Technological Change and Education: General vs. Vocational Education in Germany

David Wittekopf

Goethe University Frankfurt
M.Sc. International Economics and Economic Policy

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Supervisor:
Prof. Dr. Alexander Ludwig
Chair of Public Finance and Macroeconomic Dynamics
Department of Applied Econometrics and International Economic Policy
Goethe University Frankfurt

Abstract

The German education system promotes *occupation-specific* vocational education. However, short-term benefits of higher employment fraction for individuals holding a vocational education face long-term costs compared to general *concept-based* education. A reason for this trade-off might be that individuals with a vocational qualification are less adaptive to new technologies. By constructing a unique dataset, I am able to first, examine whether this tradeoff exists in Germany and secondly, show that there is, in fact, a negative impact by technological change for people holding a vocational degree it appears, however, to decrease slightly as the career progresses.

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1 Introduction

The academic world has ever been discussing if individuals with a vocational qualification and the society as a whole face a trade-off between short-term benefits and long-term costs of their education. Countries' educational systems differ by their emphasis on education types, which can be decomposed into two categories: general and vocational education. Vocational education provides an occupation-specific education and develops individuals to be highly skill-based. The vocational education system is designed that these skills promote the transition into the labor market and thereby, leading to a smoother school-to-work evolution. However, Autor et al. (2015) have argued that these occupation-specific skills depreciate at a faster rate than skills derived from a concept-based, general education. One argument that the literature discusses is that those vocationally educated are slower to adapt to new technologies. Gould et al. (2001) in their work describe that technological progress brings a depreciation of these technology-specific skills that are mostly obtained in vocational education. As Autor et al. (2015) further emphasize, technological change - as an indication for the development of new technologies - makes the obsoletion of specific-skills even more pronounced throughout the career.
On the other hand, following Hampf and Woessmann (2017), general education is thought to strengthen the ability to learn new competencies that facilitate life-long learning, like cognitive and transversal skills, creativity, and concept-based problem-solving. Thereby, it enhances or at least eases the adaptability to a changing technological and structural environment.

Underlying this within-country work are similar notions and therefore, this paper tries to empirically answer two questions. One, if there is technological change, how do the age-employment profiles of individuals with general and vocational education differ in Germany? Or more precisely: are there short-term and long-term differences between the two education types in Germany? And secondly, is technological change, in fact, a driver for this differences?

This study, as opposed to the vast majority of existing literature, is a within-country study. Hence the question: Why is Germany's education system worth investigating? Germany has a fundamental emphasis on vocational education

- especially, at the secondary-level. Currently roughly 60% of the population hold a vocational qualification as their highest educational degree, according to *Statistisches Bundesamt*.[1] In comparison, the US provides a more general-based education resulting in a modest share attending a vocational school.[2]
In Germany, it is compulsory to attend school fulltime until the age of 16, after that students have the option to attend vocational schooling or continue on the general education path. However, to be eligible for academic pathways (e.g. university) at least 12 years of education are necessary.[3] The German Dual System distinguishes clearly between general and vocational education. Whereat one can either join a full-time vocational education in school (*Berufsfachschule*) or they can do an apprenticeship. The apprenticeship option consists of studies completed in a vocational school - that is integrated into the *Berufsfachschule* -, while simultaneously, the trainee will work at a company as an apprentice; thereby, the industry has direct involvement in the education process.[4]

To examine the above-stated questions, a unique and comprehensive dataset[5] is constructed by adding a measure of technology and technological change on the occupational-level to the German-Socio-Economic-Panel (SOEP). The data covers every year from 1984 until 2018, including the German reunification.[6]
A descriptive analysis reveals that there is indeed an early-career stage advantage for individuals who hold a vocational qualification; i.e. employment fractions are higher for those with a vocational qualification than those that are generally educated. However, it further displays that as the career progresses this advantage turns into a disadvantage. Additionally, it shows that

[1] See https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bildung-Forschung-Kultur/Bildungsstand/Tabellen/bildungsabschluss.html [accessed October 10, 2020]

[2] According to the PIAAC employed in Hanushek et al. (2017) roughly one-third of Americans hold a vocational qualification as their highest degree.

[3] In 2017, 32% left school with a high-school degree (*Abitur*), while 23% with an intermediate (*Realschule*) and 30% with secondary general school (*Hauptschule*). Source: *Statistisches Bundesamt*

[4] See Acemoglu and Pischke (1998) for more detailed discussion.

[5] The sample includes 390,000 observations in a longitudinal format on an individual-level.

[6] Fuchs-Schündeln et al. (2010) find a sharp rise in German inequality data after the reunification. Therefore, the German reunification in 1990 is something that needs to be controlled for.

technological change, measured by either computer use or routine task intensity, evolves differently for the two education types. However, throughout their career, individuals holding a vocational degree are more exposed to technological change.

The underlying dataset is very comprehensive, thus enabling the ability to distinguish age- and cohort-effects. Further, the longitudinal format of the data allows applying a fixed-effect regression model where a fixed-effect estimator captures all of the time-invariant unobserved heterogeneity between individuals and thereby, implicitly controls for selection bias. However, the selection into the different education types has to depend on unobservables (like ability/skill) that are constant over time in order to capture the overall impact accurately. The problem might be that more able people may adapt more readily to technological change independent of the education they received, leading directly to higher employment probabilities as the career progresses.

Nevertheless, the empirical results in this paper reinforce the findings of the existing literature that there are short-term benefits and long-term costs for vocational education compared to general education. Furthermore, the fixed-effect regression is extended by technological change and its interaction. The results show that there is a negative impact of technological change on the employment probability of vocational educated compared to individuals holding a general qualification. This negative effect is present throughout the entire work-life. However, the disadvantage of vocationally educated by technological change rather decreases as the career progresses.

Generally, the analysis suffers from shortcomings (e.g. time-varying selection into education types, among others) and so the results have to be interpreted as preliminary. Nevertheless, the newly created, unique dataset provides a source for further research.

The remainder of this paper is structured as follows: an overview of the related literature is stated in Section 2, after, I present the data and the process of constructing the dataset in Section 3. Section 4 presents an in-depth descriptive statistical analysis of the data. In Section 5, I describe the methodology employed to examine the problem at hand. Finally, Section 6 shows the results and Section 7 gives concluding remarks.

2 Related Literature

My thesis combines two different strands of the pre-existing literature. First, the literature on labor market differences between general and vocational education. Primarily, this literature focuses on employment differences in the school-to-work transition. Vocationally educated workers have, at the beginning of their career, a higher probability of employment - as can be seen in the work of Ryan (2001). Further, Hanushek et al. (2017) find that the advantages in the early-career stages become disadvantageous as the career progresses.[7] They employ the IALS (*International Adult Literacy Study*) database and conduct a cross-country analysis where they find a significantly higher probability of employment for workers with general education, later in their careers. They hypothesize that one reason why vocationally educated workers have a later stage disadvantage is that more generally educated people are more adaptable to new technologies - due to their concept-based education. This effect is most pronounced in countries with a dual-system of vocational education - like Germany or Switzerland. These results are confirmed by other cross-country studies with different underlying data; such as Hampf and Woessmann (2017) that employs the PIAAC (*Programme for the International Assessment of Adult Competencies*) database or Cörvers et al. (2011) that analyze earning-profile differences of general and vocational education between Germany, Netherlands, and UK (they use SOEP dataset for Germany, as well). In the contrary, Forster et al. (2016) find no significant difference between countries' education systems, after controlling for adult-training.

Nevertheless, examining the problem in a country-specific setup enables analysis of various arguments that cannot be tackled by the cross-country literature - which mostly focuses on differences in countries' educational system. However, employing survey data in a longitude format from the SOEP and the BIBB (*Bundesinstitut der beruflichen Bildung*) surveys of the *Working Population on Qualification and Working Conditions* in Germany allows an analysis of whether technological change is, in fact, a driver of the difference between general and vocational education employment over the life-cycle. Another

[7] Hanushek et al. (2017) find that this age threshold lies across countries, on average, at 50 years.

advantage of country-specific studies is that the richness and the comprehensiveness of the data enable the control for age-, period- and cohort-effects. Unlike previous research, other than Hanushek et al. (2017), this paper is able to compare individuals across ages and gender while ensuring that employees over cohorts are otherwise similar. Although, the existing literature on within-country analysis is very limited, exceptions include; Brunello and Rocco (2017) with the example of a cohort in the United Kingdom and Weber (2014) of Switzerland. In contrary to these examples, Hall (2016) does not find a significant age pattern difference between education types, this may be because his study is based on a Swedish reform in 1988–1993 that increased the general content in upper-secondary vocational programs.

The second strand of literature my thesis is related to is the work on education and technological change. The pioneering work of Acemoglu and Autor (2011) describes the idea that technological change is biased towards certain skill groups or job tasks. Similarly Spitz-Oener (2006), by exploiting BIBB data for Germany, finds that technological change/automation (approximated by the change in computer use) changes the task framework of the German labor market. Occupations that require routine tasks are declining in relative importance, while at the same time, occupations involving non-routine analytical, manual, and interactive tasks profit from technological progress. However, high-skilled jobs have a comparative advantage, as these changes in the new task framework, alter educational demands; therefore, there is a higher demand for more education. Further, Spitz-Oener finds evidence that there is a polarization of jobs in the German labor market, where the medium-skilled group is "hollowed out". This paper contributes to the literature on job polarization in Germany due to technological change by looking at employment differences throughout individuals' careers. Furthermore, Dustmann et al. (2009) and Goos et al. (2014) show that job polarization occurred in Germany.

Incremental to this paper is the theoretical work by Krueger and Kumar (2004a,b). In their paper, they argue that the initial labor market advantage that vocational educated workers have becomes disadvantageous due to technological change. The argument is that individuals with a skill-based (vocational) education are less adaptive to new technologies than concept-based

(general) educated.[8]

3 Data

The empirical assessment of the above-stated problems requires a dataset that contains individual-level data on socio-demographics and measures for technology and technological change. Unfortunately, in Germany (to the best of my knowledge) there does not exist a comprehensive dataset that fulfills both requirements. Therefore, it is necessary to construct a new dataset by merging two of the most influential German datasets - summarized in Table 1. The primary data source is the German Socio-Economic Panel (SOEP). It is an individual-level annual longitudinal survey that was first conducted in 1984, it covers about 30,000 individuals every year.

Table 1: Comparison of SOEP and BIBB

	SOEP	**BIBB/BAuA**
Frequency	Annually: 1984-2018	1979, 1985, 1991, 1999, 2006, 2012, 2018
Type of data	Panel	Cross-Section
Individuals	30,000	20,000-30,000 each wave[9]
Relevance	Demographics; parents education	Measure of technology: Computer Use, RTI
Selection	Individuals between 17-65	Individuals between 16-65 only employed

It contains a rich variety of representative micro-data on employment, education, and other demographics; however, the SOEP does not contain any information on technology use at the workplace. Thus, it is complemented with the cross-sectional surveys of *Working Population on Qualification and Working Conditions*, overseen by the BIBB. Similarly, it is an individual-level survey conducted since 1979 in six- or seven-year waves - the frequency of the

[8]They further infer that Europe lags behind the US in adopting new technologies, is due to the relative diffusion of vocational education.

BIBB enables the construction of time-varying technology indicators by occupational groups, while at the same time, it limits its volatility. The BIBB asks survey participants about the detailed tasks they perform at work, which gives it a major advantage compared to other surveys; further, it gathers information on the computer use of individuals. Thereby, it enables the construction of two measures for technology: Computer use, a more direct measure, and Routine Task Intensity (RTI), an indirect measure of technology (or automation).[10] While the SOEP includes individuals aged between 17 and 65 that are employed, unemployed, or on leave; the BIBB contains labor force participants, exclusively. Furthermore, the SOEP tracks individuals over time, whereas, the BIBB randomly selects new participants for every wave.

Merging the datasets takes place on an occupational-level, as both the BIBB and the SOEP offer a rich set of classification for occupation. For occupation coding, I exploited the 1992 *Klassifikation der Berufe* (KldB 1992) from the German employment agency. The KldB-classification provides the most consistency in the SOEP, however, unfortunately, the BIBB waves differ as the waves until 1991 relied on the KldB-classification from 1988. Therefore, I rely on a crosswalk provided by the BIBB to obtain consistent KldB 1992 occupation codes. Additionally, the SOEP provides the data on the more granular 4-digit level and the BIBB on the 3-digit level, therefore, it was necessary to convert the SOEP to the 3-digit level.

