and international economics. In regional economics, meta-analysis has been relatively sparsely used. The earliest examples include analyses on the impact of taxes on regional development (Phillips and Goss 1995) and size of regional tourist multipliers (Baaijens et al. 1998). More recent examples are meta-analyses on estimates of urban agglomeration economies (Melo et al. 2009) and estimates that reveal the impact of migration on income growth and income convergence (Ozgen et al. 2010). The first textbook on meta-analysis in economics appeared in 2012 (Stanley and Doucouliagos 2012).

Basically, a meta-analysis comprises four different steps, which are not too dissimilar to the various steps undertaken in primary research studies (see, for example, Cooper et al. 2009). The first step concerns the *problem formulation*, which includes defining the research question to be summarised and identification of a research design that guides study sampling and data collection. The second step concerns the *data collection*, in which the literature is searched for studies that are relevant to the investigation and which meet specified criteria for inclusion. The third step involves the *data evaluation*, which includes the extraction of those bits of information that help to answer the question that impels the research. At this stage, a meta-database is constructed in which study characteristics are indexed and coded according to the objectives of the review. Additionally, study results are transformed to a common metric called the "effect size". The effect size can be any quantitative measure (e.g., standardised mean difference, regression coefficient, odd ratio, elasticity estimate) that allows the use of statistical techniques as a means for analysis. The final step, of *analysis and interpretation*, involves the actual application of these statistical techniques to arrive at conclusions about the average effect size or variation in effect sizes across studies. Also, the analysis may aim at explaining the variation in study results by fitting a model of effect-size variation. In such case, the meta-analysis takes the form of a meta-regression analysis which reveals the marginal effects of one or more selected study characteristics. The general framework of a meta-regression analysis reads as:

$$Y_i = \alpha + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \ldots + \beta_K X_{i,K} + \varepsilon_i \qquad (1)$$

where Y_i is the effect size of study i, $X_{i,k}$ are (k = 1, 2,…, K) explanatory variables that represent different characteristics of study i, α and β_k are unknown model parameters to be estimated, and ε_i is the random disturbance term of study i.

The model described by equation (1) is very suited for the evaluation of a literature that is supposedly very indecisive, like the Carlino–Mills literature. By the selection of particular study characteristics, the model facilitates testing various hypotheses about the impacts of various variations in research design (such as the use of different data samples and methodologies). In case of the Carlino–Mills literature some of these impacts have already been the subject of considerable speculation or even some initial research. For example, some studies already have explicitly varied with data samples and methodologies to shed light on the sensitivity of population–employment interaction findings (see, for example, Mulligan et al. 1999, Boarnet et al. 2002; Boarnet and Chalermpong 2002). By combining information from different studies, a meta-regression analysis can investigate a virtually endless number of different research dimensions, including those dimensions that are usually constant within individual studies. Moreover, it can quantify the relative importance of each of these dimensions as a determinant of the variation in population–employment interaction findings.

The remainder of this study follows the various steps of performing a meta-analysis described above to conclude with a meta-regression analysis. First, an overview is given of the essential features of the Carlino–Mills model, which is needed to ensure the selection of relevant studies.

The Carlino–Mills literature

Study sampling

In a meta-analysis, a precise objective decision needs to be made about the selection of studies to be investigated. Here, the decisive criteria chosen are the application and estimation of a Carlino–Mills model, leading to a selection of so-called "Carlino–Mills studies". Together these studies make up a substantial and varied literature, but which is sufficiently homogenous to permit comparison. The common methodology used in these studies is a simultaneous population and employment equations model with adjustment lags. In such model, each equation includes on the right-hand side the dependent variables of both equations. The dependent variable of the own equation appears in a time-lagged form (and is therefore exogenous), while the dependent variable of the opposite equation appears as an endogenous explanatory variable. The inclusion of time-lagged dependent variables reflects the assumption of a lagged adjustment process. The estimated parameters for these variables are also called speed-of-adjustment parameters, and reveal the lag in time with which population and employment location changes adjust to each other. The inclusion of endogenous dependent variables is the essential feature of a simultaneous equations system. In case of the Carlino–Mills model, the estimated parameters associated with these variables reveal the nature of population–employment interaction.

Over the years different models have been developed that fit the description above. Basically, there is no such thing as *the* Carlino–Mills model, as many different Carlino–Mills model specifications exist. The following equations can be used to decide whether a particular model specification can be labelled as a Carlino–Mills model specification or not.

$$\tilde{P}_t = \alpha_0 + \alpha_1 P_{t-1} + \alpha_2 (I + \tilde{W}) \tilde{E}_t + u_t \tag{2a}$$

$$\tilde{E}_t = \beta_0 + \beta_1 E_{t-1} + \beta_2 (I + \tilde{W}) \tilde{P}_t + v_t \tag{2b}$$

$$\tilde{P}_t = P_t - \delta_1 P_{t-1} \tag{2c}$$

$$\tilde{E}_t = E_t - \delta_2 E_{t-1} \tag{2d}$$

$$\tilde{W} = \delta_3 W \tag{2e}$$

where P_t (P_{t-1}) is an n by 1 vector of population levels at time t (time t–1), E_t (E_{t-1}) is an n by 1 vector of employment levels at time t (time t–1), I is an n by n identity matrix, W is a pre-determined n by n spatial weights matrix that specifies the spatial arrangement of the n units under examination, α_1, α_2, β_1, and β_2 are model parameters to be estimated, and $u_{i,t}$ and $v_{i,t}$ are n by 1 vectors with stochastic errors. Finally, δ_1, δ_2, and δ_3 denote scalars that are either 0 or 1.

Table 1. Taxonomy of Carlino–Mills model specifications

	$\tilde{P}_t / \tilde{E}_t$ (LHS) δ_1/δ_2	$\tilde{P}_t / \tilde{E}_t$ (RHS) δ_1/δ_2	$\tilde{W}$ δ_3	reference
1	0	0	0	Carlino & Mills (1987)
2	0	0	1	Deitz (1998)
3	1	0	0	Mills & Carlino (1989)
4	1	1	0	Boarnet (1992)
5	1	1	1	Boarnet (1994a, b)

See equations (2a)–(2e) for the meaning of $\tilde{P}_t$, $\tilde{E}_t$, $\tilde{W}$, δ_1, δ_2, and δ_3.

Above, equations (2a) and (2b) describe the Carlino–Mills model in its most elementary form (i.e., without extra equations and additional exogenous or endogenous variables). The differences in model specification show up in the different values of scalars δ_1, δ_2, and δ_3 in equations (2c), (2d), and (2e). The former two scalars reflect different operational definitions of the endogenous population and employment variables. They reveal whether these variables measure population and employment changes or end-of-period levels. The value for scalar δ_3 reveals whether or not spatial econometric techniques are integrated that allow for possible interactions across locations. A value of 1 indicates that the right-hand-side (RHS) endogenous variables involve a spatial lag operation, in which the population and employment numbers (changes or end-of-period levels) of individual locations are recomputed with those of "neighbouring" locations, as specified by a spatial weights matrix *W*. Table 1 presents a taxonomy of model specifications based on the different values of scalars δ_1, δ_2, and δ_3 in equations (2c), (2d), and (2e). For instance, the combination of $\delta_1 = \delta_2 = 0$ and $\delta_3 = 0$ corresponds to the original framework introduced by Carlino and Mills (1987), which measures the endogenous variables as levels and which does not involve the use of spatial econometric techniques. The spatial econometric Carlino–Mills model introduced by Boarnet (1994a, b) appears on the opposite side of the spectrum of model specifications. In this specification the variables are measured as changes, i.e., $\delta_1 = \delta_2 = 1$, and the RHS endogenous variables are calculated by a spatial lag operation, i.e., $\delta_3 = 1$. In between these two extremes, there is the modified non-spatial Carlino–Mills framework that specifies the left-hand-side (LHS) endogenous variables as changes, but the RHS endogenous variables as end-of-period levels. Finally, two uncommon specifications complete the list of alternative Carlino–Mills model specifications presented in Table 1. One is a framework introduced by Deitz (1998), which focuses on population and employment levels and in which the RHS endogenous variables are spatially weighted. The other is an altered version of the Boarnet model in which the spatial lag (the part described by the multiplication with *W*) is no longer part of the RHS endogenous variable, but in which it appears as a separate additional explanatory variable (see Boarnet 1992) or in which it is omitted all together (see Bao 1996; Schmitt et al. 1999; Henry et al. 2001).

Using equations (2a) and (2b) as a guideline to identify which studies to include in the meta-analysis, an extensive literature search was conducted to retrieve all relevant documents. Given that the thoroughness and completeness of a literature retrieval is crucial in determining the validity and the extent to which the results of a meta-analysis can be generalised (Cooper et al. 2009), various search methods were employed, including browsing the bibliographic databases of *EconLit* and *ProQuest*, consulting experts in the field, using the *Google* search engine, citation tracking through the *Social Sciences Citation* Index and screening the conference programmes of the European and North American supra-regions of the *Regional Science Association International* for relevant paper presentations. Ultimately, 37 studies published in the period 1987–2004 were identified that met the specified inclusion criteria and which allowed the quantification of study results and study features in a database.

Study results

The main results of studies that make up the database for the meta-analysis are the parameter estimates of α_2 and β_2 in equations (2a) and (2b), respectively. They reveal the impact of employment on population and the impact of population on employment, respectively. Because of the use of different model specifications across the Carlino–Mills literature, the results of studies cannot be compared by focusing on the magnitude of the effects (as revealed by the size of the parameters). Instead, the estimated parameters only permit making inferences about the sign effects of α_2 and β_2. As such, the analysis of the study results necessarily takes the form of a vote-counting procedure in which only the estimated sign and significance levels of α_2 and β_2 are used to determine whether the results of studies agree. Clearly, such a method is rather crude and over emphasises statistical significance given that economic significance, in terms of the size of the estimated effects, is ultimately more important (McCloskey 1985). Notwithstanding these reservations, the vote-counting procedure is intuitively very appealing since it links to the common practice in this literature to narrow down the interaction discussion to the simple question of whether “jobs follow people” or “people follow jobs”. For comparison purposes in a meta-analysis, the separate estimates for α_2 and β_2 are combined to give four categories of research findings:

- NI (no interaction): Both α_2 and β_2 are not significant at conventional statistical levels or do not display the theoretically expected positive sign, i.e., “jobs do not follow people nor do people follow jobs”;

- JP (jobs follow people): Only β_2 is positive and statistically significant, suggestive of unidirectional causality running from population to employment;

- PJ (people follow jobs): Only α_2 is positive and statistically significant, suggestive of unidirectional causality running from employment to population;

- DC (dual causality): Both α_2 and β_2 are positive and statistically significant, suggestive of dual or bi-directional causality, i.e., "jobs follow people and people follow jobs".

The 37 selected Carlino–Mills studies together produce a total of 308 study results that reveal the character of population–employment interaction in line with the categorisation made above. To avoid double counting, the compilation of study results only comprises those that are "exclusive", which means that each study result must differ from the other study results for at least one of the underlying study characteristics. From Table 2, which reveals the distribution of study results over the four abovementioned categories, it can be seen that the research findings for the jobs–people direction of causality are conform popular belief extremely mixed.[6] Interestingly, it is not only *between* studies, but also *within* studies that substantial variation exists in the research findings (see also Figure 3 for a graphic visualisation of the variation). Of the 26 studies that provided multiple study results, no less than 23 produced contradictory findings. This variation prevents the drawing of clear-cut inferences with regard to the nature of the population–employment interaction, and also leads to questions as to which study factors can be held responsible.

The final row of Table 2, which adds up the study results from the individual studies, shows that more findings point towards "jobs follow people". However, the numbers of study results in favour of "people follow jobs" and "no interaction" are not significantly less and "dual causality" still represents some one-fifth of all estimation results. By calculating a cross tabulation between the separate findings for α_2 and β_2 it can be seen from Table 3 that the distribution over the rows is significantly different from that over the columns (χ^2 = 11.530, Cramer's V = 0.193, p = 0.000).[7] This indicates that the Carlino–Mills studies tend to produce contrasting estimates for α_2 and β_2. For both parameters, the number of estimates that indicate the absence of a positive causal relationship exceeds the number of estimates that confirm the existence of such a relationship, albeit with ratios of 53–47 and 57–43, respectively, slightly less so for β_2 than for α_2. The overall picture, though, seems largely shaped by studies that provide

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[6] Here, 90% confidence intervals are used to determine whether the estimated parameters found in the literature are significantly different from zero, which is the standard criterion adopted in most studies. Even more importantly, several studies (including Mulligan et al. 1999) only inform about the significance of their estimates at the 10% level.

[7] Pearson's chi-square compares the observed and expected distribution over the cells to conclude whether or not association exists between the row and column elements. A large chi-square statistic corresponds to a small p-value and the null hypothesis of no association is rejected if the p-value is small enough (say < 0.05). Cramer's V is a chi-square test of nominal association that gauges the strength of the relationship and for which the upper bound is 1.

numerous estimation results. For example, the study of Mulligan et al. (1999), which appears strongly in favour of “people follow jobs”, contributes with no less than 150 study results to nearly half of the observations. Also, several of the studies included in the sample are basically part of one and the same research project (i.e., the same data are investigated and the same authors are involved), which makes it difficult to weight up the evidence. To account for multiple results within single studies and within groups of related studies, the distribution over the four categories in Table 3 is also given for a weighted sample of study results. In the weighted sample, study results are treated as *independent weighted replications* (Bijmolt and Pieters 2001) and each research project contributes equally to the analysis. Specifically, a total of 22 independent clusters of studies or research projects can be distinguished (see Figure 1), which means the 308 observations are given weights that count up to 14 per cluster (for example, the 150 observations from Mulligan et al. 1999 are each assigned a weight of 0.093; see also Figure 2).

After weighting the results, the observed and expected distributions over the categories are about similar and the outcomes for α_2 and β_2 are no longer significantly different from each other ($\chi^2 = 0.160$, Cramer’s V = 0.023, p = 0.689). The weighting of study results also has the effect that the share of findings indicating “people follow jobs” decreases considerably to the advantage of “dual causality” and “jobs follow people” in particular. With a share of 45.5% the latter category is now about twice as large as “no interaction”, which has become the second-largest category but which has seen its share being reduced to 21.8%. The share of study results pointing towards a positive impact of employment on population ($\alpha_2 > 0$) as opposed to the share of study results not indicating such an impact ($\alpha_2 \leq 0$) has become highly disproportionate in favour of the latter (33 versus 67). For β_2 this ratio has become equally disproportionate, but in contrast to α_2 in the population equation, strongly in favour of finding a positive and statistically significant estimate (67 versus 33).

From Tables 2 and 3 it appears that the empirical evidence for the nature of population–employment interaction strongly depends on the particular set of studies under examination. In this respect, the conclusion that more findings point towards “jobs follow people” is alone of limited value and requires additional insight in the characteristics of the underlying studies. The finding of one-way interaction running from population to employment (i.e., “jobs follow people”) may dominate the literature because most studies are, for example, US oriented. Similarly, there may be a considerable bias in the sample of studies in terms of the specific time periods covered. Hence, in attempting to judge the study results fairly, the different aspects of each study’s research design must be identified and coded. In the next sections, the discussion focuses on selecting those study features that can be expected to explain most of the variation in study results, before a meta-regression analysis is presented in which the impact of these features is verified.

Table 2. Overview study results across the Carlino–Mills literature

		NI	JP	PJ	DC	*n*
1	Carlino & Mills (1987)	0	0	1	1	2
2	Mills & Carlino (1989)	1	0	0	1	2
3	Danielson & Wolpert (1991)	1	0	0	0	1
4	Boarnet (1992)	3	0	0	5	8
5	Boarnet (1994a)	0	1	0	0	1
6	Boarnet (1994b)	0	1	0	0	1
7	Luce (1994)	0	1	0	0	1
8	Mills & Lubuele (1995)	0	0	0	1	1
9	Bao (1996)	2	5	1	0	8
10	Clark & Murphy (1996)	0	1	0	1	2
11	Bollinger & Ihlanfeldt (1997)	8	10	1	1	20
12	Duffy-Deno (1997a)	0	0	1	0	1
13	Duffy-Deno (1997b)	0	1	0	0	1
14	Henry et al. (1997)	1	0	0	0	1
15	Kristensen & Henry (1997)	0	1	0	0	1
16	Barkley et al. (1998)	1	0	1	0	2
17	Deitz (1998)	2	6	0	0	8
18	Duffy-Deno (1998)	0	2	2	0	4
19	Glavac et al. (1998)	0	1	1	0	2
20	Vias (1998)	2	10	0	3	15
21	Bao et al. (1999)	2	0	0	0	2
22	Mulligan et al. (1999)	28	37	66	19	150
23	Schmitt et al. (1999)	0	2	1	2	5
24	Vias & Mulligan (1999)	0	1	0	0	1
25	Schmitt & Henry (2000)	1	0	2	1	4
26	Schmitt et al. (2000)	4	0	2	0	6
27	Argo (2001)	2	1	0	0	3
28	Henry et al. (2001)	0	3	1	1	5
29	Holmberg et al. (2001)	0	0	0	1	1
30	Vergolino & Jatobá (2001)	0	2	0	0	2
31	Arauzo-Carod (2002)	1	2	2	5	10
32	Boarnet & Chalermpong (2002)	8	1	1	0	10
33	Boarnet et al. (2002)	9	1	1	1	12
34	Rosenberger et al. (2002)	0	3	0	0	3
35	Schmitt et al. (2002)	2	1	1	0	4
36	Carruthers & Vias (2003)	1	0	0	4	5
37	Edmiston (2004)	0	3	0	0	3
	Total	79	97	85	47	308

NI = no interaction; JP = jobs follow people; PJ = people follow jobs; DC = dual causality.

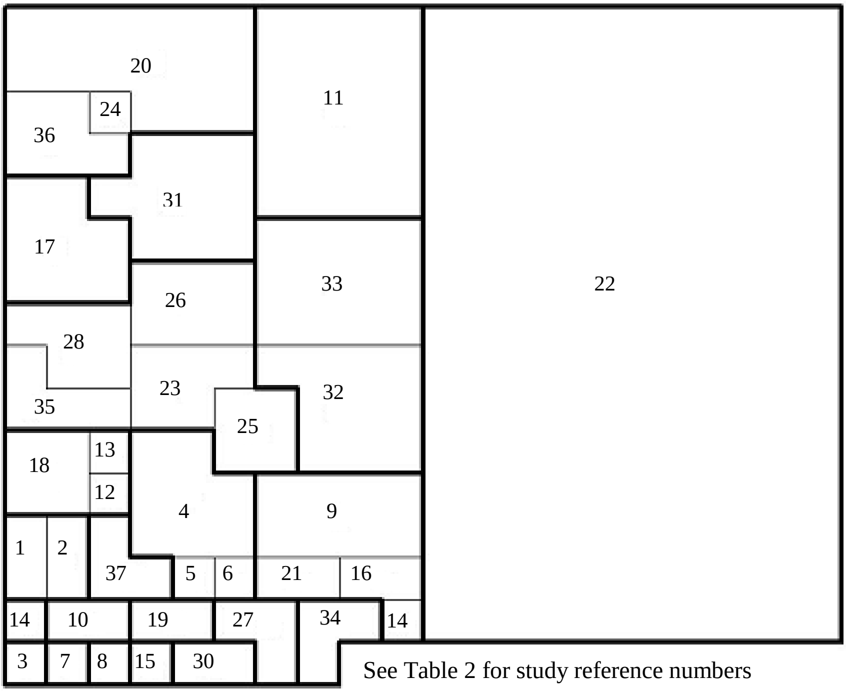

Figure 1. Contribution of (groups of) studies to the sample of study observations

0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
0.7	0.7	0.7	1.4	1.4	1.4	0.7	0.7	0.7	0.7	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
1.8	1.8	1.4	1.4	1.4	1.4	0.7	0.7	0.7	0.7	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
1.8	1.8	1.8	1.4	1.4	1.4	0.6	0.6	0.6	0.6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
1.8	1.8	1.8	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
2.3	2.3	2.3	1.4	1.4	0.6	0.6	0.6	0.6	0.6	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
2.3	2.3	2.3	1.4	1.4	1.4	1.1	1.1	1.1	1.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
3.5	3.5	4.7	1.4	1.4	1.4	1.1	1.1	1.1	1.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
3.5	3.5	4.7	4.7	1.4	1.4	1.1	1.1	1.1	1.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
14	7	7	7	7	4.7	4.7	4.7	4.7	1.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
14	14	14	14	7	7	4.7	4.7												

Figure 2. Weights assigned to observations in the weighted sample (rounded to 1 digit)

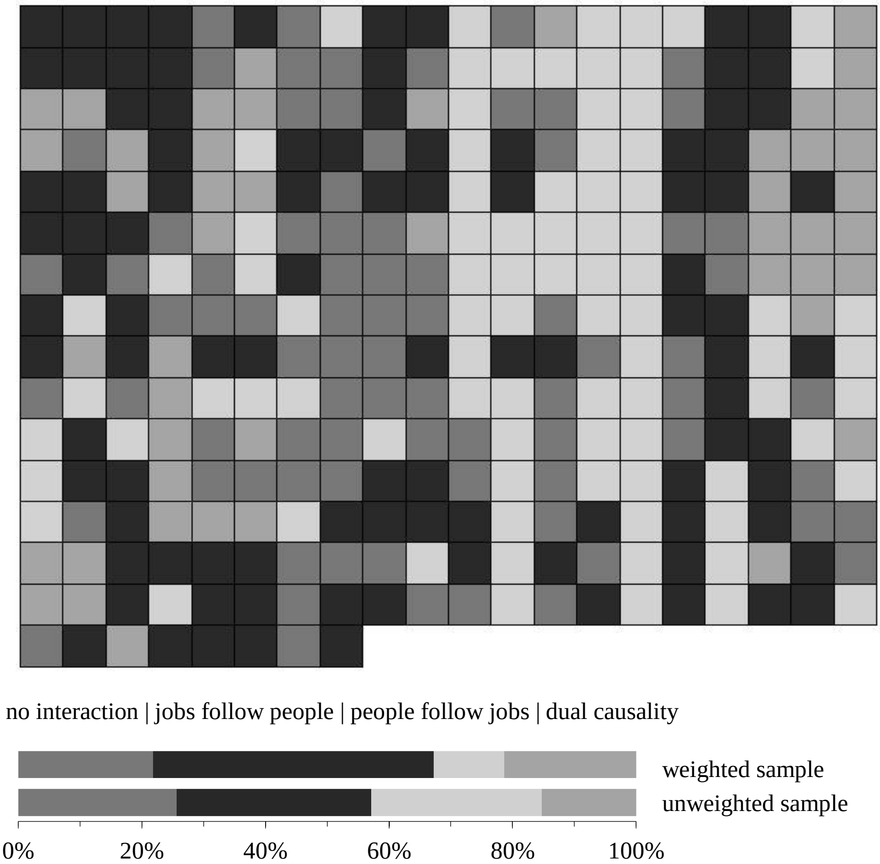

Figure 3. Distribution of study results

Table 3. Observed and expected distributions of parameter estimates (in %)

			$\beta_2 \leq 0$			$\beta_2 > 0$		Total
$\alpha_2 \leq 0$	(a)	NI	25.6	(30.4)	JP	31.5	(26.7)	57.1
	(b)		21.8	(22.3)		45.5	(44.9)	67.2
$\alpha_2 > 0$	(a)	PJ	27.6	(22.9)	DC	15.3	(20.0)	42.9
	(b)		11.4	(10.8)		21.4	(21.9)	32.8
Total	(a)		53.2			46.8		
	(b)		33.1			66.9		

(a) unweighted, (b) weighted sample of study results.
See below Table 2 for the meaning of NI, JP, PJ, and DC.
In parentheses the expected distributions, calculated by dividing the products of the row and column totals by the grand total.

Study descriptors

Basically, three broad categories of study descriptors can be distinguished that potentially impact the findings of population–employment interaction. The first and most important class of study descriptors is the set of features substantively pertinent to characterising the issue that prompts the investigation (Cooper et al. 2009). In the Carlino–Mills studies, the potentially relevant features concern a number of data characteristics, such as the geographical and temporal settings of the data and the types of jobs and people covered by the data. Accordingly, these *substantive* study characteristics need to be assessed in order to conclude whether the nature of population–employment interaction differs across space, time and between different populations and/or employment groups. The second class of study descriptors, and which are not related to substantive aspects of the phenomenon under examination, includes possible *methodological* sources of distortion, bias or artefact in the study results. Specifically, variations in model specification, variable measurement, estimation procedures etc. can produce different results even if exactly the same data were being investigated. An analysis of these features can reveal which methodologies produce similar results, and thus satisfy the criterion of "convergent validity", and which methodologies produce different results, and thus should be selected with caution in future studies. The third category of study descriptors includes features that are *extrinsic* to both the subject of study and the methodologies used. They concern characteristics of the researcher (e.g., gender, disciplinary affiliation), research context (e.g., sponsorship) and form of publication. While these characteristics are not believed to directly shape study results, they may be correlated and thus need to be controlled for.

In the Carlino–Mills literature a great variety of study descriptors can be distinguished that correspond to the categorisation outlined above (see also Appendix I). However, not all descriptors are suited for inclusion in a meta-regression analysis. For instance, some descriptors, such as data type (cross-section versus panel data), functional form, and estimation procedure simply do not display sufficient variance to permit a meaningful statistical analysis. Next to these descriptors that show little variation, there are several descriptors that show strong interrelationships. For instance, the type of region (rural, urban etc.) and spatial resolution of the data are strongly correlated with model specification (the spatial econometric Boarnet model is typically used to examine intra-urban small-area location patterns). Finally, some study descriptors only relate to a specific group of Carlino–Mills studies. For example, the possible impact of spatial weights matrix specification (see also Boarnet et al. 2002) can only be determined by investigation of the subgroup of spatial econometric Carlino–Mills studies, which reduces the sample size considerably.

Following the considerations outlined above, four substantive study factors are selected for investigation in a meta-regression analysis. First, about the geographic setting of the data, a simple distinction is made between US studies and non-US studies (note that the available data does not permit a more detailed distinction). Second, about the spatial resolution of the data, a distinction is made between US state-level data, US BEA regional data, and data that refer to both medium- and small-area observations (municipalities, census tracts etc.). Clearly, the latter category of spatial data is rather heterogeneous, but further disaggregation is not feasible given that the analysis of very small-area units strongly coincides with the use of a spatial econometric model specification. Third, about the temporal setting of the data, a straightforward distinction is made between study results based on data from the 1960/1970s, 1980s, and 1990s. Herewith, the data used in Kristensen and Henry (1997), Holmberg et al. (2001), Vergolino and Jatobá (2001), Carruthers and Vias (2003), and Edmiston (2004) refer to the 1980s but mostly to the 1990s, and hence are classified as such. Finally, a simple division is made between study results based on aggregate population and employment data and study results that reveal the jobs–people direction of causality for subgroups of jobs and/or people. Again, data limitations prevent a more detailed analysis, such as on possible differences between subgroups.

Four study factors are selected that reveal the possible impact of methodologies on study results of population–employment interactions. First, whether the accuracy of the underlying statistical analysis makes any difference is investigated through selecting a study factor that distinguishes between two groups of model estimations. The first group includes model estimations from which it can be determined that the estimated error terms are homoscedastic and/or uncorrelated. The other group includes model estimations for which this does not apply, or from which the necessary information cannot be drawn. Second, a division is made between the use of unstandardised population and employment data and data in which the population and employment numbers are standardised by the area size of the spatial units under investigation. Next, two study factors are included that are about model specification. The first of these factors focus on whether the specification used is one of LHS and RHS population and employment *changes*, *levels*, or a mixture of LHS *changes* and RHS *levels* (see also the taxonomy of model specifications in Table 1). Apart from the data and the aforementioned issue of using unstandardised data or data standardised by area size, the Carlino–Mills studies mostly differ in opting for one of these three model specifications (see Appendix I). Remind that the specification that focuses on LHS and RHS *changes* mainly reflects the spatial econometric Carlino–Mills model introduced by Boarnet (1994a, b). In this model the RHS endogenous variables are also spatially weighted to control for possible population–employment interactions across locations. Moreover, this model is almost exclusively used in combination with small urban area data. Thus, the variation in study results attributed to model specification may actually have different sources. Similarly, study results associated with the model specification of LHS *changes* and RHS *levels* may be largely shaped by the focus on one-year time lags and absence of exogenous variables in the study of Mulligan et al. (1999).

The second feature related to model specification is the number of endogenous RHS variables. A distinction is made between a regular two-equation system with one

RHS endogenous variable in each equation, and more extended frameworks that include two or more RHS endogenous variables. Usually, additional variables are included to assess spatial effects, group effects (i.e., interaction between population subgroups or employment subgroups) or impact of factors that are presumably not exogenous (for example, income [Mills and Lubuele 1995], taxes [Danielson and Wolpert 1991], endangered species preservation [Duffy-Deno 1997a], and new firm formation [Edmiston 2004]).

Finally, one study feature is selected that is not about the impact of data selection or choice of methodologies, but which is external to the analysis of population–employment interaction, namely the publication outlet of a study. A division is made between studies published in peer-reviewed academic journals and studies reported in working papers, book chapters, dissertations and other documents.

The study features outlined above all provide plausible explanations for the actual variation in population–employment interaction findings. For instance, one can think of several reasons why these results may differ between US and non-US (predominantly Europe) oriented studies. Among these reasons is the greater flexibility of US labour markets, where labour demand shocks are mostly absorbed through migration rather than through adjustments in labour participation (see, for example, Blanchard and Katz 1992; Decressin and Fatas 1995; Broersma and Van Dijk 2002). As for the spatial resolution of the data, area units (whether census tracts, municipalities or states) are essentially arbitrary groupings and the data within can be aggregated in an infinite number of ways. A problem that arises from the imposition of artificial units of spatial reporting on any continuous geographical phenomenon is the generation of artificial spatial patterns (Anselin 1988). The practical implication is that alternative aggregations of the data probably lead to different results, especially so since the strength of the population–employment relationship is known to change over distance (see, for example, Wheeler 2001). Similar to the geographical characteristics of the data shaping research outcomes, it seems reasonable to assume that the time period covered by the data has an impact. The nature of population–employment interaction may alter over time due to changing preferences for industrial and residential location, and changing economic conditions to act upon these preferences. For instance, “people follow jobs” is mainly associated with the traditional industrial society, whereas “jobs follow people” is often associated with the new emerging knowledge, information, and creativity based society (see, for example, Vias 1999; Holmberg et al. 2001; Florida 2002). Likewise, the different types of interaction are usually linked to different groups of jobs and people, and several studies have already explored this issue by performing model estimations on different population and/or employment data (see, for example, Bollinger and Ihlanfeldt 1997). The result that clearly emerges from these studies is that focusing on aggregate population and employment data may conceal some important differences in population–employment interactions between subgroups.

Regarding the selected methodological study factors, the issue of using standardised versus unstandardised data has already attracted considerable interest in the Carlino–Mills literature (as revealed by the issue showing intra-study variance in addition to the usual inter-study variance). An initial comparison of study results associated with these different measurements in Bao (1996), Glavac et al. (1998), and especially Mulligan et al. (1999) suggests that population–employment interaction findings are largely affected. Next, the absence of additional endogenous variables in many model specifications may result in an "omitted variable bias", with possible side-effects on the accuracy of parameter estimates revealing the nature of population–employment interaction. Similarly, models with known homoscedastic and/or uncorrelated error terms can be expected to give more precise results.

Finally, the possible impact of publication status on study results is an issue raised in many meta-analytical studies. Although publication of a study does not itself affect research outcomes, it may reflect the selection criteria and reporting proclivities of the authors, reviewers and editors who decide if and how a study will be published (Cooper et al. 2009). Specifically, researchers may have a tendency to self-censor the publication of negative or statistically insignificant results, a practice that may be invigorated by editorial selection processes (Sterling et al. 1995).

Meta-regression analysis

Set-up

Following the separate discussions of study results and selected study features, this section proceeds with an examination of their relationships. Specifically, multivariate regression techniques are used to evaluate the impact of each of the selected substantive, methodological and extrinsic study factors while controlling for the possible impact of all other factors. Because the study results refer to four discrete categories, the multivariate analysis takes the form of a multinomial logistic regression model. This model comprises three equations in which the dependent variables are defined as the log odds that the estimation results indicate "no interaction", "people follow jobs", and "dual causality", instead of "jobs follow people" (the reference category), respectively. From each selected study factor one category is omitted for comparison. The estimated regression coefficients reveal the additive effect of each category compared to the omitted category (for which the coefficient is 0) and can be interpreted as the change in log odds. Intuitively more appealing is the interpretation of these coefficients as factors that indicate the change in odds, which can be estimated by exponenting these coefficients (i.e., taking the antilog with the base e). A positive coefficient means a factor greater than 1 and increase in odds, while a negative coefficient implies a factor less than 1 and decrease in odds. In case the coefficient is not significantly different from zero the factor equals 1, which leaves the odds unchanged.

The multivariate logistic regression model is estimated using both the unweighted and weighted study samples. Again, using the weighted sample guarantees that the findings are not particularly biased towards studies that are overly represented. Using this sample also helps to alleviate a potential problem pertaining to the lack of independence among study results. Study results from one and the same study (or cluster of studies) are often related due to the use of similar data and methodologies. However, also between seemingly independent (groups of) studies there may be similarities in the selection of data and/or methodologies and, hence, possible interdependence between the study results. According to Florax (2002) the latter form of dependence (also referred to as "between-study dependence") is usually sufficiently accounted for by means of variability in the study characteristics that specify the heterogeneity of studies. In contrast, the form of dependence generally referred to as "within-study dependence" is typically more problematic, as it may lead to inaccurate inferences about the significance of the effects.[8]

Results

The estimation results of the multivariate logistic regression analysis are presented in Table 5 (see Table 4 for descriptive statistics and Appendices II and III for diagnostics). From the results of the first equation it can be seen that the likelihood of finding "no interaction" instead of "jobs follow people" is especially affected by the model specification (relating to population and employment levels/ changes), spatial setting of the data, and variables measurement. Specifically, the application of a model that measures LHS and RHS *levels* or LHS *changes* and RHS *levels* seems less likely (albeit the latter specification to a lesser extent) to produce study results that indicate no population–employment interaction compared to a model specification that measures both LHS and RHS *changes* (baseline category).

As for the geographical characteristics of the data, the negative coefficients associated with non-US data indicate that the log odds to find "no interaction" instead of "jobs follow people" decrease significantly when the region under examination is outside the US. Based on the estimated coefficient in the weighted study sample, such an examination is about 23 times less likely (=1/0.043) to fail in detecting any sort of interaction compared to a US oriented study. Similarly, using highly aggregate spatial data at the level of US states appears some 4 times more likely to yield findings indicative of "no interaction" compared to data with finer spatial resolutions (including the BEA regional level).[9] As far as the remaining study factors are concerned there is some evidence, albeit less robust, that publication status, period covered, employment

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[8] Future work may involve the application of formal statistical tests for the presence of dependence among study results, which has rarely been done in meta-analytical studies (Florax 2002).

[9] Because results for US states and BEA-regions are from a single study (i.e., Mulligan et al. 1999), the impact of spatial resolution is only assessed using the unweighted sample.

and/or population types covered by the data and the statistical quality of the modelling affect the likelihood of finding "no interaction" as against "jobs follow people".

After weighting the observations in the sample, the initial observation that journal articles were less likely to point towards "no interaction" was no longer evident. Likewise, using a particular dataset (referring to the 1990s and reflecting distinct population and/or employment groups) increases the odds, and making corrections for heteroscedasticity and/or autocorrelation in the error terms decreases the odds, but only in the weighted sample. Finally, both the unweighted and weighted study samples reveal no significant effect on the odds from using an extended model specification with additional RHS endogenous variables instead of a regular model specification.

From the second equation in Table 5 it can be seen that the likelihood of finding "people follow jobs" instead of "jobs follow people" increases when large-area units, like US states or BEA regions rather than more spatially detailed data are examined. The estimated coefficients for spatial resolution of the data goes some way in explaining the deviation in study results produced by Mulligan et al. (1999). Another explanation is the expansive use of unstandardised data in this study. The negative significant coefficient for the use of standardised variables indicates that the odds decrease when such variables are employed, and consequently increase when unstandardised variables (baseline category) are employed. Interestingly, the coefficient associated with standardised data switches in sign after weighting the observations from Mulligan et al. (1999) and other studies with multiple study results. This switch suggests that the impact of using standardised data depends on the particular data used.

Next, the estimated regression coefficients for publication outlet suggest that peer review is prejudiced in favour of the publication of study results revealing "people follow jobs". As far as the remaining study factors are concerned, there are signs that the presence of heteroscedasticity and/or autocorrelation among the error terms, the spatial setting of the data and the time period covered by the data impact the chances of finding one-way causality running from employment to population rather than the other way around. From the estimated coefficients in the unweighted study sample it follows that using data that refer to the 1960s or 1970s, instead of the 1980s (baseline category) increases the odds significantly. Together with the negative coefficient for data that refer to the 1990s in the weighted study sample, the estimation results reject the idea that one-way causality running from population to employment (i.e., people follow jobs) has become more important over time (see, for example, Florida 2002). Once the impact of spatial resolution, standardisation and time period covered by the data is controlled for, there is no evidence that the particular model specification of LHS *changes* and RHS *levels* used by Mulligan et al. (1999), among others, yields different study results. Similarly, the estimation results reveal no impact of focusing on subgroups of jobs and/or people or application of model specifications with additional endogenous variables.

Table 4. Distribution of study results across selected study features (in %)

	(a) unweighted sample				(b) weighted sample			
	NI	JP	PJ	DC	NI	JP	PJ	DC
Substantive study factors								
non–US	21.1	28.9	23.7	26.3	7.2	49.3	10.1	33.3
US *	26.3	31.9	28.1	13.7	26.1	44.1	11.8	18.1
states (US)	28.0	18.0	52.0	2.0				
BEA regions (US)	18.0	24.0	58.0	0.0				
other *	26.9	36.5	14.4	22.1				
1960s & 1970s	22.2	38.9	25.0	13.9	10.2	61.2	10.2	18.4
1990s	27.1	29.2	25.0	18.8	34.1	39.0	9.8	17.1
1980s *	26.6	29.3	29.3	14.9	22.0	43.1	11.9	22.9
groups	37.5	35.4	14.6	12.5	32.1	35.8	17.0	15.1
non–groups *	23.5	30.8	30.0	15.8	19.7	47.2	10.2	22.8
Methodological study factors								
corrected errors	30.5	40.7	15.3	13.6	21.8	43.6	8.9	25.7
uncorrected errors *	24.5	29.3	30.5	15.7	22.1	46.2	12.0	19.7
standardised	24.1	31.7	22.8	21.4	11.9	38.5	19.3	30.4
unstandardised *	27.0	31.3	31.9	9.8	29.7	51.2	4.7	14.5
levels–levels	10.7	58.9	10.7	19.6	5.2	54.5	9.7	30.6
changes–levels	19.2	25.7	40.1	15.0	19.5	46.3	15.9	18.3
changes–changes *	48.2	24.7	14.1	12.9	47.8	31.5	8.7	12.0
endogenous 2+	35.6	33.9	16.9	13.6	29.3	40.4	8.1	22.2
endogenous 1 *	23.3	30.9	30.1	15.7	18.4	47.8	12.6	21.3
Extrinsic study factors								
non–journal article	38.1	33.9	8.5	19.5	25.6	47.7	4.5	22.2
journal article *	17.9	30.0	39.5	12.6	17.4	42.4	19.7	20.5
Total	25.6	31.5	27.6	15.3	21.8	45.5	11.4	21.4

NI = no interaction; JP = jobs follow people; PJ = people follow jobs; DC = dual causality.
* Reference categories in the multivariate regression model.

