AGGLOMERATION OF KNOWLEDGE: A REGIONAL ECONOMIC ANALYSIS FOR THE GERMAN ECONOMY

Astrid Krenz

GEORG-AUGUST-UNIVERSITÄT GÖTTINGEN

Agglomeration of Knowledge: A Regional Economic Analysis for the German Economy

Astrid Krenz, University of Goettingen*

Abstract

We investigate the effects of job-specific knowledge for individual labor earnings of workers in the German economy. The results indicate a positive effect for earnings stemming in particular from high-knowledge in the areas of sales and marketing, computers and electronics, mathematics, biology and law and government. Investigating the geographical concentration of employment reveals, for example, that workers with high-knowledge in the field of communication and media are concentrated in just a few places whereas workers with high-knowledge in law and government and administration and management are far more dispersed over the regions. These patterns of geographical localization of employment give evidence for differences in the dissemination of knowledge across peers and customers.

*Department of Economics, Platz der Goettinger Sieben 3, 37073 Goettingen, Germany, astrid.krenz@wiwi.uni-goettingen.de

1. Introduction

Agglomeration of economic activity has received considerable interest in the past literature. Based on the elaboration of the field of New Economic Geography initiated by Paul Krugman (1991 a), studies primarily focused on the production side of economic activity and investigated the agglomeration of firms and employment in industrial (e.g. Brülhart 1998, Brülhart 2001, Midelfart-Knarvik et al. 2000, Rosenthal and Strange 2001) or services sectors (e.g. Kolko 2010, Midelfart-Knarvik et al. 2000), respectively. In the recent past, attention was drawn to the occupational side, investigating which areas of skills and knowledge are driving the geographical concentration of workers (Gabe 2009, Abel and Gabe 2011, Gabe and Abel 2011). These studies put emphasis on how the production is done and what the specific skill requirements of the workforce are rather than focusing on the outcome of production (Feser 2003).

It is relatively unexplored, though, which are the specific knowledge areas that are driving economic development (Gabe 2009, Powell and Snellman 2004). This gap of analysis is mainly attributed to the problems arising from the measurement of knowledge (Howells 2002). The past literature has mainly addressed human capital as a driver of economic development and measured human capital in terms of the level and degrees of education. However, education is only imprecisely measuring knowledge and skills (Ingram and Neumann 2006). An illustrative example is the knowledge area of mechanical tasks. For a mechanic working in a bicycle shop it is not required to have the same educational degree as a professor in mechanical engineering. However, the knowledge required in mechanical tasks might be similarly high for both types of occupations. The type of education and the degree of knowledge do not necessarily have to coincide. The methodology of Feser (2003) – which will be outlined later in this paper— offers a valuable tool to measure the degree of knowledge and thus the effects of human capital on economic development.

Recent empirical studies find evidence that knowledge and skills in the areas of law and government and medicine and dentistry, engineering and technology, production and processing are most rewarded in the US labor market whereas knowledge in chemistry, physics and biology, food production, personnel and human resources is not rewarded (Gabe 2009). In another study, Abel and Gabe (2011) find that a one percent increase in the regional share of college degree holders is associated with a two percent increase in regional GDP per capita. More specifically, producer service knowledge (which comprises the areas of administration and management, economics and accounting, customer and personal service, clerical, law and government) and knowledge in information technology (computers and electronics) are conducive for regional growth. The importance of producer services for economic development is also supported by Hansen (1990) who explains that these workers are providing a greater division of labor and as Lindahl and Beyers (1999) put it, these

workers use their creativity and abilities to work in research and development and to produce valuable products for the economy. Florida et al. (2008) found that computer science-, management and business-, and financial operations-based occupations determine regional economic development.

As regards the economic development in the German economy, a larger growth of technological employees and bohemians has been shown to be conducive for regional employment growth (Wedemeier 2010). The author further found that technological diversity is promoting productivity growth but not employment growth.

The aim of this study is to disentangle the extent to which knowledge and skills will be rewarded differently in the German labor market. Furthermore, this study analyzes the geographical clustering of workers with different knowledge across the German regions. The innovativeness of this study is to set up a regional classification of the knowledge economy in Germany in a similar way as it has been done by Florida et al. (2002) for the US. Florida et al. found that especially the creative professionals, workers in the fields of education, engineering, science and arts, are driving regional competitiveness, innovativeness and thus economic growth.

In our analysis, we first investigate the effects of job-specific knowledge for workers' earnings in the German economy. For our analysis we extract data measuring the knowledge requirements for different occupations from the US Department of Labor's O*NET system. We use data for individuals' characteristics from the German Socioeconomic Panel (GSOEP). Our analysis specifically accounts for the regional information that can be obtained with the GSOEP data through a special user contract. This information covers the 96 regional planning units in the German economy. With the regional information at hand, we investigate the geographical localization of employment. With our study, we can provide new insights about the importance of different knowledge areas for the achievement of wage premiums in the German labor market. We can show that these effects work independently from the level of individuals' education.

This paper is organized as follows. In part 2 we motivate the theoretical background for the analysis, addressing the effects of knowledge spillovers, innovativeness and economic growth. In part 3 we explain the econometric methodology, present and finally discuss the results from a Mincerian earnings regression and a geographical concentration analysis. In part 4 we conclude.