In the SOEP, some occupational information is missing; for example, if an individual is unemployed there is, of course, no information on their current occupation. To account for this, I employ the longitude characteristics of SOEP to replace the occupation of the unemployed persons with their previous occupation. Thereby, I obtain occupation-codes for long-term unemployment, as well. This methodology assumes that individuals who are currently not working, dropped out of the labor force, but still hold the skills from their past occupation. Similarly, if there is no information on their past occupation, I re-

[10] The RTI constitutes a more indirect proxy for technology because it shows the exposure of jobs to automation. It is developed by Autor et al. (2003) and quantifies the probability of workers' tasks being substituted by machines. Jobs with high RTI are thus easier to automate. To define the RTI, detailed information about the task composition is required. Among others, Goos et al. (2014) show that technological change that is biased towards routine tasks leads to a hollowing out of medium-skilled occupations.

place the missing occupation-codes with the occupation in which the individual received their vocational degree. However, this still leaves 20,000 observations unmatched; these are observations where the SOEP does not provide any information about past occupation, current occupation, or the occupation in which the degree was obtained in.[11]
Another challenge is that the BIBB comes in waves, while the SOEP is conducted annually. To merge the technology indicators of the BIBB to the annual SOEP data, I use two methodologies. I either linearly interpolate (and extrapolate) the measure or keep it constant, between BIBB waves.

Keen to this analysis is the distinction between general and vocational education as individuals are defined by education type, dependent on the highest degree they have acquired. This concept assumes that qualifications below the highest degree affect the employment probability only as they influence the eligibility of being admitted to the next highest degree (extensive discussion: see Dearden et al. (2002)). The categorization into both, the education-level and type, follows the classification of the 2011 *International Standard Classification of Education* (ISCED) by UNESCO. General education is either an academic or a school-leaving degree, whereas, vocational education can be obtained by attending a vocational school, an apprenticeship, or professional higher education institutions.

Following Hanushek et al. (2017), I model employment rather than unemployment, however, since I drop all individuals that are absent from the labor force or retired, the results should be the same. There are multiple ways employment status is defined: the SOEP inquires about the employment status in the last year or the past month, also, employment status is constructed by defining all individuals that did not receive unemployment benefits as employed. Nevertheless, the observations are robust to all definitions of employment.[12]

[11] The unmatched observation constitute 5% of the sample. Of these unmatched observations, 40% hold a general degree. The vast majority of unmatched observations are unemployed - ca. 85%.

[12] As the default option, I choose the employment status for the past month, which is the latest measure, of course, if one is employed in the last month, then it does not necessarily mean that the person was also employed the month prior. In comparison, when asking for the employment status in the last year, there may be examples of individuals working for only a portion of the year (e.g. someone working from January until July but was unemployed afterward may report employed for the entire year).

The sample is restricted to working age, which is determined by the selection of the SOEP, this includes participants between the age of 17 and 65. Further, I drop individuals who are currently completing their education - either general or vocational. Consistently with previous work, my study excludes self-employed individuals and civil or military servants. The final restriction is to exclude all individuals where there are no observations for the education-level/-type or when it is not possible to classify the degree (e.g. a degree from a foreign country) since this is an essential requirement for this thesis. While Hanushek and others are concerned over cohort-specific selection into work by gender, they restrict their analysis to men only. Since in my sample there is no such an effect (see Figure A.5), I include both women and men and control for gender instead.

One strategy to address concerns of selection bias in the type of education is to restrict the sample to comparable groups. The assumption is that education-levels are comparative regarding unobserved characteristics (e.g. ability), thus, determining the selection into vocational and general education. Therefore, a separate sample for secondary and tertiary education levels is constructed.[13]

4 Descriptives

The section is dedicated to descriptive statistics. It is extraordinarily in-depth, due to the uniqueness of this dataset and its first scrutiny. Table 2 shows the overall distribution of educational attainment and its evolvement over time in the sample. The overall sample includes roughly 390,000 observations between 1984 and 2018. On average, 29% of individuals in the sample hold a general degree as their highest qualification, while 71% obtained a vocational degree. It is important to mention that the fraction of those with a general education in Germany, compared to other countries' education systems is relatively small.[14] Of the entire sample, 57% hold a degree beyond the secondary education-level. To further distinguish: on average, 8% of individuals with a

[13]The exclusively secondary sample includes 41% of all observations, while the tertiary makes up to one-third. The remainder consists of post-secondary non-tertiary - which is purely vocational.

[14]See Hanushek et al. (2017), Hampf and Woessmann (2017), etc..

Table 2: Educational Attainment over time (in 5-year steps)

			Full sample		Secondary		Post-Secondary non-Tertiary	Tertiary	
Time	N	% beyond secondary	% completing general	% completing vocational	% completing general	% completing vocational	% completing vocational	% completing general	% completing vocational
1984-1988	20,829	42.41	16.16	83.84	4.91	95.09	100	62.58	37.42
1989-1993	34,074	55.21	20.88	79.12	5.32	94.68	100	71.02	28.98
1994-1998	38,711	60.01	23.34	76.66	7.66	92.34	100	72.88	27.12
1999-2003	67,862	58.88	25.95	74.05	7.16	92.84	100	72.93	27.07
2004-2008	66,819	60.17	29.27	70.73	7.68	92.32	100	74.97	25.03
2009-2013	80,547	58.08	31.20	68.80	7.60	92.40	100	77.15	22.85
2014-2018	81,223	60.33	37.64	62.36	10.62	89.38	100	80.44	19.56
Overall	390,065	57.30	28.81	71.19	7.72	92.28	100	75.77	24.23

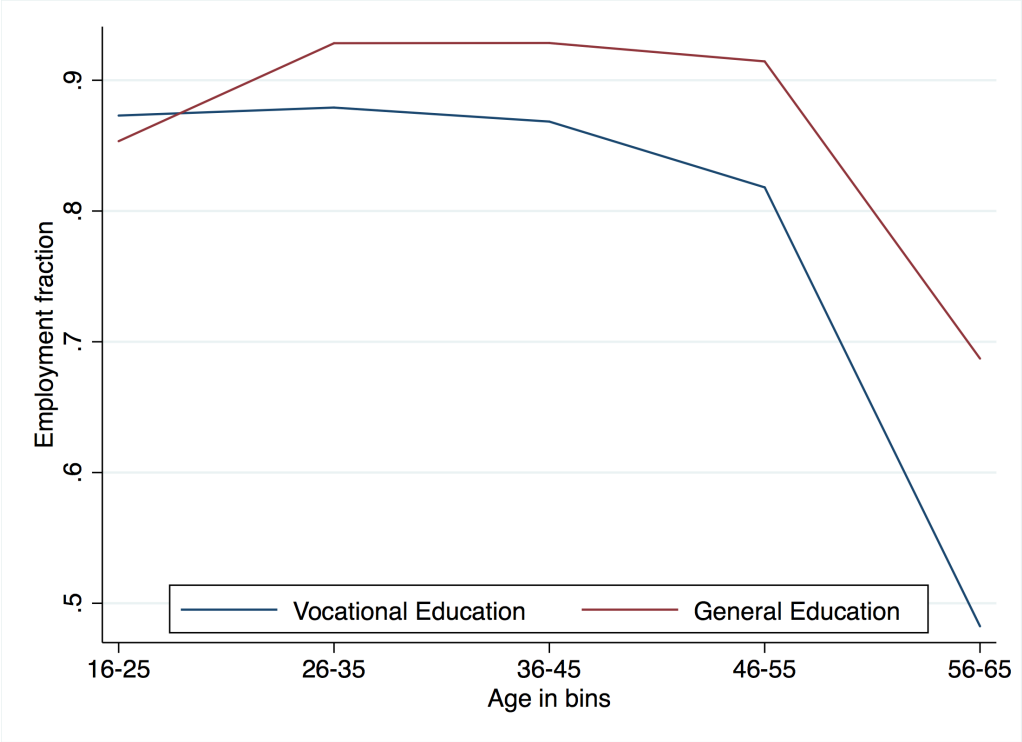
Note: Average educational attainment over time. Secondary education means either a school/high-school degree or an apprenticeship. Tertiary can either be Meister or academics. Classification by the 2011 'International Standard Classification of Education' (ISCED).

secondary education obtained a general education - meaning those individuals finished *Gymnasium*, *Realschule*, or *Hauptschule*. This leaves 92% of individuals with vocational education at the secondary level; the conventional case would be that one obtains vocational education after graduating from school. The fraction of general degrees increases with the education level - like tertiary, this includes all academic degrees: Diploma, Bachelor, Master, and Doctoral degree. However, Germany has a specific classification, due to its *Dual-system*: Post-secondary-non-tertiary education, this is a purely occupation-specific educated group. This group (roughly every fourth individual in the sample) includes individuals who obtained a second vocational degree or high-school graduates who continued with a vocational qualification. Of the individuals who pursued a tertiary degree (on average, one-third of the sample) 76% hold a general degree, while 24% are vocationally educated at a *professional higher education institution* - the German grade *Meister*.

Two trends in the average educational attainment in Germany since 1984 are noticeable. One, the educational attainment increased steadily over time. While in the 1980s 42% hold a qualification that is beyond the secondary-level, in the 2010s it is already 60%. Second, the higher educational attainment comes along with more individuals with a general qualification. In the 1980s, merely 16% obtained general education, while in the latest years 38% hold a general degree.

To assess differences between education types I begin the analysis by comparing employment rates across different ages. Figure 1 represents the fraction of those employed that hold a vocational versus a general degree over the career

Figure 1: Employment fraction over career-life cycle by type of education



Note: Weighted average of employment status by different types of education over age - clustered in nine-year bins.

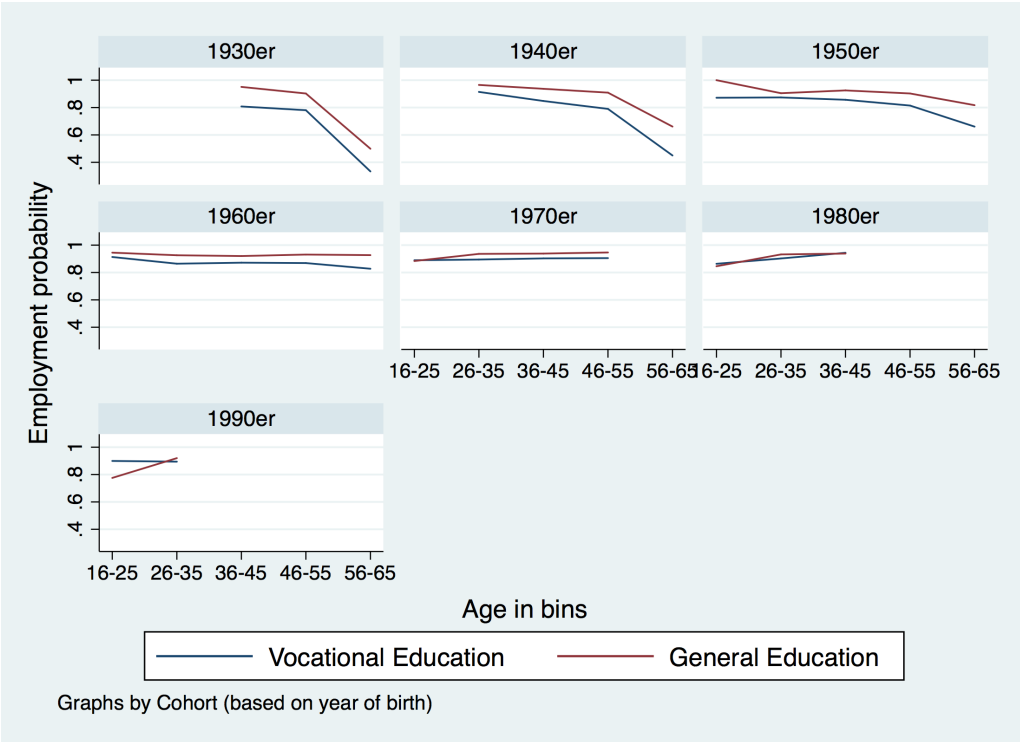
life-cycle.[15] The figure confirms the pattern described in the introduction: individuals with vocational education have an early-career stage advantage over individuals with a general education. This seems reasonable as the vocational education system is designed to ease the school-work transition. However, this advantage at the beginning of the career turns into a disadvantage as the career progresses, thereby, supporting the results of Hanushek et al. (2017). Figure A.1 shows that the difference in employment fraction by type of education is, in fact, non-linearly increasing with age. Nonetheless, as can be seen in Figure 2, the early-career advantage of being vocationally educated is not uniformly persistent throughout cohorts. For cohorts born in the 1970s and after, there appears to be an advantage for vocational education, however, it is not present for cohorts born before 1970. The reason for the cohort-effect is that - as observed above - the educational attainment increases over time as well as over cohorts (see Table A.1). Besides, with every new cohort, there is

[15] Age is categorized in bins, in order to smooth the graphs.

a higher fraction of individuals holding a general degree, and this at a higher education-level (the fraction of tertiary-degree holders increases with the cohort and its fraction of who completed a general education). Saying that a higher fraction holds a general degree on a higher educational level with each new cohort. And since academics enter the labor-market at a later age than vocationally educated, the initial employment fraction for generally educated is decreasing over cohorts. Therefore, the employment fraction at the beginning of a career is higher for older and lower for younger cohorts.[16]

More than the fundamental employment differences along the career path,

Figure 2: Employment fraction by type of education and cohort



Note: Figure 1 by cohort (based on the year of birth).

it is necessary to look in sufficient detail at the characteristics of individuals to identify the impact of education types. Therefore, basic descriptives are reported separately by type of education. Table 3 reports the number of observations as well as information on the weighted average on individual characteristics, employment, education, firm size. It further shows the sample

[16]See Boockmann and Steiner (2006) who discuss the existence of cohort-effects in Germany due to increasing educational attainment.

