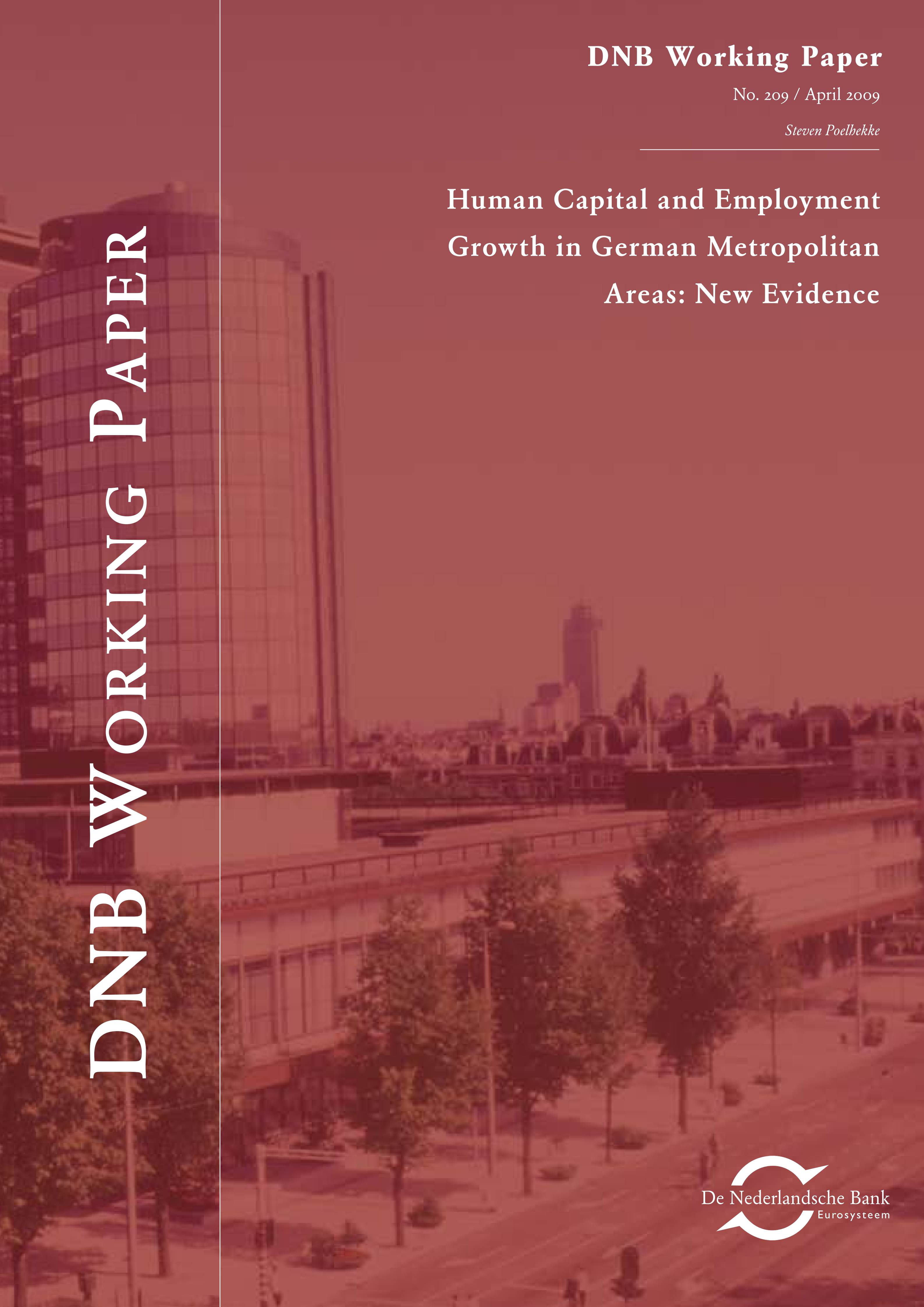

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De Nederlandsche Bank
Eurosysteem

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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

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Human Capital and Employment Growth in German Metropolitan Areas: New Evidence

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April 2009

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Abstract

German metropolitan areas with more highly skilled workers became increasingly skilled between 1975 and 2003, and this has important implications for urban employment growth. Using for the first time German metropolitan areas instead of administrative regions we show that the share of college graduates affects growth by the same magnitude as it does in US MSAs. However, conventional estimators are biased upwards. Correcting for the endogeneity of initial employment and solving a common problem of under-identification shows that the effect is at least a third smaller and closer to 0.5% employment growth for a 10% increase in the concentration of skilled workers. The effect is robust to various controls across two data sets. We additionally question the view that aggregate productivity growth is solely due to college graduates. After distinguishing between six different skill levels we find positive growth effects of high school graduates with vocational training, especially if the local concentration of technical professionals is high. The concentration of non-technical university graduates becomes more important over time, but has less bearing on the marginal growth effects of other skill groups. City success may thus depend on the 'right' combination of skills as well as college graduates.

Key words: human capital, skills, city employment growth, Germany, GMM estimation
JEL Classification: C22, J2, O47, R0, R1

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1 Introduction

German metropolitan areas with more highly skilled workers became increasingly skilled between 1975 and 2003. Cities that were very skilled in 1975 (such as Munich) have seen the share of skilled workers increase much more than initially less skilled cities (such as Bremen). This diverging pattern and the estimated effect on city employment growth are both remarkably similar to well known findings for US metropolitan areas (see for example Berry and Glaeser, 2005) and confirms the robustness of the effect of skills on growth in cities. [2] This is good news for Germany's skilled cities but bad news for lagging brownfield cities with fewer skilled workers, such as can be found in the industrial Ruhr area or former East Germany. The size of the skill-growth effect for US metropolitan areas is about 0.8% for every 10% increase in the share of college educated workers (Shapiro, 2006) and Südekum (2006) finds a similar magnitude for West German counties. If this effect is indeed this large then city mayors should make an effort to attract more skilled workers to boost slow employment growth in German cities. However, this is subject to several qualifications. Is the effect really this large? Does it also hold for metropolitan areas, or only at the county level? Are college graduates the only key to local productivity growth or could cities also improve productivity growth by attracting workers with vocational training, or even only university graduates? These are relevant questions for cities seeking to boost local economic growth.

This paper argues that the *magnitude* of the effect of skills on city growth is biased upwards, because common estimators cannot properly control for the initial employment-size effect when fixed effects such as city characteristics correlate with both growth and

my own. The views expressed in this paper are those of the author and do not necessarily reflect the views of De Nederlandsche Bank.

