Papers in Evolutionary Economic Geography

13.18

Labour market externalities and regional growth in Sweden
The importance of labour mobility between skill-related industries

Boschma, R., R.H. Eriksson and U. Lindgren

Utrecht University
Urban & Regional research centre Utrecht

Labour market externalities and regional growth in Sweden
The importance of labour mobility between skill-related industries

Boschma, R.*#, R.H. Eriksson** and U. Lindgren**

*Lund University, Center for Innovation, Research and Competence
in the Learning Economy, (CIRCLE)
#Utrecht University, Urban and Regional research centre Utrecht (URU)
**Umea University, Department of Geography and Economic History

Abstract
This study investigates the relationship between labour market externalities and regional growth based on real labour flows. In particular, we test for the importance of labour mobility across so-called skill-related industries. We make use of a sophisticated indicator that measures the degree of skill-relatedness between all industries, and we employ actual labour flows between 435 4-digit industries within 72 Swedish functional labour market regions to estimate how labour market externalities are related to regional growth in the period 1998-2002. Both our fixed effect models and GMM-estimates demonstrate that a strong intensity of intra-regional labour flows between skill-related industries impacts positively on regional productivity growth, but less so on regional employment growth. Labour mobility between unrelated industries tends to dampen regional unemployment growth while a high degree of intra-industry labour flows is only found to be associated with rising regional unemployment.

Keywords: agglomeration externalities, related variety, regional growth, labour mobility, related labour market externalities, skill-relatedness

JEL Classification: R11, R12, O18

1. Introduction

Since Glaeser *et al.* (1992), there is a growing body of literature that investigates the extent to which MAR and Jacobs' externalities matter for regional growth (Van Oort, 2004). Taking stock of this empirical literature, review studies have recently come to the conclusion that the empirical evidence is rather indecisive (Beaudry and Schiffauerova, 2009; De Groot *et al.*, 2009). Moreover, scholars have claimed that there is still little understanding of the nature and sources of agglomeration economies (Duranton and Puga, 2004; Brown and Rigby, 2010; Andersson and Thulin, 2011). In this respect, labour mobility gets more and more attention as a potential source of agglomeration economies, because it is a vehicle that matches labour supply and demand and makes knowledge circulate at the regional and international scale (Angel, 1991; Pinch and Henry, 1999; Saxenian, 1994; Ottaviano and Peri, 2006; Saxenian and Sabel, 2008; Eriksson, 2011; Huber, 2012).

However, there is increasing scepticism whether labour mobility *per se* enhances regional development. While empirical evidence indicates that labour flows produce significantly stronger effects on plant performance than "pure knowledge spillovers" that pre-assumes interaction and exchange without actually considering direct linkages between firms (Breschi and Lissoni, 2009; Eriksson and Lindgren, 2009), the role of knowledge flows tends to be moderate as compared to internal economies of scale and scope of specific plants (Eriksson and Lindgren, 2009). Thus there may be good reasons to believe that labour mobility stimulates learning across local firms, but that it also may obstruct human capital development at the regional level, because of, for example, labour poaching. Recent quantitative studies have shown that intra-regional labour mobility is not *per se* a good thing (e.g. McCann and Simonen, 2005; Eriksson, 2011).

Little attention, however, has been devoted to the types of skills that are transferred when assessing the role of labour mobility. Following Frenken *et al.* (2007) who argued that inter-industry knowledge spillovers require some degree of cognitive proximity between sectors to have substantial economic impact, Boschma *et al.* (2009) investigated how actual job moves influenced the performance of Swedish plants. They found evidence that only new employees with a background in technologically related industries had a positive impact on plant performance. So while recent micro-findings suggest that the influence of labour flows at the plant level cannot be revealed without considering the type of skills brought in to a plant (e.g. Boschma et al, 2009; Eriksson, 2011; Timmermans and Boschma, 2013), little is known about whether these micro-processes also influence growth at the regional scale.

Since the mobility of labour constitutes a direct transfer of embodied knowledge in space we argue here that these ideas can be applied to the question of whether labour mobility matters for regional growth. We claim that the transfer of skills through labour mobility will only have a positive impact on regional growth when it concerns labour flows between so-called skill-related industries. This is because regions endowed with such labour market externalities are more likely to be imbued by higher quality skill-job matches. To our knowledge, there exists no such study that assesses the relationship of actual labour flows across skill-related industries with regional growth.

This paper has two objectives. Rather than capturing agglomeration externalities via specialization or diversification indices to address potential learning economies via spillovers, the first objective is to estimate how labour market externalities are related to regional growth by means of actual labour flows within regions. This allows us to measure more directly the role of labour market externalities, because labour mobility is often regarded as a crucial mechanism for diffusing the latest knowledge and skills within regions (Duranton and Puga, 2004; Brown and Rigby, 2010). The second objective is to investigate whether labour mobility across technologically related industries is beneficial for regional growth. What we expect is that the role of labour mobility is especially large in regions where a high degree of labour mobility occurs between technologically related industries rather than high levels of mobility *per se*. This is because we expect such regions to be endowed with higher quality skill-job matching than other regions. We will capture this with a measure developed by Neffke and Svensson-Henning (2008) which determines the degree of skill-relatedness between industries on the basis of the intensity of labour flows between all manufacturing and service sectors in Sweden[i]. We will use this indicator of industry skill-relatedness to estimate the relation between labour flows between 435 4-digit industries within 72 Swedish functional labour market regions (FA-regions) and regional growth in the period 1998-2002.

The structure of the paper is as follows. In section 2, we briefly discuss the literature on labour mobility and regional growth, and we explain why labour mobility between skill-related industries within a region is expected to be positively linked to regional growth. In section 3, we introduce the Swedish data and the variables. We devote special attention to the way the degree of skill-relatedness between industries has been determined, and we explain the model used. The main findings are presented in section 4, followed by some conclusions in section 5.

2. Labour mobility across skill-related industries and regional growth

Following insights from endogenous growth theory (Lucas, 1988), human capital is widely acknowledged as a driver of regional development. The general idea is that human capital fosters knowledge spillovers and innovation (Becker, 1962). Marshall (1920) was one of the first to claim that thick specialized labour markets may bring great benefits to firms, because they reduce search costs for new employees, they match supply and demand on the labour market more smoothly, and they give access to highly productive workers (Acemoglu, 1996; Duranton and Puga, 2004; Strange *et al.*, 2006; Huber, 2012). Glaeser and Reseger (2009), for example, state that cities with higher levels of skills have higher productivity levels per worker.

The spatial behaviour of micro-economic agents is essential to understand what it is that gives raise to agglomeration economies, since the circulation embodied knowledge is assumed to be the main facilitator of localized learning (Duranton and Puga, 2004). Economic geographers have pointed to the relative fixity of human capital in space due to economic, social and institutional reasons (Storper and Walker, 1989). There is overwhelming evidence that labour mobility is still basically a phenomenon that occurs within regions (i.e. labour market areas), despite the increasing tendency of labour to flow across greater distances (Power and Lundmark, 2004). This is because searching and

[i] Acknowledgement: We are very grateful to Frank Neffke and Martin Svensson-Henning that provided us the data concerning the degree of skill relatedness between each pair of industries in Sweden.

finding a new job is time consuming and related to both monetary costs (Mortensen, 1986) and social costs (Van der Berg, 1992). Using Swedish data to examine the characteristics of job movers between 1990 and 2002, Eriksson et al (2008) show that only about 25% of all job moves are across labour market borders. They argue that the predominantly local dimension of labour market dynamics is due to the place- and sector-specific human capital of individuals. Such insider knowledge accumulated through relations to family, friends, clients and colleagues as well as experience of industry-specific norms and routines becomes a sunk cost and a barrier to moving.

The mobility of skilled workers is nevertheless regarded as an important mechanism through which knowledge and skills between firms and regions are transferred both within countries (Malmberg and Power, 2005; Iammarino and McCann, 2006) and between countries (Rodríguez-Pose and Vilalta-Bufi, 2005; Saxenian and Sabel, 2008). Scholars have argued that immigrants (often defined as foreign-born) bring in skills that might be complementary to native workers in receiving countries, boosting learning and efficiency (Ottaviano and Peri, 2006; Dustmann *et al.*, 2008; Nathan, 2011).

Labour pooling and mobility is thus often regarded as a crucial driver of regional development because it induces localized learning processes (Malmberg, 2003). Empirical studies tend to support this claim. Almeida and Kogut (1999) argued that inter-firm mobility of labour is mainly responsible for knowledge spillovers in successful regions like Silicon Valley (see also Angel, 1991; Fleming and Frenken, 2007). Pinch and Henry (1999) found that intense flows of skilled personnel within the British motor sport cluster facilitated both knowledge creation and diffusion between local firms. In the Swedish case, Eriksson and Lindgren (2009) demonstrated that labour market externalities derived via intra-regional job flows induce greater effects on plant performance as compared to the degree of regional specialization and diversity, although the overall effects of both job flows and regional industrial structure are moderate compared to plant characteristics such as size, human capital levels and sector. Andersson and Thulin (2011) claimed that higher rates of inter-firm labour mobility in urban centres might well be a likely mechanism to explain the 'urban-productivity' premium. And Breschi and Lissoni (2009) showed that labour mobility also creates social linkages between firms, which, in turn, facilitate post-mobility knowledge flows between local firms through their ties with former colleagues (Dahl and Pedersen, 2003; Bienkowska *et al.*, 2011).

While there may be good reasons to believe that labour mobility enhances learning across local firms, it may also hinder human capital development in regions, due to labour poaching. A high intensity of job-hopping may form a threat for firms to lose their key personnel to competitors, and it may lower the incentive for firms to train and upgrade the skills of their employees (Kim and Marschke, 2005; Combes and Duranton, 2006; Fallick *et al.*, 2006). Argote *et al.* (1997) found that organizational learning and productivity were negatively affected by high amounts of personnel inflow. Madsen, Mosakowski and Zaheer (2003) found that personnel mobility may provide opportunities for knowledge transfer, but firms may not necessarily exploit these opportunities. In a similar vein, Philips (2002) showed that the move of employees to other law firms in Silicon Valley had negative consequences for the firms losing their employees. Few quantitative studies in economic geography have systematically tested the net effect of labour mobility. The studies that have addressed this issue empirically found no evidence of a positive effect of intra-regional labour mobility *per se* on firm performance and regional growth (McCann and Simonen, 2005; Boschma *et al.*, 2009; Eriksson, 2011).

