Convergence of the Skill Composition across German Regions

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Abstract
There is considerable variation in the skill composition of employment across cities and regions. The way how skill compositions evolve over time sheds light on the strength of concentration forces for high-skilled workers, such as localized increasing returns to human capital. In this paper I report robust evidence that regions with a large initial share of high-skilled workers had higher *total* employment growth in West Germany (1977-2002), but lower growth of *high-skilled* jobs. There has been a convergence of local skill compositions over time, on average and even within particular industries. These stylized facts for the German economy contrast available evidence from the US, where researchers have identified a divergence trend. My findings suggest that concentration forces in Germany are not strong enough to trigger a self-reinforcing spatial concentration of high-skilled workers. Some potential reasons for the differences with the US are also discussed.

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1) Introduction

Economists have discussed various micro-foundations for agglomeration, such as pooling advantages on factor markets, more vital exchange of ideas and knowledge in dense urban areas, or linkages due to endogenous market size effects.[1] Human capital is likely to be an important catalyst for these agglomeration mechanisms. If, for example, density generates knowledge spillovers via enhanced face-to-face contact, it will mainly be the spatial concentration of high-skilled workers – rather than just workers in general – that raises local productivity and that generates agglomeration effects. In reduced form, this would suggest the presence of a *human capital externality*. Lucas (1988) emphasizes that local environments are the natural spatial scale on which these externalities should be studied, as spillovers exhibit a rapid spatial decay (Audretsch and Feldmann, 1996).

This paper is concerned with the evolution of the skill composition of West German NUTS3-regions (1977-2002), and its interrelations with local growth. If regions with a high concentration of skilled workers are more productive, they should pay a wage premium: Observationally equivalent workers should earn more in skill abundant areas, as argued by Rauch (1993) or Moretti (2004a).[2] If "skilled cities" pay a wage premium, they should attract further workers, and in particular high-skilled individuals who tend to be geographically more mobile (Dahl 2002, Gobillon and Le Blanc 2003, Hunt 2004) and who tend to earn a larger premium (Gould 2007). This may, in turn, raise local productivity even further.

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[1] For an overview of these and related issues, the readers may refer to the recent *Handbook* by Henderson and Thisse (2004), in particular to the chapters by Duranton and Puga (2004) and Rosenthal and Strange (2004).

[2] Recent attempts to identify these externalities empirically have encountered various difficulties in disentangling them from other effects and yielded inconclusive results. Whereas Rauch (1993) and Moretti (2004a) argue that externalities exist, there is an opposite view by Acemoglu and Angrist (2002) and Ciccone and Peri (2006) that they cannot be identified in US data. For an overview about human capital externalities in cities, see Moretti (2004b) or Duranton (2006). Related evidence is provided by Glaeser and Marè (2001), Yankow (2006) and Gould (2007) who find a "true" urban wage premium that does not reflect ability sorting or compensation for higher living costs, although sorting also plays an important role (see Combes et al. 2008). Moeller and Haas (2003) confirm the presence of an agglomeration wage premium in Germany, which is related to human capital externalities as highly educated people are abundant in cities. They show that the wage premium is larger for high-skilled than for low-skilled workers. This is consistent with the recent results by Gould (2007) that an urban wage premium exists for white-collar but not for blue-collar workers. In this paper I make no further attempt to measure or to quantify this wage premium. I am rather concerned with its *consequences* for the spatial evolution of the skill composition of employment.

The presumption that "smart cities" grow faster than unskilled ones has, in fact, been confirmed for the US in several papers that find a robust positive correlation between the initial employment share of college educated workers and subsequent *total* employment/population growth of MSAs and cities (Glaeser et al., 1995; Simon, 1998; Simon and Nardinelli, 2002). The main reason *why* skilled cities grow faster seems to be the positive impact on local productivity that translates into equilibrium employment gains (Shapiro, 2006; Glaeser and Saiz, 2004). Moreover, a few recent papers (Moretti, 2004b; Berry and Glaeser, 2005; Wheeler, 2006) argue that there has even been a tendency of increasing inequality in the skill composition across US cities and MSAs. Relatively skilled areas became increasingly skilled over time, i.e., there has been a *divergence* trend within the US.

This "smart city" literature has largely focussed on the US so far.[3] But do these trends show up similarly in other developed countries, such as Germany? In this paper I report some robust evidence for a positive impact of the initial employment share of high-skilled workers on subsequent *total* employment growth at the local level, which is consistent with the developments in the US. Yet, there is also an important difference. I show that there has been a *convergence* of the skill composition of West German regional employment over time, which is different from the US experience. Moreover, I not only find that high-skilled employment shares have tended to become more similar across regions *on average*, but that this convergence has even occurred within particular industries.

These stylized facts shed light on the strength of concentration forces for high-skilled workers. In a straightforward neoclassical model with identical locations and without second-nature agglomeration forces one would expect such a convergence of regional relative factor intensities of skilled and unskilled labor. According to a standard supply effect, skilled workers are more productive in areas where human capital is initially relatively scarce.

[3] There are various papers that address related issues for European countries, e.g. Ciccone (2002), Gobillon and Le Blanc (2003), Redding and Sturm (2004) or Rice et al. (2006). The most closely related study on Europe is the one by Simon and Nardinelli (1996), who address the effects of the initial high-skilled employment share for employment growth of British cities between 1861 and 1961.

