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Computers as Stepping Stones? Technological Change and Equality of Labor Market Opportunities

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This paper analyzes whether technological change improves equality of labor market opportunities by increasing the returns to skills relative to the returns to parental background. We find that in Germany during the 1990s, computer-driven technological change improved the access to technology-adopting occupations for workers with low-educated parents, and reduced their wage penalty within these occupations.We also show that this significantly contributed to a decline in the overall wage penalty experienced by workers from disadvantaged parental backgrounds over this time period.Competing mechanisms, such as skill-specific labor supply shocks and skill-upgrading, do not explain these findings.

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JEL Cassification: J21, J23, J24, J31, J62, O33

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1 Introduction

A large literature documents that technological change raises wage inequality between skill groups by increasing returns to skill (e.g. Katz & Murphy, 1992; Murnane et al., 1995; Acemoglu, 2002; Card & DiNardo, 2002; Autor et al., 2008; Dustmann et al., 2009; Autor & Dorn, 2013). Increased returns to skill should, on average, disadvantage individuals with low-educated parents since they are more likely to be low-educated themselves. However, technological progress might also improve labor market opportunities for individuals with low-educated parents via a largely overlooked mechanism: By changing the occupational task content, technological change might render parents' skills and networks obsolete, increase the relative importance of individual skills, decrease the returns to parental background and, thus, reduce the disadvantage of individuals with low-educated parents (Galor & Tsiddon, 1997; Hassler & Mora, 2000).

This paper is the first to empirically investigate the role of technological change for labor market opportunities of individuals from disadvantaged social origin through the channel of decreasing returns to parental background relative to the returns to individual skills. We do so for Germany for the period 1986 to 2012, which is a suitable case to study the proposed mechanism. First, because prior to computerization, equality of opportunity was rather low in Germany. Until the early 1990's, workers from a disadvantaged parental background earned between 5% and 9% less than workers with comparable education but from an advantaged parental background.[1] Second, the German labor market was characterized by a remarkably rapid adoption of new technologies during the 1990s, providing a window of opportunity for the proposed mechanism to unfold its effect.

We proceed in two steps. In the first step, we provide stylized facts and develop a stylized framework to derive hypotheses on the effect of technological change on the wage penalty of workers with low-educated parents. In particular, we first show that the observed decrease in the wage penalty by parental background between 1986 and 2012 in Germany was mainly due to a reduction in the wage penalty conditional on individual education. In contrast, more equal access to education played a minor role. Hence, in the following we focus on labor market opportunities within qualification groups, i.e. after individual education has taken place. We provide evidence that within qualification groups, the average wage penalty by parental background has declined in Germany since the mid 1990s and has even vanished in the 2000s. During the same period, the share of workers using computer-controlled tools more than doubled, rising from 16% in 1992 to 38% in 1999. Occupations which adopted the new technology more heavily also saw a stronger decrease in the wage penalty.

[1] See Section 2.3.

In a stylized framework, we then formalize the hypothesis that, conditional on individual skill, technological change improves labor market opportunities for disadvantaged individuals. This can be due either to an absolute decrease in the returns to parental background because parental occupation-specific knowledge becomes obsolete when the occupational tasks change and because parental networks lose in value in a rapidly changing environment. Or it can be due to a relative decrease in the returns to parental background relative to the returns to individual skills. While both mechanisms lead to better labor market outcomes of disadvantaged workers, the model predicts that, if technological change increases relative returns to skill, the positive impact of technological change on labor market opportunities of disadvantaged individuals increases in worker's skills and could be close to zero for low-skilled workers.

In the second step, we empirically test these predictions. We use occupation-year-level variation in computer-driven technological change and examine whether a causal link between technological change and labor market opportunities exists. We do so separately for high- and low-qualified workers, i.e. workers with and without a university entrance qualification. For this, we combine representative household survey data that includes a rich set of parental background characteristics with new information on technological change by occupation, which we obtain from a survey of occupational working tools. To address individual heterogeneity and selection effects, we estimate models including occupation-spell fixed effects, and apply an instrumental variable strategy. The instrument takes advantage of the well-established relationship between the task content of an occupation and its suitability for computer-driven technological change. Our results consistently prove the existence of a causal effect for high-qualified workers: In occupations with an increasing use of computer-controlled machines, employment shares of high-qualified workers with low-educated parents increased significantly, and their wages rose more than those of high-qualified workers with high-educated parents. We show that this pattern is not explained by competing mechanisms, such as skill-specific labor supply shocks or the educational expansion in Germany during the 1990s and 2000s. Furthermore, our results indicate that technological change closed the wage penalty by reducing the so-called class ceiling phenomenon, i.e. by reducing the divergence of wages and job positions over occupational experience. In sum, technological change removed disadvantages in employment and wage opportunities related to parental background for high-qualified workers. For low-qualified workers, we do not find clear evidence that technological change improved labor market opportunities. This likely reflects that the technology-induced increase in returns to skills is less prevalent in occupations with lower skill requirements. We further implement a decomposition to show that, for high-qualified workers, the reduction of the qualification-specific wage penalty was mainly linked to technological change, while for low-qualified workers the reduction of the qualification-specific wage penalty was mainly driven by composition effects. This highlights that technological change reduces intergenerational persistence on the labor market by removing disadvantages related to parental background among high-qualified workers.

These findings contribute to different strands of the literature. First, to the best of our knowledge, we are the first to empirically test whether technological change improves employment and wage opportunities for individuals from a disadvantaged parental background. In particular, we test the theoretical predictions of Galor & Tsiddon (1997) and Hassler & Mora (2000) that in times of technological progress the returns to parental background decrease relative to the returns to individual skills, and, thus, complement the scant and mostly descriptive evidence on this topic. Our results highlight that technological change could be a driver of lower entrance barriers and lower wage penalties by social class that have been found in the UK in technical professions, such as engineering and IT, as opposed to traditional professions, such as law and medicine (Laurison & Friedman, 2016). Our findings may also explain why more innovative regions tend to have higher levels of social mobility than less innovative ones, as shown for the US by Akcigit et al. (2017) and Aghion et al. (2019).

Second, our results contribute to the debate on the impact of technological change on wage inequality (e.g. Card & DiNardo, 2002; Autor et al., 2008). Skill-biased technical change has been shown to increase returns to skills, measured both by formal education and cognitive skills (e.g. Katz & Murphy, 1992; Murnane et al., 1995; Autor et al., 2008), and to contribute to higher wage inequality until the 1970s (Acemoglu, 2002). Starting in the 1980s, computer-controlled machines increasingly substituted routine, mid-wage jobs (Acemoglu & Autor, 2011), resulting in job and wage polarization in some countries, such as the US (Autor et al., 2008; Autor & Dorn, 2013), and rising wage inequality in others, e.g. Germany (Dustmann et al., 2009; Antonczyk et al., 2018). Related, recent papers have highlighted that the technology-induced decline in middle-skilled jobs, i.e. job polarization, may lead to a reduction in intergenerational occupational upward mobility when intergenerational persistence in education is high (Garcia-Penalosa et al., 2022; Hennig, 2021; Guo, 2022; Berger & Engzell, 2022). Our paper provides novel evidence on a largely overlooked aspect of technological change: it reduces wage inequality between individuals from different social origins conditional on their education and skills. In order to test the relevance of this opportunity-enhancing effect, we decompose the change in the overall wage penalty by parental background into its components. Our decomposition analysis reveals that the opportunity-enhancing impact of technological change was much larger than the opportunity-deteriorating impact via intergenerational persistence in education.

Third, our findings contribute to the increasing literature on the role of social origin for later life outcomes. Several studies find that even after conditioning on workers' skills, a large wage penalty by parental background remains.[2] Franzini & Raitano (2009) find persistent wage penalties of 10% and 16% for children of white and blue collar workers, respectively, compared to those with parents in managerial positions in 13 European countries, controlling for individual education. Franzini et al. (2020) find that, controlling for education, children of tertiary graduates in Italy earn 5% higher wages. Britton et al. (2016) report a 25% wage penalty in the UK between university graduates from higher income families and those from lower income families. Laurison & Friedman (2016) find a 17% wage penalty by parental social class in the UK even within high-status occupations. The average wage penalty of 8% by parental background, which we find conditional on education for Germany around 1990, is in line with these findings for other countries. Several explanations for this penalty in labor market returns have been put forward: job referrals and nepotism (e.g. Holzer, 1988; Loury, 2006; Ioannides & Loury, 2004; Corak & Piraino, 2011), relational capital (Franzini et al., 2020), parental specific knowledge (Laband & Lentz, 1983; Lentz & Laband, 1989; Laband & Lentz, 1992; Lentz & Laband, 1990; Dunn & Holtz-Eakin, 2000; Lindquist et al., 2015), and behavioral codes (Friedman & Laurison, 2019). Generally, these mechanisms have been argued to hinder career advancements of workers from disadvantaged backgrounds. Our analysis shows that technological change counteracts these mechanisms, improves wage and promotion opportunities of workers from disadvantaged parental backgrounds, and has lead to a decline in the wage penalty by parental background.

The remainder of the paper is structured as follows: In Section 2 we describe the data and present stylized facts on changes in the wage penalty by parental background and technological change in Germany. In Section 3 we lay out a simple stylized framework that explains our proposed mechanism and translates it into empirically testable hypotheses. In Section 4 we report our main results on the impact of technological change on equality of labor market opportunities within qualification groups. In particular, Section 4.1 estimates the effect of technological change on the wage returns to parental background and Section 4.2 analyzes how technological change affects the wage penalty with increasing work experience. In Section 4.3 we compute the contribution of technological change for qualification-specific wage penalties. Section 4.4 complements this by investigating the effect of technology use within occupations on the share of workers from disadvantaged social backgrounds employed in these occupations. Section 5 concludes.

[2]On the effect of parental background on skill formation, see e.g. Heckman & Mosso (2014).

2 Data and Stylized Facts

2.1 Data Sources

Our analysis relies on individual level information on employment careers and parental background as well as an indicator of occupation-level technological change. For the latter, we use information from the Qualification and Career Surveys (QCS), while for the former, we use the German Socio-Economic Panel (SOEP). Furthermore, we supplement our final dataset with aggregate information for each occupation using the Sample of Integrated Employment Biographies (SIAB).

Qualification and Career Survey (QCS). The QCS is a repeated cross sectional survey with waves conducted every six to seven years between 1979 and 2012 by BIBB, IAB, and BAuA.[3] The survey covers around 30,000 employees and includes questions regarding the main working tool used by each respondent. In the 1992 wave, these tools were categorized into (1) non-mechanical tools (e.g. handcart, pencil), (2) tools with some mechanization (e.g. telephone, hand drill machine), (3) tools with advanced mechanization (e.g. car, crane, copy machine), (4) semiautomatic tools (e.g. fax, milking installation, bottling machine) (5) and computer-based tools (e.g. computers, CNC machines). We adopt this categorization for all waves of the survey. Following Rohrbach-Schmidt & Tiemann (2013), we harmonize the waves and restrict the data to employees in West Germany aged 15 to 65 with a weekly working time of at least 10 hours (excluding unpaid family workers, apprentices, students, and non-German citizens).

Based on this information, we construct an indicator of occupation-specific technology use. We distinguish 62 occupations which are compatible with the other data sources.[4] For each occupation and survey wave, we compute the share of workers who are mainly using a tool of category 5, i.e. computers and computer-based tools.[5] Our measure of technological change is thus closely linked to the spread of personal computers which started in the 1980s and experienced a major breakthrough in the 1990s. In line with this, the share of workers mainly using computer-based tools more than doubled between 1986 and 1992 from 7% to 16%, and again to 38% in 1999, but increased only slightly

[3]BIBB: Federal Institute for Vocational Education and Training; IAB: Institute for Employment Research; BAuA: Federal Institute for Occupational Safety and Health.

[4]The 62 occupations result from an aggregation o the 2-digit level occupations of the German classification of occupations (KldB 1992). The resulting classification of occupations and respective sample sizes in the SOEP are provided Table B1.1 in Appendix B.1.

[5]We do not construct an indicator of *qualification*-occupation-specific technology, since the variation of working tools across qualification groups within an occupation is likely endogenous and changes endogenously over time. In addition, this would result in fewer cells and fewer observations per cell. Running our main regression with qualification-occupation-specific instead of only occupation-specific technology use provides qualitatively very similar but less precise results.

since then (42% in 2006, 44% in 2012, see Figure B1.2 in the Appendix B.1). We linearly interpolate our technology indicator for years between these survey waves.

Socio-Economic Panel (SOEP). The SOEP is a representative longitudinal survey of private households in Germany conducted annually since 1984. For more than 25,000 persons per year, it includes detailed information on education, job characteristics (including current occupation and wage), and education of the parents (Goebel et al., 2019). For our analysis, we restrict the sample to full-time dependent workers who are between 20 and 65 years old and exclude periods of vocational training and marginal employment.[6] We compute real hourly wages based on self-reported monthly gross earnings divided by self-reported actual monthly working hours and the CPI deflator, using 2015 as the base year.[7] To avoid potential confounding effects, we focus on West Germany and exclude movers from East to West Germany after reunification.

We distinguish between high-qualified workers, i.e. those with a university entrance qualification (*Abitur*), and low-qualified workers, i.e. those without such a qualification. Furthermore, following the literature, we define socioeconomic background based on retrospective questions on parental education (e.g. Björklund & Salvanes, 2011): individuals have high-educated parents if at least one parent completed a university entrance qualification, and low-educated parents if this is not the case.[8]

We focus on the university entrance qualification because it is generally considered a key qualification in Germany. This educational classification is, first, consistent for the whole time period, and, second, crucial for the subsequent career of school graduates: Those who obtain a university entrance qualification can continue with tertiary education and typically enter high-skilled jobs. Those without this qualification typically pursue an apprenticeship and begin careers in middle- or low-skilled jobs. As a result, both categories overlap remarkably little with regard to years of formal education: those without university entrance qualification have at most 13 years of education while those with university entrance qualification have at least 15 years of education with only few exceptions (see Figure B1.1 in the Appendix B.1).[9]

Hence, for both generations, we use the university entrance qualification as the relevant threshold, but refer to *education* whenever we talk about the parents' background

[6] A robustness check for workers aged between 25 and 55 confirms our results. Marginal employment refers to jobs where workers earn at most 450 Euro per month.

[7] In order to exclude outliers, we drop observations with wages above the 99$^{\text{th}}$ percentile and below the 1$^{\text{st}}$ percentile. Our results are robust to the inclusion of these observations.

[8] Our results are robust to different specifications of parental background based on parental years of education as continuous variable and based on parental occupational prestige.

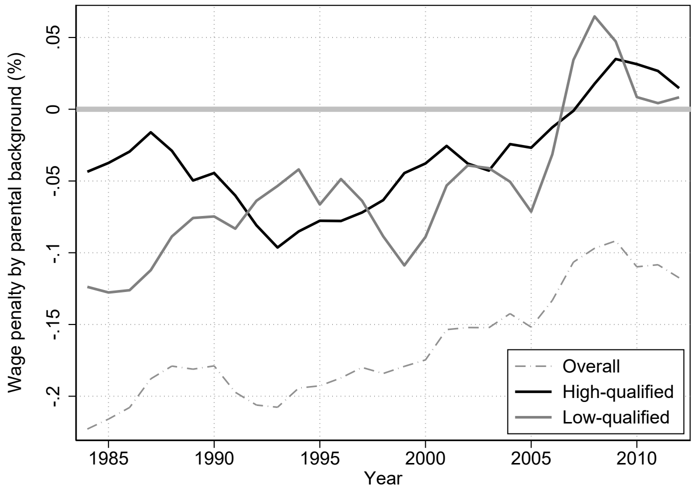
[9] The share of individuals with a university entrance qualification has been increasing steadily, reaching around 34% of the population in 2019 (Destatis, 2021). While among those born in the 1950s the share with this qualification is around 26%, it is around 50% among people born in the 1980s (DIPF, 2020).

and to *qualifications* whenever we talk about the educational attainment of their children. We introduce this different wording to reduce a potential confusion between both generations.

Sample of Integrated Labor Market Biographies (SIAB). The SIAB is a representative 2% sample of the employment biographies that are reported to the social security insurance.[10] For active employment spells on June 30th of each year, we compute average employment shares, daily median wages, and characteristics of the occupation-specific workforce (e.g. age, education, tenure). When comparing average occupational employment and wages from the SOEP (using the appropriate sampling weights) with average occupational employment and wages provided in the SIAB, their very close match suggests that the SOEP is highly representative at the occupational level and that its wage information is of high quality (see Figure S1.1 and Figure S1.2 in the Supplementary Material S.1).

Estimation Samples. From these data sources, we build two distinct estimation samples for all subsequent analyses. First, we combine the longitudinal data on employment, wages, occupation, education, and parental educational background of individuals from the SOEP with the occupation-level indicator of technology use from the QCS. We use this individual-level sample to estimate the effect of technological change on wages. Second, we use this individual-level panel dataset to construct an occupation-level panel data set using the sampling weights provided by the SOEP. This occupation-level dataset includes yearly employment shares by qualification and parental background for occupation- qualification-year cells with at least ten individual observations.[11] Time-varying occupation-level control variables for the second dataset are retrieved from the SIAB. To achieve representativeness at the occupational level, we use occupational employment shares from the SIAB as weights in the subsequent analyses. We use this sample to supplement the individual-level wage analysis by testing to what extent employment patterns across occupations are affected by technological change. Summary statistics of all individual-level and occupational variables are included in Table B1.3 and Table B1.4 in the Appendix B.1.

