// NO.22-014 | 05/2022

DISCUSSION PAPER

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

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May 16, 2022

Abstract

This paper analyzes whether technological change improves equality of labor market opportunities by decreasing returns to parental background. We find that in Germany during the 1990s, computerization 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.

Keywords: Skill-biased technical change, wage inequality, equality of opportunity, intergenerational persistence, parental background, class ceiling.

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

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We gratefully acknowledge Friedhelm Pfeiffer, Michele Raitano, Pascual Restrepo, Anna Salomons and Nicolas Ziebarth for their insightful comments. We also thank conference and seminar participants at EALE (Maastricht), ECINEQ (London), Verein für Sozialpolitik (Regensburg), 2nd LISER-IAB Conference on Digital Transformation and the Future of Work (Luxembourg), ZEW-EPos Workshop on Labour Adjustments to New Technologies and Globalization (Mannheim), Conference of Economics of ICT (Mannheim), LabFam Seminar (Warsaw), RGS Doctoral Conference (Essen), Workshop on Social Mobility and Economic Performance (Mannheim), SOEP Seminar (Berlin), TPRI Seminar (Boston), CPB-Workshop (The Hague) and at the internal seminars at Utrecht University, Heidelberg University and ZEW Mannheim. The project was financially supported by the Leibniz Association through the Leibniz Professorship for Applied Labor Economics at the University of Heidelberg (P56/2017) and ZEW Mannheim.

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 skills and networks of the parents 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 parental backgrounds through the channel of decreasing returns to parental background. We do so in two steps. In the first step, we focus on labor market opportunities within qualification groups, i.e. conditional on individual education. 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 for workers with a university entrance qualification in the early 2000s. During the same period, the German labor market was characterized by the rapid adoption of new technologies. The share of workers using computer-controlled tools more than doubled in the 1990s, rising from 16% in 1992 to 38% in 1999. In a stylized framework, we then formalize the hypothesis that, conditional on individual skill, technological change improves labor market opportunities for disadvantaged individuals. The model predicts that, if technological change increases 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.

We then empirically test these predictions. We use occupation-year-level variation in computerization 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 computerization. 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. Importantly, the wage penalty remained low even after these computer-based technologies had become a mainstream practice. 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 with increasing 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 technology-induced rising returns to skills are less prevalent in occupations with lower skill requirements.

In the second part of the paper, we put these findings in a broader perspective. By using regression-based decompositions, we demonstrate that the reduction of the wage penalty within qualification groups was the main reason for the observed decrease in the overall wage penalty by parental background across all workers between 1986 and 2012 in Germany. In contrast, increasing returns to education alone would have increased this overall wage penalty, despite the educational upgrading of workers from disadvantaged backgrounds. Furthermore, the decompositions 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. Thus, our findings highlight that technological change contributes to reducing 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.[1] 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

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

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 skill groups. In particular, Section 4.1 estimates the effect of technological change on the wage returns to parental background and analyzes how technological change affects the wage penalty with increasing work experience. Section 4.2 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 puts these findings in a broader perspective and evaluates the contribution of these effects to changes in the overall wage penalty by parental background by means of a decomposition analysis. Section 6 concludes.

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.[2] 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.[3] 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.[4] 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 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). We distinguish between high-qualified workers, i.e. those with a university entrance qualification, and low-qualified workers, i.e. those without such a qualification. We define two groups of individuals based on retrospective questions regarding their socioeconomic

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

[3]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.

[4]We do not construct an indicator of *education*-occupation-specific technology, since the variation of working tools across education 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 education-occupation-specific instead of only occupation-specific technology use provides qualitatively very similar but less precise results.

background. Following the literature, we categorize socioeconomic background based 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. We focus in both cases on the university entrance qualification (*Abitur*) 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 this qualification can continue with university education and typically enter careers in 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 Abitur have at most 13 years of education while those with Abitur have at least 15 years of education with only few exceptions (see Figure B1.1 in the Appendix B.1). Due to the selective tracking of the education system, it has been shown within the German context that a university entrance qualification is associated with both significantly higher wages and parental education (e.g. Dustmann, 2004).[5]

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.

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.[8] 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

[5]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). At the same time, 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).

[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]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.

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 B1.3 and Figure B1.4 in the Appendix B.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 all 62 occupations.[9] 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.

2.2 Stylized Evidence

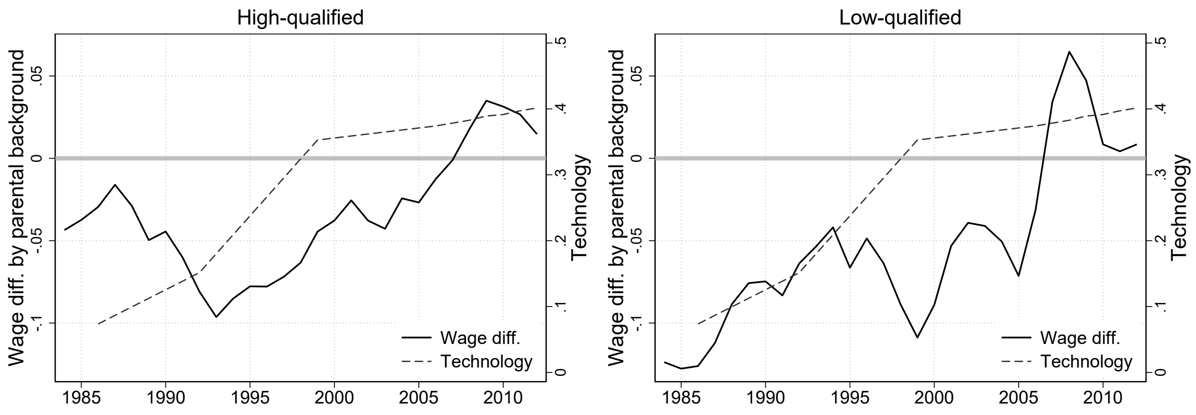
Figure 1 shows the trend in average technology use across occupations, estimated using the QCS survey, and the trend in wage penalties by parental background, estimated with individual data from the SOEP. Wage penalties are defined as the difference between the log average wage of workers with low-educated 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.[10] In the 2000s, technology adoption

[9]In this second dataset, we exclude estimates of employment shares based on less than ten individual observations. On average, an occupation-year level information on employment shares is based on 70 individual observations.

[10]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 B1.5 in the Appendix B.1.

Figure 1: 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.

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-qualified workers, wages only converged several years after the period of rapid technology adoption.[11]

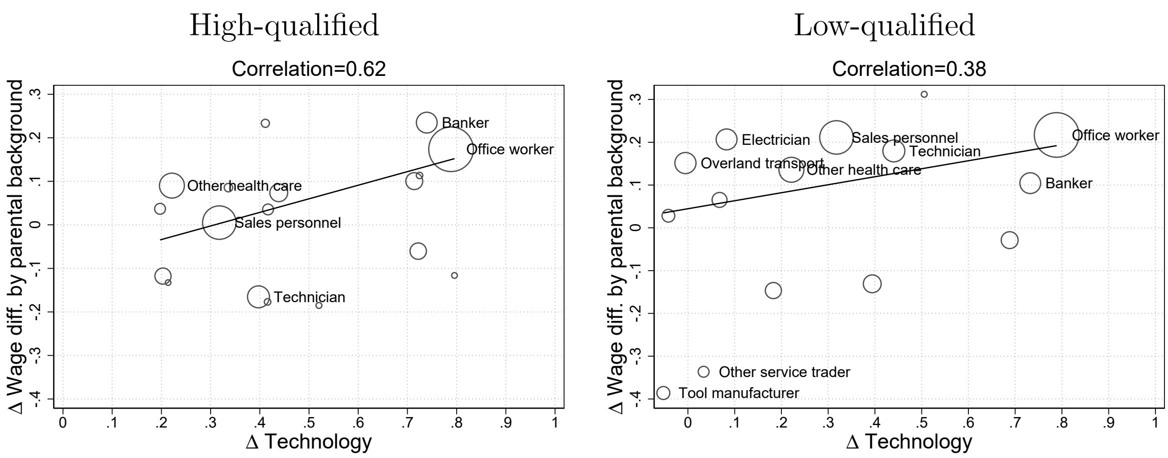
Next, we analyze whether this pattern also holds true at the occupational level. Figure 2 plots the change in technology use within occupations between 1986 and 2012 against the change in the occupation-specific wage differential over the same period. The graph suggests that, indeed, the link between 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

[11]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 5. 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.

to parental background declined afterwards, and most sharply in occupations that largely adopted computer-based technologies.

Figure 2: 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.

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.[12] 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

[12]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 5, 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.

reduces the returns to parental background in absolute terms because occupation-specific knowledge and networks of the former generation become obsolete 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 are unaffected by technological change or decrease with it. 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 with production function $Y = L_{\alpha,\beta}(\alpha t + \beta)$, 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 $f_t > 0$.[13] 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.[14] 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:

$$\frac{w_{\alpha_0,\beta_0}}{w_{\alpha,\beta}} = \frac{\alpha_0 t + \beta_0}{\alpha t + \beta} \tag{1}$$

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:

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

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

[13] 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.

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

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.[15] This implies that we expect a closing of the wage penalty by parental background conditional on skill in occupations that see a strong adoption of computers, relative to occupations that adopt less computers.

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 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).[16] 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.[17] 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.

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

[16] 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).

[17] 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.

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 do so separately for high-qualified and low-qualified workers to take into account the expected effect heterogeneity discussed above. We estimate the following baseline equation:

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

where $Tech_{jt-3}$ 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 based on the trends observed in Figure 1.[18] Parental background PB is zero for workers with high-educated parents and one for workers with low-educated parents. Hence, in equation (3) 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 technology use 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 technology use 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 (3) 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,[19] migration background, a public service indicator, firm size and federal state (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

[18] When using lags of one or five years, the estimates are very similar in size and significance; see Tables B2.4 and B2.5 in the Appendix B.2.

[19] 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.

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.[20]

We further extend the analysis by including occupation fixed effects, as there might be unobserved occupational characteristics that are correlated with the technology level in occupations and occupation-specific wage penalties by parental background. After adding occupation fixed effects, $PB \times Tech$ captures the differential within-occupation wage returns to technological change for individuals with low versus high-educated parents. However, endogenous sorting across occupations, 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.

The role of unobserved skills. Our theoretical model predicts a 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.[21]

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. 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

[20]The educational expansion leads (1) to a decrease in the share of workers with low-educated parents and (2) to an increase in the share of high-qualified workers. It thus changes the size and composition of the two qualification groups. Figure B1.6 in the Appendix B.1 plots changes in group sizes based on our data.

