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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 premium since the late 1980s was almost exclusively concentrated among workers aged 30 or below. Using a nested CES production function framework which allows for imperfect substitutability between young and old workers, we show that changes in relative labor supplies can explain these patterns very well. A cohort-level analysis reveals that distinct secular changes in the educational attainment of the native population are the primary source of the declining relative supply of medium-skilled workers in Germany. Low-skilled immigration, in contrast, only plays a secondary role in explaining the rising lower-end wage inequality in Germany over recent decades.

1. Introduction

Income inequality in most OECD countries has increased almost uninterruptedly since the mid-1980s (OECD, 2014). While capital incomes were the main driver of inequality in the US and Europe at the beginning of the 20th century, Piketty and Saez (2014) show that the recent increase is mainly due to rising inequality in labor incomes.[1] But while there seems to be a consensus on the descriptive facts, there still remains a vigorous debate over the drivers of increasing inequality (see e.g. the comprehensive survey in Acemoglu and Autor, 2011).

In this paper, we study how shifts in the supply of skills in Germany can help explain the evolution of wage differentials between different demographic groups defined by education and age. Contrary to much of the literature that has focused on aggregate skill premiums, we pay particular attention to heterogeneity across different age groups. Fig. 1 documents this heterogeneity, showing the evolution of skill premiums in Germany between 1980 and 2008 separately for young and old workers, where young workers are defined as individuals aged 21 to 30 and old workers as individuals aged 31 to 60. In the top left panel, we plot the medium-to-low skill premiums, where the low-skilled are individu-

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[1] 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.

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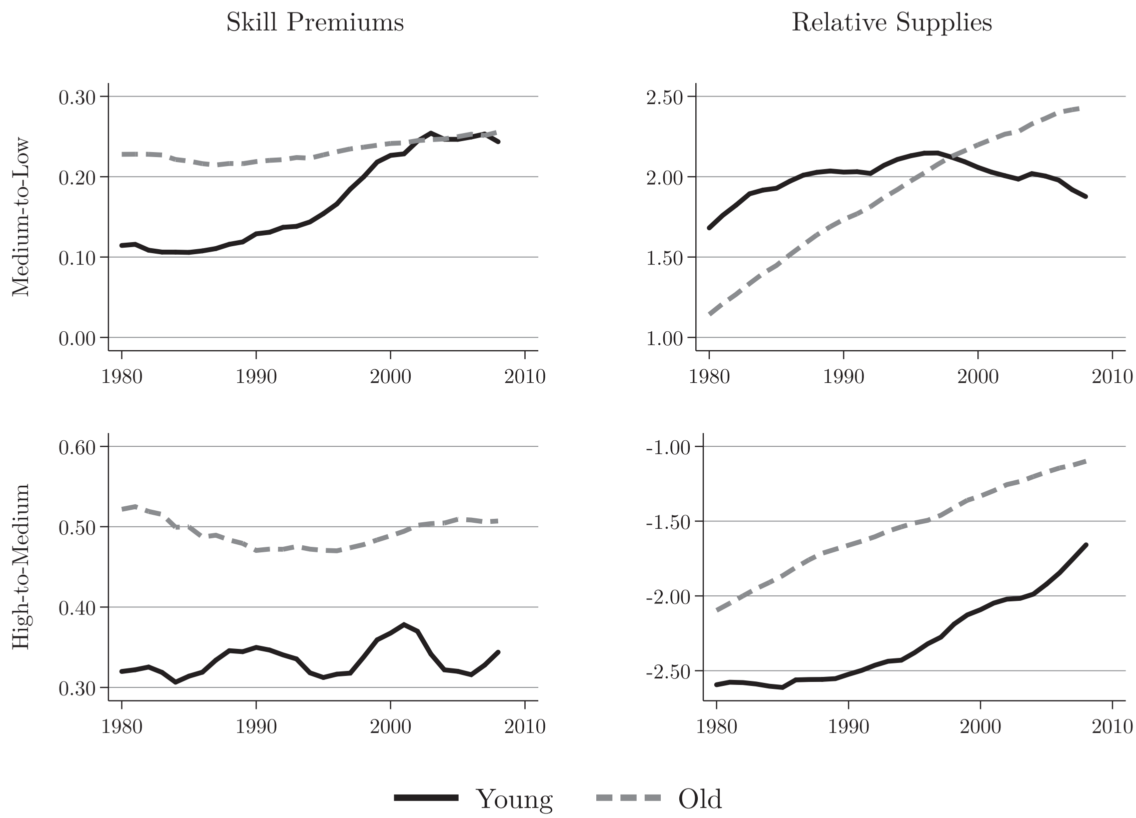


Fig. 1. Skill Premiums and Relative Supplies.
Notes: This figure plots on the left hand side the difference in composition constant mean log earnings between medium- and low-skilled workers (upper left) and high- and medium-skilled workers (bottom left) who work full-time, live in West-Germany and have not moved from East to West-Germany, separately for the young and old between 1980-2008. The right hand side depicts the corresponding difference in log supplies in efficiency units of all workers in West-Germany including full-time, part-time and vocational training spells but excluding marginal part-time spells. For more details on the construction of the skill premiums and efficiency supplies, see Section 3.3 and Appendices A.4 and A.5.

als with missing or at most lower secondary education and the medium-skilled individuals with an apprenticeship, vocational training and/or high school degree. While the premium for old medium-skilled workers remained relatively flat over the time period considered, the premium of young medium-skilled workers more than doubled, from 11 log points in the mid 1980s to 25 log points in the 2000s.[2] The development of the high-to-medium skill premium is depicted in the bottom left panel of Fig. 1, where the high-skilled are defined as individuals with a college degree. While the college premium of young high-skilled workers fluctuated around a value of 33 log points, the premium of old workers followed a mild U-shaped pattern, starting from 52 log points in 1980, passing through a low of 47 log points during the 1990s, and then increasing again to 51 log points in 2008.[3]

The distinct dynamics of age-specific skill premiums shown in Fig. 1, especially those between medium- and low-skilled workers, are striking and have largely gone unnoticed in the literature so far.[4] Our core hypothesis is that these changes in relative wages are largely driven by changes in the supplies of different skill groups in conjunction with secular increases in the demand for skilled workers. To provide some first supporting evidence, the right column of Fig. 1 plots the relative supplies of medium-to-low skilled and high-to-medium skilled labor, separately for young and old workers. Focusing on the top panel, we see that the relative supply of old medium-skilled workers increased in an almost linear fashion, similar to the relative supply of old high-skilled workers shown in the panel below. In contrast, the relative supply of young medium-skilled workers increased steadily up until the mid-1990s but then started to decline again over the following decade. This trend reversal closely mirrors the corresponding skill premium dynamics, pointing towards an important role for labor supply in determining skill premiums and wage inequality in Germany. Fig. 2 corroborates this point, plotting the medium-to-low and high-to-medium skill premiums of both young and old workers against their respective relative supplies, both linearly detrended to absorb, for instance, the impacts of secular skill-

[2] To put these numbers in perspective, according to Goldin and Katz (2009, Fig. 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 around 23 log points in 1980 to 29 log points in 2005.

[3] Since the depicted college premiums are partly based on imputed wages due to right-censoring in our administrative data, there is a concern about how accurately they represent the actual high-skilled premiums. In Appendix A.2, 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 *World Top Incomes Database* (WTID, Alvaredo et al., 2017). Theses comparisons reassure us that our skill premiums are indeed representative for the true evolution of the earnings gap between high- and medium-skilled workers in Germany.

[4] The only exception is Fitzenberger and Kohn (2006) who, similar to us, apply the CES production framework of Card and Lemieux (2001) to estimate elasticities of substitution between different age and education groups, and then use those estimates to assess which magnitude of wage changes would have been necessary to halve skill-specific unemployment rates in Germany in 1997.

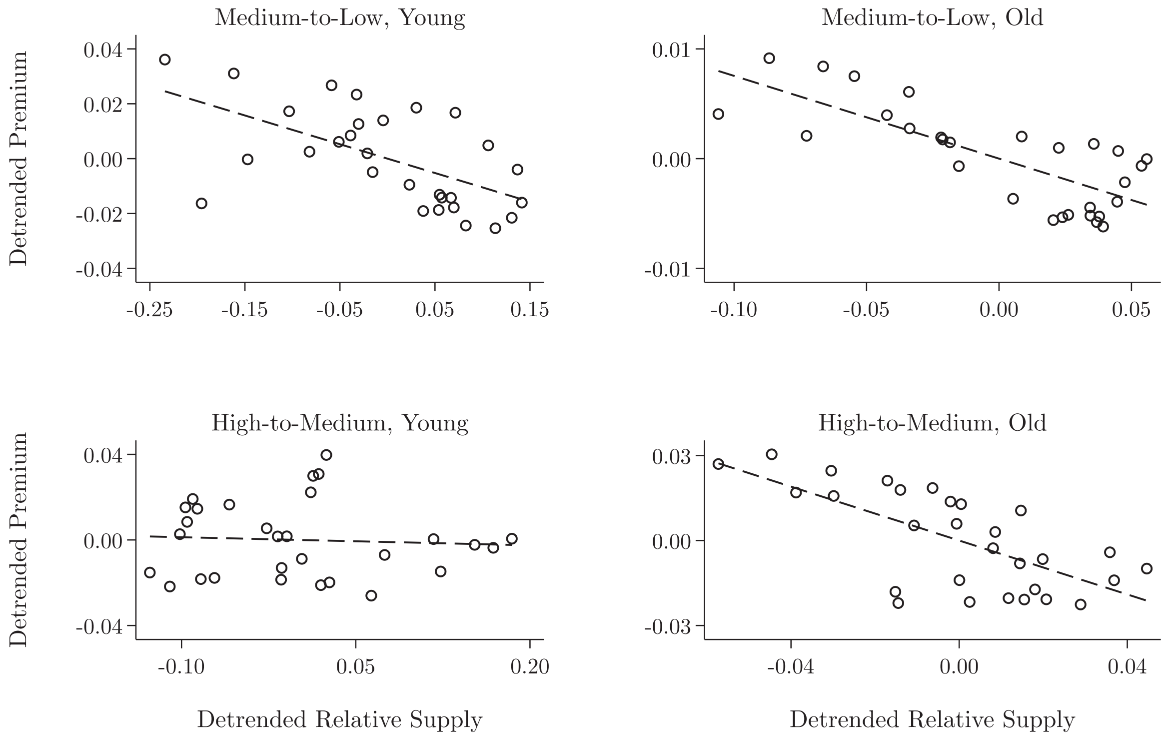


Fig. 2. Scatter Plots Premiums vs. Relative Supplies (1980-2008).
Notes: This figure plots skill premiums against their relative efficiency supplies, separately for young and old workers. Each circle represents a specific year. All variables are linearly detrended over the period 1980-2008. For more details on the construction of the skill premiums and efficiency supplies, see Section 3.3 and Appendices A.4 and A.5.

biased technological change. Except for the young high-skilled[5], there is a clear negative relationship despite the many rigidities governing the German labor market.

To test our hypothesis more rigorously, we set up an analytical production function framework in which increases in the relative supply of more skilled workers and skill-biased technological change work in opposite directions in determining wage premiums. Building on previous work by Card and Lemieux (2001), we distinguish between three different education-based skill groups and between young and old workers, emphasizing the role played by imperfect substitutability across age groups and changes in educational attainment across cohorts. Using high quality administrative data for Germany covering the period 1980-2008, we show that our proposed framework is able to account for the differential patterns in observed skill premiums very well, especially for the medium-to-low skill premium. Methodologically, we contribute to the literature by estimating standard errors in a more sophisticated way, accounting for the uncertainty induced by generated regressors and the serial and cross-equation correlation of the key variables involved using a moving block bootstrap approach (Kunsch, 1989). As it turns out, standard errors based on this method are up to five times larger than those based on conventional methods.

After having established a close link between the supply and price of skills, in the second part of the paper, we trace the precise origin of the observed shifts in relative skill supplies. Using data from the German microcensus, we document the long-term trends in educational attainment across cohorts 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, with the shares of high- and low-skilled natives relatively increasing and the share of medium-skilled natives decreasing markedly. Apart from a recent study by Antonczyk et al. (2018), who provide a detailed comparative analysis of wage inequality in the US and Germany, this observation has gained little attention in the literature. We also show that low-skilled immigration, a possible alternative explanation put forward in the literature (Dustmann et al., 2009) only plays a secondary role in explaining the rising medium-to-low skill premium after 1990.

In focusing on heterogeneity across age groups, our paper provides a more nuanced view of the main changes in wage inequality in Germany relative to the existing literature. Consistent with the findings of Card and Lemieux (2001), we find strong evidence for imperfect substitutability between different age groups, suggesting that an exclusive focus on aggregate skill premiums, as is common in much of the literature, may miss an important part of the underlying heterogeneity of a country's wage structure. Our empirical results are informative for policy makers who have an interest in identifying those subgroups of the population that are most affected by changing fundamentals in the labor market. The key finding that changes in skill premiums are largely driven by changes in relative supply is particularly meaningful since future changes in age- and skill-specific supplies are relatively easy to project based on available demographic and school enrolment data, thus allowing tentative predictions about future changes in wage inequality.

Our modelling approach is closely linked to a literature which started with the seminal paper by Katz and Murphy (1992) who use a CES-production function framework to systematically link supply and demand factors to wage premiums. In introducing imperfect substitutability between young and old workers, we build on work by Card and Lemieux (2001) who study the evolution of wage inequality across skill and age groups in the US, Canada and the UK. Our analysis also relates to a range of studies that have used German administrative data to study the rise in German wage inequality. Most closely related is the work by Dustmann et al. (2009) who document trends in German wage inequality and perform an extensive analysis of competing explanations,

[5] The relationship for 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 also the discussion in Section 4).

identifying compositional changes (DiNardo et al., 1996), a decline in unionization (Antonczyk et al., 2010; Biewen and Seckler, 2019), skill-biased demand shifts favoring the high-skilled, polarization (Goos and Manning, 2007; Autor et al., 2009; Autor and Dorn, 2014) and changes in the supply of skills (Goldin and Katz, 2009) as key contributors. Contrary to our work, Dustmann et al. (2009) do not allow for imperfect substitutability between young and old workers and focus exclusively on changes in the aggregate medium-to-low and high-to-medium skill premiums. However, as shown in Fig. 1, wage inequality does not change uniformly for young and old workers. Our findings therefore complement and extend their more aggregate analysis.

Similar to this paper, Boockmann and Steiner (2006), Reinhold and Thomsen (2017), and Antonczyk et al. (2018) emphasize the role of cohort effects as important drivers of lower-end wage inequality in Germany and show various pieces of descriptive evidence that are consistent with our findings. Card et al. (2013) identify an increasing dispersion in person- and establishment-specific wage premiums as well as increasing assortative matching as key factors behind rising wage inequality in Germany. Goldschmidt and Schmieder (2017), in turn, focus on the role of domestic outsourcing, calculating that it contributed some 10% to the increase in German wage inequality since the 1980s. Finally, Burda and Seele (2016) document a strong negative correlation between changes in relative labor supply across demographic subgroups (defined by gender, age and geographical region) and changes in these groups' relative wages following the German Hartz reforms in 2003-2005, suggesting, in line with our findings, that labor supply factors are an important driver of rising German wage inequality.

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 3, we describe our data set, explain the construction of our key variables, and present graphical evidence on the evolution of skill premiums and efficiency supplies for young and old workers. These are the patterns we aim to explain in Section 4, where we estimate the key structural parameters of our model. In Section 5, we present our cohort analysis, studying the long-term trends in educational attainment in Germany. Section 6 concludes the paper.

2. Analytical Framework

Our modelling approach and subsequent empirical analysis follows previous work by Card and Lemieux (2001), Autor et al. (2008), Dustmann et al. (2009), and Goldin and Katz (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-skilled) 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 in the production process 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 factor inputs are gross complements. If $\sigma_{hu} \geq 1$ the two factors are gross substitutes and (high-)skill-biased technological change will increase the wage differential in favor of high-skilled workers.[6]

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

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

where θ_t represents a technology or 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. We choose this particular nesting structure to allow for potentially different elasticities of substitution between high and non-high and medium- and low-skilled workers (as in Dustmann et al., 2009). Our production function collapses to the more standard one in which all three education groups are assigned to the same nest (see e.g. Fitzenberger et al., 2006, or D'Amuri et al., 2010) if $\rho = \gamma$ (in which case $\sigma_{ml} = \sigma_{hu}$).[7]

Letting α denote group-specific productivity levels, each type of labor is in turn composed of the corresponding supplies in different age groups

$$L_t = \left[\sum_j (\alpha_{lj} L_{jt}^{\eta_l})\right]^{\frac{1}{\eta_l}}$$

$$M_t = \left[\sum_j (\alpha_{mj} M_{jt}^{\eta_m})\right]^{\frac{1}{\eta_m}}$$

$$H_t = \left[\sum_j (\alpha_{hj} H_{jt}^{\eta_h})\right]^{\frac{1}{\eta_h}}$$

which implies that the elasticity of substitution across the different age groups j in skill group s is given by $\sigma_{as} = \frac{1}{1-\eta_s}$. This additional layer in the nesting structure is meant to reflect the fact that workers within the same skill group but of different ages (and thus experience levels) are likely to be imperfect substitutes. Note that, as common in the related literature, we abstract from any sectoral- or occupation-specific heterogeneity, essentially assuming that all workers of a given education-age group are equally affected by changes in relative skill supplies.

