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Wage Differentials And Educational Attainment In Germany. How Do Job Profiles Affect Earnings?

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Abstract

This paper presents the results of an empirical analysis on the issue of wage differentials occurring within education levels. The main purpose of the research is to investigate the extent to which job profiles, classified as routine and non-routine tasks can explain wage differentials within educational levels in Germany. Systematization of the literary sources and approaches for solving the problem of wage differentials indicates that in line with technological advancement witnessed over the past decades, earnings are largely determined by the nature of tasks carried out within the workplace. The relevance of this scientific problem decision is that educational systems have to keep up with advancing digitization and the rapidly changing labour market requirements. Investigation of the impact job profiles have on earnings, in the paper is carried out in the following logical sequence: firstly, a brief overview on previous research in the field is given, followed by an outline of the dataset analysed, proposed hypotheses, applied methodology and results concluding with a discussion. Methodological tools of the research methods were descriptive statistics along with OLS regression techniques. Based on German cross-sectional employee survey data from 2018 two hypotheses are tested by classifying 23 selected work activities into routine and non-routine tasks linked to the highest education level attained. In accordance with the German education system four educational levels are specified: no occupational degree, in-company or school-based vocational training, advanced vocational training degree and university degree. The results indicate that non-routine activities are on average remunerated at a higher rate compared to routine activities and non-routine analytical work is paid at a higher rate than non-routine craftmanship. Additionally, higher wages for computer assisted work activities is found. The OLS regression model results confirm both hypotheses implying increasing returns to educational attainments resulting in larger hourly pay and higher pay for those performing non-routine tasks. Pursuant to the traditional Mincer human capital approach on returns to schooling the research empirically confirms higher wages for employees completing advanced vocational training and those holding a university degree. The results of the research can be useful for policymakers in the education sector, fostering and improving analytical, data literacy and organizational skills.

Keywords: education system, Germany, skill-biased technical change, tasks, wage gap.

JEL Classification: J24; J31.

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1 Introduction

The following empirical work deals with the question of what influence job profiles have on earnings within educational levels. Several publications have appeared in recent years documenting increasing divergence in salaries regardless of the educational qualification obtained. Constant technical progress along with increasing social complexity result in continuously growing demand for highly qualified workers. One of the first publications dedicated to the proliferation of technological advancement affecting all aspects of life and the acknowledgement that modern technologies require differentiated knowledge is presented in Schelsky (1961). Since then, highly educated individuals have witnessed a considerable increase in their earnings. Due to progressive digitization, qualification requirements on the labor market are changing, which at the same time has led to the educational expansion in Germany since 1950. The latter describes the massive expansion of the education system over the past 70 years. Since 1950 Germany is witnessing a tremendous increase in the proportion of young people attending higher education institutions and obtaining higher educational qualifications. While only 7.7 percent of the population was holding a technical college or university degree in 1976, the proportion of graduates has increased to 26.6 percent by 2011 (Federal Statistical Office, 2012). Higher educational levels lead to individualization and pluralization tendencies within societies, which ultimately result in societal change (Beck, 1986). Education is pivotal for societal prosperity and in this context, it is assumed that earnings differentials among workers holding the same educational qualification are explained by differences in job profiles. The analysis is based on German cross-sectional employee survey data from 2018 provided by the Federal institute for Vocational Education and Training. According to the German education system, four educational levels are specified: no occupational degree, in-company or school-based vocational training, advanced vocational training degree and university degree. The remainder of the paper is organized as follows: section 2 presents a literature review, section 3 briefly outlines the data analyzed followed by an explanation of methods applied to test the proposed hypotheses, the research methods are described in section 4. The results are presented in Section 5. Finally, the results are summarized and discussed in a socio-political context in section 6.