[21]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.

endogenous switches into 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.[22]

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 for an occupation, the interaction between PB and time controls for such supply shifts. However, supply shifts could differ across occupations and give rise to a reverse causality issue if technological change in an occupation responds to the changing supply of skills. 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 (3) 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.[23] 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 a demand shock from offshoring. Offshoring might be correlated with computer adoption and might at the same time change the demand for skills, thus potentially affecting workers differently depending on their parental background. In particular, offshoring raises the demand for skills, similar to computerization (Becker et al., 2013). If tasks that are susceptible to offshoring overlap with tasks that are susceptible to computerization, as suggested by Blinder & Krueger (2013), our IV strategy will thus identify the causal effect of initial task shares on the returns to parental background that operates via both technology and offshoring, which are ex-

[22]If the decision to stay in technology-adopting occupations is related to parental background, the specification with spell-fixed effects might still suffer from this remaining bias. Yet, in the data we do not find evidence for this: Based on a regression equivalent to equation (3) using occupational tenure as the dependent variable, there is no significant effect of the interaction between technology and parental background on occupational tenure.

[23]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.

pected 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, but by computer-driven technological change which was particularly strong in that time period.

Other demand shocks that change the wage penalty are controlled for by PB and 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.[24]

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 in Figure 1.[25] We estimate the following equation:

$$\Delta Y_{j\tau} = \delta_1 \Delta Tech_{j\tau} + \delta_2 Z_{j\tau} + d_\tau + u_{j\tau}. \quad (4)$$

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

[24]Indeed, additionally controlling for the size of occupational employment in equation (3), does not affect the results, see Table B2.3 in the Appendix B.1.

[25]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.

$Z_{j\tau}$. 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 (3). Our main parameter of interest is the coefficient α_3 on the interaction between technology and parental background. This coefficient measures the additional returns to technological change for workers with low-educated parents compared to those with high-educated parents. Table 1 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 8% less, on average, than their counterparts with high-educated parents. Among low-qualified workers, we find a similar wage penalty of 7%. Furthermore, individuals in occupations with more widespread technology use earn higher wages. In particular, occupations with a ten percentage points higher use of technology pay 2.4% (1.6%) higher wages for high-qualified (low-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 more widespread technology use. A ten percentage point increase in technology use is associated with 0.8% (1.1%) higher wages, depending on the individual's own qualification.

Adding parental background-specific time trends in column (2) to pick up confounding time trends provides comparable results.[26] Hence, confounding background-specific time

[26]Figure B2.1 in Appendix B.2 visualizes the coefficients corresponding to the wage penalty by parental background over time.

Table 1: Wage Returns

	(1)	(2)	(3)	(4)	(5)	(6)
High-qualified						
Low PB	-0.08***					
	(0.02)					
Tech	0.24***	0.22***	0.12*	0.17*	0.06	0.09
	(0.07)	(0.08)	(0.06)	(0.09)	(0.11)	(0.14)
Low PB × Tech	0.08**	0.10*	0.08*	0.07	0.20**	0.23*
	(0.03)	(0.06)	(0.05)	(0.05)	(0.09)	(0.14)
Observations	29674	29674	29674	29674	27478	27478
F-Stat Tech				37.2		41.2
F-Stat LPB x Tech				64.3		39.8
Low-qualified						
Low PB	-0.07***					
	(0.02)					
Tech	0.16**	0.16**	-0.02	0.01	0.17	0.45***
	(0.08)	(0.08)	(0.05)	(0.08)	(0.15)	(0.16)
Low PB × Tech	0.11***	0.10**	0.10*	0.09	0.01	-0.21
	(0.04)	(0.05)	(0.05)	(0.07)	(0.14)	(0.16)
Observations	57513	57513	57513	57513	53135	53135
F-Stat Tech				18.7		45.5
F-Stat LPB x Tech				35.6		26.0
PB x Year		Yes	Yes	Yes	Yes	Yes
Occ. FE			Yes	Yes		
Spell FE					Yes	Yes

Notes: Dependent variable: Individual log wage. Controls include 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

trends related, for instance, to the overall increase in the share of workers with high-educated parents seem to play a minor role.

Column (3) further controls for unobserved time-constant occupation characteristics by adding occupation fixed effects. Hence, the estimates on technology and its interaction with parental background show the wage growth related to changes in technology use within occupations. Most notably, adding occupation fixed effects has a substantial effect on the coefficient of technology, α_2, which drops from 0.22 to 0.12 for high-qualified workers, and from 0.16 to near zero for low-qualified workers. It seems that, in general, occupations with higher technology *levels* tend to be high-wage occupations. An *increase* in the use of technology within an occupation, however, only comes with moderate wage growth for high-qualified workers, and no wage growth at all for low-qualified workers. Importantly, we still find an additional wage premium of technology adoption for high-qualified workers with low-educated parents of 0.8% associated with a ten percentage point increase in technology. For low-qualified workers the point estimate is 1.0%.

In column (4), 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 sorting of individuals into occupations where selection is based on unobservable skills. Column (5) thus shows the results of the specification including spell-fixed effects (i.e. individual-by-occupation fixed effects). Column (6) 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 identification from any sorting into occupations.

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 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.[27] 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% corresponds to

[27]Figure B2.2 in Appendix B.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.

2.3% which is roughly comparable to the average annual premium for an additional year of work experience.[28]

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 (5) of the joint estimation in Table 1, the returns to technology adoption become larger for low-qualified workers with high-educated parents, and increase substantially when adopting the IV in column (6). 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. Importantly, we show that this effect has not reversed since these computer-based technologies became mainstream practice in the 2000s, by conducting the same analysis for 1999-2012 (see Table B2.2 in the Appendix B.2). This indicates that the wage penalty by parental background has remained at a consistently low level even after the new technologies became mature and usable by everyone.

Robustness. To test the robustness of our results we perform several additional analyses, shown in Appendix B.2. 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 B2.3. This is not surprising, since occupation-level technological change and employment growth are only mildly correlated, see Figure B2.3.

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

In Tables B2.4 and B2.5 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 B2.6, 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 B2.7 provides the corresponding first stages for our main specification and the alternative IV specification. In Table B2.8, we include individuals with wages in the 99th and 1st wage percentile which were previously excluded.

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-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).

If technological change reduces such 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.[29] Note, that differences in occupational tenure by parental background are not endogenously affected by technological change in the data.[30]

We build on specification (3) from Table 1. 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

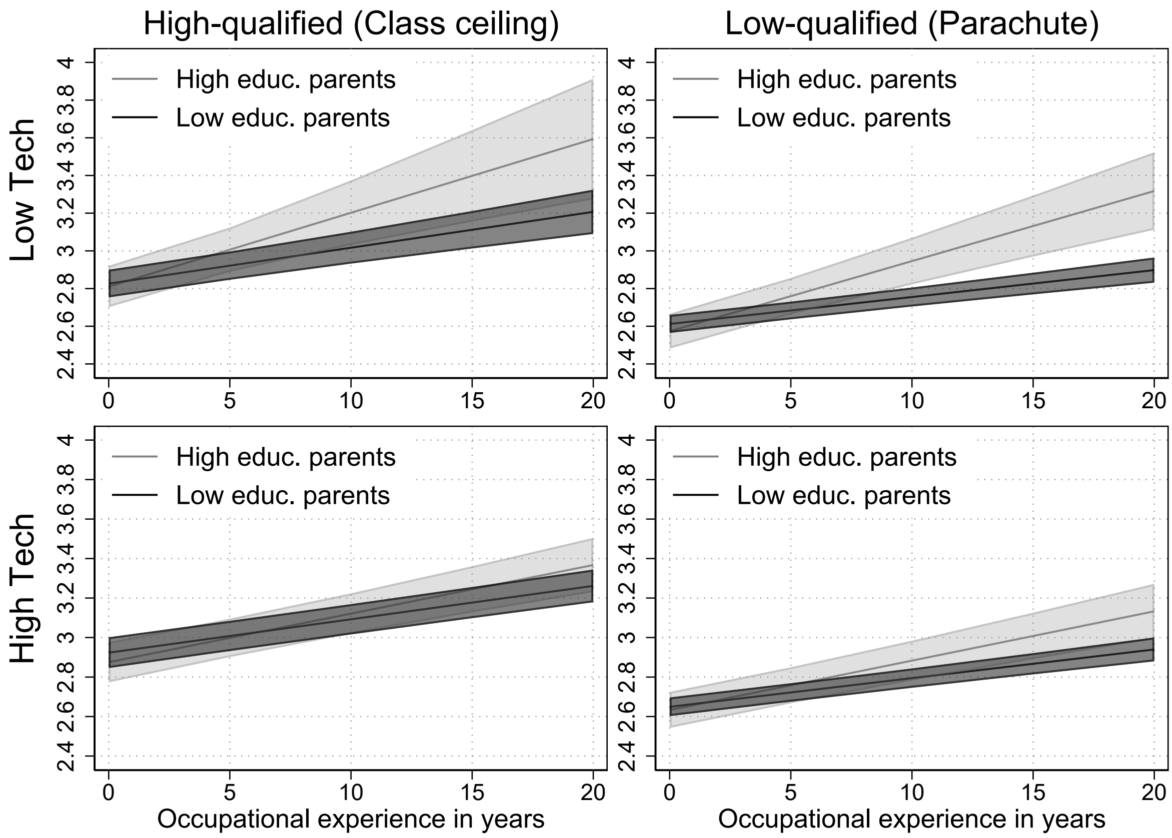
[29]To construct occupational experience, we rely on individuals for which we observe the period they enter an occupation, either because they are new labor market entrants or because they switch occupations. We set occupational experience to zero in the year the individuals enters an occupation, and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

[30]As mentioned above, the interaction effect between technology and parental background is not significant for occupational tenure.

as identified in specification (5) and the potential wage gains due to sorting of workers into technology-adopting-jobs caused by reduced entry barriers. Specification (3) encompasses both mechanisms, including the effect driven by improved employment opportunities.[31]

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 3: 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 1. 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 3 shows the results of this exercise separately for high-qualified and low-qualified workers.[32] The analysis highlights three interesting patterns. First, workers

[31] Since the results based on specification (3) may be affected by unobservable skills, we also compare the results to those based on specification (5) that, as a caveat, abstract from gains related to improved employment opportunities.

[32] A fully flexible specification of experience is included as Figure B2.4 in Appendix B.2. Since we find that wages develop almost linearly with occupational experience, we simplify the analysis assuming a lin-

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.[33] Second, in occupations with low levels of technology (upper graphs in Figure 3), 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. We relate this to reasons put forward in the literature by studying the probability of reaching a management position within an occupation over experience (Figure B2.6 in the Appendix B.2). We confirm that 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. We cannot establish a similar result for low-qualified workers since, generally, they do not have any corresponding management function. Third, in occupations with higher levels of technological change (lower graphs in Figure 3) both the slope of the experience-earnings profile and the wages are very similar among workers with advantaged and disadvantaged background. Likewise, for high-qualified workers, the probability of reaching management positions becomes similar for all workers independent of parental background. Thus, more equal promotion opportunities might be the underlying mechanism translating into more equal wage profiles over experience.

Figure B2.7 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

ear experience-earnings profile. In addition, controlling for age does not change the results qualitatively; see Figure B2.5.

[33] 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).

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 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.

4.2 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 shift 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 (4) 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 1: 1986-1992, 1992-1999, 1999-2005 and 2005-2012.[34]

Table 2 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.[35] 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.[36]

[34] Our results are robust to different specifications of these periods (see Tables B3.1 and B3.2 in Appendix B.3).