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

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

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

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

Assuming that σ_a is the same in each of the three skill groups, i.e. $\sigma_{al} = \sigma_{am} = \sigma_{ah}$ (an assumption we test later on), we obtain the following expressions for the medium-to-low skill premium

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

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

and the high-to-medium skill premium

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

[6] Acemoglu and Autor (2012) make a more careful distinction between demand and technology shifters and discuss how the effect of factor-augmenting technological change on skill premiums depends on the value of σ.

[7] We also considered the alternative approach of placing the medium- and high-skilled workers together in a separate nest but found that in this case the model fit was significantly worse. Regressing the composition-adjusted relative wages of high- and medium-skilled workers on their relative supply (using the same specification as we use for the medium-to-low skill premium in Section 4.3) yields a negative elasticity of substitution of -2.87 and a very poor R^2 of 0.13.

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

Given all σ's > 1, the model predicts that over time the premium of medium-skilled workers in age group j, ω^M_{jt}, *increases* with θ_t, the rate of skill-biased technological change (or shifts in the relative demand for workers with vocational training) and *decreases* with the aggregate 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^H_{jt} depends positively on technological progress favoring the high-skilled relative to the medium-skilled, $\frac{\lambda_t}{\theta_t}$, and negatively on the aggregate 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 4.[8]

3. Data and Descriptive Evidence

3.1. Data Set and Construction of Baseline Sample

To take the model to the data, we need to construct skill premiums and labor supplies for each individual skill-age-group. We use data from the scientific use file of the SIAB 1975-2010 (vom Berge et al., 2013), an administrative data set provided by the Institute for Employment Research. The SIAB is a 2% random sample of the official records of all employees subject to social security in Germany. It contains the labor market history of about 1.5 million individuals, including information on daily wages and employment status (full-time, part-time, unemployed, in vocational training) as well as individual characteristics such as age, gender, skill, nationality, region, occupation, and industry. Following Dustmann et al. (2009), we restrict the analysis to men and women aged between 21 and 60 living in West Germany with earnings above the official marginal earnings threshold in each year (400 euros per month in 2010).[9] Our relatively broad age range ensures that we include the relevant young subpopulations, especially among the medium- and low-skilled workers, in our sample. We exclude the years 1975-1979 from our sample due to the high incidence of censoring among the high-skilled during those years. We also drop observations from the financial crisis years 2009/2010, so that our final sample covers the time period 1980 to 2008. In preparing the data, we conduct three imputations that are by now common practice when working with the SIAB 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 proposed by Gartner (2005). Appendix A.3 provides a more detailed description of the construction of our baseline sample.

3.2. Definition of Skill and Age Groups

For our empirical 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 medium secondary education (*Realschule* or less), medium-skilled as those with apprenticeships, vocational training, and/or a high school degree (*Abitur*), and high-skilled as those with a tertiary degree (*Fachhochschule* or *Universität*). This grouping differs from many US studies where a distinction is only made between college and non-college labor (Card and Lemieux, 2001; Autor, 2014). The division into three skill groups reflects Germany's strong pillar of vocational training and is also indicated by a comparison of the wage levels of these groups (see Fig. A.1). Along the age dimension, we consider eight different age groups spanning five year intervals for ages between 21 and 60 years.[10] For most of the graphical evidence and empirical estimations, however, we only distinguish in each skill group between young (≤ 30 years) and old workers (> 30 years) as these two groups capture well the underlying trends of the more finely disaggregated age groups.[11]

3.3. Skill Premiums and Efficiency Labor Supplies

Our objective is to calculate the 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. To keep our premium sample as homogeneous as possible, we restrict our attention to men and women who work full-time and are "West German natives", i.e. we exclude individuals 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.[12] We then calculate age and gender composition constant skill premiums similar to Katz and Murphy (1992) and Dustmann et al. (2009).[13] Skill premiums can be interpreted as the (approximate) percentage difference in wages between two skill groups. Appendix A.4 describes the procedure to compute the various skill premiums in more detail.

As in Katz and Murphy (1992), our labor supply measures are expressed in efficiency units which can be understood as productivity-adjusted full-time equivalents. To compute efficiency labor supplies, we include full-time, part-time (but no marginal part-time spells as noted above) and vocational training spells of all workers registered in West Germany, i.e. we include West German natives as well as foreigners

[8] When $\ln(M_{jt}/L_{jt}) - \ln(M_t/L_t)$ in Eq. (6) varies over time as suggested by Fig. 1, observed age-group-specific skill premiums will contain significant cohort effects (compare Card and Lemieux, 2001). Fig. A.2 in the appendix shows life-cycle profiles for the medium-to-low skill premiums of different birth cohorts (aggregated into 5-year intervals). Starting with the 1971-1975 cohort, the initial skill premium at the time of labor market entry increased significantly in Germany, constituting a major driver of the rising medium-to-low skill premium of young workers depicted in the top left panel of Fig. 1. There is also evidence of a flattening of the life-cycle profiles for more recent cohorts, consistent with the relatively flat skill premium profile of older workers in Fig. 1.

[9] We exclude spells with earnings below the marginal earnings threshold since these spells were only officially recorded in the administrative data from 1999 onwards. We convert all monetary values into 2010 euros using the consumer price index of the German Bundesbank.

[10] As robustness checks, we restrict the sample to workers aged 25 to 60 or exclude workers older than 55 to address concerns related to early retirement schemes (see Table 5 in Subsection 4.5).

[11] Fig. A.3 shows the evolution of the medium-to-low and high-to-medium skill premium separately for eight different age groups, indicating that those aged above 30 and below follow a similar pattern.

[12] Ideally, we would also like to exclude ethnic Germans and those East Germans who either came to work in West-Germany during 1989-1991 or who started their employment history in West-Germany right away. However, we cannot identify these individuals in the SIAB data. We will identify these groups *as aggregates* using alternative data sets when we assess the impact of migration on skill premiums in Section 5.

[13] Fig. A.4 in the appendix compares "raw", i.e. unadjusted, and composition-adjusted skill premiums for young and old workers, showing that, while compositional changes in terms of age and gender play some role, raw and adjusted premiums generally follow the same trajectories. Holding, in addition, the occupational or sectoral composition within skill group constant does not change the main patterns either as shown in Fig. A.5, although there is evidence that some of the observed increase in the medium-to-low skill premium of young workers during the late 1990s and early 2000s is mediated by medium-skilled workers moving into relatively better paying sectors and occupations.

Table 1
Summary Statistics of Wage and Supply Sample.

	1980	1990	2000	2008
Panel A. Wage Sample (Full-Time Natives)				
Age	39.0	38.4	39.8	41.4
Young (≤ 30 years)	0.29	0.31	0.20	0.19
Female	0.32	0.33	0.34	0.33
Shares:				
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
Real monthly wage (2010 euros):				
Low-skilled	2,221	2,429	2,474	2,318
Medium-skilled	2,702	2,926	3,097	3,009
High-skilled	4,491	4,767	5,080	5,033
Std. dev. of log real wages	0.41	0.43	0.45	0.51
Person × spells in year	332,702	371,798	364,347	372,580
Unique Individuals	288,358	315,386	288,219	267,028
Panel B. Supply Sample (All Workers)				
Age	38.7	38.2	39.5	40.9
Young (≤ 30 years)	0.29	0.32	0.22	0.21
Female	0.37	0.40	0.47	0.48
German	0.90	0.91	0.88	0.86
Shares:				
Low skilled	0.25	0.17	0.14	0.12
Medium skilled	0.70	0.76	0.76	0.75
High skilled	0.05	0.07	0.10	0.13
Full-time	0.90	0.87	0.73	0.67
Long part-time	0.07	0.09	0.12	0.14
Short part-time	0.02	0.02	0.13	0.16
Vocational/other	0.01	0.02	0.02	0.03
Person × spells in year	444,080	523,422	694,593	804,389
Unique Individuals	374,722	428,417	494,159	504,943

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

and those who were first registered in East Germany and subsequently migrated to West Germany (we will refer to the latter two groups as “migrants” in what follows). In contrast to our premium data, and in line with the literature (e.g. Card and Lemieux, 2001; Dustmann et al., 2009), we choose such a broad set of workers and spell types to more comprehensively capture the overall supply of labor in the market.

Labor supplies need to be measured in efficiency units since the framework outlined in Section 2 assumes that workers within the same skill-age cell are perfect substitutes. To account for this, we allow productivities (reflected in wages) to differ by age and skill group as well as gender and West German nativity.[14] Finally, we translate spells into full-time equivalents. Since working hours are not readily observable in the IAB data, we approximate them by assigning long part-time spells (i.e. part-time spells with more than half of the hours of a comparable full-time work schedule) a weight of 2/3 and short part-time spells (i.e. part-time spells with less than half of the hours of a comparable full-time work schedule) a weight of 1/3. Vocational training spells are also assigned a weight of 1/3. In our robustness checks, we show that our results are not sensitive to the specific weighting scheme. Appendix A.5 provides more details on the construction of our efficiency supplies.

3.4. Summary Statistics

In Panel A of Table 1, we summarize some characteristics of the sample of native West German full-time workers based on which we construct the different wage premiums. Between 1980 and 2008, this group of workers became older, with the share of young workers aged below 30 dropping from around 29% in the 1980s to 19% in 2008. This is the consequence of declining cohorts sizes after the baby boom 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 changed dramatically. The share of low-skilled workers dropped from 20% in 1980 to 6% in 2008, with the largest decline occurring in the 1980s. The share of medium-skilled workers followed an inverted U-shape reaching 81% in the 1990s and then declining to 79% in 2008. The share of high-skilled workers increased threefold since 1980 in an almost linear fashion, reaching 15% in 2008. Real monthly wages in all three skill groups grew during the 1980s and the 1990s but then declined in the 2000s. Wage inequality measured as the standard deviation of log real wages remained relatively stable up to the end of the 1990s but increased considerably thereafter.[15]

Panel B summarizes our supply data. The workforce including part-time and vocational training spells is, on average, slightly younger and significantly more female than the sample of native full-time workers. The share of females rose much more over time than in the full-time wage sample since the increased participation of women was concentrated mainly in part-time jobs (see also Burda and Seele, 2016). The broader group of workers in the supply sample is also less well educated compared to the workers in the full-time wage sample summarized in Panel A.

4. Empirical Estimation

4.1. General Estimation Approach and Standard Errors

We now turn to the estimation of the model outlined in Section 2 using the skill premiums and efficiency labor supplies introduced in Section 3. We estimate the model's parameters from bottom to top in three steps. First, using the premium Eqs. (5) and (7), we estimate σ_a (the elasticity of substitution between young and old workers) and the efficiency parameters α_s. Based on these parameters, we then construct the aggregate 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 the efficiency parameters θ_t, which are needed to construct U_t, the aggregate amount of non-high-skilled labor. Finally, in the third step, we use the aggregate amounts of the different skill types to estimate σ_{hu} (the elasticity of substitution between college and non-college labor). This final step yields estimates for the various parameters estimated in the previous two steps and can therefore serve as an internal consistency check.

To compute standard errors, we rely on a moving block bootstrap approach (see e.g. Hall et al., 1995, or Antonczyk et al., 2018). Bootstrapping standard errors in our setting is necessary for various reasons. First, the three-step estimation procedure implies that we rely on

[14] One reason to allow for different efficiency weights for women is that women, on average, work less hours than men in the same age × skill group, even if both are recorded as working full-time or part-time in the IAB-data. Our results, however, do not depend on allowing for different efficiency weights by gender. Assigning the same efficiency weight to men and women leaves our main results presented in Table 4 virtually unchanged. Accounting for productivity differences between natives and migrants is also important to mitigate issues related to the potential downgrading of migrants' education and experience (see e.g. Friedberg, 2000, Dustmann et al., 2012, or Basilio and Bauer, 2017).

[15] This is in line with Dustmann et al. (2009, Fig. I, p. 850) and Card et al. (2013, Table I, p. 975) who also find an acceleration in the dispersion of log wages in the 1990s for the sample of all full-time West-German workers (including East German movers and foreigners) using IAB data. It is also in line with Biewen and Juhasz (2012) who find an unprecedented rise in net equivalized income inequality since 1999/2000 using SOEP data.

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

	(1)		(2)		(3)	
	Linear Trend (1980–2008)		Time FEs (1980–2008)		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 $(-1/\sigma_a)$	-0.116***	-0.116***	-0.127***	-0.127***	-0.132***	-0.132***
	(0.014)	(0.014)	(0.012)	(0.012)	(0.047)	(0.047)
Young	-0.050***	-0.246***	-0.049***	-0.255***	-0.047**	-0.265***
	(0.004)	(0.011)	(0.004)	(0.009)	(0.022)	(0.029)
Time	0.007***	0.004***			0.006**	0.002
	(0.001)	(0.001)			(0.003)	(0.004)
Constant	0.346***	0.250***	0.375***	0.250***	0.376***	0.241**
	(0.018)	(0.031)	(0.024)	(0.025)	(0.051)	(0.109)
Time FEs			✓	✓		
σ_a	8.6	8.6	7.9	7.9	7.6	7.6
	(1.1)	(1.1)	(0.8)	(0.8)	(2.7)	(2.7)
Observations	58	58	58	58	22	22
R^2	0.958	0.952	0.989	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. The number of observations refers to the full sample, n. Young is an indicator for age ≤ 30 years. Moving block bootstrap standard errors with block length 3 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

generated regressors in steps 2 and 3, so the estimation uncertainty induced by the previous steps needs to be accounted for. Second, the age-group-specific medium-to-low and high-to-medium skill premiums are correlated by construction since both involve the composition-adjusted observed wages of medium-skilled workers. Third, skill premiums are likely to be serially correlated over time.[16] The moving block bootstrap ensures that our estimated standard errors are robust to these types of correlation and added uncertainty by allowing the error terms within a given block to be arbitrarily correlated between equations and over time.[17] To implement it, we randomly draw blocks of observations from the sample, where each block extends across b contiguous years and comprises, for both age groups, information on the medium-to-low and high-to-medium skill premiums and their associated relative supplies. Following the suggestion of Hall et al. (1995), we choose a block length of $b = 3$.[18] Each bootstrap sample is then constructed by drawing, with replacement, the largest possible number of blocks k such that the total number of observations contained in these k blocks is not larger than the number of observations in the full sample. Hence, for the sample period 1980-2008, each bootstrap sample consists of $k = 9$ randomly drawn blocks of length $b = 3$, resulting in $n_{bs} = 54$ observations per skill premium in the first step of our estimation procedure (four less than available in the full sample where $n = 58$).

Since directly bootstrapping the various elasticities of substitution does not lead to a well-defined variance due to the discontinuity of the inverse function at zero, we compute their standard errors using the delta method, relying on the estimated bootstrap distribution of $1/\sigma$ obtained from 500 resamples. Whenever we estimate two premium equations jointly, we use a seemingly unrelated regression framework to account for possible correlation of the error terms and to impose parameter constraints across equations.

Previous related work did not consider the 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, thus ignoring the potential correlation across equations. A comparison of the different approaches in our setting shows that standard errors obtained from the moving block bootstrap are up to five times larger than 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.

4.2. 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 Eq. (5) and the first three of Eq. (7) by a linear time 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 σ_a since $\beta_a = -\frac{1}{\sigma_a}$:

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

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

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. The

[16] There is also sampling uncertainty related to the estimation of premiums and supplies. However, given the large number of observations and the extremely tight confidence intervals, this uncertainty contributes very little to the overall uncertainty related to our estimations, which is why we abstract from it in what follows. For similar reasons, we also decided to ignore the uncertainty induced by the imputation of top coded wages. Effectively, we thus take skill premiums and supplies as given.

[17] 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). Furthermore, Hall et al. (1995) show that overlapping blocks provide somewhat higher efficiency than non-overlapping ones even though the efficiency differences are likely to be small in practical applications.

[18] We also used a more conservative block length of 5 and all results remain significant at least at the 10%-level.

Table 3
Estimating the Elasticity between Medium- and Low-skilled Labor σ_{ml}.

