Skill Premiums and the Supply of Young Workers in Germany*

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Abstract

In this paper, we study the development and underlying drivers of skill premiums in Germany between 1980 and 2008. We show that the significant increase in the medium to low skill wage premiums since the late 1980s was almost exclusively concentrated among the group of young workers aged 30 or below. Using a nested CES production function framework which allows for imperfect substitutability between young and old workers, we investigate whether changes in relative labor supplies could explain these patterns. Our model predicts the observed differential evolution of skill premiums very well, in particular that of medium skilled workers. The estimates imply an elasticity of substitution between young and old workers of about 8, between medium and low skill workers of 4 and between high skilled and medium/low skilled workers of 1.6. Using a cohort level analysis based on Mikrozensus data, we find that long-term demographic changes in the educational attainment of the native (West-)German population – in particular of the post baby boomer cohorts born after 1965 – are responsible for the surprising decline in the relative supply of medium skilled workers which caused wage inequality at the lower part of the distribution to increase in recent decades. We further show that the role of (low skilled) migration – contrary to common belief – is limited in explaining the changes in relative labor supplies.

Keywords: Cohorts, Baby Boom, Labor Supply, Labor Demand, Skill Biased Technological Change, Wage Distribution, Wage Differentials

JEL codes: J110, J210, J220, J310

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I. Introduction

Income inequality has increased in most OECD countries almost uninterruptedly since the mid 1980s (OECD 2014).[1] With his seminal book Piketty (2014) returned inequality to the agenda of economists and policy makers alike. As opposed to capital incomes which were the main driver of inequality at the beginning of the 20th century in the US and Europe, Piketty and Saez (2014) show that the recent increase is mainly driven by inequality in labor incomes.[2] But while there seems to be a consensus on the descriptive facts, there still remains a vigorous debate over the *drivers* of increasing inequality.

In this paper, we study how shifts in the supply of skills can help to understand the evolution of wage differentials between different demographic groups defined by skill-level and age. These *skill premiums* are an important aspect of inequality.[3] Figure 1 plots the evolution of two skill premiums important in the context of Germany' skill structure which, besides college and university education, is characterized by a strong pillar of vocational training. The wage differential between medium (those with vocational training) and low-skilled workers (those without a post-secondary degree) decreased slightly over the 1980s and then increased by a third from 18% to 24% since the late 1980s. The high skill premium, i.e. the wage differential between those holding a college or university degree and those with vocational training followed a U-shape pattern over the same period reaching 51% in the early 1980s and late 2000s and about 47% in the mid 1990s.

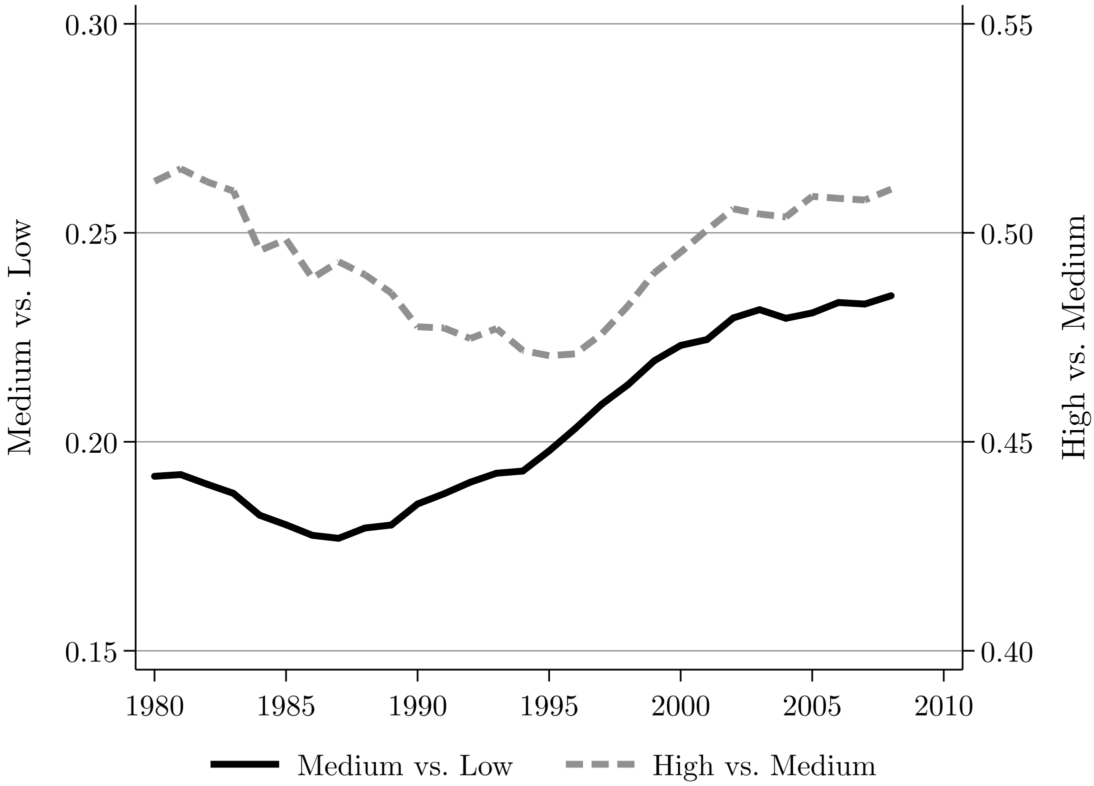
Our core hypothesis is that differential changes in the supply of skills are responsible for the observed patterns in skill premiums. In particular, we emphasize the role played by imperfect substitutability across age groups and changes in educational attainment across different cohorts. Our framework is a variant of a Tinbergen (1974) *education race* model where increases in the relative supply of more skilled workers and skill biased technological change work in opposite directions in determining wage premiums. We distinguish between three skill groups (low, medium, and high) and between young (less than 30 years) and old workers, building on previous frameworks by Goldin and Katz (2009), Card and Lemieux (2001), and Dustmann et al. (2009). To illustrate the model's core idea, in Figure 2, we scatter the skill premiums of both young and old medium (relative to low skilled) and high (relative to medium) skilled workers against their corresponding relative supplies (both linearly detrended to absorb, for instance, secular

[1] Kopczuk et al. (2010) using social security records find an increase in earnings inequality in the US since the 1950s which accelerated in the 1970 and 80s and reached its highest level in the 2000s since the start of the records in 1937. Dustmann et al. (2009) show that wage inequality has also increased considerable in (West-)Germany over the last three decades. Relying on similar administrative records as we do, they document a steady increase in inequality at the top of the earnings distribution since 1975 while wages only started to diverge in the mid 1990s at the lower half.

[2] In line with this, Biewen and Juhasz (2012) find that the largest part of the increase in overall income inequality in Germany between 1999 and 2005 was due to rising inequality of labor incomes.

[3] For instance, Goldin and Katz (2007) estimate that the increased return to schooling accounts for about 2/3 of the overall increase in the variance of log hourly wages between 1980-2005 in the US.

Figure 1: Skill Premiums



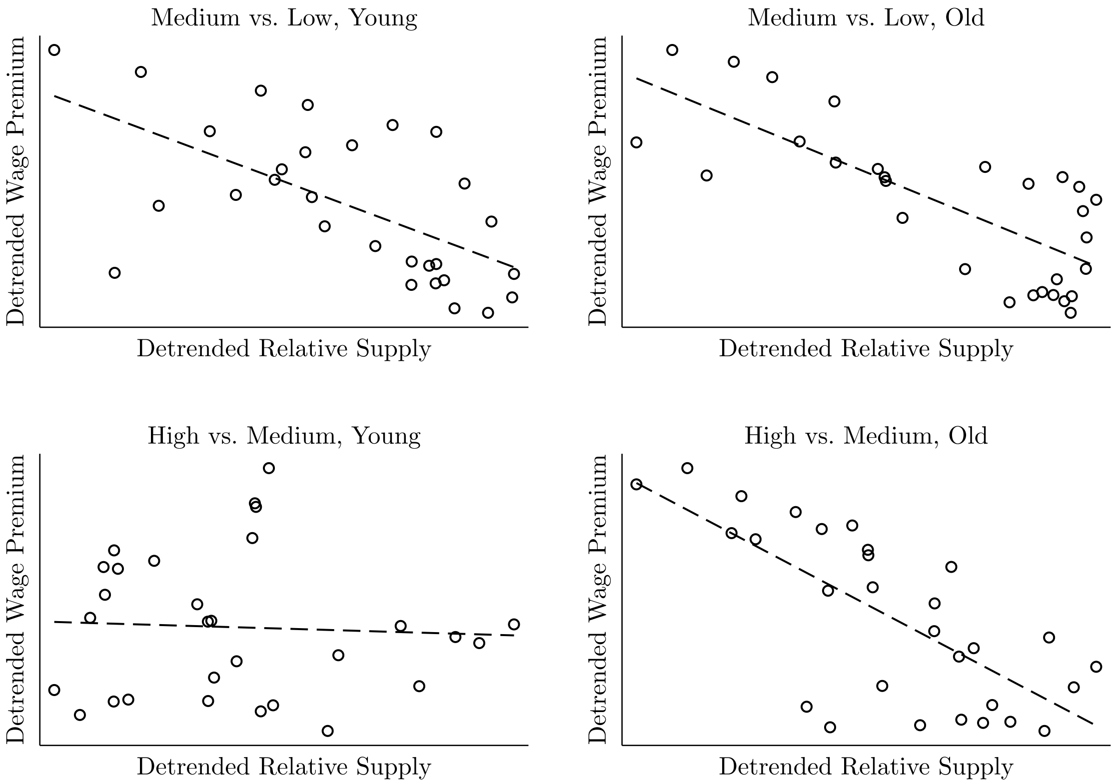
Notes: This figure plots composition constant skill premiums defined as log wage differentials between medium and low and high and medium skilled workers who work full-time, live in West-Germany and have not moved from East to West-Germany between 1980-2008. For more details on the construction of skill premiums see sections C.

skill biased technological progress). Except for the young high skilled[4], there is a clear negative relationship.

Using high quality administrative data for Germany over the period 1980-2008, we first systematically document the evolution of skill premiums along various skill levels and age groups. We show that almost the entire increase in the medium to low skill premium visible in Figure 1 is attributable to a pronounced increase in the medium skill premium of *young* workers (aged 30 and below) which increased from about 10% in 1980 to 25% in 2008 – a finding that has has gained little attention in the existing literature. Wage premiums of older medium skilled workers and of those holding a university degree have stayed remarkably stable (when separating between the young and old). Second, our proposed model which relates shifts in relative skill supplies coupled with directed technical change to skill premiums is able to account well for these differential patterns in observed skill premiums. This is especially true for the medium to low skill premium. Third, we try to be more careful about standard errors than most existing studies. We

[4]The relationship within the group of young high skilled workers is attenuated due to the pre-unification boom 1987-1990 and in particular by the dot-com/New Economy boom and bust during 1999-2002. Once we exclude these years or allow for separate intercepts for these two periods, the relationship becomes clearly negative as expected, see the discussion in section V.

Figure 2: Scatter Plots Premiums vs. Supplies (1980-2008)



Notes: This figures plots skill premiums against their relative supplies separately for young and old workers. All variables are linearly detrended. See section III for a detailed description of skill premiums and efficiency supplies.

account for the uncertainty induced by generated regressors as well as serial and contemporaneous correlation of all variables in adjacent years by means of a moving block bootstrap approach (Kunsch 1989). As it turns out, standard errors computed with this method are up to five times larger than those based on conventional methods.

After having established a close link between the supply and the price of skill, we ask in the second part of the paper *why* these shifts in skill supplies occurred. Using census data, we trace out the long-term trends in educational attainment for each cohort born between 1950 and 1981. We show that after the fertility decline starting in 1965, there was a pronounced trend break in the educational attainment of the native (West-)German population: relative to their previous trends, the shares of both high and low skilled individuals increased while the share of medium skilled individuals declined markedly. This observation, again, has gained little attention in the literature studying the evolution of skill premiums and wage inequality in Germany.

Our modeling approach is closely linked to a literature which started with the seminal paper by Katz and Murphy (1992) which uses a CES-production function framework to systematically link supply and demand factors to wage premiums.[5] Goldin and Katz (2009) extend their analysis by including historical U.S. wage data from 1890-2005 to understand the evolution of the high school and college premium in the long-term. Dustmann et al. (2009) apply the Goldin and Katz (2009) framework to study the role of supply and demand factors using the same German administrative data as we do. However, they do not allow for imperfect substitutability between young and old workers and find that the two-level CES approach might be "misspecified" (Dustmann et al. 2009, p. 867). Card and Lemieux (2001) introduce imperfect substitutability between young and old workers using data from the U.S., Canada and the UK.[6] In contrast to these papers, our setting includes three skill groups (such as Goldin and Katz 2009; Dustmann et al. 2009) and (at least) two age groups (such as Card and Lemieux 2001) and we estimate the associated substitution elasticities – key parameters in many theoretical and empirical applications in the context of, for instance, immigration or long-run growth models – consistently in one framework while adjusting standard errors appropriately to the various forms of uncertainty.[7]

Our paper also relates to a range of studies that have used German administrative labor market data to study the rise in German wage inequality. Antonczyk et al. (2010a) emphasize the role of cohort effects in Germany as an important driver of lower end wage inequality. Card et al. (2013) identify an increasing dispersion in both person- and establishment-specific wage premiums as well as an increasing assortativeness in the matching of workers and establishments as main factors behind rising wage inequality, while Goldschmidt and Schmieder (2015) emphasize the role of domestic outsourcing, calculating that it contributed some 10% to the increase in German wage inequality since the 1980s. Burda and Seele (2016) apply the Katz and Murphy (1992) framework and show that the Hartz reforms implemented in 2003 boosted labor supply and contributed to the recent German employment miracle at the cost of decreasing real wages and increasing wage dispersion. Of particular relevance in the context of our work is the study by Dustmann et al. (2009) who document the recent trends in German wage inequality and perform an extensive analysis of competing explanations, identifying compositional changes (as DiNardo et al. 1996), a decline in unionization (see also Antonczyk et al. 2010b), skill biased demand shifts favoring in particular the high skilled, polarization (as proposed by Goos and Manning 2007; Autor et al. 2009; Autor and Dorn 2014) and changes in the supply of skills (similar to Goldin and Katz 2009) as key contributors to German wage inequality. In particular, Dustmann et al. (2009) also emphasize that changes in the relative supply of medium skilled

[5]The CES-production function framework has also been applied to study the effect of migration on wages and employment, see for instance Borjas (2003), D'Amuri et al. (2010), and Ottaviano and Peri (2012).

[6]Fitzenberger and Kohn (2006) apply and extent this approach to Germany to study the wage decrease necessary to halve unemployment rates in the mid 1990s.

[7]In a recent study, Jeong et al. (2015) have proposed an alternative unifying framework to explain key empirical regularities in the US labor market. Based on a model in which workers supply two complimentary inputs, labor and experience, they show that changes in the total supply of experience due to demographic changes can fully explain the strong movements in the price of experience over the last four decades in the US. Moreover, those movements in the price of experience can account for the differential dynamics in the age premiums across education groups and the college premiums across age groups as well as the observed changes in cross-sectional and cohort-based life-cycle profiles. Contrary to the previous literature, they do not find evidence for demand shifts due to skill biased technological change.

workers are responsible for the significant increase in wage inequality at the lower tail of the wage distribution, attributing this to a deceleration in the rate of decline of low skilled employment shares in the 1990s. They hypothesize that this deceleration might be due to the "large inflow of [mainly low skilled] East Germans, Eastern Europeans, and ethnic Germans [...] into the West German labor market" (Dustmann et al. 2009, p. 867). Our findings, however, show that the decline in the relative supply of medium skilled workers is primarily due to a pronounced and so far undocumented decrease in the share of *native medium skilled* workers. Our paper thus fills an important gap when it comes to understanding the main drivers of recent changes in wage inequality in Germany.

The rest of the paper is organized as follows. In the next section, we present our model framework relating relative labor supplies to skill premiums. In section III, we then describe our data set and the construction of our key variables, skill premiums and efficiency labor supplies. Section IV presents graphical evidence on the evolution of skill premiums and efficiency supplies separately for young and old workers. These are the patterns we aim to explain in section V, where we estimate the key structural parameters of our model. In section VI, we present our cohort analysis studying the long term trends in skill attainment. Section VII concludes.

II. Analytical Framework

Our modelling approach closely follows previous work by Goldin and Katz (2009), Card and Lemieux (2001), and Dustmann et al. (2009). Suppose aggregate output at each time t is generated by a CES production function depending on college/university (or high skilled) labor H_t and non-college (or non-high) labor U_t:

$$Y_t = A_t \left[\lambda_t H_t^{\gamma} + U_t^{\gamma}\right]^{\frac{1}{\gamma}} ,$$

where A_t denotes total factor productivity and λ_t is a time-varying technology or demand shifter that reflects both the importance of each input and factor augmenting (skill-biased) technological progress. The elasticity of substitution between non-college and college labor is given by $\sigma_{hu} = \frac{1}{1-\gamma} \in [0, \infty]$. If $0 \leq \sigma_{hu} < 1$ the two factors are gross complements. If $\sigma_{hu} \geq 1$ the two factors are gross substitutes and (high-)skill biased technological progress will increase the wage differential in favor of better skilled workers.[8]

We choose this nesting structure to allow for a different elasticity of substitution between high and non-high and medium and low skilled workers as do Dustmann et al. (2009). In contrast, Fitzenberger et al. (2006) and D'Amuri et al. (2010) assume the same mutual substitution elasticities between all skill groups, i.e. they assume, for instance, that high and medium skilled workers are as substitutable as high and low skilled workers which is less flexible than the approach we follow here.

[8] See Acemoglu and Autor (2012, 433ff) for a more careful distinction between demand shifters and factor-augmenting technology terms and on how the effect of skill biased technological progress on skill premiums depends on σ.

Non-college labor is itself a CES-subaggregate of low and medium skilled labor inputs

$$U_t = [\theta_t M_t^{\rho} + L_t^{\rho}]^{\frac{1}{\rho}}\,, \tag{1}$$

where θ_t represents a demand shifter as above. The elasticity of substitution between medium and low skilled labor is given by $\sigma_{ml} = \frac{1}{1-\rho}$ defined analogously as before. Each type of labor in turn is composed of the corresponding supply in different age groups

$$L_t = \left[\sum_j (\alpha_{lj} L_{jt}^{\eta_l})\right]^{\frac{1}{\eta_l}} \qquad M_t = \left[\sum_j (\alpha_{mj} M_{jt}^{\eta_m})\right]^{\frac{1}{\eta_m}} \qquad H_t = \left[\sum_j (\alpha_{hj} H_{jt}^{\eta_h})\right]^{\frac{1}{\eta_h}}\,,$$

which implies that the elasticity of substitution across the different age groups j in skill group s is given by $\sigma_{as} = \frac{1}{1-\eta_s}$.