Table 3: Descriptive Statistics by Type of Education

	Overall Mean	***General Education*** Mean	***Vocational Education*** Mean
Individual characteristics			
Age	42.86	42.51	42.97
Male	0.53	0.55	0.52
Migration background	0.12	0.16	0.11
East1989	0.22	0.23	0.22
Employment			
Employed	0.81	0.88	0.79
Log real hourly wage	2.72	2.98	2.63
Working experience	15.91	13.98	16.55
Fulltime	0.60	0.67	0.58
Parttime	0.15	0.15	0.15
Marginal worker	0.04	0.03	0.05
Education			
Number of Years of Education	12.47	15.80	11.38
Firm size			
Firm size $<$ 20	0.29	0.25	0.30
Firm size 20-200	0.26	0.24	0.26
Firm size 200-2000	0.21	0.21	0.21
Firm size $>$ 2000	0.25	0.30	0.22
Parents education			
Lower secondary	0.11	0.05	0.13
Upper secondary	0.70	0.60	0.74
Tertiary	0.19	0.36	0.13
N	390065	112392	277673

Note: Weighted mean of descriptive variables by type of education between 1984 and 2018. Every statistic is based on the individual level. For dichotomous measures the averages equal the fraction in the respective group - hence, 55% of individuals holding a general education are male. Age, work experience, log hourly wage, and the number of years of education are continuous variables and therefore, their average is reported. The reason full-time, part-time, and marginal worker do not sum up to employed is due to rounding issues.

average of parents' education, to control for selection into education types. There are no relevant differences in individual characteristics between individuals holding a general or vocational education.[17] Of high relevance is the significant difference in labor market outcomes between the two groups. As can be seen from Figure 1 and what Table 3 confirms, is that those with general education are, on average, more likely to be employed and have higher wages (see Boockmann and Steiner (2006) for a detailed discussion on German college premium). While vocationally educated have comparatively more work experience but have no significant age difference. This can be explained by the average years of education. Individuals holding a general degree as their highest have on average 15 years of schooling, while the vocationally educated obtained 11. Therefore, individuals with a vocational degree enter the labor market earlier and thereby, have more work experience. General educated are working more frequently in larger firms (especially, those with more than 2000 employees), while individuals with vocational education are working in smaller companies because small- and medium-sized firms (e.g. craft enterprises) rely heavily on the *Dual-System* in Germany. Deissinger (2001) shows that the craft-sector, which is dominated by small firms is relying on well-trained apprentices. Lastly, to control for selection into education types, the higher the parents' education the higher the fraction of general education of the offspring.

4.1 Technological Change

This section is dedicated to descriptives of different measures for technology and its interrelation with education and labor-market outcomes. First, the analysis of technology is on the individual-level, then the interrelations with the education type and labor market outcomes are examined on the occupational-level. The focus in the present study is whether technological change is a driver for the different employment patterns over the life-cycle for individuals with general compared to vocationally educated. I make use of two different

[17] However, it is noteworthy that people holding a general degree are more likely to have a direct or indirect migration background than vocationally educated. But individuals with migration background who hold general qualification have a significant lower weighted average number of years of schooling than individuals without migration background (14 years with migration background, 16 years without).

measures for technology: computer use[18] and RTI. The BIBB asks about the use of computers, terminals, and electronic data-processing machines. Based on the response, a dummy variable for computer use is generated equaling 1 if the respondent uses such a device at the workplace and 0 if not. The construction of the RTI measure is based on the work of Brussevich et al. (2019) and relies on the task-based approach in Autor et al. (2003), that follows the categorization into routine and non-routine activities for the BIBB by Antonczyk et al. (2009). Taking the average of individual task intensities by task-group (routine/non-routine) yields to a continuous measure of RTI over time by occupation. The RTI is an index between 0 and 1 and describes the fraction of routine tasks of the respondents - the lower the index the lower the fraction of routine tasks executed in the occupation - or alternatively: the likelihood of the occupation being replaced by automation - the lower the index the lower the probability of the occupation to be automated by technology. To match the SOEP dataset, both measures are interpolated and kept constant between different BIBB survey waves.

Table 4 shows that, on average, between 1984 and 2018, 63% of the overall sample are using a computer, terminal, or comparable devices at work. The RTI can be interpreted as on average and over time with 40% of the realized tasks categorized as routine. Further, the average computer use (regardless of the methodology) - the average fraction of technology (computers) used at work - is much higher for the general educated. While for the RTI, the sample supports the results of Spitz-Oener (2006); that the higher the education level, the less routine tasks one has to execute. Figure A.2 shows that, regardless of the measure, the level of technology is always higher for individuals with a general degree.

Table 4 further reveals that, on average, between 1984 and 2018, the technological change measures do not differ significantly for the two education types.

[18]However, the first four waves of the BIBB were overseen by BIBB and the *Arbeitsmarkt- und Berufsforschung* (IAB), but in 2006 the responsibility changed to BIBB and *Bundesanstalt für Arbeitsschutz und Arbeitsmedizin* (BAuA). Thereby, some survey questions changed. E.g. before 2006 the survey asked participants whether they used a computer at work. From 2006 onwards, participants were asked how frequently they use the computer. I treat the answer such that, if the respondent uses a computer 'occasionally' at work, then the individual uses a computer. Further, the survey-method changed from CAPI (Computer-Assisted Personal Interview) to CATI (Computer-Assisted Telephone Interview). This should, however, have no impact on the consistency of the data.

Table 4: Descriptive Statistics of Technology & TC by Type of Education

	Overall Mean	***General Education*** Mean	***Vocational Education*** Mean
Technology			
Relative computer use (interpolated)	0.63	0.77	0.58
Relative computer use (constant)	0.57	0.72	0.53
Routine-task-intensity (interpolated)	0.40	0.29	0.44
Routine-task-intensity (constant)	0.42	0.31	0.45
Technological Change			
TC Computer use (interpolated)	0.02	0.02	0.02
TC Computer use (constant)	0.16	0.16	0.16
TC RTI (interpolated)	−0.01	−0.00	−0.01
TC RTI (constant)	−0.07	−0.04	−0.08

Note: Weighted mean of various technology measures and technological change between 1979 and 2018. Technological change is obtained by calculating the first difference over time.

Therefore, Table 5 describes the overall technological change over time and the differences in technological change measures by the type of education. Technological change is obtained by taking the first difference between the different BIBB waves and either keeping it constant or linearly interpolate it between waves. Overall (for the entire sample), the measure of computer use is changing at a positive rate, hence, technological progress is present. While for the RTI a negative change is equivalent to technological progress since new technologies replace routine tasks.[19] These results are in line with the findings of Autor et al. (2003) for the US and Spitz-Oener (2006) for Germany.

Panel A and B of Table 5 show the change in the interpolated and constant computer use over time for general and vocational education types. Two interesting observations need further attention. First, until 2006[20] the change in computer use is higher for the generally educated; this is in line with the theory of Skill-biased technological change (SBTC) described by Acemoglu and Autor (2011). Further, Dustmann et al. (2009) and Spitz-Oener find similar results for West German data between 1975 and 2004. The idea is that technological change is complementary towards high-skilled tasks and substitutes low- and medium-skilled tasks. However, this phenomenon changes in 2006 when those vocationally educated have a higher increase in computer use.

One reason for the higher technological change for individuals holding a vocational qualification after 1999 might be that a sectoral change occurred at that

[19] Overall for the RTI, the fraction of routine tasks decreases by 7% - see Table 4.

[20] For computer use that is kept constant, it is one BIBB wave later.

Table 5: Technological change measures over time

	1985	1991	1999	2006	2012	2018
	A. Technological Change Computer Use (interpolated)					
Overall	0.0167	0.0172	0.0356	0.0363	0.0022	0.0030
General Education	0.0215	0.0252	0.0376	0.0101	0.0206	0.0018
Vocational Education	0.0158	0.0151	0.0350	0.0451	-0.0050	0.0035
	B. Technological Change Computer Use (constant)					
Overall	0.1009	0.1135	0.2920	0.2543	0.0162	0.0189
General Education	0.1345	0.1709	0.3408	0.0708	0.1246	0.0111
Vocational Education	0.0942	0.0995	0.2775	0.3158	-0.0260	0.0227
	C. Technological Change Routine Task Intensity (interpolated)					
Overall	-0.0160	-0.0188	-0.0226	0.0023	-0.0026	-0.0005
General Education	-0.0136	-0.0149	-0.0112	0.0186	-0.0129	-0.0009
Vocational Education	-0.0165	-0.0198	-0.0262	-0.0032	0.0014	-0.0003
	D. Technological Change Routine Task Intensity (constant)					
Overall	.	-0.0963	-0.1986	0.0160	-0.0186	-0.0027
General Education	.	-0.1004	-0.1355	0.1306	-0.0785	-0.0055
Vocational Education	.	-0.0953	-0.2175	-0.0224	0.0047	-0.0014

Note: Weighted mean of different measures for technological change by different type of education over time. Measures are calculated by the first difference between the different waves. The source is BIBB-dataset merged to SOEP. Therefore, waves are every sixth/seventh year. There is no observation for the RTI (constant) change between 1979 and 1985 because the first observation for the RTI is in 1986. The interpolated measures are extrapolated as well. Overall includes the entire sample.

time. Sectoral change describes the movement of workers from one to another. Reshef (2013) finds that in the US, SBTC is in place for the aggregate economy. However, in the service sector, people with lower education levels move from occupations that are substitutable by computers into occupations that are complemented by technology. Therefore, those with lower levels of education might experience higher rates of technological change in the service sector. Similar trends seem to occur in Germany around the change of the millennium. Figure A.4 shows that, indeed, in the service sector, the rate of technological change is higher for vocationally educated - who, on average, have fewer years of education. Additionally, Table A.4 displays the fraction of employed individuals with vocational education over time. In 1991 every third worker with vocational education is in manufacturing, in 1999 there are only 28%. Inversely, in 1991 58% of vocationally educated worked in services, and

in 1999 the fraction increased to 64%. Therefore, in 1999 there was a tendency to move from the manufacturing to the service sector, where (at that time) technological change was higher for vocationally educated (see Figure A.4). Therefore, there is evidence for a sectoral change and on the aggregate, the SBTC-theory does not hold in Germany after 1999.

However, in 2012 it switches back again and SBTC holds again, as individuals with vocational education are even opposed by technological regress, saying the fraction of computer use is decreasing. Again technological progress accelerates in 2018 for both education types.

The second interesting observation is the fact that computer use is negative for people holding a vocational degree between 2006 and 2012. When examing Panel C and D the story changes marginally for the RTI. As established above, the level of routine tasks executed is on average lower for generally educated. Therefore, there are fewer routine tasks left to be replaced by new technologies/automation. Hence, the fraction of routine tasks decreases at a lower rate than for individuals with vocational education. For the RTI, similar phenomena as for computer use are observed. One, in the beginning, the RTI is increasing at a higher rate for the vocationally educated; this is in line with the results of Spitz-Oener (2006), however, it switches in 2006. One can, in fact, observe a decrease in technological change from 1999 onwards, similar to computer use. The reason might be sectoral change, too. Individuals move from manufacturing to service sector, while there are fewer routine tasks to replace.[21] And secondly, those that are vocationally educated suffer from an increase in the fraction of routine tasks.[22] Further analysis revealed that in neither of these series cohort- nor age-effects are present.

