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IZA DP No. 10901

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ABSTRACT

Skill Premiums and the Supply of Young Workers in Germany*

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

JEL Classification: J110, J210, J220, J310

Keywords: cohorts, baby boom, labor supply, labor demand, skill-biased technological change, wage distribution, wage differentials

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1 Introduction

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

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

Our core hypothesis is that differential changes in the supply of skills are responsible for the observed patterns in skill premiums. In particular, we emphasize the role played by imperfect substitutability across age groups and changes in educational attainment across different cohorts. Our framework is a variant of a Tinbergen (1974) *education race* model where increases in the relative supply of more skilled workers and skill-biased technological change work in opposite directions in determining wage premiums. We distinguish between three skill groups (low, medium, and high) and between young (less than 30 years) and old workers, building on previous frameworks by Card and Lemieux (2001), Dustmann et al. (2009), and Goldin and Katz (2009). To illustrate the model's core idea, in Figure 2 we plot the skill premiums of both young and old medium-skilled (relative to low-skilled) and high-skilled (relative to medium-skilled) workers against their corresponding relative supplies (both linearly detrended to absorb, for instance, secular skill-biased technological progress). Except for the young high-skilled[4], there is a clear negative relationship – despite many potential rigidities governing the German labor market.

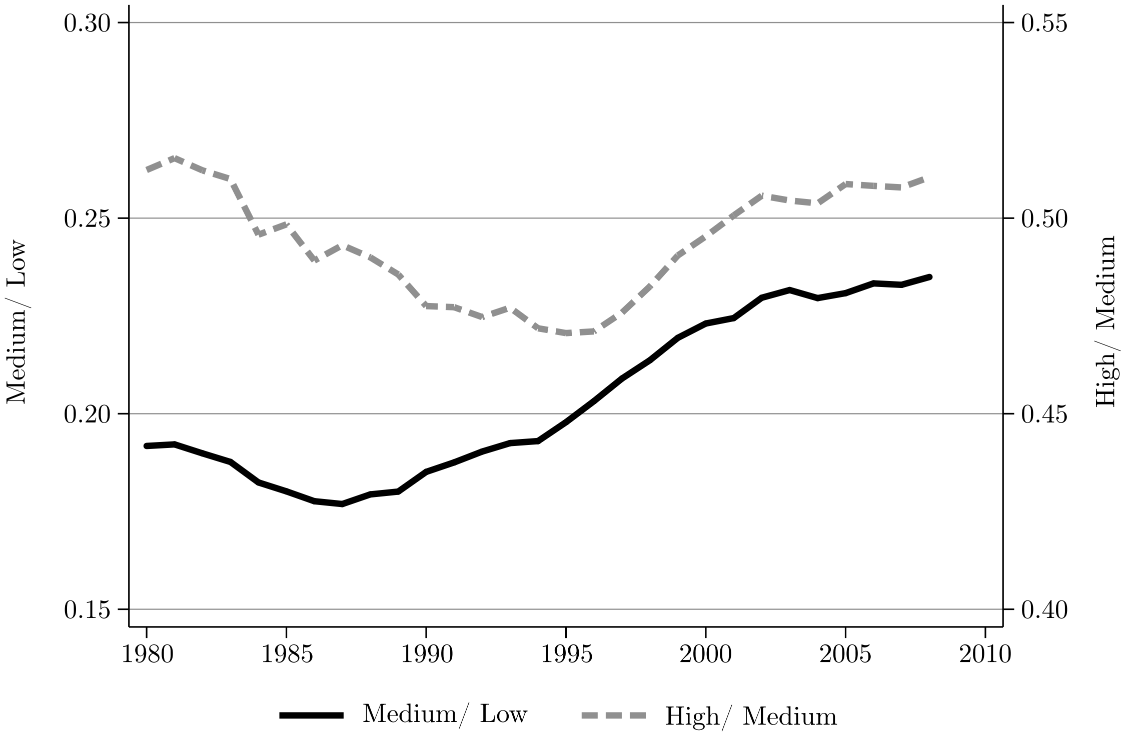
[1] Kopczuk et al. (2010) using social security records find an increase in earnings inequality in the US since the 1950s which accelerated in the 1970 and 80s and reached its highest level in the 2000s since the start of the records in 1937. Dustmann et al. (2009) show that wage inequality has also increased considerable in (West-)Germany over the last three decades.

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

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

[4] The relationship within the group of young high-skilled workers is attenuated due to the pre-unification boom 1987-1990 and in particular by the dot-com/New Economy boom and bust during 1999-2002. Once we exclude

Figure 1: Skill Premiums, Germany (1980-2008)



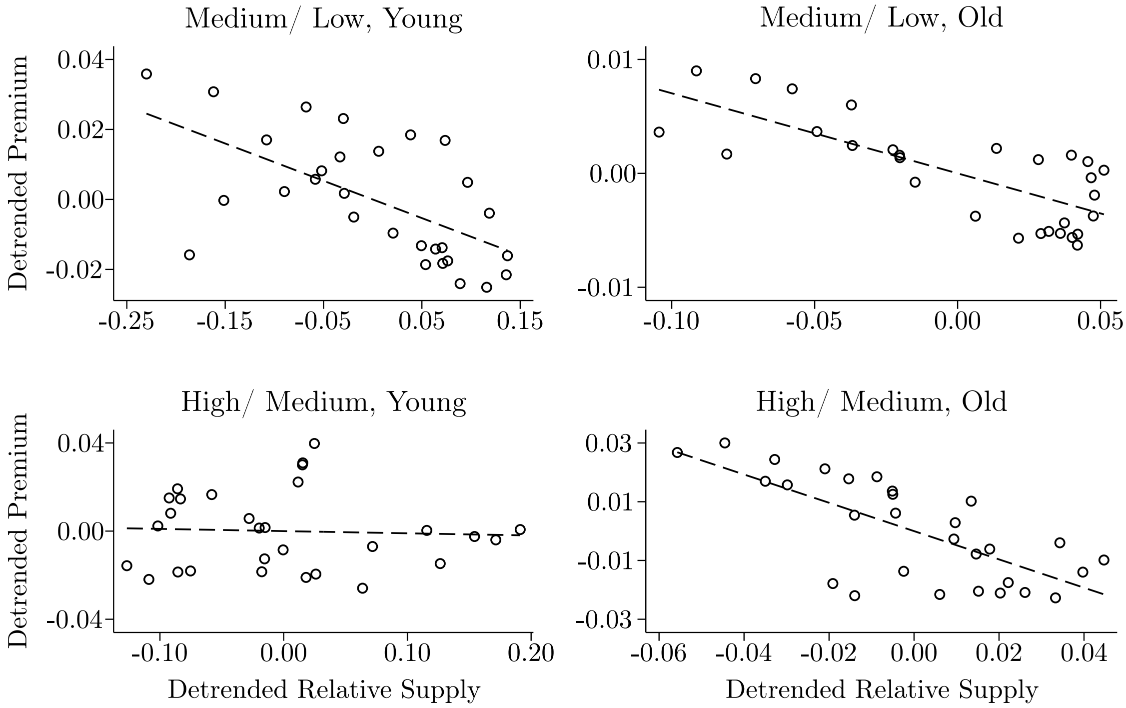
Notes: This figure plots skill premiums defined as log wage differentials between medium and low and high and medium-skilled workers who work full-time, live in West-Germany and have not moved from East to West-Germany between 1980-2008 holding the age- and gender composition constant. For more details on the construction of skill premiums see sections 3.3.

Using high quality administrative data for Germany over the period 1980-2008, we first systematically document the evolution of skill premiums along various skill levels and age groups. We show that almost the entire increase in the medium to low skill premium visible in Figure 1 is attributable to a pronounced increase in the medium skill premium of *young* workers (aged 30 and below) which increased from about 10% in 1980 to 25% in 2008 – a finding that has not been documented so far in the existing literature.[5] In contrast, wage premiums of older medium-skilled workers and of both younger and older workers holding a university degree have stayed remarkably stable. Second, our proposed model which relates skill premiums to shifts in relative skill supplies is able to account well for these differential patterns in observed skill premiums. This is especially true for the medium to low skill premium. Third, we try to be more careful about standard errors than most existing studies. We account for the uncertainty induced by generated regressors as well as serial and contemporaneous correlation of all variables in adjacent years by means of a moving block bootstrap approach (Kunsch 1989). As it turns

these years or allow for separate intercepts for these two periods, the relationship becomes clearly negative as expected, see the discussion in section 4.

[5]The only exception is Fitzenberger and Kohn (2006) who apply the CES production framework of Card and Lemieux (2001) to estimate the magnitude of wage changes that would have been necessary to halve unemployment rates in Germany in the mid 1990s.

Figure 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. All variables are linearly detrended. See section 3 for a description of skill premiums and efficiency supplies.

out, standard errors computed with this method are up to five times larger than those based on conventional methods.

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

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

Our paper also relates to a range of studies that have used German administrative labor market data to study the rise in German wage inequality. Antonczyk et al. (2010a) emphasize the role of cohort effects in Germany as an important driver of lower end wage inequality. Card et al. (2013) identify an increasing dispersion in both person- and establishment-specific wage premiums as well as an increasing assortativeness in the matching of workers and establishments as main factors behind rising wage inequality, while Goldschmidt and Schmieder (2017) emphasize the role of domestic outsourcing, calculating that it contributed some 10% to the increase in German wage inequality since the 1980s. Burda and Seele (2016) apply the Katz and Murphy (1992) framework and show that the Hartz reforms implemented in 2003 boosted labor supply and contributed to the recent German employment miracle at the cost of decreasing real wages and increasing wage dispersion. Of particular relevance in the context of our work is the study by Dustmann et al. (2009) who document the recent trends in German wage inequality and perform an extensive analysis of competing explanations, identifying compositional changes (as DiNardo et al. 1996), a decline in unionization (see also Antonczyk et al. 2010b), skill-biased demand shifts favoring in particular the high-skilled, polarization (as proposed by Autor and Dorn 2014; Autor et al. 2009; Goos and Manning 2007) and changes in the supply of skills (similar to Goldin and Katz 2009) as key contributors to German wage inequality. In particular, Dustmann et al. (2009) emphasize that changes in the relative supply of medium-skilled workers are responsible for the significant increase in wage inequality at the lower tail of the wage distribution, attributing this to a deceleration in the rate of decline of low-skilled employment shares in the 1990s. They hypothesize that this deceleration might be due to the “large inflow of [mainly low-skilled] East Germans, Eastern Europeans, and ethnic Germans [...] into the West German labor market” (Dustmann et al. 2009, p. 867). Our findings, however, show that the decline in the relative supply of medium-skilled workers is primarily due to a pronounced and so far undocumented decrease in the share of *native medium-skilled* workers. Our paper thus fills an important gap when it comes to understanding the main drivers of recent changes in wage inequality in Germany.

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

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 and the construction of our key variables (skill premiums and efficiency labor supplies) and present graphical evidence on the evolution of skill premiums and efficiency supplies separately for young and old workers. These are the patterns we aim to explain in section 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 skill attainment. Section 6 concludes the paper.

2 Analytical Framework

Our modelling approach closely follows previous work by Card and Lemieux (2001), 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) labor U_t:

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

where A_t denotes total factor productivity and λ_t is a time-varying technology or demand shifter that reflects both the importance of each input and factor augmenting (skill-biased) technological progress. The elasticity of substitution between non-college and college labor is given by $\sigma_{hu} = \frac{1}{1-\gamma} \in [0, \infty]$. If $0 \leq \sigma_{hu} < 1$ the two factors are gross complements. If $\sigma_{hu} \geq 1$ the two factors are gross substitutes and (high-) skill-biased technological progress will increase the wage differential in favor of better skilled workers.[7]

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

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 demand shifter as above. The elasticity of substitution between medium- and low-skilled labor is given by $\sigma_{ml} = \frac{1}{1-\rho}$ defined analogously as before. Each type of labor in

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

turn is composed of the corresponding supply in different age groups

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

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

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

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

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

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

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

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

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

and the high to medium skill premium

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

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

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

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 of the distinct skill-age-groups. We use administrative labor market data provided by the Institute for Employment Research in the *Sample of Integrated Labour Market Biographies* (SIAB).[8] The SIAB is a 2% random sample of the official records of all employees subject to social security in Germany between 1975 and 2010. It contains the labor market history of about 1.5 million individuals and includes information on daily wages and employment status (full-time, part-time, unemployed, in vocational training) as well as a number of individual characteristics such as age, gender, skill, German nationality, region, occupation, and industry. We restrict the analysis to men and women between 21 and 60 years of age living in West Germany with earnings above the official marginal earnings threshold (400 euros per month in 2010[9]) as marginal part-time spells were only officially recorded from 1999 onwards. In addition, we exclude the years 1975-1979 due to the very high incidence of censoring among the high-skilled and the crisis years 2009/10 such that our final sample covers the years 1980-2008. We also conduct three imputations that are by now common practice when working with IAB data: the imputation of missing education information following Fitzenberger et al. (2006), the correction for the structural break in 1984 according to Fitzenberger (1999) and Dustmann et al. (2009) and the imputation of censored wages above the upper earnings threshold for compulsory social insurance (66,000 euros per year in 2010) applying the "no heterogeneity" approach suggested by Gartner (2005).[10]

3.2 Definition of Skill and Age Groups

For our subsequent analysis, we divide workers into low-, medium- and high-skilled. Following Dustmann et al. (2009), we define the low-skilled as those with missing or at most lower secondary education (*Realschule* or less), medium as those with apprenticeships, vocational training, and/or *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 to study the college premium (Autor 2014; Card and Lemieux 2001). The division into three skill groups in Germany reflects Germany's strong pillar of vocational training and is also clearly suggested by comparing the wage levels of these groups (see Figure A.1).

[8]Specifically, we use the scientific use file of the SIAB Regional-File 1975-2010, see vom Berge et al. (2013) for a detailed description of this data set.
[9]We convert all monetary values into 2010 euros using the consumer price index of the German Bundesbank.
[10]See Appendix A.2 for a more detailed description of the derivation of our sub-sample and the imputation of censored wages.

Along the age dimension, we consider eight different age groups spanning five year intervals for ages between 21-60 years. For most of the graphical evidence and the empirical estimations, however, we just distinguish in each skill group between young (≤ 30 years) and old workers (> 30 years) as these two groups capture well the underlying trends of more finely disaggregate age groups (see section 3.5 for more details).