	(1) Simple 1980-2008 ω_t^M	(2) Simple 1980-1990 ω_t^M	(3) Simple 1980-2001 ω_t^M	(4) Trend Break 2002 ω_t^M	(5) Full Trend Break 2002 ω_t^M
Aggr. Medium-to-Low Rel. Supply $(-1/\sigma_{ml})$	-0.109	-0.242	-0.246***	-0.257***	-0.251***
	(0.088)	(0.148)	(0.078)	(0.069)	(0.074)
Aggr. Medium-to-Low Rel. Supply $(-1/\sigma_{ml})\times$ Post 2002					0.001
					(0.002)
Time	0.007*	0.012	0.013***	0.013***	0.013***
	(0.003)	(0.009)	(0.003)	(0.003)	(0.003)
Time × Post 2002				-0.007***	-0.007***
				(0.001)	(0.001)
Constant	0.313***	0.481***	0.483***	0.497***	0.490***
	(0.119)	(0.175)	(0.103)	(0.094)	(0.100)
σ_{ml}	9.2	4.1	4.1	3.9	4.0
	(7.4)	(2.5)	(1.3)	(1.0)	(1.2)
Observations	29	11	23	29	29
R^2	0.906	0.837	0.950	0.973	0.974

Notes: This table presents regressions results of the aggregate medium skill premium ω_t^M on the aggregate relative supply of medium- to low-skilled workers $\ln\left(\frac{M_t}{L_t}\right)$. 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. The number of observations refers to the full sample, n. Young is an indicator for age ≤ 30 years. Moving block bootstrap standard errors with block length 3 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

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 with a linear time trend as a sort 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 7.9, which is somewhat higher than the estimates by Card and Lemieux (2001) of around 5 for the US and 6 for Canada.[19]

In Appendix A.6, we consider the case where we allow σ_a to differ across skill groups. According to this more flexible approach, young and old workers are found to be closer substitutes within the group of low skill workers ($\sigma_{al} = 14$) than in the groups of medium- and high-skilled workers (for which σ_a is about 7). For simplicity, and since equality of σ_{al}, σ_{am}, and σ_{ah} cannot be rejected statistically, we continue assuming a common σ_a across all skill groups.

To estimate σ_{ml} in the next step, we also need to estimate the efficiency parameters α_s. Appendix A.7 contains the details related to this step. The estimated α_s suggest that one unit of young low-skilled labor is about 72-78% as efficient as one unit of old low-skilled labor, while the corresponding ratios are 68-69% for medium-skilled and 51-54% for high-skilled labor. These efficiency ratios are consistent with the different age-earnings profiles of the three skill groups which are much steeper for high-skilled workers than for medium- or low-skilled workers.

4.3. Estimating σ_{ml}

To estimate the elasticity of substitution between low- and medium-skilled labor corresponding to Eq. (1), we first construct the aggregate amounts of L_t, M_t (and H_t for later) based on $\hat{\sigma}_a$ from Model 2 of Table 2 and the various efficiency parameters $\hat{\alpha}_s$ reported in Model 1 of Table A.4.[20] We then estimate variants of the following equation which can be readily derived from our assumed production function in Section 2 (note that ω is not indexed by j and thus refers to the *aggregate* medium-to-low skill premium):

$$\ln\left(\frac{w_t^M}{w_t^L}\right) \equiv \omega_t^M = \ln\theta_t - \frac{1}{\sigma_{ml}}\ln\left(\frac{M_t}{L_t}\right)$$

In Column (1) of Table 3, we regress the medium-to-low skill premium on the aggregate relative supply of medium- to low-skilled labor $\ln\frac{M_t}{L_t}$ and a linear time trend. This model has a 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 Fig. A.6. This model predicts the medium-to-low skill premium for the years 1991–2002 very well but does a poor job afterwards. Actual premiums in 2003–2008 are much lower than predicted. To account for the different regimes, we allow for a trend break in the demand for medium-relative to low-skilled labor. A formal structural break test (Quandt-LR) picks 2002 as the pivotal year. In Column (3), we first exclude the years 2002-2008. The estimates become highly significant and are very similar in magnitude to those in Column (2). In Column (4) we allow for a separate slope in the demand for medium- relative to low-skilled labor starting in 2002. This improves the model fit significantly and yields a highly significant point estimate for the relative supply of -0.257, very similar to the point estimates in Columns (2) and (3). The estimates in Column (4) imply a substantially decelerated growth in the medium-to-low premium starting in 2002 (the combined demand trend is 54% 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 from 2002 onwards.

The observed pattern of a lower relative demand for medium-skilled workers starting in 2002 is 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 tasks primarily carried out by medium-skilled workers.[21] The decrease in relative demand could also be related to the implementation of the Hartz reforms in 2003 (coupled with some anticipation effects). Launov and Wälde (2013), for instance, find that the Hartz reforms had

[19] Card and Lemieux (2001) use seven different age groups in 5-year intervals instead of only two as in our models. Our estimates of σ_a are only slightly higher than the ones presented in Table 2 if we use eight 5-year interval age groups or if we redefine the young as being aged 35 or younger.

[20] More precisely, we compute $\hat{M}_t = \left[\sum_j (\hat{\alpha}_{mj} M_{jt}^{\hat{\eta}})\right]^{1/\hat{\eta}}$ and $\hat{L}_t = \left[\sum_j (\hat{\alpha}_{lj} M_{jt}^{\hat{\eta}})\right]^{1/\hat{\eta}}$, where $\hat{\eta} = 1 - 1/\hat{\sigma}_a$. All subsequent estimates remain virtually identical when we use alternative parameters from models including a linear time trend rather than time fixed effects or when allowing σ_a to vary across skill groups.

[21] Note that Goldin and Katz (2009) also allow for a linear trend break in relative demand and find evidence for a slowdown in demand from 1992 onwards.

Table 4
Estimating the Elasticity between High- and Non-High-Skilled Labor σ_{hu} and the Full Model.

	(1)		(2)		(3)	
	Baseline		High Young Intercepts		1980-1990 only	
	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}	ω^M_{jt}	ω^H_{jt}
Aggr. Medium-to-Low Rel. Supply $(-1/\sigma_{ml})$	-0.197**		-0.236**		-0.200	
	(0.092)		(0.092)		(0.154)	
Aggr. Non-High-to-Medium Rel. Supply $(-1/\sigma_{ml})$		-0.197**		-0.236**		-0.200
		(0.092)		(0.092)		(0.154)
Aggr. High-to-Non-High Rel. Supply $(-1/\sigma_{hu})$		-0.236		-0.551*		-0.180
		(0.323)		(0.298)		(0.335)
Adj. Age-Group-Specific	-0.123***	-0.123***	-0.125***	-0.125***	-0.099***	-0.099***
Rel. Supplies $(1/\sigma_a)$	(0.011)	(0.011)	(0.013)	(0.013)	(0.021)	(0.021)
Young	-0.049***	-0.252***	-0.049***	-0.264***	-0.063***	-0.254***
	(0.004)	(0.009)	(0.004)	(0.009)	(0.010)	(0.013)
Time	0.011***	0.009	0.013***	0.021*	0.010	0.002
	(0.004)	(0.013)	(0.004)	(0.012)	(0.009)	(0.017)
Time × Post 2002	-0.007***		-0.008***			
	(0.002)		(0.002)			
Constant	0.444***	0.001	0.494***	-0.564	0.459**	0.126
	(0.127)	(0.581)	(0.126)	(0.536)	(0.180)	(0.671)
1987-1990 Intercept × Young				✓		✓
1999-2002 Intercept × Young				✓		
σ_{ml}	5.1		4.2		5.0	
	(2.4)		(1.7)		(3.9)	
σ_{hu}		4.2		1.8		5.6
		(5.8)		(1.0)		(10.3)
σ_a	8.1	8.1	8.0	8.0	10.1	10.1
	(0.8)	(0.8)	(0.9)	(0.9)	(2.1)	(2.1)
Observations	58	58	58	58	22	22
R^2	0.975	0.949	0.977	0.972	0.998	0.996

Notes: The coefficients on the aggregate medium-to-low relative supply $\ln\left(M_t/L_t\right)$ and the aggregate non-high-to-medium relative supply $\ln\left(U_t/M_t\right)$, i.e. $-1/\sigma_{ml}$, as well as the coefficients on the adjusted age-group-specific relative supplies $(\ln(M_{jt}/L_{jt}) - \ln(M_t/L_t))$ and $(\ln(H_{jt}/M_{jt}) - \ln(H_t/M_t))$, i.e. $-1/\sigma_a$, are restricted to be the same in each model's pair of equations. The number of observations refers to the full sample, n. Young is an indicator for age $\leq$ 30 years. Moving block bootstrap standard errors with block length 3 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

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. Furthermore, Hirsch and Schnabel (2014) find a marked drop in union power at the beginning of the 2000s which is likely to have detrimentally affected medium-skilled workers for whom coverage rates were particularly high (Kohaut and Schnabel, 2003).

Our preferred specification in Column (4) implies an elasticity of substitution between medium- and low-skilled workers of 3.9 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 medium schooling degree (at most *Realschule*). Our estimate of σ_{ml} is also lower than the estimate of around 5 obtained by Dustmann et al. (2009, Table V) for Germany who, however, only consider men during the period 1975-2004.

4.4. Estimating σ_{hu} and the Full Model

Using the results from the previous step, we can now construct the aggregate amount of non-college labor U_t[22] and, in the final step of our estimation procedure, estimate Eqs. (6) and (8) jointly to identify σ_{hu}, the elasticity of substitution between college and non-college workers. Note that the coefficients on the different age-specific and aggregate relative supply measures in the two estimation equations yield new estimates for σ_a and σ_{ml}, which, in connection with the findings from the previous estimation steps, can serve as an internal consistency check of our assumed production function framework. As before, we allow for a linear trend break in 2002 for the medium-to-low premium in Eq. (6) but assume that the relative efficiency parameter $\ln(\lambda_t/\theta_t)$ corresponding to the high-to-medium premium in Eq. (8) follows a linear trend throughout the entire sample period, representing a steady shift in the demand for high-skilled workers. Table 4 reports the corresponding results, with parameter equality imposed across equations wherever indicated by Eqs. (6) and (8).

Model 1 yields a coefficient of -0.123 for the age-group-specific relative supply which is almost identical to the corresponding estimate of -0.127 obtained in Model 2 of Table 2. Thus, concerning σ_a, the estimates based on Eqs. (6) and (8) are consistent with our previous results. However, the coefficient of the aggregate medium-to-low relative supply of -0.197 is somewhat smaller in magnitude than the corresponding estimate of -0.257 reported in Column (4) of Table 3. According to the model, these two estimates should be the same. The point estimate of the aggregate high to non-high supply is -0.236 but is imprecisely estimated. These discrepancies suggest that, in particular, the specification

[22] To construct the aggregate amount of non-college labor U_t we use the estimates of Model 4 of Table 3. Apart from $\hat{\sigma}_{ml}$, we also need an estimate for the demand shifter θ_t which is recovered from the estimated coefficients as $\hat{\theta}_t = \frac{\exp(B)}{1+\exp(B)}$ where $B = \hat{\beta}_{time} \times time + \beta_{posttime} \times posttime$, where $posttime$ is 0 in the years before the break year, 1 in the break year and increasing by one in each subsequent year after the break year.

for the high-to-medium skill premium might be misspecified. Examining more closely the data reveals that the high-to-medium premium of *young* workers exhibits noticeable "bumps" that are unrelated to supply changes. As it turns out, wages and therefore the premium of young high-skilled workers show a strong comovement with the business cycle (see Fig. A.7), something that cannot be observed to the same extent for the remaining three premiums. The premium of young high-skilled workers is amplified and detached from its underlying supply especially during the pre-unification boom (1987-1990) and the boom and bust of the dot-com bubble (1999-2002, Burda and Seele, 2016). To account for this irregularity, in Model 2, we include two separate intercepts interacted with the young indicator for these two periods. The coefficient of the aggregate medium-to-low supply now changes to -0.236, which is very close to the corresponding estimate of -0.257 in Column (4) of Table 3. The coefficient of the aggregate relative supply of high-skilled to non-high-skilled labor declines to -0.551 and becomes statistically significant, even if only at the 10% level.

The estimates of our preferred specification (Model 2) imply an elasticity of substitution between college and non-college labor of 1.8, which is similar to the elasticity of substitution between college and high school labor in the US estimated by Autor et al. (2008, Table 2), Goldin and Katz (2009, Table 8.2,) and Card and Lemieux (2001, Table VI). Fitzenberger et al. (2006) and D'Amuri et al. (2010) do not estimate σ_{ml} and σ_{hu} separately but impose equality of these structural parameters in their estimations. Bearing that in mind, D'Amuri et al. (2010) estimate an elasticity of substitution between any two skill groups of 2.9 which is right between our estimated elasticities of 4.2 (σ_{ml}) and 1.8 (σ_{hu}). Fitzenberger et al. (2006) obtain an elasticity between 4.9 and 6.9, noting that their estimates imply a rather high degree of substitutability compared to findings in the related literature. Our finding that σ_{hu} is substantially smaller in magnitude than σ_{ml} provides some support for our decision to assign medium- and low-skilled workers to a separate nest in the production function. The difference between the two elasticities, however, is not statistically significant at conventional levels (p-value 0.202) so that, on statistical grounds, a production function in which all three education groups are assigned to the same nest would also be justifiable.

To get an impression of the model's out-of-sample predictive power, we plot the observed and predicted medium-to-low premium separately for young and old workers in Fig. 3. The prediction in Panel (a) is based on the estimates of Model 3 in Table 4, a specification that excludes 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 based on only the observations from 1980–1990 is able to predict quite well the differential evolution of the medium-to-low premium of young and old workers since 1990. In Panel (b), we use the estimates of Model 2, yielding a prediction that is very close to the observed premium profile. Our model is also able to predict the high-to-medium skill premium reasonably well, even without accounting for the peculiarities in the premium of young college graduates (Fig. A.8).

Based on the estimated elasticities of substitution and observed factor shares in income, we can compute own- and cross-factor price elasticities to obtain a better understanding of how changes in the supply of one labor input affect the equilibrium wages of the other inputs. Appendix A.8 provides details on the procedure we follow, with Table A.5 reporting the implied elasticities. While the own-factor price elasticities range from -0.147 for young low-skilled workers to -0.476 for old high-skilled workers, the cross-factor price elasticities giving the impact of a change in the supply of young workers on the wages of old workers are quite small, both due to the relatively low elasticity of substitution across age groups ($\sigma_a = 8.0$) and because of the low income shares of young workers in the economy. For example, a ten percent *decrease* in the supply of young medium-skilled workers leads to an increase in the wages of old medium-skilled workers of only 0.48 percent and an increase in the wages of old low-skilled workers of only 0.22 percent. These low magnitudes explain why the increase in the medium-to-low skill premium of older workers in Fig. 1, though clearly discernible from the end of the 1980s onwards, is relatively small.

4.5. Robustness Checks

To test the robustness of our findings, we present the results of some alternative specifications in Table 5. For better comparison, our preferred baseline estimates are restated in Model 1. Skill premiums do not only depend on relative supplies but may also be influenced by the business cycle. To account for this possibility, we include GDP growth in Model 2 (and also in estimation step 2) as an additional regressor. This leaves our estimates virtually unchanged, and GDP growth turns out to be statistically insignificant in both premium equations.

In our baseline model, we use composition-constant skill premiums that include both men and women. In Model 3, we redo our analysis but compute wage premiums for men only, holding their age composition constant as before. This yields overall similar results, with somewhat lower elasticities of substitution between medium- and low-skilled workers and the different age groups, and a slightly higher elasticity of substitution between college and non-college labor.

The age range considered for our baseline supply measures is 21 to 60 years. To address concerns related to early retirement, we compute premiums and supplies excluding workers older than 55. Until the mid-1990s, early retirement schemes were a politically supported measure to relieve the German labor market in times of high unemployment rates, leading to extraordinarily low employment rates of workers older than 55. The results in Model 4 show that our parameter estimates remain robust to excluding this group of workers from our sample.

Since a non-negligible fraction of individuals have not yet completed their education by the age of 21, our skill-specific supplies of young workers might be mismeasured. To address this concern, we exclude workers younger than 25 years from the sample. As reported in Model 5, this leads once again to similar estimates of the different elasticities of substitution.

Our decision to draw the distinction between young and old workers at the age of 30 was motivated by the age-specific skill premium patterns shown in Fig. A.3. As the assignment of workers aged 31 to 35 is somewhat ambiguous, we report an alternative set of results where the cutoff age between young and old workers is set to 35 years. As shown in Model 6, this has little impact on our parameter estimates.

Finally, in Model 7, we show the results for a specification in which we assign short part-time workers a weight of 1/2 (rather than 1/3), following previous work by Dustmann et al. (2009). This alternative weighting yields very similar estimates as our baseline specification.[23]

5. Determinants of Supply Changes

After having demonstrated that the heterogeneous evolution of age-specific skill premiums depicted in Fig. 1 can be readily explained by a relatively simple supply and demand framework, we now turn to the potential reasons for the underlying age- and education-specific changes in labor supply. We assess the importance of two main potential explanations. First, we look at the role of immigration. The relative decrease in the supply of medium-skilled workers, in particular among young workers, could be driven by a large inflow of mainly low-skilled migrants after the fall of the Berlin Wall as hypothesized, for instance, by Dustmann et al. (2009). To evaluate the effect of migration, we compute supply measures excluding migrants and simulate the counterfactual evolution of skill premiums under this "no-migration" scenario.

[23] When constructing supplies not based on efficiency units, i.e. not taking productivity differences into account, but rather do a simple head count similar to the approach followed by D'Amuri et al. (2010), the parameter estimates are more attenuated towards zero but the overall patterns continue to hold.