When assessing the influence of labour mobility, studies tend to focus attention on the mobility of key persons like top managers, star scientists, key engineers, highly skilled workers and top designers (Boeker, 1997; Sorenson, 1999; Power and Lundmark, 2004; Wezel *et al.*, 2006; Wenting, 2008). Little attention is, however, devoted to the type of knowledge and skills that are involved. Song *et al.* (2003) found that mobility of engineers was more likely to result in inter-firm knowledge transfer when used for exploring technologically distant knowledge, rather than reinforcing the existing expertise of the firm. According to Boschma *et al.* (2009), the effect of labour mobility on plant performance depends on the type of skills that are brought into the plant, and to what extent these new skills add to the existing knowledge base of the plant. This concerns the question whether new employees are recruited from the same industry or from an industry to which the recruiting firm is technologically related. Their idea is that a plant will perform better when a new employee brings in new skills that are related to the existing skill portfolio of the plant. This is because the plant requires absorptive capacity to understand and integrate the new skills in the organization (Cohen and Levinthal, 1990). Under this condition, the plant will be more capable of exploiting the new skills economically. This stands in contrast to the recruitment of employees that possess the same skills already present in the plant: they add nothing new to the plant, and they may even form a competitive threat to the other employees with identical skills. Based on the analysis of 100,000 moves in Sweden, Boschma *et al.* (2009) found indeed that the inflow of skills that are related to the existing knowledge base of the plant had a positive effect on plant productivity growth, while the recruitment of new employees with skills identical to the plant had a negative effect on plant performance.

Since previous empirical studies at the regional level tend to fall short in finding evidence of a general impact of mobility, we apply this line of reasoning to the debate on whether labour mobility matters for regional growth. As discussed above, we believe that labour mobility *per se* is not necessarily beneficial for regional growth since worker skills need to match the existing skill base of plants (Boschma *et al*, 2009). Instead, we claim that the regional circulation and transfer of skills through labour mobility will only have a positive impact on regional growth when it concerns a high intensity of labour flows between related industries in a region. This is because, in contrast to high mobility rates *per se* which potentially are characterised by poor skill-job matching, an efficient matching of skills across related industries within a region gives rise to production complementarities and potentially more effective labour markets (e.g. Duranton and Puga, 2004). Although previous literature mainly ascribes high quality skill-job matches to large regions with thick labour markets (e.g. Puga, 2010), we argue that it is not necessarily a function of urban size, but that it depends on how skill-related sectors in a region are.

The concept of skill-relatedness has been developed by Neffke and Svensson-Henning (2008) who argued that a high intensity of labour flows between two industries may indicate a high degree of skill-relatedness between these industries. When controlling for factors like wage differentials, a high intensity of labour mobility between two industries indicates that the skills in one industry are also relevant and of high economic value to the other industry. Consequently, one can expect that a region with a high number of skill-related industries will not only show a high degree of labour mobility but also a lot of knowledge spillovers and learning across industries due to a more effective matching of skills. This could in fact be an important vehicle for why labour market externalities (or pooling) are important. Ellison et al (2010), for example, show that pooling can work across sectors if these sectors use workers with similar skills and that this also is an important driver for further agglomeration. This high mobility of new but related skills across industries is in particular expected to enhance regional productivity growth, because it favours inter-industry learning by sharing similar labour mixes and may thus lead to much stronger externalities than intra-industry spillovers due to the potential of re-combining related (but different) pieces of knowledge.

This adds a labour mobility argument to the literature on the importance of technologically related industries for economic development (Porter, 2003). It also follows the suggestion by Frenken *et al.* (2007) that one needs to go beyond the dichotomy MAR versus Jacobs' externalities in the agglomeration economies literature. They introduced the concept of related variety to capture the idea that knowledge spillovers across industries require some degree of cognitive proximity between sectors to have economic impact. They found evidence that a high variety of related industries at the regional level enhances regional growth. Other empirical studies (e.g. Boschma and Iammarino, 2009; Quatraro, 2010; Boschma *et al.*, 2012; Zhang, 2013) have confirmed that related variety is a major economic asset for a region.

When estimating the economic effects of labour market externalities, there is a need to consider carefully how related variety and economic growth are defined and measured (Frenken *et al.*, 2007; Boschma and Iammarino, 2009; Boschma *et al.*, 2012). When considering the effect of related variety on regional productivity growth, Frenken *et al* (2007) have argued that related variety is expected to have an effect mainly on employment growth, not on productivity growth, as it gives rise to new recombinations that generate radical and product innovations, and thus new markets and new jobs. However, when concentrating on skills, related variety in skills (variety of skill-related industries) is expected to induce effective matching of existing regional skills, which is likely to enhance productivity growth. We also expect variety in skill-related industries to enhance regional employment, as it fosters efficient quality skill matching that gives rise to production complementarities (Duranton and Puga, 2010), higher levels of competitiveness of local firms, and new job creation through new recombinations and new product innovations. However, the effect on regional unemployment growth is less straightforward. On the one hand, regions with a wide range of skill-related industries may better absorb sector-specific shocks, as it enables more efficient quality matching between (skill-related) industries (Diodato and Weterings, 2012). On the other hand, regions with sectors sharing similar (related) skills may in general be less well protected from unemployment, as a substantial decline in one key sector may affect the whole regional economy, making a large share of its skill-base redundant (Ellisson et al., 2010).

By contrast, specialized regions can be assumed to have an efficient matching of skills in the local labour pool that mainly promotes incremental innovations and productivity (Marshall, 1920), but this may also imply higher risks of increasing unemployment due to rationalization processes and greater vulnerability, but also relatively poorer learning opportunities owing to the fact that the skill base among these workers are too similar (Boschma et al. 2009; Timmermans and Boschma 2013).

Moreover, such regions are less likely to be protected from sticky unemployment in case of sector-specific shocks, due to the relative shortage of other employment opportunities (Krugman, 1993). In all, we therefore expect high degrees of skill similarity to have little, if any, positive impact on regional growth. In contrast, regions with unrelated variety and a broad set of skills offer a diverse set of job opportunities, which increases the chance for a worker to eventually find a (or any) job (Puga, 2010). We therefore expect such regions, in particular, to be better equipped to withstand asymmetric shocks due to portfolio effects and therefore to be better protected against unemployment growth. However, because the probability of matching (finding a job) is not necessarily positively correlated with the matching quality (Berliant et al, 2000), unrelated externalities are less likely to facilitate learning economies due to inefficient matching and communication problems caused by cognitive distance. Such externalities are therefore not expected to induce employment effects or productivity effects due to the limited possibilities to create radical innovations based on the recombining of different pieces of complementary knowledge and technologies (cf. Frenken et al., 2007).

In the following sections, this will be explored further by investigating whether actual labour flows between skill-related industries within a region induce regional growth. This implies that we have to determine the extent to which job moves basically concern intra-industry labour flows in the region, and whether these concern labour flows between skill-related industries. As explained above, only in the latter case, we expect labour mobility to contribute to regional growth.

3. Research design

In order to assess how different types of labour flows are associated with regional growth, we follow other studies on related variety (e.g. Frenken *et al.*, 2007; Boschma and Iammarino, 2009) and use three different dependent variables – regional labour productivity growth, regional employment growth and regional unemployment growth (all defined in Table 1). These variables are based on official annual data retrieved from Statistics Sweden and calculated as annual percentage growth rates during the period 1998 to 2002[ii]. The period 1998-2002 is chosen because this is the common chronological denominator for our included variables. In particular, data on industry investments (see further description of controllers below) are unfortunately not available for other years than the chosen ones, which may cause omitted variable bias if extending the study period. All analyses are based on aggregates of 72 functional regions (FA-regions), defined by The Swedish Agency for Economic and Regional Growth. The functional regions stem from observed commuting distances between the 290 Swedish municipalities together with large investments and historical economic trends likely to determine future development. Thus, the regions reflect past and predicted future regional preconditions, which make them consistent over time and suitable for longitudinal analyses. In contrast, the Swedish local labour markets are continuously revised in according to changes in commuting flows. Since the Swedish urban hierarchy is

[ii] Regional employment has been defined as the number of persons actively participating in the labour market while unemployment is defined as the number of persons registered as active job seekers (officially unemployed) at the Swedish Public Employment Service (Arbetsförmedlingen).

structured so that some city-regions function as housing areas and some as regional centres offering a wide variety of job opportunities that in many cases serve their surrounding hinterlands with jobs, it is not sufficient to measure the effect of mobility within city-regions. Few labour flows – in especially the small municipalities in the densely populated southern part of Sweden – are confined by municipal borders. Thus, functional labour market regions, capturing the inter-municipal interdependence, are the preferred spatial unit when assessing labour market outcomes.

Our crucial set of independent variables concerns labour mobility. The measurements of all labour market externalities are derived from the ASTRID database. ASTRID is a longitudinal micro-database containing matched information on all workers (e.g. workplace, education, working experience) and characteristics of all plants (e.g. sector, spatial coordinates) in the Swedish economy. This allows us to link all employees to their workplaces and to determine the magnitude of skill relatedness in terms of labour flows between workplaces. The spatial coordinates linked to each plant also make it possible to aggregate plant-specific information to higher spatial scales.

We only include labour flows concerning skilled workers because they are assumed to matter most in knowledge economies like Sweden and are also more likely to not be subject to forced job moves. We follow other studies on labour mobility and define skilled labour as workers who have at least a bachelor degree or who are high-income earners belonging to the top 20% income strata (Power and Lundmark, 2004; Boschma *et al.*, 2009). We have defined a job change as a registered change in both workplace affiliation (plant) and the geographical coordinates of the workplace (hectare grid) between two years to secure that an actual move has taken place and to exclude administrative changes within firms. However, since we base our indicators on annual registers, an unknown share of all job moves occurring more than once during a year and/or within the same plant are omitted. Moreover, some of the registered inter-plant moves are occurring within firms. Previous studies on the national economy do however not find that the effect of such flows would significantly differ from pure inter-firm flows, since changing units within an organization may also function as a strategy to circulate knowledge between units within the same firm (Boschma *et al.*, 2009; Eriksson and Lindgren, 2009). To minimize the risk of reversed causality, all explanatory variables (mobility indicators and controllers) have been measured prior to the change in the dependent variables[iii].

