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Noncognitive Skills in Training Curricula and Nonlinear Wage Returns

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Noncognitive Skills in Training Curricula and Nonlinear Wage Returns[1]

Fabienne Kiener[2], Ann-Sophie Gnehm[3], and Uschi Backes-Gellner[4]

Structured Abstract

Purpose:

The purpose of this paper is to investigate self-competence—the ability to act responsibly on one's own—and likely nonlinear wage returns across different levels of self-competence as part of training curricula.

Design/methodology/approach:

The authors identify the teaching of self-competence at the occupational level by applying machine-learning methods to the texts of occupational training curricula. Defining three levels of self-competence (high, medium, and low) and using individual labor market data, they examine nonlinearities in wage returns to different levels of self-competence.

Findings:

The authors find nonlinear returns to teaching self-competence: a medium level of self-competence taught in an occupation has the largest wage returns compared to low or high levels. However, in occupations with a high cognitive requirement profile, a high level of self-competence generates positive wage returns.

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Originality:

This paper first adds to research on the importance of teaching noncognitive skills for economic outcomes, which recently—in addition to personality traits research—has primarily focused on social skills by introducing self-competence as another largely unexplored but important noncognitive skill. Second, the paper studies not only average but nonlinear wage returns, showing that the right level of self-competence is crucial, i.e., neither teaching too little nor too much self-competence provides favorable returns because of trade-offs with other skills (e.g., technical or professional skills). Third, the paper also examines complementarities between cognitive skills and noncognitive skills, again pointing towards nonlinear returns, i.e., only in occupations with a high cognitive requirement profile, high levels of self-competence generate positive wage returns.

Keywords: noncognitive skills, human capital, text as data, curricula content analyses, vocational education and training

JEL Classification: I26, J24, M53

1. Introduction

Economists have long been interested in the relationship between noncognitive skills and labor market returns (e.g., Goldsmith *et al.*, 1997). Economics studies started by examining the effects of personality traits, e.g., extraversion (for an overview of these studies, see e.g., Almlund *et al.*, 2011, Borghans *et al.*, 2008a; Heckman *et al.*, 2006[5]). Recently, economics studies have gone beyond personality traits and emphasize the importance of social skills, i.e., the ability to interact and collaborate within a group, on the labor market (Deming, 2017; Deming and Kahn, 2017; Palczyńska, 2021; Weinberger, 2014).

This paper investigates another type of noncognitive skill—introduced by a socio-psychological concept (Salvisberg, 2010; Roth, 1971)—self-competence, i.e., the ability to act responsibly on one's own. Self-competence—like social skills—is defined as *malleable noncognitive skills*[6] that are crucial on the job (e.g., for solving tasks independently and reliably), thereby likely increasing productivity in the workplace. Thus workers with more of these highly labor-market-relevant skills are likely to receive positive wage returns compared to workers with less of these skills. We refer to "wage returns" as correlational patterns between wages and noncognitive skills, similar to previous research on social skills (e.g., Deming and Kahn, 2017; Palczyńska, 2021). Self-competence constitutes an "*intra*-individual" skill (shown as behavior toward oneself) and therefore differs from social skills, which constitute an "*inter*-individual" skill (shown as behavior towards and with others). Self-competence is closely related to "conscientiousness"—a Big-Five personality trait linked to responsibility—but the difference is that self-competence stresses the skill perspective more than an innate ability perspective.

In addition to the social skills literature, which primarily investigates returns at the *mean* (assuming linear returns to skills), we study *nonlinear* returns across different levels of skills.[7] The possibility of nonlinearities in returns is examined by a few studies on personality traits and we can build on these studies (Heineck, 2011; Le *et al.*, 2011; Mueller and Plug, 2006). Specifically in a

[5] For specific applications, see e.g., Albandea and Giret (2018); Risse *et al.* (2018); for one of the first papers, see Goldsmith *et al.* (1997).

[6] We follow the definition of skills in terms of the human capital model, meaning that skills can be acquired by the individual and are malleable. Personality traits, while not completely defined as being inherent, are seen as much more stable.