The regression coefficients of the final equation in Table 5 indicate that the chance of finding “dual causality” rather than “jobs follow people” decreases significantly if large spatial units, such as US states or BEA regions, are investigated (note from the descriptive statistics in Table 4 that these combinations of spatial data and study results are also highly unusual). From the coefficients that reveal whether heteroscedasticity and/or autocorrelation in the error terms of the estimated Carlino–Mills model make any difference, there is some indication that the likelihood of finding “dual causality” rather than “jobs follow people” is affected, but only in the unweighted study sample. Likewise, evidence that the spatial setting of the data, the population and

Table 5. Estimation results multivariate logistic regression analysis

Logits		Logit NI vs. JP		Logit PJ vs. JP		Logit DC vs. JP	
		b	Exp(b)	b	Exp(b)	b	Exp(b)
intercept	(a)	0.335		–0.094		–1.090	
	(b)	1.247	○	–0.484		–2.551	●
non–US	(a)	–1.447	0.235 ○	1.822	6.183 ●	0.482	1.620
	(b)	–3.139	0.043 ●	–0.499	0.607	0.838	2.311 *
states	(a)	1.401	4.058 ○	1.832	6.243 ●	–2.322	0.098 *
	(b)						
BEA regions	(a)	0.619	1.858	1.714	5.550 ●	–21.859	0.000 ●
	(b)						
1960s & 1970s	(a)	0.053	1.054	–1.487	0.226 ●	–0.154	0.857
	(b)	0.211	1.234	–0.019	0.981	0.020	1.020
1990s	(a)	0.739	2.094	–0.448	0.639	0.468	1.596
	(b)	3.722	41.350 ●	2.079	7.995 ○	0.477	1.611
groups	(a)	0.722	2.058	0.606	1.834	–1.065	0.345
	(b)	1.291	3.635 ○	–0.225	0.799	–1.164	0.312 *
corrected errors	(a)	–0.765	0.466	–0.553	0.575	–0.938	0.392 *
	(b)	–1.339	0.262 ●	–1.166	0.312 ○	–0.008	0.992
standardised	(a)	1.058	2.881 ○	–0.975	0.377 ○	1.164	3.203 ○
	(b)	1.604	4.972 ○	2.489	12.048 ●	1.602	4.964 ●
levels–levels	(a)	–3.540	0.029 ●	–0.524	0.592	–1.013	0.363
	(b)	–5.252	0.005 ●	–2.145	0.117 ○	0.789	2.222
changes–levels	(a)	–2.151	0.116 ●	0.437	1.548	0.450	1.568
	(b)	–3.102	0.045 ●	–1.263	0.283	0.723	2.060
endogenous 2+	(a)	–0.754	0.470	0.218	1.243	–0.010	0.990
	(b)	0.291	1.337	0.702	2.017	1.332	3.788 ○
non–journal article	(a)	1.102	3.011 ○	–1.352	0.259 ○	0.717	2.048
	(b)	–0.554	0.574	–2.135	0.118 ●	–0.356	0.700

See Table 4 for reference categories and meaning of the labels NI, JP, PJ and DC; (a) unweighted, (b) weighted sample; Critical significance levels are signalled by * < 0.10, ○ < 0.05, ● < 0.01.

employment characteristics of the data, and the number of endogenous variables included in the model impact the odds can only be observed in the weighted sample. Finally, no matter whether the observations in the study sample are weighted or not, both publication status, model specification (levels/changes), and time period covered by the data do not appear to impact the chances of finding “dual causality” rather than “jobs follow people”.

Summary and conclusions

In this study, a statistically supported literature review and synthesis, known as a meta-analysis, has been conducted on 37 Carlino–Mills studies published between 1987 and 2004. The aims of this study were twofold: to reveal the actual variation in study results for the question of population–employment interaction; and to make sense of this variation by identifying some key study characteristics that influence these study results.

In terms of the variation in study results, a total of 308 observations were retrieved that could be distinguished into four categories of research findings: “no interaction”, “jobs follow people”, “people follow jobs” and “dual causality”. Simply tallying the observations revealed a fairly equal distribution across these four categories. The most frequent study result was that “jobs follow people” (31.5%), closely followed by “people follow jobs” (27.6%) and “no interaction” (25.6%), with “dual causality” the least common but not that infrequent (15.3%). Given that some individual studies or groups of related studies provided multiple observations, and thus overly contributed to the sample of study results, the observations were also weighted. The tallying of these weighted observations provided a greater variation between the four categories. Nearly half of the support was now for the “jobs follow people” argument (45.5%), followed at some distance by “no interaction” (21.8%) and “dual causality” (21.4%). Support for the “people follow jobs” line dropped significantly after weighting (to 11.4%) since most such findings came from a single study.

In an attempt to explain the variation in study results, different characteristics encountered in the Carlino–Mills studies were identified and broadly categorised into substantive, methodological and extrinsic study factors. Examining study features that displayed intra- and inter-study variance made it possible to develop a rich appreciation of the commonalities and peculiarities of this literature and, on the basis of this, nine study factors were selected for further investigation. Four of these factors were concerned with aspects of data sampling (geographical coverage, temporal coverage, spatial resolution and population and/or employment types) and these were selected in order to reveal substantive features of population–employment interaction. Similarly, four study features were selected to explain the variation in study results due to methodological differences: the treatment of heteroscedastic and/or autocorrelated error terms, variable measurement, model specifications of population and employment (“changes” versus “levels”), and whether the model specifications included one or more endogenous variables. Finally, one study factor was selected to investigate a possible extrinsic determinant of the variation in study results, namely, the publication status of a study. Subsequently, a multinomial logistic regression analysis was performed to quantify the impact of each of these nine features, using both the unweighted and weighted study samples.

The meta-regression analysis revealed that, of the substantive study factors considered, the spatial resolution of the data was the most critical in shaping population–employment interaction findings. Specifically, it was shown that the likelihood of finding “people follow jobs” increases, and “dual causality” decreases significantly if large-area data at the level of US states or BEA regions are investigated. Also, results from US and non-US oriented studies turned out to be significantly different from each other, as did studies that focussed on different time periods, thereby suggesting that social, cultural, economic and institutional factors shape the nature of the population–employment interaction. In comparison, using data that refer to specific populations and/or employment groups does not appear to make much of a difference, although this may be an outcome of the rather crude categorisations applied.

As for the methodological factors, it was shown that the different model specifications employed in the Carlino–Mills literature are most responsible for the variation found in study results. Specifically, the “no interaction” finding appears to be strongly associated with models in which the population and employment variables are specified in terms of changes rather than levels. However, since the use of “change” data largely coincides with the examination of growth patterns mainly in urban areas at an extremely fine spatial scale, the reasons for the strong bias towards the “no interaction” finding remain unclear. It does appear, however, that modelling population and employment dynamics is more difficult than modelling static levels. When combining this with a fine spatial scale, which involves the tricky task of controlling for spillover effects between locations, one becomes more prone to finding statistically insignificant parameter estimates that suggest the absence of interaction. How variables are measured is another methodological feature for which a systematic relationship with the population–employment interaction findings has been revealed. Interestingly, this relationship appeared to change when different study samples were investigated, suggesting that the effect of standardising population and employment numbers by area is influenced by other study characteristics such as the actual size of these spatial units or the type of region (high-density versus low-density). The estimation results of the meta-regression analyses addressing a failure to control for heteroscedasticity and/or autocorrelation in the error terms, and the effect of using an extended model specification with additional endogenous variables, revealed that these aspects had little impact. Finally, considering the possibility of publication bias, the estimation results interestingly suggested that a peer review process favours the publication of study results that indicate that “people follow jobs”.

A number of issues have been raised in this study that warrant further investigation. First, many of the study factors discerned do not seem to be independent but interrelated. For instance, it seems that the effect of standardising population and employment data by area size varies between studies, suggesting other factors may play a part. Similarly, it seems reasonable to suspect that the effects of the time period under study and the region type are conditional upon each other. Given the limited data available, such interaction effects could not be definitely investigated in this study but this may be possible in future meta-analytical work. Second, in addition to including interaction effects as suggested above, the explanatory power of the meta-regression models could improve if other features that display intra-study or inter-study variance were included. Here, future research could take advantage of recent advances with regard to the assumed functional form (non-linear rather than linear) and the type of data being used (panel data instead of cross-sectional data). Similarly, future work may benefit from the growing number of studies that assess the effects of substantive study characteristics such as the time period, region type, and employment and population types in more detail. The simple distinction between using aggregated data and data that refer to distinct employment and/or population groups, for instance, leaves much to be desired and is probably responsible for some of the still unexplained variation in study results.

To conclude, while this study has taken a significant step forward in sifting through potential substantive, methodological and extrinsic study factors that might influence results related to population–employment interactions in order to identify those that are important, it also highlights the need for stronger meta-analytical research designs.

Appendix I. Annotated bibliography of Carlino–Mills studies

Reference	Publication outlet	Geographic coverage	Pop. density (mi^2)	Spatial units
1 Carlino & Mills (1987)	JRS	US	66	C
2 Mills & Carlino (1989)	bc	US	66	C
3 Danielson & Wolpert (1991)	US	US (New Jersey)	1,448	M
4 Boarnet (1992)	PhD	US (New Jersey)	1,455	M
5 Boarnet (1994a)	PRS	US (New Jersey)	1,455	M
6 Boarnet (1994b)	JUE	US (New Jersey)	1,455	M
7 Luce (1994)	PFQ	US (Philadelphia)	1,400	M
8 Mills & Lubuele (1995)	JUE	US	332	MSA
9 Bao (1996)	PhD	US (South-Carolina)	50/121	CT
10 Clark & Murphy (1996)	JRS	US	76	C
11 Bollinger & Ihlanfeldt (1997)	JUE	US (Atlanta)	870	CT
12 Duffy-Deno (1997a)	JLR	US (IM-West)	5	C
13 Duffy-Deno (1997b)	GC	US (IM-West)	11	C
14 Henry et al. (1997)	JRS	US (South-Carolina)	50	CT
15 Kristensen & Henry (1997)	wp	Denmark	50	M
16 Barkley et al. (1998)	RRS	US (South-Carolina)	50/120	CT
17 Deitz (1998)	JUE	US (Boston)	2,400	CT
18 Duffy-Deno (1998)	JRS	US (IM-West)	5	C
19 Glavac et al. (1998)	UG	US	101	MiSA
20 Vias (1998)	PhD	US (IM-West)	4/…/16	C
21 Bao et al. (1999)	wp	US (South-Carolina)	50	CT
22 Mulligan et al. (1999)	EP	US	70	C/B/S
23 Schmitt et al. (1999)	wp	France (South-East)	66	M
24 Vias & Mulligan (1999)	GC	US (IM-West)	5	C
25 Schmitt & Henry (2000)	RSUE	France (South-East)	66	M
26 Schmitt et al. (2000)	wp	France (South-East)	66	P
27 Argo (2001)	MSc	US (IM-West/Nevada)	2/5	C
28 Henry et al. (2001)	IRSR	France (South-East)	66	M
29 Holmberg et al. (2001)	bc	Sweden	51	M
30 Vergolino & Jatobá (2001)	wp	Brazil (North-East)	?	?
31 Arauzo-Carod (2002)	wp	Spain (Catalonia)	515	M
32 Boarnet & Chalermpong (2002)	wp	US (Orange)	2,450	CT
33 Boarnet et al. (2002)	wp	US (Orange)	2,450	CT
34 Rosenberger et al. (2002)	wp	US (West-Virginia)	74/75/81	C
35 Schmitt et al. (2002)	wp	France (South-East)	66	P
36 Carruthers & Vias (2003)	wp	US (IM-West)	7	C
37 Edmiston (2004)	JRS	US (Georgia)	94	C

Appendix I. (Continued)

	Number of spatial units	Average spatial unit size (mi^2)	Time coverage	Time lag (years)	Data type	Pop./emp. types
1	2,600/3,000	985	70–80	10	CS	T/I(1)
2	2,600/3,000	985	70–80	10	CS	T/I(1)
3	365	10	80–88	8	CS	T
4	96/358	10	80–88	8	CS	T
5	358	10	80–88	8	CS	T
6	358	10	80–88	8	CS	T
7	314	10	70–80	10	CS	T/I(5)
8	320	1,684	80–90	10	CS	T
9	268/669	3	80–90	10	CS	T
10	3017	965	81–89	8	CS	T/I(5)
11	299	7	80–90	10	CS	T/I(9)/R(2)
12	250	3,077	80–90	10	CS	T
13	333	3	80–90	10	CS	T
14	268	3	80–90	10	CS	T
15	229	60	85–93	8	CS	T
16	224/264	3	80–90	10	CS	T
17	435	3	80–90	10	CS	O(8)
18	185/250	3,077	80–90	10	CS	T
19	219	667	80–90	10	CS	T
20	254/278	3,077	70–80/80–90/90–95	5/10	CS	T
21	268	3	80–90	10	CS	T
22	50/170/3,076	965/17,406/59,084	69–70/…/93–94	1	CS	T
23	3515	5	82–90	8	CS	T
24	254	3077	80–90	10	CS	T
25	859/…/3,515	5	82–90	8	CS	T
26	84/107/191	57	82–90	8	CS	T/I(2)
27	12/248	3,077/7,617	90–2000	10	CS	T
28	3515	5	82–90	8	CS	T
29	288	603	80–94	14	CS	T
30	?	?	70–80/80–96	10/16	CS	T
31	939	13	91–96	5	CS	O(10)
32	415	2	80–90/90–97	7/10	CS	T
33	415	2	80–90	10	CS	T
34	55	438	70–80/80–90/90–00	10	CS	T/I(2)
35	84/107	57	82–90	8	CS	T
36	277	3,077	82–97	5	P	T
37	154	311	84–98	1	P	T

Appendix I. (Continued)

	Estimation technique	Functional form	Variables measurement	Model specification	*W* matrix specification	Endogenous variables	Error terms	SA coef. (i)	SA coef. (ii)	SA coef. (iii)	SA coef. (iv)
1	2SLS	lin	D	LL		-	-	0	0	0	2
2	2SLS	lin	D	CL		-	-	0	0	0	2
3	OLS	lin	U	CC		+	-	0	1	0	0
4	2SLS/ML	lin	U	CC	I	-/+	-/+	0	0	7	1
5	2SLS	lin	U	CC	I	-	-	0	0	1	0
6	ML	lin	U	CC	I	-	+	0	0	1	0
7	2SLS	log	U	LL		-	-	0	0	0	1
8	2SLS	BC	U	LL		+	+	0	0	0	1
9	2SLS	lin	U/D	CC/LL	F	-/+	-/+	2	0	5	1
10	2SLS	lin	D	CL		-	+	0	0	0	2
11	2SLS	lin	U	CC	I	+	+	6	5	4	5
12	2SLS	lin	D	LL		+	-	0	0	0	1
13	2SLS	log	D	CL		+	+	0	0	0	1
14	2SLS	lin	U	CC	F	+	+	1	0	0	0
15	2SLS	lin	U	CC	F	+	-	0	1	0	0
16	2SLS	lin	U	CC	F	-	-	2	0	0	0
17	2SLS	lin	S	LL	I	-	-	0	0	0	8
18	2SLS	lin/log	D	LL		-	+	0	0	0	4
19	2SLS	lin	U/D	CL		-	-	1	0	1	0
20	2SLS/OLS/ML	lin	U	LL		-/+	-/+	7	6	0	2
21	ML	lin	U	CC		+	-	1	0	1	0
22	2SLS	lin	U/D	LL		-	-	26	36	64	24
23	2SLS	lin	D	CC	F	-/+	-/+	0	2	0	3
24	2SLS	lin	U	LL		-	-	0	1	0	0
25	2SLS	lin	D	CC	F	+	+	0	1	0	3
26	2SLS	lin	D	CC	F	+	-	3	3	0	0
27	2SLS	lin	U	CL		-	+	3	0	0	0
28	2SLS	lin	D	CC	F	-/+	-/+	0	2	0	3
29	2SLS	lin	D	LL		-	-	0	0	0	1
30	2SLS	lin	U	CL		-	-	1	1	0	0
31	2SLS	lin	S	LL		-	-	0	0	0	10
32	2SLS	lin	U	CC	I/F/X	-	-	0	10	0	0
33	2SLS	lin	U	CC	I/F/X	-	-	6	0	0	6
34	2SLS	lin	D	LL		-	+	0	2	0	1
35	2SLS	lin	D	CC	F	+	+	1	1	1	1
36	2SLS	log	D	CL		-	-	0	0	1	4
37	3SLS	lin	U	LL		-	-	0	0	0	3

Notes to Appendix I

Publication outlet: EP = *Environment and Planning A*; GC = *Growth and Change*; IRSR = *International Regional Science Review*; JLR = *Journal of Leisure Research*; JRS = *Journal of Regional Science*; JUE = *Journal of Urban Economics*; PFQ = *Public Finance Quarterly*; PRS = *Papers in Regional Science*; RRS = *Review of Regional Studies*; RSUE = *Regional Science and Urban Economics*; UG = *Urban Geography*; US = *Urban Studies*; MSc = Master's thesis; PhD = PhD dissertation; bc = book chapter; wp = working paper.

Spatial units: B = BEA regions; C = counties; CT = census tracts; M = municipalities; MiSA = micropolitan statistical areas; MSA = metropolitan statistical areas; P = provinces; S = states.

Data type: CS = cross-section; P = panel.

Population and employment type: T = total (aggregate) employment and population (i.e.; no subgroups); I = employment subgroups by industry; O = employment and population subgroups by occupations; R = population subgroups by race. In parentheses the number of subgroups.

Estimation technique: 2SLS = two stage least squares; 3SLS = three stage least squares; OLS = ordinary least squares; ML = maximum likelihood.

Functional form: lin = linear; log = logarithmic (log-linear); BC = Box-Cox transformation (quasi-linear).

Variables measurement: D = densities, population and employment numbers standardised by area size; S = shares, population (employment) numbers of subgroups standardised by total population (employment) numbers; U = unstandardised population and employment numbers.

Model specification: LL = left-hand-side (LHS) and right-hand-side (RHS) population and employment levels; CL = LHS population and employment changes and RHS population and employment levels; CC = LHS and RHS population and employment changes.

W matrix specification: F = fixed distance matrix; I = inverse distance matrix; X = other.

Endogenous variables: - = one endogenous variable on the RHS of the equations; + = multiple endogenous variable on the RHS of the equations.

Error terms: - estimated error terms not known to be homoscedastic and/or uncorrelated. + = estimated error terms known to be homoscedastic and/or uncorrelated.

SA coefficients: Number of estimated speed of adjustment coefficients within 0 and 1 that indicate model stability: i = neither population nor employment, ii = population only, iii = employment only, iv = both employment and population.

Appendix II. Diagnostics regression analysis of the unweighted sample

Model fitting information:					
	-2 Log Likelihood	Chi-square			Sig.
Intercept only	536.371				
Final model	341.511	194.861			0.000
Pseudo R-square:					
Cox and Snell	0.469				
Nagelkerke	0.502				
McFadden	0.233				
Likelihood ratio tests:					
	-2 Log Likelihood of Reduced Model	Chi-Square			Sig.
intercept	341.511				
geographic coverage	360.706	19.195			0.000
spatial resolution	398.199	56.688			0.000
time coverage	357.818	16.308			0.012
sample (group effects)	348.884	7.373			0.061
error terms	345.479	3.968			0.265
variables measurement	369.270	27.759			0.000
specification (levels/changes)	381.963	40.452			0.000
specification (endog. variables)	343.531	2.020			0.568
publication status	357.314	15.803			0.001
Classification:					
	predicted				correct
observed	NI	JP	PJ	DC	
NI	45	16	14	4	57.0%
JP	16	55	21	5	56.7%
PJ	10	8	58	9	68.2%
DC	6	13	7	21	44.7%
Overall	25.0%	29.9%	32.5%	12.7%	58.1%

* The chi-square statistic is the difference in -2 log-likelihoods between the final model and a reduced model. The reduced model is formed by omitting an effect from the final model. The null hypothesis is that all parameters of that effect are 0.

Appendix III. Diagnostics regression analysis of the weighted sample

Model fitting information:	-2 Log Likelihood	Chi-square	Sig.
Intercept only	599.319		
Final model	410.809	188.510	0.000

Pseudo R-square:	
Cox and Snell	0.458
Nagelkerke	0.497
McFadden	0.242

Likelihood ratio tests:	-2 Log Likelihood of Reduced Model	Chi-Square	Sig.
intercept	410.809		
geographic coverage	444.721	33.913	0.000
time coverage	439.057	28.248	0.000
sample (group effects)	424.507	13.698	0.003
error terms	422.888	12.079	0.007
variables measurement	438.218	27.409	0.000
specification (levels/changes)	490.150	79.341	0.000
specification (endog. variables)	417.533	6.724	0.081
publication status	426.149	15.340	0.002

Classification:	predicted				correct
observed	NI	JP	PJ	DC	
NI	43.82	21.33	1.77	0.58	64.9%
JP	8.74	124.72	2.16	4.08	89.3%
PJ	5.15	16.25	8.58	4.67	24.8%
DC	7.31	42.70	1.51	14.58	22.1%
Overall	21.1%	66.6%	4.6%	7.8%	62.3%

3.
Determinants of variation in population–employment interaction findings: A quasi-experimental meta-analysis[10]

Introduction

The question whether "jobs follow people" or "people follow jobs" has generated a vivacious discussion in the population–employment interaction literature. An obvious circumstance that triggered the debate is the allegedly striking discrepancy in the results of different empirical studies of the topic, which is well documented in both qualitative and quantitative reviews of the literature (Bollinger and Ihlanfeldt 2001; Hoogstra et al. 2005). Naturally, questions have been raised about why research findings about the jobs–people direction of causality appear so overly varied. One reason could be that the findings epitomise real-world differences in this empirical phenomenon. In this case, applications for different areas and time periods inevitably lead to divergent research findings beyond what should be expected on the basis of random sampling variation per se. Alternatively, as pointed out by Boarnet et al. (2005) and others, the mixed empirical evidence may not signal real-world variation; rather, it may represent a scientific artefact stemming from methodological differences between studies.

In the literature about population–employment interaction, virtually all studies provide a host of estimation results that can furnish preliminary insights into the effects of using a particular type of data or methodology. Given the large array of variations and the complex nature of potential interactions across variations, the identification of the robustness of study results against variations in an underlying study's characteristics requires a more rigorous assessment. Meta-analysis, constituting a set of statistical tools to synthesise research results and to identify important features explaining the variation across research results, is particularly suited for such a robustness analysis (Stanley and Jarrell 1989; Stanley 2001). Although meta-analysis is typically used to analyse what constitutes the state-of-the-art or the bottom line of an existing body of studies, meta-analytical techniques also can be used to give a systematic statistical account of research findings obtained in a quasi-experimental setup (Florax and De Graaff 2004). In general, meta-analysis is used to analyse a sample of study results obtained for different data sets. The quasi-experimental approach applied in this study involves repeated sampling from a single, well-known data set to generate artificially study results by systematically varying the specification and other aspects of the research setup. In this case, meta-analytical techniques are utilised to provide a robustness or sensitivity

[10] This chapter has also appeared as an article in *Geographical Analysis* (see Hoogstra et al. 2011). The article is co-written with Jouke van Dijk and Raymond Florax, hence the "we" and "us" mentioned in this chapter.

analysis. The existing empirical literature is used merely to identify useful dimensions of variation in research setup that should be included in the experiments (Florax et al. 2002; Banzhaf and Smith 2007).

In this study, the quasi-experimental meta-analysis technique is used to test differing hypotheses about the empirical nature of population–employment interaction as well as to identify to what extent the methodological setup of underlying (quasi) studies impacts research findings. Specifically, the robustness of findings about the jobs–people direction of causality is assessed for three substantive and three methodological study features that have been intensively debated in the literature. The substantive study features are concerned with the extraction of different samples from a data set that contains detailed temporal, spatial, and sectoral employment information. The analysis provides substantive insights into whether empirical results about the jobs–people direction of causality differ over time, over space, and between employment groups.

Methodological study features relate to the operational definition of variables, the specification of the spatial weights matrix, and model specification and estimation to identify whether these features play a role in shaping reported research findings. The selected features are particularly relevant because the operational definition of variables and the specification of the weights matrix show considerable variation across studies in this literature (see also Chapter 2). Moreover, the possible impact of these features already has been the subject of some preliminary inquiries (notably by Mulligan et al. 1999; Henry et al. 2001; Boarnet et al. 2005). Findings from these studies clearly highlight the need for further investigation. With regard to model specification and estimation, the impact of accounting for spatial dependence in the form of a spatially lagged dependent variable is investigated. Although erroneous omission of these spatially lagged variables causes omitted variable bias, this specification issue has been ignored for a very long time because of complications in the estimation of such models. However, the availability of a feasible generalised spatial two-stage least-squares estimator (GS2SLS), which is straightforward in its implementation (Kelejian and Prucha 2004), facilitates identifying the impact of differences in the specification and estimation of alternative spatial models.

The impact of the selected study features is determined by repeated testing for the nature of population–employment interaction, yielding as many as 4,050 quasi-experimental research findings. These findings are generated by means of systematic variations in a spatial econometric interaction model estimated for a single database of observations from the Northern Netherlands (1988–2002), using all possible combinations of a particular data selection (by time period, region type, and employment type), variable measurement, spatial weights matrix design, and model specification and estimation.

Quasi-experimental meta-analysis

The quasi-experimental approach adopted for this study resembles a standard meta-analysis in the sense that statistical techniques are applied to assess the robustness of a collection of study results against a variety of study characteristics. The main distinction is that the metadata are taken not from a series of primary studies using different data sets but from an exhaustive series of quasi-study results generated using one specific data set. The quasi-experimental approach circumvents some of the pitfalls associated with a standard meta-analysis (Florax et al. 2002). For instance, in the case where a meta-analysis is built on aggregate statistical summary indicators from a compilation of studies, difficulties usually arise from the heterogeneity of the underlying studies. Furthermore, uncovering features responsible for the variation in research outcomes often turns out to be rather difficult, because of strong correlations between the underlying study characteristics. Finally, closely related to the previous arguments, the novelties of individual studies are not always reproduced in great numbers later on. With replications largely lacking, the existing literature may simply not exhibit sufficient variation to permit a meaningful statistical analysis that can identify the impact of study characteristics responsible for the variation in research outcomes.

By applying meta-analytical techniques to research findings that are obtained in a quasi-experimental setup, the preceding described difficulties are partly mitigated. Instead of being at the mercy of the limitations and possibly limited availability of existing studies, the literature is used to identify the variations in study features that should be investigated in a quasi-experimental setup. By having complete control over the data-generating process in the latter setup, unobserved heterogeneity across studies should not be a problem as long as features that are not considered central to the analysis are kept constant across experiments. Similarly, potential problems due to multicollinearity or lack of variation are easily evaded, providing all, or at least a large number, of the possible combinations of the principal study features are utilised in the series of experiments. By allowing for direct control over the setup of the experiments, the quasi-experimental approach can be tailored to statistical inference in the meta-analysis to allow for proper identification of the impact of relevant study features.

The quasi-experimental approach is akin to response surface techniques developed in econometrics. Basically, these techniques hinge on the estimation of an auxiliary regression in which each observation corresponds to one experiment. The dependent variable reflects some estimated output quantity of the experiments, whereas the independent variables reflect the research dimensions that have been allowed to change across experiments. Strictly speaking, each experiment extends only to the data-generating process that underlies that particular experiment, and a series of experiments extends merely to a finite set of data-generating processes. However, by combining the various experiments in a response surface, the results can be generalised to a larger population of data-generating processes (Davidson and MacKinnon 1993; see also Florax and De Graaff 2004).

Quasi-experimental meta-analysis (or response surface analysis) has proved to be a valuable tool to evaluate the sensitivity of research outcomes to alternations in research setups. For example, it has been used with some success in the economic literature about gross domestic product growth to settle the seemingly endless list of growth determinants (see, e.g., Florax et al. 2002 and the references therein). Besides the examination of substantive issues, such as the sources of economic growth, it has become commonplace in methodological studies that need to summarise the abundant output of Monte Carlo experiments (see, e.g., Dubin 2003). Banzhaf and Smith (2007) observe that the potential of meta-analysis is not limited to such designed experiments but instead stretches to practically any research in which modelling judgments are made. Although understanding the robustness of findings is clearly important for assessing empirical work, and in many cases may be a separate source of insight, space limitations together with a desire to avoid the appearance of "data mining" mean that the role of such judgments is rarely documented. Meta-analysis, Banzhaf and Smith (2007) argue, allows researchers to document concisely and to explicate the impact of the judgments underlying their research, so that fellow practitioners also can benefit from the insights gained from model development that would otherwise have remained sorrowfully hidden.

Research design: econometric model and data

The general framework to be used in the quasi-experimental primary studies generated for this meta-analysis is Boarnet's (1992) spatial econometric version of the classic simultaneous equations system with adjustment lags introduced by Carlino and Mills (1987). Over the years, the Carlino–Mills (CM) model has been the standard for investigating population–employment interaction and has been adopted in over fifty studies, most geared toward the United States (see also Chapter 2). In broad terms, a distinction can be made between inter-regional studies that have focused on counties (or county aggregates) as the spatial units of observation (see, for instance, Carlino and Mills 1987; Mulligan et al. 1999; Carruthers and Vias 2005; Vias and Carruthers 2005; Carruthers and Mulligan 2007, 2008) and intra-regional studies that have examined the distribution of jobs and people at a finer spatial scale, such as at the municipality or census tract level (see, for instance, Boarnet 1992, 1994; Bollinger and Ihlanfeldt 1997; Henry et al. 2001; Boarnet et al. 2005; Schmitt et al. 2006). The Boarnet model differs from the regular CM model in that the spatial units under examination are no longer assumed to match regional labour markets in which population–employment interaction operates. Instead, it adjusts for the possible spatial mismatch between these units and actual labour market zones by allowing the interplay between population and employment to stretch beyond the boundaries of single observation units.

Thus, while the observational units of an intra-regional analysis usually are less similar to actual labour market zones than the corresponding units of an inter-regional analysis, and therefore, probably less suited for investigating the issue of population–employment interaction per se, intra-regional analyses allow explorations of the salient concerns about spillover effects among these units, the technical issue of how to control for these effects, and ultimately whether the spatial econometric technique being adopted affects the results in a substantial manner. Such understanding is especially useful for small area models that aim to understand local development patterns, as in large parts of the urban economics literature. The Boarnet model, which, because of the peculiarities associated with small area observations, provides the most interesting case for further exploration, is formally given by the following equations:

$$\Delta P_{i,t} = \alpha_0 + \alpha_1 X_{i,t-1} + \alpha_2 P_{i,t-1} + \alpha_3 EMP_{i,t-1} + \alpha_4 \Delta EMP_{i,t} + u_{i,t} \qquad (3a)$$
$$\Delta E_{i,t} = \beta_0 + \beta_1 Y_{i,t-1} + \beta_2 E_{i,t-1} + \beta_3 POP_{i,t-1} + \beta_4 \Delta POP_{i,t} + v_{i,t} \qquad (3b)$$

where $P_{i,t-1}$ is the population size in location i at year t–1, $\Delta P_{i,t}$ is the population change in location i between t and t–1 as defined by $P_{i,t} - P_{i,t-1}$, $POP_{i,t-1}$ is the population size of i's labour market zone, $\Delta POP_{i,t}$ is the population change in location i's labour market zone, and $X_{i,t-1}$ ($Y_{i,t-1}$) is a vector of population (employment) related location characteristics of i, preferably measured at time t–1 in order to avoid simultaneity bias. A similar set of definitions holds for the employment indicators E and EMP. Additionally, α_k and β_k are parameters to be estimated, and $u_{i,t}$ and $v_{i,t}$ denote stochastic errors.

The pivotal feature of the spatial econometric model proposed by Boarnet is the inclusion of the right-hand-side labour market variables, which are obtained by means of a spatial lag operation. This operation involves recomputing the population and employment values of individual locations in conjunction with those of their neighbours, as specified by a spatial weights matrix W. For a set of n observations, the matrix W is an $n \times n$ positive matrix in which $w_{ij} \neq 0$ defines j as being a neighbour of i, and $w_{ij} = 0$ otherwise. By convention, the elements of the diagonal are set to zero. The weights structure implied by the specification of matrix W rests on contestable assumptions about the spatial arrangement of the data at hand and can take on a variety of forms. In the meta-analysis, three alternative weighting schemes are used. Formally, the labour market variables are given by $POP = (I + W)P$, $EMP = (I + W)E$, $\Delta POP = (I + W)\Delta P$, and $\Delta EMP = (I + W)\Delta E$, where I is the $n \times n$ identity matrix. Premultiplying by I adds then location values, which, due to the zeros on the main diagonal of W, have been excluded otherwise. In case the row elements of W are standardised, such that they add up to one (which is commonly preferred as it facilitates interpretation and comparison [Anselin 2002]), the labour market variables measure the sum of a location's population or employment values and (weighted) averages of the corresponding values in neighbouring locations.

Of particular interest for this study are the endogenous labour market variables ΔPOP and ΔEMP, the parameters of which reveal the nature of population–employment interaction.[11] A statistically significant positive estimate for α_4 points to "people follow jobs", whereas a statistically significant positive estimate for β_4 points to "jobs follow people". Dual causality or two-way interaction is confirmed when both parameters reveal the same, positive, sign and they are statistically significantly different from zero. The particular form of spatial simultaneity introduced by the spatial lag of the dependent variable of each equation appearing on the right-hand side of the other equation has been termed a spatial cross-regressive model (Rey and Boarnet 2004) and implies that the estimation of α_4 and β_4 is not without complications. For instance, obtaining the predicted rather than the observed values for ΔPOP and ΔEMP in the first stage of a routine two-stage least-squares (2SLS) estimation procedure requires different procedures. In this study, we adopt a technique previously used by Bollinger and Ihlanfeldt (1997) and Henry et al. (2001), in which these values are directly obtained by using all of the model's predetermined variables, plus their spatial lags and higher-order spatial lags up to the order of three (hence, W, W^2 and W^3). According to Rey and Boarnet (2004), the chosen technique compares favourably with the traditional method of obtaining predicted values for ΔE and ΔP (by using the predetermined variables but without their spatial lags as instruments), which then are multiplied by matrix W to obtain the predicted values for ΔEMP and ΔPOP. The latter technique yields biased estimates in the likely event that these instrumented spatially weighted variables correlate with the residuals. In contrast, the approach adopted here ensures by construction that these variables are orthogonal to the residuals.[12]

A final key issue is whether other forms of spatial dependence are present in the system of equations that must be accounted for. For instance, the data-generating process may be such that spatial dependence also exists in the dependent variables (in addition to the right-hand-side endogenous variables), a complication that can be remedied by including the spatial lag of these variables on the right-hand side of the equation, or what has been called a spatial autoregressive (SAR) term. The cross-regressive model described by equations (3a) and (3b) is just one of several alternative spatial econometric models for simultaneous equations systems (see Rey and Boarnet 2004 for an overview and Henry et al. 2001 for applications), which also include an "augmented Boarnet model" in which these autoregressive terms are added. Formally, this model (called B-SAR by Henry et al. 2001) is given by the following equations:

$$\Delta P_{i,t} = \rho W \Delta P_{i,t} + \alpha_0 + \alpha_1 X_{i,t-1} + \alpha_2 P_{i,t-1} + \alpha_3 EMP_{i,t-1} + \alpha_4 \Delta EMP_{i,t} + u_{i,t} \quad (4a)$$
$$\Delta E_{i,t} = \gamma W \Delta E_{i,t} + \beta_0 + \beta_1 Y_{i,t-1} + \beta_2 E_{i,t-1} + \beta_3 POP_{i,t-1} + \beta_4 \Delta POP_{i,t} + v_{i,t} \quad (4b)$$

[11] We refrain from discussing other aspects of the model, such as the underlying assumption of a lagged adjustment process because they fall outside the scope of this study. Readers interested in more details are referred to, for instance, Carlino and Mills (1987), Boarnet (1992), and Mulligan et al. (1999).
[12] See Bollinger and Ihlanfeldt (1997, p. 185) for an intuitive reasoning behind this argument.

Crucially, in the presence of spatial dependence in the dependent variables, least-squares estimations of the model described by equations (3a) and (3b) yield biased and inconsistent parameter values, including those for α_4 and β_4. But while the B-SAR model described by equations (4a) and (4b), in contrast, does allow for spatial dependence in the dependent variables (and thus is preferred), it has long been hindered by the lack of an appropriate estimation technique. However, Kelejian and Prucha (2004) recently suggested a GS2SLS estimation procedure that has proved to yield consistent and asymptotically normal parameter estimates for this preceding case, in which spatial dependence exists in both the dependent variables and the right-hand-side endogenous variables, or put simply, simultaneity in the presence of spatial dependence. Here, together with the issue of model specification (excluding versus including the SAR lag), the impact of using this technique on the parameter estimates that indicate whether jobs follow people or people follow jobs is systematically compared with that of routine simultaneous equations estimations.

For the estimation of the model parameters, and α_4 and β_4 in particular, we use a cross-section sample of settlement-level data from Fryslân, a province in the northern part of the Netherlands (see Figure 4 for a map of the study area). Only 1,275 mi^2 in size, the study area contains no less than 392 settlements, each including an inner built-up area that is primarily surrounded by agricultural land. On average, these settlements are about 3.2 mi^2, which is about the same size as US census tracts or French communes examined in previous population–employment interaction studies (see Henry et al. 2001; Boarnet et al. 2005; Schmitt et al. 2006). A unique commuting flows data set for this region (Van der Horn et al. 2001) reveals that 54% of these flows are across different settlements, which makes these units ideal for investigation in a spatial econometric model. Also, the conditions for working and living in this region are highly fragmented, meaning that households and firms have a great deal of choice in evaluating locations, even when a decision is reduced to a relatively small geographical area within the region. Finally, the study region is economically very much internally oriented, being dominated by small- and medium-sized firms that mainly serve local and regional markets, with inter-industry linkages being maintained by local firms in particular (see RUG/CBS 1999) and with local residents holding more than 95% of all full-time jobs. Hence, this study region appears to be well suited for investigation on its own, which obviously eases the identification of the factors determining spatial change.