[2] Using a slightly different dataset and administrative regions (counties) rather than metropolitan areas Südekum (2006; 2008) estimates a decline in the coefficient of variation of skill shares, which means that the average skill level rises faster than the standard deviation. Berry and Glaeser (2005) define divergence as an increase in the standard deviation, which is the typology followed in this paper, because the absolute concentration of skills ultimately matters for growth rather than the level relative to the national mean.

initial size. We aim to improve these estimates by using recently developed GMM-IV techniques. These reveal that the effect is at least 30% smaller for each of the two different data sets. The source of this bias is rarely addressed in the context of skills and metropolitan growth [3] although it goes back to Nickell (1981) who proved that regressions in which time-invariant unobserved characteristics affect both growth and initial levels (i.e. initial employment size) lead to an downward bias in the within-estimate of the initial employment size coefficient, and an upward bias in the OLS estimate. The true value should lie in between. Failing to correct for this endogeneity bias places too much weight on the initial size effect and therefore also affects the estimation of other controls, such as human capital. The bias is especially severe if the time dimension of the panel is small - as is typically the case with city employment data. GMM estimators (Blundell and Bond, 1998) using lagged differenced equations as additional instruments can improve estimation and lead to different results. Recent versions of these estimators can solve the weak instrument problem of high persistence in the lagged dependent variable (see Bond (2002) and Windmeijer (2005)), as is the case with yearly and even 10-yearly urban employment panel data. [4]

The second contribution is to use an aggregation of counties to improve the geographical definition of cities. To the best of our knowledge, German local growth estimates have so far relied on counties or other administrative regions which makes direct comparison with US metropolitan areas difficult. Urban growth models typically assume that each city is an 'island' that freely trades with other cities. It is important to have a good definition of what a city is and it should preferably encompass a labor region in which people live and work. We will therefore use a definition very similar to US metropolitan areas (based on commuting flows between counties) as a unit of observation. The city of Munich for example becomes a metropolitan labor region of 12 counties. Many people commute into

[3] Exceptions are Blien *et al.* (2006), Suüdekum (2008), and Combes *et al.* (2004) although these results may suffer from under-identification due to persistent lagged dependent variables. We come back to this in section 3.

[4] This has for example significantly improved estimates of the effect of education on democracy (Bobba and Coviello, 2007).

the main city which is a county on its own but measures only 20km (12mi) across. Similarly, the cities of Cologne and Bonn really form only one agglomeration because many people commute between the two.

Thirdly, we argue that the share of college graduates is not necessarily the best proxy for local productivity, although it is typically used as such. Other skilled workers such as those with vocational training also contribute significantly to agglomerations' employment growth.[5] Bacolod, Blum and Strange (2008a and b) find evidence that cognitive skills rather than motor skills are productivity enhancing in cities, something which many workers with vocational training may also possess in a significant amount. It is therefore not a foregone conclusion that the share of college graduates is the best indication of local productivity. This is also important from a policy perspective. Many cities focus on how to attract as many college graduates as possible although a different mix of skills could also be a successful strategy. Apart from asking *how much* human capital is good for growth we want to ask the additional question of which *combination* of skills is beneficial. We find evidence of positive interaction between workers with vocational training and graduates from technical colleges. The productivity enhancing effect of non-technical college graduates is increasing over time, but their presence was of lesser influence to the productivity effect of workers with vocational skills.

The rest of the paper is organized as follows. Section two develops an illustrative model. Section three discusses the econometric challenges and solutions after which section four describes the data. Section five presents results on the size of the skill-growth connection and section six expands the college graduate productivity measure to include other skills and interactions. Section seven concludes.

[5] Usually the productivity effect of skilled workers is looked upon from the viewpoint of wages (see the debate on the existence of human capital externalities by Rauch (1993), Moretti (2004) and Ciccone and Peri (2006)) or whether or not workers receive higher wages if they are employed in a city (i.e. Glaeser and Maré, 2001). We will focus on the aggregate city productivity effect on city *employment*. Employment has been persistently low compared to the labor force in Germany (high unemployment) for some time.

2 Metropolitan area growth

This section briefly outlines how human capital may affect employment growth to motivate the empirical specification. We consider a standard setting similar to Glaeser *et al.* (1992) and Simon (1998) in which each metropolitan area i is a separate small open economy. Each i produces one good (which is freely traded nationally under perfect competition). The good is produced using labor L_{it}, and technology A_{it} at time t, using a production function $A_{it}(L_{it})^{1-\alpha}$, where $0 < \alpha < 1$. Firms sell the good for a numéraire price of 1. Following Glaeser *et al.* (1992) we abstract from capital or land input because we cannot measure different types of technological process with our data. Firms maximize profits taking technology, prices, and wages w_{it} as given. The wage rate (nominal and real) will thus equal the marginal product of labor:

$$w_{it} = (1-\alpha)A_{it}(L_{it})^{-\alpha}, \tag{1}$$

which expressed in terms of growth rates becomes:

$$\ln\left(\frac{w_{it}}{w_{i,t-1}}\right) = \ln\left(\frac{A_{it}}{A_{i,t-1}}\right) + \alpha \ln\left(\frac{L_{it}}{L_{i,t-1}}\right). \tag{2}$$

As in Combes *et al.* (2004) we assume that labor is imperfectly mobile such that labor growth reacts to wage growth with a strictly positive supply elasticity σ:

$$\ln\left(\frac{L_{i,t}}{L_{i,t-1}}\right) = \sigma \ln\left(\frac{w_{it}}{w_{i,t-1}}\right). \tag{3}$$

Perfect labor mobility would require wage growth to be a constant across cities, while completely immobile labor would disconnect productivity from employment growth and lead to wage growth instead.[6] We could expand this framework to include quality of life

[6] Imperfect mobility is supported by the finding that regional labor demand shocks trigger much less migration in Germany than in the US between 1960 and 1987 (Decressin and Fatás, 1995). Moreover, the gross migration rate between NUTS 2 regions has declined between 1983 and 1990, down to one percent of the population, below rates for the UK. Also, 60% of migration is between neighboring regions (Huber, 2004).

as in Shapiro (2006) and Glaeser *et al.* (1995). However, we do not observe quality of life and assume implicitly that most of it is captured by the fixed effects, which include important quality of life indicators such as climate and geography. The technology A_{it} can have both national (δ_t) and local components, where local components in turn depend on city characteristics that may be both permanent (η_i) and time-varying in nature. The local time-varying characteristics depend on human capital H_{it} and other characteristics included in X_{it} such as total initial employment to capture urbanization economies (such as local demand, labor pooling, interactions). Productivity growth can therefore be expressed as:

$$\ln\left(\frac{A_{it}}{A_{i,t-1}}\right) = \beta_1 H_{i,t-1} + \beta_2 X_{i,t-1} + \eta_i + \delta_t + v_{i,t} \tag{4}$$

where unobserved shocks are given by v_{it}. Combining equations 2, 3 and 4 leads to the main relationship of interest:

$$\ln\left(\frac{L_{it}}{L_{i,t-1}}\right) = \frac{\sigma}{1+\alpha\sigma}\left(\beta_1 H_{i,t-1} + \beta_2 X_{i,t-1} + \eta_i + \delta_t + v_{i,t}\right), \tag{5}$$

where $\sigma/(1+\alpha\sigma)$ is a positive parameter. The functional form of human capital H_{it} is commonly a single variable such as the average or median schooling or the share of workers with a college degree or higher. [7] We will experiment also by including other skill groups in H as well as interactions between skill groups. In particular we hypothesize that workers with vocational training are more productive among technical college graduates than among non-technical graduates because their tasks are more similar. This facilitates better learning than from colleagues with the same skill levels. The cognitive skills that are more typically found among technical professionals can have beneficial effects on other workers if companies employ them both. Using average years of schooling would not pick up any skill interaction effects. Our data set allows us to differentiate between 6 different levels of human capital ranging from no schooling to university graduates.