Starting off from an initial spatial distribution, skilled employment should grow faster in unskilled areas, e.g. due to the migration of skilled workers.[4] This can change if localized human capital externalities in the spirit of Lucas (1988) are introduced. If increasing returns to human capital are sufficiently strong, there will be higher nominal wages for skilled workers in skill abundant areas, which according to Moretti (2004a) is in fact the case in the US. A self-reinforcing spatial concentration of skilled workers would only occur, however, if the externalities are strong enough to compensate the neoclassical supply effect *and* other evident dispersion forces such as congestion or higher housing prices. Hence, a spatial divergence trend of local skill compositions, as observed by Moretti (2004b) or Berry and Glaeser (2005), suggests that a *strong* concentration force for high-skilled workers is operating in the US. My empirical findings of a spatial convergence trend in West Germany suggest, in contrast, that concentration forces are not sufficiently strong relative to the sum of opposing centrifugal forces to trigger a self-reinforcing divergence trend. My findings do not suggest, however, that concentration forces or human capital externalities do not exist at all.

The rest of this paper is organized as follows. In section 2 I introduce the data set and present a descriptive overview. The statistical analysis and the main results are presented in section 3. In section 4 I summarize the empirical facts for West Germany, and I discuss the differences with the related evidence from the US.

2) Data and descriptive overview

For this study I use the official employment statistics provided by the Institute of Employment Research (IAB) of the German Federal Employment Agency. This highly reliable official data

[4] An illustrative formal model has been presented by Südekum (2006a). In that model, a country consists of multiple identical locations where a single good is produced under perfect competition by using skilled and unskilled workers. Only skilled labor is mobile across space whereas unskilled labor is a fixed factor. First nature differences (amenities) are completely assumed away. A human capital externality is introduced by assuming that location-specific total factor productivity depends on the aggregate skill intensity of a city. Furthermore, housing costs rise as skilled workers concentrate in one city. That model illustrates the trade-off between human capital externalities in the spirit of Lucas (1988), and the neoclassical supply effect and housing congestion.

set entails the complete population of full-time employment relationships in West Germany (excluding West Berlin) subject to social security. Employment is observed annually from 1977 until 2002 on the spatial scale of 326 NUTS3-regions ("Landkreise"), which are roughly comparable to US counties. The data refers to *workplace* location. In each region employment in 28 different industries can be distinguished, which are reported in the appendix together with some further details about the data set. Most important for this study, I know the employment shares of three qualification groups for each local industry: workers without any vocational qualification (low-skilled workers), completed apprenticeship (medium-skilled workers), and completed tertiary education (high-skilled workers).

Turning to a brief descriptive overview, it is quite remarkable that the total number of regular full-time jobs in all of West Germany has remained almost the same over the whole observation period (at around 16.2 million). Yet, the number of high-skilled jobs has more than doubled to roughly 1.5 million in 2002. The average employment share of high-skilled workers has, thus, sharply increased from 3.7% in 1977 to 9.5% in 2002, but these numbers hide strong differences between individual regions. High-skilled employment shares differ by a factor larger than 10 across regions. Among the "smartest cities" are large metropolitan areas like Munich or Hamburg, but also several medium-sized and strongly specialized cities.

Regarding the change in this skill intensity over time, figure 1 suggests that the initial level and the long-run growth rate of the local high-skilled employment shares are decisively negatively correlated.[5] This finding of "β-convergence" can be complemented by a view on the time trend of the variation coefficient of local high-skilled employment shares (weighted standard deviation divided by the average share in every year). One finds a steady decline in cross-district dispersion ("σ-convergence") over the observation period that is particularly sharp from 1977-1995 and then flattening out in the post-unification period.

[5] In fact, the city with the highest *growth rate* (Wolfsburg, the headquarter location of *Volkswagen*) was the city with the second-lowest *initial level* in 1977, whereas Erlangen (headquarter location of *Siemens*) and Munich revealed the highest initial level of the high-skilled employment share in 1977, but were among those with the lowest growth rates of this share over the period 1977-2002.

[FIGURE 1 ABOUT HERE]

Along industry dimensions, the range of high-skilled employment shares goes from below one per cent (gastronomy) to more than 30 per cent in the education sector (in 2002). The correlation with the long-run industry employment growth rates is 0.493, which suggests that skilled industries grew faster. These numbers emphasize that industry compositions should be taken into account, in order to disentangle if there is an independent effect of skilled labor on local employment growth that does not simply reflect a spurious correlation with the local specialization pattern (see Simon 2004). Below we will also consider if the spatial trend of human capital has been different within particular industries than on average.

3) Empirical specification and results

In this section I turn to the more formal statistical analysis. First I present a simple but informative cross-section analysis on the determinants of total and qualification-specific local employment growth rates (section 3.1.), before turning to dynamic panel estimation in section 3.2 and to an industry-by-industry analysis in section 3.3.

3.1. Cross-section analysis

To test the "smart city hypothesis" in the most basic way, I regress long-run growth rates of total local employment on local base year characteristics. Growth rates are computed for the period 1985-2002, but all control variables are computed for the year 1977.[6] The central explanatory variable is the initial employment share of high-skilled workers. As additional controls I use the employment share of medium-skilled workers, employment density (total employment over area size in km^2), and a proxy for the local firm size structure.[7]

[6] This addresses issues of reverse causality. It seems implausible to argue that skilled workers have moved to a particular city in 1977 because they expected growth to be strong from 1985 onwards.

[7] A glance at correlation tables suggests that the high-skilled employment share is positively correlated with the employment share in large firms (ρ = 0.550), but that share is *negatively* correlated with employment growth

Furthermore, local growth may not only be driven by local variables, but also by the proximity to other markets. To sort this out I include a Harris-type market potential function, which is a distance-weighted sum of total employment in all other districts (see Redding and Sturm 2004). Finally, I control for the local industry composition by including the initial employment shares in 27 out of 28 industries in the base period. Table 1 reports the results.