First, we constructed a pure quantity measure of intra-regional labour mobility (MobRate), which was defined as the number of intra-regional job moves divided by the total number of employees in the region. Then, we constructed two sets of indicators of labour market externalities, which account for the types of labour mobility. The first set of indicators concerns the observed mobility of skilled labour between industries based on the hierarchy inherent in the official industry classification nomenclature (SNI02). A drawback is that the relatedness between industries is predefined by this industry classification nomenclature. Therefore, we also constructed a second set of indicators of observed mobility of skilled labour between industries that draws on the revealed

[iii] For example, all mobility flows are defined as a change in workplace between t_{-1} and t_0 and the change in all the dependent variables are measured between t_0 and t_1. This is done to separate performance enhancing voluntarily job moves from the forced job moves that tend to be induced by changes in workplace performance.

relatedness indicator developed by Neffke and Svensson-Henning (2008). This new indicator of Revealed Regional Mobility Relatedness (RRMR) is based on the intensity of labour flows between industries, and reflects more accurately the degree of technological or skill-relatedness between industries. It seems reasonable to assume that a high RRMR score, i.e. strong associations via labour mobility, is reflecting an exchange imbued with dense learning opportunities due to efficient matching mechanisms, which can be transformed into valuable innovations and higher economic performance. This is tentatively a more powerful chain of events that is more likely to discern the micro-foundations of regional learning than plainly assuming that labour flows between production output-related sectors generate knowledge spillovers. In order to compare the different specifications, all indicators are calculated for plants in sectors where skilled labour is found. By doing so, the risk of including forced labour flows due to, for example, lay-offs during the recession is mitigated. Nevertheless, despite that some of the moves may have been caused by exogenous forces rather than by choice, we argue that if employees find a new job directly after a forced move, a transfer of embodied skills would still be significant since it would involve a direct transfer of skills between the old and the new workplace.

We now present the variables measuring the two types of labour market externalities.

(1) Labour market externalities based on pre-defined inter-industry relatedness

By departing from the methodology presented by Frenken *et al.* (2007) and adopted in similar studies within this field (e.g. Boschma and Iammarino, 2009; Bishop and Gripaios, 2010; Eriksson, 2011), entropy measurements have been calculated to create indicators reflecting the degree of similar, related and unrelated labour flows within the 72 Swedish local labour markets. These indicators are based on the 5-digit standard industrial classification code (SNI02), which consists of 514 5-digit level sectors nested within 224 3-digit level sectors and 17 1-digit sectors (for the years 1998 to 2001, the old industry classification SNI92 has been converted to SNI02). Although this information is appropriate for creating labour market externalities at different digit levels, it should be kept in mind that this industrial division mainly indicates output relatedness. These externalities do therefore not necessarily contain information on the degree of technological relatedness between industries. Still, because we measure real labour flows between industries, knowledge exchange is actually observed between industries (cf. Eriksson and Lindgren, 2009), in contrast to the aforementioned studies like Frenken *et al.* (2007) that assume that knowledge spillovers occur between related industries, and therefore do not know whether actual linkages exist between these industries. Thus, in contrast to previous studies that merely consider the regional composition of economic activities, this set of variables is defined by using intra-regional flows of skilled labour within and between sectors, which potentially is a more straightforward way of capturing the mechanisms of embodied regional knowledge spillovers (Duranton and Puga, 2004; Brown and Rigby, 2011).

First, we derive the degree of similar labour market externalities by combining the share of plants within a given 5-digit industry with the share of skilled labour inflows originating from exactly the same 5-digit category. We call this variable regional specialization, which is given by summing the industry-specific shares:

$$\text{Specialization} = \sum_{i=1}^{N^V} p_i^V * f_i^V, \qquad (1)$$

where p_i^V is the share of plants within the 5-digit industry i, f_i^V is the share of skilled inflows from the same industry i and N^V is the number of five-digit classes. Regions scoring high are regarded specialized both in terms of economic activities and labour externalities. As this indicator drops, the more diversified the region is. We have chosen to define the economic structure of regions by number of plants rather than by employment for two reasons. First, according to agglomeration theory, spillovers are expected to be dependent on the presence of co-located plants within a given industry, not on the share of employment (e.g. Malmberg *et al.*, 2000). Second, using share of employment as an indicator for economic structure would imply difficulties to disentangle the regional economic structure from the observed flows since high employment sectors would be more likely to be involved in large number of flows. By using plants, it is possible to separate these from each other since a low share of plants in a given industry can employ a large share of employees and vice versa.

Whereas we do not expect that high degrees of similar local labour market flows will substantially trigger learning processes and regional growth, we anticipate that high degrees of complementary knowledge flows will be most beneficial. Following Frenken *et al.* (2007), we define two industries at the 5-digit level (e.g. two 5-digit sub-chemical sectors) as complementary or related when they share the same class at the 3-digit level (e.g. the 3-digit chemical industry). The degree of related labour market externalities is measured by calculating the share of skill inflows to a given 5-digit sector from all sectors within the same 3-digit class, excluding inflows from the same 5-digit sector. Double counting of similar inflows is thereby avoided, which allows us to extract the partial effects of the different types of labour flows. Let p_i^V be the relative size of the 5-digit industry i and r_i the share of inflows from sectors within the same 3-digit class with the exception of i, then the degree of related labour market flows is defined by summing the 5-digit scores for every region:

$$\text{RelVar} = \sum_{i=1}^{N^V} p_i^V * r_i \qquad (2)$$

Third, we expect that a too great diversity of labour inflows may not generate substantial externalities triggering regional growth, due to a too great cognitive distance between the sectors involved. To test this, we define unrelated labour market externalities by combining the relative size of 5-digit sector (p_i^V) with the share of inflows from all local sectors belonging to different 3-digit classes u_i :

$$\text{UnrelVar} = \sum_{i=1}^{N^V} p_i^V * u_i \qquad (3)$$

(2) Labour market externalities based on revealed inter-industry relatedness

The second set of variables is constructed in order to move beyond the somewhat artificial hierarchy of industry codes, as discussed earlier. We developed a Revealed Regional Mobility Relatedness indicator (RRMR), which is based on the Revealed

Skilled Relatedness (SR) measure developed by Neffke and Svensson-Henning (2008), and which is conceptually related to the notion of localized mobility clusters suggested by Eriksson and Lindgren (2009) where regional plants are linked to each other based on observed labour flows rather than by industry affiliation. By predicting the probability of job changes across industries within the entire Swedish economy – controlling for the size, wage levels and growth of industries – this procedure creates linkages between pairs of 435 different 4-digit industries, based on the extent to which the same human capital can be employed in different industries. In total, there are 188,790 possible industry combinations, but the procedure run by Neffke and Svensson-Henning ends up with 9,979 industry combinations of significant skill relatedness ($p<0.1$) at the national level, which in turn corresponds to about one third of all labour flows in this sample. Industry linkages with a relatedness score equal to zero are regarded as completely unrelated, while the higher the score, the more the intensity of labour flows across two industries that can be attributed to skill-relatedness, and the more related the industries are. Our RRMR indicator is simply defined as:

$$\text{RRMRlog } = \sum_{i=1}^{N^V} m_{ij} * SR_{ij}, \qquad (4)$$

where m_{ij} is the share of all intra-regional flows between sector i and j and SR_{ij} is the degree of skill-relatedness between sector i and j, excluding all intra-industry flows, as suggested by Neffke and Svensson-Henning (2008). Thus, their original measure of national flows (SR_{ij}) is adopted to the observed flows within each labour market region which means that regions scoring high are considered to be endowed with high degrees of labour market linkages characterized by related human capital, whereas regions scoring low are regarded endowed with highly diversified (unrelated) labour market linkages. To exemplify the relative gain of this approach as compared to the pre-defined industry structure based on output, Neffke and Svensson-Henning show that the pharmaceutical preparations industry (SNI: 2442) is related to other pharmaceutical sectors at the same 2-digit level (e.g. SNI: 2441, 2414), as expected, but also to R&D activities (SNI: 7310), specialized wholesale (SNI: 5146) and surgical equipment industry (SNI: 3310) which would have remained unnoticed if only the industry codes would have determined their relatedness. Logarithmic values are used to reduce the impacts of skewed distributions. In order to compare the RRMR indicator with a measure of specialized labour flows, we also constructed a Similarity variable by summarizing the absolute number of intra-industry labour flows m and dividing that sum with the total number of intra-regional job changes M.

$$\text{Similarity } = \frac{m}{M} \qquad (5)$$

Control Variables

A number of additional variables that are likely to co-determine growth have also been constructed. In line with several other studies (e.g. Glaeser *et al.*, 1992; Frenken *et al.*, 2007; Boschma and Iammarino, 2009; Eriksson, 2011), the main control variable included represents the general level of urbanization by means of regional population density per square kilometre due to the positive spillovers densely populated areas are assumed to generate. Per capita industry investments have also been included in each of the models, since investments usually result in higher productivity through increased efficiency. The influence of investments on employment may, however, go in different directions. On the one hand, investments in new machinery in existing plants often generate less need for labour, but on the other hand greenfield investments usually create new jobs. Moreover, three different location quotients have been calculated to determine the relative specialization of regions. These represent specialization in manufacturing, primary sectors and R&D activities, and all are based on the number of plants operating in each region. The inclusion of these indicators is motivated by Andersson (2006) who identified great differences in performance across different groups of sectors during 1998-2002, which is concealed by the average numbers on national scale. For example, manufacturing sectors (SNI-codes: 15-37) had a relatively strong period of productivity growth during these years while primary sectors (SNI-codes: 1-14) and knowledge-intensive services (KIBS, SNI-codes: 65-74) performed less well. Regional growth is thus expected to be determined by the relative concentration of different types of activities. Since the concentration of KIBS is highly correlated with urban density due to its reliance on local demand (Bishop, 2008), it was not possible to include it in our models. Instead, we included the concentration of R&D activities to measure the extent to which universities and other knowledge producing organizations are generating spillover effects that trigger regional growth (see, for example, Frenken *et al.*, 2007). A final controller was added to each of the models. NetMig is defined as the yearly quota of in- and out-migration (all ages) to control for regional amenities (e.g. Florida, 2002). We expect this indicator to be positively related to productivity and employment since regions with a positive net flow of migrants could be regarded as more expansive, and negatively correlated to unemployment since high unemployment regions are likely to trigger out-migration. It should be noted that we also created indicators for the change in capital-labour ratio, income levels and presence of human capital, but these caused multicollinearity problems. For example, both income levels and human capital were strongly related both to the degree of density and the mobility indicators (which are based on skilled workers, as explained above), and the capital-labour ratio showed strong correlation with investments. Initially, we also included an additional controller – turbulence – which was defined as the annual net change of entries and exits of firms compared to the existing stock of firms in each of the 72 Swedish local labour markets. In this way, we explicitly controlled for how the evolution of regional economies – defined as entries and exits – influences the relation between mobility and regional development. However, this indicator was not significant and did not change the outcome in either model, so it was omitted from the final analysis.

