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Noseleit, Florian; Söllner, Rene

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Diversity of human capital and regional growth

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Diversity of human capital and regional growth

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Florian Noseleit and René Söllner

Early draft!

Abstract

In this paper we study the impact of diversity on regional growth by extending the existing literature in such that we differentiate between industry diversity and human capital diversity. We argue that a more diverse human capital structure is beneficial for regional growth. In fact, based on panel data for West-German regions we find empirical evidence that regions with higher degrees of human capital diversity exhibit higher GDP-per-capita growth. The results suggest that not only the level of human capital but also the composition of human capital in terms of knowledge heterogeneity matters for growth.

***JEL classification**: O4, R0, D62, J24*

***Keywords**: Human capital, Diversity, Externalities, Regional Growth*

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Address for correspondence:

Florian Noseleit
René Söllner

Friedrich-Schiller-University Jena
School of Economics and Business Administration
Carl-Zeiss-Str. 3
D-07743 Jena
Phone: ++49 (0) 3641- 943 (226) Noseleit, (279) Söllner

florian.noseleit@uni-jena.de; rene.soellner@uni-jena.de

1. Introduction

Since the development of the New Growth Theory it is widely acknowledged in economic literature that human capital is of essential importance for economic growth (see Lucas (1988), Romer (1990), Grossman and Helpman (1991), Aghion and Howitt (1998), among others). A large number of studies using cross-country data have empirically tested the effect of human capital on economic growth (Barro, 1991, 2001; Barro and Sala-i-Martin, 1995; Bils and Klenow, 2000). In general they found that the initial stock of human capital plays a significant role for economic growth, while Gemmell (1996) has shown that both the initial stock and accumulation of human capital were significant determinants for growth. Empirical studies at the regional level also support a relationship between human capital and growth (Eaton and Eckstein (1997), Glaeser et al. (1995), Simon (1998), to mention just a few). The general idea is that enhancements of human capital lead to innovation and, through knowledge spillover and the diffusion of new technologies economic growth is generated. Although there is a large body of literature confirming the importance of human capital on economic growth surprisingly little is known about the effect of human capital diversity on growth. The aim of the current paper is to disclose this relationship at a regional level.

Our results can be briefly summarized. Based on panel data for West-German regions we find a positive association between human capital diversity, measured in terms of occupational diversity, and local GDP-per-capita growth. Our study contributes to the literature in the following ways. First, to the best of our knowledge, there is none comparable study empirically investigating the impact of occupational diversity on regional growth. Second, our study can be regarded as an extension of the literature focusing on regional effects of cultural diversity. Instead of pointing out the importance of factors like the diversity of the local cultural atmosphere and the openness towards smaller ethnical groups the current paper mainly, identifies complementarities in skills within the local workforce as a decisive source for economic progress.

The remainder of this paper is structured as follows. In section 2 we discuss some theoretical background and refer to related literature on this topic. A description of the dataset is presented in section 3. Section 4 refers to the underlying econometric methodology and reports the results of the empirical analysis. Section 5 concludes.

2. Related Literature and Theoretical Background

A research area that has been heavily influenced by a debate on the impact of diversity on economic growth is the economics of agglomeration. The economics of agglomeration address the question arising in economic geography why economic activities and firms tend to cluster geographically. Common wisdom suggests that one of the reasons is the existence of positive knowledge spillovers between firms located close to each other. Several empirical studies have shown that knowledge spillovers are indeed geographically bounded (see Jaffe (1989), Jaffe et al. (1993), among others). For this reason it is presumed that firms will benefit most from knowledge externalities if they cluster in close geographical distance. The existing literature on that topic has dealt with the impact of different types of agglomeration economies on innovation and economic growth. In particular, the debate has focused on whether regional specialization (localization or Marshallian externalities) or regional diversification (Jacobs externalities) encourage knowledge spillover and therefore promote regional growth.

The concept of localization economies dates back to Marshall's (1890) ideas of industrial districts. Based on Marshall's view knowledge is sector specific and the most important technological externalities arise within industries. In order to facilitate the transmission of ideas, and to foster the emergence of technological knowledge spillover an increased regional concentration of a particular industry is desirable. Regional specialization will then lead to economic growth for both the specialized industries and regions where the industries are located in. Jacobs externalities, however, are associated with gains that arise when firms of different industries are located close to each other. The rationale behind is that most important ideas come from outside the core industry (Jacobs, 1969). Thus in this view, the more diversified the regional industry structure, the higher local growth because diversity triggers the creation of new ideas, induces cross-fertilization through knowledge spillover, and provides resources needed for innovation to take place (Boschma and Iammarino, 2009). Accordingly, diversity of geographically close industries rather than geographical specialization is presumed to foster innovation and regional growth.