2 Literature Review

A large body of literature analyses the link between education and wage inequalities (Juhn, Murphy and Pierce, 1993; Card, 1999, 2003; Prasad, 2000; Pereira and Martins, 2000; Dahl, 2006; Lemieux, 2006). However, most studies focus on earnings inequalities related to differences between educational levels. To date, only few studies focus on wage differentials within educational levels. Further, there is lack of research linking educational disparities to the distribution of wages. Empirical studies documented both wage differentials between and within educational levels (Juhn, Murphy and Pierce, 1993; Card, 1999; Prasad, 2000; Pereira and Martins, 2000) and document that differentials within levels of education may be attributable to unobservable workers' skills or other characteristics.

Using a quantile regression approach based on the Mincer equation Pereira and Martins (2000) question whether educational attainment reduces income inequality based on data of fifteen European countries. Although the years 1980 to 1995 are considered, the focus of the analysis lies on four cross-sectional datapoints throughout the observed period. In their work, they mainly focus on wage differentials within educational levels applying the log gross hourly wage as a dependent variable and the number of years in schooling, as well as the years of professional experience as the independent variables. The authors identify four distinct ways education affects the wage distribution. For the case of Portugal, the authors document a positive and rising effect of education on income differentials within educational levels. A positive and at the same time stable impact of education related to earnings inequality is found for Austria, Finland, France, Ireland, the Netherlands, Norway, Spain, Sweden and the UK. For Germany and Greece, a negative impact of schooling on within group income inequalities is documented. Conversely, data on Denmark and Italy hardly implies evidence for any link between income inequality and education. The results suggest a causal relationship between education and skills related to the income incurred. The study finds that on the one hand income increases with educational attainments for most of the countries observed, while on the one hand investments in education are ambiguous due to its unforeseen impact. Likewise, Prasad (2000) investigates the impact of schooling on wage inequality controlling for additional factors such as returns to experience and tenure. In this study Prasad (2000) illustrates the dynamics of the German wage structure between 1984 and 1997. The second part of the analysis documents falling employment and retention rates for unskilled workers while increasing employment rates for skilled workers are presented. Contrary to Pereira and Martins (2000), Prasad (2000) considers each year of the period observed and additionally includes four dummy variables for the educational performance, instead of years of schooling in his model. The author defines the following dummy variables: school education, vocational training and higher education, thereby facilitating the quantile regression models for individual educational levels. The work varies the methodological approach of Pereira and Martins (2000) further in that Prasad (2000) creates three additional independent dummy variables that are related to education in the proposed regression model: work experience as well as its square, the duration of employment, a dummy variable for German citizenship and mediator variables between the dummy and the explanatory variables. Both studies provide comparable results. Pereira and Martins (2000) argue that the return to schooling of the entire sample is falling along with a simultaneous decrease in the wage structure. Based on their findings, workers allocated within the 10th percentile experience higher returns to education compared to those within the 90th percentile. By contrast, the analysis by Prasad (2000) including dummy variables for three educational groups, allows a more nuanced perspective. In his work, opposed to the results presented by Pereira and Martin (2000) his findings indicate a positive relation between the wage dispersion and the return to education within workers educated to degree level. For the remaining two educational groups, those holding vocational firm and college-based training a negative impact on return to education is presented. Since the latter educational groups make up the majority of the workforce in Germany, both studies are not necessarily controversial. Further, Prasad (2000) suggests that the stability of the income distribution in West Germany for the period 1984-1997 is attributable to institutional factors rather than market forces. Wage inequalities within educational groups decrease with higher educational attainment, since the wage dispersion declines for higher levels of education, and even decreases over time (Prasad, 2000). In line with Pereira and Martin (2000) this represents a necessary precondition for a negative impact of the higher educational levels on the total wage inequality, which firstly depends on the fraction of the distribution where educational upward mobility occurs and secondly on the magnitude of the return to education.