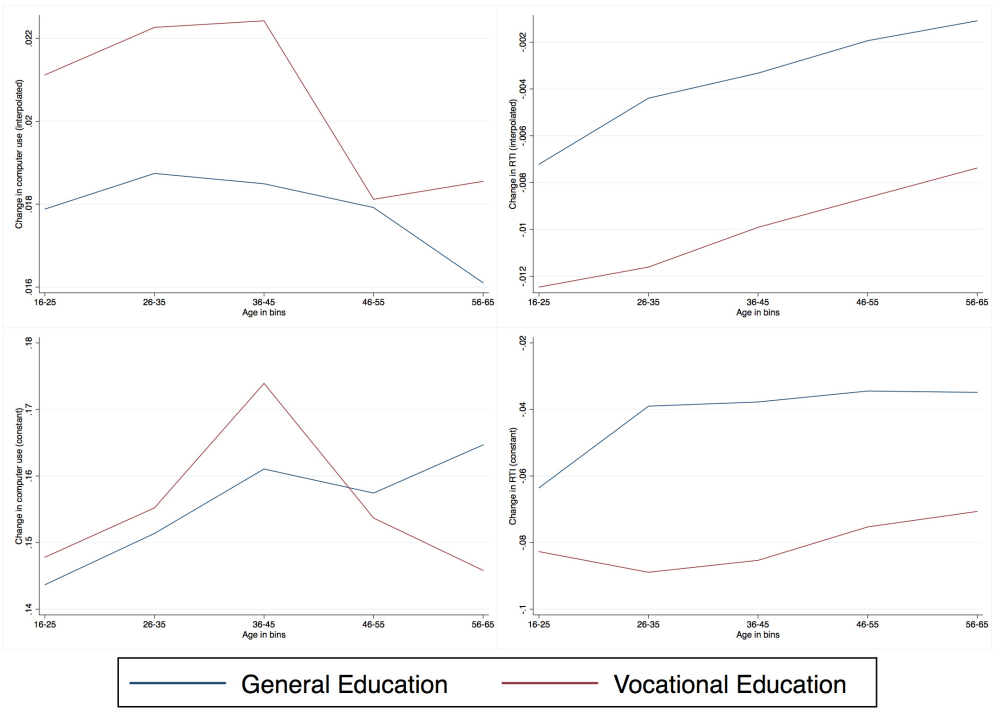
However, vocationally educated are exposed to more technological change throughout their career than individuals with general education as Figure 3 reveals.[23] The difference in technological change for the education types is, however, diminishing as the career progresses. Suggesting that at higher ages

[21]See Table A.5. Over time there is a higher decline in the fraction of routine tasks in the manufacturing, rather than in the service sector. However, this effect is most pronounced after 1999. At the time when workers moved to the service sector.

[22]As Antonczyk et al. (2009) emphasize: The task composition differs slightly over time. The reason is that some tasks reported in the past do not exist anymore.

[23]The only exemption are older individuals for computer use that is held constant.

Figure 3: Technological change over the career by education type



Note: Weighted average technological change over the career by education types. Age is organized in 10-year bins. The panel on the left hand side show the change in computer use and the right hand side panel display the change in RTI. While the upper panel present the interpolated and the lower the constant data.

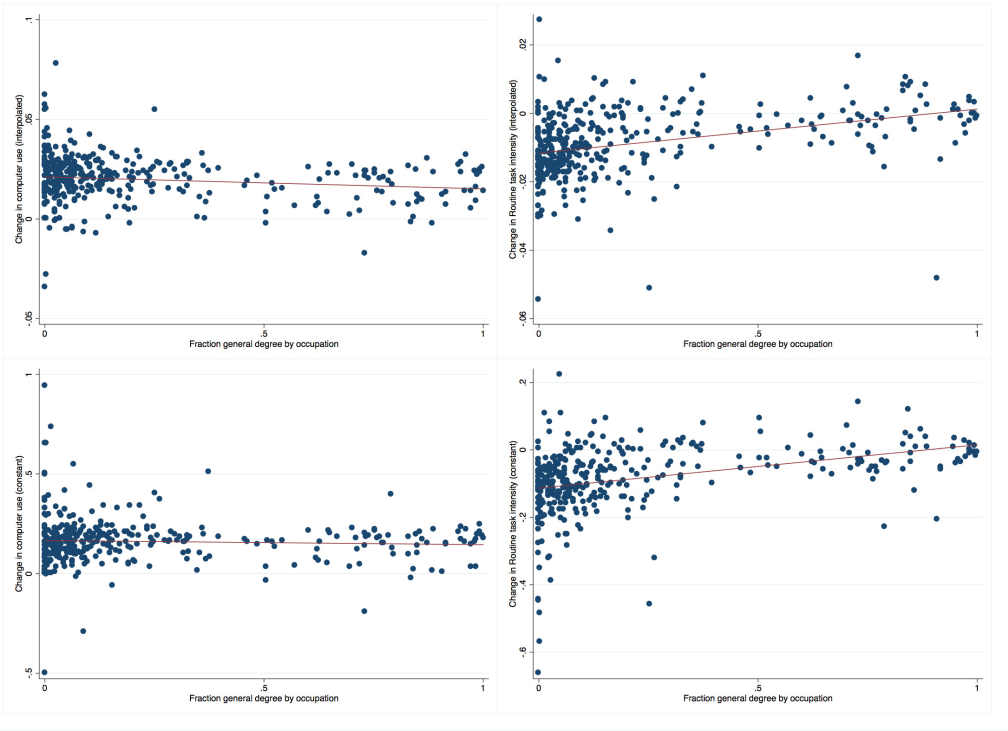
the difference in exposure towards technological change is lower than at the beginning of a career. This observation is suffering from period-effects. Between 1999 and the beginning of 2000 technological change is higher for individuals holding a vocational degree. This might have its origins in sectoral change, as described above.

After establishing individual-level descriptives of various relevant charateristics, it is now possible to describe the interrelations. The following analysis is on an occupational-level since the technology indicators were merged to the SOEP on an occupational-level.[24]

Figure 4 describes the relation of technological change and the fraction of generally educated in an occupation. As can be seen, technological change,

[24]Differences between the individual- and occupational-level descriptives are described in Table A.3.

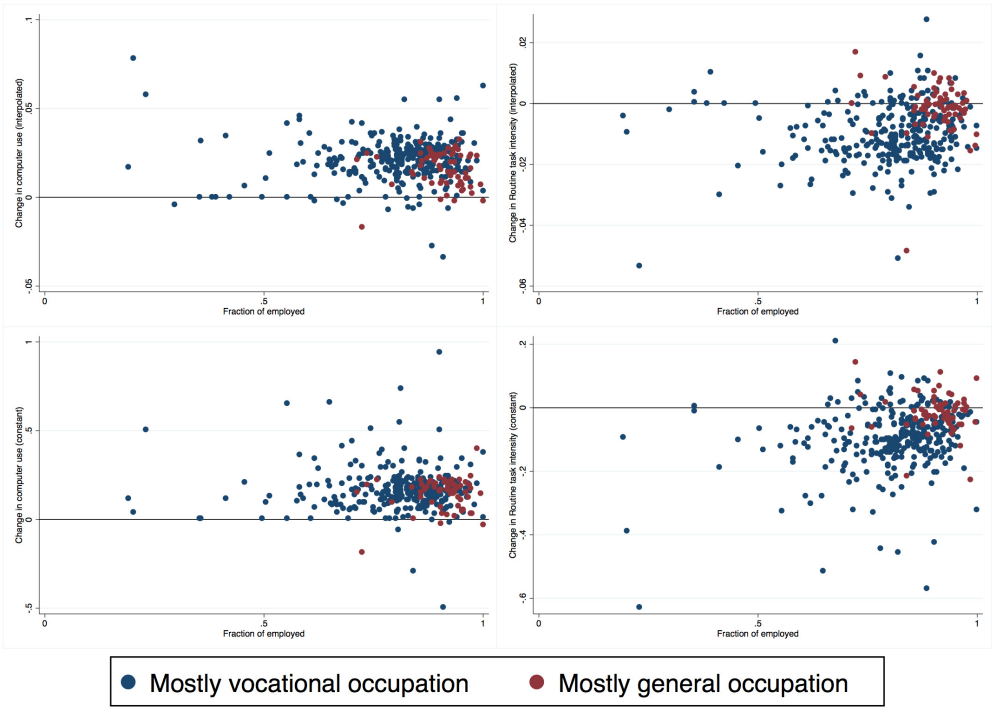
Figure 4: Scatter technological change measures vs fraction of generally educated on occupational-level



Note: Scatter of the weighted mean of various technological change measures and the fraction of generally educated within an occupation on KldB 1992 classification. The red line represents the linear regression line, while every node is one occupation. Left panel: Change in computer use; Right: Change in RTI; Upper: Interpolated; Lower: Constant.

disregarding the indicator and the methodology, seems to be more prominent in occupations that are dominated by people holding a vocational degree as their highest qualification. Phrased differently: Individuals with a vocational degree are more exposed to technological change.

Figure 5: Scatter technological change measures vs fraction of generally educated vs employment on occupational-level



Note: Mostly general occupations are occupations where more than half of the workers are educated or are currently working in that occupation - for mostly vocational occupation vice versa. For computer use, every observation above the zero-horizontal line explains technological progress, while every occupation below states technological regression. For the RTI: vice versa. Left panel: Change in computer use; Right panel: Change in RTI. Left panel: Change in computer use; Right: Change in RTI; Upper: Interpolated; Lower: Constant.

Now it is possible to examine the relation to labor market outcomes. Figure 5 combines technological change, the type of education, and the employment status. It confirms the relationship of technological change and the education type specified in Figure 4. Occupations that are *mostly general occupations* are clustered at lower average levels of technological change. For computer use, they are grouped near the zero-technological change line, while similar results hold for RTI. At the same time, *mostly vocational occupations* are exposed to

higher rates of technological change. This is in line with the findings of Spitz-Oener (2006), where the importance of routine tasks is decreasing and this is most prominent for occupations where the fraction of vocational degrees is high (for Spitz-Oener it is people with low and medium education). Furthermore, occupations, where more than half of individuals hold a general degree, have higher employment fraction as well. This result confirms the above-stated observation from Table 3: that generally educated, on average, have a higher employment fraction.

5 Methodology

The central matters of this paper are the impact of the education types on labor-market outcomes - specifically, the employment fractions - and whether technological change is contributing to that effect.[25] To assess the hypothesis that the early-career stage advantage of being vocationally educated over having a general education becomes disadvantageous to individuals in Germany, a comparative approach is taken. For that, the age-employment profiles of the two education types are compared over time and cohorts. Additionally, the analysis is extended to determine the impact of technological change on labor-market outcomes of individuals of the two education types.

The pre-existing literature on cross-country analysis follows a difference-in-difference approach (DiD) of Hanushek et al. (2017). One advantage of the DiD approach is that it addresses the concern of selection into the different types of education. The central assumption for determining the impact of the education types on labor-market outcomes over the career is that the selectivity of individuals into general and vocational education does not vary over time. However, due to the richness of the constructed dataset and its longitudinal format, it is possible to employ an even more in-depth approach. For this, a fixed-effect regression will be employed, following the within-country study of Brunello and Rocco (2017).

[25] In the following analysis, the dependent variable of the regression models is the individual's employment probability. Therefore, from now on, employment fraction and probability are used interchangeably. While the employment fraction refers to the fraction of employed in the entire sample, the employment probability regards to the individual.

The fixed-effect regression methodology (FE), enables the controlling for omitted variables and selection, especially in panel data. It should yield unbiased results if the omitted variables do not vary over time and only vary across individual entities. Therefore, by including individual-level fixed-effects it is possible to control for unobserved heterogeneity between individuals, as long as it is constant over time. Technically, the fixed-effect approach results in n different intercepts, one for each individual; the intercepts can be thought of as a set of binary variables. By that, they absorb the influence of all time-invarying omitted variables that differ across entities. Hence, changes in the dependent variable must be due to influences other than the fixed characteristics.

Generally, while fixed-effect regression requires panel data, DiD can be used with repeated cross-section data as well. The advantage of using a fixed-effect regression is that it enables one to control for time-invarying selection bias. While, when using a DiD approach one has to explicitly control for the observable selection. However, unobservable time-varying selection would lead to an omitted variable bias for both the fixed-effect and DiD methodology.
Since the fixed-effect regression covers all unobserved heterogeneity in the individual intercepts, it should deliver less biased results. Nonetheless, the fixed-effect regression eliminates variation between individuals. To correct for this possible distortion, one has to be precise in the interpretation of what variation is captured in the coefficient (see Mummolo and Peterson (2018), Wooldridge (2010) for a detailed discussion).

Following the argumentation from above, I employ an empirical fixed-effect model to investigate the life-cycle employment pattern, considering general and vocational education. To overcome the concern that the fixed-effect regression covers very specific variation, I will additionally report the results of the DiD regression. The baseline fixed-effect model is designed as follows:

$$emp_{it} = \alpha_1 \cdot age_{it} + \alpha_2 \cdot age_{it}^2 + \beta_1 \cdot gen_{it} + \beta_2 \cdot gen_{it} \cdot age_{it} + X_{it} \cdot \gamma + \alpha_i + \epsilon_{it} \quad (1)$$

Where emp_{it} represents the employment status of the individual at time t, equaling 1 if the individual is employed and 0 otherwise. Age and age squared capture the non-linear age-effect on employment - as can be observed in Figure 1. The dichotomous variable gen_{it} equals 1 if the individual holds a general

degree at time t and 0 if the person possesses a vocational degree. X_{it} is a vector of relevant control variables e.g. number of years of education. While α_i captures the time-invariant, unobserved heterogeneity between individuals and is called the individual fixed effect and ϵ_{it} is the error term of individual i at time t.

One concern From the pre-existing literature on cross-country studies is that β_1 inadequately captures the impact of the type of education on the employment status because it implicitly includes all unobserved selection into the different education types. However, this is now controlled for by the individual fixed-effect α_i. Therefore, β_1 should measure the early-career difference in employment probability between the general and vocational educated more accurately.[26]

Even more important is the coefficient β_2 which describes the evolution of the employment probability of individuals holding a general vs. a vocational degree, with each additional year of age. The identifying assumption for an accurate measure of β_2 is that the selection into the different education types is constant over time.

