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Occupational Upgrading and the Business Cycle in West Germany

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Abstract

The occupational skill structure depends on the business cycle if employers respond to shortages of applicants during upturns by lowering their hiring standards. The notion and relevance of hiring standards adjustment was advanced by Reder and investigated formally in a search-theoretic framework by Mortensen. Devereux implements empirical tests for these theories and finds affirmative evidence for the U.S. labour market. We replicate his analysis using German employment register data. Regarding the occupational skill composition we obtain somewhat lower but qualitatively similar responses to the business cycle despite of well known institutional differences between the U.S. and German labour market. The responsiveness of occupational composition wages to the business cycle is considerably lower in Germany.

JEL: J62, J31, J41, C24

Keywords: Hiring standards; business cycle adjustment; occupational upgrading; wage structure; wage setting; overqualification

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1 Introduction

The delight caused by the 2006/2007 upturn of the German business cycle was soon followed by concerns about a threatening shortage of skilled labour (in German: 'Fachkraeftemangel'). Since unemployment rates remained at significant levels, one was tempted to perceive these concerns as pure exaggeration. A closer look at the composition of the unemployment pool suggests, however, that it may indeed be difficult to fill open slots with formerly unemployed workers because they often lack the required skills or experience. The related question whether and to which extent employers respond to skill shortages by upgrading less skilled workers (or to labour supply surplus by downgrading skilled workers) is interesting both from a political and theoretical point of view.

Regarding the political aspect it is interesting to see whether employers really filled open slots with under-qualified workers in the upturns of the last decades, whether the implied change of hiring standards has a noteworthy effect on the empirical skill composition within occupations and whether past upturns provided entries to stable employment relations for low educated workers. The change of skill requirements over the business cycle would explain why unskilled workers are affected more by recessions than skilled workers. If the unskilled are crowded out by the skilled, active labour market policy should not be focused on the unskilled but be directed towards skilled workers to eliminate the primary cause of the crowding out.[1]

Regarding theory, the results of our investigation sheds light on the question whether market clearing takes place mainly through wage adjustment (as assumed in pure neoclassical theory) or through a combination of wage and hiring standards adjustment. The notion of hiring standards adjustment goes back to Reder (1955) who develops a theory of occupational wage differentials based on the idea that "... employers tend to lower the minimum standards on which they insist as a condition for hiring a worker when applicants become scarce." Although the difference between wage and quality adjustment appears to be innocuous at first glance, wage adjustment is compatible with standard neoclassical wage competition whereas quality adjustment may generate efficiency wage problems (see Thurow (1975) and Schlicht (2005) for expositions of the argument and Bewley (1999) for survey evidence). Mortensen (1970) shows (in the framework of matching theories) that firms may combine wage and hiring standards adjustment even if wages are flexible.

If employers respond to labour shortage during upturns by lowering their hiring standards instead of bidding up wages, the average skill level within occupations should decrease. Therefore an empirically testable implication of Reder's theory is that the average skill level for occupations should be counter-cyclical. Devereux (2002) implements a test using the identifying assumption that (at least in the short run) jobs in the same occupation are characterised by identical skill requirements. He selects new hires (job starters and movers between firms) from the CPS data and forms occupation-year cells. The test is conducted by computing proportions of skilled employees for each cell and regressing them on the national unemployment rate and a rich set of control variables. A positive coefficient of the unemployment

[1] Cf. Devereux (2002), p. 425.

rate indicates counter-cyclicality of the new hires' skill levels. Devereux finds the theory confirmed for the U.S. data.[2] As a further implication of Reder's theory, the responsiveness of mean qualification should be more pronounced for lower-paying occupations. Devereux tests this by ranking occupations with respect to average wages, partitioning the sample into five quintiles, and running the regressions separately for every quintile. The results are again affirmative but the evidence is less clear and the outcomes depend on the definition of the average skill measure.

A second implication of Reder's theory is that the occupational composition of employment should change systematically over the business cycle. If employers respond to labour shortage during upturns by lowering their hiring standards instead of bidding up wages, they create possibilities for employees to improve their wages by occupational upgrading, i.e. by moving from low wage occupations to more highly paid ones. The converse (downgrading) should be observed during downturns. Devereux (2002) implements a test by selecting a sample of job changes, computing a measure of occupational quality and regressing it on the unemployment rate and control variables. He finds that employees are likely to move to higher-paying jobs if the unemployment rate is falling, i.e. the occupational composition wage is procyclical in the U.S.

We replicate Devereux's analysis on skill shares and on occupational upgrading using employment register data from the German Federal Employment Agency (Bundesagentur für Arbeit) which comprise detailed wage and demographic variables for all dependent employees covered by the social security system (about 80 percent of the work force). Particular advantages of our data are their huge size (about 20 to 25 million workers per year for West Germany) and the long time period covered (1980-2004). We use similar estimation methods but have to account for small differences in the data such as censored wages. The similarity of the data and the estimation approach render us with estimation results we regard as directly comparable to the US results.

In spite of the often emphasized differences between the U.S. and German labour markets, we find noteworthy similarities in the cyclicality of the occupational skill composition for both countries. The responses for West Germany amount to about 70 percent of the U.S. values. The analysis of occupational wage upgrading yields a similar result. We find that the occupational composition wage is procyclical, but in Germany the responsiveness is substantially lower than in the U.S. At first glance these similarities are surprising because the labour markets in both countries are characterized by quite different institutional frameworks. The most striking differences relate to 1) the wage bargaining system, 2) the occupational training system and 3) the role of the government with regard to regulations such as job protection laws.[3]

A closer inspection of the impact of these institutions on the occupational skill

[2]A related analysis on crowding out of unskilled workers in the business cycle is presented in Pollmann-Schult (2005). It is, however, not informative regarding Reder's theory because it does not control for cyclical between-occupation shifts.

[3]As the differences between Germany and the U.S. are stressed frequently and explained in detail in the literature, we outline only the most important details. See Franz and Soskice (1995) or Harhoff and Kane (1997) for international comparisons of the occupational training system, and Soskice (1990) for a survey on the wage bargaining systems.

composition reveals countervailing forces. To see the implications of a tight wage bargaining system and wage rigidities consider an economy hit by a positive product demand shock. For a homogenous production function (which should be a good approximation to reality) we expect equal increases in the demand for all factors of production, hence equal increases for skilled and unskilled workers. Firms would bid up wages in their recruitment efforts for *all* skill groups. Relative employment of the skill groups should remain (almost) unchanged as long as the supply elasticities of skilled and unskilled workers do not differ too much. If firms lower hiring standards instead of bidding up wages, relative employment of the unskilled will increase. Thus, we expect wage rigidities to increase the responsiveness of skill proportions to the business cycle, which implies that effects should be *greater* for Germany. More generous unemployment benefits act in the same direction by generating a de-facto time-invariant minimum wage affecting mainly the unskilled.

Regarding occupational upgrading the same logic suggests that effects may even be more pronounced in Germany. Dependence of occupational upgrading on the business cycle is based, however, on at least two requirements: Employers must vary hiring standards in response to the business cycle *and* wage differentials between occupations must be noncompetitive. The second condition is necessary since employees had no incentive to move to more highly paid occupations if the associated wage gain compensates only for more unpleasant working conditions or additional risks (as in the case of compensating wage differentials).

Thus the less pronounced responses found in the German data should rather be caused by a less permeable occupational system in Germany. This is confirmed by a closer look at the institutional conditions: Whereas occupational training in the U.S. is almost completely in the responsibility of the employer, vocational training is well-structured, strictly regulated and standardized in Germany. Training lasts between two and three years in the so-called 'dual system' and takes place in firms (about 3-4 days per week) *and* vocational schools (1-2 days per week). Generalized curricula which are binding for (specialized) vocational schools as well as for employers are defined by national committees and monitored by the chambers of commerce and industry. The training ends with standardized theoretical and practical examinations. Its paramount importance for the German labour market is due to the fact that the entry to many jobs in industry and trade de-facto requires a certificate of completed apprenticeship and remuneration in most collective wage agreements is linked to vocational qualification.[4] Because of the importance of vocational degrees we expect low and medium skilled workers to be less substitutable in Germany which is why we expect less pronounced responses of the occupational skill composition to the business cycle in West Germany. Finally, responsiveness should be lower also due to job protection laws. They increase firing costs and the risks associated with bad matches between unskilled workers and complex tasks and thus make it less profitable to recruit unskilled workers for skilled jobs during upturns. To summarize: While wage rigidities and generous unemployment benefits strengthen the reaction of skill proportions to the business cycle, institutional rigidities should lower it. Note however, that the presence of institutional rigidities in

[4] Additionally, many craft trades may be practised only by or under the supervision of a master craftsmen.