[7] As for example in Glaeser, Scheinkman, Shleifer (1995).

3 Dealing with bias, endogeneity and weak instruments

The common specification for estimating the skill-growth relation is given as follows (reformulating eq. 5):

$$y_{i,t} = (\lambda + 1)y_{i,t-1} + \beta H_{i,t-1} + \eta_i + \delta_t + v_{i,t} \quad i = 1, ..., N; \; t = 1, ..., T \tag{6}$$

where $y_{i,t}$ is $\ln L_{i,t}$, the natural logarithm of total employment in city i and year t.[8] The η_i are (unobserved) city characteristics that do not change over time, such as for example access to a river (geography) or other inputs in production which do not vary over our sample period, such as the existence of an airport. These may correlate strongly with employment growth. $v_{i,t}$ is an error term which captures i.i.d. shocks to employment growth.

Fixed effects such as whether or not a city has a port or whether it used to be a mining town have an effect on employment each year during the sample period. These effects can also include institutions, culture and climate. They mean that employment is not strictly exogenous: $E[y_{i,t-1}, \eta_i] > 0$, and for the same reason: $E[y_{i,t-1}, v_{i,t-1}] > 0$. Even if current shocks are not correlated with previous period employment size we will still estimate a positively biased (OLS) coefficient λ because of the positive correlation between the fixed effects and initial employment. Moreover, this bias does not vanish if the sample size increases in the time dimension, nor if the within transformation is applied to purge the fixed effects. This problem has not been addressed in earlier papers by Shapiro (2006) and Simon and Nardinelli (2002), nor by Berry and Glaeser (2005) and Wheeler (2006) in the context of urban employment growth and highly skilled labor.

A commonly used solution is to use first-differences of the system of equations to remove the η_i and use lagged equation as instruments as in Arellano and Bond (1991).[9]

[8] We could have written $\Delta y_{i,t} = \lambda y_{i,t-1} + ...$ instead.
[9] We refer to this method as difference-GMM (DGMM).

To do this the errors should not be serially correlated ($E[v_{is}v_{it}] = 0$ for $s \neq t$), we need predetermined initial conditions ($E[y_{i1}v_{it}] = 0$ for $t = 2, ..., T$) and $E[\eta_i] = E[v_{it}] = E[\eta_i v_{it}] = 0$.[10] This method has been used by Blien *et al.* (2006) and Südekum (2008) for sector employment growth at the county level and Combes *et al.* (2004) for France. However, these papers use very persistent yearly employment data. This creates a serious problem for estimation with this method because λ might be close to zero. A region's employment size does not change much from year to year and is thus very persistent. λ then contains little predictive information about next year's employment size and is too weak as an instruments for employment growth, even if it is exogenous. In finite samples this problem is even more severe and may bias the estimate of the lagged dependent variable's coefficient downward and even below the within estimate (as we will later demonstrate empirically).

Blundell and Bond (1998) proposed to expand the instrument set by including additional moment conditions by using lagged first-differenced equations.[11] With time dummies this additionally assumes that mean employment evolves in a common way over time for all cities in the sample.

$$E[\Delta y_{i,t-1}, (\eta_i + v_{it})] = 0 \text{ for } t = 3, ..., T \tag{7}$$

All these assumptions can be tested with common Sargan over-identification tests. A further improvement can be made by applying Windmeijer's (2005) correction for finite sample bias in the two-step version of System-GMM, which otherwise reports standard errors which are too small.[12]

[10] AR(1) is introduced by construction. Note also that we do not require the initial conditions to be strictly exogenous which would require $E[y_{i1}v_{it}] = 0\ \forall t$. Strict exogeneity of all variables would result in a consistent within estimate for large N and T.

[11] We refer to this method as system-GMM (SGMM).

[12] Both DGMM and SGMM have one- and two-step versions which refers to the method of estimating the weight matrix for GMM. One-step requires the assumption of homeskedastic v_{it} disturbances, but two-step estimation tends to deflate the standard errors. We use the identity matrix as an initial guess for the covariance matrix of idiosyncratic errors as in Blundell and Bond (1998). See Bond (2002) for an overview.

An attractive feature of this method is that many instruments can be used. Strong and valid instruments are rare which makes solving the endogeneity issue difficult in general. The dynamic panel approach is to assume that lagged levels and lagged first differenced equations are not correlated with the current period disturbances. This means that the past concentration of skilled workers has no influence on the current shock to employment growth after controlling for fixed effects and other controls including the current concentration of skills. Since the time length of our sample is long enough (> 3 periods) we have many instruments and the system is over-identified. A common Sargan test can tell us if the assumption of predetermined initial conditions is valid. There is one pitfall with having many instruments. If the set of instruments is much larger than the number of cities (the N dimension) there is a risk of 'over-fitting' the data which decreases the power of the Sargan tests (Bowsher, 2002). On the other hand, using more instruments makes more efficient use of the available data. In general, if increasing the number of instruments does not move the lagged dependent's estimated coefficient towards the Within-estimate, then over-fitting should not be a problem.

4 German metropolitan employment data

Several German employment studies have used administrative boundaries rather than economic agglomerations because statistical offices do not readily provide data on the level of agglomerations.[13] Since we want to measure urban human capital and estimate its effect on urban employment growth we need to group the counties into labor regions or agglomerations.[14] By doing so we stay close to the commonly used US statistical metropolitan area definition[15] and circumvent bias from possible spatial dependence. To prevent this bias, the regions capture agglomerations in which people both live and work.

[13] See for example Südekum (2006) and Blien *et al.* (2006).

[14] The German counties ('Kreise' and 'Kreisfreiestädte' (NUTS III regions)) measure on average a quarter of the surface size of US counties.

[15] These are also defined on the basis of counties. See http://www.census.gov/population/www/metroareas/metrodef.html

German labor market regions are defined by Eckey *et al.* (2006) on the basis of commuting patterns (maximum commuting time of 45 to 60 minutes depending on the attractiveness of the center) and have a size of at least 50,000 inhabitants. This leads to 150 regions consisting of one or more counties that capture the area where people both work and live.