Another perspective has been adopted by Schnabel and Schnabel (2002) analyzing the impact of the family background on wages earned and the return on education in Germany. The authors explore the link by estimating the income equation and selecting variables related to the family background as additional control variables that allow heterogeneous returns to education. This approach facilitates the analysis of unobservable family-specific heterogeneity and helps to eliminate estimation errors occurring due to family-specific effects. For that reason, a fixed estimator and a correlated random effects estimator is applied to assess the impact of the family background. Schnabel and Schnabel (2002) argue that the family background is crucial and highly relevant for the amount of labour income earned, despite of policy interventions. Further, they claim that the family background largely influences the wage dispersion as well as the marginal return to education. In line with their results, individuals with well-educated parents tend to on the one hand face a lower return to education, and on the other hand, they earn a higher wage opposed to those with less educated parents. Based on their theoretical model, they explain this finding by lower marginal costs of education encountered by families that have higher human capital accumulations. In addition, Schnabel and Schnabel (2002) state that gender has a significant impact on the return to education. While women on average earn lower wages compared to men, they achieve higher returns to education than the latter. In summary, Schnabel and Schnabel (2002) claim that particularly the middle class in Germany has benefited from educational reforms. They suggest that policies targeted to increase the participation rate of individuals from precarious backgrounds should primarily aim to reduce marginal personal cost. As a result, the authors state that a trend towards limiting financial support for students is counterproductive since it hinders the utility maximization of existing human capital. This view is supported by Pereira and Martins (2000), who find majority of countries examined witnessing a positive correlation between investment and return to education. Despite finding that educational expansion has a promising positive prospect on wage inequality in Germany, Schnabel and Schnabel highlight that especially the middle class largely benefits from access to high school education in West Germany.

Thus far, previous research has established that there is a shift in demand towards better educated workers (Autor and Katz, 1999; Goldin and Katz 2008, 2009; Acemoglu and Autor, 2011). While the 'skill-biased technical change', is well documented utilizing decades of data (Goos, Manning and Salmons, 2014), the proposed theory itself does not take account of an increase in job polarization. The term 'job polarization', firstly introduces by Good and Manning (2003), proposes an explanatory concept describing the relative increase in demand for well-paid and qualified jobs that require cognitive abilities on the one hand, and poorly paid jobs with low qualification requirements on the other hand. This process gradually leads to a decrease in demand for routine job tasks performed by the middle class as a result of automatization and task outsourcing. While this phenomenon is well documented for the US (Autor, Katz and Kearney, 2006, 2008; Autor and Dorn, 2013) and the UK (Goos and Manning, 2007) the study by Spitz-Oener (2006) is one of the first studies exploring job polarization in Germany. In her research on technological change and rising educational demand, Spitz-Oener (2006) investigates whether qualification requirements for employees generally have increased and if the increase is attributable to technological change. Technological progress and programmable algorithms bear the potential of completely replacing routine job tasks. The findings for Germany are supported by those presented in a study by Author, Levy and Murnane (2003) for the US, who report a change in job profiles and competences of workers required between 1979 and 1999. Similarly, Spitz-Oener (2006) shows that the shift in job tasks away from cognitive and manual routine tasks in favour of analytical and interactive tasks, is led by changes in skill requirements and raising job polarization. In sum, numerous studies have looked at the change in job profiles and its cause, however little research based on recent data is available about the link between job tasks and wages earned. The presented study sheds light on the impact of routine and non-routine job tasks on wages in Germany.

3 Theoretical framework and hypotheses

The following section describes the theoretical foundations of this work which is mainly based on the human capital approach according to Becker (1964), a model assessing the changes of qualification requirements throughout various nations according to Autor et al. (2003), the signaling theory as well as the economic supply and demand model, as an explanatory approach for wage differences within educational groups.

The growing digital transformation increasingly leads to a shift in workers' human capital requirements. Whereby, human capital refers to the performance potential of workers attributable to individual education, knowledge and skills acquired through work experience (Becker, 1964). According to the human capital theory, investing in human capital improves individuals' long-term work results. For this reason, the human capital approach is particularly relevant to explore the link between investment and return to education. In line with the human capital theory proposition, wage differentials can be explained by differences in educational attainments.

