



The Myth of Equal Opportunity in Germany? Wage Inequality and the Role of (Non-)academic Family Background for Differences in Capital Endowments and Returns on the Labour Market

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Accepted: 15 May 2021 / Published online: 21 July 2021
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Abstract

While providing equal opportunities to all members of society independent of an individual's socio-economic background is a major objective of German policy makers, educational opportunities of children with a non-academic family background are still unequally obstructed. When analysing the labour market implications of this disadvantage, social capital as an additional source of inequality often lacks attention. Drawing on the instrumental value of rather loose contacts (i.e. weak ties) on the labour market as revealed by Granovetter (Getting a job. A study of contacts and careers, The University of Chicago Press, Cambridge, 1974), this paper goes beyond the human capital approach and includes a measure of instrumental social capital in the form of weak-tie career support in the earnings function. Applying an Oaxaca-Blinder decomposition and quantile regressions, we find a significant average wage gap between those with and without an academic family background. A large part can be explained by deficits that those from less educated families incur with respect to human and instrumental social capital: Lower educational attainment accounts for more than half of the wage gap between the two groups while fewer career support explains around five percent of the differential. Additionally, a non-academic family background is associated with a significant deficit in returns to their instrumental social capital along the wage distribution. The findings therefore suggest that inequalities of opportunity on the German labour market occur beyond the education system, as not only the quantity but also the quality of career supporting networks of those from a non-academic family are inferior.

Keywords Wage gap · Inequality · Social capital · Decomposition · Quantile regression · SOEP

JEL Classification I24 · J31 · J62

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1 Introduction and Background

A broad range of research shows that income inequality has been on the rise in many European countries in the past decades—including Germany (see for example Grabka et al., 2019; OECD, 2017; Piketty, 2014). While inequality in the distribution of disposable incomes in Germany is below the OECD average, the country has one of the most unequal distribution of market incomes, ranging even before the United States and the United Kingdom (Fratzscher, 2016; Grabka & Goebel, 2018; OECD, 2020). If social mobility is high and chances are distributed equally, income inequality is not problematic per se (Friedman, 1962). However, in Germany, Braun and Stuhler (2018) revealed that educational attainment and occupational status is much more persistent across multiple generations (i.e. the intergenerational transmission of inequality) than earlier studies suggested. In fact, the educational and occupational background of parents in Germany still matters substantially for the opportunities of their children, more than in other European countries. The share of young adults beginning their university studies is more than three times as high when having an academic family background¹ compared to those having a non-academic family background (Maaz et al., 2018). From a labour economics perspective, this unequal access to education and thus *human capital*, is mirrored in the earnings distribution as education is one of the key components determining a person's *productivity* on the labour market (Acemoglu, 2018; Becker, 1964). The Organisation for Economic Co-operation and Development (OECD) has repeatedly criticised this structural dimension of unequal opportunities in the German society (OECD, 2014). In reaction to these circumstances, the responsible ministry declared the provision of equal opportunities in educational attainment as a major objective for the upcoming years (Federal Ministry of Education & Research, 2018). While this objective is commendable, would reaching it also be sufficient?

Drawing on the *theories of capital* from Pierre Bourdieu (1986) and Nan Lin (2001), it can further be argued that in addition to structural differences in *human capital*, also the availability and quality of *social capital* in the form of *networks* contribute to the reproduction of inequalities on the labour market. This is because the social network of a person can foster the career advancement, while the initial socio-structural position of an individual provides resources for its maintenance and determines the own attractiveness as an exchange partner (Bourdieu, 1986; Diewald et al., 2006). As a result, we observe differences in the access to more or less valuable informal resources via social networks, with the educational family background being a major determinant (Voss, 2007).

The amount of jobs accessed through personal contacts depicts the importance of *social capital* on the German labour market (Brenzel et al., 2016).² However, while “social capital enhances the likelihood of instrumental returns such as better jobs, earlier promotions, higher earnings or bonuses” (Lin, 2000, p. 786), not all *social ties* in an individual's network are generating similar returns on the labour market. A wide range of research has provided evidence for Mark Granovetter's (1974)³ prominent thesis of *the strength of weak*

¹ A person is considered to have an academic family background if at least one of the parents has completed tertiary education.

² On average, 70 percent of all positions are not made public but filled through personal networks immediately, with the share being even larger the higher the job's remuneration (Schröder, 2011). In addition, many of those jobs officially made vacant are filled via personal networks (20 percent of the jobs for academics, 29 percent of those for medium skilled and 36 percent for those of untrained workers) (Brenzel et al., 2016).

³ Granovetter investigated the role of social contacts during job search in the United States and demonstrated that it were loose relationships, so called *weak ties* as opposed to *strong ties* (e.g. family members),

ties (i.e. rather loose contacts). The theoretical argument is that they provide a routine flow of less redundant and thus more valuable information as opposed to *strong ties* (Lin, 2000). Evidence on this positive association between weak ties and different forms of socio-economic attainment (e.g. occupational status, prestige or wages) was for example found in the case of the United States (Lin & Dumin, 1986; Lin et al., 1981), China (Lin, 2001) and Russia (Yakubovich, 2005) as well as the Netherlands (Sprengers et al., 1988), Switzerland (Jann, 2003) and Germany (Wegener, 1991). Most studies looking at *strong ties* or *kin ties* did not find any effect on wages (Diewald, 2007; Lin, 2000), neither in Germany (Pellizzari, 2010). What is more, the positive association between *weak ties* and wages was found independent of whether a person has in the end found a job through such ties or not. This is a result of higher *reservation wages*: The more support a person gets for her⁴ career advancement through *weak ties*, the more likely she is to attribute a higher value to her own work (Montgomery, 1992; Voss, 2007).

While findings are not always clear cut as studies exist that did not find any positive association between *weak ties* and wages (see for example Bridges & Villemez, 1986; Marsden & Hurlbert, 1988 and Berger & Kriwy, 2004 for Germany), Lin (2000) argues that previous research has missed to make an important analytical differentiation. According to the study, it is essential to analyse *capital deficits* and *return deficits* separately to understand the role of *social capital* embedded in a network for inter-group inequalities. For the subsequent analyses, we build on the *instrumental dimension* of *social capital* in the form of *weak ties* that are assumed to generate returns on the labour market by facilitating the access to valuable resources outside the own network (Holzer, 2010). We thus add value to existing research by going beyond the human capital approach and incorporating a measure of *instrumental social capital* (i.e. *weak ties*⁵ that individuals perceive to support them in their career advancement) to answer the following questions:

To what extent are those with and without an academic family background experiencing differences in earned wages? What is the role of deficits in human capital as well as instrumental social capital endowments and returns in the structure of the groups' wage gap?

We address this research objective by applying an *Oaxaca-Blinder (OB) decomposition* and *quantile regressions* to analyse data from the Socio-Economic Panel (SOEP), a representative household survey for the German population. We apply the OB decomposition to disentangle the respective wage gaps in two components as suggested by Lin (2000), estimating the extent to which wage differences are a result of (1) group differences in capital endowments (i.e. capital deficits) or (2) can be associated with different returns to such capital (i.e. return deficits). More specifically, as opposed to the standard Ordinary Least

Footnote 3 (continued)

which resulted in better job positions and/or higher earnings (Granovetter, 1974). In most cases, such detailed information is not available for the analysis which is why researchers have often operationalised *weak ties* rather loosely, e.g. as kin and non-kin ties (see for example Lin, 2001).

⁴ To facilitate the legibility of the paper, we only use the feminine form that shall incorporate also the masculine form.

⁵ It is important to note that the data available does not allow us to analyse social networks in the way Granovetter did by determining the length and frequency of a relationship (1), its emotional intensity (2) and intimacy (3) as well as the reciprocity (4) (Holzer, 2010). Similar to other researchers, we chose a rather loose operationalisation of *weak ties* as a proxy for valuable social capital on the labour market (see Sect. 2 for a detailed description).

Square (OLS) regression, we estimate what share of the wage gap can be explained with an average deficit in both *human capital* (i.e. educational attainment) and *instrumental social capital* (i.e. weak-tie career support). This allows us to elaborate on the scope of the wage disadvantage associated with the deficits in education or a valuable social network that those from less privileged educational family backgrounds incur. In order to broaden the scope of our analyses beyond the mean wage gap, we also apply quantile regressions, which allows us to study the extent of potential deficits in return to capital along the entire wage distribution. Examining return deficits for different wage levels seems particularly important as previous research suggests networks to be of greater relevance in filling better-paid jobs (Schröder, 2011). By applying these two distinct but complementary methods that can both be based on the same model specification, we are able to provide a more comprehensive answer to our research questions.

Overall, this paper contributes to existing research in two major ways. To the best of our knowledge, it is the first study that analyses the structure of the wage gap between those with and without an academic family background for the German working age population as a whole. Thereby, we quantify the impact of unequal opportunities on the German labour market. Moreover, we go beyond the *human capital* approach by extending the classical *Mincer earnings function* with a measure of *instrumental social capital* in the form of *weak-tie career support* using the most recent SOEP-data.

We find a significant average wage gap between those with and without an academic family background. The decomposition analysis reveals that the average deficit in *educational attainment* associated with a non-academic family background explains around half of the overall wage gap, while fewer career support (i.e. *instrumental social capital*) explains around five percent of the differential. The results of our decomposition analysis suggest that our model specification has a high explanatory power. Going beyond the standard *human capital* approach and including a measure of *instrumental social capital* as well as *other personal* and *employment characteristics*, we are able to explain around 97 percent of the observed wage gap. We are thus confident to have captured a significant amount of relevant components that matter in the wage formation process. The complementary quantile regression analysis further suggests a non-academic family background to be associated with a significant return deficit to *instrumental social capital* along the distribution (beyond the mean).

The subsequent chapters are organised as follows. Firstly, we describe the data including the specification of the model and the selected sample. Afterwards, we give an overview of past policy reforms as well as relevant research findings to provide some country specific information that we further complement with descriptive statistics based on the sample data. In section four, we present our methodological approach in more detail and follow with the presentation and discussion of the analyses' results. Lastly, we summarise our findings and provide conceivable policy recommendations.

2 Data

The German SOEP is a representative longitudinal household survey conducted since 1984 by the German Institute for Economic Research (DIW) (Goebel et al., 2019). It includes a wide range of subjective and objective data relevant for multiple disciplines. We chose the SOEP-data since it adequately represents all income groups in Germany and provides a wide range of biographical information such as parental education. Moreover, since 2006 a

revised concept with questions on social networks and social support is included in the survey every 5 years that allows us to operationalise *instrumental social capital*. This means that until 2023 the data used in this paper (SOEP v33) will be the most recent one available for the analysis. As all surveys, also the SOEP suffers from design and self-selection problems that can result in biased estimations (Kroh, 2010). To moderate this bias, we use cross-sectional personal weights provided along with the dataset.⁶

2.1 Model Specification and Sample Selection

The estimated model specifies log hourly wages as the *dependent variable* and further selected *independent variables* grouped into five different categories that are relevant for an individual's success on the labour market.⁷ The *dependent variable* is operationalised as *gross log hourly wages*. Gross instead of net wages are used to avoid an underestimation of wage differentials due to redistributions through the tax and transfer systems. The outcome variable includes overtime compensation but excludes any additional benefits (i.e. Christmas bonus, holiday pay and other bonuses). To reduce the influence of outliers, we winsorise the values of extreme values at the top and bottom of the wage distribution, setting them at three times the 99th percentile and at one third of the 1st percentile, respectively. This is a common approach and often preferred over trimming the sample (i.e. excluding outliers) (Ghosh & Vogt, 2012).