Definitions and descriptive statistics of all variables are displayed in Table 1. The correlation matrix in Table A1 (Appendix) shows that potential collinearity problems are not too severe since no pairs of indicators included in the same model score higher than 0.6. This notion is confirmed by a formal test of covariance (VIF). None of the specifications had a mean VIF exceeding 3 and none of the variables scored higher than 7. However, as shown in Table A1, the correlation between specialization and related variety is above 0.4, as is the correlation between population density and, respectively, revealed relatedness, mobility rate and investments. This may cause imprecise estimates, finding significant relationships where there are not and vice versa. The decomposable nature of entropy measures differentiates variety at different digit-levels which means that the three indicators based on pre-defined industry classification do not mirror each other but are based on different flows (Frenken, 2007). Thus, the correlation among the three is just a matter of the flows occurring within a region without necessarily being linked to each other. To assure this, we also stepwise omitted every variable in each correlated pair to assess the influence of potential multicollinearity, but omitting either variable influenced neither the direction nor the significance of any variable, indicating that the results could be interpreted with confidence[iv].

Table 1 about here

We applied a fixed effect model to estimate the influence of our indicators on annual regional growth between 1998 and 2002. In simple form, the equation could be specified as:

$$Growth_{it} = \beta_1 Growth_{it-1} + \beta_1 Mob_{it-1} + \beta_1 Con_{it-1} + \varepsilon_{it} \quad (6)$$

where $Growth_{it}$ is regional growth defined as productivity, employment and unemployment, respectively, in region $_i$ in year $_t$. *Mob* is a vector of mobility variables (total, pre-defined or revealed) and *Con* the vector of control variables, both measured in $_{t\text{-}1}$. Since productivity, employment and unemployment is likely to be dependent on past realisations, we also included the lag of Y in all models. Finally, ε is the error term. The rationale for using this type of model on panel data is twofold. First, based on the outcome of the Hausman specification test comparing the difference between the random and fixed effect models, we had to reject the null-hypothesis (see Tables 2-4). Moreover, the fixed effect model permits region-specific effects to be correlated with the regressors (Cameron and Trivedi, 2010). Thus, the differences between the two types of models are systematic implying that the random effects model may produce inconsistent results. Second, apart from a strict empirical reason, it is also theoretically justified to employ fixed effect models, since it allows us to explicitly control for unobserved institutional differences across regions such as local labour market conditions not captured by the controllers or by the definition of functional regions, which in itself may help reduce the impact of endogeneity. Since both the different LQ:s and the NetMig variables are highly consistent over time, reflecting the position of regions in the regional hierarchy as well as both present and previous regional economic conditions, we can capture regional attributes not accounted for by the included variables and reduce the risk of omitted variable bias. This procedure is highly relevant in the Swedish case due to the great variety of local labour markets in terms of size, population, economic structure and the predominant tradition of local wage setting. By including a full set of time dummies and having all explanatory variables measured the year prior to the change in our growth indicators as explained above, we also reduced the risk of unobserved time-specific heterogeneity and reversed causality influencing the results.

[iv] Not reported but available upon request. By investigating the S.E.s in each model this seems to be particularly the case in the productivity model in Table 3. However, these estimates remained robust also through the stepwise procedure.

Since there are reasons to believe that labour mobility cannot be regarded as a purely exogenous factor, our FE-models may however still be affected by endogeneity. Mobility-induced externalities may facilitate growth but it could also be the other way around. Sector-specific shocks reflected in changed prices and/or increased competition might induce mobility because of decreased profitability triggering lay-offs. Thulin (2009) provides suggestions for how to deal with this problem by instrumenting mobility with population density. Density is associated with the thickness of the labour market, i.e. the number of potential employers within commuting distance, which most likely influences mobility rates. This implies that the instrument is correlated with the endogenous covariate. But the instrument must also have another property – it has to be uncorrelated with the error term of the models (i.e. productivity growth, employment growth and unemployment growth). However, it is questionable whether this is the case because metropolitan regions and regional centres are often associated with stronger economic activities as compared to smaller regions. Another more general problem of using instrument variables in this study refers to the fact that there are multiple endogenous components since there are several mobility-related variables in the model. In order to identify the model, we need at least as many instruments as there are mobility-related variables, but it proved difficult to find useful valid and relevant instrument variables. To address these potential endogeneity issues and as a general robustness check of our models, difference-GMM (Arellano and Bond, 1991) with robust standard errors were also estimated. In brief, this model first differences all variables to remove the unobserved region-effect and then use internal instruments (lags of all variables in levels for the first differences variables) to solve potential endogeneity problems[v]. Thus, while both handling potential endogeneity and omitted variable bias, this model also overcomes the problem of having the lagged dependent variable included in the right hand side of the equation, something that otherwise risks producing inconsistent estimates on especially the lagged dependent (Bernard and Jensen, 2004; Boschma et al, 2013).

4. Main findings

Before turning to the regression results, a couple of short notes on the Swedish case need to be made. First, during the period under study, the Swedish economy went through a period of economic prosperity with rising employment and productivity after the depression in the early 1990s. This marked the start of the relative demise of the Fordist production system and a shift towards a more knowledge-based economy. This period was followed by a recession as a consequence of the burst of the IT-bubble in 2000 and a continued transformation towards more generic forms of production. Thus, we are able to capture the overall influence of mobility in both boom and burst. Second, in an international comparison, the number of people changing jobs is relatively small (about

[v] All mobility indicators together with density are considered endogenous while investment, the LQ:s and NetMig are considered pre-determined. For the endogenous variables, the second lag is used as instrument, and for the pre-determined the first lag (Roodman, 2006). All time-dummies are considered purely exogenous. Due to the few number of available years and large number of instruments in comparison to observations, we could not include deeper lags since that would decrease sample size considerably. It also makes the system-GMM less appropriate to use since it requires more instruments. Both the use of deeper lags as well as employing a system-GMM in this case failed to produce any significant estimates.

8-16% between 1998 and 2004), especially across local labour markets. This is partly due to institutional arrangements that favour long-term positions with relatively high incomes linked to the accumulated experience in a firm. The turnover rates are also related to the business cycle (Andersson and Tegsjö, 2006), as mobility rates are lower during troughs and higher during peaks. From a European perspective, Sweden has, however, relatively high mobility rates, similar to what is observed in Denmark, Finland and the Netherlands, whereas many countries in southern Europe (e.g. Portugal, Greece, Italy and Spain) have small flows of people changing jobs (EUROFUND, 2006).

In this study, we solely focus on intra-regional labour flows, rather than differentiating between local and non-local flows. The reason for this is that a majority of all job flows in Sweden is intra-regional (circa 75% during this period). Moreover, inter-regional job moves – mainly to large, densely populated regions – are performed by persons in their early career stages before having established themselves on the labour market while when established the majority of workers tend to remain within the same local labour market. Despite institutional arrangements trying to promote greater flexibility this general pattern remains stable over time, especially for more experienced workers (e.g. Eriksson *et al.*, 2008; Lundholm, 2007). This implies that knowledge diffusion via labour mobility is mainly a local phenomenon (e.g. Breschi and Lissoni, 2009; Boschma *et al.*, 2009; Eriksson, 2011). Table 2 shows the micro-level statistics underlying each of the different variables on labour market externalities. The distribution of different flows confirms previous findings in Sweden on the determinants of mobility (Eriksson *et al.*, 2008). The typical intra-regional job mover either resides in large diverse regions with thick labour markets or in specialized regions with distinct local labour pools. In brief, there are no major differences between the different types of flows during this period. Workers changing jobs across unrelated industries tend to be younger but also have higher incomes prior to the job change while women tend to move more often across related industries. The business-related service and labour-intensive service sectors have higher turnover rates as well as metropolitan regions and large regional centres (for more information on determinants of individual mobility in Sweden, see Eriksson *et al.*, 2008).

Table 2 about here

The estimation results are shown in Tables 3, 4 and 5 for the dependent variables regional productivity growth, regional employment growth and regional unemployment growth, respectively. Each of these three tables includes four main models: (1) a base model with all control variables since we expect these variables together with the time-dummies to explain a considerable part of the total variance (Eriksson and Lindgren, 2009); (2) a model in which the mobility rate variable is added; (3) a third model where the three labour market externalities variables Specialization, RelVar and UnrelVar based on pre-defined inter-industry relatedness are included, and from which the mobility rate variable is removed; and (4) a final model in which the two alternative labour market externalities variables (Similarity and RRMR) based on revealed inter-industry skill-relatedness are included and the three variables under (3) are removed. Despite the fact that the baseline model may suffer from omitted variable bias when significant covariates introduced in subsequent models are left out, we will be able to discern the relative gain of the different mobility specifications (total, pre-defined or revealed) by comparing the overall model fit with our baseline models, since models 2-4 all measure the same number of flows but with different definitions. To check for the consistency of our results, both the fixed-effect (FE) and difference-GMM models (GMM) are estimated for models 1-4. All models have robust standard errors to reduce the impact of heteroscedasticity.

Table 3 presents the findings concerning regional productivity growth. As expected in light of previous findings (e.g. McCann and Simonen, 2005; Eriksson, 2011), mobility *per se* has no influence on regional productivity growth (Model 2). Moreover, we can neither find any significant relationship when accounting for the types of industry-specific skills that are involved in labour mobility, and how these are related to the existing set of industry-specific skills in regions (Model 3). However, as shown in Model 4, our more sophisticated variable of related labour market externalities, based on the revealed skill-relatedness indicator (RRMR), shows a strong and positive relationship with regional productivity growth in the period 1998-2002 whereas Similarity is still not significantly related to growth. In line with our expectations, this means that high degrees of labour mobility across skill-related industries in a region implies high quality matching of local skills which contributes to regional productivity growth. These results are robust in both the FE-specification and the difference-GMM model, although the size of the coefficient is larger in the GMM model, and thus reflects the qualitative difference of conceptualizing relatedness via pre-defined industry codes or as skill-relatedness.

As shown in Table 3, the controllers are in line with our expectations. The lag of productivity is significantly related to future productivity growth. Further, population density, relative concentration of manufacturing industries as well as net migration are positively significant. The GMM-model does however not confirm the fixed effect results on primary industries and R&D, or the results on investments. The significantly negative relationship with investments is unexpected since investments are assumed to result in higher productivity by increasing relative efficiency (e.g. Solow, 1964). It is however reasonable to expect that the positive impact of investments needs some time to materialize as positive effects in the region. In addition, our investment data do not separate between investments made in capital or labour which may imply that capital-oriented investments do not increase regional income levels but rather stimulate the long-term performance of regional firms. A final observation concerns the test-statistics for the GMM-model. AR(1), which tests the null hypothesis of no first-order correlation in the differenced residuals, is rejected. This is expected since first differences in errors share an error level component. The null hypothesis of no second-order autocorrelation in levels, AR(2), was however confirmed. The outcome from the AR(2) test together with the non-significant Hansen statistic, which under the null hypothesis tests that the instruments as a group are exogenous, indicates that the instruments fulfil their purpose.