Based on their empirical work, Author et al. (2003) developed a model that measures the change in skill requirements for jobs in the US and others industrial nations. For 1970-1998 the study documents the changes in labor input in the following four job task categories: routine cognitive, routine manual, non-routine cognitive and non-routine manual. According to the terminology applied, a task ('activity') is one unit of work that produces an output. The skill of an employee is related to the sum of abilities employed to carry out distinct activities. Hence, workers offer their skills to perform work in exchange for a wage. The researchers further argue that the distinction between competencies and activities implies a nuanced view of how technological progress alters job skills requirements, qualifications and the division of labor. The evidence presented by Autor et al. (2003) indicates that labour employed for routine activities has sharply declined since 1980 due to increased machine substitutability of human labour. Moreover, a rise in areas carrying out analytically interactive activities has risen rapidly since 1980, which has led to a complementary demand for both work and computerization. While analytical and interpersonal activities increase in the workplace, their findings suggest that the proportion of cognitive and manual routine activities and non-routine manual activities has decreased during the period observed. While 1970 50 percent of the workforce was performing routine cognitive tasks, between 1980 and 2010 the share of the latter has fallen from 50 percent to just under 40 percent. Given the above evidence, the first hypothesis to be empirically tested is formulated as follows:

H1: Non-routine job tasks are paid at a higher rate than routine tasks.

The effects of educational attainments on the job-market can be explained by means of the classic Signaling Theory (Spence, 1973; Stiglitz, 1975). According to the Signalling theory individuals fundamentally differ in their abilities and education per se does not affect workers' performance. The theory is widely used to examine and explain the behaviour of individuals in contractual relationships. An asymmetric information distribution between the participants is assumed which results in inefficiencies and opportunistic behaviour. For a potential employer however, these abilities are hard to verify due to information asymmetries. In this case, both the principal (employer) and the agent (worker) strive to maximize their benefits although their objectives are not necessarily congruent. Usually, the agent has an information advantage when executing the request and thus there is an asymmetrical information distribution between both parties. These capabilities are principally based on the information asymmetry which are unobservable on the labor market. The applicant as an agent can reduce the information asymmetry providing the potential employer with degrees signaling a certain level of qualification. Thus, the comparison of signals, here educational attainments facilitate the distinction between low and highly qualified applicants. According to the theory a higher educational attainment implies a higher level of qualification.

Consistent with economic theory, the return to education is determined by the relative supply and demand of qualifications. Whereby, within-group differences in return to education result from the interaction of those market forces. As noted in Chapter 2, the Mincer equation allows the estimation of return to education resulting from an additional unit of education. Bellmann and Gartner (2003) suggest that wages increase with higher educational qualification. This hypothesis is the second to be tested:

H2: Greater educational attainment is positively linked to higher wages.

4 Sample and methods

The following section briefly outlines the data analyzed followed by an explanation of methods applied to test the proposed hypotheses. The results are then described in Chapter 5.

4.1 Dataset

The study is based on German cross-sectional Employment survey data (BIBB/ BAuA, 2018). The survey includes 20,000 employed individuals in Germany and is jointly supported by the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA). It is a repeated survey and data is collected every six years. The survey includes on the one hand, questions related to the current job tasks, working conditions, skills, knowledge requirements, work demand and workload, further training needs as well as health impairment and stress. On the other hand, it explores the link between employment and education. Respondents are aged 15 or above and engage in paid work of at least ten hours weekly. With the help of weighted results, representative statements on working conditions, the distribution of education and schooling history within Germany can be derived (Hall et al., 2012). Table 1 provides a summary of the sample which comprised 19962 employees aged between 15 and 65, of which 7,640 (38.27 percent) are academics holding a university degree, 1,593 (7.98 percent) graduates of advanced vocational training and 9,638 individuals (48.28 percent) with completed school or firm based vocational training. 1091 respondents (5.47 percent) were not holding any professional qualification. The emphasis in this analysis is placed on the highest educational attainment achieved by each respondent.

Table 1. Descriptive Statistics. Before tax hourly wage (EUR) by levels of education 2017/2018

	Freq.	Percent	Mean	Std. Dev.	Min	Max
No occupational degree	1091	5.47	14.63	8.98	1.74	96.44
In-company or school-based vocational training	9638	48.28	17.08	8.51	1.16	167.44
Advanced vocational training degree	1593	7.98	21.52	11.07	3.49	186.45
University (of applied sciences) degree	7640	38.27	25.82	13.45	1.39	232.56
Total	19962	100.00	20.64	11.69	1.16	232.56

Source: based on BIBB/BAuA Employment Survey 2018; own calculation.