Empirical studies attempting to identify the impact of industry specialization and industry diversity on growth offer ambiguous results. Using panel data over the period 1956-1987 Glaeser et al. (1992) explore the determinants of employment growth of the largest six industries within U.S Metropolitan Statistical Areas. Their results suggest that industry diversity encourages growth but specialization does not. Henderson et al. (1995), however,

find evidence for both specialization and diversity fostering employment growth. In particular, they observe positive effects of diversity for high-technology firms, whereas for mature industries no positive effect is observable. In contrast, for high-tech industries specialization fails to encourage growth, but for mature industries specialization seems to be supportive. Instead of looking at employment growth pattern of industries within certain areas, Combes (2000) considers the effects of local sectoral specialization and diversity on the employment growth of 341 local areas in France. Combes finds that specialization and diversity have a negative impact on growth in industrial sectors. The opposite is detected for service sectors which probably benefit due to market-based effects arising from the local presence of large and diversified input and output markets and to possible inter-sectoral information spillovers. In their study of Italian regions Cingano and Schivardi (2004) argue that agglomeration externalities impinge on productivity. Productivity, however can influence employment positively or negatively depending on whether productivity changes are labor saving or not. Cingano and Schivardi (2004) observe that diversified regions experience less productivity but higher employment growth

The previous paragraph has shown that the notion diversity is often associated with diversity of firms and the scope of the regional industrial structure. However, focusing on the diversity of the regional industry structure disregards that knowledge transmission merely occurs between individuals. This is a fact that was already described by Jacobs (1969), and is also recognized by Glaeser et al. (1992) who emphasize the importance of interaction between people in close geographical distance for innovation. Nevertheless, the existing literature typically relies on the regional industry diversity as an indicator for the breadth of the local knowledge base. However, we argue that the diversity of skills and knowledge at the individual level rather than the diversity of industries reflects the scope of the local knowledge base and the potential for spillover. A more fruitful approach should therefore be to take a more disaggregated view on this topic by looking at the diversity of skills and abilities at the level of individuals. This reasoning is in line with Florida (2002, 2005) arguing that people and the diversity of skills are the key regional economic growth assets. In his view, diversity is boosting innovation and growth by bringing together complementary skills, different abilities and alternative approaches to problem solving. More recently, Boschma and Fritsch (2009) using a unique dataset of more than 450 regions in eight European countries were able to confirm most of the hypotheses suggested by Florida. In particular, they observe that the share of creative people is positively related to regional employment growth and on new firm formation. A main

criticism about using the creative class in empirical analyses is that it confuses creativity and human capital (Glaeser, 2005).

A theoretical basis for our conjecture that human capital diversity (proxied by occupational diversity) is positively related with regional growth in terms of GDP can be found in Berliant and Fujita (2009). As an extension to the traditional growth literature Berliant and Fujita (2009) show that the composition of the workforce in terms of knowledge heterogeneity matters for growth – and not only the level of human capital. The respective micro foundation for this growth model is discussed in Berliant and Fujita (2008) who formally describe that the knowledge differentials between individuals are a decisive resource for the process of knowledge creation. Also the literature on the organization and the management of teams offers some insights on this issue. Page (2007), for instance, claims that growth and innovation depend less on single people with enormous IQs rather than on diverse people with disjoint skills working together. The rationale is that higher diversity will lead to more innovation and better decisions by an increase of the number of ways to solve problems. Since spatial proximity can be expected to amplify the process of communication between a diverse set of people, it positively affects knowledge transmission. Comparable arguments were put forward by Ottaviano and Peri (2005, 2006) showing that culturally diversified populations, measured in terms of the primary language spoken, are important growth determinants for cities in the U.S. Ottaviano and Peri base their empirical analysis on a model that assumes cities consisting of diverse cultural groups that interact in the production of some final goods. The assumption of a "love for variety" on the production side implies a higher productivity in manufacturing the final goods for cities exhibiting a highly fragmented labour force in terms of nationalities.[1] Recently, Blien et al. (2009) extended the analysis by Ottaviano and Peri (2005, 2006) by paying closer attention to the skill composition of the foreign workforce. In their empirical analysis using a data set for West Germany they find positive effects of cultural diversity on local productivity, but only when skilled foreign workers are taken into account. Unskilled foreign workers and their diversity do not exert influence, or even negatively affect productivity.

Even though the impact of human capital diversity on growth gained more attention in the economic literature recently, empirical studies so far mainly focus on cultural diversity as a source for economic progress. The main argument is that cultural diversity reflects complementaries of skills and abilities within the local workforce. These complementaries

[1] Note that Ottaviano and Peri (2005) also take into account negative effects of cultural diversity through transaction cost of cultural interaction.

enhance the flow and recombination of knowledge, and, therefore, contribute to regional growth. The main drawback of this approach is that cultural diversity is not able to display the diversity of skills (i.e. human capital diversity) neither directly nor comprehensively. The present paper is more elaborated in this respect since we try to capture the diversity of human capital directly by measuring the diversity of occupations within the local workforce. To the best of our knowledge this study is the first attempt exploring the effects of occupational diversity on the economic growth at the regional level.