3.3 Skill Premiums and Efficiency Labor Supplies

Our objective is to calculate the *pure* price for different skill levels net of any compositional changes due to, for instance, migration or changes in the gender or age group composition of the working population.[11] To keep our premium sample as homogeneous as possible, we restrict the attention to men and women working full-time and are "West German natives", i.e. we exclude those who started their labor market biography in East Germany and then moved to West Germany as well as those with missing or non-German nationality information.[12] We then calculate age and gender composition constant skill premiums similar to Katz and Murphy (1992). Skill premiums can be interpreted as the (approximate) percentage difference in wages between two skill groups. Section A.3 in the Appendix describes the computation of skill premiums in more detail.

Our labor supply measures are based on a broad set of individuals and 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), vocational training, and unemployment spells of all workers registered in West Germany, i.e. we include West German natives as well as foreigners and those who were first registered in East Germany and migrated to West Germany (we will refer to the latter two groups as "migrants" in what follows). In contrast to our premium data set, we choose such a broad set of workers and work types to mitigate concerns regarding the endogeneity of labor supplies. In contrast, if we computed labor supplies based on full-time spells only, we would fail to incorporate transitions to and from part-time work or unemployment induced by changes in skill premiums, or any differential effects of the business cycle on the labor supply of different skill or age groups.

Labor supplies need to be measured in efficiency units because the framework outlined in section 2 assumes that workers in the same skill-age cell are perfect substitutes. Therefore, we allow productivities (reflected in wages) to differ by age and skill group as well as gender and West German nativity. Accounting for productivity differences between natives and migrants is

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

[12] Ideally, we would also like to exclude ethnic Germans and those East Germans who 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 additional data sets when we assess the impact of migration on skill premiums in section 5.

also important to mitigate issues related to potential downgrading of migrants' education and experience, i.e. the fact that the human capital of migrants is not fully transferable (see for instance Basilio and Bauer 2010; Dustmann et al. 2012; Friedberg 2000).

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 spell) a weight of 2/3 and short part-time spells a weight of 1/2 (less than half of a full-time spell) following Dustmann et al. (2009). Vocational training and unemployment spells are assigned a weight of 1/3. In our robustness checks, we show that our results are not sensitive to the specific weighting scheme. For instance, it would also be sensible to assign a weight of 1 to those unemployed who worked full-time before. Applying this alternative weighting scheme leaves our estimates basically unchanged. Section A.4 in the Appendix contains details on on the construction of our efficiency supplies.

3.4 Summary Statistics

In panel A of Table 1, we summarize some characteristics of our wage sample based on which we construct the different wage premiums. Between 1980 and 2008, the native full-time workforce became older with the share of young workers below 30 years dropping from around 30% in the 1980s to 19% in 2008. This is the consequence of declining cohorts sizes after the baby boomer generation in the mid 1960s. The share of women working full-time remained remarkably stable over the sample period at around 33%. In contrast, the skill composition of full-time workers changed dramatically: The share of low-skilled workers dropped from 20% in 1980 to just 6% in 2008 with the largest decline occurring in the 1980s. The share of medium-skilled workers followed a reversed U-shape reaching 81% in the 1990s and then declined to 79% in 2008. The share of high-skilled workers increased more than threefold since 1980 in a virtually linear fashion reaching 15% in 2008. 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 since then.[13]

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

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

Table 1: Summary Statistics of Wage and Supply Sample

(Mean if not otherwise stated)

	1980	1990	2000	2008
Panel A. Wage Sample (Full-Time Natives)				
Age	39.0	38.4	39.8	41.4
Young ($\leq$ 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	2,319
Medium-skilled	2,702	2,926	3,097	3,009
High-skilled	4,491	4,767	5,080	5,033
Std. Dev. log real wages	0.41	0.43	0.45	0.51
Person $\times$ 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)				
Age	38.7	38.2	39.6	40.9
Young ($\leq$ 30 years)	0.29	0.32	0.22	0.21
Female	0.38	0.40	0.46	0.48
German	0.90	0.90	0.87	0.85
Shares:				
Low-skilled	0.26	0.17	0.14	0.13
Medium-skilled	0.70	0.76	0.76	0.75
High-skilled	0.05	0.07	0.10	0.12
Full-time	0.87	0.82	0.67	0.63
Long part-time	0.07	0.09	0.11	0.14
Short part-time	0.02	0.02	0.12	0.15
Vocational/other	0.01	0.02	0.02	0.02
Unemployed	0.03	0.05	0.07	0.06
Person $\times$ spells in year	499,280	597,012	853,688	992,925
Unique individuals	382,555	443,838	521,000	531,851

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-German who are non-German and/or were first registered in East Germany are excluded. The supply sample consists of full-time, part-time, vocational training, and unemployment spells of all individuals including non Germans and East-West movers. All summary statistics are weighted by spell length.

3.5 Graphical Analysis

Figure 3 plots the evolution of our key variables separately for young and old workers using comparable scales.[14] In the top left part, we plot the medium to low skill premiums of young and old workers. While the premium for old medium-skilled workers changed only little over the 1980-2008 period (from 0.23 in 1980 to 0.26 in 2008), the premium of young medium-skilled workers more than doubled over the same period (from 0.11 in the mid 1980s to 0.25 in the 2000s).[15] To put these numbers in perspective, according to Goldin and Katz (2009, Figure I, p. 27) the combined premium of young and old high school graduates in the US (relative to those who only stayed in school until 8th grade) increased from 0.23 in 1980 to 0.29 in 2005. Thus, our medium skill premium is similar in magnitude to the US high school premium.[16]

The development of the high-skilled or college premium is depicted in the bottom left part of Figure 3. The young high-skilled saw their premium fluctuating around 0.33 with considerable variation while the college premium of old workers followed a soft U-shape pattern starting from 0.52 in 1980, reaching a low of 0.47 during the 1990s to eventually increase to 0.51 in 2008. Since skills premiums are partly based on imputed wages (in particular the high to medium premium of old workers), one might be worried about how accurately they really represent the *actual* high-skilled premiums. In Appendix A.6, we show that there is no systematic divergence over time between the 85th-percentile in our data (which is always uncensored) and various top income fractiles taken from the from the *World Top Incomes Database* (WTID, Alvaredo et al. 2015). Theses comparisons make us confident that the skill premiums derived from right-censored SIAB data are indeed representative for the true evolution of the earnings gap between high- and medium-skilled workers.

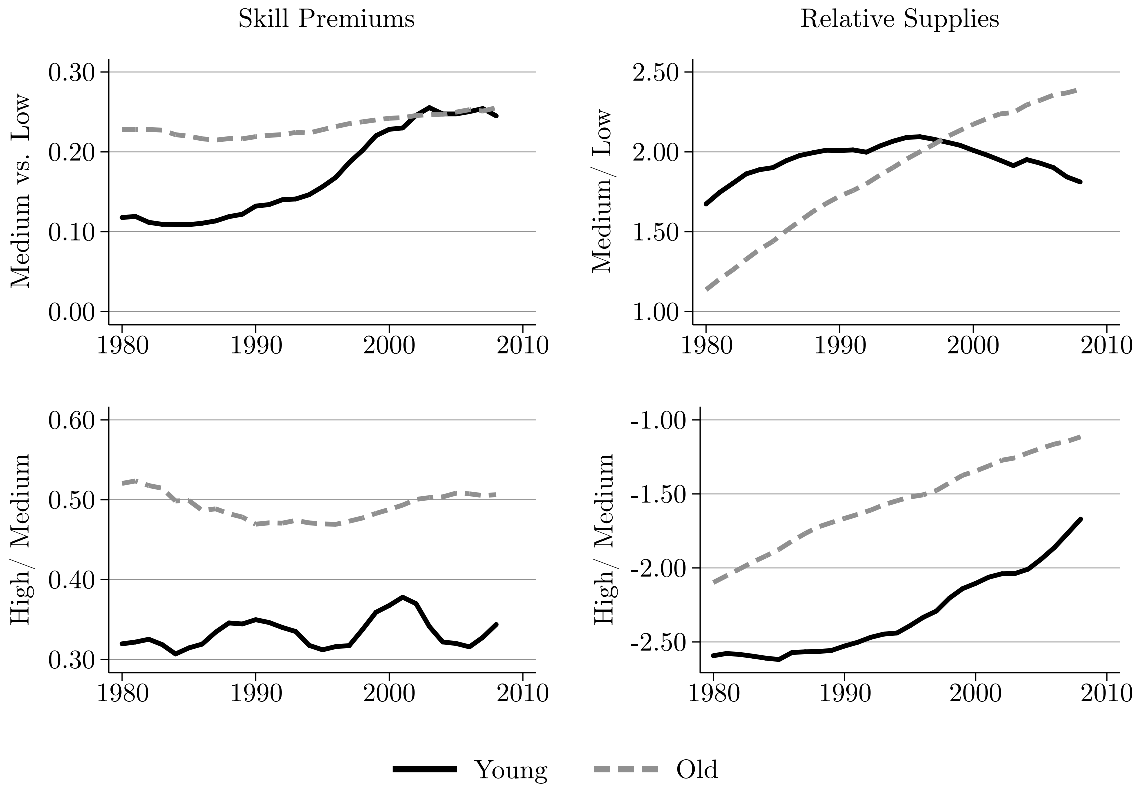
Our core hypothesis is that differential changes in the supplies of different skill groups are responsible for the observed patterns in skill premiums. To illustrate this, in the right column of Figure 3, we plot the relative supplies of medium-skilled (to low-skilled) and high-skilled (to medium-skilled)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

[14] Figure A.2 shows the evolution of the medium and high skill premium separately for eight different age groups. It shows that those aged above 30 (or 36) and below follow a similar pattern.

[15] These patterns in the skill premiums are also prevalent when looking at men and women separately (see Figure A.3). They are somewhat less pronounced for women and more pronounced for men. In both series, the medium premium of young workers has more than doubled over 1980-2008 and has increased much faster than that of old workers. Out main findings also hold when we only use skill premiums of men (see Table 5, model 3).

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

Figure 3: Skill Premiums and Relative Supplies



Notes: This figure plots on the left hand side the difference in composition constant mean log earnings between medium- and low-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 (30 years or below) and old (above 30 years) 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, unemployment and vocational training spells but excluding marginal part-time spells. For more details see sections 3.3.

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

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

Identification of our parameters of interest relies on labor supplies to be *predetermined*, i.e. that labor supplies must not be correlated with any other unobservables that also determine skill premiums and that premiums and supplies are not determined simultaneously. For two reasons we think this assumption is tenable. First, labor supplies are inelastic in the short run and are the result of past human capital investments. Thus, although an individual might invest in vocational training or college education when observing a high premium, skill supplies will only increase with a substantial lag. Second, our labor supply measures are very broad, i.e. they do not only include full-time workers, but also those who work part-time, complete vocational training, or are unemployed. Thus, our supplies capture virtually the entire labor force subject to social security and are considerably less sensitive to changes along the intensive margin (e.g. people might be more likely to work full-time when premiums are high).[17] Still, if labor supplies reacted contemporaneously to skill premiums, this would lead to an underestimation of the negative relationship between premiums and supplies. In that case, different groups of workers would appear more substitutable than they really are, i.e. our substitution elasticities would represent upper bounds.

To compute standard errors, we rely on a moving block bootstrap approach.[18] Bootstrapping standard errors is necessary for at least three reasons. First, the three-step estimation procedure implies that we rely on generated regressors in steps 2 and 3, so we need to take into account the estimation uncertainty induced by the previous step(s). Second, the theoretical model implies that skill premiums at one point in time depend on both, the supply of young and old workers of two adjacent skill groups and thus the two skill premiums are by construction correlated with each other. Third, premiums are serially correlated over time.[19] Thus, the error terms of the premium equations we are going to estimate are correlated contemporaneously across equations as well as serially over time.[20] The moving block bootstrap is a way to account for these various

[17] Fitzenberger et al. (2006) follow a similar approach and use broad measures of skill supplies derived from Microcensus data to instrument labor supplies.

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

[19] A simple Wooldridge (2002, ch. 10) test for serial correlation in panel data detects serial correlation in both premium equations.

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

types of uncertainty.[21] It divides observations in $n - b + 1$ blocks or clusters, where b indicates block length. Thus, the first block jointly contains all premiums and supplies of low, medium, and high-skilled workers of both age groups from year 1 through b, the next all observations from year 2 through $b + 1$, and so on. Each bootstrap sample is constructed by drawing (with replacement) k blocks such that the number of observations contained in these k blocks is less than or equal to the number of observations in the corresponding full sample.[22] This bootstrapping procedure is supposed to resemble the underlying data generating process and allows error terms in a given block to be arbitrarily correlated with each other across and over time. The choice of b should mimic the serial correlation of the error terms. Following the suggestions of Hall et al. (1995) we choose $b = 3$.[23] Hence, when using the full sample period 1980-2008, each bootstrap sample consists of $k = 9$ randomly drawn blocks of length $b = 3$ resulting in $n_{bs} = 54$ observations, 4 less than when using the full data where $n = 58$.

Since our parameters of interest (e.g. $-\frac{1}{\sigma_a}$) are non-smooth functions of estimated parameters (discontinuous at zero), they cannot be bootstrapped directly. Therefore, the standard errors of the parameters of interest are calculated using the delta method. We use 500 repetitions for all bootstraps. Whenever we estimate two premium equations jointly, we use a seemingly unrelated regression framework to account for error correlations across equations 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 and thus ignore the potential correlation between education and experience groups. A comparison between different standard errors in our setting shows that standard errors obtained from a moving block bootstrap are up to five times 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

[21] 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 (as we use here) provide somewhat higher efficiency than non-overlapping ones (but that the efficiency difference in likely to be small in practical applications).

[22] Formally, choose $k = \lfloor (t_{end} - t_0 + 1)/b \rfloor$ such that $n_{bs} = 2(k \times b) \leq n$ and where the 2 is coming from the two groups (young, old).

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

two terms of equation 5 and the first three of equation 7 with 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 the σ_a's as $\beta_a = -\frac{1}{\sigma_a}$:

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

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

As mentioned above, we estimate the two premium equations jointly in a seemingly unrelated regression framework to account for possible correlation of the error terms ε_{jt}^{ML} and ε_{jt}^{HM} across equations. 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 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 kind of *pseudo out-of-sample* exercise. Reassuringly, the parameter of interest changes very little. Our preferred estimate of model 2 corresponds to an elasticity of substitution between young and old workers of 8.2, which is somewhat higher than the comparable estimates by Card and Lemieux (2001) of around 5 for the US and 6 for Canada.[24]

In section A.7 in the Appendix, 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 ($\sigma_{al} = 14.7$) than in the groups of medium and high skill workers (in both σ_{al} is about 7). For the sake of simplicity and since equality of σ_{al}, σ_{am}, and σ_{ah} cannot be rejected statistically, we will continue to assume a common σ_a across all skill groups in the following sections.