2. Theoretical background

The economic literature has long ago addressed the positive effects resulting from knowledge and human capital accumulation for economic development and growth (Lucas 1988, Romer 1986). Human capital is said to promote individuals' productivity and generation of ideas (Becker 1964). Especially the creative professions are explained to be conducive for economic growth (Lucas 1988, Florida 2002). Moreover, the literature stresses

that the highly educated people in a society enhance the productivity of others (Lucas 1988, Rauch 1993, Moretti 2004).

According to Howells (2002), five elements characterize the relation between geography and knowledge activity. First, knowledge is inherent in an individual that has been shaped by social, cultural, and economic influences in a certain geographical location, second, the knowledge is formed by interactions with other human beings that are also influenced by geography, third, these human interactions are dependent on geographic distance through screening and further transaction costs, forth, gathering information and learning is location-specific and dependent on the location's social, cultural, political, economic context, and fifth, the filtering and interpretation of the gathered information will be location-specific, as well.

In the economic literature, agglomeration or geographical proximity to other people, is found to enhance the mutual exchange of ideas and knowledge (Glaeser et al. 1992). Diversity of employees in this regard is explained to foster the flow of different ideas and knowledge (Jacobs 1969, Florida 2002). These spillovers are increasing technological progress, causing innovations, and are thus conducive to economic growth (Rauch 1993, Howells 2002). This relation is contrasted by the older view of Marshall (1890) that specialization is leading to better access of inputs, labor and knowledge spillovers. Building a bridge between these contrasting views, Duranton and Puga (2001) developed a model that attributes the production of new items to diversified cities. The producers over time learn how to produce in masses and then production switches over to specialized cities. A great range of further studies support the importance of knowledge spillovers (see for example Audretsch and Feldman 1996, Audretsch and Feldman 2004).

Especially in jobs where tacit knowledge is required, proximity to peers (face-to-face contact) becomes important in order for the workers to benefit from mutual learning processes (Polanyi 1966, Howells 2002, Lever 2002, Storper and Venables 2004). Workers benefit from closer communication with each other, face fewer incentive and coordination problems, bear lower screening costs for potential new partners and can derive a higher degree of motivation (Storper and Venables 2004). Being close to peers, workers can become more productive (Lucas 1988). This view is supported by a recent contribution by Borowiecki (2013) who finds that classical composers benefitted from the clustering and quality of their peers. Their productivity in terms of written works per years significantly increased when other classical composers of high quality were close. Agglomeration, however, does not only invoke positive externalities. Workers benefitting from collaboration will benefit from clustering together whereas other workers might suffer from a higher degree of competition (Howells 2002, Lever 2002).

3. Empirical analysis

In the empirical analysis we will first construct a measure for knowledge intensity. Second, we measure the effects of knowledge on labor earnings through a Heckman selection estimation procedure. Third, we investigate the geographical localization of employment across the German regional planning units.

3.1 Construction of the knowledge index

We extracted information about different occupations' knowledge requirements from the US Department of Labor's O*NET system.[1] The data comprise –among others— information on different occupations' level and importance of knowledge in 33 subjects, as is shown in Table 1.

Table 1: Knowledge areas

Administration and management	Psychology
Clerical	Sociology and anthropology
Economics and accounting	Geography
Sales and marketing	Medicine and dentistry
Customer and personal service	Therapy and counseling
Personnel and human resources	Education and training
Production and processing	Language
Food production	Foreign language
Computers and electronics	Fine Arts
Engineering and technology	History and archaeology
Design	Philosophy and theology
Building and construction	Public safety and security
Mechanical	Law, government and jurisprudence
Mathematics	Telecommunications
Physics	Communications and media
Chemistry	Transportation
Biology	

Source: US Department of Labor, O*NET system.

The O*NET system's information has been collected from interviews with workers and professional occupational analysts. For our analysis we make use of the information about the importance and the level of knowledge. The scale measuring the importance of knowledge ranges from 1 to 5, and the scale measuring the level of knowledge ranges from 1 to 7, higher values indicating a higher degree of the level or importance of knowledge.

---

[1] See Peterson et al. 2001 for an explanation of the O*NET system.

In a next step, we matched occupations in the O*NET system with occupations in the GSOEP data. The GSOEP constitutes a representative sample of about 0.025% of the population in Germany. For the following analysis we make use of the cross-section of the year 2006.

For our analysis we assume that the categorization of knowledge requirements for different jobs as given by the US Statistics is transferable to the German occupations. This should be applicable since we can assume that a US chimney sweeper, for example, requires the same knowledge as does a German chimney sweeper. The same should be valid for the occupations of teachers, cleaners, managers etc. Given this assumption, we can make use of the very comprehensive information on knowledge rankings within the O*NET system.