Furthermore, this paper is interested in the impact of technological change on the different education types over the career-lifecycle. To empirically analyze the effect, the basic model is extended by a measure of technological change. Equation 2 summarizes the basic definition.

$$\begin{aligned} emp_{ikt} = \alpha_1 \cdot age_{it} + \alpha_2 \cdot age_{it}^2 + \beta_1 \cdot gen_{it} + \beta_2 \cdot gen_{it} \cdot age_{it} + \\ + \delta_1 \cdot Tech_{kt} + \delta_2 \cdot gen_{it} \cdot Tech_{kt} + \delta_3 \cdot age_{it} \cdot Tech_{kt} + \delta_4 \cdot gen_{it} \cdot age_{it} \cdot Tech_{kt} + \\ + X_{it} \cdot \gamma + \alpha_i + \epsilon_{it} \quad (2) \end{aligned}$$

The goal is to estimate the impact of technological change by type of education over time on the employment probability holding constant the unobserved individual characteristics, α_i. In addition to Equation 1, it includes 3-way interaction between the type of education, age and technological change. The

[26] However, keep in mind that the variation captured by β_1 in the fixed-effect regression is within individuals.

dependent variable remains the employment status of individual i at time t, however, the measure for technology is only available on the occupational-level, in occupation k. δ_1 captures the direct effect of the changing technology environment on the employment status. δ_2 covers the initial employment effect of technological change on the different education types. More importantly, δ_4 captures the effect of a simultaneous change in technological change as the career progresses for individuals with general education. While, δ_3 is the overall effect of technological change as the career progresses, regardless of the education type.[27] X_{it}, ϵ_{it} and the fixed-effect term are defined as above.

Consequently, the marginal effect of technological change on the employment probability for those with general education consists of $\delta_1 + \delta_2 + (\delta_3 + \delta_4) \cdot age$. While, the marginal effect for vocationally educated constitutes of $\delta_1 + \delta_3 \cdot age$. Therefore, the difference in the marginal effects between the two education types is $\delta_2 + \delta_4 \cdot age$ and depends on the age of the individual.

5.1 Dealing with selection bias

A prime concern of this study is that the selection into general and vocational education differs based on time-varying unobserved characteristics. As established above, the fixed-effect method relaxes the assumption that individuals select themselves into vocational or general education differently. However, to identify the impact of the type of education on employment, the self-selection has to be time-invariant[28] - so that α_i captures the unobserved heterogeneity between individuals.

The SOEP includes a short IQ test for the years 2006, 2012, and 2018; these test scores appear to be an appropriate measure of individual skill level (see Lang et al. (2007) for a discussion).[29] The problem with a time-varying selection that does not refer to observables is that changes in labor market outcomes

[27]For δ_4 to be accurate, similar notions as for β_2 have to be fulfilled; the selection into education type has to be constant over time. While for δ_2 (equivalent to β_1) to be unbiased the fixed-effect term should capture all unobserved heterogeneity between individuals.

[28]This pattern has to hold for the DiD- and fixed-effect-approach.

[29]Unfortunately, reproducing the test results for the years not covered by the ultra-short IQ test is beyond the scope of this master thesis. Therefore, for this study the social background of the individual is sufficient. But one possible approach could build on the Machine Learning method applied in Jaimovich and Siu (2012).

might stem from the changing skill/ability level of young and old employees in their respective education type. Further, more able people may adapt more readily to technological change independent of the schooling they received leading directly to higher employment probability at older ages.
Indeed, Arum and Shavit (1995) find that less competent individuals complete a vocational rather than a general degree. However, all the above-mentioned studies find that the individual ability level to complete general education does not substantially change over time (see Hanushek et al. (2017), Cörvers et al. (2011), etc.).

Since I am reporting the results of DiD regression, the selection based on observables needs to be controlled for. To address the problem of selectivity into education types a two-step strategy is applied. First, as already established in the section on Descriptives, the higher the educational degree of the parents the higher the fraction of general education for the offspring.[30] Secondly, as mentioned above, the sample is restricted to the same education level.[31] Thereby, comparing education types on the secondary- and on the tertiary-level, respectively. While the second step is applied in the following section, Figure A.6 and Table 6 show the differential social background.[32]

Table 6 shows two different empirical models where the dependent variable is the education type, equaling 1 if the highest degree is of the general type and 0 if it is of the vocational type. Both models control for individual characteristics and social background. Column (1) displays a Probit and (2) a Logit model. Regardless of the empirical model, a more favorable family background has a significantly positive effect on the selection into general education. Hence, Table 6 confirms the result from above that the higher the fathers' or mothers' education, the higher the probability of holding a general degree - compared to vocational education. However, - and this is highly relevant - the Probit and Logit models do not show that this selection varies significantly with age.[33]

[30] This observation is emphasized in Figure A.6.

[31] This is relevant for the fixed-effect regression, as well.

[32] The fixed-effect model does not require to control for the family background, since there is no variation within individuals. However, for the DiD-analysis, controlling for observable selection is essential.

[33] If one could control for individual skill, the effect would probably be of even less relevance.

Table 6: Regression selection bias

	(1) Probit	(2) Logit
General Education		
Migration background	1.023***	1.933***
	(0.00900)	(0.0173)
Male	0.0693***	0.129***
	(0.00658)	(0.0127)
Age	-0.559***	-1.000***
	(0.0260)	(0.0507)
Age × Age	0.0799***	0.145***
	(0.00231)	(0.00454)
Number of Years of Education	0.681***	1.176***
	(0.00167)	(0.00319)
Mother education level	0.178***	0.331***
	(0.0245)	(0.0472)
Mother education level × Age	-0.0122*	-0.0205
	(0.00552)	(0.0106)
Father education level	0.199***	0.394***
	(0.0271)	(0.0526)
Father education level × Age	0.00982	0.0195
	(0.00612)	(0.0117)
Constant	-9.581***	-16.73***
	(0.0799)	(0.156)
Observations	386112	386112

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As is confirmed by the fixed-effect regression, which omits the time-invarying individual observables of mothers' and fathers' education.

However, the data enables one to further control for selectivity into general and vocational education, and especially that selection is time-invarying.

6 Results

This section is dedicated to the results of the empirical models described in the section above. Furthermore, model specifications and robustness checks are presented. Throughout this section, the employment status constitutes as the dependent variable.

6.1 Impact of education type on employment over the career

To obtain the first results of the analysis, I replicate the difference-in-difference approach following Hanushek et al. (2017). Running an Ordinary-Least-Squares estimation (Equation 3) with additional individual characteristics leads to the results presented in Table A.6. The DiD approach (Column (1)-(5)) disregarding of the functional form and the quantitative results of the empirical model, all show a similar development. The results of a Probit model reinforce the DiD results. Column (1) and (2) display the baseline specification, where employment depends on age and its quadratic term, individual characteristics, social background (either fathers' or mothers' education), and whether the individuals' highest degree is general and the interaction with age. Column (3) adds the number of years of education, which differ significantly between the two education types and drops the education level of the father since it is statistically insignificant. By adding the number of years spent in education, the adjusted R^2 increases sharply, while the number of observations decreases by roughly 1.25% to 386,112. Column (4) then adds a control for the cohort of the individual.

Ceteris paribus, the DiD regression shows that the employment probability increases with age and its interaction with general education; this is in line with the results of Figure 1. Interestingly, the dummy variable on migration background is significant and negative - while we established above that individuals with a general degree have a higher probability to have a direct or indirect migration background and generally educated have higher employment fraction. However, individuals with a migration background have fewer years of school-

ing, which describes the lower employment probability in the DiD regression. Otherwise, the number of years of education, gender, and social background have the expected significant effect on the probability of being employed.

Nevertheless, the richness of the underlying panel-dataset is too compre-

Table 7: The effect of general education on employment over the career - DiD, Probit, Fixed-effect regression on the full sample

	(1) DiD	(2) Probit	(3) FE
General Education	-0.255***	-0.687***	-0.0736***
	(0.00527)	(0.0219)	(0.0133)
General Education x Age	0.0571***	0.138***	0.0497***
	(0.00120)	(0.00468)	(0.00407)
Age	0.473***	1.658***	0.407***
	(0.00372)	(0.0147)	(0.00960)
Age x Age	-0.0644***	-0.221***	-0.0585***
	(0.000439)	(0.00166)	(0.00115)
Number of Years of Education	0.0177***	0.0946***	-0.0139***
	(0.000377)	(0.00188)	(0.00220)
Constant	-0.280***	-3.364***	0.365***
	(0.00912)	(0.0399)	(0.0283)
FE	No	No	Yes
Control Var	Yes	Yes	No
Observations	386112	386112	386112

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

hensive to simply apply a DiD approach. Therefore, I run the above-stated fixed-effect regression from Equation 1. Table 7 compares the results of the DiD regression from Table A.6 Column (4) and the Probit in Column (5) with the fixed-effect regression results.

All models are applied to the same sample. The Probit and the DiD include control variables such as the social background or gender. The fixed-effect regression includes the time-invariant fixed-effects - which capture unobserved heterogeneity between individuals. All of the regression models display similar tendencies in the relevant variables, except for the number of years of

education, which has a positive effect on the employment probability in the DiD and Probit approach but is significant and negative for the fixed-effect regression.[34] The interpretation of Column (3) in Table 7 shows that individuals with vocational education are 7.36% more likely to be employed at an early-career stage. This result is supported by the existing literature that finds a significant effect, especially, in apprenticeship-countries, like Germany. However, this advantage turns into a disadvantage as the career progresses. Every 10 years the gap decreases by 4.97%.[35] This implies that by age 32, it is more likely for those holding a general degree to be employed. The gap increases further as the individuals age (see Figure A.1). As a general result, the employment probability increases with age but reaches its peak at age 52 and declines afterwards. The intercept of the fixed effect regression captures the average value of the fixed-effects and it is significant and positive.[36]

In the following, a series of further specifications and robustness checks are pursued. These address concerns over selection into the different education types and of the missing students who are currently in the education process.

Table 8 shows the fixed-effect model, specified in Equation 1, applied to various samples. Column (1) includes the full sample, as well as relevant variables that are described above. Column (4) and (5) include individuals with general or vocational education but with the same education-level, respective to either secondary or tertiary education.[37] This is one strategy used to control for selection bias because individuals with the same education-level receive comparable years of education and should have comparable levels of ability/skill. Since the number of years within the same education-level are not strikingly different, its effect is less significant. As a result of the restriction, the initial advantage of vocational educated disappears for both the secondary- and

[34]Since most of the individuals in the sample finalized their education by the time they are interviewed, the variation of the *Number of Years of Education* within an individual is rather small and thereby most variation is captured by the fixed-effect term. Therefore, if one is obtaining another year of education, one has to drop out of the labor force to receive this education, and the employment status is unemployed. This, in turn, lowers the employment probability as the years of education increase.

[35]Remember, age is divided by 10 to make the results more readable.

[36]The results are robust to different definitions of the employment status - see above for discussion.

[37]The sample sizes do not sum up to the full sample, because the post-secondary non-tertiary group is purely vocational and therefore missing.

tertiary-level. Therefore, one may argue that the early-career stage advantage originates in the difference between the education levels. Vocationally educated individuals, on average, experience fewer years of schooling (and a more occupation-specific education) and therefore, enter the labor market earlier than individuals holding a general qualification; thereby, the early-career employment fraction is higher for vocationally educated. Furthermore, the effect of an increasing employment probability with age and holding a general degree becomes insignificant for the secondary-level and decreases compared to the full sample for the tertiary-level. One reason could be that the secondary-level is likely less heterogeneous in terms of the mix of skills obtained. Therefore, it appears that the tertiary group is generating the employment premium for general education along the career path.

However, the more relevant source driving the impact is the difference between post-secondary non-tertiary level and tertiary education.[38]
For the secondary-level the constant term that captures the average value of the fixed-effects increases dramatically, suggesting that there are unobserved, time-invariant factors within the secondary education level that positively affect the employment probability. Otherwise, age behaves similarly to the full sample.

To further address the concern of missing students who are still in the education-process, the sample is restricted to individuals who are 25 and older.[39] This is done to address the problem of those individuals that are still in the education process, even if they already hold an educational degree, and thereby, might switch the type of their education; e.g. an individual who holds an apprenticeship-degree that is continuing with university.

Column (6) reports the results for people aged 25 to 65. However, overall, the results are similar to the full sample suggesting that this problem is not existent in the dataset.[40]

[38]Both Column (2) and (3) include the post-secondary non-tertiary level and secondary or tertiary education.

[39]The age of 25 is selected since a majority of Germans finished their education by that age. However, the sample is only marginally smaller than the full sample.

[40]By restricting the sample to individuals older than 25, the significant effect of the numbers of years of education becomes insignificant. This is because there are only a few individuals still changing their education type and thereby drop out of the labor force.

