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Which Types of Relatedness Matter in Regional Growth? -industry, occupation and education

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Abstract

This paper provides a conceptual discussion of relatedness, which suggests a focus on individuals as a complement to firms and industries. The empirical relevance of the main arguments are tested by estimating the effects of related and unrelated variety in education and occupation among employees, as well as in industries, on regional growth. We show that for regional productivity growth, occupational and educational related variety matter over and above industry relatedness. This supports the conceptual discussion put forward. The potential of productive interactions between employees in a region is thus greater when there is related variety in their 'knowledge base'. We also find that related variety in industries is positive for employment growth but negative for productivity growth.

Keywords: Relatedness, variety, occupation, education, regional growth.

JEL: R12, R23, J24

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1. Introduction

Within the fields of urban economics, economic geography and regional science, there has been a long-standing debate on the effects of agglomeration economies on growth. Much work in this strand of research focuses on the question whether industry specialization or diversity is more important in promoting growth (Boschma and Iammarino 2009). Glaeser et al. (1992) and Henderson et al. (1995) led the way and many researchers have followed in similar tracks. However, the point of departure for the present paper is Frenken et al. (2005; 2007) who took the question about regional diversity, or *variety*, one step further. Following Noteboom (2000), they argue that for knowledge spillovers to enhance growth, there needs to be some sort of cognitive proximity or complementarity between firms. A distinction was thus made between related and unrelated variety where related variety is defined as within-industry diversity and unrelated variety as between-industry diversity. Frenken et al. (2007) is in this regard a seminal study as it is one of the first to provide systematic evidence of that it is not variety in general, but variety in related industries that promotes regional employment growth. This finding has been confirmed in several studies using data from different countries and time periods (Boschma and Iammarino 2009; Boschma et al. 2012; Hartog et al. 2012).

A conceptual issue in relation to this concerns defining relatedness. In the present paper we address this question and argue that measuring relatedness is not straightforward since relatedness may have many dimensions. We put forth arguments and provide empirical support for that relatedness framed at the level of individuals, e.g. in terms of educational background and occupation, is at least as important as relatedness in terms of industries. Indeed, the downsides of applying standard industrial classifications to approximate relatedness have been discussed critically in a number of papers, such as Ejermo (2005), Bishop and Gripaios (2010), Brachert et al. (2011), Desrochers and Leppälä (2011) and Boschma et al. (2012).

In contemporary economies cities or regions tend to specialize in functions rather than in industries. Certain occupations are found in specific cities, due to headquarters and business services being localized in larger cities while actual production takes place in more rural areas (Duranton and Puga 2005). Larger cities are thus specialized in knowledge-intensive occupations over a wide range of industries, which implies that variety in occupations have the potential to be at least as important for growth as variety in industries. Since certain occupations are found in different cities it is also likely that certain education types are found in those cities. Education and occupation are linked together, more so than education and industry. In many cases, higher education is usually undertaken to work within a certain range of occupations, not to work in a specific industry. The relationship between education and occupation is still not clear-cut, with the consequence that education and occupation are measures of quite different things. Education measures the formal, theoretical background of employees while occupation is a measure of what the employees actually do in their daily work. Indeed, occupation is commonly used as a proxy for the skills and abilities of the employees beyond their formal education (cf. Autor et al. (2003) and Bacolod et al. (2009)). However, as Frenken et al. (2007), most research still focus on the effect of industrial specialization (or variety) on growth.

Duranton and Puga (2004) distinguish between three types of mechanisms behind agglomeration economies; *sharing* of e.g. fixed costs and risk, *matching* on the labor market, and *learning* due to knowledge spillovers and human capital accumulation. They also emphasize that heterogeneity of workers and firms is the foundation for these effects to materialize. From this perspective regional variety has the potential to give rise to agglomeration economies, which may stimulate innovation and growth. However, in a strict sense, both the matching and learning argument emphasize individuals rather than firms. Knowledge and information may not spill over between firms per se, but rather between employees, who channel that knowledge, in different firms. Cohen and Levinthal (1990) discuss this in terms of firms' absorptive capacity. There are thus arguments in favor of framing issues of cognitive proximity and relatedness in terms of individuals. On these grounds, relatedness in terms of employee education and occupation are emphasized in the present paper. Previous research have indeed expanded the measures of related variety beyond industrial classifications (cf. Boschma et al. (2012)), but the main focus is still on industry- and product level, not the specific characteristics of the employees.

To test the empirical relevance of these ideas, we make use of data on Swedish regions and estimate the respective influence of the different dimensions of relatedness on regional growth over a five-year period (2002-2007). We follow the original work by Frenken et al. (2007) and compute related and unrelated variety in terms of industries, but also include additional measures of related and unrelated variety in terms of occupation and education of the workers in each region. The inclusion of the two individual-based measures of occupational and educational variety constitutes the main novelty in the empirical analysis. We further include variables reflecting general agglomeration economies as well as a selection of control variables. The model is estimated for regions as a whole as well as for manufacturing and service industries, respectively. This is motivated by the results from Bishop and Gripaios (2010), which show different effects of unrelated and related variety on employment growth in different industries.

The results show that the effects of related and unrelated variety differ considerably, both across the different dimensions of relatedness and across sectors. This confirms the importance of expanding the concept of relatedness beyond the industrial dimension. We find that occupational and educational related variety matter over and above industry relatedness in explaining regional productivity growth. Relatedness in terms of sharing a common educational background appears to be particularly correlated with productivity growth in the manufacturing sector. These result may be appreciated as a reflection of that relatedness in terms of education and occupation stimulates matching processes on local labor markets as well as local knowledge spillovers, i.e. two established micro-foundations for agglomeration economies. Hence, regions with a variety of jobs associated with related educations and/or related tasks may facilitate matching externalities on the labor market as well as inter-firm knowledge transfers through employee mobility. We also confirm the results of Frenken et al. (2007), namely that related industry variety is negatively associated with productivity growth but positively associated with employment growth.

The rest of the paper is organized as follows. Section 2 provides further background and motivation for the paper, including related empirical research. Section 3 gives an overview of the data and the variables used in the empirical application, while section 4 presents the empirical results, which give evidence to what has been argued in the previous parts of the paper. Finally, section 5 concludes.

2. BACKGROUND AND MOTIVATION

2.1 Relatedness based on firms or individuals

Recent contributions in economic geography and regional science hold that local variety of related industries is crucial in fostering regional growth (Frenken et al. 2007). The main argument in this literature is that effective knowledge transfers and spillovers between activities in a region require that they are cognitively related, though some cognitive distance is still needed to limit overlaps and to alleviate issues of lock-in (Boschma 2005). Variety in related activities is thus maintained to stimulate productive interactions and cross-fertilizations within a region, because it ensures cognitive proximity while maintaining some distance (through variety). This line of reasoning builds on Noteboom's (2000) conjecture of "optimal cognitive distance". Noteboom states that "information is useless if it is not new, but it is also useless if it is so new that it cannot be understood" (Noteboom 2000, p.153). While the general line of argument is clear, i.e. that there is a tradeoff between cognitive distance for the sake of novelty and cognitive proximity for the sake of mutual understanding and absorptive capacity, the question is what makes relatedness in a regional context, i.e. what characteristics of a local economy bodes for cognitive proximity? This is an issue that is not only of academic interest, but is also important from a policy perspective. Any discussion of policy initiatives based on the idea of relatedness will for example bring with it a concern regarding what relatedness means and how it can be defined and assessed.[1] The idea of relatedness has had a quite large impact on both the research and

[1]For example, Frenken et al. (2007, p.696) conclude: "*Regional policies based on supporting related variety reduce the risk of selecting wrong activities because one takes existing regional competences as building blocks to broaden the economic base of the region.*" Picking the 'right' activity obviously necessitates knowledge of what makes relatedness.

the policy community, and is also embedded in the European Union current regional innovation policy concept of smart specialization (cf. McCann and Ortega-Argilés (2013).