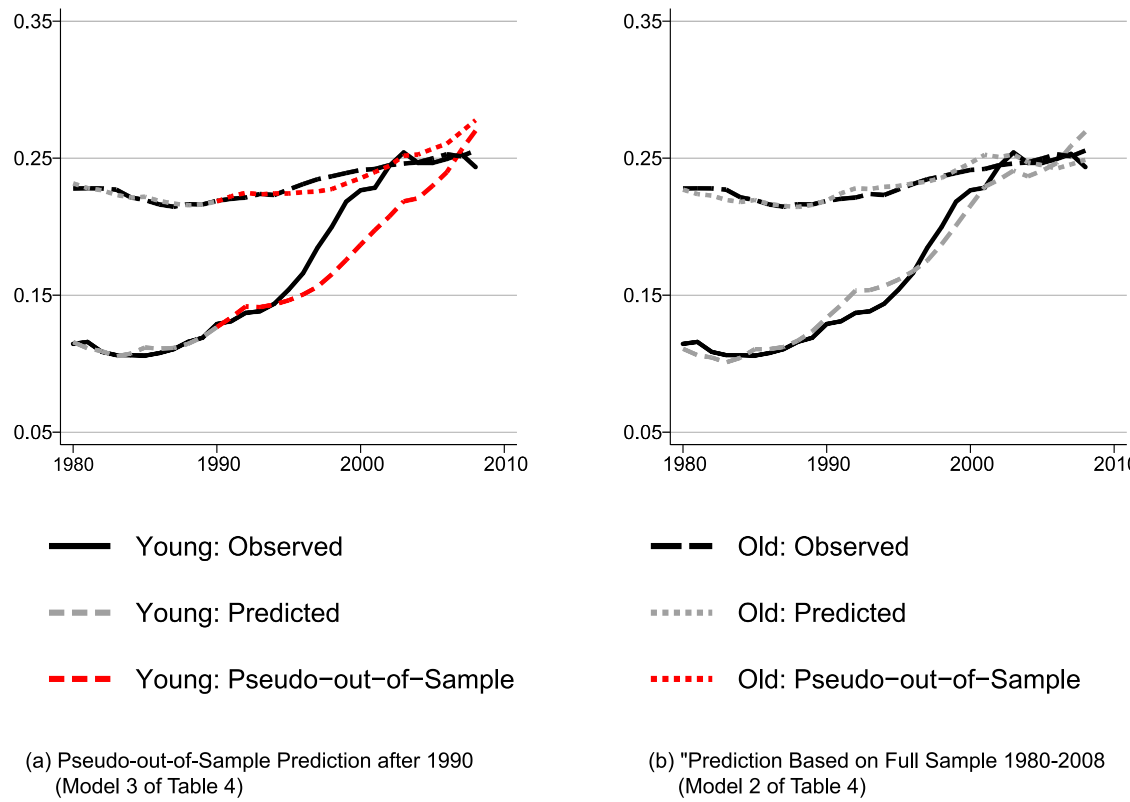


Fig. 3. Predicted vs. Observed Medium-to-Low Premiums.

Second, we investigate the role of more fundamental shifts in the educational attainment of the native West German population. To assess this alternative channel, we perform a cohort analysis using data from the German microcensus.

5.1. The Role of Migration

After the fall of the Berlin Wall in 1989, West Germany experienced large migration inflows from mainly three groups: (i) East-Germans, (ii) ethnic Germans from Eastern Europe and the former Soviet Union, and (iii) foreigners immigrating from other European countries or parts of the world. Within 15 years, about 1.5 million East Germans, 2.7 million ethnic Germans and 2.7 million foreigners migrated to West Germany where about 60 million people lived in 1989.[24]

In Fig. 4, we plot the share of different migrant groups in the total efficiency supply of each age-skill group.[25] For details on the construction of these migrant shares, see Appendix A.9. As the figure suggests, the migration inflows after the fall of the Berlin Wall into the West German labor market were substantial. During its peak in the mid-1990s and early 2000s, more than half of the efficiency supply of young low-skilled workers was supplied by migrant workers, with foreigners making up the largest part. The share of East Germans is similar across the different age-skill groups at about 3-6%.[26] In contrast, ethnic Germans and foreign migrants are mostly concentrated in the low-skilled segment. Overall, migration therefore increased low-skilled labor supply the most but also contributed significantly to medium- and high-skilled supply.

How did these migration flows affect relative labor supplies, the main driver of native skill premiums in our model? Fig. 5 depicts relative supplies with (baseline) and without migration. Because the relative supply of high- to medium-skilled workers in the migrant population was very similar to that in the native population, migration had almost no effect on the corresponding aggregate relative supply in Germany (bottom panels). We therefore focus on the medium-to-low supplies and premiums in what follows. Without migration, medium-skilled labor would be relatively more abundant, both for young and older workers (top panels). Importantly, however, migration would not have changed the general patterns in the evolution of relative medium-to-low skill supplies: an inverted U-shaped pattern for the young and a continuous increase for the old.

Given these migration flows and changes in relative supplies, how would skill premiums have evolved in the absence of migration? In particular, to what extent is low-skilled migration responsible for the pronounced increase in the medium-to-low premium of young workers? To answer these questions, we use our preferred estimates of Model 2 in

[24] These figures are calculated by summing up the corresponding flows over 1989-2003 as follows: (i) East Germans: net migration from East to West Germany (inflows minus outflows) taken from Statistisches Bundesamt (2014); (ii) ethnic Germans: inflows from Bundesverwaltungsamt (2016); (iii) foreigners: net inflows from Statistisches Bundesamt (2016) minus inflows of ethnic Germans. Using gross inflows for ethnic Germans seems justified as "only a negligible number of [ethnic Germans] have later left Germany, rendering the selection on return migration a non-issue" as Hirsch et al. (2014, p. 213) point out.

[25] Note that the official inflows do not necessarily translate into corresponding shares in labor supplies due to different participation rates of the different migrant groups. Children, students, pensioners, and other non-working migrants are included in the official figures but do not contribute to the migrant labor supply. Some shares seem high at first glance but occur in subgroups (low-skilled and/or young workers) that make up only a small share of total labor supply which is why the corresponding shares in *total* labor supply amount to only 4.3% (East Germans), 6.8% (ethnic Germans), 11.8% (foreigners), and 23.0% (all migrants) in 2008.

[26] This is consistent with the findings by Prantl and Spitz-Oener (2020, Appendix A.1), who note that "... the migration of East Germans into West Germany left the relative labor supplies of German individuals in the West quite unchanged at the level of broad educational classes."

Table 5
Robustness Checks of CES Models.

	(1) Preferred Specification		(2) + GDP Growth		(3) Premiums of Men		(4) Excluding Workers >55 Years		(5) Excluding Workers <25 Years		(6) Young Age Cut at 35		(7) Weight of 1/2 for Short Part-Time Spells	
	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}
Aggr. Medium-to-Low Rel.	-0.236**		-0.236***		-0.298**		-0.228***		-0.186**		-0.214**		-0.235***	
Supply ($-1/\sigma_{ml}$)	(0.092)		(0.091)		(0.118)		(0.060)		(0.090)		(0.084)		(0.091)	
Aggr. Non-High-to-Medium		-0.236**		-0.236***		-0.298**		-0.228***		-0.186**		-0.214**		-0.235***
Rel. Supply ($-1/\sigma_{ml}$)		(0.092)		(0.091)		(0.118)		(0.060)		(0.090)		(0.084)		(0.091)
Aggr. High-to-Non-High Rel.		-0.551*		-0.543*		-0.492		-0.657**		-0.437		-0.403		-0.558*
Supply ($-1/\sigma_{hu}$)		(0.298)		(0.289)		(0.310)		(0.334)		(0.304)		(0.268)		(0.297)
Adj. Age-Group-Specific	-0.125***	-0.125***	-0.125***	-0.125***	-0.134***	-0.134***	-0.128***	-0.128***	-0.136***	-0.136***	-0.143***	-0.143***	-0.125***	-0.125***
Rel. Supplies ($1/\sigma_a$)	(0.013)	(0.013)	(0.013)	(0.013)	(0.018)	(0.018)	(0.013)	(0.013)	(0.019)	(0.019)	(0.020)	(0.020)	(0.013)	(0.013)
Young	-0.049***	-0.264***	-0.049***	-0.264***	-0.004	-0.238***	-0.052***	-0.264***	-0.023**	-0.227***	-0.028***	-0.208***	-0.049***	-0.263***
	(0.004)	(0.009)	(0.004)	(0.009)	(0.006)	(0.014)	(0.004)	(0.010)	(0.010)	(0.011)	(0.008)	(0.008)	(0.004)	(0.009)
Time	0.013***	0.021*	0.013***	0.021*	0.016***	0.019	0.012***	0.025*	0.011***	0.015	0.012***	0.016	0.013***	0.021*
	(0.004)	(0.012)	(0.004)	(0.011)	(0.005)	(0.012)	(0.002)	(0.013)	(0.004)	(0.011)	(0.003)	(0.011)	(0.004)	(0.012)
Time × Post 2002	-0.008***		-0.008***		-0.009***		-0.008***		-0.006**		-0.007***		-0.008***	
	(0.002)		(0.002)		(0.003)		(0.002)		(0.003)		(0.002)		(0.002)	
Real GDP Growth			0.001	-0.091										
			(0.101)	(0.154)										
Constant	0.494***	-0.564	0.494***	-0.549	0.515***	-0.532	0.495***	-0.745	0.424***	-0.301	0.449***	-0.315	0.493***	-0.575
	(0.126)	(0.536)	(0.125)	(0.518)	(0.162)	(0.565)	(0.086)	(0.586)	(0.119)	(0.509)	(0.114)	(0.482)	(0.125)	(0.535)
Young $\times I(1987-1990)$		✓		✓		✓		✓		✓		✓		✓
Young $\times I(1999-2002)$		✓		✓		✓		✓		✓		✓		✓
σ_{ml}	4.2		4.2		3.4		4.4		5.4		4.7		4.3	
	(1.7)		(1.6)		(1.3)		(1.2)		(2.6)		(1.8)		(1.6)	
σ_{hu}		1.8		1.8		2.0		1.5		2.3		2.5		1.8
		(1.0)		(1.0)		(1.3)		(0.8)		(1.6)		(1.7)		(1.0)
σ_a	8.0	8.0	8.0	8.0	7.4	7.4	7.8	7.8	7.4	7.4	7.0	7.0	8.0	8.0
	(0.9)	(0.9)	(0.9)	(0.9)	(1.0)	(1.0)	(0.8)	(0.8)	(1.0)	(1.0)	(1.0)	(1.0)	(0.8)	(0.8)
Observations	58	58	58	58	58	58	58	58	58	58	58	58	58	58
R^2	0.977	0.972	0.977	0.972	0.951	0.944	0.980	0.971	0.968	0.961	0.966	0.972	0.977	0.972

Notes: The coefficients on the aggregate medium-to-low relative supply $\ln\left(M_t/L_t\right)$ and the aggregate non-high-to-medium relative supply $\ln\left(U_t/M_t\right)$, i.e. $-1/\sigma_{ml}$, as well as the coefficients on the adjusted age-group-specific relative supplies $(\ln(M_{jt}/L_{jt}) - \ln(M_t/L_t))$ and $(\ln(H_{jt}/M_{jt}) - \ln(H_t/M_t))$, i.e. $-1/\sigma_a$, are restricted to be the same in each model's pair of equations. The number of observations refers to the full sample, n. Young is an indicator for age ≤ 30 years. Moving block bootstrap standard errors with block length 3 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

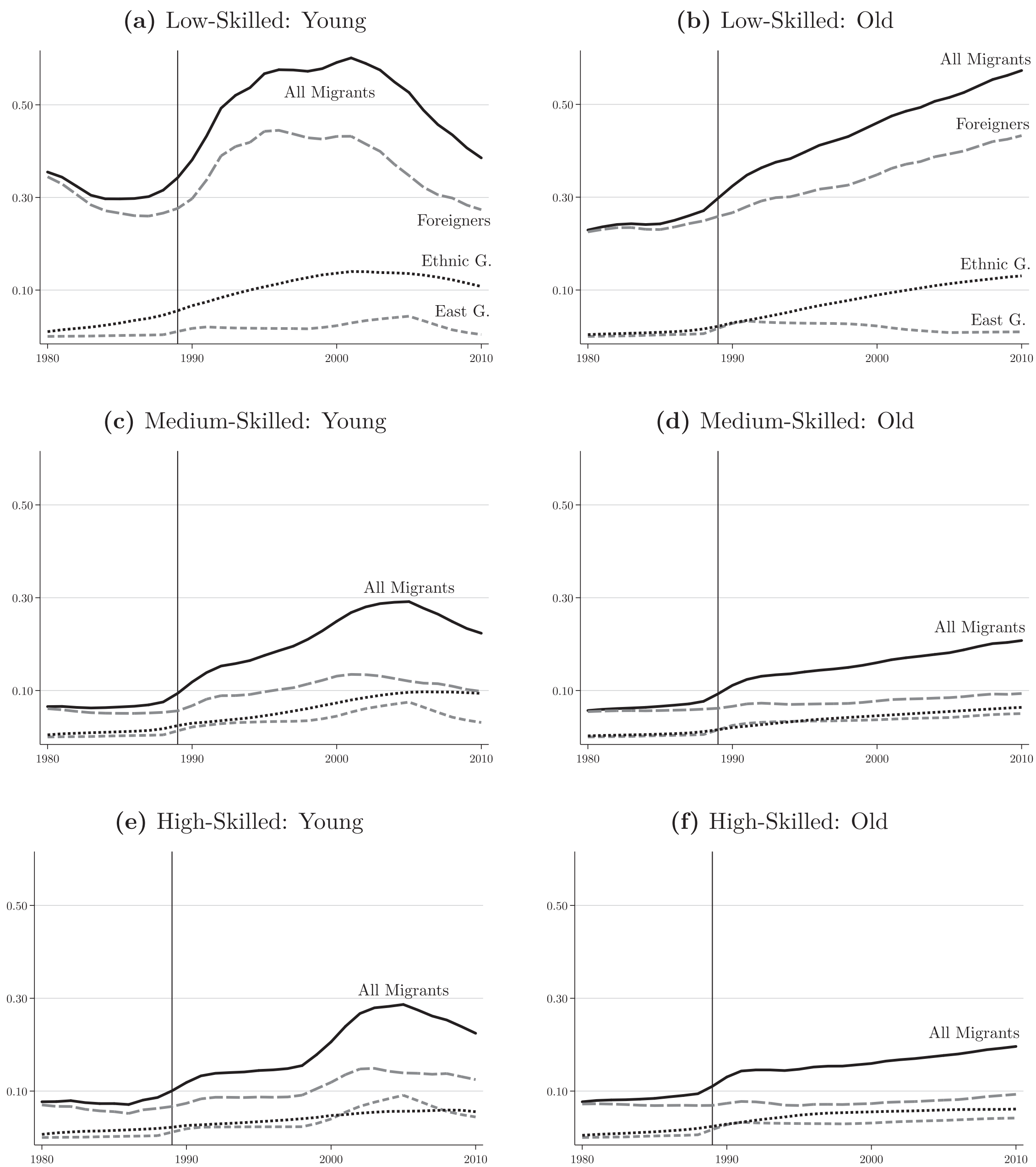


Fig. 4. Share of Different Migrant Groups in Total West Germany Supplies.
Notes: This figure plots, for each education group and separately for young (≤ 30 years) and old workers (>30 years), the share of different migrants groups in efficiency supplies.

Table 4 to simulate the counterfactual evolution of skill premiums in the absence of migration. We feel this is justified by our previous finding that the underlying structural parameter estimates obtained from the full sample are similar to those obtained from data that only cover the years 1980 to 1990 (Model 3 of Table 4), a period of no or only incipient migration flows.

It should be noted that, given our analytical framework, we implicitly assume perfect substitutability between migrants and natives within a given age-skill cell. This assumption, if incorrect, would lead to an *overestimation* of the impact of migration on native wage premiums. Since our results show that migration is *not* the main driver of rising inequality at the lower end of the German wage distribution, ignoring the issue of potentially imperfect substitutability is inconsequential for the main qualitative finding of the paper. Furthermore, we account for the different productivities of natives and migrants when constructing labor supplies, thus natives and migrants are not treated identically in this respect. Finally, substitutability between migrants and natives is likely to be relatively high in the German context given that East and ethnic Germans were more similar to natives in terms of language and culture than the typical foreign immigrant. In line with this, D'Amuri et al. (2010) estimate a rather high elasticity of substitution of around 25 between migrants and natives in Germany.