Table 1
Number of Counties Versus Labor Regions

	Labor Regions	Counties
Germany	150	439
West	112	326
East	38	113

The mean and standard deviation of the ratio of employed workers counted at place of work over place of residence is 0.98 and 0.34 for the German counties, while only 0.96 and 0.07 for the metropolitan areas, which is clearly an improvement in precision if we rely on *employed* workers to measure a city's human capital. [16]

Employment data (see the data appendix for more detail) on the very disaggregated level of counties is provided by two sources. The first is from the German Statistical Agency (DESTATIS), which publishes a 'Statistik Regional' (SR) database (2005) providing consistent data on all 439 (East and West) German counties from 1995 to 2003. These include all employed workers, excluding civil servants and the self-employed, subject to social security payments. This data set is supplemented with educational attainment data of workers counted at place of work from the Federal Office for Building and Regional Planning ('Bundesamtes für Bauwesen und Raumordnung', BBR). [17] It distinguishes three levels of human capital where employment of 'highly skilled' labor is defined as those with a degree of a specialized upper secondary school, specialized college of higher education, or institution of higher education. 'Middle skilled' workers are those with apprenticeship

[16] Single county labor regions are mostly low density rural areas. The labor regions are smaller than the NUTS II ('Bezirke') and NUTS I ('Länder': states) regions: these areas are administrative rather than economic in nature.
[17] These data come from their DUVA database and follow the same definition as the DESTATIS data.

or training on the job, qualification at a full-time vocational school or at a trade or technical school. 'Low skilled' workers are those without occupational qualification. The highly skilled resemble the widely used measure of those with a bachelor degree or higher for US studies, but are likely slightly higher educated than the US highly skilled and form a smaller share of employment.

The second source is the IAB Employment Sample (IABS) of all employees subject to social security payments. It provides a long time series from 1975 to 2001 and distinguishes between more distinct levels of human capital, as described in Table 2.

Table 2
Skill definitions (IAB Sample)

Level	Definition
6	University Degree ('Hochschule')
5	Technical college degree ('Fachhochschule')
4	High school degree and vocational training ('Abitur mit Berufsausbildung')
3	High school degree ('Abitur')
2	Vocational training ('Volks-,Haupt-,Realschule mit Berufsausbildung')
1	no degree ('ohne Berufsausbildung')

Note: A high school degree of the 'Abitur' level qualifies for university and technical college, while a high school degree from the 'Volks-,Haupt-,Realschule' does not.

In both data sets we observe that the share of skilled workers has increased the most in those cities that were already ranked as highly skilled at the start of the sample period: both from 1975-2001 and from 1995-2003 (see data appendix).

5 The overestimated effect of skills on metropolitan growth

We start the analysis with the Statistik Regional (SR) sample with population data on all German counties from 1995 to 2003. Table 3 estimates the effect of the concentration of highly skilled labor on total employment growth with controls for initial employment (the lagged dependent variable with coefficient λ), a dummy for the former Eastern agglomerations, and time dummies, as in equation (5).[18] OLS estimates λ to be close to

Table 3
SR Sample, 1995-2003

	Yearly % total employment growth						
	OLS	Within	DGMM1	DGMM2	SGMM1	SGMM2	SGMM2r
At *t-1*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln % highly skilled labor	.006	.084	.239	.223	.160	.175	.175
	(.003)*	(.015)***	(.065)***	(.020)***	(.050)***	(.018)***	(.071)**
ln total employment	-.0009	-.082	-.283	-.269	-.065	-.077	-.077
	(.001)	(.017)***	(.085)***	(.021)***	(.022)***	(.009)***	(.032)**
East Germany Dummy	-.029				-.126	-.130	-.130
	(.002)***				(.032)***	(.012)***	(.044)***
Obs.	1200	1200	1050	1050	1200	1200	1200
AR(1) test, p-value			.0007	3.85e-07	.001	2.05e-07	3.25e-07
AR(2) test, p-value			.506	.748	.194	.043	.067
AR(3) test, p-value			.489	.366	.592	.228	.235
Sargan over-id. test, p-val.			.84	.0008	.999	.0001	.0001
Adj. R2	.561	.503					

Robust and clustered standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Time dummies included. Column 7 uses the Windmeijer (2005) robust standard errors and the last digit in the column names refers to 1- and 2-step estimation.

zero which means that employment is very persistent, although the within transformation which accounts for city fixed effects finds a rate of convergence of 8.2% per year. The latter is biased downward and seems implausibly large in magnitude. We confirm that a 10% increase in the share of skilled labor leads to 0.8% more employment growth, consistent with Shapiro (2006), while keeping in mind that initial employment size is endogenous. The third column uses lagged level equations as instruments and assumes homoskedastic errors (Difference-GMM, one-step). Also allowing for heteroskedastic errors (two-step, column 4) does not perform well as λ is estimated to be even smaller, while the true value should lie in between the OLS and Within estimate. This is a sign of underidetification and we have to deal with a weak instrument problem. The fifth (one-step) and sixth (two-step) columns therefore employ also lagged differenced equations. These yield a more plausible estimate of λ. The errors in column 6 may suffer from finite sample bias making them too small, but correcting for finite sample bias in column 7 still yields significant estimates.

[18] Fixed effects regression furthermore control implicitly for density, because the initial employment size coefficient can be interpreted as the effect of a change in employment size relative to its period city average for a constant city surface area. This change is perfectly correlated to a change in density.

The Sargan test for exogeneity shows irregular performance and the test fails in columns 6 and 7 so we cannot properly identify λ. This means that also the coefficient on highly skilled labor will still be biased. Moreover, this regression does not capture other possible determinants of employment growth, such as the industrial mix. Next, we control for such omitted variable bias.

Table 4 adds more controls (and hence also more instruments). Centers of manufacturing may have had a different growth experience while possibly attracting less highly skilled labor. Competition is added to capture the effect of the local industry structure. There is a long-standing debate fueled by Glaeser *et al.* (1992) and Henderson *et al.* (1995) as to whether an industry grows faster if the local environment is competitive, diverse,

Table 4
Robustness SR Sample, 1995-2003

	Yearly % total employment growth		
	OLS	Within	SGMM2r
At *t-1*	(1)	(2)	(3)
ln % highly skilled labor	.005	.088	.043
	(.002)*	(.018)***	(.013)***
ln % Highly skilled ∗ East Dummy	.001		.006
	(.005)		(.024)
ln % medium skilled labor	.008	-.038	-.040
	(.015)	(.062)	(.093)
ln total employment	.0004	-.186	-.018
	(.001)	(.020)***	(.006)***
ln % manufacturing	.0003	.002	.019
	(.002)	(.0007)***	(.010)**
Competition Index			-.017
			(.014)
% pop. age 25-35			.010
			(.041)
% pop. age 35-45			-.057
			(.066)
% pop. age 45-60			-.137
			(.061)**
East Germany Dummy	-.016		-.011
	(.012)		(.057)
Obs.	1039	1039	1187
AR(1) test, p-value			.0002
AR(2) test, p-value			.09
AR(3) test, p-value			.104
Sargan over-id. test, p-val.			.301
Adj. R2	.624	.558	