[35] These confidence bands are more conservative compared to using the cluster robust sandwich estimator, see Table B3.3 in Appendix B.3.

[36] Without weights, i.e. when giving the same importance to each occupation, the estimates change

Table 2: 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 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).

in size and decrease in precision, but are mainly consistent with the main analysis (see Table B3.4 in Appendix B.3).

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.[37] 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 Appendix B.3. In particular, we verify that neither the quantity nor length of the stacked periods,[38] nor the specification of the IV,[39] nor the occupation weights,[40]

[37]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.

[38]Regressions based on three stacked periods of eight years each (Table B3.1) or based on five stacked periods of five years each (Table B3.2) also find significantly positive employment effects for high-qualified workers, especially in the 1990s, and no employment effects for low-qualified workers.

[39]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 B3.5 for the second stage results and Table B3.6 for the first stage results).

[40]When assigning the same weight to each occupation, most coefficients decrease in significance but the direction and magnitude remains very similar (see Table B3.4).

nor outlier[41] 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.

5 Contribution of Technological Change for Equality of Labor Market Opportunities

In the previous section, we focused on the effect of technological change on employment and wage opportunities within qualification groups. In this section, we focus on the overall wage penalty, i.e. the wage penalty by parental background across both qualification groups. This overall wage penalty declined from 18% in 1989 to 12% in 2012 (see Figure B4.1 in Appendix B.4). To determine to which extent the disappearance of the wage penalties by parental background *within qualification groups* contributed to this decline, we first decompose the change in the overall wage penalty into changes in the qualification-specific wage penalties, changes in educational attainment and changes in the returns to education in Section 5.1. In a second step, in Section 5.2 we decompose changes in the qualification-specific wage penalties to inspect the relevance of technological change as compared to other factors. Taken together, these two steps allow us to assess the contribution of technological change for narrowing the overall wage penalty by parental background in Germany over the last few decades.

5.1 Overall Wage Opportunities

A decline in the overall wage penalty may be due to four channels: (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 less often high-qualified. While Section 4 focused

[41] In Table B3.7, we include occupation-year observations with employment shares 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 excluded. Results remain by and large the same. However, there is some evidence for positive employment effects for the low-qualified as well.

on channels (i) and (ii), we now compare their importance to that of the other two channels.

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, $\tau \in (1989, 2012)$:

$$ln(w_i) = \alpha + \beta PB_i + \gamma E_i + \delta PB_i \times E_i + \epsilon_i \tag{5}$$

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:

$$\Delta ln(w_\tau) = ln(\overline{w_\tau}^{PB=1}) - ln(\overline{w_\tau}^{PB=0}) = \beta_\tau + \gamma_\tau \overline{E_\tau}^{PB=1} - \gamma_\tau \overline{E_\tau}^{PB=0} + \delta_\tau \overline{E_\tau}^{PB=1} \tag{6}$$

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:

$$\begin{aligned}
&\Delta\Delta ln(w) = \Delta ln(w_t) - \Delta ln(w_s) && (7)\\
&= (\beta_t + \delta_t - \beta_s - \delta_s)\bar{E}_s^{PB=1} && \Delta \text{ Wage Penalty High-qualified (i)}\\
&+ (\beta_t - \beta_s)(1 - \bar{E}_s^{PB=1}) && \Delta \text{ Wage Penalty Low-qualified (ii)}\\
&+ \gamma_s[(\bar{E}_t^{PB=1} - \bar{E}_s^{PB=1}) - (\bar{E}_t^{PB=0} - \bar{E}_s^{PB=0})] + \delta_s(\bar{E}_t^{PB=1} - \bar{E}_s^{PB=1}) && \\
& && \Delta \text{ Educ. Upgrading (iii)}\\
&+ (\gamma_t - \gamma_s)(\bar{E}_s^{PB=1} - \bar{E}_s^{PB=0}) && \Delta \text{ Returns to Education (iv)}\\
&+ (\delta_t + \gamma_t - \delta_s - \gamma_s)(\bar{E}_t^{PB=1} - \bar{E}_s^{PB=1}) - (\gamma_t - \gamma_s)(\bar{E}_t^{PB=0} - \bar{E}_s^{PB=0}) && \text{Interactions (v)}
\end{aligned}$$

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)).[42] The fourth term (channel (iv)) accounts for changes in the wage

[42] Workers with low-educated parents may benefit differently from educational upgrading relative to workers with high-educated parents for two reasons, see equation (7): 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 (7) 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.

Table 3: 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	$1.63^{\dagger}$	$5.79^{\ddagger}$	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 (7) 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 +0.09. ‡ - the corresponding change in regression coefficients is +0.07. Confidence bands based on 1,000 bootstrap replications of the coefficient combinations.

penalty due to changing returns to education, which materialize due to the differences in 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 3 displays the decomposition terms of the change in the overall wage penalty between 1989 and 2012 according to equation (7) 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 population share of high-qualified workers was much smaller than the share of low-qualified workers (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.

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.

5.2 Qualification-Specific Wage Opportunities

To test the contribution of technological change to the decline in the qualification-specific wage penalties, we decompose the changes in the qualification-specific wage penalties based on the coefficients from specification (3) in Table 1 with occupation fixed effects. We do so because we are interested in wage opportunities that cover both the effect of technological change on differential wage returns and indirect effects on wages stemming from reduced entry hurdles into tech-jobs. Again, we compare these results to those based on specification (5) from Table 1 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 (3):

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

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 (3)).

The average within-qualification group log wage penalty in period τ is given by

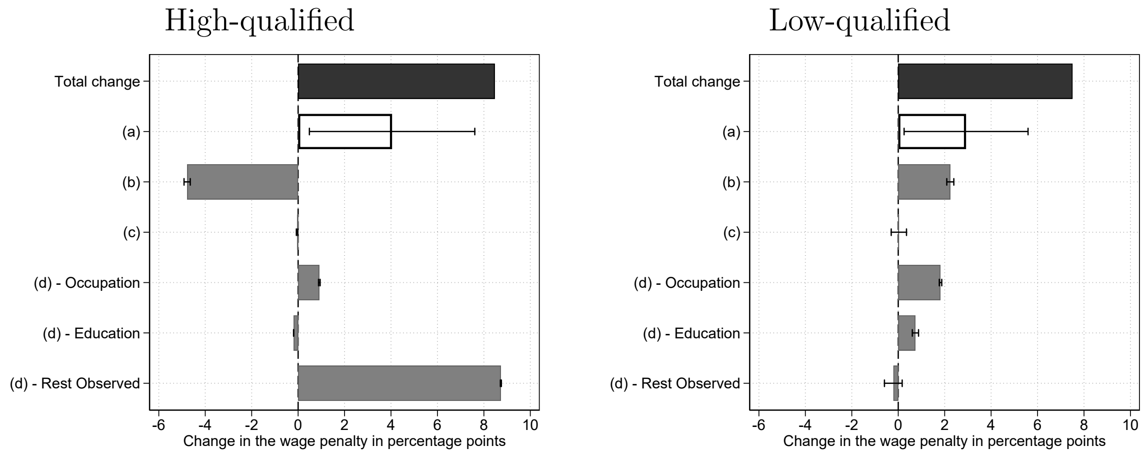
$$\begin{aligned}\Delta ln(w_\tau) &= ln(\overline{w}_\tau^{PB=1}) - ln(\overline{w}_\tau^{PB=0}) \\ &= \overline{Tech}_{\tau-3}^{PB=1}\beta + \gamma_\tau + (\overline{Tech}_{\tau-3}^{PB=1} - \overline{Tech}_{\tau-3}^{PB=0})\delta + (\overline{X}_\tau^{PB=1} - \overline{X}_\tau^{PB=0})\epsilon.\end{aligned}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

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

Figure 4: 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 (3) in Table 1. 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.

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 4 illustrates the results of this decomposition separately for high-qualified and low-qualified workers. 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 occupations 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 (3) in Table 1 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 (5) 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 (5) are shown in Figure B4.1 in Appendix B.4. 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.[43] For low-qualified workers, in contrast, the pure wage effect of channel (a) declines to zero when including spell-fixed effects.

To summarize, in the previous subsection we concluded that the reductions in the qualification-specific wage penalties were a major driver of the decline of the overall wage penalty between 1989 and 2012. The findings in this subsection further suggest that, for high-qualified workers, this 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.

6 Conclusions

A favorable parental background not only affects the chances of attaining a higher level of education, but also directly influences labor market opportunities, for example via job referrals, nepotism, and occupation-specific knowledge. This implies that wage penalties for workers with a disadvantaged parental background exist even relative to workers with the same qualifications.

We find that among high-qualified workers in Germany, this wage penalty – i.e. the difference in average wages between workers with high-educated parents and their peers with low-educated parents – was about 8% during the 1980s, but virtually disappeared during the 1990s. Our results show that this decline in the wage penalty by parental background is consistently linked to the rapid adoption of new, computer-controlled technologies on the German labor market during this time. This is because the increase in returns to skills associated with technological change also leads 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 lower 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

[43]For high-qualified workers with low-educated parents improved access to technology-intensive occupations is relevant (see Section 4.2). 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 B4.1 suggests.

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.

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.

We further establish that these technology-driven gains in equality of opportunity among high-qualified workers contributed to a declining overall wage penalty by parental background. Without technological progress, *ceteris paribus*, the wage penalty by parental background would even have increased during the last three decades, owing to a rising wage inequality between high-qualified and low-qualified workers that is not compensated by a relative educational upgrading of workers from a disadvantaged social background.

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.

Finally, whether the opportunity-enhancing effects of computerization that we find in this paper also apply to other disadvantaged groups such as migrants and whether newer waves of technological change such as the adoption of artificial intelligence exert similar effects remain questions for future research.

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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).[44] 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.