Figure 1: Trends in the Overall and Qualification-Specific Wage Penalties



Notes: Overall/high-qualified/low-qualified: Difference in log wages between all/high-qualified/low-qualified individuals with low and those with high-educated parents. Moving averages over three years. Based on the SOEP, using representative weights. West Germany only.

2.2 Decomposition of the Wage Penalty

Figure 1 shows that the overall wage penalty between workers from high- versus low-educated parents declined from 18% in 1989 to 12% in 2012. We implement a decomposition to show that most of this decline was due to a closing of the qualification-specific wage penalties, this is, the wage penalties within the group of high-qualified and the group of low-qualified workers, also depicted in Figure 1. Given that the wage penalties within qualification groups closed over time, the wage penalty remaining in 2012 is likely due to lower chances of individuals from a disadvantaged background to obtain a high level of education.[12] Our decomposition differentiates between four channels that can explain the declining wage penalty: (i) a decline in the wage penalty among high-qualified workers, (ii) a decline in the wage penalty among low-qualified workers, (iii) relative educational upgrading of workers with low-educated parents, i.e. a relative increase in the share of high-qualified workers with low-educated parents, and (iv) a reduction in returns to education, affecting the wage penalty because workers with low-educated parents are

[10]The dataset covers dependent employment only and excludes civil servants and the self-employed. We additionally drop marginal employment from our analysis, as marginal employment is reported only after 1999.

[11]On average, an occupation-year level information on employment shares is based on 70 individual observations.

[12]Due to the selective tracking of the German education system, it has been shown that a university entrance qualification is associated with both significantly higher wages and parental background (e.g. Dustmann, 2004). Indeed, among those enrolled in the highest educational track leading to a university entrance qualification in 2019, about 67% of students had parents that obtained this qualification (Destatis, 2021).

less often high-qualified.

We use our individual-level sample and estimate the wage returns to education, the wage returns to parental background, and the differential wage returns to education for workers with low-educated parents for a single year, $\tau \in (1989, 2012)$:

$$ln(w_i) = \alpha + \beta PB_i + \gamma E_i + \delta PB_i \times E_i + \epsilon_i \tag{1}$$

where E_i is an indicator for education ($E_i = 0$ for low-qualified workers and $E_i = 1$ for high-qualified workers) and PB_i for parental background ($PB_i = 0$ for workers with high-educated parents and $PB_i = 1$ for workers with low-educated parents). The average log wage penalty by parental background in year τ is:

$$\Delta ln(w_\tau) = ln(\overline{w_\tau}^{PB=1}) - ln(\overline{w_\tau}^{PB=0}) = \beta_\tau + \gamma_\tau \overline{E_\tau}^{PB=1} - \gamma_\tau \overline{E_\tau}^{PB=0} + \delta_\tau \overline{E_\tau}^{PB=1} \tag{2}$$

where $\overline{E_\tau}^{PB=1}$ is the average education of workers with low-educated parents in year τ. The change in the wage penalty between the years $s = 1989$ and $t = 2012$ can then be decomposed into the channels mentioned above:

$$\begin{aligned}
&\Delta\Delta ln(w) = \Delta ln(w_t) - \Delta ln(w_s) && (3)\\
&= (\beta_t + \delta_t - \beta_s - \delta_s)\bar{E}_s^{PB=1} && \Delta \text{ Wage Penalty High-qualified (i)}\\
&+ (\beta_t - \beta_s)(1 - \bar{E}_s^{PB=1}) && \Delta \text{ Wage Penalty Low-qualified (ii)}\\
&+ \gamma_s[(\bar{E}_t^{PB=1} - \bar{E}_s^{PB=1}) - (\bar{E}_t^{PB=0} - \bar{E}_s^{PB=0})] + \delta_s(\bar{E}_t^{PB=1} - \bar{E}_s^{PB=1}) &&\\
& && \Delta \text{ Educ. Upgrading (iii)}\\
&+ (\gamma_t - \gamma_s)(\bar{E}_s^{PB=1} - \bar{E}_s^{PB=0}) && \Delta \text{ Returns to Education (iv)}\\
&+ (\delta_t + \gamma_t - \delta_s - \gamma_s)(\bar{E}_t^{PB=1} - \bar{E}_s^{PB=1}) - (\gamma_t - \gamma_s)(\bar{E}_t^{PB=0} - \bar{E}_s^{PB=0}) && \text{Interactions (v)}
\end{aligned}$$

The first two terms represent changes in the wage penalties that take place solely within the groups of high-qualified and low-qualified workers (channels (i) and (ii)). The third term captures the change in the wage penalty due to differences in educational upgrading between workers with low-educated parents and workers with high-educated parents (channel (iii)).[13] The fourth term (channel (iv)) accounts for changes in the wage penalty due to changing returns to education, which materialize due to the differences in

[13]Workers with low-educated parents may benefit differently from educational upgrading relative to workers with high-educated parents for two reasons, see equation (3): First, if they upgrade more often compared to workers with high-educated parents. Second, if they get additional returns to their educational upgrading. More formally, the first element of channel (iii) in square brackets in equation (3) refers to the returns to a differently strong educational upgrading of workers with low-educated parents relative to the educational upgrading of workers with high-educated parents. The second element captures the educational gains of workers with low-educated parents remunerated with the additional initial returns to education of workers with low-educated parents.

initial educational attainment of workers with low-educated versus high-educated parents. The last element contains the remaining interaction terms between the different channels.

Table 1: Decomposition of the Change in the Overall Wage Penalty 1989 to 2012

	Decomposition terms				
Overall Change	HQ Penalty (i)	LQ Penalty (ii)	Educ Upgrading (iii)	Returns to Init Educ (iv)	Interaction Effects (v)
6.87	1.63†	5.79‡	0.69	-1.55	0.30
[-7.92;21.65]	[0.24;3.02]	[-0.47;12.05]	[-0.29;1.67]	[-6.06;2.97]	[-1.34;1.94]

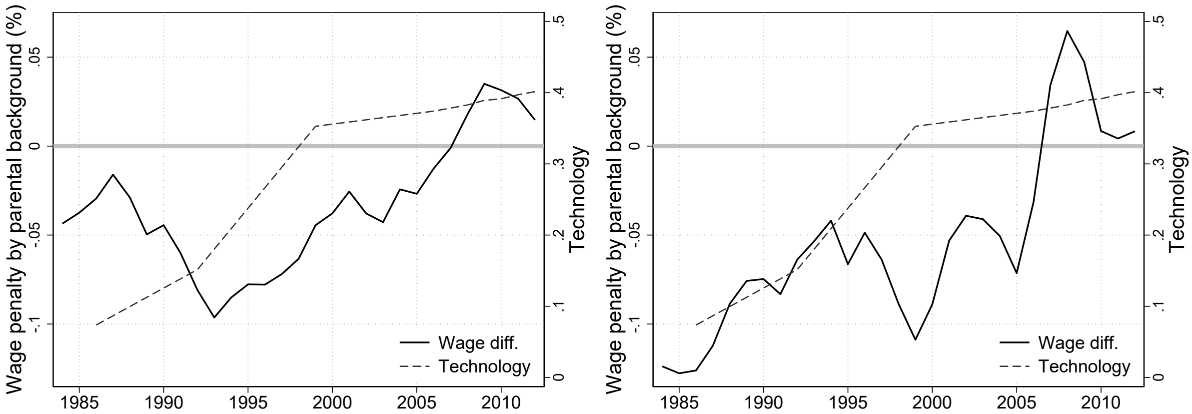
Notes: Decomposition terms according to equation (3) for a change in the overall wage penalty between $s = 1989$ and $t = 2012$ plus 90% confidence intervals. In percentage points. † - the corresponding change in regression coefficients is +0.085, which corresponds to the total change of the high-qualified in Figure 5. ‡ - the corresponding change in regression coefficients is +0.075, which corresponds to the total change of the low-qualified in Figure 5. Confidence bands based on 1,000 bootstrap replications of the coefficient combinations.

Table 1 displays the decomposition terms of the change in the overall wage penalty between 1989 and 2012 according to equation (3) and their 90% confidence intervals. The overall wage penalty by parental background decreased by 6.87 percentage points, of which 1.63 percentage points are due to a decrease in the wage penalty among high-qualified workers, and 5.79 percentage points are due to a reduction in the wage penalty among low-qualified workers. The much smaller contribution of the reduction in the wage penalty among high-qualified workers compared to low-qualified workers mainly arises because in 1989 the share of high-qualified workers among all workers with low-educated parents was much smaller than the share of low-qualified workers among all workers with low-educated parents (19% compared to 81%). The underlying changing returns to parental background (i.e. the change in coefficients) are in fact very similar in magnitude for both qualification groups and correspond to a complete closing of the wage penalties within qualification groups: The parental wage penalty declined by 8.5 percentage points among high-qualified workers and by 7.5 percentage points among low-qualified workers.

In contrast, increasing returns to education between 1989 and 2012 contributed to a widening of the overall wage penalty by parental background by 1.55 percentage points (column (iv)) because workers with low-educated parents were less likely to have a university entrance qualification in 1989. At the same time, access to education improved for individuals from a disadvantaged parental background between 1989 and 2012, contributing to a decline of the overall wage penalty by 0.69 percentage points (column (iii)).

We conclude that between 1989 and 2012, changes in the qualification-specific wage penalties (channels (i) and (ii)) are the most relevant drivers of the decline in the overall wage penalty. In the rest of the paper, we therefore focus on the wage penalties within

Figure 2: Wage Penalty by Parental Background and Technological Change: Time Trend



Notes: Solid line: Difference in log wages between high-qualified (low-qualified) individuals with low and those with high-educated parents. Moving averages over three years. Based on the SOEP, using representative weights. Dashed line: Average share of workers mainly using new technologies across all occupations. Based on the Qualification and Career Survey, occupations weighted by the initial employment shares in 1986. West Germany only, own calculations.

qualification groups.

2.3 Stylized Evidence

Figure 2 shows the evolution of the qualification-specific wage penalties, computed with individual data from the SOEP, and the trend in average technology use across occupations, estimated using the QCS survey. Wage penalties are defined as the difference between the log average wage of workers with low-educated parents and the log average wage of workers with high-educated parents who posses the same qualification.

Three different periods emerge: Until the early 1990s, the share of new technologies was rather low and the average wage penalty experienced by workers from disadvantaged parental background was rather large, around 5% among high-qualified workers and 9% among low-qualified workers. During the 1990s, new technologies were quickly adopted, and the wage penalty vanished with a time lag.[14] In the 2000s, technology adoption stagnated on a high level, while the wage penalty stagnated around zero or slightly above.

This first stylized analysis provides suggestive evidence that the returns to parental background diminished notably during the 1990s and early 2000s, and that these changes closely followed the diffusion of computer-based technologies in the German labor market. These trends are particularly evident among high-qualified workers, while among low-

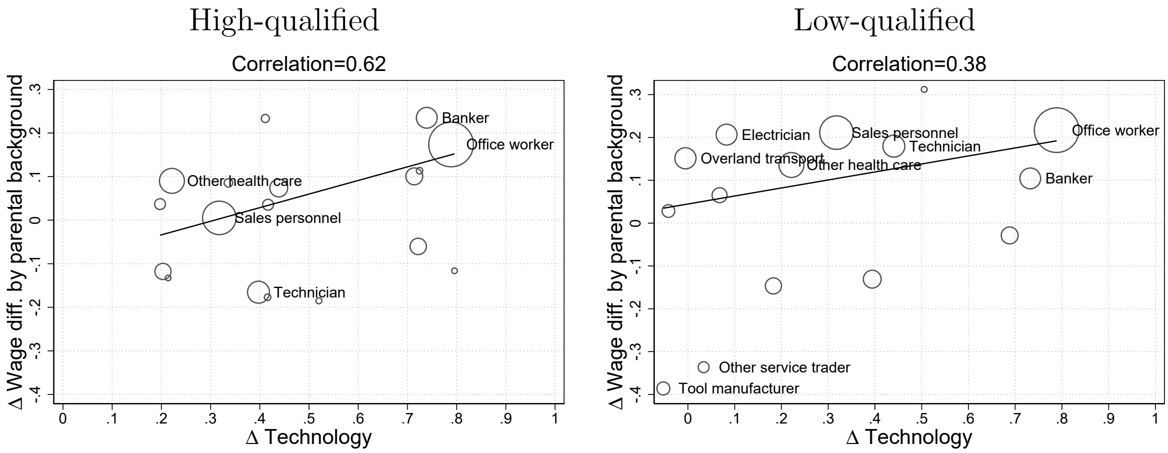
[14]Similarly, workers with low-educated parents were underrepresented in well-paid occupations within both qualification groups in the late 80s and early 90s. However, during the 90s, relatively more workers from a disadvantaged parental background became employed in well-paid occupations, see Figure B1.3 in the Appendix B.1.

qualified workers, wages only converged several years after the period of rapid technology adoption.[15]

Next, we analyze whether this pattern also holds true at the occupational level. Figure 3 plots the change in technology use within occupations between 1986 and 2012 against the change in the occupation-specific wage differential over the same period. The graph suggests that, indeed, the link between technological change and equality of opportunity holds at the occupation level as well. Occupations with stronger adoption of new technologies had larger decreases in the wage penalty, both among high-qualified and among low-qualified workers. The correlations between the change in technology use and the change in the wage differential are 0.62 and 0.38, respectively.

In summary, in the 1980s and early 1990s, workers with low-educated parents had, on average, lower wages, even conditional on their own educational attainment. Yet, returns to parental background declined afterwards, and most sharply in occupations that largely adopted computer-based technologies.

Figure 3: Wage Penalty by Parental Background and Technological Change: Occupational Variation



Notes: Vertical axis: Increase between 1986 and 2012 in the log wage difference between high-qualified (low-qualified) individuals with low and those with high-educated parents. Horizontal axis: increase in the share of new technologies over the same period. When no observation was available for an occupation for the year 1986 (2012), the earliest year after 1986 (the latest year before 2012) available was taken with minimum requirement of 10 years between starting and end year. Occupations weighted by the initial employment shares in 1986. Source: SOEP and QCS, West Germany only, own calculations.

[15] Note that the closing of the wage penalty within qualification groups does not necessarily imply a closing of the *overall* wage penalty if differences in educational attainment between workers with different parental backgrounds still exist, see Section 2.2. Indeed, as shown by Brunori & Neidhöfer (2021), from 1992 to 2016 individuals with high-educated parents and those with parents in higher ranked occupations consistently qualify at the top of the German income distribution, and children of low-educated parents at the bottom.

3 Economic Reasoning and Empirical Strategy

3.1 Conceptual Framework

In this section, we develop a stylized framework to formalize how technological change may improve the access to certain occupations for disadvantaged individuals and reduce the wage penalty by parental background. Hereby, our aim is to investigate the role of technological change for labor market opportunities conditional on skill.[16] Our framework mainly follows the theoretical models developed by Galor & Tsiddon (1997) and Hassler & Mora (2000). Galor & Tsiddon (1997) assume that wage and employment outcomes are determined by skills and parental background. If technological advances raise returns to skills relatively more than returns to parental background, this, in turn, improves the labor market opportunities of individuals from disadvantaged backgrounds (conditional on skills). Hassler & Mora (2000) show theoretically that technological progress reduces the returns to parental background in absolute terms because occupation-specific knowledge of the former generation becomes obsolete when the occupational task content changes, and because parental networks lose in value in a quickly changing environment. Our stylized framework combines both ideas, predicting an improvement in labor market opportunities of disadvantaged workers if returns to parental background decline only relative to the returns to skills, or also decline in absolute terms. This mechanism is stronger when technological change also increases returns to individual skills.

Assume that workers differ by their skill level $\alpha > 0$ and their parental background (measured by parents' education) $\beta > 0$. Each firm uses a single occupation to produce output, and firms differ in which occupation they use. Firms choose one type of labor $L_{\alpha,\beta}$ and produce output $Y = L_{\alpha,\beta}F(\alpha, \beta, t)$ with production function $F(\alpha, \beta, t) = \alpha t + \beta$, where $t > 0$ is the level of technology. We rely on an explicit production function for simplicity and discuss a generalized production function in Appendix A.

Workers' productivity rises in worker's skills α, worker's parental background β, and the level of technology t: $\frac{\partial F}{\partial \alpha} = f_\alpha > 0$, $f_\beta > 0$, and $f_t > 0$.[17] Workers supply labor with wage elasticity ϵ, $L_{\alpha,\beta} = \bar{L} w^{\epsilon}_{\alpha,\beta}$, where $\bar{L}$ is the baseline labor supply which we assume

[16] We abstract from the potential impact of technological change on educational mobility (Maoz & Moav, 1999; Aziz, 2020; Hennig, 2021). However, in the decomposition analysis in Section 2.2, we show that the overall wage penalty by parental background decreased during the 1990s and 2000s mainly due to a reduction of the wage penalty within educational groups, rather than educational upgrading of individuals with low-educated parents.