Imposing the standard assumption that each labor input is paid its marginal product yields the following wage equations for each skill-age labor type:

$$w_{jt}^{L} = \frac{\partial Y_t}{\partial L_{jt}} = Y_t^{1-\gamma}(1-\lambda_t)U_t^{\gamma-\rho}(1-\theta_t)L_t^{\rho-\eta_l}\alpha_{lj}L_{jt}^{\eta_l-1} \tag{2}$$

$$w_{jt}^{M} = \frac{\partial Y_t}{\partial M_{jt}} = Y_t^{1-\gamma}(1-\lambda_t)U_t^{\gamma-\rho}\theta_t M_t^{\rho-\eta_m}\alpha_{mj}M_{jt}^{\eta_m-1} \tag{3}$$

$$w_{jt}^{H} = \frac{\partial Y_t}{\partial H_{jt}} = Y_t^{1-\gamma}\lambda_t H_t^{\gamma-\eta_h}\alpha_{hj}H_{jt}^{\eta_h-1} \tag{4}$$

Assuming that σ_a is the same in each of the three skill groups, i.e. $\sigma_{al} = \sigma_{am} = \sigma_{ah}$ (we will relax this assumption later) we finally get the following expressions for the medium to low skill premium

$$\omega_{jt}^{M} \equiv \ln\left(\frac{w_{jt}^{M}}{w_{jt}^{L}}\right) = \ln(\theta_t) + \left(\frac{1}{\sigma_a} - \frac{1}{\sigma_{ml}}\right)\ln\left(\frac{M_t}{L_t}\right) + \ln\left(\frac{\alpha_{mj}}{\alpha_{lj}}\right) - \frac{1}{\sigma_a}\ln\left(\frac{M_{jt}}{L_{jt}}\right) \tag{5}$$

$$= \ln(\theta_t) + \ln\left(\frac{\alpha_{mj}}{\alpha_{lj}}\right) - \frac{1}{\sigma_{ml}}\ln\left(\frac{M_t}{L_t}\right) - \frac{1}{\sigma_a}\left[\ln\left(\frac{M_{jt}}{L_{jt}}\right) - \ln\left(\frac{M_t}{L_t}\right)\right] \tag{6}$$

and the high to medium skill premium

$$\omega_{jt}^{H} \equiv \ln\left(\frac{w_{jt}^{H}}{w_{jt}^{M}}\right) = \ln\left(\frac{\lambda_t}{\theta_t}\right) - \frac{1}{\sigma_{hu}}\ln\left(\frac{H_t}{U_t}\right) + \frac{1}{\sigma_a}\left(\frac{H_t}{M_t}\right) - \frac{1}{\sigma_{ml}}\ln\left(\frac{U_t}{M_t}\right) + \ln\left(\frac{\alpha_{hj}}{\alpha_{mj}}\right) - \frac{1}{\sigma_a}\ln\left(\frac{H_{jt}}{M_{jt}}\right) \tag{7}$$

$$= \ln\left(\frac{\lambda_t}{\theta_t}\right) + \ln\left(\frac{\alpha_{hj}}{\alpha_{mj}}\right) - \frac{1}{\sigma_{hu}}\ln\left(\frac{H_t}{U_t}\right) - \frac{1}{\sigma_{ml}}\ln\left(\frac{U_t}{M_t}\right) - \frac{1}{\sigma_a}\left[\ln\left(\frac{H_{jt}}{M_{jt}}\right) - \ln\left(\frac{H_t}{M_t}\right)\right]. \tag{8}$$

Given all σ's > 1, the model predicts that over time the premium of medium skilled workers in age group j, ω_{jt}^{M}, *increases* with θ_t, the rate of skill-biased technological change (or shifts in relative demand in favor of workers with vocational training) and *decreases* with the aggregated and age-group specific relative supply of medium skilled workers given by $\frac{M_t}{L_t}$ and $\frac{M_{jt}}{L_{jt}}$, respectively. Similarly, the age group specific high to medium skill premium ω_{jt}^H depends positively on technological progress favoring the high skilled relative to the medium skilled, $\frac{\lambda_t}{\theta_t}$, and negatively on the aggregated relative supply of high to non-high, non-high to medium skilled labor, and the age group specific relative supply of high skilled workers denoted by $\frac{H_t}{U_t}$, $\frac{U_t}{M_t}$ and $\frac{H_{jt}}{M_{jt}}$, respectively. These equilibrium equations will guide our empirical analysis in section V.

III. Data

A. Data Set and Derivation of Baseline Sample

To take the model to the data, we need to construct skill premiums and labor supplies for each of the distinct skill-age-groups. We use administrative labor market data provided by the Institute for Employment Research in the *Sample of Integrated Labour Market Biographies* (SIAB).[9] The SIAB is a 2% random sample of the official records of all employees subject to social security in Germany between 1975 and 2010. It contains the labor market history of about 1.5 million individuals and includes information on daily wages and employment status (full-time, part-time, unemployed, in vocational training) as well as a number of individual characteristics such as age, gender, skill, German nationality, region, occupation, and industry. We restrict the analysis to men and women between 21 and 60 years[10] of age living in West Germany with earnings above the official marginal earnings threshold (400 Euros per month in 2010[11]) as marginal part-time spells were only officially recorded from 1999 onwards. In addition, we exclude the years 1975-1979 (due to very high incidence of censoring among the high skilled) and the crisis year 2009/10 such that our final sample comprises the years 1980-2008.[12] We also conduct three imputations that are by now common practice when working with IAB data: the imputation of missing education information following Fitzenberger et al. (2006), the correction for the structural break in 1984 according to Fitzenberger (1999) and Dustmann et al. (2009) and the imputation of censored wages above the upper earnings threshold for compulsory social insurance (66,000 Euros per year in 2010) applying the “no heterogeneity” approach suggested by Gartner (2005) and Dustmann et al. (2009).[13]

B. Definition of Skill and Age Groups

For our subsequent analysis, we divide workers into low, medium and high skilled. Following Dustmann et al. (2009), we define the low skilled as those with missing or at most lower secondary education (*Realschule* or less), medium as those with apprenticeships, vocational training, and/or

[9]Specifically, we use the scientific use file of the SIAB Regional-File 1975-2010. See vom Berge et al. (2013) for a detailed description of the data set.
[10]Most high skilled have not finished their degree by 21 and enter the labor market (and thus our analysis sample) only when they are some years older.
[11]We convert all monetary values into 2010 Euros using the consumer price index of the German Bundesbank.
[12]Appendix A contains a more detailed description of our sub-sample choice.
[13]See Appendix A for more details.

Abitur, and high skilled as those with a college or university degree. This grouping differs from many US studies where a distinction is only made between college and non-college labor to study the college premium (Card and Lemieux 2001; Autor 2014). The division into three skill groups in Germany reflects Germany's strong pillar of vocational training and is also suggested by comparing the wage levels of these groups (see Figure A.4). Regarding the age dimension, we consider eight different age groups spanning five years each for ages between 21-60 years. For most of the graphical evidence and the empirical estimations, however, we just distinguish in each skill group between young (≤ 30 years) and old workers (> 30) as these two groups capture well the underlying trends of more finely disaggregated age groups (see section IV for more details).

C. Skill Premiums

Our purpose is to calculate the *pure* price for different skill levels net of any compositional changes due to, for instance, migration or changes in the gender or age group composition of the working population.[14] To keep our premium sample as homogeneous as possible, we restrict the attention to men and women working full-time and exclude those who started their labor market biography in East Germany and then moved to West Germany as well as those with missing or non-German nationality information. We then calculate age and gender composition constant skill premiums from two quantities (similar to Katz and Murphy 1992): first, the mean log real wage weighted by the share of days worked per year in each skill-age-gender-year cell (cell specific wages), and second, each cell's skill group specific share of days worked (i.e. the total number of days worked in a given cell divided by the total number of days worked by all individuals of the corresponding skill group) averaged over all years (fixed cell weights). The composition constant log real wage of a given skill group is then calculated as the weighted average of all cell specific wages and their corresponding fixed cell weights. For example, the composition constant log wage of the low skilled in t is calculated as $low_t = \sum_a \sum_g \ln wage_{s=low,a,g,t} \cdot weight_{s=low,a,g}$ where a denotes age group and g gender. Note that the weights are not indexed by time and are constant over all years. Finally, the medium to low (high to medium) skill premium is calculated as the difference between the composition constant log real wage of medium and low (high and medium) skilled workers. Thus, skill premiums can be interpreted as the percentage difference in wages between two skill groups.

D. Labor Supplies

Our labor supply measures are based on a broad set of individuals and are expressed in efficiency units which can basically be understood as productivity adjusted full-time equivalents. Labor supplies need to be measured in efficiency units because the framework outlined in section II assumes that different workers in the same skill-age cell are perfect substitutes. To compute

[14]For instance, Dustmann et al. (2009) show that it is important to account for compositional changes in the workforce but that neither lower or upper tail inequality can be fully accounted for by these compositional changes. Carneiro and Lee (2011) compute skill premiums that are also adjusted for the quality of college graduates.

efficiency labor supplies, we include full-time, part-time (but no marginal part-time spells as noted above), vocational training, and unemployment spells of both German and non-German workers and also include those who were first registered in East Germany and migrated to West Germany. In contrast to our premium data set, we choose such a broad set of workers and work types to mitigate concerns regarding the endogeneity of labor supplies. For instance, if we computed labor supplies based on full-time spells only, we would fail to incorporate all transitions to and from part-time work or unemployment induced by changes in skill premiums or any differential effects of the business cycle on the labor supply of different skill or age groups. Since we do not observe the hours worked, we approximate (potential) working hours by assigning long part-time spells (i.e. part-time spells with more than half of the hours of a comparable full-time spell) a weight of 2/3 and short part-time spells a weight of 1/2 (less than half of a full-time spell) following Dustmann et al. (2009). Vocational training and unemployment spells are assigned a weight of 1/3. In our robustness checks, we show that our results are not sensitive to the specific weighting scheme. For instance, it would also be sensible to assign a weight of 1 to those unemployed who worked full-time before. Applying this alternative weighting scheme leaves our estimates basically unchanged. The efficiency supply of a specific skill-age group is calculated as the number of spells in that group weighted by the spell length, the approximate hours of work, and the efficiency weight. The efficiency weight is time-constant and calculated based on full-time spells as the normalized wage of a skill-age-gender group relative to a baseline wage averaged over all years.[15] In an alternative approach, we allowed the productivity of women to be time-varying relative to men which, however, only has a minor effect on our estimates. Expressed more formally, the supply of skill group s in age group a in year t is computed as the weighted sum of all spells i in that cell where h denotes spell-type (full-time, part-time, vocational, unemployed) and g gender:

$$\text{Supply}_{sat} = \sum_{i \in Cell_{s,a,t}} \text{spell-length}_i \cdot \text{hours-weight}_h \cdot \text{efficiency-weight}_{sag}.$$

For instance, medium skilled men aged 31-35 working full-time all year long supply exactly one unit of efficiency labor in each year, while a high skilled female aged 41-45 working long-part time half of the year supplies 0.4 units and a low skilled men aged 26-30 who is unemployed half of the year and full-time employed the other half supplies 0.5 units of efficiency labor.[16]

E. Summary Statistics

In panel A of Table 1, we summarize some characteristics of our wage premium data set in 1980, 1990, 2000, and 2008. The full-time workforce became older with the share of young workers

[15]See Appendix A for more details.

[16]That is 0.4= 0.5 (half a year) × 2/3 (hours weight long part-time) × 1.22 (efficiency weight high skilled females aged 41-45); and 0.5= 0.5 (half of the year) × [1/3 (hours weight unemployed) + 1 (hours weight full-time)] × 0.77 (efficiency weight low skilled men aged 26-30), receptively.

Table 1: Summary Statistics of Premium and Supply Data
(Mean if not otherwise stated)

	1980	1990	2000	2008
Panel A. Premium Data				
Age	39.01	38.39	39.75	41.36
Young ($\leq$ 30 years)	0.29	0.31	0.20	0.19
Female	0.32	0.33	0.34	0.33
Low skilled	0.20	0.11	0.07	0.06
Medium skilled	0.75	0.81	0.81	0.79
High skilled	0.05	0.08	0.12	0.15
Daily real log wage	4.41	4.51	4.59	4.56
SD of log real wages	0.41	0.43	0.45	0.51
Gap 50-15	0.37	0.36	0.40	0.48
Gap 85-50	0.35	0.40	0.42	0.49
Panel B. Supply Data				
Age	38.65	38.21	39.60	40.86
Young ($\leq$ 30 years)	0.29	0.32	0.22	0.21
Female	0.38	0.40	0.46	0.48
German	0.90	0.90	0.87	0.85
Low skilled	0.26	0.17	0.14	0.13
Medium skilled	0.70	0.76	0.76	0.75
High skilled	0.05	0.07	0.10	0.12
Share full-time	0.87	0.82	0.67	0.63
Share long part-time	0.07	0.09	0.11	0.14
Share short part-time	0.02	0.02	0.12	0.15
Share vocational/other	0.01	0.02	0.02	0.02
Share unemployed	0.03	0.05	0.07	0.06

Notes: This table presents summary statistics for the premium and supply data sets. The premium data set consists of full-time employed German individuals aged 21-60 living in West-Germany. Individuals working in West-German who are non-German and/or were first registered in East Germany are excluded. The supply data set consists of full-time, part-time, vocational training, and unemployment spells of all individuals including non Germans and East-West movers. All summary statistics are weighted by spell length.

below 30 years dropping from around 30% in the 1980s to 19% in 2010. This is the consequence of declining cohorts sizes after the baby boomer generation in the mid 1960s. The share of women working full-time remained remarkably stable over the sample period at around 33%. In contrast, the skill composition of full-time workers changed dramatically: The share of low skilled workers dropped from 19% in 1980 to just 6% in 2008 with the largest decline occurring in the 1980s. The share of medium skilled workers followed a reversed U-shape reaching 81% in the 1990s and then declining to 79% in 2008. The share of high skilled workers increased more than threefold since 1980 in a virtually linear fashion reaching 15% of the labor force in 2008. Wage inequality measured as the standard deviation of log real wages remained relatively stable up to the end of the 1990s but increased considerably since then.[17] Decomposing earnings inequality

[17]This is in line with Dustmann et al. (2009, Figure I, p.850) and Card et al. (2013, Table I, p. 975) who also find –using IAB data – an acceleration for log wages in the 1990s for the sample of all full-time West-German

into lower tail (the gap between the 15th and the 50th percentile) and upper tail (50-85 gap)[18] inequality shows that lower tail inequality remained basically constant until the late 1990s and then increased sharply afterwards. Upper tail inequality increased throughout the sample period but also gained momentum in the mid/ late 1990s (compare figures A.2 and A.1).[19]

Panel B summarizes our supply data. The work force including part-time, vocational training and unemployment spells is younger and more female. The share of females increased much more than in the sample of full-time workers as the increased participation of women was concentrated mainly in part-time jobs (see also Burda and Seele 2016). The broader set of workers represented in the supply data set is also less well educated. While the share of individuals receiving unemployment insurance benefits was just 3% in the 1980s, it more than doubled at the end of the sample period.

IV. Graphical Analysis

Figure 3 plots the evolution of our key variables separately for young and old workers using comparable scales.[20] In the top left part, we plot the medium to low skill premiums of young and old workers. While the premium for old medium skilled workers changed only little over the 1980-2008 period (from 0.23 in 1980 to 0.26 in 2008), the premium of young medium skilled workers more than doubled over the same period (from 0.11 in the mid 1980s to 0.25 in the 2000s).[21] To put these numbers in perspective, according to Goldin and Katz (2009, Figure I, p. 27) the combined premium of young and old high school graduates in the US (relative to those who only stayed in school until 8th grade) increased from 0.23 in 1980 to 0.29 in 2005. Thus, our medium skill premium is similar in magnitude to the US high school premium.[22]

The development of the high skilled or college premium is depicted in the bottom left part of Figure 3. The young high skilled saw their premium fluctuating around 0.33 with considerable variation while the college premium of old workers followed a soft U-shape pattern starting from 0.52 in 1980, reaching a low of 0.47 during the 1990s to finally increase to 0.51 in 2008. Since skills premiums are partly based on imputed wages (in particular the high to medium premium of old workers), one might be worried about how accurately they really represent the "true" high skilled premiums. In Appendix B, we show that there is no systematic divergence over time between the 85th-percentile in our data (which is always uncensored) and various top income fractiles taken from the from the *World Top Incomes Database* (WTID, Alvaredo et al.

workers (including East movers and foreigners). It is also in line with Biewen and Juhasz (2012) who –using SOEP data– find an unprecedented rise in net equivalized income inequality since 1999/2000.

[18] We report the 85-percentile as it is uncensored throughout the sample period.

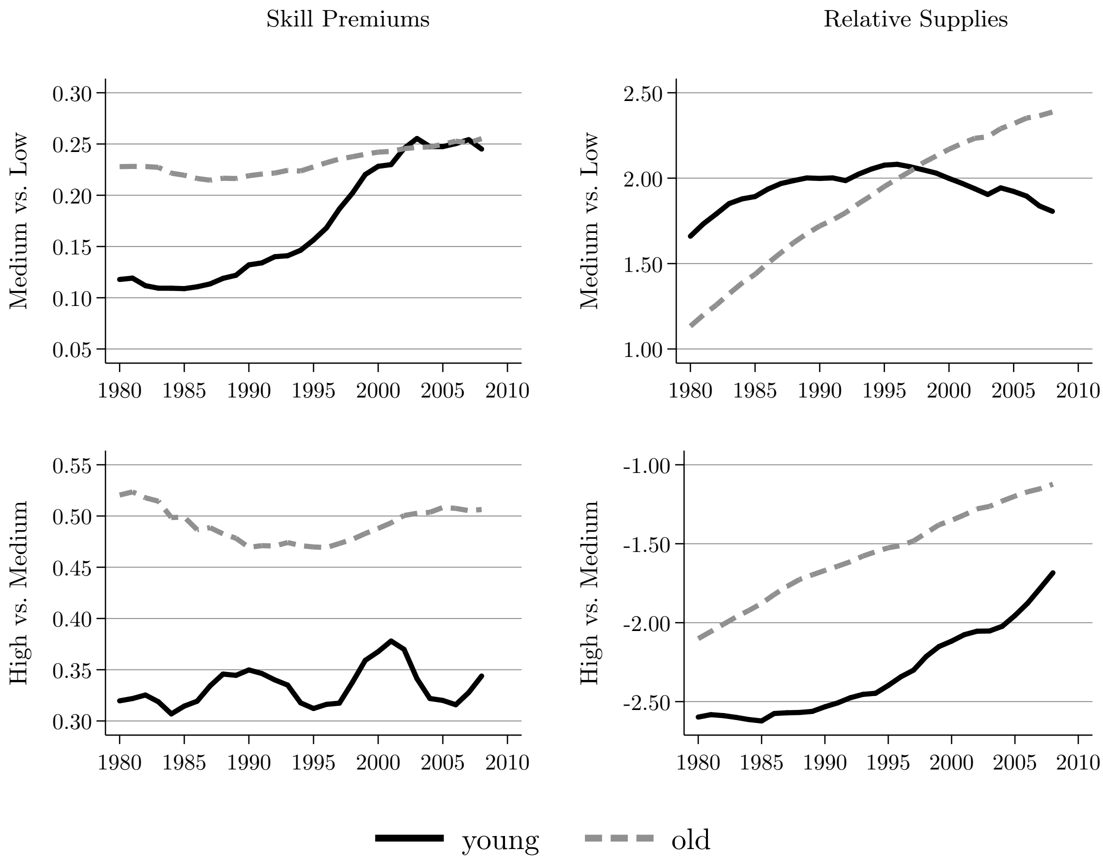
[19] Again, this is in line with Dustmann et al. (2009, Figure II, p. 851) and Card et al. (2013, Figure I, p. 969).

[20] Figure A.5 shows the evolution of the medium and high skill premium separately for eight different age groups. It shows that those aged above 30 (or 36) and below follow a similar pattern.

[21] These patterns are also prevalent when looking at men and women separately. They are somewhat less pronounced for women and more pronounced for men. In both series, the medium premium of young workers has more than doubled over 1980-2008 and has increased much faster than that of old workers, see Figure A.6.

[22] The combined medium premium of young and old workers in Germany increased from 0.19 in 1980 to 0.23 in 2005, see also Figure 1.

Figure 3: Skill Premiums and Relative Supplies



Notes: This figure plots on the left hand side the difference in composition constant mean log earnings between medium and low (upper left) and high and medium (bottom left) skilled workers who work full-time, live in West-Germany and have not moved from East to West-Germany, separately for the young (30 years or below) and old (above 30 years) between 1980-2008. The right hand side depicts the corresponding relative supplies in efficiency units of all workers in West-Germany including full-time, part-time, unemployment and vocational training spells but excluding marginal part-time spells. For more details see sections C and D.