Germany does not necessarily imply inefficiencies since they may be associated with more pronounced incentives to acquire occupation- or firm-specific human capital.

We conduct a test of the occupational rigidities hypothesis by restricting the sample for the skill proportions model to recognized occupations. The rationale for the test is that skill proportions responses should be significantly lower for this subsample if the occupational system restricts access of the unskilled to certain jobs. The hypothesis is, however, rejected by this test as the the coefficients are almost identical to the full sample. An alternative explanation for the differences between Germany and the U.S. relates to differences in the firm structure. Separate skill proportions regressions show that business cycle effects are considerably smaller for small establishments. According to this outcome, skill proportions may be less responsive in Germany simply because of the larger share of employees in small firms.

The plan of the paper is as follows. In the next section we provide a description of our data, explain data selection and processing steps and discuss differences to Devereux's data. Section 3 is on our analysis of skill proportions and Section 4 on occupational wages. Both sections start with a description of the econometric model which is followed by the estimation results. We conclude with a summary.

2 Data

Our analysis is based on the employment register of the German Federal Employment Agency that includes information of daily accuracy on all employees liable to social security in Germany. These register data stem from the employers' periodic notifications which are the basis for the calculation of individual social security contributions and social security claims such as unemployment benefits or pensions.

We choose all observations for the years 1980 to 2004 and create cross-sections for the reference date June 30. As our definition of new hires relies on information from the year before we are able to analyse 24 years from 1981 to 2004. The sample is restricted to employees who work in West Germany for two reasons. First, information for East Germany is not available before 1993. Second, the educational and vocational system in the former communist state differed considerably from the West German. More important, productivity of East German workers may have been lower in the past as they were trained and worked with different and outdated equipment in the communist economy. We keep full-time workers aged between 20 and 60 years and exclude apprentices. Marginal employees who are not liable to social security contributions because their wage is below a certain threshold are dropped because they are not included in the employment register until 1999. For employees with more than one job we keep the job with the highest wage which we consider the main job.

All employees who did not work in the same establishment on June 30 of the year before are considered new hires. They either come from the education system, from unemployment or from jobs in other establishments. Establishments are identified by the establishment id that is assigned to every establishment by the local employment agency.[5]

In our analysis of occupation wages in Section 4 we have to observe the wage before the entry into the new firm. Therefore the sample is restricted to all establishment movers who were employed for at least two months in the current year and the year before. Since 1984 bonus payments are included in wage records but cannot be identified. That is why we further exclude the years before 1984 from the wage estimation sample. Besides the information on earnings that is necessary to calculate the social security contributions, the employment register includes some basic characteristics of the employee also filled in by the employer. These are gender, educational degree, nationality, education, and occupation. This information is not relevant to social security contributions and claims. Employers misreporting on these items are not sanctioned. Nevertheless high response rates and consistency checks in general indicate a good data quality. One reservation applies, however, for our education variable. It is a mixture of schooling and vocational degree with 6 categories:

Lower/intermediate secondary school leaving certificate

1. without completed vocational training
2. with completed vocational training (completed apprenticeship or semi-skilled training, completion of a specialized vocational school)

Upper secondary school leaving certificate (general or subject-specific aptitude for higher education)

3. without completed vocational training
4. with completed vocational training (completed apprenticeship or semi-skilled training, completion of a specialized vocational school)

5. Technical college degree (formerly: advanced technical school)
6. College/university degree

Consistency checks of the education variable suggest that employers sometimes seem to infer the education level from the task performed by the employee. For example, they report a vocational degree for an unskilled employee if he is assigned to a task requiring a vocational degree. Inspection of individual worker biographies indicates that this occurs mainly for unskilled workers.[6] This implies that estimates of the occupational skill responsiveness are biased towards zero.

The qualification proportions are listed in Table 1. We group the education levels into three categories: low is without vocational degree (1 and 3), medium is with vocational degree (2 and 4), and high is with college or university degree (5 and 6). In the analysis of changing hiring standards workers with missing education information are dropped, in the wage analysis they are included and assigned to a fourth 'dummy' skill group. In analogy to Devereux (2002) our skill proportions analysis is based on the proportions of (a) high-skilled workers and (b) qualified workers (medium- and high-skilled) for each cell. The comparability of group (a) to U.S. college graduates is beyond dispute. Things are less clear regarding group (b).

[5] In rare cases the establishment id changes although the establishment stays the same, e.g. if the owner changes. In general the identification of new hires can be considered as very reliable.

[6] One way to check the consistency of the education variable is to select all employees reported to have completed vocational training. Since the register data date back to 1975 we should observe vocational training spells at least for all selected workers who were born after 1960.

We think it can be considered comparable to employees with at least a high school diploma in the U.S. as “Apprentices in Germany occupy a similar position within the German wage structure as held by high school graduates in the U.S. labour market” (Harhoff and Kane (1997)). Over all years on average 7.6 percent of the new hires are high skilled, 80 percent are qualified.

The occupational classification used in the employment register lists 331 occupations. We drop the occupations home-care nurses and household helpers as they are not included in all years. We further drop medical professions, pharmacists, lawyers and architects because the frequencies of these professions change implausibly, especially in 1998. Our final sample includes 324 occupations.[7]

Table 1 shows descriptive statistics of our two samples for 1984 and 2004.[8] The full sample column regards all employees liable to social security in West Germany who work full-time and are aged between 20 and 60. In 1984 14.98 mill. observations in the full sample amount 74.4 percent of all employees liable to social security, in 2004 14.85 mill. observations amount to 70.0 percent. The decline of the share is mainly due to the rise in part-time employment. The skill composition sample contains new hires with valid information on the education variable. The wage sample contains new hires with wage information on the year before. Therefore these samples overlap but they are not nested. The share of observations in the skill composition sample falls from 13.9 to 12.1 percent which is in part due to a rise of missing values in the education variable. The share of observations in the wage sample rises from 6.7 to 8.0 percent.

[7]As a robustness check we repeated the analysis with the occupations aggregated to 82 occupational groups on the two-digit-level. The results are not included here because deviations from the reported effects are small. They can be obtained from the authors on request.

[8]We selected these years for descriptives because the skill composition analysis includes the years 1981 to 2004 and the wage analysis the years 1984 to 2004. So these years are the first and the last year of the overlapping period.

Table 1: Descriptive statistics

	Full sample		New hires			
			Skill composition regressions		Wage regressions	
	Mean	SD	Mean	SD	Mean	SD
1984						
Age	37.91	11.27	32.31	10.56	33.82	10.58
Female	0.32	0.47	0.35	0.48	0.29	0.46
Low/intermed. school	0.23	0.42	0.23	0.42	0.18	0.38
Vocational training	0.66	0.47	0.69	0.46	0.68	0.47
Upper school	0.01	0.07	0.01	0.10	0.00	0.07
Upper school and vocational training	0.01	0.12	0.02	0.14	0.02	0.13
Technical college	0.02	0.15	0.02	0.15	0.02	0.14
University degree	0.02	0.14	0.03	0.16	0.02	0.15
Education missing	0.05	0.23	-	-	0.08	0.27
Daily wage	63.62*	22.43	54.50*	21.35	61.06*	22.02
Observations	14,980,342		2,083,308		1,011,006	
2004						
Age	39.55	9.97	35.68	10.19	37.43	9.73
Female	0.33	0.47	0.34	0.47	0.30	0.46
Low/intermed. school	0.12	0.33	0.16	0.37	0.10	0.29
Vocational training	0.61	0.49	0.65	0.48	0.56	0.50
Upper school	0.01	0.09	0.01	0.12	0.01	0.08
Upper school and vocational training	0.05	0.21	0.06	0.24	0.06	0.23
Technical college	0.04	0.19	0.04	0.20	0.04	0.20
University degree	0.05	0.22	0.07	0.26	0.06	0.24
Education missing	0.12	0.33	-	-	0.18	0.39
Daily wage	76.97*	33.80	66.22*	34.45	74.39*	34.13
Observations	14,848,781		1,803,104		1,182,873	

Skill composition regressions include the years 1981 to 2004, wage regressions the years 1984 to 2004.