[TABLE 1 ABOUT HERE]

The benchmark specification in column 1 shows that the effect of the initial employment share of high-skilled workers with university degree on total local employment growth is significantly positive and quite sizeable. One should keep in mind that the usual German university degree (diploma) is actually closer to a Master's than to a Bachelor's degree, which is the skill variable typically used in US studies. At the same time, German medium-skilled workers with completed apprenticeship have also received post-secondary education and often possess complex on-the-job-skills. They may therefore also be regarded as "skilled", although it is a well documented fact that their average earnings are considerably below those of university graduates (see e.g. Moeller and Haas 2003). Column 1 suggests that the share of medium-skilled workers also has a significantly positive, yet considerably smaller effect on total local employment growth. When combining high- and medium-skilled workers into one group (column 2), I also find a positive and significant effect on total employment growth. However, the effect of the skill composition on local employment growth appears to be mainly driven by the share of workers with a university degree in Germany.

Comparing columns 1 and 3, it becomes obvious that an omission of firm size structures leads to a downward bias in the coefficient for skill intensity (cif. footnote 7). An omission of the industry composition on the other hand leads to an upward bias, because high-skilled labor is more prevalent in booming industries. Yet, the comprehensive specification 4 shows that the

(ρ = –0.502). To avoid omitted variable bias an inclusion of proxies of the local firm size structure seems important. Another study that emphasizes the importance of firm sizes for regional employment growth is Combes et al. (2004), who have no information on local qualification structures.

impact of high-skilled workers on total employment growth remains qualitatively robust even when the industry composition is controlled for, which suggests that the effect is not simply a spurious correlation.[8] As for the other variables, I find a significantly negative impact of (log) density on total employment growth, which represents the well-documented trend of secular employment de-concentration in West Germany (see e.g. Südekum 2006b). The impact of the market potential variable is positive but statistically not distinguishable from zero.

In columns 5 and 6 the dependent variable is the long-run growth rate of low-skilled, and respectively, of high-skilled employment. The initial share of high-skilled workers strongly raises subsequent growth of low-skilled jobs. The coefficient is almost three times as large as the estimated effect on total employment growth. Yet, I find a decisively negative effect on high-skilled employment growth. This finding, which is consistent with convergence of local skill compositions, becomes even clearer in column 7. The effect of the initial level on the subsequent growth rate of the high-skilled employment share is negative and highly significant. In sum, these results suggest that "smart" German cities exhibit faster total employment growth, but that there is also a convergence of the local skill compositions.

3.2. Panel analysis

Drawing conclusions from the cross-section analysis is problematic, however, because the local skill composition might proxy for unobserved time-invariant local characteristics that drive employment growth. This approach also imposes a rigid timing: A historical high-skilled employment share is assumed to influence long-run growth. However, it may rather be the *current* skill composition that influences short-run growth. In this subsection I turn to dynamic panel analysis à la Arrelano and Bond (1991) to include fixed effects, to sort out the relevant time structure of the effects, and to control more formally for endogeneity.

[8] I omit the 27 estimated coefficients for the initial industry employment shares for brevity. The results I obtain are plausible. E.g., regions grew significantly faster if the initial employment share in industries like IT, automobile or modern services was large, whereas regions with a large agricultural share grew slower.

To verify the validity of the basic "smart city hypothesis" I estimate the following equation

$$\mathbf{log}\left(emp_{c,t}\right)=\alpha+\mu_c+\lambda_t+\sum_{s=1}^{L}\left(\rho_s\cdot\mathbf{log}\left(emp_{c,t-s}\right)+\beta_s\cdot hq_{c,t-s}+\gamma_s\cdot X_{c,t-s}\right)+\varepsilon_{c,t}\ , \qquad (1a)$$

where $emp_{c,t}$, is total city employment, $hq_{c,t-s}$ is the time-lagged high-skilled employment share in city c, $X_{c,t-s}$ are the other exogenous variables, λ_t is a time fixed effect, μ_c a regional fixed effect, and $\varepsilon_{c,t}$ is the error term. Following Arellano and Bond (1991) I use the GMM method to get consistent estimates for the unknown coefficients.[9] If the "smart city hypothesis" holds I expect to find positive coefficients β_s, since this implies a positive impact of the high-skilled employment share on total employment growth at the local level.

Secondly, to address the convergence/divergence of the local skill compositions I use the log of the high-skilled employment share in city c, $hc_{c,t}$, as the dependent variable. I estimate the following equation, also by using the GMM method described above

$$\mathbf{log}\left(hc_{c,t}\right)=\alpha+\mu_c+\lambda_t+\sum_{s=1}^{L}\left(\rho_s\cdot\mathbf{log}\left(hc_{c,t-s}\right)+\beta_s\cdot dens_{c,t-s}+\gamma_s\cdot X_{c,t-s}\right)+\varepsilon_{c,t}\ , \qquad (1b)$$

Of particular interest in this specification are the autoregressive coefficients ρ_s. If skill compositions exhibit a convergence trend, these coefficients should be well below unity. This mean reversion would be inconsistent with the idea that local growth of high-skilled employment "feeds on itself". Divergence would instead be associated with autoregressive coefficients that exceed unity.[10]

[TABLE 2 ABOUT HERE]

[9] The above equation is transformed into first differences, so that time-lagged dependent variables can be used as instruments (Anderson and Hsiao, 1982; Arellano and Bond, 1991). Crucial for their validity is the assumption about the order of autocorrelation of the error term. Under the assumption of serially uncorrelated $\varepsilon_{c,t}$, the first differenced error terms $\varepsilon_{c,t}$-$\varepsilon_{c,t-1}$ follow a MA(1) process, so $emp_{c,t-s}$ (s=2,3,…) are valid instruments for $\Delta emp_{c,t-1}$. Furthermore, we assume that other right-hand side variables $X_{c,t}$ are strictly exogenous with respect to $\varepsilon_{c,t}$. Test statistics for these assumptions are presented below.