The majority of existing analyses puts firms at the center stage and frame discussions about relatedness in an inter-firm context. A main hypothesis is that relatedness between firms hinges on their industry affiliations, such that firms operating in similar industries have shared competences and thus cognitive proximity at the organizational level (cf. Boschma and Martin (2010)). In view of this, empirical applications typically infer relatedness from pre-determined industry or product classification schemes (Frenken et al. 2007; Boschma et al. 2012). Put simply, the potential for productive inter-firm knowledge transfers and spillovers is assumed to be higher when firms operate in industries that are closer to each other in the standard industrial classification system or produce similar products (Van Oort 2013).

Following Desrochers and Leppälä (2011), it may still be argued that the firm- and industry-level focus in the literature on relatedness downplays that much of the learning and spillovers in regions occur at the level of individuals. That is, a strong case can be made that knowledge spillovers between firms in a region are to a large extent attributed to spillovers between their employees. Knowledge may flow between firms for example because their employees learn from others in their local environment, or because employees move between them, which induces cross-fertilizations. For instance, the theoretical as well as empirical literature on human capital externalities and local non-market interactions (Lucas Jr. 1988; Rauch 1993; Glaeser and Scheinkman 2003) explicitly put social interactions between individuals at center stage. Likewise, a large literature show that movements of individuals between firms is a key source of spillovers and transfers of knowledge and information (Almeida and Kogut 1999; Maskell and Malmberg 1999; Power and Lundmark 2004). It follows that the central 'agents' in the context of spillovers and knowledge transfers are not firms *per se*, but individuals. While this may seem like a trivial statement, the key point is that an emphasis on individuals have implications for the question of the dimension of relatedness that stimulate productive knowledge spillovers.

Accepting individuals as the main agents for knowledge spillovers suggest arguments in favor of framing issues of cognitive proximity in terms of individual skills, experiences and knowledge. The industry dimension can in this perspective be problematic on the grounds that experiences and knowledge bases of individual employees have more to do with their occupational and educational background. Many firms have for example a sharp division of labor where individual employees work with a narrowly defined and specialized task, often matched with their university degree. Therefore, workers' experiences and on-the-job learning may to a large extent be considered as occupation- and education-dependent, rather than industry-dependent. For example; a software engineer developing steering-systems for industrial robots at ABB Corporation may have cognitive proximity with a software engineer at an engineering service company, albeit the two industries are radically different as judged by their industrial classifications. Inter-firm job switching of personnel between such firms may also be large for the same reason. In many cases, employers also value occupational- and task-specific experiences rather than specific industry experience when hiring new personnel.

Furthermore, there is ample evidence that industries have very different occupational and educational composition in different regions, a phenomena dubbed 'functional specialization' by Duranton and Puga (2005). This means that the experiences, and hence the position in the 'cognitive space', of workers in one and the same industry may be quite different across locations. This is a potentially important aspect that the traditional industry- and product-based measures of relatedness cannot capture. Occupational and educational relatedness should thus better reflect cognitive proximity at an individual level, because they depart from what employees actually do in their work, i.e. their immediate learning and experience context, as well as their knowledge base in terms of formal education. Our basic hypothesis is that this type of individual-level relatedness is at least as important as industry relatedness in providing a breeding ground for productive local knowledge spillovers and cross-fertilizations, and thus in influencing regional growth.

Similar ideas are raised by Neffke and Henning (2013) with the concept of skill relatedness. Especially high-skilled individuals are likely to change jobs within industries that value the same types of skills. This implies that relatedness between industries can be determined based on cross-industry labor flows. Neffke and Henning (2013) use this in order to explain the diversification strategies of firms, which determine regional industrial diversification. The results show that firms are more likely to diversify into industries with which there is skill relatedness than with industries without such relatedness or with relatedness in terms of standard industrial classifications.[2] Boschma et al. (2013) investigate the importance of labour mobility across technologically related industries for regional growth, where technological relatedness is based on the skill relatedness measure developed by Neffke and Henning (2013). Boschma et al. (2013) find a positive effect on productivity growth from intra-regional labour flows between industries with a revealed relatedness in terms of skills. This strengthens our argument that relatedness in terms of individuals is an important complement to relatedness based on industry belonging. That two industries are skill-related in a local labour market, as revealed by a high intensity of inter-industry labour flows, could indeed be due to that firms in

[2] Since this characterization of relatedness is derived from actual flows of labor it is sensitive to changes in labor flows between years and differences in labor flows between regions. In addition, if employees in certain occupations are more likely to switch jobs than employees in other occupations there is a risk that relatedness between industries is not properly captured by labor flows. When instead focusing on the educational background and current occupation among employees, no matter the industry boundaries, the definition of relatedness is time-invariant and insensitive to changes on the market.

different industries require functionally similar tasks or tasks requiring related educational specializations. Relatedness based on cross industry labour flows may hence reflect that employees change jobs based on their knowledge and skills, i.e. their occupational experience and education, rather than their industry belonging. In relation to these papers, our contribution is different in that we study relatedness in terms of the educational and occupational profile of regions and test their role in explaining regional growth, alongside the industry relatedness.

2.2 Related empirical research

There are numerous empirical studies on the effects of agglomeration economies on growth. Most of these use a broad measure of industry diversity over the economy or region as a whole, that is Jacobs externalities are measured as unrelated rather than related variety (cf. Glaeser et al. (1992), Henderson et al. (1995), Duranton and Puga (2000)). However, some studies acknowledge the complexity of diversity, most notably the one by Frenken et al. (2007), who analyze the effects of unrelated and related industry variety on growth in employment, unemployment and productivity in Dutch regions. The results of the study show that, as expected, related variety enhances employment growth while unrelated variety is negatively related to unemployment growth. The productivity growth of a region is negatively associated with related variety.

Bishop and Gripaios (2010) conduct a similar study of British regions when analyzing the effects of unrelated and related variety on employment growth in different industries. The results show that the effects of unrelated and related variety differ across the examined industries, of which nearly 50 per cent benefit from either one of the two forms of variety. Unrelated variety is affecting employment growth in a larger set of industries than related variety. Regarding regional employment growth in Germany Brachert et al. (2011) find no effects from neither unrelated nor related variety. However, related variety in combination with functional specialization, in terms of more “white collar” workers, positively influences employment growth. In addition, unrelated variety among “white collar” workers and “blue collar” workers, but not R&D workers, is found to enhance growth. When analyzing growth in Spanish provinces Boschma et al. (2012) find that related variety has a positive effect on value added growth while unrelated variety has no growth effect. The results also show that the positive effect is stronger when using indicators for related variety not only based on product classifications. Boschma et al. (2012) construct one measure based on Porter’s (2003) cluster classification of industries and one based on export data. Hartog et al. (2012) analyze the effects of related variety on employment growth in Finnish regions. The results show that related variety in general has no effect but that related variety in high-tech industries positively influences employment growth. No growth effect is found from unrelated variety.