2015). Theses comparisons make us confident that the skill premiums derived from top censored SIAB data are indeed representative for the true evolution of the earnings gap between high and medium skilled workers.

Our core hypothesis is that differential changes in the supplies of skill groups are responsible for the observed patterns in skill premiums. To illustrate this, in the right column of Figure 3, we plot the relative supplies of medium (to low) and high (to medium) skilled labor separately for young and old workers. Starting with the top right panel, we see that the relative supply of old medium skilled workers increased by a factor of 2.5 in a fashion as good as linear. In contrast, the relative supply of young medium skilled increased by some 0.4 log points up to the 1990s, stayed constant and then decreased by 0.2 log points in the 2000s. The relative supply of old high skilled workers – similar to the old medium skilled – increased linearly from 1980-2008 while the relative supply of young high skilled workers increased exponentially.[23]

These figures in combination with the scatter plots presented in Figure 2 suggest that wage differentials between different skill groups are systematically related to their relative supplies. In the next section, we will use our analytical framework detailed above to investigate this relationship more rigorously.

V. Empirical Estimation

A. General Estimation Approach and Standard Errors

We now turn to the estimation of the model outlined in section II using the skill premiums and efficiency labor supplies introduced in section III. We will estimate the model's parameters from bottom to top in three steps: First, using the premium equations 5 and 7, we will estimate σ_a (the elasticity of substitution between young and old workers) and the efficiency parameters between theses two groups, α_s. With these parameters at hand, we construct the aggregated amounts of L_t, M_t and H_t. Second, using L_t and M_t we estimate σ_{ml} (the elasticity of substitution between medium and low skilled workers) and θ_t (the technology parameter shifting the demand for medium relative to low skilled workers) which are needed to construct U_t (the aggregated amount of non-high skilled labor). Finally, in the third step, using the aggregated amounts of the various skill types, we can estimate σ_{hu} (the elasticity of substitution between college and non-college labor). This final step yields estimates for the parameters estimated in the previous steps and can thus serve as a consistency check.

Identification of our parameters of interest relies on labor supplies to be *predetermined*, i.e. that labor supplies must not be correlated with any other unobservables that also determine skill premiums and that premiums and supplies are not determined simultaneously. For two reasons we think this assumption is tenable. First, labor supplies are inelastic in the short run and are the result of past human capital investments. Thus, although an individual might invest in vocational training or college education when observing a high premium, skill supplies will only increase with a lag. Correlation between current error terms and future labor supplies, however, does not pose a threat to identification.[24] Second, our labor supply measures are very broad, i.e. they do not only include full-time workers, but also those who work part-time, complete vocational training, or are unemployed. Thus, our supplies capture virtually the entire labor force subject to social security[25] and are considerably less sensitive to changes along the intensive margin (e.g.

[23] One might wonder why there are relatively more old than young high skilled worker as the proportion of those who go to college/ university is higher for recent cohorts than older ones. This is because relatively few high skilled are on the market by the age of 30, while most of the medium skilled peers are, so their relative supply is still lower than the relative supply of old high to medium skilled workers.

[24] Interestingly, relative supplies (purged of a linear trend) in our data do not seem to be influenced by lagged premiums. For instance, the the relative supply of college graduates does not seems to react to lags (up to the fifth) of the college premium (see tables in the appendix).

[25] Fitzenberger et al. (2006) follow a similar approach and use broad measures of skill supplies derived from Mikrozensus data (as IVs).

people might be more likely to work full-time when premiums are high). Still, if labor supplies reacted contemporaneously to skill premiums, this would lead to an underestimation of the negative relationship between premiums and supplies. Thus, estimated substitution elasticities would represent upper bounds.

To compute standard errors, we rely on a moving block bootstrap approach.[26] Bootstrapping standard errors is necessary for at least three reasons. First, the three-step estimation procedure implies that we rely on generated regressors in steps 2 and 3, so we need to take into account the estimation uncertainty induced by the previous step(s).

Second, the theoretical model implies that skill premiums at one point in time depend on both the supply of young and old workers of two adjacent skill groups and the two premiums (medium to low and high to medium) are by construction correlated with each other. Third, premiums are serially correlated over time.[27] Thus, the error terms of the premium equations we are going to estimate are correlated contemporaneously across equations and serially over time.[28] The moving block bootstrap is a way to account for these various types of uncertainty. It divides all data points in $n - b + 1$ blocks or clusters, where b is the block length. Thus, the first block jointly contains all premiums and supplies of low, medium, and high skilled workers and both age groups from year 1 through b, the next all observations from year 2 through $b + 1$, and so on. That is, if $b = 5$, a block consists of 3 (skill groups) $\times$ 2 (age groups) $\times$ 5 (years) = 30 observations. This resembles the underlying data generating process and allows errors in a given block to be correlated arbitrarily with each other and over time. The choice of b should mimic the serial correlation of the error terms.[29] We conservatively choose $b = 5$.[30]

Since our parameters of interest (e.g. $-\frac{1}{\beta_a}$) are non-smooth functions of estimated parameters (discontinuous at zero), they cannot be bootstrapped directly. Therefore, the standard errors of the parameters of interest are calculated using the delta method. We use 500 repetitions for all bootstraps. Whenever we estimate two premium equations jointly, we use a seemingly unrelated

[26]The overlapping block bootstrap for time series was first introduced by (Kunsch 1989). See Horowitz (2001, 3188ff) for an overview of different bootstrap methods for dependent data.

[27]A simple Wooldridge (2002, ch. 10) test for serial correlation in panel data (using `xtserial` in Stata) detects serial correlation in both premium equations.

[28]There is also sampling uncertainty related to the estimation of premiums and supplies. However, given the very large number of observations and the corresponding extremely tight confidence intervals, this uncertainty contributes very little to the overall uncertainty related to our estimations and we will abstract from it in what follows. For instance, the mean log real wage of young high skilled in 1994 (a cell with a comparatively low number of observations) is 4.56 with a bootstrapped SE of only 0.0052 (z-value of 877) resulting in an extremely tight confidence interval. For similar reasons, we also decided to ignore the uncertainty induced by imputing top coded wages. Thus, we take premiums and supplies as given.

[29]Lahiri (1999) compares different block bootstrap methods and finds that in terms of asymptotic efficiency, the block bootstrap (fixed block length) performs better than the stationary bootstrap (random block length). Hall et al. (1995) showed that overlapping blocks provide somewhat higher efficiency than non-overlapping ones (but that the efficiency difference in likely to be small in practical applications). They also show that the optimal block length is $n^{1/3}$ when estimating variances.

[30]The rule of thumb with 29 years suggests a block length of 3. A formal lag length selection based on minimizing the BIC (Stock and Watson 2010, ch. 14.5) performed on the errors terms suggests in some specifications/estimation steps a block length of 5.

regression framework to account for error correlations across equations (which affects both, the coefficients and the standard errors) and to impose parameter constraints across equations.

Previous work did not consider these various sources of uncertainty in computing standard errors. For instance, Card and Lemieux (2001) and Goldin and Katz (2009) estimate similar frameworks as ours but only report conventional standard errors. D'Amuri et al. (2010) also estimate a similar framework to study the impact of immigration to West Germany over the period 1987-2001. They cluster standard errors at the education-experience level even when estimating the elasticity of substitution between different skill groups and thus ignore the potential correlation between education and experience groups. A comparison between different standard errors in our setting shows that standard errors obtained from a moving block bootstrap are up to five times as large as conventional standard errors obtained from a seemingly unrelated regression using a small sample adjustment. Thus, using block bootstrapped standard errors is crucial for correct inference in our setting.

B. Estimating σ_a

We apply our simple model setting $j = \{\text{young} \leq 30, \text{old} > 30 \text{ years}\}$ for the period 1980-2008 using composition constant skill premiums and efficiency skill supplies as described above. To estimate the elasticity of substitution between young and old workers, σ_a, we absorb the first two terms of equation 5 and the first three of equation 7 with a linear trend or time fixed effects, and the terms containing the α's by age group fixed effects. This yields the following estimation equations which allow us to recover the σ_a's as $\beta_a = -\frac{1}{\sigma_a}$:

$$\omega_{jt}^{M} = \text{time}_t^{ML} + \text{age}_j^{ML} + \beta_a \ln\left(\frac{M_{jt}}{L_{jt}}\right) + \varepsilon_{jt}^{ML} \tag{9}$$

$$\omega_{jt}^{H} = \text{time}_t^{HM} + \text{age}_j^{HM} + \beta_a \ln\left(\frac{H_{jt}}{M_{jt}}\right) + \varepsilon_{jt}^{HM} \tag{10}$$

As mentioned above, we estimate the two premium equations jointly in a seemingly unrelated regression framework to account for possible correlation of the error terms ε_{jt}^{ML} and ε_{jt}^{HM} across equations as outlined above. In Table 2, we present three different models where in each model we restrict the elasticity of substitution between the two age groups to be the same across the three skill groups. Model 1 assumes linear time trends for time_t^s. This relatively simple model already fits the data very well with an R^2 above 0.95 for both premium equations. Model 2 allows for more flexibility by including time dummies for each year 1981-2008. The parameter of interest β_a increases slightly (in absolute terms) compared to the simple linear trend model. In model 3, we only use the years 1980-90 and apply a linear trend as a kind of *pseudo out-of-sample* exercise. Reassuringly, the parameter of interest changes very little. Our preferred estimate of model 2 corresponds to an elasticity of substitution between young and old workers of 8.1, which

Table 2: Estimating the Elasticity between Young and Old Workers σ_a
(*Constant Across Skill Groups*)

	(1) Linear Trend (1980–2008)		(2) Time FEs (1980–2008)		(3) Linear Trend (1980–1990)	
	ω_{jt}^M	ω_{jt}^H	ω_{jt}^M	ω_{jt}^H	ω_{jt}^M	ω_{jt}^H
Age Group Specific Relative Supply	-0.113***	-0.113***	-0.123***	-0.123***	-0.131***	-0.131***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.050)	(0.050)
Young	-0.051***	-0.244***	-0.051***	-0.251***	-0.048**	-0.264***
	(0.004)	(0.010)	(0.004)	(0.010)	(0.022)	(0.031)
Time	0.007***	0.004***			0.006*	0.002
	(0.001)	(0.001)			(0.003)	(0.004)
Constant	0.344***	0.254***	0.370***	0.256***	0.375***	0.240**
	(0.015)	(0.035)	(0.032)	(0.027)	(0.055)	(0.119)
Time FEs			✓	✓		
σ_a	8.8	8.8	8.1	8.1	7.6	7.6
	(1.0)	(1.0)	(0.9)	(0.9)	(2.9)	(2.9)
Observations	58	58	58	58	22	22
R^2	0.959	0.953	0.990	0.984	0.997	0.987

Notes: The coefficients of the age group specific relative supplies, $\ln(M_{jt}/L_{jt})$ and $\ln(H_{jt}/M_{jt})$, are restricted to be the same in each model's pair of equations, i.e. by assumption $\sigma_{al} = \sigma_{am} = \sigma_{ah}$. Estimates are obtained using a two-step seemingly unrelated regression framework. Young is an indicator for age $\leq$ 30 years. Moving block bootstrap standard errors with block length 5 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

is somewhat higher than the comparable estimates by Card and Lemieux (2001) of around 5 for the US and 6 for Canada.[31]

So far, we have assumed that the elasticity of substitution between age groups σ_a is identical for low, medium and high skilled labor. We can relax this assumption and allow σ_a to differ within each type of labor. By substituting in for the different σ's, the premium equations 5 to 7 can be expressed as

$$\omega_{jt}^M = \ln\theta_t + \rho\ln\left(\frac{M_t}{L_t}\right) - \eta_m \ln M_t + \eta_l \ln L_t + \ln\left(\frac{\alpha_{mj}}{\alpha_{lj}}\right) - \left(\frac{1}{\sigma_{am}}\right)\ln M_{jt} - \left(\frac{1}{\sigma_{al}}\right)(-\ln L_{jt}) \quad (11)$$

$$\omega_{jt}^H = \ln\lambda_t - \ln\theta_t + \gamma\left(\frac{H_t}{M_t}\right) + \rho\left(\frac{U_t}{M_t}\right) - \eta_h \ln H_t + \eta_m \ln M_t + \ln\left(\frac{\alpha_{hj}}{\alpha_{mj}}\right) - \left(\frac{1}{\sigma_{ah}}\right)\ln H_{jt} - \left(\frac{1}{\sigma_{am}}\right)(-\ln M_{jt}). \quad (12)$$

[31] Card and Lemieux (2001) use 7 different age groups in 5-year intervals instead of only 2 as in our models. Estimates are similar to the ones presented in table 2 (yielding a slightly higher σ_a) if we use 8 different 5-year interval age groups or if we re-define young as 35 years and younger.

Table 3: Estimating the Elasticity between Young and Old Workers σ_{as}
(*Flexible Across Skill Groups*)

	(1) Unrestricted		(2) Restricted	
	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}
$\ln L_{jt}$	-0.069*		-0.069*	
	(0.036)		(0.037)	
$\ln M_{jt}$	-0.142***	-0.132	-0.141***	-0.141***
	(0.017)	(0.180)	(0.013)	(0.013)
$\ln H_{jt}$		-0.139		-0.145***
		(0.211)		(0.051)
Young	-0.143***	-0.272	-0.142***	-0.273***
	(0.051)	(0.226)	(0.046)	(0.091)
Constant	0.503***	0.245	0.502***	0.225***
	(0.077)	(0.288)	(0.061)	(0.047)
Time FEs	✓	✓	✓	✓
p-values:				
$H_0: \sigma_{al} = \sigma_{am}$	0.33	0.47	0.34	0.34
$H_0: \sigma_{al} = \sigma_{ah}$	0.44		0.25	
$H_0: \sigma_{am1} = \sigma_{am2}$	0.96			
$H_0: \sigma_{am} = \sigma_{ah}$	0.99	0.89	0.93	0.93
σ_{al}	14.4		14.6	
	(7.5)		(7.9)	
σ_{am}	7.1	7.6	7.1	7.1
	(0.9)	(10.4)	(0.6)	(0.6)
σ_{ah}		7.2		6.9
		(11.0)		(2.4)
Observations	58	58	58	58
R^2	0.993	0.985	0.993	0.985

Notes: The coefficients on the age group specific supply of medium skilled workers, $\ln M_{jt}$, are restricted to be the same in model 2's pair of equations, i.e. by assumption $\sigma_{am1} = \sigma_{am2}$. Young is an indicator for age ≤ 30 years. Moving block bootstrap standard errors with block length 5 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

In Table 3, we estimate this system of equations, again using a seemingly unrelated regression framework. Similar to above, we replace the two last terms with the skill and age group specific labor supplies in each year, $\ln\left(\frac{\alpha_{mj}}{\alpha_{lj}}\right)$ with an indicator for the young age group and absorb the remaining terms using time dummies.[32]

The model implies that the coefficients on M_{jt} should be the same. To see if this is also implied by the data, in model 1 of Table 3, we do not restrict the coefficients on M_{jt} in the two premium equations to be identical and test for the equality of the two coefficients. It turns out that the two coefficient on the age specific supply of medium skilled workers are indeed similar and insignificantly different from each other (p-value of equality is 0.96). Therefore, in model 2, we constrain this coefficient to be the same across the two premium equations. Our estimates remain stable and the coefficients of the age-specific relative supply of high to medium skilled workers ($\ln H_{jt}$) becomes highly significant.[33] The magnitude of the coefficients are in line with expectations. Within the group of low skilled workers, the young and old are close substitutes with an estimated σ_{al} of nearly 15. Medium and high skilled workers of the two age groups are estimated to be imperfect but relatively close substitutes with an elasticity of around 7 in both groups. Although the coefficient on $\ln L_{jt}$ is significantly different from the ones on $\ln M_{jt}$ and $\ln H_{jt}$, a non-linear test shows that σ_{al}, σ_{am}, and σ_{ah} are not significantly different from each other. In light of this and for the sake of simplicity, we will therefore assume in the following that σ_a is the same in each skill group.

Our estimates on the medium and high skilled age specific relative labor supplies of about -0.14 are close to -0.16 which Card and Lemieux (2001) obtain for both for Canada (their Table III columns 5-6) and the US (their Table V column 1) when using a broader measure of college labor similar to ours[34] or when they allow the elasticities to be different for college and high-school labor (-0.18, their Table VII, column 2). D'Amuri et al. (2010) also use German IAB data to estimate the impact of immigration on native wages and employment. Instead of age groups they use potential experience along with the same three skill groups as we do here. Their comparable estimate of the skill-experience specific labor supply is about -0.30 (their Table 7, columns 1-2) implying an elasticity of substitution between different *experience* groups of about 3.2, somewhat lower that our estimates. Fitzenberger et al. (2006) estimate σ_{al} between 8.7-10.3, σ_{am} 5.3-6.0, and σ_{ah} 8.5-20.1. Our elasticities are thus slightly higher for the low and medium skilled and somewhat lower for high skilled workers.

[32]Note that the coefficients on $\ln M_{jt}$ in equations (11) and (12) should be the same except for the minus sign. This is why we use $-\ln M_{jt}$ as a regressor in equation (12) and $-\ln L_{jt}$ in equation (11) to make coefficients comparable across equations. The minus sign is omitted for simplicity.

[33]The large standard errors of the coefficients of the high to medium premium equation in model 1 are due to some extreme (and positive) estimates in some of the bootstrap samples.

[34]In their broad measure, Card and Lemieux (2001) include those with 16 and more years of education opposed to only those with exactly 16 years which is similar to our measure of high skilled labor that includes all individuals with a tertiary degree (college/ FH, university, or PhD) and not just those with say a university degree.

C. Estimating α_s

Once we obtain estimates for the σ_a's, we can back out the age group specific efficiency parameters α_{st} by rewriting equations 2-4 as follows:

$$\begin{aligned}
\widetilde{w}^L_{jt} &= \ln w^L_{jt} + \frac{1}{\sigma_{al}} \ln L_{jt} &&= \ln \alpha_{lj} + \ln \left[Y_t^{1-\gamma} (1-\lambda_t) U_t^{\gamma-\rho} (1-\theta_t) L_t^{\rho-\eta_l} \right] \\
\widetilde{w}^M_{jt} &= \ln w^M_{jt} + \frac{1}{\sigma_{am}} \ln M_{jt} &&= \ln \alpha_{mj} + \ln \left[Y_t^{1-\gamma} (1-\lambda_t) U_t^{\gamma-\rho} \theta_t M_t^{\rho-\eta_m} \right] \\
\widetilde{w}^H_{jt} &= \ln w^H_{jt} + \frac{1}{\sigma_{ah}} \ln H_{jt} &&= \ln \alpha_{hj} + \ln \left[Y_t^{1-\gamma} \lambda_t H_t^{\gamma-\eta_h} \right].
\end{aligned}$$

The terms on the left hand sides can be computed using the estimated σ_{as} either assuming that they are constant (Table 2) or allowing them to differ across skill groups (Table 3). The α_{st}'s can be recovered from regressions of the above equations where the first terms on the left hand side are captured by a dummy for being young and the second terms by a set of time dummies. This is done in Table 4. Our moving block bootstrap takes account of the uncertainty due to the generated regressors.

In model 1, we restrict the σ_a's to be constant across skill groups (model 2 of Table 2) while in model 2 we allow them to differ across skill groups (model 2 of Table 3). The estimates do not differ much and suggest that one unit of young low skilled labor is about 73-78% as efficient as one unit of old low skilled labor while the corresponding ratios are 68-69% for medium skilled and 52-54% for high skilled labor. The different efficiency ratios correspond to the different age earnings profiles of the three skill groups that are much steeper for high skilled workers than for the medium or low skilled.