[10] According to Berry and Glaeser (2005) and Wheeler (2006) this coefficient should be larger than one in the US, since they argue that local growth of high-skilled employment is self-reinforcing. Both papers do not check the robustness of their results in a dynamic GMM model, however, but they suffice with the inclusion of a lagged dependent variable in a more traditional approach.

Table 2 presents the estimation results for equations (1a) and (1b), and refers to a parsimonious specification with L=4 time lags. The left table verifies the basic "smart city hypothesis" and suggests that it is rather the current than some historical skill composition that matters for total city employment growth. There is a strongly significant positive effect of the high-skilled employment share in period t-1 on total local employment growth. Over time this effect is dying out quickly, with insignificant coefficients for s>2. Total employment exhibits mean reversion with considerable inertia. This follows from the autoregressive coefficients, which are below but fairly close to one in the short run. I.e., holding skill compositions constant, I find that small regions catch up slowly in terms of total employment. Consistent with the OLS analysis I find no significant effect stemming from market potential.

The right hand side of table 2 confirms the finding of converging skill compositions. The autoregressive coefficients on the lagged high-skilled employment shares are decisively below one, and also decrease rapidly over time: The coefficients of higher-order time lags are far smaller than ρ_{-1}, and there are no significant effects for s>3. These results turn out absolutely robust in alternative specifications of the dynamic panel model (with different time lags, two-step estimation, etc.). In sum, I find no evidence for self-reinforcing local growth of high-skilled employment, but rather for a convergence of local skill compositions.

3.3. Analysis industry-by-industry

The specification (1b) only addresses the evolution of the skill composition of entire regions. However, skill compositions within particular industries may exhibit a different trend than the average.[11] For example, human capital externalities may be internal to industries, and are supposedly stronger in modern sectors (such as information technology and business-related services) than in traditional low-tech manufacturing and basic services. This may lead to a

[11] Desmet and Fafchamps (2005, 2006) emphasize that different industries may exhibit different spatial trends. They find that service industries become increasingly concentrated in the US whereas manufacturing tends to spread out. Their focus does not lie on the evolution of local skill compositions, however.

divergence of the skill composition within certain industries despite an aggregate convergence trend. The spatial evolution of skill compositions within particular industries may also be affected by localization forces, i.e., by how strongly regions are specialized in the respective sector, and potentially also by cross-industry effects, i.e., by the diversity of human capital in other sectors in the same location.[12]

To address these issues, I re-estimate equation (1b) on the level of local industries by using the following specification for every sector $j = 1,...,28$:

$$\log\left(hc_{c,j,t}\right) = \alpha + \mu_{c,j} + \lambda_t + \sum_{s=1}^{L}\left(\rho_{s,j} \cdot \log\left(hc_{c,j,t-s}\right) + \beta_{s,j} \cdot X_{c,j,t-s}\right) + \varepsilon_{c,j,t} \qquad (2)$$

where $\mu_{c,j}$ is a location and industry specific fixed effect. The autoregressive coefficients $\rho_{s,j}$ now indicate whether local high-skilled employment shares within industry *j* converge or diverge over time.

Two additional exogenous variables are included as compared to (1b). First, to capture own-industry localization effects I include the commonly used location quotient of industry *j*, which is defined as the local over the national employment share of that industry in the respective years (see e.g. Combes 2000). To capture cross-industry effects I have experimented with different indices. The most interesting results are obtained when I include a diversity index of high-skilled employment that measures the degree of specialization of the surrounding human capital in other industries in the same location. This index, $DIV_{c,j,t} = \sum_{s=1,s\neq j}^{28}\left|\left(skilled_{s,c,t}/emp_{s,c,t}\right)-\left(skilled_{s,t}/emp_{s,t}\right)\right|$, is a variant of the familiar Krugman-index and related to the Herfindahl-specialization index. It is equal to zero if the surrounding local skill structure (measured by the high-skilled employment shares of all other local industries except *j*) exactly matches the national average. It increases with the degree of

[12] The inclusion of these variables is reminiscent of the voluminous literature on diversity vs. specialization (see Glaeser et al. 1992; Henderson et al. 1995; Henderson 1997; Combes 2000; Combes et al. 2004; Blien et al. 2006), which looks at the impact of the local economic structure on growth of local industries. That literature has traditionally used total employment growth as the dependent variables but does not address the skill composition of employment. Here I use similar RHS variables but high-skilled employment as the dependent variable.

idiosyncrasy of the local knowledge, i.e., when the industries in city *c* exhibit a different skill-intensity pattern than the national average.[13]

Table 3 presents results for the industry-by-industry analysis. For expositional purposes I do not report the detailed results for all 28 industries, but I focus on some selected findings. In short, in *none* of the industries there is evidence for a self-reinforcing spatial concentration of high-skilled employment. The autoregressive coefficients are below one throughout, and in all cases I find a predominant impact of the short-run time lags.

[TABLE 3 ABOUT HERE]

The speed of the mean reversion process of the local high-skilled employment shares differs across industries, however. The fastest convergence speed is found in “commerce and retailing”. In the business-related service sector we find instead the strongest inertia, followed by “information technology and optic industry” and “energy”. These findings appear quite plausible, since the latter are examples of modern and skill-intensive industries where the scope for knowledge spillovers and human capital externalities appear to be stronger than for the average industry. This per se suggests a more persistent spatial concentration of human capital in these sectors. Nonetheless, even for these industries there is no evidence for a divergence of the local skill compositions, but rather for a (slow) mean reversion of the industry-specific high-skilled employment shares. The strength of mean reversion in the 26 other industries ranges in between the polar cases reported in columns 4 and 5 of table 3.[14] When lumping all manufacturing and all service industries together (see columns 2 and 3), I find that the latter display a somewhat faster mean reversion of their skill compositions.