To estimate σ_{ml} in the next step, we also need to estimate the efficiency parameters α_s. Section A.8 in the appendix contains the details related to this step. The estimated α_s do not differ by much whether we assume σ_a's to be constant across skill groups or not and suggest that one unit of young low skilled labor is about 73-78% as efficient as one unit of old low-skilled labor while the corresponding ratios are 68-69% for medium-skilled and 52-54% for high-skilled labor. The different efficiency ratios are consistent with the different age earnings profiles of the three skill groups that are much steeper for high-skilled workers than for medium- or low-skilled workers.

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

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

	(1) Linear Trend (1980–2008)		(2) Time FEs (1980–2008)		(3) Linear Trend (1980–1990)	
	ω_{jt}^M	ω_{jt}^H	ω_{jt}^M	ω_{jt}^H	ω_{jt}^M	ω_{jt}^H
Age Group Specific Relative Supply	-0.112***	-0.112***	-0.123***	-0.123***	-0.129**	-0.129**
	(0.013)	(0.013)	(0.011)	(0.011)	(0.050)	(0.050)
Young	-0.051***	-0.243***	-0.050***	-0.250***	-0.047**	-0.262***
	(0.004)	(0.011)	(0.004)	(0.008)	(0.022)	(0.031)
Time	0.007***	0.004***			0.006*	0.002
	(0.001)	(0.001)			(0.003)	(0.004)
Constant	0.343***	0.256***	0.370***	0.258***	0.373***	0.243**
	(0.017)	(0.030)	(0.022)	(0.024)	(0.055)	(0.118)
Time FEs			✓	✓		
σ_a	8.9	8.9	8.2	8.2	7.7	7.7
	(1.1)	(1.1)	(0.8)	(0.8)	(3.0)	(3.0)
Observations	58	58	58	58	22	22
R^2	0.958	0.952	0.990	0.984	0.997	0.987

Notes: The coefficients of the age group specific relative supplies, $\ln(M_{jt}/L_{jt})$ and $\ln(H_{jt}/M_{jt})$, are restricted to be the same in each model's pair of equations, i.e. by assumption $\sigma_{al} = \sigma_{am} = \sigma_{ah}$. Estimates are obtained using a two-step seemingly unrelated regression framework. 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.

4.3 Estimating σ_{ml}

To estimate the elasticity of substitution between the aggregate amounts of low- and medium-skilled labor corresponding to equation 1, we construct the aggregate amounts of L_t, M_t (and H_t for later) using a model where we restrict the elasticity of substitution between age groups to be the same across skill groups and which includes time fixed effects.[25] We then estimate variants of the following equation (note that ω is not indexed by j and thus refers to the *aggregate* medium skill premium):

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

In column 1 of Table 3, we regress the medium- to low-skilled 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

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

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/ Low	-0.103	-0.275	-0.267***	-0.262***	-0.259***
Rel. Supply	(0.090)	(0.169)	(0.061)	(0.060)	(0.064)
Aggr. Medium/ Low					0.001
Rel. Supply × Post 2002					(0.002)
Time	0.006*	0.014	0.013***	0.013***	0.013***
	(0.003)	(0.010)	(0.002)	(0.002)	(0.002)
Time × Post 2002				-0.008***	-0.008***
				(0.001)	(0.002)
Constant	0.306**	0.520***	0.510***	0.502***	0.498***
	(0.122)	(0.199)	(0.080)	(0.080)	(0.086)
σ_{ml}	9.7	3.6	3.7	3.8	3.9
	(8.5)	(2.2)	(0.9)	(0.9)	(1.0)
Observations	29	11	22	29	29
R^2	0.902	0.850	0.966	0.983	0.983

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 $\ln(M_t/L_t)$. M_t and L_t are constructed using the σ_a obtained from a corresponding estimation sample in step 1 where the elasticity of substitution between young and old workers is restricted to be the same across all three skill groups using time FEs (model 2 of Table 2. 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.

estimated. In column 2, we exclude all years after 1990 and do a pseudo-out-of-sample prediction which is visualized in Figure A.4. This model predicts the medium skill premium for the years 1991–2001 very well, but does a poor job from 2002 onwards. Actual premiums in 2002–2008 are much lower than predicted. In column 3, we exclude the years 2002-2008. The estimates become highly significant and are very similar in magnitude to those in column 2. To account for the different regimes, in column 4 we allow for a trend break in the demand for medium- relative to low-skilled labor in 2002.[26] This improves the model fit significantly and yields a highly significant point estimate for the relative supply of -0.262, 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 after 2002 (the combined demand trend is 62% lower than before 2002). Finally, in column 5, we also allow the substitution elasticity to change in 2002 but find no evidence that this parameter has changed after 2001.

The observed pattern of a decreased relative demand for medium workers after 2001 are consistent with increasing polarization at the beginning of the 2000s along the lines of Autor and

[26] A formal structural break test (Quandt-LR) confirms 2002 as the break year.

Dorn (2014) implying a decreasing medium to low premium due to increasing computerization of medium-skilled tasks and a relative increase in low-skilled wages. It could also be related to the implementation of the Hartz reforms in 2003 (coupled with some anticipation effects). For instance, Launov and Wälde (2013) find that the Hartz reforms had a more adverse effect on medium-skilled workers: while *increasing* benefits and thus reservation wages for most low-skilled workers, the reforms *decreased* reservations wages for medium-skilled workers. Furthermore, Hirsch and Schnabel (2014) find a marked drop in union power at the beginning of the 2000s which could further explain decreasing wages of medium-skilled workers as coverage rates were particularly high among this group of workers.

Our preferred specification 4 implies a σ_{ml} of 3.8 which is somewhat lower than the elasticity of substitution between high school graduates and high school dropouts in the US of about 5.3 (for the post 1949-period) estimated by Goldin and Katz (2009, Table 8.4). Arguably, high school graduates and high school dropouts are closer substitutes than those with a completed vocational training specialized in a specific occupation and those without such a training holding at most a general schooling degree (at most *Realschule*). Our estimate of σ_{ml} is also lower than the estimate of 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 estimates of the previous step, we can now construct U_t, the aggregate amount of non-high skilled (or non-college) labor.[27] Using equations 6 and 8, we can then estimate σ_{hu}, the elasticity of substitution between college and non-college workers and, at the same time, assess the ability of the overall model to explain the differential evolution of the skill premiums of the different skill and age groups – the primary interest of this paper.

In Table 4, we jointly estimate the medium to low and high to medium skill premiums for each age group in a seemingly unrelated regression framework as before, this time using equations 6 and 8. These equations state that the age-specific skill premiums do not only depend on the corresponding age-specific relative labor supplies ($\ln \frac{M_{jt}}{L_{jt}}$ for the medium to low premium and $\ln \frac{H_{jt}}{M_{jt}}$ for the high to medium premium) but also on the *aggregate* relative supplies ($\ln \frac{M_t}{L_t}$ and $\ln \frac{H_t}{M_t}$, respectively). Equation 8 also implies that the age-specific high to medium premium depends on the aggregate relative supplies of high to non-high and non-high to medium labor. The coefficients on these aggregate supplies yield an estimate for the elasticity of substitution between high and non-high (σ_{hu}) and medium- to low-skilled (σ_{ml}) labor, respectively. In the following, we impose equality of the coefficients on the age-specific supplies of medium to high and high to medium labor (implying the same elasticity of substitution between young and old workers across all three skill groups, σ_a) and of the aggregate medium to low and non-high to medium supply (thus yielding the same σ_{ml} in both equations) as implied by equations 6 and 8.

[27] To construct the aggregate amount of non-college labor U_t we use the estimates of model 4 of Table 3. Apart from σ_{ml} we also need an estimate for the demand shifter θ_t which is recovered from the estimated coefficients as $\widehat{\theta}_t = \frac{\exp(B)}{1+\exp(B)}$ where $B = \widehat{\beta}_{time} \times time + \beta_{posttime} \times posttime$, 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.

Table 4: CES Regression Models including Age-Group and Aggregate Supply Measures

	(1) Baseline		(2) High Young Intercepts		(3) 1980-1990 only	
	ω_{jt}^M	ω_{jt}^H	ω_{jt}^M	ω_{jt}^H	ω_{jt}^M	ω_{jt}^H
Aggr. Medium/ Low Rel. Supply	-0.223***	-0.223***	-0.266***	-0.266***	-0.237	-0.237
	(0.085)	(0.085)	(0.086)	(0.086)	(0.167)	(0.167)
Aggr. High/ Non-High Rel. Supply		-0.250		-0.611**		-0.201
		(0.319)		(0.305)		(0.372)
Age Group Specific Rel. Supplies	-0.120***	-0.120***	-0.121***	-0.121***	-0.097***	-0.097***
	(0.010)	(0.010)	(0.013)	(0.013)	(0.027)	(0.027)
Young	-0.050***	-0.248***	-0.050***	-0.261***	-0.062***	-0.252***
	(0.003)	(0.008)	(0.004)	(0.009)	(0.012)	(0.017)
Time	0.012***	0.009	0.014***	0.023*	0.012	0.003
	(0.003)	(0.012)	(0.003)	(0.012)	(0.010)	(0.018)
Time × Post 2002	-0.008***		-0.009***			
	(0.002)		(0.002)			
Constant	0.478***	-0.041	0.533***	-0.689	0.503***	0.068
	(0.117)	(0.576)	(0.118)	(0.550)	(0.194)	(0.743)
Young $\times I(1987-1990)$				✓		✓
Young $\times I(1999-2002)$				✓		
σ_{ml}	4.5		3.8		4.2	
	(1.7)		(1.2)		(3.0)	
σ_{hu}		4.0		1.6		5.0
		(5.1)		(0.8)		(9.2)
σ_a	8.4	8.4	8.2	8.2	10.3	10.3
	(0.7)	(0.7)	(0.8)	(0.8)	(2.8)	(2.8)
Observations	58	58	58	58	22	22
R^2	0.980	0.948	0.982	0.973	0.998	0.996

Notes: The coefficients on the aggregate relative supply of medium- to low-skilled workers $\ln(M_t/L_t)$ and the aggregate relative supply of non-high to medium-skilled workers $\ln(U_t/M_t)$, i.e. σ_{ml}, as well as the coefficients on the age group specific supplies (i.e. σ_a) are restricted to be the same in each model's pair of equations. 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.

For the medium to low premium we allow for a trend break in 2002 as before. The technology-related parameter corresponding to the high to medium premium in model 1 of Table 4 is assumed to follow a linear trend throughout the whole sample period representing a linear shift in the demand for high-skilled workers. The estimates of model 1 yield a coefficient of -0.120 for the age group specific relative supply which is almost identical to the corresponding estimate for the elasticity of substitution between young and old workers obtained in column 2 of Table 2 (-0.123). Thus, concerning σ_a the estimates based on equations 6 and 8 are consistent. However, model 1 yields a coefficient of the aggregate medium to low supply of -0.223 which is somewhat different than the corresponding estimate of Table 3 of -0.262. According to the model, these two estimates should be the same. The point estimate of the aggregate high to non-high supply is -0.250 but is imprecisely estimated. These discrepancies suggest that the model – in particular the specification for the high to medium premium – might be misspecified. In particular the high to medium premium of *young* workers exhibits "bumps" that are unrelated to supply changes.[28] As it turns out, the wages and thus the premium of young high-skilled workers show a strong co-movement with the business cycle (see Figure A.6) – something that to this extent cannot be observed for the remaining three premiums. In particular, the premium of young high-skilled workers is amplified and detached from its underlying supply during the pre-unification boom (1987-1990) and the boom and bust of the dot-com bubble (1999-2002, Burda and Seele 2016, p. 5).

Therefore, in model 2, we include two separate intercepts for these two periods interacted with the young indicator to account for the two biggest "bumps" in the high to medium premium of young workers. The coefficient on the aggregate medium to low supply now changes to -0.266 and is thus very close to the corresponding estimate in Table 3 as it should be. The coefficient on the aggregate amount of high to non-high labor changes to -0.611 and becomes significant.[29]

The estimates of our preferred specification (model 2) imply an elasticity of substitution between college and non-college labor of 1.6. This happens to be identical to the elasticity of substitution between college and high school labor in the US estimated both by Goldin and Katz (2009, their Table 8.2) and Card and Lemieux (2001, Table VI). D'Amuri et al. (2010) and Fitzenberger et al. (2006) both do not estimate σ_{ml} and σ_{hu} separately but impose equality of these two parameters in their estimations (i.e. they assume that the elasticity of substitution is the same between, say, high- and low-skilled labor and high- and medium-skilled labor). This simplifying assumption is not supported by our estimation results, i.e. σ_{ml} and σ_{hu} are significantly different from each other. Bearing that in mind, D'Amuri et al. (2010, Table 7 column 3 and 4) estimate an elasticity of substitution between any two skill groups of 2.9 which is right between our corresponding elasticities of 3.8 (σ_{ml}) and 1.6 (σ_{hu}). Fitzenberger et al. (2006, Table 1) estimate a σ_s between 4.9 and 6.9 (their preferred IV estimates) and note that their estimates "imply a rather high degree of substitutability compared to findings in the related literature".