[7] Nonlinearity in wage returns means that the explanatory variable, such as noncognitive skills, is investigated by having different levels of the explanatory variable. Another approach looks at how—depending on different wage quantiles—the returns to noncognitive skills differs (i.e., quantile regressions). For example, Albandea and Giret (2018) show how returns to noncognitive skills differ depending on the wage quantiles.

training context, nonlinearities in returns are important to study because, in a given training time, there is a trade-off between teaching and learning more of one skill only at the cost of teaching and learning less of another skill. Thus insights into which skills have their highest returns at which level are essential in any training context. The crucial question is whether the returns of higher levels of noncognitive skills (such as self-competence) in training are linearly increasing or whether returns change nonlinearly across different levels of training, meaning that an infinite increase in noncognitive skills would not be an optimal solution. Only by having answers to this question, policymakers designing curricula will be able to take decisions on an optimal skill mix in an occupational or generally in any training program.[8]

This paper empirically examines such likely nonlinear returns to self-competence in existing occupational training programs. We first generate novel measures for self-competence by applying advanced machine-learning methods to a large number of occupational training curricula and we then examine whether the wage returns of individuals graduating from occupational training curricula with different *levels* of self-competence vary and in which way (see details on data and method in subsequent paragraphs). Moreover, because prior studies have found complementarities between social and cognitive skills, we also examine whether there are complementarities between self-competence and the cognitive requirement profile (i.e., our proxies for cognitive skills) and whether they are also nonlinear. Thus this paper investigates two hypotheses: (1) returns to self-competence are nonlinear across different levels of self-competence in a training curriculum and (2) returns to self-competence *and* the cognitive requirement profile are complementary but nonlinear across different levels of self-competence in a training curriculum.

For our dataset, we use the curricula of vocational education and training (VET) programs in Switzerland, which are often also called dual apprenticeship programs. These programs at the upper-secondary education level systematically combine workplace training and school-based training, both based on nationally binding and detailed curricula. VET occupations in Switzerland cover approximately 70% of a youth cohort and thus represent the entire spectrum of middle-skilled jobs in Switzerland. These programs last three or four years and—by law—have to follow a well-specified curriculum (see e.g., Backes-Gellner and Pfister, 2019). Such VET curricula provide very detailed descriptions of the training content of each occupation, including all the technical skills

[8] For many years, scholars have recognized that education and training programs need to incorporate noncognitive skills (e.g., Heckman and Kautz (2012).

and other occupational skills, as well as noncognitive skills that have to be acquired. Given that curricula determine the skills of an occupation, these texts are particularly useful for measuring workers' skills across occupations.[9] Hence, extracting skill measures from these VET curricula to analyze labor market outcomes has been successfully done in previous research (e.g., Eggenberger *et al.*, 2018, Eggenberger and Backes-Gellner, 2023, $ Kiener *et al.*, 2022b).

To identify self-competence, we apply machine-learning methods, such as deep-learning text analysis, to 166 curricula[10]. Based on the curriculum text that describes self-competence, we form three levels of self-competence (low, medium, high) for analyzing nonlinear returns. A high level of self-competence in a particular occupation means that the level is high relative to what we find in all other occupational curricula.

In addition to the occupational training curricula as data, we use two other datasets: First, to measure labor market outcomes and individual characteristics, we use the Swiss Social Protection and Labor Market (SESAM) data. SESAM constitutes a representative sample of the population in Switzerland and includes administrative wage data and information about individuals' sociodemographic characteristics and education. Second, we use a dataset to proxy the extent of cognitive skills requirement profiles in all occupations based on expert assessments (Goetze and Aksu, 2018). We use the mathematical requirements of each occupation ("Anforderungsprofile" in German) to define our "cognitive requirement profile" measure of each occupation.[11] We then link our occupational-level skill measures to individual labor market data for all graduates of these occupations, i.e., they all have finished a VET training and are therefore called "VET graduates." For the link between the occupation and the individual, we take the individuals' training occupation as stated in the labor market data, following the data construction of Eggenberger *et al.* (2018), Eggenberger and Backes-Gellner (2023), and Kiener *et al.* (2022b).

Our regressions on self-competence, using wages as the outcome variable, examine our two hypotheses. First, the results indeed show nonlinear returns to self-competence, with a medium level of self-competence in a curriculum having the strongest positive relationship with wages and

[9] Practical and school-based exams (see e.g., Backes-Gellner and Pfister, 2019) guarantee that VET students possess both the technical skills and the noncognitive skills described in the curricula. This means that in Switzerland, skills vary across occupations rather than within occupations as e.g., shown by Rinawi and Backes-Gellner (2021). See section on data for further details on curricula.