D. Estimating σ_{ml}

To estimate the elasticity of substitution between the aggregate amounts of low and medium skilled labor corresponding to equation 1, we construct the aggregated amounts of L_t, M_t (and H_t for later) using a model where we restrict the elasticity of substitution between age groups to be the same across skill groups and which includes time fixed effects.[35] We then estimate variants of the following equation (note that ω is not indexed by j and thus refers to the *aggregated* medium skill premium):

$$\omega^M_t = \ln \theta_t - \frac{1}{\sigma_{ml}} \ln \left(\frac{M_t}{L_t} \right).$$

In column 1 of Table 5, we regress the medium to low skilled premium on the aggregated relative supply of medium to low skilled labor $\ln \frac{M_t}{L_t}$ and a linear time trend.[36] This model has a

[35] I.e. we use σ_a from model 2 of Table 2 and the α_s from model 1 of Table 4. All subsequent estimates remain virtually identical when we use alternative parameters from models including a linear time trend only or when allowing the σ_a's to vary flexibly across skill groups.

[36] Note that unlike before we cannot use time dummies as this would leave all other parameters unidentified.

Table 4: Estimating the Efficiency Parameters α_{sj}

	(1) Constant σ_a			(2) Unrestricted σ_{as}		
	$\widetilde{w}_{jt}^L$	$\widetilde{w}_{jt}^M$	$\widetilde{w}_{jt}^H$	$\widetilde{w}_{jt}^L$	$\widetilde{w}_{jt}^M$	$\widetilde{w}_{jt}^H$
Young	-0.318***	-0.369***	-0.620***	-0.248***	-0.390***	-0.663***
	(0.022)	(0.019)	(0.024)	(0.039)	(0.024)	(0.091)
Constant	4.464***	4.834***	5.090***	4.382***	4.884***	5.109***
	(0.039)	(0.066)	(0.060)	(0.039)	(0.059)	(0.062)
Time FEs	✓	✓	✓	✓	✓	✓
α_s	0.73	0.69	0.54	0.78	0.68	0.52
	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)	(0.05)
Observations	58	58	58	58	58	58
R^2	0.982	0.988	0.994	0.968	0.986	0.994

Notes: $\widetilde{w}_{jt}^S = \ln w_{jt}^S + \frac{1}{\sigma_{as}} \ln S_{jt}$. The α_s's are the exponentiated coefficients of the young indicator. The standard errors of the α_s are put in parentheses below. Young is an indicator for age $\leq$ 30 years. Moving block bootstrap standard errors with block length 5 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

comparatively poor fit and the coefficient of the relative medium to low supply is imprecisely estimated. In column 2, we exclude all years after 1990 and do a pseudo-out-of-sample prediction which is visualized in Figure A.10. This model predicts the medium skill premium for the years 1991–2001 very well, but does a poor job from 2002 onwards. Actual premiums in 2002–2008 are much lower than predicted. In column 3, we exclude the years 2002-2008. The estimates become highly significant and are very similar in magnitude to those in column 2. To account for the different regimes, in column 4 we allow for a trend break in the demand for medium relative to low skilled labor in 2002.[37] This improves the model fit significantly and yields a highly significant point estimate for the relative supply of -0.261, very similar to the point estimates in columns 2 and 3. The estimates of column 4 imply a substantially decelerated growth in the medium to low premium after 2002 (the combined demand trend is 61% lower than before 2002). Finally, in column 5, we also allow the substitution elasticity to change in 2002 but find no evidence that this parameter has changed after 2001. The observed pattern of a decreased demand for medium relative to low skilled workers might be consistent with increasing polarization at the beginning of the 2000s along the lines of Autor and Dorn (2014) implying a decreasing medium to low premium due to increasing computerization of medium skilled tasks and a relative increase in low skilled wages. It could also be related to the implementation of the Hartz reforms in 2003 (coupled with some anticipation effects). For instance, Launov and Wälde (2013) find that the Hartz reforms had a more adverse effect on medium skilled workers: while *increasing* benefits and thus reservation wages for most low skilled workers, the reforms *decreased* reservations wages for medium skilled workers.

[37] A formal structural break test (Quandt-LR) also picks 2002 as the break year.

Table 5: Estimating the Elasticity between Medium and Low Skilled Labor σ_{ml}

	Dep. variable: Aggregated Medium to Low Skill Premium ω_t^M				
	(1) Simple 1980-2008	(2) Simple 1980-1990	(3) Simple 1980-2001	(4) Trend Break 2002	(5) Full Trend Break 2002
$\ln\left(\frac{M_t}{L_t}\right)$	-0.104	-0.272	-0.265***	-0.261***	-0.257***
	(0.117)	(0.168)	(0.078)	(0.080)	(0.087)
Post 2002 $\times \ln\left(\frac{M_t}{L_t}\right)$					0.001
					(0.003)
Time	0.006	0.014	0.013***	0.013***	0.013***
	(0.004)	(0.010)	(0.003)	(0.003)	(0.003)
Post 2002 × Time				-0.008***	-0.008***
				(0.002)	(0.002)
Constant	0.306*	0.514***	0.505***	0.499***	0.495***
	(0.160)	(0.196)	(0.104)	(0.111)	(0.119)
σ_{ml}	9.6	3.7	3.8	3.8	3.9
	(10.7)	(2.3)	(1.1)	(1.2)	(1.3)
Observations	29	11	22	29	29
R^2	0.904	0.855	0.967	0.983	0.983

Notes: This table presents regressions results of the aggregated medium skill premium ω_t^M on the aggregated relative supply of medium to low skilled workers $\ln(M_t/L_t)$. M_t and L_t are constructed using the σ_a obtained from a corresponding estimation sample in step 1 where the elasticity of substitution between young and old workers is restricted to be the same across all three skill groups using time FEs (model 2 of Table 2. Young is an indicator for age $\leq$ 30 years. Moving block bootstrap standard errors with block length 5 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

Our preferred specification 4 implies a σ_{ml} of 3.8 which is somewhat lower than the elasticity of substitution between high school graduates and high school dropouts in the US of about 5.3 (for the post 1949-period) estimated by Goldin and Katz (2009, Table 8.4). Arguably, high school graduates and high school dropouts are closer substitutes than those with a completed vocational training specialized in a specific occupation and those without such a training holding at most a general schooling degree (at most *Realschule*). Our estimate of σ_{ml} is also lower than the estimate of obtained by Dustmann et al. (2009, Table V) for Germany who only use men during the period 1975-2004.[38]

[38] When we use the closest possible variable and sample definition as Dustmann et al. (2009) (i.e. use 1975-2004, premiums of men only, non-age group aggregated efficiency supplies based on full- and part-time spells of men and (instead of constructing theses supplies using the estimates σ_a from step 1) we get an estimate on $\ln \frac{M_t}{L_t} of - 0.210$ which is virtually identical to the estimate Dustmann et al. (2009, Table V column 1) of -0.206.

E. Estimating σ_{hu} and the Full Model

Using the estimates of the previous step, we can construct U_t, the aggregate amount of non-high (or non-college) labor.[39] Using equations 6 and 8, we can then estimate σ_{hu}, the elasticity of substitution between college and non-college workers and, at the same time, assess the ability of the overall model to explain the differential evolution of the skill premiums of the different skill and age groups – the primary interest of this paper.

In Table 6, we jointly estimate the medium to low and high to medium skill premiums for each age group in a seemingly unrelated regression framework as before, this time using equations 6 and 8. These equations state that the age specific skill premiums do not only depend on the corresponding age specific relative labor supplies ($\ln \frac{M_{jt}}{L_{jt}}$ for the medium to low premium and $\ln \frac{H_{jt}}{M_{jt}}$ for the high to medium premium) but also on the *aggregated* relative supplies ($\ln \frac{M_t}{L_t}$ and $\ln \frac{H_t}{M_t}$, respectively). Equation 8 also implies that the age specific high to medium premium depends on the aggregated relative supplies of high to non-high and non-high to medium labor. The coefficients on these aggregated supplies yield an estimate for the elasticity of substitution between high and non-high (σ_{hu}) and medium to low skilled (σ_{ml}) labor, respectively. In the following, we impose equality of the coefficients on the age-specific supplies of medium to high and high to medium labor (implying the same elasticity of substitution between young and old workers across all three skill groups, σ_a) and of the aggregated medium to low and non-high to medium supply (thus yielding the same σ_{ml} in both equations) as implied by equations 6 and 8.

For the medium to low premium we allow for a break in the technology trend in 2002 as before (our preferred specification from column 4 of Table 5). The technology parameter corresponding to the high to medium premium in model 1 of Table 6 is assumed to follow a linear trend throughout the whole sample period representing a linear shift in the demand for high skilled workers. The estimates of model 1 yield a coefficient of -0.120 for the age group specific relative supply which is almost identical to the corresponding estimate for the elasticity of substitution between young and old workers obtained in column 2 of Table 2 (-0.123). Thus, concerning σ_a the estimates based on equations 6 and 8 are consistent. However, model 1 yields a coefficient of the aggregated medium to low supply of -0.224 which is somewhat different than the corresponding estimate of Table 5 of -0.261. According to the model, these two estimates should be the same. The point estimate of the aggregated high to non-high supply is -0.262 but it is imprecisely estimated. These discrepancies imply that the model – in particular the specification for the high to medium premium – might be mis-specified. In particular the high to medium premium of *young* workers exhibits "bumps" that are unrelated to supply changes.[40] As it turns out, the wages and thus the premium of young high skilled workers show a strong co-movement with

[39] To construct the aggregated amount of non-college labor U_t we use the estimates of model 4 of Table 5. Apart from σ_{ml} we also need an estimate for the demand shifter θ_t which is recovered from the estimated coefficients as $\widehat{\theta}_t = \frac{\exp(B)}{1+\exp(B)}$ where $B = \widehat{\beta}_t \times t + \beta_{post2002\times time} \times post2002 \times time$.

[40] As shown in the appendix, these bumps are not a peculiarity of the SIAB data (e.g. due to censoring) as similar patterns can be observed in the (virtually uncensored) Mikrozensus (see Figure A.8)

Table 6: CES Regression Models including Age-Group and Aggregate Supply Measures

	(1) Baseline		(2) Young High/Med Intercepts		(3) 1980-1990 only	
	ω_{jt}^M	ω_{jt}^H	ω_{jt}^M	ω_{jt}^H	ω_{jt}^M	ω_{jt}^H
$\ln\left(\frac{M_t}{L_t}\right)$, $\ln\left(\frac{U_t}{M_t}\right)$	-0.224**	-0.224**	-0.265**	-0.265**	-0.233	-0.233
	(0.111)	(0.111)	(0.118)	(0.118)	(0.171)	(0.171)
$\ln\left(\frac{H_t}{U_t}\right)$		-0.262		-0.608*		-0.201
		(0.333)		(0.322)		(0.296)
$\Delta\ln\left(\frac{M_{jt}}{L_{jt}}\right)$, $\Delta\ln\left(\frac{H_{jt}}{M_{jt}}\right)$	-0.120***	-0.120***	-0.122***	-0.122***	-0.098***	-0.098***
	(0.013)	(0.013)	(0.016)	(0.016)	(0.025)	(0.025)
Young	-0.051***	-0.249***	-0.051***	-0.262***	-0.062***	-0.252***
	(0.004)	(0.010)	(0.004)	(0.011)	(0.011)	(0.015)
Time	0.012***	0.010	0.014***	0.023*	0.012	0.003
	(0.004)	(0.012)	(0.004)	(0.012)	(0.010)	(0.014)
Post 2002 × Time	-0.008***		-0.009***			
	(0.002)		(0.002)			
Constant	0.478***	-0.062	0.530***	-0.684	0.496**	0.070
	(0.157)	(0.612)	(0.165)	(0.594)	(0.199)	(0.615)
1987-1990 Intercept × Young				✓		✓
1999-2002 Intercept × Young				✓		
σ_{ml}	4.5		3.8		4.3	
	(2.2)		(1.7)		(3.2)	
σ_{hu}		3.8		1.6		5.0
		(4.9)		(0.9)		(7.3)
σ_a	8.3	8.3	8.2	8.2	10.2	10.2
	(0.9)	(0.9)	(1.0)	(1.0)	(2.6)	(2.6)
Observations	58	58	58	58	22	22
R^2	0.980	0.949	0.982	0.973	0.998	0.996

Notes: The coefficients on $\ln({}^{M_t}/{}_{L_t})$ and $\ln({}^{U_t}/{}_{M_t})$, i.e. σ_{ml}, as well as the coefficients on the age group specific supplies (i.e. σ_a) are restricted to be the same in each model's pair of equations. Young is an indicator for age ≤ 30 years. Moving block bootstrap standard errors with block length 5 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

the business cycle (see figure Figure A.9) which none of the remaining three premiums exhibits. In particular, the premium of young high skilled workers is amplified and detached from its underlying supply during the pre- unification boom (1987-1990) and the boom and bust of the dot-com bubble (1999-2002, Burda and Seele 2016, p. 5).

Therefore, in model 2, we include two separate intercepts for these two periods interacted with the young indicator to account for the two biggest "bumps" in the high to medium premium of young workers. The coefficient on the aggregated medium to low supply now changes to -0.265 and is thus virtually identical to the corresponding estimate in Table 5 as implied by the model. The coefficient on the aggregated amount of high to non-high labor changes to -0.608 and becomes marginally significant.[41].

In general, the models have a very good fit and show that each age group specific premium does not only depend on its related age group specific relative supply but also on the corresponding aggregated relative supply as implied by the theoretical model. The estimates are also consistent with the previous estimation steps: the coefficients on both the aggregated relative supply of medium to low skilled (or non-high to medium skilled) and the age group specific relative supplies are insignificantly different from the ones estimated in tables 5 and 2.

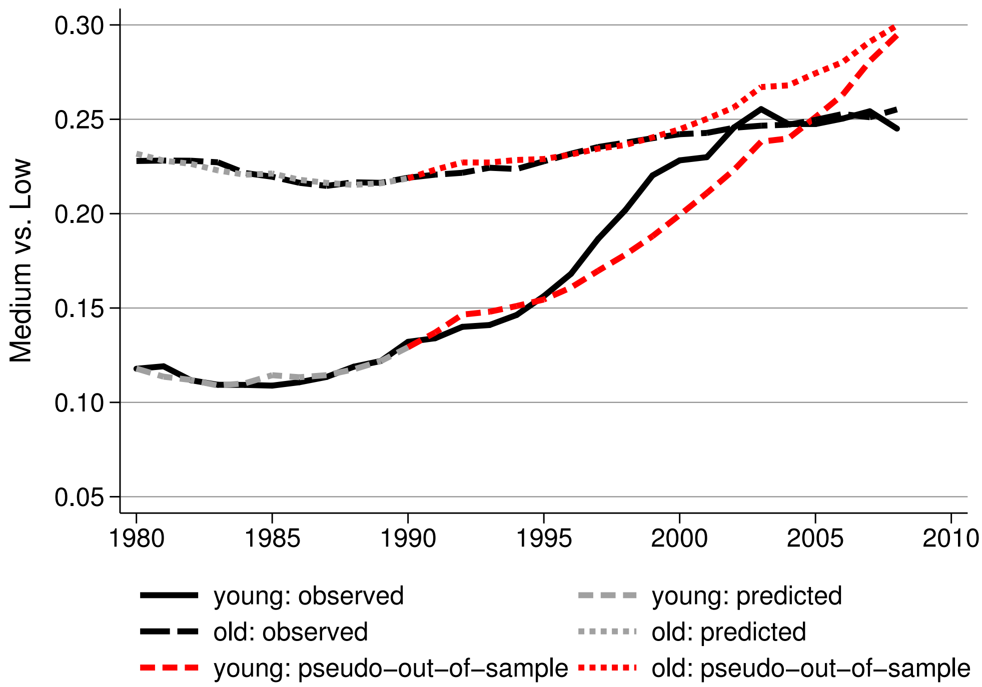
The estimates of our preferred specification (model 2) imply an elasticity of substitution between college and non-college labor of 1.6. This happens to be identical to the elasticity of substitution between college and high school labor in the US estimated both by Goldin and Katz (2009, their Table 8.2) and Card and Lemieux (2001, Table VI). D'Amuri et al. (2010) and Fitzenberger et al. (2006) both do not estimate σ_{ml} and σ_{hu} separately but impose equality of these two parameters in their estimations (i.e. they assume that the elasticity of substitution is the same between, say, high and low skilled labor and high and medium skilled labor). This simplifying assumption is not supported by our estimation results, i.e. σ_{ml} and σ_{hu} are significantly different from each other. Bearing that in mind, D'Amuri et al. (2010, Table 7 column 3 and 4) estimate an elasticity of substitution between any two skill groups of 2.9 which is right between our corresponding elasticities of 4.0 (σ_{ml}) and 1.7 (σ_{hu}). Fitzenberger et al. (2006, Table 1) estimate a σ_s between 4.9 and 6.9 (their preferred IV estimates) and note that their estimates "imply a rather high degree of substitutability compared to findings in the related literature".

To get an impression of the model's out-of-sample predictive power, we plot the observed and the predicted medium to low premium separately for young and old workers in Figure 4. The prediction in panel a) is based on the estimates of model 3 where we exclude all years after 1990. Although we lose statistical power due to the smaller sample size, the coefficients related to the medium to low and the age group-specific supply measures remain comparable in magnitude. The figure shows that the model which is only based on the observations from 1980–1990 is able to predict the differential evolution of the medium to low premium of young and old workers during the 1990s up until the early 2000s. In panel b), we use the estimates of model 1 and the prediction is very close to the observed premium. The model is also able to predict the high skill premium reasonably well – and more so if accounting for some peculiarities in the premium of young college graduates (Figure A.11).

[41] Including other sets of interacted intercepts or dummies in the high to medium specification leads to no major changes in the estimates.

