New evidence on the complementarity of education and training

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We compare the incidence of training and the changing correlation of training with formal education for German workers between 1996 and 2004. Not only do highly skilled workers receive more training than low skilled workers at any point in time, also the increase in the provision of training disproportionately benefited those with high skills. Thus, education and training appear to be complements and the gap in training provision between skill groups widened over time.

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1. Introduction

The question of whether formal education and workplace training are complements or substitutes has recently sparked new debates and research (Ariga and Brunello 2006, van Smoorenburg and van der Velden 2000, see also Krueger and Rouse 1998). The OECD emphasized the relevance of this issue since "…differences in the association of prior human capital investments and training could also have important implications for equity…" (OECD 1999, p.149). If only the highly educated received additional training, labor market differences by formal education would be reinforced. If, however, workplace training were a substitute for formal education existing differences in labor market performance and productivity could be bridged.

In this study we investigate the relationship between formal education and workplace training over time. Due at least in part to institutional changes in Germany and other European countries, workers have started to stay in the workforce longer;[1] in West Germany the average retirement age rose by about 2 years between 1980 and 2005 and by one year between 2000 and 2006 alone (DRV 2006, Hofmann 2007). When workers stay active longer, the expected returns to workplace training increase. This should render human capital investments more profitable and affect the frequency of training.[2] We first show that indeed the incidence of workplace training has increased over time. Then we investigate whether this increase in the training incidence has equally affected high and low skilled workers. If particularly the highly skilled workers received additional training rendering training a complement to education, the equity problem pointed out by the OECD intensified. If low skilled workers benefited more from human capital investments

[1] Among these changes are reduced durations of unemployment benefits for older unemployed workers, the abolition of early retirement pathways, and the introduction of benefit discounts following early retirement (see e.g. OECD (2006) for details).

[2] Puhani and Sonderhof (2008) confirm a reverse effect, i.e. that the extension of maternity leave caused a general reduction in the provision of training for women.

and training is provided as a substitute to formal education, the labor market disadvantages of the least educated workers are reduced by the recent developments.

This dynamic perspective is new to a literature that typically investigates the correlation between formal education and training at just one point in time. In an early study Lynch and Black (1998) use data on employers in the United States in 1994 to investigate both the employer- and employee-related patterns of employer-provided training. They conclude that training complements formal education and that there is a 'virtuous circle' for those who obtained schooling early on.[3] In their survey paper Bassanini et al. (2005) use data of the European Community Household Panel and confirm that education and training are positively correlated. The same conclusion is drawn by Blundell et al. (1999) in their review of the returns to the 'three main components of human capital', i.e. ability, formal education, and on the job training. Several search and matching models interested in describing equilibria with respect to training provision start out with the assumption that education and training are complements (e.g. Laing et al. 1995, Brunello and Medio 2001, or Burdett and Smith 2002).

However, the empirical evidence it not clear cut. Krueger and Rouse (1998) find a significant positive correlation between training and schooling in manufacturing but not in the service sector. Van Smoorenburg and van der Velden (2000) study the training experience of a Dutch sample of school leavers. They confirm that the more educated have a higher probability of receiving firm training. But they also show that the *over*educated receive less training while the undereducated do not receive more training as would have been suggested by a matching theory argument, according to which training bridges the differences between available and required skills. The authors find substitutability for some educational degrees and types of employment, while for others, education and

[3] Bellmann and Düll (1999) obtain similar results with German establishment data.

training are complements. Finally, Ariga and Brunello (2006) applied employee data from Thailand to study the relationship between education and training. The authors found both, significant substitutability as well as complementarity between formal education and training, here depending on the type of employer-provided training considered.

The issue remains unsettled. The assumption that formal education and training are complements is plausible, if employers' returns to training the well educated exceed the returns to training lesser skilled workers. This could be the case if the former have better learning skills and lower marginal training costs than those with less education. Also, the highly educated might be able to extend their active life by more than employees who may have damaged their health in a working life of predominantly manual labor.[4] On the other hand there are arguments for the substitutability of education and training: Groot et al. (1994) found that the better educated demand more compensation to participate in training and Sicherman (1991) shows empirically that employers invest less in overeducated workers because these are more likely to quit and move to more suitable jobs.

Using evidence from the large and representative German *Mikrozensus* datasets 1996 – 2004 we describe the incidence of training and its change for high and low skilled workers. First, we apply two different decomposition procedures to determine whether the increase in workplace training relates to changes in worker characteristics. Alternatively, changes in training incidence may be due to shifts in employer or employee behaviors regarding the provision of training. In a second step we study these behaviors and focus on the correlation between skill group and training incidence over time in multivariate regressions.

We find that generally the incidence of training increased over time. Overall, high skill workers receive more training than low skill workers, which suggests a

[4] Recent contributions by Cunha and Heckman (2007) also suggest complementarity relationships based on the technology of human capital acquisition, where "learning begets learning."

complementarity relationship of training and education in Germany. Changes in the training incidence are neither due to developments of the population skill structure nor to other shifts in the characteristics of workers and their jobs. Instead we find changes in provision of training for given worker characteristics. In a dynamic perspective the advantage of high skill workers with respect to training provision increased over time and low skill workers appear to increasingly fall behind.

2. Data and Descriptive Evidence

The German *Mikrozensus* surveys the residents of one percent of all German dwellings. The scientific use dataset provides large, nationally representative, annual samples of over 500,000 individual observations.[5] Since 1996 a random 45 percent of the full sample was asked about training. In these subsamples we consider full-time workers, aged 25-65 who have been employed over the course of the last calendar year.[6] Excluded are apprentices, military personnel, family helpers, and the self-employed. Because our results would be sensitive to a systematic shift in labor force participation over the period of our analysis we show in Figure 1 that the share of our sample as a fraction of the relevant *Mikrozensus* population did not change in a systematic way.[7]

We apply an indicator of vocational qualification to categorize workers as high or low skilled employees: those with tertiary (polytechnic and university) and advanced vocational degrees (e.g. master of crafts or technician) are defined as high skilled, all others are considered as low skilled. Based on this definition about one in three individuals is high skilled.