Table 1 shows the average gross hourly wage earned before tax classified by the respondents' qualifications in 2017-2018. Respondents' average wage was EUR 20.64 per hour with a standard deviation of EUR 11.69 per hour. Individuals without any qualification on average earned EUR 14.63, people who have completed school or in-firm based vocational training 17.08 and graduates of advanced training EUR 21.52. The highest mean wage of the respective sample was earned by university graduates with EUR 25.82 per hour. The standard deviation of EUR 13.45 per hour is the highest for degree educated respondents, of which few are earning up to EUR 232.56

per hour. Generally, the wage distribution reveals a clear trend towards a positive link between the educational qualification and the wages. Calculations based on the sample data imply that having any of the four respective qualifications versus no occupational qualification increases the hourly wage by 45 percent.

4.2 Concept specification and operationalization

The *dependent variable of* the multivariate analysis conducted is the gross hourly wage in EUR. The variable, gross hourly wage, was calculated by multiplying the hours worked out of the most extensive activity with the factor 4.3 to generate the number of hours worked per month. In a second step, the imputed wages for missing wage information and outliers were divided by the hours worked monthly basis to work out the variable *wage*. This variable allows the comparison of average wages across qualifications. The *independent variables* are the highest educational attainment and the job-task. The dataset includes a variable on the highest qualification with the values illustrated in Table 1. The variable was divided into four dummy variables whereby, the variable *no occupational degree* represents the reference group of the regression analysis. The present study is based on 23 different job profiles which are classified as either routine or non-routine job-tasks. Table 2 reveals the classification of each job-task accordingly. Respondents were also asked about their soft skills, including how often they are using professional communication with other individuals at work. For this study it is assumed that professional communication is ubiquitous at any workplace, so that the inclusion of this variable was not deemed necessary. Due to its limited statistical representation the variable related to IT activities has not been considered. In addition, variables that are not directly related to the job-task itself but rather are industry-specific were excluded from further analysis. The job-task classification is the foundation of the analysis. The classification of activities into routine and non-routine activities is based on Antonczyk et al. (2009). Denoted as routine activities are those that can be substituted by programmable machines while non-routine activities largely focus on analytical and interactive job-tasks (Murnane et al. 2003). Based on the employment survey Antonczyk et al. (2009) examined for the change in the wage structure for full-time employed men between 1999 and 2006 in West Germany. In contrast to the study by Antonczyk et al. (2009), this study distinguishes between routine and non-routine activities, a further differentiation within the two chosen categories, was waived. The 23 activities considered were classified as follows.

Table 2. Classification of occupational activities

Non-Routine-Activity	Routine-Activity
• measure, test • repair • purchase and sales • advertising • organising • research and development • teaching • documentation, research • consulting • hospitality • care • securing, protecting, guarding • using the internet/replying to mails • problem solving • decision making • independent gain of knowledge • taking responsibility • negotiating compromises	• production • cleaning, recycling • transport, storing, shelving • machine control • using/working with computers

Source: based on BIBB/BAuA Employment Survey 2018; own contribution.

The variables related to job-tasks within the dataset take the following values: never, sometimes, often and none. 'No specification' was coded as a missing value in the dataset. In order to carry out a mean value comparison as part of the analysis dummy variables were generated for each of the 23 activities. These were then coded as

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follows: 1 equals to the fact that the activity is carried out frequently within the scope of employment, while 0 indicates the associated activity is rarely or never carried out at the workplace.