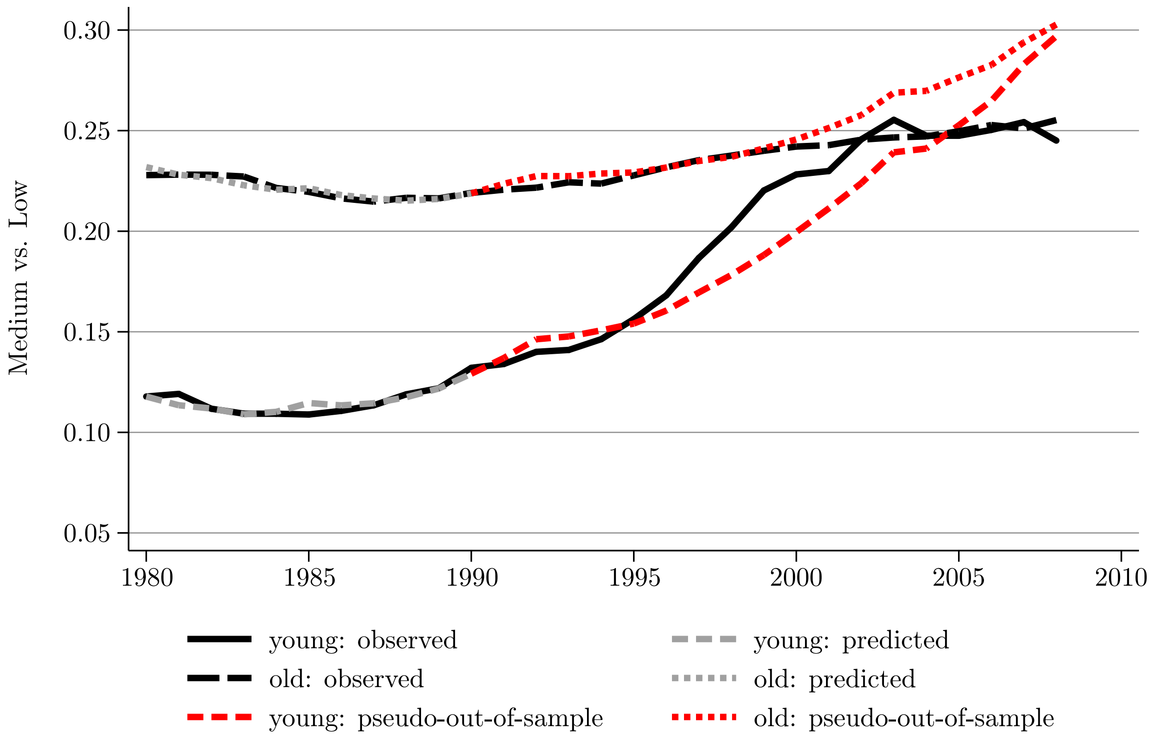
To get an impression of the model's out-of-sample predictive power, we plot the observed and the predicted medium to low premium separately for young and old workers in Figure 4. The prediction in panel a) is based on the estimates of model 3 in Table 4 where we exclude all years after 1990. Although we lose statistical power due to the smaller sample size, the coefficients related to the medium to low and the age group specific supply measures remain comparable in magnitude. The figure shows that the model based on only the observations from 1980–1990 is

[28] As shown in the appendix, these bumps are not a peculiarity of the SIAB data (e.g. due to censoring) as similar patterns can be observed in the (virtually uncensored) Microcensus (see Figure A.5)

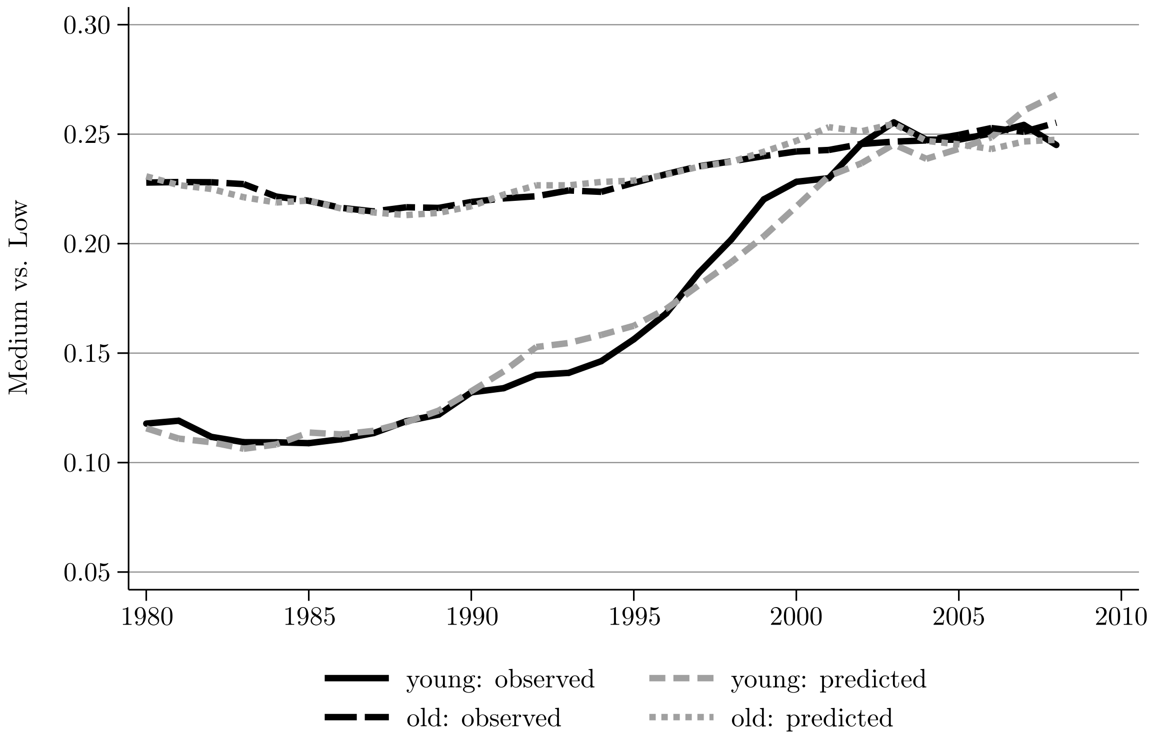
[29] Including other sets of interacted intercepts or dummies in the high to medium specification leads to no major changes of the estimates.

Figure 4: Predicted vs. Observed Medium Premiums

(a) Pseudo-out-of-Sample Prediction after 1990 (model 3 of Table 4)



(b) Prediction based on Full Sample 1980-2008 (model 2 of Table 4)



able to predict the differential evolution of the medium to low premium of young and old workers during the 1990s up until the early 2000s. In panel b), we use the estimates of model 2 and the prediction is very close to the observed premium. The model is also able to predict the high skill premium reasonably well – even without accounting for the peculiarities in the premium of young college graduates (Figure A.7).

4.5 Robustness Checks

How robust are our estimates regarding the construction of premiums and supplies? We compare alternative premium and supply measures to our preferred estimates from above which are restated in model 1 of Table 5.

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

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

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

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

Table 5: Robustness Checks of CES Models

	(1) Preferred Specification		(2) Baseline + GDP Growth		(3) Premiums of Men		(4) Weighting $w_{voc} = w_{ue} = 1$		(5) Supplies excl. Voc. Training & Unemployed		(6) Supplies as Head Count	
	ω_{jt}^{M}	ω_{jt}^{H}	ω_{jt}^{M}	ω_{jt}^{H}	ω_{jt}^{M}	ω_{jt}^{H}	ω_{jt}^{M}	ω_{jt}^{H}	ω_{jt}^{M}	ω_{jt}^{H}	ω_{jt}^{M}	ω_{jt}^{H}
Aggr. Medium/ Low Rel. Supply	-0.266*** (0.086)	-0.266*** (0.086)	-0.277*** (0.089)	-0.277*** (0.089)	-0.334*** (0.114)	-0.334*** (0.114)	-0.307*** (0.078)	-0.307*** (0.078)	-0.218** (0.091)	-0.218** (0.091)	-0.188*** (0.057)	-0.188*** (0.057)
Aggr. High/ Non-High Rel. Supply		-0.611** (0.305)		-0.612** (0.297)		-0.569* (0.318)		-0.626** (0.287)		-0.547* (0.289)		-0.336*** (0.112)
Age Group Specific Rel. Supplies	-0.121*** (0.013)	-0.121*** (0.013)	-0.121*** (0.012)	-0.121*** (0.012)	-0.132*** (0.018)	-0.132*** (0.018)	-0.111*** (0.012)	-0.111*** (0.012)	-0.132*** (0.014)	-0.132*** (0.014)	-0.105*** (0.010)	-0.105*** (0.010)
Young	-0.050*** (0.004)	-0.261*** (0.009)	-0.050*** (0.004)	-0.261*** (0.009)	-0.009 (0.006)	-0.239*** (0.014)	-0.068*** (0.003)	-0.254*** (0.009)	-0.034*** (0.005)	-0.268*** (0.010)	-0.070*** (0.003)	-0.224*** (0.007)
Time	0.014*** (0.003)	0.023* (0.012)	0.014*** (0.003)	0.023** (0.012)	0.017*** (0.004)	0.022* (0.012)	0.014*** (0.003)	0.023** (0.011)	0.012*** (0.004)	0.021* (0.011)	0.008*** (0.001)	0.011*** (0.004)
Time × Post 2002	-0.009*** (0.002)		-0.009*** (0.002)		-0.010*** (0.003)		-0.010*** (0.002)		-0.007*** (0.002)		-0.007** (0.003)	
Real GDP Growth			0.047 (0.077)	-0.054 (0.146)								
Constant	0.533*** (0.118)	-0.689 (0.550)	0.545*** (0.120)	-0.694 (0.535)	0.560*** (0.155)	-0.684 (0.583)	0.584*** (0.105)	-0.744 (0.523)	0.470*** (0.126)	-0.547 (0.522)	0.393*** (0.066)	-0.374 (0.279)
Young $\times I(1987-1990)$		✓		✓		✓		✓		✓		✓
Young $\times I(1999-2002)$		✓		✓		✓		✓		✓		✓
σ_{ml}	3.8 (1.2)		3.6 (1.2)		3.0 (1.0)		3.3 (0.8)		4.6 (1.9)		5.3 (1.6)	
σ_{hu}		1.6 (0.8)		1.6 (0.8)		1.8 (1.0)		1.6 (0.7)		1.8 (1.0)		3.0 (1.0)
σ_{a}	8.2 (0.8)	8.2 (0.8)	8.2 (0.8)	8.2 (0.8)	7.5 (1.0)	7.5 (1.0)	9.0 (1.0)	9.0 (1.0)	7.6 (0.8)	7.6 (0.8)	9.5 (0.9)	9.5 (0.9)
Observations	58	58	58	58	58	58	58	58	58	58	58	58
R^2	0.982	0.973	0.982	0.973	0.960	0.948	0.985	0.973	0.976	0.972	0.980	0.983

Notes: The coefficients on $\ln \frac{M_t}{L_t}$ and $\ln \frac{U_t}{M_t}$ (i.e. σ_{ml}) as well as the coefficients on the age group specific supplies (i.e. σ_a) are restricted to be the same in each model's pair of equations. 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.

5 Determinants of Supply Changes

After having demonstrated that the heterogeneous evolution of age-specific skill premiums depicted in Figure 3 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 the 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-immigration" scenario. Second, we investigate the role of more fundamental shifts in the educational attainment of native Germans. To assess this alternative channel, we perform a cohort analysis based on the German Microcensus to understand the dynamics of educational attainment of the native West German population.

5.1 The Role of Migration

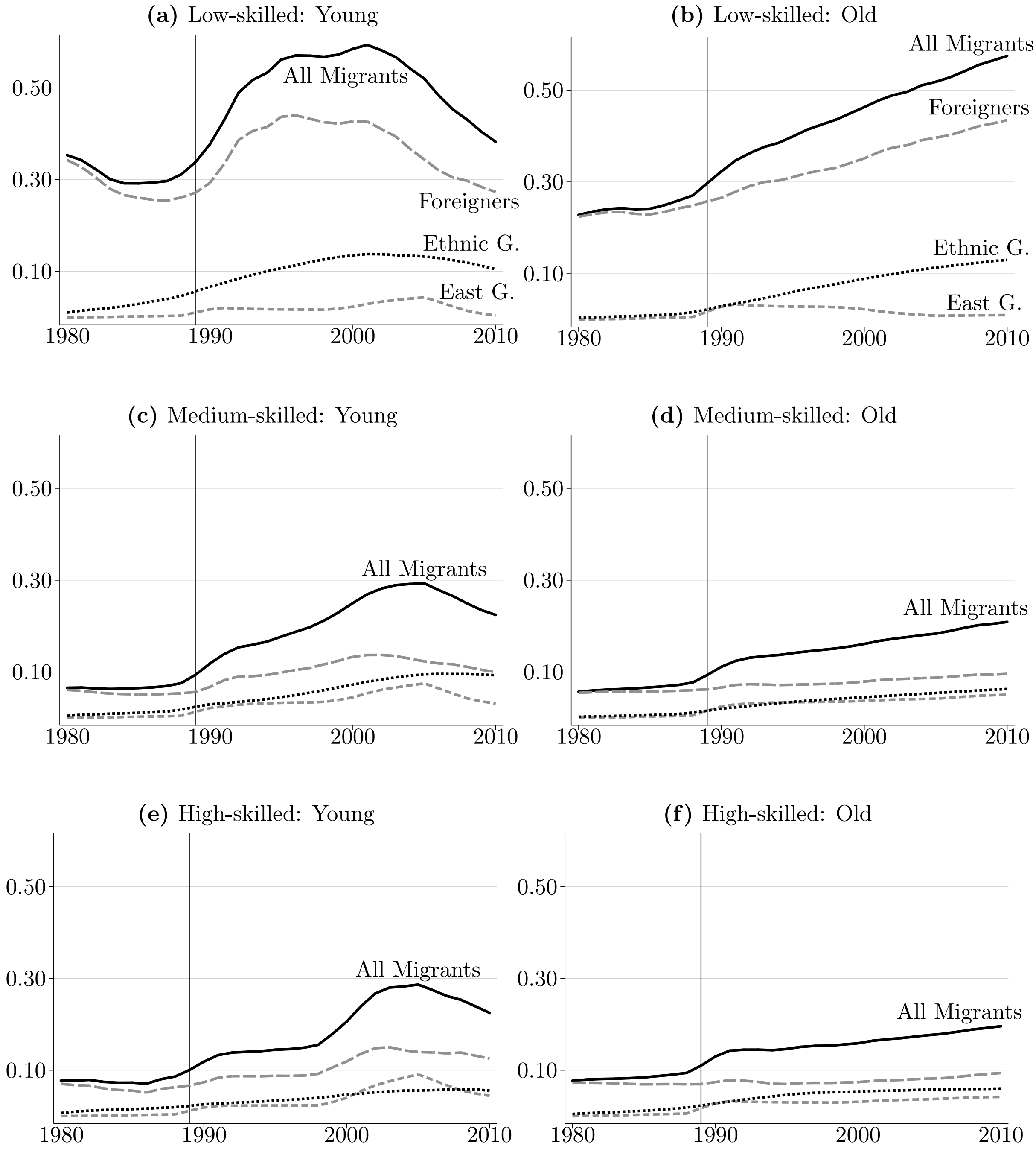
After the fall of the Berlin wall in 1989, West Germany experienced large migration inflows from essentially three groups: (i) East-Germans, (ii) ethnic Germans from Eastern Europe and the former Soviet Union, and (iii) foreigners immigrating from other European countries or parts of the world. Within 15 years after the fall of the Berlin wall, about 1.5 million East Germans, 2.7 million ethnic Germans and 2.7 foreigners migrated to (West) Germany which had an initial population of about 60 million in 1989.[30]

In Figure 5, we plot the share of different migrant groups in the total efficiency supply of each age-skill group.[31] Foreign workers can directly be identified at the individual level in the IAB-labor market data. This is not the case for East- and ethnic Germans. Their aggregate shares are derived using data from the Qualification and Career Survey (East Germans) and the Microcensus (ethnic Germans). For more details on the construction of these migrant shares see section A.9 in the appendix. 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

[30] 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.