The concept of related and unrelated variety has been quite commonly applied in relation to international trade. Saviotti and Frenken (2008) analyze the relationship between export variety and economic development in 20 OECD countries. An increase in the growth in related export variety is found to promote growth in GDP per capita, while an increase in the growth in unrelated export variety has a negative effect. However, past growth in unrelated export variety positively influences economic growth. Also Boschma and Iammarino (2009) consider export variety, when analyzing the effects on regional economic growth in Italy. Related, but not unrelated, export variety is found to significantly enhance value-added growth. In addition, as mentioned above, one of Boschma et al.'s (2012) alternative measures of related variety is based on export data.

3. Data and variables

The regions referred to in the empirical part of the paper are the 290 municipalities in Sweden.[3] These are the smallest administrative units in Sweden. All variables described below are measured at the municipal level.

3.1 Dependent variables

We employ two different dependent variables; (i) employment growth and (ii) productivity growth. Frenken et al. (2007) find that related variety has a negative influence on productivity growth but a positive influence on employment growth. They maintain that this is consistent with the idea that employment growth better reflect radical innovation as such innovations are assumed to lead to the creation of new markets and employment. Productivity growth is instead associated with process innovations and growing capital intensity in the later stages of the product life cycle (cf. Van Oort (2013)). That related variety spurs employment growth and not productivity growth is thus taken as evidence that related variety has more to do with knowledge spillovers and (radical) innovation. While this argument is conceptually appealing, it can also be argued that productivity is after all the main determinant for long-run growth (Easterly and Levine 2002). A vast literature also document the fundamental role played by innovation and new technology in stimulating productivity (Lööf and Heshmati 2002; Hall and Mairesse 2006).[4] Hence, there are also arguments in favor of that the productivity growth of a region is related to innovation. A defining characteristic of urban regions, that typically are more diversified, is indeed also higher productivity levels, not least in Sweden (cf. Andersson and Lööf (2011)).

[3] Gotland is excluded due to having no neighbors. Hence, the number of observations in the estimations is 289.
[4] In fact, it has also been argued that productivity growth may be used as an innovation indicator (Hall 2011).

We measure productivity growth as the ratio between average labor productivity in 2007 and 2002. Employment growth is measured as the ratio between total number of employed for the same set of years. However, a region might exhibit a higher growth rate simply because it has a relatively large share of one or more fast growing industries. As robustness test, we therefore also apply a shift-share procedure for both productivity growth and employment growth. This implies that the growth in each 2-digit industry is weighted by the industry's national share of production in the case of productivity growth and by the industry's share of employment in the case of employment growth. This imposes the same industrial structure in all regions and produces industry-adjusted growth rates.[5]

Productivity growth and employment growth are constructed for the whole private sector of the regional economy, as well as for the manufacturing sector and the service sector separately. The development in the public sector is more difficult to relate to spatial characteristics since it is largely dependent on political decisions. Also agriculture, fishery and mining are excluded since these industries are more or less spatially bounded due to immobile resources. This leaves the industries in standard industrial classification (SIC) codes 15 to 74, of which 15 to 45 belong to the manufacturing sector[6] while 50 to 74 are service industries.

3.2 Independent variables

All independent variables are measured for the year 2002, unless otherwise specified. The six independent variables of main interest are; related variety in industries, education and occupation, and unrelated variety in industries, education and occupation. The entropy (or the Shannon index) approach is commonly applied for measuring variety, see for example Jacquemin and Berry (1979), Attaran (1986) and Frenken et al. (2007). The entropy measure has desirable properties in that it takes the relative abundance of groups into account, and not only the absolute presence of them. The entropy for unrelated variety measures between diversity while the entropy for related variety measures within diversity, in e.g. industries. All entropies are calculated using employment in each group. The data is limited to employed individuals between 20 and 64 years of age with a positive income.

For industries the 2-digit and the 5-digit SIC codes are used where each 5-digit industry belongs to a specific 2-digit industry[7]. Following Attaran (1986), let S_g denote the 2-digit sets where $g = 1,\ldots,$ G. E_g denotes the share of employees working in the 2-digit industry g, where E_g is measured as the share of total regional employment. Furthermore, let E_{ig} denote the share of employees working in the 5-digit industry i, where $i = 1,\ldots,$ I, where E_{ig} is measured as the share of employment in the respective 2-digit industry g.

[5] See Table A1 in Van Stel and Storey (2004) for an illustration of the shift-share procedure.
[6] Including construction.
[7] An example: Industry 15111 and 15120 are sub industries to industry 15.

Unrelated variety in industries measures the distribution of employees between 2-digit industries. Using the entropy approach, unrelated variety (UV) is calculated as follows:

$$\mathrm{UV} = -\sum_{g=1}^{G} E_g \ln E_g. \tag{1}$$

The range of UV is from 0 to $\ln \mathrm{G}$ where zero variety is reached when all employees are working in the same 2-digit industry, that is when one $E_g = 1$ while the rest are zero. Maximum variety, i.e. $\ln \mathrm{G}$, is reached when there is an equal distribution of employees over all 2-digit industries, that is all E_g are identical. (Attaran 1986)

In the same manner, the distribution of employees between 5-digit industries within each 2-digit industry is calculated as follows:

$$H_g = -\sum_{i=1}^{I} E_{ig} \ln E_{ig}. \tag{2}$$

The interpretation of Equation 2 is the same as for Equation 1 with the difference that variety is measured within each 2-digit industry rather than between the 2-digit industries. Hence, there is zero within variety when all employees in the 2-digit industry g are working in the same 5-digit industry i, where $i \in S_g$. Accordingly, maximum variety for industry g, $\ln \mathrm{I}$, is achieved when there is an equal distribution of employees over all 5-digit industries i, where $i \in S_g$.

The information about the degree of within variety for each 2-digit industry g, i.e. H_g, is weighted by the relative size of industry g. Summing over all g gives the entropy measure for related variety in industries (RV), regarding the region as a whole. These two steps are formally shown by Equation 3.

$$\mathrm{RV} = \sum_{g=1}^{G} E_g H_g \tag{3}$$

Increases in the values obtained by Equation 1 and 3 imply increases in unrelated and related variety, respectively.

Unrelated and related variety for the educational and the occupational dimension are calculated as above, with the difference that the educational and the occupational codes are used instead of the SIC codes. When constructing the measures for educational variety we use a combination of education length and specialization. Employees are first categorized as either having three or more years of higher education or not. After this categorization education specialization is used at the 2- and 4-digit levels. This implies that employees belonging to the same 2-digit educational code *and* have three or more years of higher education are seen as related. Education focus is divided in 26 different 2-digit levels (see Table A1), the maximum possible G for the educational dimension is hence 52. Regarding the occupational dimension occupational codes at the 1- and 3-digit levels are used instead of the educational codes. Occupations are divided in 12 different 1-digit levels (see Table A2), which implies that the maximum possible G for the occupational dimension is 12. Figures A1-3 in Appendix 2 provide maps of Sweden, showing the distribution of related and unrelated variety over municipalities in 2002. These can also be compared to Figure A4, which presents the population density in Sweden.

Besides unrelated and related variety, we also control for the presence of general urbanization economies measured as population density, Porter externalities or competition measured as firms per employee, and localization economies or specialization. There are various approaches to measure specialization, both in absolute and relative terms. In the context of localization economies absolute specialization is relevant since it is the absolute agglomeration of employees belonging to the same industry that has the potential to give rise to knowledge spillovers. Since an increase in unrelated variety in industries implies a decrease in absolute industrial specialization the entropy for unrelated variety in industries is used also as a proxy for industrial specialization (as in Aiginger and Davies (2004)). The entropy measure is not as commonly applied to measure specialization as for example the Herfindahl index but the two are strongly correlated (Palan 2010).