[44] 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

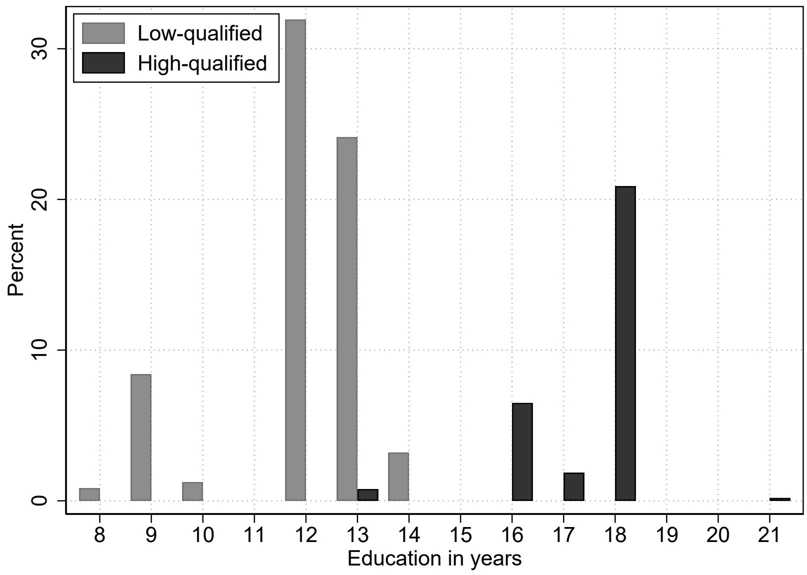
Notes: KldB 1992 occupations (2 digits, column 6) aggregated to 62 occupations (column 1) to make them comparable across all three datasets. N: Number of individual observations in the SOEP. Tech 1986 (2012): Share of individuals mainly working with new technologies in the QCS in 1986 (2012). Δ Tech: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

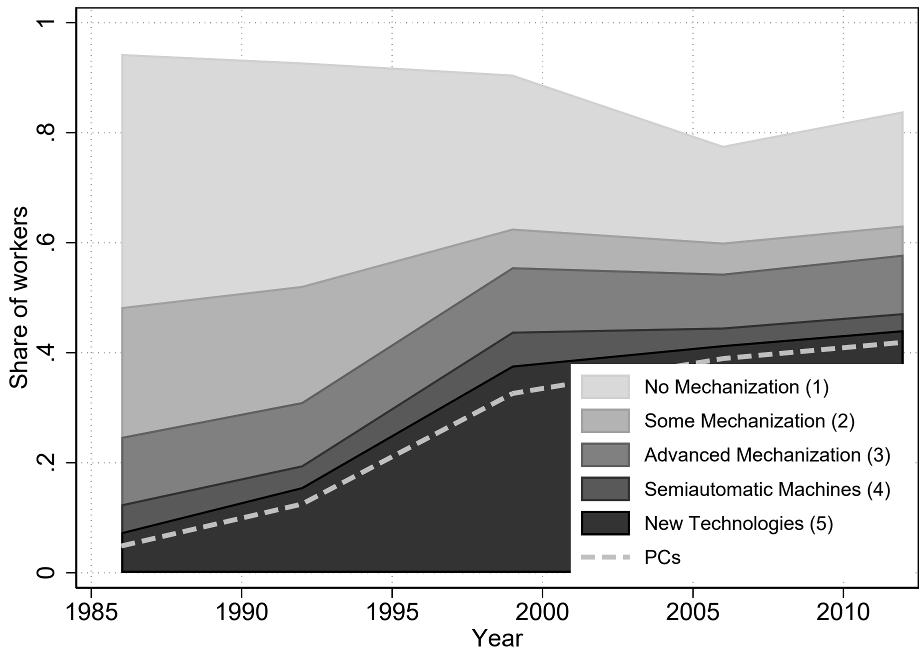
Notes: † - (Technical) college or university studies with integrated periods of practical work at companies. Education refers to the highest level of formal education accomplished and is time-constant (the maximum education ever attained) to minimize reporting errors.

Figure B1.1: Education in Years by Qualification Groups



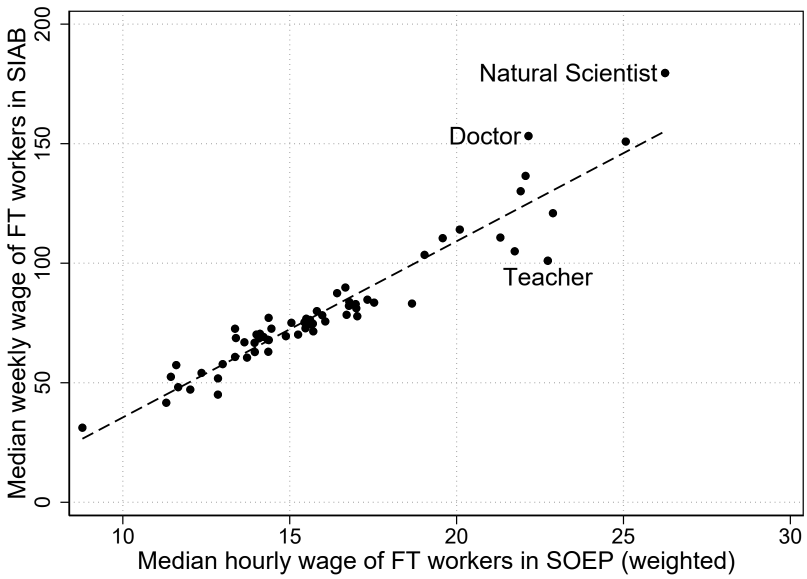
Notes: Share of observations by years of education and qualification groups. Observations weighted by representative SOEP weights, West Germany only.

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.

Figure B1.3: Wage Accuracy SOEP



Notes: Using weights provided by the SOEP to achieve representativeness. FT=full-time. For each occupation the mean over all years is shown.

Figure B1.4: Occupational Accuracy SOEP

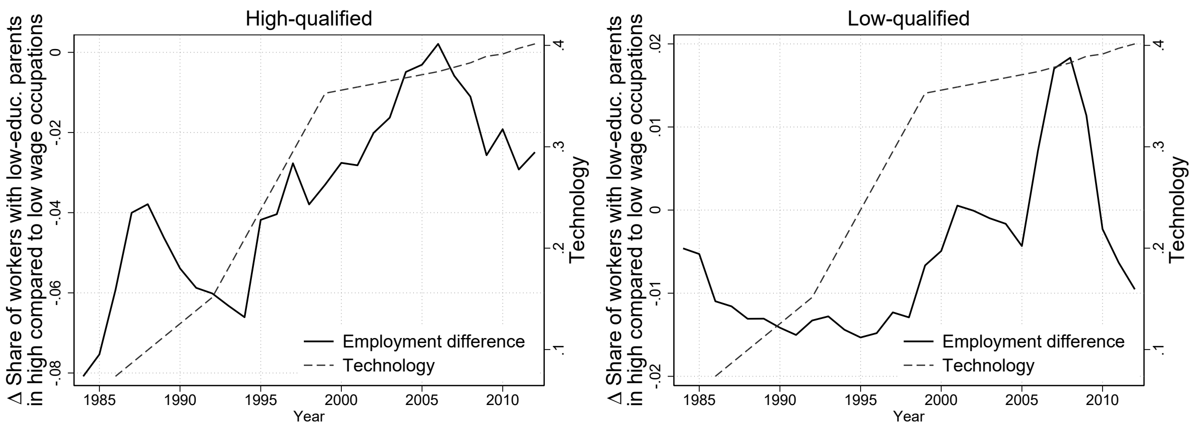
Notes: Without using weights (left panel) and using weights (right panel) provided by the SOEP to achieve representativeness. For each occupation the mean over all years is shown.

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 B1.5: Employment Shares by Parental Background: Time Trend



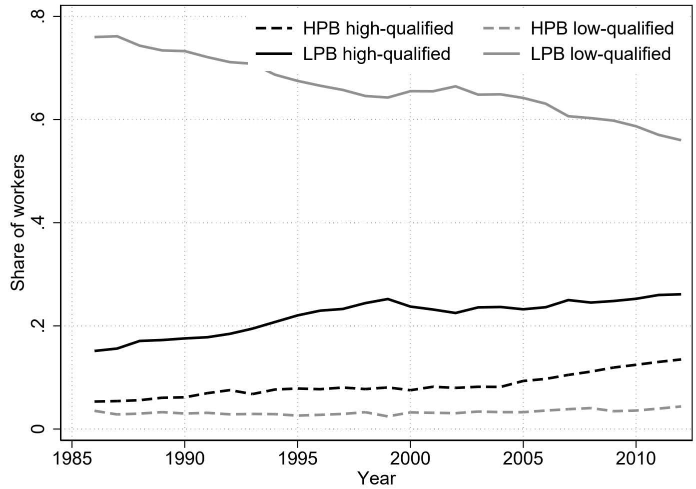
Notes: Solid line: Difference in the share of high-qualified (low-qualified) individuals with low-educated parents working in occupations earning an above median wage and the share of high-qualified (low-qualified) individuals with low-educated parents working in occupations earning a below median wage. 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.

Figure B1.6: Supply of Worker Types

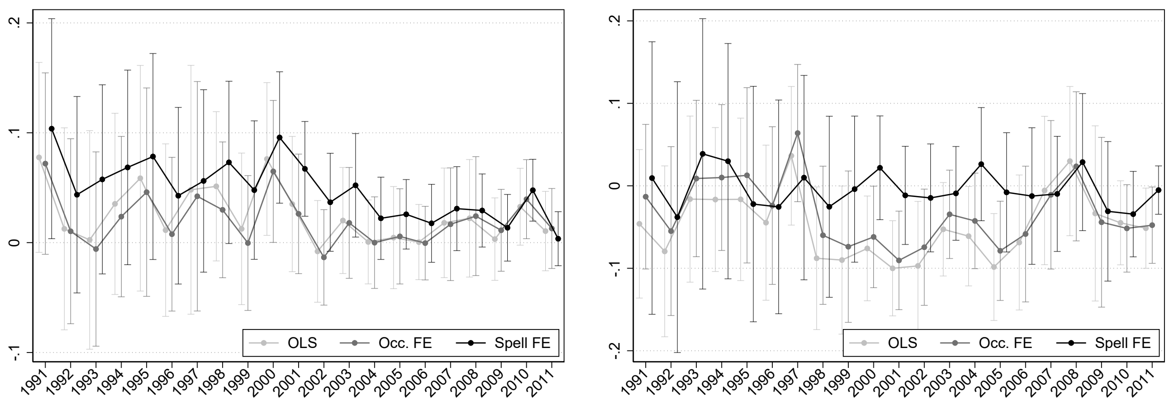


Notes: Weighted share of individuals observed in the individual dataset by education and parental background.