The main data used in this study, relating to the period 1988–2002, measure the employment and population size of settlements as the total number of full-time jobs in local establishments (which include all activities, except agriculture) and local residents, respectively. Besides these essential population and employment data, data are needed for the exogenous variables (*X* and *Y*), which for convenience are kept the same across the different model estimations. Hence, data are selected that capture some of the salient settlement-specific characteristics and that one can reasonably assume have not significantly changed over the 14-year period under examination. In short, we include

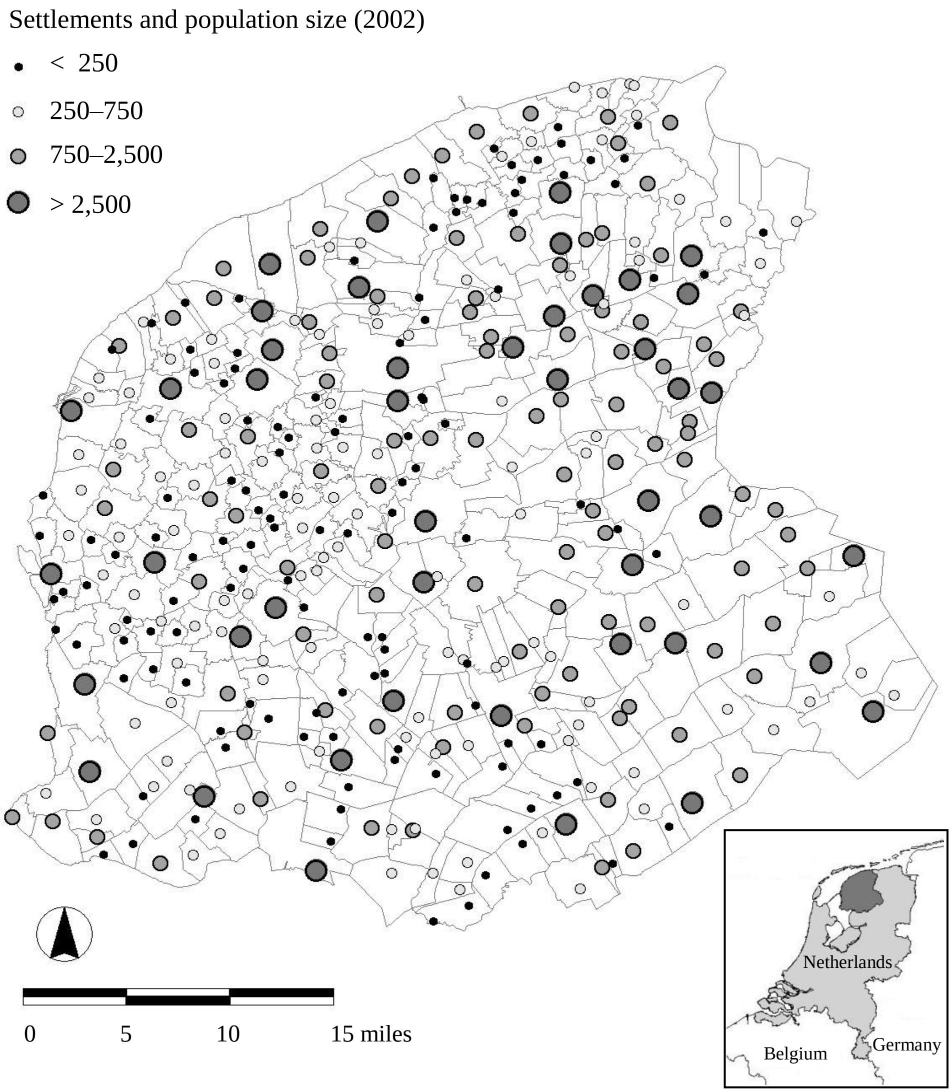

Figure 4. Study region (Province of Fryslân, the Netherlands) and settlement areas

two variables that describe the age structure of the settlements' residents (i.e., the proportion of people younger than 15 and older than 64 years, respectively), and one composite variable based on income, education, and unemployment, which can be seen as a proxy for social status (see Knol 1998). Two variables capture the access to important transport junctions as measured by the straight-line distance to the nearest railway station and motorway entrance/exit point, whereas data about the actual travel time by car to the capital city of the Netherlands (Amsterdam) are used to measure the relative location of these settlements in a national context. Next, a dummy variable is included to proxy the “Regional Plan” (*Streekplan*) of 1994, which has been the principal instrument used by provincial authorities to impose their policies about land use and locations of jobs and people. Specifically, the dummy is set to one for settlements being located in specially designated economic growth zones and individual settlements with important recreational functions, and it is set to zero for the remaining settlements. Next, we include a dummy variable to control for possible spillover effects from outside the research area. Specifically, the dummy is set to one for the border settlements where a significant proportion of the local residents works in neighbouring provinces and set to zero for the remaining interior settlements. Finally, following suggestions by Boarnet et al. (2005), we use detailed information about land use patterns to improve the reliability of the lagged adjustment parameters (an issue that is not further addressed in this study; see footnote 11). Specifically, six variables are included that measure the area in each settlement for the respective land use categories: agriculture, forests, nature, water, recreation, and infrastructure.

Experimentations

Data selection issues

Among the study features to be examined in the meta-analysis, we select three substantive ones that reflect the inner workings of population–employment interaction. Specifically, questions about the *empirics* of the jobs–people direction of causality are addressed by using different subsamples of the data. First, the model described in “Research design: econometric model and data” is repeatedly tested for different time periods to uncover whether the jobs–people direction of causality is subject to temporal changes. A priori, the idea of time effects seems very intuitive because the preferences for business and residential location, and economic conditions to act upon these preferences change over time. Such effects may reflect (short-term) business cycle fluctuations as well as fundamental (long-term) societal changes. For example, the common assumption about the transformation from an industrial-based society to a knowledge-based society is that the balance is increasingly shifting toward jobs following people instead of the other way around (see Florida 2002). The assumption of temporal shifts already has encouraged researchers to generate multiple estimation results for different time periods. In the most detailed study, Mulligan et al. (1999) report considerable variation in the results on population–employment interaction across one-year time periods between 1969 and 1994. Meanwhile, the combination and comparison of results *across* studies for different time periods, as assessed through a routine meta-analysis of CM studies (see Chapter 2), does not reveal any clear-cut time effect, although the lack of sufficient variation among these studies may be partly responsible for this result. Here we divide the population and employment data into six different, partly overlapping, four-year time periods between 1988 and 2002 to make a more accurate assessment of possible temporal shifts in the direction of causality than can be done by a standard meta-analysis. We selected a four-year time lag because the model is essentially a long-term growth model for which the use of, for instance, a one-year time lag is not particularly suited. The focus on a long time span, such as the 10-year lag often used in the literature, appears to mask too much of the varying circumstances during the 1988–2002 period, which includes a turning point in the business cycle around 1994. Somewhat in between, the use of a four-year time lag suggests a useful comparison of population–employment interaction over time and, besides, ensures that a significant number of observations can be looked upon in the subsequent meta-analysis.

The second aspect of data sampling to be investigated concerns the spatial nature of population–employment interaction. Widespread support exists among researchers for the thus far largely untested claim that estimation results supporting the jobs–people direction of causality exhibit spatial nonstationarity. Being one of the most eye-catching differences between studies, the "region under examination" is typically viewed as one of the main sources for the substantial variation in research findings that typifies this literature. However, fundamental reasons also exist to suggest that the findings are shaped by the geographical characteristics of data, which basically implies that conditions for working and living are not the same everywhere. Findings by Schmitt et al. (2006) indicate that even within a seemingly coherent group of French rural areas, considerable differences can be found in the direction of population–employment interaction, depending on factors such as the size and growth of a nearest urban centre. Likewise, separate model estimations by Boarnet (1992), with a complete data set of New Jersey municipalities and a subset of slow-growing municipalities, hint at the presence of what he refers to as "structural breaks in the data" (p. 57). He asserts that ignoring these data effects may yield misleading interpretations of results, with major consequences for policy if the described central tendencies prove not to apply to certain subsets of locations. Finally, the analysis in Chapter 2 of this book reveals that the study results from US- and non-US-oriented studies are significantly different from each other, thereby confirming the idea of spatial nonstationarity in the jobs–people direction of causality, albeit at a broad geographical scale. Here, we reveal whether spatial heterogeneity also can be observed when geographical coverage is narrowed to a single province in the Northern Netherlands by estimating the model with the complete data set as well as with four exclusive subsets of locations (spatial regimes). Specifically, a distinction is made between 347 settlements with fewer than 2,500 inhabitants, classified into the category of a "small village" (RPD 1999) and the remaining 45 "urban" settlements. Subsequently, the former category of "rural" settlements is divided into three subgroups, for which the respective population levels are 750–2,500 (102), 250–750 (118), and below 250 (127). The distinction is largely intuitively made to reflect coherent groups of locations and to ensure that each group contains a sufficient number of observations for comparison.

The third data sampling issue investigated is the possible impact of the employment data. Employment is widely known to be extremely heterogeneous, comprising various subgroups that display different preferences for industrial location (Bollinger and Ihlanfeldt 2001). On the basis of the studies that have acted upon this premise by using sectoral employment data (e.g., Bollinger and Ihlanfeldt 1997; Schmitt et al. 2006), one is inclined to conclude that important group effects need to be considered in the jobs–people direction of causality. The lack of other specific studies, however, means that the effect of using data for alternative employment groups with varying labour intensity and consumer dependency has yet to be evaluated with rigorous statistical techniques. Therefore, here the selected population–employment interaction model is estimated by using data for total employment as well as for four private employment sectors: manufacturing; construction; retail; and the combination of finance, insurance, real estate, and services (FIRES). Together, these employment groups made up 51% of all full-time jobs for 2002 and 46% of the employment growth in the preceding 14-year period.[13]

Methodological issues

The literature offers a variety of suggestions for the methodological study techniques that can be expected to influence the study results revealing population–employment interaction. Arguably the most obvious is measurement of the population and employment variables, with two techniques being in use that practically share the same amount of support, one using raw, unstandardised population and employment data, and one using standardised data by controlling for the area size of spatial units. However, as Mulligan et al. (1999, p. 857) state: "*There is no a priori reason to expect that estimates based on levels will resemble estimates based on densities, as each approach represents an entirely different conceptualisation of the space-economy*". The findings from Glavac et al. (1998), in which levels as well as densities have been used, seem to indicate that alternative measurements indeed yield different conclusions as to the direction of causality. The findings in Chapter 2 of this book appear to support this conjecture, suggesting furthermore that the nature of the effect also depends on a study's context.[14] On the basis of these arguments, a strong case exists for testing the model for both levels and densities and evaluating how exactly these different measurements change the results. Here, we go even further by distinguishing two

[13] Individually, the employment sectors contribute as follows (given as percentages of total employment in 2002 and employment growth between 1988 and 2002, respectively): manufacturing, 19.7 and 12.0; construction, 9.5 and 11.2; retail, 8.0 and 6.5; and FIRES, 14.0 and 15.9. The sectors of education, government, and health care, in particular, make up the remainder of the full-time employment (growth), with agriculture being omitted from the analyses all together.

[14] Reasons to use standardisation techniques usually refer to the examination of spatial units that do not allow a straightforward comparison because of considerable differences in area size and/or population and employment size. Naturally, the effect of using standardisation techniques seems to hinge on the combined characteristics of the spatial detail of an investigation and the region type under examination, which may differ between studies.

alternative density measures, one in which population and employment are standardised by built-up area and one in which they are standardised by total area, in addition to using the unstandardised data. Referring to the "different conceptualisations of the space-economy" previously cited, the levels reflect the spatial distribution of employment and population (changes) as if it were a point pattern, whereas the densities by total area and built-up area depict the space-economy as a partitioned landscape of contiguous and non-contiguous area units, respectively. To compare growth across locations, the standardisation by built-up area (which can be interpreted as the net size of a location) may be more appropriate than the routine standardisation by total area (which corresponds to the gross size of a location). Especially in cases where locations show considerable variation in the part of the land that has not been built upon, and thus has not been used for industrial or household residential purposes (but mostly for agricultural purposes), the measurement by total land area may lead to completely different conclusions.

The second methodological issue investigated concerns the design of the spatial weights matrix *W*, which represents one of the most difficult and controversial aspects of a spatial econometric model.[15] As estimation results directly hinge upon the definition of the weight elements, a justification for the chosen specification of *W* is crucial. Stakhovych and Bijmolt (2009) provide Monte Carlo simulations for an array of different specifications of the weights matrix and corroborate evidence that weights matrices implying a high connectivity between spatial units are detrimental in finding the true underlying model and the mean square error of the estimated parameters. Existing population–employment interaction studies clearly lack a univocal specification of *W* (see also Chapter 2), meaning that there is no consensus regarding the type of weighting scheme that most realistically imposes structure on labour market relationships between regions. The findings by Boarnet et al. (2005), in which the model described by equations (3a) and (3b) has been estimated using six alternative weight matrices, suggest that the model parameters are quite sensitive to different definitions of *W*. Here we assess the crucial role attributed to weight matrix design by comparing the estimation results for three different weighting schemes. Specifically, the focus is on two standard weight matrices that dominate the literature—the fixed distance matrix and the inverse distance matrix—and one rare flow matrix based on commuting data, which has so far been used only in Boarnet et al. (2005). The fixed and the inverse distance matrices are rather similar, and both are sparse matrices as typically the number of zero elements is rather high. The commuting flow matrix is a full matrix with, except for the diagonal elements, entries that are as a rule nonzero. Each of these matrices reflects different assumptions about the way in which spatial units of observations relate to each other and about how they are tied into larger labour market zones. The fixed

[15] This is reflected by the variety of spatial weights matrix specifications that can be encountered across the spatial econometric literature (see, e.g., Anselin 2002 for an overview) and the series of studies about the misspecification of *W* (see, e.g., Florax and Nijkamp 2005, and the references herein).

distance matrix is a binary weighting scheme in which the matrix elements w_{ij} equal one for $d_{ij} \leq \delta$, and zero otherwise (where d_{ij} is the distance between locations i and j, and δ is a chosen distance threshold value). In this case, interaction is assumed to take place only between spatial units that are within a critical distance of each other (see, e.g., Henry et al. 2001 for applications). Instead of matrix elements having values of zero or one, the weighted inverse distance matrix contains elements w_{ij} equal to $1/d_{ij}^{\alpha}$ (with α denoting an a priori determined distance decay parameter). By using such a matrix, labour market variables take the form of potential variables, with employment and population (growth) in nearby locations weighted more heavily (see, e.g., Boarnet 1992, 1994; Bollinger and Ihlanfeldt 1997). The flow matrix, with w_{ij} being a function of the number of commuters travelling between locations i and j, directly reflects the properties of labour market relations, and is, at least according to Boarnet et al. (2005, p. 32) "*closer to a theoretical ideal of a commuter-shed than any other W matrix*".[16] In contrast to the other weighting schemes, the flow matrix does not impose a rigid spatial form on labour market zones of different locations, which in a regular spatial data arrangement all would be uniformly sized. Being based on real commuting data, the flow matrix is entirely flexible and allows each location to have a uniquely shaped labour market zone in ways that incorporate variations in commuting patterns across a region. The availability of an extremely rich data set of commuting patterns (see Van der Horn et al. 2001) allows us to construct such a rare flow matrix. Based on these same data, we set the values for the threshold distance δ in the fixed distance matrix and the distance decay parameter α in the weighted inverse distance matrix to 6.8 (miles) and 0.92, respectively. The former approximates the average commuting distance, which is a standard criterion to determine the threshold value, whereas the latter is estimated from a spatial interaction model. By convention, all matrices are row standardised, which means that the row elements sum to one, although alternative coding schemes are available (see, e.g., Patuelli et al. 2006 for a more elaborate treatment).

The final, and arguably most important, issue to be investigated is that of model specification and estimation, as outlined earlier in "Research design: econometric model and data". Because of the lack of an appropriate estimation technique until recently, the issue whether to include an SAR lag because of possible spatial dependence in the dependent variables has thus far been largely ignored (with the exception of Henry et al. 2001; Carruthers and Mulligan 2008). The potential impact of failing to control for spatial dependence in the presence of such effects cannot be too strongly emphasised, as

[16] The matrix is less than ideal compared with a simple distance-based matrix specification because the weights elements are less exogenous to the model. Maintaining the weights matrix as independent is important because the model otherwise becomes highly nonlinear with endogeneity that must be instrumented out. Typically, this is not the result one has in mind when designing a weights matrix (Anselin 2002). Notice that this study is not designed to draw inferences about which matrix specification is the most appropriate; rather, it is designed to determine whether the application of the different weights matrices yields different study results.

the parameter estimates revealing the jobs–people direction of causality then are biased and inconsistent. The wide divergence in inferences that typifies this literature is an outcome that one would typically expect when parameters are not properly estimated.[17] Therefore, to make a definite assessment about the impact of model specification and estimation, we perform three series of experiments: one with the original "Boarnet model" using 2SLS and two with the augmented Boarnet model, B-SAR, using both 2SLS and the GS2SLS estimator recently proposed by Kelejian and Prucha (2004). Importantly, the latter method adds two steps to a routine 2SLS procedure. First, the estimated disturbances *u* and *v* from the initial 2SLS estimations are used to estimate the autoregressive parameters, ρ and γ, in equations (4a) and (4b), respectively, by applying the generalised moments procedure described in Kelejian and Prucha (1999). Second, by applying a Cochrane–Orcutt-type transformation, the estimated autoregressive parameters are subsequently used to account for spatial dependence in the disturbances. Note that assessing the impact of model specification and estimation is somewhat different from that of the other study features being analysed. Whereas those other features inform only about whether adopting a particular data sample or methodology affects estimation results, the issue of model specification and estimation addresses a more fundamental problem, namely, that of a possible inherent flaw, which makes a comparison of results infeasible.

Results

By changing the time period (6), region type (5), employment type (5), variable measurements (3), matrix design (3), and model specification and estimation (3), a total of $6 \times 5 \times 5 \times 3 \times 3 \times 3 = 4{,}050$ experiments were performed, generating a similar number of parameter estimates to be evaluated in the meta-analysis. Due to the different measurements of the population–employment relationship across these experiments, a comparison of the *magnitude* of the effects (as revealed by the size of the parameter estimates) is not permitted. Instead, these measurements only allow making inferences about the *sign* effects of α_4 and β_4. Accordingly, the analysis of study results necessarily takes the form of a vote-counting procedure in which the estimated sign and significance levels of α_4 and β_4 alone are used to determine whether the inferences from different experiments agree. Although such an evaluation is crude and puts considerable emphasis on statistical significance, it is intuitively very appealing because it seamlessly unites with the common practice in the literature of summarising the estimation results by discrete categories. Here, the estimates for α_4 and β_4 are jointly used to discriminate between four categories of research findings, where 10% significance levels are used to determine whether or not these estimates differ from zero:

[17] We thank an anonymous referee for pointing this out.

- (NI) no interaction (“jobs do not follow people nor do people follow jobs”): α_4 and $\beta_4 \leq 0$;
- (JP) one-way causality running from population to employment (“jobs follow people only”): $\alpha_4 \leq 0$ and $\beta_4 > 0$;
- (PJ) one-way causality running from employment to population (“people follow jobs only”): $\alpha_4 > 0$ and $\beta_4 \leq 0$; and
- (DC) dual causality (“jobs follow people and people follow jobs”): α_4 and $\beta_4 > 0$.

Considering that some of these estimates may be flawed because possible spatial dependence in the dependent variables is ignored, the ensuing discussion focuses on results not only from the entire set of estimations but also from the subset of GS2SLS-based estimations (n = 1,350) because they are known to be unbiased and consistent.

The last row in Table 6 reveals that most of the estimations (some three quarters) fail to provide any evidence for population–employment interaction (either one-way or two-way), which is not particularly unusual for small area models of population–employment interaction (see also Chapter 2). The remaining estimation results are spread over the three remaining categories that indicate a causal relation, with most of the results pointing toward PJ, closely followed by DC, and then JP. When we compare the distribution of results for the entire set of estimations with the subset of GS2SLS-based estimations, we may conclude that they are rather similar, although for the GS2SLS-based estimations slightly more results indicate the existence of a causal relation between population and employment, especially for both one-way causalities. Given the purposes of this study, the relationships with the underlying study characteristics are even more interesting than the differences in research findings per se. Table 6 furnishes an overview of the distribution of these findings across the four possible categories. Although the category “no interaction” contains the highest share for all study characteristics by far, substantial variation exists between the characteristics and between the percentages based on all estimations and those based only on GS2SLS.

Instead of discussing the results presented in Table 6, we prefer to discuss the differences between the study characteristics on the basis of a multivariate method that also gives insight into the statistical significance of the differences. Because the study results refer to four discrete categories, we adopt a multinomial logistic regression model, which reveals the influence of each of the study features on the likelihood of a categorical outcome, other things being equal (ceteris paribus). In our case, this model comprises three equations (a), (b), and (c) in which the respective dependent variables are defined as the log-odds that the estimation results indicate either JP, PJ, and DC, instead of NI (the reference alternative). From each group of study features that serve as explanatory variables, one category is omitted against which to compare. The estimated regression coefficients reveal the additive effect of each category compared with the

Table 6. Estimated outcome by characteristics, in %, for all estimates and GS2SLS estimates

Sample	All (*n* = 4,050)				GS2SLS (*n* = 1,350)			
Characteristic/outcome*	NI	JP	PJ	DC	NI	JP	PJ	DC
Time period								
1988 – 1992	74.8	4.1	11.3	9.8	70.2	9.3	10.7	9.8
1990 – 1994	80.6	7.1	3.7	8.6	81.8	6.7	3.6	8.0
1992 – 1996	85.3	5.2	5.3	4.1	82.2	6.2	8.0	3.6
1994 – 1998	73.6	6.4	11.6	8.4	68.9	9.8	13.8	7.6
1996 – 2000	65.3	6.5	15.7	12.4	64.0	8.0	15.1	12.9
1998 – 2002	65.6	8.1	12.9	13.3	60.9	10.2	14.2	14.7
Region type								
all regions	69.4	9.4	9.5	11.7	65.6	10.7	11.5	12.2
urban (≥ 2,500 inhabitants)	69.5	3.1	7.5	19.9	71.1	3.0	7.0	18.9
rural (750 – 2,500)	77.3	2.6	17.5	2.6	76.3	4.1	16.7	3.0
rural X (250 – 750)	82.5	6.3	7.3	4.0	76.3	10.7	9.3	3.7
rural XX (< 250)	72.5	9.9	8.5	9.1	67.4	13.3	10.0	9.3
Employment type								
total employment	67.4	8.0	12.3	12.2	65.2	8.9	14.4	11.5
manufacturing	83.6	3.8	8.4	4.2	79.3	5.2	10.0	5.6
construction	73.3	6.4	10.4	9.9	71.1	7.4	12.2	9.3
retail	71.1	4.3	9.1	15.4	69.3	7.0	8.5	15.2
FIRES	75.7	8.6	10.1	5.6	71.9	13.3	9.3	5.6
Variables measurement								
levels	70.4	6.6	12.9	10.1	66.2	9.8	13.8	10.2
density, built up-area	79.3	6.8	7.6	6.3	75.6	9.1	9.6	5.8
density, total area	73.0	5.3	9.7	12.0	72.2	6.2	9.3	12.2
Weights matrix specification								
fixed distance	77.6	5.7	7.8	8.9	74.9	7.6	9.8	7.8
inverse distance	75.0	5.4	8.8	10.7	72.7	7.8	9.1	10.4
flow	70.0	7.6	13.6	8.7	66.4	9.8	13.8	10.0
Model specification and estimation								
Boarnet/2SLS	75.3	4.5	10.0	10.2				
B-SAR/2SLS	76.1	5.9	9.3	8.7				
B-SAR/GS2SLS	71.3	8.4	10.9	9.4				
Overall	74.2	6.2	10.1	9.5	71.3	8.4	10.9	9.4

* The labels for the different outcomes are as follows: NI, no interaction; JP, jobs follow people; PJ, people follow jobs; and DC, dual causality.

omitted category (for which the coefficient is 0) and can be interpreted as the change in the log-odds. Intuitively more appealing is the interpretation of these coefficients as factors that indicate the change in odds, which can be estimated by exponentiating these coefficients (i.e., taking the antilog with the base e). A positive coefficient means a factor is greater than one, thereby revealing an increase in the odds and hence implyinga higher probability that this outcome occurs compared with the reference alternative. In contrast, a negative coefficient complies with a factor that is less than one, which means that the odds are decreased. In case a coefficient is not significantly different from zero, the factor equals one, which leaves the odds unchanged (for more details about the technique, see, e.g., Menard 2002), implying that for this particular study characteristic, the probability that this alternative occurs does not differ from the probability that the reference alternative occurs.

Table 7 reveals that the overall distribution of research findings mostly diverges across the content-related temporal, spatial, and sectoral employment categories, rather than across the experimental methodological issues. Specifically, the former group of study features reveals statistically significant estimates in each of the three metaregression equations, whereas these are noticeably absent for “variables measurement” in metaregression equation (a) and for most coefficients for the “weights matrix” and “model specification and estimation”. Also, for the content-related categories, the magnitude of the coefficients is larger, indicating a larger impact on the research findings. In metaregression equation (b), for example, the odds of finding “people follow jobs” instead of “neither” are lowered by 3.4 (51/0.297) when data from 1990–1994 rather than from 1988–1992 (reference category) are used. Likewise, in metaregression equation (a), examining “urban” and “rural” units rather than all spatial units decreases the odds of finding “jobs follow people” instead of “neither” by 4.1 (51/0.244) and 3.1 (51/0.323), respectively, whereas in metaregression equation (c) the change in odds (in this case of finding “dual causality” instead of “neither”) due to examining these rural units is no less than 5.2 (51/0.190). Also in metaregression equation (c), the odds decrease by 4.0 when manufacturing employment data rather than all employment data are examined. By comparison, the change in odds related to model specification and estimation, variables measurement, and matrix design is never more than 2.0.

One by one, the different study features reveal some interesting findings. For “time period”, for example, the pattern observed is not clear-cut and thus hints at the influence of economic business cycles. Yet, the impression one obtains from metaregression equation (a) is conformity with the assumption of a shift toward a knowledge-based society in which the “jobs follow people” direction of causality is gaining significance over time (Florida 2002), followed by an increase in “dual causality” and a decrease over time in “people follow jobs”. With regard to the spatial aspect of urban versus rural, the odds of finding interaction, either one-way or two-way, are usually less when subsets of more homogeneous regions (rather than all data

Table 7. Metaregression results, multinomial logit using all estimates

Logits†	(a) Logit JP vs. NI			(b) Logit PJ vs. NI			(c) Logit DC vs. NI		
	b	Exp(b)		b	Exp(b)		b	Exp(b)	
Intercept	–2.437		●	–1.580		○	–1.295		●
Time period (1988 – 1992)‡									
1990 – 1994	0.476	1.610	*	–1.215	0.297	●	–0.216	0.805	
1992 – 1996	0.090	1.094		–0.903	0.405	●	–1.053	0.349	●
1994 – 1998	0.457	1.580	*	0.044	1.045		–0.144	0.866	
1996 – 2000	0.607	1.834	○	0.488	1.630	●	0.410	1.506	○
1998 – 2002	0.834	2.302	●	0.277	1.319		0.484	1.623	●
Region type (all regions)									
urban	–1.131	0.323	●	–0.232	0.793		0.565	1.759	●
rural	–1.410	0.244	●	0.501	1.651	●	–1.658	0.190	●
rural X	–0.596	0.551	●	–0.483	0.617	●	–1.323	0.266	●
rural XX	0.004	1.004		–0.166	0.847	●	–0.313	0.731	*
Employment type (total employment)									
manufacturing	–0.990	0.372	●	–0.643	0.526	●	–1.373	0.253	●
construction	–0.320	0.726		–0.277	0.758	*	–0.325	0.722	*
retail	–0.690	0.502	●	–0.375	0.688	○	0.201	1.222	
FIRES	–0.048	0.953		–0.338	0.713	○	–0.973	0.378	●
Variables measurement (levels)									
density, built-up	–0.096	0.908		–0.681	0.506	●	–0.643	0.526	●
density, total	–0.256	0.774		–0.338	0.713	●	0.156	1.169	
Weights matrix specification (fixed distance)									
inverse distance	–0.017	0.983		0.169	1.184		0.250	1.284	*
flow	0.411	1.509	○	0.701	2.016	●	0.100	1.105	
Model specification and estimation (Boarnet/2SLS)									
B-SAR/2SLS	0.252	1.287		–0.086	0.918		–0.187	0.830	
B-SAR/GS2SLS	0.692	1.998	●	0.148	1.159		–0.033	0.968	

† See the note to Table 6 for the meaning of the labels. ‡ Omitted categories are in parentheses. Critical significance levels are signalled by * < 0.10, ○ < 0.05, ● < 0.01.

observations taken together) are being analysed. This result also may reflect that most population–employment interactions take place between different categories of settlements rather than between similar types of settlements. A notable exception is found for the “rural” and “urban” categories in metaregression equations (b) and (c), respectively, which arguably represent the most dynamic parts of the study region.

Table 8. Metaregression results, multinomial logit using only GS2SLS estimates

Logits†	(a) Logit JP vs. NI			(b) Logit PJ vs. NI			(c) Logit DC vs. NI		
	b	Exp(b)		b	Exp(b)		b	Exp(b)	
Intercept	–1.427		●	–1.180		●	–1.398		●
Time period (1988 – 1992)‡									
1990 – 1994	–0.509	0.601		–1.274	0.280	●	–0.369	0.692	
1992 – 1996	–0.580	0.560		–0.455	0.634		–1.229	0.293	●
1994 – 1998	0.072	1.075		0.285	1.329		–0.261	0.770	
1996 – 2000	–0.066	0.937		0.452	1.572		0.400	1.491	
1998 – 2002	0.240	1.272		0.441	1.554		0.596	1.814	*
Region type (all regions)									
urban	–1.397	0.247	●	–0.589	0.555	*	0.378	1.460	
rural	–1.142	0.320	●	0.203	1.225		–1.628	0.196	●
rural X	–0.167	0.847		–0.401	0.670		–1.413	0.244	●
rural XX	0.190	1.209		–0.175	0.839		–0.328	0.721	
Employment type (total employment)									
manufacturing	–0.765	0.465	○	–0.600	0.549	○	–0.992	0.371	●
construction	–0.283	0.754		–0.271	0.763		–0.330	0.719	
retail	–0.311	0.733		–0.616	0.540	○	0.248	1.281	
FIRES	0.315	1.370		–0.566	0.568	○	–0.890	0.411	●
Variables measurement (levels)									
density, built-up	–0.218	0.804		–0.525	0.591	○	–0.762	0.467	●
density, total	–0.565	0.568	○	–0.501	0.606	○	0.106	1.111	
Weights matrix specification (fixed distance)									
inverse distance	0.061	1.063		–0.040	0.961		0.359	1.432	
flow	0.399	1.491		0.489	1.631	○	0.407	1.503	

† See the note to Table 6 for the meaning of the labels. ‡ Omitted categories are in parentheses. Critical significance levels are signalled by * < 0.10, ○ < 0.05, ● < 0.01.

Similarly, the odds appear to decrease when examining specific sectoral employment data and then manufacturing data especially. A possible explanation for the low interaction of population and employment in manufacturing might be that these industries are usually located in relatively large establishments on industrial sites that hardly change location. Van Dijk and Pellenbarg (2000) find empirical evidence supporting this contention and argue that the costs of moving for the industrial sector are generally higher because investment in capital stock and capital intensity is higher. People are also reluctant to reside near industrial activities. Therefore, the observed weak population–employment relationship appears to make sense, especially in view of the positive coefficient being observed for “retail” in metaregression equation (c), a sector for which this contention obviously does not apply.

With regard to the issue of variable measurement, the difference in results caused by standardising the population and employment data is most telling when built-up areas (rather than total areas) are used as the basis for standardisation, thereby negatively affecting the odds of finding “people follow jobs” and “dual causality” in particular. As for weight matrix design, the regular fixed distance and inverse distances weighting schemes give practically the same variation in research findings, whereas the unusual, but theoretically preferred, matrix based on commuting flows especially favours the finding of people follow jobs. Finally, with regard to the distinction between the two sets of 2SLS-based estimations, on the one hand, and the GS2SLS-based estimations, on the other hand, the latter is relatively strongly in favour of “jobs follow people”. Apparently, the inclusion of an SAR lag does not make a difference, as long as the model is not properly estimated by also taking into account the spatial dependence in the dependent variables (i.e., by using GS2SLS). Accordingly, we examine the relation between the GS2SLS-based estimations and the study characteristics in more detail.

Although the preceding assessment of the impact of the individual study features is done while controlling for the influence of model specification and estimation, it may crucially rest on a comparison of biased and inconsistent parameter estimates. The significant difference in parameter estimates observed between the 2SLS- and GS2SLS-based estimations suggests that this is true for several of the former estimations (because the variation in research findings would have been the same otherwise). Thus, to assess the true impact of the selected study features, the logistic regression analysis is repeated by solely using the subset of GS2SLS-based parameter estimates, which are known to be unbiased and consistent. Table 8 reveals that inferences based on this subset of estimations are somewhat different from those previously outlined. Specifically, many regression coefficients are no longer significantly different from zero at conventional statistical levels, especially those being associated with the time period and type of region. The signs of the regression coefficients are similar to those in Table 7, with the largest change in odds, within each study feature as well as across these features, being brought about by the same categories. Thus, while the estimation results appear to be particularly varied because, for example, data are used for different time periods, much of the variation can be ascribed to a bias in these results due to the use of an inappropriate estimator. This finding implies that the results obtained by using the GS2SLS estimator are less sensitive to variation in the study characteristics and thus give more reliable answers to the central question of this study with regard to the empirical nature of population–employment interaction.

Conclusions

The quasi-experimental meta-analysis summarised in this chapter includes a number of interesting findings. First, the various aspects of data sampling, variable measurement, and spatial weights matrix specifications are clearly secondary to the main issue of model specification and estimation. They are secondary because estimates and inferences are biased and inconsistent if spatial dependence exists in the dependent variables in addition to the right-hand-side endogenous variables. Accordingly, the main methodological message from this study is that adding SAR lags offers an improvement to the regular Boarnet model. The methodology for estimating a B-SAR model is now available, thanks to Kelejian and Prucha (2004), and thus a reason for excluding these lags no longer exists.

Second, the subordinate nature of the other study features notwithstanding, these features reveal some significant impact on the findings of population–employment interaction. Specifically, the findings suggest that the parameter estimates are largely shaped by the region and time period under examination, and, equally important, employment group effects need to be considered when assessing the direction of causality. Also, the estimates appear rather sensitive to different measurements of a model’s key variables, more so than to the application of alternative spatial weights matrices, which does not appear to be an issue with which future studies should be primarily concerned.

Overall, the results from this study suggest that findings about population–employment interaction alone are of little value if the impact of the underlying study features is not properly understood. For example, without understanding why the research findings are what they are, the potential for what is called “value transfer” (Florax et al. 2002) remains remote. To illustrate this point, our knowledge still seems far from sufficient to predict the nature of causality for an unstudied site. This study shows that even when an analysis is restricted to a single province in the Netherlands, considerable spatial heterogeneity can be observed in estimates indicating population–employment interaction without having a clear understanding as to the reasons why. Having concluded that the estimates differ spatially, the next step is to understand why these differ by looking into the characteristics of the different locations in more detail.

Finally, the quasi-experimental meta-analysis proves to be a promising tool to assess the robustness of models to various implementation decisions. Staying with population–employment interaction models, one important area for further research seems to be the determination of whether, and if so how, a particular selection and combination of location-specific exogenous variables affects estimation results. Usually, variables are selected with a relatively weak justification from a set of “obvious” candidates for which data are readily available. Also, the focus of attention may be redirected toward estimation results for the model parameters that inform about the lagged adjustment process, an important issue that has largely gone unexplored (with the notable exceptions of Mulligan et al. 1999; Boarnet et al. 2005), and that has yet to be investigated using rigorous statistical techniques.

4. Spatial interactions of population and employment changes: An exploratory spatial data analysis

Introduction

The remaining chapters of this book focus on local population and employment growth patterns, as revealed by postcode-level data from the Northern Netherlands. Partly as a prelude to the next chapter in which these differences will be explained, this chapter focuses on the geographical arrangement of these data in order to gain some preliminary insights in the spatial nature of population–employment interaction. Starting point for the investigation is the idea that the two growth processes exhibit a systematic relationship in case their spatial patterns coincide, but that these patterns do not need to be confined to what is called a "point-to-point association" (Hubert et al. 1985) in order to signal such relationship. As with virtually all geo-referenced data, the underlying data generating process may not match up the scale and spatial extents of the units of observation (see, for example, Anselin 1988; Haining 1991; Bailey and Gatrell 1995). Thus, in addition to or instead of the usual association *within a pair of changes at each location*, the location patterns may reveal association *between distinct pairs across locations*, or what is usually referred to as "spatial association" (Hubert et al. 1985).

In terms of the subject of this study, the interaction across locations is rather evident, being directly reflected in people's journeys from home to work. The ongoing delinking of residential and employment location decisions (Renkow 2003) means that, for a significant and growing number of people, the places of residence and work do not coincide, especially not when measured at the level of small area units like postcode zones. To illustrate, no less than 54% of the commuter flows within and to Fryslân are between settlements (Van der Horn et al. 2001), units of which the area size is practically similar to that of postcode zones in the study region (8.4 km^2 versus 8.9 km^2). But while it is deeply intuitive that the relationship between population and employment growth stretches beyond the boundaries of small area units, it is not clear how exactly.

The potential for spatially separated locations to interact is closely linked to the concept of accessibility, which can be defined as the ease with which opportunities can be reached from a given location (Vickerman et al. 1999). This concept is widely assumed to be crucial in understanding the location decisions of households and firms, and aggregate employment and population patterns. Song (1996) describes it as "*perhaps the most important concept in defining and explaining urban form and function*" (p. 474). In the population–employment interaction literature, the premise that it is access to jobs and people that matters, and not their locations as such, has been highly influential. In fact, practically all intra-regional studies published in this literature field are based on this premise. However, despite the widespread use of the concept in these and many other studies, there is little agreement as to how accessibility is best measured. As Gould (1969) states: "*Accessibility is a slippery notion […] one of those common used terms that everyone uses until faced with the problem of defining and measuring it*" (p. 4). Usually, the potential for interaction is simply brought down to a function of distance, in line with the so-called "First Law of Geography" that everything is related to everything else, but closer things more so (Tobler 1970). Hence, it is assumed that distance has a negative impact on an area's accessibility and on the ease of interaction, with Johansson et al. (2002) arguing that this is especially true for exchanges that involve the movement of people such as with commuting. On this general level the idea about accessibility is thus quite uncontroversial, signifying that interaction disseminates with distance. The decisive problem of measuring accessibility is determining how this deterrence effect of distance exactly looks like. The literature suggests a variety of distance decay profiles, ranging from linear impedance functions (mean impedance) functions, rectangular functions (all destinations within a given impedance), to various non-linear impedance functions. One could view the specification of the form of the distance decay as essentially arbitrary. However, as Song (1996) argues, it requires rather precise definition if it is to be employed as a useful indicator in spatial analysis. With regard to models of spatial interaction, it could potentially lead to the inference of spurious relationships, since the validity of estimates is pre-conditioned by the extent to which the interaction structure is correctly reflected in the weights (Anselin 1988).