[17] Note that we assume parental background to have a direct effect on productivity. Alternatively, we could model indirect effects via search and matching by assuming that workers from advantaged socioeconomic backgrounds face lower search frictions (due to e.g. network effects). If technological change reduces related wage returns, the implications of such an alternative model would be the same, although the mechanism would differ.

to be exogenous.[18] Firms minimize their costs of production, $C = w_{\alpha,\beta} L_{\alpha,\beta}$ subject to output Y by choosing the optimal worker type, where $w_{\alpha,\beta}$ are wages. Wages are specific to the type of labor. The firms' costs per unit of output are $\frac{C}{Y} = \frac{w_{\alpha,\beta}}{\alpha t+\beta}$. Cost minimization implies that unit costs of production must be equal across all types of workers, which gives:

$$\frac{w_{\alpha_0,\beta_0}}{w_{\alpha,\beta}} = \frac{\alpha_0 t + \beta_0}{\alpha t + \beta} \tag{4}$$

where α_0 denotes low skills and β_0 a disadvantaged parental background. The wage ratio between the two worker types responds to technological change as follows:

$$\frac{\partial\left(\frac{w_{\alpha_0,\beta_0}}{w_{\alpha,\beta}}\right)}{\partial t} = \frac{\alpha_0\beta - \alpha\beta_0}{(\alpha t + \beta)^2} \tag{5}$$

Comparing two workers with the same skill level ($\alpha = \alpha_0$), the wage ratio of workers with low parental background (β_0) compared to workers with high parental background (β) increases in the technology level, $\alpha(\beta - \beta_0) > 0$. Since technology raises returns to skills, this effect is larger for workers with high skills α. Analogously, comparing two workers with the same parental background ($\beta = \beta_0$), the wage ratio of high skill workers (α) compared to low skill workers (α_0) increases in the technology level, $\beta(\alpha - \alpha_0) > 0$. Hence, technological change improves equality of opportunity by reducing the wage penalty between equally skilled workers with high versus low parental background, and increases wage inequality by widening the gap between high- and low-skilled workers.

We assume that occupations differ in their compatibility with computers. Firms adopt computers faster when they rely on an occupation that is compatible with computers.[19] Equation 5 informs us on how the wage ratio between workers who differ by parental background (or skills) changes in response to technological change in a given occupation. In particular, we expect a closing of the wage penalty by parental background conditional on skill for workers who are employed in occupations that see a strong adoption of computers.[20]

The implications for equality of opportunity in accessing occupations with increasing technological change are analogous to the implications for wage ratios because we focus on a demand shock and assume a positively sloped labor supply curve. Technology raises both the relative wages and employment shares for workers from disadvantaged

[18] We assume that $\bar{L}$ is the same for all labor types for simplicity. Note that this assumption does not affect our key results.

[19] We focus on the effect of computer adoption on the demand for workers and do not aim to endogenize the decision to adopt computers.

[20] Our model therefore zooms in on changes in relative wages for workers who remain in their occupation. We abstract from wage changes that are induced by workers who switch occupations.

backgrounds (conditional on skills).

Our results rely on the assumption that technology and skills are complements. For high-skilled workers, this assumption is well supported by empirical evidence (e.g. Acemoglu & Autor, 2011). For middle-skilled manufacturing and clerical jobs, in contrast, there is also evidence of deskilling within these occupations as technologies and related standardization processes leave less complex tasks for human workers (Cappelli, 1993; Howcroft & Richardson, 2012; Steil & Maier, 2017; Peng et al., 2018; Kunst, 2020).[21] This implies that technology adoption does not necessarily raise within-occupation skill requirements for less skilled workers, but might even result in deskilling. In this case, workers from a disadvantaged parental background would not benefit from rising returns to skills with technology adoption.[22] Therefore, we expect effect heterogeneity by workers' skill levels. We refer to this dimension of effect heterogeneity as "qualification". In particular, among high-qualified workers we expect technological change to raise relative demand and, thus, wages and employment shares for workers from disadvantaged backgrounds, while we expect weak or ambiguous effects for low-qualified workers. Note that, in addition, we need to condition on skills within both qualification groups in order to test the above hypotheses.

3.2 Empirical Strategy and Identification

3.2.1 Wage Returns to Parental Background

Baseline Specifications. In order to analyze the role of technological change for wage returns to parental background, we estimate a Mincer-type equation. We regress the log wage of individual i working in occupation j in year t on the level of occupation-year specific technology ($Tech$), i's parental background (PB), and the interaction of the two. We estimate the following baseline equation:

$$ln(w_{ijt}) \quad = \quad \alpha_1 PB_i + \alpha_2 Tech_{jt-3} + \alpha_3 PB_i \times Tech_{jt-3} + \alpha_4 \Psi_j + \alpha_5 Z_{ijt} + u_{ijt}. \quad (6)$$

We include occupation fixed effects (Ψ), which control for, among other things, the level of technology within an occupation and thereby make the coefficients α_2 and α_3 capture returns to *changes* in technology use within an occupation. We perform the regression

[21] Note that in our model and empirical analysis, we focus on within-occupation task and skill shifts that are responsible for the vast majority of the overall change in task and skill requirements (Spitz-Oener, 2006).

[22] To model deskilling for low-skilled workers, we could alternatively assume that technology substitutes for workers' skills in low-skill jobs, which would flip around the results for low-skilled workers in our model. However, we keep the model simple and leave it to the empirical results whether de- or upskilling dominates for less-skilled workers.

separately for high-qualified and low-qualified workers to take into account the expected effect heterogeneity discussed above.

$Tech_{jt-3}$ measures the share of workers mainly using technology-intensive tools per occupation and year. Since wages tend to be sticky, we lag technology use by three years.[23] Parental background PB is zero for workers with high-educated parents and one for workers with low-educated parents. Hence, in equation (6) the coefficient of PB yields the average difference between log wages of workers with low-educated parents and workers with high-educated parents (i.e. the wage penalty by parental background). The coefficient of $Tech$ corresponds to the average returns to technological change across all occupations and years for workers with high-educated parents. Similar to a Difference-in-Differences setting, the interaction term $Tech \times PB$ identifies our main effect of interest, namely the difference in the wage returns to technological change between workers with low-educated parents and their peers with the same qualification but high-educated parents.

In order to control for confounding mechanisms, we estimate different specifications of equation (6) using different sets of covariates, included in Z_{ijt}. In all specifications, Z_{ijt} includes individual control variables which are typically included in Mincerian wage equations, such as gender, age, labor market experience, years of education,[24] migration background, a public service indicator, firm size, federal state and calendar year (all of them as categorical variables).

We extend this basic specification and remove confounding time trends in the interaction term $PB \times Tech$ by including interactions between PB and year fixed effects. These interaction terms absorb parental background-specific time trends in wages that might occur due to a changing composition of worker groups, for instance due to educational upgrading.[25]

However, endogenous occupation switches, selection based on unobservable skills and confounding demand and supply shocks may bias these estimates. We discuss the role of these potential confounders and how we address them below.

[23] Since technological change within an occupation is highly persistent over time, we do not expect the results to differ importantly with the time lag. Indeed, when using lags of one or five years, the estimates are very similar in size and significance; see Tables S2.5 and S2.6 in the Supplementary Material S.2.

[24] Controlling for years of education is a first attempt to control for individual skills, which is necessary since the model predicts a decrease in returns to parental background with technological change *conditional on individual skills*. We rely on five education categories for high-qualified workers and seven education categories for low-qualified workers to control for observable skills. For the definition of these categories, see Table B1.2 in the Appendix B.1.

[25] The educational expansion leads i) to a decrease in the share of workers with low-educated parents and ii) to an increase in the share of high-qualified workers. It thus changes the size and composition of the two qualification groups. Figure S2.1 in the Supplementary Material S.2 plots changes in group sizes based on our data.

The Role of Unobserved Skills. Our theoretical model predicts a relative decrease in returns to parental background with technological change conditional on individual skills. In practice, however, we can only condition on observed formal years of education, whereas a variety of relevant skills, such as soft skills, remains unobserved. These unobserved skills are likely correlated with technology use and wages. In particular, we expect that high-qualified individuals are positively selected into technology-intensive occupations in terms of unobserved skills and that, among high-qualified workers, unobserved skills are positively correlated with parental background (see e.g. Anger & Schnitzlein, 2017). Moreover, the relative selectivity based on skills of workers with low-educated parents as compared to workers with high-educated parents might change across time if, as discussed in Section 3.1, technological change dismantles barriers to technology-adopting occupations for workers from a disadvantaged parental background. As a result, the inflow of workers with low-educated parents into technology-adopting occupations would be increasingly negatively selected subject to an ongoing technological change.[26]

In order to isolate the effect of technological change on wage returns to parental background from these forces along unobserved dimensions, our final specification includes spell-fixed effects i.e. individual-by-occupation fixed effects. In addition to controlling for occupation-specific individual unobserved skills, this specification has the advantage that technological change is exogenous to the individual, in the sense that the technological change experienced by an individual is not impacted by potentially endogenous switches across occupations. In particular, the coefficient of interest is identified only through parental background-specific differences in individual wage growth within occupations with strong technological change compared to occupations with weak technological change.

This final specification including spell-fixed effects could still be biased because of two reasons: First, if the decision to stay in technology-adopting occupations is related to parental background. Yet, in the data we do not find evidence for this: Based on a regression equivalent to equation (6) using occupational tenure as the dependent variable, there is no significant effect of the interaction between technology and parental background on occupational tenure. Second, there might remain a bias since spell fixed effects control for endogenous occupation switches but do not control for endogenous initial occupation choices. Hence, this specification identifies an average treatment effect conditional on the initially realized distribution of individuals across occupations. Also,

[26] For low-qualified workers, the direction of the corresponding bias is less clear as this depends on whether technology is associated with up- or deskilling for this group. Moreover, low-qualified individuals with high-educated parents might either be endowed with better soft skills thanks to their favorable background, or be negatively selected given that they did not earn a university entrance qualification despite their advantaged social origin.

individuals may choose their initial occupations in anticipation of future technological change. In that case, individual-occupation fixed effects would not solve the problem of selection bias because individual unobserved skills would be correlated with the technology *trend* and not only with technology *levels* which are absorbed by the fixed effects. In additional analyses, we address this issue by relying uniquely on spells which started before technological change was anticipated by most of the workforce and, reassuringly, do not find evidence that this initial distribution across occupations is endogenous to technological change (see Table S2.1 in the Supplementary Material S.2).

Confounding Demand and Supply Shocks. Another potential threat to identification stems from confounding supply shocks. As mentioned previously, educational upgrading implies a decline in the supply of workers with low-educated parents. As long as this decline is not simultaneously correlated with the rate of technology adoption within an occupation, the interaction between PB and time controls for such supply shifts. However, supply shifts could differ across occupations and be related to technological change, giving rise to counteracting wage effects. In order to ensure the regression coefficient is free from the effects of such confounding supply shocks, we adopt an Instrumental Variable (IV) approach.

We follow the literature, i.e. Autor et al. (2003), which suggests that computers and computer-controlled machines are adopted mainly in jobs where they either substitute routine cognitive tasks or complement non-routine analytic tasks. Hence, we instrument technology adoption in equation (6) with the sum of the initial shares of routine cognitive tasks and non-routine analytic tasks multiplied by the rate of technology adoption at the national level.[27] The identifying assumption is that initial task shares affect returns to parental background relative to returns to individual skills exclusively via technology, but neither directly nor via a different supply or demand shock.

This assumption could be challenged by parallel changes in labor demand that are correlated with initial task shares and have a differential effect on workers with low- and high-parental background. One labor demand shift that might be related to the occupation's initial task structure, and thus computer-driven technological change, while simultaneously changing the demand for skills, is offshoring. In particular, offshoring raises the demand for skills, similar to technological change (Becker et al., 2013). If tasks that are susceptible to offshoring overlap with tasks that are susceptible to technology adoption, as suggested by Blinder & Krueger (2013), our IV strategy will thus identify

[27] Technology adoption at the national level is computed as the weighted average of technology adoption in all occupations, except for the occupation in question. Weights are based on initial employment shares. Alternatively, we instrument technological change by two separate instruments based on the initial shares of routine cognitive tasks and non-routine analytic tasks. This more flexible version provides very similar results.

the causal effect of initial task shares on the returns to parental background that operates via both technology and offshoring, which are expected to operate in the same direction. However, trade with the two main offshoring destinations for German firms – Eastern Europe and China – took off only in the early 2000s, when China entered the WTO (2001) and trade barriers with several Eastern European countries vanished due to their accession to the European Union in 2004 (e.g. Dauth et al., 2014). This suggests that effects before the 2000's were not primarily driven by offshoring.

Technology adoption in response to an occupation's initial task structure could also be related to changes in managerial practices and work organization. In fact, such changes are likely to be induced by technology adoption (e.g. Hanelt et al., 2021). If changes in work organization and managerial practices affect the demand for skills, e.g. by raising the demand for interactive skills, this might also affect workers differently depending on their parental background. In that case, our IV strategy identifies the causal effect of initial task shares on the returns to parental background that operates via both technology and (potentially related) organizational and managerial changes.

Other demand shocks that change the wage penalty are controlled for by the interaction of PB with time. $Tech$, on the other hand, captures occupation-specific demand shocks that only affect technology adoption. If, for instance, technology-adopting occupations generally experience an increasing labor demand such that employment in these occupations grows, this would not result in a differential wage growth by parental background as long as the increasing demand for labor is not accompanied by changing returns to skills and neither type of parental background is scarce. Hence, such general demand shocks related to technology-adoption would be captured by $Tech$ and would not affect our coefficient of interest.[28]

3.2.2 Employment Returns to Parental Background

From a theoretical point of view, the relative strength of wage and employment effects depends on the elasticity of labor supply: If workers can easily switch occupations, a demand shock results in large employment but small wage adjustments; vice versa if the labor supply is inelastic. We therefore complement our wage analysis by studying employment responses. For this, we turn to the occupation level and regress changes in the share of workers with low-educated parents within occupation j in period τ among high-qualified (or, respectively, low-qualified) workers ($\Delta Y_{j\tau}$) on changes in technology adoption ($\Delta Tech_{j\tau}$). We stack time periods of 6-7 years, reflecting the periods mirrored

[28] Indeed, additionally controlling for the size of occupational employment in equation (6), does not affect the results, see Table S2.3 in the Supplementary Material S.2.

in Figure 2.[29] We estimate the following equation:

$$\Delta Y_{j\tau} = \delta_1 \Delta Tech_{j\tau} + \delta_2 Z_{j\tau} + d_\tau + u_{j\tau}. \tag{7}$$

Occupation-specific demand shocks that are common across worker types are controlled for using long differences. Time-period dummies control for business cycle fluctuations. In order to mitigate potential biases from a changing composition of workers related to supply and demand dynamics, we add time-varying, occupation-level controls $Z_{j\tau}$. These controls are measured at the start of the respective period and include the average age, average tenure as well as the share of female, foreign, and college-educated workers in an occupation. In addition, we also control for the relative employment share of the occupation and the median wage at the start of the period. Overall composition changes in the share of workers by qualification group and parental background, for instance due to educational expansions, are picked up by the period dummies. In addition, controlling for the share of high-educated workers in an occupation absorbs occupation-specific effects of educational expansions. To address endogeneity issues, we apply the same IV strategy as above and exploit the initial task structure of the occupation as an instrumental variable for $Tech$.

4 Technological Change and Returns to Parental Background

4.1 Wage Returns

In this section, we provide estimation results showing the effect of technological change on wage returns to parental background based on equation (6). Our main parameter of interest is the coefficient α_3 on the interaction between technology and parental background. Note that by focusing on within-occupation changes in technology use in all specifications as explained in Section 3.2, this coefficient measures the additional returns to technological change for workers with low-educated parents compared to those with high-educated parents. Table 2 shows the results separately for high-qualified and for low-qualified workers.

The baseline specification in column (1) confirms the existence of a wage penalty by parental background within qualification groups: high-qualified individuals with low-educated parents earn 7% less, on average, than their counterparts in the same occu-

[29]We stack time periods of 6-7 years as we consider employment effects to take effect mainly in the medium term. In addition, we estimate an analogous model using a yearly occupation-level panel and including occupation and year fixed effects, see Appendix C.

pation but with high-educated parents. Among low-qualified workers, we find a similar wage penalty of 6%. Furthermore, high-qualified individuals in occupations with faster technology adoption earn higher wages. In particular, occupations with a ten percentage points higher increase in technology use pay 1.3% higher wages for high-qualified workers with high-educated parents. As hypothesized, technological change reduces the wage penalty: workers with low-educated parents receive an additional wage premium in occupations with faster technology adoption. A ten percentage point increase in technology use is associated with 0.7% higher wages for high-qualified individuals. Low-qualified individuals with high-educated parents do not experience wage gains from technological change, while low-qualified individuals with low-educated parents receive 0.8% higher wages for each ten percentage point increase in technology use.[30]

Adding parental background-specific time trends in column (2) to pick up confounding time trends provides comparable results. Hence, confounding background-specific time trends related, for instance, to the overall increase in the share of workers with high-educated parents seem to play a minor role.

In column (3), we adopt the instrumental variable strategy outlined in Section 3.2.1 to control for confounding labor supply shocks. For both groups – high-qualified and low-qualified workers – the estimates change only slightly compared to column (3): The coefficient of technology use slightly increases, while the interaction effect with PB remains approximately constant, but becomes statistically insignificant.

However, as discussed in Section 3.2.1, these estimates may still be affected by selection into occupations based on unobservable skills. Column (4) thus shows the results of the specification including spell-fixed effects (i.e. individual-by-occupation fixed effects). Column (5) shows the same specification applying the instrumental variable strategy. The spell-fixed effects ensure that identification stems from changes in technology levels for workers staying in the same occupation. They hereby remove variation from any occupation switches and control for occupation-specific individual unobservable skills.

We first focus on the estimates for high-qualified workers: By including spell-fixed effects, the coefficient of technological change declines to 0.06, while the coefficient of the interaction, which shows the wage premium of technological progress for workers with low-educated parents, increases to 0.2. In the IV estimation, the corresponding coefficients are 0.09 and 0.23, respectively. Separate estimations for workers with high-educated parents and workers with low-educated parents in Table B2.1 in the Appendix B.2 reveal that this notable increase in the coefficient of interest reflects the two selection mechanisms

[30]Consistent with the conceptual framework, estimations without occupation fixed effects suggest that occupations with higher technology levels have both higher returns to skills and lower wage penalties by parental background for both qualification groups. These results may, however, to some extent reflect otherwise unobserved occupation differences.