Considering previous studies of regional productivity growth, the capital-labor ratio is introduced as a control variable when estimating growth in productivity. Size effects are controlled for by introducing absolute values for 2002. All independent variables, besides population density, are calculated for industry 15-74 as a whole but also for the manufacturing sector and the service sector separately. Appendix 3 provides tables with descriptive statistics for the variables regarding the private sector as a whole, as well as for the manufacturing sector and the service sector separately. To reduce heteroscedasticity, as well as to facilitate the interpretation of the coefficients to be estimated, all variables are log transformed. Appendix 4 presents correlation matrices over all independent variables for the total private sector, the manufacturing sector and the service sector. Regarding the service sector, there is strong correlation between related and unrelated variety in industries. To avoid problems with multicollinearity, unrelated variety in industries is excluded when estimating models for the service sector. In addition, the initial employment level is excluded due to problems with multicollinearity. Besides this correlation between explanatory variables is not an issue, which is confirmed when running post diagnostic tests for multicollinearity.

4. MODEL AND EMPIRICAL ESTIMATIONS

The model used as a point of departure for estimations is given by equation 5:

$$Growth_r = \alpha + RV_r\beta_1 + UV_r\beta_2 + Control_r\ \beta_3 + \varepsilon_r \qquad (5)$$

in which $Growth_r$ refers to growth in either productivity or employment in municipality r. RV_r is a row vector of related variety in industries, education and occupation, respectively and UV_r is the corresponding vector for unrelated variety. $Control_r$ contains the set of control variables, which depends on the *Growth* variable in question. ε_r is the error term, which by assumption is uncorrelated with the individual variables. The parameters are estimated by ordinary least squares (OLS), with robust standard errors in the cases where heteroscedasticity is detected. However, since the data is based on geographic units there is a potential issue of spatial dependence, municipalities might be correlated simply due to geographic proximity. This is tested by Moran's I on the residuals from the OLS regressions. In the presence of spatial autocorrelation the coefficients from the OLS regressions are inefficient why spatial error and spatial lag models are estimated by maximum likelihood (ML). The use of spatial econometrics to deal with spatial dependence is debated, mostly due to issues of identification (Gibbons and Overman 2012). Hence, the spatial models are estimated mainly as robustness checks for the OLS models and will not be analyzed in detail. More information about the spatial models as well as the results from these estimations are presented in Appendix 5.

Table 1 presents the results for productivity growth and employment growth for the private sector as a whole, including both unadjusted and industry-adjusted growth rates. Spatial autocorrelation is present in the model for industry-adjusted employment growth since Moran's I is statistically significant for this model.

The results show that the relationships between the different dimensions of related and unrelated variety and growth differ considerably, which gives evidence to the importance of distinguishing between various forms of variety. As in Frenken et al. (2007), related variety in industries is positive for employment growth, both unadjusted and adjusted, while it is negative for unadjusted productivity growth. The results for related variety in education are consistent when it comes to growth in productivity. Higher related variety in education is associated with higher unadjusted as well as adjusted productivity growth.[8] The estimated relationship is significantly larger than the relationship between related variety in industries and employment growth.

[8] The same patterns are found when conducting the analysis at the level of functional regions. However, due to few observations at this level as well as recent research showing that agglomeration economies, in particular concerning knowledge spillovers, attenuate sharply with distance (cf. Baldwin et al. (2008) and Andersson et al. (2012)), municipalities are chosen as the level of analysis.

Table 1. Estimated coefficients for productivity growth and employment growth in the total private sector, standard errors in brackets.

Variables	**1a Productivity**	**1b Productivity Adjusted**	**2a Employment**	**2b Employment Adjusted**
RV Industry	-0.130**	0.026	0.097***	0.162***
	(0.054)	(0.075)	(0.029)	(0.051)
UV Industry	0.097	0.497***	-0.042	0.041
	(0.115)	(0.181)	(0.082)	(0.143)
RV Education	0.562***	0.515***	0.018	-0.036
	(0.129)	(0.191)	(0.097)	(0.219)
UV Education	0.227	0.308	0.023	-0.320*
	(0.156)	(0.284)	(0.096)	(0.187)
RV Occupation	0.097	0.108	-0.083	0.032
	(0.178)	(0.199)	(0.076)	(0.142)
UV Occupation	-0.468**	-0.574	0.068	0.371
	(0.218)	(0.413)	(0.150)	(0.305)
Competition	0.020	-0.047	0.049**	-0.097*
	(0.030)	(0.058)	(0.022)	(0.050)
Population density	0.002	0.027***	-0.002	0.024***
	(0.008)	(0.009)	(0.004)	(0.006)
Capital-labor growth	0.149***	0.046		
	(0.031)	(0.043)		
Productivity 2002	-0.223***	-0.119		
	(0.056)	(0.088)		
Constant	1.44***	0.052	0.143	-0.350
	(0.356)	(0.561)	(0.114)	(0.243)
F-value	11.7***	11.9***	7.43***	9.85***
R^2	0.286	0.178	0.175	0.227
Moran’s I p-value	0.374	0.446	0.398	0.045
Observations	289	289	289	289

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in Model 1a, 1b and 2b.

Hence, the results for related variety in industries for the Swedish economy is in line with Frenken et al.’s (2007) findings for the Netherlands. The higher employment growth in regions with greater related variety is consistent with the argument that related variety in sectors spur knowledge spillovers that in turn influence employment growth. The finding that related but not unrelated variety in education is positively associated with unadjusted and adjusted productivity growth may be interpreted as a reflection of that there needs to be complementarity in educational background among employees for knowledge spillovers to be productive. A mechanical engineer may learn more from a materials engineer than a sales representative, no matter their industry. One reason for this could be that they share a common knowledge base. We find no clear association between related and unrelated variety in occupation and the two measures of growth.

Tables 2 and 3 present the results for growth in productivity and growth in employment, when the private sector is split into manufacturing and services. Regarding productivity, we find spatial autocorrelation in the model for adjusted growth in the manufacturing sector and unadjusted growth in the service sector. For employment growth spatial autocorrelation is detected for the service sector only, in both unadjusted and adjusted growth rates.

Table 2. Estimated coefficients for productivity growth in the manufacturing sector and the service sector, standard errors in brackets.

Variables	3a Manufacturing	3b Manufacturing Adjusted	4a Services	4b Services Adjusted
RV Industry	-0.106***	0.087	-0.133***	-0.129*
	(0.036)	(0.060)	(0.046)	(0.073)
UV Industry	0.043	0.149		
	(0.062)	(0.102)		
RV Education	0.659***	1.36***	-0.045	0.091
	(0.150)	(0.247)	(0.116)	(0.167)
UV Education	-0.102	0.168	0.731***	0.820*
	(0.187)	(0.308)	(0.261)	(0.434)
RV Occupation	0.026	0.083	0.260***	0.425*
	(0.077)	(0.126)	(0.090)	(0.226)
UV Occupation	-0.186	0.023	-0.382	-0.492
	(0.138)	(0.228)	(0.236)	(0.687)
Competition	0.052*	0.062	-0.052	0.044
	(0.028)	(0.046)	(0.035)	(0.094)
Population density	-0.006	0.034***	0.011*	0.017*
	(0.007)	(0.011)	(0.006)	(0.010)
Capital labor growth	0.154***	-0.008	0.064**	0.087**
	(0.022)	(0.036)	(0.028)	(0.044)
Productivity 2002	-0.211***	-0.132**	-0.492***	-0.300
	(0.041)	(0.067)	(0.100)	(0.221)
Constant	1.54***	0.207	2.74***	1.61
	(0.269)	(0.444)	(0.546)	(1.22)
F-value	12.4***	15.1***	8.65***	2.26**
R^2	0.308	0.352	0.253	0.085
Moran's I p-value	0.143	0.001	0.028	0.346
Spatial coefficient				
Observations	289	289	289	289

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in Model 4a and 4b.

