Assimilation and Cohort Effects for German Immigrants

CAWM-Discussion Paper No 6

by

Sebastian Gundel
Centrum für angewandte Wirtschaftsforschung
University of Muenster
Am Stadtgraben 9
D-48143 Münster
Germany

and

Heiko Peters*
Institute for Economic Education
University of Muenster
Scharnhorststr. 100
D-48151 Münster
Germany

Abstract

Demographic change and the rising demand for highly qualified labor in Germany attracts notice to the analysis of immigration. In addition, the pattern of immigration changed markedly during the past decades. Therefore we use the latest data of the German Socioeconomic Panel up to the year 2006 in order to investigate the economic performance of immigrants. We perform regressions of three pooled cross sections (1986, 1996, 2006) to estimate assimilation and quality of immigrants as reflected by their earnings. Further we take the heterogeneity of immigrants into account by separating them by country of origin. The rising wage inequality in Germany since the mid nineties will also be considered. We find a negative wage gap and a yearly assimilation rate of 2.3 percent. Due to a changing immigration pattern the cohort quality is declining.

* Corresponding author.

1. Introduction

Globalization brought a deterioration of the economic position of low qualified workers and an increased need for human capital. In combination with the demographic development of many industrialized countries, immigration policy is becoming an important instrument for economic growth. The goal should be to attract and successfully integrate highly qualified “white collar” workers and try to retain the “blue collar” workers.

As a result of the compressed earnings distribution in Germany compared to other industrial, emerging and developing countries and due to the beneficial social security system, Germany attracts less qualified immigrants (see Borjas (1987), pp. 532-534; Gernandt and Pfeiffer (2006), p. 1). After the huge influx of guest workers between 1961 and 1973, due to a strong demand for relative unskilled workers, Germany became an immigration country like Australia, Canada and the United States. During the first oil crisis the hiring of guest workers ended with a recruitment ban and a period mainly dominated by family reunification began. Since 1989 the fall of the “Iron Curtain” defined the picture of immigration. During that time a large remigration of ethnic Germans and immigration from former communist countries of Eastern Europe took place and changed the pattern of immigration origin markedly (see Zimmermann *et al.* (2006), pp. 16-29).

Today, Germany faces a high level of low qualified unemployed and the need for a positive immigration balance in order to soften the ageing of the German population. Particularly the need for high qualified workers is of crucial importance. According to the OECD study on migration even the highly qualified immigrants have a higher probability of becoming unemployed than Germans obtaining the same educational level (see OECD (2007)). This highlights the importance of labour market efficiency as reflected by the possibility to absorb the new immigrants and successfully overcome demographic change. The intensity, the arrival, the quality and the assimilation of immigrants differ strongly between economies and are important parameters for assessing the success of immigration. If the new immigrants are not successfully integrated they are an additional burden for the public welfare system.

For the first time, Chiswick (1978) analyzed the assimilation of immigrants as reflected by their earnings using the 1970 Census for the United States. Chiswick indicated an initial wage gap of immigrants relative to natives of 17 per cent. 10-15 years after immigration the earnings of the immigrants equal the natives' and start to exceed them with each year of labour experience in the host country. Thus the assimilation rate corresponds to the variable years since migration, sometimes called years of residence. The theoretical explanations are twofold: Initially, immigrants earn less than natives because they have lower country specific human capital like labour market customs, language skills and business practices. Each subsequent year that immigrants build up country specific skills is rewarded by the labour market. Therefore they experience steeper earnings growth compared to natives which leads to a narrowed gap. The argument explaining the immigrants' wages exceeding the natives' ones derives from selection. The decision to emigrate and start a new life allow the immigrants to become a positive selected group that is more ambitious to work harder and longer (see Borjas (1994), pp. 1671f.; Carliner (1980), pp. 88f.; Chiswick (1978), pp. 899-901). Chisiwick's seminal article was followed by a huge literature (Borjas (1985, 1987, 1989, 1995); Chiswick (1986); LaLonde and Topel (1990, 1991)) on the assimilation hypothesis for immigrants in the United States.

Different empirical approaches to the study of immigrants' assimilation can be found in the literature. Chiswick (1978) used a cross-sectional standard OLS estimation of the human capital earnings function[1] to estimate the assimilation of immigrants in the USA.[2] A correlation of the year since migration variable and the wage of immigrants could be caused by either age (assimilation) or cohorts effects (quality change). If the less successful have a higher propensity to remigrate or the most recent immigration cohorts have a lower unobserved ability relevant for the labor market, the simple OLS cross-section estimation of the assimilation is biased upwards. To account for this bias, the cohort effects have to be taken into consideration. Because of identification problems the separation of age and cohorts effects is not possible with single cross section estimation. Cohort or longitudinal data are necessary for this kind of analysis. Borjas (1985, 1995) uses different cross-sections in his estimations. Assuming the same period effect for immigrants and natives, it is possible to identify age and cohort effects simultaneously. This approach poses problems due to selective emigration, changes in the composition of the samples over time and the difficulty of disentangling longitudinal changes and period effects (Chiswick *et. al* (2002), p. 1). Instead of using different cross-sections with the restriction of the same period effects, panel data techniques could be used. Borjas (1989) and Hu (2000) estimated a system of natives and immigrants human capital functions using longitudinal data. The main problem using panel data techniques is panel attrition. Panel attrition will bias the estimation results if the probability to leave the sample is systematically linked to labor market developments.

---

1 See Mincer (1974) for a theoretical derivation of the human captial earnings function.

2 Carlinger (1980) and De Freitas (1980) use also a simple cross section estimation of the assimilation of immigrants in the USA.

Because of the high panel data attrition of the immigrants in the German socioeconomic panel (GSOEP) we do not use panel data techniques.[3] Instead, we use a similar empirical framework as Borjas (1985, 1995) to identify assimilation and cohort effects of immigrants in Germany simultaneously.

For Germany, Pischke (1992) analyzed the assimilation of guestworkers using data from the GSOEP 1984-1989 and different estimation methods. Pooled cross-section and panel estimates yield similar results indicating no assimilation. After controlling for different variables, the assimilation effect is insignificant and negative, indicating lower earnings growth for immigrants than for Germans. Dustmann (1993) differs between temporary and permanent migrants using the expected length of stay variable to disentangle. Estimating a cross-section of the 1984 wave of the GSOEP, Dustmann found a positive but insignificant yearly assimilation rate. The absent significant assimilation is explained with the low incentive of temporary migrants to invest into host country specific human capital. Licht and Steiner (1994) perform fixed effects panel estimates based on the first six waves of the GSOEP. They found no evidence of the assimilation hypothesis. Schmidt (1997) compared the assimilation of ethnic Germans and German guest workers and couldn't find a stable pattern. His analysis was based on cross-sections from two different sources, from which one was the GSOEP wave 1984. Bauer *et al.* (2005) couldn't support the assimilation hypothesis either. However, Constant and Massey (2005) found a positive assimilation rate that equates the earnings of immigrants and natives after 17 to 23 years analyzing the GSOEP waves from 1984-1997. Most recently, Fertig and Schurer (2007) analyzed the assimilation hypothesis using a longitudinal panel data

[3] A balanced panel would contain 1288 (1015 natives and 273 immigrants) individuals over the period of 23 years. After correcting for missing values and our data selection we would have only 207 (180 natives and 27 immigrants) individuals.

set of 21 waves lasting from 1984 to 2004. They estimated the assimilation for four different entry cohorts in order to control for immigrant heterogeneity using fixed effects models. They found positive assimilation rates for two cohorts lasting 9 and 16 years, respectively. Summing up the existing literature, there is no consistent picture about the catching up process. However a large initial earnings differential in Germany exists. Further there is no unambiguous evidence about the development of cohort quality so far.

This paper uses the latest data of the GSOEP to estimate the earnings equations in a pooled cross section of the years 1986, 1996 and 2006 and thus incorporates the development of the changing immigration pattern of the past 15 years. Further we want to account for the changing wage structure that occurred in Germany at the end of the 20th century (see Gernandt and Pfeiffer (2006); Peters (2007)).

The remainder of this paper is organized as follows. The next section describes the underlying data and some stylized facts. We will exhibit the wage differential between immigrants and Germans for each survey year and different immigrant cohorts. The changing and group-specific differently affecting wage structure will be accounted for by using two different wage deflators. The empirical model will be compiled in section 3. After discussing the different model specifications and the results, section 4 concludes with a short summary.