*) Median instead of mean due to the upper censoring of wages (wages are in Euro and deflated with base year 1995).

As can be expected new hires are younger on average than all full time employees. New hires in the skill composition sample are even younger than those in the wage sample. Average age is considerably higher in 2004 than in 1984. Compared to the full sample the proportion of women is higher in the skill composition sample but lower in the wage sample in both years. The education level is rising over time but shows only small differences between the samples. In agreement with the age pattern the median wage is lower for new hires and lowest in the skill composition sample. The unemployment rate for West Germany in the years 1981 to 2004 is taken from the official employment statistics of the German Federal Employment Agency (BA-Statistik).

There are some minor differences between our and Devereux's data and definitions. First, we define prime age 20 to 60, Devereux 18 to 64. The upper limit is decreased in our study to 60 to avoid bias due to early retirement practices in Germany. Second, we identify new hires using establishment ids, Devereux uses job descriptions or industries. And third, Devereux's occupational classification scheme seems to be slightly finer than ours.[9] In general the samples can be considered very similar so that differences in results can be attributed to institutional differences between the U.S. and Germany.

3 Explaining the occupational skill composition

As the main intention of our paper is to compare the U.S. and German labour markets, our estimation procedures follow Devereux (2002) closely. Minor variations are introduced because our data allow for additional checks and extensions or urge us to minor changes because of the censoring of wages.

3.1 Empirical model

To investigate the cyclicality of the occupational skill composition, Devereux (2002) runs regressions of the proportion of qualified workers in occupation-year cells ot on the unemployment rate U_t, a quadratic trend and fixed occupation effects γ_o:

$$s_{ot} = \beta_0 + \beta_1 U_t + \beta_2 t + \beta_3 t^2 + \gamma_o + v_t + \epsilon_{ot} \tag{1}$$

ϵ_{ot} denotes a white noise residual and v_t an unobservable time shock.[10] Direct estimation of this model using the standard OLS coefficient variance formula would yield severely biased standard errors because U_t is constant for all cells within a year.[11] This problem can be solved either by computing the covariance matrix in a way that allows for clustering by year or by the application of a two-step procedure.

[9] As reported above, we use 324 different occupations. Devereux does not report this number. It can, however be inferred from the cell numbers given in his Table 2b. He uses 6508 occupation-year cells for 17 years. A balanced panel with 383 occupations and 17 years would amount to 6511 cells (some cells may be empty in some years.)

[10] Note that v_t cannot be estimated because of the dimension of U_t.

[11] See Moulton (1986) for an exposition of the issue.

In the first step the shares are regressed on occupation and time dummies:

$$s_{ot} = \delta\,\gamma_o + \sum_{t=1}^{T} \phi_t\, D_t + \;\epsilon_{ot} \tag{2}$$

Each occupation-year cell is weighted by its number of individuals. In the second step the time dummy coefficients (which can be interpreted as composition-corrected proportions) are regressed on a quadratic trend and the unemployment rate.

$$\hat{\phi}_t = \alpha_1 + \alpha_2\, U_t + \alpha_3\, t + \alpha_4\, t^2 + \nu_t \tag{3}$$

Again each observation is weighted by the number of individuals. Amemiya (1978) shows that this two-step procedure is equivalent to one-step GLS. The fact that the second stage is a simple time series regression makes it simple to allow for serial correlation of residuals either by computing Newey-White standard errors or by including lags of the unemployment rate. Both extensions lead to negligible differences in the estimation results.

However, since the dependent variable is a proportion, the linear model can only be regarded as an approximation. In a more structural approach, one would assume that the qualification proportions within cells are generated by the aggregation of individual decisions to the occupation level.[12] The individual decisions (whether to employ a high-skilled worker in a particular occupation) follow Bernoulli sampling, which is why we estimate a grouped probit model with log-likelihood

$$\ln L = \sum_{o,t} n_{ot}\left\{ s_{ot}\,\ln\Phi(x_{ot}\,\beta + \gamma_o) + (1 - s_{ot})\,\ln\big(1 - \Phi(x_{ot}\,\beta + \gamma_o)\big)\right\} \tag{4}$$

where $\Phi(\cdot)$ denotes the standard normal distribution function and n_{ot} is the number of employees per cell.

Some problems also remain with the grouped probit model. First, nonlinear fixed effects models are inconsistent if the number of fixed effects increases proportionally with the sample size and sufficient statistics for the other parameters of interest are not available.[13] This bias should be negligible in our estimation with 24 observations (years) per occupation.

Second, the dependent variable is zero or one for some cells.[14] This generates surprisingly low standard errors in large samples and is a feature of the model. An ad-hoc patch to this problem is to add or subtract a small number, say 0.001 from corner values of the dependent variable. Fortunately this problem disappears when bootstrapped standard errors are used instead of asymptotic ones. Devereux has to restrict his analysis to linear models because in his sample the dependent variable

[12] See Greene (2002) for a textbook introduction to proportions data models.

[13] A sufficient statistic for the *linear* fixed effects model is the within-transformation because the transformed model is purged of the fixed effects. Papke and Wooldridge (2008) present an alternative way incorporate fixed effects in fractional response models for panel data. They apply the Chamberlain device which avoids estimation of all individual fixed effects application of a conditional normality assumption for the fixed effects. The Chamberlain device is, however, valuable or even necessary only for panels with short time dimension.

[14] See Table 10 in the appendix.

is zero or one for a large number of cells – rendering the grouped probit model infeasible.

As a further shortcoming the grouped model does not allow to include individual level control variables (e.g. age, sex, establishment size). We checked this by running linear index models with binary dependent variables[15] and control variables age, sex and establishment size at the individual level. Since this has only negligible effects on the unemployment coefficients, we apply the simpler grouped models.

In the grouped probit model the marginal effect of the unemployment rate on skill shares is

$$\frac{\partial s_{ot}}{\partial u} = \phi(x_{ot}\beta)\,\beta_u \tag{5}$$

where $\phi(\cdot)$ denotes the density of the standard normal distribution function and β_u the coefficient of the unemployment rate. The marginal effects depend on the characteristics x_{ot} and all coefficients β and thus vary over occupation-year cells. We compute the average marginal effect as

$$\overline{ME(x)} \equiv \overline{\frac{\partial s}{\partial u}} = \frac{1}{OT}\sum_o \sum_t \phi(x_{ot}\beta)\,\beta_u \tag{6}$$

where O and T denote the number of occupations and years. An alternative estimate often used in the literature (and implemented in the Stata® mfx command) is

$$ME(\bar{x}) \equiv \left.\frac{\partial s}{\partial u}\right|_{x=\overline{x}} = \phi(\bar{x}\beta)\,\beta_u, \tag{7}$$

i.e. the marginal effect evaluated at the average characteristics vector. $\overline{ME(x)}$ and $ME(\bar{x})$ are different because of the nonlinearity of $\phi(\cdot)$. We consider the $\overline{ME(x)}$ to be the adequate measure but report both.[16]

The presence of the aggregated regressor U_t generates an additional problem for the computation of standard errors. We apply a blocks bootstrap procedure to solve it. Our bootstrap samples S_b consist of blocks containing all observations from one year. The grouped probit model is computed for every bootstrap sample to obtain $\overline{ME(x)}$ and $ME(\bar{x})$. Inference is based on the vectors of bootstrap results $(\overline{ME(x)}_{b=1},\ldots,\overline{ME(x)}_{b=1000})$ and $(ME(\bar{x})_{b=1},\ldots,ME(\bar{x})_{b=1000})$.[17]

Inspection of the time series of fixed effects $\hat{\phi}_t$ points to a structural break in

[15] The dependent variables are – in analogy to the definitions of proportions – (1) 'the individual has a college or technical college degree yes/no' and (2) 'at least a completed apprenticeship yes/no'.