The results for the manufacturing sector and the service sector in Tables 2 and 3 show both similarities and differences from the private sector as a whole, which points to the importance of distinguishing between different parts of the economy. The negative productivity effect from related variety in industries is present in the service sector for both unadjusted and adjusted growth rates. In addition, this effect is found for unadjusted growth in the manufacturing sector. Hence, the result that related variety in industries negatively associated with productivity growth is robust. The positive employment effect from this variable is significant only for unadjusted growth in the service sector. In addition, higher unrelated variety in industries is found to be negative for unadjusted employment growth in manufacturing. Since unrelated variety in industries measures inverse industrial specialization this implies that positive localization economies is found for employment growth and not productivity growth.

Table 3. Estimated coefficients for employment growth in the manufacturing sector and the service sector, standard errors in brackets.

Variables	5a Manufacturing	5b Manufacturing Adjusted	6a Services	6b Services Adjusted
RV Industry	-0.019	-0.019	0.076***	0.048
	(0.029)	(0.068)	(0.029)	(0.043)
UV Industry	-0.146***	0.042		
	(0.050)	(0.141)		
RV Education	0.170	0.580**	0.130	0.155
	(0.118)	(0.240)	(0.105)	(0.202)
UV Education	-0.140	-0.446	-0.264*	-0.165
	(0.149)	(0.305)	(0.154)	(0.204)
RV Occupation	0.109*	0.377***	0.009	0.109
	(0.061)	(0.146)	(0.093)	(0.142)
UV Occupation	0.008	0.315	-0.447*	-0.378
	(0.110)	(0.232)	(0.235)	(0.333)
Competition	0.068***	-0.003	0.089***	0.025
	(0.022)	(0.043)	(0.032)	(0.066)
Population density	-0.016***	0.040***	0.013**	0.015**
	(0.005)	(0.011)	(0.005)	(0.007)
Constant	0.261	-0.471**	0.683***	0.401
	(0.106)	(0.215)	(0.187)	(0.262)
F-value	7.24***	10.63***	5.50***	3.77***
R^2	0.171	0.245	0.123	0.080
Moran’s I p-value	0.375	0.380	0.000	0.004
Observations	289	289	289	289

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in Model 5b, 6a and 6b.

Regarding related variety among employees, the positive productivity effect from related variety in education is robust for the manufacturing sector. The magnitude of this effect is particularly strong for the industry-adjusted growth. In addition, this variable is positively enhancing adjusted employment growth in the manufacturing sector. Hence, related variety in education is an important variable in general and for the manufacturing sector in particular. For the private sector as a whole no effect was found from related variety in occupation. However, the results regarding the service sector show that related variety in occupation has a significant positive effect on both unadjusted and adjusted productivity growth. This may be interpreted as that cognitive proximity among employees is important for productivity growth in both sectors. For manufacturing, relatedness in terms of educational background still matters while for services it is relatedness in current occupation. Related variety in occupation is also positively enhancing employment growth in manufacturing, implying that cognitive proximity is important for the manufacturing sector in general terms.

A somewhat contradicting result is that unrelated variety in education is productivity enhancing for services. The magnitude of the effect is robust across unadjusted and adjusted growth rates. This shows a difference from the manufacturing sector in that the service sector benefits from broad diversity among employees as well. On the other hand, unrelated variety in occupation has a negative impact on unadjusted employment growth in the service sector, and related variety in education has a positive impact when controlling for spatial autocorrelation (see Appendix 5). Hence, it is not possible to draw general conclusions for the service sector, as above for the manufacturing sector. This could be due to that the service sector is comprised of a more diverse set of industries than the manufacturing sector.

Regarding the control variables, competition has a positive impact on unadjusted employment growth, both for the overall private sector and for manufacturing and services separately. In addition, we find a weakly significant positive competition effect for unadjusted productivity growth in the manufacturing sector. Regarding adjusted employment growth, the competition effect is negative for the private economy as a whole but insignificant for manufacturing and services separately. Moreover, we find that population density is positive for adjusted growth in both productivity and employment.

5. Conclusions

In this paper we tested the role that related variety in education and occupation play in regional growth. While most analyses of regional variety put firms and industries in center stage, we argue that knowledge spillovers occur primarily between individuals. Relatedness between individuals in terms of education and occupation may be at least as important as relatedness between industries in stimulating knowledge spillovers and regional growth. To test the empirical relevance of these arguments we added measures of educational and occupational variety (related and unrelated) to the basic empirical model of Frenken et al. (2007) and estimated the relative importance of the three dimensions of related variety. As in previous findings, we found that related variety in industries has a positive effect on growth in employment but a negative effect on growth in productivity.

However, we also show that related variety in education is positively associated with productivity growth in the private sector in general and the manufacturing sector in particular, while related variety in occupation is positively related to productivity growth in the service sector. These results broadly support that relatedness in terms of the education and occupation of employees are conducive for knowledge spillovers that stimulate the productivity growth of a region. The potential of productive interactions between employees in a region is thus greater when there is related variety in their knowledge base.

The findings also bear on policy in the sense that they illustrate the multi-dimensional nature of the notion of relatedness. The recent policy concept of smart specialization suggest for instance that regions should focus on locally strong areas, and develop into areas that are related to these. The way in which relatedness is conceptualized clearly plays a crucial role in such efforts. Relatedness in industries and relatedness in employee education and skills do not necessarily go hand-in-hand, especially in view of that many regions are functionally specialized such that the functions within a given industry differ widely across regions.

While the results in this paper is consistent with the idea that knowledge spillovers works better in contexts when related variety is high, it should be stated that the analysis does not inform about the mechanisms. For example, we do not know whether the estimated relationships reflect pure knowledge spillovers, better local matching efficiency, or embodied knowledge flows mediated by local inter-firm labor mobility. Related variety in either industries, education or occupation could stimulate either of these mechanism. Further work may focus on untangling the mechanism behind the empirical regularity of a strong association between related variety and growth.

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APPENDIX 1

Table A1. Educational codes.

Educational code (Sun2000Inr)	Education focus
01	General education
08	Reading and writing for adults
09	Personal development
14	Pedagogics and teaching
21	Arts and media
22	The humanities
31	Social and behavioral science
32	Journalism and information
34	Business
38	Law and legal science
42	Biology and environmental science
44	Physics, chemistry and geoscience
46	Mathematics and natural science
48	Computer science
52	Engineering: Technical, mechanical, chemical and electronics
54	Engineering: Manufacturing
58	Engineering: Construction
62	Agriculture
64	Animal healthcare
72	Healthcare
76	Social work
81	Personal services
84	Transport services
85	Environmental care
86	Security
99	Unknown

Table A2. Occupational codes.