[5] Other national data on training such as the German Socioeconomic Panel (GSOEP) or *Berichtssystem Weiterbildung* (BMBF 2003) have substantially smaller samples. There either the dataset or the questions on training are not available on an annual basis.
[6] The age-restriction alone reduces the sample size by 43 percent.
[7] We also inspected Figure 1 by sex and did not find vast shifts in labor force participation either.

The first part of our analysis compares the training propensity for the years 1996 and 2004, when individuals were asked about their participation in training for professional purposes over the course of the last year.[8] After omitting observations with missing values e.g. on vocational qualification our sample contains 49,768 and 45,860 observations for 1996 and 2004 respectively.[9]

Figure 2(a) describes the incidence of training by age and skill group in 1996 and 2004. Over time the propensity to participate in training increased for both groups, which, however, may in part be due to the changed wording of the question. Low skill employees have a lower training incidence. Training is less common at higher age for both skill groups in both years. Figure 2(b) describes the change in the training incidence by skill and age group over time.[10] For both skill groups particularly those above age 45 experienced increases in training probabilities over time, flattening the age profile of training provision.[11] Table 1 depicts the change in training incidence by skill group and industry across all age groups. The training incidence increased for all groups and always more so for high than for low skill workers.

In order to test whether these overall trends are specific to the *Mikrozensus* data we consulted evidence on the change in training incidence based on the German Socioeconomic Panel (GSOEP) data (SOEP Group 2001). In this survey the exact same questions on training were asked at different points in time. Table 2 presents the share of individuals indicating that they participated in any training over the last three years as well

[8] The wording of the question on training participation changed somewhat between surveys.
[9] The questionnaire explicitly states that the information on vocational qualification is provided on a voluntary basis for individuals age 51 and above. However, the share of missing values on the vocational degree does not increase vastly for older age groups. Those who do not provide the information on vocational training are more likely to be non-German and blue collar workers than those who do.
[10] To calculate these differences we first normalized the observed values for 2004. All age group-specific probabilities were adjusted by the constant ratio of the 1996 probability of training across all age groups relative to the same 2004 probability. The ratio amounts to 0.15 / 0.30 for high skill workers and to 0.06 / 0.11 for low skill workers.
[11] These patterns are similar for both sexes when considered separately.

as their participation in specific types of training.[12] The sample consists of full time employed males and females aged 25-65. As in the *Mikrozensus* the sample shares receiving training increased over the considered period and particularly so for older workers. Our subsequent analyses are performed with *Mikrozensus* data as it provides substantially larger samples.

3. Algebraic Decomposition of Changes in Training

In order to determine the relevance of changes in the population skill-structure for the observed increase in the training incidence we decompose the total change in the probability of training between 1996 and 2004. The overall probability of training at time t, $P_t(tr)$, can be described as the weighted sum of skill group (j)-specific training probabilities:

$$P_t(tr) = \sum_j \left[P_t\left(tr \middle| Skill_j\right) \cdot P_t\left(Skill_j\right) \right] \tag{1}$$

To see how the change in training propensities between 1996 and 2004 can be decomposed into changes in (a) the skill group-specific training propensities and (b) the population skill distribution, consider the following decomposition:

$$\begin{aligned}
\Delta P(tr) &= P_{04}(tr) - P_{96}(tr) \\
&= \sum_j \left[P_{04}\left(tr \middle| Skill_j\right) \cdot P_{04}\left(Skill_j\right) \right] - \sum_j \left[P_{96}\left(tr \middle| Skill_j\right) \cdot P_{96}\left(Skill_j\right) \right] \\
&= \sum_j \left[P_{04}\left(tr \middle| Skill_j\right) - P_{96}\left(tr \middle| Skill_j\right) \right] P_{04}\left(Skill_j\right) - \sum_j P_{96}\left(tr \middle| Skill_j\right) \left[P_{96}\left(Skill_j\right) - P_{04}\left(Skill_j\right) \right] \\
&= \sum_j \left[\Delta P\left(tr \middle| Skill_j\right) \cdot P_{04}\left(Skill_j\right) \right] + \sum_j \left[\Delta P\left(Skill_j\right) \cdot P_{96}\left(tr \middle| Skill_j\right) \right] \\
&= \qquad \textit{shift effect} \qquad + \qquad \textit{skill structure effect}
\end{aligned} \tag{2}$$

We label the first part of this expression the "shift effect" because it reflects the share of the total change, $\Delta P(tr)$, that is independent of changes in the population skill structure

[12] One reason for the somewhat higher training participation in the GSOEP compared to the *Mikrozensus* data relates to the fact that the GSOEP asked about the previous three years, whereas the *Mikrozensus* collects information on the last calendar year only.

and due only to (e.g. behavioral) shifts in skill-specific training probabilities. In contrast, the second part labeled "skill structure effect" measures that part of the total change, $\Delta P(tr)$, that is due to observable changes in the population skill structure.