2. Data and Summary Statistics

For the analysis we use the GSOEP, collected for the period 1984 through 2006. The GSOEP is a yearly conducted household survey.[4] The data we are using are limited to men, aged 18-65, working at least 1820 hours per year with an hourly wage higher than 1€ and living in West Germany[5]. The individual real hourly wages are calculated deflating the nominal yearly labor earnings by the harmonized consumer price index based on the year 2000 and divided by yearly hours worked. We are focusing on three cross sections, derived from the latest one in year 2006, 1996 and 1986, respectively. After correction for individuals exhibiting missing values the 2006 wave consists of 2576 natives and 431 immigrants (1996: 1916, 688; 1986: 2255, 1011).[6] As can be seen from table 1 the natives earn 2.0 € more than immigrants in the year 2006. Twenty years before both groups earned approximately 26 per cent less. Respectively, the absolute wage increase is higher for natives compared to immigrants.

[Table 1 about here]

The age composition of immigrants and natives is quite stable in both 1986 and 1996 but rose considerably for the last period. Since the individual investment in formal education is an important factor determining the wage level, the change in the

4 See Wagner et al. (2007) and Haisken-DeNew and Frick (2005) for a detailed description of the GSOEP.

5 The immigration sample D for the period 1984-1993 is restricted to West Germany due to few observations in the eastern states of Germany. See Pannenberg *et al.* (2005), p. 180.

6 See Appendix A1 for the variables of the GSOEP we are using.

educational pattern of natives and immigrants affects the wage differential between both groups. For example, if the educational level of natives vis à vis immigrants increases, the immigrants fall behind even if they exhibit an increase their selves. The general expansion of the educational level is expressed for natives and immigrants regarding the increase of the years of schooling variable for the period 1986 through 2006. The educational level of natives exceeds that of immigrants for approximately 1.5 years. For a more detailed assessment we turn to educational attainment. Higher education yields higher returns to skill. Accordingly, the highest educational attainment is critical. The fraction of higher education for Germans is 8.9 percent higher than for immigrants and increased stronger in the period we observed. In this sense, the quality of immigrants and their skill distribution relative to natives declined during the past two decades. The fact that the GSOEP oversamples the guest workers who started to immigrate in the late 1950s results in the high value of the years since migration variable.[7] The age at immigration variable accounts for the fact that younger immigrants can better build up country specific human capital as pointed out by Friedberg (1993). The age at immigration in our sample is declining by four years.

To take into consideration the heterogeneity of immigrants, table 2 displays the stylized facts for immigrants differentiated by country of origin. We separated four country groups: High income countries according to the classification of the World Bank, Turkey because of their high share of the population in Germany, ethnic

[7] The high value of the ysm variable indicates the problem of the GSOEP that the bulk of the assimilation process of the relatively old guestworkers may be already over (see also Pischke (1992), p. 12).

Germans because of their huge influx after the fall of the Iron Curtain and the low income countries (also according to the classification of the World Bank).

[Table 2 about here]

As expected, the mean real hourly wage of immigrants from the high income countries is highest and the one of the low income countries the lowest. The ethnic Germans hold the highest educational level followed by high income countries, and Turkey ranking last. The high level of years since migration for the high income countries can be explained by the high share of guestworkers in this group. The other groups exhibit four to five years less. The Turkish immigrants arrived youngest.

Immigrants earn less than natives, because they don´t have specific skills required by the labor market of the host country.[8] The negative log hourly wage gap of immigrants vis à vis natives increased from 5.4 percent in the year 1986 to 16.8 percent in the year 1996 and remained at this level in 2006. The declining quality of immigrants due to the changed pattern of the immigration in Germany during the period from 1950 to 2006 can be seen as a possible reason for the widening wage gap. We separated the immigrants into five different decennial cohorts. Table 3, left side, exhibits the regression results of log hourly wages on dummy variables for each decennial arrival cohort. The most recent arrival cohort in each cross section exhibits the highest wage differential relative to natives. For the year 2006 the wage gap of the latest immigrant cohort was 41.8 percent. Compared to this the cohort in 1996 earned 34.2 percent less and in 1986 14.6 percent less. Thus, the cohort quality

[8] Another reason might be discrimination of immigrants (see Constant and Massey (2005)).

seems to decline. The prior to 1966 cohort is the only one with a positive wage gap relative to natives. Tracking this cohort over each cross section exhibits a widening of the positive wage gap by 12.8 percent. The effect of the wage increase relative to natives can be observed for all cohorts compared from 1986 to 2006 – indicating a higher ageing or assimilation effect. It is not possible to compare the arrival cohorts in each single cross section, because the widening of the wage gap could stem from both changes in quality and age.

[Table 3 about here]

In order to make this comparison possible we assessed the age-adjusted wage differential by adding the age variable up to the third order to the regression (see table 3, right side). The development of the wage gap between immigrants and natives keeps almost stable. By 1986, the positive wage gap of the prior 1966 cohort turned negative, because of the higher age compared to the reference group. Tracking the cohorts over time yields qualitatively similar results for the prior to 1966 and the 1986-1995 cohorts. The uneven pattern for the 1966-1975 and 1976-1985 cohort can be explained with their younger age structure relative to the rest. The comparison of cohort quality within each cross sectional is now possible. The cohort quality is declining through all cross sections except for the 1976-1985 cohort. By 2006, the relative negative wage gap between the oldest and the youngest cohort is 36.8 percent and between the worst cohort and the natives it is almost 30 percent.

After a stable wage distribution until the mid nineties Germany experienced a widening of the wage structure thereafter. The upper half of the wage structure is widening since the mid nineties and the lower half since the end of the nineties (see Gernandt and Pfeiffer (2006); Peters (2007)). Especially return to skill regarding the highest educational attainment is rising relative to lower educational attainments. Since immigrants are less qualified than natives, this can result in an underestimation of assimilation. The mean educational level of Germans is higher than the mean educational level of immigrants. Thus, a rise in the returns to skill leads to a widening wage gap between Germans and immigrants – even in the absence of changes in the relative skills of the groups – and prolongs the assimilation period. In this sense, the differences in earnings between immigrants and natives may reflect changes in the skill distribution and not time residing in Germany. To account for this fact, we use two different ways to deflate the wage. First we use the age-education deflator (see for similar procedure Borjas (1995)), second the percentile deflator (see for similar procedure LaLonde and Topel (1990)).

The age-education deflator nets out the changes in the native wage structure coming from changes due to returns to skill and age. In this sense, we expect a narrowing of the wage gap when comparing the change of the cross sections 2006 and 1996 relative to the not deflated wage gap change. Therefore we segmented the native population and built two age and six education cells. The age group separates individuals above and below 40 years. The education cells are built according to ISCED-1997-Classification. This yields 12 age-education cells.[9] To calculate the deflator in equation (1) for age cell a and education cell e we subtracted the mean log hourly wage (lhwage) of each age-education cell of base year 1986 from the corresponding wage of the cross sections 1996 and 2006.

[9] Because of too few observation we cannot built more age-education cells out of our sample.

(1) $\Delta_{a,e,t} = mean(lhwage)_{a,e,t} - mean(lhwage)_{a,e,1986},\quad t = 1996, 2006$

Finally, we subtract the deflator ($\Delta_{a,e,t}$) in equation (2) from the log hourly wage and receive the age-education deflated log real hourly wage ($lhwageae_{a,e,t}$).

(2) $lhwageae_{a,e,t} = lhwage_{a,e,t} - \Delta_{a,e,t},\quad t = 1996, 2006$

This deflator has the advantage to account for the rising wage inequality between age-education cells. Unfortunately we cannot control for changes within groups.

With the percentile deflator we can control these within group changes. To account for changes of the natives wage distribution the log real hourly wage will be deflated using the changes of each decile i of the cross sections relative to the base year 1986. To set up the percentile deflator ($\Delta_{i,t}$) we proceed similar as before (equation (3)).

(3) $\Delta_{i,t} = decile(\text{lhwage})_{i,t} - decile(\text{lhwage})_{i,1986},$
$t = 1996, 2006 \; and \; i = 1, 2, \ldots, 9$

In equation (4) we calculate the percentile deflated log real hourly wage by subtracting the percentile deflator from the log real hourly wage for each census year.

(4) $lhwagep_{(i-1)..i,t} = lhwage_{(i-1)..i,t} - \Delta_{i,t},\quad t = 1996, 2006 \; and \; i = 1, 2, \ldots, 9$

The assumption that natives and immigrants are equally skilled at each decile is a problematic facet of this deflator. We might face the problem that newly arrived immigrants experience wage disadvantages because they lack country specific skills. Thus, they are in different deciles although they have the same skill level. In this sense, none of the deflators can completely capture the changes of the native wage structure affecting immigrants.

Table 4 incorporates the changes of the wage structure of natives when calculating the immigrant wage differential. The left side depicts the wage gap using the age-education-deflator.