Fig. 6 shows the results from our counterfactual exercise. Without migration, the young medium-to-low skill premium would have declined slightly until the mid-1990s and then strongly increased to the same level as the actual premium by 2008. Thus, migration seems to have advanced the divergence in wages between young medium- and low-skilled workers by around 5 years. The strong increase, however, would have occurred even without the large migration flows of the 1990s. The conclusion is somewhat different for the medium-to-low

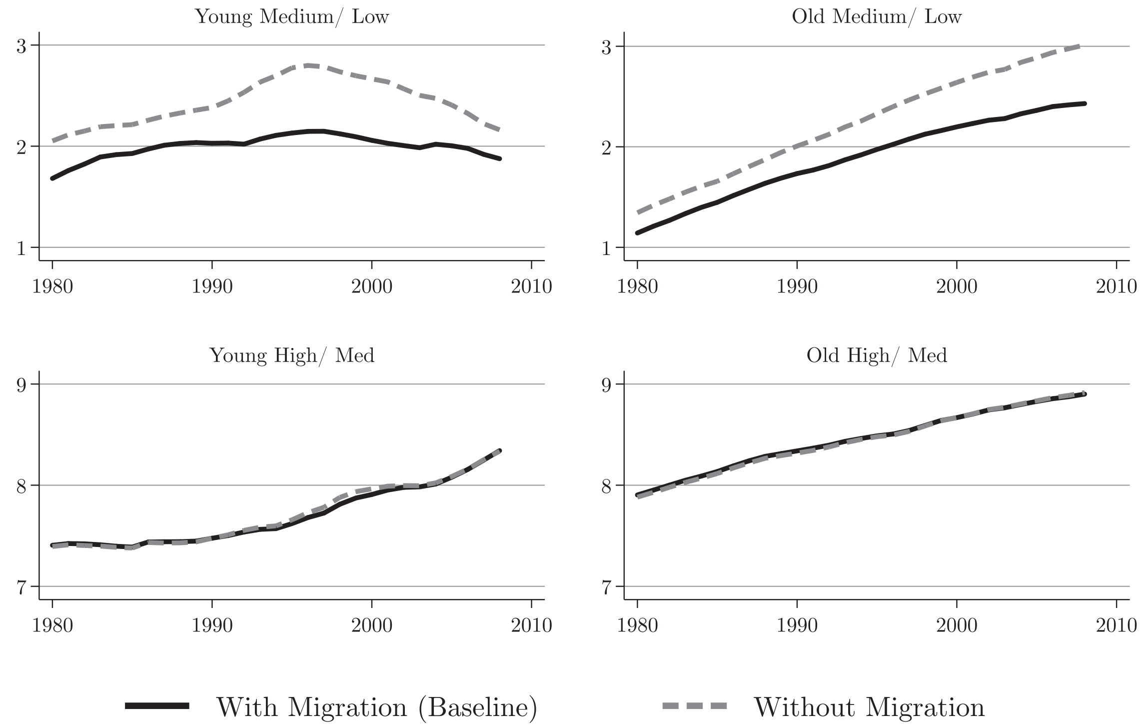


Fig. 5. Relative Efficiency Supplies with and without Migration.

premium of older workers. Here, migration kept that premium on a slightly increasing path whereas, in the absence of migration, the premium would have decreased by some five percentage points relative to its 1990 level. In sum, while migration did have a notable impact on wage premiums of medium-skilled workers, it cannot explain the strong increase for young workers that eventually occurred during the 1990s and 2000s. In the next section, we will therefore turn to the educational attainment of *native* workers as an alternative driver of supply changes.

5.2. Cohort Analysis of Skill Acquisition

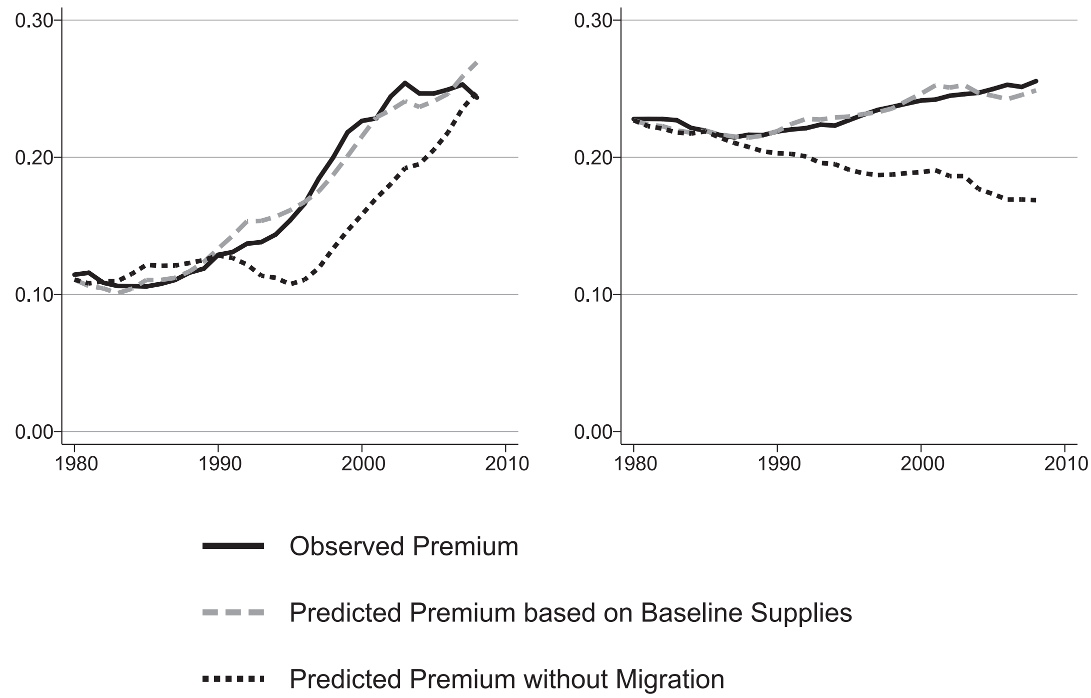
To better understand the origin of the observed supply changes, we use data from the German microcensus, an annual survey of a 1% random cross-section of the German population. We pool the waves 2005 to 2011 and restrict the sample to individuals residing in West Germany at the time of the interview. We focus on native West Germans and exclude from the sample individuals who were born or migrated from outside Germany, who have a non-German nationality, have been naturalized, or obtained a school degree in the former East Germany. Furthermore, we only consider individuals who are at least 30 years old to ensure they have completed their education, grouping individuals into the same three education groups as in our main SIAB sample.

Using this sample of native West Germans with completed education, we plot for each birth cohort the share of low-, medium- and high-skilled individuals in Fig. 7a. We focus on cohorts born between 1950 and 1981 since these are the relevant cohorts determining the inflow of young workers into the labor market during our study period.[27] The figure reveals a striking pattern: the share of medium-skilled workers shows a pronounced inverted U-shaped pattern, with the turning point occurring around the 1965 birth cohort. In the 15 years leading up to that point, the share of individuals with completed vocational training increased from 67% to 71% but then started to decrease rapidly, falling back to only 64% in the 1981 cohort, a value comparable to that of the 1940 cohort (not shown). At the same time, the share of low-skilled individuals stopped its continuous decrease over the previous decades to stabilize at around 11%. The share of individuals holding a university degree, in contrast, started to increase strongly from 1965 onwards after remaining virtually flat for most of the 1950s and early 1960s cohorts.

The trend break in educational attainment of native West Germans around the 1965 cohort is even more salient in Fig. 7b where we estimate linear skill-specific trends for the cohorts 1950-1965 and plot the deviations from these trends over time. This plot reinforces the impression from the previous figure. The evolution of the educational attainment of natives is characterized by a type of "polarization", with a marked drop in the share of those acquiring vocational training on the one hand, and a relative increase in the share of high- and low-skilled individuals on the other hand. The figures also show that while low-skilled immigration might have played some role, the main force behind the overall decrease in the relative supply of young medium-skilled workers in the 1990s and 2000s was a strong decline in the share of natives with vocational training starting around the 1965 cohort.

More research is needed to understand the reasons behind these dramatic trend breaks in educational attainment. Here we can only offer some tentative explanations. One likely reason is the so-called "educational expansion" (*Bildungsexpansion*), a broad series of reforms implemented during the 1960s and 1970s with the objective of expanding and improving secondary and tertiary education in West Germany (Führ, 1997; Bartz, 2007). At first sight, the timing of these reforms appears to be inconsistent with the documented trend break since members of the pivotal 1965 birth cohort started their vocational training or university education only in the early 1980s, some 15-20 years after the first reforms were implemented. However, due to the early and strict tracking in the German school system, the key decision for future access to university education is usually taken at a very young age (around 10) when students (or their parents) determine which type of secondary school to

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



(a) Young (b) Old

Fig. 6. Observed vs. Predicted Medium-to-Low Premiums with and without Migration.

attend. Much of the impact of the reforms initiated during the 1960s and 1970s therefore only became visible in terms of final educational attainment with significant delay.[28]

Rather than an expansion on the supply side of higher education, it might be that the demand for workers with vocational training took a turn in the early 1980s. Indeed, between 1982 and 1986, in the wake of the second oil crisis, the number of youths looking for an apprenticeship position in Germany far exceeded the number of available places (Schier, 2019), likely pushing some of these youths into tertiary education. However, by the end of the 1980s already, firms' demand for apprentices outstripped supply substantially, so that this particular episode cannot explain the persistent decline of vocational training depicted in Fig. 7.

The salience of the 1965 cohort as the pivotal inflection point suggests that the observed trend break in educational attainment might be related to the evolution of German birth cohort sizes. After gradually increasing during the post-war period, these cohort sizes peaked in 1964 at 1.36 million births (fertility rate of 2.54) but then rapidly declined over the next ten years, stabilizing in 1975 at around 780 thousand (fertility rate of 1.45). This precipitous decline in fertility, observed in many other developed countries around the same time as well, is generally attributed to a combination of different demand- and supply-side factors, including changes in women's labor force participation and the introduction of the birth control pill in the early 1960s (Watkins, 1987; Bailey, 2010; Buis et al., 2012; Bailey et al., 2014). The interaction between shrinking cohort sizes and expanding university capacities may have made it easier for the post baby boomers, especially those on the margin between vocational training and tertiary education, to obtain a place at university. Smaller family sizes may also have freed up economic and parental resources, raising investments into children's education and pushing them increasingly into the tertiary education track. However, the empirical evidence on whether such a quantity-quality trade-off exists is not conclusive (for Germany, see Bauer and Gang, 2001), suggesting that, if present at all, the trade-off is more pronounced in developing than developed countries (for a summary of this literature, see Liu, 2015).

Finally, the changing social norms of the 1960s and the extensive public debate on educational reform at the time (Führ, 1997) may have shifted parents' preferences away from traditional vocational careers for their children towards a more academic university education. The strong trend reversal around the 1965 birth cohort shown in Fig. 7 is therefore most likely due to a combination of institutional, demographic and societal changes in West Germany at the time.

6. 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. This is certainly true in Germany, where the medium-to-low skill premium closely tracks the evolution of inequality at the lower end of the wage distribution (usually measured as the 50th to 15th percentile gap). In this paper, we ask whether skill-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 (with a trend break

[28] Another driving force behind the observed trend break could have been the emergence of the smaller and more specialized universities of applied sciences in Germany (so-called *Fachhochschulen*), which saw their capacity increase significantly from the late 1970s onwards (Wienert, 2014). Due to their less theoretical curriculum, this type of university may have attracted some of the young people who would otherwise have opted for a vocational training. However, as Fig. A.9 in the appendix demonstrates, there was no noticeable trend break in the share of workers with a degree from a *Fachhochschule* until the later cohorts of the mid-1970s.

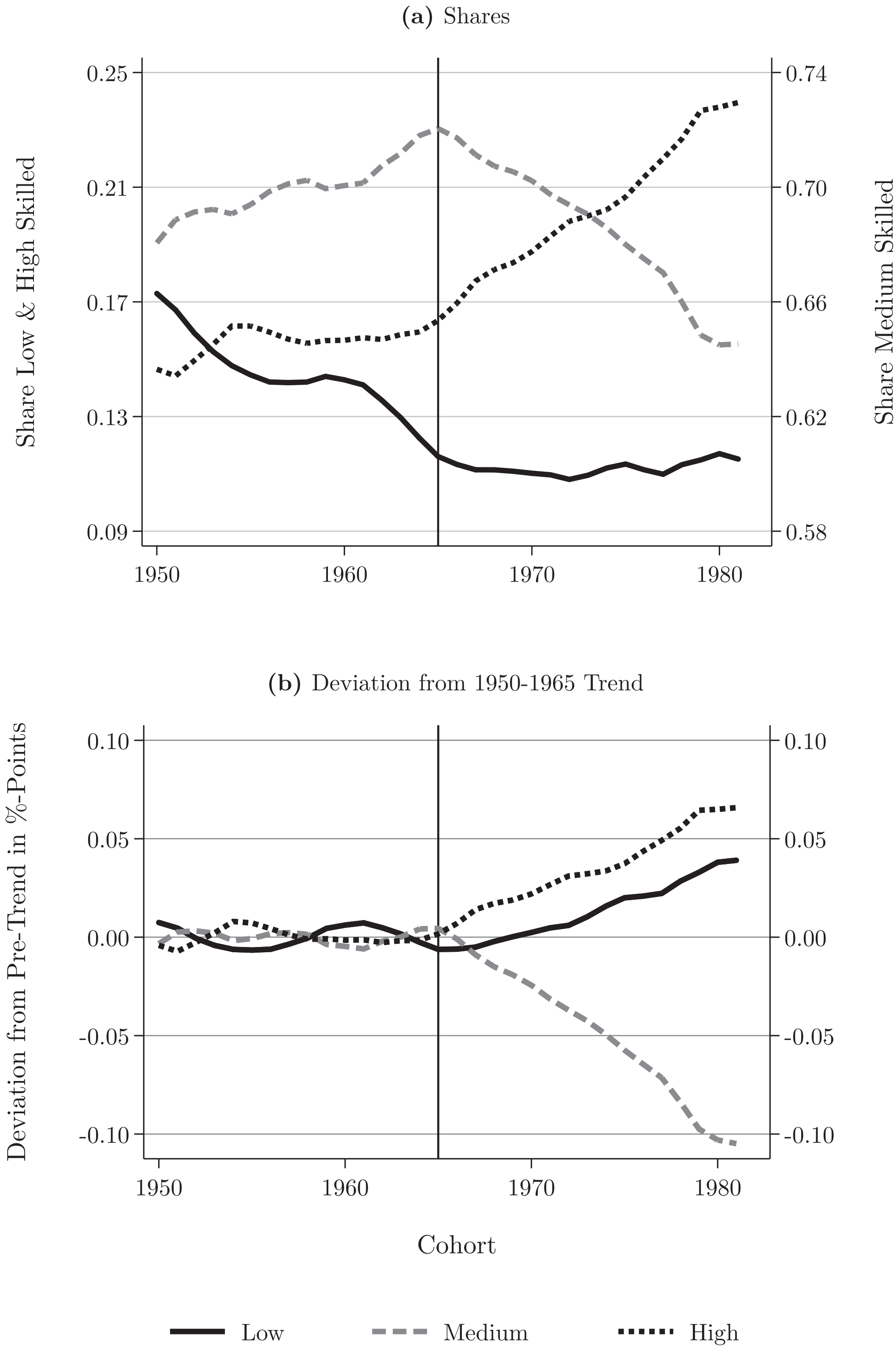


Fig. 7. Educational Attainment by Cohorts.

in 2002) 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 workers from 10% in the 1980s to 25% in the 2000s very well. Wage premiums for high-skilled relative to medium-skilled workers show no systematic upward or downward trend despite a pronounced increase in relative demand. Our framework suggests that this was because the supply of high-skilled workers kept pace with this rising demand, tripling from a share of 5% among full-time workers at the beginning of the 1980s to 15% at the end of the 2000s. Of course, since our empirical analysis is guided by a relatively stylized production function, it cannot entirely rule out other explanations for the observed patterns in the data. Indeed, as shown in Fig. A.5, at least some of the changes in relative skill premiums are also driven by shifts in the sectoral and occupational composition of the workforce.

Through a cohort-level analysis, we show that the rapid increase in the skill premium for young medium-skilled workers is rooted in a pronounced trend reversal in the educational attainment of the native population. The share of individuals with completed vocational training decreased significantly after the 1965 birth cohort while the share of individuals with university education rose strongly and the long-term decline in the share of low-skilled individuals came to a halt. Our study suggests that a considerable part of recent changes in earnings inequality between different skill groups in Germany are the result of long-term changes in the educational choices of the population and therefore, ultimately, driven by labor supply.

Appendix A

A.1. Additional Figures

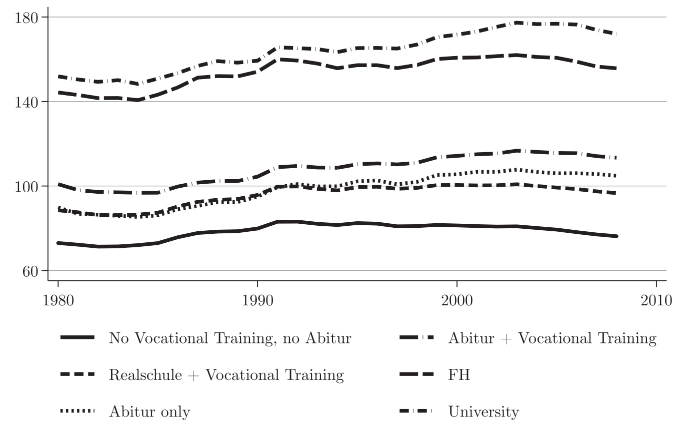


Fig. A.1. Mean Real Daily Wage By Disaggregated Education Groups.
Notes: This figure plots the mean real daily wage aggregated by six different educational attainment categories. *Realschule* denotes an secondary degree after ten years of schooling (ISCED level 2), *Abitur* denotes an advanced secondary degree after 12 or 13 years of schooling (ISCED level 3), an applied university degree corresponds to a degree from a *Fachhochschule* (ISCED level 5a).