Next, we can decompose the "shift effect" further, to describe changes in training probabilities for the two skill groups:

$$\begin{aligned} shift &= \sum \left[\Delta P\left(tr \middle| Skill_j\right) \cdot P_{04}\left(Skill_j\right) \right] \\ &= \overline{\Delta P\left(tr \middle| Skill_j\right)} + \sum \left\{ \left[\Delta P\left(tr \middle| Skill_j\right) - \overline{\Delta P\left(tr \middle| Skill_j\right)} \right] \cdot P_{04}\left(Skill_j\right) \right\} \\ &= \overline{\Delta P\left(tr \middle| Skill_j\right)} + \sum \delta j \end{aligned} \tag{3}$$

where $\overline{\Delta P\left(tr \middle| Skill_j\right)} = \frac{1}{2} \sum_j \left[\Delta P\left(tr \middle| Skill_j\right) \right]$ describes the "Average Shift" of skill-specific training probabilities over time. It would also capture the effects of changes in the wording of the survey question over time. The second term of the equation, $\sum \delta_j$, sums the weighted "specific skill effects", δ_j. If the training propensities had changed in exactly the same manner for all skill groups, then all specific skill effects, δ_j, were zero. If, however, particularly high skill workers receive more training than before, we would expect larger "specific skill effects" for these than for low skill workers.

The results are summarized in Table 3: the increase in the training incidence results predominantly from a shift effect, which explains 8.08 percentage points of the total 8.38 percentage point change. The skill-structure effect is small (about 3.5 percent of the total effect) indicating that population skill changes *per se* do not drive the increase in the overall training probability over time. Applying the decomposition of equation (3) to the behavioral shift effect we find that it is mostly due to an overall increase in average training probabilities: the average shift dominates, while the specific skill effects are small and negative in total. The specific-skill changes are positive for the high and negative for the low skill group. This indicates that the high skill group benefited slightly more from the change in training propensities over time than the low skill group. Overall, it appears that it is behavior that drives the increase in training incidence rather than changes in the skill composition of the population. This behavior change is predominantly a general development with only a slight advantage for high skilled workers.

4. Regression-Based Decomposition

After finding that most of the increase in training probabilities was due to a general increase in training probabilities, we now apply a different approach to study the determinants of the increased training incidence. Instead of differentiating only the effects of the population *skill structure* from general behavioral changes we now look at the changes of *all* potential training determinants. In the spirit of Oaxaca-Blinder decompositions we separately evaluate the effects of changes (a) in the *values* of training determinants and (b) in these determinants' *association with* the incidence of training.

The individual- and employment-specific determinants of the incidence of training are described in the first two columns of Table 4 for the full sample in 1996 and 2004. A comparison of the covariate means for the two years indicates that the characteristics of the sample have changed only somewhat over time: on average the fraction of high skill workers increased slightly, workers aged, the share of blue collar workers declined and that of white collar workers increased.

The last two columns of Table 4 provide the probit marginal effects of the determinants of individual training in 1996 and 2004. We observe a substantially higher incidence of training for high skill workers. The age effect implies that the training probability falls with age for all workers above age 34. Over time the negative marginal effect for older workers declined. Males and natives receive significantly more training, however, their advantage declined over time. Interestingly, civil servants have the highest training incidence. The pseudo R^2 values are relatively low suggesting that only a small fraction of the overall change in the training probability is subject to the systematic impact of the considered determinants.

Next, we apply a version of the Oaxaca-Blinder decomposition to quantify the relative impact of changes in the explanatory variables and of changes in their effects for the overall development of training propensities over time. We apply the procedure developed by Fairlie (1999, 2005) to translate the Oaxaca-Blinder decomposition for a situation with a bivariate dependent variable. The effects of changes in parameters (α) and covariates (X) can be distinguished using equation (4):

$$\begin{aligned} \Delta P(tr) &= \left\{ \overline{P}(\alpha_{04}, X_{04}) - \overline{P}(\alpha_{96}, X_{04}) \right\} + \left\{ \overline{P}(\alpha_P, X_{04}) - \overline{P}(\alpha_P, X_{96}) \right\} \\ &= \quad \textit{parameter effect} \quad + \quad \textit{characteristics effect} \end{aligned} \qquad (4)$$

$\overline{P}(\alpha_{04}, X_{04})$ represents the average predicted probability of receiving training, where every worker's characteristics (X) are as observed in 2004 and the parameters (α) are taken from the probit estimation for 2004. The first term in equation (4) ("parameter effect") considers the differential in average training probabilities that results when the 2004 characteristics are used with both the 2004 and the 1996 parameter vector. We focus on the second term, the "characteristics effect." It evaluates the difference in predicted training probabilities when the individual characteristics of different years are applied to a parameter vector α that is held constant. The particular values of α (indicated P in equation 4) can be set to those of the 1996, 2004, and a pooled regression. We provide evidence for all three scenarios. The characteristics effect indicates the extent to which the change in training probabilities over time can be attributed to changes in worker or employment characteristics.

An interesting option within this framework of analysis is to decompose the "characteristics effect" further and to measure the extent to which the change in the values of certain groups of covariates explains the overall "characteristics effect." To measure the effect of changes in only the group of covariates X^k we determine

$$\overline{P}\left(\alpha_P^k X_{04}^k + \alpha_P^{\neg k} X_{04}^{\neg k}\right) - \overline{P}\left(\alpha_P^k X_{96}^k + \alpha_P^{\neg k} X_{04}^{\neg k}\right). \tag{5}$$

Each group of covariates k can be evaluated separately and their individual contributions add up to the total "characteristics effect" as in equation (4). The distinguishing feature of the Fairlie approach is that it calculates the average of individual predictions instead of predicting at average covariate values, which is usually done (see e.g. Shields 1998).[13] The problem of matching observations on X^k from different years is solved using a procedure akin to propensity score matching (c.f. Fairlie 2005). The standard errors are calculated using the delta method.[14]