4.3 Methods

In this study bivariate and multivariate analysis was carried out using the statistical software package STATA to test the previously stated hypotheses linked to the impact of selected job profiles. The OLS regression model results are presented in Table 3 in Chapter 5. Table 3 shows the results of the multiple regression model with the gross hourly wage variable considered as the dependent variable. The coefficients presented in (1) and (2) are the results of a bivariate regression. In the first regression model, (1), the independent variable controlled for is the highest educational qualification and in (2) the activity carried out within the workplace. The values for the adjusted R-squared allows to determine the proportion of the variance in wages explained by the independent variables, in (1) the highest educational qualification and the activity performed (2). The derived regression coefficients (b =.) in (1) describe the extent to which hourly wage of individuals with the respective qualification is higher compared to those without any occupational qualifications, who serve as a reference group in (1). In (2), the increase in dummy-coded independent variables (activities) by one unit equals to an increase from 0 to 1. A change from 0 to 1 corresponds to a change within the category from "activity is not carried out at workplace" to "activity is carried out at workplace". The calculated coefficients indicate a rise in wages given that the independent variable increases by one unit from 0 to 1. As a result, the regression coefficients indicate the extent to which the hourly wage is higher if the activity is carried out at work compared to not being carried out. The multivariate regression model (3) assesses the influence of the described independent variables on gross hourly wage. The p-values are used to determine the significance of the difference in wages between workers carrying out a particular activity and those who do not.

5 Results

Strong evidence of a positive relationship between wages and occupational qualification was found, which agrees well with existing studies on the link between education and wages earned. Access to education constitutes a key determinant of earned wages.

The results, as seen in Table 1, confirm the hypothesis set out under H2 in Chapter 3, saying that a higher occupational qualification implies a higher salary. It is found that workers having an advanced occupational training degree earn around 26 percent more on average compared to those graduating with an in-company or school-based vocational training. The gross hourly wages of workers without occupational degree (EUR 14.63) and those with in-company or school-based vocational training (EUR 17.08) indicate that these particular groups are earning less based on the sample average of EUR 20.64 per hour. While the average wage of workers holding an advanced vocational training degree with EUR 21.52 is higher than the sample average, the findings demonstrate that they earn 20 percent less compared to university graduates. By means of the standard deviation, it is possible to determine the dispersion of wages compared to the calculated mean wage. With regards to the average gross hourly wage of workers with university degrees, a comparatively high standard deviation of EUR 13.4 was found. This in turn reveals that the spread of wages for workers holding university degrees is higher and therefore, it can be interpreted in a way that this sample group can select from a wider range of jobs, including those requiring lower occupational qualifications and those jobs solely accessible for university graduates.

One of the key observations of this study is the wage differential between workers performing routine-activities at their workplace earning EUR 17.54 per hour (std. err. .2257) and those executing non-routine tasks earning EUR 19.37 (std. err. .4910) on average. On annual basis, for an individual employed 40 hours per week this implies a gross difference in salaries amounting to EUR 3840. These findings are consistent with the results of Autor et al. (2003) and affirm the first hypothesis outlined in H1. The following part focuses on the main empirical findings. Table 3 shows the results of the OLS regression models analyzing the extent to which occupational qualifications and job activities can explain the wage differentials.

Table 3. OLS Regression Models

	(1)	(2)	(3)
	Dependent variable: Hourly wage		
Reference: no occupational degree	-	-	-
Vocational training	2.446***		1.161***
	(.347)		(.338)
Advanced vocational training	6.889***		3.554***
	(.427)		(.423)
University degree	11.193***		6.456***
	(.352)		(.361)
Production		-.655***	-.466**
		(.215)	(.21)
Measuring		.912***	.671***
		(.186)	(.182)
Machine control		.235	.674***
		(.187)	(.184)
Repairing		-.702***	-.347*
		(.188)	(.185)
Purchasing		-.253	-.189
		(.169)	(.166)
Transport, shelving, storing		-2.702***	-2.116***
		(.172)	(.169)
Advertising		.652***	.096
		(.169)	(.166)
Organising		.844***	.71***
		(.202)	(.198)
Research and development		2.641***	1.658***
		(.174)	(.174)
Teaching		1.705***	1.348***
		(.175)	(.172)
Documentation and research		1.138***	.776***
		(.287)	(.281)
Consulting		.41	.264
		(.291)	(.284)
Hospitality		-1.481***	-1.152***
		(.214)	(.21)
Care		-.983***	-1.028***
		(.204)	(.2)
Securing, protecting, guarding		-.713***	-.519***
		(.178)	(.175)
Working with computers		3.903***	3.141***
		(.294)	(.29)
Using the Internet/mails		2.662***	1.764***
		(.312)	(.307)
Cleaning, recycling		-3.506***	-2.793***
		(.195)	(.192)
Problem solving		-.833	-.894
		(.58)	(.569)
Decision making		1.733***	1.512***
		(.266)	(.261)
Independent gain of knowledge		-.437	-.602*
		(.338)	(.331)
Taking responsibility		.893***	.703***
		(.209)	(.204)
Negotiating compromises		.624**	.333
		(.282)	(.276)
_Cons	14.629***	12.245***	11.72***
	(.329)	(.644)	(.67)