B.2 Additional Tables and Graphs for Section 4.1

Figure B2.1: Estimate +95% Confidence Intervals of the Coefficient Low PB × Year

High-qualified | Low-qualified



Notes: Coefficients and 95% confidence bands of the dummy variables Low PB × Year for three different specifications of the individual-level log wage regression, corresponding to columns 2, 3 and 5 of Table 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		
Spell FE			Yes	Yes			Yes	Yes

Notes: Dependent variable: Individual log wage. Controls include 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2.2: Wage Effects - Period 1999-2012 Only

	(1)	(2)	(3)	(4)	(5)	(6)
High-qualified						
Low PB	-0.08***					
	(0.02)					
Tech	0.25***	0.24***	0.27**	0.43**	0.18	0.18
	(0.06)	(0.07)	(0.13)	(0.17)	(0.13)	(0.21)
Low PB × Tech	0.08**	0.11*	0.08*	0.05	0.10	0.17
	(0.03)	(0.05)	(0.04)	(0.04)	(0.13)	(0.28)
Observations	29674	29674	22982	22982	20980	20980
F-Stat Tech				14.3		18.9
F-Stat LPB x Tech				62.6		19.3
Low-qualified						
	(1)	(2)	(3)	(4)	(5)	(6)
Low PB	-0.07***					
	(0.02)					
Tech	0.20***	0.21***	0.08	0.22*	0.42	-0.08
	(0.06)	(0.06)	(0.06)	(0.13)	(0.29)	(0.43)
Low PB × Tech	0.11***	0.10**	0.10*	0.10	-0.17	0.35
	(0.04)	(0.05)	(0.05)	(0.07)	(0.30)	(0.44)
Observations	57513	57513	37313	37313	33813	33813
F-Stat Tech				42.9		52.1
F-Stat LPB x Tech				48.8		44.6
PB x Year		Yes	Yes	Yes	Yes	Yes
Occ. FE			Yes	Yes		
Spell FE					Yes	Yes

Notes: Dependent variable: Individual log wage. Controls include gender, migration background, migration background × gender, parental background, five age categories, 6 dummies on labor market experience, education dummies, a public service indicator, four firm size categories, 9 federal state dummies, 62 occupation 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2.3: Wage Effects - Controlling for Occupation Size

	(1)	(2)	(3)	(4)	(5)	(6)
High-qualified						
Low PB	-0.08***					
	(0.02)					
Tech	0.25***	0.24***	0.12*	0.17*	0.06	0.08
	(0.06)	(0.07)	(0.06)	(0.09)	(0.11)	(0.14)
Low PB × Tech	0.08**	0.11*	0.08*	0.07	0.20**	0.23*
	(0.03)	(0.05)	(0.05)	(0.05)	(0.09)	(0.14)
Observations	29674	29674	29674	29674	27478	27478
F-Stat Tech				39.6		42.9
F-Stat LPB x Tech				64.6		40.7
Low-qualified						
	(1)	(2)	(3)	(4)	(5)	(6)
Low PB	-0.07***					
	(0.02)					
Tech	0.20***	0.21***	-0.02	0.03	0.17	0.45***
	(0.06)	(0.06)	(0.05)	(0.08)	(0.15)	(0.16)
Low PB × Tech	0.11***	0.10**	0.10*	0.09	0.01	-0.21
	(0.04)	(0.05)	(0.05)	(0.07)	(0.14)	(0.16)
Observations	57513	57513	57513	57513	53135	53135
F-Stat Tech				21.0		43.9
F-Stat LPB x Tech				35.9		26.6
PB x Year		Yes	Yes	Yes	Yes	Yes
Occ. FE			Yes	Yes		
Spell FE					Yes	Yes

Notes: Dependent variable: Individual log wage. Controls include occupation size (the share of workers employed in an occupation), 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2.4: Wage Effects - Technology Lagged by One Year

High-qualified						
	(1)	(2)	(3)	(4)	(5)	(6)
Low PB	-0.07***					
	(0.02)					
Tech	0.24***	0.21***	0.08	0.12	0.05	0.02
	(0.07)	(0.08)	(0.06)	(0.09)	(0.10)	(0.14)
Low PB × Tech	0.06**	0.10*	0.08*	0.07	0.17*	0.28*
	(0.03)	(0.05)	(0.05)	(0.05)	(0.09)	(0.16)
Observations	30790	30790	30790	30790	28521	28521
F-Stat Tech				38.1		43.2
F-Stat LPB x Tech				68.6		40.8
Low-qualified						
	(1)	(2)	(3)	(4)	(5)	(6)
Low PB	-0.07***					
	(0.02)					
Tech	0.16**	0.16**	-0.04	-0.02	0.14	0.41***
	(0.07)	(0.07)	(0.05)	(0.08)	(0.13)	(0.14)
Low PB × Tech	0.10***	0.09**	0.09*	0.09	0.04	-0.17
	(0.03)	(0.05)	(0.05)	(0.06)	(0.12)	(0.13)
Observations	61778	61778	61778	61778	57154	57154
F-Stat Tech				19.1		42.5
F-Stat LPB x Tech				36.8		22.7
PB x Year		Yes	Yes	Yes	Yes	Yes
Occ. FE			Yes	Yes		
Spell FE					Yes	Yes

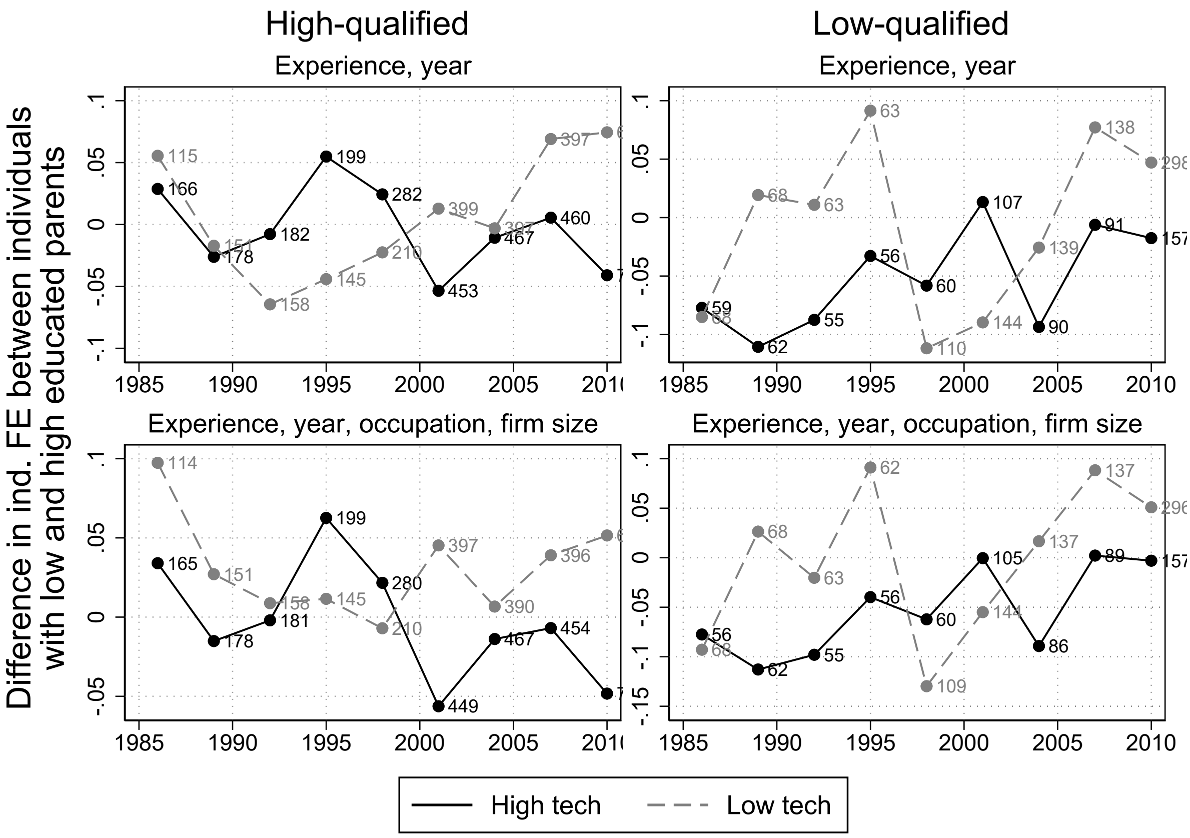
Notes: Dependent variable: Individual log wage. Controls include gender, migration background, migration background × gender, five age categories, six dummies on labor market experience, education dummies, a public service indicator, four firm size categories, nine federal state dummies and 27 year dummies.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

Table B2.5: Wage Effects - Technology Lagged by Five Years

	(1)	(2)	(3)	(4)	(5)	(6)
High-qualified						
Low PB	-0.08***					
	(0.02)					
Tech	0.25***	0.23***	0.11	0.17*	0.03	0.12
	(0.07)	(0.08)	(0.07)	(0.09)	(0.12)	(0.16)
Low PB × Tech	0.08**	0.11*	0.09*	0.07	0.23**	0.21
	(0.03)	(0.06)	(0.05)	(0.05)	(0.10)	(0.15)
Observations	28439	28439	28439	28439	26291	26291
F-Stat Tech				37.5		41.4
F-Stat LPB x Tech				62.0		39.4
Low-qualified						
	(1)	(2)	(3)	(4)	(5)	(6)
Low PB	-0.07***					
	(0.02)					
Tech	0.17**	0.17**	-0.01	0.03	0.15	0.39**
	(0.08)	(0.08)	(0.05)	(0.08)	(0.15)	(0.17)
Low PB × Tech	0.11***	0.11**	0.11**	0.09	0.02	-0.18
	(0.04)	(0.05)	(0.05)	(0.07)	(0.14)	(0.18)
Observations	53043	53043	53043	53043	48917	48917
F-Stat Tech				18.6		42.4
F-Stat LPB x Tech				34.4		23.0
PB x Year		Yes	Yes	Yes	Yes	Yes
Occ. FE			Yes	Yes		
Spell FE					Yes	Yes

Notes: Dependent variable: Individual log wage. Controls include 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 B2.2: Negative Selection



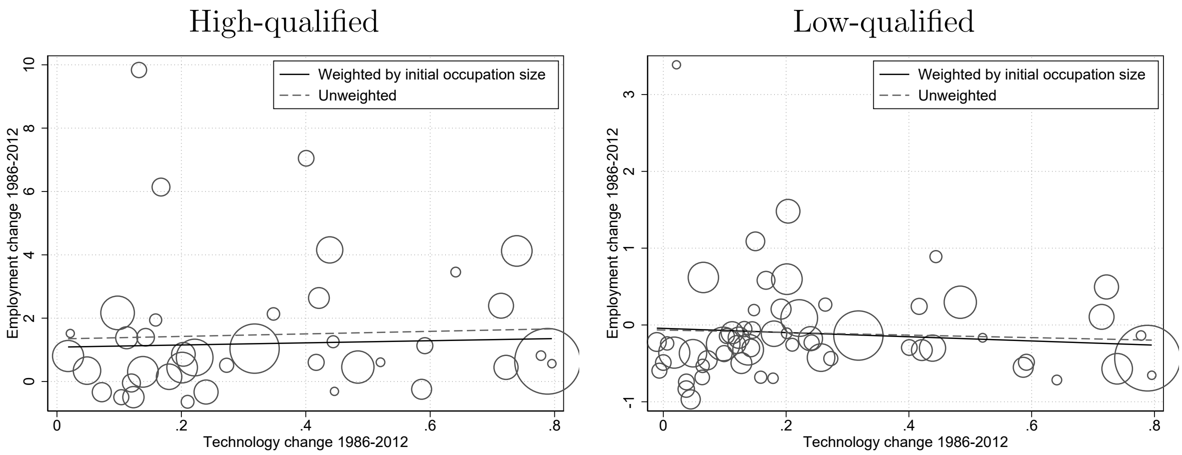
Notes: Difference between the mean individual fixed effects between high-qualified (low-qualified) males with low versus high-educated parents. Based on four separate regressions for males with (1) low educ. parents, low technology, (2) low educ. parents, high technology, (3) high educ. parents, low technology, and (4) high educ. parents, high technology. Control variables as indicated above each figure. High tech: increase in the share of new technologies between 1986 and 2012 in the upper quartile of the occupational distribution. Low tech: increase in the share of new technologies between 1986 and 2012 in the lower three quartiles. Value labels indicate the number of observations the regression of the subgroup (high versus low-educated parents) with fewer observations relies on. Weighted by representative SOEP weights, West Germany only.

