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General Education, Vocational Education, and Labor-Market Outcomes over the Life-Cycle*

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Abstract

Policy proposals promoting vocational education focus on the school-to-work transition. But with technological change, gains in youth employment may be offset by less adaptability and diminished employment later in life. To test for this trade-off, we employ a difference-in-differences approach that compares employment rates across different ages for people with general and vocational education. Using micro data for 11 countries from IALS, we find strong and robust support for such a trade-off, especially in countries emphasizing apprenticeship programs. German Microcensus data and Austrian administrative data confirm the results for within-occupational-group analysis and for exogenous variation from plant closures, respectively.

Keywords: Vocational education; apprenticeship; employment; wages; life-cycle; adult education; International Adult Literacy Survey (IALS)

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I. Introduction

Most advanced economies are concerned about the ease with which young workers can make the transition from school to work. The unemployment rate for youth invariably exceeds that for the economy as a whole, contributing to a variety of social problems. In addition, many young workers struggle to find their place in the labor force, changing not only employers but also occupations multiple times before they settle down to stable jobs. One appealing way to deal with these transition problems is to link students more closely to jobs through vocational education programs and through apprenticeships with firms (see Ryan (2001); Zimmermann et al. (2013)). Moreover, the potential for improving youth labor markets in this manner has considerable political support around the world – with even President Obama suggesting that the United States might re-invigorate its vocational training to get youth into jobs.[1] In contrast to previous research that has focused almost entirely on the school-to-work transition of youth, this paper studies the difference in life-cycle work outcomes – employment, wages, and career-related training – between individuals receiving vocational and general education.

Countries have actually adopted very different schooling structures that differ fundamentally in their focus on the job transition. Some stress vocational education that develops specific job-related skills in order to prepare students to work in specific occupations, while others emphasize general education that provides students with broad knowledge and basic skills in mathematics and communication and serves as the foundation for further learning and on-the-job training. The United States, for example, has largely eliminated vocational education as a separate track in secondary schools on the argument that specific skills become obsolete too quickly and that it is necessary to give people the ability to adapt to new technologies. On the

[1] See http://www.ed.gov/blog/topic/career-and-technical-education/ [accessed June 28, 2014].

other hand, many European and developing countries, led by Germany's "dual system," provide extensive vocational education and training at the secondary level including direct involvement of industry through apprenticeships. The underlying rationale is that by concentrating on specific vocational skills, it is possible to improve the entry of workers into the economy and to make them productive at an earlier point.[2]

These differing perspectives suggest a possible trade-off between short-term and long-term costs and benefits for both individuals and the entire society: The skills generated by vocational education may facilitate the transition into the labor market but may become obsolete at a faster rate. Our main hypothesis is thus that any initial labor-market advantage of vocational relative to general education decreases with age.[3]

The existing empirical analysis of the impact of educational type on individuals is fairly limited and provides mixed information about either the existence or magnitude of our hypothesized trade-off. The general-vocational education debate has centered on whether vocational education is effective in facilitating youth school-to-work transition.[4] However, even at job entry, existing studies have not found a universal advantage of vocational over academic

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[2] A different rationale common in the U.S. is that the practical focus of vocational courses can motivate some students who might otherwise drop out of formal schooling to stay in school. Our analysis, which is restricted to people who have finished at least secondary schooling, does not provide any insights into this rationale.

[3] This argument is related to the macroeconomic perspective of Krueger and Kumar (2004a, 2004b) who have argued that the propensity to use vocational rather than general education may be an underlying cause of growth-rate differentials between the U.S. and Europe. Their argument is that vocational ("skill-based") as opposed to general ("concept-based") education leads to slower adoption of new technologies. While similar notions underlie our work here, we are really interested in the other side of the relationship: If there is rapid technological and structural change, what does this mean for hiring workers with vocational and general education? The pattern we study is also in line with the model by Gould, Moav, and Weinberg (2001) where technological progress leads to a higher depreciation of technology-specific skills vs. general skills. See also Bertocchi and Spagat (2004) for a model of how the different education systems developed in a historical perspective.

[4] Another larger literature focuses on the firm side of the market and their incentives to invest in general or specific education; see the initial work by Becker (1964) and more recent analysis by Acemoglu and Pischke (1998, 1999).

education for youth's labor-market outcomes, although the analysis has been problematic.[5] As Paul Ryan (2001) states: "The merits of vocational curricula and work-based preparation are particularly difficult to evaluate statistically, given the potential importance of selection around unobservables, the near-absence of experimental evidence, and the paucity of prior labor market experience to use in econometric modeling" (p. 73).

The main analysis of this paper employs an international sample of labor-market outcomes for workers across the age spectrum, using micro data from the International Adult Literacy Survey (IALS). The database is unique because it provides detailed information about the education and skills of workers across the life-cycle in countries with varying structures of vocational schooling and training. To address the concern of selection into different types of education, we propose a difference-in-differences framework, comparing labor-market outcomes across different ages for people with general and vocational education. Under the assumption that conditional selectivity into education types does not vary over time, this approach allows us to identify how relative labor-market outcomes of different education types vary with age cohorts. While it is difficult to remove all concerns about unobserved changes over time in selectivity into education types, we pursue a variety of specification and robustness tests that significantly reduce the potential threats to identification. Larger concerns about identification still remain about estimates of the initial employment advantage from vocational education, but our attention throughout most of the analysis is on relative skill obsolescence with age.

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[5] For examples, see Arum and Shavit (1995); Malamud and Pop-Eleches (2010); and the reviews and discussions in Ryan (2001), Müller (2009), Wolter and Ryan (2011), and Zimmermann et al. (2013). Meer (2007), Oosterbeek and Webbink (2007), and Fersterer, Pischke, and Winter-Ebmer (2008) are recent examples studying the labor-market outcomes of vocational education. Cörvers et al. (2011), Hall (2013), Weber (2014), Stenberg and Westerlund (2014), and Golsteyn and Stenberg (2014) are recent examples of labor-market analyses beyond the entry phase that are in line with our interpretation here.

Pooling individuals from the 11 countries with sizeable vocational education systems, we find that individuals with general education initially face worse employment outcomes but experience improved employment probability as they become older relative to individuals with vocational education. The pattern is most pronounced in the apprenticeship countries of Denmark, Germany, and Switzerland. In these countries, the easier entry into the labor market is balanced by noticeably greater withdrawal at older ages.

Two additional sets of analyses strengthen the interpretation that the distinct age pattern reflects depreciated skills rather than other forces inducing retirement. First, using data from the German Microcensus, we show that the same pattern holds in much larger and more recent samples and in estimation within occupational groups that excludes occupations where brawn is important. This indicates that the differential movement out of employment is not simply a matter of physical wear and tear of people in specific vocationally intensive occupations. Second, using Austrian Social Security data, we show that after a plant closure, the relative employment rates of displaced blue-collar workers (with more vocational training) are above those of white-collar workers at younger ages, but below them at ages above 50. The exogenous nature of the employment shock removes concerns about unobserved retirement preferences that could threaten identification.

The decrease in the relative labor-market advantage of vocational education with age is apparent not only in employment, but also in income. One reason underlying the estimated labor-market patterns in the apprenticeship countries seems to be adult training. With increasing age, individuals with general education are more likely to receive career-related training relative to those with vocational education.

II. Data

Our primary data source, the International Adult Literacy Survey (IALS),[6] provides a unique opportunity to investigate the impact of education type.[7] Conducted in the participating countries between 1994 and 1998, IALS provides us with data for 18 countries: 15 European countries plus the U.S., New Zealand, and Chile.[8] The IALS contains information about respondents' years of schooling and whether they completed a vocational program or general program in secondary and post-secondary education for a representative sample of adults between 16 and 65 years of age in each country. Obviously, average educational attainment varies across countries and over time, which is the topic of an extensive literature already, but what we are most interested in here is the distinction between general and vocational programs.

While other datasets may also record employment patterns for different age cohorts, a key element of the IALS is its extensive data on other individual employment-related characteristics including age, gender, years of schooling, employment status, earnings, adult training, parents' educational attainment, and, for a subset of countries, father's occupation. Additionally, each individual was given a series of assessments of cognitive skills (called "literacies") that are comparable within and across countries. The literacy tests in prose, document, and quantitative domains are designed to measure basic skills needed to participate fully in modern society. The development of these assessments was innovative, because no prior attempts had been made to assess the adult competencies on a comparable basis across nations. One of the key issues was developing questions that could cover a broad range of adult contexts

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[6] The IALS survey was developed by the Organisation for Economic Co-operation and Development (OECD). A follow-on – the Programme for the International Assessment of Adult Competencies (PIAAC) – has recently been conducted.

[7] For an overview of economic studies using the IALS data, see section 5 in Hanushek and Woessmann (2011).

[8] Another country with IALS data is Canada, but it could not be included in the analysis because it only provided bracketed age information.

and that would not advantage or disadvantage particular groups or countries (see Kirsch (2001)). Test items were scaled using procedures of Item Response Theory. As discussed in Hanushek and Zhang (2009), the test scores appear to be a reasonable index of general levels of cognitive skills as valued in the labor market.[9] These detailed individual measures are important in investigating any changes across time in the selectivity of general and vocational programs.

For the empirical analysis, we restrict our sample to individuals who completed at least secondary education and who are currently not students. This is the sample on which general and vocational education types can be defined for individuals' final schooling level. We also restrict our analysis to males, because of their historically stable aggregate labor-force participation patterns in prime-age groups across most countries in our sample. This circumvents concerns about cohort-specific selection into work by females that would be problematic when we compare younger and older workers.

For individuals who finished secondary education, a general education is defined if their education program is academic or college preparatory; a vocational education is defined if their education program is business, trade, or vocational. Some individuals report their education type as secondary-level equivalency or simply as "other"; since it is not clear what exactly these programs entail, we classify this as a separate category.[10] For individuals who finished the first

[9] Hanushek and Zhang (2009) also show that the scores on the IALS assessments are highly correlated with the more academic international tests (i.e., TIMSS) used in school-based testing as opposed to labor-force testing. No clear measures of non-cognitive dimensions of skills are available in the IALS data.

[10] According to the Organisation for Economic Co-operation and Development (2010), at the secondary level, general programs are programs that are not designed explicitly to prepare participants for a specific class of occupations or trades or for entry into further vocational or technical education programs, while vocational education prepares participants for direct entry, without further training, into specific occupations.

stage of tertiary education, a general program is one that leads to a university degree (BA/BS), and a vocational program is one that does not lead to a university degree.[11]

We concentrate on institutional differences in the degree to which programs are linked to jobs and vocations, but clearly schooling systems across countries differ in other ways including the scope and quality of the curriculum in both vocational and general education programs. For example, Germany takes pride in the quality of classroom instruction in its vocational schooling, and this quality could even be greater than seen in general education programs of other countries. Nonetheless, all of our subsequent analysis considers just within-country variation. Vocational programs necessarily involve less time and attention to developing general skills compared to general education *within any country*, and this difference – which is presumed to show up directly in differences in general skills – is what drives our analytical results.[12]

A. Descriptive Patterns

Table 1 shows the overall distribution of education types by country.[13] On average, 35 percent of males in our sample completed a general education and 47 percent completed a vocational education (the remainder being in the residual "other" category). Of the 73 percent of individuals in our sample whose final education is at the secondary level, about one quarter completed a general education and one half a vocational education. More than half of those completing a tertiary education finished with a bachelor's degree.

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[11] We essentially define the tertiary type-A programs as general education and tertiary type-B programs as vocational. The former are largely theory-based and are designed to provide sufficient qualifications for entry to advanced research programs and professions with high skill requirements, such as medicine, dentistry, or architecture. The latter are typically shorter and focus on practical, technical, or occupational skills for direct entry into the labor market (Organisation for Economic Co-operation and Development (2010)).

[12] Vocational education, particularly when it is firm-based, undoubtedly includes more firm- and industry-specific training for individuals, but this is not well-measured. Our presumption is that these specific skills depreciate more rapidly than general skills, particularly with rapid technological change.

[13] Note that the samples in Ireland and Sweden are particularly small because they include only individuals with tertiary education, as information on the secondary education types is unavailable.

The variation across countries is striking, especially at the secondary level. The share of individuals completing a general secondary education ranges from under five percent in the Czech Republic to 72 percent in Italy. Most European countries heavily emphasize vocational programs at the secondary level, with less than one-third completing a general secondary education, while Chile reports a majority completing a general secondary education.[14] At the tertiary level, the variation across countries is smaller. For all but a few countries, between one third and two thirds of individuals completing a tertiary education received a university degree, and the U.S. and Chile fall right in the middle. Overall, the U.S. has the largest share completing tertiary education.

The clear picture from Table 1 is the significant differences in how school systems around the world are organized. These institutional differences represent distinct policy choices that presumably affect the labor-market outcomes across countries.[15]

An important issue, particularly when looking across time within countries, is whether the relative skills of those in general and vocational programs are changing. The battery of literacy tests in IALS permits direct observations of cognitive skills by age and schooling type. The literacy score we use is the average of the three test scores in prose, document, and quantitative literacy, normalized to have mean zero and standard deviation one within each country.[16] Figure A1 in the appendix shows that individuals with general education have on average higher scores than those with vocational education. But there is substantial overlap in

[14] Inaccurate reporting of education type at the secondary level is a substantial problem for the U.S.; 60 percent report “secondary-school equivalency” and do not distinguish general and vocational schooling. The problem is also quite severe for the Czech Republic and Norway, and, to a lesser extent, for Finland.

[15] See the working-paper version (Hanushek, Woessmann, and Zhang (2011)) for details on the distribution of educational attainment by country and age group.