[16] It is simple to construct examples where $ME(\bar{x})$ gives meaningless results. Consider a simple grouped probit model with only one regressor x and a positive correlation between x and the dependent variable. If the sample contains only observations with very low and very large x values, then the marginal effects for both groups of observations are small because $\phi(\cdot)$ is flat for extreme values. Misleadingly the marginal effect evaluated at $\hat{x}$ may be of considerable size because $\phi(\cdot)$ obtains its maximum in the center.

[17] Stata's® mfx command has a cluster option that allows for clustering of standard errors by year (as required in our case). But the implementation is not applicable if the number of regressors exceeds the number of clusters which is the case in our model with more than 300 fixed effects but only 24 clusters (years).

1998/1999 for the high-skilled shares. This break is likely to be caused by changes of the reporting rules in 1999. To capture the break, a dummy for the years 1999-2004 and interactions between the linear and squared trend with this dummy are added to the model.

3.2 Results

Figure 1 gives a visual impression of the correlation between skill levels within occupations and the unemployment rate over time. The proportions are coefficients on year dummies obtained from the linear estimation of Equation 2. All series are detrended to focus on the cyclical component.[18] The positive correlation is apparent for both the proportion of graduates and the proportion with vocational degree or more. Table 2 shows the results of the estimation of Equations 3 and 4. The

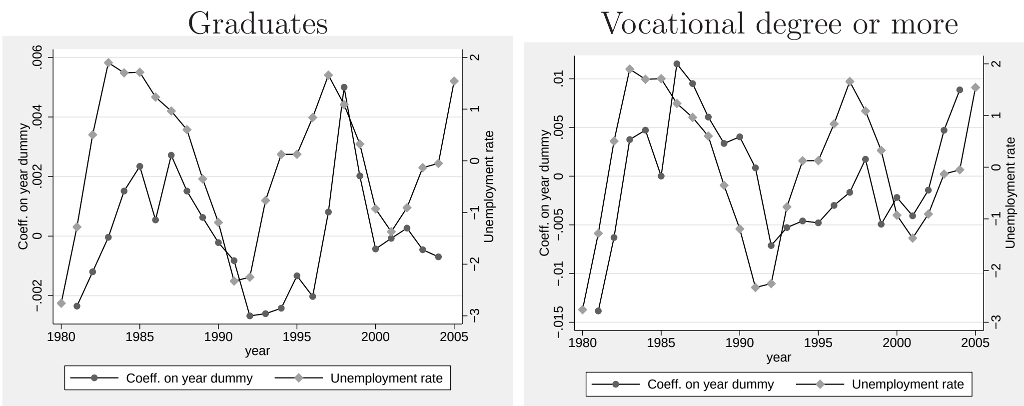

Figure 1: Detrended skill proportions within occupations and the detrended unemployment rate

marginal effect of 0.109 for the proportion of graduates means that this proportion among new hires increases by roughly 0.11 percentage points if the unemployment rate rises by one percentage point. The corresponding value for the share of employees with a vocational degree or more is 0.35 percentage points. All effects are significant at the 5 percent confidence level. Note that $ME(\bar{x})$, the marginal effect computed at the average characteristics vector, is considerably lower for the regressions explaining graduate shares.[19] As explained above, we consider $\overline{ME(x)}$ to be the more meaningful measure. Note furthermore that $\overline{ME(x)}$ and marginal effects from the linear model are quite similar, indicating that the linear model provides good approximation.

Given the disclaimers regarding the comparability of the educational systems in the U.S. and West Germany, a comparison of Devereux's and our results reveals unexpected similarities. He obtains a marginal effect of 0.16 (with standard error 0.07) for the proportion of graduates and 0.53 (with standard error 0.10) for the

[18] To eliminate the trend we regress the original time series on linear and squared trends and plot the residuals.

[19] The $ME(\bar{x})$ is lower because the proportion of high-skilled in the estimation sample is about 7.6 percent, which implies that most observations fall in the lower (convex) part of the normal distribution function. Thus $ME(\bar{x}) < \overline{ME(x)}$ by Jensens's inequality.

Table 2: Marginal effects of the unemployment rate on skill proportions of new hires

	Type of marg. effect	(1) Proportion of graduates		(2) Proportion with voc. degree or more	
		Marg. eff.	SD	Marg. eff.	SD
Linear, 2-step		0.098	0.020	0.314	0.060
Grouped probit	$\overline{ME(x)}$	0.109	0.035	0.349	0.109
	$ME(\bar{x})$	0.065	0.021	0.381	0.119

Notes: All coefficients and standard errors are multiplied by 100.
The estimation sample contains $324 \times 24 = 7776$ occupation-year cells. $\overline{ME(x)}$ and $ME(\bar{x})$ denote marginal effects as defined in Equations 6 and 7.
All regressions include linear and squared trend terms, a full set of fixed occupation effects, and dummy and trend interaction terms for the period 1999-2004. Newey-West standard errors allowing for serial correlation (up to 2 lags) are reported for the linear model. Standard errors for the grouped probit model are computed using a block bootstrap procedure that allows for clustering by year. Some cells are 'censored', see appendix Table 10.

proportion of employees with high school diploma or more. In both cases the U.S. point estimates exceed our estimates for West Germany by about 50 percent but the differences are statistically insignificant. These similarities are surprising if we consider that the U.S. labour market is almost free of occupational regulations whereas the German vocational training system is highly regulated.

A related hypothesis is that tight standardizations and regulations related to vocational training lower the substitutability between skilled and unskilled jobs and therefore are responsible for less pronounced responses in Germany. This can be tested indirectly by restricting the estimation sample to occupations covered by the dual vocational training system (recognized occupations, 'anerkannte Ausbildungsberufe'). The results in Table 3 show, however, that deviations from the base sample are negligible and insignificant.

As laid out Section 1, the theoretical model implies that skill proportions in occupations with generally low skill requirements should react stronger to the business cycle. To analyse this hypothesis with our data, we again follow Devereux (2002) and distinguish occupations with different levels of skill requirements by grouping the occupations according to their general wage level. The latter is calculated as the median deflated wage per occupation over all years.[20] We group the occupations by median wage quintiles and run separate regressions for every quintile. Marginal effects for the grouped probit are shown in Table 4.[21] As expected, all point estimates of the marginal effects are positive. They are significant at the 5 percent level for the lower four quintiles for graduates and for the three lower quintiles for employees

[20] We use the median instead of the average wage because of right censoring. The median is below the censoring limit for all occupations.

[21] The linear model and the $ME(\bar{x})$ of the grouped probit yield very similar results that are shown in Table 11 in the Appendix.

Table 3: Marginal effects of the unemployment rate on skill proportions of new hires, restricted sample of (state-approved) recognized occupations

	Type of marg. effect	(1) Proportion of graduates		(2) Proportion with voc. degree or more	
		Marg. eff.	SD	Marg. eff.	SD
Linear, 2-step		0.109	0.016	0.318	0.055
Grouped probit	$\overline{ME(x)}$	0.090	0.021	0.369	0.107
	$ME(\bar{x})$	0.043	0.010	0.409	0.119

Notes: All coefficients and standard errors are multiplied by 100.
The estimation sample contains $184 \times 24 = 4416$ occupation-year cells. $\overline{ME(x)}$ and $ME(\bar{x})$ denote marginal effects as defined in Equations 6 and 7. The register of recognized occupations contains 184 items, covering about 66 percent of the employees in our base sample. The specification is identical to the model in Table 2.

with at least a vocational degree.

Table 4: Marginal effects of the unemployment rate on skill proportions of new hires by quintiles, grouped probit, $\overline{ME(x)}$

	Proportion of graduates		Proportion with voc. degree or more	
	Marg. eff.	SD	Marg. eff.	SD
1st quintile	0.066	0.015	0.444	0.138
2nd quintile	0.045	0.010	0.469	0.151
3rd quintile	0.072	0.018	0.456	0.166
4th quintile	0.070	0.031	0.232	0.165
5th quintile	0.234	0.130	0.058	0.053

Notes: All coefficients and standard errors are multiplied by 100.
$\overline{ME(x)}$ denotes the sample average of marginal the effects as defined in Equation 6.