Table B2.6: Wage Effects - Alternative Instruments - 2nd Stage

	High-qualified			
	Occup. FE		Spell FE	
	(1) Combined IV	(2) Separate IVs	(3) Combined IV	(4) Separate IVs
Tech	0.17*	0.16*	0.09	0.04
	(0.09)	(0.08)	(0.14)	(0.15)
Low PB × Tech	0.07	0.07	0.23*	0.30**
	(0.05)	(0.05)	(0.14)	(0.15)
Observations	29674	29674	27478	27478
F-Stat Tech	37.2	31.3	41.2	19.2
F-Stat LPB x Tech	64.3	53.0	39.8	35.0
	Low-qualified			
	Occup. FE		Spell FE	
	(1) Combined IV	(2) Separate IVs	(3) Combined IV	(4) Separate IVs
Tech	0.01	-0.01	0.45***	0.27*
	(0.08)	(0.07)	(0.16)	(0.16)
Low PB × Tech	0.09	0.09	-0.21	-0.05
	(0.07)	(0.07)	(0.16)	(0.16)
Observations	57513	57513	53135	53135
F-Stat Tech	18.7	24.7	45.5	49.4
F-Stat LPB x Tech	35.6	59.9	26.0	27.3

Notes: Dependent variable: Individual log wage. Combined 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. Separate IVs: One instrument defined as the initial task intensity of routine cognitive tasks multiplied by the aggregate technology level across all occupations but individual's own and the second instrument defined as the non-routine analytic tasks intensity multiplied by the aggregate technology level across all occupations but individual's own. Standard errors are clustered on the occupational and individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure B2.3: Employment and Technology Growth of Occupations 1986 to 2012



Notes: Relative employment change (difference in absolute employment between 1986 and 2021 divided by the initial absolute employment in 1986 based on the SOEP using representative weights) and increase in new technologies in percentage points over the same time period. West Germany only, own calculations.

Table B2.7: Wage Effects - Alternative Instruments - 1st Stage

	High-qualified			
	Occup. FE		Spell FE	
	(1) Combined	(2) Separate	(3) Combined	(4) Separate
Analytic + routine cog.	2.74***		2.55***	
	(0.34)		(0.31)	
Routine cognitive		3.35***		2.99***
		(0.89)		(0.77)
Analytic		1.86*		1.93**
		(1.06)		(0.84)
Observations	29674	29674	27478	27478

	Low-qualified			
	Occup. FE		Spell FE	
	(1) Combined	(2) Separate	(3) Combined	(4) Separate
Analytic + routine cog.	3.16***		3.21***	
	(0.52)		(0.37)	
Routine cognitive		4.23***		4.54***
		(1.13)		(0.61)
Analytic		0.17		-0.36
		(1.61)		(1.34)
Observations	57513	57513	53135	53135

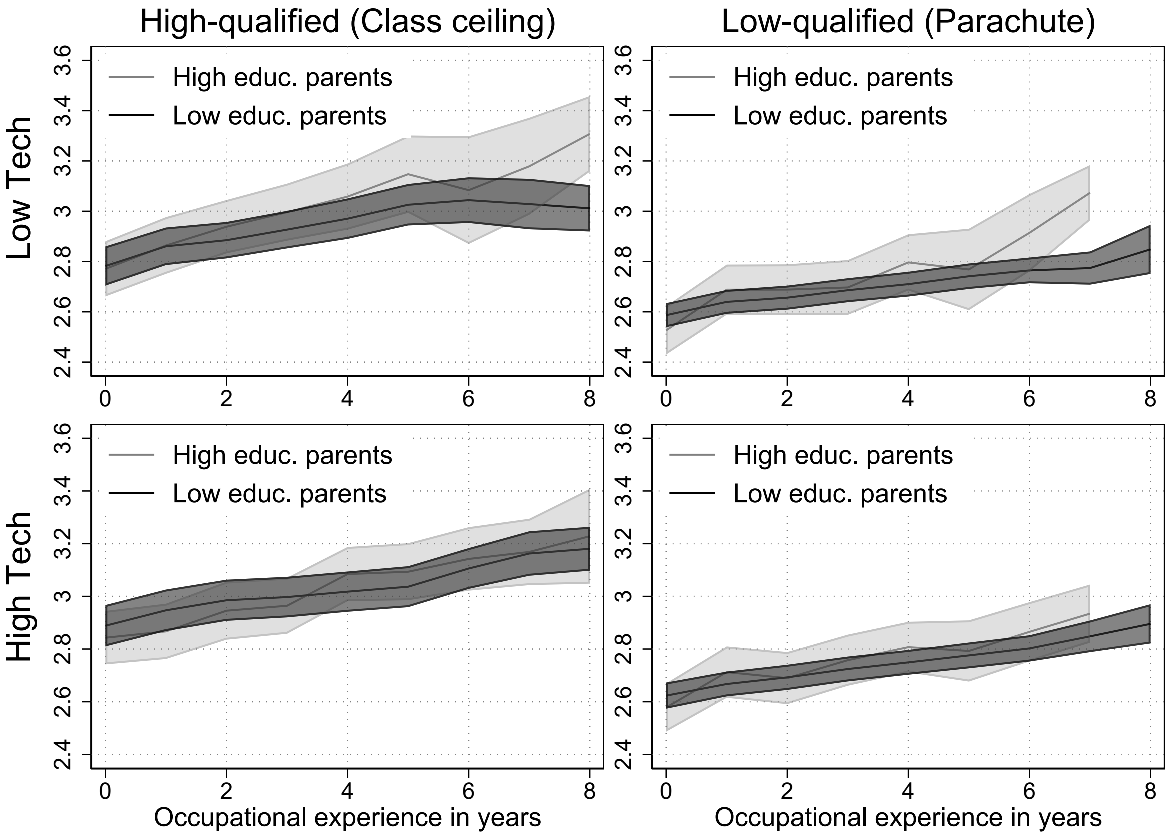
Notes: Dependent variable: Share of new technologies used. First stage results for Table B2.6. Combined IV: sum of the initial task intensity of routine cognitive and non-routine analytic tasks multiplied by the aggregate technology level across all occupations but individual's own. Separate IVs: One instrument defined as the initial task intensity of routine cognitive tasks multiplied by the aggregate technology level across all occupations but individual's own and the second instrument defined as the non-routine analytic tasks intensity multiplied by the aggregate technology level across all occupations but individual's own. Standard errors are clustered on the occupational and individual level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2.8: Wage Effects - Including Outlier

	(1)	(2)	(3)	(4)	(5)	(6)
High-qualified						
Low PB	-0.12***					
	(0.04)					
Tech	0.21***	0.18*	0.09	0.19*	0.08	0.15
	(0.08)	(0.10)	(0.09)	(0.11)	(0.14)	(0.16)
Low PB × Tech	0.10*	0.14	0.11	0.10	0.21*	0.25
	(0.05)	(0.09)	(0.07)	(0.07)	(0.13)	(0.18)
Observations	31146	31146	31146	31146	28963	28963
F-Stat Tech				35.5		41.7
F-Stat LPB x Tech				62.6		41.7
Low-qualified						
	(1)	(2)	(3)	(4)	(5)	(6)
Low PB	-0.07***					
	(0.02)					
Tech	0.15*	0.15*	-0.05	-0.02	0.22	0.50***
	(0.08)	(0.08)	(0.07)	(0.09)	(0.17)	(0.19)
Low PB × Tech	0.12**	0.13*	0.13*	0.14*	-0.04	-0.27
	(0.05)	(0.07)	(0.07)	(0.08)	(0.15)	(0.17)
Observations	58094	58094	58094	58094	53670	53670
F-Stat Tech				18.8		45.5
F-Stat LPB x Tech				36.1		25.2
PB x Year		Yes	Yes	Yes	Yes	Yes
Occ. FE			Yes	Yes		
Spell FE					Yes	Yes

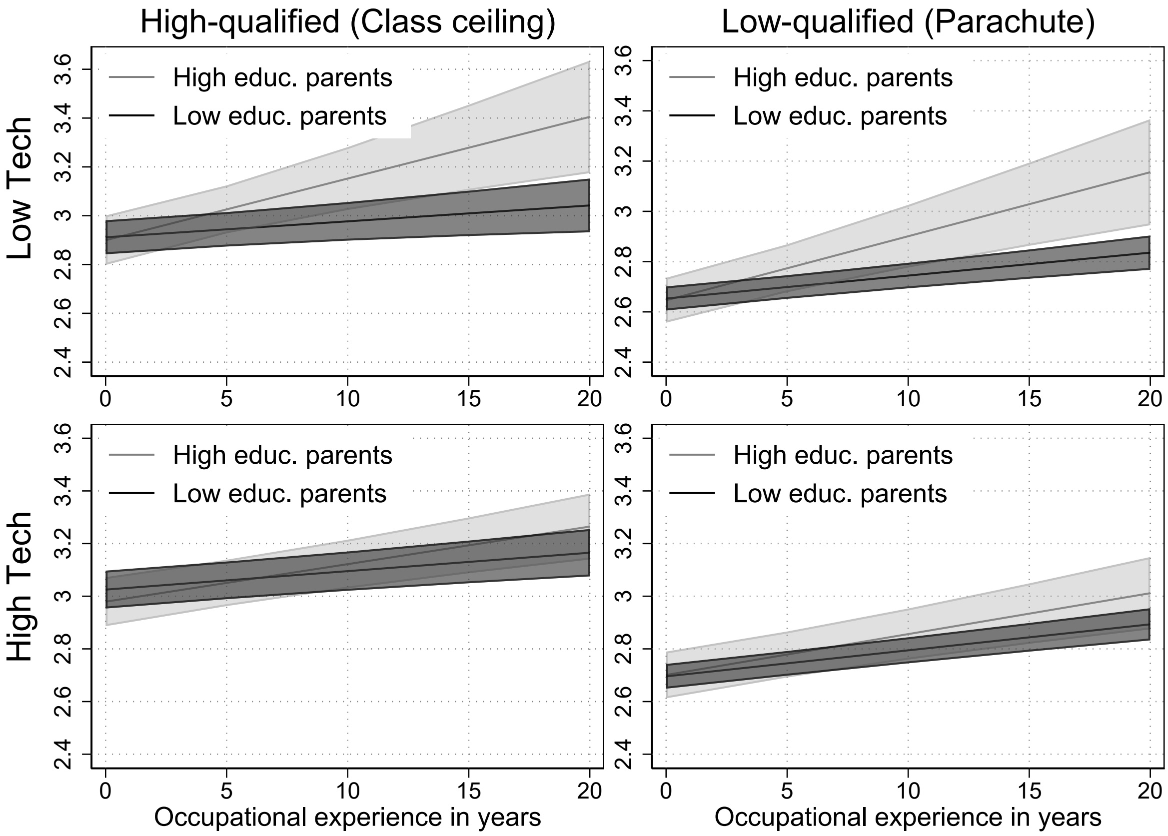
Notes: Dependent variable: Individual log wage. Controls include gender, migration background, migration background × gender, parental background, five age categories, 6 dummies on labor market experience, education dummies, a public service indicator, four firm size categories, 9 federal state dummies, 62 occupation 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure B2.4: Experience-Earnings-Profile - Non-Parametric Experience