Based on Mincer's human capital earnings function,⁸ we include measures of *education* and *work-related human capital* as independent variables. We measure *education related human capital* with three aggregated categories of the latest International Standard Classification of Education (ISCED, 2011): (1) *Basic Education* (No, Primary or Lower-Secondary education (Haupt- and Realschule)) (2) *Medium Education* (Upper- or Post-Secondary education (A-levels or apprenticeship)) and (3) *Higher Education* (Tertiary education (Meister,⁹ Bachelor, Master and PhD)). Besides the standard variables of *work related human capital* used in Mincer's earnings function (i.e. *full-time work experience* and a squared term¹⁰ of it), we include a binary variable indicating whether a person is *trained for the occupation* and a measure of *unemployment experience*. The latter is often included due to the negative health consequences of long-term unemployment and its devaluating effect on attained qualifications (i.e. human capital), which ultimately has an impact on future earnings (Oschmiansky & Berthold, 2020).

We further extend the basic earnings equation with variables of *instrumental social capital*, *other employment* and additional *personal characteristics*:

Instrumental social capital is operationalised using a measure of the number of *weak ties* who foster a respondent's *career advancement*. The corresponding survey question allowed respondents to name up to five people from a list with 26 categories (TNS Infratest Sozialforschung, 2016). Similar to Lin (2001), we approximate *weak ties* by counting only

⁶ See "Appendix 7" for one exception as a robustness check.

⁷ See "Appendix 1" for a detailed overview of all variables included and their operationalisation.

⁸ In its basic form, the function is comprised of *log wages* as a dependent variable and *education* (measured in years of schooling), *work experience* (measured in years of labour market experience) and a *squared term of work experience* as its predictors (Chiswick, 2003).

⁹ In Germany, an advanced technical certificate leading to a *Meister* is classified as ISCED 5b which is equivalent to a bachelor's degree (Schneider, 2015).

¹⁰ To reduce the impact of multicollinearity, we standardise *full-time work experience* before squaring it.

those supporters who can be considered as being more likely from outside a person's close network (i.e. work colleagues, superiors at work and paid assistants/outpatient care providers/social workers). We do not count supporters from marriage and partners, family members and relatives as well as neighbours, people from school, clubs or recreational activities and the category other. Since some of them might also be rather loose relationships (e.g. from the category other), the chosen operationalisation represents a rather conservative measure of *weak-tie career support*. The number of people named serve as a proxy for a person's *instrumental social capital*: The more *weak ties* supporting an individual's career, the higher the *instrumental social capital* of the person.

We consider additional *employment characteristics* that were found to determine wages and likely differ between the two groups: (1) a binary variable indicating whether the respondent works in a *larger company* to account for significantly broader collective wage agreement coverage in companies with more than 200 employees (Institute for Work, Skills and Training, 2018; German Federal Statistical Office, 2016); (2) measures of *occupational status*¹¹ as well as *occupational prestige*.¹² This is important as previous research suggests a mediating relationship between *occupational prestige* and other socio-economic determinants (i.e. *educational attainment* and *occupational status*) (Lin, 2001) as well as *instrumental social capital* (Wegener, 1991). Hence, including *occupational status* and *prestige* is important to gauge the direct relationship between the other wage-determining variables (e.g. *weak-tie career support*) and the dependent variable.¹³

Finally, we include *other personal characteristics* as control variables that were found to influence wages on the German labour market—*gender* (Arulampalam et al., 2007; German Federal Statistical Office, 2017), *working region* (Kluge & Weber, 2016) approximated by region of residence, as well as *marital status* (Polachek, 2007) and *number of children* (Misra et al., 2011).

To disentangle the structure of the wage gap between individuals with different initial conditions, an important question is how to best capture family background. Empirically, it has been proxied via the education, occupation or income of the parents. These characteristics are highly correlated, each capturing a slightly different angle of the family background. If only one variable is selected, the total effect of family background is likely underestimated and the influence of the chosen variable overestimated (Bukodi & Goldthorpe, 2013). However, amongst the different measures, parental education was found to have the largest explanatory power for children's labour market outcomes (Erola et al., 2016). It is the one that precedes the formation of other parental characteristics, such as occupation and income, and is therefore less endogenous. What is more, other than parental education, parental income and occupation likely vary during childhood. Including a variable that rightly captures these socio-economic factors is hence challenging and

¹¹ We use a pre-generated SOEP variable aggregated into five categories of the Erikson–Goldthorpe–Portocarero class scheme (Erikson & Goldthorpe, 1992). It captures working sector and scope of autonomy at the same time and is a recommended alternative to manually coding more than 200 sectors which has proven to be error-prone (Connelly et al., 2016; Ganzeboom & Treiman, 2003).

¹² We capture this variable using a pre-generated continuous SOEP variable that is based on the *Magnitude-Prestige-Scale (MPS)* pioneered by Wegener (1984, 1988) and specifically designed for Germany (SOEP Group, 2018). See Frietsch and Wirth (2001) for a documentation of the procedure used for the SOEP.

¹³ To investigate the assumed mediating relationship, we decompose the wage gap while excluding *occupational prestige*. The results are presented in “Appendix 7” and serve as a robustness check of the model specification.

prone to error. An additional advantage of using parental education is that it is often used as a proxy capturing cognitive skills and non-cognitive traits (Bukodi & Goldthorpe, 2013; Erola et al., 2016).

To apply the decomposition approach, we thus use (*non-*)*academic family background* as a binary *group indicator* variable, a common and meaningful operationalisation of parental education: The respondent is coded as *one* if neither of the parents has tertiary education and as *zero* if at least one of the parents has studied. This allows us to explore the extent to which the observed wage gap is due to differences in the composition of characteristics between the two groups with respect to their *instrumental social capital*, *education* and *work related human capital*, and *other employment* and *personal characteristics*, or to differences in returns to these characteristics.

The *sample selected* for the analysis based on wave v33.1 comprises the data of 29,713 realised interviews. For the purpose of this analysis, we restrict the sample to individuals who live in private households, are aged between 24 and 63 and are part of the employed labour force.¹⁴ We follow a common solution to the problem of multiple factors feeding into the wage of a self-employed (Chiswick, 2003) by excluding this group. To avoid bias from lopsided participation in tertiary education as well as early retirement, the age restriction is chosen so that the lower bound corresponds to the median age of university graduates (Buschle & Hähnel, 2016) and the upper bound to the average effective age of retirement in Germany (OECD, 2018). These restrictions as well as missing values yield 9635 observations remaining in the base sample with 1914 having an academic and 7721 having a non-academic family background.

3 The Distribution of Human and Instrumental Social Capital

In what follows, we recapitulate past policy reforms aimed at enhancing equal opportunities in the German education system and provide descriptive evidence on disadvantages based on social background with respect to *education related human capital* (3.1) as well as *instrumental social capital* (3.2). Additional descriptive statistics and the estimation of the raw wage gaps indicate what impact the unequal distribution of different forms of capital might have (3.3).

3.1 Past Educational Reforms and Descriptive Evidence

Already in the 1960s and 70s, the fact that educational opportunities and with it subsequent life chances strongly depended on the social background, provoked an academic discussion (see for example Dahrendorf, 1965; Picht, 1965) leading to several policy reforms with the aim to undo this relationship (El-Mafaalani, 2014). Measures taken ranged from the abolition of tuition fees in schools and universities and the introduction of means-tested income support for students, to the building of additional schools and universities (Schnabel & Schnabel, 2002). The lower costs of higher education resulted in a sharp increase in educational attainment in the 1970s and 80s. This rise was particularly high for females, however, children coming from non-academic family backgrounds still remained underrepresented

¹⁴ This generally excludes all unemployed as well as those employed in apprenticeships or sheltered workshops.

in tertiary education compared to their peers with more advantageous social origins (Schnabel & Schnabel, 2002).

More recent analyses of students' educational attainment suggest that not much has changed: The access to educational opportunities is still unequally distributed between children with and without an academic family background at several stages in the German education system (Herbold et al., 2017). After primary school, children are sent to one of three schools (i.e. Hauptschule, Realschule or Gymnasium) based on the teacher's perception of a child's performance and the preferences of the parents. It is well known that a significantly lower share of children with non-academic family background are sent to the *Gymnasium* which is the only school providing the degree to access university. Analyses on reading competencies of primary school children and their subsequent schooling trajectories have repeatedly shown that this is often due to both—the diverging perception of teachers as well as preferences of parents (Stubbe et al., 2017). Despite having the same cognitive abilities, children from families with a lower socio-economic position are significantly less likely to receive a recommendation for the *Gymnasium* from their teachers. On top of that, the lower the education of the parents, the lower their own preferences for sending their kids to the *Gymnasium*. As a result, already after primary school, children from less educated families have significantly lower chances to move onto the trajectory granting access to higher education despite having the same cognitive abilities as those from better educated families. This trend continues even throughout tertiary education—at any given stage, children from a non-academic family background are more likely to drop out, resulting in the number of children obtaining a PhD being ten times higher for children from an academic family background (Herbold et al., 2017).

This is mirrored in the data we use for the subsequent analyses: Fig. 1 displays the shares of the two groups having obtained *basic*, *medium* or *higher education*. While only 2.8 percent of those coming from well-educated families happen to leave school without any, primary or lower secondary education, 8.5 percent of those from less educated families do. This difference is even more pronounced regarding medium educational attainment, which only 37.7 percent of the more privileged group obtains compared to 69.7 percent of the less

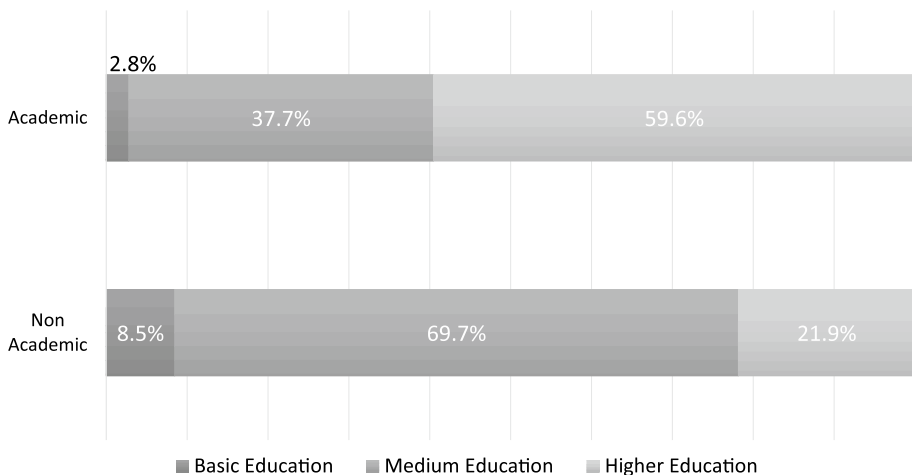


Fig. 1 Educational attainment by family background (aggregated based on ISCED, 2011). *Source:* Authors' own calculations (weighted) based on SOEP v33.1

privileged. Complementary to this, the share of those with an academic family background completing higher education (i.e. tertiary education) is nearly three times as large with 59.6 versus 21.9 percent.