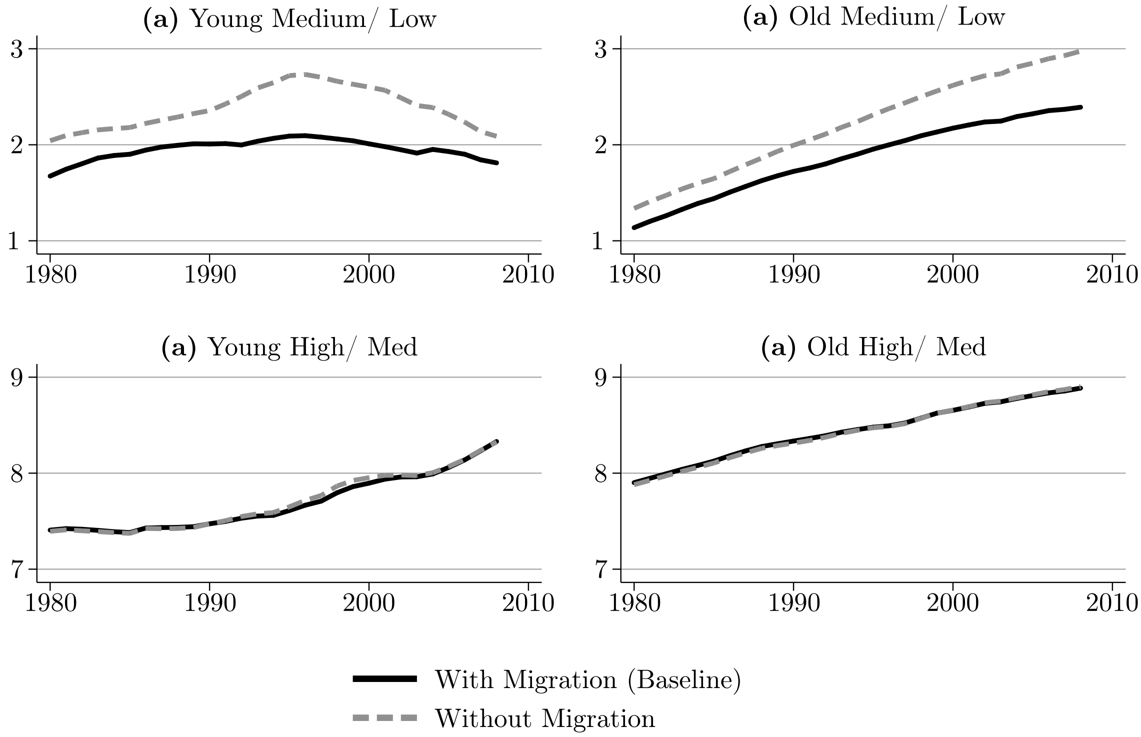
[31] Note that the official inflows do not necessarily translate into corresponding shares in labor supplies due to different participation rates of the different migrant groups. Children, students, pensioners, and other non-working migrants are included in the official figures but do not contribute to the migrant labor supply. Furthermore, some shares might seem high at first glance, but they occur in subgroups (low-skilled and/or young workers) that make up only a smaller 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.

Figure 5: Share of Different Migrant Groups in Total West Germany Supplies



Notes: This figure plots for each education group and separately for young ($\leq$ 30 years) and old workers (>30 years) the share of different migrants groups in efficiency supplies.

Figure 6: Relative Efficiency Supplies with and without Immigrants

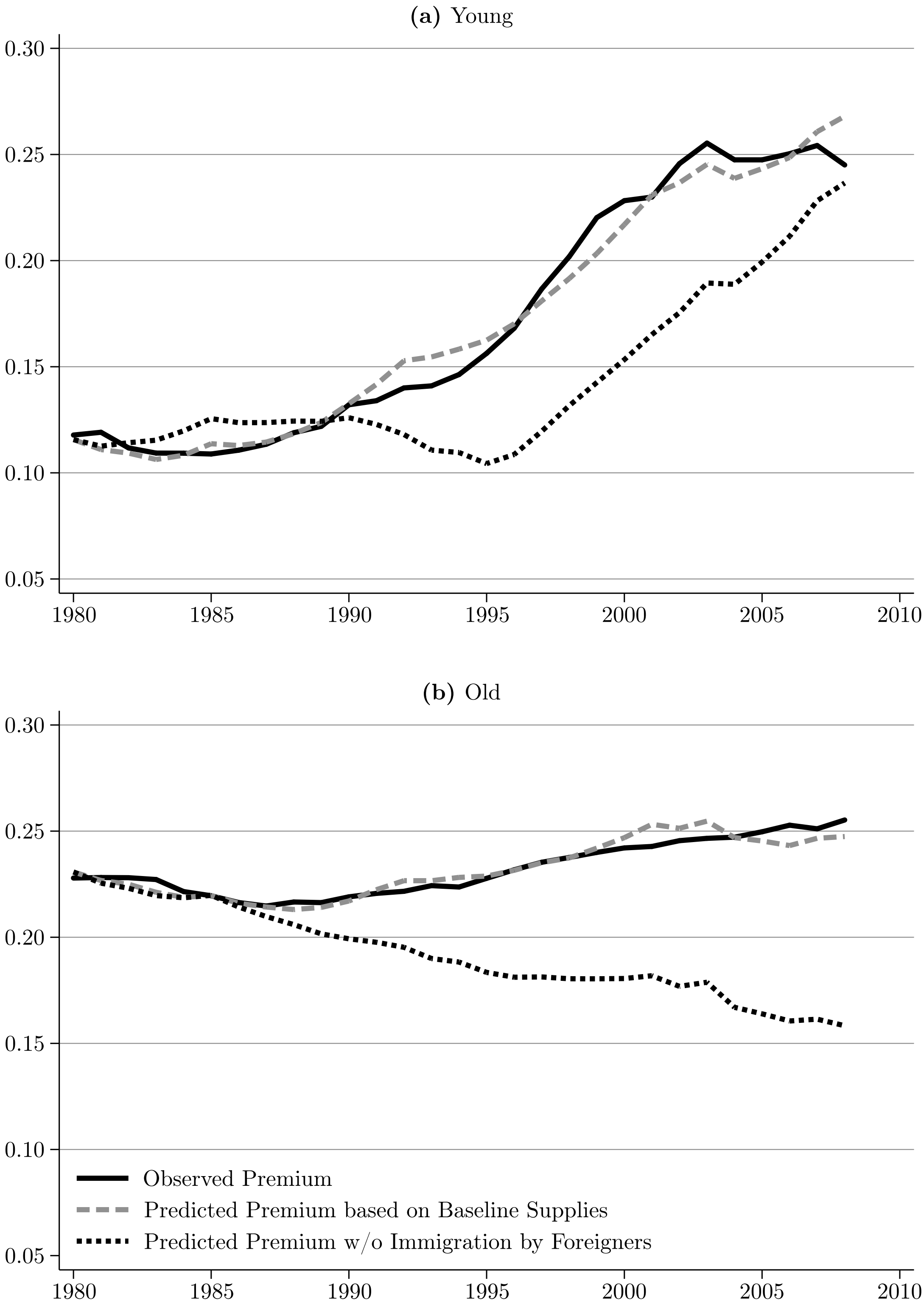


was supplied by migrant workers with foreigners making up the largest part. The share of East Germans is similar across the different age-skill groups at about 3-6%.[32] Ethnic Germans and foreign migrants are mostly concentrated in low-skilled labor. All in all, migration affects low-skilled labor supplies the most, but are still sizable in the groups of medium- and high-skilled supplies.

How did these migration flows affect relative labor supplies - the quantity our model links to skill premiums of natives? Figure 6 depicts relative supplies with (baseline) and without migration. Migration of the three groups left the relative supply of high-skilled labor basically unchanged (panels c and d), which is why we will focus on the medium- to low-skilled supplies and premiums in what follows. Without migration, medium-skilled labor would be more abundant both for young and old workers as less low-skilled labor would be available under this scenario (panels a and b). However, migration would not have changed the general patterns in the evolution of relative medium supplies - a reverse U-shape pattern for the young and a continuous increase for the old.

[32]In line with this, Prantl and Spitz-Oener (2014, p. 5) note that "[t]he German-German migration wave [..] does not include workers of any education class over-proportionally. Hence, the educational distribution of German workers in West Germany remained stable".

Figure 7: Observed vs. Predicted Medium to Low Premiums with and without Migration



Given these migration flows and changes in the relative supplies - how would skill premiums have developed in the absence of migration?[33] In particular, 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 parameter estimates (model 2 of Table 4) to simulate the counterfactual evolution of skill premiums in the absence of migration. We feel comfortable doing this as the underlying structural parameter estimates are very similar in magnitude when using the full period or only data over 1980-90, a period of no or only incipient immigration 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 *overestimate* 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, remember that 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.

Figure 7 shows the results of our counterfactual exercise. Without migration, the young medium to low premium would have first declined slightly into the mid 1990s to then strongly increase to the same level as the actual premium in 2008. Thus, migration seems to have advanced the divergence in wages between young medium- and low-skilled workers by around 5 years. Its 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 premium of older workers. Here, migration seems to have kept that premium at a rather stable or slightly increasing path which in the absence of migration would have decreased by some five percentage points compared to its 1990 level. All in all, migration did have a considerable impact on wage premiums of medium-skilled workers, but cannot explain the strong increase in the skill premium of young workers that eventually occurred over the 1990s and 2000s. In the next section, we will therefore turn to the educational attainment of *native* workers as an alternative source of supply changes.

5.2 Cohort Analysis of Skill Acquisition

To proceed in understanding the drivers of the observed supply changes, we use data from the German Microcensus, an officially conducted yearly survey based on a 1% random cross-section of the German population similar to the US Current Population Survey (CPS). Participation in the Microcensus is compulsory and non-compliance can be fined or even punished. Most

[33] Of course, this is a static counterfactual exercise, native labor supplies could have developed differently had the Berlin wall not come down.

official German population and labor market statistics are based on the Microcensus. We pool Microcensus waves 2005-2011 and restrict the sample to individuals residing in West-Germany at the time of the interview. In the following, we focus on native West-Germans by excluding individuals who were born or migrated from outside Germany, who have a non-German nationality, have been naturalized, or obtained a school degree from former East Germany. We furthermore consider only individuals who are at least 30 years old to make sure they have finished their formal education.[34] We group individuals in the same three education groups as defined in our 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 Figure 8a. We focus on cohorts born between 1950-1981 as these are the relevant cohorts determining the inflows of young workers over our study period.[35] The figure reveals a striking pattern which, to the best of our knowledge, has not been documented in the literature so far. The share of individuals with completed vocational training, i.e. the medium-skilled, shows a reversed U-shaped pattern with the turning point occurring at the peak baby boomer cohort around 1965. In the 15 years up to that point, this share was increasing from 67% to 71% but then started to decrease quite rapidly reaching only 64% in the 1981 cohort, a share comparable to that of the 1940 cohort (not shown). At the same time, the share of low-skilled stopped its continuous decrease over the previous decades to stabilize at around 11%. Finally, the share of individuals holding a university degree started to increase strongly after it had stayed virtually flat throughout for most of the 1950-1965 cohorts.

The break in educational attainment of native West Germans around the 1965 cohort becomes even more salient in Figure 8b where we estimate a linear trend for the cohorts 1950-1965 and plot the deviation from this trend.[36] This plot reinforces the impression from the previous figure. The educational attainment of natives shows a marked drop in the share of those acquiring vocational training, an accelerated increase in tertiary education and a relative increase in the share of the low-skilled.

These figures show that while low-skilled immigration played some role, the major force behind the overall decrease in the relative supply of young medium-skilled workers in the 1990s and 2000s was a strong reversal in the trend towards medium-skilled education of natives around the 1965 cohort.

More research is needed to understand the reasons behind the break in educational attainment that decisively influenced labor supplies and thus, via wage premiums, inequality of labor incomes

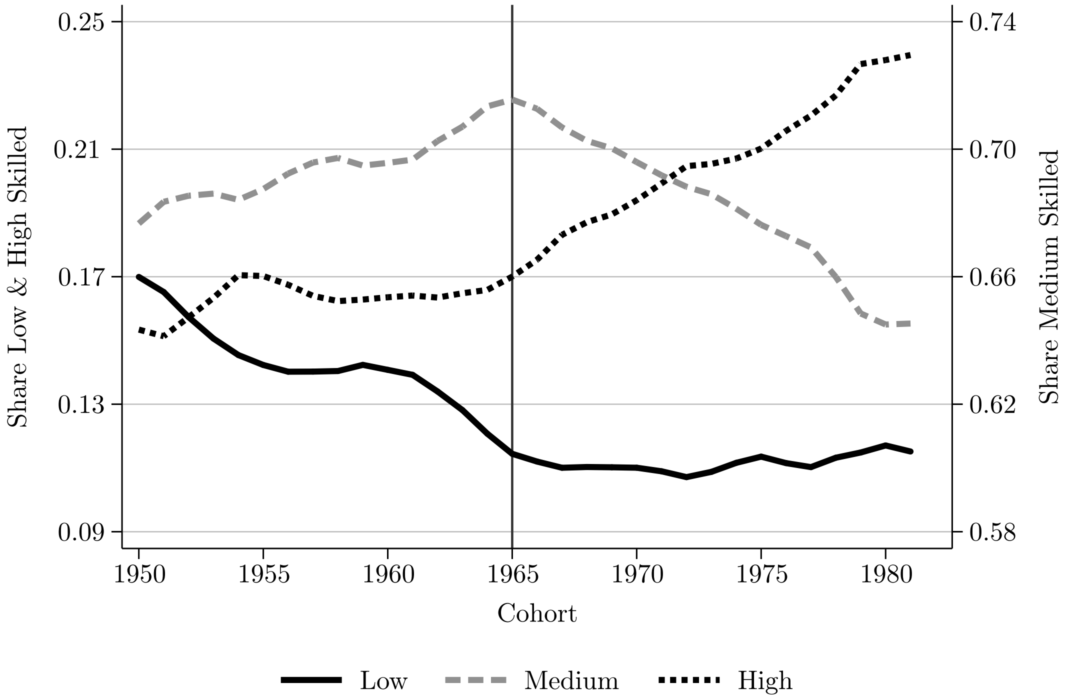
[34] Unlike in some previous years, answering the question about the highest formal occupational degree is mandatory for all age groups from Microcensus wave 2005 onwards. See Fitzenberger et al. (2004) for an imputation method of the education information in case the related questions are voluntary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

[35] 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.