Figure 4: Predicted vs. Observed Medium Premiums

a) Medium vs. Low: Pseudo-out-of-Sample until 1990 (model 3 of Table 6)



b) Medium vs. Low: all years 1980-2008 (model 1 of Table 6)

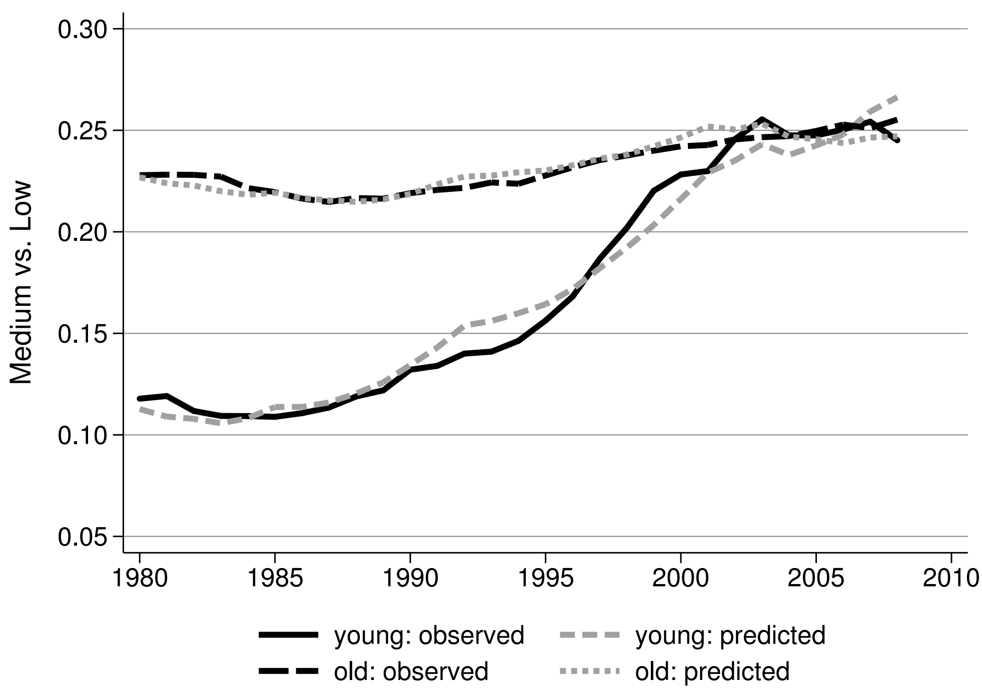


Table 7: Robustness Checks of CES Models

	(1) Baseline		(2) Baseline + GDP Growth		(3) Premiums of Men		(4) Weighting $w_{voc} = w_{ue} = 1$		(5) Supplies excl. Voc. Training & Unemployed		(6) Supplies as Head Count		(7) Supplies excl. East-West Movers & Foreigners	
	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}
$\ln\left(\frac{M_t}{L_t}\right)$, $\ln\left(\frac{U_t}{M_t}\right)$	-0.265**	-0.265**	-0.277**	-0.277**	-0.332**	-0.332**	-0.305***	-0.305***	-0.218*	-0.218*	-0.188**	-0.188**	-0.268*	-0.268*
	(0.118)	(0.118)	(0.120)	(0.120)	(0.158)	(0.158)	(0.107)	(0.107)	(0.118)	(0.118)	(0.074)	(0.074)	(0.139)	(0.139)
$\ln\left(\frac{H_t}{U_t}\right)$		-0.608*		-0.611**		-0.565*		-0.621**		-0.546*		-0.336***		-0.572*
		(0.322)		(0.307)		(0.336)		(0.305)		(0.299)		(0.118)		(0.298)
$\Delta\ln\left(\frac{M_{jt}}{L_{jt}}\right)$, $\Delta\ln\left(\frac{H_{jt}}{M_{jt}}\right)$	-0.122***	-0.122***	-0.122***	-0.122***	-0.133***	-0.133***	-0.111***	-0.111***	-0.133***	-0.133***	-0.105***	-0.105***	-0.096***	-0.096***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.025)	(0.025)	(0.015)	(0.015)	(0.018)	(0.018)	(0.013)	(0.013)	(0.026)	(0.026)
Young	-0.051***	-0.262***	-0.051***	-0.262***	-0.010	-0.240***	-0.069***	-0.255***	-0.035***	-0.269***	-0.070***	-0.224***	-0.048***	-0.242***
	(0.004)	(0.011)	(0.004)	(0.011)	(0.007)	(0.021)	(0.004)	(0.010)	(0.006)	(0.014)	(0.004)	(0.007)	(0.008)	(0.017)
Time	0.014***	0.023*	0.014***	0.023**	0.017***	0.021*	0.014***	0.023**	0.012***	0.021*	0.008***	0.011**	0.016**	0.021*
	(0.004)	(0.012)	(0.004)	(0.012)	(0.006)	(0.013)	(0.004)	(0.011)	(0.004)	(0.012)	(0.002)	(0.004)	(0.007)	(0.011)
Post 2002 × Time	-0.009***		-0.009***		-0.010***		-0.010***		-0.007***		-0.007***		-0.011***	
	(0.002)		(0.002)		(0.003)		(0.002)		(0.002)		(0.002)		(0.003)	
Real GDP Growth			0.053	-0.048										
			(0.076)	(0.160)										
Constant	0.530***	-0.684	0.544***	-0.693	0.556**	-0.677	0.580***	-0.737	0.469***	-0.547	0.393***	-0.374	0.579***	-0.617
	(0.165)	(0.594)	(0.168)	(0.564)	(0.221)	(0.632)	(0.146)	(0.566)	(0.167)	(0.554)	(0.090)	(0.296)	(0.211)	(0.556)
1987-1990 Intercept × Young		✓		✓		✓		✓		✓		✓		✓
1999-2002 Intercept × Young		✓		✓		✓		✓		✓		✓		✓
σ_{ml}	3.8		3.6		3.0		3.3		4.6		5.3		3.7	
	(1.7)		(1.6)		(1.4)		(1.1)		(2.5)		(2.1)		(1.9)	
σ_{hu}		1.6		1.6		1.8		1.6		1.8		3.0		1.7
		(0.9)		(0.8)		(1.1)		(0.8)		(1.0)		(1.0)		(0.9)
σ_a	8.2	8.2	8.2	8.2	7.5	7.5	9.0	9.0	7.5	7.5	9.5	9.5	10.4	10.4
	(1.0)	(1.0)	(1.0)	(1.0)	(1.4)	(1.4)	(1.2)	(1.2)	(1.0)	(1.0)	(1.1)	(1.1)	(2.8)	(2.8)
Observations	58	58	58	58	58	58	58	58	58	58	58	58	58	58
R^2	0.982	0.973	0.983	0.973	0.960	0.949	0.985	0.973	0.976	0.973	0.980	0.983	0.961	0.975

Notes: The coefficients on $\ln\frac{M_t}{L_t}$ and $\ln\frac{U_t}{M_t}$ (i.e. σ_{ml}) as well as the coefficients on the age group specific supplies (i.e. σ_a) are restricted to be the same in each model's pair of equations. Young is an indicator for age $\leq$ 30 years. Moving block bootstrap standard errors with block length 5 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

F. Robustness Checks

How robust are our estimates regarding the construction of premiums and supplies? We compare alternative premium and supply measures to our baseline estimates from above which are restated in model 1 of Table 7.

Premiums do not only depend on supplies but are likely also influenced by the business cycle. To capture fluctuations around the underlying longer-term trends, we include GDP growth in model 3 (and in step 2). This leaves our estimates basically unchanged and GDP growth turns out insignificant in both premium equations.

So far, we used composition constant skill premiums that included both men and women. In model 2, we compute age-composition constant premiums of men only and re-do our previous estimation steps. Using premiums of men only yields similar results with a somewhat lower degree of substitutability between medium and low skilled workers and a slightly higher between college and non-college labor.

A possible concern is that our results depend on the specific weighting scheme used to construct the efficiency supplies. In particular, we assigned an "hours weight" of 1/3 to vocational training and unemployment spells which we think is a reasonable assumption. One could argue, however, that these two groups of workers are (in their great majority) willing to work full-time and thus should be assigned an hours weight of 1. This is what we do in model 4. Re-weighting of this kind makes the estimates slightly more pronounced but the differences to the estimates in model 1 are small. Thus, our results are not driven by the particular weighting scheme (we experimented with other weighting schemes as well and results remain robust). The same is true when we completely exclude vocational training and unemployment spells from our efficiency supply measures (model 5). σ_{ml} and σ_{hu} increase slightly likely because the group of those working full- or part-time are closer substitutes than when also including those in vocational training and currently unemployed.

When constructing supplies not based on efficiency units, i.e. not taking productivity differences into account, but rather do a simple head count (model 6, but still weighted by spell duration) similar to the approach followed by D'Amuri et al. (2010) the estimates are more attenuated towards zero but the overall patterns in our results continue to hold.

Finally, in model 7 we only exclude workers whose first record is in East-Germany and those with missing or non-German nationality. This supply measure thus approximates the *native* West-German labor force. The coefficients of interest remain largely unaffected by this change in the construction of labor supplies – already hinting at a more limited role of immigration by foreigners and East-West movers which we will explore in more detail in the next section.

VI. Determinants of Supply Changes

What is the reason behind the supply changes we have linked to the evolution of skill premiums in the previous section? To see how educational attainment changed over time, we perform a cohort analysis based on data from the German Mikrozensus. One possibility is that the changes in skill supplies are driven by (low skilled) immigration. Alternatively, they could reflect a more fundamental change in the behavior of natives. To tackle these questions, we first compare supplies with and without foreigners and East-West movers and, second, we perform a cohort-based analysis using Mikrozensus data.

A. Comparison of Different Supply Measures

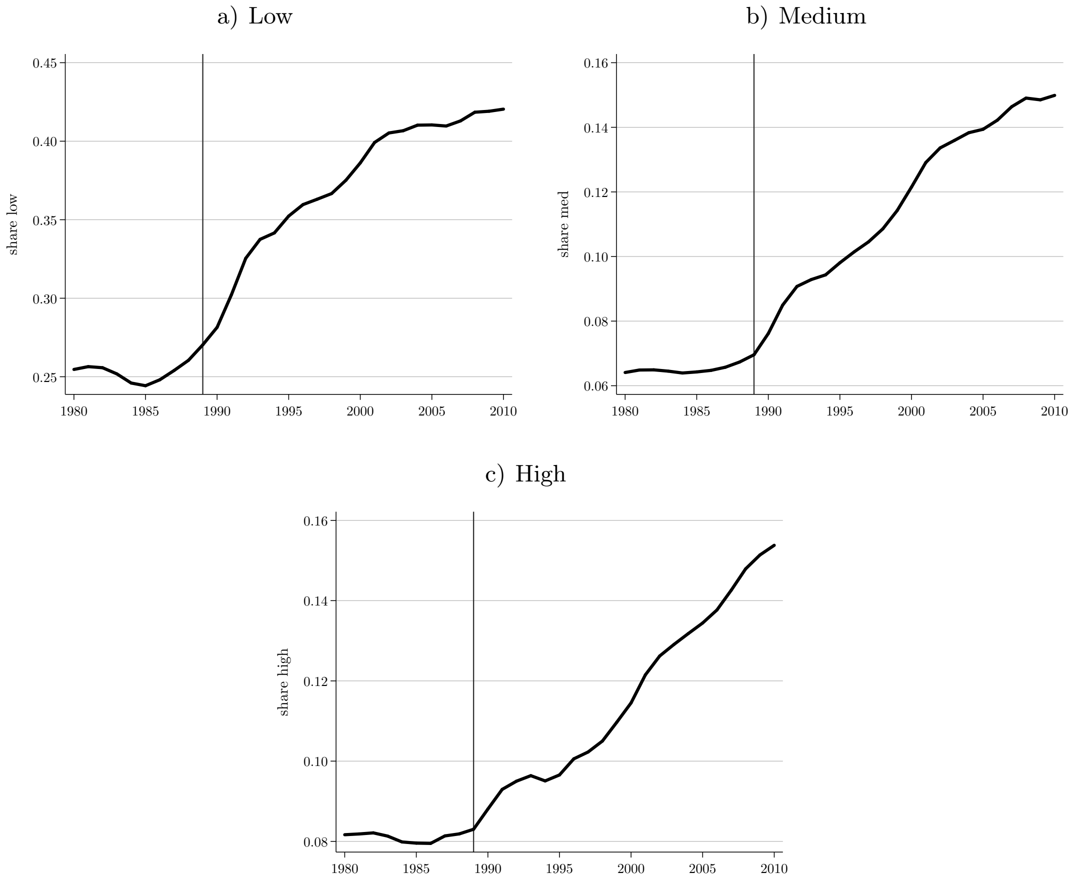
We start by comparing labor supplies with and without East-West movers and foreigners ('migrants'). This is only an approximation to the true number of workers who are non West-German natives as we do not observe those starting their first job subject to social security and (i) have moved from East-Germany without ever been registered as employed or unemployed in East-Germany before and (ii) those foreigners or migrants who become naturalized before starting their first job (e.g. *Spätaussiedler*). To demonstrate that we still do approximate a large portion of migrants moving in after the fall of the Berlin wall in 1989, we plot the share of East-West movers and foreigners in each skill group in Figure 5. The influx in all three skill groups was substantial. Within the group of low skill workers, the share of East-West movers and foreigners increased from 25% in the 1980s to more than 40% in the 2000s. The corresponding share more than doubled in the group of medium skilled workers (from 6% to 15%) and increased at a similar rate within the high skilled (from 8% to 15%).

However, when we compare the *relative* labor supplies with and without 'migrants' (Figure 6), we see that – maybe surprisingly – these large migration inflows left relative supplies largely unaffected. The relative supplies of medium to low skilled workers - apart from a level shift - move practically in parallel and share the same growth patterns. The high to medium relative supplies are unchanged whether 'migrants' are included or not. This is because newly arriving workers increased skill supplies in a virtually *proportional* fashion. This confirms a finding by Prantl and Spitz-Oener (2014, p. 5) that "[t]he German-German migration wave [..] does not include workers of any education class over-proportionally. Hence, the educational distribution of German workers in West Germany remained stable."

B. Cohort Analysis of Skill Acquisition

To advance further, we use data from the German Mikrozensus, an officially conducted yearly survey based on a 1% random cross-section of the German population. The Mikrozensus is similar to the US Current Population Survey (CPS). Participation in the Mikrozensus is compulsory and non-complicance can be fined or punished. Most official population and labor market statistics are based on the Mikrozensus. To proceed in understanding the drivers of the observed supply changes, we pool Mikrozensus waves 2005-2011 and restrict the sample to individuals residing in West-Germany at the time of the interview and who are at least 30 years old to make sure

Figure 5: Approximate Share of East-West Movers and Foreigners in Each Skill Group



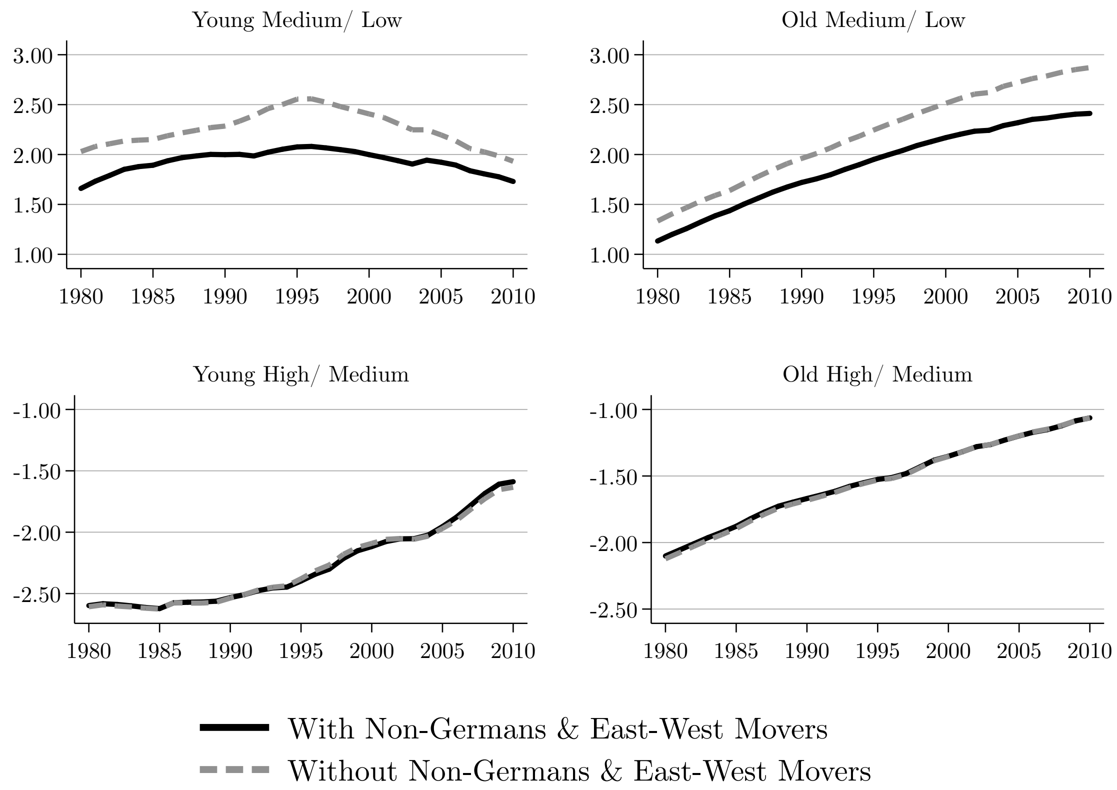
they have finished their formal education.[42] We group individuals in one of three education groups defined as in our SIAB sample, i.e. the low skilled are those without vocational training or tertiary education, the medium skilled those with vocational training (including *Meister*) and/ or *Abitur*, and high skilled those with a college or university degree (*Fachhochschule, Universität, Promotion*). Our Mikrozensus sample is broader than our SIAB sample as the Mikrozensus also includes self-employed, civil servants, unemployed and non-working individuals apart from regularly employed individuals. Using this pooled sample of six Mikrozensus waves, we calculate for each birth cohort the share of low, medium and high skilled individuals.

In Figure 7, we plot the shares of the three skill groups for each cohort born between 1915 and 1979.[43] For comparison, we also plot the same series using SIAB data where the same general trends are visible.

[42]Unlike in some previous years, answering the question about the highest formal occupational degree is mandatory for all age groups from Mikrozensus wave 2005 onwards. See Fitzenberger et al. (2004) for an imputation method of the education information in case the related questions are voluntary for some age groups and thus suffer from selection.

[43]These time series are smoothed using a moving average including one lag, the current value and one lead. Non-smoothed series are very similar and available from the authors.

Figure 6: Relative Supplies with and without Foreigners and East-West Movers



There has been a marked overall improvement in educational attainment over the 20th century. The share of low skilled individuals dropped from 56% in the 1915 cohort to 19% in the 1979 cohort, the share of medium skilled per cohort increased from 39% to 60% and the share of those holding a college or university degree more than quadrupled from 5% to 22% over the same time horizon. Note that these trends did not change monotonically. In particular, there seems to be a break in the trends around the mid 1960s. This becomes more apparent in Figure 8a) where we plot the evolution of the three education shares focusing on the cohorts born in or after 1950 (note the change of scaling, the medium skilled share is now depicted on the right scale). In the 15 years up to the 1964 cohort, the share of medium skilled individuals was increasing from 62% to 66% but then started to decrease quite rapidly, reaching 60% in the 1979 cohort, a share comparable to that of the 1940 cohort. At the same time, the share of low skilled increased after it had reached a low at the end of the 1960s. Finally, the university share started to increase again after it had stayed virtually flat throughout the 1950-1964 period.

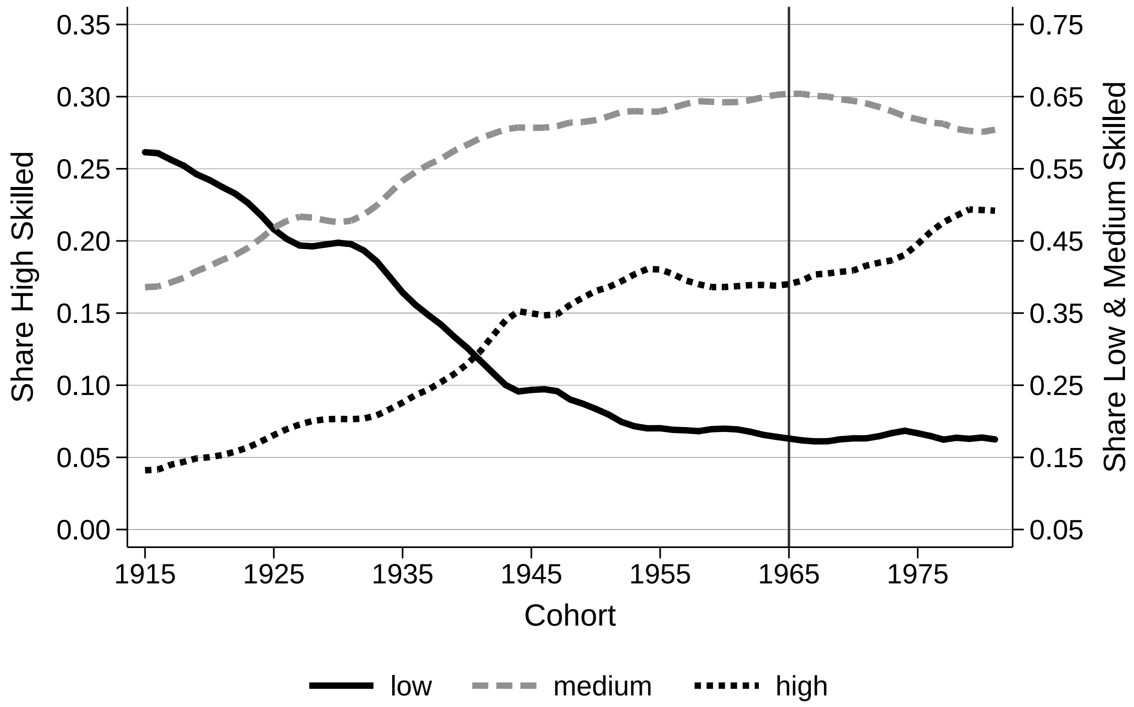
In the previous analysis, we showed that the relative supply of young medium to low skilled workers started to decline at the end of the 1980s and that his was associated with a pronounced increase in the corresponding wage premium of young medium skilled workers. The cohort analysis of this section suggests that this was due to both a decline in the share of medium skilled workers and an increase in the share of low skilled. But why did the share of medium skilled workers decrease and the share of low skilled workers increase for post-1965 cohorts, triggering a significant decline in the relative supply of medium skilled workers? As mentioned in the introduction, Dustmann et al. (2009, p. 867) hypothesize that this deceleration might be due to the "large inflow of [mainly low skilled] East Germans, Eastern Europeans, and ethnic Germans [...] into the West German labor market".