Table 8: The effect of general education on employment over the career - FE robustness checks

	(1) Full	(2) Post-sec, tertiary	(3) Post-sec, secondary	(4) Secondary	(5) Tertiary	(6) 25 and older
General Education	-0.0736***	-0.107***	0.0254	-0.00624	-0.0323	-0.111***
	(0.0133)	(0.0238)	(0.0328)	(0.0780)	(0.0321)	(0.0187)
General Education × Age	0.0497***	0.0549***	0.0174	0.0269	0.0360***	0.0476***
	(0.00407)	(0.00502)	(0.0115)	(0.0139)	(0.00799)	(0.00430)
Age	0.407***	0.462***	0.388***	0.362***	0.532***	0.525***
	(0.00960)	(0.0125)	(0.0118)	(0.0155)	(0.0184)	(0.0113)
Age × Age	-0.0585***	-0.0642***	-0.0568***	-0.0540***	-0.0693***	-0.0706***
	(0.00115)	(0.00152)	(0.00142)	(0.00186)	(0.00208)	(0.00131)
Number of Years of Education	-0.0139***	-0.00752	-0.0205***	-0.0288*	-0.0113*	-0.00606
	(0.00220)	(0.00410)	(0.00578)	(0.0117)	(0.00493)	(0.00320)
Constant	0.365***	0.170**	0.483***	0.617***	0.0295	0.00322
	(0.0283)	(0.0523)	(0.0670)	(0.128)	(0.0659)	(0.0424)
Observations	386112	224685	255724	161182	131039	362142

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 Impact of technology & education types on employment over the career

The previous section provided an empirical analysis that concluded that there is a differential employment-age pattern between education types in Germany, now, this section is dedicated to the second question of this thesis: whether technological change is a driver for this difference. As presented above, there are various measures for technology available, for this analysis I employ interpolated computer use, as it shows the highest variance between and within individuals over time and covers the largest sample size.[41] However, the results are robust to the other measures of technology as well.

Table 9 shows four different regression models. Column (1) is the baseline fixed-effect specification from Equation 1 and Column (3) that constitutes the baseline DiD model, on the entire sample. Column (2) runs Equation 2 with the inclusion of interactions with technological change; the change in computer use is linearly interpolated between the different BIBB waves. Column (4) runs a DiD regression that includes technological change.[42] Again, the fixed-effect regression includes individual fixed-effects such that the analysis is intra-individual, while the DiD includes the same control variables as in Table A.6. It is important to notice that when running the model the basic qualitative observation, the initial 'employment penalty' for those with a general education turns into an advantage as the career progresses, from before does not change. In general, the addition of technological change does not impact the magnitude of the age-employment pattern of the fixed-effect regression. However, for the DiD regression, the impact of *General Education x Age* decreases. This stems from the significant impact of technological change.

Column (2) shows that by adding technological change and its interactions, there is no difference between the two education types that is significant. The only significant effect stems from the interaction of technological change and age. Thereby suggesting that - ceteris paribus - technological change as the

[41] The interpolation of technological change assumes a gradual, annual change in technology, while keeping technological change constant assumes that technology leaps every couple of years.

[42] Since 20,000 observation could not be matched, the sample size decreases by roughly 5%. For details: see Section 3.

Table 9: The effect of technological change on employment by education type over the career - DiD and FE regression

	(1) FE-Full	(2) FE-TC	(3) DiD-Full	(4) DiD-TC
General Education	-0.0736***	-0.0740***	-0.255***	-0.141***
	(0.0133)	(0.0142)	(0.00527)	(0.00530)
General Education x Age	0.0497***	0.0537***	0.0571***	0.0442***
	(0.00407)	(0.00430)	(0.00120)	(0.00127)
Age	0.407***	0.432***	0.473***	0.406***
	(0.00960)	(0.00985)	(0.00372)	(0.00356)
Age x Age	-0.0585***	-0.0620***	-0.0644***	-0.0575***
	(0.00115)	(0.00118)	(0.000439)	(0.000429)
Number of Years of Education	-0.0139***	-0.0190***	0.0177***	0.00861***
	(0.00220)	(0.00226)	(0.000377)	(0.000337)
TC Computer use (interpolated)		0.189		0.401***
		(0.107)		(0.0725)
General Education x TC Computer use		0.225		0.665***
		(0.251)		(0.165)
TC Computer use x Age		-0.102***		-0.155***
		(0.0255)		(0.0171)
General Education x TC Computer use x Age		-0.0148		-0.145***
		(0.0603)		(0.0398)
Constant	0.365***	0.423***	-0.280***	0.102***
	(0.0283)	(0.0291)	(0.00912)	(0.00827)
FE	Yes	Yes	No	No
Control Var	No	No	Yes	Yes
Observations	386112	366107	386112	366107

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

career progresses (an additional year of age) decreases the employment probability across all individuals. This seems plausible, since with age the adaptability to new technologies decreases (see Morris and Venkatesh (2000)) and, therefore, the employment probability.

However, as established above, the difference in the marginal effect of a changing technological environment for education types consists of the impact of $\delta_2 + \delta_4 \cdot age$, at a given an age-level. Even though Column (2) shows no significant effect for both coefficients, they qualitatively express some tendencies. δ_2 captures the initial advantage for generally educated compared to vocationally educated, as technology changes. This impact appears to be positive. While δ_4 describes the impact of technological change for general educated as the career

progresses, this coefficient is negative (even though it is highly insignificant). However, it suggests that the advantage of technological change for general education is decreasing with age - most of the age-effect is captured by *TC Computer use x Age*. However, the initial gap is decreasing such that it would disappear as individuals are in retirement age, it is persistent throughout the entire career. The results imply that vocationally educated have lower employment rates as new technologies arise, but this disadvantage diminishes as the career progresses as individuals are less adaptive to new technologies anyhow. The results confirm the pattern of technological change throughout the career for vocationally and generally educated individuals. As can be seen in Figure 3 individuals holding a vocational education are exposed to more technological change along with their career, however, this gap diminishes as the career progresses.

To tackle the concerns that the fixed-effect regression only captures the within-individual variation, I run the DiD regression from Column (3) including technological change. Column (4) summarizes the results. The DiD approach reinforces the results from the fixed-effect model, further, the observations from above are now significant.

Nevertheless, this analysis has to be interpreted as preliminary, since it suffers from severe weaknesses and constraints.
For example, there is the problem of the reduced sample size with respect to the full model in Column (1). As described in the data section, by merging the technology measures to the SOEP, 20,000 individual observations (ca. 5% of the overall sample) are not matched and therefore, drop out of the sample when technological change is controlled for. Nearly 85% of these unmatched are long-term unemployed individuals, which are likely to reinforce the results of the long-term costs of vocational education (since the majority of unmatched are vocationally educated who report unemployed).
Additionally, the measure of technology is on the occupational-level, while the SOEP provides individual-level data. It would be preferable to use an individual measure of technology to obtain more specific results. However, the occupational coding is rather granular and, thereby, sufficient variation is included. Another caveat is the selection of education types. The fixed-effect

regression enables one to control for time-invariant unobservables. However, if selection varies over time, i.e. if individuals selecting general education have higher ability, then the fixed-effect regression would yield biased results. Therefore, it is necessary to control for individual's skill-/ability-level over time. Finally, further research should consider a richer model that captures the effect of the change in technology by education type more accurately.

7 Concluding Remarks

This thesis constructs a unique dataset to analyze labor-market outcome differences for individuals with different educational types in Germany. The aim of this study was twofold: Scrutinize whether there are in fact distinct age-employment patterns by type of education in Germany and decompose this effect in whether technological change is a driver for the different labor market outcomes.

After a comprehensive descriptive analysis of the new dataset, an empirical evaluation was conducted. Given the longitudinal format and the richness of the newly constructed dataset, it proved to be beneficial to apply a fixed-effect regression. As a fixed-effect estimator captures all of the time-invariant unobserved heterogeneity between individuals and thereby implicitly controls for selection bias.[43] To further address the selectivity into the different types of education, the samples are restricted to different education-levels. On the one hand, the analysis revealed that there exists an early-career stage advantage for individuals with vocational education compared to generally educated. This initial advantage of a higher employment probability, however, becomes disadvantageous as the career progresses. To be more precise, people holding a vocational qualification as their highest degree are less likely to be employed after the age of 32 than individuals with general education.

Robustness checks show that this result stems from the difference between different education-levels and exists within the tertiary education-level.

The pre-existing literature argues that one reason for the different age-employment pattern for general compared to vocational education is the different adapt-

[43] However, the fixed-effect regression captures the within-individual variation.

ability to technological change. Further, Hanushek et al. (2017) point out that a general *concept-based* education enables its graduates to be better prepared for a technically changing environment than a vocational *skill-based* education. To empirically assess the negative impact of technological change, the baseline specification is extended by a measure for technological change. The analysis showed that, in fact, changing technology negatively impacts the vocationally educated. However, this effect is decreasing as the career progresses. Further examination showed that people with a vocational education are exposed to more technological change throughout their careers. However, the gap diminishes as individuals age. This result stands in contrast to the theory of Krueger and Kumar (2004a,b) who argued individuals that hold a vocational qualification are less adaptive to changing technologies over time. While the initial negative impact of technological change is persistent throughout the career it decreases slightly as the career progresses.
In general, the results have to be treated as preliminary as the empirical examination suffers from several weaknesses, e.g. time-varying selection into education type.

While other reasons for the different age-employment patterns might an early-retirement, which has mitigated relative employment effects for older ages. Additionally, the literature cites different adaptability to a changing occupational structure as a result of globalization and digitization as another possible driver.
Further research in the field of within-country analysis should focus on richer techniques to overcome selection bias. However, further evaluation of the underlying dataset is possible. E.g. this paper does not encounter adult-training. Controlling for training when comparing different education-levels is important to confront the argument that certain education groups get more on-the-job training and, therefore, can more easily adjust to new technologies. Hanushek et al. (2017) find that in Germany workers with general education receive significantly more training than workers with vocational education throughout their career. This finding is supported by the work of Grund and Martin (2012) and Tamm and Görlitz (2011). The SOEP provides adult-training data and further, as discussed above, the SOEP provides three waves of short IQ tests, which proved to be a reasonable approximation of one's skill/ability. By

employing machine learning techniques, one could estimate test scores based on observable characteristics and thereby, improve the control for selectivity into the different education types.

As a general result of this master thesis, in the discussion about the education system in Germany, the advantage of the smooth school-to-work transition by the vocational education system has to be put in the context of the disadvantage later in the career. Further, technological change has an impact on the age-employment profiles between individuals holding a general vs. a vocational qualification. Whether the difference in adaptability to a changing technological environment is a driver for the employment differences cannot be determined, since the impact slightly decreases with age and, so, further research is necessary. However, the newly created dataset should enable a more in-depth analysis of this problem.

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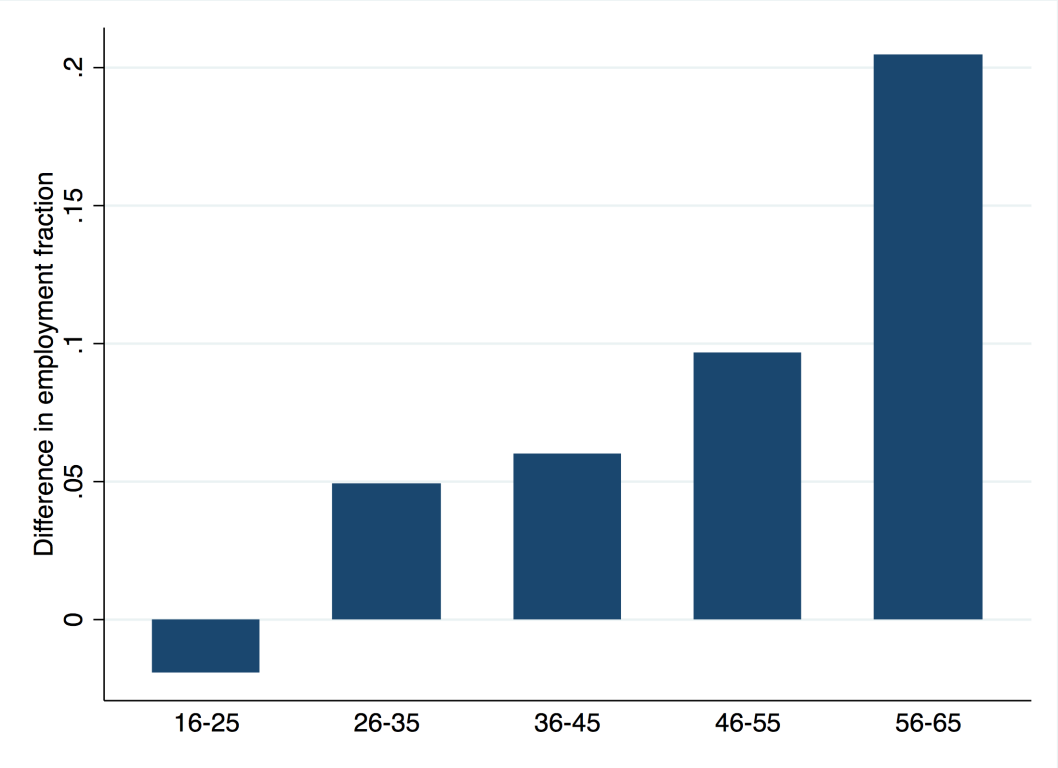
A Appendix

Figure A.1: Employment fraction difference between general and vocationally educated



Note: Differences in employment fraction by type of education over the career life-cycle.