Overall, this shows that an essential resource, namely *education related human capital*, is not proportionally distributed between children with and without an academic family background. This underlines prevailing disadvantages based on social background (El-Mafaalani, 2014; Geißler, 2013).

3.2 Deficits in Instrumental Social Capital

In addition to the unequal distribution of educational attainment, children from less educated backgrounds are more likely to struggle in finding an apprenticeship position after graduating from school, compared to those from better educated families (Fratzscher, 2016). As a result, they enter the labour market much more often untrained. This indicates that parental education matters on the labour market even beyond educational attainment. In fact, findings from social elite researchers suggest that family background still plays a role even for the highly educated (Hartmann, 2002, 2013). In a comprehensive study of PhD graduates from five disciplines, a larger share with an academic family background were found to be significantly more successful in their professional career (i.e. occupying top positions) compared to PhD graduates without an academic family background (Hartmann, 2002). The researcher explains this to be a result of subtle discrimination—managers, often coming from privileged and highly educated families, are more likely to select candidates who resemble them in behaviour and attitudes.¹⁵ Following this argumentation, university graduates with the same level of education, but from a less educated family, might face an additional hurdle when pursuing their professional career, which could translate into wage differentials. Also Aladin El-Mafaalani suggests that the societal structures in Germany contain further filters at different stages of life, despite those found in the education system (El-Mafaalani, 2014). In his study on the so called “*educational climbers*” (ger.: *Bildungsaufsteiger*) El-Mafaalani conducted interviews with successful professionals with a non-academic family background (El-Mafaalani, 2012). Each of the individuals perceived it as a major determinant of their success, that they had someone from *outside their close network* (i.e. *weak ties*) who supported them in their educational and career advancement (El-Mafaalani, 2012, 2014). This underlines the importance of *instrumental social capital* for the success of an individual on the labour market in addition to *human capital*—especially for those with a non-academic family background.

Looking at the distribution of *weak-tie career support* (i.e. *instrumental social capital*) shows that those from less educated families indeed have a significantly lower mean value and thus potentially a *capital deficit*. Less than one fourth (23.84%) of those with a non-academic family background receive *weak-tie career support* compared to nearly one third (31.78%) of those with an academic family background. This is in line with the work of Pierre Bourdieu (1986) and Nan Lin (2001) according to which those from less educated family backgrounds have access to less and/or poorer *instrumental social capital* as a result of their lower initial socio-economic position.

¹⁵ Hartmann (2002) bases his reasoning on the habitus theory of Pierre Bourdieu (1986), arguing that a higher social class is associated with certain personal character traits and behaviour as well as extent and type of general knowledge. Such characteristics are mostly acquired during childhood and cannot easily be obtained by an individual from a different social context during adulthood (Hartmann, 2002).

Based on existing theory and empirical research, we thus expect that the observed differences in average capital endowments (i.e. *educational attainment* and *weak-tie career support*) contribute to the wage gap.

3.3 Additional Descriptive Statistics and Raw Wage Gaps

Before turning to the raw wage gaps, we provide an overview of the population based on the sample data. Table 1 presents summary statistics for selected explanatory variables by family background.¹⁶

Looking at the additional variables of *human capital* and *other employment characteristics*, it can be noted that those coming from a highly educated family have higher average values for most of them. On average they are significantly more often *trained for their occupation*, a significantly larger average share occupies a position that falls in the *highest occupational class* and they have jobs that are on average significantly more *prestigious*. A significant average *capital deficit* of those with an academic family background is only found with respect to *full-time work experience* that is around five years lower. This is due to the larger share amongst those from academic families obtaining higher education which requires around six additional years before joining the labour force.

Estimating raw wage gaps between those with and without academic family background gives a first indication of the extent to which the unequal distribution of *human* and *instrumental social capital* might translate into differences in wages. Those from an academic family background earn on average 19.81 Euro per hour, while those from a non-academic family background have an average hourly wage of 16.99 Euro. The overall raw wage gap¹⁷ amounts to 14.24 percent and is statistically significant.

When comparing the hourly wages between those with and without *weak-tie career support* within each group as depicted in Fig. 2, we find a statistically significant intra-group wage gap, with those from non-academic families having *weak-tie career support* earning

Table 1 Summary statistics of selected variables by family background. *Source:* Authors' own calculations (weighted) based on SOEP v33.1

Variable	Academic family background		Non-academic family background	
	Mean	SD	Mean	SD
Mean hourly wage (in Euro)	19.81	11.74	16.99	9.52
Full-time work experience (in years)	11.56	10.21	16.98	12.00
Instrumental social capital (in number of weak-tie career supporters)	0.42	0.67	0.31	0.60
Occupational prestige (in MPS-value/10)	8.34	3.69	6.25	2.60
	Share (in %)		Share (in %)	
Highest occupational status	65.87		39.41	
Trained for occupation	67.18		60.48	
Number of observations	1914		7721	

¹⁶ See "Appendix 2" for an overview of the summary statistics for all variables included in the analysis.

¹⁷ The raw wage gap is calculated as $Wage\ Gap = \frac{Mean\ hourly\ wage_{academic} - Mean\ hourly\ wage_{non-academic}}{Mean\ hourly\ wage_{academic}} * 100$.

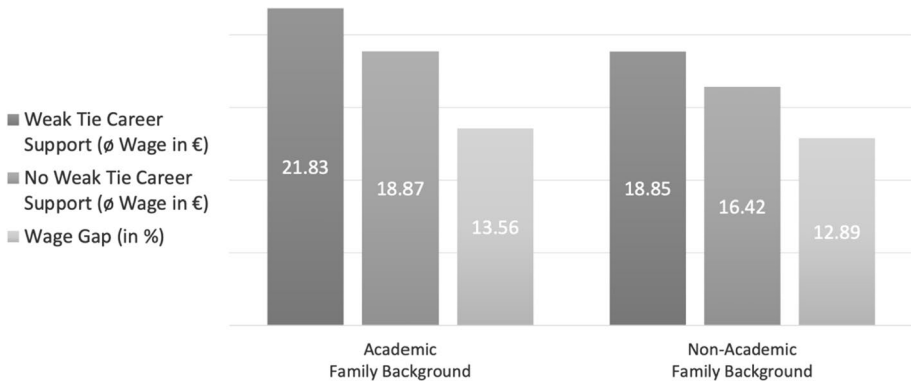


Fig. 2 Mean hourly wages and raw wage gaps by weak-tie career support and family background. *Source:* Authors’ own calculations (weighted) based on SOEP v33.1

significantly higher wages (12.89 percent) than their peers without such support. The same holds for the group with an academic family background where those with *weak-tie career support* earn on average 13.56 percent more compared to their peers who have no such career support. The respective wage gaps are a first indication for a positive association between *instrumental social capital* and *hourly wages*.

4 Methodology

To investigate the structure of the wage gap between those with and without an academic family background, we apply an OB decomposition (Blinder, 1973; Oaxaca, 1973). It is a popular technique used to explain the difference in mean outcomes between two groups. Its original application was targeted towards the analysis of the gender wage gap and potential discrimination against women (Blinder, 1973; Oaxaca, 1973). Recent applications cover a wide range of topics, such as health inequalities (O’Donnell et al., 2008) or educational policy outcomes (Barrera-Osorio et al., 2011). It is a regression-based decomposition method which estimates two linear regressions of the outcome of interest (*W*) against its determinants (vector *X*), separately for the two population sub-groups; here (1) those from *academic (A)* and (2) *non-academic (NA)* family backgrounds:

$$W_A = \alpha_A + \beta_A X_A + \epsilon_A \tag{1}$$

$$W_{NA} = \alpha_{NA} + \beta_{NA} X_{NA} + \epsilon_{NA}, \tag{2}$$

where *W* is the dependent variable measured as log hourly wages; α is the intercept; *X* is a vector of the selected wage-determining characteristics with the coefficient β which indicates the average return to these characteristics; and ϵ is the error term¹⁸ of the respective linear estimation. On this basis, a *counterfactual equation* is constructed, where the intercept and coefficient of *NA* are replaced with those from *A*

¹⁸ The results of the Breusch and Pagan (1979) and Cook and Weisberg (1983) test for heteroscedasticity suggest the application of robust standard errors which are used throughout the entire analysis.

$$W_{NA}^* = \alpha_A + \beta_A X_{NA} + \epsilon_A \tag{3}$$

This equation is then used to express the subtraction of W_A (2) and W_{NA} (1) as

$$\bar{W}_A - \bar{W}_{NA} = \bar{W}_A - W_{NA}^* + W_{NA}^* - \bar{W}_{NA} \tag{4}$$

which can be rewritten as

$$\bar{W}_A - \bar{W}_{NA} = (\bar{X}_A - \bar{X}_{NA}) \hat{\beta}_A + (\hat{\beta}_A - \hat{\beta}_{NA}) \bar{X}_{NA} \tag{5}$$

The last equation allows the decomposition of the mean wage difference (left side) into two terms (right side)—the *endowment effect* expressed by the first half of the equation and the *price effect* expressed by the second half. Using this counterfactual decomposition allows us to disentangle the part of the wage differential between the two groups that is *explained* by group differences in wage-determining characteristics, from the residual part which remains *unexplained* in the sense that it is not a result of group differences in the respective characteristics (Jann, 2008). The *unexplained part* or *price effect* can also be expressed using the following mathematical tools as shown by Jann (2008):

$$W = \begin{cases} \alpha_A + \beta X + \epsilon, & \text{if academic family background} \\ \alpha_{NA} + \beta X + \epsilon, & \text{if non-academic family background} \end{cases} \tag{6}$$

with β being the coefficients of the vector of wage-determining characteristics X and the group related intercepts $\alpha_A = \alpha$ and $\alpha_{NA} = \alpha + \delta$, where δ depicts the unexplained parameter. This can be re-written as:

$$W = \alpha + \beta X + \delta NA + \epsilon. \tag{7}$$

NA is an indicator for *non-academic family background*. An estimation of $\delta < 0$ is often interpreted as degree of discrimination a group experiences on the labour market (Jann, 2008). However, caution is required as δ and the unexplained part respectively, also capture any other kind of unobserved heterogeneity (i.e. group differences in other wage-determining characteristics that the specified model does not account for such as genetic ability) (Jann, 2008). Moreover, it has to be noted that the twofold decomposition of the wage gap relies on the assumption that discrimination is directed only towards one of the two groups (Jann, 2008). In this case, the estimation in (5) uses the coefficients of the group with an academic family background, implicitly assuming only negative discrimination towards those from a non-academic family background and no positive discrimination against those from an academic family background. Thus, the unexplained part asks how the distribution of wages of those without an academic family background would look like if they were paid like those with an academic family background. Even though the study of Hartmann (2002) suggests subtle discrimination against those without an academic family background in certain occasions (see Sect. 3.2), the investigation of potential discrimination is not the major motivation of this analysis. Hence, being aware of the underlying assumption made by the model specified in (5), we estimated a *pooled decomposition model* as a robustness check (see "Appendices 3 and 7"). In this model, the assumption of one-directional discrimination is relaxed by taking the coefficients from a pooled regression. To avoid the decomposition results to be biased as a result of residual group differences spilling over into the slope parameters of the pooled regression model, we include the group indicator as a predictor variable (Jann, 2008).