[Table 4 about here]

Focusing on the period when Germany experienced the widening wage structure we compare the change of the wage differential between 2006 and 1996. As expected above, the wage gap of all immigrants declined by 3.8 percent, whereas the immigrants experienced an increase of 0.5 percent using the not deflated wage differential. The pattern of a narrowing wage gap between 2006 and 1996 remains stable for all cohorts. Using the percentile deflator (right side) yields qualitatively comparable results regarding the narrowing wage gap change between the relevant years 2006 and 1996.

Summing up, we find that immigrants from the cohort 1996-2006 and 1986-1995 are the least qualified as reflected by their earnings gap. The earliest cohort performs best and the 1976-1985 cohort exceeds the 1966-1975 cohort.

3. Empirical Methodology and Results

3.1 *Econometric Specification*

After the descriptive analysis we turn to a regression analysis in order to further assess the performance of the immigrants. Mincer (1974) was the first who uses the classic Mincer equation to determine individual earnings. We augmented this equation with more socioeconomic and immigrant specific variables to account for observable differences in characteristics.

In our basic regression the endogenous variable is the log real hourly wage lhwage.[10] We regress lhwage on the following exogenous variables. The socioeconomic variables for both natives and immigrants are educational attainment according to ISCED-1997-Classification dummies dik (k=1,2,4,5,6)[11] and marital status dummy dm. We also used regional dummies to control for regional wage disparities between north drn, south drs and middle of West Germany being the reference category. Mincerian Experience[12] ex and quadratic values of Mincerian Experience are estimated separately for natives and immigrants. Further we use immigrant specific variables. To determine the assimilation affect we use the years since migration variable ysm up to the third order that counts the years an immigrant resides in Germany. The third order polynomial is done to account for the nonlinear wage growth with more years since migration. The year since migration variable is

---

[10] We use the log real hourly wage in order to eliminate the influence of working time on wages.

[11] We use the ISCED-1997-Classification instead of years of schooling because there is no linear relationship between years of schooling and wage. Each further step in educational attainment yields a disproportionate wage increase.

[12] Mincer (1974) defined potential job experience as age-years of schooling-6.

calculated as year of questionnaires minus year of migration.[13] Immigrants catch up vis à vis natives if the experience plus the year since migration effect exceeds the experience effect of natives. The changing cohort quality is captured by five cohort dummy variables (d66: prior to 1966, d76: 1966-1975, d86: 1976-1985, d96: 1986-1995, d06: 1996-2006) interacted with an immigration dummy (dn).[14] The intention to stay in Germany is reflected by the question on the expected duration of stay. The dummy variable dstay takes the value one if the immigrant wants to stay forever. This controls at least for some of the remigration problem. The error term u catches all unobserved characteristics and is normally identically independently distributed.

We included period dummies to sweep out time effects (dc96, dc06) of business cycle variation. According to our dummy selection the base period is 1986. Simultaneously estimating the period, cohort and assimilation effect yields an identification problem. The identification problem is a result of the assimilation effect being a linear combination of period and cohort effects. Since we want to concentrate on cohort and assimilation effects, we have to impose the identifying restriction of period effects equally affecting natives and foreigners on the model. The intercept α_0 indicates the log real hourly wage of a native without experience, an educational attainment of middle vocational, not married, from the mid of Germany and from cross-sectional 1986.

[13] We also used a linear and quadratic specification, but a third order polynomial better fits the characteristics of years since migration and wage relationship traced over the years.

[14] We also used a different cohort classification according to Zimmermann *et al.* (2006) reflecting the different immigration periods. The results are robust to ours, but we used decennial cohort classification to better compare the cohorts between and within the three cross section exhibiting a ten year intervall as well.

$$(5)\quad lhwage_i = \alpha_0 + \alpha_1 ex_i + \alpha_2 ex_i^2 + \alpha_3 di1_i + \alpha_4 di2_i + \alpha_6 di4_i + \alpha_7 di5_i + \alpha_8 di6_i + \alpha_9 dm_i + \alpha_{10} drs_i + \alpha_{11} drn_i + \alpha_{12} dc96_i + \alpha_{13} dc06_i + \alpha_{14} ex_i dn_i + \alpha_{15} ex_i^2 dn_i + \alpha_{16} ysm_i dn_i + \alpha_{17} ysm_i^2 dn_i + \alpha_{18} ysm_i^3 dn_i + \alpha_{19} d66_i dn_i + \alpha_{20} d76_i dn_i + \alpha_{21} d86_i dn_i + \alpha_{22} d96_i dn_i + \alpha_{23} d06_i dn_i + \alpha_{24} dstay_i dn_i + u_i$$

We pooled the data of the three cross sections of 2006, 1996 and 1986 and estimate the following basic equation (5) with OLS. To correct for possible heteroskedasticity we use White consistent standard errors (see White (1980)).

3.2 Estimation Results

Table 5 depicts the regression results of the variables of interest.[15] In regression (1) to (4) the endogenous variable is each the log real hourly wage but four different sets of exogenous variables. To net out the changes in the wage structure we used age-education deflated and percentile deflated log real hourly wage for the regression (5) to (8) and (9) to (12), respectively. For each wage specification the regression results from column (1) through (12) remain robust considering the socioeconomic variables ex, dik (k=1,2,4,5,6), dm, drs and drn (see Appendix table A2).

[Table 5 about here]

Column (1) describes the simplest specification of the regression of the log real hourly wage on quadratic experience, educational attainment, marital status, period effects, immigrant dummy, years since migration and a constant. We find a negative wage gap of immigrants relative to natives of 40.6 percent. The immigrants reduce this wage gap with a yearly assimilation rate of 3.2 percent.[16] The period effects are

---

[15] For more detailed regression results see Appendix table 2.

[16] In table 5 we calculated the effect of one more year of ysm on the wage. We are aware of our calculation error stemming from using this assimilation rate instead of the correctly use of the estimated coefficients of the third order ysm polynomial. This error is negligible if the percental change is small.

both positive and highly significant. In column (2) we split the immigrants by time of arrival and add cohort dummies in order to control the declining productivity of the most recent immigrants as noted above. Further we included dstay to control the problem of remigration. The inclusion of the cohorts yields considerably different negative wage gaps and reduces the assimilation rate by 0.8 percent, as expected from theoretical considerations above.[17] Yet, adding cohorts reduces the significance of the years since migration variable. We can confirm the results of the above descriptive analysis. The cohort quality is declining in the following order: d66, d86, d76, d96 and d06. However, the results for d76 and d86 are not significant. The declining cohort quality explains the reduction of the assimilation effect. Without controlling for cohorts the assimilation effect in column (1) was biased upwards. The influence of the remigration decision is negative but insignificant. The negative sign suggests a negative remigration selection. Regression (3) controls for regional disparities (see Appendix table A2 for details). As expected, individuals from the northern part earn less than individuals from the middle. Individuals from the south earn more, though this effect is insignificant. In addition, the d76 cohort turns significant. All remaining results stay robust. Column (4) represents our basic model from equation (5). We controlled for different labor market experience depending on being native or immigrant. There is no significant difference in the experience effect

[17] In several other specifications in order to check for robustness we also estimated regression (2) without dstay. The main changes on ysm stem from the cohort dummies.

for natives and immigrants.[18] Immigrants from the d66 cohort earn 13.7 percent and from d76 24.1 percent less than natives. The negative wage gap for d86 is insignificant. The d96 and d06 cohorts are the worst earning 41.3 percent and 55.8 percent less than Germans respectively. Not differentiating after cohorts, the yearly assimilation rate of immigrants is 2.2 percent.[19]

According to the Akaike information criterion, the value of the adjusted R-squared and the inclusion of all relevant variables we chose model (4) as our preferred reference model. In column (5) to (8) and (9) to (12) we proceeded with our specifications identically to column (1) to (4) but used the age-education deflated log real hourly wage and percentile deflated real log hourly wage as endogenous variable. Comparing both the results in column (5) to (8) and column (9) to (12) we have qualitatively similar effects on the results by adding new exogenous variables as for the not deflated wage. Thus, we concentrate on a comparison of specification (8) and (12) with the one in (4). The age-education deflator sweeps out the period effects. As expected, we find a higher assimilation rate of 2.3 percent for the age-education adjusted wage structure. The wage gap of the different cohorts in column (8) declined slightly compared to column (4). The d06 cohort earns 52.6 percent less than natives; immigrants who arrived between 1986 and 1995 earned 38.5 percent less. All other results are robust. To illustrate the catching up of immigrants, figure 1

[18] Further we interacted the educational attainment, the marital status and the regional disparities with the immigrant dummy. All interacted expressions were insignificant meaning no difference between natives and immigrants. All other variables were robust. So we used the simpler specifications in table 5. According to Friedberg (1993) age at migration has an influence on wages. For all specifications we controlled for age at migration. To add the age at migration variable we had to impose on the model a second identifying restriction of equal experience effects for natives and immigrants. The variable has the theoretically expected negative sign but is insignificant throughout all regressions. All other results were not affected.