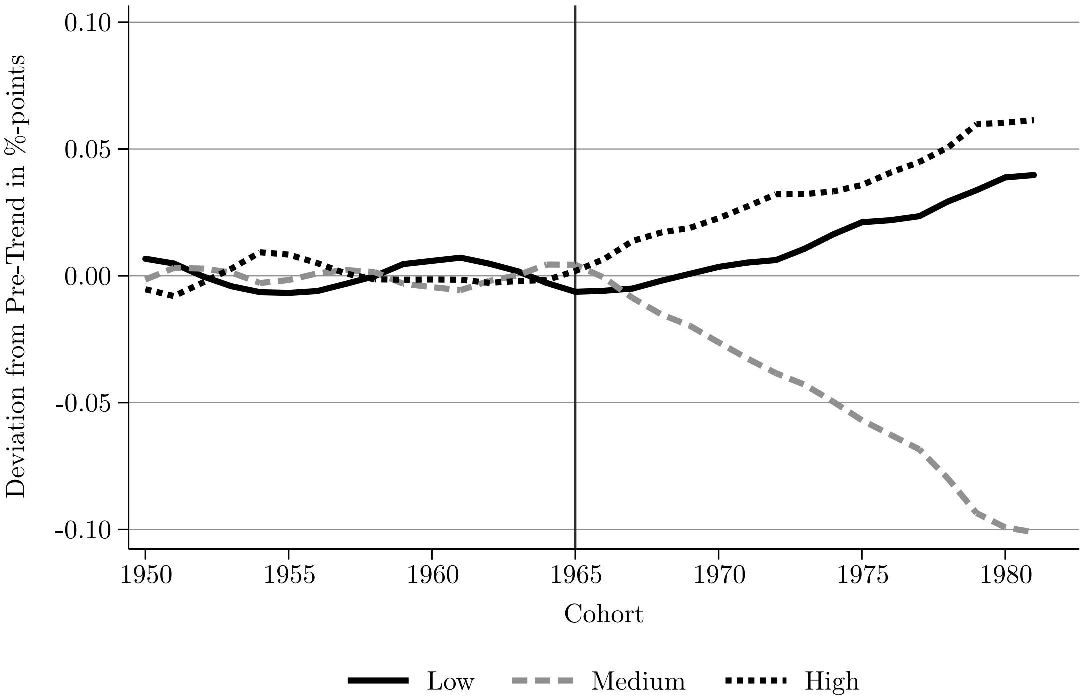
[36] A structural break test (maximum F-value) picks 1965 (low-skilled), 1965 (medium), and 1966 (high) as the break points. We also estimated a linear trend using the cohorts 1945-1965 or allowed for a quadratic pre-trend with similar results.

Figure 8: Educational Attainment by Cohorts

(a) Shares



(b) Deviation from 1950-1965 Trend



in Germany. Here we can only offer some speculative explanations. One potential reason could be related to cohort sizes. Cohort sizes increased gradually in Germany in the post-war period, reaching their peak in 1964 with 1.35 million individuals. After that, cohort sizes decreased rapidly to 0.8 million in the mid 1970s. While cohorts became smaller, university capacity continued to increase. Thus, for the post baby boomers, it might have been easier to get into college and university. Other possible reasons may include societal changes in the 1960s that shifted parents' preferences away from traditional vocational careers for their children towards more academic university education, or a signaling story along the lines of Bedard (2001) in which wider access to universities reduced the incentive for individuals to "pool" in the medium education group to take advantage of high-ability individuals who are constrained from entering university. Finally, it could also be that due to the smaller cohort sizes and, consequently, smaller families, parents had more resources to invest in the education of each of their children (quality-quantity trade-off), pushing them increasingly into the tertiary education track.

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. 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 and observed changes in skill supplies go a long way in explaining the peculiar patterns of skill premiums in Germany. In particular, our model is able to explain the pronounced increase in the wage premium of young medium-skilled worker from 10% in the 1980s to 25% in the 2000s very well. Premiums for both young and old high-skilled workers show no systematic upward or downward trend despite a pronounced increase in their relative demands. Our framework suggests that this was because the corresponding supply of high-skilled workers has kept pace with increased demand. The share of high-skilled workers among all full-time workers has tripled from 5% at the beginning of the 1980s to 15% at the end of the 2000s and continues to increase.

Our cohort analysis suggests that the rapid increase in the skill premium for young medium-skilled workers is rooted in a pronounced change in the educational attainment of the native (West-) German population that occurred for cohorts born after 1965 and which reversed previous trends in the acquisition of different types of education. The share of individuals with completed vocational training decreased strongly and was as large for the 1980s cohorts as it was for the 1940s cohorts while the share of individuals with tertiary education increased to unprecedented levels and the long-term decline in the share of low-skilled individuals came to a hold. All in all, our study suggests that a considerable part of recent changes in earnings inequality between different skill groups in Germany are the result of longer term educational choices of the population and hence, ultimately, driven by labor supply.

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APPENDIX

A.1 Additional Figures

Figure A.1: Real Wage By Disaggregated Education Groups

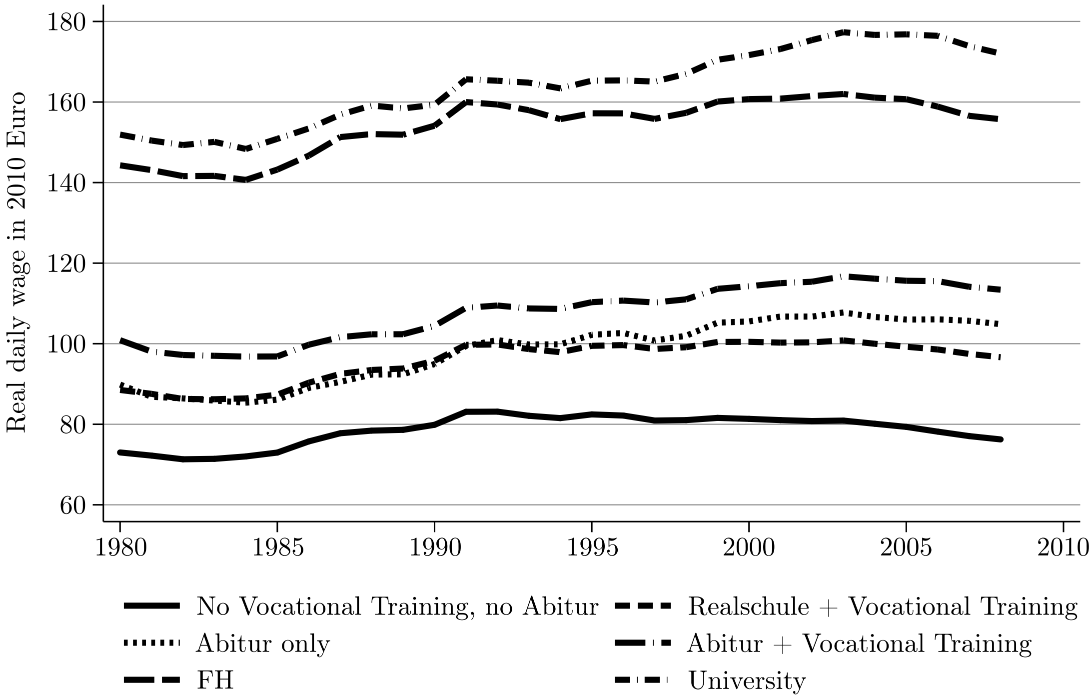
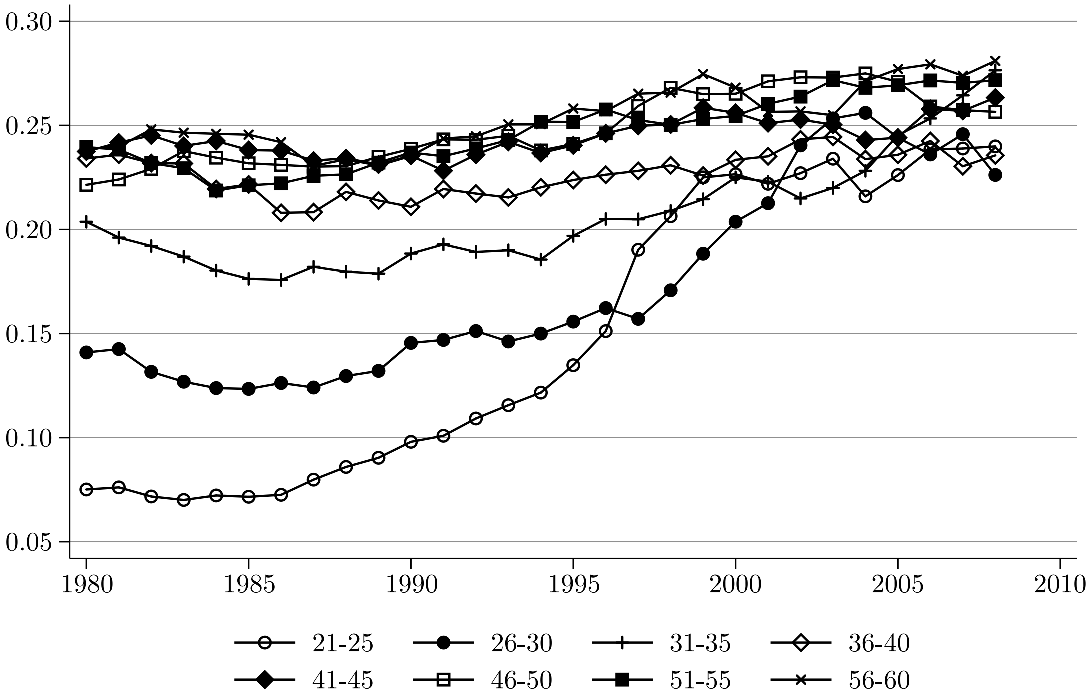


Figure A.2: Skill Premiums by Eight Different Age Groups

(a) Medium to low



(b) High to Medium

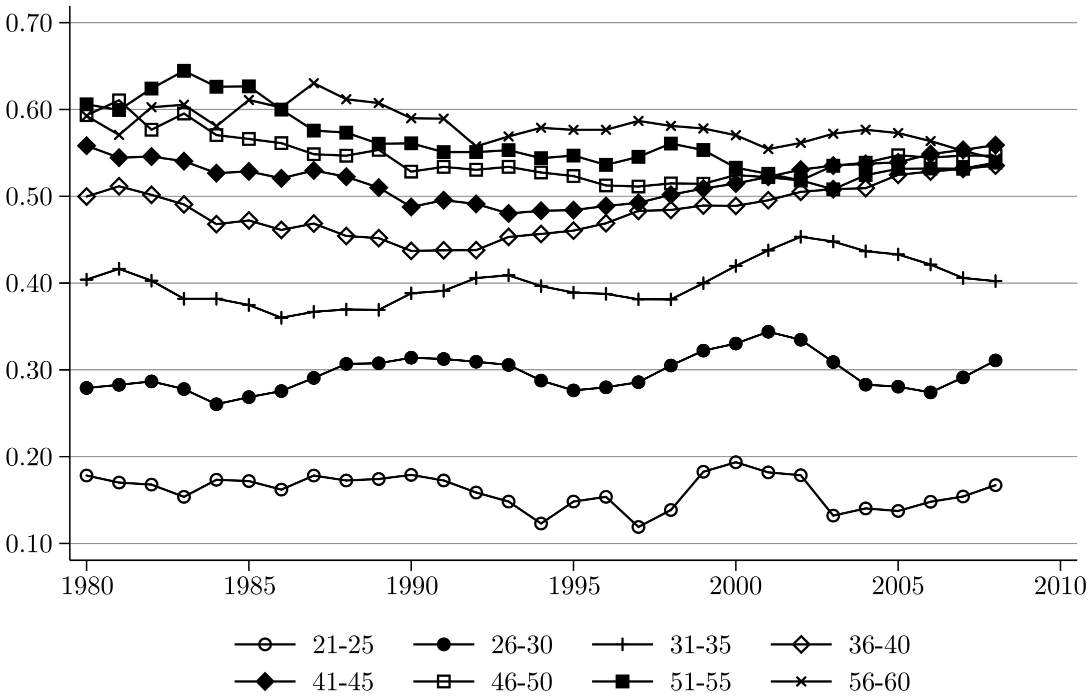


Figure A.3: Skill Premiums Separately for Men and Women

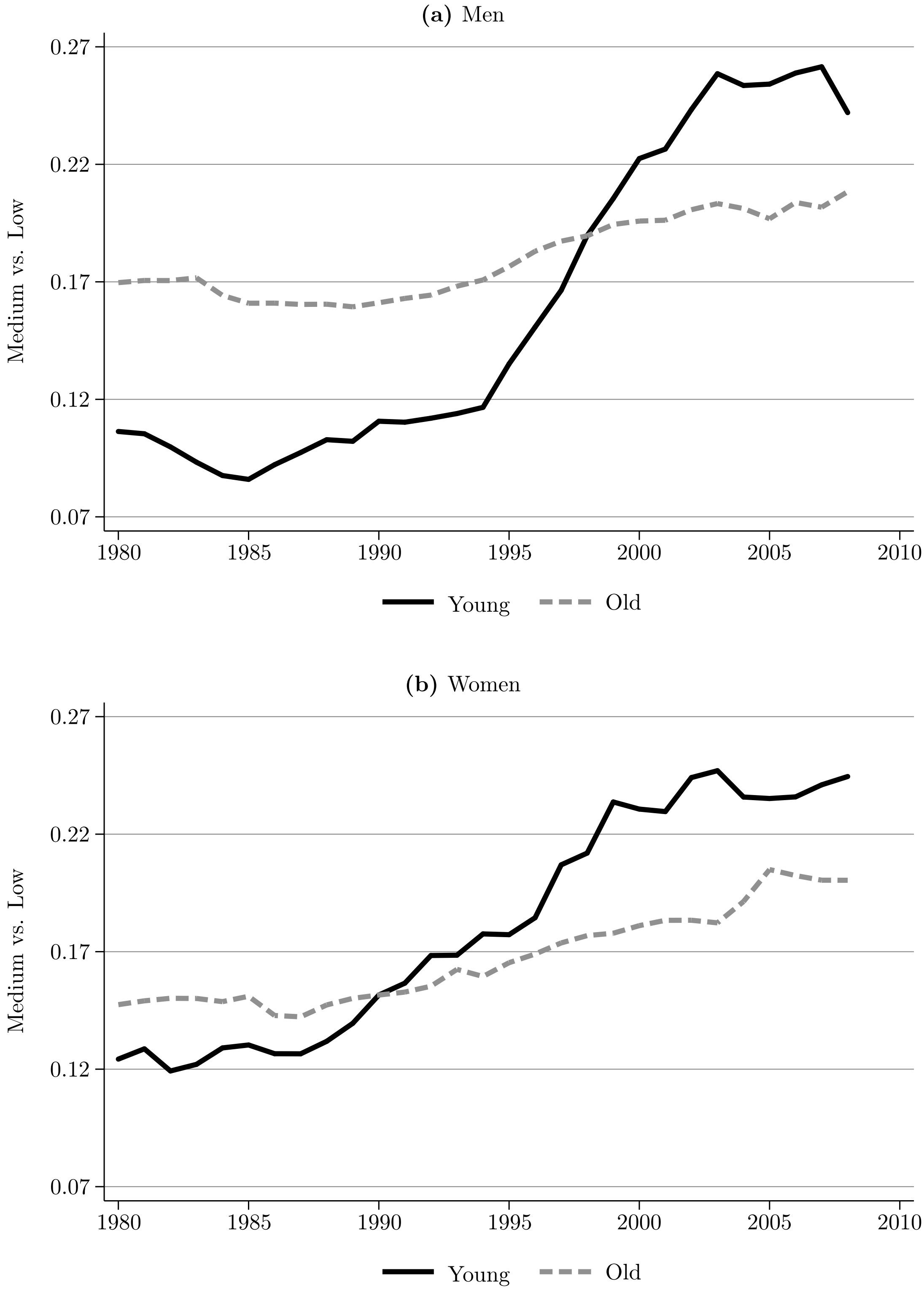


Figure A.4: Observed vs. Fitted Aggregated Medium- to Low-skilled Premium (corresponding to model 2 of Table 3)