[16] Results are virtually identical when using any of the three sub-domains separately instead of their average in our analyses, which is not particularly surprising since the pairwise correlations of the separate components are all above 0.9. Although scores differ across countries, the normalization has no impact on the results, which are based on just within-country variation through inclusion of country fixed effects.

literacy scores between the two types, suggesting that individuals completing general and vocational education share a common support in this important characteristic. Detailed inspection in Hanushek, Woessmann, and Zhang (2011) suggests that, with few exceptions, in each country the literacy scores for each education type follows a similar pattern over age cohorts, providing some general evidence that the relative selectivity between vocational and general education programs has not changed substantially over time. We return to these issues below.

The focus of our analysis is employment patterns over the life-cycle. In the IALS data, employment is defined by the current work situation at the time of the interview, where not being employed includes the unemployed, the retired, and homemaking at the time of the survey.[17] Figure A2 in the appendix shows the percentage employed of males with different education types across age cohorts in each country. In the figure, each line is smoothed by locally weighted regressions using Cleveland (1979)'s tricube weighting function for each year of age. Many countries show a distinct age-employment profile by education type: Individuals with vocational education tend to have a higher employment rate than individuals with general education for the youngest cohorts; but for older cohorts, individuals with general education are more likely to be employed than those with vocational education, and this is most pronounced at the end of the work life-cycle. The employment pattern is not, however, uniform across countries, with some countries like the U.S. having almost identical employment patterns by education type and others like Germany displaying widely different patterns. Our analysis flows from these differences.

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[17] Results are very similar when using the additional information on whether individuals worked at any time in the past 12 months.

B. Defining Country Groups by Institutional Variations

There is substantial variation across countries in the relative size of the general and vocational programs and in the specific organization of the vocational programs. The U.S. has virtually no vocational program at the secondary level by the official definitions (although some community colleges may fit closer). In contrast, a number of the European countries such as Belgium, Finland, and the Netherlands have most of their vocational students in school-based programs. Finally, Germany, Denmark, and Switzerland stand out by having large combined school and work-based vocational programs that emphasize apprenticeships.

We thus classify countries into different categories based on both information from the IALS sample and the statistics from OECD's *Education at a* Glance (EAG).[18] We define "*vocational*" countries as those countries whose vocational share is at least 40 percent in IALS data and is at least 50 percent in 1996 EAG or 2007 EAG. Eleven countries belong to this category: Belgium, Czech Republic, Denmark, Finland, Germany, Hungary, the Netherlands, Norway, Poland, Switzerland, and Slovenia. Of these eleven vocational countries, six (Czech Republic, Denmark, Germany, Hungary, Poland, and Switzerland) have a vocational sector with at least 25 percent in combined school and work-based programs. We dub these six countries as "*non-school based*" vocational countries.

Additionally, in a finer look at the mix of school and work programs, we classify Denmark, Germany, and Switzerland as "*apprenticeship*" countries, signifying that the share in combined school and work-based programs exceeded 40 percent in both 1996 and 2007. Earlier

[18] See Organisation for Economic Co-operation and Development (2010)). Each year, EAG provides administrative information on the distribution of upper-secondary-school students between general and vocational programs. Furthermore, it provides the percentage of students in the vocational program that are in "combined school and work-based" programs. In these latter programs, instruction is shared between school and the workplace and may even take place primarily in the workplace. A good example of the latter is the "dual system" in Germany where at least 25 percent of the instruction takes place in the work place. For descriptive details, see Hanushek, Woessmann, and Zhang (2011).

literature suggests that the apprenticeship vocational programs are the most effective in facilitating youths' school-to-work transition (see, for example, Lerman (2009) and the larger review in Wolter and Ryan (2011)). Therefore, the lifetime employment experience of individuals completing general or vocation education in these countries is particularly interesting from a policy perspective. Four countries – Chile, Italy, New Zealand, and the U.S. – are "*non-vocational*" countries based on these criteria.[19]

We generally interpret the aggregate institutional differences, moving from non-vocational to apprenticeship countries, as treatment intensity. The apprenticeship programs with their substantial industry-based education receive more vocational experience and necessarily less general education. Countries choose the portfolio of specific vocational offerings, possibly based on projections of where future skill demand will lie. While the specifics of the portfolio may change over time, the broad pattern of the mix of general and occupation-specific skills does not.

The top panel of Figure 1 reproduces the age-employment profiles of Figure A2 in the appendix for the groups of eleven vocational countries and three apprenticeship countries. The descriptive pattern that a relative labor-market advantage of vocational education decreases with age is clearly visible in the vocational countries and is more pronounced in the apprenticeship countries. Given that the definition of general vs. vocational education types is clearest for these groups of countries, most of our subsequent analysis will focus on them.[20]

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[19] Although Italy has a significant share in vocational programs from EAG, in the IALS data the share is very small, at 15.7 percent. Our classification does not apply to Great Britain, Ireland, and Sweden, because information about education programs for individuals completing secondary school for these countries is missing in the IALS.

[20] As an indication of the vagueness of the definition of education types in non-vocational countries, the National Center for Education Statistics (1996) classifies only 8 percent of secondary degrees in the U.S. as vocational (IALS: 20 percent), 32 percent as college preparatory (IALS: 18 percent academic/college preparatory), and 60 percent as other (IALS: 62 percent). Thus, some of the NCES "other" category seem to be classified as vocational in IALS and some of the NCES college preparatory category seem to be classified as other in IALS.

III. Identification of the Impact of Education Type

We are interested in the impact of education types on labor-market outcomes over the life-cycle. To test our main hypothesis that the relative labor-market advantage of vocational over general education decreases with age, we compare the age-employment patterns of workers of the two education types within each country. In the simplest difference-in-differences form, we permit the age pattern of employment for those with a general education to diverge linearly from the pattern for the remainder of workers:

$$(1) \qquad emp_i = \alpha_0 + \alpha_1 age_i + \alpha_2 age_i^2 + \beta_1 \cdot gen_i + \beta_2 \cdot gen_i \cdot age_i + X_i \cdot \gamma + \varepsilon_i$$

In Equation (1), emp_i = 1 if individual i is currently employed and 0 otherwise; age and age squared capture the normal age-employment pattern in the economy; gen_i is an indicator equaling 1 if individual i has a general education type and 0 otherwise;[21] and X is a vector of control variables for other factors that might affect employment patterns including, importantly, country fixed effects to eliminate overall country differences and various measures of individual labor-market skills (other than education type). The coefficient β_1 measures the initial employment probability of those with general education relative to those with vocational education (normalized to age 16 in the empirical application), while β_2 measures the differential impact of a general relative to a vocational education on employment with each year of age.

The simple linear-in-age functional form of the interaction in our basic specification follows the descriptive pattern observed in the bottom panel of Figure 1, which suggests a rather continuous impact of education type on employment by age at least starting at age 30. In our IALS analyses, we do look at nonlinearities, but the analysis does not have much power to detect

[21] This stripped-down presentation considers schooling type as dichotomous. The sample for the empirical analysis includes those who reported completing secondary-school equivalency or other programs. In the estimation, they are treated as a separate category (“other” type), and its interaction with age is also included.

them. [22] The Microcensus analysis reported in Section V below, which has considerably more power to detect nonlinear differences, provides additional evidence supporting the basic linear specification.

The overall difference in employment probabilities between general education and vocational education reflected in β_1 does not adequately identify the impact of general education. This parameter implicitly includes any elements of selectivity in the completion of different types of schooling not captured in X, and we doubt that the measured influences on employment found in our data (and most other surveys) fully capture the systematic differences across schooling groups. (Note that this is precisely the challenge for attempts to estimate the impact of vocational education on the school-to-work transition, and highlights the existing uncertainty about the efficacy of common vocational education policies).

The key parameter for our analysis, however, is β_2. In this difference-in-differences formulation, this reflects the divergence in employment patterns by education type over age cohorts. The crucial assumption for identifying the causal impact of education type on changes in employment patterns over the life-cycle is that the selectivity of people into general and vocational education (conditional on the X) does not vary over time. In other words, we assume that today's old people (in each education category) are a good proxy for today's young people in 30 years,[23] allowing us to estimate the impact of education type by the divergence in age-employment patterns across the life-cycle.

[22] An interaction term between the general-education indicator and age squared is not statistical significant in our main specification; additionally, several spline estimates that allow the interaction effect to differ at different age ranges never produced estimates that differed statistically significantly from one another. In robustness analyses below, we report results of a model that allows the impact of general education on employment to differ for each age cohort defined by ten-year age intervals.

[23] This assumption of comparability of age cohorts is of course identical to the normal assumption in estimating Mincer earnings functions and other applications that make cohort comparisons with cross-sectional data; see the specific earnings analysis in Hanushek and Zhang (2009). Heckman, Lochner, and Todd (2006) directly compare

If general education becomes less selective relative to vocational education over time in ways that are not captured by the X, then the changes in the labor market may reflect simply the varying ability of young and old workers in the different education categories (e.g., Caucutt and Kumar (2003)). Descriptive inspection shows that there was no systematic or significant overall change in the differences in parental education and occupation between individuals with different types of education over age cohorts. There was, however, some decline in the difference in literacy scores of individuals with general and vocational education from older to younger ages (see Hanushek, Woessmann, and Zhang (2011)). But, in the estimation we explicitly condition on individual school attainment and literacy scores along with a series of alternative proxies for selectivity of education within each country.[24] In particular, we provide standardization across the age groups by conditioning on country-specific changes in the size and ability composition of the different education types over cohorts. We also employ propensity-score matching estimators that match each individual with vocational education to an observationally comparable individual with general education, and we consider the potential role of selection on unobservables.

IV. The Impact of Education Type on Employment

Our investigation begins with basic estimates of how employment patterns over the life-cycle are affected by general and vocational education in the group of eleven "vocational

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synthetic cohort information (using a single cross-section) with repeated cross-section analyses and find that the synthetic cohort analysis of Mincer earnings models provides inaccurate estimates of ex post rates of return to schooling.

[24] The choice of level of attainment is typically made simultaneously with type of education. There is the possibility that, as argued in the U.S., an advantage of vocational training is getting some students who are not motivated by more abstract academic material to complete secondary school by altering their motivation. If generally true, conditioning on school attainment would lead to understating the impact of vocational education. This does not appear to be the motivation of vocational education in the vocational countries.

countries." We then pursue a series of alternative specifications, samples, and robustness checks.

A. Basic Results

Table 2 reports OLS regression results of equation (1) for males, in which the impact of education type on employment status changes linearly with each year of age.[25] The sample pools individuals from all eleven vocational countries in IALS, but all specifications control for country fixed effects so that the employment impacts are estimated by just the within-country variation. Column 1 is the most basic specification, where employment status is a function of age, age squared, years of schooling, as well as whether one's highest level of education is general education and its interaction with age. *Ceteris paribus*, employment rates generally increase with age, reach the peak at age 36, and then start to decline, consistent with the description in Figure 1. They also increase with years of schooling: one more year of schooling increases the employment rate by 1.2 percentage points.

Most important to our purpose, while individuals with a general education are initially (normalized to an age of 16 years) 6.9 percentage points less likely to be employed than those with a vocational education, the gap in employment rates narrows by 2.1 percentage points every ten years. This implies that by age 49, on average, individuals completing a general education are more likely to be employed than individuals completing a vocational education. Individuals completing a secondary-school equivalency or other program (the "other" category) have a virtually identical employment trajectory as those completing a vocational education.

As noted in the previous section, the coefficient on the general education-age interaction (β_2) can be interpreted as the causal impact of general education on the employment change over

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[25] Estimates from a probit model of employment are substantively the same.

the life-cycle as long as any selectivity into education type has not changed over time. In the subsequent columns, we employ varying strategies to account for potential biases from unmeasured ability or other possible influences on employment (that might vary over time for people in the different education-type categories).

B. Addressing Time-Varying Selectivity into Education Types

A prime concern is that the ability level of individuals completing a general education may have changed over time with the expansion of education systems around the world, implying that the coefficient on education type and its interaction with age would also capture the impact of unmeasured ability on employment at different ages. For example, more able people may adapt more readily to a changed environment regardless of schooling, making them more likely to be employed at older age. Because of the centrality of possible selection effects to our estimation, we pursue a range of formal and informal tests for age-varying selection into education types.

We begin by adding the literacy score and its interaction with age (Column 2 of Table 2). The coefficient on the literacy score is already positive at the age of 16, and the coefficient on its interaction with age is also significantly positive – implying that more able workers continue their employment at higher rates with age. The time pattern of literacy skills on employment underscores exactly the concern with identification of the impact of education types (and shows the importance of the IALS data). Note, however, that the age pattern of employment by type of education is identified entirely by the portion of the general education system that is orthogonal to realized skills.[26] The coefficient on the interaction of general education type with age

[26] The fact that the IALS literacy score is measured at the time of labor-market observation, rather than when the initial decision between entering a general or vocational program is made, suggests that the measured score may be affected by both the schooling and the employment history, which includes both occupation-specific skill obsolescence and continuing adult education. Existing evidence (Ludwig and Pfeiffer (2006)) and our analysis

becomes slightly smaller in magnitude – precisely what would be expected with the expansion of general education and the relatively lower ability of the average young person in general education. But, importantly, both the general-education indicator and its interaction with age remain statistically significant.[27] In this specification, individuals with general education overtake those with vocational education in employment probability at age 54.