A.2. 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[29], 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 in our analysis, 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 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 the WTID.[30] If the average income of the top 15% of the labor income distribution systematically diverged from the 85th percentile of the earnings distribution, and assuming that most individuals in the top 15% are high-skilled, we would underestimate the high-to-medium skill premium. Fig. A.10 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 (in the case of the difference to the top 10-5 fractile even considerably, see Panel (a) of Fig. A.10).

A.3. Data Preparation and Sample Restrictions

- **Imputation of Missing Values** Using the full SIAB-R 7510 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. If the two do not agree, no imputation is performed.
- **Correction of Structural Break 1984** 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, in turn, builds on Fitzenberger (1999).
- **Imputation of Censored Wages** We 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., 2009). This is likely because of the high share of censored wages in those 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 from our sample.
- **Sample Restrictions** We 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

[29] 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).

[30] The WTID (World Top Income Database) 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.

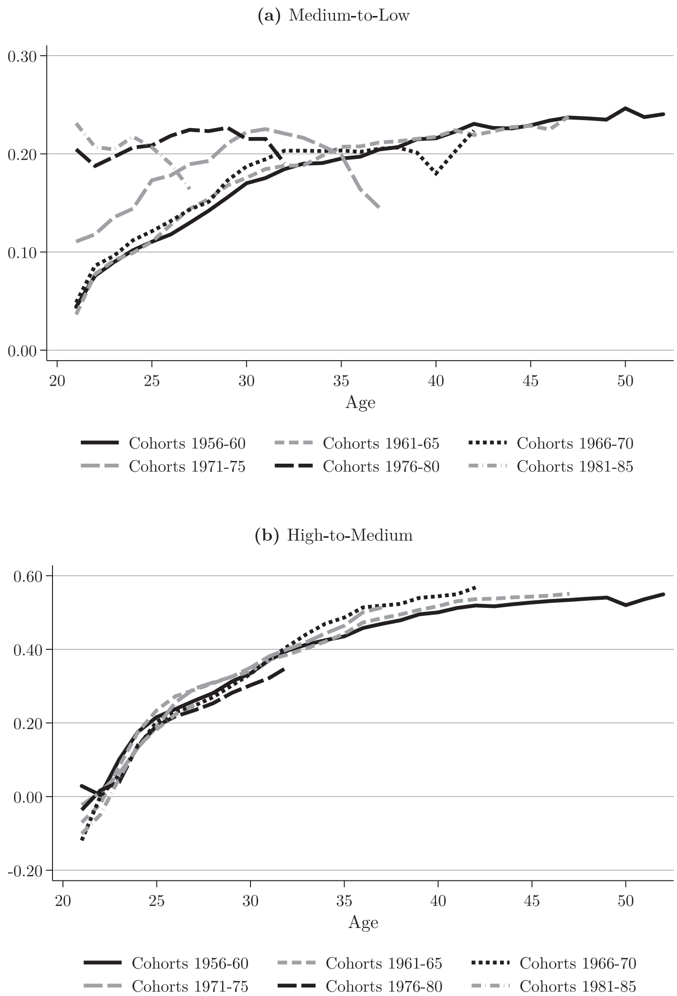


Fig. A.2. Evolution of Premiums by Birth Cohorts.
Notes: This figure plots the medium-to-low and high-to-medium skill premium for different birth cohorts using wage observations for the period 1980 to 2008.

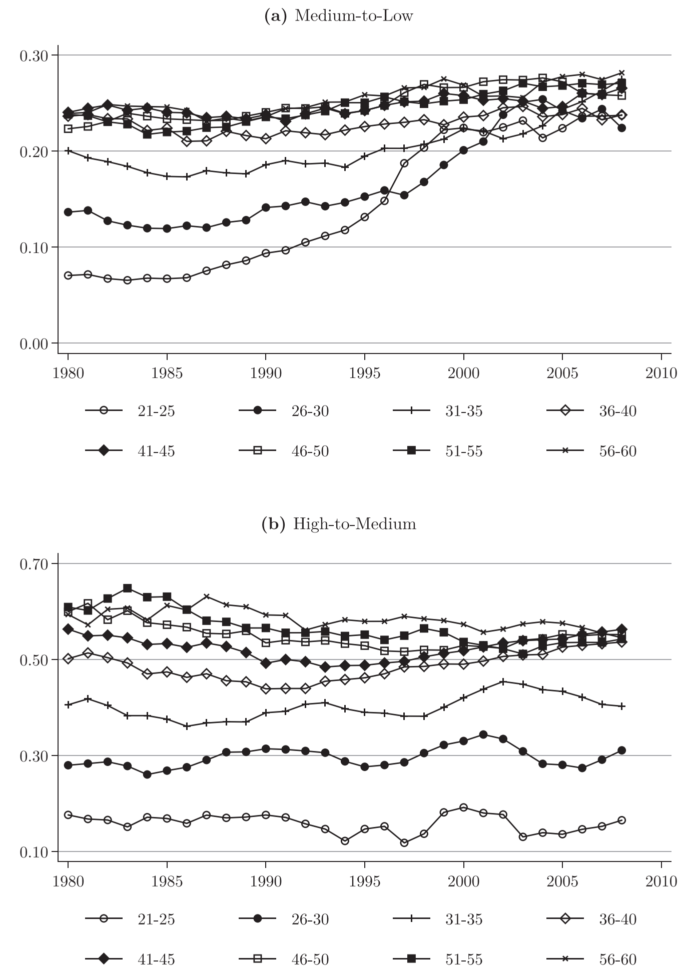


Fig. A.3. Skill Premiums by Eight Different Age Groups.

day (2.1% of all 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".

- **Exclusion of Crisis Years 2009/2010** A closer examination of the data suggests that the years 2009/2010 are unusual, in particular for young workers who experience an abnormal depression in their medium-to-low skill premium. This is likely to be related to the global financial crisis that started in 2007/08. Although unemployment levels in Germany were only mildly affected by the crisis, many workers – in particular medium-skilled worker in manufacturing – had to go on short-term work, which was associated with temporary wage cuts (supplemented by public transfers). As a result, short-term work spiked strongly in 2009 and 2010.[31] Given this anomaly, we decided to exclude the years 2009/2010 from the estimation sample. Specifications including these crisis years yield slightly larger but overall similar estimates of the underlying elasticities of substitution: 9.4 vs. 8.0 for σ_a, 4.8 vs. 4.2 for σ_{ml} and 1.9 vs. 1.8 for σ_{hu}.

A.4. Skill Premiums

Our skill premiums are based on a sample restricted to native West-Germans (i.e. excluding those ever reported to be non-German or have missing nationality information and those first registered in East Germany). To compute the skill price unconfounded by changes in the age and gender composition within skill groups, we proceed as follows. First, we calculate the mean log real wage in each education-age-gender-year cell (cell-specific wages) weighted by the share of days worked per year. Second, in each year we calculate the share of each cell in the total supply of a corresponding skill group (measured in days worked) and then average these shares for each cell across 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 corresponding cell-specific wages using the fixed cell weights as weights. For instance, the composition-adjusted log wage of low-skilled workers at time t is calculated as $\ln wage_{s=low,t} = \sum_{a=1}^{8} \sum_{g=0}^{1} \ln wage_{s=low,a,g,t} \cdot weight_{s=low,a,g}$ where a denotes one of eight different 5-year age groups (the young comprise age groups 1 and 2, the old age groups 3 to 8) and g gender. Note that the weights are constant over time. Finally, the medium-

[31] Statistik der Bundesagentur für Arbeit, Berichte: Analyse Arbeitsmarkt, Zeitreihen, August 2019, pp. 37/38.

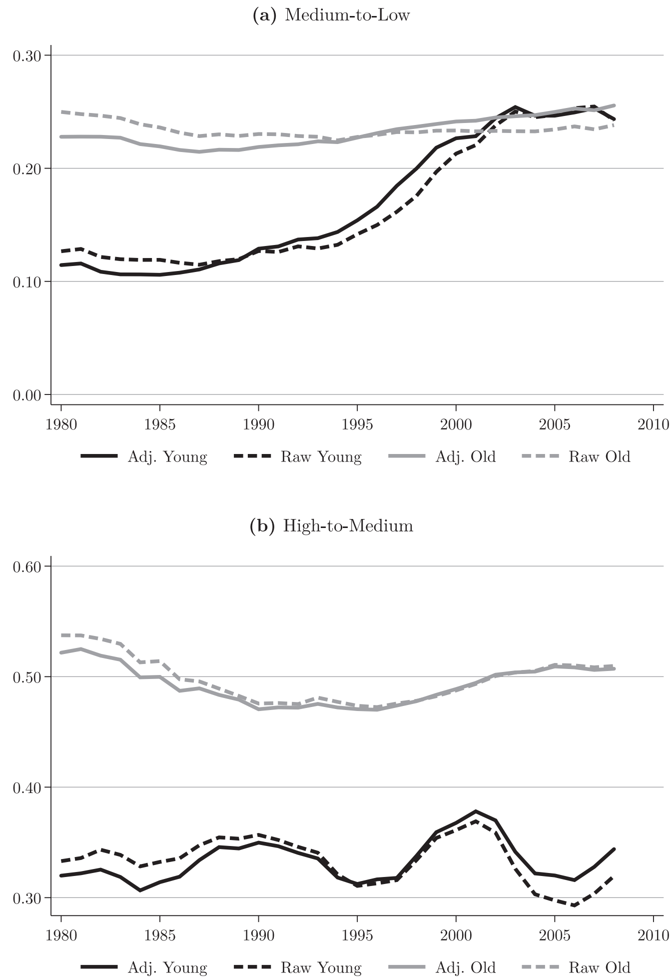


Fig. A.4. Raw and Composition-Adjusted Skill Premiums.
Notes: This figure plots adjusted skill premiums holding the age and gender composition of workers constant as described in the main text along with "raw", i.e. unadjusted, skill premiums for young and old workers.

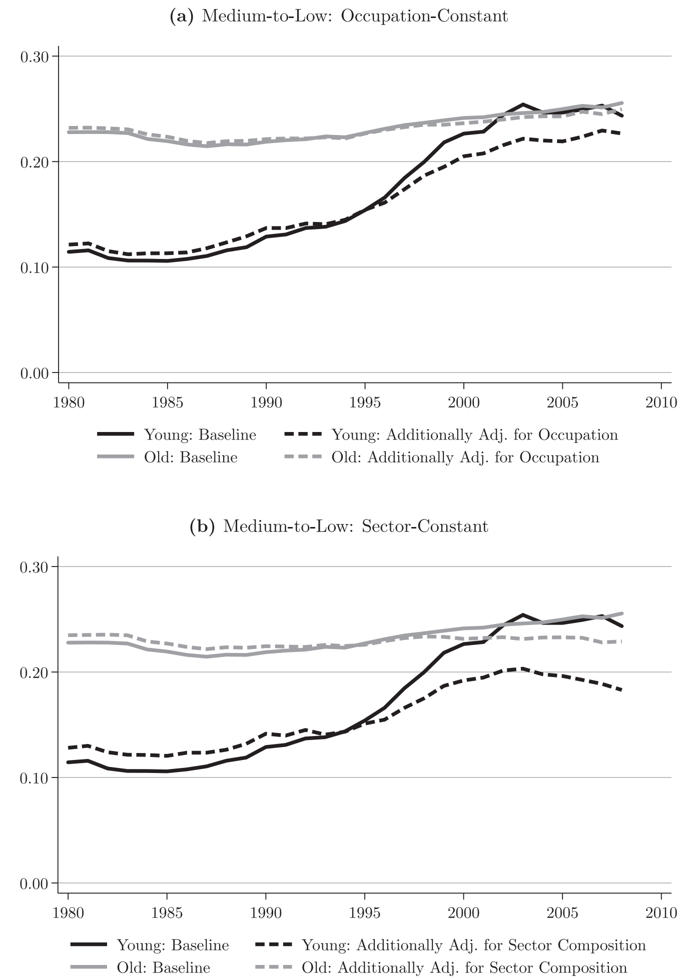


Fig. A.5. Comparison of Premiums when Holding the Occupation- and Sector-Composition Constant Comparison of medium-to-low and high-to-medium premiums holding the age-gender (baseline) and the age-gender-occupation or age-gender-industry composition constant. We distinguish 30 different occupation groups according the *Berufsabschnitte* of the *Klassifikation der Berufe 1988* and 14 different industries used in the IAB wage data, respectively.

to-low (high-to-medium) skill premium is calculated as the difference between the composition-adjusted log real wage of medium- and low-skilled (high- and medium-skilled) workers. Skill premiums can thus be interpreted as the percentage difference in wages between two skill groups. Age-group-specific premiums are calculated by restricting the above calculations to the corresponding age groups of young and old workers.

A.5. *Efficiency Labor Supplies*

The labor supply in efficiency units of a specific skill-age group is calculated as the number of individual employment spells in that group weighted by the spell length, the spell type (full-time, long part-time, short part-time, vocational) and the efficiency weight. The efficiency weight is time-invariant and calculated based on full-time spells as the normalized wage of a skill-age-gender-nativity group relative to a base group, averaged across all years in the sample. Specifically, the efficiency weights are computed by first averaging full-time wages by year t, skill s, age a, gender g, and West German nativity m. Let $\bar{w}^t_{sagm}$ denote these cell-specific average wages, which can be thought of as the product of the equilibrium skill price for the particular skill-age group considered and the average amount of efficiency units supplied by members of subgroup $sagm$: $\bar{w}^t_{sagm} = p^t_{sa} \times efficiency_{sagm}$. These average wages are then divided by (indexed to) the average wage of some base group $\bar{w}^t_b$, which we choose to be West German native male medium-skilled workers aged 31-35. To obtain the time-invariant efficiency weights, we then average these wage ratios for each group over the entire sample period, so that $efficiency-weight_{sagm} = \frac{1}{T}\sum_t \frac{\bar{w}^t_{sagm}}{\bar{w}^t_b}$. Thus, women and men as well as West German natives and non-natives within the same skill-age group are assigned different efficiency weights. Because skill prices are assumed not to vary across subgroups within a broader skill-age group, the measured differences in the efficiency weights between those subgroups directly reflect differences in their underlying efficiency supplies:

$$efficiency-weight_{sagm} - efficiency-weight_{sag'm'}$$
$$= (efficiency_{sagm} - efficiency_{sag'm'})\left(\frac{1}{T}\sum_t \frac{p^t_{sa}}{\bar{w}^t_b}\right)$$

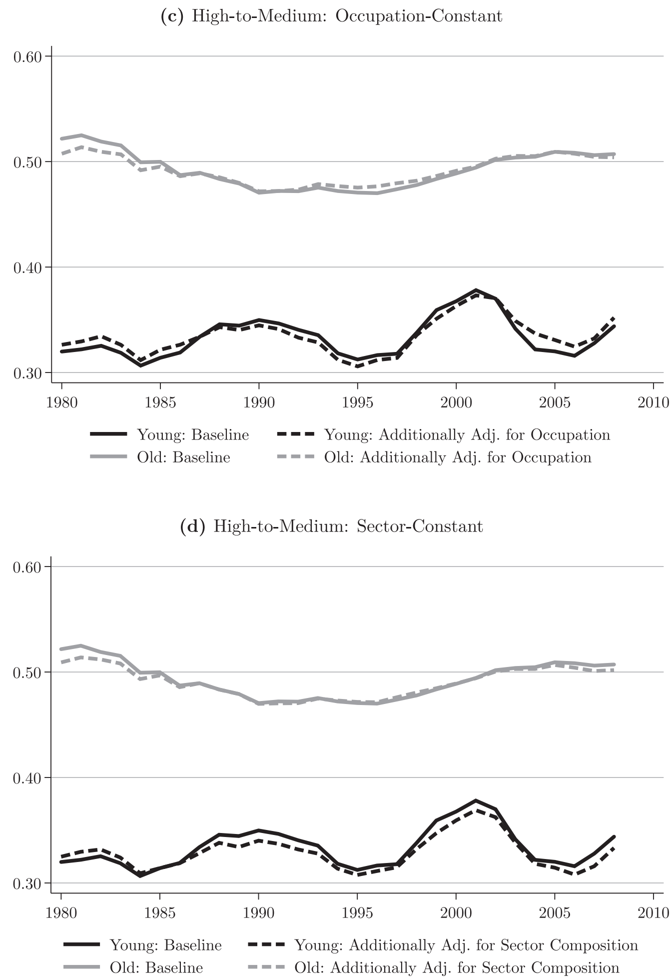


Fig. A.5. Continued

Note that the specific normalization underlying these efficiency weights ($\bar{w}_b^t$) is inconsequential for the subsequent analysis since the time-invariant term ($\frac{1}{T}\sum_t \frac{p_{sa}^t}{\bar{w}_b^t}$) can be factored out of the skill-age-specific aggregate supply measure and will, after taking logs, be absorbed by the constant term in the estimations (see the next equation). Table A.1 lists the full set of efficiency weights for all subgroups in our sample.