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[13] The measure *DIVc,j,t* can be seen as a specialization index for the local stock of knowledge from the point of view of an industry *j*. I have also performed several further regressions where *DIVc,j,t* is replaced by the average high-skilled employment share of all other industries except *j* in the same city, or with a conventional Herfindahl-index of (high-skilled) employment shares of other industries. These specifications yielded mostly insignificant coefficients, however. The other estimated coefficients, notably the autoregressive ones, turned out to be very robust to different specifications of cross-industry effects.

[14] This finding is consistent with descriptive evidence. I have computed industry-specific variation coefficients for local high-skilled employment shares. For all sectors I find a declining time trend in cross-city dispersion.

As for the other control variables, I find that density and market potential do not play important roles for high-skilled employment growth on average, although denisty does matter in some industries such as the business-related services. Consistent with several previous studies I find mostly significantly negative effects of localization on employment growth (see Glaeser et al. 1992; Combes 2000; Blien et al. 2006), even though there are also some exceptions. This result should be viewed with caution, however, since the dependent variable does not measure productivity directly, so that there is still room for intra-industry knowledge spillovers (MAR externalities) although they do not seem to translate into employment gains for high-skilled workers (on that point, see Cingano and Schivardi 2004). Furthermore I find that high-skilled employment growth of local industries is positively affected when the skill structure of the local environment does not mirror the average national pattern, but if it is idiosyncratic in the sense that some industries are skill intensive in the region that are not as skill intensive in the national average (and vice versa). More generally, this finding suggests that industries are also affected by the skill composition of other industries in the same location. The main message of table 3, however, is that there is no evidence for self-reinforcing spatial concentration of high-skilled workers within particular sectors.

4. Summing up and interpreting the evidence

I will now summarize the stylized facts for West Germany, and contrast them with previous findings from the related literature. I hope to have conveyed the following three main facts:

1. The local share of high-skilled workers is positively related to subsequent total local employment growth. I.e., “skilled” German regions have exhibited faster total employment growth than “unskilled” German regions, overall.

2. In contrast, the local share of high-skilled workers is robustly negatively related to subsequent growth of high-skilled employment. There has been a convergence of the skill composition of employment across regions over time.
3. This convergence trend has occurred, at different speed, even within single industries. In none of the cases there is evidence for a divergence of the local skill compositions.

There is a substantial literature that has established fact 1 for US cities and metropolitan areas, see Glaeser et al. (1995), Simon (1998, 2004), Simon and Nardinelli (2002), Glaeser and Saiz (2004), or Shapiro (2006). It seems warranted to conclude that this stylized fact also shows up in West Germany. This is already an important observation, because the robustness of the "smart city hypothesis" in countries other than the US has rarely been studies so far.

The main difference between West Germany and the US refers to fact 2. Only few papers have analyzed the evolution of local skill compositions of employment. These papers, namely Moretti (2004b), Berry and Glaeser (2005) and Wheeler (2006), interestingly find an opposite trend of spatial divergence in the US. My findings suggest that this development has been different in West Germany, since there is clear evidence for a convergence trend. Fact 3 makes this observed difference even stronger: Even within certain modern industries, where the scope for spatial concentration forces is supposedly stronger than on average, I cannot observe a divergence trend. To my knowledge, such industry-specific spatial trends in the skill composition of employment have not been studied so far.

These stylized facts for the German economy suggest that concentration forces for high-skilled workers are not sufficiently strong to generate a self-reinforcing spatial concentration. This does *not* imply, however, that agglomeration effects are absent in Germany. The findings by Moeller and Haas (2003) which are based on individual earnings data suggest that an agglomeration wage premium exists in Germany as well. This may be interpreted as indirect evidence for the existence of localized increasing returns to human capital. But this effect is apparently not strong enough to outweigh countervailing dispersion forces.

The natural next question to ask is: *What* explains the difference between Germany and the US? W*hy* has there been a divergence in local skill compositions in one country but not in the other? In this paper I do not aim at providing an in-depth answer for this difficult question, but I have concentrated on taking the first step: To collect new stylized facts, and to contrast them with existing ones. Providing a detailed explanation for these differences is left for further research.

Nonetheless, it seems tempting to discuss at least some possible causes. The cross-country difference in the spatial trends of local skill compositions will probably be related to other well known differences between the labor markets in these two countries. Firstly, it is well documented that regional labor mobility is considerably lower in European countries than in the US (Decressin and Fatas 1995). Consistent with the large body of literature (e.g., Gobillon and Le Blanc 2003), it is still the case that high-skilled workers are geographically more mobile than unskilled workers in West Germany (Hunt 2004, Haas 2000). Mobility, in particular among high-skilled workers, has also increased during the 1990s in West Germany (Haas 2000), but it still remains low compared to the US. Oswald (1999) argues that one crucial reason for lower overall labor mobility is a higher rate of homeownership, and more generally, the stiffer regulation of housing markets in Europe which tend to increase moving costs. Another reason for the lower mobility of Europeans may be the stronger attachment to home, i.e., a higher implicit willingness to pay for certain regional amenities. A second well-documented difference is that access to post-secondary education in Germany has been tuition-free over the observation period, i.e., the direct costs of education have been lower.

Coupling these lower education costs with the lower labor mobility may lead to one interesting story for approaching the cross-country differences. As a result of the higher overall spatial mobility and the higher direct costs of education, college attendance rates tend to be lower in poor, low-human capital states in the US (IES 2006).[15] Fewer people can afford college enrolment in poorer states, and more students migrate to high-skilled areas. These developments are consistent with a divergence trend of local skill compositions. The relationship between human capital intensity and college attendance rates is much less clear for German regions; the two variables are in fact virtually uncorrelated.[16] This together with the lower overall labor mobility suggests that endogenous education decisions are not likely to trigger a divergence trend of local skill compositions, but rather an equalizing convergence trend, which is consistent with the empirical evidence that is established in this paper.