In general, the OB decomposition allows us to compute the extent to which average differences in endowments and returns for single variables as well as grouped components (i.e. instrumental social capital, education and work related human capital, other employment and personal characteristics) contribute to the wage gap. This caters to the underlying research questions, as we assume inequalities of opportunity on the labour market to prevail, if a less privileged group has (1) significantly lower capital endowments (e.g. education, social networks) and/or (2) significantly lower return to those capital endowments. While the first is a question of quantity, the latter is a question of quality. Lin (2000) underlined the importance of taking into account this analytical differentiation when assessing the role of social capital on the labour market. According to this study, it is essential to analyse capital deficits and return deficits separately to understand the role of social capital embedded in a network for intergroup inequalities. This is precisely what the decomposition approach allows us to do.

The sensitivity of wage decompositions is discussed at length in Huber (2015) and Huber and Solovyeva (2020). They underline that the standard decomposition literature based on Blinder (1973) and Oaxaca (1973) oftentimes ignores the potential endogeneity of the observed characteristics in the standard wage models, which may hinder the policy conclusions that can be drawn from the analysis. However, relating back to the standard gender wage gap approach, they propose controlling for a potential confounder determined at or prior to birth, such as parental education, as a way to reduce the endogeneity bias (Huber & Solovyeva, 2020). Our model specification is thus in line with this approach as we control for parental education by using (*non-academic family background*) as our group variable.

Beside the role of family background ('nurture') for the intergenerational transmission of inequalities, the literature also refers to the heritability of genetic abilities ('nature') as another potential transmission channel (Sacerdote, 2002), which remain unobserved in our model, a source of endogeneity bias. Though several studies suggest that it is the family environment ('nurture') that matters most for the intergenerational transmission of inequalities (see for example Anger & Heineck, 2010; Black et al., 2020; Engzell & Tropf, 2019; Wendelspiess Chávez Juárez, 2015). Hence, we nonetheless consider our analysis as meaningful to learn about the role of (*non-academic family background*) for differences in earned wages as a result of heterogeneous *human* and *instrumental social capital* accumulation.

What is more, since the decomposition method focuses on differences in mean outcomes between groups, we further explore the relationship between dependent and independent variables along different points of a distribution by using quantile regressions. Such regressions predict a quantile of the dependent variable y_i , where $i = 1, \dots, n$ is the sample population, conditional on a set of explanatory variables (x_i) so that the quantile regression can be expressed as $Q_\tau(y_i|x_i)$, with τ being the quantile level defined as $\tau \in (0, 1)$ (Chiswick et al., 2006). The quantile level can also be perceived as the probability of an individual falling below a certain value of y . This is because a certain quantile τ indicates the share of the population that falls below a specific value of y and $1-\tau$ the share of the population that exceeds this y (Rodríguez & Yao, 2017). Hence, in the case of the median regression, where $\tau=0.5$, exactly 50 percent of the observations fall below and 50 percent above a certain value of y . Technically, similar to OLS estimations, applying quantile regression also requires solving a minimisation problem (Koenker & Hallock, 2001). In the case of the median regression, the sum of absolute residuals is minimised. For other quantiles, the estimation is obtained by assigning different weights to positive and negative residuals and then minimising the asymmetrically weighted sum of the respective absolute error values

(Koenker & Hallock, 2001). Expressed formally, the τ th conditional quantile regression estimator for β is computed by solving the subsequent minimisation problem (Chiswick et al., 2006):

$$\min_{\beta} \left[\sum_{\{i: y_i \geq x_i \beta\}} \tau |y_i - x_i \beta| + \sum_{\{i: y_i < x_i \beta\}} (1 - \tau) |y_i - x_i \beta| \right] \quad (8)$$

Following Armstrong et al. (1979), linear programming techniques are used to set up the minimisation problem. The required linear objective function is obtained by introducing two slack variables. See Koenker (2005) for a detailed description of this procedure.

For the estimation of quantile regressions, we use the same model specification as for the OB decomposition with the only differences of applying quantile weights (τ) and adding the binary group variable as a control when estimating the pooled regression model. This allows us to estimate the remaining influence of family background that cannot be explained by differences in the wage-determining characteristics included in the model.

Generally, by applying quantile regressions, we estimate the association between different forms of *human* or *instrumental social capital* and log hourly wages at various points of the wage distribution. For example, quantile regressions allow comparing the association between the dependent and an independent variable at the 10th percentile with the respective association at higher percentiles such as at the median or 90th percentile of the log wage distribution, holding all other variables constant. Understanding the association along the wage distribution is especially relevant as the number of jobs given away through personal contacts was found to vary with the employees' skill levels and remuneration (Brenzel et al., 2016; Schröder, 2011).

From a more technical point of view, two things have to be noted. Firstly, the maximum and minimum quantiles estimated at the tails of the distribution are Q95 and Q5, respectively. The estimation of extreme quantiles is not recommended if a larger number of parameters are included, making results for extreme tails prone to errors (Chernozhukov, 2000; Azevedo, 2011). Secondly, the error terms of a quantile regression can be estimated in different ways, i.e. using heteroscedasticity robust or bootstrapped standard errors. We focus on the results obtained by weighted quantile regression estimates using robust standard errors (see Sect. 5.2). The unweighted model estimation using bootstrapped standard errors with 100 repetitions only serves as a robustness check (see Fig. 7 in "Appendix 7").

In sum, combining the OB decomposition with quantile regressions provides a more comprehensive picture of potential *capital* and *return deficits* between the two groups. By focussing on the relationship between *education related human capital* as well as *instrumental social capital* and wages, we facilitate a more detailed evaluation of the effects that the assumed *capital* and *return deficits* of those from a non-academic family background might have on the labour market.

5 Results and Discussion

We first turn to the results of the OB decomposition and shed light on the structure of the mean wage gap (5.1). Afterwards, the results of the quantile regression estimates are depicted (5.2) allowing us to analyse potential return deficits along the wage distribution.

5.1 Decomposing the Structure of the Mean Wage Gap

The model used to decompose the wage gap between the working age population of the groups with and without an academic family background extends Mincer's *human capital earnings function* (i.e. education, work experience and a squared term of work experience) by a measure of *instrumental social capital* (i.e. weak-tie career support) and additional *employment* and *personal characteristics* as control variables (see chapter 2). Table 2 depicts the results of the OB decomposition analysis. It shows the estimated *mean wage difference* between the two groups, the *endowment effect/capital deficit* (i.e. explained part) and the *price effect/return deficit* (i.e. unexplained part). Moreover, it provides detailed estimations of the extent to which differences in *human* and *instrumental social capital* endowments as well as *other employment* and *personal characteristics* explain the mean wage gap.¹⁹ The results show that there is a statistically significant mean wage gap of approximately 14.6 percent²⁰ between the two groups of which the largest share (96.88 percent) can be explained by differences in endowments between those with and without an academic family background. The part that remains unexplained is a result of differences in returns to these endowments, amounting to 3.12 percent, but not statistically significant.

Hence, the existing average wage gap is not a result of *return deficits* but can be attributed only with certainty to *deficits in different forms of capital* and *other employment characteristics* that are predominantly experienced by those coming from less educated families. Additionally, the fact that we are able to explain around 97 percent of the observed wage gap suggests that our model specification has a high explanatory power. We are thus confident to have captured a significant amount of relevant components that matter in the wage formation process by going beyond the standard *human capital* approach and including a measure of *instrumental social capital* as well as *other personal* and *employment characteristics*.

To further facilitate the interpretation of the components that comprise the explained part, Fig. 3 depicts the estimations for the grouped results in terms of shares. The largest share of the wage gap (62.61 percent) can be explained by differences in *other employment characteristics*. Most of it is a result of those with an academic family background having a higher *occupational status* and more *prestigious jobs* (see left column of "Appendix 3"). *Work related human capital* on the contrary, reduces the wage gap by 20.77 percent. If those without an academic family background would have the same average amount of *full-time work experience* as those with an academic family background, namely fewer (see Sect. 3.3), the wage gap would be even larger. Note that besides *full-time work experience*, further variables are grouped under *work related human capital*. The detailed table in "Appendix 3" shows that differences in *unemployment experience* as well as being *trained for an occupation* in fact increase the wage gap. In the grouped results, however, these effects are dominated by more *full-time work experience* of those from less educated backgrounds which curbs the wage difference between the two groups. This *work related human capital deficit* of those with an academic family background can be explained with

¹⁹ The estimates are the results obtained by grouping different variables together. The detailed estimates of the explained and unexplained part for all variables included in the decomposition model can be found in the left column of "Appendix 3".

²⁰ Since the dependent variable is expressed in logarithmic terms, the mean difference can approximately be expressed as the percentage difference in average hourly wages.

Table 2 Oaxaca-Blinder decomposition (grouped estimates). *Source:* Authors' own calculations (weighted) based on SOEP v33.1

	Log hourly wages
<i>Group 1</i> (Academic family background)	2.859*** (152.14)
<i>Group 2</i> (Non-academic family background)	2.713*** (299.41)
<i>Difference</i>	0.146*** (6.98)
<i>Explained</i>	0.141*** (7.21)
<i>Unexplained</i>	0.00455 (0.25)
<i>Grouped components of the explained part</i>	
Instrumental social capital (i.e. weak-tie career support)	0.00768** (2.58)
Education related human capital	0.0773*** (5.71)
Work related human capital	-0.0303** (-2.74)
Other employment characteristics	0.0912*** (5.83)
Other personal characteristics	-0.00476 (-0.91)
Number of observations	9635

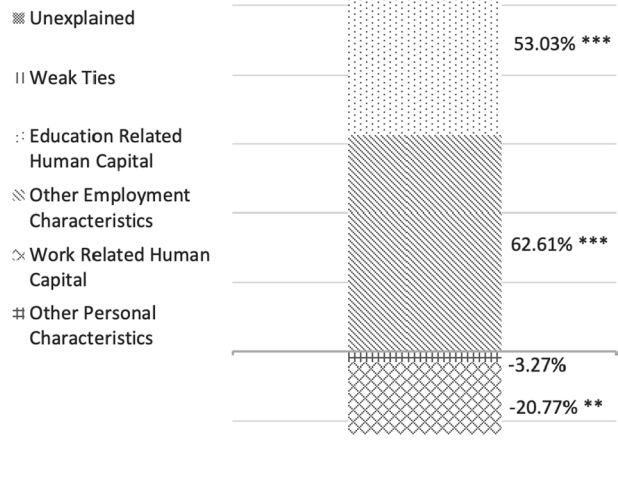
t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

their higher educational attainment that is accompanied by significantly lower average *full-time work experience* (Table 1 and Fig. 1).