Table 2: Wage Returns

High-qualified					
	(1)	(2)	(3)	(4)	(5)
Low PB	-0.07***				
	(0.02)				
Tech	0.13***	0.12*	0.17*	0.06	0.09
	(0.05)	(0.06)	(0.09)	(0.11)	(0.14)
Low PB × Tech	0.07**	0.08*	0.07	0.20**	0.23*
	(0.03)	(0.05)	(0.05)	(0.09)	(0.14)
Observations	29674	29674	29674	27478	27478
F-Stat Tech			37.2		41.2
F-Stat LPB x Tech			64.3		39.8
Low-qualified					
	(1)	(2)	(3)	(4)	(5)
Low PB	-0.06***				
	(0.02)				
Tech	-0.01	-0.02	0.01	0.17	0.45***
	(0.05)	(0.05)	(0.08)	(0.15)	(0.16)
Low PB × Tech	0.08**	0.10*	0.09	0.01	-0.21
	(0.04)	(0.05)	(0.07)	(0.14)	(0.16)
Observations	57513	57513	57513	53135	53135
F-Stat Tech			18.7		45.5
F-Stat LPB x Tech			35.6		26.0
Occ. FE	Yes	Yes	Yes		
PB x Year		Yes	Yes	Yes	Yes
Spell FE				Yes	Yes

Notes: Dependent variable: Individual log wage. Controlling for gender, migration background, migration background × gender, five age categories, six dummies on labor market experience, education dummies, a public service indicator, four firm size categories, nine federal state dummies and 27 year dummies. IV: sum of the initial task intensity of routine cognitive and non-routine analytic tasks multiplied by the aggregate technology level across all occupations but individual's own. Standard errors are clustered on the occupational and individual level. Observations weighted by representative SOEP weights, West Germany only. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

described in Section 3.2.1: workers with high-educated parents are positively selected in terms of unobserved skills into high-paying occupations with rapid technological change, while workers with low-educated parents are negatively selected. The first selection effect confirms a positive correlation between parental background and unobserved skills in occupations with fast technology adoption, and the latter selection effect likely reflects that entry barriers to these occupations declined for workers with low-parental background. As a result, the marginal entrant with low-educated parents is equipped with less unobserved skills and the average unobserved skill level of this group declines.[31] Removing these selection biases by including spell-fixed effects increases our coefficient of interest and confirms the existence of a sizable additional return to technological change for workers with low-educated parents: The additional premium for workers with low-educated parents when technology use increases by 10 percentage points corresponds to 2.3% which is roughly comparable to the average annual premium for an additional year of work experience.[32]

For low-qualified workers, the results including spell-fixed effects reveal a different picture: The separate estimations by parental background in Table B2.1 in Appendix B.2 suggest a negative selection into occupations with fast technology growth with respect to unobserved skills for both worker groups, with this negative selection being even more pronounced for workers with high-educated parents. This negative selection could result from technology-induced deskilling of the occupations carried out by low-qualified workers. If skill requirements decline due to technological change, workers in such occupations are likely less endowed with unobserved skills than in an occupation with less technological change. Hence, when taking this negative selection into account by including spell-fixed effects in column (4) of the joint estimation in Table 2, the returns to technology adoption become larger for low-qualified workers with high-educated parents, and increase substantially when adopting the IV in column (5). At the same time, the additional premium of working in technology-adopting jobs for low-qualified workers with low-educated parents declines when including spell-fixed effects, and is not significantly different from zero.

In conclusion, low-qualified workers with low-educated parents do not seem to gain any additional wage returns from technological change when taking selection effects into account. In contrast, the results for high-qualified workers suggest that technological change leads to higher relative returns to technology growth for workers with low-educated parents. We test whether this effect has reversed since these computer-based technologies became mainstream practice in the 2000s, by conducting the same analysis for 1999-2012 (see Table S2.2 in the Supplementary Material S.2). The results indicate that the wage penalty by parental background has remained at a consistently low level during the first decade of the 2000's.[33]

[31] Figure S2.2 in Appendix S.2 displays the difference in average individual fixed effects from log wage regressions between workers with low-educated parents as compared to workers with high-educated parents, separately in occupations with low and high increases in technology use across time. Indeed, we find evidence that the average skill level of individuals with low-educated parents working in occupations with high technology growth decreases over time relative to workers with high-educated parents.

[32] In specification (4), the coefficient on the experience category 6-10 years is 0.24, with the reference group being 0-12 months.

[33] Our employment effects in Section 4.4 provide indications for a reversal towards the end of our time period, although this effect is not statistically significant. A reversal would be in line with the theory

Robustness. To test the robustness of our results we perform several additional analyses, shown in the Supplementary Material S.2. Most importantly, even in the specification including spell fixed effects, our estimated effect is identified only conditional on the initial distribution of individuals across occupations. This might be problematic if this initial distribution is endogenous to technological change. We check whether our results are robust to only using spells which started until 1990. The underlying idea is that these individuals entered an occupation before technological change was anticipated by most of the workforce and that, hence, the choice of the initial occupation is exogenous to technological change. The results in Table S2.1 indicate that our estimated effect is even stronger when using this sample.

Next, to check whether improved wage opportunities are indeed due to occupation-level technological change, and not due to occupation-level demand shocks combined with labor supply being fix in the short term, we add occupation size, e.g. the share of workers employed in an occupation, to the set of control variables. Our results are not affected, as demonstrated in Table S2.3. This is not surprising, since occupation-level technological change and employment growth are only mildly correlated, see Figure S2.3.

Furthermore, we use an alternative measure of parental background, namely the status of parental occupation, see Table S2.4. Consistent with our main specification, we find a significantly positive effect of technological change on wages of workers with parents in lower-status occupations compared to workers with parents in high-status occupations.

Finally, we perform several additional tests: In Tables S2.5 and S2.6 we show that relying on a time-lag of technology use of one or five years (instead of three years in our baseline) does not affect the results. In Table S2.7, we use an alternative IV specification, where technological change is not predicted by a single instrument based on the sum of the initial intensity of non-routine analytic tasks and routine cognitive tasks, but by two separate instruments based on the initial shares. This more flexible version provides very similar results. Table S2.8 provides the corresponding first stages for our main specification and the alternative IV specification. In Table S2.9, we include individuals with wages in the 99th and 1st wage percentile which were previously excluded.

4.2 The Role of Experience.

There is evidence in the literature that the wage penalty by parental background widens with workers' experience; i.e. the slope of the so-called experience-earnings profile is significantly steeper for individuals from an advantaged socio-economic background (Hudson & Sessions, 2011; Raitano & Vona, 2018). Reasons put forward are different self-

by Galor & Tsiddon (1997), who argue that greater accessibility of new technologies reduces returns to ability relative to parental background.

perceptions of individuals depending on their social background, which affect networking, self-promotion, career goals and, ultimately, wage negotiations, as well as differential treatment by the employer depending on the social origin of the worker (Friedman & Laurison, 2019). Indeed, it has been shown that behavioral codes and cultural similarity significantly affect promotion decisions, and, therefore, individuals from the working class are less likely to reach top positions (e.g. Rivera & Tilcsik, 2016; Friedman & Laurison, 2019; Amis et al., 2020; Jackson, 2021).

While we control for workers' experience in our main analyses, the effects of technological change may vary with workers' experience: if technological change increases returns to individual ability relative to returns to parental background, we would expect technological change to have a stronger effect on wage increases over occupational experience rather than on starting salaries. In order to analyze this, we estimate experience-earnings profiles and test whether this relationship is affected by technological change. For this purpose, we estimate augmented Mincer regressions for both qualification groups, including the control variables from the previous estimations, allowing parental background-specific returns to technological change to vary with occupational experience.[34] Note, that differences in occupational tenure by parental background are not endogenously affected by technological change in the data, since, as mentioned above, the interaction effect between technology and parental background is not significant for occupational tenure.

We build on specification (2) from Table 2. The reason for choosing the specification with occupation fixed effects instead of spell-fixed effects is that technological change affects wage opportunities via two mechanisms; the pure effect on differential wage returns as identified in specification (4) and the potential wage gains due to sorting of workers into technology-adopting-jobs caused by reduced entry barriers. Specification (2) encompasses both mechanisms, including the effect driven by improved employment opportunities.[35]

To measure different slopes of the experience-earnings profiles at different levels of technology, we evaluate the partial correlations obtained from the regression at the 25th and the 75th percentile of the technology distribution.

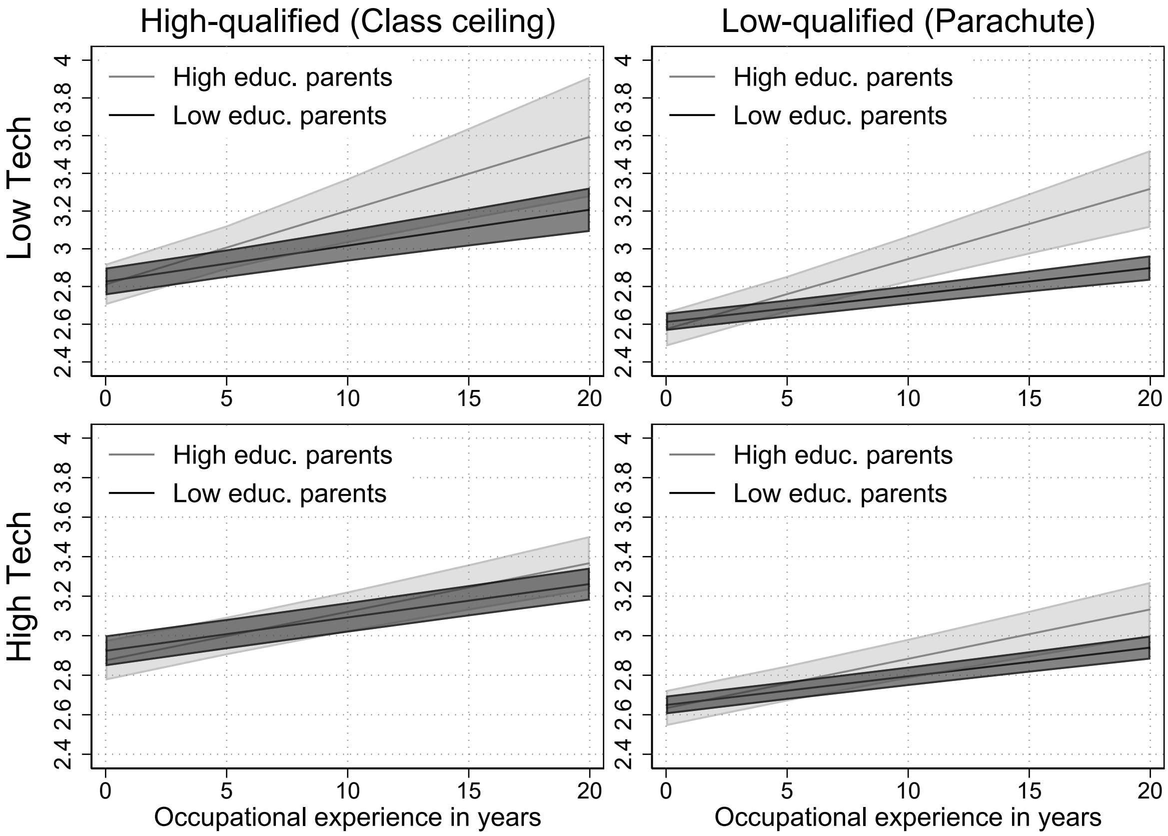
Figure 4 shows the results of this exercise separately for high-qualified and low-qualified workers.[36] The analysis highlights three interesting patterns. First, workers

[34]To construct occupational experience, we rely on individuals for which we observe the period they enter an occupation, either because they are new labor market entrants or because they switch occupations. We set occupational experience to zero in the year the individuals enters an occupation, and continuously increase occupational experience for every year the individual works in this occupation.

[35]Since the results based on specification (2) may be affected by unobservable skills, we also compare the results to those based on specification (4) that, as a caveat, abstract from gains related to improved employment opportunities.

[36]A fully flexible specification of experience is included as Figure S2.4 in the Supplementary Material S.2. Since we find that wages develop almost linearly with occupational experience, we simplify the analysis assuming a linear experience-earnings profile. In addition, controlling for age does not change the results qualitatively; see Figure S2.5.

Figure 4: Experience-Earnings-Profile



Notes: Predicted individual log wage, and 90% confidence intervals based on a regression with occupational experience (linear), parental background (binary), technology (linear) and all possible interaction terms on the right hand side, controlling for gender, migration background, migration background × gender, education dummies, public service indicator, firm size (4 categories), federal state (10 categories), 62 occupation and 27 year dummies, corresponding to column (3) in Table 2. Evaluated at the 25th ("Low Tech") and the 75th ("High Tech") percentile of the technology distribution. Observations weighted by representative SOEP weights, West Germany only.

with a disadvantaged parental background starting in an occupation (either by switching into this occupation or by newly entering the labor market) do not experience a wage penalty, independent of the technology level in this occupation.[37] Second, in occupations with low levels of technology (upper graphs in Figure 4), the slope of the experience-earnings profile is, indeed, steeper among workers with high-educated parents than among their peers with low-educated parents. In occupations with little technology use, high-qualified individuals with low-educated parents earn roughly 20% less after ten years of occupational experience than those with high-educated parents. Accordingly, technological change reduced the parental wage gap by equalizing returns to experience between workers with low- and high-educated parents.

[37] One potential explanation for this could be related to collective wage agreements, which are common in the German labor market context, though coverage has generally declined (Addison et al., 2011).

If more equal promotion opportunities in occupations exposed to technological change are the main cause for more equal wage profiles over experience, we expect similar findings for direct measures of career progressions and promotions. We first study the number of accumulated promotions over occupational experience. We define promotion based on a variable in the SOEP that captures job changes with the same employer associated with a positive wage change. Table B2.1 in Appendix B.2 reveals that the results are consistent with the main analysis for wages: In high-tech occupations, the increase in the promotion probability over occupational experience are very similar for individuals with low-educated parents and for those with high-educated parents, whereas they are suggestively different in low-tech occupations. Similar results are obtained when studying the probability of reaching a management position over occupational experience (Figure B2.2 in the Appendix B.2). Again, we confirm that, in low-tech occupations, high-qualified workers with high-educated parents are almost twice as likely to move up to leadership positions than high-qualified workers with low-educated parents over 20 years of occupational work experience, while the chance to reach a management position is quite similar among high-qualified workers with advantaged and disadvantaged background in high-tech occupations.[38] We conclude that more equal promotion opportunities might be the underlying mechanism translating into more equal wage profiles over experience.

Figure B2.3 in Appendix B.2 shows the results including spell-fixed effects. Consistent with the baseline analysis, among high-qualified workers and low levels of technology, the slopes of the experience-earnings profile differ by social origin, although the effects turn statistically non-significant because we loose precision when controlling for spell-fixed effects. The slopes are indistinguishable for high levels of technology, as in the baseline specification. Among low-qualified workers, the slopes are rather flat and do not differ in occupations with low versus high technology growth. These findings are consistent with our results reported in Section 4.1, which show that among low-qualified individuals the effect of technology on wage opportunities, and generally the wage penalty, seem primarily driven by individual level heterogeneity.

These results confirm the general findings of the literature about the experience-earnings profile (e.g. Raitano & Vona, 2018), and also add a more nuanced view. In particular, we confirm the existence of what has been called the *parachute effect* for low-qualified workers and the *class ceiling effect* for high-qualified workers, in both cases referring to a steeper experience-earnings profile for workers from advantaged social origin in comparison to workers from disadvantaged social backgrounds. However, these effects seem to be mainly present in occupations experiencing low technological change. Our

[38] We cannot establish a similar result for low-qualified workers since, generally, they do not have any corresponding management function.

results suggest that technological change mainly counteracts a widening wage penalty for disadvantaged workers staying in the same occupations over time by improving their promotion opportunities, rather than reducing the wage penalty for new entrants. Independent of social background, these results also corroborate the findings of Deming & Noray (2020), which show that returns to experience are lower in quickly changing occupations, such as those undergoing technological change.