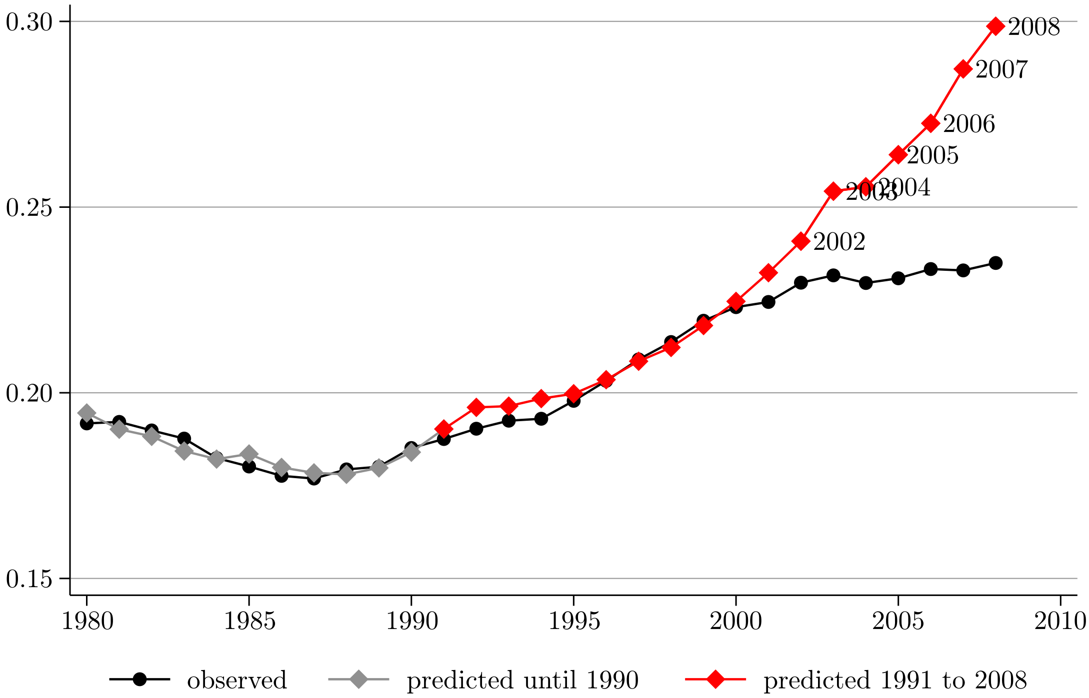
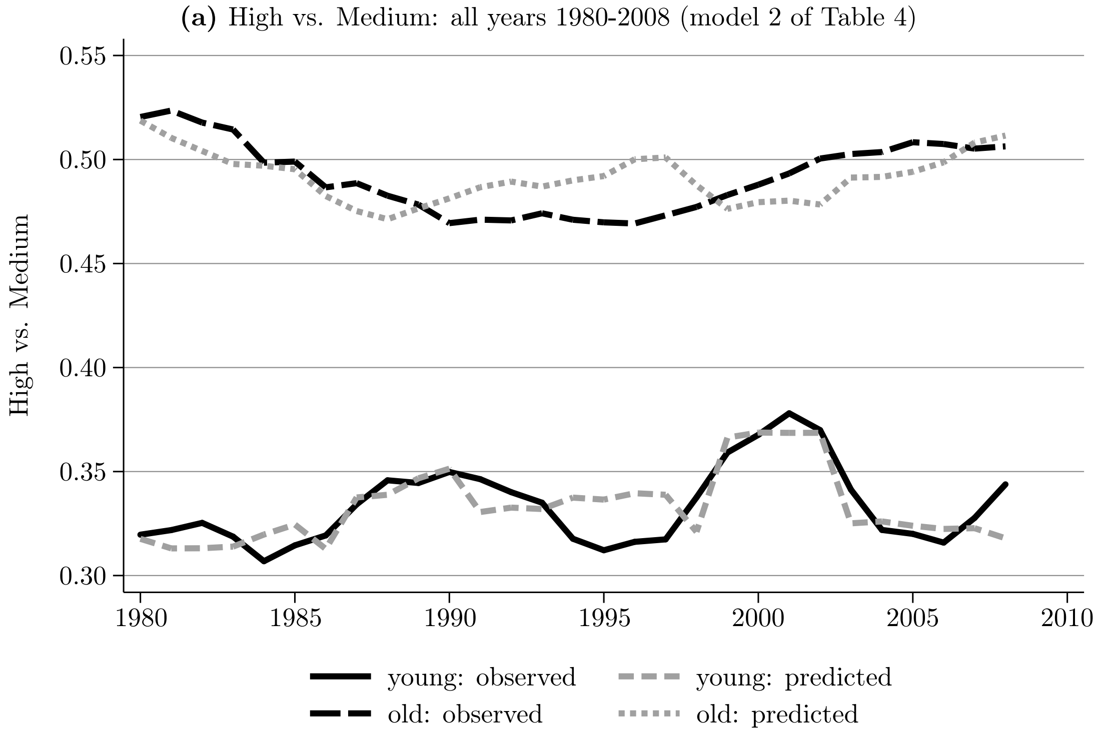
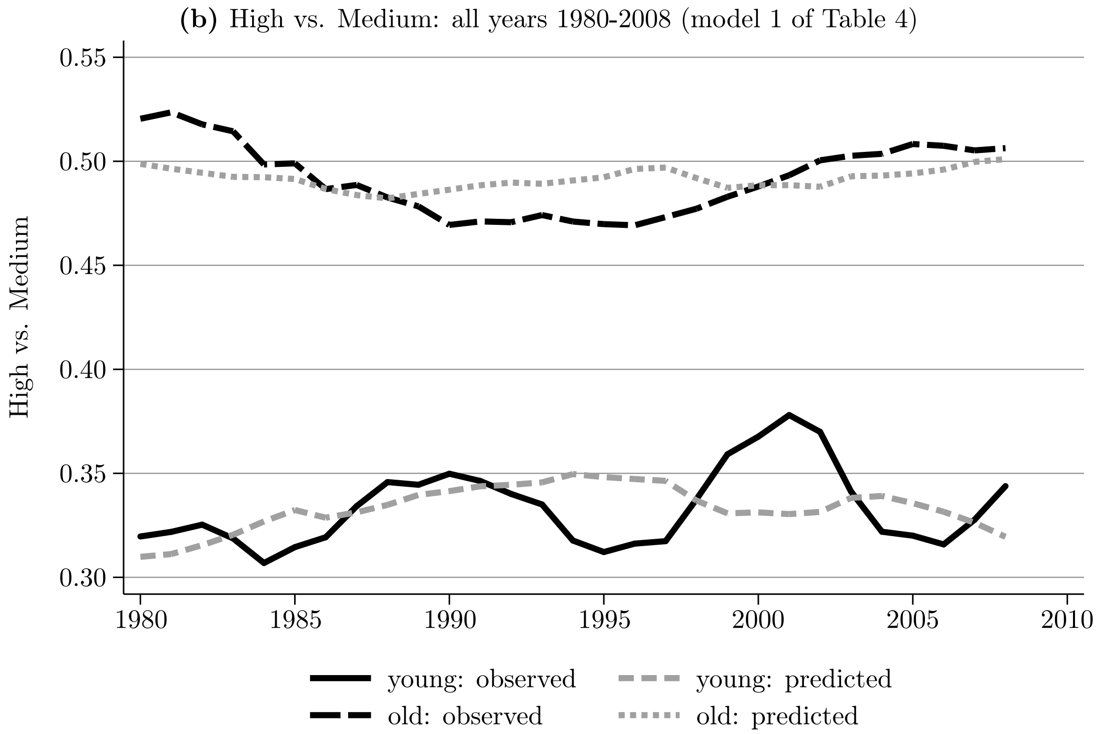


Figure A.5: Comparison of Young High to Medium Premiums (SIAB vs. Mikrozensus)

Figure A.6: Co-Movement of the High Skill Premium of Young Workers and GDP Growth

Figure A.7: Predicted vs. Observed High-skilled Premiums





A.2 Data Preparation and Sample Restrictions

Imputation of Missing Values Using the universe of SIAB7510 data, we impute missing education information following Fitzenberger et al. (2006). For each individual we also impute missing location with the last non-missing location information. We impute missing German nationality and gender information by first computing the minimum and maximum of these dummy variables by each individual. If these two values are the same, then all missing values of a given individual are replaced by his/her unambiguous value of the variable. 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 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. 2008; Dustmann et al. 2009). This is likely because of the high share of censored wages in these years (up to 18% after the structural break correction as compared to around 10% from 1980 onwards). This is why we exclude observations from 1976-1979.

Sample Restrictions We then drop all individuals living in East Germany and those younger than 21 and older than 60 years. Following common practice, we also exclude spells that start and end on the same day (2.1% of all initial spells in West Germany), spells that overlap with one or more parallel full-time spells (∼1.4%), spells of doctors and pharmacists (∼0.8%) as their records are corrupted and missing between 1996-1998 (see vom Berge et al. 2013, for further details), and spells of individuals who are registered as "not unemployed, but registered as a job seeker with the BA", "without status", or "seeking advice".

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

A.3 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 price of skills not confounded 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 skill-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 as days worked and then average these shares for each cell over all years (fixed cell weights). The composition constant log real wage of a given skill-age 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 constant log wage of low-skilled workers at time t is calculated as $low_t = \sum_{a=1}^{8} \sum_{g=0}^{1} \ln wage_{s=low,a,g,t} \cdot weight_{s=low,a,g}$ where a denotes one of eight different age group (the young comprise age groups 1 and 2, the old 3 to 8) and g gender. Note that the weights are not indexed by time meaning that they are constant over time. Finally, the medium to low (high to medium) skill premium are calculated as the difference between the composition constant log real wage of medium- and low-skilled (high- and medium-skilled) workers. Thus, skill premiums can 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 (age groups 1 and 2) and old workers (age groups 3 to 8).

A.4 Efficiency Labor Supplies

The efficiency labor supply of a specific skill-age group is calculated as the number of spells in that group weighted by the spell length, the approximate hours of work, and the efficiency weight. The efficiency weight is time-constant and calculated based on full-time spells as the normalized wage of a skill-age-gender-nativity group relative to a baseline wage averaged over all years. Specifically, the efficiency weights are computed by first aggregating full-time wages by year, skill, age, West German nativity and gender. Analogously to our wage sample, we classify all individuals who ever report to be non-German or have missing nationality information and/or those who started their first spell in East Germany as non West German natives. These cell averages are then divided in each year by the corresponding baseline wage of West German native male medium-skilled workers aged 36-40. Thus, women and men as well as West German natives and non-natives in the same skill-age group are assigned different efficiency weights. Then, we average these weights over the entire sample period for each group. Table A.1 lists the full set of efficiency weights used to construct our baseline efficiency supplies. In an alternative approach, we allowed the productivity of women and non-natives to be time-varying relative to native men. This, however, has only a minor effect on our estimates. Spells are further weighted by their approximate hours of work (or spell type specific weights) which are listed in Table A.2. Expressed more formally, the supply of skill group s in age group a in year t is computed as the weighted sum of all spells i in that cell where h denotes spell-type (full-time, part-time, vocational, unemployed), g gender and m West German nativity:

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

For instance, medium-skilled native men aged 31-35 working full-time all year long supply exactly one unit of efficiency labor in each year, while a high-skilled native female aged 41-45 working long part-time for half of the year supplies 0.41 units (= 0.5 (half a year) $\times$ 2/3 (spell type weight long part-time) $\times$ 1.22 (efficiency weight high-skilled females aged 41-45)) and a low-skilled non-native men aged 26-30 who is unemployed half of the year and full-time employed the other half supplies 0.49 (= 0.5 (half of the year) $\times$ [1/3 (spell type weight unemployed) + 1 (spell-type weight full-time)] $\times$ 0.74 (efficiency weight non-native low-skilled men aged 26-30)) units of efficiency labor.

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 gender × West German nativity × skill group × age group cells. Each entry corresponds to full-time year-round spells. The baseline group with an efficiency weight of 1 are medium-skilled native men between 31-35 years.

Table A.2: Spell Type Specific Weights

	Spell Type Weight	
Spell Type	Baseline	Alternative
Full-Time	1	1
Long Part-Time	2/3	2/3
Short Part-Time	1/3	1/3
Trainees & Unemployed	1/3	1

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

A.5 Imputation of Missing Unemployment Spells

In our baseline efficiency supplies, we also include unemployment spells. These include ALG, ALH, and ALG II spells. ALG II spells are missing in 2005/06. We therefore linearly interpolate aggregated unemployment spells in these two years separately for each skill and age groups. Also note that the number of unemployed drops between 2003/04 which leads to the bump in the medium to low-skilled supply of young workers visible in the top right part of Figure 3. This is likely due to a change in the data collection procedure of the IAB (compare vom Berge et al. 2013, p. 30).

A.6 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.