In Column 3, in another expansion to allow for time-changing patterns of ability by school type, we add dummy variables for mother's education and their interactions with age. The coefficient estimates on these controls are insignificant in themselves, and they have little impact on the estimates of other variables relative to Column 2. As a result, we do not control for mother's education in later specifications. In Column 4, because parents may directly influence the educational choices of children, we add a dummy variable for father's occupation, taking a value of 1 for professional, and its interaction with age. However, due to missing information, our sample now only includes four countries (Czech Republic, Finland, Hungary, and Poland). Estimates on these added controls are insignificant, and again, the estimates on the main variables of interest – general education type and its interaction with age – are qualitatively the same as in Columns 1-3.

In Column 5, we return to the full sample and add three control variables at a more aggregate level: the percentages completing general and vocational education, respectively, in each country for each ten-year age cohort, and the average literacy test score for individuals completing a particular type of education by country and ten-year age cohort. These variables

below suggests that both aspects work against people with vocational education, which introduces bias against our reported findings and suggests that these may be lower-bound estimates.

[27] In a specification that interacts the main effects with individuals' literacy scores, estimates on these interactive terms are small in magnitude and statistically insignificant, indicating that the overall pattern that is general across ability levels.

reflect variations in labor skills that change over time and that might distort the selectivity of education choices over time. The aggregate composition of the labor force may also affect the market returns to training and skills. A higher average test score indicates higher overall ability of individuals completing a particular type of education; a larger share of individuals completing a particular type of education indicates lower selectivity of that education type. The estimates in Column 5 appear to confirm that, *ceteris paribus*, the employment probability is positively related to the average test score. Nonetheless, estimates for the key interaction of general education with age (and other variables) are again almost identical to those in Column 2. In subsequent estimations, we take Column 5 as our primary specification.

The relative stability of our main effect of interest to the inclusion of the different control variables is reassuring. However, rather than only relying on the common heuristic of looking at the stability of results to adding controls, we can additionally employ the more formal approach of Oster (2014)'s expansion of the idea suggested by Altonji, Elder, and Taber (2005) of using coefficient stability as a test for selection on unobservables. Our treatment effect varies with age, requiring some adaptation in order to fit our analysis to a homogenous-treatment-effect setup. As shown in Table A1 in the appendix, we do this by focusing separately on the direct effect of general education at early ages (where vocational education is dominant) and at late ages (where general education is dominant). The test assesses both the stability of the estimated general education treatment effect with the addition of key observable factors and the importance of these observables in explaining employment rates.[28] In line with our main specification, general-type education is associated with lower employment for younger workers but with higher

[28] In our context, the further controls are literacy and an indicator for the mother having at least high-school education. Father's occupation is only available for four (non-apprenticeship) countries, and the additional cohort-specific controls in column 5 of Table 2 are effectively contained in this cohort-specific analysis.

employment for older workers.[29] In the case of older workers, the estimate of the coefficient of proportionality (suggested by Oster (2014) as a summary of the robustness of results) implies that unobservables would have to be substantially more important than observables in explaining the treatment effect in order for the actual treatment effect to be zero. In the case of younger workers, adding the controls even moves the estimated treatment effect further away from zero in absolute terms. Thus, while not entirely conclusive in this modified testing, this exercise does not suggest that selection on unobservables is the main driver of our results for either young or old individuals.

Finally, a straightforward way to assess the degree to which there is varying selection into education types by cohort is to investigate directly the correlates of education type. Table A2 in the appendix indicates that individuals with higher literacy scores and more favorable family backgrounds (as measured by mother's education) are indeed more likely to select into general types of education. Importantly, however, this selection does not significantly vary with age. Thus, to the extent that this pattern is informative for the variation in selection on unobservables across cohorts, there is little indication that cohort-specific selection into education types is a major concern for our analysis.

C. Excluding the Youngest Cohorts from the Sample

An additional concern is the potential impact of missing students who are still in school. Column 6 therefore reports results of another robustness check, where we restrict the sample to individuals aged 20 to 65. The concern is that many of the very young people are still in school, and this may vary with type of education. Hence, when we exclude current students from the

[29] This result indicates that despite the fact that the turning point by which employment of those with a general education overtakes those with a vocational education is only around age 50, there is a considerable age range (56-65 in this case) over which the probability of employment of those with a general education exceeds those with a vocational education by a statistically significant amount. For the sample of three apprenticeship countries, this is in fact true for much wider age ranges, including the 25-year range of those aged 41-65.

analysis, the young people included in the analysis may not be representative of the youth who eventually finish school and start the school-to-work transition. With the youngest of all individuals dropped, the young people remaining in the sample will more closely represent the overall youth population. Indeed, of the males aged 16 to 19, two thirds are still in education, while of those aged 20 to 25, only one quarter are currently in education.[30] These shares of current students in different age groups also suggest that we do not want to drop all the 16- to 25-year-old group; otherwise, we lose too many young people who are already potentially in the labor force, and we will not be able to obtain the estimate of the relative impact of different education types on the school-to-work transition. The choice of age cutoff in this column is a compromise between these two competing forces related to the youngest people. Regardless, results from the restricted sample are quite similar to the results in Column 5 for the corresponding specification with a larger age range.

Column 7 goes even further and restricts the sample to individuals aged 30 to 65. In this specification, the change in the effect of education type with age is not affected by the school-to-work transition but just identified from subsequent employment changes. In addition, the bottom panel of Figure 1 suggests that the effect may be expected to be well represented by a linear-in-age specification. Results are again very similar to the base specification, indicating that they are not just driven by changes over the age range of young people. The robustness of the results prompts us to focus on the entire 16-to-65 age group in virtually all later analysis.

D. Effects by Treatment Intensity

Table 3 estimates our preferred specification (Column 5 in Table 2) for different country groupings, representing varying treatment intensities. In the full set of 18 countries available in

[30] Of the males aged 26 to 30, about 3 percent are currently students.

IALS (Column 1), we observe the same significant pattern with slightly reduced point estimates. However, Column 2 reveals that the pattern does not hold at all for the non-vocational countries: The estimates are insignificant, and there is virtually no difference in employment patterns between individuals completing different education programs.[31] This is in clear contrast to the group of eleven vocational countries (Column 3, reproduced from Column 5 in Table 2).[32]

Moving from Columns 3 to 5, the samples of countries have increasingly larger shares of vocational education in the form of combined school and work-based programs, which also makes the definition of the vocational education type clearer and more consistent. Tracing through these groups, the initial employment gap between individuals finishing vocational and general education becomes larger, while the rate at which this gap narrows with age also becomes higher.

The age-employment pattern is most pronounced in the group of apprenticeship countries which have large shares of vocational education in the form of combined school and work-based programs (Denmark, Germany, and Switzerland). In each of the three apprenticeship countries, the general education-age interaction is significantly positive (Columns 6 to 8): The employment gains from vocational education early in the life-cycle are balanced by later employment losses.[33,34]

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[31] This pattern may also reflect the fact that in countries like the United States with few vocational programs, students may not know what specific course counts as general or vocational (Rosenbaum (1980)), introducing measurement error in the "non-vocational" countries. By contrast, there seems to be little confusion across the vocational countries about the specific track, particularly because it generally represents separate schools.

[32] To ensure that no particular country drives the pooled results in Table 2, we also re-estimated the aggregate vocational-country model dropping one country at a time. The main results remain in each of the restricted samples.

[33] This is despite the fact that there is mobility across occupations among German apprenticeship graduates (Fitzenberger and Kunze (2005)) and that there is considerable transferability of skills across occupations when applying a task-based approach (Gathmann and Schönberg (2010)).

[34] Table A3 in the appendix reports estimation results separately for all eleven vocational countries.

In sum, the disaggregation of the IALS sample by intensity of vocational education shows clear heterogeneity of employment effects. Specifically, countries at the more vocational end of the spectrum see stronger interactions of the age-employment pattern with vocational training.[35,36]

E. Propensity-Score Matching

Figure A1 in the appendix shows a substantial overlap in literacy test scores between individuals completing general and vocational education in all countries, even though there are average skill differences across the groups in most countries. Indeed, this substantial overlap is also found for age, years of schooling, and family background between individuals completing different types of education. As a further approach to limit possible concerns of selection bias, we can estimate our main model using propensity-score matching to ensure that the sample of individuals with a vocational education is directly comparable to that for general education. While this procedure cannot address selection on unobservables, it can guard against having the results be driven by outliers in the education decisions.

Matching allows us to compare observationally similar individuals, providing greater confidence in our ability to isolate the impact of the education type itself. The sample is selected by comparing, for each country, the propensity scores of completing a vocational education between those individuals who actually completed a vocational education and those individuals who completed a general education. Individuals in the latter group whose propensity scores are closest to those in the former group are included in the sample, along with all individuals in the

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[35] The same result is obtained in a pooled specification that interacts the main effects with countries' shares of generally-educated individuals.

[36] We report robust standard errors throughout. All results that are statistically significant in the different country groups of Table 3 also reach statistical significance at conventional levels when standard errors are clustered at the level of the identifying variation, i.e., at the education type-by-age-by-country level.

former group who share a common support in propensity score with the latter group.[37] Specifically, in a first stage we estimate a probit model for each country of vocational education type on age, years of schooling, literacy test scores, and whether mother or father completed a high-school education. With the predicted propensity score, we use the nearest-neighbor matching algorithm to match each individual completing a vocational education to one completing general education. Post-matching tests lend credibility to the matching procedure.[38] In the matched sample, the disparity between the two groups has been reduced in the majority of countries such that individuals completing the two types of education are statistically identical in each of the matching variables and the matching variables jointly have no predictive power for the probability of completing a vocational education.

The first two columns of Table 4 report the results of the matching estimator for the groups of vocational and apprenticeship countries, respectively. The matched sample is reduced by 20 to 23 percent in the two samples. Still, results on the matched sample are very close to the previous results, indicating that the latter are unlikely to be driven by nonlinearities in the selection on observables into different education types.

While the reported estimation already imposes a common support by dropping vocational-education individuals whose propensity score is above the maximum or below the minimum propensity score of the general-education individuals, our results are confirmed in additional analyses (not shown) that further improve the common support by trimming 1 (or even 10) percent of the vocational-education observations for whom the propensity-score density of the general-education observations is the lowest or by imposing a tolerance level (caliper) of 5 (or even 0.5) percent on the maximum propensity score distance between vocational-education

[37] In the matched sample, the group with "other" types of education drops out.

[38] Detailed results are available from the authors upon request.

and general-education individuals. Furthermore, results using alternative matching algorithms such as radius or kernel matching (not shown) also yield qualitatively similar results.

F. Additional Robustness Specifications

Tertiary vocational education is likely more heterogeneous in terms of the mix of general skills obtained. To ensure that tertiary education is not driving the results, Columns 3 and 4 of Table 4 report results that restrict the sample to individuals completing just secondary education. We lose about one quarter of the sample who had tertiary schooling. The results again are quite similar to those in Table 3.

While there is a general presumption that the vast majority of males not employed – including those entering early retirement – in the later age groups do so involuntarily, it is possible that generous early-retirement schemes may be differentially available to workers with vocational and general education. In this case, the detected age-employment pattern may not necessarily be driven by differential adaptability to changing economic conditions, but rather by specifics of the existing retirement policies. As another robustness test to address this possibility, Columns 5 and 6 restrict the sample to those employed and those unemployed but looking for work, effectively dropping those from the not employed category who are retired, homemakers, or not employed for other reasons.[39] Results confirm the differential age-employment pattern by education type, showing that people with vocational education who

[39] We view this specification as a particularly low lower bound, as it selectively drops a large part of those who leave the labor market at older ages. For example, in the case of Germany it is much documented that older people who have a significant spell of unemployment simply change over into the status of early retirement (e.g., Brussig 2007; Fitzenberger and Wilke 2010). In fact, as soon as they are eligible for other benefits such as early retirement benefits, they lose entitlement to unemployment benefits and have to terminate their unemployment status. And there is an explicit entitlement for early retirement at age 60 (postponed to age 63 recently) after having been in unemployment for 12 months. Our pattern of results also holds when restricting our analysis of the German Microcensus (see below) to only the unemployed among the nonemployed, although again with substantially lower effect sizes. There, we can show that much of the reduction comes from ignoring those who went into early retirement from unemployment.

would like to work are increasingly becoming more unemployed with age relative to people with general education (the interaction term in Column 5 is significant at the 13 percent level). This pattern of involuntary unemployment indicates that the main finding is not just driven by voluntary early retirement.[40]

Alternatively, since many in vocational education start careers at a younger age (because they have less average school attainment), the age pattern could simply reflect a tendency to retire after a fixed number of years in the labor market. But, estimation of employment models (not shown) based on potential experience – time since completion of schooling – and its interaction with type of education yields the same qualitative pattern.

Finally, we consider a more flexible, nonlinear model that allows the impact of education type on employment status to vary for different ten-year age cohorts (Table A4 in the appendix). Both the vocational and the apprenticeship country groups show the age-employment pattern in a nonlinear way. The pattern is most striking in the three apprenticeship countries, with the 56-65 age group completing a general education having the largest employment advantage over those completing a vocational education. Results are largely similar in a slightly different nonlinear model which restricts the sample to 20-65-year olds and defines the young as 20-30, the middle aged as 31-50, and the old as 51-65 (see Hanushek, Woessmann, and Zhang (2011)).