The results of our analysis are summarized in Table 5. We start with raw differences in training probabilities of 8.4 percentage points between 1996 and 2004. Depending on the choice of coefficients (based on the 1996, 2004, or pooled regression) between 3 and 9 percent of this 8.4 point difference can be explained by changes in characteristics over time. This by itself suggests that it is not a change in characteristics which drives the increase in training probabilities. The bottom part of Table 5 lists the key covariates behind the explainable part of changes in training probabilities over time. The change in worker age had a considerable effect, however, it yields a *decline* in probabilities rather than the observed increase. All other effects contribute to explain the observed increase in training probabilities with large effects resulting from the change in the skill distribution, the workforce's marital status, region of residence and sizeable effects deriving from shifts between blue and white collar workers over time. However, as worker characteristics explain only a small portion of the total changes in training

[13] In a logit model with a constant term the average of the predicted values exactly matches the sample average, i.e. equation (4) holds exactly. This is neither the case for the probit estimator when the predicted values are calculated based on average covariate values.
[14] We apply the Stata9 algorithm "fairlie" provided by Jann (2006).

probabilities, this leaves most of the increase in training propensities to be explained by changes in the association between characteristics and the dependent variable, be it through changes in employee and employer behaviors, changes in survey design, or other "unexplained" factors.

In order to test whether this outcome is specific to the decomposition method as proposed by Fairlie (1999, 2005) we repeated the analysis applying alternative decomposition procedures. We use (a) the standard Oaxaca procedure applied to the linear probability models (b) a decomposition method as proposed by Bauer and Sinning (2006), which applies the approach proposed by Oaxaca and Ransom (1994) to a nonlinear estimator with alternative reference years, and (c) a procedure proposed by Bartus (2006) who also applied a nonlinear estimator but who applies marginal effects instead of coefficient estimates. The results are summarized in Table 6 and confirm the robustness of our findings. Independent of the decomposition method none of the approaches can explain more than about nine percent of the total increase in the training propensity based on changes in explanatory variables. Therefore changes in characteristics are not behind the increase in the training propensity.

5. Multivariate Analysis of the Change in Training Probabilities over Time

So far we used decompositions to study the development in training probabilities over time and to evaluate the relevance of sample composition effects. Since changes in training provision do not derive from changes in sample characteristics we focus now on the behavioral patterns behind the provision of workplace training and study the complementarity vs. substitutability of training and education over time. We consider training to be a complement to formal education if high skill workers – ceteris paribus – receive more training than low skill workers. We assume that the skill level of a worker is predetermined in the employment relationship and therefore exogenous to the training decision.

Empirically, we explain the probability of individual training applying probit models to annual data for all years from 1996 to 2004. As a first step we pool the annual data and reestimate the specifications as in Table 4 jointly for all annual observations. We control for the individual skill level and consider individual year dummies to control for mean differences in the training propensity by year. This flexibly accounts for general trends in the training incidence as well as for changes in answering behavior over time.

The estimation results are presented in Table 7. They yield a significant average marginal effect of high skill of about 4 percentage points for the entire period. It indicates – in view of the overall training participation rate of 9.1 percent - that high skill workers enjoy substantially higher access to training. The year effects yield some heterogeneity in the annual training incidence with a significant increase in the two most recent years. Overall the model confirms that the training probability is highest for high skilled, young, male, native civil servants.

In order to determine whether the relationship between formal education and training incidence changed over time we reestimated the probit model separately for each year.[15] This generates annual marginal skill effects which are depicted in Figure 3. [16] The marginal effects are without exception statistically significant and positive, which confirms that training was always provided as a complement to formal education. While the irregular pattern over the years is somewhat surprising, the overall effect indicates a

[15] Estimating separate models for each year most flexibly allows for changes in the relevance of all the other covariates. Alternatively, one might estimate year interaction terms in a pooled probit model. However, as their marginal effects cannot be interpreted by inspection (cf. Ai and Norton 2003) and because the pooled probit model imposes constant covariate effects on the other covariates, we prefer the more flexible annual estimations.

[16] The complete annual estimation results are not provided to save space and are available upon request.

positive trend over time. This positive trend suggests that training has increasingly been provided as a complement to formal schooling benefiting those with high skills.

One might additionally ask, whether the increasing complementarity of formal education and training interacts with the changing age structure of the society and whether formal education plays a constant role over the life cycle; i.e. is it only one specific age group which benefits from the increase in training or is this a development that encompasses workers of all ages. Also, does high formal education play the same role for the training participation of old and young workers? In order to answer these questions we repeated the analyses separately for four age groups.

The marginal effects of the high skill indicator by year and age group are depicted in Figure 4. The marginal effects followed a similar pattern for all age groups. It is always positive and significant confirming that the general complementarity between training and formal education is not driven by the developments for one specific group of workers. Figure 4 reveals that the increase in the level of complementarity between formal education and training in recent years appears for all age groups in similar ways. Further, we find that the advantage of the high skill workers is highest among young workers (aged 25-35) where the marginal effects reach and surpass ten percentage points in 2004. The marginal effect declines with age which suggests that the relevance of formal education is subdued for older workers and that the complementarity of education and training not only changed over time but also features a life cycle perspective which has not been pointed out in the literature so far.

6. Conclusions

This study uses German *Mikrozensus* data of the last decade (1996–2004) on high and low skill workers in order to answer the question whether education and training are complements or substitutes. Overall, the incidence of training rose over time. It increased at a time when due to institutional changes and demographic aging the expected duration of employees' work lives went up.

We first apply a decomposition analysis in order to determine the relative importance of changes in the population skill distribution behind the increase in worker training: the slightly increasing share of high skilled workers does not appear to be the key determinant of the rising training incidence over time. In a regression-based decomposition we find that neither the population skill structure nor other shifts in worker characteristics over time contribute substantially to explain the observed change in training. More than 90 percent of the increase in the training incidence remains to be explained by other factors, such as changes in the behavior of employers and employees.