4.3 Contribution of Technological Change for Qualification-Specific Wage Penalties

In this section, we quantify the contribution of technological change to the decline in the qualification-specific wage penalties and compare it to the contribution of other factors, such as compositional changes in the groups of individuals form a disadvantaged parental background and from advantaged parental backgrounds. To do so, we decompose changes in qualification-specific wage penalties based on the coefficients from specification (2) in Table 2 with occupation fixed effects. We rely on the specification with occupation fixed effects instead of spell fixed effects because we are interested in both the effect of technological change on differential wage returns within an occupation and indirect effects on wages stemming from reduced entry hurdles into tech-jobs. Again, we compare these results to those based on specification (4) from Table 2 with spell-fixed effects, capturing the differential returns to technological change by parental background when abstracting from any wage gains via reduced entry hurdles.
For the ease of exposition, we re-write equation (6):

$$ln(w_{ij\tau}) = (PB_i \times Tech_{j\tau-3})\beta + PB_i\gamma_\tau + Tech_{j\tau-3}\delta + X_{i\tau}\epsilon + \zeta_{i\tau} \tag{8}$$

where the log wage $ln(w)$ of individual i in time period τ is determined by the interaction term $PB \times Tech$, by a dummy variable for parental background (high versus low) with time-variant returns, by lagged occupational technology levels $Tech$, and by the vector of characteristics X (including occupation and year fixed effects, and the individual characteristics included in equation (6)).
The average within-qualification group log wage penalty in period τ is given by

$$\begin{aligned}\Delta ln(w_\tau) &= ln(\overline{w}_\tau^{PB=1}) - ln(\overline{w}_\tau^{PB=0})\\ &= \overline{Tech}_{\tau-3}^{PB=1}\beta + \gamma_\tau + (\overline{Tech}_{\tau-3}^{PB=1} - \overline{Tech}_{\tau-3}^{PB=0})\delta + (\overline{X}_\tau^{PB=1} - \overline{X}_\tau^{PB=0})\epsilon.\end{aligned} \tag{9}$$

We decompose the change in the average qualification-specific wage penalty between $s = 1989$ and $t = 2012$ ($\Delta\Delta ln(w)$) into four channels:

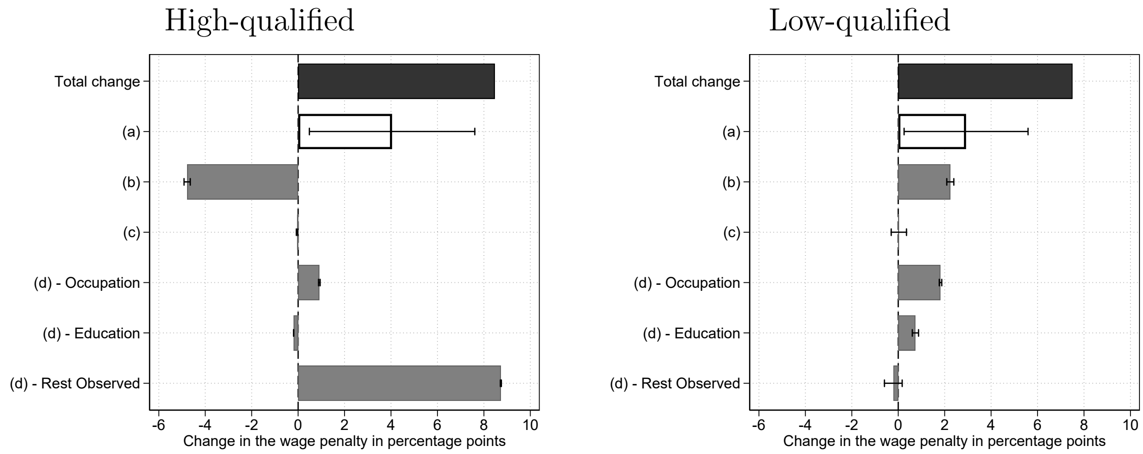
$$
\begin{aligned}
\Delta\Delta ln(w) &= \Delta ln(w_t) - \Delta ln(w_s) && (10)\\
&= (\overline{Tech}_{t-3}^{PB=1} - \overline{Tech}_{s-3}^{PB=1})\beta && \Delta \text{ Differentially rewarded technology use (a)}\\
&+ (\gamma_t - \gamma_s) && \Delta \text{ Residual wage penalty (b)}\\
&+ [(\overline{Tech}_{t-3}^{PB=1} - \overline{Tech}_{t-3}^{PB=0}) - (\overline{Tech}_{s-3}^{PB=1} - \overline{Tech}_{s-3}^{PB=0})]\delta && \Delta \text{ Difference in technology use (c)}\\
&+ [(\overline{X}_t^{PB=1} - \overline{X}_t^{PB=0}) - (\overline{X}_s^{PB=1} - \overline{X}_s^{PB=0})]\epsilon && \Delta \text{ Difference in other characteristics (d)}
\end{aligned}
$$

Channel (a) captures changes in the qualification-specific wage penalty due to changing technology use of workers with low-educated parents, given that technology use is rewarded differently for workers with low-educated parents than workers with high-educated parents. This is our main channel of interest. Channel (b) captures changes in the residual wage penalty, while channel (c) captures differences in changing technology use of workers with low-educated parents compared to workers with high-educated parents, given that technology adoption leads to wage increases. Channel (d) reflects the contribution of changes in all other observable characteristics of workers with low-educated parents relative to workers with high-educated parents. These are changes in occupations ((d) - Occupation), relative educational improvements within the broad qualification groups ((d) - Education) and changes in all other observable characteristics ((d) - Rest Observed). Note that the effect of improved equality in access to technology-adopting occupations is not only reflected in channel (c), but also in channel (a) and (d): if better employment opportunities in technology-adopting occupations increase the technology use of disadvantaged individuals, this lowers the observed wage penalty via channel (a). Additionally, if technology-adopting occupations have higher overall wage levels (i.e. higher occupation fixed effects), this will impact the change in the observed wage penalty via channel (d) - Occupation.

Figure 5 illustrates the results of this decomposition separately for high-qualified and low-qualified workers.[39] For both qualification groups, roughly 40% of the change in the wage penalty is due to differential returns to an increase in technology use between 1989 and 2012, i.e. channel (a). Conversely, sorting of individuals with low-educated parents into technology-adopting occupations (channel (c)) does not seem to contribute to closing the wage penalty for either qualification group. However, this does not mean that improved equality in access to technology-adopting occupations did not contribute to closing the wage penalty at all. It merely means that improved access to technology-intensive oc-

[39] Figure 5 decomposes the change in the qualification-specific wage penalties, whereas Table 1 contains the contribution of these changes to changes in the overall wage penalty. These numbers differ because the contribution is the product of the change in qualification-specific wage penalties and the relative share of individuals in the respective qualification groups (see equation (3)).

Figure 5: Decomposition of the Change in the Qualification-Specific Wage Penalties 1989 to 2012



Notes: Decomposition terms according to equation (10) for the change in the wage penalty among high-qualified and low-qualified workers between $s = 1989$ and $t = 2012$ plus 90% confidence bands. Corresponding to specification (2) in Table 2. Channels: changes in in the qualification-specific wage penalty due to (a) differently rewarded technology use of workers with low-educated parents compared to workers with high-educated parents; (b) the change in the residual wage penalty; (c) differences in changing technology use of workers with low-educated parents compared to workers with high-educated parents; (d) changes in all other observable characteristics of workers with low-educated parents compared to workers with high-educated parents, namely occupation, education, and all other observable characteristics. Confidence bands based on 1,000 bootstrap replications of the coefficient combinations.

cupations did not lead to stronger wage increases for disadvantaged individuals (channel (c)), while it may have led to higher wage levels (channel (d) - Occupations) and to larger decreases in the penalties (channel (a)). Indeed, we find a reduction in the wage penalty due to changes in occupations (channel (d) - Occupation) of 0.9 percentage points for high-qualified workers and 1.8 percentage points for low-qualified workers.

For high-qualified workers, changes in educational attainment are rather irrelevant for the change in the wage penalty (channel (d) - Education), likely because the group of high-qualified workers is very homogeneous in years of education. In contrast, educational attainment is more heterogeneous across low-qualified workers. Low-qualified individuals with low-educated parents gained access to better-paid educational qualifications such as vocational training, which significantly contributed to closing the qualification-specific wage penalty by 0.7 percentage points.

Relative to those with high-educated parents, high-qualified workers with low-educated parents experienced relative wage gains due to changes in other observable characteristics (channel (d) - Rest Observed). This latter term is mainly driven by a mechanical effect: as more and more parents achieve a university entrance qualification, fewer young workers belong to the group of individuals with low-educated parents, such that over time this group grows older, on average, than the group of individuals with high-educated parents. The positive correlation between age and individual wages explains the magnitude of the effect.

Finally, the negative term for the residual wage penalty (channel b) for high-qualified workers suggests that the penalty of having low-educated parents would have increased by 4.8 percentage points, all else equal, due to factors unrelated to technological change. This might be related to the qualification upgrading discussed in the previous section. If individuals with low-educated parents experience a relatively stronger rise in the likelihood of having a university entrance qualification than individuals with high-educated parents, their unobserved skill distribution shifts to the left compared to individuals with high-educated parents. For low-qualified workers, in contrast, the penalty of having low-educated parents would have decreased, all else equal, for reasons unrelated to technological change.

Since the above decomposition is based on specification (2) in Table 2 with occupation fixed effects, the decomposition terms capture improved equality of opportunity that operates both via higher wage returns to technological change for disadvantaged workers and via a better access to technology-adopting occupations for disadvantaged workers. In contrast, specification (4) including spell-fixed effects controls for unobservable characteristics but abstracts from effects working via the channel of improved access to technology-adopting occupations. The decomposition terms based on specification (4) are shown in Figure B2.4 in Appendix B.2. In line with our wage results, the decomposition term (a) increases dramatically to 11.6 percentage points for high-qualified workers when controlling for unobserved skills.[40] For low-qualified workers, in contrast, the pure wage effect of channel (a) declines to zero when including spell-fixed effects.

To summarize, from Section 2.2 we know that the reductions in the qualification-specific wage penalties were a major driver of the decline in the overall wage penalty between 1989 and 2012. The findings in this subsection further suggest that the reduction in the wage penalty of high-qualified workers was to a large extent caused by the increased use of technology at the workplace. In contrast, for low-qualified workers, we cannot establish a direct link between the decline in the wage penalty and technological change. The contribution of improved employment opportunities in technology-adopting occupations is not made explicit in the decomposition because it is part of the three channels (a), (c) and (d) (Occupation). We hence turn to the direct effects that technological change has on improving equality of employment opportunities.

[40] For high-qualified workers with low-educated parents, improved access to technology-intensive occupations is relevant (see Section 4.4). Since the access effect is missing in channel (a) when controlling for spell-fixed effects, the total contribution of technological change to a reduction of the qualification-specific wage penalty is likely even larger than channel (a) in Figure B2.4 suggests.

4.4 Employment Returns

According to the theoretical framework in Section 3, technological change should not only contribute to improving the wage opportunities of workers from a disadvantaged social background, but should also enhance equality of employment opportunities by reducing entry hurdles to occupations with strong technological change. Hence, we turn to the occupation level and extend our analysis by testing whether technological change in an occupation has a positive impact on the share of workers from a disadvantaged social background in that occupation. Again, we estimate this effect separately for high-qualified and low-qualified workers.

We estimate equation (7) using a long (stacked) difference model in which the time periods τ span 6-7 years each, reflecting the assumption that technological change does not occur abruptly but typically involves a diffusion process whose impact may take time to unfold. In particular, we stack four time periods, which we choose based on the evolution shown in Figure 2: 1986-1992, 1992-1999, 1999-2005 and 2005-2012.[41]

Table 3 shows the results for high-qualified workers (columns (1)-(4)) and low-qualified workers (columns (5)-(8)). We cluster standard errors on the occupation level. Since we rely on a rather small number of occupations, we use cluster wild t-bootstraps following Cameron et al. (2008) and report the 95% confidence bands of the parameters in the regression tables.[42] To take into account size differences between occupations when estimating average effects, and to give less weight to smaller occupations where indicators rely on fewer observations, we weight occupations by their initial employment share in 1986.[43]

The baseline coefficient of 0.41 in column (1) for high-qualified workers implies that an increase in an occupation's share of workers mainly using new technologies by ten percentage points increases the share of high-qualified workers with low-educated parents by around four percentage points. We find an even stronger, but non-significant effect when applying the same IV strategy as before in column (3). Hence, if at all, confounding supply shocks seem to downward rather than upward bias our coefficient of interest.

The results shown in column (2) suggest that the gain in employment opportunities for individuals from disadvantaged parental backgrounds is mainly driven by the 1992-1999 period, and possibly the 1999-2005 period, which shows a larger coefficient but with a wider confidence interval. In contrast, for 2005-2012, the coefficient is negative and

[41] Our results are robust to different specifications of these periods (see Tables S2.10 and S2.11 in the Supplementary Material S.2).

[42] These confidence bands are more conservative compared to using the cluster robust sandwich estimator, see Table S2.12 in the Supplementary Material S.2.

[43] Without weights, i.e. when giving the same importance to each occupation, the estimates change in size and decrease in precision, but are mainly consistent with the main analysis (see Table S2.13 in the Supplementary Material S.2).

Table 3: Employment Effects - Long Differences

	High-qualified				Low-qualified			
	Baseline		IV	Tasks	Baseline		IV	Tasks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech	0.40**		0.82	0.07	0.04		0.08	-0.01
	[0.02,0.80]		[-0.15,1.76]	[-1.82,1.83]	[-0.02,0.09]		[-0.09,0.23]	[-0.22,0.20]
Effect heterogeneity across time periods								
Tech ×								
× 1986-92		0.05				-0.09		
		[-0.83,0.86]				[-0.23,0.07]		
× 1992-99		0.47*				0.05		
		[-0.06,1.09]				[-0.01,0.10]		
× 1999-05		0.68				-0.01		
		[-2.09,2.56]				[-0.14,0.15]		
× 2005-12		-0.36				0.19		
		[-3.89,1.86]				[-0.08,0.46]		
Effect heterogeneity by initial occupational task content								
Tech ×								
× Analytic				3.39**				-0.11
				[0.57,9.38]				[-0.97,0.64]
× Interact.				-3.07***				0.35
				[-7.07,-0.89]				[-0.27,1.10]
Observations	98	98	98	98	201	201	201	201
F-Stat			32.5				24.6	

Notes: Dependent variable: Change in the share of high-qualified (low-qualified) workers with low-educated parents among all high-qualified (low-qualified) workers. Control variables include the average age, the share of female/foreign/highly educated individuals, the average tenure, the relative employment share and the median wage at the start of the period. IV: sum of the initial task intensity of routine cognitive and non-routine analytic tasks multiplied by the aggregate increase in technology across all occupations but occupation's own. Column (4) and (8): Interaction of technology with the interactive and analytic task intensity at the start of the period. Additionally controlling for the intensity of non-routine analytic, non-routine interactive, non-routine manual, routine manual and routine cognitive tasks at the start of the period. 95% confidence bands in square brackets and significance stars based on wild t-bootstraps. Observations weighted by the employment share in 1986, West Germany only. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

non-significant. This might reflect that the expansion of computer-based technologies mainly captured by our technology indicator was most pronounced during the 1990s and stagnated thereafter. Moreover, the effect of technological change might fade out as the technology becomes more mature (Galor & Tsiddon, 1997; Beaudry et al., 2016).

These findings confirm the hypothesis that technological progress enhances equality of employment opportunities among high-qualified workers. Yet, unobservable skills such as non-cognitive skills might affect our estimates because these skills are likely positively correlated with parental background (see e.g. Anger & Schnitzlein, 2017). If technological change increases the demand for both cognitive and non-cognitive skills, individuals from a disadvantaged parental background might actually face stronger entry barriers in occupations where technological change mainly increases the demand for non-cognitive skills. We test this by distinguishing occupations by their share of interactive and analytic tasks at the start of each period. The underlying idea is that the intensity of interactive tasks performed in an occupation approximates the non-cognitive skill requirements in this occupation, while analytic tasks should reflect cognitive skill requirements. Hence, if workers with low-educated parents have lower non-cognitive skills and the returns to these skills increase with technological change, entering these occupations should actually be more difficult than entering occupations with higher shares of analytic tasks. The results in column (4) support this hypothesis.[44] An increasing use of technology raises the share of high-qualified individuals from disadvantaged backgrounds in occupations with a higher intensity of analytic tasks, while a higher intensity of interactive tasks comes with higher entry barriers.

For low-qualified workers, the results shown in columns (5) to (8) show no significant gain in employment opportunities from technological change for disadvantaged workers. The coefficients of both the baseline and the IV regression seem rather accurate estimates of an effect close to zero. These results are in line with the impression from the previous wage regressions which already suggested that there is no sorting of low-qualified individuals with low-educated parents into technology-intensive occupations. Hence, low-qualified workers with a disadvantaged parental background do not seem to experience notable gains in equality of opportunity.

Robustness. We perform similar robustness checks as for the wage results which can be found in the Supplementary Material S.2. In particular, we verify that neither the quantity nor length of the stacked periods,[45] nor the specification of the IV,[46] nor the occupation weights,[47] nor outlier[48] exert substantial effects on the results.

In our main estimations above we analyze the medium-term effects of technological change by stacking time periods. For comparison, we also estimate the short-term effects of technological change on equality of opportunities in access to occupations by estimating an occupation fixed effects model based on a yearly panel. The results are shown in Appendix C. The results confirm the findings of the main analysis: we find positive employment effects for high-qualified workers and no effects for low-qualified workers.

[44] Note that the specification in column (4) also includes the intensity of non-routine analytic, non-routine interactive, routine cognitive, routine manual, and non-routine manual tasks at the start of the period as further control variables.

[45] Regressions based on three stacked periods of eight years each (Table S2.10) or based on five stacked periods of five years each (Table S2.11) also find significantly positive employment effects for high-qualified workers, especially in the 1990s, and no employment effects for low-qualified workers.

[46] When using two separate IVs based on the initial intensity of non-routine analytic tasks and routine cognitive tasks, instead of the combined IV based on their sum, provides substantially similar results (Table S2.14 for the second stage results and Table S2.15 for the first stage results).

[47] When assigning the same weight to each occupation, most coefficients decrease in significance but the direction and magnitude remains very similar (see Table S2.13).

[48] In Table S2.16, we include occupation-year observations with employment shares of disadvantaged workers below the lower threshold (first quartile subtract 1.75 multiplied by the interquartile range) or above the upper threshold (third quartile subtract 1.75 multiplied by the interquartile range) which were previously top-coded. Results remain by and large the same. However, there is some evidence for positive employment effects for the low-qualified as well.

5 Conclusions

In the last three decades, the wage penalty by parental background has declined in Germany, mainly caused by a reduction in the wage penalty within qualification groups. The wage penalty among high-qualified workers – i.e. the difference in average wages between high-qualified workers with high-educated parents and their peers with low-educated parents – was about 5% during the 1980s, but virtually disappeared during the 1990s. Without this decline in the qualification-specific wage penalties, *ceteris paribus*, the overall penalty would have increased, owing to a rise in the wage inequality between high-qualified and low-qualified workers.