V. Evidence from the German Microcensus 2006

There are two important topics that could not be addressed with the IALS data. First, because some institutional contexts like early retirement legislation or economic productivity regimes have changed since the IALS surveys in the mid-1990s, does a similar pattern of

[40] In this regard, it might be indicative to look at the age-employment pattern for blue-collar and white-collar workers separately. Unfortunately, though, in the IALS data occupational information is available only for the employed and not for those not working at the time of the survey.

declining relative employment of vocational education with age still exist today? Second, because exit out of employment at later ages will be partly related to health, is the vocational education effect driven by the greater likelihood that vocationally trained workers are found in brawn-intensive occupations where health-related concerns are more important?[41]

Both topics can be addressed with the Microcensus dataset in Germany, one of the apprenticeship countries. The Microcensus is a one percent sample of German households, 70 percent of which are contained in the scientific use file. We focus on the 2006 wave as the latest wave available before the financial crisis of 2008 in order to ensure that the results are not driven by peculiarities of the recession. However, as reported below, results are very similar for the latest available wave in 2012. When applying the sample restrictions used in the IALS analysis – males aged 16 to 65 who completed at least secondary education and are not currently in education – the Microcensus 2006 provides 118,604 observations. These observations give us considerably more precision in our estimates than in the smaller samples of the IALS analysis.

Importantly, the Microcensus records not only the occupation of those currently employed but also the last occupation of those not currently employed. Using the standard German occupational classification (*Klassifikation der Berufe 1992*), we can subdivide occupations either into 10 one-digit occupation groups or 88 two-digit occupation groups. This allows us, first, to include fixed effects for occupation groups so that only within-group variation is used for identification and, second, to exclude occupation groups that are brawn-intensive and thus particularly prone to health problems at later ages.

These advantages of the Microcensus are potentially offset by the fact that it does not have direct measures of ability such as the literacy test that was included in our main IALS

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[41]Again, an analysis of this latter issue is not possible with the IALS data because IALS does not survey occupational information for those not currently employed.

analyses to address potential issues of selectivity into vocational education. However, based on the IALS estimation, we are not overly concerned about this missing information. In Germany, there has been no aggregate trend across age groups in literacy scores (see Hanushek, Woessmann, and Zhang (2011)), and including the literacy controls does not significantly alter the estimate of the interaction between education type and age in the German IALS sample: a coefficient estimate of 0.064 (standard error 0.027) without literacy controls compared to 0.055 (0.028) with literacy controls (see Table 3).[42]

We limit our analysis to persons who have successfully finished an upper-secondary or tertiary degree. At the upper-secondary level, we classify apprenticeship degrees as vocational and baccalaureate degrees (higher education entrance qualification) as general. At the tertiary level, we classify certified-engineer and masters degrees as well as degrees from polytechnics as vocational and university degrees as general.[43]

As is evident from the first column of Table 5, in a specification mirroring the first column of Table 2, there is the same pattern in the German data for 2006: People with a general education are initially less likely to be employed, but this turns around with increasing age. The next two columns show that this pattern is evident both within the secondary level and within the tertiary level of education, with slightly more pronounced estimates at the secondary level.

Table A5 in the appendix reports equivalent results for the 2012 wave of the German Microcensus. While the overall pattern has hardly changed, the age pattern has become even more pronounced at the secondary level and somewhat weaker at the tertiary level. It seems that

[42] A cross-equation test indicates that the two estimates are not significantly different ($p = 0.29$).

[43] Note that there is some movement between vocational and general programs, and we use final program status. Results are qualitatively similar when classifying degrees from polytechnics as general rather than vocational.

at the secondary level, a general type education has proven even more valuable in adjusting to the changes brought about by the financial crisis.

While the IALS estimates may have lacked statistical power to find significant nonlinear age interactions, the large Microcensus sample allows for more accurate testing for nonlinearities. When adding an interaction of general education type with age squared in Column 4 of Table 5, the estimate on the quadratic interaction is statistically insignificant, quantitatively very small, and positive. The graphical depiction of this nonlinear specification by the dark line in Figure 2 indicates that the quadratic interaction is not only statistically, but also quantitatively insignificant. This validates the specification of an interaction that is linear in age, as adopted throughout this paper.

Including fixed effects for 10 one-digit occupational groups in Column 5 reduces the point estimates slightly, but leaves the overall pattern perfectly intact. This also holds when fixed effects for all 88 two-digit occupational groups are included in Column 6.[44]

To classify occupations as brawn-intensive, we use information from the German Employment Survey 2005/06, a survey conducted by the Federal Institute for Vocational Education and Training (BIBB) and the Federal Institute for Occupational Safety and Health (BAuA) where employees respond how often they perform certain tasks (see, e.g., DiNardo and Pischke (1997); Spitz-Oener (2006); Gathmann and Schönberg (2010)). Using responses from 15,871 males in 357 three-digit occupations, we classify occupations as brawn-intensive if 50 percent of respondents of the occupation report that they “often” “lift and carry loads weighing

[44] Obviously, some occupations are heavily weighted towards one type of education. To check that results are not driven by this skewness, we dropped all occupations where one education type made up less than 5 percent. This leaves qualitative results unaffected, only slightly lowering the point estimate on the general education-age interaction to 0.043 (std. err. 0.003).

more than 20 kg" or "often" "stand while working."[45] As seen in Columns 7 and 8, dropping the 7 percent of the sample who have occupations where a majority of workers often carry heavy loads[46] and even dropping more than half of the sample who have occupations where a majority of workers often stands hardly affects the results and if anything makes them stronger.

Interestingly, the magnitude of the estimate of the interaction is quite close to the IALS estimate for Germany in Column 7 of Table 3. For example, the estimates in the final column suggest that individuals with a general education are initially 13.6 percentage points less likely to be employed, but this turns around at age 43, and by the age of 65 individuals with a general education are 11.5 percentage points more likely to be employed.

Overall, the results from the German Microcensus indicate that the age-employment pattern by type of education is evident in more recent years and is robust to using just variation within occupational groups and to excluding brawn-intensive industries from the analysis.

VI. Evidence from Austrian Plant Closures

The prior analyses focus on life-cycle comparisons of workers with different kinds of education. A significant remaining concern with them is that the workers with vocational education simply prefer to retire earlier for some unmeasured reason that is not a reflection of their depreciated skills. To address this possibility, we introduce additional evidence about the impact of education and training on employment for older workers that comes from Austrian data on plant closures.

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[45] While building on similar parameters of standing and carrying as used by the U.S. Dictionary of Occupational Titles (DOT) to estimate the overall strength requirement of an occupation in its Physical Demands Strength Rating, the German Employment Survey classification does not have to rely on expert ratings but rather uses direct responses from workers on the kind of activities they perform on the job (see Spitz-Oener (2006)).

[46] Results are very similar when using alternative cut-offs such as occupations where more than a quarter of workers often carry heavy loads (32 percent) or occupations where more than a half the workers often or sometimes carry heavy loads (28 percent).

The idea behind the analysis in this section is straightforward. If the closure of a plant is exogenous to workers' employment plans and prospects, we can compare the employment rates of those suffering a plant closure to matched people not suffering a closure to obtain an estimate of the labor demand for these skills.[47] Our central hypothesis is that later in the work life-cycle, the relative demand for vocationally trained workers falls when compared to the relative demand for those with general education, leading the vocationally trained displaced workers to have lower re-employment rates after the plant closure.

We can test this hypothesis with matched employer-employee data from administrative employment records in the Austrian Social Security Database (ASSD). Austria, while not included in the IALS database, is particularly appropriate for this analysis because it operates an apprenticeship system that is very similar to that in Germany and Switzerland. The longitudinal data from Austria allow us to identify workers who lose their jobs due to plant closures and to compare subsequent employment patterns to similar workers who did not lose their jobs as a result of a plant closure. These data have been used previously to study the overall impacts of displacement on careers but have not directly addressed relative age patterns and particularly the later life outcomes by training (e.g., Ichino et al. (2007); Schwerdt (2011)).

These administrative data are not perfect because they lack information on educational attainment. However, all employees in Austria are obliged by the General Social Security Act (ASVG) to register to a mandatory social insurance, which classifies workers as either blue-collar or white-collar workers.[48] We then interpret occupational status as a noisy proxy for the

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[47] Other studies using job separations due to mass layoffs or plant closures in administrative data to identify involuntary job losses include Jacobson, LaLonde, and Sullivan (1993) and von Wachter and Bender (2006).

[48] White-collar and blue-collar workers are defined according to administrative rules: white-collar workers comprise all clerical workers and higher non-clerical occupations, including salespersons (excluding waiters and salespersons in bakeries, etc.); blue-collar workers are typically manual workers.

type of education, because the two measures are highly correlated. Based on independent survey data from the Austrian Microcensus, a simple cross-tabulation reveals that at least 13.4 percent of workers classified as white-collar workers obtained a general education, whereas virtually no blue-collar workers did.[49]

The data for our analysis include all private-sector workers in Austria employed between 1982 and 1988 at risk of a plant closure. We observe male workers' employment histories by quarter in the four years prior to potential displacement and up to ten years afterwards. Workers included in the sample are between 35 and 55 years old at the time of potential displacement and were employed in firms with more than 5 employees at least in one quarter during the period 1982-1988.[50] We further restrict the sample to workers with at least one year of tenure with a firm because legal probation periods might make layoff easier for low-tenure workers. We identify plant closures by the disappearance of an establishment identifier in the ASSD without having more than 50 percent of the employees continue under a new employer identifier (which could indicate a merger or plant relocation).

To increase comparability between displaced and non-displaced workers, we develop a matched analytical sample. Our matching is exact between treated and control subjects on the following criteria: sex, age, location of firm (9 provinces), industry (30 industries), and

[49] The fact that there is so little clearly general education in Austria implies that any results based on the white-collar vs. blue-collar approximation should underestimate the actual impact. The breakdown provided is based on classifying only the obviously general-type Allgemeinbildende Höhere Schule (AHS) and university graduates as general education. It is less clear how to classify Berufsbildende Mittlere Schule (BMS) and Berufsbildende Höhere Schule (BHS), as both types of schools are explicitly meant to convey both general and vocational content. When classifying the latter two also as general (as opposed to the clearly vocational apprenticeship degrees), then 46.0 percent of white-collar workers obtained a general education, whereas only 4.9 percent of blue-collar workers did.

[50] We exclude the tourism and construction industries because they have high seasonal unemployment and because they often close down out-of-season only to reopen several months later with the same workers. We stop at age 55 so that we can observe differences in employment patterns for the ten-year period after any displacement but ending at normal retirement age.

employment history in the eight quarters before plant closure.[51] We match by categories on continuous variables: average daily wages in the quarters 8, 9, 10, and 11 before plant closure are matched by decile, and plant size two years before potential plant closure is matched by quartile. Applying this matching procedure allows us to identify at least one control subject for 3,417 displaced workers, who are matched to 21,504 non-displaced workers.[52]

Our analysis follows a generalized difference-in-differences procedure where we are interested in how firm closures alter the relative employment patterns of blue-collar and white-collar workers. We first collapse the raw data into cells defined by quarter of calendar time for the 1982-1988 sample period, by quarter for the four years before potential closure and ten years after, by age at potential closure, and by occupational status (blue- or white-collar). Within each cell, we calculate the relative employment rate for those displaced through plant closure and those in the control group that is not displaced.

To investigate the age pattern of employment effects, we divide our workers into four age categories (35-39, 40-44, 45-49, and 50-55) and then separately estimate our basic difference-in-differences model:

$$RelEmp_{ct} = \alpha + \beta_1 Blue_{ct} + \beta_2 After_{ct} + \beta_3 \left(Blue_{ct} \times After_{ct} \right) + \varepsilon_{ct} \tag{2}$$

where $RelEmp_{ct}$ is the average employment of displaced workers relative to average employment of non-displaced workers in calendar quarter t and quarter relative to closure c; $Blue_{ct} = 1$ for blue-collar workers and 0 for white-collar workers; $After_{ct} = 1$ for all quarters after the plant

[51] The sample selection and matching strategy closely follows Schwerdt et al. (2010) except that we expand their sample to include workers between 51 and 55 years of age at the time of potential displacement.

[52] Descriptive statistics and evidence on the quality of the matching procedure are available from the authors upon request.

closure and 0 for quarters up to closure; and ε_{ct} is a stochastic error.[53] If the treatment and control workers are well-matched, we expect that $\alpha = 1$ (i.e., equal employment rates before closure) and $\beta_1 = 0$ (i.e., match holds for both blue- and white-collar workers).[54]

The parameter of interest is β_3, which indicates how post-closure relative employment rates for blue-collar workers behave relative to those for white-collar workers. By our hypothesis, β_3 should fall at least for the oldest group – indicating that those with vocational training are less demanded and that their finding a job is relatively more difficult after the exogenous layoff that follows the plant closure.

Table 6 displays the results of our estimation by age group. The estimated constant terms, which are not significantly different from one at the 10 percent level, indicate that prior to potential displacement employment rates of displaced and non-displaced white-collar workers are almost identical. The same is true for blue-collar workers as indicated by the estimated coefficients on the blue-collar dummy, which are all insignificantly different from zero. After plant closure, employment losses of white-collar workers amount to roughly 20 percent for workers below age 50 and 26 percent for workers above age 50.

Looking at the interaction term in the first row, for blue-collar workers – our proxy for vocational education – we find that the relative employment rates after closure are above those of white-collar workers below age 50. However, for workers above age 50, the significant and

[53] We focus on the average employment rates in the ten years following a plant closure, but using just five years yields very similar results. The employment patterns flatten out over the ten-year period.