The variable covering occupations in the German economy in the GSOEP is called *Occupation of Individual*, consisting of 296 different occupations. The O*NET system currently covers 974 different occupations. As such, we combined more than one occupation from the O*NET system with an occupation from the GSOEP in several cases.[2] We did not, however, match every occupation from the O*NET system to a German occupation, since there is no exact correspondence between all occupations across the two countries.[3] When we combined more than one occupation, we used the average value of level and importance of knowledge across the occupations. We finally calculated a knowledge index by multiplying the level of knowledge score with the importance of knowledge score in a similar way as it is done in Feser (2003) or Gabe and Abel (2011). We defined high-knowledge requirements covering the occupations that score an index value of at least 60% of the score of the occupation with the highest value of the knowledge index. This cutoff is chosen admittedly arbitrary, but deals with the fact that several other occupations also require a certain degree of knowledge in a given subject.[4]

3.2 The effect of knowledge on earnings

We investigate the effect of knowledge requirements on individuals' earnings by estimating a common Mincerian earnings equation (Mincer, 1974; Gabe 2009), supplementing it with our knowledge indicators:

$$\ln(earnings)_i = \beta_0 + \beta_{1i}educ_i + \beta_{2i}age_i + \beta_{3i}age_i^2 + \beta_{4i}X_i + \beta_{5i}Z_i + \varepsilon_i.$$

(1)

---

[2] The data on matching of occupations is available from the author upon request.
[3] Note that several occupations like "armed forces" or "legislator" or "other labourer" were not given knowledge ratings in the O*NET system and as such could not be used in the analysis.
[4] The cut-off taken in Gabe (2009), for example, is 75%.

The dependent variable is the natural logarithm of monthly individual labor earnings, *educ* is a variable indicating whether the individual has received the A-levels, *X* is a set of variables capturing individual characteristics (married, immigrant, male, job status), *age* and the square of *age* are taken to capture effects of labor market experience. *Z* is the vector of high-knowledge indicators. We estimate the equation for the full-time employed persons with a Heckman selection procedure. In the first stage, we estimated the selection into full-time employment with a Probit model, in the second stage we estimated the earnings equation. We omitted those individuals from the sample who were of age less than 18 and more than 65, as well as those with unknown occupation.

Our approach suffers less from the ability bias usually found in Mincerian earnings regressions (Card 1999). The reason for this is that by focusing on workers' occupations we can capture elements of education, experience, as well as inherent abilities, all of which made workers attain their occupation (Gabe 2009).

The results in Table 2 show in the second column the results from the Probit regression of selection into full-time employment and in the third column the earnings regression outcome. We choose a sample selection estimation procedure since not all of the individuals in the sample work full-time (around 65 % work full-time, see the summary statistics in the Appendix). We follow Gabe (2009) and used a variable capturing the difference of other household income to individual income as exclusion restriction in the selection equation. The idea behind is that people would be less eager to work full-time if other household income was very high.

The results show that particularly knowledge in the areas of sales and marketing, computers and electronics, mathematics, biology and law and government enhances the individual's earnings. In contrast to Gabe's analysis for the US (2009), we find that in the German economy knowledge in clerical tasks, personnel and human resources, mechanical tasks, biology, philosophy and theology is rewarded, as well, whereas knowledge in building and construction, psychology, public safety and security, telecommunications and transportation is not rewarded or even penalized in the labor market.

We computed the percentage wage premium for the variables as $(\exp(\beta)\text{-}1)$. For those variables that are entering both the selection and the earnings equation, the literature points to the necessity to first calculate marginal effects for the outcome regression coefficients which account for the selection into full-time employment, as well. The coefficient that is obtained from the earnings regression is thus corrected. We computed the correction according to the following formula (see Greene 2012, Sigelman and Zeng 1999)[5]:

---

[5] Note that with this methodology we will compute the conditional marginal effects which account for those individuals who participate in full-time employment in the labor market.

$$\frac{\delta E(y_i | z_i^* > 0)}{\delta x_{ik}} = \beta_k - \gamma_k \rho \frac{\sigma_\epsilon}{\sigma_u} \delta(\alpha_u)$$

(2)

with $\delta_i = \lambda_i^2 - \alpha_i \lambda_i$ and $\alpha_u = -\gamma' \frac{z_i}{\sigma_u}$.

The marginal effect of the kth element of x (the regressors) on y_i (here earnings) conditional on the probability that z_i^* is positive (here full-time employment) is composed of two terms where β_k denotes the coefficient of the outcome equation, γ_k is the coefficient from the selection equation, ρ is the correlation between the disturbance terms of the selection and outcome equation, σ_ϵ is the standard deviation of the disturbance term of the outcome equation, σ_u is the standard deviation of the disturbance term of the selection equation – here it is assumed that σ_u is normally distributed with mean and variance (0, 1)-- and $\delta(\alpha_u)$ is a function of the inverse Mills ratio λ.

Table 2: Effects of Knowledge on Earnings

VARIABLES	Selection equation (Probit) full-time working	Earnings equation ln(individual labor earnings)	Percentage wage premium
Education	0.0309***	0.0338***	3.34 %
	(0.00441)	(0.00227)	
Age	0.120***	0.0587***	5.68 %
	(0.00994)	(0.00588)	
Age²	-0.00128***	-0.000550***	-0.05 %
	(0.000116)	(6.55e-05)	
Male	1.204***	0.360***	38.42 %
	(0.0304)	(0.0391)	
Immigrant	-0.0603	0.0616***	6.53 %
	(0.0456)	(0.0204)	
Married	-0.191***	0.0798***	8.9 %
	(0.0331)	(0.0150)	
Blue-collar worker	1.581***	0.400***	42.5 %
	(0.0985)	(0.108)	
Clerk	1.844***	0.672***	85.61 %
	(0.0973)	(0.111)	
Civil servant	2.015***	0.679***	86.0 %
	(0.110)	(0.115)	
Self-employed	1.757***	0.488***	54.82 %