Analogous to Devereux's results, our findings do not indicate evidence of a systematic pattern for the graduates. The marginal effect for the 5th quintile is considerably larger compared to the lower quintiles, but insignificant. For the proportion of new hires with at least a vocational degree we find roughly equal marginal effects for the first three quintiles and a decline for the 4th and 5th quintile. These results are in line with our hypothesis and similar to Devereux's results. In contrast to our results his estimates decline more evenly from 0.1 (0.14) in the 1st quintile to -0.21 (0.07) in the 5th quintile. Regarding the hypothesis that the effect of the business cycle on hiring standards should be larger for occupations with generally low skill requirements we find similar evidence for West Germany as Devereux found for the U.S.: high-skilled proportions are equally affected across occupation types but medium-or-more skilled proportions are more reactive in low wage occupations.

Table 5: Marginal effects of the unemployment rate on skill proportions of new hires by establishment size, grouped probit, $\overline{ME(x)}$

Estab. Size	Proportion of graduates		Proportion with voc. degree or more	
	Marg. eff.	SD	Marg. eff.	SD
1-19	0.088	0.018	0.296	0.097
20-99	0.123	0.026	0.394	0.098
≥ 100	0.159	0.050	0.321	0.172

Notes: All coefficients and standard errors are multiplied by 100.
$\overline{ME(x)}$ denotes the sample average of marginal the effects as defined in Equation 6. See Table 10 in the appendix for shares of corner solutions (skill proportion is zero or one).

A possible explanation for the lower responses of the occupational skill composition in Germany may be found by separating the effects by establishment size. Table 5 shows marginal effects for small, medium size and large establishments. The responses are more pronounced for medium size and large establishments. Several reasons might explain these differences. First, large establishments have alternative jobs for unskilled workers if it turns out that the hired person does not meet the requirements of the particular job he was hired for. Second, helpers and handymen can be utilized better in larger teams because in teams they can specialize on certain tasks.[22]

Devereux's analysis does not differentiate by establishment size. Thus we do not know whether the impact of establishment size on the response of skill proportions in the U.S. is similar to Germany. In this case establishment size could explain part of the differences between the U.S. and Germany. Table 6 shows that Germany has considerably more small (1-4 employees) and less large (more than 500) establishments than the U.S.

Table 6: Comparison of establishment size distributions in 1990

Country	0-4*	5-9	10-19	20-99	100-499	500+
Germany	63.26	17.56	9.32	7.87	1.69	0.30
U.S.	49.10	15.72	9.71	9.56	4.13	11.78

Note: * U.S.: 0-4 employees (establishments with 0 employees have no paid employees in the mid-March pay period, but at least one in some other period of the year), Germany: 1-4 employees liable to social security.
Source: U.S.: U.S. Census Bureau, County Business Patterns, Germany: Employment Register (BEH), reference date June 30, 1990.

[22]Note however, that small firms are exempted from job protection laws in Germany. This lowers the risk associated with hiring unskilled workers. Apparently, these exemptions do not play a significant role. See Bauer et al. (2007) for a systematic investigation of the issue.

4 Explaining occupational composition wages

In this section we isolate the component of the cyclical variation of wages that is due to occupational up- and downgrading. We answer the question "how would aggregate wages respond to the business cycle if wages remained constant within all occupations?" In this case all wage variation is caused *purely* by changes of the occupational employment structure (composition). Note that this question is complementary to the empirical literature on the cyclicality of wages which puts focus on gross wage changes.[23] To avoid misunderstandings we introduce a new label for this measure: *occupational composition wage*.

4.1 Empirical model

As in the preceding sections, our analysis follows Devereux (2002). To investigate the cyclicality of the occupational composition wage he runs regressions of the change of an indicator for occupational quality on demographic control variables (dummies for black, married, white, graduate, high school, a cubic polynomial in experience), a time trend and the change of the national unemployment rate. The dependent variable is constructed as follows. First, compute mean wages for every occupation $z_o := (1/n_o) \sum_t \sum_i D(i,o,t) \ln(w_{it})$ where the dummy $D(i,o,t)$ is one if individual i works in occupation o in year t (and zero otherwise) and $n_o = \sum_i \sum_t D(i,o,t)$. The dependent variable of the regression is computed as change of the occupation wage induced by a change of occupation, i.e. $\Delta z_{iot} = z_{o'} - z_o$ if individual i moves from occupation o to o' in year t and zero if i remains in the same occupation. This implies that the wage gain (or loss) of a worker switching between occpuations o and o' is equal to the (long term) mean wage difference between these occupations. The estimation model has the form

$$\Delta z_{iot} = \alpha_1 + \alpha_2 \, \Delta U_t + \alpha_3 \, x_{iot} + \alpha_4 \, t + v_t + \epsilon_{iot} \tag{8}$$

Here U_t denotes the unemployment rate, x_{oit} contains individual level control variables for individual i, t is the time trend, v_t is a time shock and ϵ_{iot} a white noise residual.

Specification (8) is similar to the one used frequently in the wage cyclicality literature[24] but inconsistent with the standard Phillips curve specification where the change of the unemployment rate enters instead of the level. A simple way to test between these two specifications (proposed by Card and Hyslop (1997)) is to replace ΔU_t in the regression above by $\alpha_2^0 U_t + \alpha_2^1 U_{t-1}$. Then the H_0 related to the Phillips-Curve is $H_0^P : \alpha_2^1 = 0$ whereas $H_0^C : \alpha_2^1 = -\alpha_2^0$ is compatible with the standard cyclicality formulation. Application of the test to our data delivers moderate though not fully conclusive evidence in favour of the standard wage cyclicality formulation. The estimates for α_2^0 and α_2^1 (and standard errors in brackets) are -0.397 (0.062) and 0.290 (0.052) for men and -0.679 (0.066) and 0.363 (0.052) for women, respectively.

[23] 'Composition bias' is a central issue in this literature. These studies investigate, however, the composition of the labour force with respect to employed and unemployed workers but *not* the occupational structure of the employed. See Abraham and Haltiwanger (1995) for a survey.

[24] See Abraham and Haltiwanger (1995) for an overview and references.

Although the coefficients of the lagged unemployment rate are highly significant and thus clearly reject H_0^P, the difference between α_2^0 and α_2^1 is large enough to reject H_0^C, too. We proceed with the difference specification for two reasons. First, we regard the estimates as being more in line with H_0^C. And second, the estimation of a dynamic model would add several technical problems but should deliver similar results for our purposes.[25]

In order to calculate wage differences we restrict the estimation sample to all job movers who were employed in the current year and the year before for at least two months. As in the previous section, Devereux implements the estimation in two stages. In the first stage, changes of occupational mean wages are regressed on individual characteristics and a full set of year dummies.

$$\Delta z_{iot} = \alpha_1 + \alpha_3\, x_{iot} + \sum_{t=1}^{T} \phi_t\, D_t + \epsilon_{iot} \tag{9}$$

The coefficients of the year dummies can be interpreted as occupational composition effects by year. In the second stage they are regressed (using cell size as weight) on a linear time trend and the change of the unemployment rate.[26]

$$\hat{\phi}_t = \alpha_2\, \Delta U_t + \alpha_4\, t + \epsilon_{ot} \tag{10}$$

The two-stage approach is computationally convenient to obtain unbiased standard errors in the presence of the aggregated regressor but not necessary. Alternatively, one can estimate in one step and cluster standard errors by year. We experimented with both approaches because the two-stage approach is slightly more flexible,[27] but report only the one-step results because the differences in results are small.

Our specifications differs in two aspects from Devereux's model. First, we use a slightly different set of control variables. We do not include a dummy for marriage because this information is not contained in our data. Variations of the set of individual level control variables, however, seem to have a small impact on the results. The second and more important difference to Devereux is, that in our data about 10 percent of the wages are right censored. Before we calculate the average wages for each occupation, we replace these censored wages with predictions of the unobserved wages.[28]

[25]As is well known, standard fixed effects models are biased due to correlation of the lagged endogenous variable with the error term. Alternative GMM estimators require good instruments and appeared to be unstable in empirical applications. If the dynamics is not relevant *per se*, the difference model provides a good approximation to short run effects which are in our focus, see e.g. Baltagi and Griffin (1984).

[26]The linear trend is used instead of a quadratic because the model is formulated in first differences.