ISCO/SSYK code	Occupation
0	Militaries
1	Managers, legislators and senior officials
21 & 31	Physical, mathematical and engineering science professionals and associate professionals
22 & 32	Life science and health professionals and associate professionals
23 & 33	Teaching professionals and associate professionals
24 & 34	Other professionals and associate professionals
4	Office and customer services clerks
5	Salespersons, demonstrators, personal and protective services workers
6	Market-oriented skilled agricultural and fishery workers
7	Extraction, building, metal, machinery, handicraft and related trades workers
81	Stationary-plant, machine, mobile-plant and related operators
91	Sales and services elementary occupations, agricultural, mining, transport and related laborers

APPENDIX 2

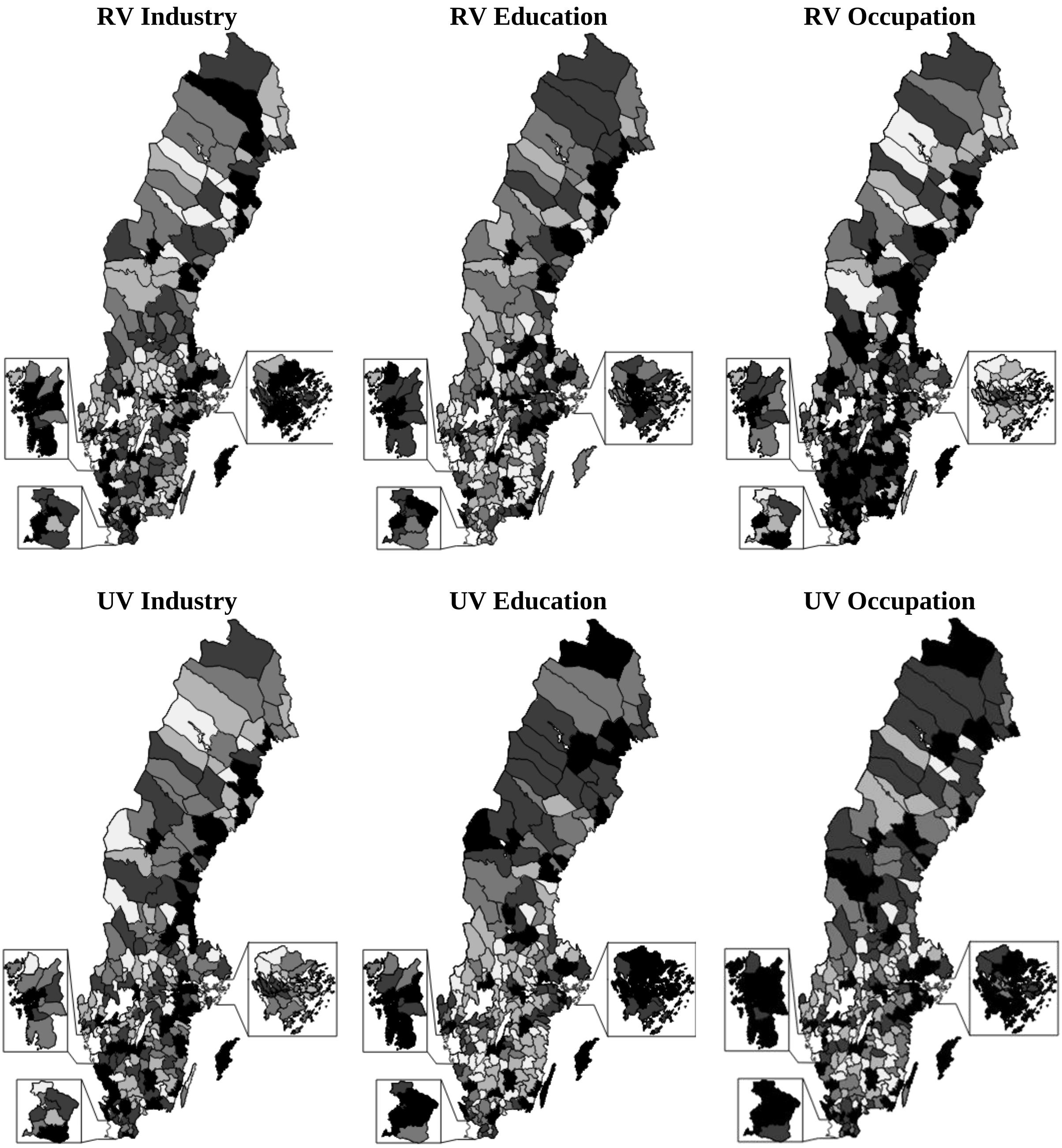

Figure A1. Quantile maps of related and unrelated variety, the private sector (darker color implies greater variety).

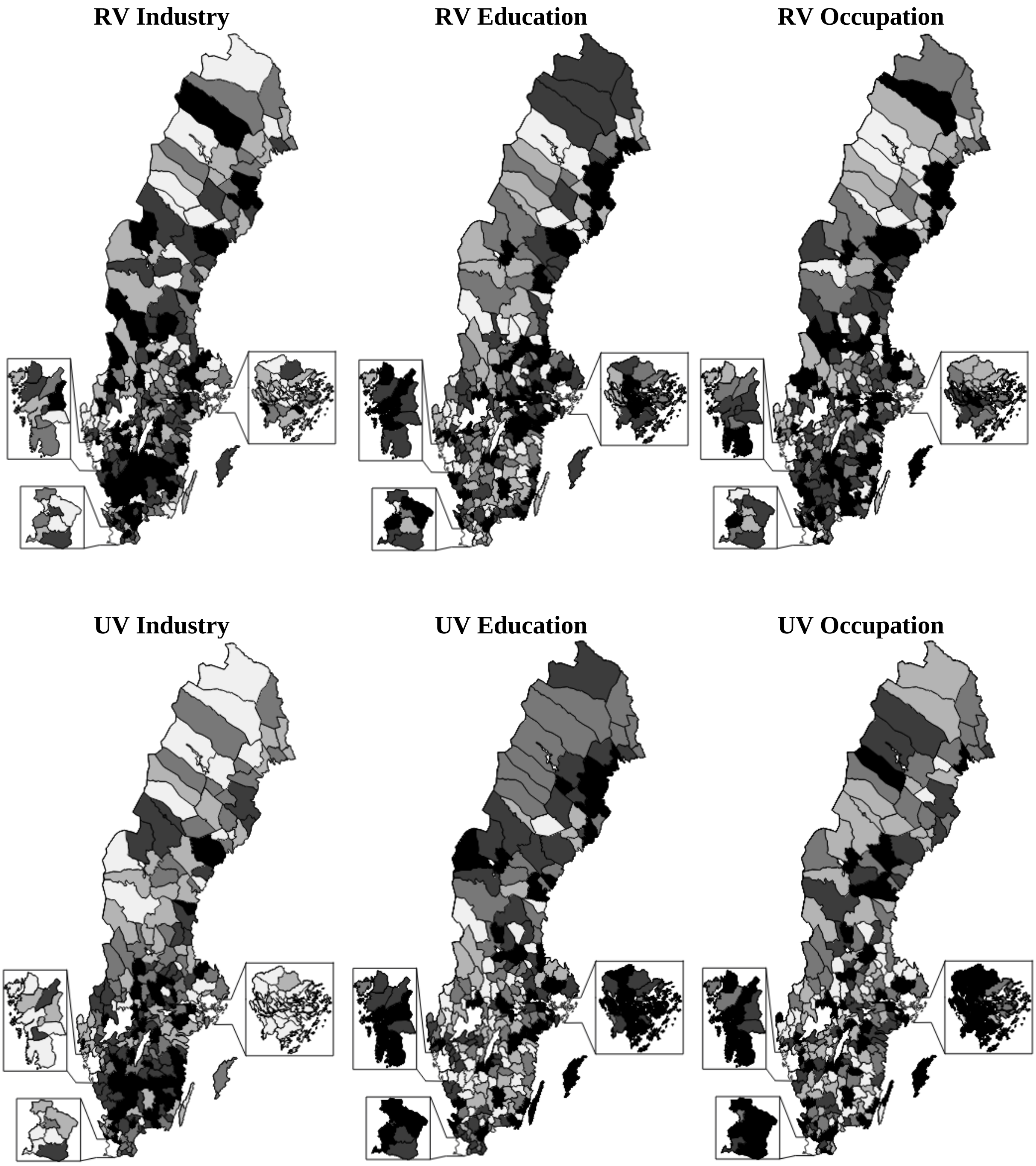

Figure A2. Quantile maps of related and unrelated variety, the manufacturing sector (darker color implies greater variety).