To assess whether this was indeed driven by immigration, in Figure 8b), we show the education shares for each cohort born in or after 1950 but restricting the sample to native Germans.[44] The general trends in the sample including migrants is also apparent in the natives-only sample: a marked drop in the share of those acquiring vocational training, an accelerated increase in tertiary education and a standstill or slight increase in the share of low skilled. The comparison of the two figures suggests that the increase in the low skill share within the cohorts born at the end of the 1960s and afterwards is mainly driven by non-natives who most likely migrated to West-Germany around 1990 after the Berlin wall came down.

[44] Specifically, in the Mikrozensus we exclude all those born outside Germany, those who lived for more than 6 months outside Germany, those who do not have the German citizenship, and those who were naturalized and had a different nationality before. This sample of "native Germans" consists of about 81% of our full "natives and migrants" sample. Note, however, that we cannot identify East-Germans who moved to West-Germany after the Berlin wall came down.

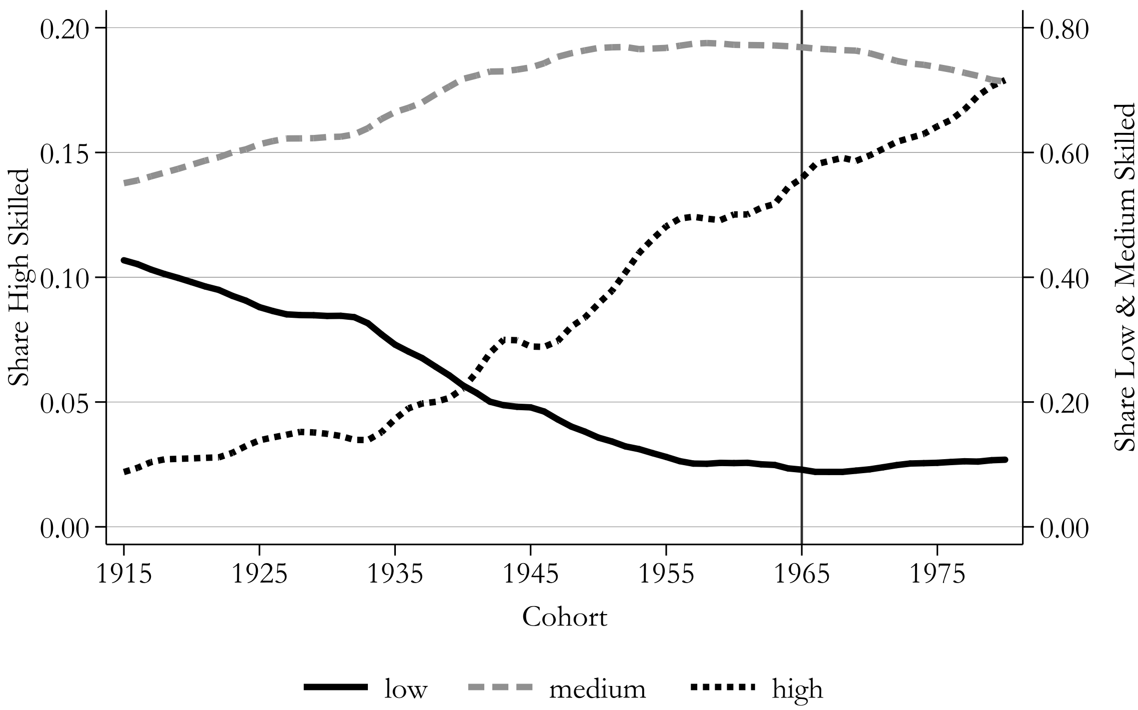
Figure 7: Educational Attainment by Cohorts

a) Mikrozensus



Source: Mikrozensus, West Germany, natives and migrants, all income sources, smoothed

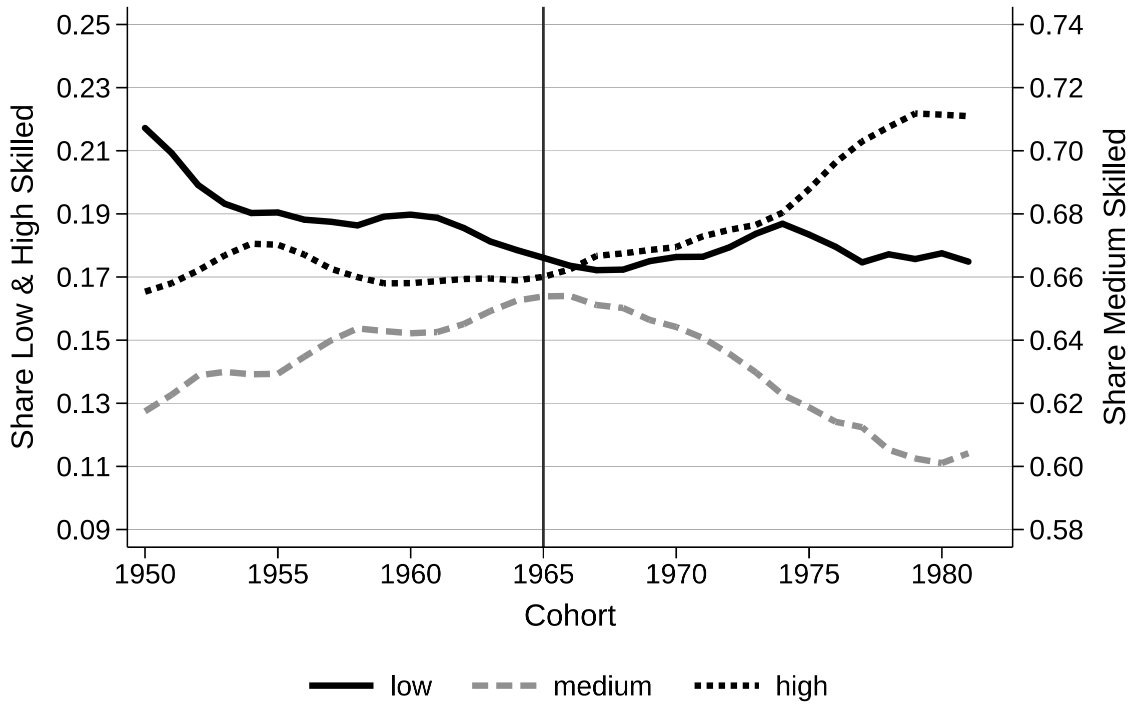
b) SIAB



Source: SIAB7510, West-Germany, Germans and non-Germans, non-weighted, full- or part-time employed, smoothed

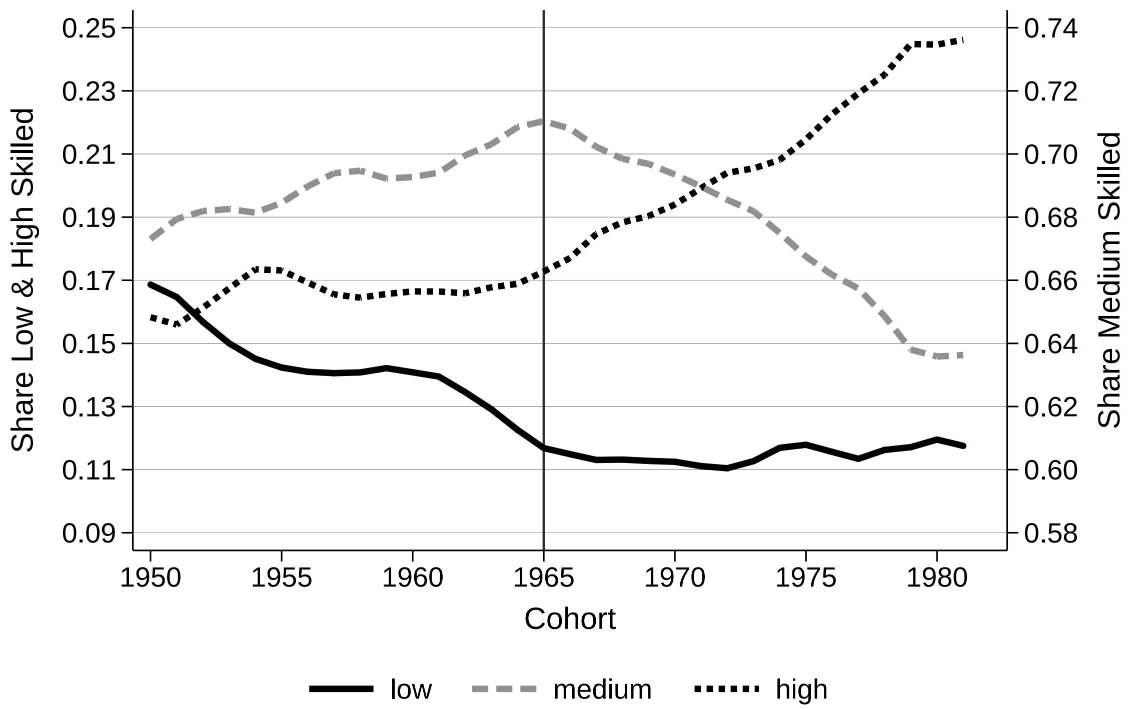
Figure 8: Educational Attainment by Cohorts

a) Natives and migrants



Source: Mikrozensus, West Germany, natives and migrants, all income sources, smoothed

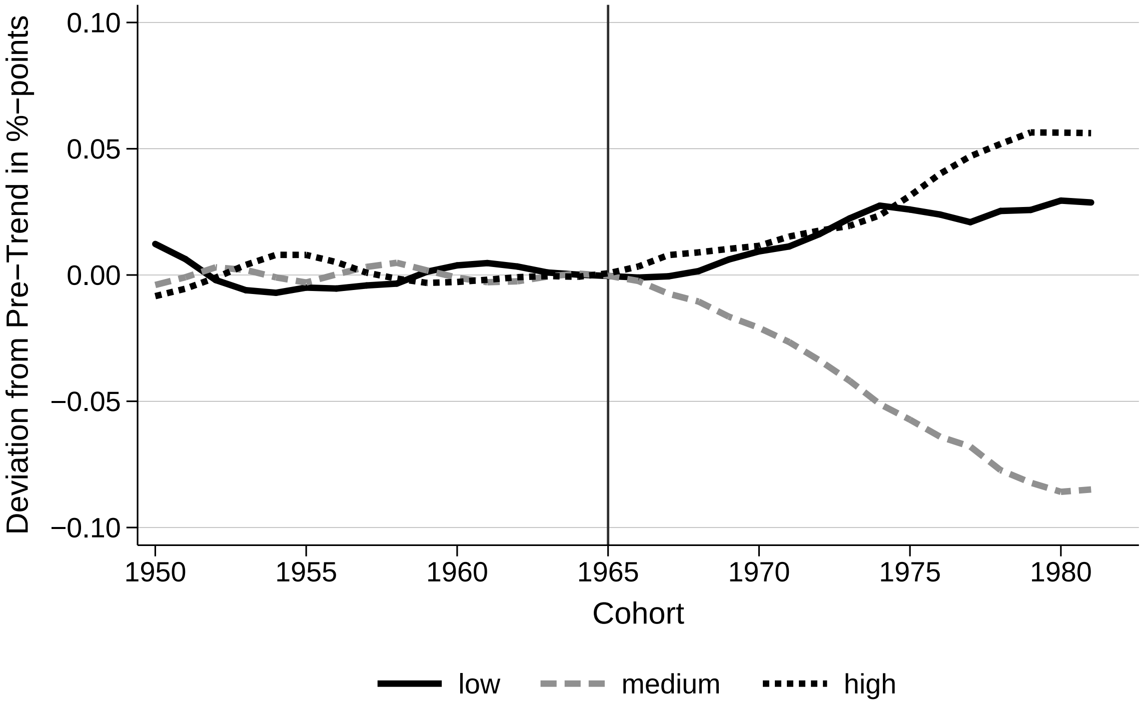
b) Native Germans



Source: Mikrozensus, West Germany, natives only, all income sources, smoothed

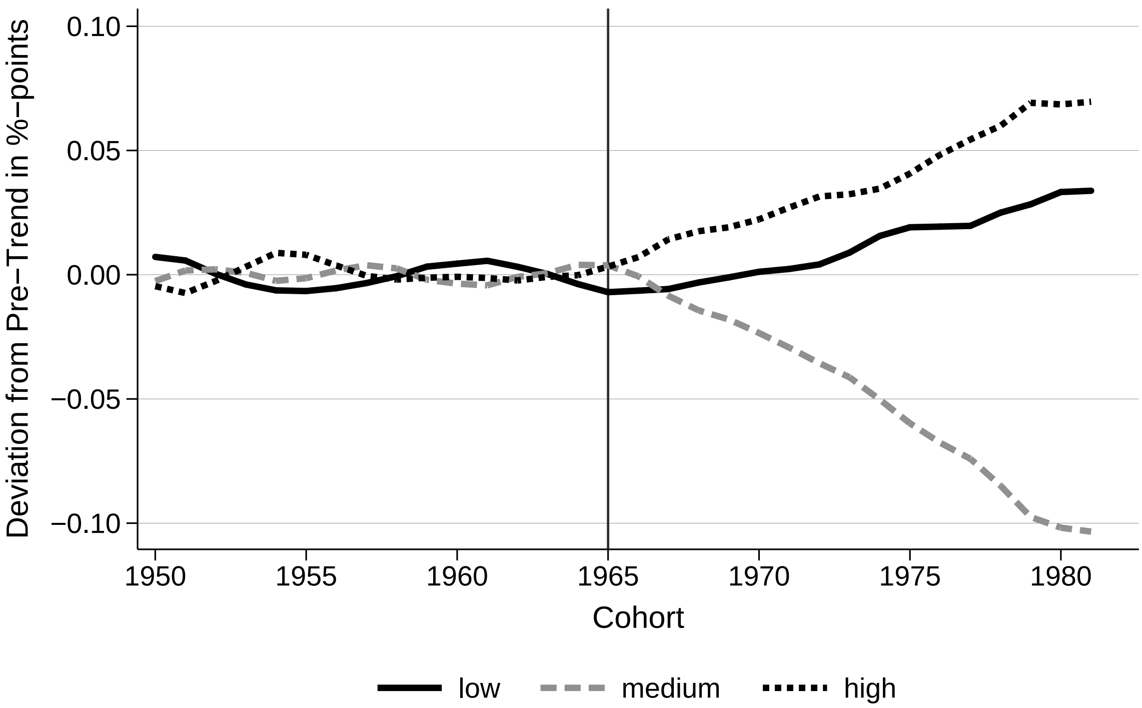
Figure 9: Deviation from 1950-1964 Trend

a) Natives and migrants



Source: Mikrozensus, West Germany, natives and migrants, all income sources, smoothed

b) Native Germans



Source: Mikrozensus, West Germany, natives only, all income sources, smoothed

To get a more systematic impression of the deviation, we estimate a linear trend for the cohorts 1950-1965 and plot the deviation from this pre-period trend in Figure 9b).[45] We find a striking break from the previous trend for the cohorts born around 1965 regarding their educational attainment.

A possible explanation for the increased share of high skilled at the expense of the middle skilled might be related to cohort sizes. Cohort sizes increased gradually and reached their peak in 1964 (the "baby boomers" with the 1964 cohort reaching 1.35 million). After that, cohort sizes decreased to 0.8 million in the mid 1970s. While cohorts became smaller after 1964, university capacity continued to increase. Thus, for the post baby boomers, it was easier to get into college and university. Other possible reasons may include societal changes in the 1960's that shifted parents' preferences away from traditional vocational careers for their children towards more academic university education or a signaling story along the lines of Bedard (2001). Another potential explanation is the increasing scarcity of available apprenticeship positions in the early 1990s, in particular for manufacturing and trade-related occupations due to secular restructuring processes and for occupations in the public sector due to ongoing privatizations. Finally, it could also be that with the smaller cohort sizes and, consequently, smaller families, parents had more resources to invest in the education of each of their children (quality - quantity trade-off), pushing them into the tertiary education track.

VII. Conclusion

The rise in inequality in many OECD countries over the last decades has triggered a rich body of academic work. Scholars agree in general that recent changes in inequality are mainly driven by inequality of labor incomes which in turn are closely related to skill premiums. In this paper, we ask whether skilled biased technological change and, in particular, shifts in the supply of different skill groups – both along the age and the education dimension – can explain the observed evolution of skill premiums in Germany over the last three decades.

Our estimations based on a model comprising three skill and two age groups show that linear technological progress and observed changes in skill supplies go a long way in explaining the peculiar patterns of skill premiums in Germany. In particular, our model is able to explain the pronounced increase in the wage premium of young medium skilled worker from 10% in the 1980s to 25% in the 2000s. Premiums for high skilled workers – despite a pronounced increase in their relative demand – show no systematic upward or downward trend. Our framework suggests that this was because the supply of high skilled workers has kept pace with increased demand. The share of high skilled workers among all full-time workers has tripled from 5% at the beginning of the 1980s to 15% at the end of the 2000s and continues to increase. Our cohort analysis suggests that this development is rooted in a distinct change in the educational attainment of the native

[45] A structural break test (maximum F-value) picks 1965 (low skilled), 1964 (medium), and 1966 (high) as the break points. We also estimated a linear trend using the cohorts 1945-1964 or allowed for a quadratic pre-trend with similar results.

(West-) German population that occurred for cohorts born after 1965 and which reversed previous trends in the acquisition of different types of education. The share of individuals with completed vocational training decreased strongly and was as large for the 1980s cohorts as it was for the 1940s cohort while the share of individuals with tertiary education increased to unprecedented levels and the decline in the share of low skilled individuals came to a hold.

All in all, our study suggests that a considerable part of recent changes in earnings inequality between different skill groups are rooted in longer term educational choices of the population and hence, ultimately, driven by labor supply.

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Appendix A. Further Details on Sample and Variable Construction

Derivation of Baseline Sample

Using the universe of SIAB7510 data, we impute missing education information following Fitzenberger et al. (2006). For each individual we also impute missing location with the last non-missing location information. We impute missing German nationality and gender information by first computing the minimum and maximum of these dummy variables by each individual. If these two values are the same, then all missing values of a given individual are replaced by his/her unambiguous value of the variable. We then drop all individuals living in East Germany and those younger than 21 and older than 60 years. Following common practice, we also exclude spells that start and end on the same day (2.1% of all initial spells in West Germany), spells that overlap with one or more parallel full-time spells (∼1.4%), spells of doctors and pharmacists (∼0.8%) as their records are corrupted and missing between 1996-1998 (see vom Berge et al. 2013, for further details), and spells of individuals who are registered as "not unemployed, but registered as a job seeker with the BA", "without status", or "seeking advice".