Robust and clustered standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Time dummies included. Column 3 uses the Windmeijer (2005) robust standard errors and 2-step estimation.

specialized, or a combination of those three.[19] We do not observe enough industry information in the SR sample to include diversity or specialization save for the share of manufacturing. We measure competition as the local average number of employees per firm divided by the national average number of employees per firm. The age distribution of employees (relative to the national average) might be relevant because the education level reported is based on the highest acquired degree. With progressive advancement of technology it might be that a worker with a recent degree is actually more skilled than a worker with a degree from 30 years earlier. Young employees might thus be more productive. Medium skilled workers contain workers with a level of education that could be considered of equivalent to college level in the US (trade and technical schooling). These controls improve identification as column 3 shows. We find a plausible rate of conditional employment convergence of 1.8%, and a positive effect of highly skilled labor, which is however now smaller at 0.4% for a 10% increase in the concentration skilled workers (which is not different in the former East). Since we find some weak evidence for AR(2) we only use lags 3 and up as instruments. Controlling for the effects of competition does not affect our results. Demographics have the expected effect that cities with a higher share of persons between 45 and 60 years of age tend to grow more slowly. Omitting the age variables would have given us a high skilled workers effect of 0.36%, which is only slightly smaller.

Table 5 repeats the exercise for the longer IAB sample, covering the years 1975-2001. S5+6 refers to skill levels 5 and 6 (see Table 2 in the previous section) which is equivalent to highly skilled labor in the SR sample. S2+3+4 refers to middle skilled labor. The IAB sample allows us to add a measure of local industry diversity as a control to account for the possibility of diversity or specialization being beneficial to growth. We define diversity as minus the natural logarithm of the sum of 16 squared industry shares in each city.

$$\text{diversity} = -ln\left[\sum_{s=1}^{S}\left(\frac{L_{ist}}{L_{it}}\right)^2\right] \tag{8}$$

[19] See Duranton, Puga (2004) for an extensive overview of this literature.

Table 5
IAB Sample, 1975-2001

	Yearly % total employment growth						
	OLS	Within	SGMM2r	OLS	Within	SGMM2r	SGMM2r
At *t-1*	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln S5+6	-.0008	.003	.059	.002	.006	.043	.025
	(.002)	(.004)	(.017)***	(.001)	(.004)	(.018)**	(.013)**
ln total employment	-.003	-.035	-.030	-.0009	-.042	-.003	-.019
	(.0007)***	(.008)***	(.007)***	(.0005)	(.008)***	(.006)	(.017)
ln S2+3+4				.008	.036	.236	.106
				(.008)	(.020)*	(.061)***	(.051)**
ln % manufacturing				.004	-.012	.033	.008
				(.002)**	(.012)	(.013)**	(.031)
Diversity index				-.0007	-.027	-.076	-.012
				(.002)	(.008)***	(.024)***	(.017)
Average worker age				-.005	.002	-.016	.0003
				(.0005)***	(.001)	(.004)***	(.004)
East Germany Dummy	-.028		-.061	-.024		-.030	-.045
	(.002)***		(.011)***	(.002)***		(.013)**	(.025)*
Obs.	3252	3252	3252	3252	3252	3252	3252
AR(1) test, p-value			3.61e-20			1.42e-19	1.24e-19
AR(2) test, p-value			.415			.773	.69
Sargan over-id. test, p-val.			.419			.593	-
Adj. R2	.721	.729		.729	.731		

Robust and clustered standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Time dummies included. Columns 3 and 6 use the Windmeijer (2005) robust standard errors and 2-step estimation. Column 7 uses all available instruments.

where $S = 1, ..., 16$ is our set of 16 industries in city i at time t. This Herfindahl-type index is very similar to the diversity indices used in Glaeser *et al.* (1992) and Combes *et al.* (2004), except that we focus on city employment growth rather than industry employment growth. Unfortunately, the IAB sample does not contain representative information at the county level on the number of firms. We include the average age of employees within a city to account for the possibly negative age effect.

The same basic patterns holds. After correcting for endogeneity of initial employment in columns 3 and 6 (with more controls) we conclude that the effect of highly skilled labor on employment growth is smaller than previously reported. A 10% higher share of skilled labor leads to 0.43% more employment growth. The initial employment size variable now lies between the OLS and Within estimates and the Sargan tests are passed meaning that the GMM estimator is well specified. Diversity enters with a negative sign, which means that less diverse cities tend to grow faster in Germany, as do cities with an increasing share of manufacturing.[20] As in the SR sample we find that an older work force tends to lead to less employment growth. Recently acquired degrees seem to be more important than experience. We also find evidence that middle skilled workers affect employment growth positively and strongly, which warrants further investigation in the next section. Lastly, we include column 7 where we appeal to the efficiency argument and use all the information available. We include all lags of the variables in the instrument set so that we have 1975 instruments for 150 agglomerations. On the downside, the Sargan test is now uninformative due to over-fitting (the lagged dependent variable's coefficient has moved in the direction of the within estimate), so we cannot test the validity of the instruments. The skill effects are still there but turn out to be slightly smaller.

6 Growth and skill interactions

This section explores whether or not the share of college graduates is the most appropriate skill definition to capture the effect of education on aggregate productivity. Figure 1 graphs the average share of skilled workers across all agglomerations over time, for 6 different skill groups.[21] The technical colleges (level five) are engineering schools which also issue Master's degrees. The difference compared to a university (which provides other disciplines) is that they do not award PhDs. There is furthermore no clear difference in educational level between levels one and three, except that 'Abitur' allows a student to enter schools of levels five and six. By far the largest shares are taken up by the lowest

[20] Blien *at al.* (2006) find a positive effect of diversity on *industry* employment, and a lagged negative effect. Our negative effect is robust to using their diversity measure (the measures correlate by 0.81; coefficient of -0.12*** in that case, available on request). It appears that employment in metropolitan areas benefits from overall specialization, even though industries may benefit from surrounding diversity on a smaller geographical scale. Since we use metropolitan areas as observations instead of counties and industries these results should be seen as complementary.

[21] Because reporting of skill levels about their workers is done by companies themselves there are some inconsistencies. We used imputation method IP3 as described in Fitzenberger *et al.* (2005) to make sure that the highest attained degree did not *decrease* over time for the same worker. This may overreport the skill level but it yielded more similar skill levels compared to the SR sample for the years 1995-2001 than other imputation methods or the raw data.