Figure A.1 shows that the initial advantage for individuals holding a vocational degree becomes disadvantageous as the career progresses. However, this is not a linear increase, but rather a non-linear relation, as the older the individual gets, the higher the employment fraction difference. Therefore, at the highest age (56-65), the difference is the most pronounced.

Table A.1 shows that cohorts differ first-of-all by the number of observations. The baby-boomer generation of the 1960s is strongly represented with 112,000 observations. Since individuals born in the 1990s are still young when the SOEP is conducted, the number of observations is rather low and all numbers are preliminary. However, another trend is that the overall educational attainment increased with the cohort. The younger the cohort, the more people received a tertiary degree. The other trend is that individuals in Germany are

Table A.1: Educational Attainment over cohorts

			Secondary and Tertiary (full sample)		Secondary		Tertiary	
Cohort	N	% tertiary level	% completing general	% completing vocational	% completing general	% completing vocational	% completing general	% completing vocational
1930s	21,461	26.99	18.93	81.07	1.77	98.23	69.64	30.36
1940s	51,800	32.40	26.14	73.86	2.54	97.46	77.38	22.62
1950s	90,878	36.21	30.56	69.44	4.40	95.60	79.46	20.54
1960s	112,142	32.57	26.99	73.01	6.66	93.34	74.75	25.25
1970s	72,119	34.45	30.27	69.73	9.27	92.32	76.66	23.34
1980s	33,172	37.28	34.68	65.32	16.49	83.51	73.55	26.45
1990s	8,493	34.55	40.14	59.86	45.21	54.79	46.59	53.41
Overall	390,065	33.81	28.81	71.19	7.72	92.28	75.77	24.23

Note: Average educational attainment over cohorts. The last cohort of individuals born in 1990 is too new to be interpreted in the context and has too few observations.

receiving more general educations rather than vocational educations.

Table A.2: Descriptive Statistics by Type of Education (continued)

	Overall Mean	***General Education*** Mean	***Vocational Education*** Mean
Armed forces	0.00	0.00	0.01
Senior officials and managers	0.06	0.09	0.05
Professionals	0.18	0.55	0.05
Technicians	0.24	0.21	0.25
Clerks	0.13	0.06	0.15
Service workers	0.10	0.03	0.13
Skilled agricultural workers	0.01	0.00	0.02
Craft and related trade workers	0.16	0.02	0.20
Plant and machine operators	0.06	0.01	0.08
Elementary occupations	0.05	0.01	0.06
Agriculture, hunting, forestry and fishing	0.02	0.01	0.02
Mining and quarrying	0.00	0.00	0.00
Manufacturing	0.25	0.18	0.27
Electricity, gas and water supply	0.01	0.01	0.01
Construction	0.07	0.03	0.08
Wholesale and retail trade	0.12	0.05	0.15
Hotels and restaurants	0.02	0.01	0.03
Transport and communication	0.06	0.04	0.06
Financial intermediation	0.04	0.04	0.05
Real estate, renting and business activities	0.08	0.14	0.06
Public administration	0.09	0.12	0.08
Education	0.07	0.18	0.03
Health	0.11	0.12	0.11
Other services	0.04	0.05	0.04
Activities of households	0.00	0.00	0.00
Extra-territorial organizations	0.00	0.00	0.00

Note: Table 3 continued. Occupational level was classified by the 1992 'International Standard Classification of Occupation'.

Table A.2 reveals that vocationally educated individuals (on average) mostly work in manufacturing (27%), as technicians (every fourth), or in craft and related trade work (every fifth). On the other hand, individuals holding a gen-

eral qualification work as Professionals (55%), in education or manufacturing (each 18%).

Table A.3: Descriptive Statistics Occupational-Level

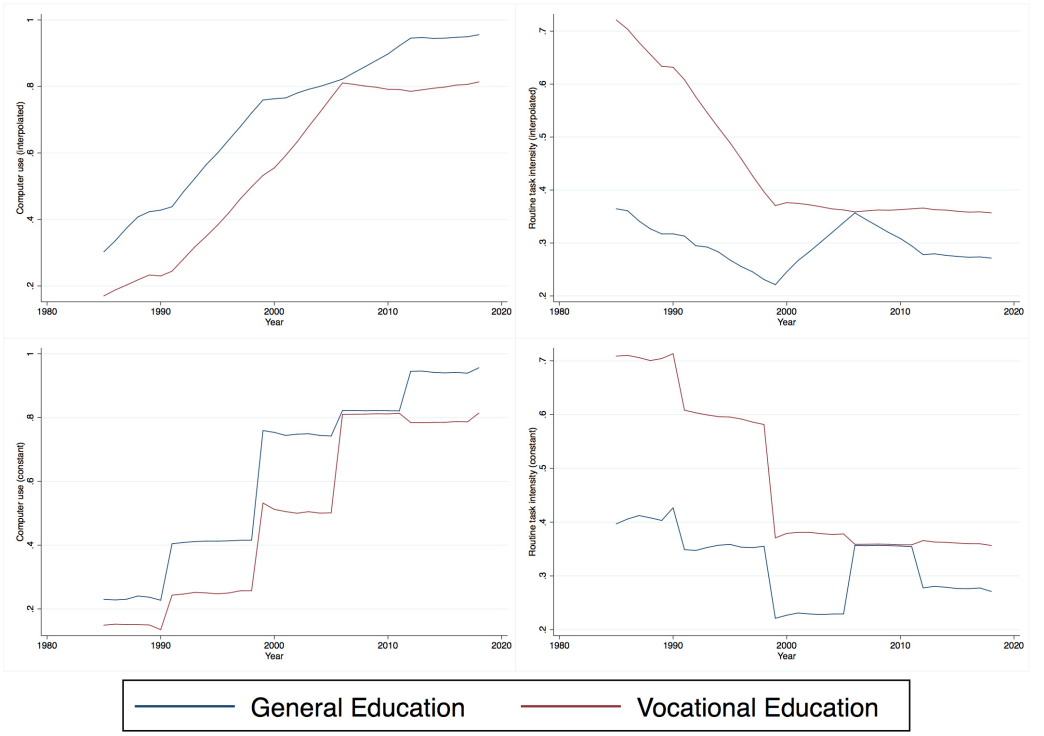
	Overall Mean	***General Occupation*** Mean	***Vocational Occupation*** Mean
Individual characteristics			
Age	42.64	42.71	42.62
Male	0.64	0.61	0.64
Migration background	0.12	0.12	0.12
East1989	0.26	0.21	0.27
Employment			
Employed	0.82	0.91	0.80
Log real hourly wage	2.66	2.97	2.60
Fulltime	0.65	0.71	0.64
Parttime	0.11	0.14	0.10
Education			
Number of Years of Education	12.24	15.44	11.57
Fraction of general education	0.21	0.78	0.10
Firm size			
Firm size $<$ 20	0.32	0.29	0.33
Firm size 20-200	0.27	0.24	0.28
Firm size 200-2000	0.21	0.19	0.21
Firm size $>$ 2000	0.20	0.27	0.19
Parents education			
Lower secondary	0.13	0.06	0.14
Upper secondary	0.69	0.57	0.71
Tertiary	0.18	0.38	0.14
Technology			
Relative computer use (interpolated)	0.55	0.79	0.51
Routine-task-intensity (interpolated)	0.48	0.28	0.52
Relative computer use (constant)	0.51	0.74	0.46
Routine-task-intensity (constant)	0.49	0.29	0.53
Technological Change			
TC Computer use (interpolated)	0.02	0.02	0.02
TC RTI (interpolated)	−0.01	−0.00	−0.01
TC Computer use (constant)	0.16	0.14	0.16
TC RTI (constant)	−0.08	−0.02	−0.10
N	370	64	306

Note: Weighted mean of the variables derived from an individual-level, but collapsed on occupational-level. The sample includes 374,622 observation, hence, not the entire sample, because some occupations were not matched.

Generally, the occupations are polarized (as can be seen in Table A.3) in the fraction of education types. There are many occupations where individuals exclusively hold a vocational degree (on average 10% of vocationally dominated occupations hold a general degree). Overall, there are 370 occupations in this sample. 64 have more than half of its employees holding a general degree, 306 include more than 50% with a vocational qualification. Otherwise, this Table

shows similar results to the individual-level descriptives. For the discussion on the measures for technology and technological change on the occupational-level, see Section 4.1.

Figure A.2: Technology level measures over time

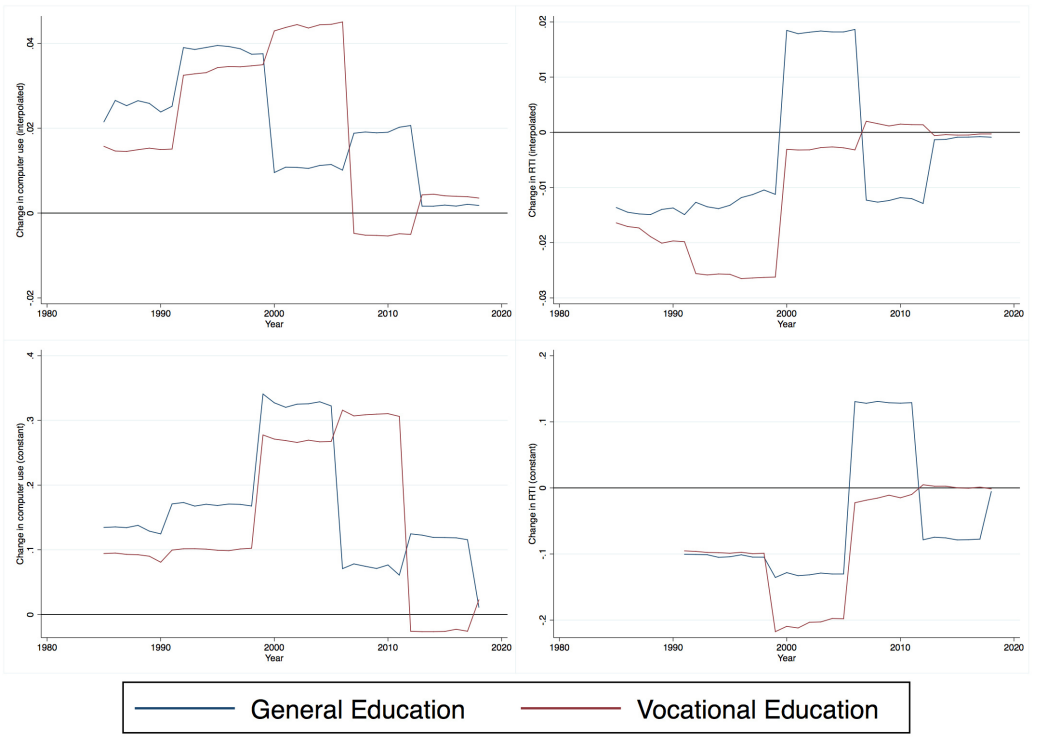


Note: Various measures for technology over time. Left panel: Change in computer use; Right: Change in RTI; Upper: Interpolated; Lower: Constant. Source: BIBB.

Figure A.2 shows the four different measures for technology over time for the two different education types. The change in computer use is always higher for generally educated. While the technology measure of RTI reveals the same. Individuals holding a general degree are doing fewer routine tasks in their occupation and therefore, have a higher level of technology in place. This observation holds over time. The measures are obtained for the BIBB dataset and either interpolated or kept constant between the corresponding BIBB waves.