From 1984 onward the IAB wage measure also includes bonuses and other one-time payments. We correct for this structural break following the non-parametric method proposed by Dustmann et al. (2009) (which builds on Fitzenberger 1999) and impute censored wages above the upper earnings threshold for compulsory social insurance (66,000 Euros per year in 2010) using the "no heteroskedasticity" approach by Gartner (2005) and Dustmann et al. (2009). Specifically, we consider wages as censored that were up to two Euros below the maximum wage value observed in each year and then estimate for each year and for males and females separately a censored regression of log wages on indicators of eight age groups, three skill groups and all their possible interactions, assuming that the error term is normally distributed and has the same variance across age and skill groups. We also imputed wages assuming different censoring limits and assumptions on the variance of the error term but found the "no heteroskedastity" approach to be more robust with respect to different censoring limits and the share of censored observations (confirming Dustmann et al. 2008, who imputed wages over 1975-2004 using the "no heterogeneity" approach to calculate and analyze skill premiums). Both imputation methods, however, yielded implausibly high wages (e.g. compared to series derived from the Mikrozensus) for high skilled workers between 1975-1979 (as also noted by Dustmann et al. 2008; Dustmann et al. 2009). This is likely because the of high share of censored wages in these years (up to 18% after the structural break correction as compared to around 10% from 1980 onwards). This is why we exclude observations from 1976-1979.

A closer examination of the data suggests that the years 2009-10 are unusual, in particular for old medium skilled workers who see an abnormal depression in their wages. This is likely to be related to the global financial crisis that started in 2007/08. Although unemployment in Germany did not increase during the financial crisis, many workers – in particular medium skilled worker in manufacturing – had to go on short-term work which was associated with temporary wages cuts (supplemented by public transfers). We therefore exclude observations from 2009 and 2010. Estimates including these crisis years are slightly lower but all conclusions continue to hold.

Efficiency Weights

The efficiency weights used to construct the efficiency supplies are computed by first aggregating full-time wages by year, skill, age group, and gender and then divide these aggregated wages in each year by the corresponding mean wage of male medium skilled workers aged 36-40. Thus women and men in the same skill-age group are assigned different efficiency weights. Then, we average these weights over the entire sample period for each group.

Imputation of Missing Unemployment Spells

For our efficiency supply measures, we also include unemployment spells. These include ALG, ALH, and ALG II spells. ALG II spells are missing in 2005/06. We therefore linearly interpolate aggregated unemployment spells in these two years separately for each skill and age groups. Also note that the number of unemployed drops between 2003/04 which leads to the bump in the medium to low skilled supply of young workers visible in the top right part of Figure 3. This is likely due to a change in the data collection procedure: "Durch einen internen Systemwechsel kommt es 2004 zu einem Bruch in der Erfassung von Sperr- und Säumniszeiten [in der Leistungsempfängerhistorik]" (vom Berge et al. 2013, p. 30).

Appendix B. Robustness of High to Medium Premium

We present two different pieces of evidence that corroborate the robustness of the high to medium premium derived from SIAB data.

First, Dustmann et al. (2008) perform an extensive evaluation of various imputation methods. They take an uncensored distribution of wages available for 2001[46], artificially censor it at the same thresholds as in the SIAB data and compare several statistics of the imputed distribution with the true counterparts from the uncensored distribution. Their comparisons show that the "no heterogeneity" imputation approach (which we also use here) matches the standard deviation and in particular the high to medium skill premium of the uncensored distribution very well (true 0.472, no heterogeneity 0.471). This shows that the imputation method works well in a particular year (2001).

Second, we can compare the evolution of the 85th percentile (of gross earnings) observed in the SIAB which is always uncensored in 1980-2008 with the top fractiles (of labor incomes) from

[46] This uncensored wage distribution comes from the GSES a survey of 27,000 establishments with compulsory participation conducted by the German Federal Statistical Office. For more details see Dustmann et al. (2008, section 2, pp. 6f).

the WTID[47]. If the top 15% of the income distribution systematically diverged from the bottom 85% and assuming that most individuals in the top 15% are high skilled, we would underestimate the high to medium premium. Figure A.7 shows that this is not the case. It depicts the log difference between the average incomes of the five top fractiles observed in the WTID and the 85th percentile observed in the SIAB. Although there is considerable variation in these gaps, there is no clear upward trend in neither of them. All gaps stayed roughly the same or even decreased somewhat (or even considerably in case of the difference to the top 10-5 fractile, see panel a of Figure A.7).

[47]The WTID data is based on the incomes of all individuals who file an income tax report and thus also includes self-employed, civil servants, members of the armed forces, and other who are not observed in the SIAB.

Appendix C. Additional Tables

Table A.1: Young Medium to Low Skill Supply and Corresponding Premium

	Dependent variable: medlow relative supply of young workers					
	(1)	(2)	(3)	(4)	(5)	(6)
L.Med/Low Premium	-2.341***					-0.561
	(0.487)					(1.307)
L2.Med/Low Premium		-2.443***				0.571
		(0.380)				(2.255)
L3.Med/Low Premium			-2.465***			-0.388
			(0.297)			(2.595)
L4.Med/Low Premium				-2.373***		-0.611
				(0.280)		(2.384)
L5.Med/Low Premium					-2.096***	-1.483
					(0.325)	(1.714)
Time	2.373***	2.305***	2.155***	1.919***	1.516***	1.893***
	(0.004)	(0.003)	(0.002)	(0.001)	(0.002)	(0.005)
Observations	28	27	26	25	24	24

Notes: The dependent variable is the current relative supply of young medium skilled workers to young low skilled workers. Robust standard errors in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

Table A.2: Young High to Medium Skill Supply and Corresponding College Premium

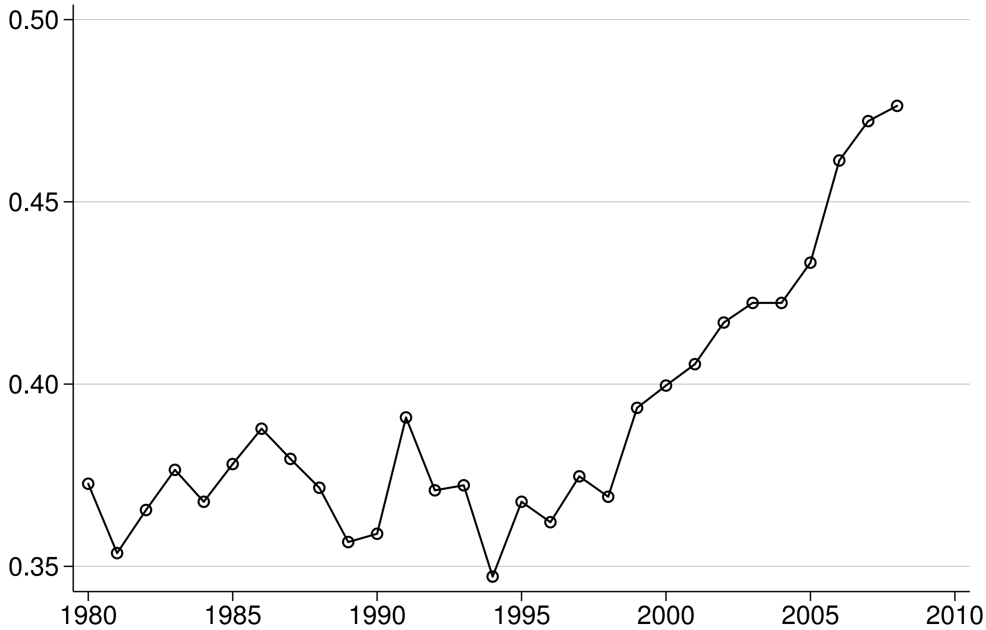
	Dependent variable: highmed relative supply of young workers					
	(1)	(2)	(3)	(4)	(5)	(6)
L.High/Med Premium	-0.069					-0.034
	(0.713)					(1.933)
L2.High/Med Premium		-0.109**				-0.096
		(0.694)				(2.244)
L3.High/Med Premium			-0.123***			0.040
			(0.621)			(2.209)
L4.High/Med Premium				-0.114**		-0.084
				(0.631)		(1.999)
L5.High/Med Premium					-0.054	-0.055
					(0.599)	(1.870)
Time	0.978***	1.001***	1.023***	1.034***	1.011***	1.070***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	28	27	26	25	24	24

Notes: The dependent variable is the current relative supply of young high skilled workers to young medium skilled workers. Robust standard errors in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

Appendix D. Additional Figures

Figure A.1: Difference in log wages between selected percentiles

a) Gap 50-15th Percentile



b) Gap 85-50th Percentile

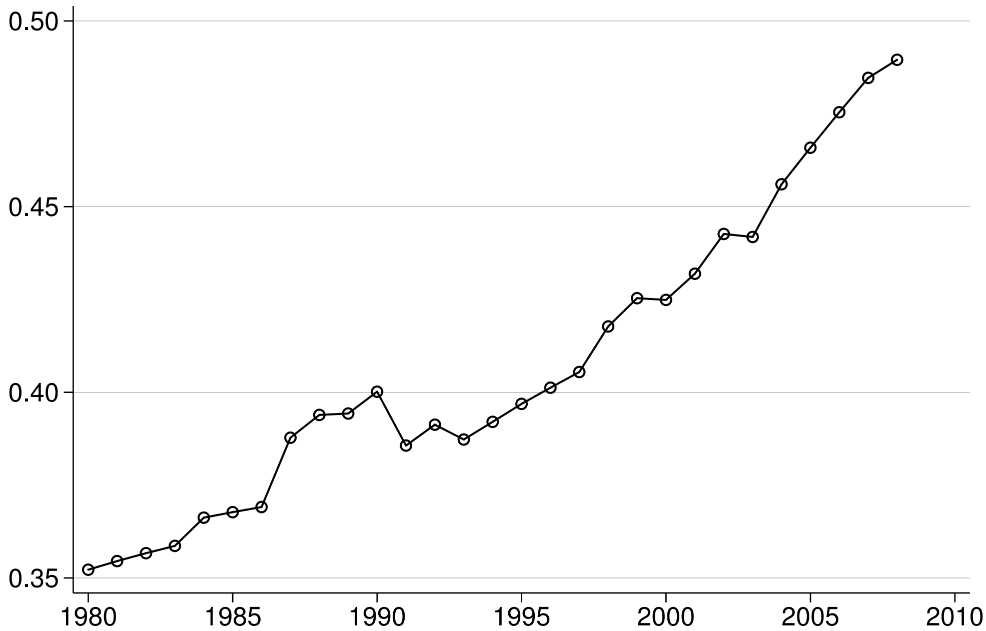
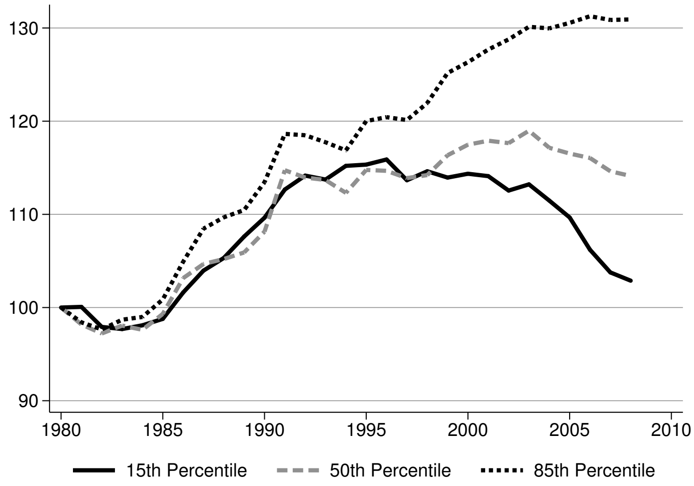
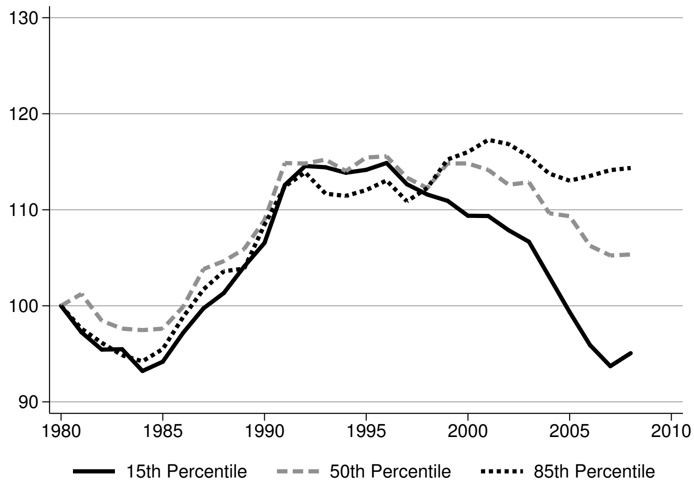


Figure A.2: Indexed real wage growth of the 15th, 50th, and 85th percentile, 1980=100

a) All



b) Young



c) Old

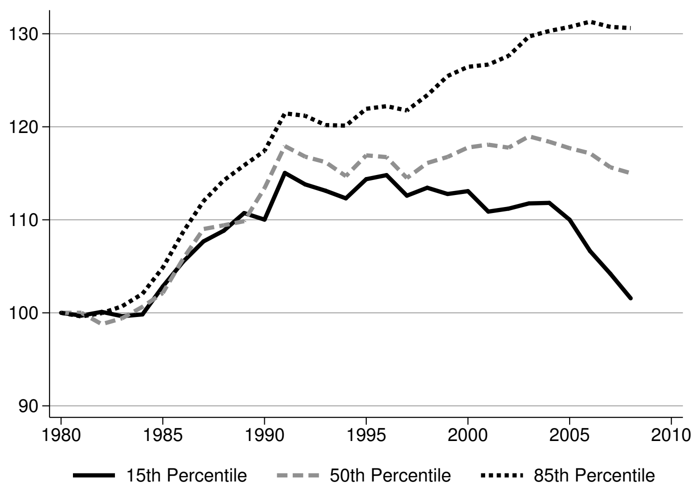


Figure A.3: Log real wages of low, medium, and high skilled workers

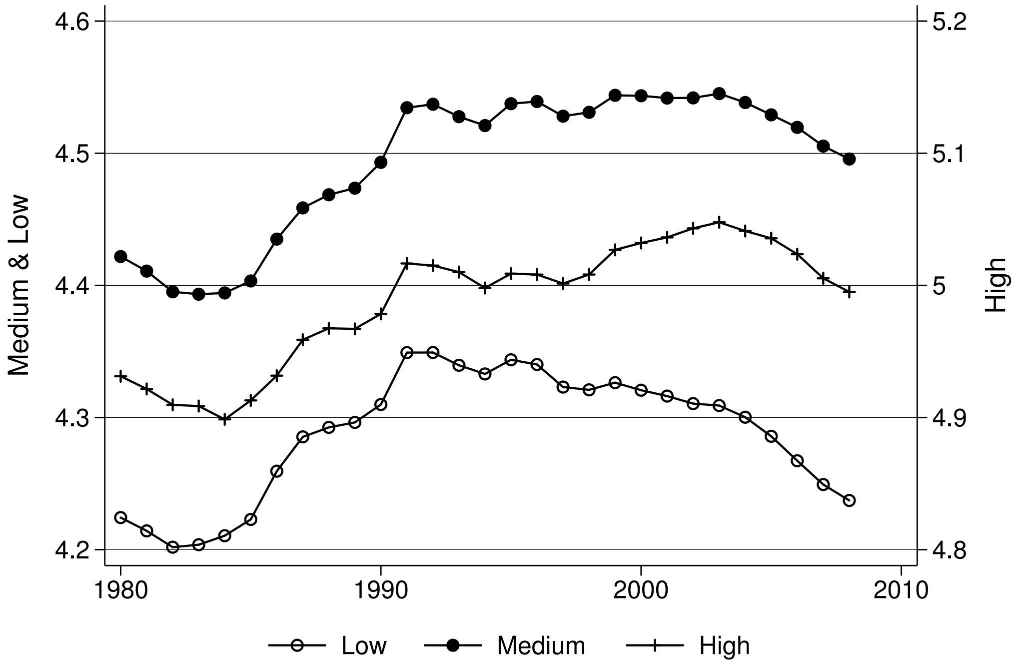


Figure A.4: Real wage 1980-2008 by disaggregated skill groups

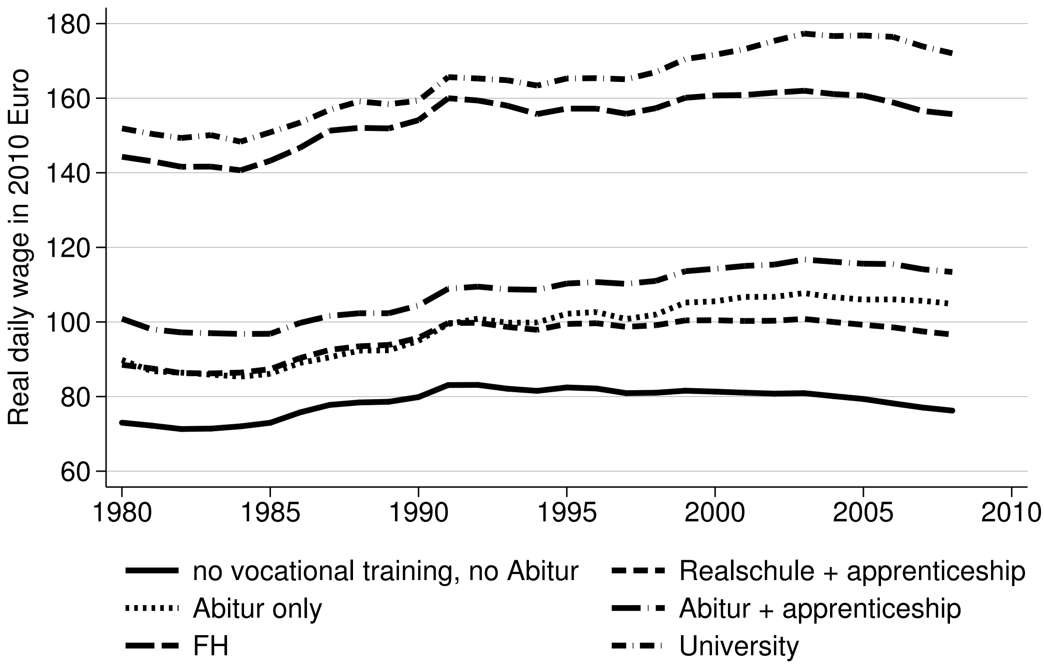
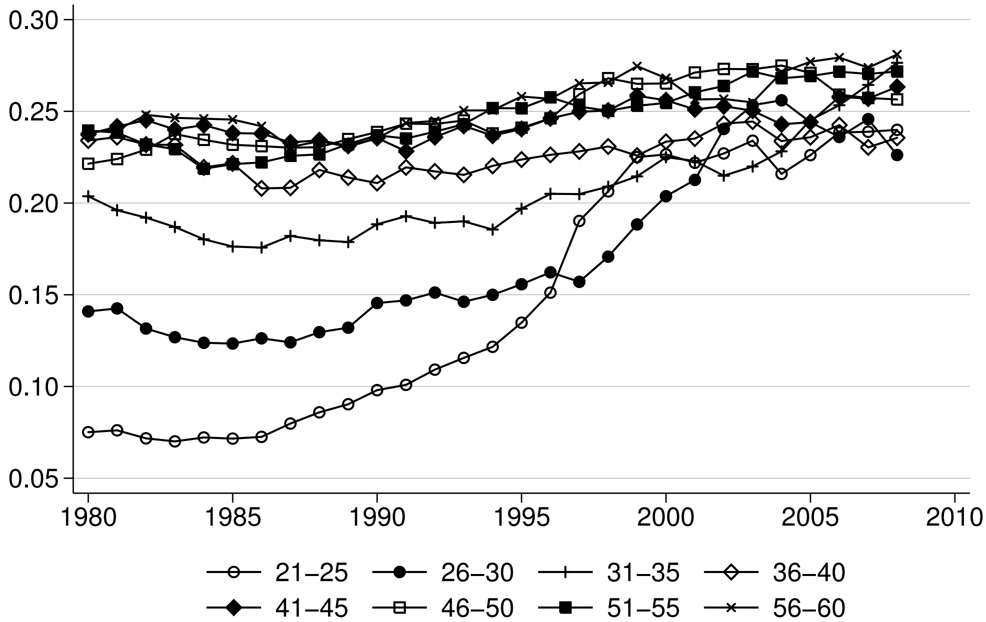