To construct our baseline supply measures, spells are further weighted by their spell type, where we distinguish between full-time, long part-time, short part-time, and vocational employment spells. The corresponding weights assumed for these spell types are listed in Table A.2. The efficiency labor supply of skill group s in age group a in year t is then computed as the weighted sum of all spells i in that skill-age cell:

$$\begin{aligned} efficiency-supply_{sat} = \sum_{i \in Cell_{sat}} & spell-length_i \cdot spell-type_i \\ & \cdot efficiency-weight_{sagm} \end{aligned}$$

For instance, a medium-skilled native man aged 31-35 working full-time all year long supplies exactly one efficiency unit of labor in each year, while a medium-skilled foreign woman aged 41-45 working long part-time for half of the year supplies 0.25 units (= 0.5 (half a year) × 2/3 (spell type long part-time) × 0.74 (efficiency weight medium-skilled foreign women aged 41-45)).

A.6. Flexibly Estimating σ_a

In our main analysis, we assume 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 skill group. By substituting in for the different σ's, premium Eqs. (5) and (7) can be expressed as

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

In Table A.3, we estimate this system of equations, using again 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 A.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 of 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 14. Medium- and high-skilled workers of the two age groups are estimated to be less substitutable with an elasticity of around 7 in both groups.

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 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 we distinguish as well. Their comparable estimate of the education-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 than our estimates. Fitzenberger et al. (2006) estimate σ_{al} to lie in the range of 8.7-10.3, σ_{am} 5.3-6.0, and σ_{ah} 8.5-20.1. Our elasticities are thus a bit higher for

[32] Note that the coefficients on $\ln M_{jt}$ should be the same in both equations except for the minus sign. This is why we use $-\ln L_{jt}$ as a regressor in the first equation and $-\ln M_{jt}$ as a regressor in the second equation as this ensures that coefficients are comparable across equations.

[33] The large standard errors of the coefficients of the high-to-medium premium equation in Model 1 are due to some extreme 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, university, or PhD) and not just those with, say, a university degree.

Table A.1
Efficiency Weights for Baseline Supplies.

	Low		Medium		High	
	(1) Native	(2) Foreign/ East German	(3) Native	(4) Foreign/ East German	(5) Native	(6) Foreign/ East German
Panel A: Men						
Age 21-25	0.68	0.66	0.76	0.74	0.93	0.98
Age 26-30	0.77	0.74	0.89	0.84	1.21	1.23
Age 31-35	0.84	0.79	**1.00**	0.90	1.49	1.45
Age 36-40	0.88	0.83	1.06	0.93	1.69	1.61
Age 41-45	0.89	0.85	1.10	0.95	1.81	1.70
Age 46-50	0.90	0.86	1.11	0.94	1.86	1.73
Age 51-55	0.90	0.87	1.11	0.94	1.88	1.74
Age 56-60	0.89	0.85	1.09	0.93	1.86	1.74
Panel B: Women						
Age 21-25	0.56	0.53	0.65	0.61	0.78	0.83
Age 26-30	0.63	0.58	0.75	0.71	1.00	1.02
Age 31-35	0.64	0.60	0.78	0.74	1.15	1.16
Age 36-40	0.64	0.61	0.77	0.74	1.20	1.22
Age 41-45	0.64	0.62	0.78	0.74	1.22	1.26
Age 46-50	0.65	0.63	0.79	0.75	1.25	1.23
Age 51-55	0.66	0.65	0.79	0.75	1.27	1.22
Age 56-60	0.65	0.64	0.79	0.75	1.29	1.23

Notes: This table shows the full set of efficiency weights for each of the 96 skill group × age group × gender × West German nativity cells. Each entry corresponds to full-time year-round spells. The baseline group with an efficiency weight of 1 are medium-skilled native men aged between 31 and 35 years.

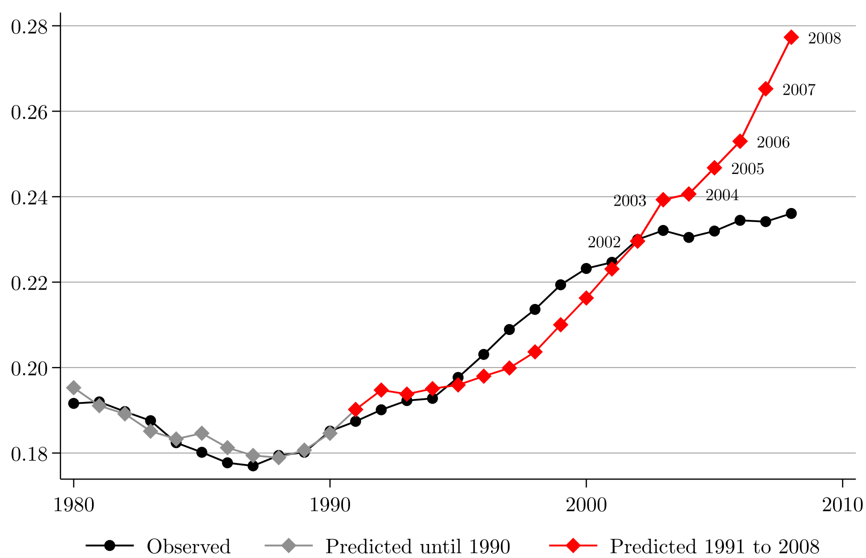


Fig. A.6. Observed vs. Fitted Aggregated Medium-to-Low Skill Premium.
(Corresponding to Model 2 of Table 3).

Table A.2
Spell Type Specific Weights.

	Spell Type Weight	
Spell Type	Baseline	Robustness Check 7 Table 5
Full-Time	1	1
Long Part-Time	2/3	2/3
Short Part-Time	1/3	1/2
Vocational	1/3	1/3

Notes: This table shows the different spell-type-specific weights used to construct efficiency supplies.

low- and medium-skilled workers and somewhat lower for high-skilled workers.

A.7. Estimating α_s

Using the estimates for σ_a, we can back out the age-group-specific efficiency parameters α_{st} by rewriting Eqs. (2) to (4) as follows:

$$\tilde{w}^L_{jt} = \ln w^L_{jt} + \frac{1}{\sigma_{al}} \ln L_{jt} \qquad = \ln \alpha_{lj} + \ln \left[Y_t^{1-\gamma} U_t^{\gamma-\rho} L_t^{\rho-\eta_l} \right]$$

$$\tilde{w}^M_{jt} = \ln w^M_{jt} + \frac{1}{\sigma_{am}} \ln M_{jt} \qquad = \ln \alpha_{mj} + \ln \left[Y_t^{1-\gamma} U_t^{\gamma-\rho} \theta_t M_t^{\rho-\eta_m} \right]$$

$$\tilde{w}^H_{jt} = \ln w^H_{jt} + \frac{1}{\sigma_{ah}} \ln H_{jt} \qquad = \ln \alpha_{hj} + \ln \left[Y_t^{1-\gamma} \lambda_t H_t^{\gamma-\eta_h} \right]$$

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 A.3). The α_{st} can be recovered from regressions of the above equations where the first terms on the right hand sides are captured by a dummy for being young and the second terms by a set of time dummies. The results from these regressions are shown in

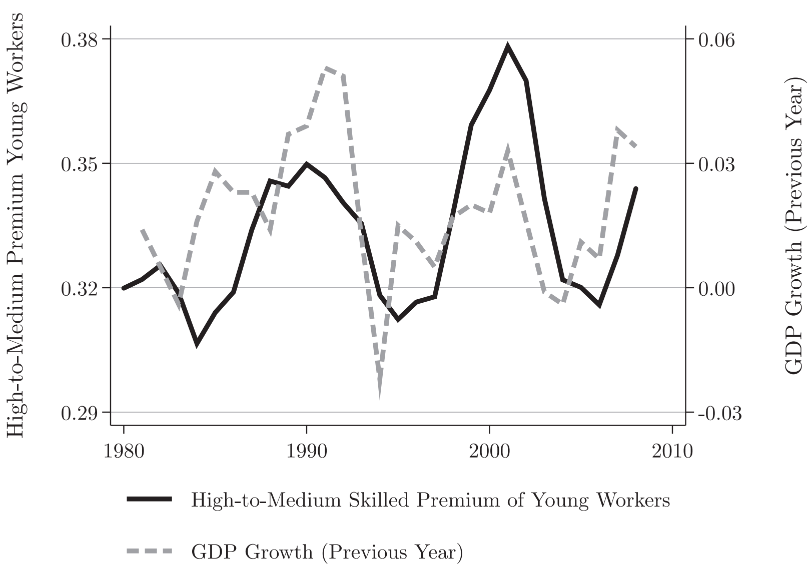


Fig. A.7. Comovement of the High-to-Medium Premium of Young Workers and GDP Growth.

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

	(1)		(2)	
	Unrestricted		Restricted	
	ω_{jt}^{M}	ω_{jt}^{H}	ω_{jt}^{M}	ω_{jt}^{H}
$\ln L_{jt}$	-0.072**		-0.071**	
	(0.032)		(0.032)	
$\ln M_{jt}$	-0.146***	-0.136	-0.145***	-0.145***
	(0.011)	(0.098)	(0.010)	(0.010)
$\ln H_{jt}$		-0.144		-0.151***
		(0.117)		(0.037)
Young	-0.144***	-0.278**	-0.144***	-0.280***
	(0.041)	(0.128)	(0.037)	(0.062)
Constant	0.510***	0.241	0.508***	0.219***
	(0.051)	(0.166)	(0.043)	(0.023)
Time FEs	✓	✓	✓	✓
$H_0: \sigma_{al} = \sigma_{am}$ (p-value)	0.25	0.18	0.23	0.23
$H_0: \sigma_{al} = \sigma_{ah}$ (p-value)	0.11		0.17	
$H_0: \sigma_{am1} = \sigma_{am2}$ (p-value)	0.92			
$H_0: \sigma_{am} = \sigma_{ah}$ (p-value)	0.99	0.80	0.84	0.84
σ_{al}	13.9		14.0	
	(6.1)		(6.2)	
σ_{am}	6.8	7.4	6.9	6.9
	(0.5)	(5.3)	(0.5)	(0.5)
σ_{ah}		6.9		6.6
		(5.6)		(1.6)
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 $\sigma_{am1} = \sigma_{am2}$. The number of observations refers to the full sample, *n*. Young is an indicator for age ≤ 30 years. Moving block bootstrap standard errors with block length 3 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

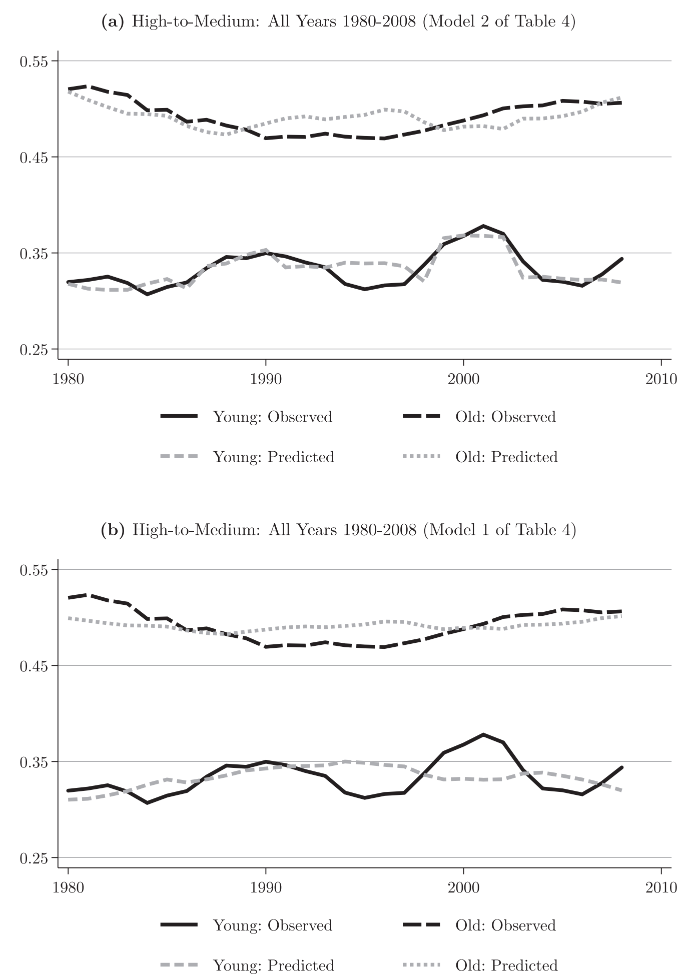


Fig. A.8. Predicted vs. Observed High-to-Medium Premiums.

Table A.4. Our moving block bootstrap accounts for the uncertainty due to the generated regressors. We interpret the results in the main text.

A.8. Factor Price Elasticities

As Hamermesh (1993) shows, factor price elasticities giving the impact of an increase in the supply of factor z on the wage of factor y are given by

$$\varepsilon_{yz} = \frac{\partial \ln w_y}{\partial \ln L_z} = s_z \frac{Q_{yz}Q}{Q_y Q_z},$$

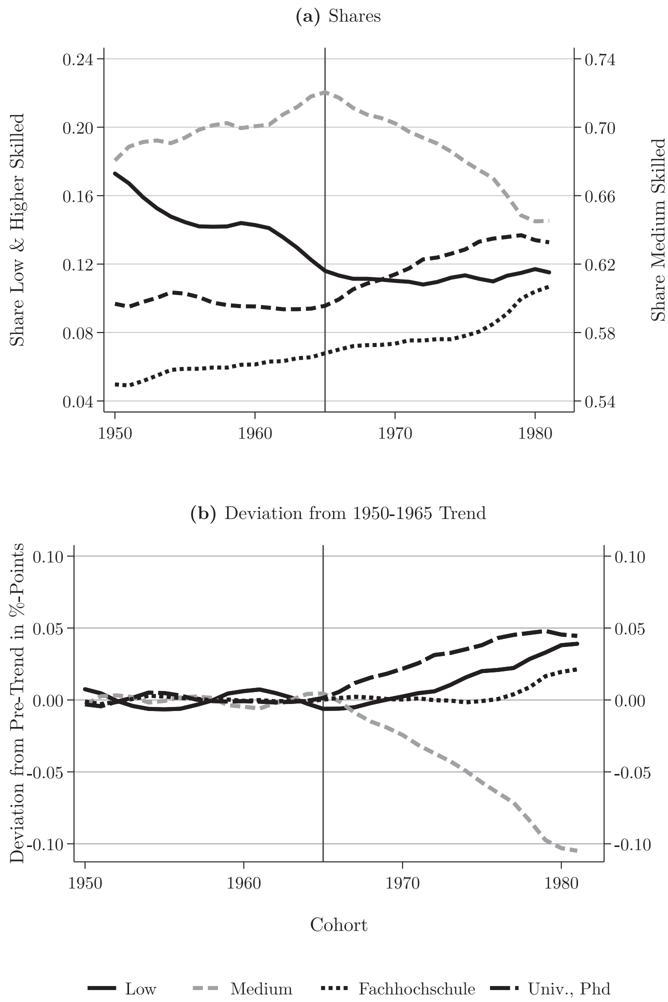


Fig. A.9. Educational Attainment by Cohorts.

where s_z is the share of income accruing to factor z, and $Q_y = \partial Q/\partial L_y$, $Q_z = \partial Q/\partial L_z$, and $Q_{yz} = \partial^2 Q/(\partial L_y \partial L_z)$. To compute the factor price elasticities implied by our estimates, we make a slight modification to our production function by allowing capital to enter in a standard separable way, leading to the following nested CES production function:

$$Q_t = \left[\delta_t K_t^{\tau} + E_t^{\tau}\right]^{1/\tau},$$

where Q denotes output, K denotes capital, E denotes the aggregate labor input, and $\tau = 1 - 1/\sigma_{ke}$, with σ_{ke} being the elasticity of substitution between capital and labor. Note that the labor aggregate input E_t corresponds to our original expression for Y_t in Section 2. This nested CES technology then implies (compare Borjas, 2003) that the own factor price elasticities for high-, medium- and low-skilled workers of age group j are given by

$$\varepsilon_{hj,hj} = -\frac{1}{\sigma_a} + \left(\frac{1}{\sigma_a} - \frac{1}{\sigma_{hu}}\right)\frac{s_{hj}}{s_h} + \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{hj}}{s_e} + \frac{1}{\sigma_{ke}}s_{hj} \tag{A.1}$$

$$\varepsilon_{mj,mj} = -\frac{1}{\sigma_a} + \left(\frac{1}{\sigma_a} - \frac{1}{\sigma_{ml}}\right)\frac{s_{mj}}{s_m} + \left(\frac{1}{\sigma_{ml}} - \frac{1}{\sigma_{hu}}\right)\frac{s_{mj}}{s_u} + \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{mj}}{s_e} + \frac{1}{\sigma_{ke}}s_{mj} \tag{A.2}$$

$$\varepsilon_{lj,lj} = -\frac{1}{\sigma_a} + \left(\frac{1}{\sigma_a} - \frac{1}{\sigma_{ml}}\right)\frac{s_{lj}}{s_l} + \left(\frac{1}{\sigma_{ml}} - \frac{1}{\sigma_{hu}}\right)\frac{s_{lj}}{s_u} + \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{lj}}{s_e} + \frac{1}{\sigma_{ke}}s_{lj} \tag{A.3}$$

where s_{ij} gives the share of income accruing to group (i, j), s_i gives the share of income accruing to education group i, and s_e gives labor's share of income.