[27]It allows to account for serial correlation in the computation of standard errors in a simple form.

[28]First we run tobit regressions of individual log wages on control variables (the same as in the final regressions) and year dummies separately for every occupation and sex. Then we predict censored wages and add residuals drawn from a truncated normal distribution with the standard deviation estimated by the tobit models. Finally means of the imputed wages are computed for every occupation.

Reder's theory predicts that the extent of occupational upgrading should vary over the wage distribution. If high wage occupations respond to increasing product demand by poaching workers from lower paying occupations, then in the lower paying occupations also the slots of the poached workers have to be filled. Therefore the possibilities (measured as vacancies) to move to better-paying occupations should be higher for employees with low wages and skills. To test this, Devereux sorts workers into quintile groups using a simple measure of personal skills. The measure is the predicted wage from a regression of (log) wages on personal characteristics.[29] We created two slightly different skill measures. The first one is the predicted wage from a regression including a cubic in experience, education dummies, and a set of year dummies (but year dummies do not enter the prediction). For the second measure, job characteristics such as a second order polynomial in log establishment size, a dummy for white collar workers and 27 sector dummies are added to the first specification, but as the year dummies these are not used for the prediction. The second specification should deliver a more precise estimate of personal productivity since correlations with establishment or sector level variables are eliminated. The difference between both specifications is small with respect to the second step estimates. In the next section we show the results based on the second measure which is more conservative (i.e. it produces slightly less pronounced differences between quintile groups).

4.2 Results

The occupational composition wage depends on the mean occupation wages and the occupational composition of employment. As the mean occupation wages are by construction constant over time, the business cycle must create employment shifts between occupations to exert an impact on the occupational composition wage. Thus we start our investigation with a descriptive analysis of whether and to what extent occupation changes are induced by the business cycle.

Table 7: Shares of up- and downgraders in Germany and the U.S.

	Men			Women		
Occ. wage	Up	Down	Const.	Up	Down	Const.
Germany	22	24	55	17	22	62
U.S.	38	36	26	-	-	-

Notes: Upgrades (downgrades) are establishment changes associated with an occupation wage increase (decrease), const. stands for employees who change the establishment but not the occupation.
Source: U.S. numbers are taken from Devereux (2002), p. 438., values for Germany are based on our establishment mover sample.

Table 7 shows that up- and downgrading are about as common in general but

[29] Devereux uses education indicators, a cubic in experience, race dummies and a marriage indicator.

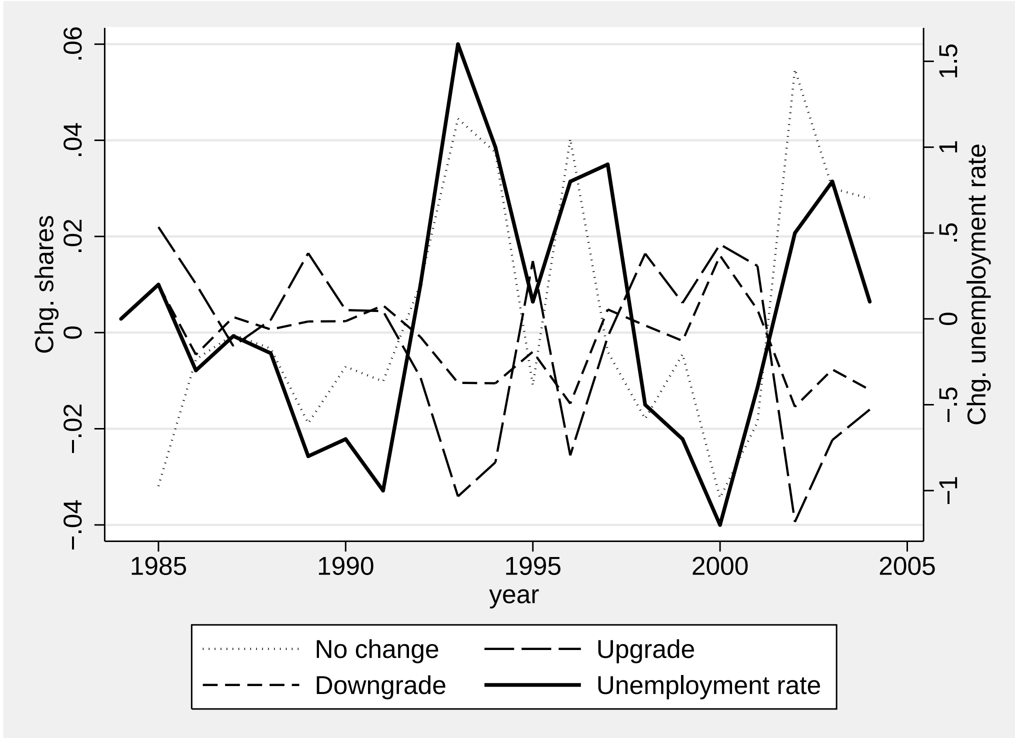

Figure 2: Occupation changes of new hires versus unemployment rate

occurs more often for men. As expected, the numbers for the U.S. indicate a greater flexibility. Devereux finds a much higher share of occupation changers, only 26 percent remain in the same occupation. The relation between up- and downgrading and the business cycle can be shown graphically. We partition the sample of job changers into workers who move to better paid occupations (upgrade), lower paid occupations (downgrade) and workers who stay in the same occupation (no change). The shares of these groups are plotted against the unemployment rate in Figure 2. It is clear at a glance that the shares of upgraders and downgraders are procyclical whereas the share of stayers is countercyclical. This visual impression is confirmed by regressions of the change of these shares on a constant, a linear trend and the change of the unemployment rate. This yields the coefficients (standard errors in brackets) -0.018 (0.004) for upgraders, -0.007 (0.002) for downgraders, and 0.025 (0.005) for stayers.[30] Note that upturns also increase the share of downgraders. But the effect is less pronounced than the effect on upgrades. In Figure 3 we give a visual impression of the correlation between the occupational composition wage and unemployment. It plots the coefficients of year dummies from the first step regression against the change of the unemployment rate. By construction, these coefficients represent the pure occupational composition effect. It is clear from the figure that rising unemployment coincides with falling occupational composition wages and that this correlation is strong for men and women.

Table 8 contains the estimation results for several specifications of the model. Note that the large sample for the proportions models in Section 1 was necessary

[30] Adding a squared trend term to the regression does not change the results.

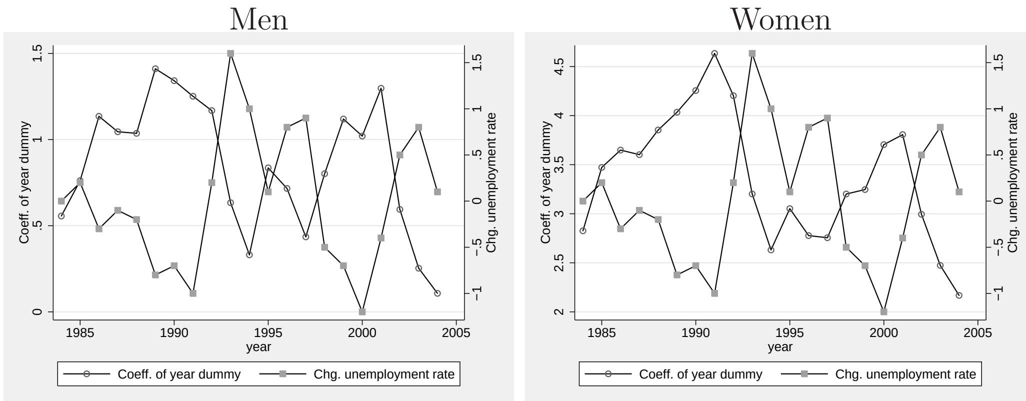

Figure 3: Changes of the unemployment rate and aggregate wage changes due to changes of the occupational employment structure

to avoid proportions of zero and one. As this problem does not arise here, the wage analysis in this section is based on a 25 percent random sample to reduce the computational burden. To start with consider column (1) relating to the base sample (all establishment movers). By definition of the dependent variable and other regressors, the constant gives the average percent change of the occupational composition wage for unskilled blue collar workers with zero years of experience for the estimation period 1985-2002. It amounts to about 2.7 percent for men and 7.6 percent for women. This implies that there is (on average) a net flow from lower to higher paid occupations. The negative trend coefficient shows that this effect has diminished slightly. The big difference between men an women may be explained by the important role of maternity leave for young women, who apparently restart their carrier after maternity leave spells in low paid jobs and advance in the sequel.[31] Furthermore the average upgrading effect is significantly higher for employees with completed apprenticeship but lower for college and technical college graduates. The first effect may be explained by the fact that vocational training has an important signalling function in Germany but apprenticeship training positions are scarce especially in the well paid occupations. Apparently labour market entrants respond to this by using apprenticeship training in less attractive occupations as vouchers to the more attractive ones. At a glance, the coefficient of the white collar dummy appears huge. Note, however, that this dummy is (in contrast to the other dummies) time-variable. Thus it seems to reflect promotions that go along with the occupation change.[32]