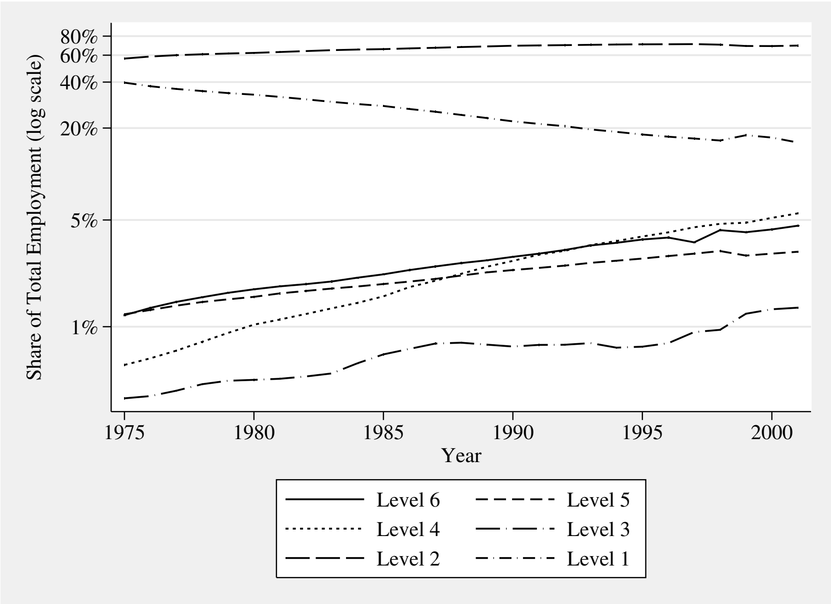

Fig. 1. Change in Skill Concentration Over Time (IAB Sample, West Germany)

two schooling levels (upper two lines in the graph), of which the share of workers without a degree is steadily decreasing over time. The left scale is in logs, so the fastest relative increase in education was among level four: high school + vocational training (dotted line).

Table 6 differentiates between more than two skill levels. Unskilled labor is the reference skill level as it is the only level that has decreased over time. All other shares have increased but unequally so across cities, leading to various rates of employment growth over time. We group levels two and four together because both list vocational training as tertiary education. Column 2 finds a positive interaction effect between high skilled labor and workers with vocational training (ln S5+6 * ln S2+4) and no interaction effect with high school graduates. To interpret the size and significance of the marginal effect of vocationally trained workers on employment growth we need to calculate how it depends on the share of skilled workers in a city: [22]

$$\frac{\partial \Delta y_{it}}{\partial \ln \text{ S2+4}} = \beta_1 + \beta_2 * \ln \text{ S5+6} \tag{9}$$

[22] By the same reasoning the marginal effect of ln S5+6 will now depend on the sample values of the other skill groups and cannot be interpreted directly.

Table 6
Skill interactions (IAB Sample, 1975-2001)

	Yearly % total employment growth (SGMM2r estimator)					
interactions with:		S5+6	S5	S6	S5+6 & time trend	
At *t-1*	(1)	(2)	(3)	(4)	(5)	(6)
ln S5+6	.063 (.014)***	.160 (.042)***			-.025 (.019)	.013 (.038)
ln S5			.060 (.045)	.013 (.010)		
ln S6			.017 (.008)**	.077 (.032)**		
ln S2+4	.073 (.048)	1.008 (.235)***	1.119 (.284)***	.928 (.219)***	.143 (.064)**	-.015 (.308)
ln S3	-.017 (.005)***	-.018 (.020)	-.046 (.030)	-.027 (.019)	.037 (.007)***	.038 (.007)***
ln total employment	-.023 (.006)***	-.025 (.005)***	-.014 (.005)***	-.015 (.005)***	-.038 (.009)***	-.037 (.009)***
ln S5+6 * ln S2+4		.250 (.060)***				.007 (.080)
ln S5+6 * ln S3		-.001 (.007)				
ln S5 * ln S2+4			.240 (.063)***			
ln S5 * ln S3			-.009 (.007)			
ln S6 * ln S2+4				.190 (.048)***		
ln S6 * ln S3				-.003 (.005)		
ln S56 * time trend					.003 (.0007)***	
ln S5+6 * ln S2+4 * time trend						-.003 (.0009)***
time trend					.007 (.002)***	.0003 (.001)
Obs.	3207	3207	3204	3204	3207	3207
AR(1) test, p-value	5.19e-19	9.84e-18	4.59e-19	1.30e-18	2.82e-18	3.35e-18
AR(2) test, p-value	.72	.666	.839	.791	.063	.055
Sargan over-id. test, p-val.	.407	.332	.34	.361	.227	.215

ln Sx denotes the ln of the share of workers of skill level(s) x. Windmeijer (2005) robust standard errors in parentheses (two-step estimation). * significant at 10%; ** significant at 5%; *** significant at 1%. East Germany dummy included, and time dummies in columns 1 to 4..

The standard errors follow as:

$$\text{s.e.} = \sqrt{Var(\hat{\beta}_1) + (\ln \text{S5+6})^2 + Var(\hat{\beta}_2) + 2(\ln \text{S5+6})Cov(\hat{\beta}_1, \hat{\beta}_2)} \tag{10}$$

where we estimate $\Delta y_{it} = \alpha y_{i,t-1} + \beta_1 \ln \text{S2+4}_{i,t-1} + \beta_2 \ln \text{S5+6} * \ln \text{S2+4}_{i,t-1} + \text{controls} + \eta_i + v_{it}$ and $\hat{\beta}_1 = 1.008$ and $\hat{\beta}_2 = .25$. Using this calculation for all the sample values of ln S5+6 we find that the effect of workers with vocational training is significant across all observed values of the share of highly skilled workers, although it nears insignificance as the share of skilled workers becomes high in the sample. This means that in all cities in our sample, there is a significant positive productivity enhancing effect of highly skilled workers. Workers with vocational skills become more productive in more highly skilled cities. A further qualification is made by columns 3 and 4. They show that the positive interaction between the highly skilled and workers with vocational training is stronger for graduates of technical colleges than for university graduates. Presumably the former two are closer in terms of knowledge which facilitates better learning and hence larger productivity effects on employment growth. These effects add a new dimension to human capital externalities in the spirit of Lucas (1988). The productivity effect of skilled workers may be best captured by a group which is more broadly defined than college graduates alone. Furthermore, skills from different levels of formal education seem to complement each other.

Columns 5 and 6 show that the effect of highly skilled labor interacts positively with a time trend, indicating that the effect of highly skilled labor is increasing over time. Moreover, the interaction between the trend and the ln S5+6 ln S2+4 interaction term shows that the spillovers on workers with vocational training decreases over time. This is consistent with our finding that the productivity effect of these workers nears insignificance as the share of skilled workers becomes high. These effect are robust to including controls for the local industry structure and age of the work force (see Table B.1 in the appendix). As a second robustness test we exclude those workers that are in training. Many of the vocational training school include 'on the job' training which might increase the measured share of this human capital group while their effect on productivity might be lower in reality. Comparing Table 2 and Table B.2 shows that some workers without formal education (level 1) and those with only high school (level 3) were in training while at their job. However, Table B.3 in the appendix does not find qualitatively different results.