Differences in *education related human capital* make up the second largest component of the observed wage gap. More than half of this gap is estimated to result from lower educational attainment of those coming from a non-academic household. This quantifies the extent to which the well-known social disadvantage in *education related human capital* that has been dunned by researchers and international organisations alike (Braun & Stuhler, 2018; Fratzscher, 2016; OECD, 2014), contributes to differences in earned wages. The lower educational attainment indirectly affects the average wage gap also through lower *occupational status* and *job prestige* (see left column of "Appendix 3"), meaning that inequality of educational opportunities further translates into other wage-determining employment characteristics. We also find support for previous findings showing that those from less educated family backgrounds enter the job market more often untrained compared to those with an academic family background (see Sect. 3.1). The detailed results show that this is a significant factor contributing to the lower average wages earned by those from less privileged backgrounds (see left column of "Appendix 3").

What is more, *instrumental social capital* in the form of *weak ties* supporting one's career is found to be associated with significantly higher log hourly wages (see OLS-estimation in "Appendices 4, 5 and 6"). The observed differences in this kind of support (see

Fig. 3 Oaxaca-Blinder decomposition (grouped estimates as shares of the wage gap). *Source:* Authors' own calculations (weighted) based on SOEP v33.1



Sect. 3.2), indeed translate into a wage differential between the two groups. The respective deficit of those with a non-academic family background explains around five percent of the observed wage gap (see Fig. 3). This is obviously a rather small share compared to the explanatory power of differences in *human capital* and *other employment characteristic*. Yet, it is in line with existing evidence and theories of the role of social capital on the labour market.

Two explanations can be brought forward to reason the positive association between *instrumental social capital* and wages. First, in line with Granovetter's (1974) thesis of the *strength of weak ties*, it can be argued that job searchers are more likely to find better and higher paid jobs through loose contacts (i.e. *weak ties*). On the German labour market, where a large share of the jobs is given away via personal networks (Brenzel et al., 2016; Schröder, 2011), this effect is likely substantial. Second, since we do not investigate the role of *instrumental social capital* in the specific case of job searchers, the observed positive association could result from an increase in the *reservation wage* of individuals receiving *weak-tie career support*. According to Lin (2000, 2001) and Montgomery (1992), *weak ties* result in higher *reservation wage* by connecting usually separated networks that provide a routine flow of valuable labour market information. Hence, the observed positive association might not only be a result of the usefulness of *weak ties* in directly finding a job through informal networks but suggests that any deficit in *instrumental social capital* can be expected to result in significantly lower wages. Moreover finding those without an academic family background to experience a deficit in such *instrumental social capital* is in line with the theoretical argumentation that the availability of it is determined by the initial socio-structural position, for which parental education is crucial (Bourdieu, 1986; Lin, 2001).

In aggregate, the results of the OB decomposition give important insights into the structure of the mean wage gap between the two groups. We emphasise two important findings.

First, the results suggest that, holding everything else constant, the significantly lower average *educational attainment* associated with a non-academic family background plays an important role for lower average remunerations compared to those whose parents have studied. Second, the observed average difference in *instrumental social capital* to the disadvantage of those from a non-academic family background indeed explains a significant part of the wage gap even though to a much smaller extent than differences in *education related human capital*.

5.2 Return Deficits along the Wage Distribution

The subsequent application of quantile regressions complements the decomposition analysis in two ways. First, the pooled quantile regression includes an additional group dummy variable (i.e. non-academic family background) which allows the estimation of the unexplained difference in hourly earnings between those with and without an academic family background along the wage distribution (see Fig. 4). Second, estimating quantile regressions for each group separately provides insights into potentially different capital returns the two groups experience along their wage distribution (see Figs. 5 and 6).

Figure 4 presents the log hourly wage differential between the two groups estimated by pooled quantile regressions as well as the OLS estimation for the purpose of comparison.²¹ The solid lines depict the point estimates of the OLS and quantile regressions, respectively. The dashed and dotted lines are the regressions' corresponding 95 percent confidence interval (CI) estimations. The log hourly wage differential represents the coefficient of the group dummy variable, holding all other variables constant. If it is significantly different from zero, it can be interpreted as a remaining influence of mere group membership that cannot be explained by differences in the wage-determining characteristics included in the model.

While a simple OLS regression predicts family background to have no significant effect on average, the point estimates of the quantile regressions (thick solid line) suggest that the respective effect slightly varies across the wage distribution and is statistically significant around the 80th and 85th quantile, holding everything else constant. Hence, at this part of the distribution, coming from a non-academic household is associated with a significant wage penalty of around 4.9 percent that is not explained by group differences in *various forms of capital* as well as *other employment* and *personal characteristics* included in the estimation. Since this finding has proven to be robust (see Fig. 7 in Appendix "7"), it is worth considering a potential explanation for it:

Similar to the *price effect*, the significant wage penalty experienced at the upper part of the distribution could be due to employer discrimination occurring in jobs with higher remuneration. The study of Hartmann (2002) and his theoretical explanation for finding PhD graduates with a non-academic family background significantly less likely to realise a particularly successful career (see Sect. 3.2) could be a possible reason. Following Hartmann's argument, managers who often come from highly educated families, prefer to employ someone with a *habitus* resembling their own (i.e. behaviour and attitudes that are common for a higher social class) and thereby unequally obstruct the career opportunities of those from less educated families. However, the argument has to be brought forward with reservation as the wage differential might also be a result of other types of unobserved heterogeneity such as different forms of *non-monetary compensation*, *labour market*

²¹ See "Appendix 4" for the results of OLS and pooled quantile regression estimations.

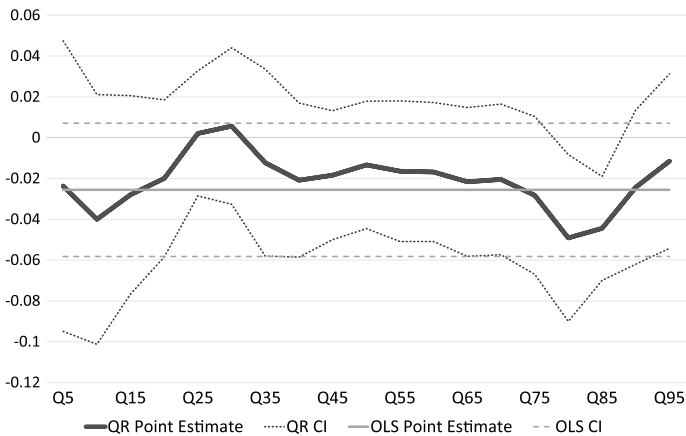


Fig. 4 Log hourly wage differential between those with and without academic family background along the distribution. *Source:* Authors' own calculations (weighted) based on SOEP v33.1

imperfections (Acemoglu, 2018), or *personality traits* such as ambitiousness and reliability, which is not accounted for in our analysis due to measurement and data constraints.

We now turn to the results estimated with group-specific quantile regressions, which predict the respective returns to selected forms of capital at different points of the groups' wage distribution.²² Figure 5 shows the coefficient estimates and CIs of the quantile as well as OLS regressions for *education related human capital* (i.e. medium and higher education compared to basic education) for those with and without an academic family background.

The results predict a similar average return to having medium compared to basic education for both groups. However, for those from an academic family background, the returns are not statistically significant on average but only in the middle of the wage distribution (Q50–Q75), ranging between 16 and 20 percent. For those from a non-academic family background, the significant positive association estimated by the OLS regression underestimates the returns to medium education at the upper part (above Q50) and overestimate them at the lower end of the distribution (below Q15). This is particularly the case at the very bottom (below Q10) where the quantile regression estimates are not statistically significant at any conventional level. Regarding the estimated returns to higher compared to basic education, the point estimates of the OLS regressions predict the average return for those with and without an academic family background to be 30 and 24 percent, respectively, holding everything else constant. The estimations along the distribution depict that the returns to higher education tend to be lower at the bottom of the distribution and higher at the top for both groups.

Overall, when comparing the returns to medium as well as higher education between the two groups, it has to be noted that the groups' coefficients estimated with an OLS regression are not significantly different from each other.²³ Moreover, neither do the results of the

²² The detailed results of the estimations can be found in "Appendix 5" for those from an academic family background and in "Appendix 6" for those from a non-academic family background.

²³ Differences between OLS group-coefficients were formally tested by performing a Wald test.

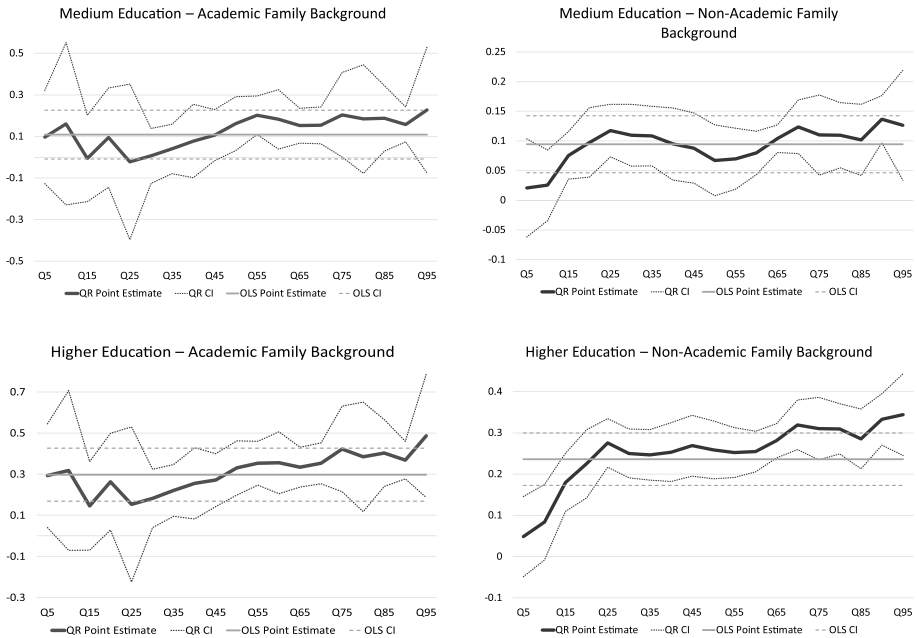


Fig. 5 Coefficient estimates for medium and higher education (The reference category for *medium* and *higher education* is *basic education*). *Source:* Authors’ own calculations (weighted) based on SOEP v33.1

quantile regressions indicate a significant difference in returns to medium as well as higher education between those with and without an academic family background, since the estimated 95 percent CIs widely overlap along the distribution.

Figure 6 graphs the returns to *instrumental social capital* (i.e. weak-tie career support) estimated by quantile as well as OLS regressions.

Simple OLS regression predicts the association between *instrumental social capital* and wages to be statistically significant for both groups. An additional *weak tie* supporting a person’s career is on average associated with 7.2 percent higher hourly wages for those from an academic family background and with 3.7 percent higher hourly wages for those from a non-academic family background, holding everything else constant. While the point estimates are higher for those from an academic family background, the difference in estimated average returns is not statistically significant at any conventional level. Estimating the effect of *instrumental social capital* using group-specific quantile regressions provides further insights into the association between *weak-tie career support* and log hourly wages along the distribution. For those from an academic family background we find a statistically significant positive association at most parts of the distribution except at the top (Q80–Q95).