[10] The curriculum database is the same as in Kiener *et al.* (2022b).

[11] Given that Kuhn and Weinberger (2005) use standardized cognitive tests, we also use the mathematical difficulty level (instead of, e.g., language difficulty level) of each training occupation.

with both ends having a lower return.[12] Thus investing *more* self-competence in a curriculum with a *low* self-competence level induces *higher* returns (in an occupation with an average cognitive requirement profile). A possible mechanism behind this result is that a curriculum taking more time to teach workers to become more self-competent rather than teaching more detailed technical skills is more favorable on the labor market (assuming an average cognitive requirement profile). However, taking much more time to teach workers to become even more self-competent and thereby reducing time to teach maybe even basic technical skills is not favorable anymore (if it is not an occupation with very high cognitive requirement profiles, see the second result).

Second, the results on complementarities between self-competence and the cognitive requirement profile also show nonlinear returns. There are only complementary returns between a high level of self-competence and a high cognitive requirement profile. A possible mechanism behind this result is that for occupations with a *high cognitive requirement profile*, workers are required to be able to work independently on challenging, frequently changing, and multiple tasks and to take responsible decisions at any point in time on their own, which is only possible with a high level of self-competence.

While the main focus of this paper is on self-competence, our study also examines social skills[13] to connect it to the results of previous literature and to investigate whether the patterns of returns to the two types of noncognitive skills (self-competence vs. social skills) are different. Results show that the patterns for self-competence are similar but not identical to those for social skills, indicating that these two dimensions of noncognitive skills are indeed different and worth studying separately. Notably, our analyses of social skills also show that examining nonlinearities in returns is important.

While our approach has many advantages (new skill, new measuring method, and novel results), we recognize that our findings primarily show correlational patterns, which is, however, similar to previous studies such as Deming and Kahn (2017) and Palczyńska (2021) (see subsection 5.2 on limitations and future work). Nonetheless, our results also lead to novel policy recommendations: instead of teaching low levels of self-competence and focusing mainly on technical or other professional skills, it seems advantageous to increase the emphasis on teaching

[12] Our results on nonlinear returns to self-competence are very pronounced, such that average returns to self-competence would not be significantly positive.

[13] To identify social skills in curricula, we apply the same methods as for identifying self-competence but, of course, the definition of and words describing social skills—the ability to interact—differs from that of self-competence. Importantly, we analyze self-competence and social skills in separate regressions due to their high correlation, thus we cannot infer from our results which of the two dimensions of noncognitive skills is more important.

self-competence even at the cost of lowering knowledge on technical or other professional details. However, infinitely increasing self-competence will not be valuable because taking too much time to teach very high levels of self-competence at the cost of lowering even basic technical or other professional skills is no longer advantageous because it no longer increases productivity and wages. The only exception is for occupations with very high cognitive requirement profiles for which even high levels of self-competence have higher marginal returns than medium levels.

Section 2 discusses the literature, section 3 describes our data and summarizes our method to measure noncognitive skills, section 4 shows our labor market analyses, and section 5 presents limitations and conclusions. In appendices, we describe in detail our method to identify noncognitive skills in curricula text as data, show in-depth the additional analyses on social skills, as well as present the results for several robustness tests.

2. Lessons from the Literature on Noncognitive Skills and Labor Market Returns

Analyzing *skills* and labor market outcomes has a long tradition in economics, starting with the human capital theory by Becker (1964). Furthermore, economics research studied the transfer of human capital from one firm to the next, leading to the distinction between general and firm-specific human capital (Becker, 1964; Lazear, 2009; Gathmann and Schönberg, 2010; Eggenberger *et al.*, 2018; Eggenberger and Backes-Gellner, 2023). Many further studies have added to the human capital literature, e.g., by introducing psychological capital (Goldsmith *et al.*, 1997) or complementarities between skills and technology (Goldin and Katz, 1998).