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Table 3 (cont.). OLS Regression Models

	(1)	(2)	(3)
Dependent variable: Hourly wage			
Observations	19962	19962	19962
R-squared	.135	.173	.207
F-stat	1038.062	180.728	200.717
Adj R^2	.135	.172	.206
Standard errors are in parentheses			
**** p<.01, ** p<.05, * p<.1*			

Source: based on BIBB/BAuA Employment Survey 2018; own contribution.

The gross hourly wage in EUR is the dependent variable in all three regression models. Model 1 (M1) controls for occupational degrees attained. It shows that workers with an in-company or school-based vocational training earn almost EUR 2.50 (2.45) more compared to those without any occupational degree. The difference is highly significant (p <0.001). Those having completed an advanced vocational training, earn an average of EUR 7 (6.89 per hour) more than those without any qualification. The largest wage differential is found among those holding a University degree, with a difference of EUR 11 (11.19) in hourly wages compared to those without any degree or training. All three occupational degrees are highly significant (p <0.001) in explaining wage differentials compared to those without any occupational qualification. In M1, R-squared equals to 0.135, implying that 13.5 percent of the variation in gross hourly wages can be explained by occupational degrees.

M2 only contains variables related to the activities that are performed as part of job profiles.

Firstly, the following 5 routine activities are listed: production, cleaning, transporting, controlling machines, working with computers. In line with the survey data, *working with computers*, largely compromises data entry and therefore in the scope of this study was classified under routine-tasks. The model shows that workers who, as part of their employment often or sometimes are involved in production processes compared to those who stated to never execute this task, earn EUR 0.65 (-0.655) less per hour. Those whose job profile includes *cleaning or recycling* tasks earn EUR 3.50 (-3.506) less per hour compared to those indicating to never execute this task at work. Likewise, workers involved in *transport* or *storing* on average earn EUR 2.7 less (-2.702) per hour than those who never perform this activity. The frequent exercise of the activities, *controlling machines* and *working with computers*, in the workplace is linked to higher wages. Individuals working with computers earn almost EUR 4 (3.903) more than people who do not use computers work. For *controlling machines* in the context of employment, workers earn EUR 0.23 more (0.235). The difference in wages for the execution of the following routine work activities: *Transporting, producing, cleaning* and *working with computers* is highly significant (p <0.001). However, the wage difference found for *controlling machines* is not significant. The following evaluations relate to the wage differentials occurring in line with performing non-routine activities at work, 18 selected non-routine tasks are listed in Table 2. It is found that those who *measure* earn EUR 0.9 (0.912) more while those involved into *repair*, approximately earn EUR 0.7 (-0.702) less. In both cases, the difference is highly significant (p <0.001). For the job tasks, *organizing* and *advertising* highly significant wage differences have been found, while the difference for *purchasing* is not significant. Further, the wage difference for the following non-routine tasks (*research and development*, *teaching* and *documenting research data*) is highly significant. Consequently, those who are involved in research and development processes earn EUR 2.64 more per hour, teaching EUR 1.70 (1.705) more, and workers documenting and analyzing research data EUR 1.1 (1.138) more per hour compared to those who never do. Opposed to the expectation, no significant wage differences (p> 0.05) were found for advisory activities, *problem-solving* and autonomously *identifying knowledge gaps*. Tasks such as *care* and *securing* activities are remunerated at almost one euro less per hour and *hospitality* EUR 1.50 less compared to those who are not performing these tasks (-0.983; -0.713 and -1.481). For the latter tasks, the wage difference is highly significant (p <0.001). In the event of *negotiating* at the workplace, the wage difference is highly significant (p <0.001). According to the calculation, employees earn EUR 0.6 (0.624) more per hour. The largest wage difference is arising from *computer work* which includes but is not limited to the use of the internet. If that is the case, workers