3. Data

For this study we exploit several data sources. In order to grasp the diversity of human capital in a region we rely on information about employment shares of different occupations in the local workforce. The necessary occupational employment data at the regional level is provided by the German Federal Employment Agency. The data allows distinguishing employees in 336 different occupations. Additionally detailed information about regional characteristics was used to construct region-specific control variables. The corresponding data was derived from the Establishment History Panel which is available at the Institute for Employment Research (IAB) of the German Federal Employment Agency.[2] This data set contains establishment aggregated data that allows analyzing regional based research questions. Since the data is based on official employment statistics derived from social security it can be regarded as highly reliable. Data about regional GDP and population was reported by the Federal Statistical Office. The units of observation are 326 NUTS3 West German regions (Landkreise), which are roughly comparable to U.S. counties.[3] The analysis of the relationship between occupational diversity and GDP growth is performed using a panel data set comprising the years 1995 to 2004. In order to verify our results we further use employment growth as an alternative measure for regional growth. By doing so were are able to extend our analysis to 17 years (1987 to 2004).

[2] Civil servants and self-employed individuals are not incorporated in our data since they are not subject to social security.

[3] We limit our analysis to West Germany because of a lack of reliable data and the specific conditions for East-German regions after reunification.

4. Empirical Analysis

Since occupations reflect differences in skills and abilities far beyond the scope of formal degrees, we regard them to be an ideal tool to construct a proxy for human capital diversity. In order to quantify the occupational diversity in regions we computed an entropy index as proposed by Jacquemin and Berry (1979), that is defined as $\sum s_i * \ln(1/s_i)$.[4] To give an impression about the regional distribution of human capital diversity, figure 1 shows the percentage deviation from the average diversity over all regions for the period 1995-2002.

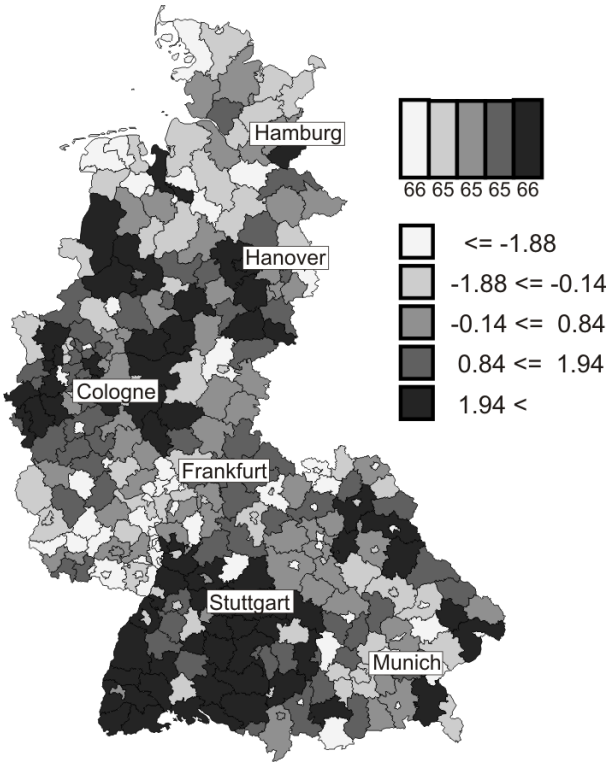

Figure 1. Regional distribution of human capital diversity (percentage deviation from the average regional diversity of human capital, 1995-2002)

To test the "diversity of human capital hypothesis" we regress GDP-per-capita growth on occupational diversity. Alternatively, we consider regional employment growth as a dependent variable for which we have a much longer time period.

We apply two strategies to assure that our measure of human capital diversity is not just a proxy of the regional industrial structure. First we calculate a variable for the regional industry diversity that is computed equivalent to the occupational diversity using regional

[4] Alternatively we also calculate a Herfindahl-based diversification index that was developed by Berry (1971). The index takes the form $1-\sum s_i^2$ where s_i denotes the employment share of occupation i in a region. This Herfindahl index and several modified versions are the most commonly used diversity measures applied in the literature.

industry employment shares at the three digit industry level instead. Second we incorporate regional employment shares of 27 out of 28 aggregated industries as additional explanatory variables in our regression. The inclusion of a wide set of industry employment shares is expected to capture effects arising from a diverse or specialized industry structure more adequate than a single industry diversity index. Furthermore, skill complementarity and substitutability in production, as well as differences in the importance of knowledge spillovers should be addressed with a detailed consideration of changes in the regional industry structure. The regional industry structure also reflects differences in the factor input combinations across industries (see Peneder, 2002).