This suggested interpretation is of course just one hypothesis what may be behind the observed differences between Germany and the US. Another interesting hypothesis that future work may want to explore is that the mean reversion of skill compositions in Germany is driven by older generations, whereas the spatial trends of the skill composition of younger age cohorts are more similar to those observed in the US. Peri (2002) argues that young skilled workers are, in particular, attracted by other skilled workers due to localized externalities in the process of human capital accumulation. I.e., among young workers it appears more plausible to expect a divergence trend of local skill compositions than among all workers. Given that young workers in Germany are more mobile than older workers (Hunt 2004), and that labor mobility has generally increased in Germany recently (Haas 2000), it may even be that the spatial trends of local skill compositions in Germany change in the future and become more similar to those in the US.

[15] College attendance rates measure the share of students who enrol in a college in the same state where they received their college attendance eligibility (high school diploma).

[16] Regional college attendance rates are note available for NUTS3-regions in Germany, but for German federal states (Länder). They are provided by the Higher Education Information System (www.HIS.de) for the year 2002. The correlation of the college attendance rates by state with the average share of high-skilled workers in total state employment is as low as 0.02. Also for other European countries there is little systematic evidence that the skill composition of regional employment affects individual decisions to enrol in post-secondary education. Rephann (2002) uses Swedish panel data to estimate the determinants of individual schooling decisions. He finds a predominant impact of individual and family background variables, whereas current characteristics of local labor markets have no or only a very modest effect.

Appendix: Details about data set

The data in the balanced spatial panel is not subject to any censoring. For each local industry and year the following information is available:

- the total employment level of full-time employees ($\geq$ 35 working hours per week) referring to workplace location
- the employment shares in medium-sized (20-99) and large (>100) establishments. Residual share is employed in small establishments (<20 workers).
- employment share of workers with completed tertiary education, respectively with completed apprenticeship. Residual share: Workers without formal vocational qualification.

The 28 different industries that are distinguished in the data set are: Agriculture, Mining, Electronics, Chemical Industry, Synthetic Material, Non-metallic Mineral Mining, Glass & Ceramics, Primary Metal Manufacturing, Machinery, Automobile, Office Supplies & IT, Toys & Jewellery, Wood-working, Paper & Printing, Leather & Textile, Food & Tobacco, Building & Construction, Transportation, Banking & Insurance, Hotels & Gastronomy, Health Care, Business-Related Services, Education, Leisure-Related Services, Household-Related Services, Social Services, Commerce and the public sector. Data for the public sector contains only public employees with social security contributions but no civil servants, who are exempted from the social security system.

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Figure 1: Initial level and long-run growth rate of local human capital shares (N=326)

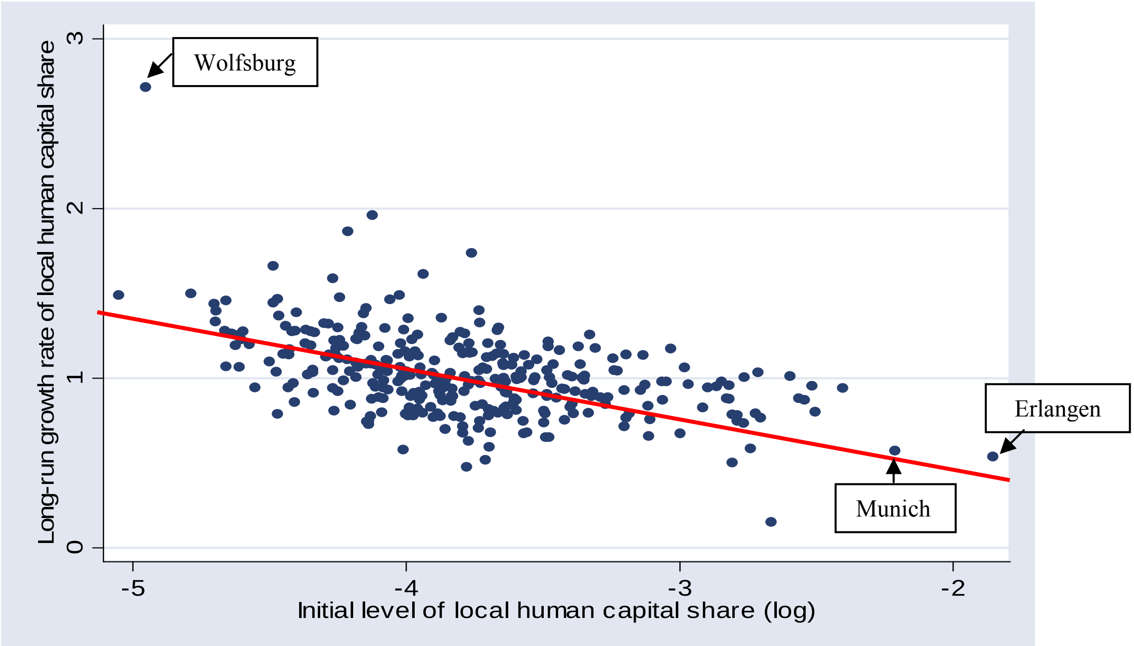

Table 1: Cross-section analysis (N=326)