	(0.104)	(0.110)	
Administration and management	--	0.157***	17 % ***
		(0.0296)	
Clerical	--	0.141***	15.14 % ***
		(0.0214)	
Economics and accounting	--	0.0697*	7.22 % *
		(0.0391)	
Sales and marketing	--	0.282***	32.58 % ***
		(0.0307)	
Customer and personal service	--	-0.0120	-1.19 %
		(0.0206)	
Personnel and human resources	--	0.194***	21.41 % ***
		(0.0449)	
Production and processing	--	0.119***	12.64 % ***
		(0.0251)	
Food production	--	-0.377	-31.41 %
		(0.493)	
Computers and electronics	--	0.224***	25.11 % ***
		(0.0279)	
Engineering and technology	--	-0.0116	-1.15 %
		(0.0576)	
Design	--	-0.0421	-4.12 %
		(0.0468)	
Building and construction	--	0.0152	1.53 %
		(0.0345)	
Mechanical	--	0.150***	16.18 % ***
		(0.0214)	
Mathematics	--	0.261***	29.82 % ***
		(0.0343)	
Physics	--	-0.00305	-0.3 %
		(0.0766)	
Chemistry	--	0.0828	8.63 %
		(0.0617)	
Biology	--	0.349***	41.76 % ***
		(0.0579)	
Psychology	--	-0.0994*	-9.46 % *
		(0.0592)	
Sociology and anthropology	--	-0.232	-20.71 %
		(0.404)	
Geography	--	-0.0640	-6.2 %
		(0.0657)	

Medicine and dentistry	--	0.171***	18.65 % ***
		(0.0514)	
Therapy and counseling	--	0.159***	17.23 % ***
		(0.0527)	
Education and training	--	-0.00594	-0.59 %
		(0.0371)	
Language	--	0.0687***	7.11 % ***
		(0.0264)	
Foreign language	--	-0.130	-12.19 %
		(0.251)	
Fine arts	--	-0.0240	-2.37 %
		(0.100)	
History and archeology	--	0.0431	4.4 %
		(0.203)	
Philosophy and theology	--	0.0913**	9.56 % **
		(0.0411)	
Public safety and security	--	-0.102**	9.7 % **
		(0.0522)	
Law and government	--	0.217***	24.23 % ***
		(0.0422)	
Telecommunications	--	-0.230	-20.55 %
		(0.189)	
Communication and media	--	0.133	14.22 %
		(0.117)	
Transportation	--	-0.0213	-2.11 %
		(0.0510)	
Difference household to individual income	-4.59e-06***	--	--
	(4.03e-07)		
Lambda	--	0.0588	--
		(0.0608)	
Constant	-4.604***	7.484***	--
	(0.198)	(0.240)	
Observations	11,049	11,049	--

Source: US Department of Labor, O*NET system and German SOEP data.

Notes: This table displays results from a Heckman two-step selection regression for individual labor earnings with a Probit regression for selection into full-time employment. *** denotes significance at a 1% level, **denotes significance at a 5% level, * denotes significance at a 10% level. The mills ratio (lambda) indicates that selection is not important in this regression. Standard errors are shown in the parentheses.

3.3 Agglomeration of employment in jobs with high-knowledge requirements

In this part of the analysis, we investigate the geographical localization of employment in different jobs with high-knowledge requirements. To run the analysis we make use of the regional information in addition to the individual data of the GSOEP. We obtained additional information on 96 so called "Raumordnungsregionen" (see the Appendix for a list of regions), the regional planning units in the German economy. These units consist of one or several "Stadtkreise" and "Landkreise", the urban districts and counties, and the construction is based on commuter flows. Our data set reduced to 6265 observations which is due to the fact that on the one hand we considered only those individuals who provided information on whether their workplace is located at their place of residence. For the other ones, we considered only those individuals who lived in a commuting distance to the workplace of up to 20 kilometers.

To measure geographical localization, we employed the Krugman concentration index (1991 b) in a modified way similar to the methodology taken by Midelfart-Knarvik et al. (2000):

$$KI_k = \sum_{r=1}^{R} |\frac{e_{kr}}{e_k} - \frac{1}{K-1} \sum_{k=1}^{K} \frac{e_{kr}}{e_k}|$$

(3)

where k denotes the knowledge area, e is employment, and r denotes the region. The higher the index value, the higher is the degree of geographical concentration.

The results in Table 3 display that particularly workers with high-knowledge in communication and media, physics, fine arts, chemistry and geography are more concentrated across German regions, whereas workers with high-knowledge in production and processing, philosophy and theology, clerical tasks, customer and personal services and language are more dispersed across regions.

Table 3: Agglomeration of employment in high-knowledge activities

Knowledge areas	Krugman index	Knowledge areas	Krugman index
Communication and media	1.3907	Law and government	0.5577
Physics	1.1649	Computers and electronics	0.5501
Fine arts	1.0499	Mechanical	0.5462
Chemistry	1.0352	Sales and marketing	0.5242
Geography	0.9906	Design	0.4958
Transportation	0.881	Administration and management	0.4915
Public safety and security	0.8678	Psychology	0.4836

Biology	0.7387	Mathematics	0.4692
Building and construction	0.709	Education and training	0.4598
Personnel and human resources	0.6697	Production and processing	0.4532
Economics and accounting	0.6535	Philosophy and theology	0.4392
Therapy and counseling	0.5944	Clerical	0.3502
Engineering and technology	0.581	Customer and personal service	0.3284
Medicine and dentistry	0.563	Language	0.287

Source: US Department of Labor, O*NET system and German SOEP data.