As an additional control variable we include the share of high qualified workers which is defined as the share of workers with completed tertiary education over the total workforce. The share of high qualified workers is a conventional human capital measure in order to capture knowledge spillover that occur due to spatial concentration of high qualified labour force accompanied by a rapid spatial decay (Lucas, 1988; Audretsch and Feldman, 1996).

In order to control for urbanization economies we use population density (total population over area size in km²). Moreover, since regional growth may not only be determined by characteristics of the respective region, but also by the proximity to other regions we include a Harris-type market potential function. This market potential function is defined as the distance weighted sum of total population in all other districts (see Redding and Sturm (2004); Südekum (2008)).

We estimate a fixed effects model since human capital diversity might only be a proxy of time invariant region specific characteristics. Correlation tables of the central variables that have been used for estimation are presented in tables A1 and A2 in the appendix. Finally, the following econometric model is estimated

(1) $$\log(gdp_cap)_{r,t=0} - \log(gdp_cap)_{r,t-1} = \alpha + \mu_r + \lambda_t + \beta_1 od_{r,t-1} + \beta_2 id_{r,t-1} + \gamma X_{r,t-1} + \varepsilon_{r,t}$$

where $gdp_cap_{r,t}$ is the regional gross domestic product per capita, $od_{r,t-1}$ is the time-lagged occupational diversity, $id_{r,t-1}$ is the time-lagged regional industry diversity, $X_{r,t-1}$ are other exogenous variables, μ_r is a regional fixed effect, λ_t a time fixed effect, and $\varepsilon_{r,t}$ is the error term. Table 1 reports our estimation results for a fixed effects regression.

Table 1: The impact of human capital diversity on regional GDP-per-capita growth

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Human capital diversity, t-1			0.0577***	0.0554***			0.0501***	0.0470***
			(0.0088)	(0.0087)			(0.0087)	(0.0085)
Industry diversity, t-1		0.00537**		0.00337*		0.00575***		0.00419***
		(0.0021)		(0.0018)		(0.0016)		(0.0015)
Share of employees in large firms, t-1	-0.0223**	-0.0173*	-0.0225**	-0.0194**	-0.0226**	-0.0186	-0.0206**	-0.0178*
	(0.0099)	(0.010)	(0.0092)	(0.0095)	(0.011)	(0.011)	(0.010)	(0.011)
Share of high qualified workers, t-1	0.0194***	0.0218***	0.0275***	0.0287***	0.0338***	0.0359***	0.0368***	0.0381***
	(0.0049)	(0.0051)	(0.0047)	(0.0049)	(0.0052)	(0.0053)	(0.0050)	(0.0052)
Population density (log), t-1	0.0691***	0.0701***	0.0601***	0.0611***	0.0592***	0.0614***	0.0533***	0.0552***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)	(0.016)
Market potential (log), t-1	0.0331	0.0131	0.0173	0.00540	0.0238	0.00655	0.0474	0.0333
	(0.062)	(0.062)	(0.061)	(0.061)	(0.073)	(0.071)	(0.071)	(0.070)
Constant	-0.806	-0.586	-0.816	-0.677	-0.574	-0.390	-1.063	-0.899
	(0.74)	(0.74)	(0.74)	(0.74)	(0.88)	(0.86)	(0.85)	(0.84)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls for industry structure	No	No	No	No	Yes	Yes	Yes	Yes
F-test	1566	1506	1356	1303	527.4	524.6	517.1	520.5
Log-likelihood	10044	10049	10073	10075	10121	10126	10138	10141
R-squared - within	0.654	0.655	0.661	0.661	0.672	0.673	0.676	0.676
R-squared – between	0.000201	0.00100	0.000829	0.00170	0.000173	0.00000945	0.00158	0.000668
R-squared - overall	0.0110	0.0135	0.0176	0.0196	0.0112	0.0129	0.00934	0.0107

Note: Diversity is measured as $-\sum s_i * \ln s_i$, where s_i denotes the employment share of occupation (industry) i. The estimation method is fixed effects regression. Robust standard errors are reported in parentheses. The total number of observation (regions; years) is 2934 (326; 9). The coefficients for 27 out of 28 industry shares and the year dummies are omitted for brevity. Significant at *** 1%, ** 5%, * 10%.

In column one in table 1 we estimate a benchmark fixed effects model including only the basic control variables and time dummies but without controls for the industry structure. We find a significant negative coefficient for the share of employees in large firms, a positive coefficient for the share of high qualified workers and population density. Market potential appears to have no significant impact. Note that market potential is positively related to the levels of GDP-per-capita in a region but apparently has a negative impact on GDP-per capita growth.[5] In column 2 we include an additional control for regional industry diversity which is positively related to GDP per capita growth. When including our occupation based measure for diversity of human capital (column 3) we observe a significant positive impact as well. Sign and significance levels of all other results remain the same as in column 1. In column 4 we include industry and occupational diversity together. We can see that both diversity measures have a significant positive relation to GDP-per-capita growth, although industry diversity is only significant at the ten percent level. We tested also squared terms of the respective diversity measures which turned out to be insignificant.