[19] We did not add interaction between both cohorts and years since migration and experience because of the heterogeneity within each cohort yielding biased results. However, as we focus on changing cohort quality the mean rate of assimilation and experience is sufficient.

depicts the experience-earnings profiles of immigrants vs. natives (left side) and of each immigrant cohort vs. natives (right side). According to figure 1, immigrants assimilate vis à vis natives due to a steeper experience-earnings profile, yet they never equal native earnings. When differentiating for cohorts we can clearly identify the different cohort quality. As a result, the d66, d76 and d86 could fully catch up to native earnings when assuming the average immigrant assimilation rate. Due to their low quality, the d96 and d06 cohorts never achieve this.

[Figure 1 about here]

Using the percentile deflated wage yields qualitatively worse results. The period effect dc96 is insignificant and the period effect dc06 is negative. Between 1986 and 1996 the wage distribution shifts to the right for about 16 percent at all deciles. From 1986 to 2006 the shift is more unequal. The wage distribution rises almost gradually from 20 percent at the first decile to 29 percent at the ninth decile. The wage increase used for deflation turned the period effect 2006 significantly negative. Because immigrants are located more on the left side of the wage distribution, the negative wage gap increases for approximately one percent in column (12) relative to column (4). As expected, the year since migration variable increases slightly in column (9). For all other specifications the year since migration variable turns out to be insignificant. Still cohort quality reduces significantly throughout the immigration period and the negative difference is augmented compared to not deflated results.[20] We suspect either the period or cohort effects to reduce the significance of the year since migration variable.

---

[20] We suspect the increasing wage gap to be caused by a rising wage inequality within education and age groups.

In the following empirical specification we allow differences among immigrants in country of origin. This is done because of the influence of the heterogeneity of immigrants on the results. Therefore we added four country dummies instead of the immigrant dummy. If immigrants come from high income countries we introduced dic, from Turkey dtur, from low income countries dlic. For ethnic Germans we set up deg. We also controlled for the interaction of these dummies with experience and years since migration, respectively. We drop the cohort dummies because the interaction with the country of origin dummies would result, for some interactions, into too few observations for a reliable estimation. The cohort quality aspect is negligible if using heterogeneous country cohorts. This is particularly applicable, because the bulk of the immigrants from dlic immigrated within the d76 cohort, from deg within the d96 cohort, dtur within d76 and d86 and finally dic within the d66 and d76 cohort. Accordingly, the most recent cohorts consist mainly of deg as a result of the opening up of Eastern Europe. The d86 consists of dtur as reflecting the period of family reunification; the d76 consists of dlic, dtur and dic, thus representing mainly the guest workers. Finally, the d66 represents mainly the earliest guest workers from classical guest worker countries, namely Italy, Spain and Greece. In this sense, there already is a timely order inherent in the construction of the country dummies reflecting the changing immigration pattern in Germany. As proceeded before, we use the same three endogenous variables and tested different specifications for the robustness of our results. The socioeconomic variables are robust for the different specifications, likewise. After robustness check our preferred models are column (14), (16) and (18) where we concentrate on the assimilation and quality of immigrants. The results are shown in table 6.

[Table 6 about here]

We now turn to column (13) where we used the simplest specification. The results indicate a negative wage gap over all immigration groups, explicitly 55.4 percent for low income countries, 39.9 percent for ethnic Germans, 38.5 percent for Turks and 26.2 percent for high income countries. The mean yearly assimilation rate is 3.2 percent. In column (14) we allow immigration group specific experience and years since migration profiles. We obtain an insignificant and the smallest negative wage gap for the immigrants from high income countries. This may result because they attain similar characteristics as natives relevant for the labor market and come from an industrial country comparable to Germany. The older immigrants from high income countries came mainly as guest workers to Germany, whereas the younger immigrants are not guest workers coming from industrial countries. They have a positive assimilation. Compared to the industrial countries, Turkey is economically behind. Thus, they have a high but insignificant negative wage gap. There is no proof of a catching up process. Ethnic Germans emigrated from Eastern Europe are supposed to have a slightly negative wage gap due to unequal educational systems compared with industrial countries. However the wage gap might remain small because of being enrooted to Germany. Compared to German wage growth they are falling behind. The last group of immigrants from low income countries should have the highest negative wage gap because they are negatively selected due to the very high wage inequality compared to Germany. Indeed they have a significant large negative wage gap, but a high positive and significant assimilation rate.

Using the age-education deflator (column (16)) we obtain better results considering the adjusted R-squared and the information criterion. Compared to column (14), we expect an adjustment of the wage gap as well as the assimilation rate according to the development of the age-education distribution of specific immigrant groups compared to natives. In general, the assimilation rate should increase as it turns out to be for dic, dtur and dlic. Except the marginal changes due to the deflation the results of the wage gap remain qualitatively stable. We obtain a positive assimilation rate of 4.9 percent for high income countries, of 10.5 percent for low income countries and a negative rate of 1.4 percent for ethnic Germans. In the case of high and low income countries there is a significant difference compared to natives regarding the experience effect. The Turks exhibit a positive but insignificant assimilation rate. For the purpose of better perception of the assimilation process this is plotted using the experience-earnings profiles in figure 2.

[Figure 2 about here]

Except for ethnic Germans all experience-earnings profiles are concave indicating an increase of earnings with years since migration at a decreasing rate. In contrast, the profile is convex for ethnic Germans. The immigrants from high income countries start with a negative wage gap, quickly assimilate and finally exceed the natives. The ethnic Germans equal native Germans after approximately 20 years. Immigrants from Turkey and low income countries exhibit the typical steeper experience-earnings profile than Germans but never reach the same wage level. Interestingly, when controlling for country of origin we find a significant negative selection of immigrants. Individuals who want to stay permanently in Germany earn 6.7 percent less than individuals who want to remigrate. Thus immigrants who want to stay permanently might be a negative selected group with respect to wages.

As in table 5, the percentile deflated model yields the worst results. As expected, the assimilation rate increases compared to the non deflated model.

4. Conclusion

Our descriptive analysis of the immigrants in Germany yielded a negative and increasing wage gap between immigrants and natives over the period 1986 through 2006. Differentiating for time of arrival we found a decreasing cohort quality. Earlier immigrants earn more than the latest immigrants coming to Germany. Due to rising wage inequality and especially due to the increase of the returns to skill of higher education Germany has experienced since the mid nineties, we used an age-education and percentile deflator. This yielded a narrowing of the negative wage gap change. The latest immigrants still earned least.

Turning to a more formal analysis we can confirm the descriptive analysis results reveal a negative wage gap and declining cohort quality as reflected by a rising wage gap. Immigrants arriving between 1986 and 1995 earn 38.5 percent less, immigrants arriving since 1996 earn even 52.6 percent less than natives. Compared to this, the earliest immigrants arriving prior to 1966 exhibited only a wage disadvantage of 8.6 percent. Further we find an average assimilation rate of 2.3 percent. The immigrants arriving prior to 1986 could reach earnings equality vis à vis natives. The others, although exhibiting steeper experience-earnings profiles than natives, cannot fully catch up because of their high initial wage gap. As expected, the wage deflators correct for the underestimation of the assimilation rate.

Since the pattern of immigration changed during the period of observation in Germany we take into account the heterogeneity of the immigration groups. Doing so, we find a negative wage gap for immigrants from high income countries, Turkey, low income countries and for ethnic Germans. But for assessing the ability to absorb immigrants into the labor market their assimilation is crucial. We uncovered a positive assimilation rate of 4.9 percent for high income countries and of 10.5 percent for low income countries. We cannot confirm an assimilation rate for Turks. For ethnic Germans we show a negative yearly rate of 1.4 percent. Due to the convex experience-earnings profile they could assimilate after approximately 20 years.

Owing to the deterioration of the position of low qualified as reflected by the high unemployment and the continuously rising demand for highly qualified the integration of immigrants into the labor market will be a challenge for immigration policy regarding declining cohort quality. This fits with the negative selection of immigrants we found. Permanent immigrants earn 6.7 percent less than immigrants who just came to Germany to improve their human capital or to work here for a part time of their life cycle. One possible reason for this selection could be the beneficial social system in Germany. This could be of interest to investigate more deeply by assessing the determinants of the migration movements and the selection process.