Notably, a novel strand of economics literature emphasizes the relevance of *noncognitive* skills—using psychological measures—for labor market outcomes (Heckman *et al.*, 2006; Almlund *et al.*, 2011; Borghans *et al.*, 2008a; Goldsmith *et al.*, 1997). Many studies investigate the importance of personality traits such as the Big-Five, grit, or locus of control on labor market outcomes, but only a few investigate *nonlinearities* in returns to personality traits (Heineck, 2011; Mueller and Plug, 2006; Le *et al.*, 2011).[14] As this paper also aims at examining nonlinear returns, this paragraph points out what we can learn from the few papers that study nonlinearities (we focus on studies on nonlinear returns to "conscientiousness" because this personality trait is connected to our primary focus, self-competence). Heineck (2011)—in the UK—e.g., observes lower wages for individuals in the top 25% of conscientiousness than for those in the middle of the distribution.

[14] Furthermore, Anger and Heineck (2010) focus on interactions between ability and education levels, which is less relevant in our setting with a focus on one education level (VET).

Similarly, Le *et al.* (2011) find—in the Midwest of the US—an inverse U-shaped relationship, for example, for conscientiousness. Moreover, they find that having high levels of conscientiousness is only beneficial for complex jobs. However, coming from psychology, the authors do not use the term complementarities when interpreting their results.[15] In contrast to Heineck (2011) and Le *et al.* (2011), Mueller and Plug (2006) find—in Wisconsin—primarily linear patterns of returns to conscientiousness. In sum, findings from Heineck (2011), Mueller and Plug (2006) and Le *et al.* (2011) point towards nonlinear returns to personality traits, but results are inconclusive (vary across different contexts).

Additionally, a recent strand of economics literature focuses on social skills (Deming, 2017; Deming and Kahn, 2017; Palczyńska, 2021; Weinberger, 2014). These studies show positive wage returns to social skills on average, but they have not investigated nonlinearities so far. Nonetheless, Deming (2017), Deming and Kahn (2017), and Weinberger (2014) point out the importance of complementary returns between social and cognitive skills. Similarly, Palczyńska (2021) analyzes the returns to cognitive skills, Big-Five, and social skills (taking the measures "extraversion" from the Big-Five as well as collaborative job tasks) and finds complementarities between cognitive skills and emotional stability in Poland; however, she does not find evidence for complementarities between cognitive skills and social skills.

While recent economics literature focused on social skills and earlier economics and psychological literature focused on personality traits, the sociological literature has pointed to the importance of *self-competence* as another type of noncognitive skill crucial in the workplace (Salvisberg, 2010).[16] According to Salvisberg (2010), examples of self-competence are being motivated, reliable, autonomous, discrete, even-tempered, enthusiastic, and having perseverance. Self-competence is a noncognitive skill useful in many occupations and jobs, thus analyzing its returns is important.

[15] The results mentioned here are from study 1 of Le *et al.* (2011). Job performance was rated by the supervisor of roughly 600 individuals. The paper is published in a psychology outlet. Of course, they also do not look at training and do not use labor market data from a big representative sample.

[16] See the introduction for the definition of self-competence and its distinction to social skills and personality traits, respectively.

3. Data, Method to Identify Noncognitive Skills in Curricula, and Sample

We use three datasets for our empirical analyses: one for self-competence and social skills in occupational curricula, one for the cognitive requirement profile of occupations, and one for the individual labor market data for VET graduates.

3.1 Curriculum Texts as Data and Methods to Identify Noncognitive Skills

We use the full texts of occupational training curricula to measure the level of self-competence for almost all middle-skilled workers in Switzerland. We use the same curricula as in Kiener *et al.* (2022b)—the 166 Swiss Vocational Education and Training (VET) curricula from 2018 that lead to a three or four year upper-secondary federal diploma (in German, "Eidgenössisches Fähigkeitszeugnis EFZ"). These curricula comprise 8,102 pages, averaging 44 pages for each occupational curriculum, and a total of approximately 1.5 million words, averaging 8,030 for each curriculum.

We argue that VET curricula are suitable to measure noncognitive skills of workers who graduate in the corresponding VET occupations for two main reasons: First, final examinations in each occupational training program ensure that all VET graduates have acquired the skills prescribed in the curricula. The examinations are both practical and school-based and follow the curriculum content (Backes-Gellner and Pfister, 2019). These practical exams help assess that VET students actually learn all the skills (including the noncognitive skills) that are prescribed in the curricula. Second, in Switzerland, it can be assumed that VET training is the main driver of workers' skills (as argued by Rinawi and Backes-Gellner, 2021). Therefore, previous research has shown that occupational training and the respective skills from training curricula (so far only other than noncognitive skills) are closely linked to important labor market outcomes of VET graduates (Eggenberger *et al.*, 2018; Eggenberger and Backes-Gellner, 2023; Kiener *et al.*, 2022b). Thus we argue that VET curricula are an excellent source for measuring and also representing noncognitive skills. Nevertheless, we recognize that our occupational-level skill measures from curricula also have limitations and discuss them in the subsection on limitations and future work in the conclusion.