-Table 3 about here -

The results of the regional employment models are displayed in Table 4. Similar to the results on productivity growth, no significant relationship between regional employment growth and labour mobility rate is identified (Model 2). However, unlike the findings on productivity, the outcomes in Model 3 show that related labour market externalities (RelVar) has a positive relationship with regional employment growth, unrelated flows (UnrelVar) a significant negative relationship, while no significant relationship is found for the variable Specialization. This suggests that only related labour market flows within regions enhance regional employment growth, not labour mobility *per se*, nor intra-industry mobility, nor mobility across unrelated industries. These results are in line with findings from other studies applying predefined industries to capture inter-industry relatedness (e.g. Frenken *et al.*, 2007; Boschma and Iammarino, 2009), These studies have shown that it is mainly related spatial externalities that correlate with employment growth. This is because a regional industrial portfolio characterized by related variety is assumed to enhance spillovers and new firm formation and thus to stimulate job creation, while a portfolio of highly unrelated activities is not expected to induce sufficient complementarities but is rather expected to protect regions from external shocks, thereby, dampening unemployment. This finding is however not replicated in the GMM-model where only UnrelVar is significant. Thus, the significant score on RelVar in the FE-model may suffer from endogeneity and should therefore be interpreted with some caution. Further, Model 4 shows that, in contrast to the productivity model, revealed skill-relatedness has no significant relationship with regional employment growth, and neither has the share of job flows within the same sector. Thus, quality of matching seems to be of less importance for employment than for productivity growth, which is a rather unexpected outcome. A possible explanation may be that productivity gains may not lead to employment growth in regions with a high variety of skill-related industries, as productivity growth produces not only employment gains but also losses due to the adoption of labour-saving innovations. In all, this implies that the net effect on employment growth of skill-related externalities is negligible while the gross flows across firms and industries may be relatively high.

As for the controllers, only population density, the location quotient for primary sectors and NetMig show significant relationships with regional employment growth. The lag of employment growth is not significant in any of the GMM-models. Finally, it should be noted that both the AR(1) and Hansen tests fulfil the underlying assumptions of the GMM-models while the AR(2) test does not for model 1, 2 and 4. This suggests that the instruments used in these models are weak. One plausible solution would be to introduce further lags, but due to our short panel, this is not feasible because it would reduce the sample size. However, the test is only significant at the 5% level which implies that the instruments still contribute to the models. Further, despite the potential limitations of the GMM estimations, the overall results of the analysis indicate the fact that only the conventional indicator for labour market externalities matters for regional employment growth.

-Table 4 about here -

Table 5 displays the relationship between labour market externalities and regional unemployment growth. The base model (Model 1) indicates that densely populated areas show higher unemployment growth. This finding together with the negative sign on NetMig and of density on employment (in previous models) may be the result of a relatively greater increase in population in these areas via both migration and birth rates (e.g. Lundholm, 2007), which thus implies that the number of people living in these areas is increasing faster than the number of available jobs. Neither investments nor any of the location quotients show any significant relationship with unemployment in the FE-models, while the location quotient for manufacturing sectors is positively (though moderately) significant in the GMM-model, which together with the findings reported in Table 3 on productivity suggests that manufacturing industries during this period underwent a period of increasing productivity through labour saving rationalizations.

Similar to productivity and employment, the general labour mobility rate has no significant influence on unemployment growth (Model 2). Neither do any of the flows based on pre-defined sectors have any significant relationship with unemployment (Model 3). The positive signs of Similarity and RRMR in Model 4 however suggest that unrelated labour market externalities are associated with lower unemployment growth. This implies that regions endowed with high degrees of skill-related flows are on the one side vulnerable to unemployment but on the other side tend to have higher levels of productivity growth. Together with the non-significant estimate of skill-relatedness on employment, this leads us to conclude that skill-relatedness enhances productivity but also produces unemployment by making labour redundant. In all, these results confirm previous findings at the regional level (e.g. Frenken *et al.*, 2007), which showed that unrelated variety may act as an absorber of regional unemployment, just as our study shows that highly diversified labour market flows may act as a check on regional unemployment, but as shown in the employment model it is less likely to promote job creating externalities due to too great variety.

There could be two main reasons for the different influence that the two alternative measures for capturing unrelated externalities have on employment and unemployment. First, from an empirical point of view, these two indicators capture different aspects of the regional economy. The conventional indicator is more related to the regional composition of industries (whether there are many different types of industries present) while the revealed indicator captures the extent to which skills are transferable across sectors. Second, the qualitative difference between the two types of indicators is also likely to matter. The diverse regional portfolio of industries (as captured in the conventional indicator) is typically associated with low rate of new successful combinations leading to radical or product innovations and new firms, and is therefore not expected to promote job creation but rather to facilitate portfolio effects that are better equipped to withstand unemployment (c.f., Frenken et al. 2007). Further, it is reasonable to expect that unemployment could be pronounced by high degrees of skill-related flows, since they are more associated with high concentrations of inter-industry labour pooling (Ellison et al, 2010), meaning that regions with low degrees of skill-relatedness are less vulnerable to asymmetric job destruction due to their diverse labour pool (Diodato and Weterings, 2012). In Model 4, we also observe that a high degree of intra-industry labour flows is positively linked to unemployment growth. This confirms our overall expectation that intra-industry labour mobility is not beneficial for regional development. While we could not find any association with productivity, the incremental innovations and process innovations usually assumed to be triggered by specialization seem to have an effect on rising unemployment, which points to the fact that such externalities induce relatively higher efficiency, but are mainly labour saving since the productivity effects are negligible. For unemployment, the AR(1) test on autocorrelation in first-order errors is only fulfilled in Model 4, while all models have satisfactory test statistics for the AR(2) and Hansen tests. This, together with the only moderate influence of the past realization of unemployment in the GMM models, suggests that past unemployment growth has little to do with future unemployment growth since no correlation is identified in the first differences residuals.

-Table 5 about here -

A final comment needs to be made regarding the explanatory power in the three output tables. While we can identify significant relationships between our mobility indicators and the different indicators for regional growth, this effect is moderate as compared to our controllers and the regional fixed effects. This is expected given previous findings that primarily plant characteristics (Boschma *et al.*, 2009; Eriksson and Lindgren, 2009) and secondly regional attributes (Eriksson, 2011) explain a considerable part of the total variation in regional performance. Thus, despite the notion that knowledge flows are more likely to be a more efficient medium for transferring knowledge than are "pure knowledge spillovers" (Breschi and Lissoni, 2009), it is plant- and region-specific attributes that explain a considerable part of regional variations in growth.

5. Conclusions

The aim of our study is to shed more light on the degree and nature of agglomeration externalities on regional growth. Our main findings based on unique Swedish data on actual labour flows between 435 manufacturing and service industries in 72 labour market areas indicate that labour market externalities are related to regional growth, but that the effects depend on how externalities and growth are defined.

Our study shows that the general labour mobility rate itself does not provide a comprehensive picture of the relationship between labour market externalities and regional development. Broadly speaking, intra-regional labour mobility *per se* showed no impact on regional growth. This result confirms similar findings in other studies (McCann and Simonen, 2005; Eriksson, 2011). Therefore, it is necessary to differentiate between types of labour flows to assess more accurately the relation between labour mobility and regional growth. We therefore tested our expectation that this relationship is especially strong in regions where labour mobility occurs between technologically related industries. In our study, we used two alternative measures to capture labour mobility-induced externalities between related industries. The first concerned a pre-defined inter-industry relatedness indicator based on the Standard Industrial Classification, as in other studies (e.g. Frenken *et al.*, 2007). The second concerned a revealed inter-industry relatedness indicator based on the skill-relatedness measure developed by Neffke and Svensson-Henning (2008).

The main findings can be summarized as follows. First, we found evidence for the fact that labour mobility across related industries in a region is positively related to regional productivity growth and, to some extent, regional employment growth. In particular, our more sophisticated measure of skill-relatedness indicates that high quality regional matching of skills (high concentrations of skill-related industries) promotes production complementarities that stimulate productivity growth. This finding points to the fact that labour pooling can work across regional sectors if they rely on similar skills. This outcome extends the traditional Marshallian notion of labour pooling and contributes to the literature on matching as a source for agglomeration (Puga, 2010). Second, intra-industry labour mobility had no significant relationship with productivity growth or employment growth, and it even increased regional unemployment. In sum, intra-industry mobility is not an economic blessing for regions, because it does not generate much opportunities for real learning and renewal in a region. Combined with the finding on skill-relatedness in the unemployment model, this indicates that sharing labour pool (within or across industries) may increase regional vulnerability for unemployment. Third, labour mobility across unrelated industries tends to dampen regional unemployment levels in particular. The conventional indicator had a negative relation with employment growth, whereas its relation with regional productivity growth was dependent on the chosen indicator of unrelated labour mobility (non-significant for the conventional indicator, negative for the revealed indicator). Since the conventional indicator better reflects the industrial composition within regions while the revealed indicator reflects the inter-industry transferability of skills, it is possible to conclude that unrelated externalities (proxied as a diverse portfolio of skills) are good for protecting regions from an increase in unemployment, but that they do not enhance employment due to the relative absence of learning inducing complementarities (when proxied as a diverse portfolio of sectors).

These findings could be further elaborated in future studies by incorporating more information about the working-life history of the labour. Previous research clearly points to the importance of knowledge exchange and more specifically knowledge matching, but we seem to have less insights about how the different pieces of inflow and in-house knowledge should look like for fitting in this jigsaw puzzle. One way of taking a step forward is to learn more empirically about the different layers of individuals' histories of competence, skill accumulation and of the social dimension of mobility and how that is related to plant performance and regional growth and decline (Breschi and Lissoni, 2003; Agrawal *et al.*, 2006; Timmermans, 2008; Timmermans and Boschma 2013). If more were known about the detailed shapes of the knowledge profiles of the individuals, our understanding of why certain knowledge flows are more beneficial to firms and regions would most likely increase. Given the negative sign of the conventional indicator of unrelated flows in the employment model and the positive sign of skill-related flows in the unemployment model, future studies could also more carefully consider the difference between labour flows that concern gross job flows rather than changes in net employment and those that are driven by spinoffs or start-ups (Essletzbichler, 2007).