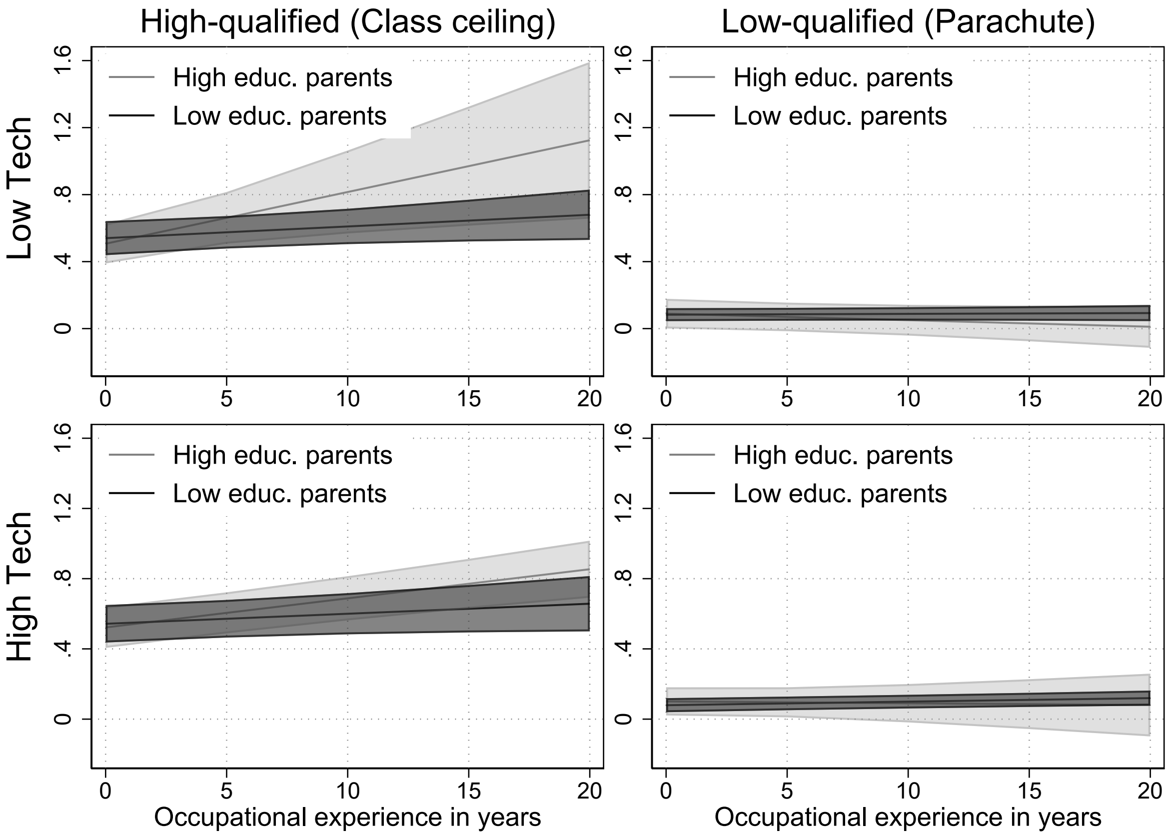
Notes: Predicted individual log wage plus 90% confidence intervals based on an OLS regression with occupational experience (categorical), parental background (binary), technology (linear) and all possible interaction terms on the right hand side, controlling for gender, migration background, migration 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 1. 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 B2.5: Experience-Earnings-Profile - Controlling for Age



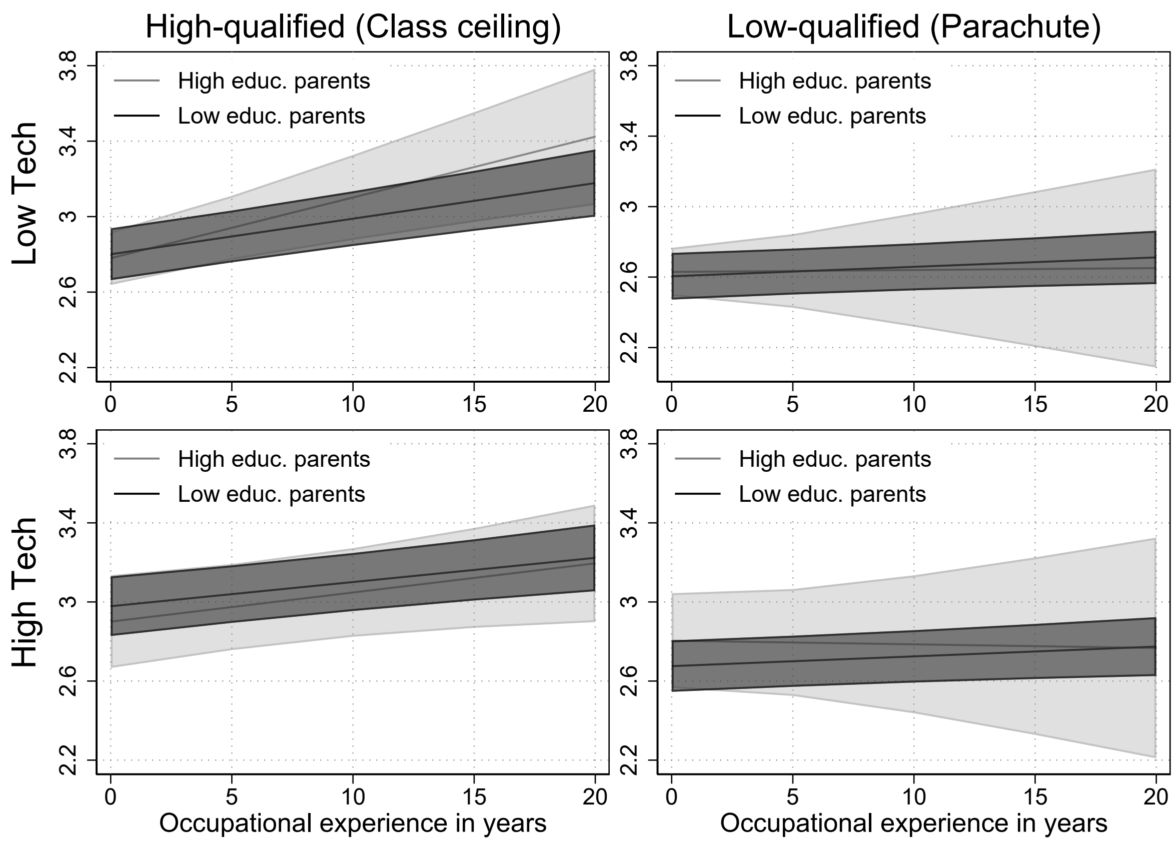
Notes: Predicted individual log wage plus 90% confidence intervals based on an OLS regression with occupational experience (linear), parental background (binary), technology (linear) and all possible interaction terms on the right hand side, controlling for gender, migration background, migration background × gender, education dummies, public service indicator, firm size (4 categories), federal state (10 categories), age (4 categories), 62 occupation and 27 year dummies, corresponding to column (3) in Table 1. 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 B2.6: 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 B2.7: 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 1), 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.

B.3 Additional Tables and Graphs for Section 4.2

Table B3.1: Employment Effects - Long Differences - 3 Stacked Periods

	High-qualified				Low-qualified			
	Baseline		IV	Tasks	Baseline		IV	Tasks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech	0.43*		0.49	0.75**	-0.01		0.07	-0.12
	[-0.11,0.81]		[-0.44,1.47]	[0.05,1.35]	[-0.08,0.09]		[-0.07,0.26]	[-0.34,0.07]
Effect heterogeneity across time periods								
Tech ×								
× 1986-94		-0.11				-0.02		
		[-0.75,0.63]				[-0.12,0.08]		
× 1994-02		0.82*				0.01		
		[-0.05,1.35]				[-0.07,0.10]		
× 2002-10		0.46				0.10		
		[-2.30,2.71]				[-0.24,0.33]		
Effect heterogeneity by initial occupational task content								
× Analytic				2.72				0.25
				[-2.21,7.58]				[-0.30,0.77]
× Interact.				-1.87				0.32
				[-5.47,3.02]				[-0.16,0.88]
Observations	71	71	71	71	154	154	154	154
F-Stat			31.0				20.0	

Notes: Dependent variable: Change in the share of high-qualified workers with low-educated parents among all high-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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3.2: Employment Effects - Long Differences - 5 Stacked Periods

	High-qualified				Low-qualified			
	Baseline		IV	Tasks	Baseline		IV	Tasks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech	0.40**		0.58**	0.45	0.00		0.07	0.03
	[0.00,0.87]		[0.05,1.18]	[-0.27,1.19]	[-0.06,0.08]		[-0.05,0.26]	[-0.17,0.19]
Effect heterogeneity across time periods								
Tech ×								
× 1986-91		-0.06				-0.06		
		[-1.65,0.99]				[-0.23,0.24]		
× 1991-96		0.15				0.04		
		[-0.59,0.96]				[-0.04,0.11]		
× 1996-01		0.91**				-0.02		
		[0.05,1.45]				[-0.17,0.25]		
× 2001-06		0.19				-0.09		
		[-1.02,1.71]				[-0.42,0.15]		
× 2006-11		1.48				0.08		
		[-2.03,4.00]				[-0.18,0.32]		
Effect heterogeneity by initial occupational task content								
× Analytic				-0.02				-0.24
				[-5.34,2.60]				[-1.15,0.51]
× Interact.				0.60				0.11
				[-1.62,4.90]				[-0.59,0.63]
Observations	123	123	123	123	260	260	260	260
F-Stat			36.6				21.7	

Notes: Dependent variable: Change in the share of high-qualified workers with low-educated parents among all high-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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3.3: Employment Effects - Long Differences - Cluster Robust Sandwich Standard Errors

	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
	(0.19)		(0.45)	(0.70)	(0.03)		(0.07)	(0.08)
Effect heterogeneity across time periods								
1986-92 × Tech		0.05				-0.09*		
		(0.26)				(0.05)		
1992-98 × Tech		0.47*				0.05*		
		(0.24)				(0.03)		
1998-05 × Tech		0.68				-0.01		
		(0.85)				(0.07)		
2005-12 × Tech		-0.36				0.19		
		(1.08)				(0.13)		
Effect heterogeneity by initial occupational task content								
Tech × Analytic				3.39**				-0.11
				(1.63)				(0.34)
Tech × Interact.				-3.07**				0.35
				(1.25)				(0.30)
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 workers with low-educated parents among all high-qualified workers. Control variables include the average age, the share of female/foreign/highly educated individuals, the average occupational 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. Standard errors in parentheses clustered on the occupational level using the sandwich estimator. Observations weighted by the employment share in 1986, West Germany only. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3.4: Employment Effects - Long Differences - No Weights