[54] An alternative model would estimate the absolute impact on employment probabilities for individual workers instead of the relative loss to the group still employed at each age. Such an analysis could be done either with cell aggregates or the individual level employment data (in a triple difference-in-differences form). In such a model, we find the same declining employment with age as in Table 6, but the absolute employment probabilities are equal for blue- and white-collar workers in the 50-55 age group (see Table A6 in the appendix).

negative estimate on the interaction term now indicates that blue-collar workers indeed suffer more from a reduction in relative employment probabilities due to displacement.[55]

The pattern up to age 50 is exactly consistent with the detailed analysis of Austrian plant closures on employment. While possibly somewhat at odds with U.S. experience (Podgursky and Swaim (1987)), blue-collar workers at younger ages have shown an employment resiliency in Austria – perhaps reflecting less firm-specific rents (Lazear (1979)) or lower reservation wages. But the impact on older blue-collar workers had not been previously analyzed, and the pattern in the over-50 age group is entirely consistent with our hypothesis about depreciated skills and less adaptability for those with vocational training.

Our necessary sample restriction to just employed workers with at least one year of tenure (caused by labor laws) is likely to bias our results towards finding smaller reductions in employment probabilities induced by plant closure among blue-collar workers. First, it restricts the analysis to workers with reasonably stable employment histories. As a consequence, re-employment of blue-collar workers estimated in our sample is probably more positive than would be the case for the whole population because those with unstable employment histories are likely to be overrepresented among blue-collar workers. Second, given that employment probabilities of older blue-collar workers are lower than those of white-collar workers, the blue-collar workers in our sample are likely more positively selected based on unobserved favorable characteristics. Both make our findings all the more remarkable.

The advantage of this analysis over that in the prior sections is that the exogenous plant closures provide a way of focusing on labor demand late in the life-cycle. Thus, for example,

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[55] While the pattern presented in Table 6 indicates that the effect is non-linear in age in this analysis, a model that pools all age cohorts 35-55 and adds linear age interactions yields a highly significant negative triple interaction between blue-collar workers, post-closure indicator, and age (coef. -0.0069, std. err. 0.001). That is, the relative employment advantage of blue-collar workers after displacement declines on average by 0.7 percentage points per year of age at displacement.

any tendency of blue-collar workers to retire early – say, because of physical wear and tear – can be eliminated from the analysis of skill effects. The disadvantage of this analysis is that we have only a noisy measure of vocational education (blue-collar work). However, the consistency with the prior analyses of the IALS and the German Microcensus data further strengthens the conclusion that the type of education has important life-cycle impacts.

VII. The Impact of Education Type on Income and on Adult Education

So far, the analysis has been restricted to consideration of employment as the outcome. In this section, we consider two additional outcome variables related to education type: income and career-related adult education.

A. Income

We start by estimating an earnings equation for individuals who work full-time in the 12 months before the survey in the IALS data. This is a straightforward extension of a Mincer earnings function with an addition of a possible age-related difference in earnings patterns for those with general and vocational education. The first two columns of Table 7 report the estimates on the initial wages of general education individuals and the interactions with age and age squared for the groups of vocational countries[56] and of apprenticeship countries.

Just as in the employment analysis, there is a significant age pattern in earnings: General-education individuals earn initially less and later more than vocational-education individuals. In the earnings analysis, there is a negative interaction with age squared (significant at 14 percent in the first column), indicating that the wage differential between the two education types flattens off at around age 50.[57]

[56] Belgium does not have earnings information in the survey.

[57] The results in the table include linear interactions with the literacy score and with other education types. Expanding that to include interactions with quadratic age leaves all results qualitatively the same.

The IALS earnings analysis must contend with small samples, particularly when we go to the apprenticeship countries. In order to corroborate the IALS results, we return to the German Microcensus. This again allows replicating the analysis on a much richer and more recent dataset with occupation-specific information, although it does lack the literacy scores. For comparison, Columns 3 and 4 show that the same significant pattern visible in the two country groups is also visible in the German IALS sample by itself (the negative coefficient on general type is significant at 12 percent in Column 4), despite the fact that the sample is quite small. The pattern is hardly affected when excluding the literacy controls, which are not available in the Microcensus data. Column 5 reveals that the much larger and more recent sample of the German Microcensus yields very similar results. The same pattern is visible both within secondary education and within tertiary education, with somewhat stronger effects in secondary education, and it is again fully robust to including 10 or 88 occupation-group fixed effects and to dropping brawn-intensive occupations (not shown). The nonlinear specification implies that the earnings advantage turns from vocational to general education around age 30 and flattens off around age 50 (Figure 2).

B. Adult Education

Adult education may help explain the difference in age-employment trends for individuals finishing different education programs, as people taking more career-related education are likely more employable given their updated knowledge and skills. In the IALS data, about one third of all males received some career-related adult education during the 12 months leading to the survey. Individuals with a general education are somewhat more likely to have had career-related training (37 percent) compared to individuals with a vocational education (30 percent). In fact, while we think in terms of the adaptability to technological change of those with general education, it could simply be that general education makes subsequent educational investments cheaper. By investing in more skills, these workers have better employment opportunities over time, independent of any technological change. We cannot, however, distinguish between these two paths within our analysis.

When using the indicator of receiving career-related adult education as dependent variable in a linear age-education specification similar to Equation (1) in Table 8, there is no significant difference in the full group of vocational countries. But in the group of apprenticeship countries, individuals completing a general education are more likely to receive career-related education as they become older. The pattern is particularly pronounced in Germany. Again, the Microcensus data confirm the same pattern. While an interaction of general type with age squared is never significant in the IALS data, in the large Microcensus sample, there is an indication in the non-linear model that the pattern flattens off at around age 50, with individuals completing a general education having significantly higher propensity to receive adult education.[58]

VIII. Lifetime Earnings

Our analysis points to a clear trade-off between early career employment and employment later in the life-cycle. In closing, we thus ask the simple question of whether the early employment gains outweigh the later losses from the viewpoint of individual labor-market earnings, as observed in the IALS analysis.

Importantly, while we have clear causal estimates of the impact of education type on the age-employment profile, our estimates of the initial differential in employment are less well

[58] While there is a similar pattern in the IALS data for the total number of hours of career-related adult education received during the past 12 months, the hours do not differ significantly between education types in the Microcensus data.

identified. The identification of the initial impact of education type rests on adequately separating the influence of education type from other market-related factors correlated with these choices (through the observed skill and background factors). Nonetheless, using the estimate of the initial employment losses from general education (β_1 in Equation (1)), we calculate the present value of lifetime employment for workers with different schooling types in the three apprenticeship countries for which we found clearest evidence of the age-employment pattern.[59] We weight the employment at each age by the average earnings for each age cohort by schooling type.[60] Future earnings are discounted back to age 16 at 3 percent.

These calculations produce very interesting results, suggesting that aspects of the larger labor market are important for evaluating the efficacy of apprenticeship programs. For Germany and Denmark, the present value of earnings favors those with a general education. Over the lifetime, the German worker with a general education will have 24 percent higher earnings than the one with a vocational education, while a Dane with general education will see six percent higher earnings. For Switzerland, however, the higher present value goes to those with vocational education; the early earnings gains more than make up for the gains in later earnings that accrue to workers with general training, and vocational workers have eight percent higher lifetime earnings.[61] As an alternative exercise, we can calculate the discount rate at which the present value is the same for those with vocational and general education. This discount rate at which the advantage switches over to the other type of education is 0.096 for Germany, 0.054 for

[59] To the extent that β_1 incorporates a combination of the causal impact of general education plus an element of selection involving other factors, the interpretation would be limited to the impact on the typical worker observed in general education as opposed to inferences about the impact of bringing a different group into general education.

[60] As an alternative, we also use the estimated earnings functions to provide the age-by-schooling information. This approach acts to smooth out cohort jumpiness in the averages, recognizing that some of the age cohort samples become fairly small. Nonetheless, the qualitative results with this approach do not differ from using the simple age cohort earnings averages.

[61] Detailed results are available from the authors on request.

Denmark, and 0.01 in Switzerland, indicating that the relative assessment of the two education types in Germany and Switzerland is not very sensitive to the choice of any sensible discount.

An obvious explanation of the country differences follows the motivation for this analysis. In faster growing societies, with commensurately larger technological change, we expect the greater adaptability of general education coupled with the added adult employment to yield advantages to the workers. The Swiss annual growth rate in GDP per capita from 1970-2000 was just 1.1 percent (Heston, Summers, and Aten (2011)). This is less than half the comparable OECD growth rate (2.4 percent). The Danish growth rate of 2.1 percent and German growth rate of 2.2 percent suggest much more dynamic economies, where the flexibility of general education has a much greater payoff. [62,63]

Interestingly, Wolter and Ryan (2011) indicate that, from the viewpoint of the firm, Swiss apprenticeships are also beneficial while German apprenticeships are not.[64] This raises a small puzzle, because lower relative wages of trainees partially contribute to the net benefits to Swiss firms. Thus, at least during the training period, one might expect that the worker would see lower net benefits in Switzerland. By our data, this training-period disadvantage relative to Germany is overcome by smaller reductions in subsequent employment and wages of workers with vocational education relative to Germany.

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[62] The very same pattern emerges when looking at total factor productivity (TFP) rather than GDP per capita, where TFP is defined as output per capita minus physical capital per capita times the capital share (assumed at 0.3) and where the physical capital stock is constructed using a classic perpetual inventory method assuming a depreciation rate of 6 percent (as, e.g., in Hall and Jones (1999) and Vandenbussche, Aghion, and Meghir (2006)). From 1970-2000, TFP per capita grew by 0.4 percent in Switzerland, 1.3 percent in Denmark, and 1.5 percent in Germany.

[63] This may not, however, be the correct comparison. The Swiss economy did suffer a growth slowdown that is often attributed to the financial sector. It may be more appropriate to compare the vocational employment results to the rate of innovation in the economies, something that is intrinsically hard to measure.

[64] There is a substantial variation across firms, but Wolter and Ryan (2011) report that "in Switzerland 60% of all training firms obtain positive net benefits, while in Germany, 93% of training firms incur net costs. A complementary difference between the countries shows up in labor turnover. In Germany more apprentices remain with their training company after completion than in Switzerland: 50% and 36% of apprentices stay put for at least a year afterwards, respectively" (p. 543).

The overall employment effects of training are undoubtedly related in part to the social safety net in the specific country being considered. Without early retirement options, it is likely that a significant fraction of those leaving the labor force in their mid-fifties would actually stay employed. Thus, for example, in a developing country without a mature system for retirement income, we might see a very different pattern of employment across the life-cycle along with a potentially different wage structure. Moreover, the interaction of the lifetime incomes with government policies and programs makes it clear that these calculations do not represent a benefit-cost analysis. Both workers and the government see a different total economic impact, something that goes beyond our analysis here.

IX. Conclusions

Our estimates of the impact of vocational education on age-employment profiles indicate that much of the policy discussion about education programs is too narrow. Vocational education has been promoted largely as a way of improving the transition from schooling to work, but it also appears to have an impact on the adaptability of workers to technological and structural change in the economy. As a result, the advantages of vocational training in smoothing entry into the labor market have to be set against disadvantages later in life.

We estimate the impact of education type on employment over the life-cycle in a difference-in-differences approach, comparing the relative performance of individuals with different education types at different ages. The results show that in the group of vocational countries, individuals completing a vocational education are more likely to be employed when young, but this employment advantage diminishes with age.

The estimation of cross-over ages is quite imprecise and varies across specifications, but individuals completing a general education start to experience higher probabilities of employment as early as age 50. While this might seem quite late, it is important to bear in mind that this analysis refers to employment and to males. Due to breadwinner role models or other reasons, males may accept substantial employment hardships before accepting nonemployment during their prime age. Consistent with this interpretation, the cross-over age for incomes comes much earlier (see Figure 2). Furthermore, at any given time skill-specific demand will drop for just some specific vocational skills and it is difficult to predict which ones will face falling demand over the next several decades. But, decade by decade, some additional vocational degrees will lose further in employment, even though some will not become obsolete over an entire work life. While this rolling obsolescence implies that it may take some time for the average employment effect to cross over, lifetime earnings calculations suggest that the average net effect of vocational education can well become negative.

The pattern of results is most pronounced in the apprenticeship countries, and it is robust to adding more control variables, dropping the youngest groups in the sample, and using a matched sample. Results are also robust when considering only individuals completing just secondary education and when considering only the unemployed among the not employed. Thus, the raw employment patterns in Figure 1 cannot be attributed simply to varying selectivity into general and vocational education but instead appear to be caused by the different focus of the schools.

We also conclude that the impact of vocational education varies considerably with the specific institutional structure of schooling and work-based training. While the declining age-employment pattern for those with vocational education relative to those with general education is found in all vocational education countries, it is most acute in the three apprenticeship countries in our sample. The balance of early gains against later losses for vocational relative to general education is, however, not uniform across these countries: In line with the relative pace of economic change in their economies, the balance in lifetime earnings appears to be in favor of vocational education in the slower growing Switzerland but in favor of general education in the more rapidly growing Denmark and Germany.

It is of course difficult to rule out conclusively that cohort differences, say in terms of systematic changes over time in education programs, are driving the effects and not depreciation of skills with age. Nonetheless, the consistency across country groupings and the relationship to treatment intensity supports our skill depreciation view of the difference-in-differences results.

Our measured treatment is obviously heterogeneous as vocational programs in all of the countries cover a range of occupations and skills. They also differ over time as industries develop and as industries wane and disappear in each country. We interpret our vocational training indicator as relating to a portfolio of training opportunities relevant at each time period and chosen by a combination of industry and government projections of future demands. But in all cases, the first decision involves deciding on the mix of general education and more occupation-specific education, the subject of this analysis.