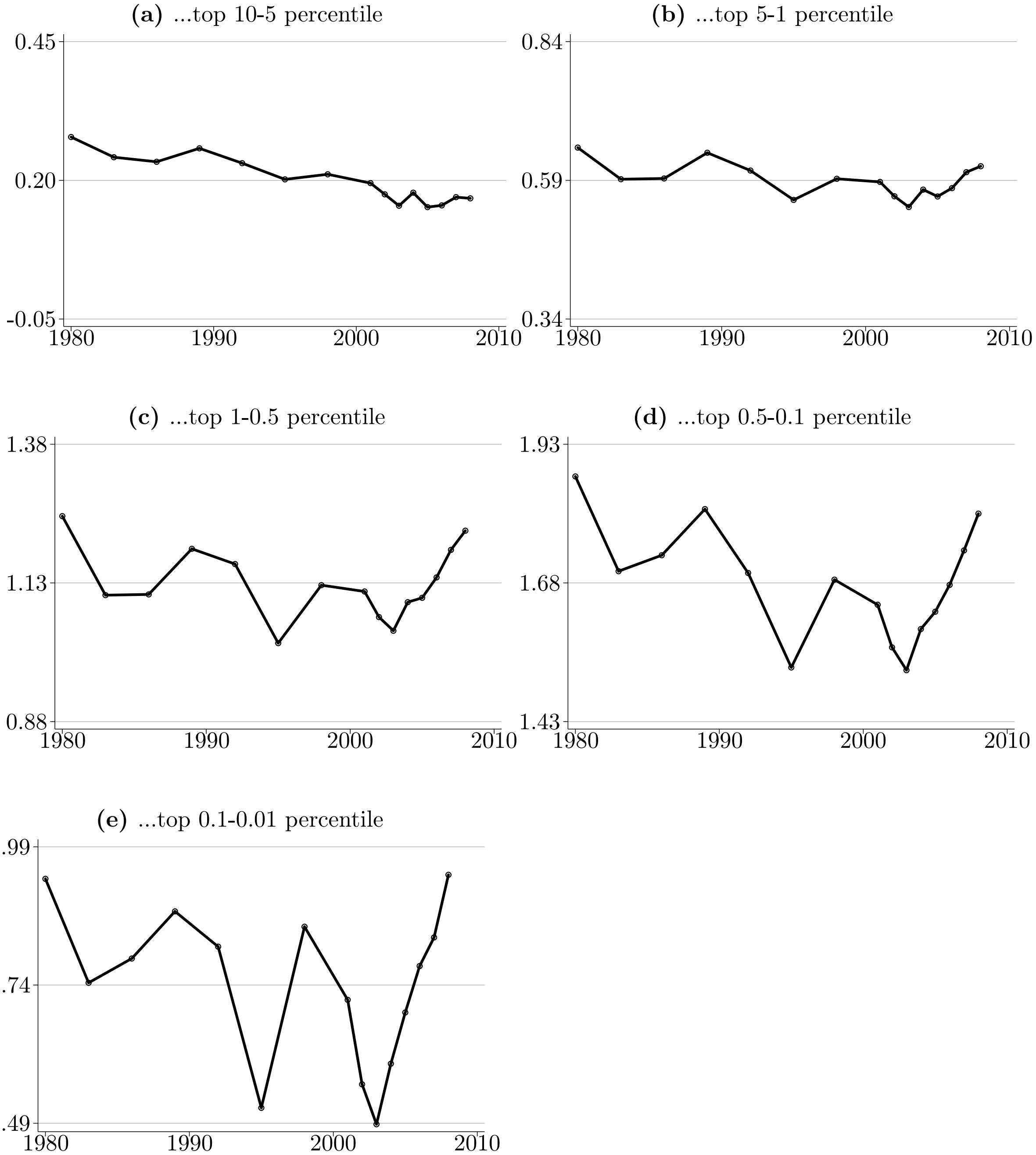
First, Dustmann et al. (2008) perform an extensive evaluation of various imputation methods. They take an uncensored distribution of wages available for 2001[37], artificially censor it at the same thresholds as in the SIAB data and compare several statistics of the imputed distribution with the true counterparts from the uncensored distribution. Their comparisons show that the "no heterogeneity" imputation approach (which we also use here) matches the standard deviation and in particular the high to medium skill premium of the uncensored distribution very well (true 0.472, no heterogeneity 0.471). This shows that the imputation method works well in a particular year (2001).

Second, we 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.[38] If the top 15% of the income distribution systematically diverged from the bottom 85% and assuming that most individuals in the top 15% are high-skilled, we would underestimate the high to medium premium. Figure A.8 shows that this is not the case. It depicts the log difference between the average incomes of the five top fractiles observed in the WTID and the 85th percentile observed in the SIAB. Although there is considerable variation in these gaps, there is no clear upward trend in neither of them. All gaps stayed roughly the same or even decreased somewhat (or even considerably in case of the difference to the top 10-5 fractile, see panel a of Figure A.8).

[37] 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).

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

Figure A.8: Log Gap between the 85th percentile (SIAB) and the average income (WTID) of...



A.7 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 equations 5 and 7 can be expressed as

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

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

In Table A.3, we estimate this system of equations, again using a seemingly unrelated regression framework. Similar to above, we replace the two last terms with the skill and age group specific labor supplies in each year, $\ln\left(\frac{\alpha_{mj}}{\alpha_{lj}}\right)$ with an indicator for the young age group and absorb the remaining terms using time dummies.[39]

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 on the age specific supply of medium-skilled workers are indeed similar and insignificantly different from each other (p-value of equality is 0.96). Therefore, in model 2, we constrain this coefficient to be the same across the two premium equations. Our estimates remain stable and the coefficients of the age-specific relative supply of high- to medium-skilled workers ($\ln H_{jt}$) becomes highly significant.[40] The magnitude of the coefficients are in line with expectations. Within the group of low-skilled workers, the young and old are close substitutes with an estimated σ_{al} of nearly 15. Medium- and high-skilled workers of the two age groups are estimated to be imperfect but relatively close substitutes with an elasticity of around 7 in both groups.

Our estimates on the medium- and high-skilled age specific relative labor supplies of about -0.14 are close to -0.16 which Card and Lemieux (2001) obtain for both for Canada (their Table III columns 5-6) and the US (their Table V column 1) when using a broader measure of college labor similar to ours[41] or when they allow the elasticities to be different for college and high-school

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

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

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

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

	(1) Unrestricted		(2) Restricted	
	ω_{jt}^{M}	ω_{jt}^{H}	ω_{jt}^{M}	ω_{jt}^{H}
$\ln L_{jt}$	-0.069**		-0.068**	
	(0.030)		(0.029)	
$\ln M_{jt}$	-0.141***	-0.130	-0.140***	-0.140***
	(0.011)	(0.094)	(0.009)	(0.009)
$\ln H_{jt}$		-0.138		-0.146***
		(0.111)		(0.036)
Young	-0.142***	-0.272**	-0.142***	-0.274***
	(0.040)	(0.121)	(0.035)	(0.061)
Constant	0.503***	0.251	0.501***	0.227***
	(0.052)	(0.160)	(0.042)	(0.022)
Time FEs	✓	✓	✓	✓
$H_0: \sigma_{al} = \sigma_{am}$ (p-value)	0.24	0.18	0.22	0.22
$H_0: \sigma_{al} = \sigma_{ah}$ (p-value)	0.12		0.16	
$H_0: \sigma_{am1} = \sigma_{am2}$ (p-value)	0.91			
$H_0: \sigma_{am} = \sigma_{ah}$ (p-value)	0.98	0.81	0.85	0.85
σ_{al}	14.6		14.7	
	(6.4)		(6.3)	
σ_{am}	7.1	7.7	7.1	7.1
	(0.5)	(5.6)	(0.5)	(0.5)
σ_{ah}		7.2		6.9
		(5.8)		(1.7)
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.

labor (-0.18, their Table VII, column 2). D'Amuri et al. (2010) also use German IAB data to estimate the impact of immigration on native wages and employment. Instead of age groups they use potential experience along with the same three skill groups as we do here. Their comparable estimate of the 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} between 8.7-10.3, σ_{am} 5.3-6.0, and σ_{ah} 8.5-20.1. Our elasticities are thus slightly higher for low- and medium-skilled workers and somewhat lower for high-skilled workers.

A.8 Estimating α_s

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

$$\widetilde{w}_{jt}^{L} = \ln w_{jt}^{L} + \frac{1}{\sigma_{al}} \ln L_{jt} = \ln \alpha_{lj} + \ln \left[Y_t^{1-\gamma} (1-\lambda_t) U_t^{\gamma-\rho} (1-\theta_t) L_t^{\rho-\eta_l} \right]$$

$$\widetilde{w}_{jt}^{M} = \ln w_{jt}^{M} + \frac{1}{\sigma_{am}} \ln M_{jt} = \ln \alpha_{mj} + \ln \left[Y_t^{1-\gamma} (1-\lambda_t) U_t^{\gamma-\rho} \theta_t M_t^{\rho-\eta_m} \right]$$

$$\widetilde{w}_{jt}^{H} = \ln w_{jt}^{H} + \frac{1}{\sigma_{ah}} \ln H_{jt} = \ln \alpha_{hj} + \ln \left[Y_t^{1-\gamma} \lambda_t H_t^{\gamma-\eta_h} \right].$$

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}'s can be recovered from regressions of the above equations where the first terms on the left hand side are captured by a dummy for being young and the second terms by a set of time dummies. This is done in Table A.4. Our moving block bootstrap takes account of the uncertainty due to the generated regressors. We interpret the results in the main text.

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

	(1) Constant σ_a			(2) Unrestricted σ_{as}		
	$\widetilde{w}_{jt}^{L}$	$\widetilde{w}_{jt}^{M}$	$\widetilde{w}_{jt}^{H}$	$\widetilde{w}_{jt}^{L}$	$\widetilde{w}_{jt}^{M}$	$\widetilde{w}_{jt}^{H}$
Young	-0.318***	-0.368***	-0.618***	-0.247***	-0.389***	-0.663***
	(0.018)	(0.016)	(0.020)	(0.030)	(0.017)	(0.063)
Constant	4.461***	4.831***	5.089***	4.381***	4.882***	5.109***
	(0.027)	(0.043)	(0.034)	(0.033)	(0.035)	(0.036)
Time FEs	✓	✓	✓	✓	✓	✓
α_s	0.73	0.69	0.54	0.78	0.68	0.52
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.03)
Observations	58	58	58	58	58	58
R^2	0.982	0.988	0.994	0.968	0.986	0.994

Notes: $\widetilde{w}_{jt}^{S} = \ln w_{jt}^{S} + {}^{1}/_{\sigma_{as}} \ln S_{jt}$. The α_s's are the exponentiated coefficients of the young indicator. The standard errors of the α_s are put in parentheses below. 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.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 micro 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, p. 21), but substantial inflows of East Germans already occurred in 1989-1991 (see Figure A.9). 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), or information on whether an individual obtained any kind of school or tertiary degree from East Germany (waves 2005/06 and 2012).[42] We can then calculate the share of East Germans in each age-skill 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 Figure A.9 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.

Ethnic Germans Ethnic Germans cannot be identified in the IAB-data since, upon arrival, they were given German citizenship and are thus indistinguishable in the data from native West Germans. We therefore use 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 in the Microcensus by year of arrival and official inflow figures from Bundesverwaltungsamt (2016) shows a close correspondence of the two (compare Figure A.10). To then calculate, for instance, the share of young low-skilled ethnic Germans in a given year between 1986-2008, 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 it by the total number of individuals of that same age-skill cell in that year. Thus, migration rates and age-skill shares are obtained retrospectively from individuals living in West-Germany sometime between 2005-11. Since out-migration of ethnic Germans was

[42] 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.

basically a “non-issue” as pointed out by Hirsch et al. (2014, p. 213), and to the extent that labor force participation and mortality of ethnic and native Germans are comparable, this approach yields reliable estimates of the necessary quantities.

Native Efficiency Supplies Once we obtain the complete time series of all age-skill shares for each of the three migrant groups, we deduct the corresponding portions in each age-skill cell from our total migrant-including efficiency supplies to obtain the native efficiency supplies used in the counterfactual simulations of the no-migration scenario.

Figure A.9: Net Official East-West Migration (Statistisches Bundesamt 2014)

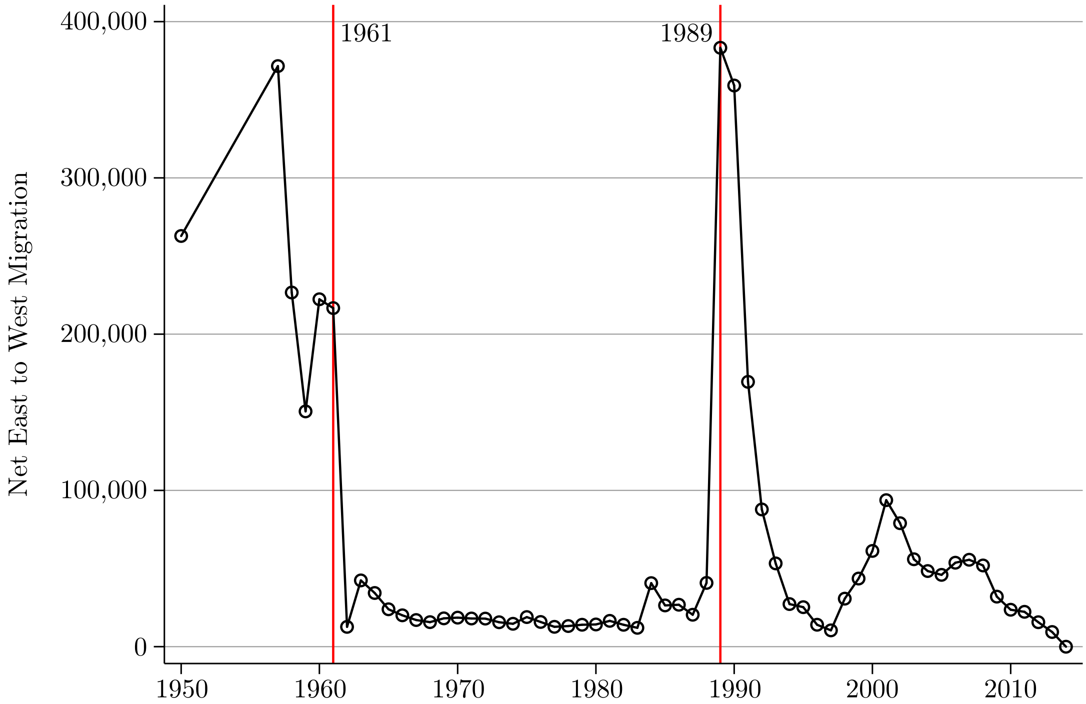


Figure A.10: Yearly Inflows of 18-59 Year Old Ethnic Germans (West Germany w/o Berlin)