When including our alternative controls for the industry structure (column 5 to column 8) the central results are largely comparable to the specification without controls for the industry structure since the independent variables keep their sign and are still significant. The explanatory power of the model increases only slightly when including the set of industry share variables. The last column contains the results for a full model including all controls and year fixed effects. The coefficient of human capital diversity is significantly positive. We see that the inclusion of additional control variables does not affect the basic results and interpret this as an indication that human capital diversity does not solely grasp the scope of the regional industrial structure.

Next we split up the entropy measure of human capital diversity into two additive components that allow us to measure impact of diversity at different levels of aggregation:[6] an "unrelated" component that measures to which a region's employment is distributed across unrelated occupational groups (i.e. distributed *across* two-digit occupational groups); a related component that measures the distribution of occupations within related occupational groups (i.e. the distribution of three-digit occupations *within* two-digit occupational groups). Related diversity is defined as the weighted sum of the entropy at the

[5] The positive relation with levels of GDP-per-capita that we also observe in our data is consistent with earlier observations using cross country data (Redding and Venables (2004)).
[6] Jacquemin and Berry (1979) offer a detailed discussion about the decomposition of the entropy measure of diversification.

three-digit level within each two-digit occupational group. Unrelated human capital diversity per region is indicated by the entropy obtained through the shares of each two-digit occupational group in the region's total employment.

Maps of the geographical distribution of related and unrelated diversity of human capital are reported in figure A1 and A2 in the appendix. We observe that unrelated diversity is mainly found in less agglomerated regions while related diversity is mainly apparent in the Ruhr-area, around Hanover, and Stuttgart. Introducing related and unrelated diversity into the regressions we find that both, related diversity of human capital is significantly positive correlated to GDP-per-capita growth as long as these variables are separately introduced into the regression (table 2). However, when including related and unrelated diversity into the estimated equation, the coefficient for unrelated diversity is not significant anymore.

Table 2: The impact of related and unrelated human capital diversity on regional GDP-per-capita growth

	IX	X	XI	XII
Human capital diversity I	0.101***	–	0.101***	0.0956***
(related diversity), t-1	(0.017)		(0.018)	(0.018)
Human capital diversity II	–	0.0328**	0.0176	0.0168
(unrelated diversity), t-1		(0.014)	(0.014)	(0.013)
Industry diversity, t-1	0.00357**	0.00537***	–	0.00348**
	(0.0015)	(0.0016)		(0.0015)
Share of employees in	-0.0183*	-0.0181	-0.0204**	-0.0181*
large firms, t-1	(0.011)	(0.011)	(0.010)	(0.010)
Share of high qualified	0.0374***	0.0370***	0.0367***	0.0379***
workers, t-1	(0.0052)	(0.0052)	(0.0050)	(0.0052)
Population density (log), t-1	0.0498***	0.0609***	0.0482***	0.0501***
	(0.016)	(0.016)	(0.016)	(0.016)
Market potential (log), t-1	-0.00675	0.0296	0.0156	0.00569
	(0.069)	(0.072)	(0.072)	(0.071)
Constant	-0.245	-0.793	-0.567	-0.458
	(0.83)	(0.88)	(0.88)	(0.87)
Time dummies	Yes	Yes	Yes	Yes
Controls for industry structure	Yes	Yes	Yes	Yes
F-test	533.5	511.7	516.5	519.8
Log-likelihood	10146	10130	10145	10147
R-squared - within	0.677	0.674	0.677	0.678
R-squared – between	0.0000309	0.000281	0.000307	0.0000389
R-squared - overall	0.0173	0.0104	0.0142	0.0153

Note: Diversity is measured as $-\sum s_i * \ln s_i$, where s_i denotes the employment share of occupation (industry) i. The estimation method is fixed effects regression. Robust standard errors are reported in parentheses. The total number of observation (regions; years) is 2934 (326; 9). The coefficients for 27 out of 28 industry shares and the year dummies are omitted for brevity. Significant at *** 1%, ** 5%, * 10%.

In summary our empirical findings leave us with the strong belief that there is a positive association between regional human capital diversity and growth. This result suggests the

possibility that spillover at the individual level can be beneficial for local economic development.