List of Figures

Figure 1: Experience-earnings profiles

Figure 2: Experience-earnings profiles, by country of origin

List of Tables

Table 1: Stylized facts, differentiated by natives and immigrants

Table 2: Stylized facts, pooled immigrants differentiated by country of origin

Table 3: Immigrant wage differential

Table 4: Immigrant wage differential, age-adjusted and deflated by changes in wage structure

Table 5: Regression results

Table 6: Regression results, country of origin

Figures and Tables

Table 1: Stylized facts, differentiated by natives and immigrants

		natives			immigrants		
		1986	1996	2006	1986	1996	2006
observations (numbers)		2255	1916	2576	1011	688	431
real hourly wage (mean)		13,4 €	16,2 €	16,9 €	11,7 €	13,3 €	14,9 €
age (mean)		40,52	40,75	43,71	40,40	40,79	44,70
years of schooling (mean)		11,76	12,18	12,83	10,36	11,06	11,33
	inadequately	0,8%	1,3%	1,3%	15,3%	9,4%	5,0%
educational attainment	general elemantary	15,6%	12,3%	8,7%	24,2%	20,9%	13,4%
	middle vocational	54,3%	51,9%	45,5%	41,1%	39,4%	45,1%
	vocational plus abi	2,3%	4,8%	7,1%	7,2%	12,6%	10,9%
	higher vocational	11,7%	9,8%	10,9%	3,8%	3,1%	7,9%
	higher education	15,4%	20,0%	26,5%	8,4%	14,6%	17,6%
years since migration (mean)		-	-	-	16,49	18,08	23,64
age at migration (mean)		-	-	-	23.38	21.63	19.56

Source: Own calculation with SOEP data based on cross-section weights.

Table 2: Stylized facts, pooled immigrants differentiated by country of origin

	Immigrants from			
	high income countries	Turkey	ethnic Germans	low income countries
observations (numbers)	765	559	465	341
real hourly wage (mean)	15.07 €	11.95 €	13.79 €	10.93 €
age (mean)	43.97	39.04	41.39	42.70
years of schooling (mean)	10.88	9.94	11.87	10.67
years since migration (mean)	22.45	18.24	17.91	17.03
age at migration (mean)	21.52	20.80	23.48	25.67

Source: Own calculation with SOEP data based on cross-section weights.

Table 3: Immigrant wage differential

	not age-adjusted			age-adjusted		
	1986	1996	2006	1986	1996	2006
all immigrants	-0.054**	-0.168***	-0.165***	-0.091***	-0.151***	-0.156***
<1966 arrivals	0.069	0.134	0.197	-0.058	0.009	0.069
1966-1975 arrivals	-0.082***	-0.121***	-0.076	-0.153***	-0.207***	-0.188
1976-1985 arrivals	-0.146***	-0.165***	-0.038	0.034	-0.066	-0.079
1986-1995 arrivals	-	-0.342***	-0.321***	-	-0.221***	-0.212***
1996-2006 arrivals	-	-	-0.418*	-	-	-0.299
Note.- * significant at 10%; ** significant at 5%; *** significant at 1%						

Source: Own calculation with SOEP data based on cross-section weights.

Table 4: Immigrant wage differential, age-adjusted and deflated by changes in wage structure

	by age-education-deflator			by percentile-deflator		
	1986	1996	2006	1986	1996	2006
all immigrants	-0.091***	-0.195***	-0.157***	-0.091***	-0.164***	-0.155***
<1966 arrivals	-0.058	-0.042	0.099	-0.058	0.013	0.058
1966-1975 arrivals	-0.153***	-0.284***	-0.131	-0.153***	-0.227***	-0.182
1976-1985 arrivals	0.034	-0.091	-0.085	0.034	-0.077	-0.075
1986-1995 arrivals	-	-0.244***	-0.242***	-	-0.235***	-0.213***
1996-2006 arrivals	-	-	-0.311	-	-	-0.313

Note.- * significant at 10%; ** significant at 5%; *** significant at 1%

Source: Own calculation with SOEP data based on cross-section weights.

Table 5: Regression results

	lhwage				lhwage, using age-education deflator				lhwage, using percentile deflator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ex	0.056***	0.056***	0.056***	0.055***	0.055***	0.055***	0.055***	0.055***	0.056***	0.056***	0.056***	0.055***
dc96	0.165***	0.173***	0.173***	0.173***	-0.029	-0.020	-0.020	-0.020	0.017	0.025	0.025	0.025
dc06	0.112***	0.129***	0.127***	0.128***	-0.042**	-0.022	-0.024	-0.024	-0.098***	-0.080***	-0.083***	-0.082***
dn	-0.406***	-	-	-	-0.413***	-	-	-	-0.417***	-	-	-
ex*dn	-	-	-	0.008	-	-	-	0.004	-	-	-	0.009
ysm	0.032***	0.024*	0.024*	0.022*	0.034***	0.022*	0.022*	0.023*	0.035***	0.024	0.024	0.021
d66	-	-0.075*	-0.086*	-0.137*	-	-0.042**	-0.051*	-0.086**	-	-0.080*	-0.092*	-0.147*
d76	-	-0.186	-0.193*	-0.241***	-	-0.146	-0.152	-0.176	-	-0.191	-0.199*	-0.250*
d86	-	-0.156	-0.159	-0.215	-	-0.149	-0.152	-0.181	-	-0.162	-0.167	-0.227
d96	-	-0.362***	-0.361***	-0.413***	-	-0.360***	-0.358***	-0.385***	-	-0.372***	-0.371***	-0.426***
d06	-	-0.494*	-0.496*	-0.558*	-	-0.493**	-0.494**	-0.526**	-	-0.521**	-0.523*	-0.591**
dstay	-	-0.049	-0.049	-0.049	-	-0.051	-0.051	-0.052	-	-0.048	-0.048	-0.048
Observations	8754	8754	8754	8754	8754	8754	8754	8754	8754	8754	8754	8754
adj. R-squared	0.297	0.299	0.300	0.300	0.311	0.313	0.314	0.314	0.279	0.281	0.282	0.282
AIC	11627	11607	11597	11597	11542	11517	11508	11511	12273	12253	12241	12240

Note.- * significant at 10%; ** significant at 5%; *** significant at 1%

In case of the aggregated effects of the variables ex, ex*dn and ysm, the total effect and the significance level of the Wald test (see appendix table A2) are specified. A list of the complete regression results can be found in appendix table A2.

Source: Own calculation with SOEP data based on cross-section weights.

Table 6: Regression results, country of origin

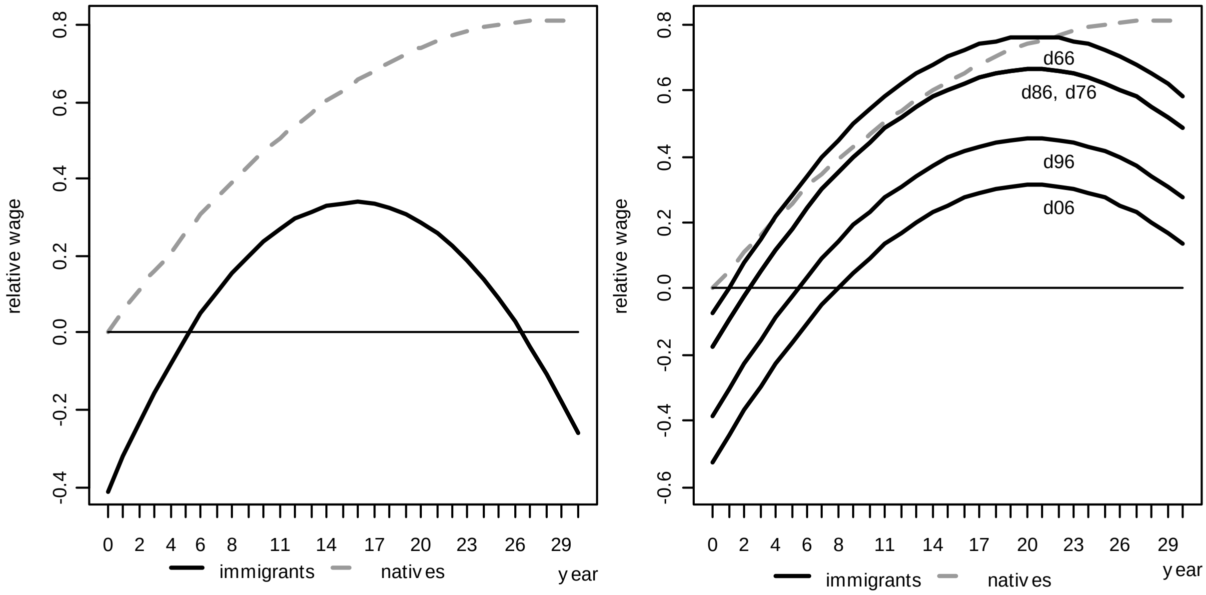
	lhwage		lhwage, using age-education deflator		lhwage, using percentile deflator	
	(13)	(14)	(15)	(16)	(17)	(18)
ex	0.056***	0.055***	0.055***	0.055***	0.056***	0.055***
dc96	0.167***	0.171***	-0.027	-0.023	0.019	0.023
dc06	0.116***	0.122***	-0.039*	-0.033	-0.094***	-0.088***
dic	-0.262***	-0.098	-0.277***	-0.125	-0.265***	-0.167
dtur	-0.385***	-0.475	-0.389***	-0.511**	-0.402***	-0.489*
deg	-0.399***	-0.128	-0.413***	-0.120	-0.412***	-0.099
dlic	-0.554***	-1.155***	-0.539***	-0.981	-0.571***	-1.167***
ex*dic	-	-0.024*	-	-0.026*	-	-0.019
ex*dtur	-	-0.007	-	-0.004	-	-0.008
ex*deg	-	0.002	-	0.003	-	0.000
ex*dlic	-	0.046***	-	0.029***	-	0.045**
ysm	0.032***	-	0.034***	-	0.033***	-
ysm*dic	-	0.065**	-	0.075***	-	0.066**
ysm*dtur	-	0.062	-	0.065	-	0.067
ysm*deg	-	-0.013***	-	-0.014***	-	-0.019***
ysm*dlic	-	0.074***	-	0.076***	-	0.078***
dstay	-	-0.058	-	-0.067*	-	-0.058
Observations	8754	8754	8754	8754	8754	8754
adj. R-squared	0.300	0.303	0.313	0.316	0.281	0.285
AIC	11596	11575	11518	11503	12241	12219