In an increasingly flexible multivariate analysis we measure the association of skill level with the training incidence first on pooled data, then on an annual basis and finally on an annual basis for different age groups. This yields the following findings: first, high skilled individuals receive on average more training rendering general training a complement to formal education. Second, the positive association of training with skill level increased over time such that the relative labor market opportunities of the lower skilled workers did not improve over time. Third, the positive time trend in the complementarity of training with formal education can be observed for all age groups. However, not only do we observe a negative age gradient in the provision of training but also the complementarity between training and education features a life cycle effect in that formal education appears to matter most for the young whereas its relevance seems to disappear for older workers.

Overall, the incidence of training differs vastly by the skill level of workers and the increase in training provision over time did not change this pattern. The increase in the overall incidence of training benefited the group of skilled more than the group of low skilled workers. The complementarity relationship between education and training intensified over time and low skilled workers fell even further behind with respect to their stock of human capital and earnings potential in the labor market. Apparently, training is not provided in a manner that balances the existing labor market problems of low skill workers.

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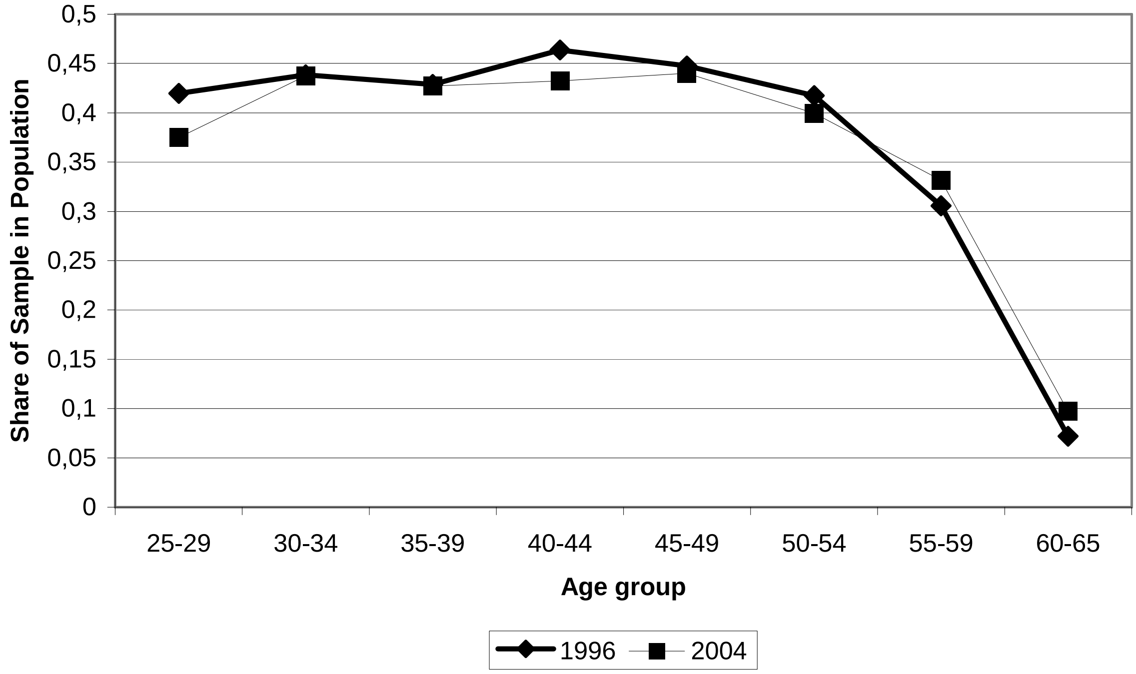
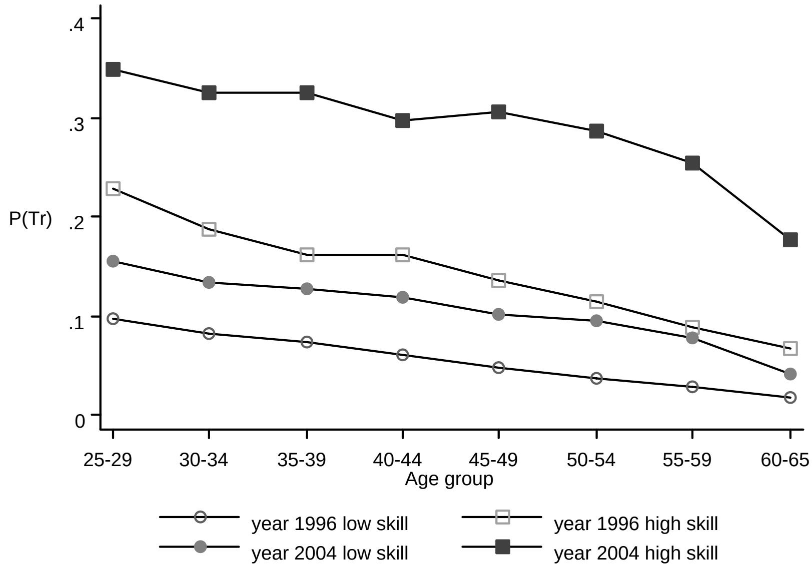
Figure 1 Population share of our sample over time