Regarding the main objective of the study, we find highly significant but rather small effects of the business cycle on occupational upgrading. A one percent decrease of the (national) unemployment produces a 0.34 and 0.51 percent increase of the occupational composition wage for men and women, respectively. These effects are considerably smaller than Devereux's results for the U.S. (-0.91 percent for men and

[31]Note that our sample contains only job-to-job movers, i.e. employees who had a job at the reference date of the previous year. Since maternity leave spells last longer than one year in most cases, its downgrade effect (women worked in a better paid occupation before the maternity leave period than afterwards) is not included in our analysis.

[32]Typical examples are promotions of production workers to executive postions.

-1.04 percent for women).

Our focus on occupations (as units defining homogenous skill requirements) appears sensible for this application. Nevertheless it is off the beaten track of the empirical literature which concentrates on industry wage differences. Since occupations are not evenly distributed over industries, and our model does not account for transitions between industries, the unemployment coefficients may capture *sectoral* upgrading effects. A further competing explanation for wage upgrading refers firm size wage differentials. Large firms which pay rents to their employees may exploit this in upturns to poach workers from smaller firms. A simple way to check the relevance of both issues is to restrict the estimation sample to new hires who remain in the same two digit industry (see columns with header (2) in Table 8)[33] or the same establishment size group (see columns with header (3)). The definition of the establishment size change indicator is described in the appendix. To make the industry and establishment size change indicators comparable, they were constructed such that they produce similar shares of movers: According to our definition, 52 percent the new hires in sample (1) change establishment size and 48 percent change the two-digit industry code. From columns (2) and (3) it is evident at a glance that sectoral upgrading explains the lion's share of cyclical occupational upgrading: The coefficients for sample (2) of new hires who stay in the same industry are much lower in absolute value, whereas sample (3) of new hires who stay in the same establishment size class shows negligible differences to sample (1). Note that the lower unemployment coefficient for sample (2) does not invalidate the role of occupations for wage upgrading. It only tells us that a good deal of occupational composition wage effects are intrinsically related to industry changes.

Devereux points to the problem that observed wages may not indicate the desirability of an occupation if *compensating differentials* play an important role or if wage differentials are *noncompetitive*. In the case of compensating differentials, higher occupation wages reflect higher risks or worse working conditions but not more productive or better skilled employees. In the case of a noncompetitive wage setting, e.g. efficiency wage problems may foster the transformation of small (or unobserved) productivity or skill differences into large wage markups. To check for that, Devereux replaces the dependent variable (*observed* occupation wages) by 'occupation skill' wages. Occupation skill wages are obtained by replacing individual observed wages with predicted wages in the definition of the occupational wage, i.e. $\tilde{z}_o := (1/n_o)\sum_t \sum_i D(i,o,t)\ln(\hat{w}_{it})$, where $\hat{w}_{it}$ is the predicted wage from an auxiliary regression.[34] The occupation skill wage should be free of noncompetitive wage markups and components compensating for extra risk or bad working conditions. If the occupational composition wage effects found above are mainly due to com-

[33] We use a classification containing 28 groups. Because the industry classification changes in an incompatible form in 2002, we are urged to restrict the samples (2) to the period 1985-2002. To check whether the period change has an impact on our results in columns (1), we reran these regressions for the period 1985-2002 but found only negligible differences.

[34] Individual wages are regressed on personal characteristics and control variables. Personal characteristics are the education dummies and a cubic polynomial in (potential) experience. Control variables are year dummies, 27 sector dummies, a white collar dummy and a second order polynomial in log establishment size. Note that only personal characteristics enter the prediction.

pensation or noncompetitive wage differentials, they should vanish after replacing occupational wages by occupational skill wages. In our application, this replacement shrinks the sample (1) coefficients (in absolute value) from -0.342 to -0.045 for men and from -0.512 to -0.216 for women. For men the coefficient becomes insignificant (standard errors are 0.034 for men and 0.029 for women). This indicates that noncompetitive or compensating wage differentials are important determinants of the occupational composition wage effect. When Devereux replaces observed by occupation skill wages for the U.S. data, his estimates shrink from -0.91 to -0.37 for men and from -1.04 to -0.34 for women but remain significant at the five percent level. Thus, the relevance of compensating and noncompetitive wage differentials is similar in both countries.

Under a Reder competition regime, high wage occupations absorb employees from lower paid occupations during upturns. This generates additional demand in the lower paid occupations which in turn should increase the wage upgrading effect for employees in the lower part of the skill distribution. We test this by sorting all new hires in five quintile groups using predicted wages from an auxiliary regression of wages on personal characteristics and control variables (see footnote 34). The resulting unemployment change coefficients are listed in Table 9. To start with, consider columns with header (1). Here the first quintile response for men (-0.49 percent) exceeds the fifth quintile response (-0.16 percent) by a factor of about three. The relation is similar for women although the levels are higher. Furthermore, the differences between the first three and the fifth quintile are significant at the five percent confidence level for men as well as women.[35] The comparison with Devereux's results again reveals similar structures between the U.S. and Germany. For the men sample he obtains an effect of -2.22 percent (with se. 0.66) for the first and 0.37 percent (with se. 0.53) for the fifth quintile. Corresponding results for women are -0.97 (with se. 0.26) for the first and 0.62 (with se. 0.27) for the fifth quintile.

As in the section above, columns relating to the employees remaining in the same two-digit industry (2) and the ones remaining in the same establishment size class (3) suggest that industry changes play an important role for the business-cycle component of occupational composition wages. Although wage effects become smaller for all quintiles, the ranking of the effects by quintile remains the same.

5 Conclusion

In this paper we estimate the responsiveness of the occupational skill structure and occupational composition wages to the business cycle and compare the estimates with corresponding results from a study using U.S. data (Devereux (2002)). This comparison is particularly interesting because of striking differences between U.S. and German labour market institutions. Whereas the German labour market is characterized by a highly regulated and standardized vocational training system and a canonical structure of occupations, a standardized vocational training system

[35] P-values of the tests are $PV(H_0 : b_1 = b_5) = 0.000$, $PV(H_0 : b_2 = b_5) = 0.011$ and $PV(H_0 : b_3 = b_5) = 0.028$ for men and $PV(H_0 : b_1 = b_5) = 0.035$, $PV(H_0 : b_2 = b_5) = 0.076$ and $PV(H_0 : b_3 = b_5) = 0.032$ for women.

with approved examinations does not exist in the U.S., the occupational structure is less formalized and occupational mobility is much higher than in Germany.

Our estimates show that *within* occupations the skill level of new hires rises significantly in recessions and decreases in upturns. The effects for West Germany amount to about 70 percent of the corresponding U.S. results. They are, however, larger than expected given the striking institutional differences mentioned above. Separate estimation of the model by establishment size groups suggests that effects are lower for small establishments, implying that a good deal of the difference between both countries may already be explained by a greater share of small establishments in Germany. Further differentiation of the sample into low and high wage occupations reveals that the share of unskilled is affected stronger in low wage occupations than in high wage occupations whereas no clear pattern can be found for the high-skilled. Several checks show that the results are robust to changes of the occupational classification level, the choice of the estimation model, and the time period considered.