7 Conclusion

This paper shows that well known estimates of the size of the effect of skills on metropolitan area growth are biased because endogeneity of the initial employment size is not sufficiently accounted for when fixed effects matter for both growth and initial city characteristics. Adjusting the estimates using two data-sets on German metropolitan areas and recently improved dynamic panel GMM techniques shows that the effect is significant but 30% smaller. We also demonstrate that other skill groups matter for growth, namely those with vocational training. We find robust evidence that technical college graduates such as engineers interact positively with workers with vocational training and reinforce the latter's positive effect on employment growth. This effect is slightly decreasing over time however, while non-technical university graduates are becoming more important. City success may depend on the right combination of skills and not only on the percentage of college graduates. Micro-data at the firm level may shed more light on this link in the future.

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A Data appendix and descriptive statistics

Figures A.1 and A.2 show the divergence of human capital levels in both data sources, although only in West Germany. Table 3 shows that skill levels were very high in East Germany in 1995 compared to the West. Part of the anomaly might be due to data quality, but an alternative explanation comes from specific labour market characteristics of the former DDR. Before unification it was standard to acquire at least medium skills in the former East and unemployment did not exist because each worker was assigned a job by the government. The resulting over-employment and subsequent closure of inefficient plants after unification led to sudden unemployment of many workers. Party members also lost their job, but many of them were highly skilled. [23] The latter presumably had an easier time to find new employment (in the private sector) while medium skilled workers likely moved West or waited for new employment opportunities. If the out-migration of mainly medium skilled workers had been going on for some time prior to 1995, then that might explain the relatively high share of high skilled workers in the East. For this reason it may be important to include an East Germany dummy and experiment with an interaction term between Eastern agglomerations and the effect of skills on growth.

Access to the factually anonymous IAB Employment Sample (IABS) (years 1975 - 2001) was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) (see Drews *et al.*, 2006). It comprises a 2% random sample of employees subject to social security payments. [24]

Tables A.1 to A.3 provide descriptive statistics for the German metropolitan areas

[23] Thanks to Matthias Hertweck for pointing this out to me.

[24] We select a cross-section of individuals at date June 30th of each year, which corresponds to the cross-section date of the SR sample, and aggregate (or average) variables within counties, which are then aggregated (or averaged if applicable, with a weight by employment size) to metropolitan areas. Other details: employment is counted as those with main employment (to prevent double counting), with regional observations and those who are not apprentices.

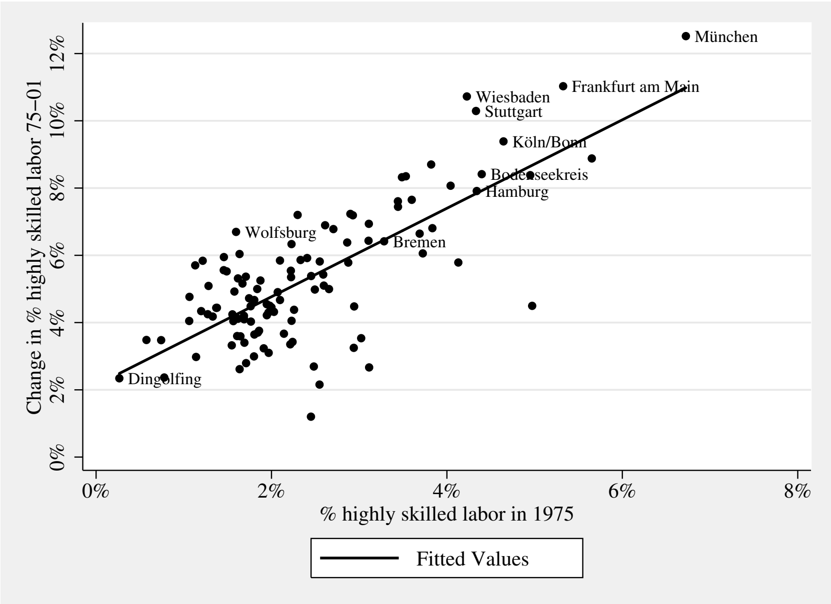

Fig. A.1. Change in % Highly Skilled Labor (IAB Sample)

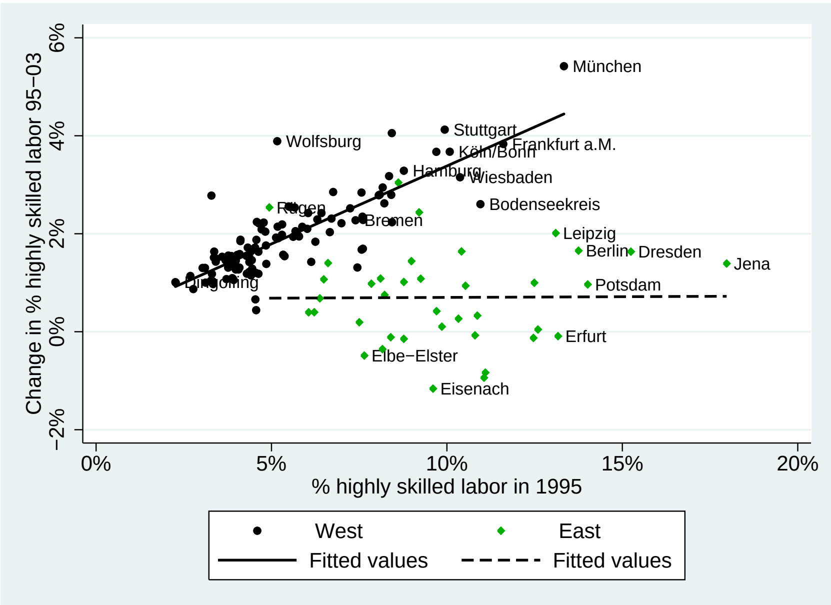

Fig. A.2. Change in % Highly Skilled Labor (SR Sample)

from the two data sources and the definition for six skill groups in the IAB sample. Employment growth since 1995 has been distinctly lower than before and even negative on average. The tables also show that there are important differences in the data between the former Eastern and the Western agglomerations. For example, the East reports higher formal education levels yet worse growth performance. [25] The tables also show that manufacturing has continued to be an important employer and has even expanded as a share of employment in the former East. A competition index larger than one means that there is more competition than the national average. The diversity index reaches its minimum at 0 and its maximum at 2.77 ($= -\ln(1/16)$, 16 industry groups).

Table A.1
Sample Employment Growth Rates

	West		East	
	mean	sd	mean	sd
IAB Employment Growth (75-01)	1.5%	4.1%	-1.1%	3.9%
SR Employment Growth (95-03)	-0.1%	1.6%	-2.7%	2.0%

Table A.2
SR Sample Descriptive Statistics

SR Sample	1995 (West)		2003 (West)		1995 (East)		2003 (East)	
	mean	sd	mean	sd	mean	sd	mean	sd
% highly skilled	5.4%	2.1%	7.3%	2.8%	9.9%	2.8%	10.6%	3.0%
% medium skilled	69.9%	3.3%	71.0%	3.6%	79.4%	3.0%	78.2%	3.5%
% lowest skilled	24.6%	3.5%	21.6%	3.0%	10.7%	1.4%	11.2%	1.4%
Total employment	195,599	239,145	195,167	242,877	164,019	256,398	134,645	219,147
% Manufacturing	30.2%	8.5%	28.4%	9.2%	11.7%	3.5%	15.2%	5.6%
Competition	1.34	0.46	1.26	0.44	0.79	0.27	1.10	0.39
Rel. % Pop. 25-35	1.03	0.05	1.02	0.07	0.92	0.05	0.93	0.07
Rel. % Pop. 35-45	0.98	0.04	1.01	0.04	1.07	0.04	0.98	0.05
Rel. % Pop. 45-60	0.99	0.06	0.98	0.03	1.03	0.04	1.07	0.03

Note: Manufacturing includes WZWG C to D ('Wirtschaftszweig', Industrial classification): manufacturing and mining (no reliable separate series were available). Age distributions are relative to the national average.