As a further test for the robustness of our findings we run separate regressions for more homogenous region types by distinguishing agglomerations, moderately congested regions, and rural regions (see table A3). This can be important because diversity of human capital might largely be driven from effects in less dense areas but not in agglomeration, and thus display only a catch-up process[7] – i.e. due to convergence in the share of high qualified workers as documented for West German regions by Südekum (2008). We discover that the effect of human capital diversity only appears to be significant in agglomerations and moderately congested areas. For rural regions we do not see a significant effect for human capital diversity. This finding is in line with the expectation that knowledge spillovers are particularly efficient in dense urban areas where enhanced face-to-face contacts are more likely to occur. Similar arguments can be found in Berliant et al. (2006) illustrating in a search-theoretic framework that agglomerations allow more selective patterns of knowledge exchange, and, therefore, foster the effective transmission of ideas. To check the robustness to different diversity measures, table A4 and A5 in the appendix reports the results when occupational diversity is calculated based on the Herfindahl index. To test an alternative growth measure we also run regressions for regional employment growth in the private sector. Our estimates confirm the significant positive relationship between diversity of human capital and growth when measuring human capital diversity based on the Herfindahl-index. However, when applying the Entropy-index to measure human capital diversity we find only weak evidence for a significant relation at the ten percent level. Another central difference is that population density is negatively related to employment growth (see table A6 in the Appendix). This finding is in line with earlier results for West-German regions.

5. Conclusions

A more vital exchange of knowledge in urban areas is one of the main ideas behind the presence of human capital externalities. In this respect the spatial concentration of high qualified workers is one of the main factors that are important for regional growth. Endogenous growth theories emphasized the importance of human capital to increase

[7] There are two reasons why we believe this robustness check might be of importance. First figure 1 revealed that several dense areas tend to be more specialized with respect to human capital diversity, and second we observe a negative correlation between occupational diversity and population density (see table A1 in the appendix.)

innovative capacities that stimulate continuous growth. In this paper we extend previous literature on local knowledge spillover by considering the skill diversity of human capital. Using detailed regional data on the occupation of employees we are able to proxy the diversity of human capital more accurately then previous studies. We find evidence that diversity of human capital is positively associated with regional growth. Our results are robust to different growth measures, types of regions, time periods, and diversity measures. This illustrates that spillover resulting from diversity in worker skills and abilities can be an important factor for growth. With respect to the micro-foundations of human capital externalities this is a noteworthy result. Nevertheless, future work is needed to expand the findings reported in this paper. At the present stage of analysis we cannot clearly identify where and to which degree externalities occur. Answering the question whether spillover at the level of individuals predominantly emerge within or between firms and industries can be a promising future research direction.

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Appendix:

Table A1. Pairwise correlation coefficients for the GDP-per-capita growth equation:

		1	2	3	4	5	6	7	8	9
1	ΔGDP	1								
2	Human capital diversity (Entropy)	0.045	1							
3	Human capital diversity (Herfindahl)	0.083	0.800	1						
4	Industry diversity (Entropy)	-0.099	0.583	0.284	1					
5	Industry diversity (Herfindahl)	-0.047	0.427	0.206	0.888	1				
6	Share of employees in large firms	0.126	-0.153	-0.211	-0.578	-0.589	1			
7	HQ workers	0.062	0.113	0.117	-0.243	-0.274	0.322	1		
8	Population density	0.028	-0.210	-0.488	-0.175	-0.155	0.587	0.018	1	
9	Market potential	-0.150	0.017	-0.179	0.038	-0.002	0.292	0.110	0.512	1

Abbreviations: ΔGDP: GDP-per-capita growth; Occupational Herfindahl: Human capital diversity calculated as 1-$\sum s_i^2$; Sectoral Herfindahl: Industry diversity calculated as 1-$\sum s_i^2$; Occupational entropy: Human capital diversity calculated as -$\sum s_i$*ln s_i ; Sectoral entropy: Industry diversity calculated as -$\sum s_i$*ln s_i ; HQ-workers: Share of high qualified workers

Note: The number of observations (regions; years) is 2934 (326; 9).

Table A2. Pairwise correlation coefficients for the employment growth equation:

		1	2	3	4	5	6	7
1	Employment growth	1						
2	Human capital diversity (Herfindahl)	0.003	1					
3	Share of employees in large firms	0.032	0.808	1				
4	Human capital diversity (entropy)	-0.041	-0.027	-0.107	1			
5	HQ workers	-0.001	-0.085	-0.347	0.488	1		
6	Population density	-0.055	-0.113	-0.392	0.595	0.638	1	
7	Market potential	-0.050	0.032	-0.152	0.289	0.347	0.510	1

Abbreviations: Employment growth: employment growth in private sector; Human capital diversity (Herfindahl): Human capital diversity calculated as 1-$\sum s_i^2$; Human capital diversity (entropy): Human capital diversity calculated as -$\sum s_i$*ln s_i ; HQ-workers: Share of high qualified workers

Note: The number of observations (regions; years) is 5868 (18; 326). * Significant at 5%.