Note.- * significant at 10%; ** significant at 5%; *** significant at 1%

In case of the aggregated effects of the variables ex, ex*dic, ex*dtur, ex*deg, ex*dlic and ysm, ysm*dic, ysm*dtur, ysm*deg, ysm*dlic the total effect and the significance level of the Wald test (see appendix table A2) are specified. A list of the complete regression results can be found in appendix table A2.

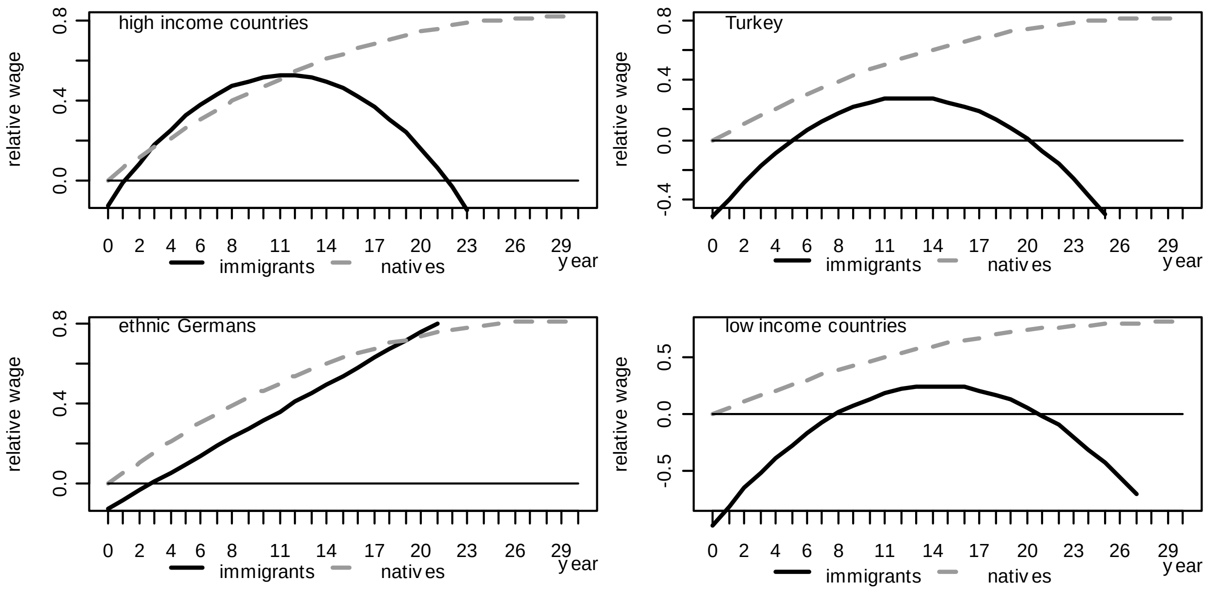
Source: Own calculation with SOEP data based on cross-section weights.

Figure 1: Experience-earnings profiles



Source: Own calculation with SOEP data based on cross-section weights.

Figure 2: Experience-earnings profiles, by country of origin



Source: Own calculation with SOEP data based on cross-section weights.

References

Bauer, T. *et al.* (2005) German migration: Development, assimilation, and labor market effects, in European Migration What do we know? (Ed.) K.F. Zimmermann, Oxford, pp. 197-261.

Borjas, G. J. (1985) Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants, *Journal of Labor Economics,* **3**, 463-489.

Borjas, G. J. (1987) Self-Selection and the Earnings of Immigrants, *The American Economic Review,* **77**, 531-553.

Borjas, G. J. (1989) Immigrant and Emigrant: A Longitudinal Study, *Economic Inquiry,* **27**, 21-37.

Borjas, G. J. (1994) The Economics of Immigration, *Journal of Economic Literature,* **32**, 1667-1717.

Borjas, G. J. (1995) Assimilation and Changes in Cohort Quality Revisited: What Happened to Immigrant Earnings in the 1980s?, *Journal of Labor Economics*, **13**, 201-245.

Carliner, G. (1980) Wages, Earnings and Hours of First, Second and Third Generation American Males, *Economic Inquiry,* **18,** 87-102.

Chiswick, B. R. (1978) The Effect of Americanization on the Earnings of Foreign-born Men, *Journal of Political Economy,* **86**, 897-921.

Chiswick, B. R. (1986) Is the New Immigration Less Skilled Than the Old?, *Journal of Labour Economics,* **4**, 168-192.

Chiswick, B. R.; Lee, Y. L.; Miller, P. W. (2002) Longitudinal Analysis of Immigrant Occupational Mobility: A Test of the Immigrant Assimilation Hypothesis, *Institute for the Study of Labor Discussion Paper Series No. 452*.

Constant, A.; Massey, D. S. (2005) Labor market sementation and the earnings of German guestworkers, *Population Research and Policy Review*, **24**, 489-512.

DeFreitas, G. (1980) The Earnings of Immigrants in the American Labor Market, *Unpublished doctoral dissertation, Columbia University,* 1980.

Dustmann, C. (1993) Earnings adjustment of temporary migrants, *Journal of Population Economics*, **6**, 153-168.

Fertig, M.; Schurer, S. (2007) Earnings Assimilation of Immigrants in Germany: The Importance of Heterogeneity and Attrition Bias, *SOEPpapers No. 30/2007*.

Friedberg, R. (1993) The Labor Market Assimilation of Immigrants in the United States: The Role of Age at Arrival, *Mimeo, Brown University, 1993*.

Gernandt, J.; Pfeiffer, F. (2006) Rising Wage Inequality in Germany, *ZEW Discussion Paper No. 06-019*.

Haisken-DeNew, J. P.; Frick, J. R. (2005) Desktop Companion to the German Socio-Economic Panel Study (GSOEP), Version 8.0 – Update to Wave 21, *DIW Berlin*.

Hu, W.-Y. (2000) Immigrant Earnings Assimilation: Estimates from Longitudinal Data, *The American Economic Review,* **90**, 368-372.

LaLonde, R. J.; Topel, R. H. (1990) The Assimilation of Immigrants in the U.S. Labor Markets, *NBER Working Paper No. 3573*.

LaLonde, R. J.; Topel, R. H. (1991) Immigrants in the American Labor Market: Quality, Assimilation, and Distributional Effects, *The American Economic Review,* **81**, 297-302.

Licht, G.; Steiner, V. (1994) Assimilation, labour market experience and earnings profiles of temporary and permanent immigrant workers in Germany, *International Review of Applied Economics,* **8**,130-156.

Mincer, J. (1974) Schooling, Experience and Earnings, *New York, London*.

OECD (2007) International Migration Outlook, *Annual Report 2007*.

Pannenberg, M. *et al.* (2005) Sampling and Weighting, in Desktop Companion to the German Socio-Economic Panel (SOEP) (Ed.) J.P. Haisken-DeNew; J.R. Frick, chapter 5, pp. 153-186, Version 8.0, Dec. 2005.

Peters, H. (2007) Lohnungleichheit innerhalb und zwischen Bevölkerungsgruppen in Deutschland und den USA, *SOEPpapers No. 36*.

Pischke, J.-S. (1992) Assimilation and the Earnings of Guestworkers in Germany, *ZEW Discussion Paper No. 92-17*.