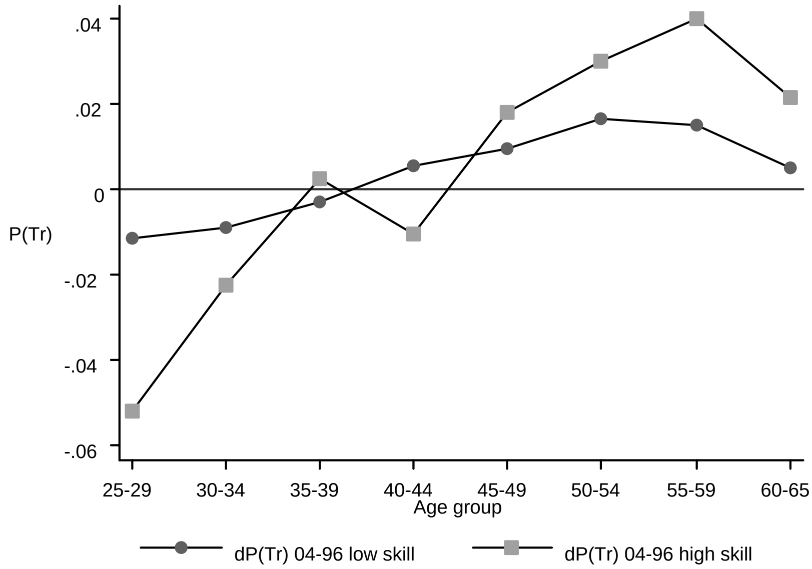
Source: Own calculations based on German Mikrozensus 1996 and 2004.

Figure 2 Training Incidence by Age Group, Skill Group, and Year

(a) Levels of Training Incidence by Age Group, Skill Group, and Year



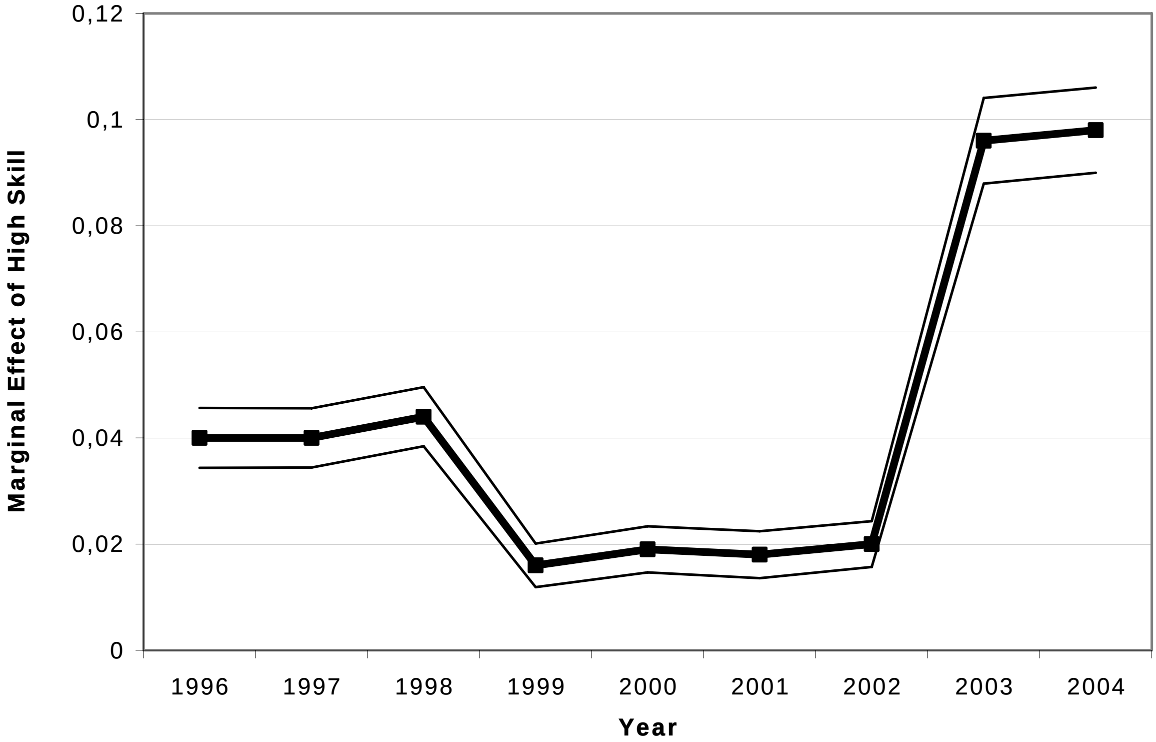
(b) Changes in the Training Incidence over Time by Age and Skill Group



Note: Figure 2(b) provides the difference of the normalized training incidence in 2004 and the observed training incidence in 1996. The 2004 data were normalized to account for the overall increase in the training incidence that might be due to changes in the questionnaire. The normalization was performed by dividing all observed age group-specific training probabilities of 2004 by the same ratio of the overall average training probability for 1996 over that of 2004, for high skill workers 0.15 / 0.30 and for low skill workers 0.07 / 0.12.

Source: Own calculations based on German Mikrozensus 1996 and 2004.