B Robustness

[25] However, the focus of this paper is not on differences between East and West, but the statistics are provided because the Eastern agglomerations enter the data in 1991 (IAB sample) and 1995 (SR sample) and thus show their relative weight in the data.

Table A.3
IAB 2% Sample Descriptive Statistics

	1975 (West)		2001 (West)		2001 (East)	
	mean	sd	mean	sd	mean	sd
% level 6	1.2%	0.8%	4.6%	2.2%	7.1%	2.3%
% level 5	1.2%	0.5%	3.1%	0.9%	4.7%	0.9%
% level 4	0.6%	0.3%	5.5%	1.9%	4.5%	0.9%
% level 3	0.3%	0.2%	1.3%	0.7%	1.0%	0.5%
% level 2	57.0%	5.1%	69.4%	4.8%	75.5%	4.3%
% level 1	39.7%	5.8%	16.1%	2.8%	7.2%	1.2%
Total employment	3183	4056	4378	5261	3414	4586
% Manufacturing	46.2%	10.4%	32.9%	9.0%	19.9%	6.2%
Diversity	2.36	0.27	2.45	0.14	2.51	0.10
Average Age	34.1	1.1	39.2	0.5	40.0	0.4

Note: Manufacturing includes WZWG 2 to 6 ('Wirtschaftszweig', Industrial classification): (consumer) goods manufacturing, steel, machines, metal, transportation manufacturing, processed foods. Total employment is a sample of individuals. Age is averaged over metropolitan areas.

Table B.1
Skill interactions with additional controls (IAB Sample, 1975-2001)

	Yearly % total employment growth (SGMM2r estimator)			
interactions with:	S5	S6	S5+6 & time trend	
At *t-1*	(3)	(4)	(5)	(6)
ln S5	.043	.025		
	(.055)	(.013)*		
ln S6	.023	.072		
	(.010)**	(.039)*		
ln S2+4	1.932	1.418	.323	-.466
	(.398)***	(.300)***	(.075)***	(.355)
ln S3	-.096	-.048	.038	.036
	(.033)***	(.025)*	(.007)***	(.006)***
ln total employment	-.013	-.017	-.031	-.030
	(.007)*	(.006)***	(.009)***	(.009)***
ln S5 * ln S2+4	.390			
	(.086)***			
ln S5 * ln S3	-.025			
	(.008)***			
ln S6 * ln S2+4		.265		
		(.059)***		
ln S6 * ln S3		-.012		
		(.007)*		
ln S5+6 * time trend			.006	
			(.001)***	
time trend			.015	.005
			(.002)***	(.002)***
ln S5+6 * S2+4 * time trend				-.007
				(.001)***
ln S5+6 * ln S2+4				-.124
				(.092)
ln % manufacturing	-.010	.012	.087	.074
	(.023)	(.023)	(.026)***	(.022)***
Diversity index	-.106	-.082	-.032	-.049
	(.030)***	(.027)***	(.030)	(.030)*
Average worker age	-.015	-.010	.0005	-.0005
	(.005)***	(.004)***	(.003)	(.003)
Obs.	3204	3204	3207	3207
AR(1) test, p-value	5.86e-19	3.87e-18	1.58e-17	1.46e-17
AR(2) test, p-value	.739	.819	.075	.068
Sargan over-id. test, p-val.	.374	.371	.176	.169

ln Sx denotes the ln of the share of workers of skill level(s) x. Windmeijer (2005) robust standard errors in parentheses (two-step estimation). * significant at 10%; ** significant at 5%; *** significant at 1%. East Germany dummy included, and time dummies in columns 1 and 2..

Table B.2
Skill shares without workers in training (IAB Sample)

Level	Av. share in 1975	Av. share in 2001
6	1.3%	5.4%
5	1.3%	3.6%
4	0.6%	5.4%
3	0.3%	0.8%
2	60.1%	74.0%
1	36.4%	10.7%

Note: 2001 includes East Germany.

Table B.3
Without workers in training (IAB Sample, 1975-2001)

	Yearly % total employment growth (SGMM2r estimator)				
	(1)	(2)	(3)	(4)	(5)
ln S5+6	.052			-.057	.043
	(.017)***			(.024)**	(.048)
ln S5		.374	.046		
		(.071)***	(.019)**		
ln S6		.040	.227		
		(.016)**	(.045)***		
ln S2+3+4	.202				
	(.073)***				
ln S2+4		1.815	1.118	.521	.572
		(.456)***	(.288)***	(.102)***	(.407)
ln S3		.144	.094	.064	.070
		(.035)***	(.024)***	(.007)***	(.008)***
ln total employment	-.005	-.025	-.025	-.035	-.041
	(.006)	(.009)***	(.008)***	(.012)***	(.012)***
ln S5+6 * ln S2+4					.092
					(.106)
ln S5 * ln S2+4		.353			
		(.100)***			
ln S5 * ln S3		.034			
		(.009)***			
ln S6 * ln S2+4			.193		
			(.058)***		
ln S6 * ln S3			.022		
			(.006)***		
ln S5+6 * time trend				.006	
				(.001)***	
time trend				.013	.0007
				(.003)***	(.002)
ln S5+6 * S2+4 * time trend					-.006
					(.002)***
ln % manufacturing	.033	.037	.055	.091	.089
	(.014)**	(.024)	(.022)**	(.026)***	(.025)***
Diversity index	-.072	-.077	-.056	-.045	-.060
	(.026)***	(.041)*	(.036)	(.035)	(.040)
Average worker age	-.016	-.012	-.009	-.006	-.005
	(.003)***	(.007)*	(.007)	(.004)	(.004)
Obs.	3250	3115	3115	3117	3117
AR(1) test, p-value	3.43e-15	1.57e-16	5.32e-07	1.53e-15	7.20e-15
AR(2) test, p-value	.670	.943	.671	.077	.068
Sargan over-id. test, p-val.	.605	.481	.695	.186	.165

ln Sx denotes the ln of the share of workers of skill level(s) x. Windmeijer (2005) robust standard errors in parentheses (two-step estimation). * significant at 10%; ** significant at 5%; *** significant at 1%. East Germany dummy included, and also time dummies in column 1.

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