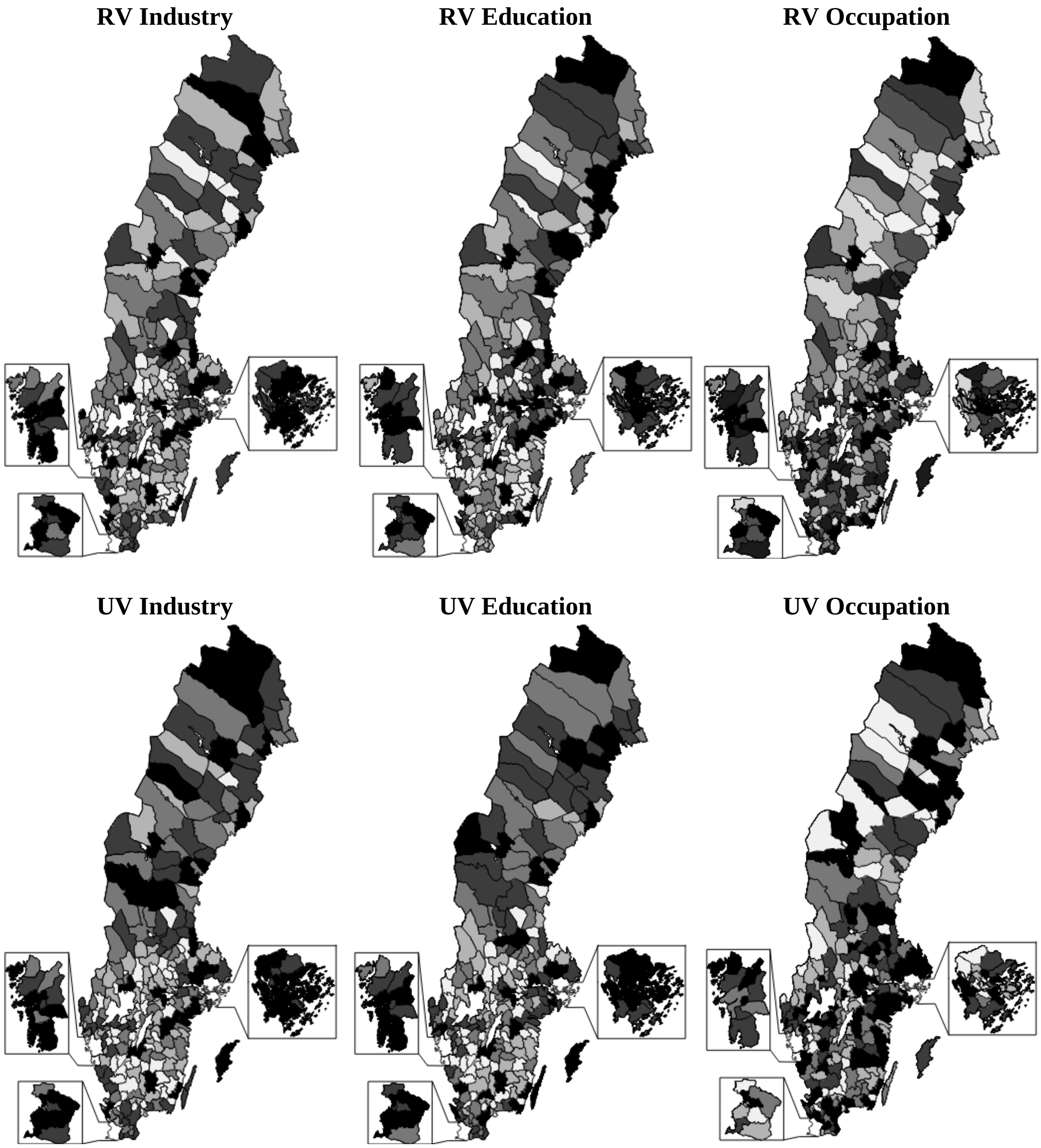

Figure A3. Quantile maps of related and unrelated variety, the service sector (darker color implies greater variety).

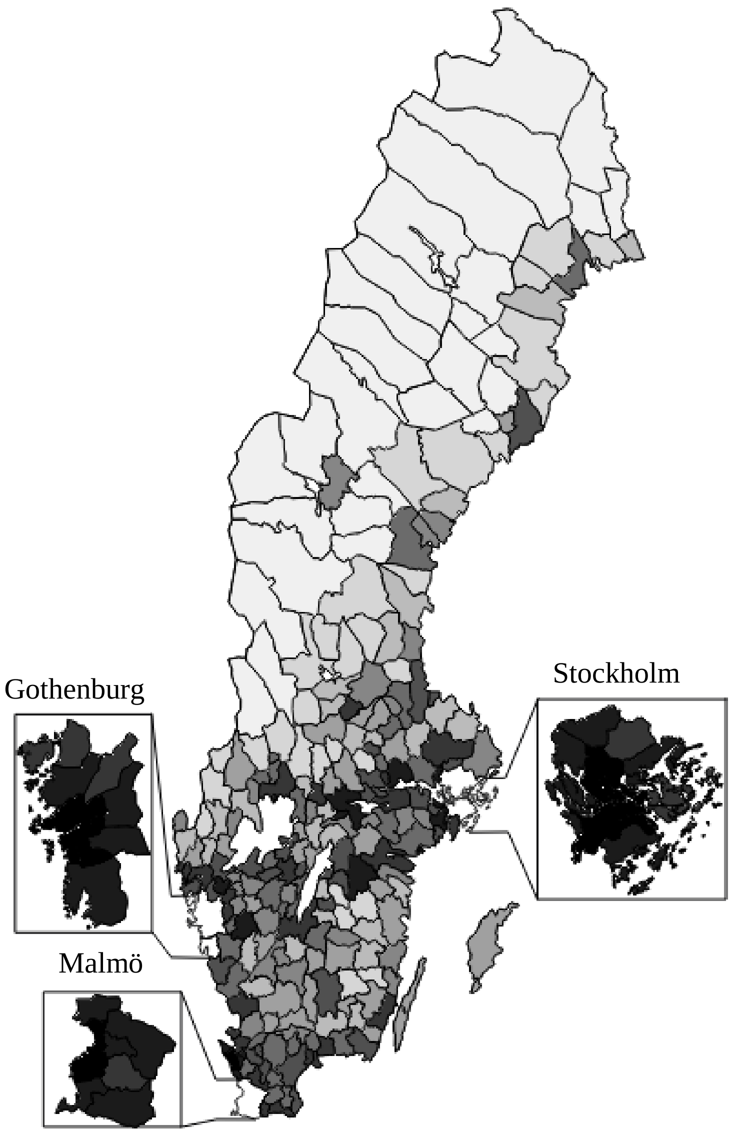

Figure A4. Quantile map of the population density in Sweden 2002 (darker color implies greater population density).

APPENDIX 3

Table A3. Descriptive statistics for the private sector.