Similarly, the (within branch) cross-factor price elasticities giving the impact of an increase in the supply of group (i, j') on the wage of group (i, j), with $j \neq j'$, are

$$\varepsilon_{hj,hj'} = \left(\frac{1}{\sigma_a} - \frac{1}{\sigma_{hu}}\right)\frac{s_{hj'}}{s_h} + \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{hj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{hj'} \tag{A.4}$$

$$\varepsilon_{mj,mj'} = \left(\frac{1}{\sigma_a} - \frac{1}{\sigma_{ml}}\right)\frac{s_{mj'}}{s_m} + \left(\frac{1}{\sigma_{ml}} - \frac{1}{\sigma_{hu}}\right)\frac{s_{mj'}}{s_u} + \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{mj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{mj'} \tag{A.5}$$

$$\varepsilon_{lj,lj'} = \left(\frac{1}{\sigma_a} - \frac{1}{\sigma_{ml}}\right)\frac{s_{lj'}}{s_l} + \left(\frac{1}{\sigma_{ml}} - \frac{1}{\sigma_{hu}}\right)\frac{s_{lj'}}{s_u} + \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{lj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{lj'} \tag{A.6}$$

Finally, the (across branch) cross-factor price elasticities giving the impact of an increase in the supply of group (i', j') on the wage of group (i, j), with $i \neq i'$ and $j' \in (young, old)$, are

$$\varepsilon_{hj,mj'} = \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{mj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{mj'} \tag{A.7}$$

$$\varepsilon_{hj,lj'} = \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{lj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{lj'} \tag{A.8}$$

for high-skilled workers,

$$\varepsilon_{mj,hj'} = \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{hj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{hj'} \tag{A.9}$$

$$\varepsilon_{mj,lj'} = \left(\frac{1}{\sigma_{ml}} - \frac{1}{\sigma_{hu}}\right)\frac{s_{lj'}}{s_u} + \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{lj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{lj'} \tag{A.10}$$

for medium-skilled workers, and

$$\varepsilon_{lj,hj'} = \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{hj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{hj'} \tag{A.11}$$

$$\varepsilon_{lj,mj'} = \left(\frac{1}{\sigma_{ml}} - \frac{1}{\sigma_{hu}}\right)\frac{s_{mj'}}{s_u} + \left(\frac{1}{\sigma_{hu}} - \frac{1}{\sigma_{ke}}\right)\frac{s_{mj'}}{s_e} + \frac{1}{\sigma_{ke}}s_{mj'} \tag{A.12}$$

Table A.4
Estimating the Efficiency Parameters α_{sj}.

	(1)			(2)		
	Constant σ_a			Unrestricted σ_{as}		
	$\widetilde{w}^L_{jt}$	$\widetilde{w}^M_{jt}$	$\widetilde{w}^H_{jt}$	$\widetilde{w}^L_{jt}$	$\widetilde{w}^M_{jt}$	$\widetilde{w}^H_{jt}$
Young	-0.322***	-0.370***	-0.625***	-0.248***	-0.392***	-0.672***
	(0.019)	(0.016)	(0.022)	(0.033)	(0.017)	(0.065)
Constant	4.465***	4.840***	5.089***	4.383***	4.891***	5.110***
	(0.029)	(0.045)	(0.035)	(0.035)	(0.035)	(0.036)
Time FEs	✓	✓	✓	✓	✓	✓
α_s	0.72	0.69	0.54	0.78	0.68	0.51
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)	(0.03)
Observations	58	58	58	58	58	58
R^2	0.982	0.987	0.994	0.967	0.986	0.994

Notes: $\widetilde{w}^S_{jt} = \ln w^S_{jt} + 1/\sigma_{as} \ln S_{jt}$. The α_s are the exponentiated coefficients of the young indicator. The standard errors of the α_s are put in parentheses below. The number of observations refers to the full sample, n. Young is an indicator for age $\leq$ 30 years. Moving block bootstrap standard errors with block length 3 and 500 replications in parentheses. ***/**/* indicate significance at the 1%/5%/10% level.

Table A.5
Implied Factor Price Elasticities.

Education Group	Age Group	Share in Income	Own Elasticity	Cross Elasticity within Edu. Group	Cross Elasticity across Edu. Group		
					Low	Medium	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Low-skilled	Young	0.010	-0.147	-0.022		-0.002	0.004
	Old	0.047	-0.227	-0.102		-0.009	0.017
Medium-skilled	Young	0.120	-0.173	-0.048	-0.022		0.043
	Old	0.408	-0.288	-0.163	-0.076		0.145
High-skilled	Young	0.011	-0.167	-0.042	0.004	0.004	
	Old	0.093	-0.476	-0.351	0.033	0.033	

Notes: This table reports the factor price elasticities implied by our nested CES production function, as shown in Eqs. (A.1) to (A.12). For a 1 percent increase in the number of workers of any specific group listed in the first column, the own factor price elasticity gives the percent change in that group's wage, the cross elasticity within an education group the percent change in the wage of a group with the same education level but different age, and the cross elasticity across education group the percent change in the wage of groups that have a different education level. The income shares used in these calculations are the annual group-specific income shares averaged over the period 1980-2008.

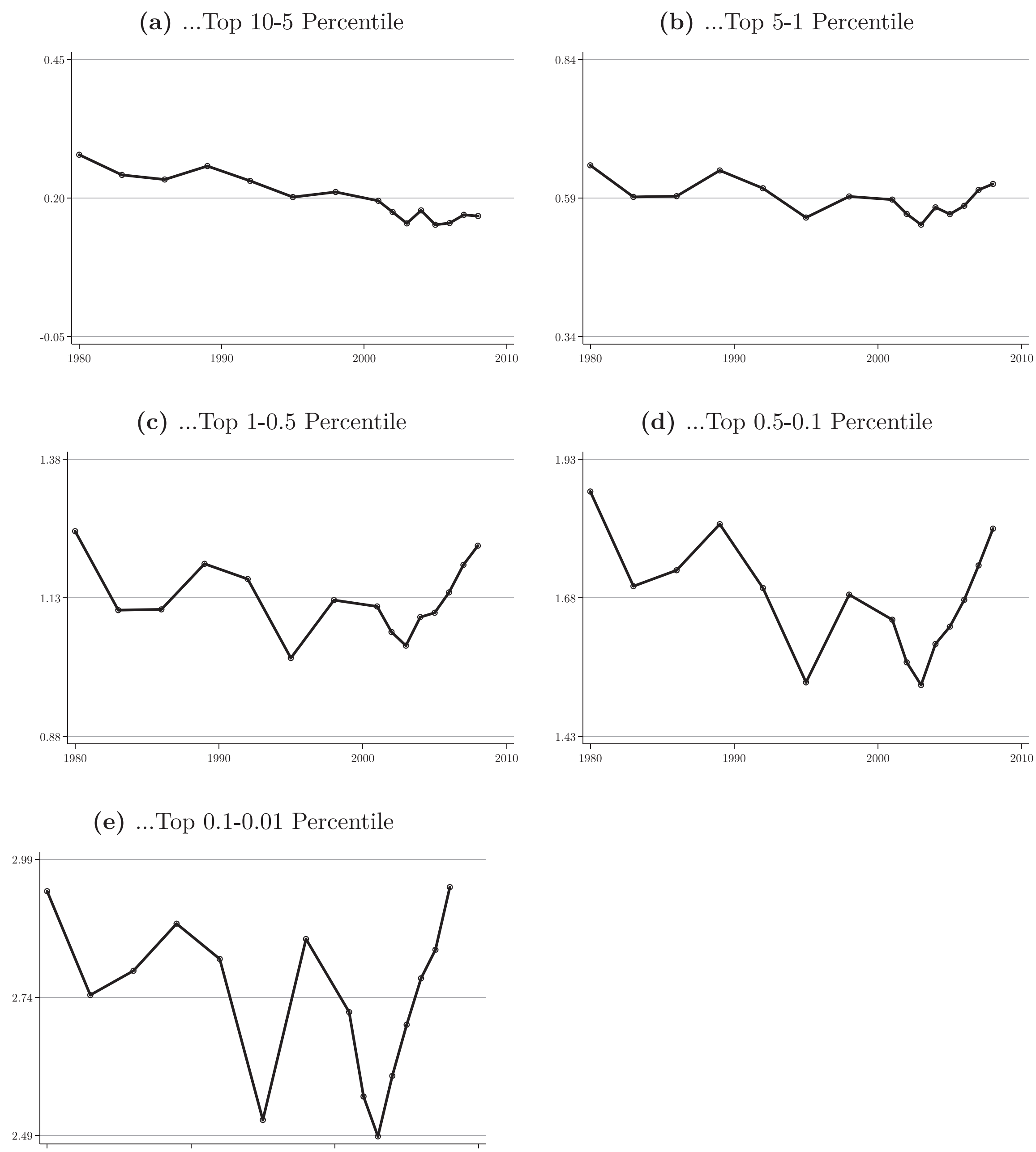


Fig. A.10. Log Difference Between the 85th Percentile (SIAB) and the Average Income (WTID) of.

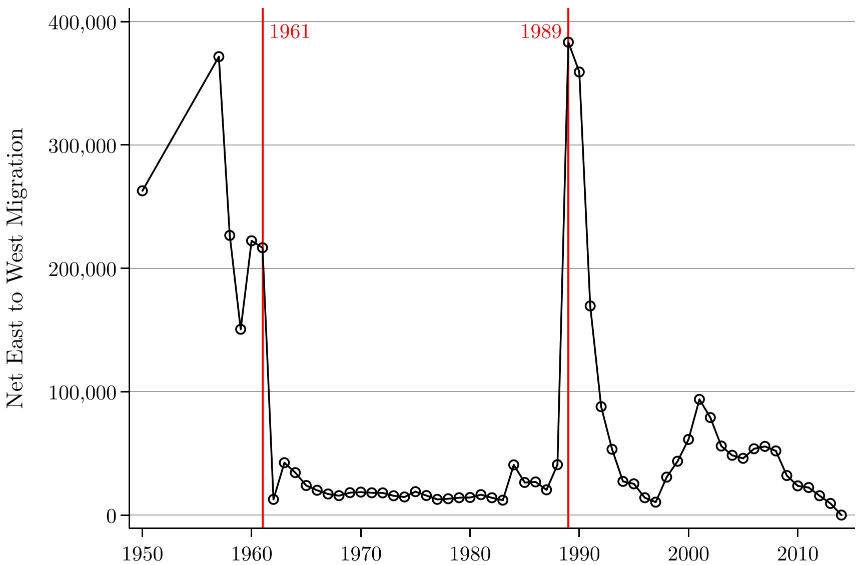


Fig. A.11. Net Official East-West Migration (Statistisches Bundesamt, 2014).

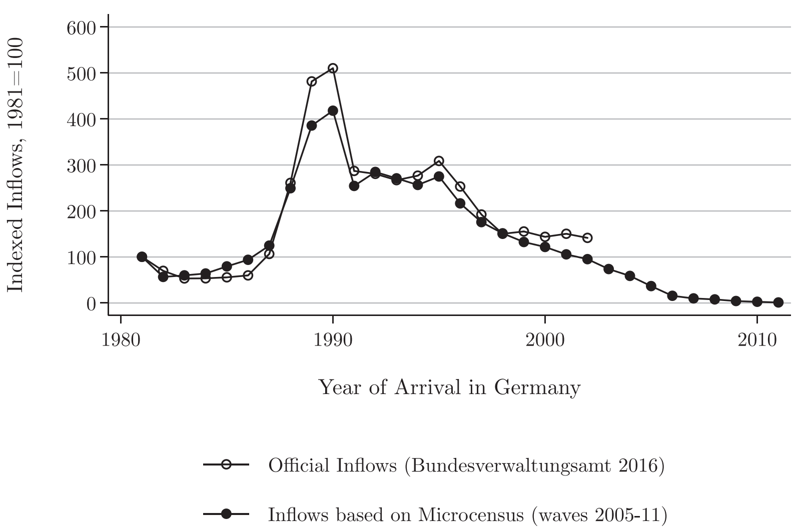


Fig. A.12. Yearly Inflows of 18-59 Year Old Ethnic Germans (West Germany w/o Berlin).

for low-skilled workers. To calculate these factor price elasticities, we assume that the elasticity of substitution between capital and labor σ_{ke} is equal to 1 and calibrate labor's share of income s_e to be 0.69, the average labor income share in Germany over the period 1980 to 2008 according to the EU KLEMS Growth and Productivity Accounts (O'Mahony and Timmer, 2009). To obtain the individual factor shares, we first compute the average share of total annual earnings accruing to each education-age group ($w_{ij}L_{ij}/\sum_i\sum_j w_{ij}L_{ij}$) and then transform these shares into average shares in income using the fact that $\sum_i\sum_j w_{ij}L_{ij} = 0.69 \times TotalIncome$. Finally, we set $\sigma_a = 8.0$, $\sigma_{ml} = 4.2$ and $\sigma_{hu} = 1.8$ in line with the estimated coefficients reported in Column (1) of Table 5. Table A.5 reports the resulting own and cross-factor price elasticities.

A.9. Construction of Migrants' Age-Skill Shares in Labor Supplies

- **Foreign Workers** In the IAB-data, German nationality can be directly observed. We define as foreigners all individuals who are at least once either classified as non-German or have missing nationality information. The shares of foreigners in each age-skill group are then directly computed from the IAB-data.
- **East Germans** In previous work (e.g. D'Amuri et al., 2010), East Germans have been identified in the IAB-data by classifying all individuals who are first registered in East Germany. The problem with this approach is that spells in East Germany are only reliably recorded from 1992 onwards (vom Berge et al., 2013), but substantial inflows of East Germans already occurred in 1989-1991 (see Fig. A.11). To construct the stock of East Germans in the West German labor supply, we therefore rely on external data, namely the 1991/92, 1998/99, 2005/06 and 2012 waves of the BIBB/IAB- and BIBB/BAuA-Surveys of the Working Population, which are representative cross-sectional surveys of the working population in Germany covering about 20,000-30,000 individuals per year. We identify East Germans using the place of birth (wave 1991/92), the region where an individual grew up (wave 1998/99), and information on whether an individual obtained any kind of school or tertiary degree from East Germany (waves 2005/06 and 2012).[35] We can then calculate the share of East Germans in each skill-age cell of the West German labor force. We set the share of East Germans to zero in 1980 and then use the official net-inflow rates in Fig. A.11 to interpolate between waves, i.e. we assume that x% of the difference in shares between two BIBB years is closed in the years in which x% of the overall inflow between those years occurred.

[35] In waves 2005/06 and 2012, we are thus not able to identify individuals who finished their high school degree after German unification and then directly moved to West Germany to work or obtain further qualification.

- **Ethnic Germans** Ethnic Germans cannot be identified in the IAB-data since, upon arrival, they were given German citizenship and are thus indistinguishable from native West Germans in the data. We therefore use German microcensus waves 2005-11 to calculate the necessary age-skill shares. To identify ethnic Germans, we focus on private households at their main place of residence in West Germany who are born outside today's Germany (including East Germany) who have the German citizenship and who have migrated to Germany since 1980. Reassuringly, a comparison of ethnic Germans identified in this way by year of arrival in the microcensus and official inflow figures from the Bundesverwaltungsamt (2016) shows a close correspondence of the two (compare Fig. A.12). To then calculate, for instance, the share of young low-skilled ethnic Germans in a given year between 1980 and 2008, we calculate the number of ethnic Germans who were 30 or younger in that year, had immigrated to Germany between 1980 and the year of interest, and are low-skilled, and divide this number by the total number of individuals of that same skill-age cell in that year. Thus, migration rates and skill-age shares are obtained retrospectively from individuals living in West Germany at some time between 2005 and 2011. Since outmigration of ethnic Germans was basically a "non-issue" as pointed out by Hirsch et al. (2014), and to the extent that labor force participation and mortality of ethnic and native Germans are comparable, this approach yields reliable estimates of the required quantities.
- **Native Efficiency Supplies** Once we obtain the complete time series of all skill-age shares for each of the three migrant groups, we deduct the corresponding portions from our total migrant-including efficiency supplies in each cell to obtain the native efficiency supplies used in the counterfactual simulations of the no-migration scenario.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi10.1016/j.labeco.2021.102034

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