On the contrary, for those from less educated families the positive association is significant only at some parts of the distribution (i.e. at the very bottom, in the middle and again at the very top). In both cases, the returns to *weak-tie career support* tend to be higher at the very bottom compared to the rest of the distribution. Comparing the predicted returns to *instrumental social capital*, we find a statistically significant difference between the two groups at the lower end (Q10 and Q15) as well as in the upper middle part of the

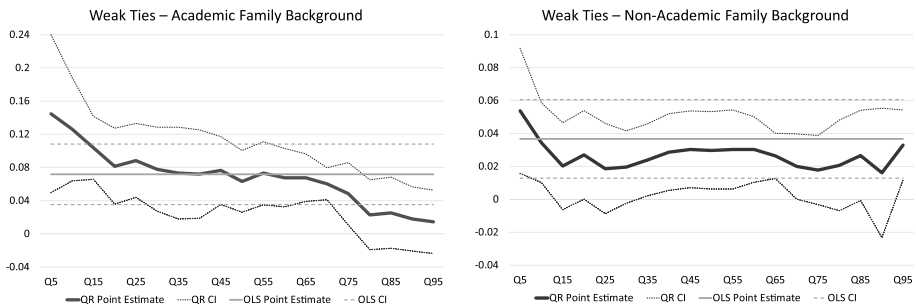


Fig. 6 Coefficient estimates for weak-tie career support. *Source:* Authors' own calculations (weighted) based on SOEP v33.1

distributions (Q70).²⁴ Around these parts of the wage distributions, individuals from a non-academic family background experience significantly lower returns to *instrumental social capital* (i.e. a return deficit) than those from an academic family background.

Summing up, while we find no evidence for deficits in returns to *education*, the results suggest that those from non-academic family backgrounds do indeed experience significantly lower returns to *weak-tie career support* at the bottom as well as at the top of the distribution. Hence, in the case of *instrumental social capital*, we find those with a non-academic family background to experience not only an average *capital deficit* but also a *return deficit* along the distribution compared to those from highly educated families.

This *return deficit* could be explained by drawing on the theoretical framework of Bourdieu (1986). *Weak ties* supporting an individual's career serve as a *multiplier* of her own capital²⁵ that, in turn, is determined by the family background (Bourdieu, 1986). This means that the initial advantages in average capital endowments of those from more educated families is amplified by *instrumental social capital*. Additionally, it can be argued that the career supporting network of those coming from academic families is likely richer in valuable resources since those from better educated families are more attractive as an exchange partner in a network (Bourdieu, 1986; Diewald et al., 2006). It has to be noted that the analysis relies on a self-reported variable which implies that the measure captures the number of *weak ties* a person consciously perceives as supporting her career advancement. In fact, the survey question is phrased in present tense inviting respondents to rather recall those contacts that still support or have supported them more recently. Hence, when interpreting the results, we have to keep in mind that the measure of *weak-tie career support* might not capture *social capital* that has been *instrumental* for an individual's advancement over the entire course of her career. However, this does not explain why we find the respective *return deficit* only at some parts of the distribution. To make sense of this result, we interpret it in its country-specific labour market context. As a previous study of the German Institute for Employment Research (IAB) suggests, the importance of informal

²⁴ For better illustration of the differences in returns, see Fig. 8 in "Appendix 8" that includes the quantile regression estimations of returns to *weak-tie career support* for both groups in one graph. It shows that the lower bound 95%-CI of those with an academic family background lies above the upper bound 95%-CI of those with a non-academic family background at Q10, Q15 and Q70.

²⁵ Note that in this case, *capital* refers to forms of capital beyond mere *human capital* and includes—in line with Bourdieu's theory—also social, cultural and economic capital (Bourdieu, 1986).

networks on the German labour market varies for different kinds of jobs (Brenzel et al., 2016). According to the authors, the share of jobs which are officially made vacant but eventually given away through personal contacts is largest for untrained workers. This indicates that informal networks can be particularly useful at the lower end of the distribution. Those with an academic family background seem to reap additional benefits (i.e. higher returns) from their networks, which are richer in resources at this part of the distribution, yielding a *return deficit* for those from less educated families. Concerning the return deficit at the top of the distribution, we should take into account the general tendency that *weak-tie career support* is less relevant at upper quantiles for both groups. Firstly, the study of the IAB suggests that academics are much more likely to be recruited through online job markets compared to medium-skilled and untrained workers (Brenzel et al., 2016). Platforms such as LinkedIn are becoming an increasingly popular tool for recruiting, particularly of university graduates. Hence, *weak-tie career support* might be less important when it comes to actually finding a job through such ties. It is worth mentioning the study of Berger and Kriwy (2004) who found no positive association between *weak ties* and earned wages for a group of German sociology graduates. Assuming that sociology graduates earn wages that are situated rather in the upper half of the distribution, our results do not stand in contrast to those of Berger and Kriwy, but rather underline the contribution we made by investigating the role of *weak-tie career support* for the overall working age population along the wage distribution.

6 Conclusion

The aim of this paper is to shed light on the wage gap and its structure between those with and without an academic family background by extending Mincer's human capital earnings function with a measure of *instrumental social capital*. We analyse the role of deficits in as well as returns to *human* and *instrumental social capital*. By investigating average *capital* and *return deficits* separately, our study contributes towards filling an existing research gap.

Our study provides three important findings. We find that the average difference in hourly wages amounts to approximately 14.6 percent with wages being lower for those from a non-academic family background. Secondly, investigating the structure of the average wage gap reveals that *capital deficits* are predominantly incurred by those from a non-academic family background with the only exception of *work related human capital*. Without higher average work experience of those from a non-academic family background, the average wage gap would be even larger. The unequal obstruction of educational opportunities to the disadvantage of those from less educated families, results in *human capital deficits* that constitute a large part of the existing average wage gap. However, we find no significant *return deficit* to educational attainment along the wage distribution. Thirdly, for both groups, *instrumental social capital* in the form of *weak-tie career support* is found to be significantly positively associated with hourly wages, on average and at most parts of the wage distribution. The analysis reveals that those from less educated families do on average experience a *deficit* in *instrumental social capital* that significantly contributes to the overall wage gap, however to a smaller extent than *deficits* in *educational attainment*. While we find no *return deficit* on average, we do find evidence that those from non-academic families have lower returns to *instrumental social capital* at some parts of the wage distribution. This implies that coming from highly educated families is associated not only

with higher *availability*, but in some cases also with better *quality* of *instrumental social capital*, potentially due to their supporting network being richer in resources.

In sum, the key results of the analyses suggest that opportunities to succeed on the labour market are unequally distributed between those with and without an academic family background not only as a result of lower levels of *human capital* (i.e. educational attainment) but also to a certain extent due to deficits in the *endowment* with and *return* to *instrumental social capital*. As opportunities often open up through informal networks also on the German labour market, the social disadvantages experienced by those from less educated families go beyond educational attainment and affect labour market outcomes throughout working life.

We thus argue that providing equality of opportunity in *educational attainment* is still the most important lever for German policy makers. However, further identifying and addressing what causes the unequal distribution of and return to *instrumental social capital* ought to be acknowledged as an additional and complementing avenue to foster equality of opportunity on the German labour market. A promising way to do this could be the institutionalisation of free mentoring in schools for children from less educated families as this has already proven to raise their level of “pro-sociality”—an important skill to build up and maintain a social network—to that of children from families with higher socio-economic status (Kosse et al., 2016). While this is one way to address the issue in the longer run, implementing policies that limit the number of positions staffed without official job postings should also be considered as a measure to increase equality of opportunity on the labour market. Additionally, further research is needed to better understand the mechanisms underlying the formation of career supporting networks and their mode of action on the German labour market.

Appendix 1: Overview and Operationalisation of the Group, Dependent and Independent Variables

Variable	Operationalisation
<i>Group variable</i>	
Family background	<i>Dummy variable</i> 1 = non-academic family background (i.e. neither mother nor father has a university degree), 0 = academic family background (at least one of the parents has a university degree)
<i>Dependent variable</i>	
Log hourly wage	<i>Metric variable</i> $\ln W_h = \ln \left(\frac{W_m}{H_w * 4.33} \right)$, where W_m is gross monthly wage, H_w the actual hours worked per week, and 4.33 are the average weeks of a month [Min 0.21; Max 4.97]
<i>Independent variables</i>	
Instrumental social capital	
Weak-tie career support	<i>Metric variable</i> In number of people categorised as weak ties (i.e. work colleagues, superiors at work and paid assistants/outpatient care providers/social workers) [Min 0; Max 4]

Variable	Operationalisation
Education related human capital	
Education	<i>Categorical variable—3 aggregated dummy variables based on ISCED (2011)</i> Basic Education (No, primary and lower secondary (Haupt- and Realschule)) Medium Education (Upper and post-secondary (A-levels or apprenticeship)) Higher Education (First- and second-stage tertiary (Meister, Bachelor, Master or PhD))
Work related human capital	
Full-time work experience	<i>Metric variable</i> In number of years [Min 0; Max 47] (standardised for analysis of inferential statistics)
Unemployment experience	<i>Metric variable</i> In number of years [Min 0; Max 27.2]
Trained for occupation	<i>Dummy Variable</i> 1 = yes, 0 = no
Other employment characteristics	
Occupational status	<i>Categorical variable—five aggregated dummy variables based on the EGP Scheme (pre-generated in SOEP and further aggregated)</i> Service class (Professionals, administrators and managers; higher grade technicians; supervisors of non-manual workers) Routine non-manual workers (routine non-manual employees in administration and commerce; sales personnel; other rank-and-file service workers) Skilled workers (lower grade technicians; supervisors of manual workers, skilled manual workers) Non-skilled workers (semi- and unskilled manual workers not in agriculture) Agricultural labourers (agricultural and other workers in primary production)
Occupational prestige	<i>Metric variable based on Wegener's MPS value (pre-generated in SOEP and adjusted)</i> The original scale ranges from 30.1 to 216 and has been divided by 10 for more convenient interpretation in terms of a 10-point increase in prestige [Min 3.01; Max 21.6]
Larger company	<i>Dummy Variable</i> 1 = more than 200 employees, 0 otherwise
Other personal characteristics	
Gender	<i>Dummy Variable</i> 1 = female, 0 = male
Marital status	<i>Dummy Variable</i> 1 = married/registered same sex partnership and living together or spouse abroad, 0 otherwise
Working region	<i>Dummy Variable</i> 1 = East Germany, 0 = West Germany
Number of children	<i>Metric variable</i> In number of children [Min 0; Max 8]

Source: Authors' own compilation based on SOEP v33.1

Appendix 2: Summary Statistics for All Variables Included in the Model

Variable	Academic family background		Non-academic family background	
	Mean	SD	Mean	SD
Log hourly wage (in Euro)	2.86	0.50	2.71	0.49
Full-time work experience (in years)	11.56	10.21	16.98	12.00
Unemployment experience (in years)	0.40	1.23	0.72	1.95
Number of children	0.59	0.92	0.50	0.84
Instrumental social capital (in number of weak-tie career supporters)	0.42	0.67	0.31	0.60
Occupational prestige (in MPS-value/10)	8.34	3.69	6.25	2.60
	Share (in %)		Share (in %)	
Female	45.02		48.92	
Married	47.86		56.23	
East	23.99		15.77	
<i>Educational attainment</i>				
Basic	2.76		8.45	
Primary education	0.02		0.97	
Lower secondary education	2.74		7.48	
Medium	37.68		69.70	
Upper, post-secondary education	37.68		69.70	
Advanced	59.55		21.85	
Bachelor	30.49		12.86	
Master	25.96		8.19	
PhD	3.11		0.81	
<i>Occupational status</i>				
Service class	65.87		39.41	
Routine non-manual workers	20.30		29.26	
Skilled workers	7.84		15.19	
Non-skilled workers	5.62		15.34	
Agricultural labourers	0.37		0.79	
<i>Trained for occupation</i>	67.18		60.48	
<i>Working in larger company</i>	57.35		52.22	
Number of observations	1914		7721	