Our results regarding occupational composition wages also indicate a lower responsiveness to the business cycle than in the U.S. The estimates amount to about 30 and 40 percent of their U.S. counterparts for men and women, respectively. We should, however, be cautious to interpret this as a clear indication for more important wage rigidities in Germany. Responses of the occupational composition wage to the business cycle are based on two components. First, more higher paying occupations can attract workers during upswings only if there exist noteworthy *noncompetitive* wage differentials. And second, the occupational system must be flexible enough to allow employees to switch between occupations. Effectiveness of the first component (noncompetitive wage differentials) requires rigidities, the second flexibility. Thus lower responsiveness of the German occupational composition wage may be either due to less pronounced noncompetitive wage differentials or due to a less permeable occupational system. U.S. transition probabilities between occupations approximately double their German counterparts. If these numbers are based on roughly comparable data, they already explain the lion's share between U.S. and German responses of the occupational composition wage to unemployment. Consequently, noncompetitive wage differentials do *not* appear to be much more pronounced in Germany. Finally, we should be keep in mind that greater occupational mobility in the U.S. does not necessarily imply efficiency. It comes at the cost of lower occupation-specific human capital which is likely to enhance productivity but this is out of regard in this analysis.

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Table 8: Effect of unemployment rate changes on occupational composition wage changes.

	Men			Women		
Sample	(1)	(2)	(3)	(1)	(2)	(3)
Change of	-0.342	-0.096	-0.255	-0.512	-0.091	-0.303
unempl. rate	0.063	0.034	0.045	0.124	0.048	0.093
Experience	-0.000	0.042	0.028	-0.238	0.004	-0.072
	0.019	0.012	0.017	0.026	0.015	0.014
Experience^2/100	-0.529	-0.538	-0.544	0.866	-0.108	0.168
	0.104	0.070	0.094	0.117	0.080	0.072
Experience^3/1000	0.099	0.090	0.094	-0.124	0.014	-0.024
	0.016	0.011	0.015	0.018	0.012	0.012
WHITE COLLAR	2.717	1.805	2.354	1.756	1.270	2.173
	0.108	0.082	0.092	0.172	0.032	0.056
MEDIUM QUAL.	0.160	0.355	0.296	-1.555	-0.360	-1.218
	0.051	0.032	0.047	0.097	0.052	0.093
HIGH QUAL.	-0.149	0.081	0.339	-0.068	1.160	0.588
	0.104	0.078	0.111	0.202	0.144	0.221
MISSING QUAL.	0.117	0.371	0.213	-1.300	-0.103	-0.572
	0.037	0.059	0.052	0.132	0.074	0.096
Trend	-0.019	-0.011	-0.015	-0.045	-0.004	-0.032
	0.011	0.005	0.009	0.018	0.007	0.014
Constant	2.665	1.231	1.864	7.611	0.525	4.211
	0.993	0.519	0.822	1.655	0.626	1.335
Observations	5035738	2323853	5035738	2268876	1131037	2268876

Notes: All coefficients and standard errors are multiplied by 100.

Robust standard errors that allow for clustering by year are given below coefficients.

Results are based on a 25 percent random sample of persons from the full sample of all job movers.

Legend: (1) base sample including all individuals who changed jobs, (2) workers remaining in the same sector only, (3) workers remaining in establishments of similar size only. The construction of the samples (2) and (3) is detailed in the appendix.

dummy variables are printed in uppercase letters.

Samples (2) and (3) relate to the shorter period 1985-2002 because of an incompatible change of the industry classification in 2002/2003.

Table 9: Effect of unemployment rate changes on occupation wage changes, by quintiles

	Men			Women		
Sample	(1)	(2)	(3)	(1)	(2)	(3)
1st quintile	-0.490	-0.187	-0.347	-0.828	-0.169	-0.452
	0.085	0.045	0.064	0.259	0.094	0.201
2nd quintile	-0.426	-0.108	-0.314	-0.589	-0.106	-0.344
	0.094	0.049	0.072	0.155	0.077	0.123
3rd quintile	-0.306	-0.081	-0.206	-0.593	-0.193	-0.425
	0.079	0.040	0.049	0.100	0.033	0.052
4th quintile	-0.277	-0.116	-0.216	-0.223	-0.006	-0.061
	0.052	0.048	0.056	0.114	0.044	0.077
5th quintile	-0.160	-0.031	-0.124	-0.348	-0.007	-0.215
	0.045	0.037	0.041	0.115	0.051	0.102

Notes: All coefficients and standard errors are multiplied by 100.
Robust standard errors that allow for clustering by year are given below coefficients.
Results are based on a 25 percent random sample of persons from the full sample of all job movers.
Legend: (1) base sample including all individuals who changed jobs, (2) workers remaining in the same sector only, (3) workers remaining in establishments of similar size only. The construction of the samples (2) and (3) is detailed in the appendix.
dummy variables are printed in uppercase letters.
Samples (2) and (3) relate to the shorter period 1985-2002 because of an incompatible change of the industry classification in 2002/2003.

A Appendix

Definition of establishment size changes

It is impossible to provide a fully consistent and theoretically meaningful definition of establishment size changes for movers. An establishment size change from 1000 to 1001 is a change, but it is economically not meaningful. In order to include meaningful changes only, our definition uses relative changes combined with thresholds depending on establishment size. Furthermore it is constructed to yield a number of establishment size changes that is similar to the number of two-digit industry changes. With our definition, 52 percent of the new hires change establishment size and 48 percent change two-digit industry. The establishment size change indicator used to define the sample in columns (3) of Tables 8 and 9 is constructed as follows: First we define five establishment size groups for 1-19, 20-49, 50-99, 100-199 and 200+ employees. Then establishment size change Indicator I_t depends on the mean $\bar{e}_t := (e_t + e_{t-1})/2$ of the previous and the current year's establishment size and the absolute value of the log difference $g_t := |\ln(e_t) - \ln(e_{t-1})|$ in the following way:
if $20 \leq \bar{e}_t < 50$, then $I_t := 1(g_t > 1.5)$, if $50 \leq \bar{e}_t < 100$, then $I_t := 1(g_t > 1)$ if $100 \leq \bar{e}_t < 200$, then $I_t := 1(g_t > 0.8)$ if $\bar{e}_t \geq 200$, then $I_t := 1(g_t > 0.6)$. Here $1(\cdot)$ denotes the boolean indicator function evaluating to one if its argument is true and zero otherwise.

Table 10: Number of cells with skill shares of zero or one

	Value	Frequency	Share	
			Unweighted	Weighted
Full sample				
Graduates	0	408	0.052	0.004
	1	0	0.000	0.000
Vocational degree or more	0	0	0.000	0.000
	1	12	0.002	0.000
Small establishments (1-4 employees)				
Graduates	0	1399	0.180	0.016
	1	0	0.000	0.000
Vocational degree or more	0	5	0.006	0.000
	1	0	0.000	0.002
Medium size establishments (5-99 employees)				
Graduates	0	1708	0.220	0.032
	1	0	0.000	0.000
Vocational degree or more	0	5	0.000	0.000
	1	51	0.007	0.000
Large establishments ($\geq$ 100 employees)				
Graduates	0	1342	0.173	0.018
	1	3	0.000	0.000
Vocational degree or more	0	12	0.002	0.000
	1	54	0.007	0.002

The full estimation sample contains 7776 cells. The small, medium and large establishment size samples contain 7776, 7765 and 7768 cells, respectively. The last column is calculated by weighting each cell with the respective number of employees.

Table 11: Marginal effects of the unemployment rate on skill proportions of new hires by quintiles, alternative estimations

	Proportion of graduates		Proportion with voc. degree or more	
	Marg. eff.	SD	Marg. eff.	SD
Linear model, 2-step				
1st quintile	0.030	0.003	0.405	0.084
2nd quintile	0.027	0.004	0.480	0.094
3rd quintile	0.116	0.016	0.343	0.072
4th quintile	0.045	0.015	0.243	0.095
5th quintile	0.224	0.073	0.072	0.025
Grouped probit, marg. eff. evaluated at sample averages ($ME(\bar{x})$)				
1st quintile	0.036	0.008	0.538	0.166
2nd quintile	0.030	0.007	0.540	0.174
3rd quintile	0.034	0.009	0.518	0.188
4th quintile	0.033	0.015	0.235	0.168
5th quintile	0.343	0.191	0.042	0.038

Note: All coefficients and standard errors are multiplied by 100.