The main objectives of the study presented in this chapter are: (1) to disclose whether or not population and employment changes in the Northern Netherlands are systematically distributed across postcode zones, and (2) to gauge the relationship between population and employment changes in space, with the purpose of revealing the friction effect of distance. Besides, this study aims (3) to reveal local instabilities in the relationship, suggestive of spatial clusters or atypical locations in the study region. The selected methodology to achieve these objectives is an Exploratory Spatial Data Analysis (ESDA). This type of spatial data analysis entails a set of techniques aimed at describing and visualising spatial distributions, at identifying atypical localisations or spatial outliers, at detecting patterns of spatial association, clusters of hot spots, and at suggesting spatial regimes or other forms of spatial heterogeneity (Anselin 1998). Here, specific ESDA techniques are used that are concerned with the relatively new concept of bivariate spatial association, which measures the extent to which the values of two variables show a systematic relationship in space (Lee 2001a). The central idea is that by examining this association at various distance intervals the distance decay profile can be empirically derived from the data.

The findings from this study may contribute to the literature in two ways. First, by establishing the geographic extent to which the postcode-level associations are statistically significant, the results may provide some useful insights for studies that aim to spatially delineate labour markets, daily urban systems or functional economic areas (see also Wheeler 2001). Second, by revealing the pattern that governs the decay of spatial associations with distance, the results may benefit studies dealing with spatial accessibility in general and that of jobs and people in particular. So far, most of the interest in population–employment interaction has been on the direction of interaction, and little on the spatial nature of interaction. In fact, inter-regional studies tend to ignore this issue all together. They generally treat the spatial units of observation as isolated entities, as if their locations in space and potential inter-regional linkages do not matter. By contrast, intra-regional studies usually allow for the possibility of spillover effects, but mainly so for statistical reasons and not because of an intrinsic interest. Most of these studies simply assume that the accessibility measure chosen will capture the actual spatial interaction between locations. While these studies regularly demonstrate the presence of spatial effects, they do not provide information that help establish the critical distance beyond which these effects become negligible. Similarly, an assessment as to whether and/or how the strength of population–employment interactions change with distance is rarely addressed.

The remainder of this chapter is organised as follows. The next section presents a literature review about the assumptions made and evidence found for the friction effect of distance in spatial interactions. Subsequent sections describe the data, measurement of population and employment growth, and selection of ESDA techniques, respectively, followed by a discussion and evaluation of the results of the analysis. The chapter ends with a summary and conclusions.

Literature review

The literature deemed relevant for this study can broadly be distinguished into three groups. The first group consists of studies that focus on spatial interaction and accessibility, and which assume a particular distance decay profile. The second group consists of studies that have derived the friction effect of distance from commuting data. The third group have addressed the same issue, but have done so by examining population and employment data and by applying spatial analytical techniques. The regular analysis of flow data and explicit spatial analysis of area data basically represent two distinct approaches for detecting spatial interaction, which are largely complementary to one another. A spatial analysis represents a good alternative when flow data are not readily available, a problem that generally becomes more urgent once the investigation gets more spatially detailed. There may also be a strong reason to prefer one approach over the other, depending on the research question being asked. The present study, for example, is first and foremost motivated by spatial differences in population and employment growth, and therefore best served by an inquiry into the spatial association among these data observations. It should be noted, though, that such investigation does not necessarily proof the existence of interaction between locations, as spatial association may result from parallel but independent changes in nearby locations (Portnov and Wellar 2004). Also, unlike an analysis of flow data, it cannot discriminate between various mechanisms (such as inter-firm, labour market, and consumer market linkages) that may lie beneath the association.

To start with the first group of studies discerned, the literature offers a variety of suggestions on how to measure accessibility (see, for example, Song 1996; Geurs and Ritsema van Eck 2001; Feser 2002 for overviews). At its core, a simple distinction can be made between cumulative-opportunity and gravity-type accessibility measures. The former give equal weight to nearby opportunities and those further away within a pre-selected boundary distance, whereas the latter discount opportunities with increasing distance so that nearer opportunities are weighted more heavily. This weighting can take on different forms. For example, the decline with distance can either be linear or varying over unit distance, as suggested by various non-linear distance decay profiles. In itself, the lack of a univocal measure in the literature is not surprising since there is no such thing as a "true" or "universal" accessibility function. Naturally, it must reflect the properties of a particular phenomenon, properties which are bound to differ from field to field (Bavaud 1998). However, even within a single field of research the measurement of accessibility is often not straightforward either. In the commuting literature, for example, the distance decay is usually assumed to be an inverse power or negative exponential function, with no strong theoretical arguments provided in favour of one specification over the other. Instead, the choice of the distance deterrence function is widely regarded to be essentially a pragmatic one, being largely influenced by the particular spatial setting. For example, it is suggested that the exponential function represents a more accurate description of the deterrence effect at short distances (intra-regional scale), whereas the power function is generally believed to be more appropriate for analysing interactions at a broader geographical (extra-regional) scale (see, for example, Fotheringham and O'Kelly 1989). Some researchers prefer a logistic decay function, which unifies the properties of a negative exponential function at short distances and inverse distance function at intermediate distances. Specifically, a logistic function produces an S-shaped curve, which starts rather flat, then becomes steeper, and subsequently gradually flatters again. The flat part at the end of this curve very much fits in with the idea that there is an absolute maximum people are willing to commute. This idea of a critical distance threshold is echoed in the so-called "Law of Commuting" (Garreau 1991), which states that "*no matter what the transportation technology, the maximum desirable commute has been 45 minutes*" (p. 89). Also the flat part, at the beginning of the S-shaped curve, has much intuitive appeal as it fits with the idea that distance decay will not start immediately, but only beyond a certain threshold. As Camstra (1996) notes: "*The selection of a job (location) and a (place of) residence are two relatively autonomous processes, as long as the distance does not become too great*" (p. 285). In fact, the idea that short distance trips give random commuter flows explains why such trips are often excluded from the estimation of spatial interaction models (Sen and Smith 1995).

The variety of ways in which the effect of distance can be conceptualised is also reflected in studies on spatial interaction and accessibility in the Netherlands. For example, Van Ham (2002) has measured employment accessibility at the level of four-digit postcodes as a rectangular (cumulative-opportunity) function that aggregates all jobs within 15-minutes, 30-minutes, or 45-minutes car travel distance, conform the idea of a critical distance threshold. Focusing on the same postcode data, Louter (2002) has used a linear decay function that ceases at 10 km Euclidean (straight-line) distance. A similar lack of agreement about which decay function reflects the friction effect of distance best can be observed in the Carlino–Mills literature. Two alternative specifications dominate the spatial econometric studies in this literature, i.e., the inverse distance function and fixed or critical distance threshold function. Choosing between these different weighting schemes is, however, just one element of the specification problem faced by these studies. The other is deciding on a particular parameter value, and again here the Carlino–Mills studies have been much divided. The common approach in these studies is to test the robustness of the model's estimation results against a variety of conventional parameter values derived from theory (see, for example, Bollinger and Ihlanfeldt 1997; Deitz 1998). Alternatively, studies have empirically derived these values by analysing commuting data (see, for example, Boarnet 1992; Boarnet et al. 2005; see also Chapter 3 of this book). What is clear is that the estimated parameter values very much depend on the data under consideration. By performing different estimations of a spatial interaction model on Dutch commuting data, Vermeulen (2003) have found considerable variation across COROP-zones for the value of the distance decay parameter. In a more recent study, McArthur et al. (2011) observe the same for Norwegian regions. They conclude that the possibilities of transferring the parameter values from one site to another, and making reasonable predications about commuting flows, remain limited.

In the aforementioned studies the spatial interaction structure is preconditioned on a chosen accessibility function. Alternatively, attempts have been made to derive this function directly from the data, which concern the second and third group of studies of this literature review. Part of the second group are various analyses on Dutch commuting data, which suggest that that these data are best described by a power function (Blijie 2004) or logistic function (Geurs and Ritsema van Eck 2001). Based on Danish commuting data, De Vries et al. (2009) conclude that neither a power function nor an exponential function reflects the distance decay in commuting very well. They estimated a piecewise power function, and found that people have rather different sensitivities toward small (< 10 km), intermediate (10–60 km), and long (> 60 km) commuting distances, which can be approximated by using a logistic distance decay function. Johansson et al. (2002, 2003) have come up with a similar finding in an analysis based on Swedish commuting data. They observed an S-shaped curve with inflexion points around the 20 minute and 45 minute time marks, with the latter corresponding remarkably well to Garreau's (1991) notion of the maximum time people are willing to commute.

Most relevant to the present study, in terms of data and methodology, is the third group of studies. This group notably includes a study by Wheeler (2001) who assumed that, if firms and workers tend to situate themselves no further than roughly forty miles apart, then the spillover effects on population and employment growth must also be confined geographically. By estimating a series of covariograms based on US county-level population and employment data, Wheeler found that cross-county growth correlations were relatively stable within forty miles, but decreased rapidly thereafter. In another study, Khan et al. (2001) argued that the spatial limits of a location's labour market can be determined by whether its population increases or decreases in response to employment changes in neighbouring locations. They concluded that the impact of employment growth on county-level population growth stretches over a three-county radius, which they considered to be consistent with standard delineations of spatial labour markets. Moreover, their findings show that the impact decreases as distance from the county increases, conform Tobler's (1970) "First Law of Geography". Specifically, employment growth of 10% raises population by 2.3% when the employment growth is in the own county, by 0.7% when this growth is in adjacent counties, and by 0.2% when this growth is two counties away. Most relevant to the present study are the ESDA-based studies by Barkley et al. (1995) and Portnov and Wellar (2004). The techniques used in these two studies of univariate spatial association closely resemble those that will be used hereafter for the analysis of bivariate spatial association. Barkley et al. (1995) used local Moran's *I* statistics to reveal similarities in growth between a central area and surrounding bands of census tracts in US functional economic areas. Their results showed significant differences in core–hinterland similarities both within and across these areas. Also, counter to the "First Law of Geography" they revealed that spatial associations not necessarily decline with distance. Finally, Portnov and Wellar (2004) investigated whether neighbouring towns in Canadian urban clusters have similar values for various indicators of socioeconomic development (higher education, homeownership, income and unemployment alongside population growth). By estimating a series of Moran's *I* statistics for various distance intervals, they found that all these indicators exhibit spatial autocorrelation (albeit with different intensities) that tends to decline as inter-town distances grow. For population growth, the autocorrelation ranges from 20–40 km in the most densely populated clusters to 60–100 km in the less densely populated clusters.

Data and variables

The employment data used in this study are taken from the "Establishment and Employment Registers" of the Northern Netherlands, which form part of the LISA database, the "National Information System for Employment" (see http://www.lisa.nl).

By means of a yearly questionnaire, these registers provide information on the locations of firms and employment in practically all economic sectors (including government, education, and healthcare, but excluding agriculture). Population data at the four-digit postcode-level are taken from the Postcode Registers of Statistics Netherlands (*Centraal Bureau voor de Statistiek*) and are based on official municipal population registers. The data analysis concentrates on employment and population changes in 939 postcode zones over the period 1994/1995–2002/2003. Distances between these zones are calculated as straight-line distances, thereby using the geographical centres of the zones' built areas as reference points. The reason for not simply using ordinary centroids, which reflect the centres of the zones' entire territories (i.e., with unbuilt land included), is that these latter seem, at least in the context of a semi-urbanised region such as the Northern Netherlands, less precise in pointing out the locations of jobs and residences.

Before discussing analytical techniques, it is important to consider how the data described above will be used since the findings may be influenced by the way in which "growth" is measured. A basic distinction can be made between growth being thought about as an additive process (absolute changes) on the one hand, and as a multiplicative process (proportional changes) on the other hand. Depending on initial population and employment levels, the focus on proportional changes may not always be particularly useful. For example, with regard to the data used in this study, the inclusion of many postcodes with rather few residents and jobs actually prevents a meaningful interpretation of proportional changes, and rules out using such measurements a priori. In particular, when measuring proportional changes, many postcodes appear "successful" simply because of their small size, and not because of the growth itself. Further, one could falsely gain the impression that postcodes with large populations and numerous jobs are fairly static by overlooking the considerable dynamics that may have taken place. Accordingly, a more intuitive picture of the spatial distribution of growth is obtained by measuring growth in absolute numbers since these are directly interpretable and comparable. However, such measurements are also not without complications. In fact, several arguments can be brought forward against a straightforward use of absolute changes, which practically all come down to the observation that initial population and employment levels can neither be entirely ignored.

First, the absolute changes in some postcodes do not allow a direct comparison with those observed in other postcodes, simply because of completely different population and employment base levels. Whereas the observed population and employment expansions could, at least in theory[18], have taken place everywhere, a similar reasoning does not apply to the some of the population and employment losses being observed. For example, the decline of 1,944 full-time jobs in postcode zone 7821

[18] In practice, though, employment growth usually owes considerably to the employment dynamics of *in-situ* firms (rather than firm start-ups and inward-moving firms). Therefore, the highest growth scores will naturally be observed in zones with considerable employment sizes (see also Hoogstra 2004, 2007).

could potentially only have been observed in 68 other postcode zones, as the remaining 870 postcode zones have lower initial employment levels. So, by the incidence of considerable employment losses alone, the distribution of growth across these postcodes cannot be regarded as a spatial random process.

Second, just as with relative changes, there will be a strong correlation with initial size (not only for negative growth, but also for positive growth), which considerably complicates the examination of a possible spatial relationship between the two growth processes. Note that for such relationship to be confirmed, neighbouring postcodes must show similar values for population and employment growth. However, this can only be observed in case these postcodes have rather similar population and employment levels. In other words, the patterns of spatial association will be governed by the spatial configuration of the postcodes' employment and population *sizes*, rather than their *changes*, which means the spatial nature of population–employment interaction is likely to remain undetected.

To accomplish the seemingly impossible task of comparing growth among postcodes that are basically not comparable, there are different ways to proceed. First, the analysis may be limited to observations with similar sizes to facilitate comparison. For instance, the sample may be restricted solely to postcodes that meet a minimum population and employment level. In this way, "empty" postcodes are excluded from the analysis. Second, the absolute changes may be standardised to permit a reasonable comparison between *all* observations. The latter approach leaves the datasample intact and overall appears to be more constructive in managing differences in growth and variability with respect to size.[19] Having observed a similar relation between size and various growth indicators for US counties, Wheeler (2001) suggests standardising absolute growth by the mean and standard deviation calculated from a group of reference observations that correspond to a particular size class. Here, the same method will be adopted, but with a slight modification with regard to the selection of these size classes. Rather than calculating the relevant statistics for a limited number of exclusive size classes, a more advantageous approach is used that allows for moving or overlapping size classes.

Determining which observations belong to a particular reference group and size class is facilitated by the use of a matrix that depicts differences in size for each pair of observations. The approach is comparable to the application of a spatial weights matrix that reflects pair-wise distances in the spatial domain, but for a different conceptualisation of the "distance" between locations.[20] Applying the *k*-nearest

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[19] Aggregating postcodes into larger regions in order to increase the minimum population and employment size was not considered feasible. First, this study explicitly aims to study growth patterns at the postcode level, and second, the difficulties related to the size–growth relationship would not necessarily be eased.

[20] While employed here for practical reasons, non-geographic distance matrices are also used for substantive reasons. For example, Brett and Pinkse (1997) used a distance matrix that depicts differences in municipality size in a study of tax rates (Brett and Pinkse 1997) and Conley and Topa (2002) used a distance matrix that depicts differences in occupational structure and racial composition of census tracts in a study of unemployment rates.

neighbours criterion yields a binary matrix that reveals for each observation i the respective group of reference observations j (for which $w_{ij} = 1$). Formally, the transformed values of postcode growth are calculated by the following formula:

$$x_i^* = \frac{x_i - \left(\dfrac{w_{ij} x_j}{\sum_j w_{ij}} \right)}{\left(\dfrac{\sum_j (w_{ij} x_j^{\,2}) - (\sum_j w_{ij} x_j)^2}{(\sum_j w_{ij}) - 1} \right)^{0.5}} \tag{5}$$

where
$w_{ij} = 1$ if $d_{ij} \le D_i(k)$ and $w_{ij} = 0$ otherwise;
$k = 120$ ($\sum_j w_{ij} = 120$);
$d_{ij} = |(x_{i,t} + x_{i,t-1}) - (x_{j,t} + x_{j,t-1})|$ and
$x_i = x_{i,t} - x_{i,t-1}$.

Above, x_i is the change in the population (employment) size of postcode i between 1994/1995 ($x_{i,t-1}$) and 2002/2003 ($x_{i,t}$), which is standardised by the mean and standard deviation of the population (employment) changes in 120 postcodes that are "nearest" to i in terms of the population (employment) size. The decision to standardise with 120 observations is made to ensure a significant basis for comparison and fairly homogenous reference groups.[21]

Standardising the original data on population and employment changes has some major advantages in relation to the application of statistical techniques for detecting spatial association. Most importantly, it sanctions recomputing the values of individual observations in conjunction with those of its neighbours through a row-standardised spatial weights matrix, which is the preferred way to implement these tests (Anselin 1988, 2002). However, row-standardisation also puts considerable emphasis on the neighbourhood structure of locations. The implications of this for the results of the analysis are discussed later in this chapter.

Finally, it is worth noting that the standardised population and employment growth values compare reasonably well with those that would be obtained by a logarithmic transformation (compare C and D in Tables 10 and 11). Logarithmic transformations are commonly used in studies of firm growth, (e.g., Hoogstra 2004), regional and urban growth (e.g., Combes 2000), as well as in several Carlino–Mills studies (e.g., Carruthers and Mulligan 2007).

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[21] Obviously, even greater homogeneity could be obtained by allowing the k-number of neighbours to vary for each observation. For the purposes of this study, this more complicated approach was not considered necessary.

Table 10. Summary statistics alternative growth measures

	Mean	St. dev.	Min.	Median	Max.	Kurtosis	Skewness
Population growth variable (*P*)							
A	77.27	380.76	–1350.00	10.00	5355.00	54.65	5.33
B	0.13	1.12	–0.50	0.02	26.00	367.76	17.96
C	0.05	0.25	–0.69	0.02	3.30	63.83	6.41
D	0.03	1.14	–2.88	–0.12	12.86	30.08	4.03
Employment growth variable (*E*)							
A	95.88	340.40	–1944.00	9.00	3811.00	39.65	5.11
B	0.62	1.99	–0.86	0.21	32.11	103.93	8.86
C	0.27	0.53	–1.95	0.19	3.50	6.45	1.41
D	0.06	1.08	–3.50	–0.04	5.82	3.32	0.89

A = $x_{i,t} - x_{i,t-1}$; B = $(x_{i,t} - x_{i,t-1})/\, x_{i,t-1}$; C = $\ln(x_{i,t}/x_{i,t-1})$; D = x_i^* ; see also equation (5).

Table 11. Correlation coefficients alternative growth measures (Pearson's *r)*

	A–B	A–C	A–D	B–C	B–D	C–D	A–A	B–B	C–C	D–D
P	0.31	0.49	0.67	0.82	0.63	0.84				
E	0.08	0.15	0.53	0.78	0.58	0.83				
P, E							0.20	0.37	0.28	0.30

See below Table 10 for the meaning of abbreviations.

Measuring bivariate spatial association

In this study, an *Exploratory Spatial Data Analysis* (ESDA) is used to examine the relationship between population and employment changes. An ESDA is especially suited for such investigation since it has at its core a formal treatment of the concept of spatial dependence, which points to the propensity for nearby locations to influence each other and to possess similar attributes (Anselin 1988). Spatial dependence is traditionally associated with univariate spatial dependence, or spatial autocorrelation, which measures the extent to which spatial similarity is matched by attribute or value similarity for a single variable. Over the years, most endeavours in ESDA have concentrated on developing alternative autocorrelation statistics, extending the measurement of spatial autocorrelation to a local setting, elaborating on significance testing methods, and proposing related graphical and mapping techniques. Until recently, similar progress had not been made for the analysis of multivariate spatial dependence, which measures the extent to which values for one variable (say population growth) observed at a given location show a systematic relationship with the values of another variable (say employment growth) observed in the neighbourhood of that location. However, the need to do so had been long recognised with the first attempts dating back to the beginning of the 1980s when Hubert and Golledge (1982) and Hubert et al. (1985) proposed a non-parametric bivariate spatial association measure.[22] Also at that time, Wartenberg (1985) made the first comprehensive attempts to formulate a parametric bivariate spatial association measure. He suggested a matrix algebraic form for a bivariate Moran's *I*, which was later called Cross-Moran's *I* by Griffith (1993, 1995). It was, however, not until some fifteen years after Wartenberg's pioneering work that the greatest strives towards the integration of bivariate spatial association in ESDA were made, mainly thanks to Lee (2001a, b; 2004). Lee (2001a, b) not only introduced an alternative parametric bivariate spatial association statistic, called *L*, to Cross-Moran's *I*, he also demonstrated that these measures basically combine two standard association measures: Pearson's *r* for the point-to-point association between two variables and Moran's *I* for the spatial association of a single variable. Moreover, he extended techniques on the visualisation of spatial autocorrelation to a multivariate setting by suggesting a bivariate Moran scatterplot matrix and associated cluster and significance maps (Lee 2001b). Finally, Lee (2004) can be accredited with successfully extending the Mantel test (Mantel 1967), thereby providing a generalised significance testing method that can be applied to any form of spatial association (both univariate and bivariate), irrespective of the spatial weights matrix being used.[23]

Global bivariate spatial association

The analysis in this study starts with the formal testing of dependence, against the alternative hypothesis of spatial randomness in the postcode-level distribution of population and employment growth. For two variables of interest, *X* (say population growth) and *Y* (say employment growth), the literature offers a variety of cross-product statistics that can be used to test whether or not spatial association exists (see Table 12) The salient feature of these indices, which distinguishes them from non-spatial association measures, is that at least one of the variables contains "continuous spatial data", i.e., data that are weighted across spatial observations (Bailey and Gatrell 1995). For example, in Table 12, $\tilde{x}_i$ and $\tilde{y}_i$ denote the spatially weighted growth values of observation *i*, calculated as $\sum_j w_{ij}x_j$ and $\sum_j w_{ij}y_j$ respectively, where w_{ij} correspond to the column elements *j* in row *i* of a spatial weights matrix *W*. Importantly, the spatial weights matrix can be specified in different ways, reflecting different assumptions about the possible interaction between pairs of observations (see, for example, Bavaud 1998; Stakhovych and Bijmolt 2009). Here, it is specified as a fixed distance matrix that defines for each observation *i* the observations *j* that are within (w_{ij} = 1), respectively outside (w_{ij} = 0) a particular distance range. About this range, $\tilde{x}_i$ and $\tilde{y}_i$ are calculated

[22] Notice that the cited lack of progress only applies to the analysis of multivariate spatial correlation for lattice data, i.e., spatial objects represented as fixed points or polygons. In geostatistics, where the spatial data used represent sample points from a continuous surface, techniques for determining spatial cross-correlation, such as using a variogram, have long been available.

[23] Previously, researchers had difficulties in dealing with spatial weights matrices containing nonzero diagonal elements, and determining an appropriate significance testing method.

by using multiple matrices that reflect different distance intervals (i.e., 0–10 km, 0–20 km, 0–30 km, etc.) to reveal the changes in spatial association with distance.

With regard to the construction of the spatial weights matrices, two issues merit further discussion. The first is whether to row-standardise these matrices so that the row elements sum up to one. If one uses standardised data on population and employment changes, one cannot use an unstandardised weights matrix, as summing these data offers no meaningful interpretation. With row-standardisation, the obtained values can simply be read as *average* growth scores of neighbouring locations. The second issue is whether to set the diagonal elements of the weights matrix to zero or not. This issue reflects two different perspectives on how to measure spatial dependence: one comparing a reference area with its neighbours and the other comparing a reference area with a focal set that not only includes its neighbours but also the reference area itself (Lee 2004). The former approach corresponds to a spatial lag (SL) operation and is common in univariate spatial association measures. However, such approach may not be appropriate in a bivariate setting. From studies focusing on accessibility, for instance, it is well known that using a focal set that excludes the own location may be give spurious results. Specifically, it may produce a "donut-shaped" map pattern where accessibility is lower in the inner area than in the outer area (Kelly and Horner 2003). Here, a similar reasoning applies, but mainly due to the way in which the spatial transformations are performed. That is, rather than reflecting rings of exclusive distance zones (e.g., 0–10 km, 10–20 km, etc) the selected spatial matrices reflect overlapping distance zones, i.e., with increasing distance radii. By using row-standardised matrices with non-zero elements on the main diagonal, the spatial transformations performed in this study take the form a spatial moving average (SMA) operation.

The cross-product statistics of bivariate spatial association shown in Table 12 produce different information about the spatial relationship between two variables. The quasi-spatial Pearson's *r* statistics correspond to a regular correlation coefficient, but with either one or both of the variables being spatially weighted. A similar distinction applies to the truly spatial measures of association, with one of the variables being spatially weighted in Cross-Moran's *I* and both variables in Lee's *L*. For the purposes of this study, the one-sided weighted association measures provide the most meaningful information, as they reveal whether local growth for one variable is systematically related to growth in and around that locality for the other variable. If the estimated cross-statistics are positive and significant, nearby localities evidently have similar attribute values and local and regional dynamics move in the same direction. A negative but significant statistic would also confirm a systematic arrangement of the attribute values in space. However, rather than providing evidence for the spatial clustering of similar attribute values this would indicate the clustering of dissimilar values (negative association), which is against the presumption that local population (employment) growth and regional employment (population) growth go hand in hand. Likewise, this

Table 12. Global measures of bivariate spatial association

Statistic	Summation notation
Quasi-spatial measures	
1. One-sided Pearson's *r*	$r_{X,\tilde{Y}} = \dfrac{\sum_i (x_i - \bar{x})(\tilde{y}_i - \bar{\tilde{y}})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (\tilde{y}_i - \bar{\tilde{y}})^2}}$
2. Two-sided Pearson's *r*	$r_{\tilde{X},\tilde{Y}} = \dfrac{\sum_i (\tilde{x}_i - \bar{\tilde{x}})(\tilde{y}_i - \bar{\tilde{y}})}{\sqrt{\sum_i (\tilde{x}_i - \bar{\tilde{x}})^2}\sqrt{\sum_i (\tilde{y}_i - \bar{\tilde{y}})^2}}$
Truly spatial measures	
3. Cross-Moran's *I* (one-sided)	$I_{X,\tilde{Y}} = \dfrac{\sum_i (x_i - \bar{x})(\tilde{y}_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}}$
4. Lee's *L* (two-sided)	$L = \dfrac{\sum_i (\tilde{x}_i - \bar{x})(\tilde{y}_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}}$

See main text for the meaning of variables $X, Y, \tilde{X}, \text{and}\, \tilde{Y}$. In the summation notation of the truly spatial measures the factor *n*/*S* (with *n* being the number of observations and *S* the sum of all elements of matrix *W*) is excluded, because *n* = *S* in a row-standardised matrix.

presumption is rejected in case of a statistically insignificant coefficient, which indicates a random arrangement of attribute values. The fundamental difference between the pseudo and truly spatial measures is that the former essentially assess numerical covariance, without consideration of the variances in the values of individual locations that make up a focal set (Lee 2001a). By contrast, in the truly spatial association measures, spatially varying variances or local instabilities are as crucial as spatially varying averages. To illustrate this difference, Lee introduced the concept of a spatial smoothing scalar (*SSS*), which he defined "*as the degree of spatial smoothing when a geographical variable is transformed to its spatially smoothed vector in which each observation is recomputed in conjunction with its neighbours as defined in a spatial weights matrix*" (2001b, p. ii). When using a row-standardised weights matrix, the spatial smoothing scalar is calculated as:

$$SSS_X = \frac{\sum_i (\tilde{x}_i - \bar{\tilde{x}})^2}{\sum_i (x_i - \bar{x})^2} \tag{6}$$

From the equation above it can be seen that an *SSS* measures the ratio of two sums of squares: the spatially weighted variable's variance to the original variable's variance. By revealing the proportion of a variable's variance that remains after the variable is spatially smoothed, the concept is equivalent to that of a variance-reducing factor in general smoothing techniques (see, for example, Loader 1999). The *SSS* can be interpreted as a direction free univariate spatial association (autocorrelation) measure that theoretically ranges between 0 and 1. If a variable is spatially clustered its *SSS* is large, because the variance of the original vector is less reduced when it is spatially smoothed. Moreover, in combination with Pearson's correlation coefficient r the *SSS* can be used to calculate the truly spatial measures of bivariate spatial association, Cross-Moran's I and Lee's L. Specifically, Lee (2001a, b; 2004) has shown that the following formulas apply:

$$I_{X,\tilde{Y}} = \sqrt{SSS_X} \cdot r_{X,\tilde{Y}} \tag{7}$$

$$L = \sqrt{SSS_X} \cdot \sqrt{SSS_Y} \cdot r_{\tilde{X},\tilde{Y}} \tag{8}$$

Local bivariate spatial association

The statistics discussed so far are global statistics that reveal average spatial association over a whole study area and as such do not allow an assessment of local structures of spatial association. However, one may be interested in specific local spatial clusters of high and low values, locations that contribute most to the global association, and atypical localisations or "pockets of nonstationarity" that remain masked in the global measures of association. Here, two complementary ESDA tools are used to assess local patterns of bivariate spatial association. The first is a Moran scatterplot for multivariate data (Anselin 1996), which plots the standardised spatial moving average values of one variable (vertical axis) against the standardised, unweighted, "local" values of the other variable (horizontal axis). With a mean of zero and standard deviation of one by construction, these scores can be interpreted as multiples of standard deviational units. Accordingly, outliers and leverage points can easily be made out. Also, the scatterplot provides an easy way to visualise global spatial association, since the slope coefficient of a linear regression corresponds to Cross-Moran's I (provided the spatially weighted scores are calculated by a row-standardised matrix, as in this study). Finally, the standardisation allows four types of spatial association to be distinguished: high–high (HH) association in the upper right quadrant, low–low (LL) association in the lower left quadrant, high–low (HL) association in the lower right quadrant, and low–high (LH) association in the upper left quadrant, where "high" and "low" refer to above-average and below-average scores, respectively. The spatial clustering of similar values in HH and LL points at positive spatial association, whereas that of dissimilar values in HL and LH indicates negative spatial association.

The second technique used to assess location patterns of bivariate spatial association involves the estimation of a local version of Cross-Moran's I, which is formally specified in equation (9). A Cross-Moran's I for individual observations corresponds to what is called a "Local Indicator of Spatial Association" or LISA (Anselin 1995), which serves two purposes. First, similar to the use of a Moran scatterplot, a LISA informs about the extent of local instability by assessing the contribution of each individual observation to the global indicator of association. From equation (10) it can be seen that Cross-Moran's I is equivalent to the average of all local Cross-Moran's Is. Second, unlike a scatterplot, a LISA allows the estimation of significance levels and assessment of the level of spatial clustering around an individual location. Among those locations that show greater similarities than indicated under spatial randomness (spatial clusters), a distinction can be made between locations that belong to the upper right quadrant (hot spots) and between locations that belong to the lower left quadrant (cold spots). In the other quadrants, spatial outliers or a-typical locations may be identified that reveal significant dissimilarity or lack of clustering of similar values, more so than would be the case in a random pattern.

$$I_{i\,(x,\tilde{y})} = n \cdot \frac{(x_i - \bar{x})(\tilde{y}_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}} \tag{9}$$

$$I_{X,\tilde{Y}} = \frac{\sum_i I_{i\,(x,\tilde{y})}}{n} \tag{10}$$

Results

Global bivariate spatial association

The discussion of findings starts with the variance reducing effects that stem from smoothing the values of employment growth and population growth across neighbouring postcode zones. From Table 13 two findings stand out. First, the variables' variances decrease very quickly. Using a very narrow neighbourhood criterion of only 2 km already reduces the original variances to 52% and 38%, respectively. Moreover, less than 5% of the variances remain after the variables' values are averaged across observations that lie within a 10 km distance radius. Second, the degree of smoothing at short distances is particularly strong for population growth, which means that nearby locations show greater similarities for employment growth than for population growth. In other words, employment growth appears to be less fragmented and more spatially clustered than population growth, a finding that has also been observed by Van Oort (2002) for Dutch municipalities as well as for four-digit postcode-zones in the province of South-Holland. The results can be taken as a confirmation of the idea that, at least in the Netherlands, housing markets are tighter than business property markets (see also Rietveld and Wagtendonk 2004; Ritsema van Eck et al. 2009).

Table 13. Spatial smoothing scalars

W	$\widetilde{E}$	$\widetilde{P}$			
1 km	0.8572	0.7691	20 km	0.0142	0.0184
2 km	0.5221	0.3787	30 km	0.0074	0.0115
3 km	0.2963	0.2516	40 km	0.0043	0.0070
4 km	0.1826	0.1599	50 km	0.0025	0.0041
5 km	0.1273	0.1102	60 km	0.0016	0.0025
6 km	0.1024	0.0915	70 km	0.0010	0.0013
7 km	0.0780	0.0753	80 km	0.0005	0.0005
8 km	0.0625	0.0612	90 km	0.0001	0.0001
9 km	0.0494	0.0552	100 km	0.0000	0.0000
10 km	0.0425	0.0465			

See equation (6) for measurement of the smoothing scalars; $\widetilde{E}$ and $\widetilde{P}$ denote the spatial moving average standardised employment and population growth variables, respectively.

Table 14. Spatial association statistics

	Pearson's r			Cross-Moran's I		Lee's L
W	$P-\widetilde{E}$	$\widetilde{P}-E$	$\widetilde{P}-\widetilde{E}$	$P-\widetilde{E}$	$\widetilde{P}-E$	$\widetilde{P}-\widetilde{E}$
1 km	0.2686	0.2806	0.3026	0.2487	0.2461	0.2457
2 km	0.1639	0.1814	0.2592	0.1184	0.1116	0.1152
3 km	0.1610	0.1632	0.2957	0.0877	0.0819	0.0808
4 km	0.1385	0.1409	0.3569	0.0592	0.0563	0.0610
5 km	0.1311	0.1267	0.4178	0.0467	0.0421	0.0495
6 km	0.1352	0.1301	0.4452	0.0432	0.0393	0.0432
7 km	0.1249	0.1235	0.4868	0.0348	0.0339	0.0374
8 km	0.1341	0.1415	0.5336	0.0335	0.0350	0.0330
9 km	0.1332	0.1326	0.5512	0.0296	0.0311	0.0288
10 km	0.1339	0.1282	0.5980	0.0276	0.0276	0.0266
……..	……..	……..	……..	……..	……..	……..
20 km	0.1158	0.1048	0.7207	0.0137	0.0142	0.0117
30 km	0.1049	0.0910	0.7393	0.0088	0.0096	0.0069
40 km	0.0745	0.0676	0.7686	0.0047	0.0055	0.0043
50 km	0.0721	0.0655	0.8269	0.0033	0.0040	0.0027
60 km	0.0682	0.0608	0.9065	0.0024	0.0028	0.0018
70 km	0.0478	0.0351	0.9474	0.0013	0.0011	0.0011
80 km	–0.0009	–0.0061	0.9470	0.0000	–0.0001	0.0004
90 km	–0.0125	–0.0119	0.9192	–0.0001	–0.0001	0.0001
100 km	–0.0238	–0.0193	0.8806	–0.0001	–0.0001	0.0000

P, E (W_0 km) = 0.3033; see also Table 11.

Table 15. Pseudo-significance Cross-Moran's *I* (9,999 permutations)

	$P-\widetilde{E}$			$\widetilde{P}-E$		
W	mean	St.dev.	p-value	mean	St.dev.	p-value
1 km	0.2725	0.0176	0.9022	0.2729	0.0175	0.9226
2 km	0.1785	0.0271	0.9904	0.1784	0.0267	0.9961
3 km	0.0995	0.0231	0.7008	0.0999	0.0234	0.8054
4 km	0.0549	0.0156	0.3871	0.0550	0.0157	0.4631
5 km	0.0362	0.0126	0.2030	0.0362	0.0124	0.3126
6 km	0.0257	0.0104	0.0551	0.0257	0.0104	0.1056
7 km	0.0190	0.0088	0.0448	0.0191	0.0089	0.0532
8 km	0.0145	0.0074	0.0117	0.0145	0.0075	0.0059
9 km	0.0115	0.0066	0.0083	0.0119	0.0068	0.0170
10 km	0.0092	0.0060	0.0280	0.0093	0.0060	0.0040
……..	………	………	………	………	………	………
20 km	0.0024	0.0030	0.0011	0.0023	0.0029	0.0004
30 km	0.0010	0.0020	0.0012	0.0010	0.0020	0.0009
40 km	0.0005	0.0014	0.0116	0.0005	0.0014	0.0035
50 km	0.0003	0.0010	0.0125	0.0003	0.0011	0.0064
60 km	0.0002	0.0008	0.0131	0.0002	0.0008	0.0066
70 km	–0.0003	0.0005	0.3800	–0.0003	0.0005	0.5800
80 km	–0.0003	0.0004	0.7570	–0.0003	0.0004	0.4860
90 km	–0.0003	0.0002	0.4100	–0.0003	0.0003	0.4180
100 km	–0.0003	0.0001	0.3310	–0.0003	0.0001	0.2310

The variance reducing effects shown in Table 13 give some essential information for the remainder of this study. Specifically, they indicate a severe lack of univariate association, which implies that the one-sided tests will also show rather low levels of bivariate spatial association. Note that for a strong bivariate relationship, locations with similar values for one of the variables must also have similar values for the other variable. In the one-sided tests, the great similarity in values of neighbouring locations that can naturally be observed for the spatially weighted variable is missing for the other variable, as the tests above clearly indicate. Moreover, as the values of neighbouring locations for the spatially weighted variable become more similar with increasing levels of spatial smoothing, the strength of the relationship naturally decreases with distance. Naturally, this pattern of decline is most profound for Cross-Moran's *I*, as the decrease in numerical covariance is further downsized by the decline in the spatially weighted variable's *SSS*.

Confirmation of what can logically be expected following the results for the smoothing scalars is given in Table 14, which reveals how the bivariate spatial associations change with increasing distance radii. When focusing on the results of the one-sided tests, two findings stand out. First, it hardly differs as to whether the relationship between a postcode's own growth and growth in the wider region of that postcode is examined from a population or employment perspective (compare the first column of estimation results with the second and the fourth with the fifth). Second, the substantial decline in univariate association at short distances (1–2 km) observed earlier can also be observed for bivariate association. The level of association measured by Pearson's *r* remains relatively stable within the 4–10 km range (and later on within the 40–60 km range), whereas for Cross-Moran's *I* the results indicate a continuous decline over distance.