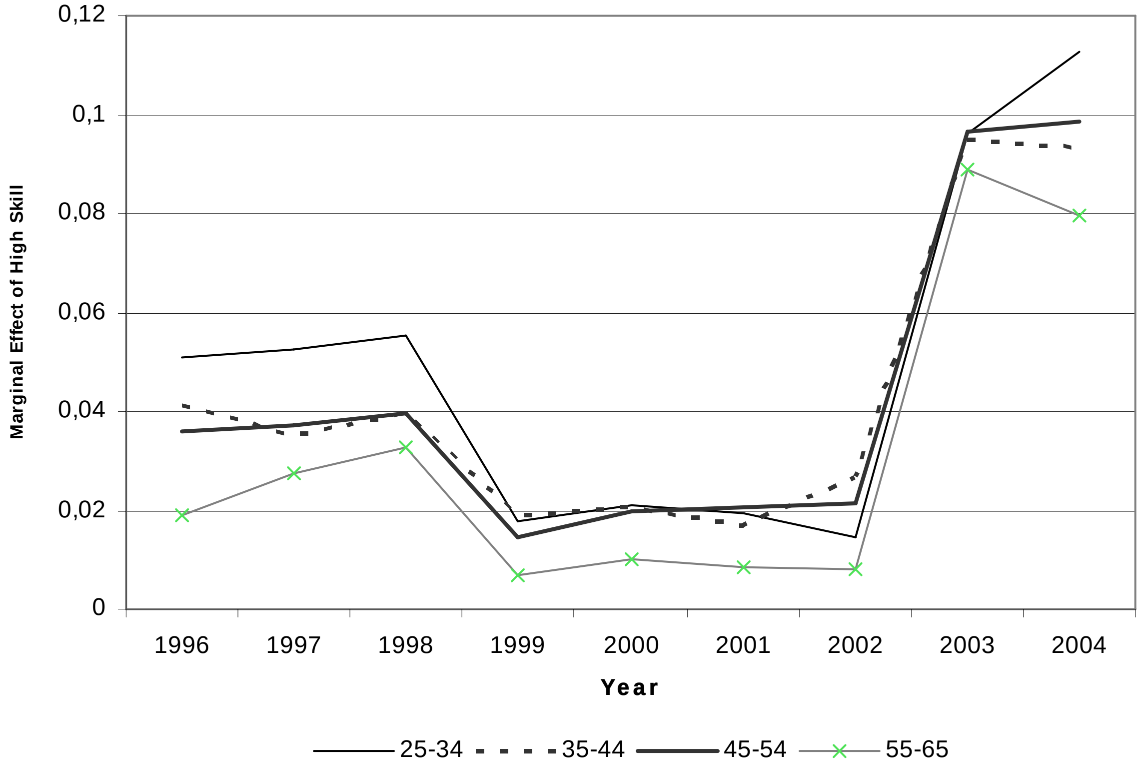
Figure 3 Probit Marginal Effect of High Skill on the Probability of Receiving Training – Based on Separate Annual Estimations



Note: The fine lines present the 95 percent confidence bands of the estimated marginal effects.

Source: Own calculations based on German Mikrozensus 1996 to 2004.

Figure 4 Probit Marginal Effect of High Skill on the Probability of Receiving Training – Based on Separate Annual Estimations by Age Group and Year



Note: All marginal effects are statistically significantly different from zero at the 5 percent level.
Source: Own calculations based on German Mikrozensus 1996 to 2004.

Table 1 Training Incidence by Skill Level, Industry and Changes over Time

		Low skill			High skill			Difference
Industry	**Share**	**1996**	**2004**	**Diff.**	**1996**	**2004**	**Diff.**	**Diff.Hi - Diff.Lo**
Electricity, Gas, Water	0,014	0,09	0,17	0,07	0,12	0,35	0,24	0,16
Mining	0,007	0,04	0,07	0,02	0,08	0,24	0,15	0,13
Education	0,055	0,11	0,21	0,11	0,20	0,42	0,23	0,12
Health Sector	0,083	0,11	0,18	0,07	0,22	0,41	0,19	0,12
Manufacturing	0,300	0,05	0,08	0,03	0,12	0,23	0,12	0,09
Services	0,039	0,08	0,10	0,03	0,15	0,26	0,11	0,08
Agriculture, Forestry	0,015	0,02	0,05	0,04	0,08	0,20	0,12	0,08
Hotels and Restaurants	0,016	0,02	0,05	0,03	0,09	0,19	0,11	0,08
Wholesale, Retail Trade	0,110	0,05	0,10	0,05	0,11	0,23	0,12	0,07
Finance, Insurance	0,042	0,14	0,24	0,10	0,18	0,36	0,17	0,07
Construction	0,087	0,03	0,08	0,05	0,10	0,21	0,11	0,07
Real Estate and Rental	0,056	0,08	0,14	0,06	0,15	0,26	0,11	0,06
Public Administration	0,108	0,10	0,17	0,07	0,18	0,30	0,12	0,05
Transport, Communic.	0,067	0,07	0,11	0,04	0,14	0,22	0,09	0,04
Internat. Organizations	0,001	0,10	0,23	0,12	0,09	0,23	0,14	0,02
All	1,000	0,06	0,11	0,05	0,15	0,30	0,15	0,10

Source: Own calculations based on German Mikrozensus 1996 and 2004.

Table 2 Training Incidence by Age over Time - GSOEP Data (in percent)

	Any training last 3 yrs		Type of Training					
			Regular Reading		Conferences&Conventions		Vocational Courses	
Agegroup	**1993**	**2004**	**1993**	**2004**	**1993**	**2004**	**1993**	**2004**
All	28.7	34.0	42.2	55.1	20.9	30.3	24.8	34.2
25-39	32.7	36.7	42.6	50.6	21.4	28.4	33.7	36.8
40-65	24.9	32.3	41.9	57.8	20.3	31.4	26.0	32.7

Source: Own calculations based on German Socioeconomic Panel (GSOEP).

Table 3 Results of the Algebraic Decomposition of Changes in Training Incidence

Total Change	Shift-Effect			Skill-Structure
	Total	Average	Specific-Skill	
0.0838	0.0808			0.0030
		0.099	-0.0182	

Note: The Specific-Skill shift-effect is composed of an effect of -0.033 for the low and of 0.015 for the high skill workers.
Source: Own calculations based on German Mikrozensus 1996 and 2004.