Figure A.4 displays the change in computer use over time by sector and education type. For the agriculture, hunting, forestry, and fishing sector the measure for technological change is evolving as for the aggregate economy (see descriptives to Table 5). Similar notions are seen in the service sector and

Figure A.3: Technological change measures over time

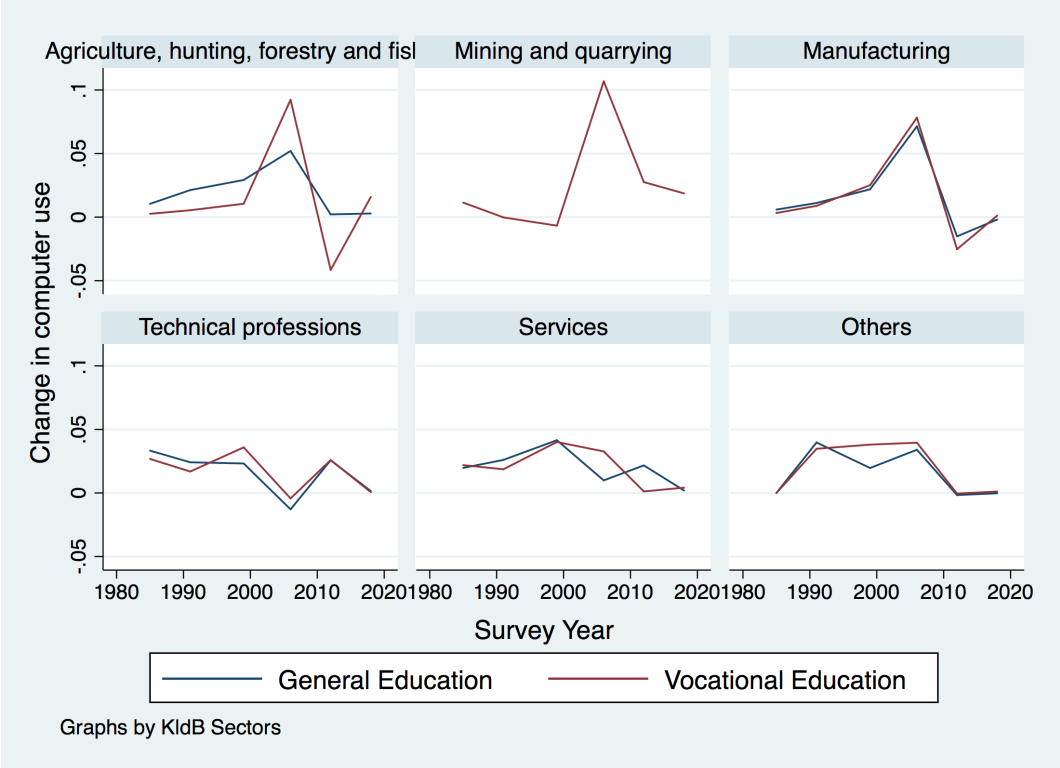


Note: See note Table 5 in Section 4.1. Left panel: Change in computer use; Right: Change in RTI; Upper: Interpolated; Lower: Constant.

manufacturing. However, in mining and quarrying there are only vocationally educated workers, therefore, there is no difference between the education types in that sector. Further, technical professions experienced more technological change for the vocationally educated than for the generally educated (except for the first couple of years).

To show that a sectoral change for individuals with a vocational qualification in Germany took place as mentioned for the US by Reshef (2013), Table A.4 describes the employment fraction of workers by sector but for the vocational educated exclusively. The years represent the different BIBB waves available. In 1985, 2% of the vocationally educated worked in agriculture, 32% in manufacturing, 6% in technical professions, and the majority with 60% in service. The trend is that the fraction of service sector workers increases even more and represented in 2018, 69% of overall workers with vocational education. Hence, there is a trend of workers leaving the manufacturing sector (32% in

Figure A.4: Technological change over time by education type and sector



Note: Technological change, measured by the change in the interpolated computer use over time, by education type and industry sector. Sector codes are derived from the KldB 1992 classification at a one-digit-level.

Table A.4: Fraction of workers by sector for vocationally educated

	1985 Mean	***1991*** Mean	***1999*** Mean	***2006*** Mean	***2012*** Mean	***2018*** Mean
Agriculture, hunting, forestry and fishing	0.02	0.02	0.02	0.02	0.02	0.02
Mining and quarrying	0.00	0.00	0.00	0.00	0.00	0.00
Manufacturing	0.32	0.33	0.28	0.27	0.24	0.22
Technical professions	0.06	0.06	0.05	0.04	0.05	0.06
Services	0.60	0.58	0.64	0.66	0.68	0.69
Others	0.00	0.01	0.01	0.01	0.01	0.01

Note: Weighted average fraction of employed individuals who hold a vocational qualification as their highest by industry sector and over time. Sector codes are derived from the KldB 1992 classification at one-digit-level.

1985; 2018 merely 22%) and moving to the service sector.

Table A.5 summarizes the weighted average of Routine-Task Intensity for workers in the manufacturing and service sector because these are the most relevant

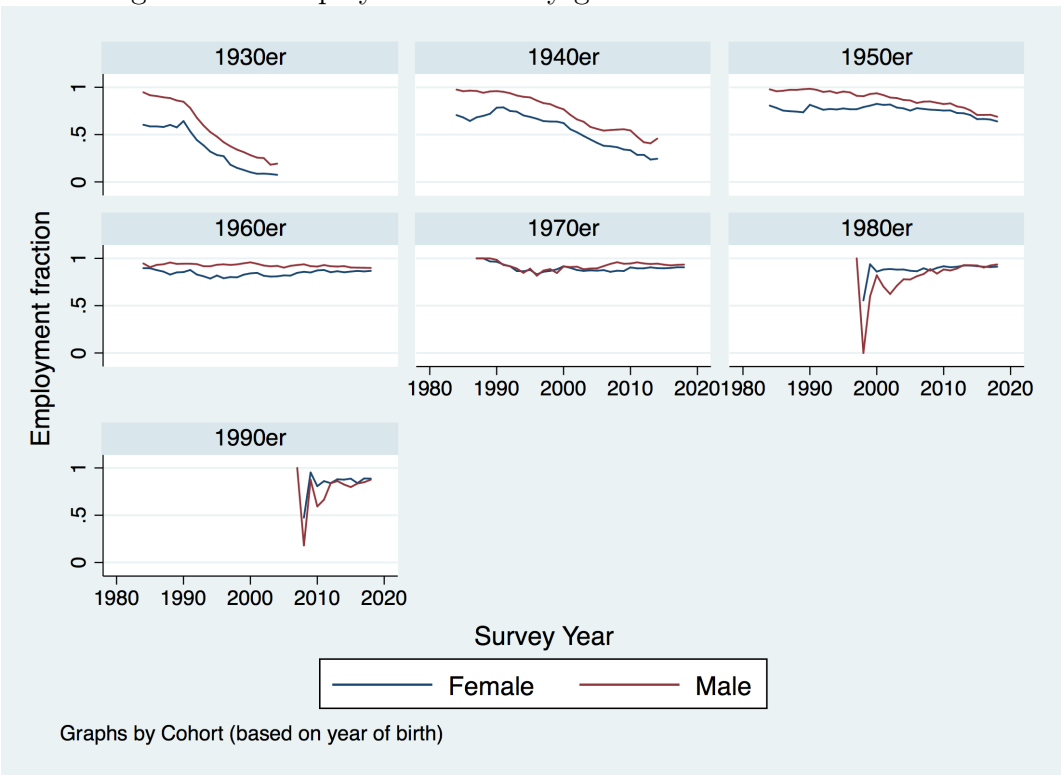
Table A.5: RTI service and manufacturing sector

	1985	*1991*	*1999*	*2006*	*2012*	*2018*
Service sector	0.57	0.47	0.23	0.36	0.29	0.29
Manufacturing sector	0.85	0.80	0.65	0.36	0.50	0.49

Note: Weighted average interpolated Routine-Task-Intensity for workers in manufacturing and service sector.

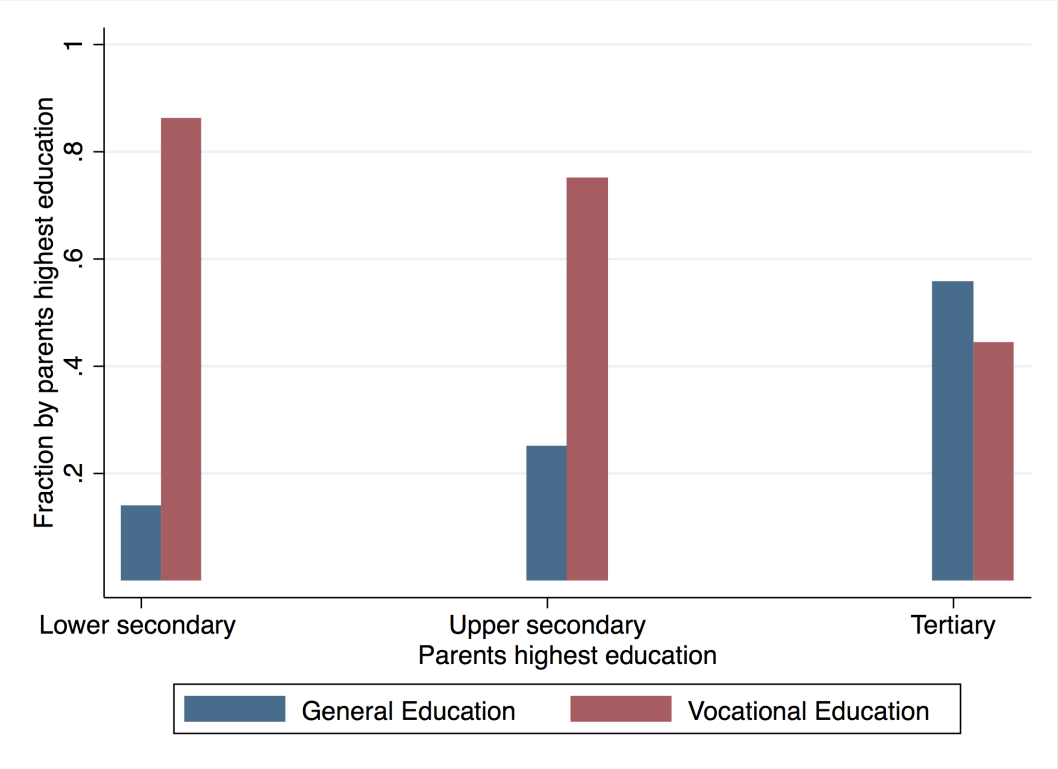
sectors.

Figure A.5: Employment rates by gender and cohort over time



Note: Employment fraction by gender.

Figure A.6: Type of education by parents' highest education



Note: Parents' highest education in ISCED-classification by type of education of offspring. Figure reads the following way: If the parents hold a lower secondary degree as their highest degree, then 14% of the children hold a general while 86% hold a vocational degree.

Table A.6: The Effect of Education type on employment over the career

	(1) DiD	(2) DiD	(3) DiD	(4) DiD	(5) Probit
General Education	-0.208***	-0.202***	-0.248***	-0.255***	-0.687***
	(0.00511)	(0.00511)	(0.00527)	(0.00527)	(0.0219)
General Education × Age	0.0642***	0.0638***	0.0548***	0.0571***	0.138***
	(0.00119)	(0.00119)	(0.00121)	(0.00120)	(0.00468)
Age	0.465***	0.464***	0.456***	0.473***	1.658***
	(0.00366)	(0.00365)	(0.00371)	(0.00372)	(0.0147)
Age × Age	-0.0659***	-0.0661***	-0.0645***	-0.0644***	-0.221***
	(0.000433)	(0.000433)	(0.000439)	(0.000439)	(0.00166)
Migration background	-0.0643***	-0.0653***	-0.0446***	-0.0542***	-0.236***
	(0.00175)	(0.00176)	(0.00176)	(0.00178)	(0.00750)
Male	0.0879***	0.0874***	0.0901***	0.0928***	0.427***
	(0.00114)	(0.00114)	(0.00115)	(0.00115)	(0.00516)
East1989	-0.0479***	-0.0437***	-0.0414***	-0.0422***	-0.185***
	(0.00138)	(0.00136)	(0.00138)	(0.00138)	(0.00586)
Mother education level	0.0186***		0.0101***	0.00224	0.0117*
	(0.00113)		(0.00115)	(0.00117)	(0.00523)
Father education level		-0.000606			
		(0.00124)			
Number of Years of Education			0.0193***	0.0177***	0.0946***
			(0.000373)	(0.000377)	(0.00188)
Cohort (based on year of birth)				0.0233***	0.0919***
				(0.000639)	(0.00285)
Constant	0.0555***	0.0921***	-0.149***	-0.280***	-3.364***
	(0.00771)	(0.00786)	(0.00858)	(0.00912)	(0.0399)
Observations	390065	390065	386112	386112	386112
Adjusted R^2	0.156	0.155	0.162	0.165	

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: For description see Section 6.1

The Table from above runs the following difference-in-difference regression:[44]

$$emp_{it} = \alpha_0 + \alpha_1 \cdot age_{it} + \alpha_2 \cdot age_{it}^2 + \beta_1 \cdot gen_{it} + \beta_2 \cdot gen_{it} \cdot age_{it} + X_{it} \cdot \gamma + \epsilon_{it} \quad (3)$$

Where emp_{it} represents the employment status of the individual at time t, equaling 1 if the individual is employed and 0 otherwise. Age and age squared capture the non-linear age-effect on employment. The dichotomous variable gen_{it} equals 1 if the individual holds a general degree at time t and 0 if the person possesses a vocational degree. X_{it} is a vector of relevant control variables e.g. number of years of education, individual characteristics, social background, and cohort. ϵ_{it} is the error term of individual i at time t.

[44]Similarly, a Probit regression is run.