Particularly interesting about the estimates shown in Table 14 is whether they are statistically significant, as this would indicate a systematic spatial relationship between population and employment growth. In other words, it is asked whether the tendency of neighbouring locations to have similar growth values (i.e., more similar than between locations that are further apart) is sufficiently strong that it is unlikely to be due to chance alone. Statistical significance can be determined by means of a permutation approach, which involves randomly reshuffling the data and recomputing a particular statistic in order to assess the likelihood of a particular outcome for that statistic.

Table 15 reveals the mean and standard deviation of the Cross-Moran's *I* statistic, obtained by performing 9,999 permutations (using the algorithm for generating spatially random data sets available in *GeoDA* [Anselin et al. 2006]). In addition, pseudo p-values are given that indicate the likelihood of the estimated statistics presented in Table 14. These p-values are calculated as the ratio of the number of statistics for the randomly generated data sets that equal or exceed the estimated statistic + 1, over the number of permutations used + 1. For example, the pseudo p-value of 0.3871 for 4 km in the fourth row of Table 15 reveals that 3,870 random data sets produce Cross-Moran's *I*s similar to or larger than 0.0592. Thus, in this particular case it is found that the data can be reshuffled without really affecting the information content of the data. In other words, the observed spatial pattern of growth values across the postcode zones is equally likely as any other spatial pattern. An example of Cross-Moran's *I* that is significant at conventional statistical levels can be seen in the ninth row of Table 15. Here, the value of 0.0083 indicates that the level of association observed between local population growth and spatially weighted average employment growth within a 9 km distance radius (as revealed by a Cross-Moran's *I* of 0.0296) is rather special, being matched in only 82 out of 9,999 permutations. Likewise, just 3 permutations produce at least the same the level of spatial association shown by the real data for local employment growth and spatially weighted population growth within a 20 km distance radius. Overall, the findings clearly indicate the presence of spillover effects between postcode zone in the population–employment interaction. The estimated Cross-Moran's *I* statistics are significant at the 0.05 level for distance radii that range from 7 km to 60 km. Accordingly, at rather short distances (< 7 km) no systematic relationship can be observed between local population (employment) growth and employment (employment) growth of neighbouring locations, which is in line with the idea that short distances given random commuter flows. Similarly, the observed maximum distance of 60 km beyond which Cross-Moran's *I* becomes insignificant corresponds remarkably well the findings from previous studies, such as those by De Vries et al. (2009) for Danish commuting data. Using the level of association at the 10 km range as the baseline, one can infer that the level of association is halved after 25 kilometres, and decreased by some 80% after 40 kilometres.

Local bivariate spatial association

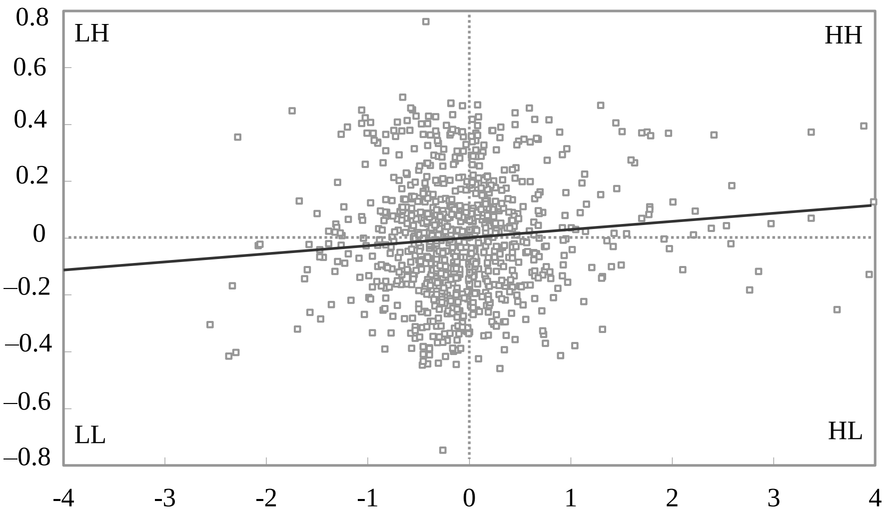
The local measures of association add some useful information to the global patterns of association outlined above. Below, findings for these local measures are discussed based on a 10 km neighbourhood criterion, the distance beyond which the global association statistics overall decline. From Figures 5 and 6, which plot the standardised values of the spatial moving average scores for one variable (vertical axis) against standardised values of the original "local" scores for the other variable (horizontal axis), it can be seen that the postcode observations are rather evenly distributed over the four quadrants of the respective scatterplots (as also revealed by the practically flat regression lines, of which the slope coefficient corresponds to Cross-Moran's *I*). As for the association between local population growth and "regional" employment growth (Figure 5), a mere 54.3% of the postcodes show the theoretically predicted association of similar values (22.4% in quadrant HH and 31.9% in quadrant LL), while for 45.7% of the postcodes the spatial association is negative (27.7% in quadrant LH and 18.0% in quadrant HL). Positive association is even less when local employment growth is related to regional population growth (see Figure 6): 51.8% of the postcodes belong to either quadrant HH (22.9%) or quadrant LL (28.9%), and 47.9% of the postcodes belong to either quadrant LH (26.0%) or quadrant HL (21.9%). Apparently, local population growth but especially local employment growth is hardly influenced by growth in the wider region.

Figures 7 and 8 combine a significance and scatterplot map to display the spatial distribution of the four types of spatial association, while highlighting the observations for which the local Cross-Moran's *I* is statistically significant at the 0.05 level. To facilitate identification of the broad (regional) trends of employment growth (Figure 7) and population growth (Figure 8), the postcodes in the lower two and upper two quadrants of the scatterplots are shaded in contrasting colours (white and light-grey versus black and dark-grey, respectively). From Figure 7 it can be seen that the spatial moving average employment growth among postcodes within a 10 kilometres radius has been above average mainly in the southern part of Fryslân, the area stretching from Groningen to Assen, the southwestern part of Drenthe (in and around Meppel), and parts of the border region with Germany.[24] Most of these postcode zones also appear in Figure 8 as zones with above-average SMA scores for population growth, notably in the

[24] See Appendix IV for a map showing the locations of places and areas referred to.

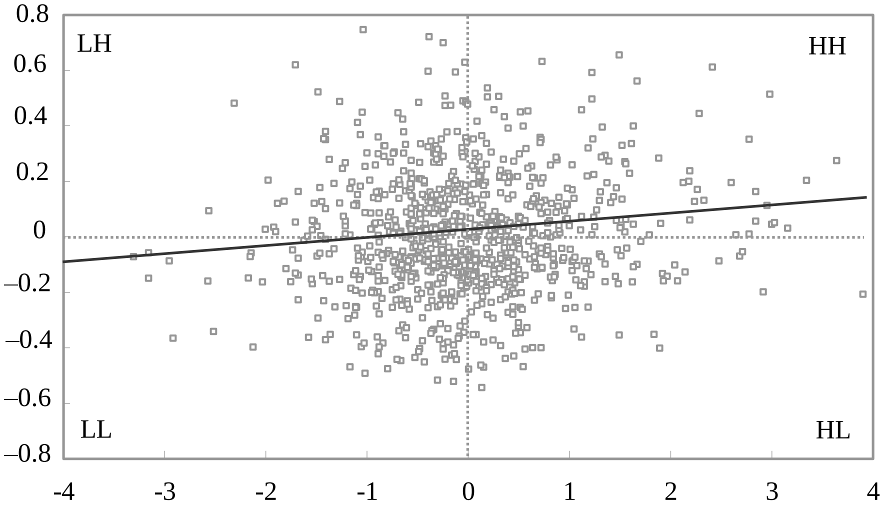
southern part of Fryslân and in the cities and immediate surroundings of Groningen, Assen, and Meppel. In contrast to Figure 7, much of the western and southern parts of Drenthe are now darkly coloured, whereas postcodes in the north of Drenthe and along the border with Germany no longer reveal above-average SMA scores. Similar to Figure 7, the spatially weighted scores are below average in a band of peripheral postcodes along the northern shore, stretching all the way from Fryslân to Groningen. A more instant view of the similarities and dissimilarities among the SMA values for the different growth indicators can be obtained from a so-called *L*-scatterplot map (Lee 2001a). Such map corresponds to a multivariate scatterplot in which both variables are spatially weighted (i.e., the vertical axes of Figures 5 and 6 are combined). From Figure 9 it appears that the movement southwards in Fryslân is particularly strong in terms of population growth. For many postcodes along the Leeuwarden–Groningen axis, as well as in the west of Fryslân, the SMA scores for population growth lag behind those for employment growth, which is quite the opposite in the southwest of Fryslân. Also in the province of Drenthe, relatively many postcodes show a discrepancy in SMA scores, in favour of employment growth in the north and east and in favour of population growth in the west and south. In case of the province of Groningen, hardly any of such discrepancies can be observed, apart from some postcodes in the east and southeast. Here, the overall pattern is very clear: SMA scores are above-average in the “urban core” (Groningen-city) and below-average in the more peripheral areas.

The most striking observation to emerge from the scatterplot maps is the patchwork or mosaic pattern of local population growth (Figure 7) and employment growth (Figure 8). Neighbouring postcodes that belong to one and the same labour market zone clearly experience rather contrasting local growth. Because locations in quadrants HH and LL perform as expected, the atypical locations in quadrants HL and LH provide the greatest puzzle. Note that there is an important difference between locations belonging to quadrant HL and locations belonging to quadrant LH. The former have performed well against the odds, whereas the latter have performed below par considering growth in the wider region has been above average. The results here indicate that the former type of association is more common for local employment growth than for population growth. Of the 480 postcodes with below-average SMA scores for population growth (LL and HL in Figures 6 and 8), 43.5% still had achieved greater-than-average local employment growth. In comparison, local population growth has been above average in 36.0% of the 469 postcodes with below-average SMA scores for employment growth (LL and HL in Figures 5 and 7). Thus, while it appears that both population growth and employment growth can do without each other, this seems to apply to employment growth in particular. Interestingly, the local performance of postcodes is mostly unexpected in the better performing regions. Only 44.7% of the 470 postcodes with above-average SMA scores for employment growth (470) have also local scores for population growth that are above average. Similarly, only 46.8% of the 459 postcodes with above-average SMA scores for population growth also have above-



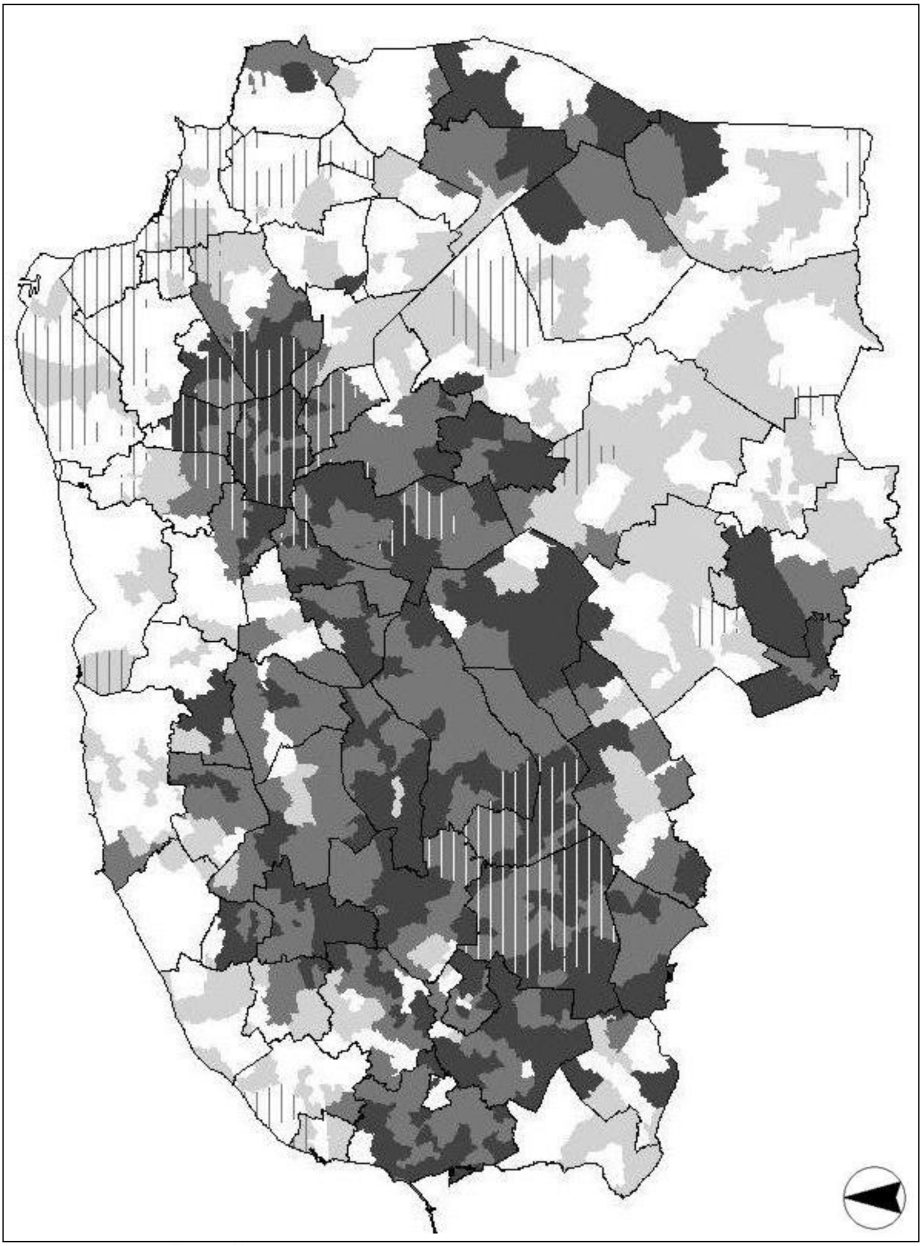
Not displayed, but included in the calculation of the regression line: 9213 [De Wilgen]: (4.2, 0.0); 9734 [Groningen]: (4.5, 0.4); 8448 [Heerenveen]: (4.9, 0.5); 8919 [Leeuwarden]: (5.3, 0.1); 9746 [Groningen]: (5.8, 0.4); 8445 [Heerenveen]: (6.2, 0.4); 9085 [+9086+8939] [Teerns/Hempens/Leeuwarden]: (6.6, 0.0); 9403 [Assen]: (6.7, 0.0); 8494 [Nes]: (7.9, 0.2); 9735 [Groningen]: (11.3, 0.4).

Figure 5. Bivariate Moran scatterplot: local population growth (x-axis) versus spatial moving average employment growth (y-axis), *W*_10



Not displayed, but included in the calculation of the regression line: 9735 [Groningen]: (4.0, 0.3); 9723 [Groningen]: (4.2, 0.2); 9085 [+9086+8939] [Teerns/Hempens/Leeuwarden]: (4.6, 0.1); 8448 [Heerenveen]: (5.2, 0.4); 8466 [Nijehaske]: (5.4, 0.4).

Figure 6. Bivariate Moran scatterplot: employment growth (x-axis) versus spatial moving average population growth (y-axis), *W*_10

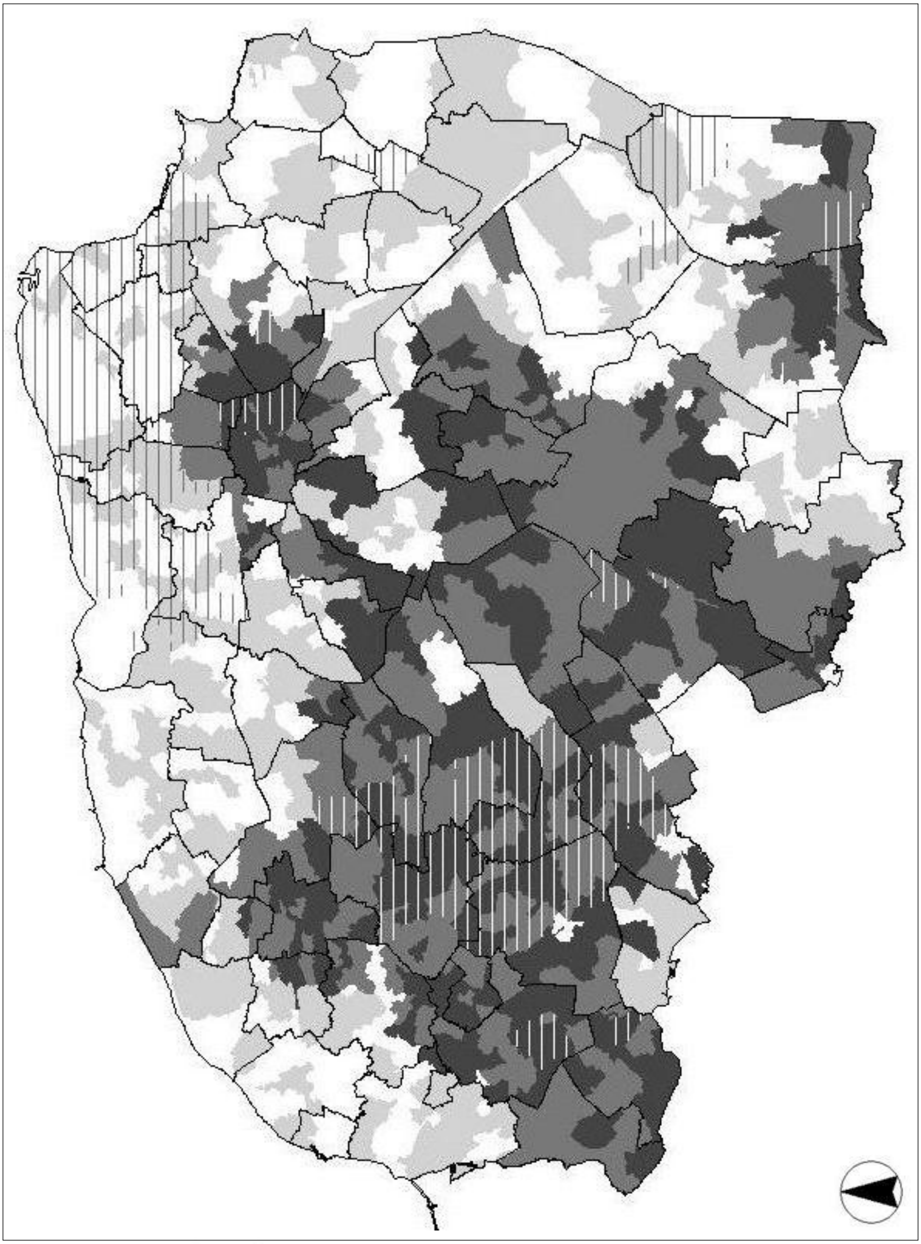


Not significant: HH (159) LL (253) LH (204) HL (156)

Significant (0.05-level): HH (51) LL (47) LH (56) HL (13)

See Figure 5 for the meaning of categories

Figure 7. Bivariate Moran scatterplot and significance map: population growth (H/L) versus spatial moving average employment growth (H/L), *W*_10



Not significant: HH (174) LL (216) LH (199) HL (177)

Significant (0.05-level): HH (41) LL (55) LH (45) HL (32)

See Figure 6 for the meaning of categories

Figure 8. Bivariate Moran scatterplot and significance map: employment growth (H/L) versus spatial moving average population growth (H/L), *W*_10

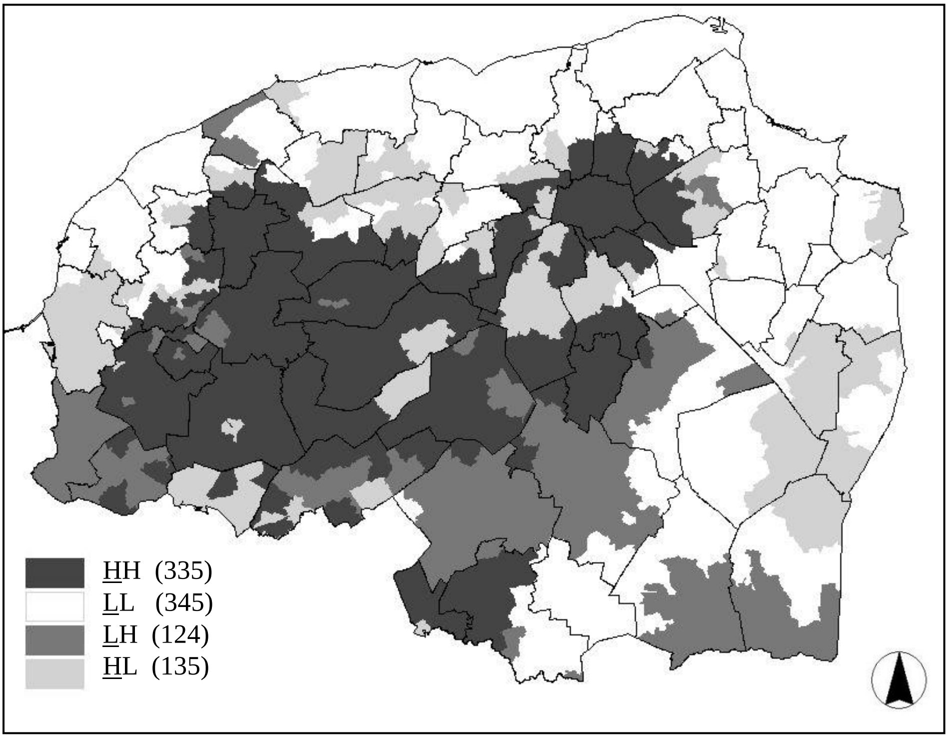


Figure 9. *L*-scatterplot map: spatial moving average employment growth (H/L) versus spatial moving average population growth (H/L), *W*_10

average local employment growth scores. A natural conclusion is that there are factors at work that hold back local growth, and especially local population growth. Even though practically the same percentages of postcodes are "underperforming" in terms of both population growth and employment growth, this seems somewhat less of a surprise for the latter given that the percentage of "overperforming" postcodes is also relatively large.

Evaluation and discussion

The findings obtained so far raise a number of issues that deserve further investigation. First, there is the empirical issue as to whether land use regulation and zoning policies hindering local population growth has been crucial in shaping the patterns of spatial association. Second, there is concern about the way these patterns have been analysed given doubts recently expressed in the population–employment interaction literature as to whether using a row-standardised matrix is appropriate (see also Boarnet et al. 2005).

To start with the former issue, data provided by Statistics Netherlands (*Centraal Bureau voor de Statistiek*) and the Netherlands Institute for Spatial Research (*Rijksplanbureau*) are used to construct a new variable that measures the postcode-level changes in housing stock during the period of study. In the context of the Netherlands these changes are a good proxy for spatial planning policies, because especially at the local level, housing construction is strongly regulated (see, for example, Vermeulen and Rouwendal 2007). Similar to the measurement of population growth, the stock change of individual postcodes is standardised by the corresponding mean and standard deviation of these changes in 120 postcodes that are “nearest” in terms of population size, so as to make a fair comparison. A correlation coefficient (Pearson’s *r*) of 0.744 definitely reveals a strong relationship between the standardised changes in population and housing stock at the postcode-level. Figure 10 shows the differences in standardised housing stock changes among the four groups of postcodes that reveal different types of spatial association (see the quadrants of Figures 5 and 7). Not surprisingly, postcodes with above-average scores for local population growth (i.e., postcodes belonging to quadrants HH and HL), generally also reveal higher housing stock growth scores (compared to postcodes that belong to quadrants LH and LL).

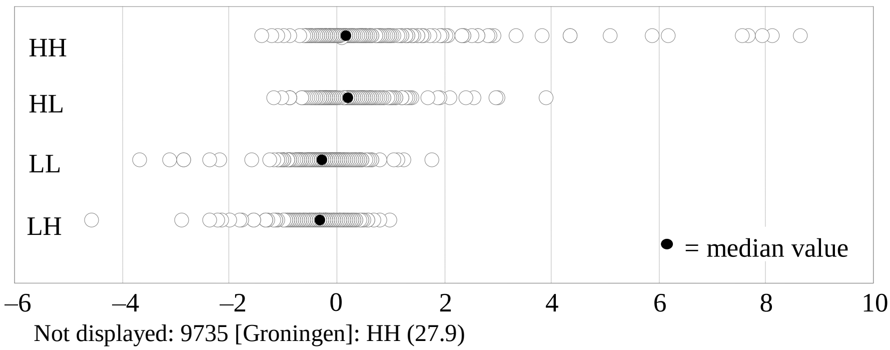


Figure 10. Standardised changes in housing stock for different categories of postcodes (corresponding to the quadrants of Figures 5 and 7)

To assess the extent to which the global patterns of spatial association so far observed have been clouded by policies that have hindered (or stimulated) population growth, the previous analysis of one-sided bivariate associations is repeated for four mutually exclusive regimes of postcode zones that reflect the quartiles of the housing stock growth variable. Figure 11 shows substantial differences in the patterns of spatial association across these groups of postcode zones. At short distances, the relationship between population growth and employment growth is particularly strong for the 235 postcodes in the upper quartile of the housing stock growth variable, which have been the least hindered (or most stimulated) by spatial policies. By contrast, the postcodes that belong to the remaining quartiles show very low levels of spatial association. Overall, these findings clearly confirm the supposed pivotal role played by policies of housing construction on the distribution of people, and on the patterns of spatial association that can be observed.

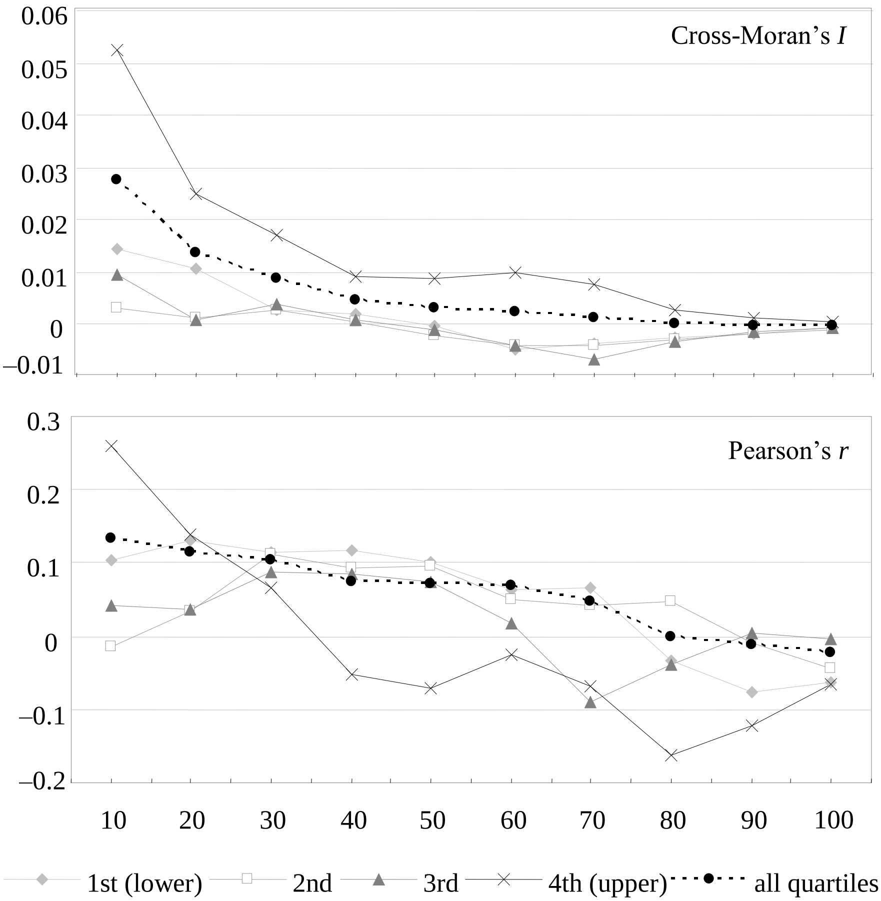


Figure 11. Bivariate spatial associations for different categories of postcodes (corresponding to quartiles of the housing stock variable): population growth versus spatial moving average employment growth

To assess the robustness of findings obtained in this study, it seems useful to adopt an alternative approach that focuses on absolute rather than standardised postcode population and employment changes. Focusing on absolute changes facilitates using a non-row standardised spatial weight matrix. By using such a matrix, the spatially weighted population and employment changes are directly calculated in the number of people and jobs, respectively. By contrast, row-standardisation yields a composite index with a less direct interpretation; the obtained values do not read as totals but as weighted averages of population and employment, with weights that are governed by number of neighbours in a certain distance band. Hence, row-standardisation puts considerable emphasis on the neighbourhood structure and growth of individual locations, whereas it is arguably the aggregate changes in jobs and people that can be reached from a given location that matters. The difference between aggregate and average numbers could have been ignored if the neighbourhood structures had been the same across observations. From Table 16 it can be seen, however, that the number of neighbours in the various distance bands diverges considerably, especially at intermediate ranges (50–60 km). With row-standardisation, a postcode with access to, let say, 10,000 jobs may have a similar SMA score as a postcode from which only 1,000 jobs can reached (with the former number distributed over ten postcodes and the latter over one postcode). Thus, averaging the numbers by using a row-standardised matrix scores may actually poorly reflect true labour market conditions and may give spurious results.

Table 16. Linkages (nonzero row elements) in spatial weights matrices

W	Average	Min.	Max.	*W*	Average	Min.	Max.
1 km	1.2	1	6	20 km	130.3	32	217
2 km	2.6	1	17	30 km	253.6	68	399
3 km	4.8	1	25	40 km	387.5	130	594
4 km	7.8	1	29	50 km	520.1	188	800
5 km	11.4	1	35	60 km	642.8	276	924
6 km	15.5	1	42	70 km	749.6	367	939
7 km	20.2	1	46	80 km	835.6	506	939
8 km	25.6	3	54	90 km	892.4	636	939
9 km	31.5	5	66	100 km	923.3	741	939
10 km	38.2	5	79				

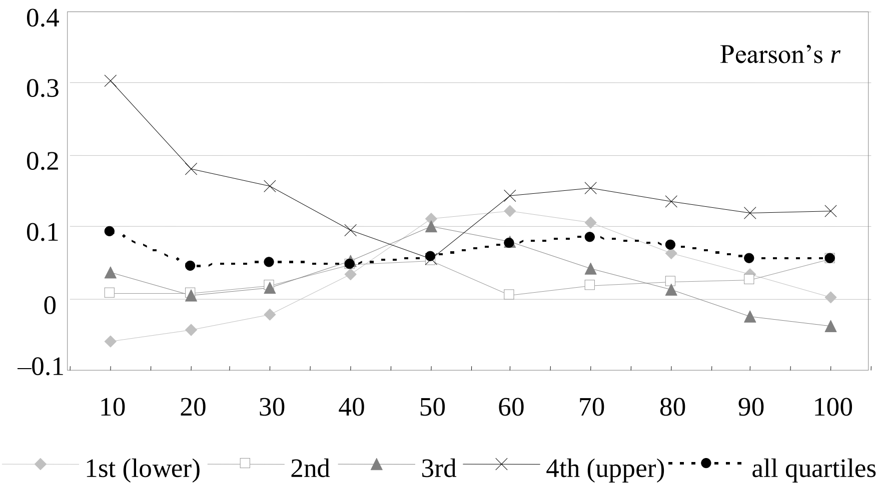


Figure 12. Bivariate spatial associations for different categories of postcodes (corresponding to quartiles of the housing stock variable): population growth versus spatial aggregate absolute employment growth

Figure 12 reveals how the patterns of global bivariate association (Pearson's *r*) look like when standardised values of population growth are compared with spatial *aggregate* values of *absolute* employment growth, rather than spatial *average* values of *standardised* employment growth.[25] Similar to Figure 11, one can observe some striking differences in the population–employment relationship among postcodes that have experienced different housing stock changes. Postcodes that have been the least restricted or most stimulated by policies affecting housing construction (upper quartile) again show a stronger population–employment relationship than any other group of postcodes. Note that the level of spatial association for these postcodes decreases until some 50 km, which compares reasonably well with earlier findings in this study about the range of spatial labour markets.

Conclusions

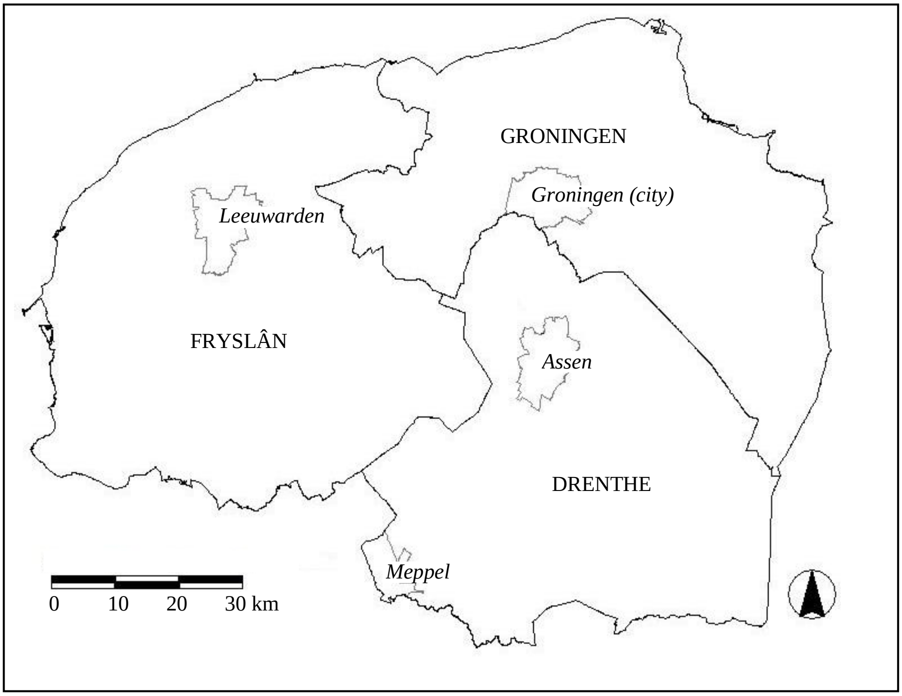
The aim of the study presented in this chapter has been to explore the postcode-level distribution of population and employment changes in the Northern Netherlands using newly developed techniques of Exploratory Spatial Data Analysis (ESDA). First, global bivariate spatial association statistics were calculated to test whether population and employment growths across these postcode zones are random or systematically related. If the population and employment changes within and around individual postcodes covariate, this is evidence of a relationship between them, and the findings presented in this study clearly support such a relationship. Further, by defining the "neighbourhood" of a postcode in various ways, this study suggests that the spatial range at which population and employment changes relate to each other stretches from a minimum of some 7 km up to some 60 km. Between these distances, the strength of the relationship rapidly decreases with increasing distance. Overall, the results suggest that the influence of neighbouring locations on local growth patterns can probably best be described by an S-shaped curve. Second, several tools for the analysis of local bivariate association were used to assess the contribution of individual postcodes to the overall, or global, level of association and to identify possible instabilities in the population–employment relationship across space. It was found that, for many postcodes, local growth runs counter to the regional trend. Further, very contrasting results could be observed in local growth performance between neighbouring postcode zones, both in successful and not so successful regions, and in terms of both population and employment growth. Given these results, it is argued that regional trends are not always felt locally because of the impact of spatial policies. Subsequently looking in detail at housing stock changes supported the impact of such policies on postcode population growth in the study region.

[25] Note that the focus on absolute changes only permits an assessment of spatial association by Pearson's *r*, as the concept of spatially varying variance instability (integral to Cross–Moran's *I*) no longer has any meaning.

The results of this study suggest that careful consideration should be given to the construction of spatial weight matrices when studying spatial interactions. The method selected for analysing spatial associations at different distance intervals appears very useful for future small-area growth models that depend on the configuration of labour market zones, and for which the specification of W is key.

Finally, this study has touched upon a number of issues where further research could be valuable. For instance, the observed systematic differences in growth with respect to size suggests a need to use standardised growth data, which in turn necessitates the use of a row-standardised spatial weight matrix when measuring spatial association. However, theoretically, there is much to recommend using absolute growth data. Calculating such data in conjunction with a non-standardised matrix provides data that can be interpreted as the total number of jobs and/or people within a certain distance of a given location. At face value, such data seem more relevant in explaining population and employment growth patterns than weighted average standardised numbers of jobs and people. It would be interesting in future research to carry out an analysis similar to the one in this study but based on a regular grid of uniformly sized observations since the spatial observations would then have the same neighbourhood structure. As such, averaging the growth values of neighbouring locations would not influence the results. Another unresolved issue is the appropriate spatial scale for analysis. It seems likely that the rather low levels of spatial association observed are connected with the focus on very small data observations (see also Chou 1991). Thus, another useful extension of the present study would be to repeat the analysis using different data to see how the spatial scale of the analysis impacts the results. As such, the Exploratory Spatial Data Analysis used in this chapter can serve as a starting point for a confirmatory analysis in which the aim is to explain, rather than merely explore, spatial growth patterns. This challenge is taken up in the next chapter.

Appendix IV. Study region and geographic references



5.
Gender, space, and the location changes of jobs and people: A spatial simultaneous equations analysis[26]

Introduction

In the past two decades, urban economics, regional science, and geography have seen the emergence of an impressive literature dealing with the long-standing classic chicken-or-egg question “do jobs follow people or people follow jobs?” (e.g., Borts and Stein 1964; Muth 1971; Steinnes and Fisher 1974). This literature, which currently counts over fifty different studies, has greatly enhanced our knowledge of population and employment location changes. Now, further insights can be gained by more sophisticated analyses that distinguish between different groups of people or firms and different types of interactions, and by a more detailed focus on the impact of space.

This study explores the extent to which distinguishing between gender-specific employment is relevant in relation to population–employment interaction and interaction within and among employment groups. Also, it analyses spatial effects in a more comprehensive way by discriminating between various distance intervals to detect the specific spatial range at which these interactions occur. Especially for men’s and women’s employment, the use of alternative distance intervals may reveal some significant differences in the spatial scale of population–employment interaction because of gender differences in commuting.

Most studies about population–employment interaction use highly aggregated data and thus do not take into account possible group effects. The few studies that acknowledge these effects mostly divide employment by industry (e.g., Duffy-Deno 1998; Schmitt et al. 2006; Hoogstra et al. 2011). Only sporadically are alternative segmentations used, such as the divisions of population by race (e.g., Bollinger and Ihlanfeldt 1997), and population and employment by occupation (e.g., Deitz 1998). One of the most potentially interesting data divisions that has not been dealt with is gender. Traditionally, studies about location patterns say very little about the possible impact of gender. They have an inherent bias toward male workers and typically view people as individuals detached from any social relations other than employment (Hanson and Pratt 1995; Burnell 1997). At the same time, a growing recognition exists that gender and space are inextricably intertwined, especially among studies of labour market differences between men and women (see the next section). This study is particularly motivated by two renowned gender differences, which intriguingly suggest that the employment locations of men and women are not the same. One is the difference in occupations, or what is known as “occupational gender segregation”: most women work

[26] This chapter has also appeared as an article in *Geographical Analysis* (see Hoogstra 2012).

in occupations in which the workers are predominantly female, while men mostly work in male-dominated occupations (e.g., Hwang and Fitzpatrick 1992). The other is the difference in commuting, or what is known as the "gender-commuting differential": women work closer to home than men do (e.g., Camstra 1996). Naturally, these differences in location raise some interesting questions, such as how these employment groups interact with the population and with each other. Questions of this sort are not merely of academic interest but also of practical concern. For instance, they reveal whether one of the employment types is more favourable to population growth than the other, which is especially relevant now that women increasingly contribute to the employment growth of regions (e.g., 62% in the region studied here). Also, for reasons of equity (emancipation) and efficiency (economic growth), a strong public and policy interest exists in the factors determining women's participation in the labour market, with much of the interest focusing on the access to and location of women's jobs.