Figure A.5: Skill premiums by eight different age groups

a) Medium to low



b) High to Medium

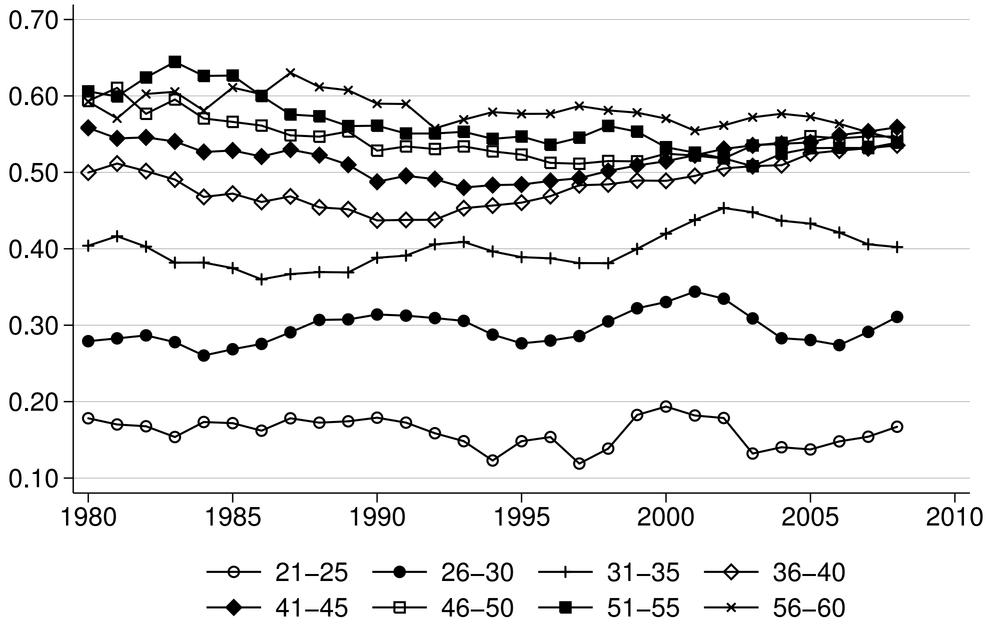
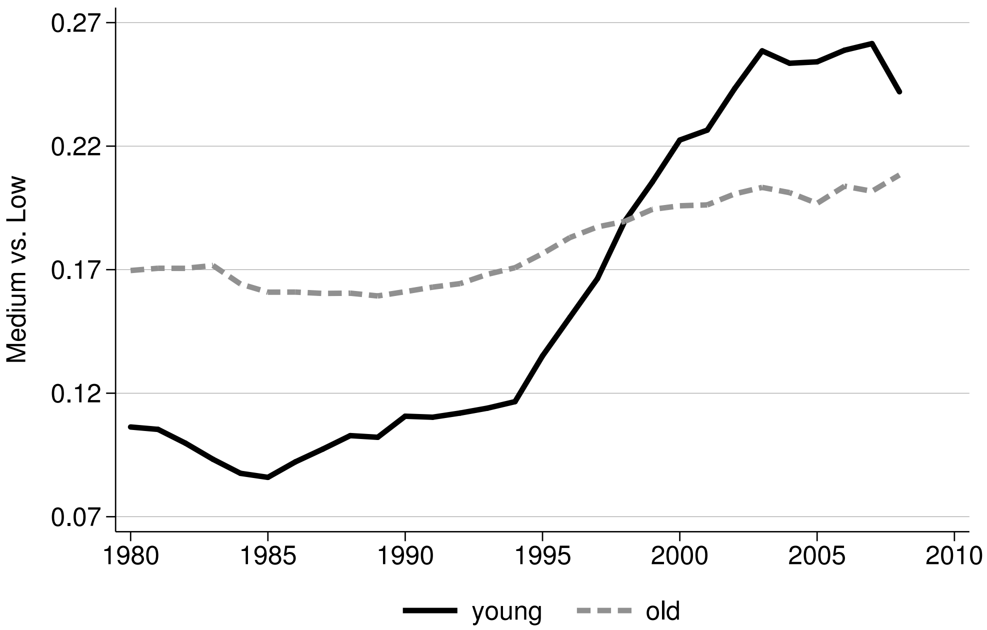


Figure A.6: Skill premiums of men and women separately

a) Men



b) Women

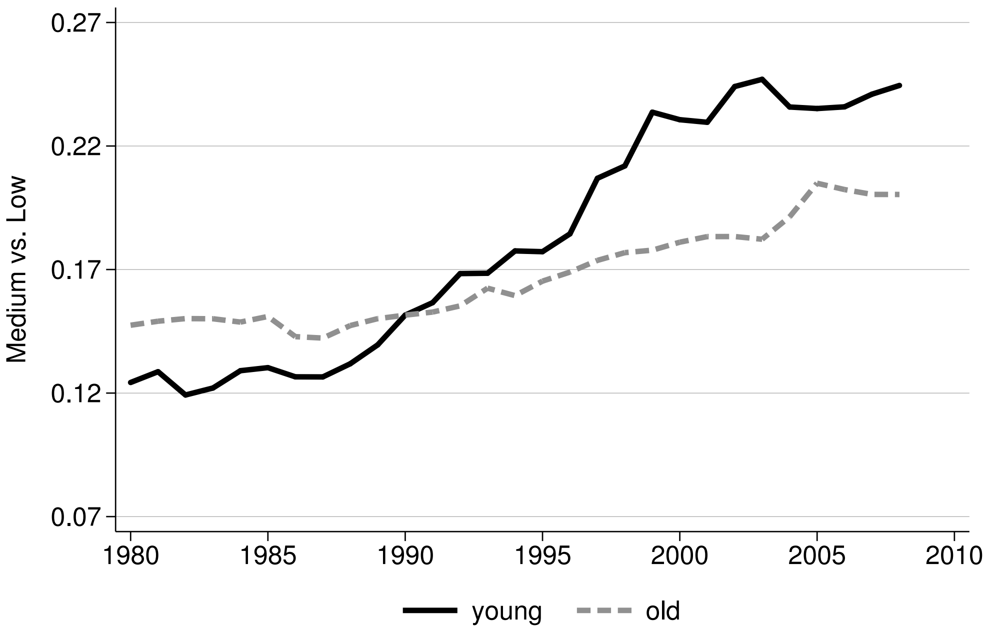
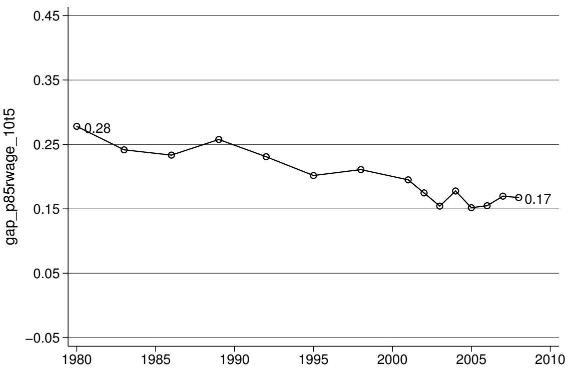
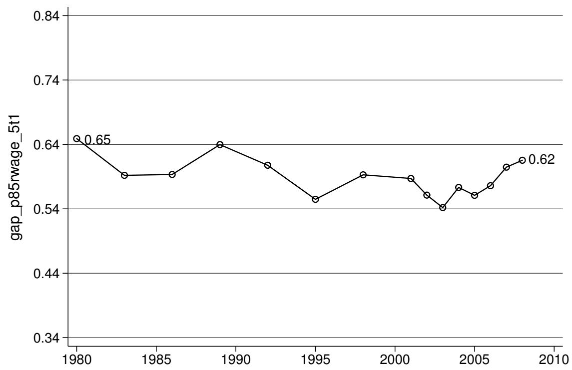


Figure A.7: Gap between the 85th percentile and average income of...

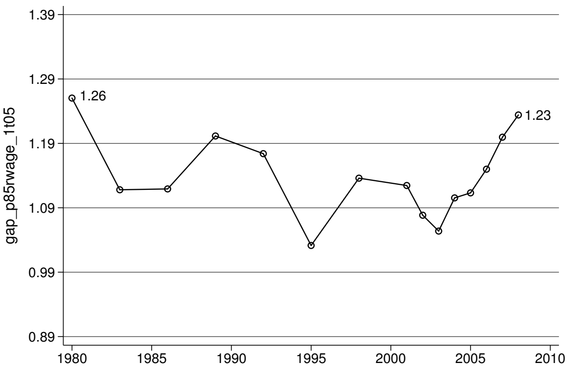
a) top 10-5 percentile



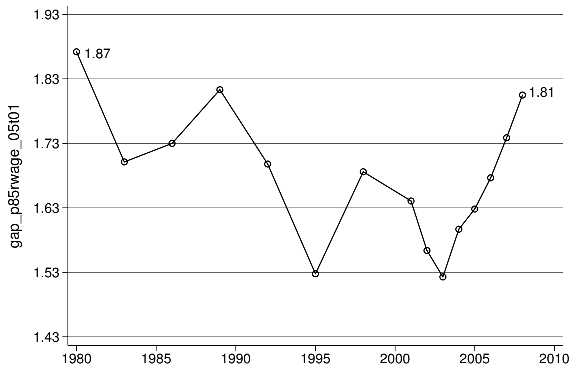
b) top 5-1 percentile



c) top 1-0.5 percentile



d) top 0.5-0.1 percentile



e) top 0.1-0.01 percentile

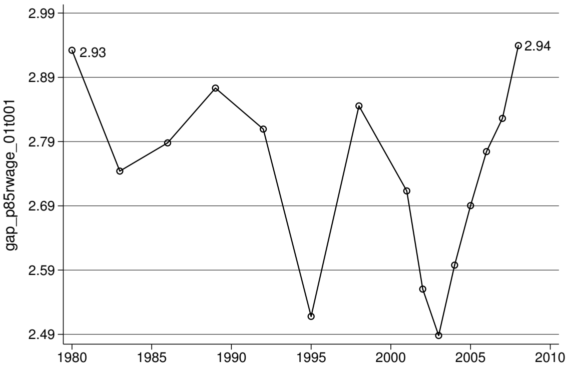


Figure A.8: Comparison of Young High to Medium Premiums (SIAB vs. Mikrozensus)

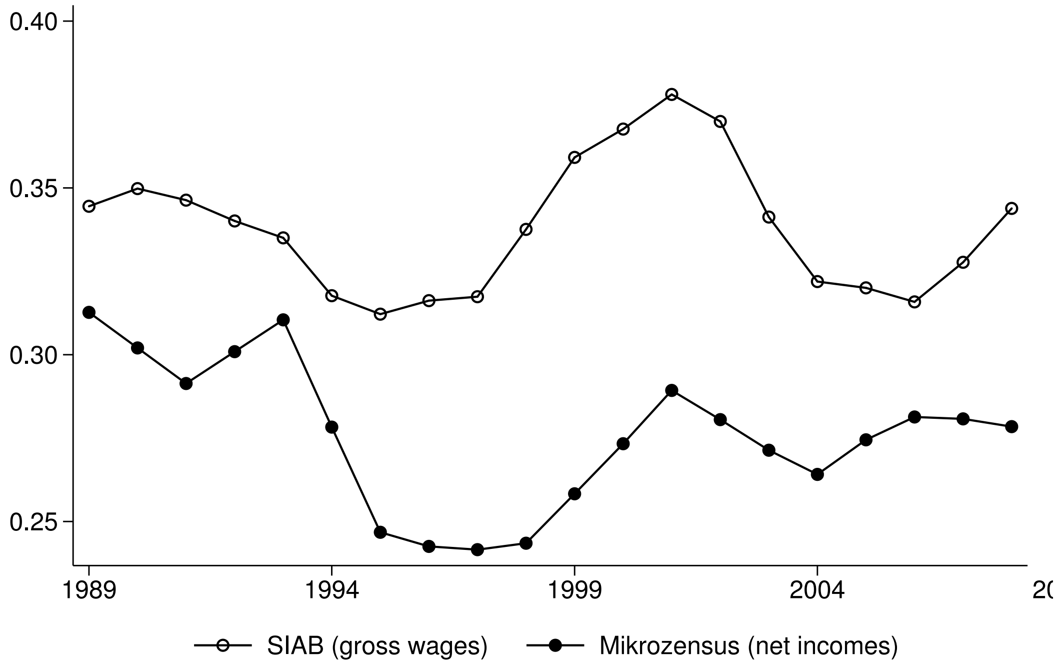


Figure A.9: Co-Movement of the High Skill Premium of Young Workers and GDP Growth

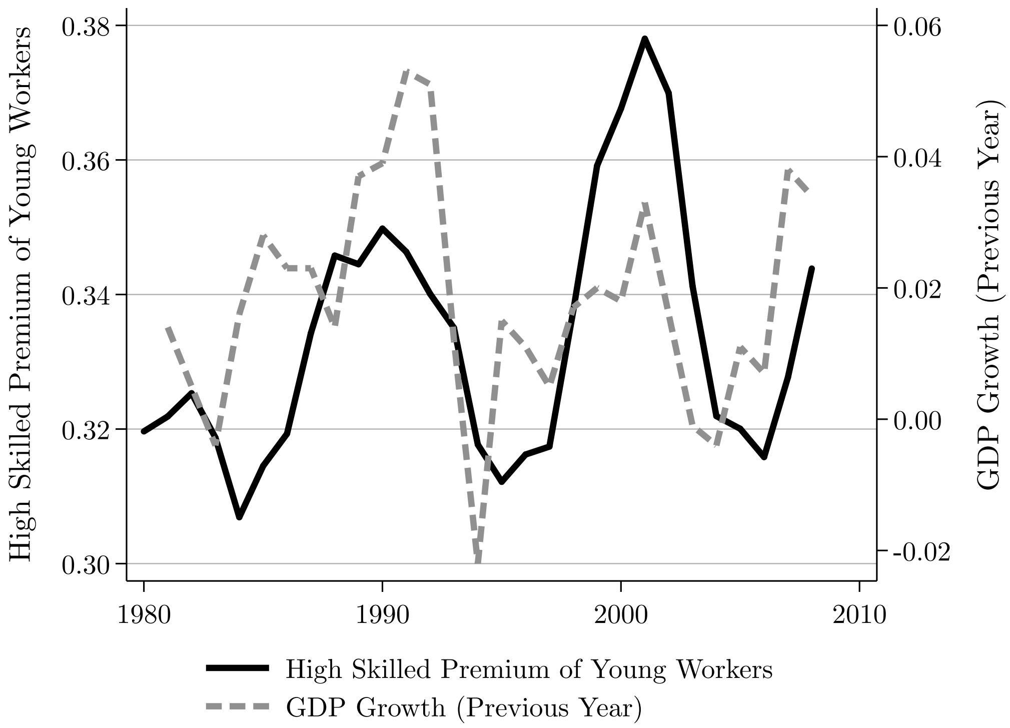


Figure A.10: Observed vs. Fitted Aggregated Medium to Low Skilled Premium (corresponding to model 2 of Table 5)

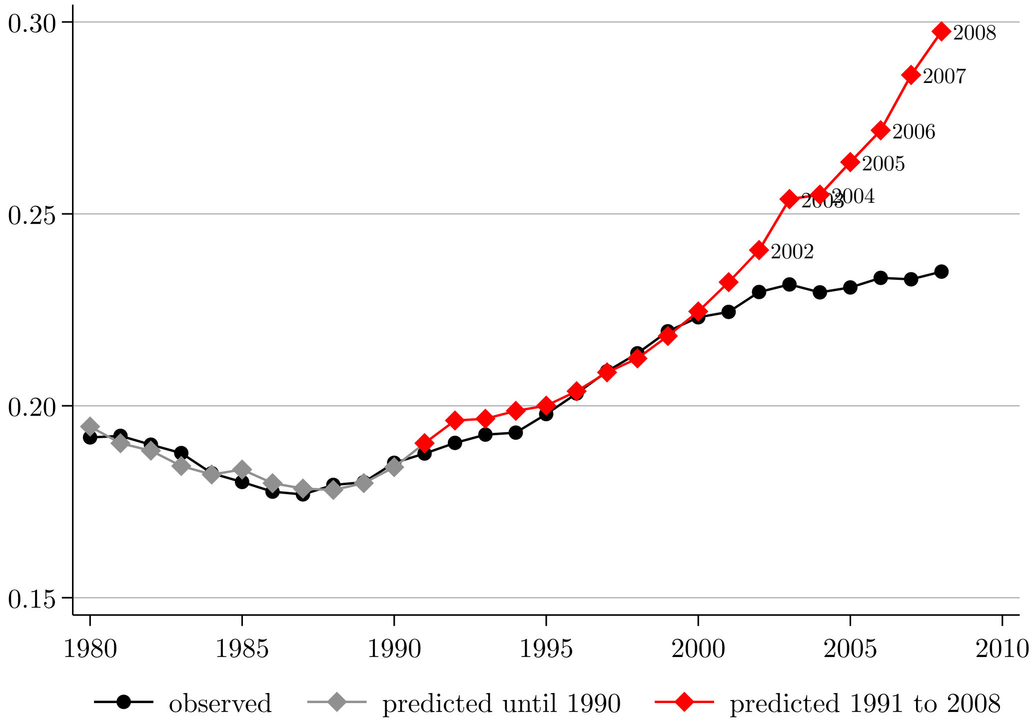
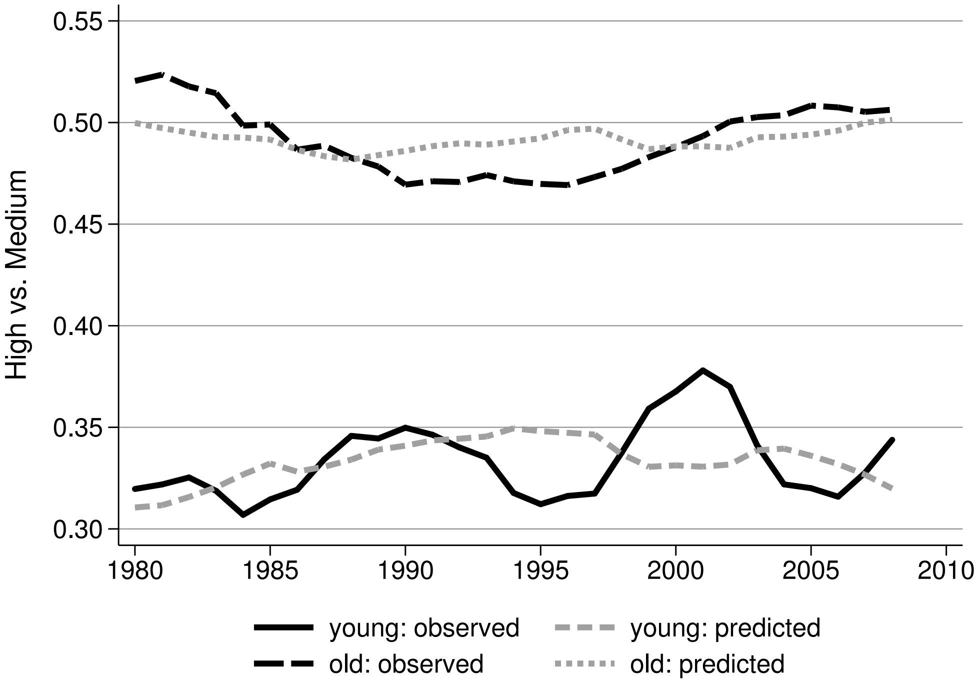


Figure A.11: Predicted vs. Oberved High Skilled Premiums

a) High vs. Medium: all years 1980-2008 (model 1 of Table 6)



b) High vs. Medium: all years 1980-2008 (model 2 of Table 6)