Another factor is related to time-specific effects. After the burst of the IT bubble in the year 2000, the Swedish economy fell into a relatively long recession. We have, however, controlled for such an effect by both including year-specific dummies in all models and by running additional separate regressions on the years 1998-2000 and 2000-2002, respectively. Although some of the results are subject to minor time-related effects as reported in the previous section[vi], no substantial differences in the outcomes could be reported. However, future studies should consider the time-specific effects more carefully and adopt a more dynamic perspective, in order to investigate the complex interaction

[vi] For instance, the negative influence of UnrelVar on employment growth is found during the growth period prior to year 2000.

between industry life cycle stages and various types of externalities (e.g. Neffke e*t al.*, 2011b). This would also shed light on the importance of different types of labour mobility during the industry life cycle, as there is still little understanding of the effect of labour mobility on the emergence, growth, decline and revival of industries at the regional level.

References

ACEMOGLU D. (1996) A microfoundation for social increasing returns in human capital accumulation, *Quarterly Journal of Economics* **111**, 779-804.

AGRAWAL A., COCKBURN I. and MCHALE J. (2006) Gone but not forgotten: knowledge flows, labor mobility, and enduring social relationships, *Journal of Economic Geography* **6**, 571-591.

ALMEIDA P. and KOGUT B. (1999) Localization of knowledge and the mobility of engineers in regional networks, *Management Science* **45**, 905-917.

ANDERSSON J. and TEGSJÖ B. (2006) En rörlig arbetsmarknad - dynamiken bland jobb, individer och företag [Labour market mobility – dynamics among jobs, individuals and business]. In: *Statistics Sweden: Fokus på näringsliv och arbetsmarknad våren 2006 [Focus on economy and labour market, spring 2006]*. Statistics Sweden (SCB), Stockholm.

ANDERSSON L-F. (2006): Företagsdynamik och tillväxt [Business dynamics and growth]. Swedish agency for growth policy studies (ITPS) Report no: 2006:016, Östersund

ANDERSSON M. and THULIN P. (2011) *Labor mobility and spatial density*. CESIS Eletronic Working Paper Series, No 248, Stockholm.

ANGEL D. (1991) High-technology agglomeration and the labor market: the case of Silicon Valley, *Environment and Planning A* **23**, 1501-1516.

ARGOTE L., EPPLE D., RAO R. and MURPHY K. (1997) *The acquisition and depreciation of knowledge in a manufacturing organization*. Working paper, Carnegie Mellon University, Pittsburgh, PA.

ARELLANO M. and BOND S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies* **58**, 277 – 297.

BEAUDRY C. and SCHIFFAUEROVA A. (2009) Who's right, Marshall or Jacobs? The localization versus urbanization debate, *Research Policy* **38**, 318-337.

BECKER G. S. (1962) Investment in human capital: A theoretical analysis, *Journal of Political Economy* **70**, 9-49.

BERLIANT M., REED R.R. and WANG, P. (2000) Knowledge Exchange, Matching, and Agglomeration, Discussion Paper 135, Federal Reserve Bank of Minneapolis.

BERNARD A. B. and JENSEN J. B. (2004) Why some firms export, *Review of Economics and Statistics* **86**, 561–569.

BIENKOWSKA D., LUNDMARK M. and MALMBERG A. (2011) Brain circulation and flexible adjustment: Labour mobility as a cluster advantage, *Geografiska Annaler B* **93**, 21-39.

BISHOP P. (2008) Spatial spillovers and the growth of knowledge intensive services. *Tijdschrift voor Economische en Sociale Geografie* **99**, 281-292

BISHOP P. and GRIPAIOS P. (2010) Spatial externalities, relatedness and sector employment growth in Great Britain. *Regional Studies* **44**, 443-454.

BOEKER W. (1997) Executive migration and strategic change – The effect of top manager movement on product-market entry, *Administrative Science Quarterly* **42**, 213-236.

BOSCHMA R. A., ERIKSSON, R. and LINDGREN U. (2009) How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity, *Journal of Economic Geography* **9**, 169-190.

BOSCHMA R. A. and IAMMARINO S. (2009) Related variety, trade linkages and regional growth in Italy, *Economic Geography* **85**, 289-311.

BOSCHMA R. A., MINONDO A. and NAVARRO M. (2012) Related variety and regional growth in Spain. *Papers in Regional Science* **91** (2), 241-256.

BRESCHI S. and LISSONI F. (2009) Mobility of skilled workers and co-invention networks: An anatomy of localized knowledge flows. *Journal of Economic Geography* **9**, 439-468.

BROWN W. M. and RIGBY D. L. (2010) *Marshallian localization economies: Where do they come from and to whom do they flow?* Paper presented at the DIME workshop 'Industrial Dynamics and Economic Geography', Utrecht, September.

CAMERON, A.C. and TRIVEDI, P.K. (2010) *Microeconomics using STATA. Stata Press, College Station.*

COHEN M. D. and LEVINTHAL D. A. (1990) Absorptive capacity – A new perspective on learning and innovation, *Administrative Science Quarterly* **35**, 128-152.

COMBES P. and DURANTON G. (2006) Labour pooling, labour poaching and spatial clustering, *Regional Science and Urban Economics* **36**, 1-28.

COOPER D. (2001) Innovation and reciprocal externalities: Information transmission via job mobility, *Journal of Economic Behavior and Organization* **45**, 403-425.

DAHL M. S. and PEDERSEN C. O. R. (2003) Knowledge flows through informal contacts in industrial clusters – Myth or reality? *Research Policy* **33**, 1673-1686.

DE GROOT H. L. F., POOT J. and SMIT M. J. (2009) Agglomeration externalities, innovation and regional growth: theoretical perspectives and meta-analysis, in CAPELLO R. and NIJKAMP P. (Eds) *Handbook of Regional Growth and Development Theories*, 256-281. Edward Elgar, Northampton MA.

DIODATO D. and WETERINGS A. (2012) *The resilience of Dutch regions to economic shocks. Measuring the relevance of interactions among firms and workers*, Papers in Evolutionary Economic Geography, no. 12.15, Utrecht University.

DURANTON, G and PUGA D. (2004): Micro-Foundations of Urban Agglomeration Economies, in HENDERSON J.V. and THISSE J.V. (Eds) *Handbook of Regional and Urban Economics*, *Vol 4,* 2063-2117. North-Holland, Amsterdam

DUSTMANN C., GLITZ, A. and FRATTINI T. (2008) The labour market impact of immigration, *Oxford Review of Economic Policy* **24**, 3, 477-494.

ELLISON G., GLAESER E.L and KERR W. (2010) What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns, *American Economic Review*, **100,** 1195-1213

EUROFOUND (2006) *Mobility in Europe. Analysis of the 2005 Eurobarometer survey on geographical and labour market mobility*. Office for Official Publications of the European Communities, Luxembourg.

ERIKSSON R. and LINDGREN U. (2009) Localized mobility clusters: Impacts of labour market externalities on firm performance. *Journal of Economic Geography* **9**, 33-53.

ERIKSSON R., LINDGREN U. and MALMBERG G. (2008) Agglomeration mobility: effects of localisation, urbanisation, and scale on job changes, *Environment and Planning A* **40**, 2419-2434.

ERIKSSON R. H. (2011) Localized spillovers and knowledge flows – How does proximity influence the performance of plants, *Economic Geography* **87**, 127-152.

ESSLETZBICHLER J (2007) The Geography of Gross Employment Flows in British Manufacturing, *European Urban and Regional Studies* **14**, 7-26.

FALLICK B., FLEISCHMAN C. A. and REBITZER J. B. (2006) Job-hopping in Silicon Valley: Some evidence concerning the microfoundations of a high-technology cluster, *The Review of Economics and Statistics* **88**, 472-481.

FLEMING L. and FRENKEN K. (2007) The evolution of inventor networks in the Silicon Valley and Boston regions, *Advances in Complex Systems* **10**, 53-71.

FRENKEN K., VAN OORT F. and VERBURG T. (2007) Related variety, unrelated variety and regional economic growth, *Regional Studies* **41**, 685-697.

FRENKEN, K. (2007) Entropy statistics and information theory. In: H. HANUSCH and A. PYKA (eds) *The Elgar Companion to Neo-Schumpeterian Economics*. Cheltenham, UK: Edward Elgar, 544–555.

GLAESER E. L., KALLAL H. D., SCHINKMANN J. A. and SHLEIFER A. (1992) Growth in cities, *Journal of Political Economy* **100,** 1126–1152.

GLAESER E. L. and RESSEGER M.G. (2009) The complementarity between cities and skills, NBER working paper series, no. 15103, Cambridge (MA).

HUBER F. (2012) Do clusters really matter of innovation practices in Information Technology? Questioning the significance of technological knowledge spillovers, *Journal of Economic Geography* **12**, 107-126

IAMMARINO S. and MCCANN P. (2006) The structure and evolution of industrial clusters – Transactions, technology and knowledge spillovers, *Research Policy* **35**, 1018-1036.

KIM J. and MARSCHKE G. (2005) Labor mobility of scientists, technological diffusion, and the firm's patenting decision, *RAND Journal of Economics* **36**, 298-317.

KRUGMAN P.R. (1993) Lessons of Massachusetts for EMU, in TORRES F. and GIAVAZZI F. (Eds) Adjustment and Growth in the European Monetary Union, pp. 241–269, Cambridge University Press, Cambridge.

LACETERA N., COCKBURN I. M. and HENDERSON R. (2004) Do firms change capabilities by hiring new people? A study of the adoption science-based drug discovery, in BAUM J. and MCGAHAN A. (Eds) *Advances in Strategic Management*, 133-159. Elsevier, New York.

LUCAS R. E. (1988) On the mechanics of economic development, *Journal of Monetary Economics* **22**, 3-42.

LUNDHOLM E. (2007) Are movers still the same? Characteristics of interregional migrants in Sweden between 1970-2001. *Tijdschrift voor Economische en Sociale Geografie* **98**, 336-348.

MADSEN T. L., MOSAKOWSKI E. and ZAHEER S. (2003) Knowledge retention and personnel mobility. The non-disruptive effects of inflows of experience, *Organization Science* **14**, 173-191.

MALMBERG A., MALMBERG B. and LUNDEQVIST B. (2000) Agglomeration and firm performance: economies of scale, localisation, and urbanisation among Swedish export firms. *Environment and Planning A,* **32**, 205-321.

MALMBERG A. (2003) Beyond the cluster – Local milieus and global connections, in PECK J. and YEUNG H. W. C. (Eds) *Remaking the Global Economy*, 145-162. Sage Publications, London.

MALMBERG A. and POWER D. (2005) (How) Do (Firms in) Clusters Create Knowledge? *Industry and Innovation* **12**, 409-431.

MARSHALL A. (1920) Principles of economics – An introductory volume. London, MacMillan.