We do not view this analysis as an indictment of the school policy regimes of countries that rely to varying degrees on vocational education, but we do believe that the potential trade-offs should enter into policy debates on the degree of reliance on vocational programs. Most importantly, vocational training should not substitute for providing strong basic skills, because this and other analyses underscore the necessity in modern economies of developing general cognitive skills. Further, countries might want to contemplate programs that would ameliorate any later life disadvantages of vocational programs. For example, a European Commission (2010) communique emphasizes the need for enhanced vocational programs, largely to deal with high youth unemployment in Europe, but also recognizes that there must be a concomitant investment in “lifelong learning.” The best way to provide incentives to both individuals and employers so that workers obtain additional education and training throughout the career is not well understood, but this analysis suggests the task should receive the attention of policy makers, particularly if they contemplate moving school systems toward more vocational education.

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Table 1: Educational Attainment and Type by Country

			Secondary and tertiary		Secondary		Tertiary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Country	N	% beyond secondary	% completing general	% completing vocational	% completing general	% completing vocational	% completing general
Belgium	680	26.6	34.0	64.9	27.8	70.7	49.2
Chile	722	23.3	51.4	46.1	49.1	47.5	57.7
Czech Rep.	917	2.8	4.8	71.8	4.4	71.6	19.8
Denmark	1,006	23.1	23.4	60.1	14.3	63.8	51.0
Finland	1,021	22.7	42.8	56.1	36.5	61.9	60.2
Germany	748	16.0	25.6	66.7	15.0	75.7	81.0
Great Britain	639	15.6	58.2	41.8	–	–	58.2
Hungary	1,022	25.1	34.3	64.4	26.1	72.3	79.5
Ireland	119	18.6	41.1	58.9	–	–	41.1
Italy	809	10.7	75.2	21.0	72.2	23.3	91.8
Netherlands	1,111	24.6	46.8	53.2	29.3	70.7	100.0
New Zealand	1,229	25.7	25.6	65.9	23.0	64.5	31.0
Norway	897	19.0	17.8	57.8	8.3	59.0	45.9
Poland	919	15.5	14.3	85.7	4.4	95.6	68.0
Slovenia	1,097	13.7	47.2	47.7	45.7	48.4	56.9
Sweden	245	29.0	58.1	41.9	–	–	58.1
Switzerland	1,228	27.7	7.7	91.8	9.1	90.3	2.2
USA	809	40.6	34.4	32.5	17.9	19.8	53.1
All countries	15,218	26.6	35.2	47.2	23.2	50.4	59.2

Note: Data source: International Adult Literacy Survey (IALS). Sample includes all males who finished secondary education or the first stage of tertiary education and are not currently enrolled in school. Secondary education is classified as one of three types: general for academic or college preparatory programs; vocational for business, trade, or vocational programs; and other for secondary level equivalency or other programs. First stage of tertiary education is classified as general or vocational. A general program is one that leads to a university degree (BA/BS); a vocational program is one that does not lead to a university degree, which is typically shorter and focuses on practical, technical, or occupational skills for direct entry into the labor market. For Great Britain, Ireland, and Sweden, information on the secondary education types is unavailable. The difference between 100 and the sum of columns 3 and 4 (respectively columns 5 and 6) provides the percentage attributed to the "other" category.

Table 2: The Effect of General vs. Vocational Education on Employment over the Life-Cycle

	(1)	(2)	(3) Control for mother's education	(4)	(5) Base specification	(6) 20+ age sample	(7) 30+ age sample
General education type	-0.069	-0.072	-0.066	-0.083	-0.095	-0.084	-0.083
	*(0.019)******	*(0.019)******	*(0.019)******	*(0.037)****	*(0.021)******	*(0.021)******	*(0.030)******
General education type * age/10	0.021	0.019	0.018	0.024	0.022	0.019	0.018
	*(0.007)******	*(0.007)******	*(0.007)****	*(0.013)**	*(0.007)******	*(0.007)******	*(0.010)**
Other education type	-0.002	-0.003	-0.001	0.068	0.024	-0.001	-0.020
	(0.032)	*(0.032)*	*(0.033)*	*(0.050)*	*(0.033)*	*(0.034)*	*(0.054)*
Other education type * age/10	-0.019	-0.016	-0.019	-0.039	-0.021	-0.013	-0.006
	(0.012)	*(0.012)*	*(0.013)*	*(0.019)****	*(0.012)**	*(0.013)*	*(0.018)*
Age/10	0.381	0.372	0.360	0.411	0.370	0.363	0.637
	*(0.013)******	*(0.014)******	*(0.023)******	*(0.024)******	*(0.014)******	*(0.014)******	*(0.028)******
$(\text{Age}/10)^2$	-0.094	-0.091	-0.089	-0.101	-0.088	-0.087	-0.127
	*(0.003)******	*(0.003)******	*(0.003)******	*(0.004)******	*(0.003)******	*(0.003)******	*(0.005)******
Years of schooling	0.012	0.005	0.005	0.012	0.004	0.004	0.005
	*(0.001)******	*(0.001)******	*(0.001)******	*(0.003)******	*(0.001)******	*(0.001)******	*(0.002)******
Literacy score		0.021	0.024	0.056	0.020	0.025	0.030
		*(0.010)****	*(0.010)****	*(0.018)******	*(0.010)****	*(0.010)****	*(0.016)**
Literacy score * age/10		0.014	0.012	-0.0001	0.013	0.012	0.009
		*(0.004)******	*(0.004)******	*(0.006)*	*(0.004)******	*(0.004)******	*(0.005)**
Father has professional occupation				0.034 *(0.034)*			
Father has professional occupation * age/10				-0.014 *(0.014)*			
Average lit. score, country-cohort-educ. type					0.065	0.065	0.090
					*(0.024)****	*(0.024)******	*(0.026)******
% with general education, country-cohort					-0.070	-0.097	-0.262
					(0.169)	*(0.171)*	*(0.234)*
% with vocation education, country-cohort					0.244	0.200	0.240
					(0.161)	*(0.162)*	*(0.211)*
Constant	0.444	0.532	0.527	0.366	0.396	0.442	-0.080
	*(0.026)******	*(0.027)******	*(0.059)******	*(0.044)******	*(0.159)****	*(0.161)******	*(0.203)**
Observations	10,615	10,615	10,472	3,532	10,615	10,368	7,892
Countries	11	11	11	4	11	11	11
Adjusted R^2	0.24	0.26	0.26	0.26	0.26	0.26	0.31

Note: Linear probability models. Dependent variable: Individual is employed. Sample includes males aged 16 to 65 with secondary or first stage of tertiary education in the 11 vocational countries. All specifications control for country fixed effects. Omitted education type is vocational. Age variable subtracted by 16 throughout. Column 3 controls for indicators for mother's education and their interaction with age (which turn out insignificant, not shown). Data source: International Adult Literacy Survey (IALS). Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table 3: The Effect of Education Type on Life-Cycle Employment: Country Groups and Vocational Education Countries

	(1) All countries	(2) Non-vocational countries	(3) Vocational countries	(4) Non-school based vocational countries	(5) Apprentice-ship countries	(6) Denmark	(7) Germany	(8) Switzerland
General education type	-0.075	0.023	-0.095	-0.121	-0.209	-0.042	-0.403	-0.333
	*(0.017)****	*(0.034)*	*(0.021)****	*(0.033)****	*(0.043)****	*(0.062)*	*(0.137)****	*(0.076)****
General education type * age/10	0.016	-0.017	0.022	0.032	0.051	0.073	0.055	0.104
	*(0.006)****	*(0.013)*	*(0.007)****	*(0.011)****	*(0.016)****	*(0.028)****	*(0.028)**	*(0.029)****
Observations	15,038	3,421	10,615	5,819	2,970	1,006	744	1,220
Countries	18	4	11	6	3	1	1	1

Note: Linear probability models. Dependent variable: Individual is employed. Sample includes males aged 16 to 65 with secondary or first stage of tertiary education. Each column is a separate regression with the same controls as in Column 5 of Table 2 (including country fixed effects). Age variable subtracted by 16 throughout. Countries are grouped based on the shares of upper-secondary-school students in vocational programs, school-based vocational programs, and apprenticeship reported in the OECD Education at a Glance or calculated from the IALS data (see text for details). Non-vocational countries are Chile, Italy, New Zealand, and the U.S. Apprenticeship countries are Denmark, Germany, and Switzerland. Non-school based vocational countries are the apprenticeship countries plus the Czech Republic, Hungary, and Poland. Vocational countries are the non-school based vocational countries plus Belgium, Finland, the Netherlands, Norway, and Slovenia. (Great Britain, Ireland, and Sweden are in the full sample of countries but in no sub-sample as the information on secondary school type required for the classification is missing.) Data source: International Adult Literacy Survey (IALS). Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table 4: Employment Probabilities: Propensity-Score Matching and Additional Robustness Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
	Propensity-score matching		Sample of individuals with just secondary education		Sample of individuals in labor market	
	Vocational countries	Apprenticeship countries	Vocational countries	Apprenticeship countries	Vocational countries	Apprenticeship countries
General education type	-0.108	-0.215	-0.092	-0.253	-0.057	-0.115
	*(0.027)******	*(0.050)******	*(0.026)******	*(0.057)******	*(0.019)******	*(0.036)******
General education type * age/10	0.027	0.069	0.015	0.065	0.010	0.024
	*(0.009)******	*(0.019)******	*(0.009)** *	*(0.021)******	*(0.007)*	*(0.011)*** **
Observations	8,216	2,379	8,092	2,248	9,198	2,617
Countries	11	3	11	3	11	3

Note: Linear probability models (unless noted otherwise). Dependent variable: Individual is employed (unless noted otherwise). Sample includes males aged 16 to 65 with secondary or first stage of tertiary education (unless noted otherwise). Each column is a separate regression with the same controls as in Column 5 of Table 2 (including country fixed effects). Age variable subtracted by 16 throughout. Columns 1 and 2 are estimated by nearest-neighbor propensity-score matching, with vocational types matched to general types based on age, years of schooling, literacy scores, and parental education; see text for details. Columns 5 and 6 consider only the unemployed in the not employed category, i.e., those not in the labor force are excluded. Data source: International Adult Literacy Survey (IALS). Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table 5: Education Type and Life-Cycle Employment within Occupation Groups: Evidence from German Microcensus 2006

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Base model				Adding fixed effects for occupation groups		Dropping brawn-intensive occupations	
	All	Only secondary education	Only tertiary education	All	10 one-digit occupation groups	88 two-digit occupation groups	Often carrying heavy loads	Often carry-ing heavy loads and often standing
General education type	-0.218	-0.238	-0.129	-0.192	-0.140	-0.147	-0.140	-0.136
	(0.009)***	*(0.018)****	*(0.011)****	*(0.019)****	*(0.009)****	*(0.009)****	*(0.009)****	*(0.011)****
General education type * age/10	0.078	0.064	0.052	0.056	0.054	0.052	0.050	0.051
	(0.003)***	*(0.008)****	*(0.004)****	*(0.014)****	*(0.003)****	*(0.003)****	*(0.003)****	*(0.004)****
General education type * $(\text{age}/10)^2$				0.0039				
				(0.0025)				
Age/10	0.331	0.328	0.378	0.334	0.306	0.307	0.308	0.338
	(0.005)***	*(0.005)****	*(0.010)****	*(0.005)****	*(0.005)****	*(0.005)****	*(0.005)****	*(0.007)****
$(\text{Age}/10)^2$	-0.078	-0.079	-0.083	-0.079	-0.074	-0.075	-0.074	-0.079
	(0.001)***	*(0.001)****	*(0.002)****	*(0.001)****	*(0.001)****	*(0.001)****	*(0.001)****	*(0.001)****
Tertiary education	0.082			0.083	0.061	0.046	0.041	0.024
	(0.003)***			*(0.004)****	*(0.003)****	*(0.003)****	*(0.003)****	*(0.004)****
One-digit occupation groups (10)					Yes			
Two-digit occupation groups (88)						Yes	Yes	Yes
Observations	118,604	80,686	37,918	118,604	117,906	117,906	110,628	57,188
Adjusted R^2	0.165	0.158	0.158	0.165	0.173	0.183	0.181	0.195

Note: Linear probability models. Dependent variable: Individual is employed. Sample includes males aged 16 to 65 with at least secondary education completed (and not currently in education). All models include a constant. Omitted education type is vocational. Age variable subtracted by 16 throughout. In columns 4 and 5, occupation groups refer to the German Classification of Occupations. In columns 6 and 7, three-digit occupations are classified as brawn-intensive if more than 50 percent of respondents in the German Employment Survey 2005/06 report that they often have to carry heavy loads and often have to stand, respectively. Data source: German Microcensus, 2006. Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table 6: Relative Employment after Plant Closure by Age and Occupational Category: Evidence from Austria

	(1)	(2)	(3)	(4)
Age at potential displacement:	35-39	40-44	45-49	50-55
Blue * After	0.126	0.097	0.155	-0.067
	*(0.011)******	*(0.012)******	*(0.015)******	*(0.025)******
After	-0.210	-0.187	-0.207	-0.259
	*(0.008)******	*(0.008)******	*(0.011)******	*(0.017)******
Blue	0.004	0.005	-0.001	0.010
	(0.009)	*(0.010)*	*(0.013)*	*(0.020)*
Constant	0.996†	0.992†	1.002†	0.999†
	(0.006)	*(0.007)*	*(0.009)*	*(0.013)*
Observations (cells)	14,926	14,005	13,588	11,953
R^2	0.076	0.057	0.043	0.045

Note: Linear probability models. Dependent variable: relative employment = (average employment displaced workers) / (average employment non-displaced workers) in each cell. A cell is defined by calendar time, relative distance to potential displacement, age at potential displacement, and occupational status. Employment is measured quarterly in the four years prior to potential displacement and up to ten years afterwards. *Blue* identifies blue collar workers and *After* identifies quarters after potential displacement. Original samples include male private-sector workers in Austria employed between 1982 and 1988 at risk of a plant closure. Each actually displaced worker is matched to similar non-displaced workers based on an exact matching algorithm. The header indicates age at potential displacement. Data source: Matched employer-employee data from the Austrian Social Security Database (ASSD). Clustered standard errors in parentheses. Significantly different from 0 at *** 1%, ** 5%, * 10%; † not significantly different from 1 at 1%.