Table A3. The impact of human capital diversity on regional GDP-per-capita growth

	Agglomerations	Moderately congested regions	Rural regions
Human capital	0.0393**	0.0607***	-0.0150
Diversity, t-1	(0.019)	(0.012)	(0.019)
Industry	0.00697**	0.00291	0.00881***
Diversity, t-1	(0.0029)	(0.0019)	(0.0029)
Share of employees in	-0.0215	-0.0372**	0.0208
large firms, t-1	(0.022)	(0.016)	(0.017)
Share of high qualified	0.0648***	0.0271***	0.0287***
Workers, t-1	(0.0094)	(0.0080)	(0.0077)
Population density (log), t-1	-0.00584	0.0726***	0.0796**
	(0.035)	(0.021)	(0.038)
Market potential (log), t-1	-0.0276	0.155	0.318**
	(0.14)	(0.10)	(0.13)
Constant	0.240	-2.580**	-4.196***
	(1.68)	(1.30)	(1.48)
Time dummies	Yes	Yes	Yes
Controls for industry structure	Yes	Yes	Yes
F-test	164.9	349.5	708.1
Log-likelihood	3611	4434	2256
R-squared - within	0.637	0.694	0.827
R-squared – between	0.00851	0.00836	0.0253
R-squared - overall	0.155	0.0224	0.0327

Note: Diversity is measured as $-\sum s_i * \ln s_i$, where s_i denotes the employment share of occupation (industry) i. The estimation method is fixed effects regression. Robust standard errors are reported in parentheses. The total number of observation (regions; years) is 952 (119; 8) in column 1, 1128 (141; 8) in column 2, and 528 (66; 8) in column 3. The coefficients for 18 out of 19 private industry shares and the year dummies are omitted for brevity. Significant at *** 1%, ** 5%, * 10%.

Table A4. Human capital diversity measure based on Herfindahl-index

	(I)	(II)	(III)
Human capital diversity, t-1	–	0.595***	0.592***
		(0.18)	(0.18)
Industry diversity, t-1	0.00907	–	0.00338
	(0.018)		(0.018)
Share of employees in large firms, t-1	-0.0220*	-0.0230**	-0.0228**
	(0.011)	(0.011)	(0.011)
Share of high qualified workers, t-1	0.0340***	0.0347***	0.0348***
	(0.0052)	(0.0051)	(0.0051)
Population density (log), t-1	0.0596***	0.0589***	0.0590***
	(0.016)	(0.016)	(0.016)
Market potential (log), t-1	0.0211	0.0270	0.0260
	(0.073)	(0.072)	(0.072)
Constant	-0.551	-1.186	-1.175
	(0.88)	(0.87)	(0.87)
Time dummies	Yes	Yes	Yes
Controls for industry structure	No	No	No
F-test	521.9	511.1	509.1
Log-likelihood	10121	10128	10128
R-squared - within	0.672	0.673	0.673
R-squared – between	0.0000997	0.000127	0.000102
R-squared - overall	0.0115	0.0116	0.0118

Note: Diversity is measured as $1-\sum s_i^2$, where s_i denotes the employment share of occupation (industry) *i*. The estimation method is fixed effects regression. Robust standard errors are reported in parentheses. The total number of observation (regions; years) is 2608 (326; 8). The coefficients for 27 out of 28 industry shares and the year dummies are omitted for brevity. Significant at *** 1%, ** 5%, * 10%.

Table A5. Human capital diversity measure based on Herfindahl-index –results for different region types

	Agglomerations	Moderately congested regions	Rural regions
Human capital diversity, t-1	0.684* (0.35)	0.719*** (0.27)	-0.276 (0.30)
Industry diversity, t-1	0.0317 (0.036)	-0.0126 (0.014)	0.0451 (0.028)
Share of employees in large firms, t-1	-0.0299 (0.022)	-0.0400** (0.017)	0.0177 (0.016)
Share of high qualified Workers, t-1	0.0626*** (0.0093)	0.0262*** (0.0081)	0.0278*** (0.0079)
Population density (log), t-1	-0.00382 (0.036)	0.0810*** (0.021)	0.0748* (0.039)
Market potential (log), t-1	-0.0385 (0.15)	0.0726 (0.10)	0.353*** (0.13)
Constant	-0.120 (1.77)	-1.994 (1.35)	-4.411*** (1.56)
Time dummies	Yes	Yes	Yes
Controls for industry structure	Yes	Yes	Yes
F-test	157.8	363.9	723.2
Log-likelihood	3609	4426	2254
R-squared - within	0.635	0.690	0.826
R-squared – between	0.00224	0.0159	0.0211
R-squared - overall	0.158	0.0272	0.0297

Note: Diversity is measured as $1-\sum s_i^2$, where s_i denotes the employment share of occupation (industry) *i*. The estimation method is fixed effects regression. Robust standard errors are reported in parentheses. The total number of observation (regions; years) is 952 (119; 8) in column 1, 1128 (141; 8) in column 2, and 528 (66; 8) in column 3. The coefficients for 18 out of 19 private industry shares and the year dummies are omitted for brevity. Significant at *** 1%, ** 5%, * 10%.