	Mean	Std. dev.	Min	Max
Productivity growth	1.26	.178	.824	2.28
Productivity growth adjusted	1.14	.412	.519	5.70
Employment growth	1.06	.091	.726	1.45
Employment growth adjusted	1.03	.165	.539	1.82
RV Industry	1.33	.344	.455	2.16
UV Industry	2.68	.234	1.69	3.12
RV Education	1.52	.138	1.18	1.86
UV Education	2.14	.177	1.69	2.88
RV Occupation	1.55	.129	.885	1.82
UV Occupation	1.97	.118	1.58	2.25
Competition	.142	.050	.051	.303
Pop. density	125	420	.257	4,040
Capital-labor growth	1.18	.422	.353	4.57
Productivity 02	521	107	250	1,070
Employment 02	8,430	24,500	285	353,000

Table A4. Descriptive statistics for the manufacturing sector.

	Mean	Std. dev.	Min	Max
Productivity growth	1.30	.240	.711	2.84
Productivity growth adjusted	1.01	.388	.432	4.90
Employment growth	1.03	.128	.656	1.71
Employment growth adjusted	.923	.266	.357	2.66
RV Industry	.535	.151	.102	1.13
UV Industry	1.32	.260	.420	2.18
RV Education	1.43	.157	.948	1.83
UV Education	2.10	.177	1.69	2.88
RV Occupation	1.53	.190	.573	1.86
UV Occupation	1.69	.144	1.20	2.00
Competition	.102	.057	.018	.391
Capital-labor growth	1.25	.576	.299	4.59
Productivity 02	545	153	196	1,350
Employment 02	3,480	6,120	101	67,700

Table A5. Descriptive statistics for the service sector.

	Mean	Std. dev.	Min	Max
Productivity growth	1.22	.214	.861	2.86
Productivity growth adjusted	1.25	.696	.566	9.97
Employment growth	1.10	.117	.737	1.56
Employment growth adjusted	1.10	.201	.667	2.52
RV Industry	.791	.331	.241	1.78
UV Industry	1.37	.292	.627	2.09
RV Education	1.45	.175	1.04	1.85
UV Education	2.12	.187	1.67	2.88
RV Occupation	1.23	.137	.855	1.54
UV Occupation	2.04	.071	1.61	2.29
Competition	.200	.051	.050	.317
Capital-labor growth	1.15	.577	.257	6.83
Productivity 02	475	63.4	333	823
Employment 02	4,950	18,900	181	285,000

Appendix 4

Table A6. Correlation matrix for independent variables (in logarithmic form), the private sector.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. RV Industry	1										
2. UV Industry	.620	1									
3. RV Education	.488	.261	1								
4. UV Education	.571	.331	.664	1							
5. RV Occupation	.376	.574	.120	.002	1						
6. UV Occupation	.693	.577	.569	.668	.150	1					
7. Competition	.256	.229	-.276	.158	-.162	.371	1				
8. Pop. density	.384	.062	.449	.425	.007	.273	-.167	1			
9. Capital-labor gr.	-.108	-.105	-.139	-.119	-.055	-.113	.020	-.097	1		
10. Productivity 02	.004	-.120	.414	.156	.038	.037	-.441	.389	-.248	1	
11. Employment 02	.582	.348	.693	.471	.372	.326	-.512	.614	-.118	.412	1

Table A7. Correlation matrix for independent variables (in logarithmic form), the manufacturing sector.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. RV Industry	1										
2. UV Industry	.525	1									
3. RV Education	-.073	-.067	1								
4. UV Education	-.240	-.474	.606	1							
5. RV Occupation	.407	.250	.272	.248	1						
6. UV Occupation	.015	-.141	.487	.602	.379	1					
7. Competition	.069	-.374	-.478	.099	.048	.159	1				
8. Pop. density	-.167	-.307	.464	.511	.108	.345	-.105	1			
9. Capital-labor gr.	-.032	-.044	-.055	-.093	-.082	-.157	-.023	-.086	1		
10. Productivity 02	-.097	-.010	.452	.217	.022	.169	-.391	.315	-.183	1	
11. Employment 02	.123	.099	.794	.467	.372	.332	-.572	.552	-.023	.409	1

Table A8. Correlation matrix for independent variables (in logarithmic form), the service sector.

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1. RV Industry	1										
2. UV Industry	.897	1									
3. RV Education	.750	.636	1								
4. UV Education	.786	.791	.725	1							
5. RV Occupation	.568	.409	.650	.466	1						
6. UV Occupation	.230	.173	.200	.189	.366	1					
7. Competition	-.403	-.358	-.638	-.436	-.523	.143	1				
8. Pop. density	.456	.267	.456	.433	.496	.099	-.323	1			
9. Capital-labor gr.	-.053	-.033	-.183	-.063	-.141	-.086	.095	-.042	1		
10. Productivity 02	.346	.205	.498	.375	.469	.092	-.476	.553	-.253	1	
11. Employment 02	.752	.586	.817	.655	.745	.149	-.743	.610	-.138	.564	1

APPENDIX 5

In the spatial error model the error term of equation 5, ε_r, is replaced by u_r where:

$$u_r = \lambda W_r' u + v_r$$

in which W_r is a spatial weight matrix taking the travel time distances between municipalities into account. λ is the spatial error coefficient, which is equal to zero when there is no spatial correlation in the error terms. The spatial lag model includes a spatially lagged dependent variable as an additional explanatory variable. Hence, $\rho W_r' Growth$ is introduced on the right hand side of Equation 5. ρ is the spatial coefficient, which is zero when there is no spatial dependence, implying that the municipal growth is independent of the growth in neighboring municipalities. (Anselin 2003) Model selection is based on maximum likelihood values, which implies that in each case the model with the largest maximum likelihood value is presented.

Table A9. Estimated coefficients for the spatial models regarding productivity growth and employment growth. Standard errors in brackets.

Variables	**2b' Private Employment ML(lag) Adjusted**	**3b' Manufacturing Productivity ML(error) Adjusted**	**4a' Services Productivity ML(error)**	**6a' Services Employment ML(error)**	**6b' Services Employment ML (lag) Adjusted**
RV Industry	0.157***	0.081	-0.133***	0.074***	0.043
	(0.050)	(0.058)	(0.030)	(0.024)	(0.040)
UV Industry	0.049	0.159			
	(0.139)	(0.101)			
RV Education	0.050	1.35***	0.000	0.192**	0.194
	(0.169)	(0.251)	(0.123)	(0.098)	(0.153)
UV Education	-0.298*	0.260	0.726***	-0.246**	-0.170
	(0.163)	(0.309)	(0.147)	(0.123)	(0.191)
RV Occupation	0.005	0.068	0.247**	-0.029	0.071
	(0.129)	(0.123)	(0.099)	(0.081)	(0.131)
UV Occupation	0.306	0.051	-0.410*	-0.510***	-0.370
	(0.255)	(0.223)	(0.242)	(0.196)	(0.322)
Competition	-0.094***	0.048	-0.045	0.093***	0.016
	(0.036)	(0.047)	(0.038)	(0.030)	(0.050)
Population density	0.016**	0.028**	0.010	0.011*	0.010
	(0.007)	(0.014)	(0.007)	(0.006)	(0.007)
Capital labor growth		-0.014	0.063***		
		(0.036)	(0.019)		
Productivity 2002		-0.161**	-0.503***		
		(0.067)	(0.076)		
Constant	-0.326*	0.297	2.83***	0.713***	0.366
	(0.194)	(0.437)	(0.478)	(0.169)	(0.280)
Spatial coefficient	0.333**	0.365**	0.260	0.478***	0.338**
	(0.145)	(0.154)	(0.177)	(0.143)	(0.156)
R^2	0.236	0.346	0.255	0.128	0.088
Observations	289	289	289	289	289

Notes: *** p<0.01, ** p<0.05, * p<0.1. R^2 is a psuedo-R^2 corresponding to the variance ratio.