Schmidt, C. M. (1997) Immigrant Performance in Germany: Labor Earnings of Ethnic German Migrants and Foreign Guest-Workers, *The Quarterly Review of Economics and Finance,* **37***, Special Issue*, 379-397.

Wagner, G. G.; Frick, J. R.; Schupp, J. (2007) The German Socio-Economic Panel Study (SOEP) – Evolution, Scope and Enhancements, *Schmollers Jahrbuch,* **127**, 139-169.

White, H. (1980) A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity, *Econometrica,* **48**, 817-838.

Zimmermann, K. F. *et al.* (2006): Immigration Policy and the labor market, *Berlin et al*.

Appendix

Table A1: Used variables from GSOEP and Bundesbank

our variable names	Varname	Label
- dn di1..di6 dstay - age dm - - drn,drs,drw - - dc86,dc96,dc06 -	IMMIYEAR NATION$$ ISCED$$ BISTAY D11102LL D11101$$ D11104$$ D11109$$ E11103$$ L11101$$ E11101$$ I11110$$ erhebj phrf	Year Of Immigration To Germany Nationality ISCED-1997-Classification Desire To Stay In Germany Gender of Individual Age of Individual Marital Status of Individual Number of Years of Education Employment Level of Individual State of Residence Annual Work Hours of Individual Individual Labor Earnings year of questionnaire Cross sectional individual weighting factor
calculated variables		
exp hwage ysm ageimmi d06,d96,d86,d76,d66	D11101$$-D11109$$-6 I11110$$/E11101$$ erhebj-immiyear age-ysm cohorts calculated with immiyear	
variables from other data sources		
HVPI	Source: Deutsche Bundesbank	

Table A2: Complete regression results for table 5

	lhwage				lhwage, using age-education deflator				lhwage, using percentile deflator			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ex	0.058	0.058	0.058	0.057	0.057	0.057	0.057	0.057	0.058	0.058	0.058	0.057
	(14.81)***	(14.86)***	(14.91)***	(13.84)***	(15.34)***	(15.31)***	(15.35)***	(13.98)***	(14.63)***	(14.67)***	(14.73)***	(13.63)***
ex²	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(12.55)***	(12.61)***	(12.64)***	(11.67)***	(12.84)***	(12.83)***	(12.85)***	(11.57)***	(12.25)***	(12.30)***	(12.34)***	(11.33)***
di1	-0.165	-0.183	-0.183	-0.171	-0.329	-0.352	-0.352	-0.344	-0.163	-0.182	-0.181	-0.167
	(1.68)*	(1.82)*	(1.82)*	(1.69)*	(3.90)***	(4.09)***	(4.06)***	(3.87)***	(1.57)	(1.71)*	(1.70)*	(1.56)
di2	-0.116	-0.117	-0.116	-0.116	-0.158	-0.160	-0.160	-0.160	-0.120	-0.122	-0.121	-0.121
	(5.04)***	(5.09)***	(5.07)***	(5.08)***	(7.11)***	(7.17)***	(7.16)***	(7.16)***	(5.24)***	(5.28)***	(5.25)***	(5.26)***
di4	0.139	0.144	0.144	0.143	-0.001	0.004	0.004	0.003	0.137	0.142	0.142	0.140
	(4.06)***	(4.23)***	(4.25)***	(4.19)***	(0.02)	(0.12)	(0.13)	(0.10)	(3.96)***	(4.13)***	(4.16)***	(4.09)***
di5	0.068	0.067	0.066	0.066	0.043	0.043	0.042	0.042	0.071	0.071	0.069	0.070
	(2.37)**	(2.36)**	(2.30)**	(2.33)**	(1.53)	(1.53)	(1.48)	(1.49)	(2.43)**	(2.43)**	(2.36)**	(2.39)**
di6	0.460	0.459	0.459	0.459	0.507	0.506	0.506	0.506	0.499	0.498	0.498	0.499
	(21.80)***	(21.75)***	(21.79)***	(21.84)***	(24.20)***	(24.17)***	(24.22)***	(24.24)***	(21.97)***	(21.93)***	(22.00)***	(22.05)***
dm	0.122	0.125	0.123	0.122	0.114	0.117	0.116	0.115	0.127	0.130	0.128	0.127
	(6.20)***	(6.32)***	(6.19)***	(6.17)***	(5.98)***	(6.13)***	(5.99)***	(5.98)***	(6.24)***	(6.36)***	(6.23)***	(6.22)***
dc96	0.165	0.173	0.173	0.173	-0.029	-0.020	-0.020	-0.020	0.017	0.025	0.025	0.025
	(8.91)***	(9.17)***	(9.18)***	(9.18)***	(1.61)	(1.08)	(1.09)	(1.08)	(0.87)	(1.27)	(1.26)	(1.28)
dc06	0.112	0.129	0.127	0.128	-0.042	-0.022	-0.024	-0.024	-0.098	-0.080	-0.083	-0.082
	(5.34)***	(5.86)***	(5.78)***	(5.82)***	(2.04)**	(1.03)	(1.11)	(1.09)	(4.57)***	(3.59)***	(3.69)***	(3.66)***
dn	-0.406	-	-	-	-0.413	-	-	-	-0.417	-	-	-
	(4.02)***				(4.22)***				(4.06)***			
ex*dn	-	-	-	0.008	-	-	-	0.004	-	-	-	0.009
				(0.79)				(0.54)				(0.87)
ex²*dn	-	-	-	-0.000	-	-	-	-0.000	-	-	-	-0.000
				(0.91)				(0.69)				(1.02)
ysm	0.036	0.026	0.026	0.024	0.038	0.026	0.026	0.025	0.037	0.026	0.026	0.023
	(2.11)**	(1.58)	(1.57)	(1.46)	(2.30)**	(1.64)	(1.63)	(1.54)	(2.05)**	(1.52)	(1.50)	(1.39)
ysm²	-0.002	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
	(1.78)*	(1.83)*	(1.81)*	(1.74)*	(1.94)*	(1.98)**	(1.95)*	(1.88)*	(1.68)*	(1.72)*	(1.69)*	(1.61)

ysm^3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(1.88)*	(2.08)**	(2.05)**	(2.03)**	(2.03)**	(2.23)**	(2.20)**	(2.17)**	(1.74)*	(1.92)*	(1.89)*	(1.87)*
drs	-	-	0.009	0.009	-	-	0.008	0.009	-	-	0.014	0.015
			(0.48)	(0.49)			(0.47)	(0.48)			(0.77)	(0.78)
drn	-	-	-0.039	-0.039	-	-	-0.037	-0.036	-	-	-0.040	-0.040
			(1.79)*	(1.79)*			(1.71)*	(1.71)*			(1.78)*	(1.79)*
d66	-	-0.075	-0.086	-0.137	-	-0.042	-0.051	-0.086	-	-0.080	-0.092	-0.147
		(1.91)*	(1.87)*	(1.90)*		(2.01)**	(1.96)*	(1.96)**		(1.83)*	(1.79)*	(1.81)*
d76	-	-0.186	-0.193	-0.241	-	-0.146	-0.152	-0.176	-	-0.191	-0.199	-0.250
		(1.63)	(1.68)*	(1.69)*		(1.30)	(1.35)	(1.33)		(1.63)	(1.68)*	(1.70)*
d86	-	-0.156	-0.159	-0.215	-	-0.149	-0.152	-0.181	-	-0.162	-0.167	-0.227
		(0.59)	(0.64)	(0.50)		(0.05)	(0.01)	(0.10)		(0.52)	(0.58)	(0.40)
d96	-	-0.362	-0.361	-0.413	-	-0.360	-0.358	-0.385	-	-0.372	-0.371	-0.426
		(2.94)***	(2.79)***	(2.89)***		(3.61)***	(3.46)***	(3.52)***		(2.90)***	(2.73)***	(2.84)***
d06	-	-0.494	-0.496	-0.558	-	-0.493	-0.494	-0.526	-	-0.521	-0.523	-0.591
		(1.77)*	(1.72)*	(1.80)*		(2.07)**	(2.02)**	(2.07)**		(1.96)**	(1.90)*	(2.00)**
dstay	-	-0.049	-0.049	-0.049	-	-0.051	-0.051	-0.052	-	-0.048	-0.048	-0.048
		(1.34)	(1.35)	(1.38)		(1.51)	(1.51)	(1.53)		(1.26)	(1.26)	(1.29)
constant	1.627	1.622	1.628	1.635	1.634	1.628	1.633	1.637	1.608	1.602	1.605	1.613
	(39.38)***	(39.30)***	(38.59)***	(36.43)***	(40.34)***	(40.25)***	(39.27)***	(36.70)***	(38.40)***	(38.31)***	(37.45)***	(35.34)***
Observations	8754	8754	8754	8754	8754	8754	8754	8754	8754	8754	8754	8754
adj. R-squared	0.297	0.299	0.300	0.300	0.311	0.313	0.314	0.314	0.279	0.281	0.282	0.282
AIC	11627	11607	11597	11597	11542	11517	11508	11511	12273	12253	12241	12240
Wald test for significance of ysm	8.68	2.13	2.12	2.34	9.85	2.11	2.10	2.24	8.28	1.75	1.75	2.03
ysm^2 ysm^3	(0.000)	(0.094)	(0.095)	(0.071)	(0.000)	(0.097)	(0.098)	(0.081)	(0.000)	(0.154)	(0.155)	(0.108)
Wald test for significance of ex*dn	-	-	-	0.53	-	-	-	0.37	-	-	-	0.71
ex^2*dn				(0.5877)				(0.693)				(0.493)

Note.- Robust t statistics in parentheses, for Wald test p-values, respectively. * significant at 10%; ** significant at 5%; *** significant at 1%

Source: Own calculation with SOEP data based on cross-section weights.