Table 4 Data Description and Probit Marginal Effects for the Probability of Reporting Training

	Mean 1996	Mean 2004	ME Probit 1996	ME Probit 2004
Dep. Var.:Training	0.088	0.172	–	–
High skilled	0.278	0.312	0.098**	0.040**
			(23.92)	(13.90)
Age group 25-34	0.313	0.232	ref.	ref.
Age group 35-44	0.302	0.344	-0.010*	-0.019**
			(2.32)	(7.01)
Age group 45-54	0.253	0.291	-0.036**	-0.042**
			(7.73)	(15.11)
Age group 55-65	0.132	0.133	-0.079**	-0.057**
			(14.91)	(18.26)
Sex (male=1)	0.674	0.665	0.021**	0.018**
			(5.55)	(6.95)
Marital status (married=1)	0.686	0.636	-0.018**	-0.021**
			(4.91)	(8.06)
Nationality (German=1)	0.950	0.948	0.058**	0.028**
			(7.10)	(4.77)
Civil servant	0.090	0.085	ref.	ref.
White collar worker	0.516	0.566	-0.044**	-0.014**
			(7.14)	(3.64)
Blue collar worker	0.394	0.349	-0.150**	-0.064**
			(22.03)	(14.18)
Firmsize 1-10 workers	0.125	0.128	ref.	ref.
11-19 workers	0.096	0.099	-0.003	-0.005
			(0.43)	(0.90)
20-49 workers	0.139	0.139	0.018**	0.012*
			(2.68)	(2.41)
at least 50 w.	0.634	0.621	0.026**	0.019**
			(4.74)	(5.06)
unknown	0.007	0.011	-0.027	-0.008
			(1.65)	(0.55)
Observations	49,768	45,860	49,768	45,860
Pseudo R-squared	-	-	0.0902	0.1077

Notes: The columns entitled M.E. provide marginal effects and absolute values of z-statistic in parentheses. ** and * indicate statistical significance at the 1 and 5 percent level. Not presented are the marginal effects for 15 federal states and 10 industries.

Table 5 Results of Regression Decomposition: Effect of Changed Characteristics

	1996-coeff.		2004-coeff.		Pooled-coeff.	
Percentage point difference to be explained:	0.084		0.084		0.084	
Share of total difference explained:	3.15%		9.26%		8.13%	
Explained effect due to:						
High Skill / Low Skill	2,84%	**	2,91%	**	2,47%	**
Age	-10,55%	**	-6,11%	**	-6,42%	**
Sex	0,54%	**	0,18%	**	0,25%	**
Marital Status	2,39%	**	1,40%	**	2,66%	**
Nationality	0,10%	**	0,11%	**	0,10%	**
Region of Residence	2,55%	**	2,82%	**	2,40%	**
Blue / White Collar / Civil Servant	2,73%	**	6,03%	**	4,27%	**
Firmsize	0,12%		-0,01%		0,03%	
Industry	2,43%	**	1,92%	**	2,38%	**

Note: ** and * indicate statistical significance at the 1 and 5 percent level. The standard errors were obtained using the delta method. The percentages in the bottom part of the table indicate the share of the total difference (0.084) that is explained by the considered group of covariates. The percentages in each column add up to the "share of total difference explained" provided in row 2.

Table 6 Robustness Check: Comparison of Different Decomposition Methods

	(1) Fairlie	(2) Oaxaca	(3) Bauer,Sinning(2006) omega=0	(3) Bauer,Sinning(2006) omega=1	(4) Bartus (2006)
Change in Training Probability	0,084	0,084	0,084	0,084	0,084
- explained by change in variables	0,0068	0,003	0,0078	0,0026	0,0075
- explained by change in coefficients	8,1%	3,6%	9,3%	3,1%	8,9%

Note: All estimates provide decompositions of the percentage point difference in training probabilities observed for the full sample (cf. last column of Table 5). The estimates in column (2) are standard Oaxaca decompositions using linear probability models for the years 1996 and 2004. The year 2004 is the reference year. Column (3) presents decompositions of the mean outcome differential of non-linear regression models, where omega is the general weighting matrix which is set to either set the coefficient vector of 1996 or of 2004 as reference (see Bauer and Sinning (2006) and Oaxaca and Ransom (1994)). In column (4) generalized Blinder-Oaxaca decomposition is used, using marginal effects instead of coefficients to evaluate the developments over time in a standard Oaxaca decomposition (see Bartus 2006). The decompositions were performed using the Stata commands fairlie, decomp, nldecompose, and gedecomp.

Table 7 Pooled Probit Marginal Effects for the Probability of Reporting Training

	M.E. (z-statistic)
Time indicators, reference = 1996	
1997	-0.000
	(0.10)
1998	-0.002
	(1.17)
1999	-0.031**
	(21.30)
2000	-0.030**
	(20.71)
2001	-0.029**
	(19.93)
2002	-0.031**
	(21.55)
2003	0.065**
	(36.11)
2004	0.068**
	(37.40)
Skill group, reference = low skill	
High Skill	0.041**
	(43.21)
Age group dummies, reference = 25-35	
35-44	-0.018**
	(19.20)
45-54	-0.032**
	(33.84)
55-65	-0.051**
	(47.11)
Other personal characteristics	
Sex (male = 1)	0.013**
	(15.11)
Marital Status (married = 1)	-0.015**
	(17.69)
Nationality (German = 1)	0.026**
	(14.26)
Employee category, reference = civil servant	
White collar worker	-0.013**
	(10.02)
Blue collar worker	-0.065**
	(43.17)
Observations	431358
Pseudo R squared	0.1144

Notes: Presented are marginal effects and absolute values of z-statistic in parentheses. ** and * indicate statistical significance at the 1 and 5 percent level. Not presented are the marginal effects for 5 firm sizes, 15 federal states, and 10 industries.