The main questions addressed in this study ask: (1) if a difference exists between men's and women's employment in the nature (strength, direction, and spatial range) of interaction with the population; (2) if a difference exists in the interaction across locations within each group; and (3) whether these employment groups interact with each other, and if so, how. These and other questions are answered by estimation of an augmented version of Boarnet's (1994) spatial econometric Carlino–Mills model. What is different from a regular Boarnet model is the inclusion of a second employment equation, which results in a three-equation system. Also, a spatial autoregressive lag is added to the regular inclusion of a cross-regressive lag in the equations. Other novelties are the use of different weights matrices W for the calculation of these lags and the use of travel time for the specification of these matrices. The data used to estimate the model are postcode observations from the Netherlands for the years 1994/1995 to 2002/2003.

Literature review

This study starts with a literature review to derive hypotheses about the nature of population–employment interaction for men's and women's employment. While the empirical analysis here is for aggregate population and gender-specific employment changes, the review mainly focuses on studies of the underlying location behaviour of firms and households. In the absence of macro studies of the interaction between population- and gender-specific employment, these micro studies provide most of the insights relevant for this study.

Impacts of gender and space are mostly examined in studies of labour market differences between men and women (e.g., in commuting, participation, occupations). As far as gender, the central idea is that women do the majority of childcare and housekeeping. The additional space–time constraints they experience from these household responsibilities restrict them to part-time, low-paying, and low-status jobs, but crucially also to jobs close to their home (e.g., Kwan 1999). Besides these constraints from gender roles, men and women do not have access to the same set of job opportunities because work is deeply gendered, and the different types of jobs are not similarly distributed over space. This distribution may explain women's shorter commutes, as well as women's working in female-dominated occupations. Women do not need to travel long distances if suitable jobs are more evenly distributed over space (e.g., Hanson and Pratt 1995; Wyly 1999), while space–time constraints force them to work in jobs that are simply closer (e.g., Hwang and Fitzpatrick 1992). A central idea emerging from this literature, which is particularly highlighted by studies of the spatial entrapment and containment of women (e.g., England 1993;Wyly 1999), is that especially the labour market outcomes of women hinge on residential location, because gender roles render them dependent on locally available job opportunities. Interestingly, attempts in this literature to establish the impact of job accessibility on labour outcomes are very similar to those in the population–employment literature to determine interaction across locations. These studies also tend to make very rigid assumptions about the impact of distance and often have difficulties providing conclusive evidence (Hanson et al. 1997).

Another group of studies also attaches great importance to residential location but does not take this as a given. These studies elaborate on gender roles by asking: How is the residential location decision negotiated within families, and who is gaining and who is losing from a residential change? The traditional view about family migration is that relocations are made for the sake of the husband's labour career, with little or no regard for the wife's labour career (thereby making her a so-called "tied-mover"). The priority given to a husband's labour career may explain why women more often than men stop working after relocation and change jobs without improving income or occupational status (e.g., Camstra 1996; Clark and Withers 2002). Similarly, women may work in female-dominated occupations because they choose jobs that can be found anywhere and avoid jobs that might require geographic mobility for career advancement (e.g., Green 1997). With changing gender roles, the traditional view of men dominating residential decision making has made way for suggestions that the decision-making power is now more equally shared. Initially, women were only said to prevent their families from moving, turning their husbands into so-called "tied-stayers". However, more recent studies show that women make residential moves for their own careers and turn their partners into "tied-movers" (e.g., Smits et al. 2003).

Another group of studies focuses on commuting and the spatial context within which workers make their employment and residential location decisions. One of the questions is: How sensitive are households to commuting distances? These studies find that, generally, the greater the distance between residence and workplace, the greater the likelihood of a residential (or employment) change and decrease in commuting (e.g., Van Ommeren et al. 1997; Clark et al. 2003). Still, several studies claim the existence of an "indifference zone" within which commuters are indifferent to access to work. As

Camstra (1996, p. 285) notes: "*The selection of a job (location) and a (place of) residence are two relatively autonomous processes, as long as the distance does not become too great*". About the distance at which these decisions may start to influence each other, Clark et al. (2003) find what they call "critical isochrones" of 13 km and 19 km–26 km for single-worker and dual-worker households, respectively. Also, many studies point out that a maximum exists at which people are willing to commute, beyond which the likelihood of a residential (or employment) change is likely to be constant with distance. Empirical observations about such a "tolerance zone" are remarkably similar and suggest a break point of about 45 min travel time for a single work trip (e.g., Van Ommeren et al. 1997; Wheeler 2001). Another question is: How does commuting affect the residential location decision of dual-worker households? The case of these households attracts special attention because their residential location must accommodate two usually different job locations, which makes their decision making considerably more complex and may explain why these households are less migration prone and less inclined to reduce their commuting distances (e.g., Green 1997; Clark et al. 2003). Consistent with the idea that men dominate residential decision making, these studies suggest that dual-worker households adjust their place of residence to the male's place of work. Then again, with women being more sensitive to commuting distance than men, one may equally suggest that these households feel a stronger pressure to find a residence close to the job of the woman. Indeed, Clark et al. (2003) find that women are more likely than men to decrease their commuting distance after relocation. Camstra (1996) observes for the Netherlands that households adjust their residence to women's employment location in short-distance moves and to men's employment location in long-distance moves. Deding et al. (2009) find that, irrespective of the distance of a move, men's commuting distance is more important, unless these households have children.

A few studies focus on how the residential and employment location choices of households are made in conjunction with each other. The question they ask is: Does the choice of residence precede or follow the choice of employment location? Usually, studies overlook this question and either treat residential location or workplace as exogenous. For instance, the first group of studies discussed assumes that residential location is fixed and prior to the employment location decision. Similarly, the second group of studies discussed accords priority to the workplace decision and assumes that this decision is made before the residential location decision. One of the reasons given to assume that workers first accept a new job and then search for a new residence is that finding a job is more difficult (e.g., Clark et al. 2003). Then again, where housing markets are strongly regulated and where no shortage of jobs exists, finding a new residence actually may be more difficult (e.g., Deding et al. 2009). Van Ommeren et al. (1997) conclude that in the Netherlands, employment location is more responsive to residential location than vice versa. Clark and Withers (1999) find that in the United States, job changes significantly trigger residential mobility, although they do not examine whether this effect is greater than the effect of residential change on job mobility. Hanson and Pratt (1995) find that especially women choose a residential location prior to an employment location (93% of their female survey respondents versus 63% of their male respondents).

With the population–employment relationship having long been regarded as only running from employment to population (as exemplified by the classic monocentric city model; see, e.g., Boarnet 1994), relatively little is known about the impact of household location on firm location, let alone the possible effect of gender. Common knowledge suggests that different types of firms (e.g., labour-intensive versus labour-extensive industries, producer versus consumer industries) have different incentives to locate near potential employees and consumers. Similarly, the constraints firms face when trying to fulfil their locational preferences are likely to be different, too, given that, for example, some activities are more footloose than others. The dominance of women in service industries suggests that women's employment is more population oriented (and more footloose) than men's employment and thus presumably more responsive to population changes (e.g., Hanson and Pratt 1995; Wyly 1999). Also, firms may well be aware of the characteristics of their desired employees, such as women's greater restrictions in mobility. Studies of women's spatial entrapment and containment suggest that women's working in typically female-dominated jobs has as much to do with their greater space–time constraints from gender roles as from the location behaviour of firms that wish to avail themselves to these female workers (e.g., England 1993; Hanson and Pratt 1995).

This literature review suggests several hypotheses about the nature of population–employment interaction for men's and women's employment. First, the relationship is probably stronger for men's employment than for women's employment because of the domestic division of labour and the role of men as main income providers. Second, the traditional greater say men have in residential decision making (with women allegedly mostly searching for jobs from their residential location) suggests that the platitude "people follow jobs" can be mainly associated with men's employment. Conversely, the population-serving nature of women's employment as well as a possible awareness by firms that women often do not decide residential moves both give rise to the idea that "jobs follow people" mostly applies to women's employment. Finally, population–employment interaction is likely more localised for women's employment than for men's employment. For the latter, the interaction possibly stretches across locations that are as far as 45 min apart, whereas it may be absent over short distances because of an indifference zone.

Econometric model

The model used in this study is an augmented version of Boarnet's (1994) spatial econometric variant of the simultaneous equations system with adjustment lags introduced by Carlino and Mills (1987). This system (whose foundations were laid by

Borts and Stein 1964; Muth 1971; and Steinnes and Fisher 1974) has become the standard methodology for analysing location changes. Not only is it straightforward in its use, but it is also relatively easily modified for specific research needs. Here, this flexibility helps determine whether a more explicit interest in gender and space enhances our understanding of location changes and whether the modifications offer an improvement over existing models.

Two fundamental assumptions underlie the Carlino–Mills model. One is that households and firms have an incentive to co-locate because of consumer and labour market relations, and that a location change of the one leads to a location change of the other (hence, the use of simultaneous equations). The second is that firms and households do not adjust to each other instantaneously; time is necessary to recognise that circumstances have changed and to act thereupon (hence, the use of adjustment lags). To suit a local analysis, the Boarnet model additionally assumes that interactions between firms and households go beyond geographic units that seem too small to be their own labour markets (hence, the use of spatial econometrics). These assumptions provide the theoretical foundations for what is above all an empirical model. Their validity can be evaluated by estimating the model's key parameters. A significant and positive estimate for the parameters describing the relation between population and employment implies a confirmation that labour and/or consumer market relations mutually link firms and households.[27] Similarly, so-called lagged adjustment parameters reveal the speed with which firms and households react to changing labour market conditions. For the assumption of a lagged adjustment process to be true, these parameters must lie within a particular range. Finally, so-called spatial lag parameters inform whether the relations stretch over a wider area than the spatial units under investigation.

The use of the Boarnet model is typical for intra-regional studies of spatial units as small as census tracts or municipalities (e.g., Bollinger and Ihlanfeldt 1997; Deitz 1998; Henry et al. 2001). The Carlino–Mills model is standard in the inter-regional counterparts of this literature in which the need to control for commuting effects is less urgent because of a focus on large spatial units like US counties or county aggregates (e.g., Carruthers and Mulligan 2007). The purpose of this study supports the use of an intra-regional analysis and a Boarnet model. Not only is an intra-regional analysis more apt to address spatial effects, but the role of gender can also be better examined. Gender differences in employment (growth) are mostly manifest at the local level, whereas an inter-regional analysis would conceal differences in commuting.

This study compares two different Boarnet models. The first is a baseline two-equation system, described by equations (11a) and (11b), which is estimated with

[27] Note that if the estimation results fail to establish such a relationship, the validity of this assumption does not necessarily need to be questioned. For instance, the relationship possibly is obscured by households and firms not being entirely free to choose locations (e.g., because of land use policies). For the model to yield realistic results, it needs to include explanatory variables that account for this lack of locational freedom.

aggregate population and employment data. The second is a three-equation system, described by equations (12a)–(12c), which is estimated with employment data disaggregated by gender.[28]

The two-equation system:

$$\begin{aligned}\ln P_{i,t} - \ln P_{i,t-1} = {} & \alpha_0 + \alpha_1 R_{i,t-1} + \alpha_2 \ln P_{i,t-1} + \alpha_3 (I+W)\ln E_{i,t-1} + \\ & \alpha_4 (I+W)(\ln E_{i,t} - \ln E_{i,t-1}) + \alpha_5 W(\ln P_{i,t} - \ln P_{i,t-1}) + u_{i,t}\end{aligned} \tag{11a}$$

$$\begin{aligned}\ln E_{i,t} - \ln E_{i,t-1} = {} & \beta_0 + \beta_1 S_{i,t-1} + \beta_2 \ln E_{i,t-1} + \beta_3 (I+W)\ln P_{i,t-1} + \\ & \beta_4 (I+W)(\ln P_{i,t} - \ln P_{i,t-1}) + \beta_5 W(\ln E_{i,t} - \ln E_{i,t-1}) + v_{i,t}\end{aligned} \tag{11b}$$

The three-equation system:

$$\begin{aligned}\ln P_{i,t} - \ln P_{i,t-1} = {} & \alpha_0 + \alpha_1 R_{i,t-1} + \alpha_2 \ln P_{i,t-1} + \alpha_{3.1} (I+W)\ln E^{f}_{i,t-1} + \\ & \alpha_{3.2} (I+W)\ln E^{m}_{i,t-1} + \alpha_{4.1} (I+W)(\ln E^{f}_{i,t} - \ln E^{f}_{i,t-1}) + \\ & \alpha_{4.2} (I+W)(\ln E^{m}_{i,t} - \ln E^{m}_{i,t-1}) + \alpha_5 W(\ln P_{i,t} - \ln P_{i,t-1}) + u_{i,t}\end{aligned} \tag{12a}$$

$$\begin{aligned}\ln E^{f}_{i,t} - \ln E^{f}_{i,t-1} = {} & \beta_0 + \beta_1 S_{i,t-1} + \beta_2 \ln E^{f}_{i,t-1} + \beta_3 (I+W)\ln P_{i,t-1} + \\ & \beta_4 (I+W)(\ln P_{i,t} - \ln P_{i,t-1}) + \beta_5 W(\ln E^{f}_{i,t} - \ln E^{f}_{i,t-1}) + \\ & \beta_6 (I+W)\ln E^{m}_{i,t-1} + \beta_7 (I+W)(\ln E^{m}_{i,t} - \ln E^{m}_{i,t-1}) + v_{i,t}\end{aligned} \tag{12b}$$

$$\begin{aligned}\ln E^{m}_{i,t} - \ln E^{m}_{i,t-1} = {} & \delta_0 + \delta_1 T_{i,t-1} + \delta_2 \ln E^{m}_{i,t-1} + \delta_3 (I+W)\ln P_{i,t-1} + \\ & \delta_4 (I+W)(\ln P_{i,t} - \ln P_{i,t-1}) + \delta_5 W(\ln E^{m}_{i,t} - \ln E^{m}_{i,t-1}) + \\ & \delta_6 (I+W)\ln E^{f}_{i,t-1} + \delta_7 (I+W)(\ln E^{f}_{i,t} - \ln E^{f}_{i,t-1}) + w_{i,t}\end{aligned} \tag{12c}$$

where

P is an $n \times 1$ vector of population (n denotes the number of spatial observations);
E is an $n \times 1$ vector of employment;
R is an $n \times j$ matrix with j population-related characteristics;
S is an $n \times k$ matrix with k employment-related characteristics;
T is an $n \times l$ matrix with l employment-related characteristics;

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[28] Alternative models with population divided by gender were also tried, but this division often considerably complicated interpretation and did not seem to give fundamentally different results. Residential locations of men and women also largely overlap. For the spatial units examined here, a Pearson's correlation coefficient of 0.91 (0.75) exists between the population growth of men and women (in parentheses, the estimated coefficient based on logarithmic numbers). By comparison, the coefficient between men's and women's employment growth is 0.54 (0.45).

I is an $n \times n$ identity matrix; W is an $n \times n$ spatial weights matrix;
$\alpha_0, \alpha_2, \ldots, \alpha_5, \beta_0, \beta_2, \ldots, \beta_7, \delta_0, \delta_2, \ldots, \delta_7$ are scalar parameters to be estimated;
α_1 (β_1, δ_1) are vectors of j (k, l) parameters to be estimated;
u, v, w are independent identically distributed error terms;
"i" subscripts refer to regions; "t" subscripts refer to years; "m" superscripts refer to male categories; and "f" superscripts refer to female categories.

The two preceding models, which measure population and employment by the number of residents (male and female) and the number of jobs held by men and/or by women, respectively, furnish the following descriptions. Population change in location i [$\ln P_{i,t} - \ln P_{i,t-1}$ or $\ln(P_{i,t}/P_{i,t-1})$] between times t–1 and t depends on (1) a set of population-related characteristics of i [$R_{i,t-1}$]; (2) initial population size of i [$\ln P_{i,t-1}$]; (3) initial employment size [$(I + W)\ln E_{i,t-1}$]; (4) contemporaneous employment change [$(I + W)(\ln E_{i,t} - \ln E_{i,t-1}$] in i and its neighbouring locations; and (5) contemporaneous population change in its neighbouring locations [$W(\ln P_{i,t} - \ln P_{i,t-1}$]. Likewise, employment change in location i between times t–1 and t [$\ln E_{i,t} - \ln E_{i,t-1}$] depends on (1) a set of employment-related characteristics of i [$S_{i,t-1}$ or $T_{i,t-1}$]; (2) initial employment size of i [$\ln E_{i,t-1}$]; (3) initial population size [$(I + W)\ln P_{i,t-1}$]; (4) contemporaneous population change [$(I + W)\ln P_{i,t} - \ln P_{i,t-1}$] in i plus its neighbouring locations; and (5) contemporaneous employment change in its neighbouring locations [$W(\ln E_{i,t} - \ln E_{i,t-1}$]. Alternatively, in the model description furnished by equations (12a)–(12c), population change in location i depends on employment and employment change in and around i of men and women separately, thereby substituting the parts described by points (3) and (4) for equation (11a). Also, employment change in location i of each group depends on (6) employment and (7) employment change in and around i of the other employment group.

The first part of these systems, which contains the elements up to and including point (4), corresponds to a regular Boarnet model. Akin to the model introduced by Carlino and Mills, inferences about the speed of adjustment and whether the equations system is dynamically stable can be made with the parameter estimates for the lagged population and employment variables. Specifically, the absolute values of α_2, β_2, and δ_2 are assumed to lie between zero and one, and express how far the observed changes have come in solving the difference between the initial (beginning-of-period) and equilibrium (unobservable long-run) population or employment levels (see, e.g., Mulligan et al. 1999 for details). The inclusion of the population (employment) change variable on the right-hand side of the employment (population) change equation reflects the key issue of interaction. If both α_4 and β_4 (δ_4) are not significantly different from zero, population and employment changes are unrelated. Evidence of one-way interaction exists if one of the parameters is statistically significant and shows a positive sign. This directional interaction is from employment to population (people follow jobs) for α_4, and from population to employment (jobs follow people) for β_4 (or δ_4). Evidence of two-way interaction exists if both parameters are positive and significant. The relative size of these parameters indicates which effect (people follow jobs versus jobs follow people) is stronger.[29] The model allows for the possibility that population–employment interaction occurs across locations. Hence, unlike in the original Carlino–Mills model, the construction of the relevant right-hand-side variables encompasses a spatial lag operation. In such an operation, the population and employment data of individual locations are recalculated in conjunction with those of their "neighbours", as specified through a spatial weights matrix W. Specifically, location j is specified as a neighbour of location i if $w_{ij} \neq 0$, $w_{ij} = 0$ otherwise, and, by convention, $w_{ii} = 0$. Importantly, various specifications of matrix W exist, based on different ideas about the impact of distance (see, e.g., Tiefelsdorf et al. 1999; Anselin 2003; Patuelli et al. 2006).

Regarding the spatial lag operations, this study differs from previous population–employment interaction studies in two ways. First, instead of straight-line or network distances, travel time by car determines the distance between locations. For commuting travel, the time to traverse space matters more than the amount of space traversed. Second, instead of a single matrix, three different but complementary matrices that represent simple distance intervals (0–15, 0–30, and 0–45 min of travel time by car) specify the assumed relationships between spatial observations. Using multiple matrices circumvents the need to make the highly difficult and controversial decision about the likely impact of distance, which gets even more complicated when it needs to be made for different groups of jobs and/or people. Moreover, if differences exist in the impact of distance between groups (which commuting data clearly suggest with regard to gender), these differences cannot be captured by a single matrix. Finally, using multiple matrices allows insights into whether a lower and upper distance threshold and distance decay exist in interaction across locations.

In the second part of the models, the regular Boarnet specification is extended by one element previously described by point (5), and in the case of the employment equations (12b) and (12c), by two further elements previously described by points (6) and (7). The former addition, which is generally known as a spatial autoregressive lag, again involves a spatial lag operation. However, this lag serves to control for possible spatial dependence in the dependent variable rather than in the right-hand-side endogenous variable (which the spatial cross-regressive lag already controls). Mainly due to complications with estimation, simultaneous equations models with cross-regressive lags usually are without autoregressive lags. However, omitting this autoregressive lag and subsequently failing to control for this form of spatial dependence may generate inconsistent, inefficient, and biased parameter estimates (e.g., Anselin 2003). A comparison of different Boarnet models in Hoogstra et al. (2011) shows that misspecification (along with inappropriate estimation techniques)

[29] Similarly, the parameter estimates in the extended population change equation (12a) can be compared to determine whether people follow women's jobs more strongly than men's jobs ($\alpha_{4.1} > \alpha_{4.2}$), or vice versa ($\alpha_{4.1} < \alpha_{4.2}$).

considerably affects the findings of population–employment interaction. Importantly, the spatial autoregressive parameters (α_5, β_5, and δ_5) also inform about the presence of spread effects (in the case of a positive parameter) and backwash effects (in the case of a negative parameter; see also Henry et al. 2001; Rey and Boarnet 2004).

Finally, the employment equations of the three-equation system include two extensions, previously described by (6) and (7), which reveal relations among employment groups. Few earlier studies link the equations of distinct employment groups to reveal inter-industry linkages (e.g., Deitz 1998; Duffy-Deno 1998). Only Sohn and Hewings (2000) and Schmitt et al. (2006) do so by also including a spatial autoregressive lag in their equations (similar to the approach here). While men and women are segregated across industries, and the divisions largely overlap, the interpretation of employment interactions here is somewhat different. In the case of gender, underlying employment location changes are not only the location and growth decisions made by firms but also the decisions about job allocation. A positive estimate for β_7 (δ_7) may indicate that male- and female-dominated industries stimulate each other, yet also that within industries male and female workers are complementary to rather than substitutes for one another. Similarly, a negative parameter may indicate competition between industries (e.g., for space) and between men and women for jobs. The selected model cannot disentangle these different mechanisms but allows inferences about the relation between men's and women's employment within geographic areas.

Data, specification and estimation issues

In this study, data for 939 postcodes in the Northern Netherlands (see Figure 13) are used to estimate the models described by equations (11a) and (11b) and (12a)–(12c). The Northern Netherlands is a semiurban region, which makes the results of the analysis more generalisable than would be possible by an analysis of rural or metropolitan areas (such as the western Netherlands), which have their own specific problems.[30] The postcodes in the Northern Netherlands are also ideal for an intra-regional analysis of population and employment changes. Because the average size of these observations is only 15.1 km^2 (similar to most US census tracts), interaction across locations can be determined for very small distances. Furthermore, substantial local variation in residential and industrial conditions exists across these postcodes, which is reflected in a highly uneven spatial distribution of population and employment growth (see Figures 14–17). During the period of study, 1994/1995 to 2002/2003, the population grew by 4.5% (to 1,684,315), whereas men's and women's employment increased by 11.2% (to 341,785) and 38.2% (to 200,936), respectively. The region experienced rapid growth especially in consumer services (e.g., retail, government, education, and health care),

[30] Ideally, the analysis would have been for all regions in the Netherlands. However, employment data for Dutch postcodes are not very reliable. The data used in this study were extensively checked and corrected.

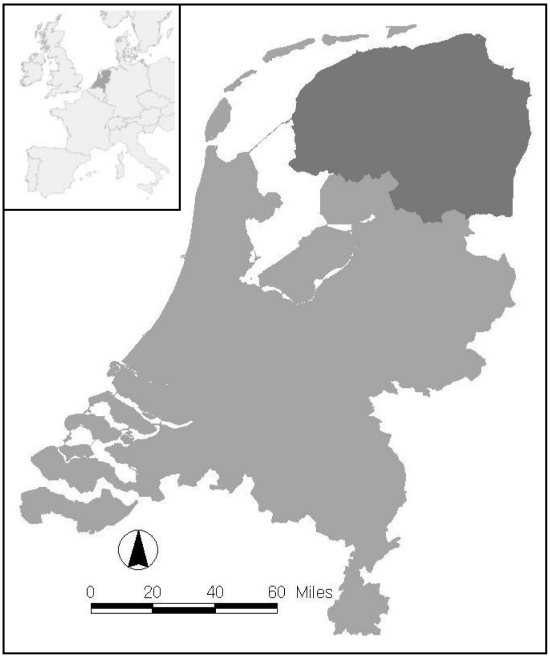

Figure 13. The Netherlands and the selected study region

which traditionally contain most of women's jobs (i.e., 69% in 1994). Together, these services contributed nearly 52% to the overall employment growth and nearly 67% to the growth of jobs held by women. By contrast, the region experienced only modest growth in the manufacturing and distribution industries, which are traditionally dominated by men (in 1994, 87% of the workers in these industries were male). Still, women took most of the new jobs and somewhat decreased the gender segregation in these industries.

A variety of data are used for the set of exogenous variables, described before as *R*, *S*, and *T*. First, both the population and employment equations include three variables that measure distance to the nearest motorway exit/entrance point (*MOTORW*) and to the nearest railway station (*RAILW*), and average travel time by car to other postcodes in the Netherlands (*CENTRL*). The population equations additionally include a distances-to-services variable for each postcode (*SERVIC*, measuring average distance to nearest school for elementary education, childcare facility, daily store, and medical service). Better-located postcodes should experience more growth. Next, the population equations include one variable for social status (*STATUS*, an index variable calculated on the basis of unemployment, education, and income data; see Knol 1998 for details) and one variable for the age composition of the people living in each postcode (*AGE*, measuring the share of people 64 years of age or older). Higher status postcodes should be more attractive for residing, while the younger populated postcode should experience

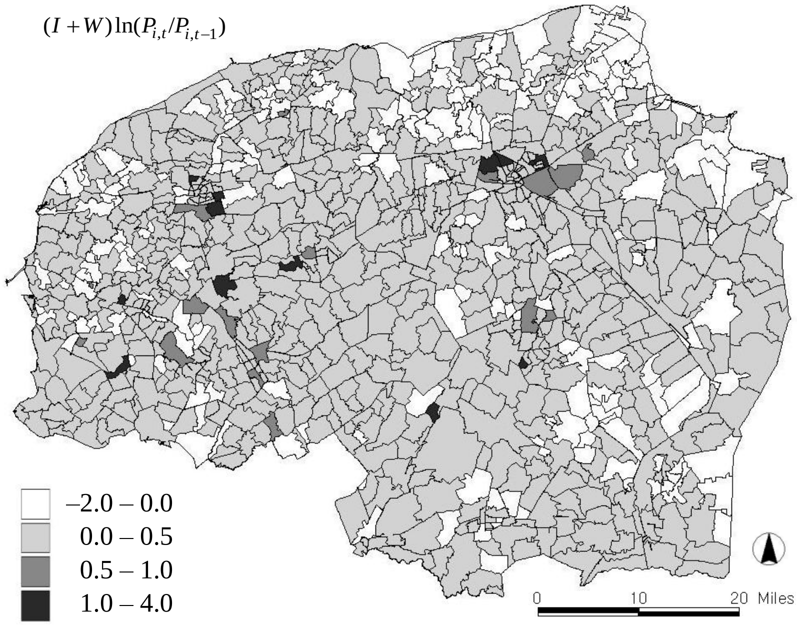

Figure 14. Geographic variation of spatially weighted postcode population growth within 15 minutes travel distance (*W*_15)

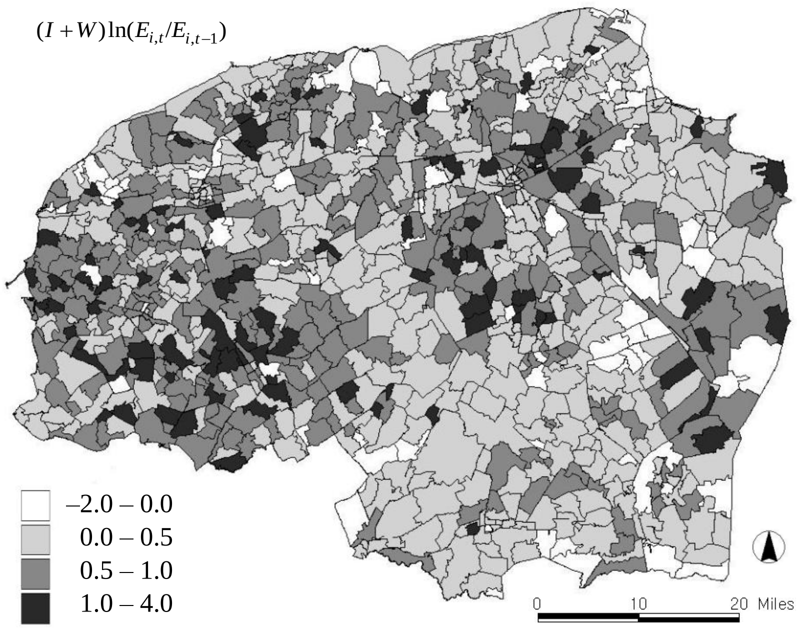

Figure 15. Geographic variation of spatially weighted postcode total employment growth within 15 minutes travel distance (*W*_15)

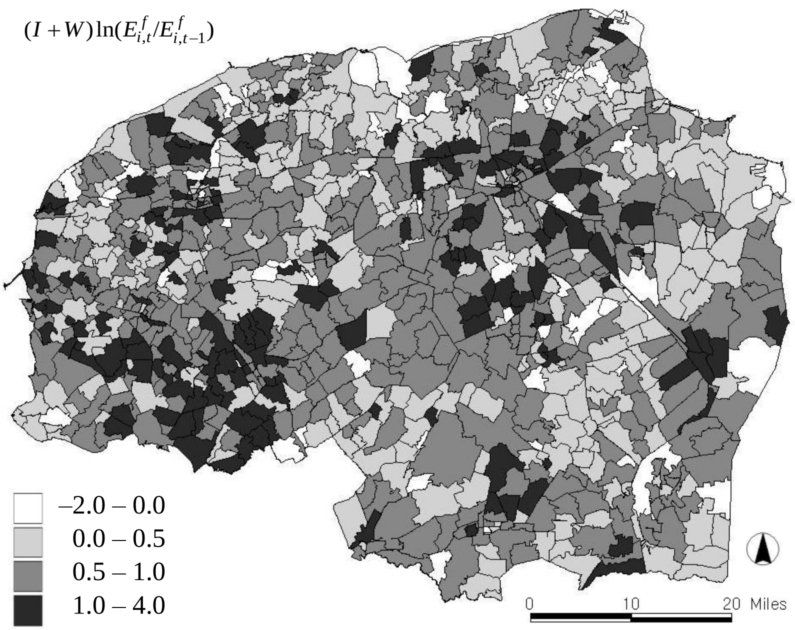

Figure 16. Geographic variation of spatially weighted postcode women's employment growth within 15 minutes travel distance (*W*_15)

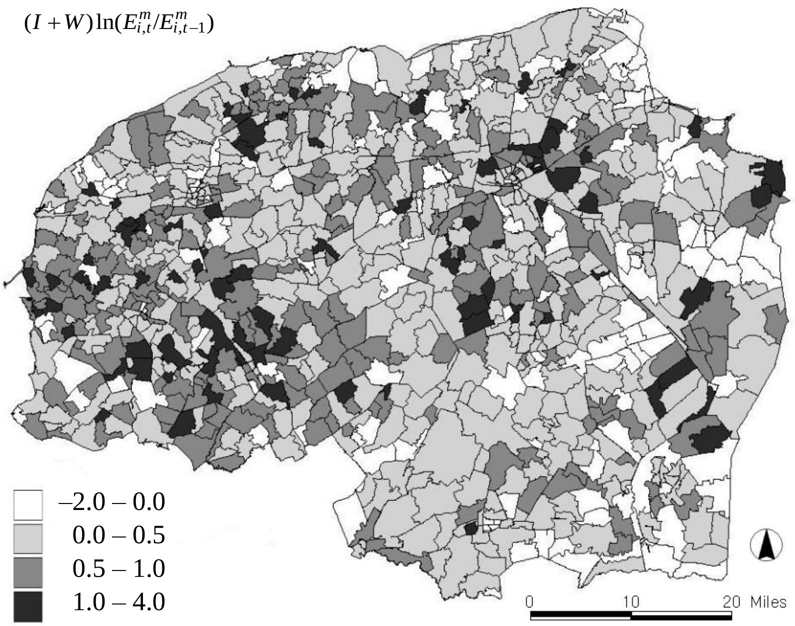

Figure 17. Geographic variation of spatially weighted postcode men's employment growth within 15 minutes travel distance (*W*_15)

more population growth because of higher birth and lower death rates. The population equations further include two variables that measure the attractiveness of the natural environment by the area of surface waters (*WATER*) and area of parks and forests (*GREEN*) within a 2-km radius around a postcode centre, and a dummy variable for the attractiveness of the built environment, indicating whether a postcode has a protected cultural heritage site (*HERITG*). The more attractive postcodes are expected to experience more population growth. To control for the impact of land use policies, all equations include two other dummy variables, one indicating whether a postcode is part of a municipal head town or city (*MUNICP*) and one indicating whether it is part of an "economic core zone" (*ZONE*). These core zones reflect a regional policy to concentrate residential and employment activities in several zones of conterminous municipalities.

Within municipalities, most local policies aim to cluster these activities in the principal town or city. The impact of policy is also examined directly at postcode level. The population equations include a variable for the changes in housing stock (*HOUSI*), while the employment equations include a variable measuring increases in square meters of office space (*OFFIC*) and a variable measuring increases in hectares of industrial space (*INDUS*). In the Netherlands, housing and business property markets are highly regulated, particularly at the local level of postcodes. Naturally, population growth and housing stock changes are strongly correlated (much more so than employment changes and increases in office or industrial space). To focus on housing stock changes that are truly exogenous to population growth, the variable *HOUSI* measures the variance of these changes, which cannot be explained by the social status and access to employment of postcodes. These residual values, obtained through a regression analysis, can be interpreted as the extent to which governments have stimulated or prevented housing construction beyond or below the amount that otherwise would likely have been realised (see, e.g., Duffy-Deno 1998 for a similar variable construction). Finally, to capture local attitudes toward women's labour participation, the employment growth equation of women includes two variables that measure the average household size (*HOUSHL*) and share of jobs held by men (*EMPMAL*), and one dummy variable indicating whether orthodox church services are held (*RELIG*).

Following the selection of data, a few issues still need to be clarified. One is the use of a log-linear model specification in which the population and employment numbers are transformed into natural logarithms prior to estimation. Although less common than a linear specification, a log-linear specification is rapidly gaining popularity among studies of population–employment interaction (see, e.g., Carruthers and Mulligan 2007). A log-linear specification casts the population and employment changes as multiplicative rather than additive changes. Such an approach is needed here because considerable differences in the employment and population sizes within postcodes prevent a straightforward comparison. Also from a theoretical viewpoint, the focus on growth rates makes sense as new jobs and people typically are produced by existing ones, while allowing the parameter estimates to be read as elasticities. Note that a logarithmic transformation has several implications. One is that row standardisation of a spatial weight matrix considerably facilitates the calculation of values in a spatial lag operation, because growth rates cannot simply be summed. Another implication is that the error structure is multiplicative rather than additive, while for a comparison with other models the transformed values of population and employment need to be back-transformed to their original values after estimation.

Estimation of the models also needs further discussion. As noted, the joint use of a spatial cross-regressive and autoregressive lag in a simultaneous equations system is rather unusual, mainly because of complications for estimation that could not be solved until recently. A generalised spatial two-stage least-squares (GS2SLS) procedure (Kelejian and Prucha (2004) is now available that generates consistent and asymptotically normal parameter estimates when spatial dependence exists in both the dependent variables and the right-hand-side endogenous variables. In this procedure, the models are first estimated by 2SLS, after which the resulting disturbances are used in a generalised moments procedure to calculate the spatial autoregressive parameters. Subsequently, these parameters are used in a Cochrane–Orcutt-type transformation to control for remaining dependence in the disturbances. The predicted values of the endogenous variables, needed for the second stage in a 2SLS estimation, are obtained by using the predetermined variables plus their spatial lags (thereby also using higher order W matrices) as instruments. This technique ensures, by construction, that the endogenous variables are orthogonal to the disturbances (see Bollinger and Ihlanfeldt 1997 and Rey and Boarnet 2004 for further details).

Results

Population equations

The estimation results for the population equations (11a) and (12a) are shown in Table 17. The first column of results shows that the absolute value of the lagged adjustment parameter for $\ln(P_{i,t-1})$ is both significant and within the expected range (0–1). The estimated value of 0.071, which reads as the share of the equilibrium rate of population growth that was realised over the 8-year period, is very close to zero and indicates that households react very slowly to changing labour market conditions. Next, population growth in a postcode depends on beginning-of-period employment, $[(I + W)\ln E_{i,t-1}]$, and contemporaneous employment growth, $(I + W)\ln(E_{i,t}/\ln E_{i,t-1})$, in and around that postcode. The parameters and significance levels increase as the travel time used to define the band of surrounding postcodes approaches 45 min. This outcome suggests that households are rather indifferent to residing in close proximity of jobs (see also Camstra 1996). The finding that places of residence and of work are considered too far apart beyond 45 min[31] corresponds remarkably well with ideas about the maximum desirable commuting distance, which also has been observed in other countries (such as the United States; see Wheeler 2001). Next, the positive and significant parameter estimate for $W\ln(P_{i,t}/P_{i,t-1})$ reveals the presence of spread effects in population growth from neighbouring postcodes. This impact is not only greater than that of employment growth but also more localised. In this case, the relevant neighbourhood consists of

Table 17. Parameter estimates population equations

	(11a) $\ln(P_{i,t}/P_{i,t-1})$			(12a) $\ln(P_{i,t}/P_{i,t-1})$		
	coefficient	t		coefficient	t	
Intercept	0.385	2.84	●	0.646	4.12	●
$\ln P_{i,t-1}$	–0.071	–7.90	●	–0.078	–8.35	●
$(I+W)\ln E_{i,t\;1}$						
W_15	0.025	4.27	●			
W_30	0.035	4.86	●			
W_45	0.044	4.86	●			
$(I+W)\ln E^{f}_{i,t-1}$						
W_15				0.063	3.33	●
W_30				0.054	2.80	●
W_45				0.047	2.21	○
$(I+W)\ln E^{m}_{i,t-1}$						
W_15				–0.032	–1.80	*
W_30				–0.012	–0.68	
W_45				0.000	–0.02	
$(I+W)\ln(E_{i,t}/E_{i,t-1})$						
W_15	0.063	1.72	*			
W_30	0.110	2.58	○			
W_45	0.177	3.37	●			
$(I+W)\ln(E^{f}_{i,t}/E^{f}_{i,t-1})$						
W_15				0.084	1.76	*
W_30				0.042	0.86	
W_45				0.045	0.78	
$(I+W)\ln(E^{m}_{i,t}/E^{m}_{i,t-1})$						
W_15				–0.019	–0.38	
W_30				0.056	1.23	
W_45				0.108	2.10	○

[31] This conclusion is based on alternative model estimations, in which weight matrices representing a 60-min travel distance were used. The findings of these estimations are not presented here, but the full set of results is available upon request.