Table A3: Complete regression results for table 6

	lhwage		lhwage, using age-education deflator		lhwage, using percentile deflator	
	(1)	(2)	(3)	(4)	(5)	(6)
Ex	0.058	0.057	0.057	0.057	0.058	0.057
	(14.99)***	(13.88)***	(15.41)***	(14.04)***	(14.80)***	(13.66)***
ex^2	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(12.73)***	(11.70)***	(12.90)***	(11.63)***	(12.42)***	(11.36)***
di1	-0.174	-0.171	-0.339	-0.344	-0.172	-0.166
	(1.75)*	(1.66)*	(3.97)***	(3.78)***	(1.64)	(1.53)
di2	-0.117	-0.117	-0.160	-0.160	-0.122	-0.121
	(5.10)***	(5.08)***	(7.17)***	(7.16)***	(5.29)***	(5.26)***
di4	0.143	0.143	0.003	0.003	0.141	0.141
	(4.18)***	(4.21)***	(0.09)	(0.09)	(4.09)***	(4.13)***
di5	0.068	0.067	0.044	0.043	0.072	0.070
	(2.38)**	(2.34)**	(1.55)	(1.51)	(2.44)**	(2.40)**
di6	0.458	0.456	0.506	0.504	0.497	0.496
	(21.71)***	(21.73)***	(24.11)***	(24.13)***	(21.89)***	(21.95)***
Dm	0.122	0.122	0.114	0.115	0.124	0.128
	(6.20)***	(6.18)***	(5.97)***	(5.94)***	(6.25)***	(6.24)***
dc96	0.167	0.171	-0.027	-0.023	0.019	0.023
	(9.03)***	(9.14)***	(1.50)	(1.27)	(0.99)	(1.20)
dc06	0.116	0.122	-0.039	-0.033	-0.094	-0.088
	(5.53)***	(5.80)***	(1.89)*	(1.62)	(4.43)***	(4.13)***
Dic	-0.262	-0.098	-0.277	-0.125	-0.265	-0.167
	(2.68)***	(0.59)	(2.89)***	(0.75)	(2.66)***	(0.94)
Dtur	-0.385	-0.475	-0.389	-0.511	-0.402	-0.489
	(3.65)***	(1.84)*	(3.76)***	(2.14)**	(3.75)***	(1.86)*
Deg	-0.399	-0.128	-0.413	-0.120	-0.412	-0.099
	(4.29)***	(0.71)	(4.48)***	(0.65)	(4.28)***	(0.52)
Dlic	-0.554	-1.155	-0.539	-0.981	-0.571	-1.167
	(4.96)***	(3.33)***	(5.18)***	(3.30)***	(5.07)***	(3.42)***
ex*dic	-	-0.024	-	-0.026	-	-0.019
		(2.24)**		(2.36)**		(1.66)*
ex^2*dic	-	0.000	-	0.000	-	0.000
		(2.13)**		(2.34)**		(1.44)
ex*dtur	-	-0.007	-	-0.004	-	-0.008
		(0.56)		(0.36)		(0.62)
ex^2*dtur	-	0.000	-	0.000	-	0.000
		(0.90)		(0.78)		(0.93)
ex*deg	-	0.002	-	0.003	-	0.000
		(0.14)		(0.20)		(0.03)
ex^2*deg	-	-0.000	-	-0.000	-	-0.000
		(0.13)		(0.23)		(0.01)
ex*dlic	-	0.048	-	0.031	-	0.047
		(2.33)**		(2.16)**		(2.32)**
ex^2*dlic	-	-0.001	-	-0.001	-	-0.001
		(2.71)***		(3.02)***		(2.71)***
ysm	0.036	-	0.038	-	0.037	-
	(2.24)**		(2.40)**		(2.20)**	
ysm^2	-0.002	-	-0.002	-	-0.002	-
	(2.01)**		(2.14)**		(1.91)*	
ysm^3	0.000	-	0.000	-	0.000	-

	(2.11)**		(2.24)**		(1.97)**	
ysm*dic	-	0.071	-	0.083	-	0.074
		(2.62)***		(2.88)***		(2.49)**
ysm^2*dic	-	-0.003	-	-0.004	-	-0.004
		(2.34)**		(2.66)***		(2.18)**
ysm^3*dic	-	0.000	-	0.000	-	0.000
		(2.16)**		(2.54)**		(2.01)**
ysm*dtur	-	0.070	-	0.073	-	0.075
		(1.69)*		(1.86)*		(1.77)*
ysm^2*dtur	-	-0.004	-	-0.004	-	-0.004
		(1.86)*		(1.94)*		(1.95)*
ysm^3*dtur	-	0.000	-	0.000	-	0.000
		(2.01)**		(1.98)**		(2.09)**
ysm_deg	-	-0.015	-	-0.016	-	-0.021
		(0.75)		(0.82)		(0.96)
ysm^2_deg	-	0.001	-	0.001	-	0.001
		(1.08)		(1.21)		(1.34)
ysm^3*deg	-	-0.000	-	-0.000	-	-0.000
		(0.94)		(1.11)		(1.26)
ysm*dlic	-	0.082	-	0.084	-	0.086
		(1.40)		(1.53)		(1.49)
ysm^2*dlic	-	-0.004	-	-0.004	-	-0.004
		(1.18)		(1.28)		(1.24)
ysm^3*dlic	-	0.000	-	0.000	-	0.000
		(1.21)		(1.31)		(1.25)
Dstay	-	-0.058	-	-0.067	-	-0.058
		(1.57)		(1.85)*		(1.48)
Drs	-	0.011	-	0.010	-	0.017
		(0.60)		(0.58)		(0.89)
Drn	-	-0.036	-	-0.035	-	-0.037
		(1.68)*		(1.65)*		(1.67)*
Constant	1.628	1.635	1.634	1.638	1.608	1.613
	(39.62)***	(36.41)***	(40.46)***	(36.69)***	(38.63)***	(35.32)***
Observations	8754	8754	8754	8754	8754	8754
adj. R-squared	0.300	0.303	0.313	0.316	0.281	0.285
AIC	11596	11575	11518	11503	12241	12219
Wald test for significance of ysm ysm^2 ysm^3	6.80	-	8.12	-	6.41	-
	(0.000)		(0.000)		0.000	-
Wald test for significance of ysm ysm^2 ysm^3 for dic	-	2.74	-	3.26	-	2.87
		(0.042)		(0.021)		(0.035)
Wald test for significance of ysm ysm^2 ysm^3 for dtur	-	1.86	-	1.49	-	1.78
		(0.135)		(0.216)		(0.148)
Wald test for significance of ysm ysm^2 ysm^3 for deg	-	4.93	-	5.21	-	4.78
		(0.002)		(0.001)		(0.003)
Wald test for significance of ysm ysm^2 ysm^3 for dlic	-	4.72	-	4.74	-	4.51
		(0.003)		(0.003)		(0.004)
Wald test for significance of ex*dic ex^2*dic	-	2.50	-	2.81	-	1.49
		(0.082)		(0.060)		(0.225)
Wald test for significance of ex*dtur ex^2*dtur	-	0.98	-	1.25	-	0.88
		(0.375)		(0.288)		(0.415)

Wald test for significance of ex*deg ex^2*deg	-	0.01	-	0.03	-	0.00
		(0.990)		(0.969)		(0.998)
Wald test for significance of ex*dlic ex^2*dlic	-	4.41	-	7.33	-	4.48
		(0.001)		(0.001)		(0.011)

Note.- Robust t statistics in parentheses, for Wald test p-values, respectively

* significant at 10%; ** significant at 5%; *** significant at 1%

Source: Own calculation with SOEP data based on cross-section weights.