MCCANN P. and SIMONEN J. (2005) Innovation, knowledge spillovers and local labour markets, *Papers in Regional Science* **84**, 465-485.

MORTENSEN D.T. (1986) Job Search and Labor Market Analysis. In: ASHENFELTER O. and LAYARD R. (Eds) *Handbook of Labor Economics*, *Volume 2,* 849-919. Elsevier Science Publications, Amsterdam.

NATHAN M. (2011) The long term impacts of migration in British cities: diversity, wages, employment and prices, SERC discussion paper no. 67.

NEFFKE, F., HENNING, M., BOSCHMA, R.A. (2011a) How Do Regions Diversify Over Time? Industry Relatedness and the Development of New Growth Paths in Regions. *Economic Geography,* **87 (3)**: 237-265.

NEFFKE, F., HENNING, M., BOSCHMA, R.A., LUNDQUIST, K.-J., OLANDER, L.-O. (2011b) The dynamics of agglomeration externalities along the life cycle of industries. *Regional Studies*, **45 (1)**: 49-65.

NEFFKE F. and SVENSSON-HENNING M. (2008) *Revealed relatedness. Mapping industry space*. Department of Economic Geography, Utrecht.

NUTEK (2000) Labour market mobility: A lubricant for growth. Report 2000:15, Swedish Business Development Agency. Stockholm, Sweden.

OTTAVIANO G.I.P. and PERI G. (2006) The economic value of cultural diversity: evidence from US cities. *Journal of Economic Geography* **6**, 9-44.

PINCH S. and HENRY N. (1999) Paul Krugman's geographical economics, industrial clustering and the British motor sport industry, *Regional Studies* **33**, 815-827.

PHILIPS D. J. (2002) A genealogical approach to organizational life chances. The parent-progeny transfer and Silicon Valley law firms 1946-1996, *Administrative Science Quarterly* **47**, 474-506.

PORTER M. E. (2003) The economic performance of regions. *Regional Studies*, **37**, 549-578.

POWER D. and LUNDMARK M. (2004) Working through knowledge pools: Labour market dynamics, the transference of knowledge and ideas, and industrial clusters. *Urban Studies* **41**, 1025-1044.

PUGA D. (2010) The magnitude and causes of agglomeration economies, *Journal of Regional Science* **50** , 203-219

QUATRARO F. (2010) *Knowledge coherence, variety and economic growth. Manufacturing evidence from Italian regions*. Research Policy, doi:10.1016/j.respol.2010.09.005

RODRÍGUEZ-POSE A. and VILALTA-BUFI M. (2005) Education, migration, and job satisfaction. The regional returns of human capital in the EU, *Journal of Economic Geography* **5**, 545-566.

ROODMAN, D.M. (2006) How to do xtabond2: an introduction to "Difference" and "System" GMM in Stata. *Center for Global Development Working Paper Number 103*.

SAXENIAN A. L. (1994) *Regional advantage. Culture and competition in Silicon Valley and Route 128. Harvard University Press*, Cambridge.

SAXENIAN A.L. and SABEL, C. (2008): Roepke Lecture in Economic Geography. Venture Capital in the "Periphery": The New Argonauts, Global Search, and Local Institution Building. *Economic Geography* **84**, 379-394

SOLOW R. (1957) Technical change and the aggregate production function, *Review of Economics and Statistics* **39**, 312-320.

SONG J., ALMEIDA P. and WU G. (2003) Learning-by-hiring: When is mobility more likely to facilitate interfirm knowledge transfer? *Management Science* **49**, 351-365.

SORENSON J. B. (1999) Executive migration and interorganizational competition, *Social Science Research* **28**, 289-315.

STORPER M. and WALKER R. (1989) *The capitalist imperative: Territory, technology and industrial growth.* Blackwell, Oxford.

STRANGE W., HEJAZI W. and TANG J. (2006) The uncertain city: Competitive instability, skills, innovation, and the strategy of agglomeration, *Journal of Urban Economics* **59**, 331-351.

TIMMERMANS B. (2008) *Who do I hire first? The effect of first year employees' social capital on firm survival*. Paper presented at DRUID Winter Conference in Aalborg.

TIMMERMANS B. AND BOSCHMA R. (2013) The effect of intra- and inter-regional labour mobility on plant performance in Denmark: the significance of related labour inflows, *Journal of Economic Geography*, forthcoming, doi:10.1093/jeg/lbs059

THULIN P. (2009) *Labor mobility, knowledge diffusion and regional growth*. CESIS Electronic Working Paper Series, No. 209, Stockholm.

VAN DER BERG G.J. (1992) A Structural Analysis of Job Turnover and The Costs Associated with Moving to Another Job, *The Economic Journal* **102,** 1116-1133

VAN OORT F. G. (2004) *Urban growth and innovation. Spatially bounded externalities in the Netherlands*. Ashgate, Aldershort.

WENTING R. (2008) Spinoff dynamics and the spatial formation of the fashion design industry 1858-2005, *Journal of Economic Geography* **8**, 593-614.

WEZEL F. C., CATTANI G. and PENNINGS J. M. (2006) Competitive implications of interfirm mobility, *Organization Science* **17**, 691-709.

ZHANG J. (2013) Related variety, global connectivity and institutional embeddedness: Internet development in Beijing and Shanghai compared, *Regional Studies* **47** (7), 1065-1081.

Table 1: Variables and descriptive statistics (n=360)

Variables (year 1998-2002)	Definition	Mean	Std. Dev.	Min	Max
Dependent variables					
Productivity growth	Annual change in labour productivity (%) measured as regional purchase power	0.05	0.54	-4.25	3.30
Employment growth	Annual change in number of people employed within FA-region (%)	0.00	0.02	-0.10	0.05
Unemployment growth	Annual change in number of people unemployed within FA-region (%)	-0.08	0.07	-0.29	0.21
Total mobility					
MobRate	Number of intra-regional job moves divided by number of employees	0.05	0.03	0.00	0.21
Labour market ext.					
Specialization	Degree of intra-industry labour market flows	0.01	0.01	0.00	0.09
RelVar	Degree of related labour market flows	0.02	0.01	0.00	0.10
UnrelVar	Degree of unrelated labour market flows	0.95	0.11	0.00	0.99
Revealed relatedness					
Similarity	Number of intra-regional labour flows within the same industry / total number of intra-regional flows	0.32	0.16	0.00	0.86
RRMR	Revealed Regional Mobility Relatedness (log)	0.76	0.80	-4.25	4.58
Controllers					
PopDensLog	Number of people per square kilometer (log)	1.00	0.64	-0.59	2.14
Inv/capLog	Industry investments per employed (log)	1.17	0.30	0.26	2.21
LQ_Primary	Location quotient of regional concentration of primary industries (NACE: 1-14)	1.84	0.98	0.21	6.30
LQ_Manu	Location quotient of regional concentration of manufacturing industries (NACE: 15-37)	1.25	0.52	0.28	3.03
LQ_R&D	Location quotient of regional concentration of research and development activities (NACE: 73, 803)	1.02	0.22	0.56	1.92
NetMig	Number of people (all ages) moving to the region divided with the number of people moving out	0.86	0.17	0.38	1.35

Table 2: Micro-descriptives (means) of all intra-regional flows (All), intra-industry flows (Sim), within the same 3-digit industry class (Rel), between different 3-digit industry classes (Unrel) and Skill-related flows with p<0.1 (SR) during 1998-2002. Definitions of industry groups are adopted from NUTEK (2000)

Description	**All**	**Sim**	**Rel**	**Unrel**	**SR**
Individual attributes					
Age (25-65)	41.86	43.00	43.30	40.66	42.45
Sex (Dummy =1 if man)	0.55	0.57	0.43	0.57	0.48
Annual income (thousands of SEK)	387.83	387.02	360.71	396.52	366.47
Type of sector					
Knowledge-intensive manufacturing (Dummy =1 if NACE: 22, 24, 29, 30, 32, 33, 34, 35)	0.16	0.15	0.06	0.17	0.19
Capital-intensive manufacturing (Dummy =1 if NACE: 21, 23, 27)	0.01	0.01	0.03	0.01	0.01
Labour-intensive manufacturing (Dummy =1 if NACE: 15, 16, 17, 18, 19, 20, 21, 25, 25, 28, 36, 37)	0.05	0.03	0.02	0.06	0.05
R&D activities (Dummy =1 if NACE: 73, 803)	0.06	0.03	0.10	0.07	0.12
Business related service (Dummy = 1 if NACE: 65, 66, 67, 72, 74)	0.37	0.34	0.50	0.37	0.30
Capital-intensive service (Dummy = 1 if NACE: 60, 61, 62, 63, 64, 70, 71)	0.13	0.19	0.08	0.10	0.12
Labour-intensive service (Dummy = 1 if NACE: 45, 50, 51, 52, 55, 90, 93, 95)	0.21	0.22	0.18	0.20	0.20
Other capital-intensive activities (Dummy = 1 if NACE: 1, 2, 5, 10, 11, 12, 13, 14, 40. 41)	0.02	0.02	0.02	0.02	0.01
Type of region (N=72)					
Metropolitan regions (N=3)	0.72	0.75	0.68	0.72	0.67
Large regional centres (N=19)	0.23	0.21	0.26	0.23	0.26
Small regional centres (N=20)	0.04	0.03	0.05	0.04	0.05
Small regions dominated by private sector (N=14)	0.01	0.01	0.01	0.01	0.01
Small regions dominated by public sector (N=16)	0.01	0.01	0.01	0.01	0.01
Year					
Dummy =1 if 1998	0.11	0.14	0.10	0.10	0.11
Dummy =1 if 1999	0.14	0.16	0.14	0.13	0.15
Dummy =1 if 2000	0.27	0.29	0.20	0.27	0.25
Dummy =1 if 2001	0.22	0.23	0.14	0.24	0.21
Dummy =1 if 2002	0.26	0.18	0.42	0.27	0.28
N (thousands)	321.47	109.06	49.02	163.39	118.66

Table 3: Fixed effect (FE) and difference-GMM (GMM) estimates on annual regional productivity growth (%) 1998-2002. Coefficients and robust standard errors (within brackets) are reported except for AR(1)/(2) and Hansen J where p-values are reported. Significant at the *** 0.01 level, ** 0.05 level and * 0.10 level.