	Total city employment growth				Low-skilled empl. growth	High-skilled empl. growth	Growth rate of high-skilled empl. share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
High-skilled employment share	2.0436*** (.6231)	--	2.2209*** (.4822)	1.3672** (.6739)	3.7678*** (1.0711)	- 2.5277** (1.090)	- 3.9290*** (1.098)
Medium-skilled employment share	0.4523*** (.1493)	--	0.3959*** (.1228)	- 0.0540 (.1327)	0.3559* (.2109)	- 0.1898 (.2737)	- 0.1293 (.2163)
(High- + medium-skilled) employment share	--	0.5649*** (.1541)	--	--	--	--	--
employment density (log)	- 0.0763*** (.0071)	- 0.0667*** (.0058)	- 0.0564*** (.0084)	- 0.0439*** (.0110)	- 0.0298* (.0175)	- 0.0058 (.0227)	0.0381** (.0179)
market potential (log)	0.0107 (.0240)	0.0166 (.0240)	0.0151 (.0249)	- 0.0177 (.0274)	0.0850* (.0435)	0.0659 (.0565)	0.0824* (.0446)
large firms employment share	--	--	- 0.3781** (.1684)	- 0.7012*** (.2224)	- 1.9721*** (.3535)	- 0.769* (.4588)	- 0.0729 (.3626)
medium-sized firms employment share	--	--	- 0.1819 (.3153)	- 0.4991 (.3371)	- 1.9226*** (.5357)	- 0.6376 (.6953)	- 0.1452 (.5494)
Constant term	- 0.0919 (.2913)	- 0.2305 (.2940)	0.0333 (.3374)	0.0364 (.4339)	- 0.8586 (.6896)	- 0.2138 (.8951)	- 0.2352 (.7073)
Control for initial industry composition	NO	NO	NO	YES	YES	YES	YES
R^2	0.3518	0.3312	0.3786	0.6287	0.6165	0.4040	0.3449

Note: The estimated specification in columns 1-4 is $log\left(emp_{c,2002}/emp_{c,1985}\right) = \alpha + \beta \cdot X_{c,1977} + \varepsilon_c$, where $emp_{c,t}$ is total employment of city c=1,…,326 in year t=1977,…2002. In column 5 the dependent variable is $log\left(unskilled_{c,2002}/unskilled_{c,1985}\right)$ and in column 6 it is $log\left(skilled_{c,2002}/skilled_{c,1985}\right)$. In column 7 the dep.var. is $log\left(hq_{c,2002}/hq_{c,1985}\right)$, where $hq_{c,t}=skilled_{c,t}/emp_{c,t}$ is the high-skilled employment share in city c at t. The control variables $X_{c,1977}$ are for the base period 1977. Employment density is defined as $dens_{c,1977} = emp_{c,1977}/areasize_{c,1977}$. Market potential is defined as $MP_{c,1977} = \sum_{c' \neq c}\left(emp_{c,1977}/dist_{c,c'}\right)$ where $dist_{c,c'}$ is the distance in km between the geographical centres of local areas c and c´. Large (medium-sized) firms are defined as having more than 100 (resp., 20-99) full-time employees. In columns 4-7 we include the initial employment shares of 27 industries in city c, leaving one employment share out to avoid perfect multi-collinearity. We omit the estimated coefficients for brevity. Estimation method is OLS with robust standard errors. Robust standard errors are reported in parentheses. Significance levels are indicated as: ***) 1%, **) 5%, *) 10%.

Table 2: Dynamic panel analysis – total local employment (NOBS=6846, number of groups=326)

Dep. var.: *log(employment$_{c,t}$)*		**eq. (1a)**	
employment$_{c,t-s}$ (log)	t-1	0.9586***	(.018)
	t-2	0.1631***	(.018)
	t-3	-0.0204	(.017)
	t-4	-0.0180	(.015)
High-skilled employment share	t-1	1.0100***	(.150)
	t-2	-0.4390*	(.198)
	t-3	-0.1579	(.174)
	t-4	-0.4549	(.164)
large firms employment share	t-1	-0.6572***	(.031)
	t-2	-0.0415	(.029)
	t-3	-0.0023	(.029)
	t-4	0.0491	(.030)
market potential (log)	t-1	-0.1864	(.118)
	t-2	-0.1480	(.135)
	t-3	0.0568	(.125)
	t-4	0.0634	(.104)
Time fixed effects		YES	
Control for initial industry comp.		YES	
Sargan test overidentifying restr.		$\chi^2(290) = 305.28$ (P=0.2575)	
No second-order auto-correlation		Z = 0.29 (P=0.7722)	

Dep. var.: *log(hq$_{c,t}$)*		**eq. (1b)**	
High-skilled employment share	t-1	0.6338***	(.017)
	t-2	0.0484***	(.013)
	t-3	0 0926***	(.012)
	t-4	-0.0131	(.010)
employment density (log)	t-1	0.1766***	(.031)
	t-2	-0.0584*	(.033)
	t-3	-0.0308	(.032)
	t-4	0.0224	(.031)
large firms employment share	t-1	0.1783***	(.056)
	t-2	-0.0932*	(.054)
	t-3	0.0429	(.054)
	t-4	0.1396	(.056)
market potential (log)	t-1	-0.1669	(.224)
	t-2	0.2203	(.250)
	t-3	0.1551	(.231)
	t-4	0.1565	(.208)
Time fixed effects		YES	
Control for initial industry comp.		YES	
Sargan test overidentifying restr.		$\chi^2(290) = 309.15$ (P=0.2102)	
No second-order auto-correlation		Z = -0.12 (P=0.9013)	

Note: The estimated specification in the left table refers to equation (1a) in the main text. The dependent variable is *log(emp$_{c,t}$)*, where *emp$_{c,t}$* is total employment of city c in year t. The right table refers to equation (1b) with L=4. The dependent variable is *log(hq$_{c,t}$)*, where *hq$_{c,t}$* is the employment share of high-skilled workers in city *c* and time *t*. Market potential and the employment share in large firms are defined as for table 1. In both tables we include the employment shares of 27 industries in city c at times t-s, but we omit the estimated coefficients for brevity. The estimation method is GMM (one-step Arrelano Bond dynamic panel estimation) with L=4 time lags for the lagged dependent variable and all exogenous RHS variables. Time fixed effects are included. Standard errors are reported in parentheses next to the coefficients. Significance levels are indicated as: ***) 1%, **) 5%, *) 10%.