Our empirical measure essentially captures the importance of self-competence in each curriculum by identifying words describing self-competence based on machine learning methods, which we describe in detail in appendix A. Our machine-learning methodology follows two steps. First, we apply a deep-learning language processing method to the text of all our VET curricula.

This method recognizes all text passages describing all sorts of noncognitive skills that may be taught in an occupation (e.g., creativity, critical and contextual thinking, problem-solving, etc.).

Second, within these text passages on noncognitive skills, we identify the text that describes self-competence by applying further machine-learning methods. In this second step, our methods also account for word similarities following Salvisberg's (2010) self-competence definition, resulting in text that include, for example, "autonomous," "resilience," "dutifully," "independent," "sense of responsibility," "motivated," "readiness to perform," "reliability," "accuracy." All texts passages describing self-competence according to these definitions are used to calculate the levels of self-competence in a curriculum, which is, in essence, the relation of words labeled as describing self-competence over all words in the curriculum, excluding stop words. Thus our measure of self-competence captures the importance of self-competence in relation to the rest of the skills described in an occupational curriculum.

3.2 Further Datasets

As a second dataset, we use a dataset from a career advising context that contains data on the cognitive requirement profile of each occupation as rated by educational and career experts. Specifically, we use their assessment of the math requirement profile of each VET occupation (see Goetze and Aksu, 2018, for their methodology). This measure is very similar to standardized cognitive tests used in previous research (e.g., Kuhn and Weinberger, 2005). Accordingly, we call our variable, which contains the cognitive difficulty level in math, the "cognitive requirement profile" of an occupation.

As a third dataset, we use labor market data for VET graduates from SESAM (a representative dataset for the whole Swiss labor market combining survey and administrative data), which includes data on the individual's training occupation, wages (administrative), sociodemographic characteristics, and education level. In 2010, SESAM changed its survey frequency from annually for a five-year period to quarterly for a one-and-a-half-year period. Given this change in survey frequency, researchers typically use either the pre-2010 or the post-2010 data. Because we are interested in the most recent developments, we use the post-2010 data (i.e., from 2010 through 2018).

3.3 Sample

To build our sample, we match VET graduates from the SESAM data (specifically the working population in Switzerland, aged 18 to 64,[17] with a VET diploma as their highest educational level) to our skill measures at an occupational level. We link the datasets through the individuals' training occupations (following Eggenberger *et al.*, 2018, Eggenberger and Backes-Gellner, 2023, and Kiener *et al.*, 2022b). We do not include observations with missing values for variables needed for the empirical analyses.[18] We calculate the annual wages in full-time equivalents (following Kiener *et al.*, 2022b),[19] and, to avoid outliers in our sample, we exclude observations in the first and last percentiles of the wage distribution.

Our final sample comprises 105,315 observations from 65,349 individuals. For the empirical analyses, we standardize cognitive requirement profiles and the self-competence measure on our sample. Subsequently, to investigate nonlinear returns to self-competence, we build three groups (terciles) of self-competence: occupations with a low, medium, or high level of self-competence.

We display the summary statistics of our sample in three tables. The first table (table I) includes the variables annual wages, cognitive requirement profiles, age, gender, and Swiss nationality. In our sample, the mean of annual wages is approximately 81,000 Swiss francs (roughly $86,000) (calculated in full-time equivalents), cognitive requirement profiles are standardized, and the average age is 44. Moreover, in our sample, 44% are female, and 69% are Swiss nationals. For a more in-depth insight into our main explanatory variable (self-competence), we show the summary statistics of this variable in two tables. In table II, we present the proportion of a curriculum dedicated to self-competence across the self-competence levels.[20] In table III, we

[17] We choose this age range because VET students generally finish their training at age 18, and 64 is the earliest legal retirement age with a full pension.