Notes: This table displays Krugman concentration indices for employment in different jobs with high-knowledge requirements. We do not show results for food production, sociology and anthropology, foreign language, history and archeology and telecommunications, since the number of employees in the sample was very small.

We can graphically depict the distribution of employment for different knowledge areas by plotting the values of regional Balassa indices per subject of knowledge. The Balassa index is measured as follows:

$$B_r = \frac{\frac{e_{kr}}{e_r}}{\frac{e_k}{E}} \; .$$

(4)

The same notation as for the Krugman index applies. The Balassa index captures a relation between the regional and the knowledge area's employment level. The geographical coordinates for the 96 regional planning units have been obtained from the "Bundesinstitut fuer Bau-, Stadt- und Raumforschung" (BBSR).

From Figure 1 we can conclude that workers in professions that require high-knowledge in communication and media localize in only a few regions, specifically in the regions of Munich, Augsburg, Donau-Wald, Braunschweig, Westmecklenburg, Bremerhaven, Hamburg, Berlin, Dortmund, Rheinhessen Nahe, Rhein-Main and Unterer Neckar. In these regions the TV and movie industry is present (especially in Munich, Berlin, Hamburg), as well as newspapers and radio stations. Clustering of activity indicates that fewer contact with people in other knowledge areas but more contact with peers is demanded. It is worthwhile to stress one more time that it is not the product, for example the TV show or the radio broadcast, which is relevant for this type of analysis, but it is the inherent knowledge about the topic of communication and media of the workforce. The use of the product of communication and media would be widely spread over the regions, however, the concentration of the workforce follows a different pattern.
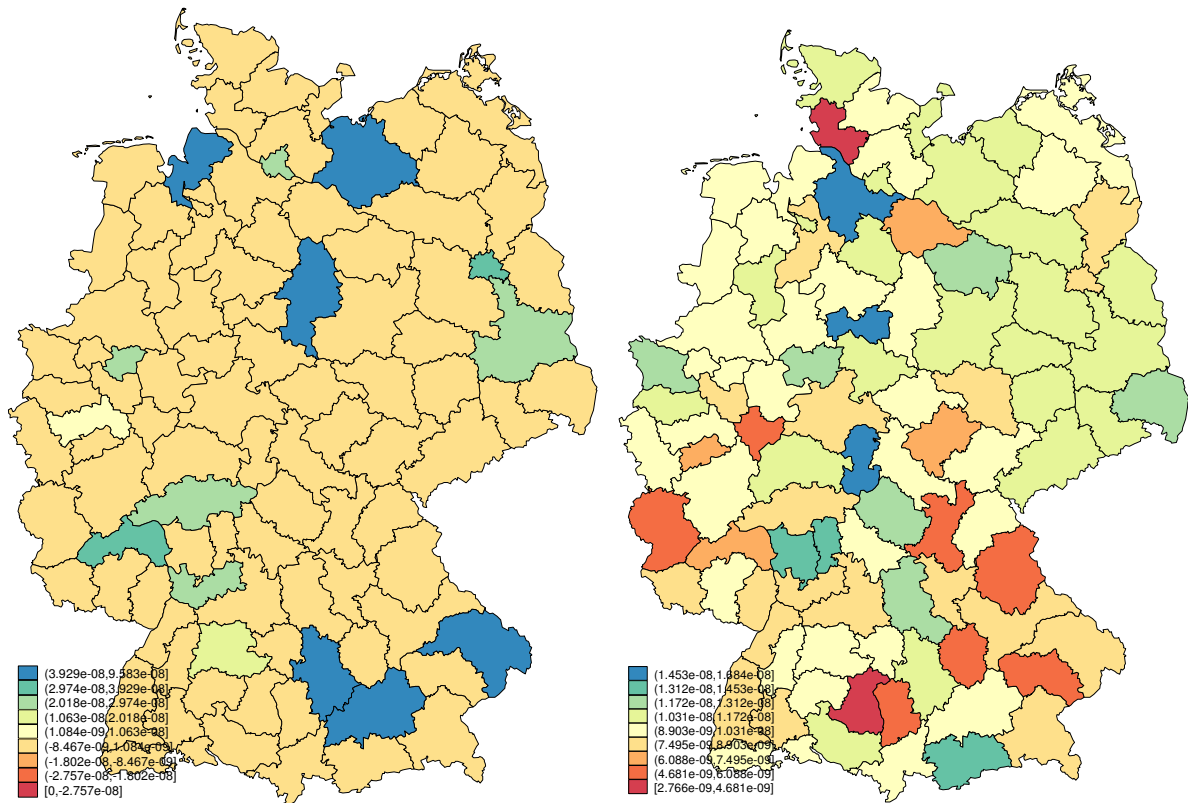
Figure 1: Regional distribution of employment in jobs with high-knowledge in communications and media (left depiction) and in jobs with high-knowledge in customer and personal service (right depiction)

Source: BBSR, author's own illustration.

Note: Regional Balassa indices are depicted on a scale ranging from low (red color) to high (blue color) values.

For the knowledge area of customer and personal service a different picture emerges. Figure 1 shows a greater dispersion of employment across regions. Customer and personal service knowledge is demanded by different people and not only the peers.