Table 3: Dynamic panel analysis – industry-by-industry analysis

Dep. var.: $log\left(hq_{c,j,t}\right)$		(1) all industries		(2) all manufacturing industries		(3) all service industries		(4) *business-related services*		(5) *commerce & retailing*	
High-skilled employment share own local industry	**t-1**	**0.5696*** **	(.008)	**0.5942*** **	(010)	**0.5056*** **	(.008)	**0.8928*** **	(.003)	**0.2237*** **	(.000)
	t-2	**0.1031*** **	(.006)	**0.1084*** **	(.007)	**0.1070*** **	(.006)	**0.0182*** **	(.000)	**0.0009* **	(.000)
	t-3	**0.0624*** **	(.005)	**0.0404*** **	(.006)	**0.0719*** **	(.006)	**0.0100*** **	(.000)	**-0.0291*** **	(.000)
	t-4	**0.0189*** **	(.005)	**0.0131* **	(.006)	**0.0081**	(.005)	**0.0047*** **	(.000)	**-0.0316*** **	(.000)
employment density (log) city c	t-1	0.0597	(.280)	-0.2069	(.319)	0.1735	(.347)	0.1521***	(.027)	0.2775***	(.019)
	t-2	-0.0951	(.285)	0.1280	(.346)	-0.2331	(.365)	0.1237***	(.025)	-0.1007***	(.018)
	t-3	-0.0152	(.243)	-0.2864	(.281)	0.0911	(.357)	0.0796***	(.020)	0.2132***	(.024)
	t-4	-0.2293	(.307)	-0.0652	(.352)	-0.3982	(.436)	-0.0731*	(.019)	-0.2004	(.018)
market potential (log) city c	t-1	-2.2962	(2.15)	2.0443	(2.86)	0.3050	(3.01)	-0.9303	(.459)	0.0183	(.352)
	t-2	0.5229	(2.19)	-2.9155	(2.62)	4.3782	(3.12)	-0.9559	(.594)	0.3103	(.321)
	t-3	1.0503	(2.22)	0.7343	(2.76)	-1.9153	(3.11)	1.1586**	(.495)	-0.1891	(.364)
	t-4	1.2825	(2.09)	1.2624	(2.63)	-1.7691	(2.54)	-0.4017	(.333)	0.2970	(.336)
large firms employment share own local industry	t-1	0.1630	(.115)	0.0999	(.124)	0.2964*	(.164)	0.1338***	(.007)	0.0106***	(.018)
	t-2	0.0841	(.101)	-0.0312	(.110)	0.0684	(.122)	-0.0375***	(.006)	0.0608***	(.014)
	t-3	0.0196	(.099)	0.0306	(.105)	0.1614	(.151)	-0.0130*	(.006)	-0.1458	(.019)
	t-4	0.0292	(.104)	0.0545	(.113)	-0.0341	(.130)	0.0521	(.007)	0.2252	(.014)
Location quotient own local industry	t-1	-0.8637***	(.083)	-0.8072***	(.081)	-0.3167**	(.131)	0.2587***	(.005)	0.1794***	(.013)
	t-2	-0.2634***	(.061)	-0.1512***	(.064)	-0.3240***	(.121)	0.0167***	(.005)	-0.1212***	(.010)
	t-3	-0.0542	(.066)	-0.0972	(.063)	-0.0534	(.100)	0.0175***	(.005)	0.1897***	(.013)
	t-4	-0.0267	(.069)	0.0351	(.073)	0.0827	(.111)	-0.0404*	(.005)	-0.2342***	(.014)
Diversity index (log) high-skilled workers	t-1	1.3436***	(.094)	1.1224***	(.118)	0.9179***	(.113)	0.4236***	(.010)	-0.0263***	(.005)
	t-2	0.1898***	(.068)	0.1612*	(.091)	0.2055***	(.080)	0.0586***	(.007)	-0.0258***	(.004)
	t-3	0.2012***	(.064)	0.2409***	(.070)	0.0936	(.082)	0.0168***	(.005)	-0.0272***	(.005)
	t-4	0.1370*	(.069)	0.0162	(.090)	0.1725*	(.097)	0.0397***	(.005)	0.0250***	(.004)
Sargan test overidentifying restr.		χ^2 (279)=303.86 (P=0.15)		χ^2 (279)=305.19 (P=0.25)		χ^2 (279)=294.34 (P=0.26)		χ^2 (290)=298.10 (P=0.36)		χ^2 (290)=296.71 (P=0.38)	
No second-order auto-correlation		Z = 1.61 (P=0.11)		Z = -0.09 (P=0.92)		Z = 0.60 (P=0.55)		Z = 0.57 (P=0.56)		Z = -0.04 (P=0.97)	
NOBS / number of groups		167,743 / 8,921		84,963 / 4,527		55,746 / 2,934		6,846 / 326		6,846 / 326	

Note: Dependent variable is $log(hq_{c,j,t})$, where $hq_{c,j,t}$ is the employment share of high-skilled workers in industry j, city *c* and time *t*. Market potential and employment density are measured for location c in the same way as described above. The employment share in large firms (>100 full-time workers) is measured for industry j, city c, time t. The location quotient is defined as $\left(emp_{c,j,t}/emp_{c,t}\right)/\left(emp_{j,t}/emp_t\right)$. The diversity index of high-skilled employment faced by industry j in city c (*DIVc,j,t*) is defined as $DIV_{c,j,t}=\sum_{s=1,s\neq j}^{28}\left|\left(skilled_{s,c,t}/emp_{s,c,t}\right)-\left(skilled_{s,t}/emp_{s,t}\right)\right|$. Estimation method is GMM (one-step Arrelano Bond) with L=4 incl. time fixed effects. Std errors are displayed in parentheses. Significance levels: ***) 1%, **) 5%, *) 10%.