$W \ln(P_{i,t} / P_{i,t-1})$						
*W*_15	0.517	3.21	●	0.408	2.37	○
*W*_30	–0.187	–0.58		–0.110	–0.36	
*W*_45	–0.474	–0.90		–0.258	–0.51	
MOTORW	0.000	0.37		0.001	0.50	
RAILW	0.001	0.98		0.002	1.18	
CENTRL	0.000	0.29		0.000	–0.61	
SERVIC	–0.033	–4.65	●	–0.036	–4.81	●
STATUS	0.026	3.70	●	0.021	2.76	○
AGE	–0.001	–0.52		–0.002	–1.33	
WATER	0.000	0.31		0.001	0.51	
GREEN	0.001	1.09		0.000	–0.01	
HERITG	–0.019	–0.84		–0.026	–1.17	
MUNICP	0.064	2.69	●	0.043	1.73	*
ZONE	–0.006	–0.34		–0.020	–1.05	
HOUSI	0.001	12.06	●	0.001	11.86	●

* P < 0.10, ○ P < 0.05, ● P < 0.01.
Gray-shaded areas indicate selected parameter estimates from model estimations with different specifications of *W* (0–30-min and 0–45-min travel distance, respectively). Parameter estimates in non-shaded areas are from using a 0–15-min travel distance matrix. Additional parameter estimates of the variables that do not involve a spatial lag operation are not given, because they change little in terms of size and significance across the different model estimations.

postcodes that are no farther than 15 min away. Beyond this distance, these spread effects seem to make way for backwash effects in which neighbouring postcodes lose growth to one another (as the parameter turns negative, if not statistically significant). Finally, the results reveal no relation between postcode population growth and distance to motorway exit/entrance point (*MOTORW*), railway station (*RAILW*), or other postcodes (*CENTRL*). However, they show a significant parameter for *SERVIC*, with the negative sign indicating an adverse effect of distance. Postcode population growth also relates to community characteristics, not with regard to *AGE* but to *STATUS* only. The positive parameter indicates that high-status areas experience more population growth than low-status areas, which is in line with expectations. Next, the results show no covariation with *WATER* and *GREEN* or *HERITG*. This is in contrast to most of the variables for government policies, which by *HOUSI* reveal the strongest relationship with population growth. The significant and positive parameter for *MUNICP*, which indicates that the central postcodes of a municipality experience superior population growth, confirms the important role of policies. However, no effect is found for *ZONE*, which may be explained by the regional focus of these policies (for it deviates from the local level at which population changes are studied here).

The division of employment by gender in the population equation (12a) of the three-equation system adds some significant information to the preceding findings (see the second column of results in Table 17). The already established employment growth covariation with population growth can also be seen for men's as well as women's employment growth. Yet, the magnitude of the relationship and its spatial range is rather different, with the results suggesting that people follow men's jobs more strongly but women's jobs more closely. This finding appears to confirm the more restricted spatial labour markets of women and the greater significance attached within households to the employment position of the man. Also, similar to, for example, Camstra (1996), it rejects the traditional idea that residential locations are primarily selected on the basis of access to male employment opportunities with little or no regard for female employment opportunities.

Table 18. Parameter estimates employment equations

	(11b) $\ln(E_{i,t}/E_{i,t-1})$			(12b) $\ln(E^f_{i,t}/E^f_{i,t-1})$			(12c) $\ln(E^m_{i,t}/E^m_{i,t-1})$		
	coef.	t		coef.	t		coef.	t	
Intercept	–0.118	–0.31		–0.504	–1.13		–0.027	–0.08	
$\ln E_{i,t-1}$	–0.155	–11.41	●						
$\ln E^m_{i,t-1}$							–0.191	–10.53	●
$\ln E^f_{i,t-1}$				–0.140	–5.21	●			
$(I+W)\ln P_{i,t-1}$									
W_15	0.074	5.66	●	0.099	3.11	●	0.060	2.63	●
W_30	0.111	7.22	●	0.070	2.41	○	0.056	2.73	●
W_45	0.112	5.48	●	0.077	2.82	●	0.102	3.84	●
$(I+W)\ln(P_{i,t}/P_{i,t-1})$									
W_15	0.290	2.55	○	0.440	1.79	*	0.234	1.33	
W_30	0.416	3.30	●	0.146	0.62		0.130	0.79	
W_45	0.644	3.50	●	0.289	1.21		0.780	3.57	●
$W\ln(E_{i,t}/E_{i,t-1})$									
W_15	0.582	4.22	●						
W_30	1.004	6.98	●						
W_45	0.671	2.66	●						
$W\ln(E^f_{i,t}/E^f_{i,t-1})$									
W_15				0.437	2.11	○			
W_30				1.065	4.22	●			
W_45				0.759	1.70	*			
$W\ln(E^m_{i,t}/E^m_{i,t-1})$									
W_15							0.632	3.93	●
W_30							1.454	7.68	●
W_45							1.044	3.38	●

$(I+W)\ln E^{f}_{i,t-1}$									
*W*_15							0.032	1.27	
*W*_30							0.106	4.16	●
*W*_45							0.039	1.03	
$(I+W)(\ln E^{m}_{i,t-1})$									
*W*_15				–0.032	–0.87				
*W*_30				0.110	2.82	●			
*W*_45				0.226	4.70	●			
$(I+W)\ln(E^{f}_{i,t}/E^{f}_{i,t-1})$									
*W*_15							–0.002	–0.03	
*W*_30							0.095	1.45	
*W*_45							–0.004	–0.04	
$(I+W)\ln(E^{m}_{i,t}/E^{m}_{i,t-1})$									
*W*_15				–0.241	–1.76	*			
*W*_30				–0.113	–1.01				
*W*_45				0.150	1.21				
MOTORW	0.002	0.99		0.003	0.89		0.003	1.22	
RAILW	0.001	0.29		0.001	0.33		0.000	0.14	
CENTRL	–0.002	–1.46		–0.004	–1.98	○	–0.002	–1.75	*
HOUSI				0.063	0.75				
RELIG				–0.057	–0.45				
EMPMAL				0.004	1.62				
MUNICP	0.193	3.89	●	0.267	4.22	●	0.173	3.51	●
ZONE	–0.008	–0.23		0.021	0.51		–0.045	–1.19	
OFFIC	0.038	3.65	●	0.052	4.40	●	0.039	3.55	●
INDUS	0.089	5.03	●	0.098	3.68	●	0.106	5.58	●

See notes in Table 17 for clarification.

Employment equations

The estimation results for the employment equations (11b), (12b), and (12c), for total, women's, and men's employment growth are shown in Table 18. As for the population equations, the lagged adjustment parameters are significant and within the expected range, which means the systems of equations are dynamically stable.[32] However, now

[32] The stability of the models also was tested by calculating the characteristic roots of a matrix that contains the lagged adjustment parameters estimated from a reduced-form population and employment equation. For equations (9a) and (9b), the following reduced-form adjustment parameters for population and employment were found: $\begin{bmatrix} 0.07 & 0.02 \\ 0.07 & 0.15 \end{bmatrix}$. Similarly, for equations (10a)–(10c), the following reduced-form adjustment parameters for population, women's employment, and men's employment were found: $\begin{bmatrix} 0.07 & 0.05 & 0.00 \\ 0.06 & 0.20 & 0.14 \\ 0.02 & 0.12 & 0.20 \end{bmatrix}$. Because the dominant characteristic roots of these matrices (0.167 and 0.341, respectively) are below zero, the models prove to be dynamically stable. See Carruthers and Mulligan (2007) for more details about the characteristic roots test.

the parameters are at least twice as large, indicating that firms react more quickly than households to changing labour market conditions. Also, men's employment shows a greater adjustment speed than women's employment, with the former realising nearly 20% of the equilibrium rate of employment growth, as opposed to 14% by the latter. Next, most parameter estimates associated with lagged population, $(I + W)(\ln P_{i,t-1})$, and contemporaneous population growth, $(I + W)\ln(P_{i,t}/P_{i,t-1})$, are positive and significant. As for the latter set of parameter estimates, which indicate whether jobs follow people, the results again confirm that using aggregate employment data conceals important differences between subgroups. Specifically, the covariation with population growth is strongest within a distance range of a 45-min travel time for men's employment growth (as well as total employment growth) but is limited to a 15-min travel time for women's employment growth. Hence, similar to the implied impact of employment growth on population growth, the results suggest that the impact of population growth on employment growth is also more localised for women's employment. Interestingly, this finding suggests that the reasons for women's shorter commuting trips lie not only in the residential choices of households but also, and more so, in the location choices of firms. Finally, a comparison of the parameter estimates across Tables 17 and 18 suggests that population growth has a greater impact on employment growth than employment growth has on population growth. At its maximum, a 10% change in employment growth generates a 1.77% change in population growth (from total employment growth, within a 45-min travel distance; see Table 17), whereas the reverse impact of a 10% change in population growth is, at its maximum, 7.80% (on men's employment growth, within a 45-min travel distance; see Table 18).

The finding, that jobs follow people is stronger than people follow jobs, is also the most common outcome of studies of population–employment interaction (see also Chapter 2), especially among US-oriented intra-regional studies (e.g., Boarnet 1994; Bollinger and Ihlanfeldt 1997; Deitz 1998). As with postcode population growth, the results reveal spread effects in employment growth, which decline after a 30-min rather than a 15-min travel distance, and have a much greater impact. The spread effects are strongest for men's employment growth; those for women's employment growth more closely resemble those for total employment growth. Clearly, each of the employment groups has a self-reinforcing tendency in that local employment growth stimulates similar growth in neighbouring locations. The results for the interaction between men's and women's employment indicate the absence of a feedback relationship. Instead, they show some repellent forces, from men's employment on women's employment growth, within very small geographical areas. Specifically, women's employment growth seems to respond adversely to men's employment growth within a 15-min travel distance $(I+W)\ln(E^m_{i,t}/E^m_{i,t-1})$. This suggests a competitive relationship and a tendency toward further segregation of men's and women's employment across small clusters of adjacent postcodes. Finally, the parameter estimates for the distances to motorway entrance/exit points (*MOTORW*) and railway stations (*RAILW*) do not differ from those found for the population equations, falling well short of conventional statistical levels and, contrary to expectation, revealing a positive sign. In contrast, the parameter estimates for travel time to other postcodes (*CENTRL*) now show the expected negative sign and are significant in both women's and men's employment equations. Apparently, firms find being centrally located important, which is not surprising because they might struggle in peripheral locations, especially if they operate in nationwide and highly competitive markets. Next, none of the variables that proxy the local attitudes toward women's employment (*HOUSHL*, *RELIG*, and *EMPMAL*) show a relationship with women's employment growth. Possibly these variables do not properly reflect these attitudes, but most likely, these attitudes do not play a major role at the local level of analysis. Finally, the variables for policy influence are again highly significant (apart from *ZONE*), similar to the population equation estimates. They also reveal that women's employment growth is more related to municipal capitals (*MUNICP*) and the expansion of office parks (*OFFIC*). By comparison, men's employment growth is more related to the expansion of industrial sites (*INDUS*), although the parameter estimates differ only slightly.

Summary and conclusions

The estimation of two different population and three different employment equations yields the following results. First, postcode population growth depends partly on total employment growth in neighbouring postcodes up to a 45-min travel time away but mostly on population growth in neighbouring postcodes within a 15-min travel time. Second, men's employment growth has a somewhat greater impact than women's employment growth on population growth, and the impact also stretches over a larger region (between postcodes 30 min and 45 min apart, compared with postcodes 15 min apart for women's employment growth). Third, a reverse impact of population growth on total employment growth (again stretching over a distance range of 45 min) also exists, which is much stronger than the impact of employment growth on population growth. Hence, at least in the study region, jobs follow people more than people follow jobs. However, even more important than population growth is the employment growth in neighbouring postcodes. In comparison with the spillover effects of population growth (that influence postcode population growth), the spillover effects of employment growth are much stronger and decline beyond a distance of a 30-min rather than a 15-min travel time. Fourth, the greater impact of population growth on total employment growth also applies to women's employment growth. However, the impact is somewhat weaker and more spatially restricted. Similar to the reverse impact of women's employment growth on population growth, the impact of population growth on women's employment growth is limited to postcodes that are a maximum of 15 min apart. Also, for women's employment growth, the same employment growth in neighbouring postcodes is more important than population growth (and similar in terms of magnitude and spatial range of the spillover effects observed for total employment growth). For the interaction between employment groups, women's postcode employment growth may be adversely affected by men's employment growth within a 15-min travel time. Fifth, population growth has a greater impact on men's employment growth than it has on women's employment growth but, again, only over long distances (between postcodes 30 min and 45 min apart). Also, while similar in spatial range, the spillover effects of men's employment growth are even more important than those observed for total employment and women's employment growth. Finally, women's employment growth has no impact on men's postcode employment growth.

These results offer some important insights into the different spatial effects of population and employment growth. For instance, local employment growth appears to have relatively little impact on population growth but considerable impact on employment growth in neighbouring sites. Local population growth seems to have a more varied impact: not limited to population growth in neighbouring sites, it extends to employment growth in neighbouring sites. The impacts of women's employment growth seem mostly confined to small geographic areas, whereas men's employment growth also affects sites farther away. Finally, population growth seems to have a localised impact on women's employment growth but a widespread (regional) impact on men's employment growth.

Additionally, the results shed light on the aggregate outcomes of residential and employment location decisions of households. The finding that population changes mostly precede employment changes suggests that residential location decisions usually are made before employment location decisions and that people typically search for jobs from a fixed residential location. That the relationship with population growth is spatially different between men's and women's employment growth is consistent with what we know about commuting. For men's employment growth, the results are similar to previous empirical observations that indicate a commuting tolerance of 45 min travel time (e.g., Van Ommeren et al. 1997; Wheeler 2001). Also, the absence of a relationship with population growth over short distances (within a 30-min travel time) points at an indifference zone within which male workers are unconcerned about travel distances. The finding that population growth responds to women's employment growth suggests that women's job location (and labour career) also plays a role in the residential location decision of households (see, e.g., Smits et al. 2003). The results also intriguingly indicate that while households primarily follow men's jobs, they follow women's jobs more closely, that is, within shorter distances. This confirms the greater spatial mobility of men compared with women and supports a previous observation for the Netherlands (Camstra 1996) that households adjust their place of residence to the job location of the male worker only for long-distance relocations.

Overall, the analysis of local population and employment changes in the Northern Netherlands yields some convincing results, largely consistent with findings from previous studies and probably generalisable to many other regions. However, outcomes about the direction of population–employment interaction are very much place specific and are also arguably very dependent on the spatial detail of the analysis. For instance, Mulligan et al. (1999) show that at the inter-regional level in the United States, people follow jobs rather than jobs follow people. Households more easily change residential location, and migration arguably plays a more prominent role in the adjustment of labour markets (e.g., Blanchard and Katz 1992). Broersma and Van Dijk (2002) show, in an analysis comparable to Blanchard and Katz, that for the Netherlands, just like for most European countries, changes in participation are a much more important adjustment mechanism than migration. Similar to a comparison between countries, one needs to be done between, for example, highly metropolitan and rural regions, where conditions are more extreme than in the region studied here. Future studies should use large data samples that allow the investigation of spatial nonstationarity in the various relationships. Also, to understand how location changes of men's and women's employment come about, changes should be examined in the distribution of male and female workers within industries and firms.

This study reveals several important methodological messages. The finding of important group and spatial effects suggests that using disaggregated data along with various spatial weighting schemes is an important way to expand our knowledge of local growth patterns. This study shows that the analysis of group effects alone is of limited value if spatial effects are not explicitly considered, and vice versa. Also, the novelty in this study of specifying the spatial weighting schemes by travel times shows great promise and seems to justify a more prominent role in future spatial interaction studies. Finally, the comparison of interaction within and across population and employment groups clarifies that the interaction within groups is of paramount importance and that local growth models need to include a spatial autoregressive lag.

6. Summary and conclusions

Introduction

Recently, there has been a considerable amount of research that has focused on location changes of jobs and people, and the way these changes interact (i.e., “do jobs follow people or people follow jobs?”). This renewed surge of interest (the issue of population–employment interaction was first raised in the 1960s and 1970s) basically started in 1987 with the publication of Carlino and Mills’ *The Determinants of County Growth*. Ranked as the most frequently cited regional science publication of its year (see Isserman 2004), this article has become a true modern classic by the introduction of what is now known as the “Carlino–Mills model”. With the introduction of this model, a highly intuitive, flexible and user-friendly econometric framework became available that has since been used in most inter-regional location studies of jobs and people. Since the 1990s, this CM model has also been the standard methodology in intra-regional location studies. The major impetus for these studies was the integration, initially by Boarnet (1992), of techniques developed in the then relatively new field of spatial econometrics. Typically, what happens in one place has an impact on what happens in other places, which means that data observations used in spatial analysis are usually not independent, and therefore not suited to investigation by routine, i.e., non-spatial, statistical techniques.

Alongside the methodological progress, studies on location patterns have also greatly benefitted from the development of computer technologies. Here, the proliferation of user-friendly Geographic Information Systems (GIS), for the visualisation and manipulation of spatial data (see, for example, Longley et al. 2011), and specialised software (for example, *SpaceStat* and *GeoDa*), for the analysis of these data by spatial econometric tools (see Anselin 2010), have been particularly important.

Finally, and as least as important as the progress in methodologies and technologies, there has been the growing amount and richness of geographical data becoming available. Until the late 1980s, most intra-regional analyses estimated density gradients from highly aggregated spatial data divided simply into city centre and suburban areas. In fact, the county-level analysis by Carlino and Mills (1987) was the first US nationwide study of population and employment changes on such a detailed spatial scale. Today, such changes can, and have been, investigated on virtually any spatial scale as well as for many different geographical settings, time periods and subgroups of jobs and people.

Besides the greater ease and opportunities for analysis, the research interest in location patterns has also grown for several more fundamental reasons. Recently, some major societal developments, or megatrends, have given rise to suggestions that the landscapes of jobs and people are, or are about to, radically change, on a scale similar or even more dramatic than that seen during the period of industrialisation in the late 19th and early 20th centuries (see, for example, Florida 2002). In particular, much is being made of the impact of technology, and especially the development of Information and Communication Technologies. It is suggested that these technologies will render obsolete the need for spatial clustering and shift the balance between the centripetal and centrifugal forces of urbanisation in favour of the latter. Some researchers have gone as far to claim the "death of distance", the "end of geography" or that the "world will become flat", and foresee the very existence of cities under threat (see, for example, Friedman 2006 and Cairncross 1997).[33] In addition to technology, much has recently also been made of social-cultural developments affecting the landscapes of jobs and people. For example, in the ground-breaking and best-selling book *The Rise of the Creative Class* (2002), urban theorist Richard Florida highlighted the growing value attached to human creativity, which he argues is even more important than technological progress. As such, rather than foreseeing the end of cities, or geography for that matter, he predicts the world to remain "spiky" (Florida 2005). In his view, cities will continue to thrive, but only those that are able to attract and retain the talented people who belong to what he calls "the creative class". In *The Great Reset* (2010), about the impact of the current financial and economic crisis, Florida describes how, similar to after the crises of the 1870s and 1930s, new ways of living and working will emerge that will see radically different landscapes of jobs and people. He foresees the mortgage-financed home and car ownership based suburban lifestyle, which emerged after the 1930s, being replaced by a more environmentally friendly and flexible urban lifestyle, and that jobs and people will increasingly concentrate in a smaller number of larger cities that will merge into mega-regions. Finally, especially in Europe, Russia and Japan, there is a great deal of interest in the possible impact of demographic changes on the geographies of jobs and people. Here, the interest centres on the ageing of the population and the prospect of a declining population, and on how these changes will especially hit peripheral areas outside the main urban agglomerations (see, for example, Haartsen and Venhorst 2010).

Amidst the discussions on whether the urban landscape is, or may be, radically changing, questions have also been raised about a possible change in the way the location choices of firms and households interact. For example, Glaeser (2000) has argued that with workers becoming richer and firms becoming more mobile, the location choices are increasingly based as much on the advantages for workers as on the advantages for firms. Likewise, Pink (2001) has observed that more and more people work for themselves, rather than for an employer, and that this gives them great flexibility when choosing a place to live. Finally, Florida in particular has stirred interest in the question as to whether "people follow jobs or jobs follow people" by

[33] Note that these ideas have also been fiercely criticised (see, e.g., Leamer 2007; McCann 2008).

claiming that, with the transformation to a society in which human creativity is key, the balance will shift from the former to the latter. He argues that, for creative people, jobs are not all that matters when choosing a place to live. Rather, the overall quality of living and the opportunities they have to satisfy their creative needs are more important to them, implying that they will look for places that are diverse, tolerant and technologically advanced. As to firms, which will become increasingly dependent on innovation and creativity, they will have to move to where the creative people are (Florida 2002).[34]

Another fundamental reason for the growing research interest is the call from policymakers for practical insights into the location choices of firms and households and the way these choices interact. This is of interest because, for example, depopulation and employment losses play a crucial role in the self-reinforcing circle of decline or deprivation that a town, city or region may get trapped in once the numbers of people and jobs fall below a critical mass. Understanding the location choices of firms and households may help to understand the many different manifestations of decline, to predict which locations may suffer such a decline, as well as to come up with useful policies to mitigate or counteract such a decline. Similarly, policymakers could be confronted with population and employment growth in places where this may be neither needed or wanted (for example, because of environmental, economic or socio-cultural reasons). Whether it is to tackle inequalities or inefficiencies, policymakers need to have a clear understanding of the nature of the population–employment interaction if they are to control the distribution tendencies of jobs and people. Basically, they have to choose between different types of strategies, of which some may be inefficient or ineffective. For example, they could adopt policies that first and foremost try to stimulate job growth under the assumption that people will automatically follow. Such policies typically focus on interventions in the business climate of identified locations to make them more attractive to firms (such as through financial, fiscal or infrastructural measures). However, for such policies to be successful, the location decision of firms should not be driven by the availability of potential workers *and* people need to find job opportunities more important than the residential amenities a place offers. Specifically, the concern is that if the authorities decide to allocate most of their funds and resources to firms that this may be at the expense of retaining or improving the residential amenities. Consequently, people may want to leave, or not want to move to an area, which, in turn, will lead to employment losses if jobs do indeed follow people. Likewise, the opposite strategy of trying to first attract households by improving the residential qualities of a place (anticipating that jobs will automatically follow) only works if jobs do follow people, and not the other way around (see also Henry et al.

[34] Note that several criticisms have been directed at some of Florida's claims, such as that the creative class, or people with high levels of human capital, prefer city locations (see, e.g., Glaeser 2005); or that location decisions are made principally in response to quality of life features or amenities, rather than the employment opportunities a place offers (see, e.g., Storper and Scott 2009).

1997; Freeman 2001). Recently, policymakers have become increasingly aware that it is possible that jobs may follow people. As such, many regional development and city-marketing programmes now focus on attracting people, by investing in lifestyle options and amenities in order to create an attractive place to live. Florida (2002), in particular, has argued that catering to the preferences of the creative class is a far better strategy for growth than the more traditional economic development strategy of catering to the companies that employ these workers. He notes that while it remains important to have a solid business climate, having an effective "people climate" is more valuable (for contrary arguments, see, for example, Storper and Scott 2009).

Besides the implications for policy, the issue of population–employment interactions has implications for theory and research. For example, interdependencies between the location decisions of firms and of households play a central role in theories that try to explain the spatial clustering of economic activities by factors other than the distribution of the so-called "first nature" geographical features. Such approaches include the cumulative causation theory and New Economic Geography developed by Nobel laureates Gunnar Myrdal and Paul Krugman respectively (see, for example, Meardon 2001; Fujita and Thisse 2009). Also, many research fields show a particular interest in the exact nature of the population–employment interaction, as succinctly summarised by the question "do jobs follow people or people follow jobs". For example, in the interdisciplinary human ecology literature, the chicken-or-egg question reflects two contrasting views on the redistribution tendencies of jobs and people across communities. Proponents of the so-called deconcentration perspective claim that these tendencies need to be understood in the context of changing residential preferences and greater freedom of households to act upon these preferences, i.e., that jobs follow people. In contrast, proponents of the so-called restructuring perspective place a greater emphasis on the changing production requirements and greater spatial flexibility of firms, i.e., people follow jobs (see Bierens and Kontuly 2008 for a discussion and empirical evidence for these perspectives). Similarly, two main paradigms exist in the literature on human migration, one stating that people predominantly move for "production-related" motives (that people follow jobs), and one stating that "consumption-related" motives (i.e., access to residential amenities) have the upper hand (see Partridge 2010 for a discussion and empirical evidence). Related to this, there is some literature that has focused on the role of commuting in the location decisions of people, and that has addressed the issue of causality by asking whether the residential location decision is made before or after the job location decision (see Waddell et al. 2007; Deding et al. 2009). Finally, economists touch upon the issue of jobs–people causality in making a distinction between supply-side and demand-side explanations for differences in economic growth. Here, a critical role is usually attributed either to fluctuations in labour supply, i.e., jobs follow people, or to fluctuations in labour demand, i.e., people follow jobs (see, for example, Freeman 2001).

In short, the chicken-or-egg question as to whether "people follow jobs" or "jobs follow people" appears in many fields of research, and generally serves to highlight the fact that very contrasting theories exist that may emphasise particular choices, behaviours or changes as independent, exogenous, primary or causal. The answer to this question becomes particularly important when models are used that do not allow for the possibility of endogeneity, simultaneity or two-way interaction. For example, regional growth models often focus solely on either the demand or the supply side, and assume that either labour demand or labour supply is highly wage elastic, but not both. Similarly, commuting models usually treat the residential location or workplace as fixed and ignore the possible simultaneity among these location decisions. A good example is the classic mono-centric city model that has been at the heart of the urban economic literature on residential land-use patterns. This model assumes that households adjust their locations to the locations of firms but, crucially, not the other way around. Questioning this assumption, many studies have shown that, due to apparent feedback effects, this model yields biased and inconsistent results, and potentially leads to inappropriate policy suggestions (see Boarnet 1994 for a discussion).

Finally, much of the growing research interest in the issue of population–employment interactions can be attributed to the ambiguity that surrounds the findings of empirical studies. The popular impression is that these findings are extremely mixed and conflicting. As a result, the issue of population–employment interaction is generally thought of as an enigma, a puzzle that like other chicken-or-egg dilemmas is fascinating in itself, and not necessarily because of what it means in relation to the spatial changes taking place or policies that may be used to channel these changes. The lack of consensus among empirical findings has provoked further research since the possibilities for out-of-sample prediction, or the transfer of values obtained for one site to another, seem fairly limited. Also, it has prompted researchers to experiment with different data and methodologies in an attempt to explain the variations in the findings.

Research questions, methodologies and findings

The overall aim of this study was to enhance the understanding of population and employment location changes: first, by making sense of the already existing body of research, and second, by investigating several largely unexplored issues. To this end, four main research questions were formulated. The first of these questions focused on the findings of previous studies for the question of population–employment interaction, in order to reflect on the popular assumption that these findings are extremely mixed:

1. *What do research findings on population–employment interactions indicate about whether "jobs follow people" or "people follow jobs"?*

The approach used to answer this question, and to determine if and to what extent the findings of empirical studies disagree, was a systematic quantitative literature review, an approach known as meta-analysis. In the first step of the meta-analysis, the literature was meticulously screened for relevant and comparable studies. The criteria used for selecting these studies were: (a) the use of a Carlino–Mills model specification, i.e., a simultaneous population and employment equations system with adjustment lags; and (b) the inclusion of estimation results for the model's parameters that indicate whether or not people follow jobs and/or jobs follow people. Eventually, thirty-seven "Carlino–Mills studies", published between 1987 and 2004, were identified. The second step of the meta-analysis involved the retrieval of relevant data from these studies. A database was compiled that included a total of 308 unique research findings related to the direction of the jobs–people causality, which were classified into four categories: "no interaction", "people follow jobs", "jobs follow people" and "dual causality". The final step of the meta-analysis involved a statistical summary of these findings. It was revealed that slightly more findings pointed towards "jobs following people" (31.5%), than to "people following jobs" (27.6%) and to "no interaction" (25.6%). The least common, but not that infrequent, finding pointed towards "dual causality" (15.3%). With many of the sample findings originating in relatively few studies (one study contributed no fewer than 150 study results), the results were then also weighted to ensure that each unique study, or group of related studies, contributed equally to the sample of study results. Again, and even more so than in the unweighted sample of study results, the weighted evidence pointed most strongly towards "jobs follow people" (45.5%). After weighting, the evidence for the "people follow jobs" hypothesis dropped considerably (to 11.4%), indicating that this outcome is not very common across different studies. Support for "no interaction" (21.8%) and "dual causality" (21.4%) was practically identical after weighting. In conclusion, the analysis confirmed the popular view that the evidence from empirical studies on the issue of the population–employment interaction is very mixed (and therefore difficult to translate into clear policy recommendations and to use in generalisations and for making predictions). To add to the confusion, variations in research findings are not only found between studies but also within individual or groups of related studies that have practically identical research designs.

The observation that the empirical evidence on the nature of the population–employment interaction is unclear is important, but on its own has limited value. For instance, the dominant finding that "jobs follow people" may simply be because of the focus of previous studies on location changes in particular regions or particular eras. In other words, additional insights are needed into those characteristics of the studies that could explain the variation in results, for without such insights it remains unclear why the results of a study *are what they are*, how robust or much more representative they are than other results, and whether they are a sound basis on which to make predictions. With regard to the variation in study results, the central remaining question is whether the observed variations in findings over causality in the jobs–people relationship has an empirical explanation (i.e., the direction of causality varies between regions, time periods, subgroups of jobs and people), or whether the variation reflects a scientific artefact that stems from the differing methodologies, or some combination of both. Revealing whether it is data selection and/or methodological issues that lead to most of the differences offers more than an understanding of the variation in previous findings: it can inform future studies about which research choices require careful consideration. This leads to this study's second research question:

2. *Why do research findings on population–employment interactions differ, and what are the sources of this variation: are they empirical, intrinsically related to variations in the nature of population–employment interactions over time, or space or between subgroups of jobs and people; or methodological, related to the way in which the issue is investigated?*

Two approaches were used to answer this question. First, further data from the 37 selected Carlino–Mills studies were added to the meta-database including 308 study results. The additional data retrieved were all characteristics included in the studies that underlie, and possibly influence, the results. Subsequently, several study characteristics were selected for examination in combination with the findings on population–employment interaction. The study characteristics selected concerned the following four substantive, data-related, factors: geographical coverage (non-US versus US data), time coverage (1960s/1970s versus 1980s versus 1990s data), spatial resolution (US states versus US BEA regions versus medium- and small-area observations) and type of population and employment data (subgroups versus total population and employment data). Further, to assess the possible impact of methodologies, four study factors were selected: the operational definition of the employment and population variables (numbers of jobs and people versus numbers of jobs and people standardised by area size), the specification of the right-hand-side and left-hand-side population and employment variables (changes-levels versus changes-changes versus levels-levels) and the number of endogenous variables included on the right-hand side of the equations (one versus more than one). Finally, one extrinsic study factor was included, namely the publication outlet of a study (journal article versus other publication).

Linking the various study factors to the findings on the population–employment interaction (by means of a multivariate logistic regression analysis) yielded the following findings related to the intrinsic study features. First, the spatial resolution, geographical coverage and time coverage of the data clearly all have an impact on the results for the population–employment interaction. More specifically, using data with a large scale spatial resolution significantly decreases the likelihood of finding evidence of dual causality or two-way interactions. Also, these observations show a much stronger association with the "people follow jobs", rather than "jobs follow people", argument compared to small-area observations. As for the impact of the geographical area, the results of the multivariate logistic regression analysis suggest that using data from the United States is more likely to yield findings that are indicative of "no interaction" and less likely of "dual causality". In terms of the impact of the time period covered, the results somewhat surprisingly reveal that the "jobs follow people" finding is most common when using data from the 1960s and 1970s. Also, the data from the 1990s shows a significant increase over the 1980s' data in the probability of finding "no interaction" rather than "jobs follow people". In comparison, comparing data that refer to different population and/or employment types suggests that these aspects do not appear to make much difference. However, this may be due to the rather crude categorisation applied (all data versus subsamples), which could average out possible differences between subgroups.

As for the impact of the various methodological factors, the population–employment interaction results in the Carlino–Mills literature are mostly influenced by whether the relevant RHS and LHS variables measure absolute population and employment sizes or changes within them. Specifically, significantly more findings indicate "no interaction" when these inferences are based on models of population and employment changes. However, given that such models have almost exclusively been used in intra-regional Carlino–Mills studies, the spatial level of the analysis may play a decisive role. Accordingly, the results can also be seen as confirming that local population and employment analyses are especially prone to producing statistically insignificant parameter estimates. Also, the results provide statistical evidence that Carlino–Mills studies based on population and employment "densities" produce different parameter estimates than studies that do not control for differences in the size of the spatial units observed. Specifically, using standardised population and employment data seems to be particularly strongly associated with a finding of "dual causality". In addition, there is some suggestion that standardisation also impacts on the probability of finding that "people follow jobs". The exact impact, however, is not entirely clear as the meta-regression analyses of the weighted and unweighted samples of Carlino–Mills observations give very contrasting results. Similarly, only the weighted results suggest that controlling for heteroscedastic and/or autocorrelated error terms will produce different population–employment interaction findings. However, both the weighted and unweighted samples provided no evidence that including additional endogenous variables will impact on findings concerning the issue of population–employment interaction. Finally, for the extrinsic study factor (the publication outlet of a study), the meta-regression analysis revealed that it is especially journal articles that provide evidence supporting the "people follow jobs" hypothesis.

The second approach used to answer Research Question 2 again involved a meta-regression analysis, but this time using data obtained from a series of new 'experiments' rather than from existing Carlino–Mills studies. The aim of this investigation was to gain more precise insights into the possible impact of particular methodological and data-related issues than could be obtained from a standard meta-analysis. In more detail, a total of 4,050 quasi-experimental empirical results related to the jobs–people direction of causality were generated for three specifications and estimations of a spatial econometric Carlino–Mills model, for three specifications of a spatial weights matrix, for three operational definitions of the population and employment variables, for six time periods, for five employment groups, and for five settlement types in the province of Fryslân in the Northern Netherlands. The subsequent meta-regression analysis confirmed that both the geographical coverage and the time coverage of the data play a crucial role in shaping the research findings on population–employment interaction. More specifically, in addition to the between countries and decades variations (see above), some significant differences in the population–employment interaction could be observed between locations within regions and between rather short time frames. The new meta-regression analysis also supported the importance of group effects in the population–employment interaction, something that could not be observed in the standard meta-analysis of existing Carlino–Mills studies. In addition to these data-related issues, the results regarding the population–employment interaction also depend on both the specification of the spatial weights matrix and more especially on the measurement of population and employment growth. Again, similar to with the routine meta-analysis, the results very much depend on whether population and employment numbers are standardised by area size. The most important determinant of the variation in results for the job–people direction of causality is, however, the chosen specification and estimation of the Carlino–Mills model. The results of the meta-regression analysis indicate that models that include both auto-regressive and cross-regressive spatial lags, and which are estimated by the relatively new and generalised spatial two-stage least-squares (GS2SLS) procedure, are more likely to find evidence of "jobs following people" than models that only allow spatial dependence in right-hand-side endogenous variables (by including cross-regressive lags but excluding autoregressive lags) or which are estimated using a two-stage least-squares (2SLS) procedure. Crucially, by failing to properly treat spatial dependence, the parameter estimates from the latter model specifications and estimations can be biased and inconsistent. Comparing the different model specifications and estimations reveals that parameters estimated by GS2SLS procedures, with models that include both cross-regressive and auto-regressive lags, are more robust and less sensitive to variations in data sampling, variable measurement and weight matrix specification.

To summarise, both the standard meta-analysis of Carlino–Mills studies and the quasi-experimental meta-analysis using a series of generated experiments confirmed that results for the jobs–people direction of causality are influenced by both data selection and the choice of a particular methodology. The impacts of various aspects of the data clearly indicate that population–employment interactions vary across space and time, and between employment groups. Moreover, these differences remain even when the data selection becomes very specific, i.e., when the analysis of space and time effects is narrowed to rather small geographical units or rather short time periods. Turning to the impact of methodologies, the analyses revealed a variety of sources for the variations in research findings. Here, the model specification and estimation is of overriding importance, as failing to effectively address spatial dependence may induce bias in the estimation results, and inaccurate inferences about the direction of causality in the jobs–people relationship. As such, it is possible that model misspecification and the use of inappropriate estimation techniques may explain much of the discrepancy in findings across the Carlino–Mills literature. Whether inferences are based on model parameter estimates that describe the relationship between population and employment levels or between changes in these levels is particularly important. Although model specification issues are a clear source of the variation in the results, other factors also play a role and need careful consideration. For example, how should the relevant population and employment variables be defined? Should they simply measure population and employment numbers or, rather, numbers standardised by area size?

An important but somewhat neglected issue in the analysis of population–employment interactions is the role of distance. Distance can be expected to have a negative impact on population–employment interaction in the sense that the strength of any interaction will typically decline over distance. Further, the fact that intra-regional and inter-regional studies produce very contrasting research findings suggests that inferences about the jobs–people direction of causality very much depend on the distance over which the relationship is being investigated. Accordingly, it seems that distance may not only impact on the strength, but also on the direction, of the interaction. Knowing how population–employment interactions change with distance would help in understanding how population or employment changes in one place also affect other places, an aspect which is particularly relevant for policy. Further, research could also very much benefit from such insights. Research studies usually make some strong assumptions about the range and decay with distance of spatial interactions and, if such assumptions are inappropriate, studies may wrongfully conclude that distance does not matter. It is also possible for studies to corroborate the impact of distance on the location decisions of firms and households, and aggregate employment and population patterns, but without revealing the exact nature of this impact. This leads to the third research question posed in this study:

3. *What are the spatial dimensions of population–employment interactions: how far do they stretch, and how quickly do they fall away with distance?*

Two complementary methodologies were used to answer Research Question 3. The first was an Exploratory Spatial Data Analysis of postcode-level employment and population data from the Northern Netherlands for the years 1994/1995 and 2002/2003 (Chapter 4). The aim of this analysis was to gain insights into the spatial nature of the population–employment relationship by calculating various bivariate spatial association statistics that would reveal whether the population and employment growths of neighbouring postcodes are more similar than would be expected for a spatially random distribution.