	1 (FE)	2 (FE)	3 (FE)	4 (FE)	1 (GMM)	2 (GMM)	3 (GMM)	4 (GMM)
Y_lag (Prod)	-0.342***	-0.341***	-0.322***	-0.331***	-0.576***	-0.584***	-0.548***	-0.584***
	(0.049)	(0.049)	(0.049)	(0.050)	(0.072)	(0.065)	(0.059)	(0.062)
Specialization			-1.749				-5.092	
			(3.794)				(4.650)	
RelVar			3.083				0.595	
			(3.705)				(4.821)	
UnrelVar			1.242				1.011	
			(0.816)				(0.759)	
Similarity				-0.012				0.083
				(0.299)				(0.299)
RRMR				0.069**				0.185**
				(0.040)				(0.077)
MobRate		0.140				0.234		
		(0.585)				(0.868)		
PopDensLog	1.224**	1.212**	1.252**	1.109*	2.086**	2.063**	1.961**	1.793**
	(0.587)	(0.590)	(0.582)	(0.581)	(0.844)	(0.903)	(0.762)	(0.840)
Inv/CapLog	-0.285	-0.287	-0.291	-0.297	-0.385**	-0.448**	-0.234**	-0.364**
	(0.196)	(0.196)	(0.188)	(0.197)	(0.178)	(0.186)	(0.177)	(0.180)
LQ_Primary	-0.358**	-0.358**	-0.234*	-0.336*	-0.381	-0.493	-0.218	-0.434
	(0.174)	(0.174)	(0.155)	(0.174)	(0.430)	(0.416)	(0.288)	(0.401)
LQ_Manu	1.123*	1.123*	1.244*	1.153*	2.103**	1.697**	2.137**	2.142**
	(0.666)	(0.667)	(0.704)	(0.656)	(0.852)	(0.837)	(0.928)	(0.964)
LQ_R&D	1.203*	1.206*	1.295**	1.183*	1.140	1.208	0.850	1.420
	(0.609)	(0.614)	(0.587)	(0.619)	(0.882)	(0.833)	(0.797)	(0.874)
NetMig	0.774**	0.772**	0.724**	0.735**	1.241**	1.292**	1.125**	1.111**
	(0.359)	(0.359)	(0.356)	(0.358)	(0.519)	(0.494)	(0.513)	(0.488)
Intercept	-20.567**	-20.397**	-22.567**	-19.622**				
	(9.368)	(9.388)	(9.643)	(9.409)				
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.773	0.774	0.776	0.786				
Hausman Chi^2	147.83***	83.82***	64.14***	29.20***				
VIF	1.81	2.14	1.79	2.49				
Instruments					30	33	39	34
AR(1)					0.067	0.006	0.001	0.004
AR(2)					0.367	0.281	0.244	0.318
Hansen J					0.834	0.882	0.544	0.794
N	360	360	360	360	288	288	288	288

Note: The GMM models are estimated on the years 1999-2002 due to inclusion of 2-year lags as instruments.

Table 4: Fixed effect (FE) and difference-GMM (GMM) estimates on annual regional employment growth (%) 1998-2002. Coefficients and robust standard errors (within brackets) are reported except for AR(1)/(2) and Hansen J where p-values are reported. Significant at the *** 0.01 level, ** 0.05 level and * 0.10 level.

	1 (FE)	2 (FE)	3 (FE)	4 (FE)	1 (GMM)	2 (GMM)	3 (GMM)	4 (GMM)
Y_lag (Emp)	-0.088*	-0.089*	-0.083*	-0.084*	-0.061	-0.070	-0.063	-0.048
	(0.050)	(0.050)	(0.050)	(0.051)	(0.058)	(0.059)	(0.061)	(0.057)
Specialization			0.092				0.098	
			(0.113)				(0.134)	
RelVar			0.201**				0.122	
			(0.102)				(0.127)	
UnrelVar			-0.016**				-0.021**	
			(0.008)				(0.008)	
Similarity				0.006				0.008
				(0.007)				(0.007)
RRMR				-0.002				-0.000
				(0.001)				(0.002)
MobRate		0.008				0.054		
		(0.038)				(0.040)		
PopDensLog	-0.083***	-0.084***	0.087***	-0.080***	-0.098***	-0.100***	-0.097***	-0.091***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.017)	(0.017)	(0.017)	(0.017)
Inv/CapLog	0.002	0.002	0.002	0.002	0.003	0.002	-0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
LQ_Primary	-0.010*	-0.010*	-0.011*	-0.011*	-0.014*	-0.021**	-0.015*	-0.013*
	(0.006)	(0.006)	(0.007)	(0.006)	(0.011)	(0.010)	(0.010)	(0.009)
LQ_Manu	0.011	0.011	0.012	0.010	-0.021	-0.011	-0.020	-0.011
	(0.013)	(0.013)	(0.012)	(0.013)	(0.018)	(0.019)	(0.017)	(0.019)
LQ_R&D	0.020	0.020	0.017	0.020	0.004	0.025	-0.002	0.014
	(0.015)	(0.015)	(0.015)	(0.015)	(0.023)	(0.025)	(0.018)	(0.022)
NetMig	0.031***	0.031***	0.032***	0.032***	0.027**	0.030***	0.029***	0.027***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)	(0.011)	(0.010)
Intercept	1.216***	1.224***	1.277***	1.171***				
	(0.216)	(0.217)	(0.225)	(0.215)				
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.695	0.695	0.702	0.697				
Hausman Chi^2	480.24***	523.45***	974.66***	15.82				
VIF	2.02	2.30	1.95	2.76				
Instruments					30	33	39	34
AR(1)					0.004	0.008	0.002	0.004
AR(2)					0.042	0.025	0.330	0.032
Hansen J					0.540	0.469	0.606	0.728
N	360	360	360	360	288	288	288	288

Note: The GMM models are estimated on the years 1999-2002 due to inclusion of 2-year lags as instruments.

Table 5: Fixed effect (FE) and difference-GMM (GMM) estimates on annual regional unemployment growth (%) 1998-2002. Coefficients and robust standard errors (within brackets) are reported except for AR(1)/(2) and Hansen J where p-values are reported. Significant at the *** 0.01 level, ** 0.05 level and * 0.10 level.

	1 (FE)	2 (FE)	3 (FE)	4 (FE)	1 (GMM)	2 (GMM)	3 (GMM)	4 (GMM)
Y_lag (Unemp)	-0.259***	-0.243***	-0.252***	-0.256***	-0.127*	-0.132*	-0.156*	-0.172**
	(0.078)	(0.077)	(0.079)	(0.075)	(0.072)	(0.069)	(0.086)	(0.073)
Specialization			-2.685				-3.931	
			(2.274)				(2.633)	
RelVar			-0.345				1.440	
			(1.740)				(2.095)	
UnrelVar			-0.043				-0.094	
			(0.175)				(0.185)	
Similarity				0.259***				0.254**
				(0.098)				(0.101)
RRMR				0.052***				0.041**
				(0.017)				(0.024)
MobRate		0.698				0.418		
		(0.555)				(0.561)		
PopDensLog	1.260***	1.237***	1.252***	1.274***	0.804***	0.746**	1.061***	0.976***
	(0.300)	(0.293)	(0.312)	(0.298)	(0.299)	(0.287)	(0.297)	(0.298)
Inv/CapLog	0.041	-0.049	-0.041	-0.047	0.145	0.124	0.068	0.139
	(0.076)	(0.073)	(0.075)	(0.067)	(0.099)	(0.090)	(0.077)	(0.088)
LQ_Primary	0.033	0.033	0.019	0.042	0.065	0.036	0.042	0.112
	(0.060)	(0.060)	(0.071)	(0.058)	(0.103)	(0.103)	(0.101)	(0.096)
LQ_Manu	0.078	0.071	0.054	0.013	0.460*	0.399*	0.003*	0.521*
	(0.249)	(0.234)	(0.271)	(0.234)	(0.284)	(0.276)	(0.332)	(0.266)
LQ_R&D	-0.122	-0.102	-0.123	-0.173	-0.114	-0.098	-0.042	-0.227
	(0.213)	(0.215)	(0.214)	(0.213)	(0.314)	(0.309)	(0.302)	(0.275)
NetMig	-0.439**	-0.446**	-0.440**	-0.466**	-0.560***	-0.607***	-0.447**	-0.522***
	(0.195)	(0.190)	(0.197)	(0.192)	(0.161)	(0.139)	(0.206)	(0.175)
Intercept	-18.492***	-18.203***	-18.250***	-19.070***				
	(4.632)	(4.509)	(4.922)	(4.602)				
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 (within)	0.774	0.777	0.776	0.786				
Hausman Chi^2	408.70***	6.70	65.61***	48.65***				
VIF	2.27	2.58	2.19	2.92				
Instruments					30	33	39	34
AR(1)					0.335	0.208	0.176	0.070
AR(2)					0.290	0.400	0.702	0.995
Hansen J					0.339	0.369	0.550	0.649
N	360	360	360	360	288	288	288	288

Note: The GMM models are estimated on the years 1999-2002 due to inclusion of 2-year lags as instruments.

APPENDIX

Table A1: Correlation matrix

	Productivity growth	Employment growth	Unemployment growth	MobRate	Specialization	RelVar	UnrelVar	Similarity	RRMR	PopDensLog	Inv/capLog	LQ_Primary	LQ_Manu	LQ_R&D	NetMig
Productivity growth	1.00														
Employment growth	0.09	1.00													
Unemployment growth	-0.05	0.10	1.00												
MobRate	0.08	0.11	0.00	1.00											
Specialization	0.06	-0.16	-0.09	-0.29	1.00										
RelVar	0.10	-0.10	0.04	-0.18	0.48	1.00									
UnrelVar	0.29	0.03	-0.19	0.24	0.12	0.16	1.00								
Similarity	0.05	0.06	-0.04	0.05	0.31	0.23	0.23	1.00							
RRMR	0.13	0.31	0.01	0.74	-0.48	-0.25	0.28	0.02	1.00						
PopDensLog	0.16	0.42	0.01	0.46	-0.37	-0.14	0.25	0.13	0.57	1.00					
Inv/capLog	0.05	0.15	-0.06	0.15	-0.21	-0.07	0.14	0.09	0.31	0.44	1.00				
LQ_Primary	-0.05	-0.21	0.01	-0.37	0.19	0.10	-0.14	-0.02	-0.48	-0.37	-0.31	1.00			
LQ_Manu	0.08	0.17	0.01	-0.06	-0.23	-0.11	0.06	-0.11	0.12	0.39	0.36	-0.15	1.00		
LQ_R&D	0.05	-0.10	0.00	-0.06	0.36	0.34	0.06	0.18	-0.13	-0.16	-0.22	0.00	-0.47	1.00	
NetMig	0.12	0.39	-0.07	0.34	-0.31	-0.35	0.16	0.14	0.32	0.38	-0.22	-0.31	-0.21	0.03	1.00