Table 7: The Effect of General vs. Vocational Education on Income over the Life-Cycle

	IALS				Microcensus
	(1)	(2)	(3)	(4)	(5)
	Vocational countries	Apprenticeship countries	Germany	Germany	Germany
General educ. type	-0.208	-0.407	-0.426	-0.381	-0.651
	*(0.097)***	*(0.151)****	*(0.339)*	*(0.242)*	*(0.035)****
General educ. type * age/10	0.168	0.388	0.576	0.578	0.532
	*(0.084)***	*(0.127)****	*(0.221)****	*(0.221)****	*(0.027)****
General educ. type * $(age/10)^2$	-0.025	-0.081	-0.103	-0.103	-0.071
	(0.017)	*(0.026)****	*(0.042* **	*(0.043)***	*(0.005)****
Controls for age, age^2, and schooling	Yes	Yes	Yes	Yes	Yes
Controls as in Column 5 of Table 2	Yes	Yes	Yes	No	No
Observations	5,885	1,964	395	395	85,680
Countries	10	3	1	1	1

Note: Dependent variable is natural logarithm of annual wage (IALS) and natural logarithm of net income in past month (Microcensus), respectively. Sample includes males aged 16 to 65 with at least secondary education completed who worked full-time during the 12 months prior to the survey (IALS) and who report to normally work at least 30 hours per week (Microcensus), respectively. Each column is a regression including age, age^2, and years of schooling (indicator for tertiary education in the case of Microcensus) as control variables; columns 1-3 additionally control for all control variables as in Column 5 of Table 2. Age variable subtracted by 16. Data sources: International Adult Literacy Survey (IALS) and German Microcensus 2006. Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

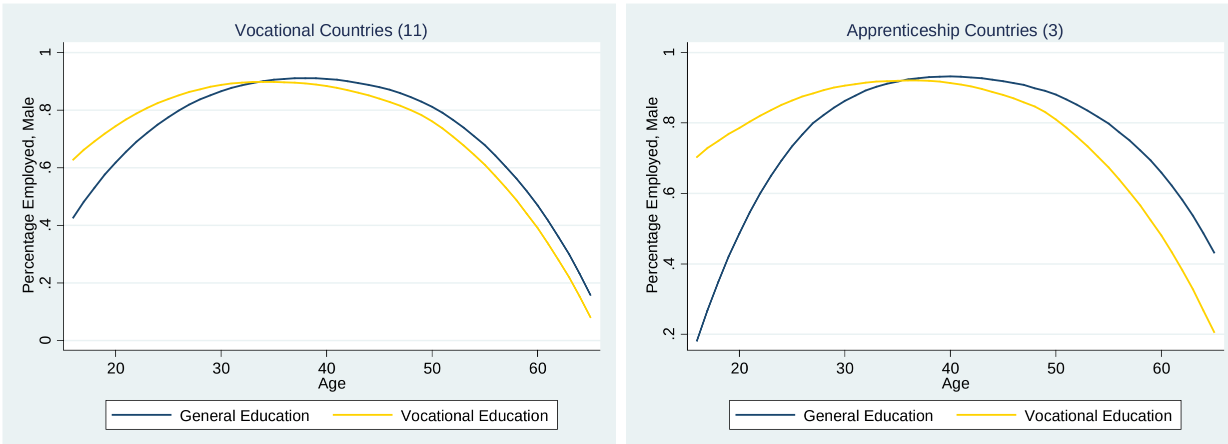
Table 8: The Effect of General vs. Vocational Education on Adult Education over the Life-Cycle

	IALS			Microcensus	
	(1)	(2)	(3)	(4)	(5)
	Vocational countries	Apprenticeship countries	Germany	Germany	Germany
General educ. type	0.024	-0.038	-0.161	0.006	-0.097
	(0.024)	*(0.061)*	*(0.111)*	*(0.009)*	*(0.015)****
General educ. type * age/10	-0.002	0.034	0.060	0.019	0.108
	(0.007)	*(0.019)**	*(0.024)***	*(0.003)****	*(0.012)****
General educ. type * $(age/10)^2$					-0.016
					(0.002)***
Controls for age, age^2, and schooling	Yes	Yes	Yes	Yes	Yes
Controls as in Column 5 of Table 2	Yes	Yes	Yes	No	No
Observations	9,817	2,170	744	118,604	118,604
Countries	11	3	1	1	1

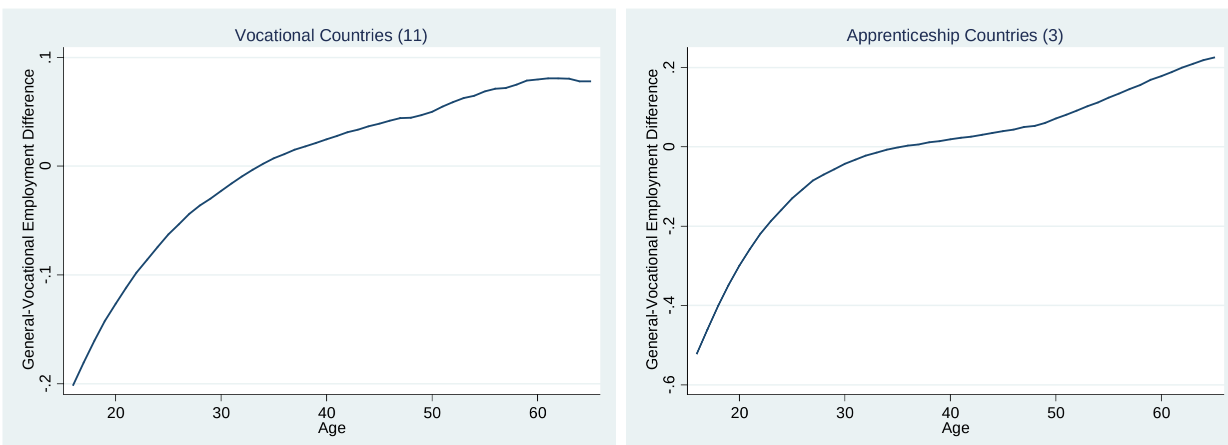
Note: Linear probability models. Dependent variable is a dummy variable for whether one received any career-related adult education during the 12 months prior to the survey. Sample includes males aged 16 to 65 with at least secondary education completed (and not currently in education). Each column is a regression including age, age^2, and years of schooling (indicator for tertiary education in the case of Microcensus) as control variables; columns 1-3 additionally control for all control variables as in Column 5 of Table 2. Age variable subtracted by 16. Data sources: International Adult Literacy Survey (IALS) and German Microcensus 2006. Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Figure 1: Education Type and Life-Cycle Employment in Country Groups

(1) Male employment rate by age and education type

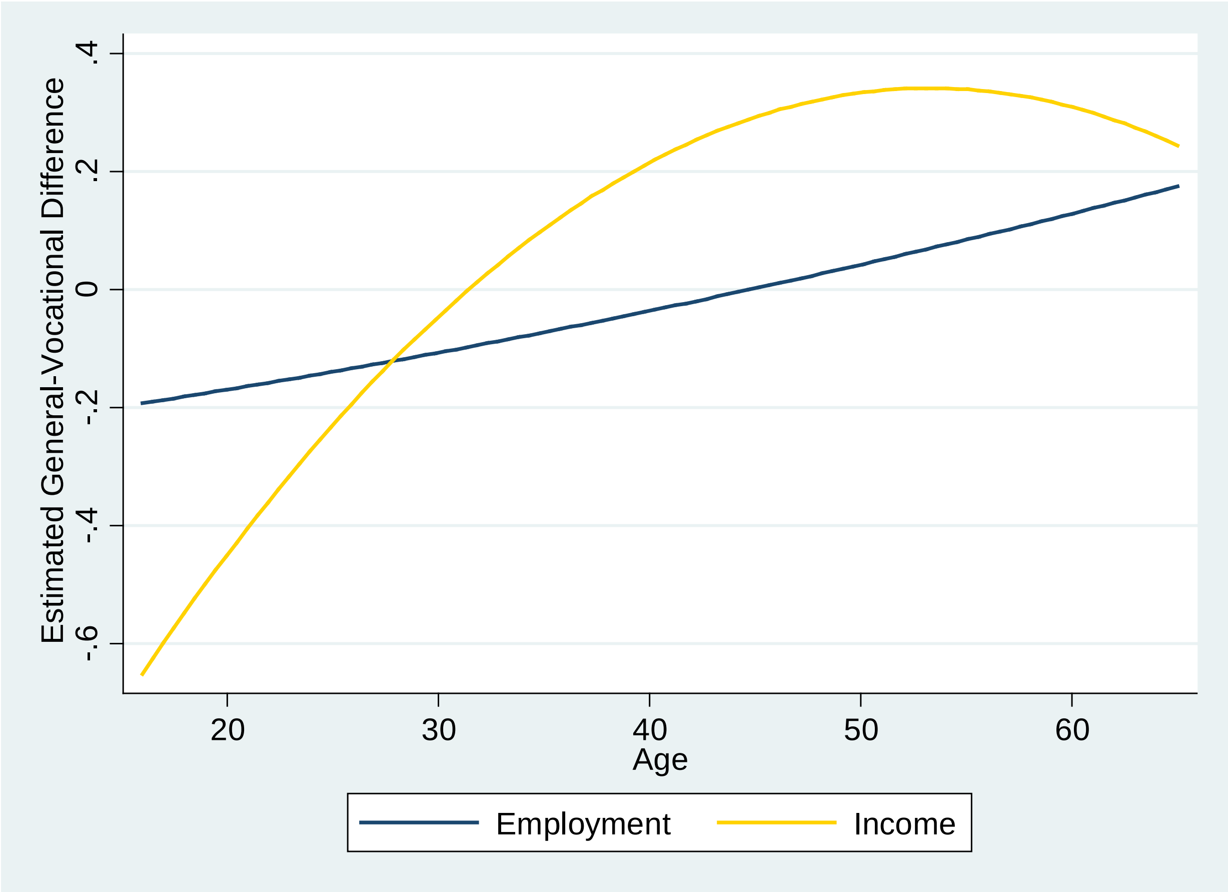


(2) Difference in male employment rate between education types by age



Note: Top panels: Smoothed scatterplots using locally weighted regressions (Stata command “lowess”, Cleveland (1979)). Bottom panels: Difference of two graphs in top panels. Left panel: 11 vocational countries. Right panel: 3 “apprenticeship” countries (Denmark, Germany, and Switzerland). Sample includes all males who finished secondary education or the first stage of tertiary education and are not currently enrolled in school. See note to Table 1 for definition of education types and notes to Table 3 for details of country groups. Individuals employed are those who are employed at the time of the survey; individuals not employed include retired, unemployed who are looking for work, homemakers, and others. Data source: International Adult Literacy Survey (IALS).

Figure 2: Nonlinear Estimate of Effect Education Type on Employment and Income: German Microcensus 2006



Note: Estimate of effect of general education type (compared to vocational education type) on employment and on log income, respectively, implied in a nonlinear specification that interacts general education type with age and with age squared. Graphical depiction of Column 4 of Table 5 and of Column 5 of Table 7, respectively. Data source: German Microcensus 2006.