Table A6. The impact of human capital diversity on regional employment growth in private sectors (1987 to 2004)

	(I)	(II)	(III)
Human capital diversity (Entropy), t-1	–	0.0559*	–
		(0.033)	
Human capital diversity (Herfindahl), t-1	–	–	1.245***
			(0.41)
Share of employees in large firms, t-1	-0.401***	-0.420***	-0.420***
	(0.11)	(0.12)	(0.12)
Share of high qualified workers, t-1	0.883**	1.036**	1.021**
	(0.41)	(0.46)	(0.45)
Population density (log), t-1	-0.0570**	-0.0774***	-0.0714**
	(0.026)	(0.029)	(0.028)
Market potential (log), t-1	-0.136	-0.101	-0.113
	(0.22)	(0.23)	(0.23)
Constant	2.061	1.490	1.593
	(2.74)	(2.82)	(2.60)
Time dummies	Yes	Yes	Yes
Controls for industry structure	Yes	Yes	Yes
F-test	135.7	127.6	128.4
Log-likelihood	11662	10915	10922
R-squared - within	0.352	0.360	0.362
R-squared – between	0.0460	0.0433	0.0430
R-squared - overall	0.0316	0.0281	0.0289

Note: Diversity for the Herfindahl index is measured as $1-\sum s_i^2$ and diversity for the entropy index is measured as $-\sum s_i * \ln s_i$., where s_i denotes the employment share of occupation i. The estimation method is fixed effects regression. Robust standard errors are reported in parentheses. The total number of observation (regions; years) is 5542 (326; 17). The coefficients for 27 out of 28 industry shares and the year dummies are omitted for brevity. Significant at *** 1%, ** 5%, * 10%.

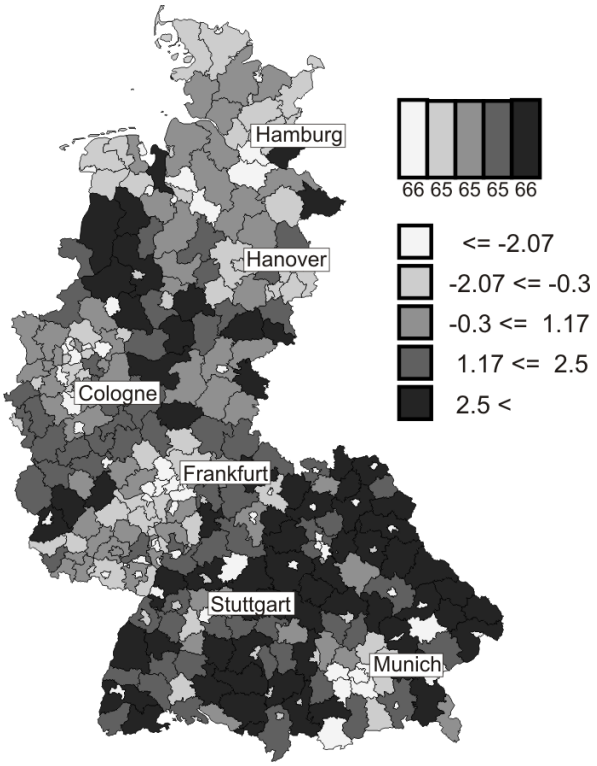

Figure A1. Regional distribution of unrelated-diversity of human capital (percentage deviation from the average regional unrelated-diversity of human capital, 1995-2002)

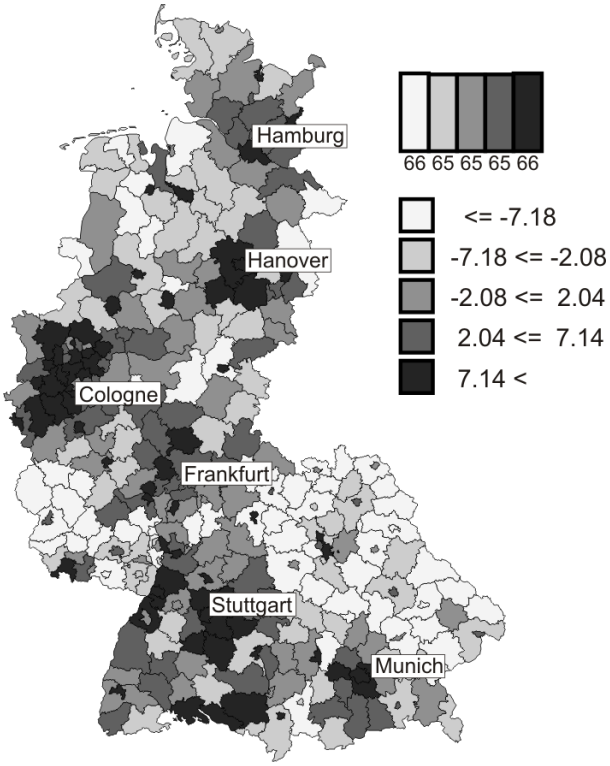

Figure A2. Regional distribution of related-diversity of human capital (percentage deviation from the average regional related-diversity of human capital, 1995-2002)