This paper shows that the decline in the wage penalty by parental background for high-qualified workers was consistently linked to the rapid adoption of new, computer-controlled technologies on the German labor market during this time. This is because the changing task content and the increase in returns to skills associated with technological change lead to a relative decrease in returns to parental background. In our analysis, we find that technological change causes a reduction of the wage penalty within technology-adopting occupations, but also lowers entry barriers to these occupations for high-qualified workers with disadvantaged social backgrounds. Furthermore, our results suggest that the effect of technological change on equality of opportunity works via improved career prospects in technology-adopting occupations, as our results indicate that technological change mainly breaks through the class ceiling, i.e. the widening wage penalty related to parental background along the experience-earnings profile. According to the mechanism at play, we expect similar effects on equality of labor market opportunities for later technology waves, such as artificial intelligence, as long as these technologies alter the task mix of an occupation.

Our paper thus provides evidence for a much neglected effect of technological change. It highlights that, besides causing higher wage inequality between skill groups, technological change also exerts positive externalities on equality of opportunity in terms of wages and employment chances within skill groups. While we find this effect for high-qualified workers, we find no clear evidence for such gains among low-qualified workers. A potential explanation for this result could be related to the differential effect of technological change on skill requirements in occupations carried out by low-qualified and high-qualified workers. While technological change exerts a positive effect on returns to skills required by high-qualified workers, it may not increase returns to skills or even induce deskilling in occupations mainly employing low-qualified workers.

From a policy perspective, our findings stress the double importance of reducing the education gap by parental background during times of technological change. This is because workers from a disadvantaged background additionally benefit from higher level qualifications by gaining access to technology-adopting occupations and earning a technology-related skill premia. Moreover, our findings indicate that measures to increase occupational mobility might disproportionately benefit workers with a low parental background in times of technological change.

Whether the opportunity-enhancing effects of technological change that we find in this paper also apply to other disadvantaged groups such as migrants remains a question for future research.

References

Acemoglu, D. (2002). Technical change, inequality, and the labor market. Journal of Economic Literature, 40(1), 7–72.

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In Handbook of Labor Economics (Vol. 4, pp. 1043–1171). Elsevier.

Addison, J. T., Brysonnn, A., Teixeira, P., & Pahnke, A. (2011). Slip sliding away: Further union decline in Germany and Britain. Scottish Journal of Political Economy, 58(4), 490–518.

Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R., & Hémous, D. (2019). Innovation and top income inequality. Review of Economic Studies, 86(1), 1–45.

Akcigit, U., Grigsby, J., & Nicholas, T. (2017). The rise of American ingenuity: Innovation and inventors of the golden age (Tech. Rep.). Cambridge: National Bureau of Economic Research.

Amis, J. M., Mair, J., & Munir, K. A. (2020). The organizational reproduction of inequality. Academy of Management Annals, 14(1), 195–230.

Anger, S., & Schnitzlein, D. D. (2017). Cognitive skills, non-cognitive skills, and family background: evidence from sibling correlations. Journal of Population Economics, 30(2), 591–620.

Antonczyk, D., DeLeire, T., & Fitzenberger, B. (2018). Polarization and rising wage inequality: Comparing the U.S. and Germany. Econometrics, 6(2), 1-33.

Autor, D. H., & Dorn, D. (2013). The growth of low skill service jobs and the polarization of the u.s. labor market. American Economic Review, 103, 1553-1597.

Autor, D. H., Katz, L. F., & Kearney, M. S. (2008). Trends in us wage inequality: Revising the revisionists. Review of Economics and Statistics, 90(2), 300–323.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics, 118(4), 1279–1333.

Aziz, I. (2020). Skill-biased technical change and the intergenerational mobility of skills. (Unpublished Manuscript)

Beaudry, P., Green, D. A., & Sand, B. M. (2016). The great reversal in the demand for skill and cognitive tasks. Journal of Labor Economics, 34(S1), S199–S247.

Becker, S., Ekholm, K., & Muendler, M.-A. (2013). Offshoring and the onshore composition of tasks and skills. Journal of International Economics, 90(1), 91-106.

Berger, T., & Engzell, P. (2022). Industrial automation and intergenerational income mobility in the united states. Social Science Research, 104(102686).

Björklund, A., & Salvanes, K. G. (2011). Education and family background: Mechanisms and policies. In Handbook of the Economics of Education (Vol. 3, pp. 201–247). Elsevier.

Blinder, A. S., & Krueger, A. B. (2013). Alternative measures of offshorability: a survey approach. Journal of Labor Economics, 31(S1), S97–S128.

Britton, J., Dearden, L., Shephard, N., & Vignoles, A. (2016). How English domiciled graduate earnings vary with gender, institution attended, subject and socio-economic background (Tech. Rep.). London: IFS Working Papers.

Brunori, P., & Neidhöfer, G. (2021). The evolution of inequality of opportunity in Germany: A machine learning approach. Review of Income and Wealth, 67(4), 900–927.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. The Review of Economics and Statistics, 90(3), 414–427.

Cappelli, P. (1993). Are skill requirements rising? evidence from production and clerical jobs. ILR Review, 46(3), 515–530.

Card, D., & DiNardo, J. E. (2002). Skill-biased technological change and rising wage inequality: Some problems and puzzles. Journal of Labor Economics, 20(4), 733–783.

Corak, M., & Piraino, P. (2011). The intergenerational transmission of employers. Journal of Labor Economics, 29(1), 37–68.

Dauth, W., Findeisen, S., & Suedekum, J. (2014). The rise of the east and the far east: German labour markets and trade integration. Journal of the European Economic Association, 12(6), :1643–1675.

Deming, D., & Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers. The Quarterly Journal of Economics, 135(4), 1965–2005.

Destatis. (2021). Bevölkerung nach Bildungsabschluss in Deutschland (Tech. Rep.). Statistisches Bundesamt. Retrieved from https://www.destatis.de/

DE/Themen/Gesellschaft-Umwelt/Bildung-Forschung-Kultur/Bildungsstand/Tabellen/bildungsabschluss.html

DIPF. (2020). Bildung in Deutschland 2020: ein indikatorengestützter Bericht mit einer Analyse zu Bildung in einer digitalisierten Welt. Bielefeld: DIPF – Leibniz-Institut für Bildungsforschung und Bildungsinformation, wbv Media GmbH & Co. KG. doi: https://doi.org/10.3278/6001820gw

Dunn, T., & Holtz-Eakin, D. (2000). Financial capital, human capital, and the transition to self-employment: Evidence from intergenerational links. Journal of Labor Economics, 18(2), 282–305.

Dustmann, C. (2004). Parental background, secondary school track choice, and wages. Oxford Economic Papers, 56(2), 209–230.

Dustmann, C., Ludsteck, J., & Schönberg, U. (2009). Revisiting the German wage structure. Quarterly Journal of Economics, 124(2), 843–881.

Franzini, M., Patriarca, F., & Raitano, M. (2020). Market competition and parental background wage premium: the role of human and relational capital. Journal of Economic Inequality, 18(3), 291–317.

Franzini, M., & Raitano, M. (2009). Persistence of inequality in Europe: the role of family economic conditions. International Review of Applied Economics, 23(3), 345–366.

Friedman, S., & Laurison, D. (2019). The class ceiling: Why it pays to be privileged (1st ed.). Bristol University Press.

Galor, O., & Tsiddon, D. (1997). Technological progress, mobility, and economic growth. American Economic Review, 363–382.

Garcia-Penalosa, C., Petit, F., & van Ypersele, T. (2022). Spreading the polarization disease: From the labour market to social mobility. (Unpublished Manuscript)

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., & Schupp, J. (2019). The German Socio-Economic Panel (SOEP). Jahrbücher für Nationalökonomie und Statistik, 239(2), 345–360.

Guo, N. (2022). Hollowing out of opportunity: Automation technology and intergenerational mobility in the united states. Labour Economics, 75(102136).

Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. Journal of Management Studies, 58(5), 1159–1197.

Hassler, J., & Mora, J. V. R. (2000). Intelligence, social mobility, and growth. American Economic Review, 90(4), 888–908.

Heckman, J. J., & Mosso, S. (2014). The economics of human development and social mobility. Annu. Rev. Econ., 6(1), 689–733.

Hennig, J.-L. (2021). Labor market polarization and intergenerational mobility: Theory and evidence. (Unpublished Manuscript)

Holzer, H. J. (1988). Search method use by unemployed youth. Journal of Labor Economics, 6(1), 1–20.

Howcroft, D., & Richardson, H. (2012). The back office goes global: exploring connections and contradictions in shared service centres. Work, Employment and Society, 26(1), 111–127.

Hudson, J., & Sessions, J. G. (2011). Parental education, labor market experience and earnings: new wine in an old bottle? Economics Letters, 113(2), 112–115.

Ioannides, Y. M., & Loury, L. D. (2004). Job information networks, neighborhood effects, and inequality. Journal of Economic Literature, 42(4), 1056–1093.

Jackson, M. O. (2021). Inequality's economic and social roots: The role of social networks and homophily. Available at SSRN 3795626.

Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963–1987: supply and demand factors. Quarterly Journal of Economics, 107(1), 35–78.

Kunst, D. (2020). Deskilling among manufacturing production workers (Tech. Rep.). Amsterdam: Tinbergen Institute Discussion Paper TI 2019-050/VI, Version from Dec 30, 2020.

Laband, D. N., & Lentz, B. F. (1983). Occupational inheritance in agriculture. American Journal of Agricultural Economics, 65(2), 311–314.

Laband, D. N., & Lentz, B. F. (1992). Self-recruitment in the legal profession. Journal of Labor Economics, 10(2), 182–201.

Laurison, D., & Friedman, S. (2016). The class pay gap in higher professional and managerial occupations. American Sociological Review, 81(4), 668–695.

Lentz, B. F., & Laband, D. N. (1989). Why so many children of doctors become doctors: Nepotism vs. human capital transfers. Journal of Human Resources, 396–413.

Lentz, B. F., & Laband, D. N. (1990). Entrepreneurial success and occupational inheritance among proprietors. Canadian Journal of Economics, 563–579.

Lindquist, M. J., Sol, J., & Van Praag, M. (2015). Why do entrepreneurial parents have entrepreneurial children? Journal of Labor Economics, 33(2), 269–296.

Loury, L. D. (2006). Some contacts are more equal than others: Informal networks, job tenure, and wages. Journal of Labor Economics, 24(2), 299–318.

Maoz, Y. D., & Moav, O. (1999). Intergenerational mobility and the process of development. Economic Journal, 109(458), 677–697.

Murnane, R. J., Willett, J. B., & Levy, F. (1995). The growing importance of cognitive skills in wage determination. Review of Economics and Statistics, 77(2), 251–266.

Papke, L. E., & Wooldridge, J. M. (2008). Panel data methods for fractional response variables with an application to test pass rates. Journal of Econometrics, 145(1-2), 121–133.

Peng, G., Wang, Y., & Han, G. (2018). Information technology and employment: The impact of job tasks and worker skills. Journal of Industrial Relations, 60(2), 201–223.

Raitano, M., & Vona, F. (2018). From the cradle to the grave: The influence of family background on the career path of Italian men. Oxford Bulletin of Economics and Statistics, 80(6), 1062–1088.

Rivera, L. A., & Tilcsik, A. (2016). Class advantage, commitment penalty: The gendered effect of social class signals in an elite labor market. American Sociological Review, 81(6), 1097–1131.

Rohrbach-Schmidt, D., & Tiemann, M. (2013). Changes in workplace tasks in Germany — evaluating skill and task measures. Journal for Labour Market Research, 46(3), 215–237.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. Journal of Labor Economics, 24(2), 235–270.

Steil, J. J., & Maier, G. W. (2017). Digitalized workplace. The Wiley Blackwell handbook of the psychology of the internet at work, 403.

Treiman, D. J. (1977). Occupational prestige in comparative perspective. New York: Academic Press.

Wegener, B. (1985). Gibt es Sozialprestige? Zeitschrift für Soziologie, 14(3), 209–235.

Wegener, B. (1988). Kritik des Prestiges. Opladen: Westdeutscher Verlag.

Data Sources:

BIBB/IAB and BIBB/BAuA Erwerbstätigenbefragung (Qualification and Career Survey, QCS), waves from 1979 to 2012, DOI: http://dx.doi.org/doi:10.4232/1.1243, http://dx.doi.org/doi:10.4232/1.1790, http://dx.doi.org/doi:10.4232/1.2565, http://dx.doi.org/doi:10.4232/1.12247, http://dx.doi.org/doi:10.4232/1.11072, and http://dx.doi.org/doi:10.7803/501.12.1.1.40

Socio-Economic Panel (SOEP), Data for years 1984-2017, Version 34, DOI: 10.5684/soep.v34.

Antoni, Manfred; Berge, Philipp vom; Ganzer, Andreas (2019): "Factually anonymous Version of the Sample of Integrated Labour Market Biographies (SIAB-Regionalfile) – Version 7517 v1". Research Data Centre of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB), DOI: 10.5164/IAB.SIAB-R7517.de.en.v1 Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

A Theoretical Framework

We use an explicit production technology in our baseline framework in order to keep the analysis simple and traceable. In this section, we show that our results are robust to functional form assumptions by using a generalized production technology. Instead of a linear production technology, we assume that firms produce with a general production technology

$$Y = L_{\alpha,\beta} F(\alpha, \beta, t) \tag{11}$$

where where $t > 0$ is the level of technology. We assume that workers' productivity rises in workers' skills α, workers' parental background β, and in the level of technology t: $\frac{\partial F}{\partial \alpha} = f_\alpha > 0$, $f_\beta > 0$, and $f_t > 0$.

Analogous to the steps in the main paper, cost minimization implies that unit costs of production must be equal across all types of workers, which implies:

$$\log\left(\frac{w_{\alpha_0,\beta_0}}{w_{\alpha,\beta}}\right) = \log\left(\frac{F(\alpha_0,\beta_0,t)}{F(\alpha,\beta,t)}\right) \tag{12}$$

Workers supply labor with wage elasticity ϵ, $L_{\alpha,\beta} = \bar{L} w^{\epsilon}_{\alpha,\beta}$, where $\bar{L}$ is the baseline labor supply which we assume to be exogenous. Under these assumptions, the log wage ratio between two workers responds to technological change as follows:

$$\frac{\partial \log\left(\frac{w_{\alpha_0,\beta_0}}{w_{\alpha,\beta}}\right)}{\partial t} = \frac{\partial F(\alpha_0,\beta_0,t)/\partial t}{F(\alpha_0,\beta_0,t)} - \frac{\partial F(\alpha,\beta,t)/\partial t}{F(\alpha,\beta,t)} \tag{13}$$

Let us compare two workers with the same skill level ($\alpha = \alpha_0$). The wage ratio of workers with low parental background (β_0) compared to workers with high parental background (β) increases in the technology level, ($\partial \log\left(\frac{w_{\alpha,\beta_0}}{w_{\alpha,\beta}}\right)/\partial t > 0$), if two conditions are met: $F(\alpha,\beta_0,t) < F(\alpha,\beta,t)$ and $\partial F(\alpha,\beta_0,t)/\partial t \geq \partial F(\alpha,\beta,t)/\partial t$. Note that the first condition holds by definition: Workers with high-educated parents are more productive than workers with low-educated parents (*ceteris paribus*). The sign of equation (13) therefore depends on the second condition: The technology-induced marginal increase in productivity must be at least as large for workers with low-educated parents as for those with high-educated parents. Two scenarios can lead to this situation.

In the first, simple scenario, technological change has a direct, negative effect on the returns to parental background, $\partial^2 F/\partial\beta\partial t = \partial f_\beta/\partial t < 0$, as in Hassler & Mora (2000). In that case $\partial F(\alpha,\beta_0,t)/\partial t > \partial F(\alpha,\beta,t)/\partial t$, because technological change reduces the value of parents' education for their children's careers. Technological change then reduces the wage penalty by parental background, i.e. equation (13) is positive.

In a second scenario, technological change does not affect returns to parental background (i.e. $\partial f_\beta/\partial t = 0$). Technological change then reduces the wage penalty by parental background under either constant or diminishing returns to scale, $\frac{\partial^2 F}{\partial \beta^2} = f_{\beta^2} \leq 0$, and $f_{t^2} \leq 0$. The intuition of this scenario is as follows: Workers with lower parental background (all else equal) start off from a lower productivity level. This implies that their increase in marginal productivity, scaled by their initial productivity level, is larger, and their productivity rises relative to workers with higher parental background (all else equal).[49] Technological change then reduces the wage penalty between workers with high versus low-educated parents conditional on skill levels.

The effect of technological change on the wage penalty is homogeneous across skill groups if technology does not interact with workers' skills. However, a large body of literature on skill-biased technical change highlights that technological change raises returns to skills. Imposing the additional assumption that technological change raises returns to skills ($\partial f_\alpha/\partial t > 0$) implies that the effect of technological change on the wage penalty for workers with low-educated parents increases in workers' skills. This is comparable to the argument by Galor & Tsiddon (1997): Technological change raises workers productivity, particularly among skilled workers, and by that reduces the relative returns to parental background, leading to a decline in wage differences between workers from differential parental backgrounds. The effect of technological change on the decline in the wage penalty by parental background then is particularly strong among skilled workers due to skill-biased technical change, but weak or zero among unskilled workers. Our explicit functional form in the main paper is an example of such a production function.