	High-qualified				Low-qualified			
	Baseline		IV	Tasks	Baseline		IV	Tasks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech	0.11		0.62	0.52	0.04*		0.04	0.05
	[-0.42,0.63]		[-0.41,1.64]	[-1.98,3.47]	[-0.01,0.10]		[-0.08,0.15]	[-0.11,0.20]
Effect heterogeneity across time periods								
Tech ×								
× 1986-92		-0.10				-0.01		
		[-1.65,0.77]				[-0.11,0.10]		
× 1992-99		0.18				0.04		
		[-0.45,0.87]				[-0.01,0.09]		
× 1999-05		0.50				0.02		
		[-1.64,3.01]				[-0.11,0.15]		
× 2005-12		-0.88				0.10		
		[-3.68,1.17]				[-0.06,0.41]		
Effect heterogeneity by initial occupational task content								
Tech ×								
× Analytic				2.00				-0.25
				[-1.41,6.72]				[-0.68,0.19]
× Interact.				-4.34				0.27
				[-9.87,0.95]				[-0.36,0.98]
Observations	98	98	98	98	201	201	201	201
F-Stat			37.4				35.6	

Notes: Dependent variable: Change in the share of high-qualified workers with low-educated parents among all high-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 technology level 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. West Germany only. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3.5: Employment Effects - Long Differences - Alternative Instruments - 2nd Stage

	High-qualified		Low-qualified	
	Combined IV	Separate IVs	Combined IV	Separate IVs
	(1)	(2)	(3)	(4)
Tech	0.82	0.56	0.08	0.10
	[-0.15,1.76]	[-0.31,1.47]	[-0.09,0.23]	[-0.05,0.27]
Observations	98	98	201	201
F-Stat	32.5	22.3	24.6	15.3

Notes: Dependent variable: Increase in the share of high-qualified workers with low-educated parents among all high-qualified workers. Combined 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. Separate IVs: one instrument defined as the initial task intensity of routine cognitive tasks multiplied by the aggregate technology level across all occupations but occupation's own and a second instrument defined as the non-routine analytic task intensity 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3.6: Employment Effects - Long Differences - Alternative Instruments - 1st Stage

	High-qualified		Low-qualified	
	(1)	(2)	(3)	(4)
	Combined IV	Separate IVs	Combined IV	Separate IVs
Analytic + routine cog.	2.70***		2.47***	
	(0.47)		(0.50)	
Routine cognitive		3.28***		2.72***
		(0.79)		(0.74)
Analytic		1.13		1.42
		(1.12)		(1.43)
Observations	98	98	201	201

Notes: Dependent variable: Increase in the share of new technologies used. First stage results for Table B3.5. Combined 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. Separate IVs: one instrument defined as the initial task intensity of routine cognitive tasks multiplied by the aggregate technology level across all occupations but occupation's own and a second instrument defined as the non-routine analytic tasks intensity multiplied by the aggregate technology level across all occupations but occupation's own. Standard errors in parentheses clustered on the occupational level using the sandwich estimator. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

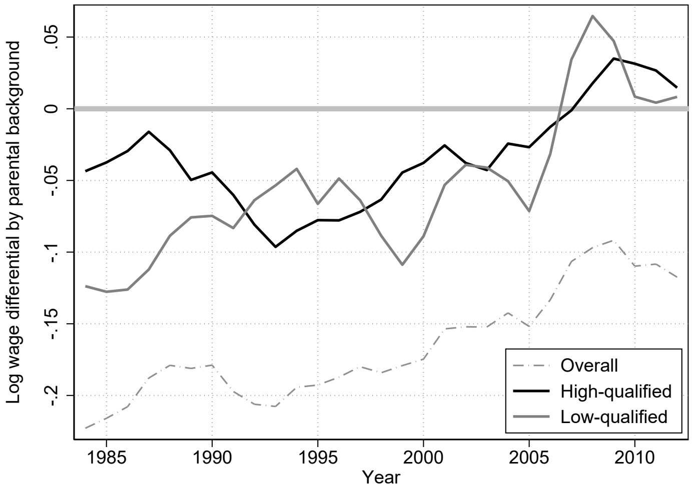
Table B3.7: Employment Effects - Long Differences - Including Outlier

	High-qualified				Low-qualified			
	Baseline		IV	Tasks	Baseline		IV	Tasks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tech	0.45**		0.79*	0.16	0.06*		0.21**	-0.19*
	[0.10,0.83]		[-0.07,1.66]	[-1.54,1.66]	[-0.02,0.14]		[0.01,0.45]	[-0.47,0.01]
Tech ×								
Effect heterogeneity across time periods								
× 1986-92		0.03				-0.03		
		[-0.83,0.87]				[-0.26,0.17]		
× 1992-99		0.50*				0.07**		
		[-0.03,1.07]				[0.00,0.15]		
× 1999-05		0.81				-0.08		
		[-2.11,2.42]				[-0.30,0.09]		
× 2005-12		0.33				0.35*		
		[-2.68,1.86]				[-0.03,0.77]		
Effect heterogeneity by initial occupational task content								
× Analytic				3.33**				0.54
				[0.57,9.43]				[-0.42,1.46]
× Interact.				-3.02***				0.79**
				[-5.89,-0.94]				[0.04,1.72]
Observations	101	101	101	101	221	221	221	221
F-Stat			33.4				28.1	

Notes: Dependent variable: Change in the share of high-qualified workers with low-educated parents among all high-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 technology level 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. West Germany only. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

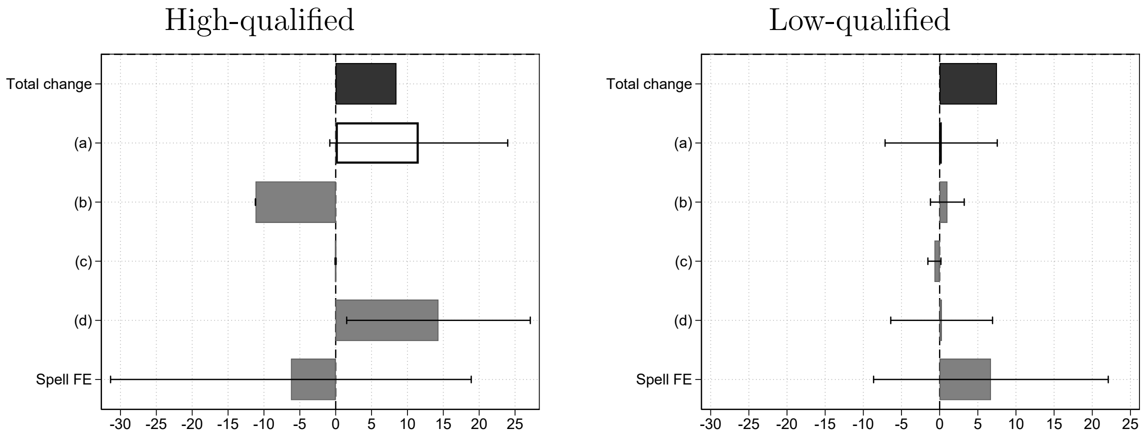
B.4 Additional Tables and Graphs for Section 5

Figure B4.1: Trends in the Overall and Qualification-Specific Wage Penalties



Notes: Overall and qualification-specific log wage penalties. Moving averages over three years. Based on the SOEP, using representative weights. West Germany only.

Figure B4.2: 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 1. 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 1, we adopt a lag of three years, i.e. $Tech_{jt-3}$, in our main specification.[45] Z_{jt} is a vector including the same control variables as in equation (4) 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

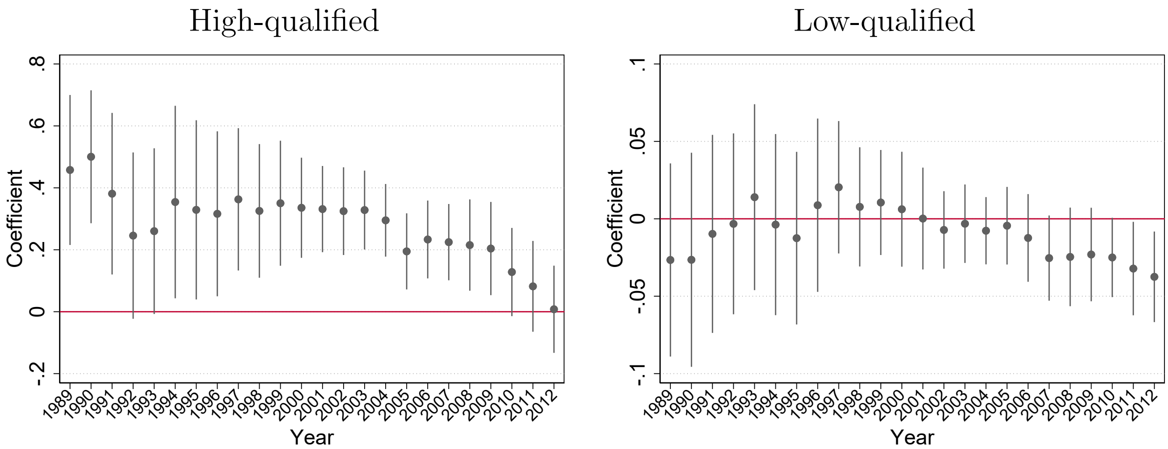
Notes: Dependent variable: Share of high-qualified (low-qualified) workers with low-educated parents among all high-qualified (low-qualified) workers. Control variables include the average age, the share of female/foreign/highly educated individuals, the average tenure, the relative employment share 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.[46] The smaller size of the effect

[45] When using a lag of one year (Table C2), the estimates are extremely similar in size and slightly more significant. When using a lag of five years (Table C3), the estimates decrease in size but remain similar.

[46] 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.

Table C2: Employment Effects - Occupation Fixed Effects, Technology Lagged by One Year

	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	0.22**	0.22	0.38***	0.48***	-0.01	0.02	0.01	0.12***
	[0.02,0.56]	[-0.14,0.68]	[0.11,0.72]	[0.10,0.91]	[-0.03,0.04]	[-0.06,0.11]	[-0.04,0.06]	[-0.03,0.28]
Observations	737	737	505	505	1410	1410	1023	1023
F-Stat		36.4		43.9		37.2		29.4

Notes: Dependent variable: Share of high-qualified workers with low-educated parents among all high-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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Employment Effects - Occupation Fixed Effects, Technology Lagged by Five Years

	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	0.14	-0.03	0.41**	0.29***	-0.03**	-0.04	-0.01	-0.02**
	[-0.10,0.34]	[-0.41,0.40]	[0.08,0.71]	[-0.26,0.89]	[-0.05,-0.01]	[-0.11,0.03]	[-0.07,0.04]	[-0.29,0.28]
Observations	651	651	419	419	1196	1196	808	808
F-Stat		34.0		35.8		26.1		15.1

Notes: Dependent variable: Share of high-qualified workers with low-educated parents among all high-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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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