Appendix

Table A1: Unobservable Selection and Coefficient Stability: Robustness Analysis based on Oster (2014)

	(1)	(2)	(3)	(4)
Age group	Young (ages 21-30)		Old (ages 56-65)	
	Vocational countries	Apprenticeship countries	Vocational countries	Apprenticeship countries
Baseline model				
General education type	-0.047	-0.067	0.061	0.198
	*(0.017)******	*(0.032)******	*(0.027)****	*(0.063)******
Observations	2,283	654	1,460	478
Countries	11	3	11	3
R^2	0.050	0.039	0.288	0.274
Extended model				
General education type	-0.055	-0.084	0.053	0.187
	*(0.017)******	*(0.032)******	*(0.027)****	*(0.063)******
Observations	2,283	654	1,460	478
Countries	11	3	11	3
R^2	0.058	0.048	0.295	0.290
δ to match β_1=0	Controls move coefficient further from null	Controls move coefficient further from null	2.915	2.549

Note: Linear probability models. Dependent variable: Individual is employed. Sample includes males with secondary or first stage of tertiary education aged 21 to 30 in columns (1)-(2) and males aged 56 to 65 in columns (3)-(4). Omitted education type is vocational. Baseline model includes controls for other education type, age, age squared, years of schooling, and country fixed effects. Extended model adds controls for literacy score and mother's education. Last row reports Oster (2014)'s coefficient of proportionality, δ, required to match a true effect of education type of zero. δ is calculated using the assumption that the unobservables explain as much of the variation in the outcome as the observables. For details see Oster (2014). Data source: International Adult Literacy Survey (IALS). Standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table A2: Correlates of General Education Type

	(1)
Literacy score	0.049
	(0.012)***
Literacy score * age/10	-0.003
	(0.004)
Mother has high-school education	0.040
	(0.022)*
Mother has high-school education * age/10	0.003
	(0.009)
Age/10	-0.029
	(0.016)*
$(\text{Age}/10)^2$	0.010
	(0.003)***
Years of schooling	0.042
	(0.002)***
Constant	-0.238
	(0.029)***
Observations	9,818
Countries	11
Adjusted R^2	0.18
F(literacy score * age, mother education * age)	0.33
Prob > F	*(0.719)*

Note: Linear probability model. Dependent variable: 1 = education type of individual is general; 0 = vocational. Sample includes males aged 16 to 65 with secondary or first stage of tertiary education; individuals with “other” education type excluded. All specifications control for country fixed effects. Age variable subtracted by 16 throughout. Data source: International Adult Literacy Survey (IALS). Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table A3: The Effect of Education Type on Life-Cycle Employment: Vocational Education Countries

	(1) Belgium	(2) Czech Rep.	(3) Denmark	(4) Finland	(5) Germany	(6) Hungary	(7) Netherlands	(8) Norway	(9) Poland	(10) Slovenia	(11) Switzerland
General educ. type	0.039	0.143	-0.042	-0.151	-0.403	-0.027	-0.032	-0.022	0.380	-0.137	-0.333
	(0.104)	*(0.131)*	*(0.062)*	*(0.064)***	*(0.137)****	*(0.068)*	*(0.115)*	*(0.098)*	*(0.331)*	*(0.050)****	*(0.076)****
General educ. type	-0.019	-0.018	0.073	0.049	0.055	0.0004	-0.001	0.030	0.011	0.045	0.104
* age/10	*(0.026)*	*(0.043)*	*(0.028)****	*(0.025)***	*(0.028)**	*(0.025)*	*(0.023)*	*(0.026)*	*(0.041)*	*(0.020)***	*(0.029)****
Observations	670	914	1,006	1,021	744	1,016	1,111	897	919	1,097	1,220

Note: Linear probability models. Dependent variable: Individual is employed. Sample includes males aged 16 to 65 with secondary or first stage of tertiary education. Each column is a separate regression with the same controls as in Column 5 of Table 2 (including country fixed effects). Age variable subtracted by 16 throughout. Data source: International Adult Literacy Survey (IALS). Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table A4: Nonlinear Specification of the Effect of Education Type on Life-Cycle Employment

	(1) Vocational countries	(2) Apprenticeship countries
General educ. type	-0.129	-0.308
	*(0.029)******	*(0.066)******
General educ. type * Cohort 26-35	0.061	0.215
	*(0.030)***	*(0.067)******
General educ. type * Cohort 36-45	0.112	0.225
	*(0.030)******	*(0.068)******
General educ. type * Cohort 46-55	0.084	0.217
	*(0.033)***	*(0.071)******
General educ. type * Cohort 56-65	0.112	0.307
	*(0.038)******	*(0.088)******
Observations	10,615	2,970

Note: Linear probability models. Dependent variable: Individual is employed. Sample includes males aged 16 to 65 with secondary or first stage of tertiary education. Each column is a separate regression controlling for dummy variables for "other education type", age cohorts, their interactions, and all other control variables in Column 5 of Table 2 (including country fixed effects). Data source: International Adult Literacy Survey (IALS). Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table A5: Education Type and Life-Cycle Employment: German Microcensus 2012

	(1) All	(2) Only secondary education	(3) Only tertiary education
General education type	-0.215	-0.318	-0.094
	(0.008)***	*(0.016)****	*(0.010)****
General education type * age/10	0.070	0.092	0.035
	(0.003)***	*(0.006)****	*(0.003)****
Age/10	0.261	0.249	0.314
	(0.004)***	*(0.005)****	*(0.008)****
$(\text{Age}/10)^2$	-0.063	-0.062	-0.068
	(0.001)***	*(0.001)****	*(0.001)****
Tertiary education	0.081		
	(0.002)***		
Observations	167,937	112,056	55,881
Adjusted R^2	0.110	0.108	0.096

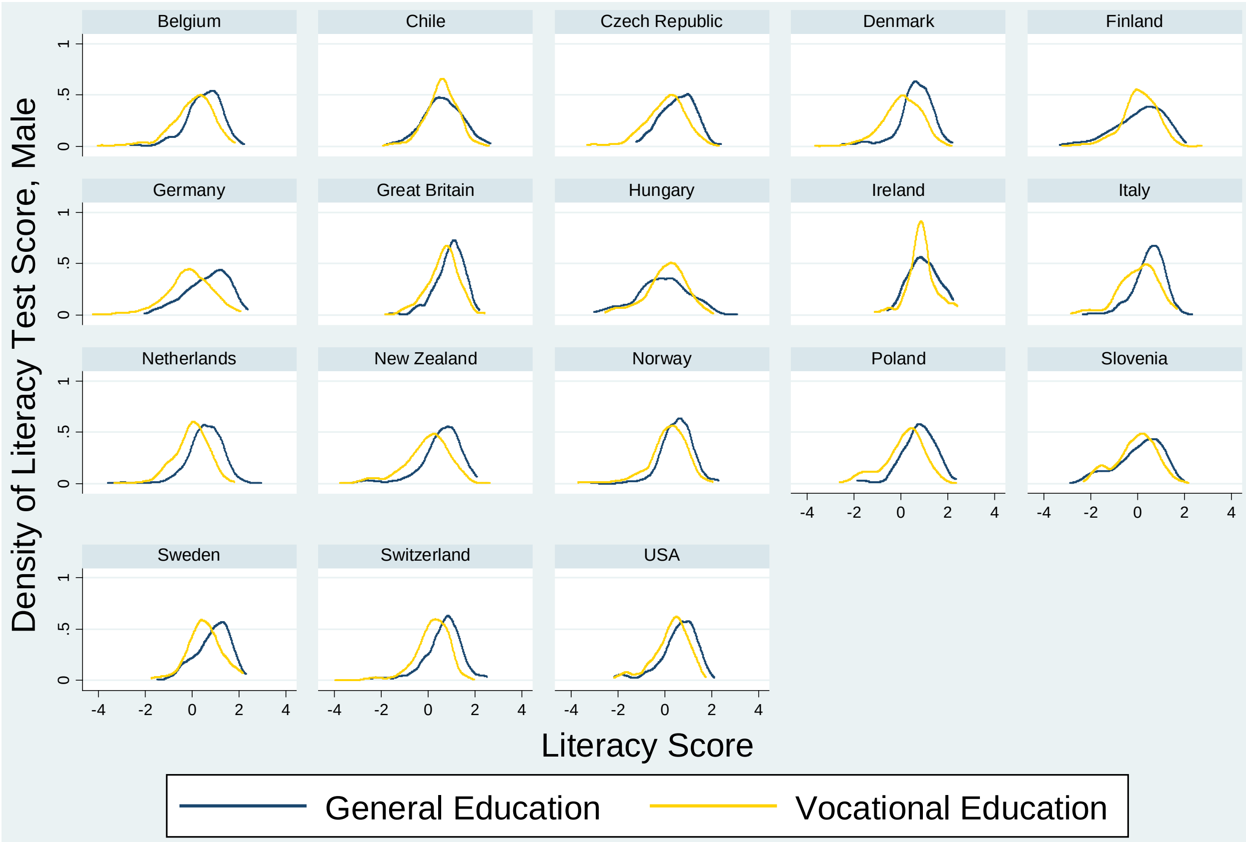
Note: Linear probability models. Dependent variable: Individual is employed. Sample includes males aged 16 to 65 with at least secondary education completed (and not currently in education). All models include a constant. Omitted education type is vocational. Age variable subtracted by 16 throughout. Data source: German Microcensus, 2012. Robust standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Table A6: Displacement Effects on Employment by Age and Occupational Status

	(1)	(2)	(3)	(4)
Age group	35-39	40-44	45-49	50-55
PC * Blue * After	0.116	0.092	0.120	0.022
	*(0.024)******	*(0.023)******	*(0.027)******	*(0.028)*
PC * After	-0.198	-0.167	-0.179	-0.154
	*(0.017)******	*(0.015)******	*(0.020)******	*(0.022)******
Blue * After	-0.004	-0.020	-0.073	-0.108
	(0.01)	*(0.011)**	*(0.012)******	*(0.015)******
After	-0.089	-0.093	-0.121	-0.404
	*(0.007)******	*(0.006)******	*(0.008)******	*(0.011)******
Constant	0.982	0.984	0.987	0.990
	*(0.004)******	*(0.004)******	*(0.005)******	*(0.005)******
Worker fixed effects	Yes	Yes	Yes	Yes
Observations	325,356	393,243	336,129	365,769
Workers	5,708	6,899	5,897	6,417
R^2	0.452	0.442	0.412	0.442

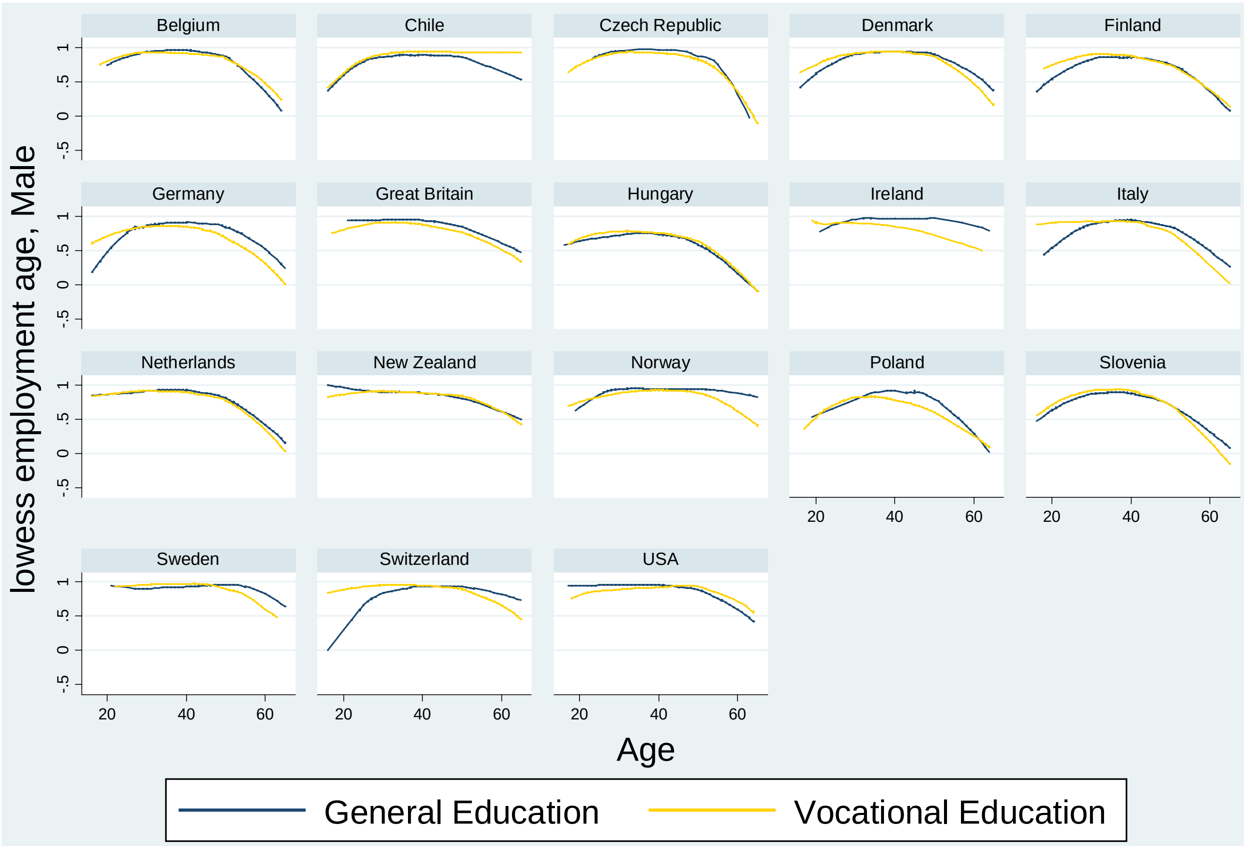
Note: Weighted linear probability panel models. Dependent variable: Individual is employed. Samples include male private-sector workers in Austria employed between 1982 and 1988 at risk of a plant closure. Each actually displaced worker is matched to similar non-displaced workers based on an exact matching algorithm. Weights are one for each displaced worker and are one over the number of controls matched to each displaced worker for non-displaced workers. Employment is measured quarterly in the four years prior to potential displacement and up to ten years afterwards. *Blue* identifies blue collar workers, *After* identifies quarters after potential displacement, and *PC* identifies workers displaced due to a plant closure. The header indicates age at potential displacement. Data source: matched employer-employee data from the Austrian Social Security Database (ASSD). Clustered standard errors in parentheses. Significant at *** 1%, ** 5%, * 10%.

Figure A1: Density of Literacy Test Score of Males by Education Type



Note: See note to Table 1 for data source, sample, and definition of education types. Literacy score is the average of prose, document, and quantitative test scores and is normalized to have a mean of 0 and a standard deviation of 1 within each country. Data source: International Adult Literacy Survey (IALS).

Figure A2: Male Employment Rate by Age and Education Type



Note: Smoothed scatterplots using locally weighted regressions (Stata command "lowess", Cleveland (1979)). Sample includes all males who finished secondary education or the first stage of tertiary education and are not currently enrolled in school. See note to Table 1 for definition of education types. Individuals employed are those who are employed at the time of the survey; individuals not employed include retired, unemployed who are looking for work, homemakers, and others. Data source: International Adult Literacy Survey (IALS).