For employment that requires high-knowledge in the areas of mechanical tasks and administration and management, Figure 2 displays that employment is far more dispersed over the regions. High-knowledge in these activities yields positive effects on individuals' earnings and the dispersion of employment indicates that knowledge is disseminated not specifically to peers but to other clients in the economy. However, a greater clustering of economic activity becomes present in case of mechanical tasks in the regions of Schwarzwald-Baar-Heuberg, Donau-Iller, Allgäu, Bodensee, Ostwürttemberg, Osthessen, Arnsberg and Braunschweig. In some of these regions important automobile companies operate like VW in the "Raumordnungsregion" Braunschweig. In Ostwürttemberg and Arnsberg a large intermediate firm activity for automobile parts is present. In the current phase of globalization and the splitting-up of value chains it is not surprising that especially the intermediate
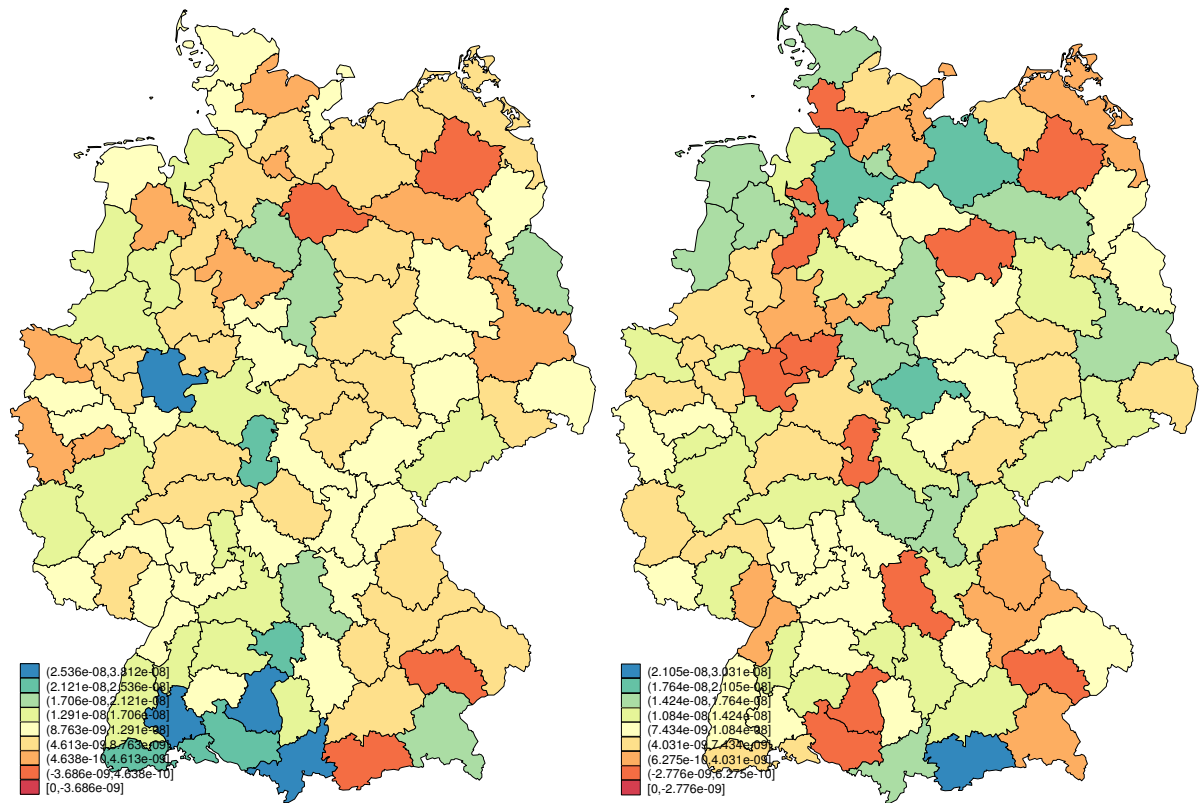
Figure 2: Regional distribution of employment in jobs with high-knowledge in mechanical tasks (left depiction) and in administration and management (right depiction)

Source: BBSR, author's own illustration.

Note: Regional Balassa indices are depicted on a scale ranging from low (red color) to high (blue color) values.

goods production instead of the final good production apparently dominates the regional distribution of employment. Baden-Würtemberg, the very South-Western state in Germany, is well-known for its automobile production which is last not least due to the invention of the first automobile with a combustion engine by Carl Benz in 1886 in Mannheim.

4. Conclusions

Our analysis revealed that particularly high-knowledge in sales and marketing, computers and electronics, mathematics, biology and law and government generates a positive wage premium for workers in the German economy. Education serves as an important positive influential factor for earnings, however, impacts stemming from high-knowledge exist independently from the level of education. High-knowledge in food production, design, building and construction, chemistry, psychology, sociology and anthropology, geography, foreign language, public safety and security, telecommunications, communication and media, and transportation appears

not to be specifically rewarded or even be penalized in the German labor market. In our analysis, we found that in the German economy the effects for earnings due to high-knowledge in the areas of clerical tasks, personal and human resources, mechanical tasks, biology, philosophy and theology are positive which contrasts recent results for the US (see Gabe 2009).