The discussion above has zoomed in on comparing workers with the same skill level but different parental backgrounds. Analogously, one can use equation (13) for comparing two workers with the same parental background ($\beta = \beta_0$) but different skill levels to study effects of technological change on wage disparities by skill level.

[49] We exclude the scenario that $\partial f_\beta/\partial t > 0$, because it would imply that parental background would be complementary to technology – contrary to the descriptive evidence.

B Additional Tables and Graphs

B.1 Additional Tables and Graphs for Section 2

Table B1.1: Classification of Occupations

Aggregated occupation	N	Tech 1986	Tech 2012	Δ Tech	KldB 1992, 2-digits
Deputy	2,827	0.09	0.88	0.80	76
Office worker	11,051	0.10	0.89	0.79	78
Journalist/librarian	604	0.06	0.83	0.78	82
Banker	4,147	0.18	0.92	0.74	69
Ingenieur	4,425	0.15	0.87	0.72	60
Auditor	4,622	0.11	0.82	0.71	75
Scientist	913	0.14	0.78	0.64	88
Other service trader	1,451	0.09	0.69	0.59	70
Technical specialist/drawer	740	0.08	0.67	0.59	63,64
Security/Law protector	3,878	0.02	0.54	0.52	80,81
Technician	3,699	0.17	0.65	0.48	62
Physicist/Chemist/Mathematician	498	0.40	0.85	0.45	61
Artist	534	0.03	0.47	0.44	83
Accountant/Data processor	4,731	0.43	0.87	0.44	77
Metal processor	1,173	0.10	0.52	0.42	22
Teacher	4,852	0.01	0.43	0.42	87
Print worker	792	0.14	0.54	0.40	17
Doctor	734	0.05	0.39	0.35	84
Sales personnel	6,341	0.04	0.36	0.32	66, 67, 68
Communication	511	0.02	0.29	0.27	73
Paper producer/processor	270	0.10	0.36	0.26	16
Other metal jobs	1,434	0.04	0.30	0.26	32
Plastics processor	468	0.05	0.29	0.24	15
Product/Dispatch inspector	1,331	0.04	0.28	0.24	52
Other health care	3,856	0.06	0.28	0.22	85
Confectioner	522	0.02	0.23	0.21	39
Social care	2,886	0.00	0.20	0.20	86, 89
Warehouse worker	2,723	0.02	0.23	0.20	74
Ceramist/Glass maker	222	0.08	0.29	0.20	12, 13
Food processor	875	0.00	0.19	0.19	41
Mechanics	1,954	0.03	0.21	0.18	28
Wood processor	134	0.02	0.20	0.18	18
Guarding worker	922	0.03	0.20	0.17	79
Agricultural/Breeding jobs	258	0.08	0.24	0.16	1, 2, 3
Guest attendant	751	0.02	0.17	0.15	91
Beverage/other food producer	345	0.29	0.43	0.15	42, 43
Domestic service worker	344	0.01	0.16	0.14	92
Machine operator	1,305	0.11	0.25	0.14	54, 55
Electrician	3,044	0.07	0.21	0.14	31

Continued on next page

Aggregated occupation	N	Tech 1986	Tech 2012	Δ Tech	KldB 1992, 2-digits
Other laborer	869	0.08	0.21	0.13	53
Chemical worker	1,188	0.28	0.41	0.13	14
Carpenter/Interior designer	1,276	0.01	0.13	0.12	49, 50
Horticultural/Forestry jobs	778	0.00	0.12	0.12	5, 6
Blacksmith	2,501	0.01	0.12	0.11	25, 26
Road/Underground builder	365	0.00	0.10	0.10	46
Metal compounder/finisher	633	0.03	0.13	0.10	23, 24
Locksmith	2,262	0.03	0.12	0.10	27
Tool manufacturer	1,318	0.04	0.11	0.07	29, 30
Cleaning worker	948	0.01	0.08	0.07	93
Meat processor	299	0.03	0.09	0.06	40
Metal producer/Cast moulder	274	0.23	0.29	0.06	19, 20
Bricklayer/Roofer	1,152	0.01	0.06	0.05	44
Textile processor	353	0.01	0.06	0.04	35, 36
Textile/Leather producer	304	0.05	0.08	0.04	33, 34, 37
Ressource producer/processor	314	0.05	0.09	0.04	7, 8, 9, 10, 11
Water/Air transport	203	0.03	0.05	0.02	72
Overland transport	3,141	0.02	0.04	0.02	71
Metal processor (chipless)	123	0.13	0.14	0.02	21
Construction outfitter	860	0.04	0.05	0.01	48
Body care worker	290	0.00	0.00	0.00	90
Construction laborer	321	0.01	0.00	-0.01	47
Painter	960	0.01	0.00	-0.01	51

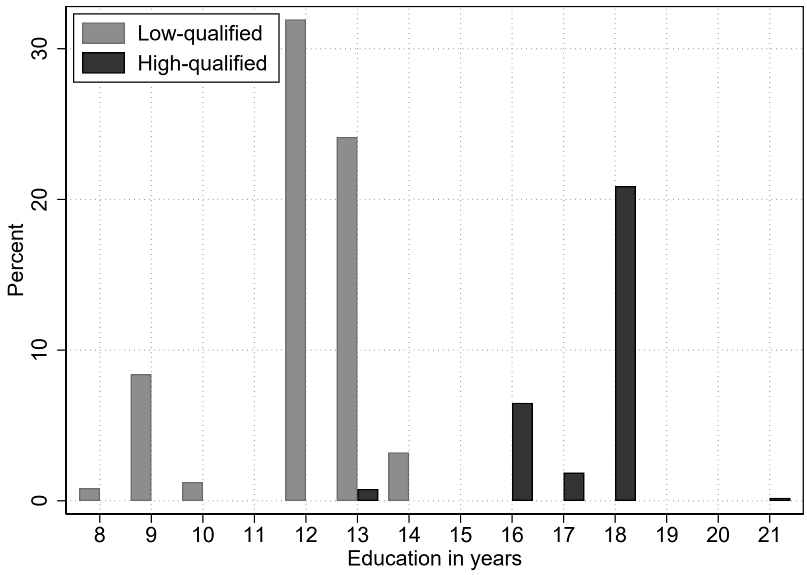
Notes: KldB 1992 occupations (2 digits, column 6) aggregated to 62 occupations (column 1) to make them comparable across all three datasets. N: Number of individual observations in the SOEP. Tech 1986 (2012): Share of individuals mainly working with new technologies in the QCS in 1986 (2012). Δ Tech: Difference in the share of individuals mainly working with new technologies in the QCS between 2012 and 1986.

Table B1.2: Definition of Education Groups

	Highest qualification	Years of education	Percent of observations
	High-qualified		
1	University entrance qualification (Abitur)	13	0.8
2	University entrance qualification (Abitur) + vocational training	16	6.5
3	University entrance qualification (Abitur) + vocational training + master craftsmen	17	1.9
4	(Technical) college/university degree incl. dual study program†	18	20.9
5	Doctorate	21	0.2
	Low-qualified		
1	No school-leaving qualification	8	0.8
2	Secondary school with 9 years of schooling (Hauptschule) or other school-leaving qualification	9	8.4
3	Secondary school with 10 years of schooling (Realschule)	10	1.2
4	Hauptschule + vocational training, or other school-leaving qualification + vocational training	12	31.9
5	Realschule + vocational training	13	20.7
6	Hauptschule + vocational training + master craftsmen, or other school-leaving qualification + vocational training + master craftsmen	13	3.4
7	Realschule + vocational training + master craftsmen	14	3.2

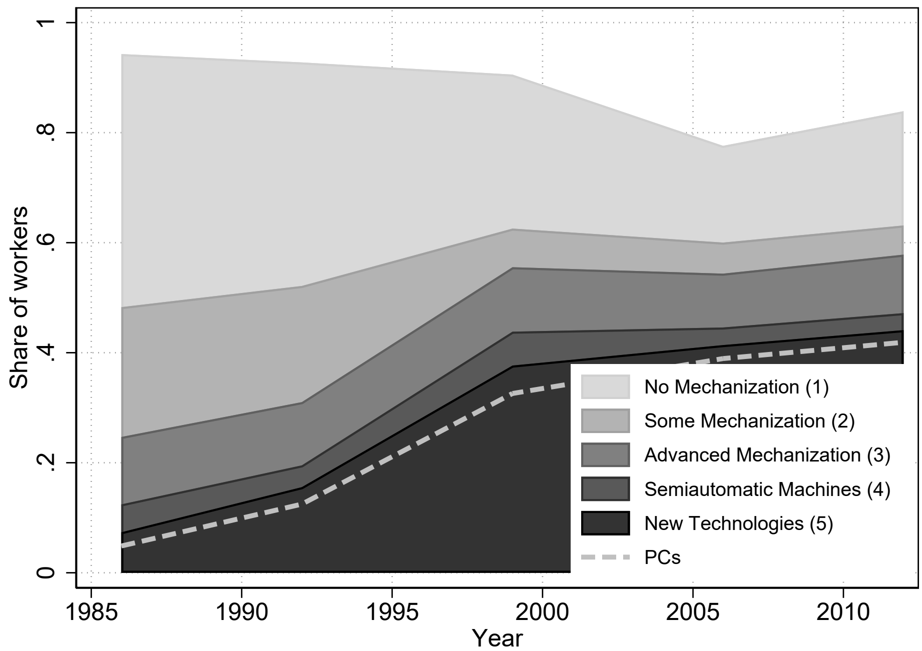
Notes: † - (Technical) college or university studies with integrated periods of practical work at companies. Education refers to the highest level of formal education accomplished and is time-constant (the maximum education ever attained) to minimize reporting errors.

Figure B1.1: Education in Years by Qualification Groups



Notes: Share of observations by years of education and qualification groups. Observations weighted by representative SOEP weights, West Germany only.

Figure B1.2: Share of Workers by Main Working Tool over Time



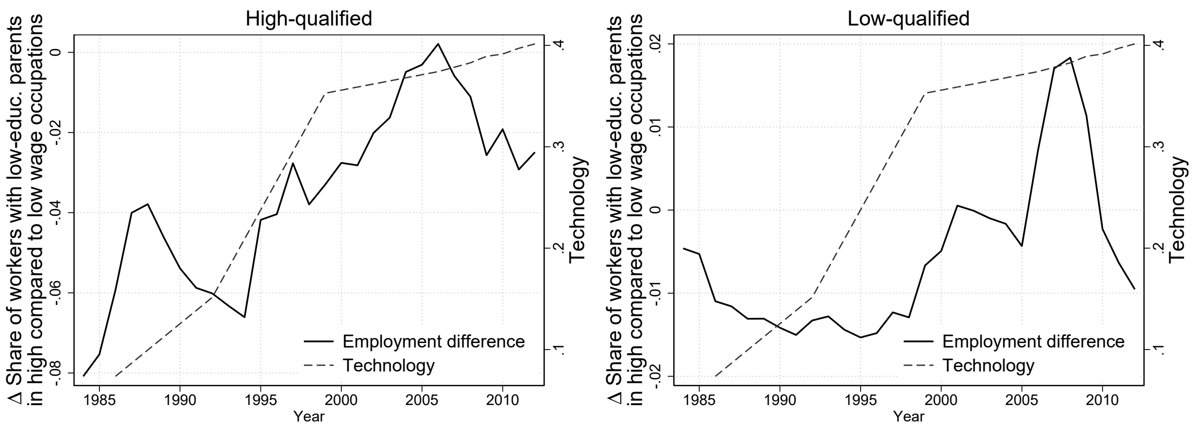
Notes: Source: Qualification and Career Survey, West Germany only, own calculations. Representative for the size of occupations as suggested by the SIAB.

Table B1.3: Descriptive Statistics on the Individual Level

	Overall	1986	2012
High-qualified (%)	.3	.2	.4
Low educ. parents (%)	.88	.91	.82
Mean log hourly wage	2.8	2.66	2.81
Technology (%)	.33	.08	.49
Female (%)	.31	.3	.32
Age - 20-25 years	.13	.06	.22
26-30 years	.1	.16	.06
31-35 years	.13	.15	.11
36-50 years	.14	.12	.12
51-65 years	.4	.36	.43
Foreign (%)	.23	.21	.29
Work experience (full-time) - up to one year	.03	.02	.04
1-2 years	.06	.08	.06
3-4 years	.07	.08	.05
5-9 years	.16	.16	.14
10-29 years	.49	.45	.51
30+ years	.19	.21	.2
Firm size - 1-19 employees	.45	.42	.43
20-199 employees	.25	.25	.25
200+ employees	.3	.33	.32
Public service (%)	.29	.31	.27

Notes: Mean values for the entire dataset (column 1), for 1986 only (column 2), and 2012 only (column 3). Based on the SOEP, using representative weights, West Germany only.

Figure B1.3: Employment Shares by Parental Background: Time Trend



Notes: Solid line: Difference in the share of high-qualified (low-qualified) individuals with low-educated parents working in occupations earning an above median wage and the share of high-qualified (low-qualified) individuals with low-educated parents working in occupations earning a below median wage. The median wage is based on qualification-specific wage distribution from the SOEP using representative survey weights. Dashed line: Average share of workers mainly using new technologies across all occupations. Based on the Qualification and Career Survey, occupations weighted by the initial employment shares in 1986. West Germany only, own calculations.

Table B1.4: Descriptive Statistics on the Occupational Level

	Overall	1987	2011
Outcomes			
Share high-qualified†	.19	.15	.24
Share high-qualified with low educ. parents†	.77	.78	.74
Share low-qualified with low educ. parents†	.96	.96	.94
Wage penalty by parental background - high-qualified†	-.03	-.07	.04
Wage penalty by parental background - low-qualified†	-.05	-.1	0
Treatment			
Technology (%)*	.28	.09	.4
Controls			
Tertiary educated (%)‡	.09	.06	.12
Female (%)‡	.4	.4	.4
Age‡	39.02	37.04	41.04
Foreign (%)‡	.09	.07	.1
Rel. occ. empl. share (%)‡	4.41	4.25	4.33
Daily median wage‡	.09	.09	.09
Mean occ. tenure (years)‡	.02	.02	.03

Notes: Mean values for the entire dataset (column 1), for 1987 only (column 2), and 2011 only (column3). Levels for 1987 and 2011 pooled over three years. † - SOEP, * - Qualification and Career Survey, ‡- SIAB. Observations weighted by the initial employment share of the occupation in 1986.

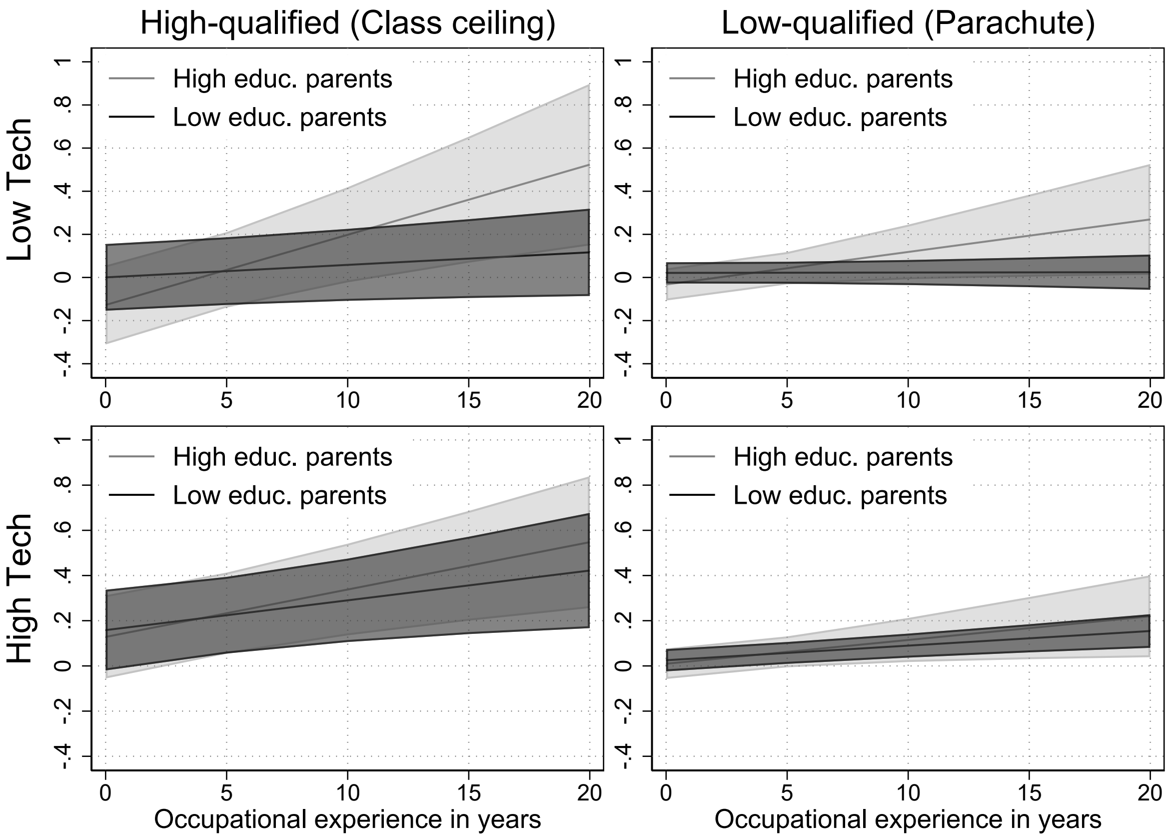
B.2 Additional Tables and Graphs for Section 4.1