Source: Authors' own calculations (weighted) based on SOEP v33.1

Appendix 3: Oaxaca-Blinder Decomposition (Detailed Estimates)

	<i>Log hourly wages</i>	<i>In % of wage gap</i>	<i>Log hourly wages (pooled model coef- ficients)</i>	<i>In % of wage gap</i>
<i>Group 1</i>	2.859***		2.859***	
(Academic family background)	(152.14)		(152.55)	
<i>Group 2</i>	2.713***		2.713***	
(Non-academic family background)	(299.41)		(299.61)	
<i>Difference</i>	0.146***		0.146***	
	(6.98)		(7.00)	
<i>Explained</i>	0.141***	96.88	0.120***	82.46
	(7.21)		(7.73)	
<i>Unexplained</i>	0.00455	3.12	0.0256	17.54
	(0.25)		(1.54)	
<i>Grouped components of the explained part</i>				
Instrumental social capital		5.27		3.12
Weak-tie career support	0.00768**	5.27	0.00454**	3.12
	(2.58)		(2.65)	
Education related human capital ^a		53.03		43.74
Medium education	-0.0349	-23.95	-0.0301***	-20.66
	(-1.81)		(-3.97)	
Higher education	0.112***	76.98	0.0938***	64.37
	(4.38)		(7.81)	
Work related human capital		-20.77		-32.12
Full-time work expe- rience	-0.0812***	-55.70	-0.0744***	-51.08
	(-7.56)		(-9.68)	
Full-time work experience ²	0.0275***	18.85	0.0117***	8.02
	(4.57)		(4.60)	
Trained for occupa- tion	0.00932*	6.40	0.00792**	5.44
	(2.31)		(2.96)	
Unemployment experience	0.0141***	9.68	0.00802***	5.51
	(4.09)		(5.07)	
Other employment characteristics		62.61		74.45
Occupational status				
Service Class	0.141**	96.73	0.0754***	51.75
	(3.04)		(6.30)	

	<i>Log hourly wages</i>	<i>In % of wage gap</i>	<i>Log hourly wages (pooled model coef- ficients)</i>	<i>In % of wage gap</i>
Non-manual routine workers	-0.0355* (-2.10)	-24.36	-0.0166*** (-3.52)	-11.37
Skilled workers	-0.0265* (-1.99)	-18.20	-0.0121*** (-3.57)	-8.33
Non-skilled workers	-0.0354* (-2.05)	-24.27	-0.0128** (-3.03)	-8.77
Occupational prestige	0.0411* (2.39)	28.19	0.0650*** (6.62)	44.64
Larger company	0.00659* (2.07)	4.52	0.00951* (2.31)	6.53
Other personal characteristics		-3.27		-6.73
Female	0.00400 (1.57)	2.75	0.00434 (1.74)	2.98
East	-0.0101** (-3.27)	-6.94	-0.0150*** (-4.56)	-10.28
Married	-0.00160 (-0.61)	-1.10	-0.00244 (-1.92)	-1.67
Number of children	0.00295 (1.84)	2.03	0.00327* (2.24)	2.24
<i>Unexplained</i>				
Instrumental social capital		7.49		9.64
Weak-tie career support	0.0109 (1.58)	7.49	0.0141 (1.60)	9.64
Education related human capital ^a		16.20		25.50
Medium education	0.0102 (0.23)	6.97	0.00536 (0.21)	3.68
Higher education	0.0135 (0.84)	9.23	0.0318 (0.79)	21.82
Work related human capital		-50.96		-39.61
Full-time work experience	0.00426 (1.09)	2.92	-0.00248 (-0.66)	-1.70
Full-time work experience ²	-0.0787*** (-3.71)	-53.98	-0.0629*** (-3.68)	-43.15
Trained for occupation	0.0151 (0.56)	10.41	0.0166 (0.56)	11.37

	<i>Log hourly wages</i>	<i>In % of wage gap</i>	<i>Log hourly wages (pooled model coef- ficients)</i>	<i>In % of wage gap</i>
Unemployment experience	-0.0150* (-2.28)	-10.31	-0.00894* (-2.29)	-6.13
Other employment characteristics		78.29		66.45
Occupational status ^b				
Service class	0.118 (1.72)	80.79	0.183 (1.69)	125.77
Non-manual routine workers	0.0725 (1.42)	49.75	0.0536 (1.44)	36.75
Skilled workers	0.0337 (1.28)	23.14	0.0194 (1.29)	13.28
Non-skilled workers	0.0400 (1.48)	27.46	0.0174 (1.46)	11.96
Occupational prestige	-0.114* (-2.01)	-78.02	-0.138* (-2.02)	-94.46
Larger company	-0.0362* (-2.13)	-24.84	-0.0391* (-2.14)	-26.85
Other personal characteristics		6.37		9.83
Female	0.00508 (0.29)	3.49	0.00474 (0.29)	3.26
East	0.0114* (2.17)	7.81	0.0162* (2.21)	11.14
Married	-0.00617 (-0.32)	-4.24	-0.00533 (-0.32)	-3.66
Number of children	-0.00101 (-0.12)	-0.69	-0.00132 (-0.13)	-0.91
Constant	-0.0791 (-0.44)	-54.26	-0.0791 (-0.44)	-54.26
Number of observations	9635		9635	

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ^aBasic Education as reference group; ^bAgricultural Labourer as reference group

Source: Authors' own calculations (weighted) based on SOEP v33.1

Appendix 4: Pooled Quantile Regressions

<i>Log hourly wages</i> (dependent variable)	OLS	Q10	Q25	Q50	Q80	Q90
Non-academic family background	-0.0256 (-1.53)	-0.0400 (-1.28)	0.00210 (0.13)	-0.0133 (-0.84)	-0.0492* (-2.36)	-0.0243 (-1.26)
Weak-tie career support	0.0425*** (4.10)	0.0455*** (3.34)	0.0305** (2.62)	0.0434*** (4.28)	0.0220 (1.80)	0.0221 (1.54)
Medium education ^a	0.0940*** (4.12)	0.0384 (1.70)	0.107*** (5.89)	0.0890*** (3.57)	0.112*** (3.68)	0.138*** (7.22)
Higher education ^a	0.249*** (8.69)	0.126** (3.18)	0.276*** (11.20)	0.273*** (9.12)	0.309*** (9.29)	0.333*** (13.05)
Full-time work experience	0.155*** (17.09)	0.170*** (13.80)	0.143*** (17.50)	0.140*** (18.95)	0.146*** (17.88)	0.162*** (16.94)
Full-time work experience ²	-0.0435*** (-6.34)	-0.0499*** (-5.32)	-0.0404*** (-6.39)	-0.0391*** (-7.73)	-0.0411*** (-6.25)	-0.0509*** (-7.88)
Trained for occupation	0.118*** (7.87)	0.180*** (9.59)	0.140*** (9.46)	0.113*** (8.05)	0.0512*** (3.31)	0.0197 (1.12)
Unemployment experience	-0.0252*** (-7.93)	-0.0209** (-3.05)	-0.0244*** (-9.40)	-0.0289*** (-9.99)	-0.0243*** (-7.19)	-0.0242*** (-3.68)
Service class ^b	0.285*** (7.27)	0.203 (1.69)	0.173 (1.69)	0.278*** (12.84)	0.302*** (10.89)	0.275*** (7.73)
Non-manual routine workers ^b	0.185*** (4.97)	0.0666 (0.56)	0.0742 (0.74)	0.188*** (9.87)	0.222*** (9.15)	0.201*** (5.64)
Skilled workers ^b	0.165*** (4.58)	0.0454 (0.39)	0.0602 (0.59)	0.176*** (9.74)	0.197*** (7.58)	0.237*** (5.15)
Non-skilled workers ^b	0.131** (3.24)	-0.0235 (-0.19)	0.0138 (0.14)	0.119*** (6.45)	0.148*** (4.65)	0.180*** (4.00)
Occupational prestige	0.0311*** (7.59)	0.0254*** (3.73)	0.0293*** (6.95)	0.0317*** (8.61)	0.0350*** (10.47)	0.0415*** (9.95)
Larger company	0.185*** (14.54)	0.235*** (11.76)	0.191*** (14.23)	0.180*** (15.13)	0.188*** (14.08)	0.191*** (13.58)
Female	-0.111*** (-7.12)	-0.142*** (-6.34)	-0.125*** (-8.35)	-0.0995*** (-7.30)	-0.0924*** (-6.28)	-0.0545*** (-3.43)
East	-0.182*** (-12.18)	-0.173*** (-7.97)	-0.193*** (-12.98)	-0.186*** (-13.61)	-0.213*** (-14.97)	-0.231*** (-14.11)

<i>Log hourly wages</i> (dependent variable)	OLS	Q10	Q25	Q50	Q80	Q90
Married	0.0291* (2.21)	0.0213 (1.01)	0.0110 (0.75)	0.0319* (2.53)	0.0213 (1.52)	0.0254 (1.86)
Number of children	0.0363*** (3.90)	0.0195** (2.66)	0.0237*** (3.30)	0.0196** (3.12)	0.0319*** (4.01)	0.0437*** (4.29)
Number of observations	9635	9635	9635	9635	9635	9635

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ^aBasic Education as reference group; ^bAgricultural Labourer as reference group.