Taking a look at the geographical distribution of employment, our results suggest that workers in jobs with high-knowledge requirements which generate positive wage premiums like mechanical tasks or administration and development are more dispersed across regions. This result is in line with the categorization of Gabe and Abel (2011), indicating that the dissemination of knowledge does involve people outside the knowledge area and is not narrowed to peers. Our analysis was focusing on the workers' knowledge in specific subjects rather than on the outcome of production. We argued that the consumption of the product and the distribution of high-knowledge employment well followed different patterns.

Given the regional distribution of knowledge-intensive employment in the German economy, in a follow-up study we will conduct further investigations about the interdependencies between knowledge and regional growth.

Literature

Abel, J. R.; Gabe, T. M. (2011). Human Capital and Economic Activity in Urban America, Regional Studies, 45, 1079-1090.

Audretsch, D.; Feldman, M. (1996). Spillovers and the geography of innovation and production, American Economic Review, 86, 630-640.

Audretsch, D.; Feldman, M. (2004). Knowledge spillovers and the geography of innovation, in Henderson, J. and Thisse, J. (eds) Handbook of Regional and Urban Economics, Vol. 4, Chapter 61.

Becker, G. (1964). Human Capital, Columbia University Press, New York.

Borowiecki, K. J. (2013). Agglomeration Economies in Classical Music, ACEI Working Paper.

Brülhart, M. (2001). Evolving Geographical Concentration of European Manufacturing Industries, Weltwirtschaftliches Archiv, 137, 215-243.

Brühlhart, M. (1998). Economic Geography, Industry Location and Trade: The Evidence, The World Economy, 21, 775-801.

Card, D. (1999). The Causal Effects of Education on Earnings, in O. Ashenfelter and D. Card: Handbook of Labor Economics, Amsterdam, 1801-1863.

Duranton, G.; Puga, D. (2001). Nursery Cities: Urban diversity, process innovation, and the life cycle of products, The American Economic Review, 91, 1454-1477.

Feser, E. J. (2003). What Regions Do Rather than Make: A Proposed Set of Knowledge-based Occupation Clusters, Urban Studies, 40, 1937-1958.

Florida, R.; Mellander, C.; Stolarick, K. (2008). Inside the black box of regional development—human capital, the creative class and tolerance, Journal of Economic Geography, 8, 615-649.

Florida, R. (2002). The Rise of the Creative Class and How It's Transforming Work, Leisure, Community, and Everyday Life, New York.

Gabe, T. (2009). Knowledge and Earnings, Journal of Regional Science, 49, 439-457.

Gabe, T.; Abel, J. R. (2011). Agglomeration of Knowledge, Urban Studies, 48, 1353-1371.

Glaeser, E. (1999). Learning in Cities, Journal of Urban Economics, 46, 254-277.

Glaeser, E.; Kallal, H.; Scheinkman, J.; Shleifer, A. (1992). Growth in cities, The Journal of Political Economy, 100, 1126-1152.

Greene, W. (2012). Econometric Analysis, 7th edition, Pearson, Prentice Hall, Upper Saddle River, NJ.

GSOEP, German Socioeconomic Panel, data available through the DIW Berlin.

Hansen, N. (1990). Do producer services induce regional economic development?, Journal of Regional Science, 30, 465-476.

Howells, J. R. L. (2002). Tacit knowledge, Innovation and Economic Geography, Urban Studies, 39, 871-884.

Jacobs, J. (1969). The Economy of Cities, New York.

Ingram, B.; Neumann, G. (2006). The Returns to Skill, Labour Economics, 13, 35-59.

Kolko (2010). Urbanization, Agglomeration, and Coagglomeration of Service Industries, in Agglomeration Economics, ed.: E. L. Glaeser, The University of Chicago Press, 151-180.

Krugman, P. (1991 a). Increasing Returns and Economic Geography, Journal of Political Economy, 99, 483-499.

Krugman, P. (1991 b). Geography and Trade, MIT Press, Cambridge, Massachusetts.

Lever, W. F. (2002). Correlating the Knowledge-base of Cities with Economic Growth, Urban Studies, 39, 859-870.

Lindahl, D.; Beyers, W. (1999). The creation of competitive advantage by producer service establishments, Economic Geography, 75, 1-20.

Lucas, R. (1988). On the Mechanics of Economic Development, Journal of Monetary Economics, 22, 3-42.

Marshall, A. (1890). Principles of Economics, London Macmillan.

Midelfart-Knarvik, K.H.; Overman, H.G.; Redding, S.J.; Venables, A.J. (2000). The Location of European Industry, European Economy-Economic Papers No. 142.

Mincer, J. (1974). Schooling, Experience and Earnings, New York, NBER Press.

Moretti, E. (2004). Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data, Journal of Econometrics, 121, 175-212.

Peterson, N.; Mumford, M.; Borman, W.; Jeanneret, R.; Fleishman, E.; Levin, K.; Campion, M.; Mayfield, M.; Morgeson, F.; Pearlman, K.; Gowing, M.; Lancaster, A.; Silver, M.; Dye, D. (2001). Understanding work using the occupational information network (O*NET): implications for practice and research, Personnel Psychology, 54, 451-492.

Polanyi, M. (1966). The logic of tacit inference, Philosophy, 41, 1-18.

Powell, W.; Snellman, K. (2004). The knowledge economy, Annual Review of Sociology, 30, 199-220.

Rauch, J. (1993), Productivity Gains from geographic concentration of human capital: evidence from the cities, Journal of Urban Economics, 34, 380-400.

Romer, P. (1986). Increasing returns and long-run growth, Journal of Political Economy, 94, 1002-1037.