Table B2.1: Wage Effects Separately by Parental Background

	High-qualified							
	High PB				Low PB			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech	0.17**	0.23**	0.05	0.06	0.16***	0.18**	0.26***	0.32***
	(0.07)	(0.10)	(0.11)	(0.15)	(0.05)	(0.09)	(0.06)	(0.10)
Observations	8079	8079	7305	7305	21595	21595	20173	20173
F-Stat Tech		47.1		67.9		72.8		78.4
	Low-qualified							
	High PB				Low PB			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech	-0.09	0.06	0.19	0.47***	0.08*	0.10**	0.18***	0.24***
	(0.08)	(0.13)	(0.15)	(0.17)	(0.04)	(0.05)	(0.04)	(0.05)
Observations	2748	2748	2424	2424	54765	54765	50711	50711
F-Stat Tech		72.8		70.1		36.2		44.9
Occ. FE	Yes	Yes			Yes	Yes		
PB x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Spell FE			Yes	Yes			Yes	Yes

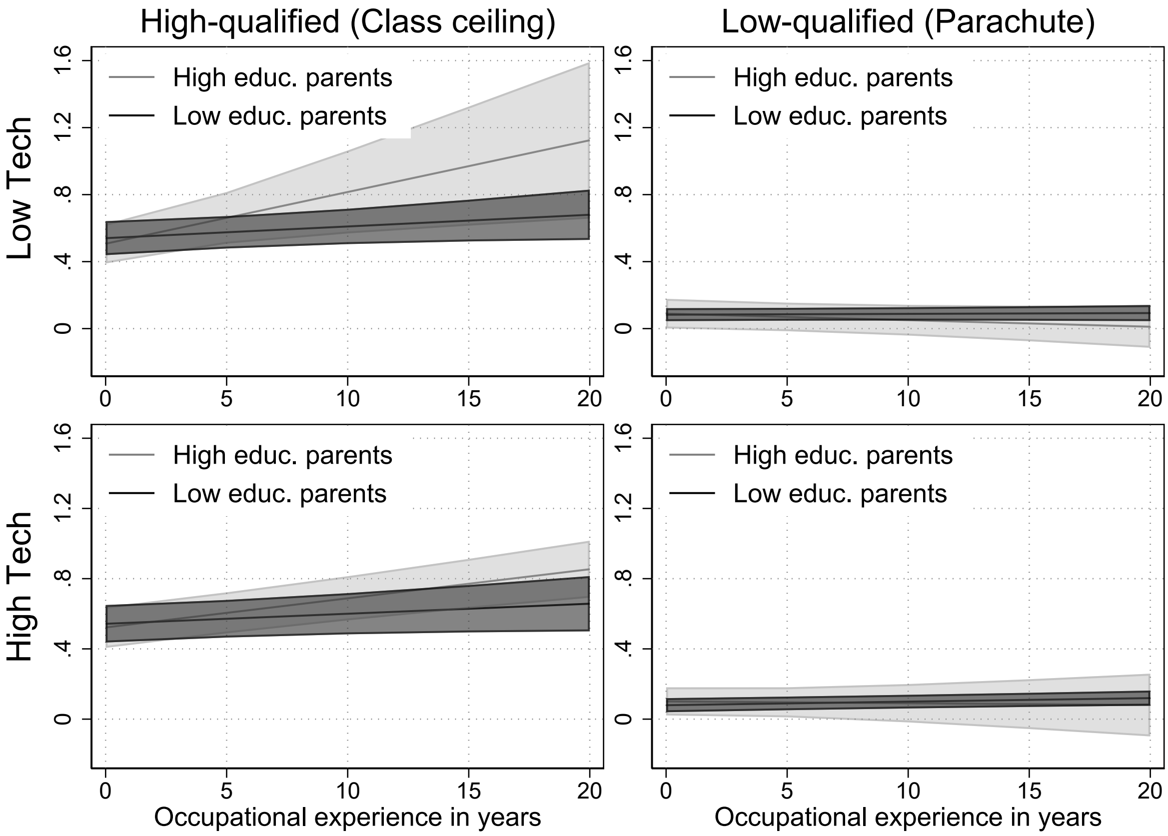
Notes: Dependent variable: Individual log wage. Controlling for gender, migration background, migration background × gender, five age categories, six dummies on labor market experience, education dummies, a public service indicator, four firm size categories, nine federal state dummies and 27 year dummies. Standard errors are clustered on the occupational and individual level. Observations weighted by representative SOEP weights, West Germany only. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B2.1: Experience-Earnings-Profile - Accumulated promotions



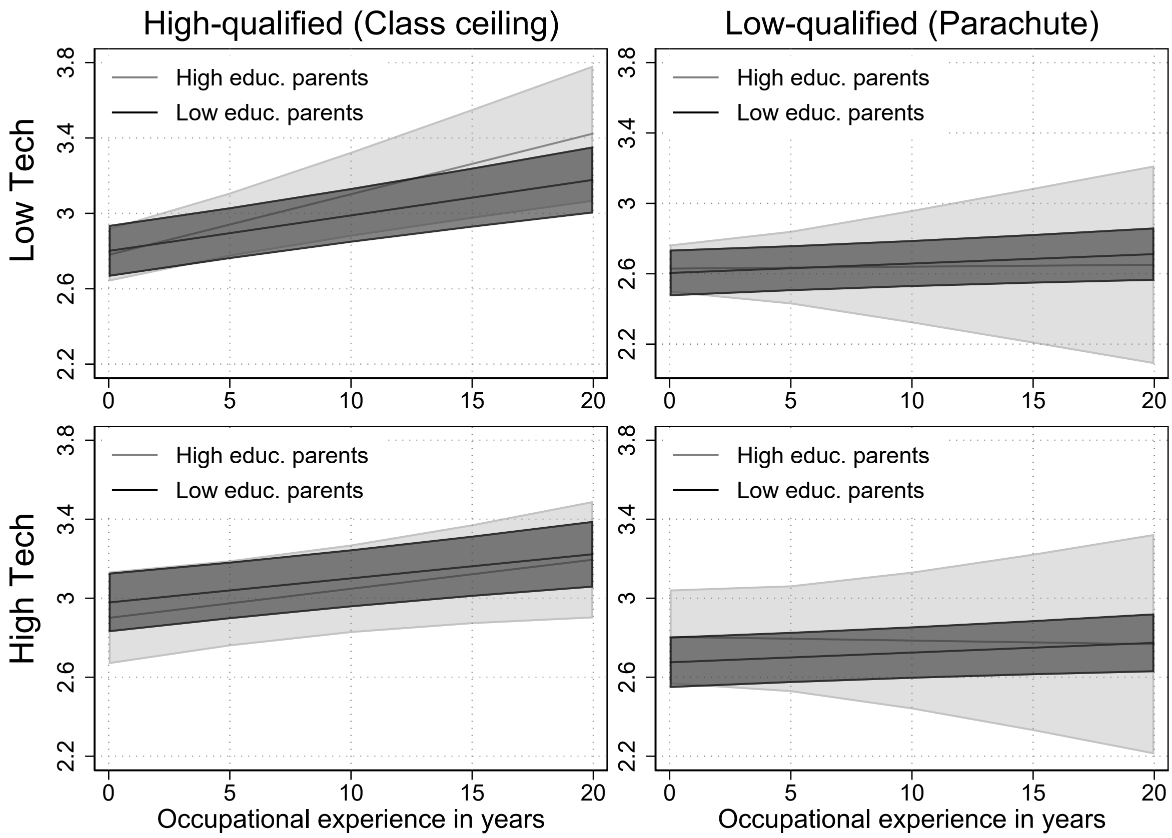
Notes: Predicted individual accumulated promotions within an occupation, and 90% confidence intervals. It captures the accumulated promotions over time, where promotion is a binary variable taking the value of one if the individual has changed the job within the same employer (and occupation) and experienced a positive wage change. Based on a regression with occupational experience (linear), parental background (binary), technology (linear) and all possible interaction terms on the right hand side, controlling for gender, migration background, migration background × gender, education dummies, public service indicator, firm size (4 categories), federal state (10 categories), 62 occupation and 27 year dummies, corresponding to column (3) in Table 2. Evaluated at the 25th ("Low Tech") and the 75th ("High Tech") percentile of the technology distribution. Observations weighted by representative SOEP weights, West Germany only.

Figure B2.2: Experience-Earnings-Profile - Management Position



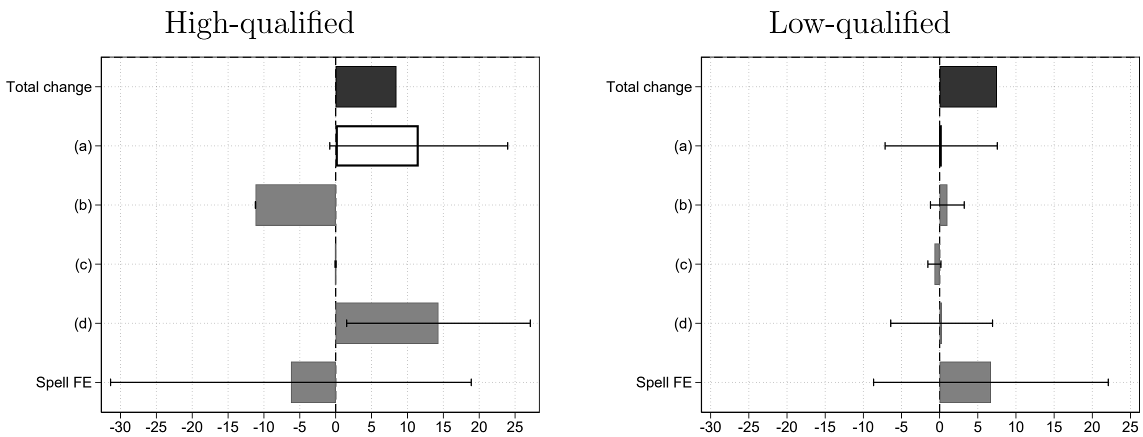
Notes: Predicted individual probability to have a management position plus 90% confidence intervals based on an OLS regression, including occupational experience (linear), parental background (binary), technology (linear) and all possible interaction terms on the right hand side, controlling for gender, migration background, migration background × gender, education dummies, public service indicator, firm size (4 categories), federal state (10 categories), 62 occupations and 27 year dummies. Evaluated at the 25th ("Low Tech") and the 75th ("High Tech") percentile of the technology distribution. Observations weighted by representative SOEP weights, West Germany only.

Figure B2.3: Experience-Earnings-Profile - Including Spell-Fixed Effects



Notes: Predicted individual log wage plus 90% confidence intervals based on an OLS regression including spell-fixed effects (corresponding to column (5) in Table 2), including occupational experience (linear), parental background (binary), technology (linear) and all possible interaction terms on the right hand side, controlling for gender, migration background, migration background × gender, education dummies, public service indicator, firm size (4 categories), federal state (10 categories) and 27 year dummies. Evaluated at the 25th ("Low Tech") and the 75th ("High Tech") percentile of the technology distribution. Observations weighted by representative SOEP weights, West Germany only.

Figure B2.4: Decomposition of the Change in the Qualification-Specific Wage Penalties 1989 to 2012 - Including Spell-Fixed Effects



Notes: Decomposition terms according to equation (10) for a change in the high-qualified and low-qualified wage penalty between $s = 1989$ and $t = 2012$ plus 90% confidence bands. Corresponding to column (4) in Table 2. Channels: changes in in the qualification-specific wage penalty due to (a) differently rewarded technology use of workers with low-educated parents compared to workers with high-educated parents; (b) the change in the residual wage penalty; (c) differences in changing technology use of workers with low-educated parents compared to workers with high-educated parents; (d) changes in all other observable characteristics of workers with low-educated parents compared to workers with high-educated parents. Confidence bands based on 1,000 bootstrap replications of the coefficient combinations. The value for the spell-fixed effects and its confidence band is obtained by substituting all observed decomposition terms (or their upper and lower bound, respectively) from the observed total change.

C Employment Effects - Short-Term Variation

For comparison, we estimate a model including fixed effects (FE) at the occupation and year level, i.e. we estimate

$$Y_{jt} = \alpha_1 Tech_{jt-s} + \alpha_2 Z_{jt} + c_j + d_t + v_{jt} \tag{14}$$

where Y_{jt} is the share of workers with low-educated parents within occupation j in year t among high-qualified (or, respectively, low-qualified) workers. By exploiting year-by-year variation, this FE model captures short-term effects compared to the long-term effects captured in the stacked long difference estimations in the main text. As a key advantage of the FE approach, we can rely on more observations and use lagged values of the technology indicator in order to reduce potential reverse causality issues. Based on Figure 2, we adopt a lag of three years, i.e. $Tech_{jt-3}$, in our main specification.[50] Z_{jt} is a vector including the same control variables as in equation (7) but on a yearly level, c_j are occupational fixed effects, and d_t year fixed effects.

Table C1: Employment Effects - Occupation Fixed Effects

	High-qualified				Low-qualified			
	1986-2012		*1986-2005*		*1986-2012*		*1986-2005*	
	Baseline	IV	Baseline	IV	Baseline	IV	Baseline	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech	0.18*	0.09	0.42**	0.44***	-0.02	-0.01	0.00	0.05***
	[-0.03,0.43]	[-0.28,0.58]	[0.08,0.80]	[-0.05,1.05]	[-0.04,0.02]	[-0.09,0.07]	[-0.05,0.06]	[-0.15,0.28]
Observations	696	696	464	464	1304	1304	916	916
F-Stat		34.8		40.6		27.9		14.2

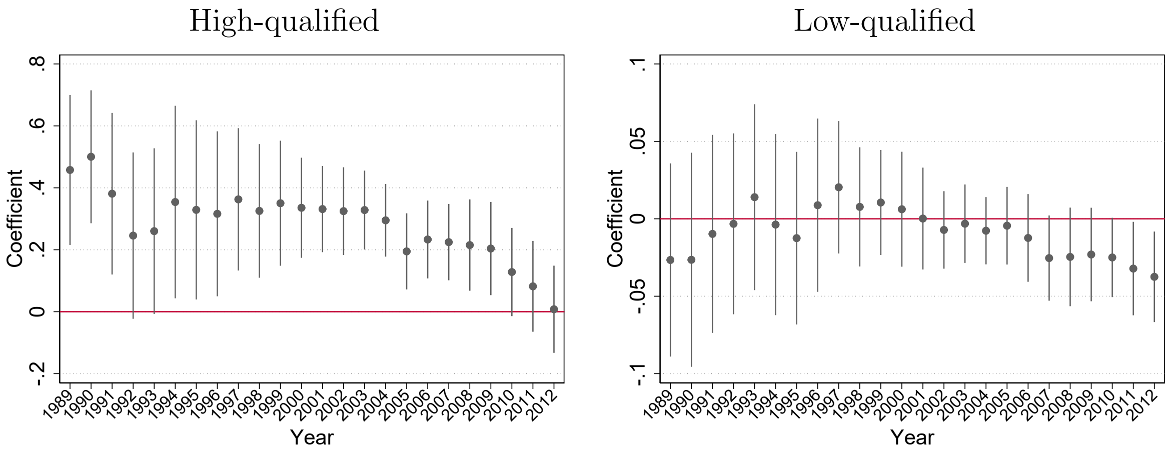
Notes: Dependent variable: Share of high-qualified (low-qualified) workers with low-educated parents among all high-qualified (low-qualified) workers. Control variables include the average age, the share of female/foreign/highly educated individuals, the average tenure, the relative employment share and the median wage. IV: sum of the initial task intensity of routine cognitive and non-routine analytic tasks multiplied by the aggregate technology level across all occupations but occupation's own. 95% confidence bands in square brackets and significance stars based on wild t-bootstraps. Observations weighted by the employment share in 1986, West Germany only. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Since the last period in the stacked difference regression (2006-2012) distorts the results due to a fading out of the technology indicator, we focus on the period 1986-2005 in columns (3) to (4) and (7) to (8). For high-qualified workers, the baseline estimate in column (1) shows that an increase in the share of individuals mainly using new technologies by 10 percentage points increases the share of high-qualified workers with low-educated parents in those occupations by 1.8 percentage points.[51] The smaller size of the effect

[50] When using a lag of one year (Table S2.17), the estimates are extremely similar in size and slightly more significant. When using a lag of five years (Table S2.18), the estimates decrease in size but remain similar.

[51] The linear model yields predictions for the share of workers with low-educated parents that are outside the range of $Y_{jt} \in [0, 1]$. Estimating a fractional logit model instead (Papke & Wooldridge, 2008), results in average partial effects similar in size to the one of the linear model in column 1: 0.29

Figure C1: Employment Effects - Interaction Effect Technology × Year



Notes: Estimation coefficients plus 90% confidence intervals of the interaction term Technology × Year. Standard errors are clustered on the occupation level. Regression with occupation fixed effect analogously to equation (14). Dependent variable: share of high-qualified (low-qualified) workers with low-educated parents among all high-qualified (low-qualified) workers.

compared to the stacked differences results is likely due to the restriction to short-term effects. When focusing on the period 1986-2005, the estimates double in size. Hence, the FE model confirms that technological change contributes to improved labor market opportunities of high-qualified individuals with low-educated parents. This finding is also robust to instrumenting the technology indicator with the same instrumental variable used before (columns (2) and (4)). Moreover, when extending the main specification to allow for time-varying effects of technological change, by interacting $Tech_{jt-3}$ with year dummies, we find positive and significant effects at the 10% significance level for high-qualified workers for all years from 1989 to 2010, see Figure C1.

For low-qualified workers (columns (5) to (8)), we do not find evidence for an improvement of employment opportunities due to technological change, confirming the results from the stacked difference analysis.

(bootstrap standard error=0.17). We hence conclude that the simplification to a linear specification does not distort the size of the effect.