Further, rather than using a single "neighbourhood" criterion, the statistics were calculated for nearby postcodes at various distance intervals. Subsequently, the impact of distance could be empirically derived by comparing the size, sign and significance of the association statistics at the different intervals. It was found that, at straight-line distances shorter than approximately 7 km, the bivariate spatial association statistics were insignificant. Between 7 km and around 60 km, the association statistics are significant and this indicates that 'neighbouring' postcodes have greater similarities in population and employment growths than would be expected based on spatial randomness. Beyond 60 km, the association statistics are again insignificant.

The second method used to determine the impact of space involved comparing the parameter estimates of a spatial econometric Carlino–Mills model for different specifications of a spatial weights matrix (Chapter 5). Estimated using the same postcode-level data from the Northern Netherlands as before, the model will reveal whether population (or employment) growth in a postcode zone can be explained by the spatial moving average employment (or population) growth within postcode zones at various distances. In this instance, distance was measured by car travel time, rather than geographic distance, in order to gain more realistic insights into the impact of space. Using the population equation it was found that local population growth depends on employment growth in postcodes within 15 minutes, 30 minutes and up to 45 minutes travel time. Using the employment equation, it was found that similar ranges apply for the reverse impact of population growth on local employment growth.

To summarise, the results of the various analyses offer some important insights as to what constitutes a spatial labour market and to what extent developments in one location have broader spatial implications, rather than only a local impact. Specifically, they suggest that the population–employment interaction stretches across locations that are no more than 45 minutes drive or 60 km straight-line distance apart, a finding that is very similar to observations made in previous studies (see, for example, Wheeler 2001). Also, at very short distances (less than 7 km) there may be no population–employment interaction, a finding that is line with the idea of an indifference zone in commuting (see, for example, Camstra 1996). Taken together, the results suggest that the impact of neighbouring locations on local growth patterns can probably be best described by an S-shaped curve that starts flat, subsequently steepens, and finally flattens again.

Finally, just as with the impact of distance, relatively little is known about the impact of gender on location patterns. It is well known that men and women tend to work in different occupations and have different commuting times, which implies that their employment locations are not the same. Naturally, this raises some interesting questions such as whether differences exist in the nature of the population–employment interactions, and interactions within and across gender-specific employment groups. As such, there could be differences in the strength, direction and spatial range of the different types of interaction. Assessing the interaction in terms of gender differences could potentially produce some important insights into the changing location patterns of jobs, and the relative importance of employment-population linkages and of different types of employment linkages. These insights have an increasing relevance as women increasingly contribute to regional employment growth. Consequently, the fourth research question was formulated as:

4. *What is the impact of gender on the location changes of jobs and people: is there a difference between men's and women's employment in the strength, direction and spatial range of population–employment interactions, interactions within employment groups, and interactions between employment groups?*

The methodology used to answer Research Question 4 was a spatial econometric Carlino–Mills model with one population and two gender-specific employment equations, and with both autoregressive and cross-regressive spatial lags on the right-hand side of each equation (Chapter 5). Spatial lags were calculated by spatial weights matrices to reflect different distance bands in order to reveal possible gender variations in the spatial range of the population–employment interaction, and in the interactions within and across employment groups. Again, distances were specified in terms of travel time by car, and the postcode-level data from the Northern Netherlands used in the Exploratory Spatial Data Analysis (Chapter 4) were again used to estimate the model. The estimation results failed to reveal any gender difference in the direction of the population–employment interaction. The employment growths of both men and women are more influenced by population growth than vice versa. However, for women's employment, the interaction is very localised, stretching across postcodes that are no more than 15 minutes travel time apart. Within this distance, there is no population–employment interaction with regard to men's employment. For men, an interaction can only be observed within distances of 30 to 45 minutes travel time. Overall, the population–employment relationship is somewhat stronger for men's employment than for women's employment. As for the interaction within employment groups, it was found that local employment growth for men, and to a lesser extent for women, depends on similar employment growth in neighbouring locations. For both groups of employment, the spillover effects decline beyond a distance of 30 minutes travel time. Finally, with regard to a possible interaction between the gender-specific employment groups, the results revealed that a growth in women's employment has no impact on men's local employment growth. However, women's local employment growth is negatively affected by a growth in men's employment within 15 minutes travel time.

Overall, the results leave no doubt that gender has an impact on local growth patterns. More generally, they highlight the importance of distinguishing subgroups within jobs and people since, without making subdivisions, some important insights may remain hidden. For example, the analysis has shown that the nature of the population–employment interaction is not the same for different employment groups, although spillover effects in employment growth are even more important. In addition, subgroups may differ in the degree to which the interactions are affected by distance. In this regard, the observation that the spatial range of the population–employment interaction differs for men's and for women's employment is a significant addition to the findings related to Research Question 3. It also shows that an analysis of spatial effects based on aggregated population and employment data can produce general results in which variations are lost. In this instance, the previous general findings of an indifference zone at short distances and a maximum interaction range of about 45 minutes have been shown to apply largely to men.

Implications and suggestions

One of the main reasons for the recent research interest in the changing locations of jobs and people is the considerable uncertainty surrounding the issue of whether "jobs follow people or people follow jobs". This study has taken away some of this uncertainty by systematically analysing a range of factors that explain some of the variation in study results for the direction of causality in the jobs–people relationship. In particular, this study has shown that results very much depend on the time period, geographic setting (see notably the analysis in Chapter 3), and type of employment (see the analysis in Chapter 5) investigated. As such, these are important issues to consider in future research studies. Ideally, future studies will provide details about the research choices that were made, both with regard to data selection and the methods of investigation, combined with some sort of sensitivity analysis that indicates the robustness of the results given these choices. Without such details, it is difficult to value the findings from a particular piece of research and then draw inferences that may help other researchers and inform policymakers.

Another important suggestion from this study is that careful consideration should be given to the choice of methodologies to ensure that estimation results are reliable and meaningful. For example, for applications of the Carlino–Mills model at the intra-regional scale, it is essential to properly control for different forms of spatial dependence given that the findings of the quasi-experimental meta-analysis in Chapter 4 clearly demonstrate that this influences the inferences drawn. These same findings also suggest that misspecification and the use of inappropriate estimation techniques are important explanations for the variation in previous research findings within the Carlino–Mills literature. The wide divergence in research findings in this literature is what one would typically expect when model estimates are biased and inconsistent. So, for this stream of literature to lose its tag of being inconclusive and not particularly meaningful, more attention should first be paid to how the results are obtained.

Moving on, several methodologies have been employed in this study that also seem to hold great promise in investigating several salient issues that have so far remained largely unaddressed. For example, an interesting and important issue, both for research and policy, is the speed at which population and employment changes adjust to each other. Further, the geographies of jobs and people are also determined by various factors apart from the impact of population changes on employment changes and vice versa. The Carlino–Mills literature provides information on both of these under-researched issues, which can be investigated using meta-analytical techniques. Also, the simultaneous equations analysis in Chapter 5 can fairly easily be extended to predict the impact of possible exogenous shocks. An example of this can be found in De Graaff et al. (2012a), who have used the estimation results of a Carlino–Mills model to show the regional impact of a local housing construction policy, in the Dutch city of Almere, on population and employment growth in neighbouring municipalities. When used as a forecasting or scenario-analysis model, the Carlino–Mills model can greatly facilitate policymakers in deciding what kinds of strategies to adopt.

From a policy and academic perspective, it would be interesting to compare the results with those of a Carlino–Mills model that was able to reveal the impact of space but without using spatial weights matrices *W*. Recently, in this respect, alternative methods to the standard, rigid *W*-based approach to modelling spatial interactions have been proposed that involve the inclusion of latent variables and allow a much richer representation and assessment of the spatial interaction structure (Folmer and Oud 2008).

Perhaps more than anything, this study has shown that, despite researchers and policymakers at times suggesting otherwise, we still know relatively little about the population–employment interaction, and probably not enough to make reliable policy recommendations. While the belief that jobs follow people is becoming increasingly popular, it remains to be seen whether policy strategies based on this assumption are really effective and efficient. We especially need to know more about why the nature of the population–employment interaction differs across locations. The observation made in this study that US and non-US oriented studies produce very different findings clearly hints at the impact of social, cultural and institutional factors. For the Netherlands, a municipality-level analysis of population and employment changes by De Graaff et al. (2008) found that the mechanisms were also quite different in urban, peri-urban and rural zones. The work undertaken here has shown that considerable differences exist even within very small geographical areas, a reality that would have been concealed had the analysis not been performed on such a detailed spatial level.

To understand more about spatial heterogeneity, it could be worthwhile to focus more closely on the population and employment structure of places. The results of the gender-specific analysis in Chapter 5 indicate that using highly aggregated data masks some important differences between subgroups. For example, it might be particularly interesting to examine population–employment interactions in locations where many independent free-agent workers or workers that belong to the creative class reside. The suggestion in the literature is that these workers are especially associated with the “jobs follow people” causality (see, for example, Pink 2001; Florida 2002). One should also consider that what really separates one group from another may not necessarily be the direction of interaction, but the spatial range and the decay with distance of the interaction. Accordingly, future subgroup analyses of population–employment interactions should preferably focus on the impact of distance. Given the increasing availability of micro-level data on firms and households that can be aggregated to virtually any spatial scale and subgroup (most recently by De Graaff et al. 2012b) there is no practical reason to restrict the analysis to investigating total population and employment changes, and ignoring spatial effects. Further, linked employer–employee data (LEED) are now available that allow a simultaneous analysis of the demand and supply sides of labour markets. For example, these data are particularly suited for revealing how workers choose their residential and employment locations and the trade-off among commuting costs, working hours and wages. With the weakening of traditional employer–employee ties and the growing possibilities of teleworking etc., there will be an increasing relevance in addressing these issues. Possibly, people will experience greater flexibility in choosing a place to work and a place to live, the spatial size of labour markets will increase and the impact of population changes on employment changes and vice versa will stretch over longer distances. Alternatively, increases in travel costs may mean that the traditional space–time constraints on people and firms will largely remain, and that population–employment interaction will remain predominantly localised. Using longitudinal LEED, one could track workers and their firms or workplaces over time and perform a rigorous assessment of causal processes. For example, one could investigate whether the residential decision is made before or after the employment decision, how workers respond to a firm's relocation, and whether and how the fortunes (survival, growth) of firms are linked to worker flows (the exit and entry of workers). By enriching these data even further by linking in household data, one could gain a better insight into the role of gender and how decisions about employment location, residential location, commuting time and working hours are negotiated within families. Finally, and a key policy issue, is whether the marginal effects that one can discern from a Carlino–Mills model are likely to sustain in a shrinking population, an issue that appears increasingly relevant to the Netherlands and many other countries. Accordingly, it could also be valuable to investigate possible instabilities in the parameter estimates of the Carlino–Mills model across regions with different population dynamics.

The discussion above suggests that, with some additional research, it should become possible to make some clear and sound policy recommendations. The necessary data are now available to investigate the decision-making of firms and people in great detail, and to aggregate employment and population location changes on virtually any spatial scale, for any subgroup, and for all kinds of locations. Moreover, spatial econometric modelling techniques and GIS-related software are now available that greatly facilitate the analysis of space and time effects and, thanks to the development of sound estimation techniques, researchers can be more confident in the results of their analyses.

Samenvatting (Summary in Dutch)

Tussen regio's en locaties binnen regio's bestaan doorgaans grote verschillen in economische groei. In onderzoek naar deze groeiverschillen, en dan gemeten naar de ontwikkeling van het inwonertal en de werkgelegenheid, staat de laatste jaren één vraag centraal: gaan bevolkingsveranderingen vooraf aan werkgelegenheidsveranderingen of gaan werkgelegenheidsveranderingen vooraf aan bevolkingsveranderingen? (of ook wel: *volgt werken wonen of wonen werken*?).

Het onderwerp is vooral weer actueel door allerlei sociaal-culturele, economische, demografische en technologische ontwikkelingen.[35] Deze hebben er toe geleid dat de interacties tussen bevolkingsgroei en werkgelegenheidsgroei niet langer eenduidig zijn. Voorheen bestond er weinig onduidelijkheid: mensen gingen in de regel daar wonen waar de banen waren. De ruimtelijk-economische structuur werd dan ook voornamelijk bepaald door de locatiekeuzes van bedrijven. Vandaag de dag lijkt het echter anders: de voorheen nauwe ruimtelijke samenhang tussen wonen en werken bestaat niet meer, mede door ontwikkelingen op het gebied van mobiliteit en arbeidsrelaties (parttime werken, telewerken etc.) en doordat tweeverdieners hun woonlocatie veelal moeten afstemmen op twee verschillende werklocaties. Ook veranderen werknemers steeds vaker van baan dan vroeger het geval was en werken er meer mensen voor zichzelf. Daarnaast laat men zich niet langer alleen leiden door economische motieven, maar spelen ook factoren als welzijn en de aanwezigheid van voorzieningen een rol bij de woonplaatskeuze.

Voor bedrijven en werkgelegenheid geldt dat zich een verschuiving heeft voorgedaan van industrieën naar diensten. Ook is het belang van kennis, informatie en creativiteit toegenomen en zitten bedrijven ogenschijnlijk minder 'vast' aan een bepaalde locatie. Door met name ontwikkelingen op het gebied van Informatie en Communicatie Technologieën, die de invloed van afstand doen verminderen, is de noodzaak om te clusteren voor veel bedrijven mogelijk aan het verdwijnen.[36]

Het antwoord op de vraag of wonen werken volgt of werken wonen heeft belangrijke implicaties voor ruimtelijk-economisch beleid. Traditioneel beleid dat is gericht op het aantrekken van bedrijven lijkt weinig effectief als het vooral bevolkingsveranderingen zijn die de economische groei aansturen. Sterker nog, een dergelijk beleid kan contraproductief werken als de inzet van doorgaans beperkte middelen (zeker in tijden van economische crisis) ten koste gaat van de woonkwaliteiten van een locatie. Omgekeerd geldt ook dat een beleid dat met name is gericht op het

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[35] Het onderwerp stond eerder in de belangstelling in de jaren 60 en 70 toen zich door suburbanisatie, counterurbanisatie en andere ruimtelijke trends grote verschuivingen in de ruimtelijke spreiding van de bevolking en werkgelegenheid in Westerse landen voordeden.

[36] Er zijn ook tegengeluiden dat ruimtelijke concentratie van belang blijft (zie voor discussie bijvoorbeeld McCann 2008).

vasthouden en aantrekken van huishoudens, onder het mom van "werken volgt wonen", alleen succesvol kan zijn als bedrijven daadwerkelijk hun locatiekeuzes laten beïnvloeden door die van huishoudens.

De mogelijkheden om met onderzoek meer inzicht te krijgen in de interacties tussen bevolkingsgroei en werkgelegenheid zijn sterk toegenomen en is een belangrijke verklaring voor de toename in onderzoeksstudies. Met name dankzij de ontwikkeling van een econometrisch model door Carlino and Mills (1987) is er een methode voorhanden gekomen waarmee bevolkings- en werkgelegenheidsveranderingen op regionaal niveau betrekkelijk eenvoudig kunnen worden geanalyseerd. Meer recent zijn ruimtelijk-econometrische technieken in het model geïntegreerd die het mogelijk maken het model ook bij gedetailleerde gebiedsindelingen zoals gemeenten, wijken, buurten of postcodegebieden toe te passen. Bij dergelijke kleinschalige ruimtelijke eenheden beperken de interacties tussen bevolkingsgroei en werkgelegenheidsgroei zich niet tot de afzonderlijke eenheden, maar strekken deze zich uit over een groter arbeidsmarktgebied, met als gevolg dat de dataobservaties ruimtelijke afhankelijkheden vertonen en 'gewone' statistische analysetechnieken niet voldoen.

Ondanks de sterke toename van het aantal studies lijkt de onduidelijkheid die bestaat met betrekking tot de vraag of wonen werken volgt, of omgekeerd, niet te zijn afgenomen. Sterker nog, het lijkt er op dat met de toename van het aantal studies de verwarring alleen maar groter is geworden. Het beeld bestaat dat de uitkomsten van de studies grote verschillen vertonen en dat de literatuur hiervoor geen afdoende verklaring kan geven. De mogelijkheden om de uitkomsten van bestaande studies te gebruiken lijken dan ook gering, met als gevolg dat er veelal voor elke afzonderlijke regio nieuw onderzoek wordt uitgevoerd. De ogenschijnlijk grote variatie in studieresultaten heeft er ook toe geleid dat de vraag of wonen werken volgt of werken wonen met mystiek is omgeven en tot de verbeelding is gaan spreken. Om deze mystiek te ontrafelen zijn onderzoekers dan ook met allerlei data en onderzoeksmethoden gaan variëren die mogelijk iets van de verschillen in studieresultaten verklaren.

In de onderhavige studie is voor het eerst systematisch onderzoek gedaan naar wat al die studies die zich eerder hebben beziggehouden met de vraag of wonen werken volgt of werken wonen ons nu allemaal hebben opgeleverd. Daarnaast is onderzoek gedaan naar een aantal aspecten van de interacties tussen bevolkingsgroei en werkgelegenheidsgroei die veelal onderbelicht zijn gebleven in de eerdere studies. De volgende vier onderzoeksvragen zijn geformuleerd:

1) Hoe groot zijn de verschillen in onderzoeksresultaten van studies met betrekking tot de vraag "volgt wonen werken of volgt werken wonen"?

2) Welke factoren verklaren deze verschillen; zijn de verschillen een *empirisch fenomeen* en moeten de verklaringen worden gezocht in de data gerelateerde aspecten van studies en/of zijn de verschillen een *methodologisch artefact* en

moeten de verklaringen worden gezocht in de onderzoekstechnische aspecten van studies?

3) Wat zijn de ruimtelijke dimensies van de interacties tussen bevolkingsgroei en werkgelegenheidsgroei; is er een maximale afstand waarop ontwikkelingen in de ene locatie een effect hebben op andere locaties, en hoe snel is het verval met afstand?

4) In hoeverre speelt ‘gender’ een rol in de ruimtelijke verdeling van de bevolking en werkgelegenheid; is er een verschil tussen de werkgelegenheid van mannen en vrouwen in de interacties met de bevolking, de interacties binnen de eigen groep en de interacties met de andere groep?

Voor het beantwoorden van onderzoeksvraag 1 is in deze studie gekozen voor een “meta-analyse”, een kwantitatief literatuuronderzoek. Een dergelijk onderzoek houdt in dat op objectieve en systematische wijze een aantal studies wordt verzameld, waarna een database met allerlei studiegegevens wordt aangemaakt en deze studiegegevens uiteindelijk met behulp van statistische technieken worden geanalyseerd. Als criterium voor de selectie van studies is hier gekozen voor de toepassing van een Carlino–Mills model. Dat heeft geresulteerd in een verzameling van 37 studies gepubliceerd in de periode 1987–2004 met in totaal 308 modelschattingen die inzicht geven in de relatie wonen–werken.

Om de schattingsresultaten van verschillende studies te kunnen vergelijken, zijn vier categorieën relaties tussen wonen en werken onderscheiden: “geen interactie”, d.w.z., wonen volgt werken niet en omgekeerd ook niet, “wonen volgt werken” (omgekeerd niet), “werken volgt wonen” (omgekeerd niet), en tenslotte “wonen volgt werken en werken volgt wonen”. De verdeling van de schattingresultaten over deze categorieën laat zien dat de uitkomsten vooral wijzen op “werken volgt wonen” (31,5%). Deze categorie wordt op korte afstand gevolgd door “wonen volgt werken” (27,6%) en “geen interactie” (25,6%). Op iets grotere afstand, maar toch nog altijd 15,3% van de schattingsresultaten volgt “wonen volgt werken en werken volgt wonen”.

Omdat de bijdrage van verschillende studies aan de verzameling studieresultaten sterk uiteenloopt en het beeld dus vooral wordt bepaald door een klein aantal grotere studies [zo is er één studie met maar liefst 150 schattingsresultaten] is er ook gekeken naar een gewogen verdeling van de studieresultaten, waarbij de bijdrage van elke studie gelijk is. Ook voor de gewogen studieresultaten geldt dat deze vooral wijzen op “werken volgt wonen” en dan met een aandeel van 45,5%. Het aandeel “wonen volgt werken” daalt aanzienlijk (naar 11,4%), wat betekent dat deze uitkomst in betrekkelijk weinig studies voorkomt. Na weging is het aandeel van de categorieën “geen interactie” en “wonen volgt werken en werken volgt wonen” vrijwel gelijk (respectievelijk 21,8% en 21,4%). Kortom, de meta-analyse bevestigt het beeld dat de uitkomsten van studies naar de relatie wonen–werken sterk uiteenlopen. Veelzeggend is dat de onderzoeksresultaten niet alleen variëren tussen studies, maar ook binnen studies die veelal toch op dezelfde data en onderzoeksmethoden zijn gebaseerd.

Voor het beantwoorden van de vraag welke factoren de verschillen in onderzoeksresultaten verklaren (onderzoeksvraag 2) zijn twee technieken toegepast. Allereerst is er een meta-regressie analyse uitgevoerd op de verzamelde gegevens van de Carlino–Mills studies. In deze analyse zijn de onderzoeksresultaten van deze studies gerelateerd aan een aantal studiekenmerken die mogelijk de variatie in uitkomsten verklaren zoals de verschillende data en onderzoeksmethoden die in de studies zijn gebruikt. De uitkomsten van de regressie analyse laten zien dat zowel de geografische en temporele kenmerken als ook de ruimtelijke resolutie van de data de onderzoeksresultaten sterk beïnvloeden. Zo zijn er significante verschillen in de resultaten van op de Verenigde Staten georiënteerde studies en studies van andere landen, tussen studies gericht op de jaren zestig en zeventig, jaren tachtig of jaren negentig en tussen studies van bevolkings- en werkgelegenheidsveranderingen op een laag (bijvoorbeeld gemeenten, steden, wijken en buurten) en op een hoog (bijv. provincies en landsdelen) ruimtelijk schaalniveau. De invloed op de studieresultaten geldt niet alleen voor verschillende aspecten van de data, maar ook voor verschillende onderzoekstechnische aspecten. Zo blijken verschillende specificaties van het Carlino–Mills model en verschillende metingen van bevolkings- en werkgelegenheidsgroei (wel of niet gecorrigeerd voor oppervlakteverschillen) tot verschillende uitkomsten te leiden.

Omdat aan de hand van de bestaande Carlino–Mills studies niet alle mogelijke invloeden op de studieresultaten kunnen worden bepaald, is in aanvulling op de standaard meta-analyse ook een quasi-experimentele meta-analyse uitgevoerd. In een dergelijke analyse worden niet de uitkomsten en kenmerken van bestaande studies aan elkaar gerelateerd, maar wordt de literatuur gebruikt om een aantal suggesties op te doen. Deze suggesties worden vervolgens toegepast in een aantal eigen experimenten, waarna met behulp van een regressiemodel wordt vastgesteld welke experimenten de grootste wijzigingen in studieresultaten teweegbrengen.

In deze studie zijn in totaal 4.050 experimenten gedaan met een ruimtelijk-econometrisch Carlino–Mills model op data van dorpsgebieden in de provincie Friesland. Uit de regressie analyse op deze experimenten blijkt dat de relatie wonen–werken niet alleen geografische en temporale verschillen vertoont, maar ook varieert tussen economische sectoren. Zo is de relatie tussen bevolkingsgroei en werkgelegenheidsgroei minder sterk bij de industriële sector dan bij andere sectoren en geldt het adagium “wonen volgt werken en werken volgt wonen” vooral voor de detailhandel. Naast deze empirische factoren brengt de quasi-experimentele meta-analyse ook een aantal belangrijke methodologische factoren aan het licht: de specificatie van de ruimtelijke gewichtenmatrix voor het weergeven van interacties tussen gebieden en wederom, net als in de meta-analyse, de meting van de bevolkings- en werkgelegenheidsvariabelen. De allerbelangrijkste methodologische factoren zijn echter de ruimtelijk-econometrische specificatie van het Carlino–Mills model en de methode waarmee de parameters van het model worden geschat. De toepassing van een model dat niet corrigeert voor verschillende vormen van ruimtelijke afhankelijkheid tussen de dataobservaties kan, samen met een verkeerde schattingsmethode, tot onjuiste onderzoeksresultaten leiden.

Samengevat, de standaard meta-analyse en quasi-experimentele meta-analyse tonen aan dat er zowel inhoudelijke als methodologische verklaringen zijn voor de verschillen in uitkomsten van studies naar de relatie tussen wonen en werken. Uit de inhoudelijke verklaringen volgt dat de relaties duidelijk variëren in de tijd, ruimte en tussen werkgelegenheidsgroepen. Dit betekent dat de analyse van verschillende data logischerwijs tot verschillende uitkomsten leidt. Maar ook als dezelfde data worden geanalyseerd kunnen uitkomsten verschillen. De verschillen zijn dan een methodologisch artefact en meer specifiek het resultaat van de keuze voor een bepaalde model specificatie, schattingsmethode en meting van de variabelen in het model.

Voor het beantwoorden van de vraag met betrekking tot de ruimtelijke dimensies van de interacties tussen bevolkingsgroei en werkgelegenheidsgroei (onderzoeksvraag 3) zijn twee onderzoeksmethoden gebruikt. Allereerst is een zogenaamde *verkennende* ruimtelijke data analyse uitgevoerd op bevolkings- en werkgelegenheidsdata van postcodegebieden in Noord-Nederland (de provincies Friesland, Groningen en Drenthe). Met behulp van statistische technieken voor het meten van ruimtelijke correlaties is vastgesteld in welke mate de verdelingen van de bevolkings- en werkgelegenheidsgroeicijfers over de postcodegebieden een systematisch patroon vertonen. Van een dergelijk patroon is sprake als de scores van naburige postcodegebieden een sterkere samenhang laten zien dan die van willekeurige ruimtelijke verdelingen van deze scores. Uit de berekeningen blijkt dat de samenhang in de scores van naburige postcodegebieden binnen een afstand van ongeveer 7 kilometer (hemelsbreed gemeten) niet significant afwijkt van andere verdelingen. Na 7 kilometer zijn de ruimtelijke correlaties statistisch significant en neemt de mate van samenhang snel af. De afstand waarop de ruimtelijke correlaties niet langer significant zijn, bedraagt ongeveer 60 kilometer, wat impliceert dat de interacties tussen bevolkingsgroei en werkgelegenheidsgroei zich over maximaal 60 kilometer uitstrekken.

In aanvulling op de beschrijvende statistiek van een verkennende ruimtelijke data analyse is de invloed van afstand op de interacties tussen bevolkingsgroei en werkgelegenheidsgroei ook bepaald aan de hand van een *verklarend* ruimtelijk-econometrisch Carlino–Mills model. Hierbij zijn de onderzoeksresultaten van meerdere modelschattingen met elkaar vergeleken die inzicht geven in de interacties op verschillende afstandsintervallen, waarbij de afstand niet hemelsbreed maar naar reistijd is gemeten. Het blijkt dat de bevolkingsgroei van een postcodegebied in Noord-Nederland kan worden verklaard door de werkgelegenheidsgroei in postcodegebieden binnen afstanden van 15, 30 en 45 minuten reistijd. Omgekeerd gelden deze afstanden ook voor de invloed van bevolkingsgroei op de werkgelegenheidsgroei in een postcodegebied.

De verkennende ruimtelijke data analyse en ruimtelijk-econometrische analyse leveren een aantal interessante inzichten op in hoe de interacties tussen bevolkingsgroei en werkgelegenheidsgroei zich ruimtelijk ontvouwen. Allereerst laten de analyses duidelijk zien dat de effecten van groei niet alleen plaatselijk zijn, maar zich over een groot gebied uitstrekken. Zo hebben de lokale veranderingen in bevolkings- en werkgelegenheidsaantallen in Noord-Nederland grensoverschrijdende effecten die zich uitstrekken over afstanden van ongeveer 60 kilometer (hemelsbreed gemeten) en 45 minuten reistijd. De grens van 45 minuten komt overeen met veel gebruikte afbakeningen van arbeidsmarktgebieden en wordt algemeen gezien als de maximale afstand waarover mensen bereid zijn naar hun werk te reizen. Dit is eerder ook in andere, vergelijkbare studies waargenomen (bijvoorbeeld Wheeler 2001). De uitkomsten van de verkennende ruimtelijke data analyse geven aanleiding tot de veronderstelling dat er naast een maximum afstand ook een minimum afstand is waarop de interacties tussen bevolkingsgroei en werkgelegenheidsgroei zich voordoen. Deze minimum afstand zou in het Noorden van Nederland op ongeveer 7 kilometer liggen. Deze veronderstelling strookt met de bevindingen van eerdere studies naar pendelgedrag die aangeven dat zolang de woon-werk afstand binnen een bepaalde marge blijft de keuzes van de woon- en werkplaats elkaar niet beïnvloeden (zie bijvoorbeeld Camstra 1996).

Voor het beantwoorden van de vraag naar de mogelijke invloed van ‘gender’ op veranderingen in de ruimtelijk verdeling van de bevolking en werkgelegenheid (onderzoeksvraag 4) is wederom een ruimtelijk-econometrisch Carlino–Mills model geschat op data van postcodegebieden in Noord-Nederland. Het gebruikte model maakt onderscheid in de werkgelegenheid van mannen en vrouwen. Het omvat zowel crossregressieve als autoregressieve *spatial lags* om naast de interacties met de bevolking tevens de interacties binnen als ook tussen de werkgelegenheidsgroepen te meten. Voor het vaststellen van de interacties op verschillende afstanden zijn de *spatial lags* berekend voor afstandsintervallen van 15, 30, 45 en 60 minuten reistijd.

De resultaten van de ruimtelijk-econometrische analyse laten zien dat de richting van de interacties tussen bevolkingsgroei en werkgelegenheidsgroei in Noord-Nederland niet fundamenteel verschilt tussen de gender-specifieke werkgelegenheidsgroepen: voor zowel de werkgelegenheid van mannen als vrouwen geldt dat, meer dan dat de bevolking de werkgelegenheid volgt, de werkgelegenheid de bevolking volgt (m.a.w. “wonen volgt werken” maar vooral “werken volgt wonen”). Het grote verschil tussen de groepen is de afstand waarop de interacties zich voordoen. Bij de werkgelegenheid van vrouwen blijven de interacties beperkt tot een gebied van ongeveer 15 minuten reistijd. Voor de werkgelegenheid van mannen geldt dat de interacties met de bevolking zich niet op korte afstand voordoen, maar op een afstand van tussen de 30 en 45 minuten reistijd. Belangrijker dan de interacties met de bevolking zijn echter de interacties binnen de gender-specifieke werkgelegenheidsgroepen. Voor zowel de werkgelegenheid van mannen als vrouwen geldt dat deze interacties zich uitstrekken over een afstand van zo’n 30 minuten reistijd. Tenslotte laten de resultaten zien dat interacties tussen de gender-specifieke werkgelegenheidsgroepen een betrekkelijk kleine rol spelen. Zo heeft de groei van de werkgelegenheid van vrouwen geen effect op de groei van de werkgelegenheid van mannen op postcodeniveau. Andersom heeft de werkgelegenheidsgroei van mannen in een postcodegebied mogelijk wel een negatief effect op de groei van de werkgelegenheid van vrouwen in naburige postcodegebieden binnen een afstand van 15 minuten reistijd.

Kortom, de onderzoeksresultaten van de ruimtelijke econometrische analyse onderschrijven dat ‘gender’ een belangrijke rol speelt in de ruimtelijke verdeling van de bevolking en werkgelegenheid. Meer in het bijzonder laten ze zien dat met name de afstand waarop de interacties tussen bevolkingsgroei en werkgelegenheidsgroei zich voordoen sterk verschilt tussen de werkgelegenheid van mannen en vrouwen. Deze bevinding vormt een belangrijke aanvulling op de conclusies die eerder zijn getrokken uit de resultaten van de ruimtelijk-econometrische analyse waarbij geen onderscheid naar werkgelegenheidsgroepen is gemaakt (voor het beantwoorden van onderzoeksvraag 3). In overeenstemming met wat bekend is over het woon-werk verkeer van mannen en vrouwen en omvang van de verschillende arbeidsmarktgebieden, lijkt de maximale afstand van 45 minuten waarop mensen bereid zijn naar hun werk te reizen vooral van toepassing te zijn op mannen. Daarnaast lijkt de keuze van de werklocatie van mannen geen invloed te hebben op de keuze van de woonlocatie (en andersom) zolang de reistijd binnen zo’n 30 minuten blijft. Voor vrouwen daarentegen lijken de keuzes van de woon- en werkplaats alleen op korte afstanden (binnen 15 minuten reistijd) aan elkaar gerelateerd te zijn.

De antwoorden die zijn gevonden op de verschillende onderzoeksvragen leiden tot een aantal conclusies en suggesties. Allereerst is op basis van bestaande studies moeilijk vast te stellen of wonen werken volgt of werken wonen. De uitkomsten van empirische studies vertonen grote tegenstrijdigheden en laten zich dus maar moeilijk gebruiken voor generalisaties, prognoses of beleidsaanbevelingen. Omgekeerd betekent dit ook dat de nodige vraagtekens moeten worden geplaatst bij bestaande beleidsmaatregelen die uitgaan van een bepaalde veronderstelling zoals “werken volgt wonen”.

Voor toekomstig onderzoek is het belangrijk om in ogenschouw te nemen dat de keuze van data en onderzoekstechnieken de uitkomsten sterk kunnen beïnvloeden. Idealiter nemen studies dan ook een gevoeligheidsanalyse in hun publicatie op waarmee duidelijk wordt welke keuzes zijn overwogen en in hoeverre deze keuzes een effect hebben op de onderzoeksresultaten. Zonder een dergelijke analyse blijft het moeilijk om conclusies te trekken die ook andere onderzoekers kunnen helpen bij hun onderzoek en op basis waarvan betrouwbare beleidsaanbevelingen kunnen worden gedaan.

Een ander belangrijk aandachtspunt voor toekomstige toepassingen van het Carlino–Mills model, en dan met name bij analyses op een laag ruimtelijk schaalniveau, is de keuze van de ruimtelijk-econometrische specificatie en de schattingsmethode. De bevindingen uit de quasi-experimentele meta-analyse tonen duidelijk aan dat misspecificaties en het gebruik van een ongeschikte schattingsmethodes de resultaten sterk kunnen beïnvloeden en mogelijk een belangrijke verklaring vormen voor de grote variatie in onderzoeksresultaten die zo kenmerkend voor deze literatuur is.

Het Carlino–Mills model biedt ook de mogelijkheid de ruimtelijke effecten van bepaalde ontwikkelingen te meten. Een voorbeeld hiervan is een toepassing van het model in een studie door De Graaff et al. (2012a) waarin de mogelijke gevolgen van woningbouw in Almere op de bevolkingsgroei en werkgelegenheidsgroei in nabijgelegen gemeenten zijn blootgelegd. Het gebruik van het model voor het maken van prognoses of voor het vergelijken van verschillende scenario's kan dus belangrijke inzichten voor beleid opleveren en verdient dan ook meer navolging. Ook biedt het model de mogelijkheid om meer inzichten te krijgen in de tijd dat het duurt dat bepaalde ontwikkelingen effect hebben. Het model bevat namelijk parameters die zowel voor bedrijven als huishoudens weergeven hoe lang het duurt dat ze op veranderende arbeidsmarktomstandigheden reageren. In navolging van de meta-analyse op de parameters die weergeven of wonen werken volgt of werken wonen zouden ook de zogenaamde *speed of adjustment* parameters uitstekend aan een meta-analyse kunnen worden onderworpen.

Om inzicht te krijgen in de groeiverschillen tussen regio's en binnen regio's is het uiteindelijk vooral zaak om te begrijpen waarom de interacties tussen bevolkingsgroei en werkgelegenheidsgroei niet overal hetzelfde zijn. Zo heeft de meta-analyse in deze studie laten zien dat de uitkomsten van Amerikaanse studies afwijken van die van andere landen, wat wijst op de mogelijke invloed van institutionele, sociaal-culturele en economische factoren. Voor Nederland hebben De Graaff et al. (2008) aangetoond dat de interacties op gemeenteniveau niet hetzelfde zijn in de Randstad, de omliggende intermediaire zone en de "periferie" waar Noord-Nederland deel van uitmaakt. De quasi-experimentele meta-analyse op data van dorpsgebieden in de provincie Friesland in deze studie heeft aangetoond dat zelfs binnen een betrekkelijk klein geografisch gebied aanzienlijke verschillen in de interacties tussen bevolkingsgroei en werkgelegenheidsgroei kunnen bestaan. Deze verschillen zouden verhuld zijn gebleven als de analyse niet op een dergelijk laag ruimtelijk schaalniveau zou zijn uitgevoerd.

Om de ruimtelijke verschillen in de interacties tussen bevolkingsgroei en werkgelegenheidsgroei te begrijpen zou vooral meer aandacht moeten worden besteed aan de bevolkings- en werkgelegenheidssamenstelling van plaatsen. De resultaten van de gender-specifieke analyse in deze studie geven aan dat bij het gebruik van zeer geaggregeerde bevolkings- en werkgelegenheidsdata belangrijke verschillen tussen subgroepen onbelicht blijven. Het kan met name interessant zijn de relaties te onderzoeken in plaatsen waar veel zelfstandigen wonen of mensen die tot de zogenaamde "creatieve klasse" behoren. De suggestie in de literatuur is dat vooral voor deze groepen het adagium “werken volgt werken” geldt (zie bijvoorbeeld Pink 2001; Florida 2002). Ook moet rekening worden gehouden met het feit dat wat een groep onderscheidt van een andere groep niet noodzakelijkerwijs de richting van de interactie tussen bevolkingsgroei en werkgelegenheidsgroei is, maar de ruimtelijke bereik en het verval met afstand van de interactie. Daarom moeten toekomstige analyses naar de woon-werk dynamiek bij subgroepen zich bij voorkeur ook richten op ruimtelijke effecten.

Gezien de toenemende beschikbaarheid van micro-data van bedrijven en huishoudens die kunnen worden geaggregeerd naar elk gewenst groepsniveau en ruimtelijk schaalniveau, is er geen praktische reden om de analyse te beperken tot het onderzoeken van globale bevolkings- en werkgelegenheidsveranderingen en zonder naar de ruimtelijke effecten te kijken. Met name databestanden waarin gegevens van huishoudens gekoppeld zijn aan gegevens van bedrijven kunnen helpen om na te gaan hoe locatiekeuzes worden bepaald, wat de gevolgen zijn van een verandering in woonlocatie of verandering in bedrijfslocatie en of uiteindelijk bevolkingsveranderingen vooraf gaan aan werkgelegenheidsveranderingen of juist omgekeerd.

De discussie hierboven maakt duidelijk dat met een aantal aanvullende onderzoeken het relatief eenvoudig moet zijn om meer inzichten te krijgen in de ruimtelijke dynamiek van wonen en werken en de interacties hiertussen. De benodigde gegevens zijn in principe voorhanden en vooral dankzij ontwikkelingen op het gebied van Geografische Informatie Systemen en ruimtelijke econometrie kunnen de gegevens steeds beter worden geanalyseerd.

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