Rosenthal, S.; Strange, W. (2001). The determinants of agglomeration, Journal of Urban Economics, 50, 191-229.

Sigelman, L; Zeng, L. (1999). Analyzing Censored and Sample-Selected Data with Tobit and Heckit Models, Political Analysis, 8, 167-182.

Storper, M.; Venables, A. J. (2004). Buzz: face-to-face contact and the urban economy, Journal of Economic Geography, 4, 351-370.

Wedemeier, J. (2010). The impact of the creative sector on growth in German regions, European Planning Studies, 18, 505-520.

Appendix

Summary Statistics

Variable	Definition	Mean	St. Dev.
Full-time status	1 if the individual is fully employed in 2006, 0 otherwise	.6523667	.4762404
Individual income	Individual labor earnings in 2006	31644.82	31754.88
Ln (individudal income)	Natural logarithm of individual income	9.994505	1.000886
Education	1 if the individual attained the A-levels, „Abitur", 0 otherwise	.2472622	.43144

Age	Individual's age in years	42.5253	11.15022
Male	1 if the individual is a male, 0 otherwise	.5255679	.4993685
Immigrant	1 if the individual immigrated to Germany after 1948, 0 otherwise	.1027242	.3036121
Married	1 if the individual is married and lives together with his/her partner, 0 otherwise	.625577	.4839955
Difference household to individual income	Household labor income minus individual labor earnings in 2006	24971.46	35113.86
Blue-collar worker	1 if individual is blue-collar worker, 0 otherwise	.2594805	.4383694
Clerk	1 if individual is a clerk, 0 otherwise	.5066522	.4999784
Civil servant	1 if individual is a civil servant, 0 otherwise	.0750294	.2634507
Self-employed	1 if individual is self-employed, 0 otherwise	.1096027	.312408
Administration and management		.0798262	.2710363
Clerical		.1472531	.3543741
Economics and accounting		.030953	.1731983
Sales and marketing		.0610915	.2395089
Customer and personal service		.2829215	.450439
Personnel and human resources		.0257037	.158257
Production and processing		.0823604	.2749254
Food production		.000181	.0134535
Computers and electronics		.052765	.223574
Engineering and technology		.0429903	.2028445
Design		.0568377	.2315428
Building and construction		.0343923	.1822428
Mechanical		.0916825	.2885903
Mathematics		.0695991	.2544816
Physics		.0094126	.0965653
Chemistry		.0101367	.1001739
Biology		.0195493	.1384516
Psychology		.052946	.2239358
Sociology and anthropology		.0002715	.0164763
Geography		.0084171	.0913617
Medicine and dentistry		.0432618	.2034551

Therapy and counseling	.0293239	.1687205
Education and training	.0734003	.2608043
Language	.2078016	.4057524
Foreign language	.0009956	.0315383
Fine arts	.0086886	.0928109
History and archeology	.0011766	.0342826
Philosophy and theology	.0811838	.2731296
Public safety and security	.0180107	.1329958
Law and government	.0343017	.1820114
Telecommunications	.0009956	.0315383
Communication and media	.0062449	.0787812
Transportation	.015929	.1252067

List of regional planning units, "Raumordnungsregionen":

Schleswig-Holstein Mitte, Schleswig-Holstein Nord, Schleswig-Holstein Ost, Schleswig-Holstein Süd, Schleswig-Holstein Süd-West, Hamburg, Braunschweig, Bremen-Umland, Bremerhaven, Emsland, Göttingen, Hamburg-Umland-Süd, Hannover, Hildesheim, Lüneburg, Oldenburg, Osnabrück, Ost-Friesland, Südheide, Bremen, Aachen, Arnsberg, Bielefeld, Bochum/Hagen, Bonn, Dortmund, Duisburg/Essen, Düsseldorf, Emscher-Lippe, Köln, Münster, Paderborn, Siegen, Mittelhessen, Nordhessen, Osthessen, Rhein-Main, Starkenburg, Mittelrhein-Westerwald, Rheinhessen-Nahe, Rheinpfalz, Trier, Westpfalz, Bodensee-Oberschwaben, Donau-Iller (BW), Heilbronn-Franken, Hochrhein-Bodensee, Mittlerer Oberrhein, Neckar-Alb, Nordschwarzwald, Ostwürttemberg, Schwarzwald-Baar-Heuberg, Stuttgart, Südlicher Oberrhein, Unterer Neckar, Allgäu, Augsburg, Bayerischer Untermain, Donau-Iller (BY), Donau-Wald, Industrieregion Mittelfranken, Ingolstadt, Landshut, Main-Rhön, München, Oberfranken-Ost, Oberfranken-West, Oberland, Oberpfalz-Nord, Regensburg, Südostoberbayern, Westmittelfranken, Würzburg, Saar, Berlin, Havelland-Fläming, Lausitz-Spreewald, Oderland-Spree, Prignitz-Oberhavel, Uckermark-Barnim, Mecklenburgische Seenplatte, Mittleres Mecklenburg/Rostock, Vorpommern, Westmecklenburg, Oberes Elbtal/Osterzgebirge, Oberlausitz-Niederschlesien, Südsachsen, Westsachsen, Altmark, Anhalt-Bitterfeld-Wittenberg, Halle/S., Magdeburg, Mittelthüringen, Nordthüringen, Ostthüringen, Südthüringen