earned around EUR 2.70 (2.662) more. Model M3 assesses the impact of occupational qualifications and the job activities on the gross hourly wage collectively. The results confirm that higher occupational qualifications imply higher hourly wages. Workers having completed vocational training EUR 1.16 more than those without any professional qualification. Holders of advanced training earn around EUR 3.5 (3.554) more and those who graduated from university almost EUR 6.5 (6.456) more than people without any qualification. The wage differentials for all three groups are highly significant. Based on the results reported in M3 it can be seen that the following routine-tasks: *producing*, *cleaning*, *transporting* are linked to lower wages obtained compared to those who stated not to perform those activities. The regression results in M3 are largely confirmed by the results in M1 and M2. Individuals who frequently work with computers and use the Internet in scope of their work activities, show the highest and at the same time a highly significant ($p < 0.001$) wage difference. Opposed to M2, in M3 the wage difference for *advertising* is not significant. Occupational qualifications paired with job tasks explain 20 percent (M3, R^2=0.207) of the variation in gross hourly wages while the job-tasks (activities) explain 17.3 percent of it (M2, R^2=0.173). M1 and M3 confirm hypothesis H2. The most important results of the OLS regression carried out can be summarized as follows. The assumption of increasing returns to education with higher qualifications is confirmed. In particular, there is an increase in income for employees with advanced vocational training and those with a university degree. This result is in line with the hypothesis of increasing returns to education proposed by Becker (1964). A rather mixed picture emerges for the wage differentials between the activities within the two classifications made. Although for most of the examined non-routine activities it is found that a higher wage is earned compared to routine activities, there is a lower pay in particular for non-routine activities related to craftmanship compared to non-routine activities requiring analytical skills. Moreover, the results demonstrate that jobs involving computer work tend to be paid at a higher rate.

6 Discussion and Conclusion

The results indicate that activities that are exposed to a high risk of substitution due to programmable machines are comparatively paid less. This applies as established by Autor et al. (2003) in particular to routine activities and manual non-routine activities. In addition, Autor et al. (2003) highlight how advanced automation changes the demand for professional skills. With the help of an estimated model, their results explain 60 percent of the estimated shift in demand towards a highly qualified workforce. The trend towards a digitized world implies that jobs increasingly require computer-aided activities. While in line with growing digitization a sharp decline in demand for routine activities is witnessed, there is also a rising demand for highly qualified specialists in the information technology sector as well as research and development. Technological progress and the related change in qualification requirements in the labor market explain the rapidly rising demand for more education. Occupational activities along with the educational qualification explain 20.6 percent of the variation in wages. Accordingly, differences in wages within levels of education result from the interplay of a variety of socio-economic factors. Job profiles included into this analysis are on the one hand occupational activities and on the other hand, general soft skill requirements, such as critical thinking, work ethics and leadership. It is worth noting, that the inclusion of the latter to the regression model can lead to distorted results since these are not necessarily directly executable activities. The results shed light on the fact that occupational activities involving computer work tend to result in higher remuneration. Yet, due to limitations of data, no differentiation was made in terms of qualification requirements for computer-assisted work. In summary, the results indicate that technological change in the long run will eventually lead to decreasing demand for routine job-tasks. In any event, cognitive and social skills can hardly be substituted. In order to remain competitive in the labor market continuous development and training are indispensable in the context of progressive digitalization.

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