Source: Authors' own calculations (weighted) based on SOEP v33.1

Appendix 5: Quantile Regressions Academic Family Background

<i>Log hourly wages</i> (dependent variable)	OLS	Q10	Q25	Q50	Q75	Q90
Weak-tie career support	0.0718*** (3.86)	0.126*** (3.98)	0.0885*** (3.90)	0.0632*** (3.33)	0.0484* (2.53)	0.0178 (0.91)
Medium education ^a	0.109 (1.82)	0.161 (0.81)	-0.0221 (-0.12)	0.163* (2.47)	0.204* (1.97)	0.158*** (3.72)
Higher education ^a	0.298*** (4.52)	0.318 (1.61)	0.153 (0.80)	0.330*** (4.93)	0.423*** (3.98)	0.369*** (7.91)
Full-time work experience	0.169*** (9.88)	0.182*** (4.68)	0.141*** (7.72)	0.147*** (9.18)	0.171*** (9.19)	0.160*** (15.13)
Full-time work experience ²	-0.102*** (-6.26)	-0.0937* (-2.09)	-0.0919*** (-6.74)	-0.0922*** (-5.52)	-0.103*** (-5.28)	-0.105*** (-7.98)
Trained for occupation	0.139*** (3.33)	0.226*** (3.59)	0.115*** (3.32)	0.0982** (3.00)	0.0394 (0.92)	0.0522*** (3.32)
Unemployment experience	-0.0443*** (-5.21)	-0.0185 (-0.77)	-0.0385** (-3.28)	-0.0511*** (-7.60)	-0.0525* (-2.47)	-0.0469*** (-6.32)
Service class ^b	0.533** (3.13)	0.396 (1.33)	0.680 (0.48)	0.497 (0.45)	0.364 (1.11)	0.366** (2.90)
Non-manual routine workers ^b	0.396* (2.32)	0.137 (0.45)	0.538 (0.38)	0.346 (0.31)	0.257 (0.78)	0.266* (2.02)
Skilled workers ^b	0.360* (2.12)	0.0991 (0.31)	0.565 (0.40)	0.336 (0.31)	0.212 (0.64)	0.364** (2.72)
Non-skilled workers ^b	0.364* (2.11)	0.108 (0.32)	0.555 (0.39)	0.313 (0.28)	0.181 (0.51)	0.365** (2.84)

<i>Log hourly wages</i> (dependent variable)	OLS	Q10	Q25	Q50	Q75	Q90
Occupational prestige	0.0197* (2.43)	-0.00144 (-0.11)	0.0200** (3.09)	0.0226*** (4.82)	0.0310*** (4.95)	0.0465*** (9.87)
Larger company	0.128*** (4.39)	0.200*** (3.30)	0.140*** (3.84)	0.120*** (3.86)	0.112*** (3.53)	0.110*** (5.36)
Female	-0.103** (-3.25)	-0.130* (-2.44)	-0.141*** (-3.90)	-0.0910** (-3.25)	-0.0478 (-1.38)	-0.0152 (-0.50)
East	-0.123*** (-4.39)	-0.156** (-3.22)	-0.133*** (-4.57)	-0.118*** (-3.64)	-0.119*** (-4.20)	-0.195*** (-11.29)
Married	0.0191 (0.61)	0.0137 (0.26)	-0.00740 (-0.22)	-0.00164 (-0.05)	0.0100 (0.28)	0.0582* (2.50)
Number of children	0.0328* (2.48)	0.0427* (1.97)	0.0136 (0.86)	0.0232 (1.44)	0.0366** (2.59)	0.0469*** (3.53)
Number of observations	1914	1914	1914	1914	1914	1914

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ^aBasic Education as reference group; ^bAgricultural Labourer as reference group

Source: Authors' own calculations (weighted) based on SOEP v33.1

Appendix 6: Quantile Regressions Non-academic Family Background

<i>Log hourly wages</i> (dependent variable)	OLS	Q10	Q25	Q50	Q75	Q90
Weak-tie career support	0.0367** (3.02)	0.0344** (2.77)	0.0187 (1.34)	0.0298* (2.49)	0.0178 (1.66)	0.0161 (0.80)
Medium education ^a	0.0944*** (3.86)	0.0252 (0.83)	0.117*** (5.18)	0.0672* (2.20)	0.110** (3.20)	0.137*** (6.74)
Higher education ^a	0.236*** (7.29)	0.0833 (1.78)	0.275*** (9.17)	0.258*** (7.21)	0.310*** (8.02)	0.333*** (10.43)
Full-time work experience	0.147*** (14.17)	0.150*** (10.45)	0.136*** (12.89)	0.134*** (15.39)	0.138*** (16.34)	0.149*** (12.68)
Full-time work experience ²	-0.0353*** (-4.62)	-0.0341** (-3.21)	-0.0338*** (-4.87)	-0.0334*** (-5.34)	-0.0337*** (-5.12)	-0.0436*** (-5.23)
Trained for occupation	0.114*** (7.31)	0.173*** (7.47)	0.139*** (7.66)	0.120*** (7.86)	0.0727*** (4.45)	0.0127 (0.60)
Unemployment experience	-0.0234*** (-6.93)	-0.0201* (-2.15)	-0.0234*** (-13.02)	-0.0252*** (-7.82)	-0.0216*** (-5.40)	-0.0202** (-2.97)

<i>Log hourly wages</i> (dependent variable)	OLS	Q10	Q25	Q50	Q75	Q90
Service class ^b	0.234*** (6.62)	0.0846 (1.04)	0.133** (2.80)	0.271*** (10.78)	0.256*** (6.87)	0.281*** (7.09)
Non-manual routine workers ^b	0.148*** (4.47)	-0.00432 (-0.06)	0.0540 (1.24)	0.195*** (9.48)	0.172*** (4.85)	0.206*** (5.54)
Skilled workers ^b	0.139*** (4.23)	-0.00558 (-0.07)	0.0432 (1.02)	0.173*** (8.02)	0.149*** (3.87)	0.236*** (5.60)
Non-skilled workers ^b	0.103** (2.70)	-0.0783 (-0.97)	-0.00638 (-0.14)	0.123*** (5.67)	0.0925* (2.48)	0.172*** (4.37)
Occupational prestige	0.0379*** (9.26)	0.0439*** (5.85)	0.0358*** (6.74)	0.0349*** (7.31)	0.0338*** (9.65)	0.0366*** (6.49)
Larger company	0.198*** (14.01)	0.238*** (10.67)	0.208*** (13.24)	0.185*** (13.44)	0.200*** (14.54)	0.221*** (11.87)
Female	-0.113*** (-6.32)	-0.151*** (-5.98)	-0.132*** (-7.23)	-0.114*** (-7.30)	-0.0976*** (-6.39)	-0.0776*** (-3.81)
East	-0.195*** (-11.15)	-0.173*** (-6.33)	-0.200*** (-10.82)	-0.187*** (-10.78)	-0.231*** (-13.19)	-0.263*** (-10.65)
Married	0.0301* (2.09)	0.0312 (1.25)	0.0176 (1.08)	0.0289* (1.97)	0.0121 (0.82)	0.0186 (1.03)
Number of children	0.0348** (3.14)	0.0139 (1.19)	0.0220* (2.35)	0.0181** (2.68)	0.0229** (2.70)	0.0320** (2.75)
Number of observations	7721	7721	7721	7721	7721	7721

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ^aBasic Education as reference group; ^bAgricultural Labourer as reference group

Source: Authors' own calculations (weighted) based on SOEP v33.1

Appendix 7: Robustness Checks

Three alternative estimations serve as a robustness check for the afore presented results. Firstly, we find that excluding *occupational prestige* increases the estimated price effect (i.e. share of the wage gap that cannot be explained by differences in wage-determining characteristics) (see table below).

Oaxaca-Blinder Decomposition Results With and Without Prestige (Grouped Estimates)

	<i>Log hourly wages</i>	
	With prestige	Without prestige
<i>Group 1</i>	2.859***	2.859***
(Academic Family Background)	(152.14)	(152.39)
<i>Group 2</i>	2.713***	2.713***
(Non-Academic Family Background)	(299.41)	(298.33)
<i>Difference</i>	0.146***	0.146***
	(6.98)	(6.99)
<i>Explained</i>	0.141***	0.137***
	(7.21)	(7.16)
<i>Unexplained</i>	0.00455	0.00858
	(0.25)	(0.46)
<i>Grouped components of the explained part</i>		
Instrumental social capital (i.e. Weak Ties)	0.00768**	0.00830**
	(2.58)	(2.59)
Education related human capital	0.0773***	0.0885***
	(5.71)	(6.28)
Work related human capital	-0.0303**	-0.0258*
	(-2.74)	(-2.34)
Other employment characteristics	0.0912*** ^a	0.0705*** ^b
	(5.83)	(6.06)
Other personal characteristics	-0.00476	-0.00442
	(-0.91)	(-0.84)
Number of observations	9635	9635

t statistics in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ^aOut of which 0.0436 (i.e. 29.90% of the wage gap) is due to differences in occupational status; ^bOut of which 0.0635 (i.e. 43.59% of the wage gap) is due to differences in occupational status

Source: Authors' own calculations (weighted) based on SOEP v33.1

While it is still not significant, it underlines that the price effect captures any unobserved heterogeneity. Moreover, the results confirm the assumed mediating relationship between *occupational prestige* and the predictors of *educational attainment*, *occupational status* and *instrumental social capital*. It is particularly pronounced in the case of *educational attainment* and *occupational status* and rather small for *instrumental social capital*. It can be concluded that the direct association between the respective predictors and the dependent variable is predicted more reliably by including variables for *occupational status* and *prestige*.

As a second robustness check of the OB decomposition, the preferred model is estimated using the coefficient results from a pooled linear regression for the counterfactual estimation (see right column of “Appendix 3”). Overall, the alternative estimation confirms the robustness of the results as group differences in capital endowments still explain a significant part of the wage gap. While the share of the unexplained part of the wage gap is slightly higher, it is also not significant at any conventional level.

Thirdly, we estimate pooled quantile regressions using bootstrapped standard errors to check the robustness of the log hourly wage differential estimated with robust standard errors (see Fig. 7). Since the estimation does not allow the application of sample weights only the general trend should be considered. The increasing wage differential along the distribution is more pronounced when applying bootstrapped standard errors. All in all, both estimations show a similar tendency, predicting those from a non-academic family background to experience a wage penalty that cannot be explained by differences in any other wage-determining characteristics at the upper middle part of the distribution, confirming the robustness of the afore presented results.

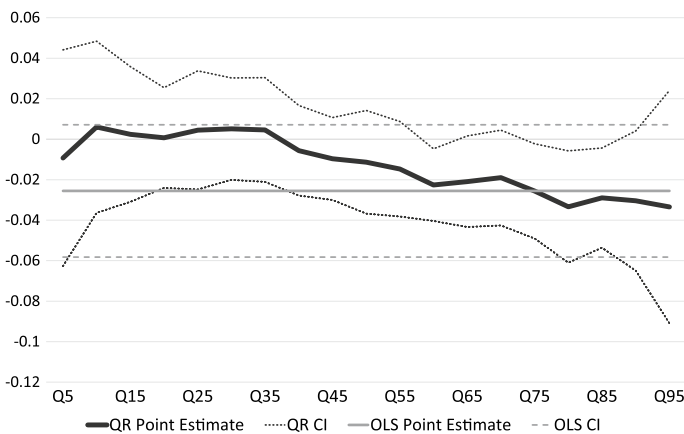
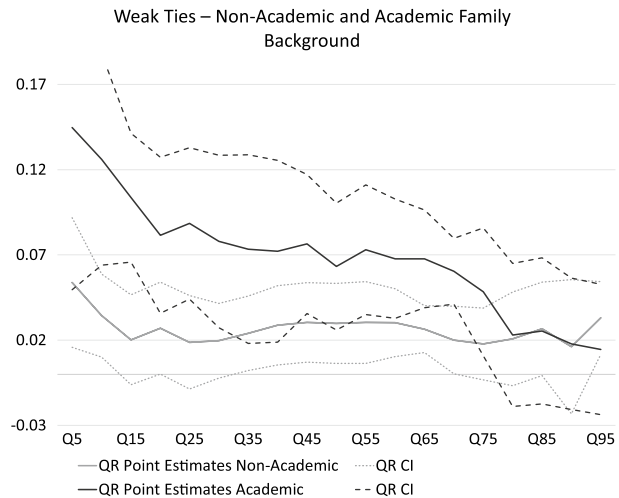


Fig. 7 Group log hourly wage differential along the distribution using bootstrapped standard errors. *Source:* Authors' own calculations (unweighted except OLS) based on SOEP v33.1

Appendix 8: Returns to Weak-Tie Career Support

Fig. 8 Coefficient estimates weak-tie career support for both groups (quantile regressions). *Source:* Authors' own calculations (weighted) based on SOEP v33.1



Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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