[18] From our skill measures from 166 VET occupations for which we have curriculum texts, we match the labor market data and drop observations without data on the cognitive requirement profile (6,153 out of 115,121 observations). The other controls do not produce further dropped observations. In addition, we drop the first and last percentile of the wages (1,074 and 2,579 additionally dropped observations) to exclude extreme outliers. This leaves us with a final dataset of 105,315 observations.

[19] Full-time equivalent means that for part-time workers, we adjusted the wage to 100% for a full year. Our main results are robust whether we take full-time equivalents or not.

[20] Our measures are the relative proportion of a curriculum dedicated to self-competence and thus two questions may arise: First, does the length of a curriculum (total number of words) drive our results? We do not find that the total number of words is systematically different across curricula in a way that may distort our results. Second, does taking a measure with the absolute number of words dedicated to self-competence lead to any different results? We find that our main results do not change.

show the standardized values for each level of self-competence because we form the terciles from these standardized values.

Table I: Summary statistics of wages, the cognitive requirement profile, age, female, and Swiss.

Variable	*Mean*	*St. dev.*	*Min*	*Max*	*N*
Annual wages	81,116	33,625	8,313	233,667	105,315
Cognitive requirement profile	0.0	1	-2.06	2.32	105,315
Age	43.61	11.64	18	64	105,315
Female	0.44	0.50	0	1	105,315
Swiss nationality	0.69	0.46	0	1	105,315

Notes: Authors' calculations of the summary statistics from their sample (a representative sample of VET workers in Switzerland, from SESAM, 2010–2018, matched to their skills measures, without observations with missing values of the needed variables, without the first and last percentile of wages). The values cover overall observations. The cognitive requirement profile stems from expert rating on the cognitive difficulty level in math and is standardized on the labor market sample.

Table II: Summary statistics of self-competence across levels (proportion).

Variable	*Mean*	*St. dev.*	*Min*	*Max*	*N*
low self-competence level	0.07%	0.11%	0%	0.34%	37,476
medium self-competence level	0.42%	0.04%	0.34%	0.48%	36,949
high self-competence level	1.34%	0.94%	0.50%	4.40%	30,890

Notes: Authors' calculations of the summary statistics from their sample (a representative sample of VET workers in Switzerland from SESAM, 2010–2018, matched to their skills measures, without observations with missing values of the needed variables, without the first and last percentile of wages). The values cover overall observations. Self-competence is standardized on the sample and then grouped into three levels (terciles).

Table III: Summary statistics of self-competence across levels (values standardized on the sample).

Variable	*Mean*	*St. dev.*	*Min*	*Max*	*N*
low self-competence level	-0.68	0.15	-0.77	-0.31	37,476
medium self-competence level	-0.20	0.05	-0.31	-0.11	36,949
high self-competence level	1.06	1.28	-0.09	5.25	30,890

Notes: Authors' calculations of the summary statistics from their sample (a representative sample of VET workers in Switzerland from SESAM, 2010–2018, matched to their skills measures, without observations with missing values for the required variables, without the first and last percentile of wages). The values relate to overall observations. Self-competence is standardized on the wage sample and then grouped into three levels (terciles). This table displays the standardized values of each level of self-competence.

4. Empirical Analyses: Noncognitive Skills and Wage Returns

Before turning to our hypothesis tests on nonlinearities in returns to self-competence, we illustrate the interpretation of our skill measures with a couple of illustrative example occupations. We do so to have a better foundation for understanding the subsequent results from the wage analyses.

4.1 Noncognitive Skills in Illustrative Example Occupations

In this subsection, we provide descriptive results for six occupations as illustrations. These six occupations are among the most common occupations on the Swiss labor market, and they are only meant to intuitively understand our skill measures (in the later hypothesis testing, we use the full dataset with all occupations). The six occupations are: automotive technician, cook,

commercial employee (an office worker carrying out administrative tasks), hairdresser, logistician (involved in transporting, storing, and distributing goods), and laboratory assistant.[21]

Table IV shows the values for self-competence and the cognitive requirement profile of these example occupations. For self-competence, the table shows at which level (low, medium, or high) the occupation lies in comparison to all occupations in our labor market sample. For the three levels of self-competence, the high level is the third tercile; the medium level, the second; and the low level, the first. For cognitive requirement profiles, the table shows the standardized values in our sample. Due to the standardization, positive (negative) values indicate that the occupation demands a cognitive requirement profile above (below) the average of all individuals in our labor market sample.

Table IV: Examples of occupations (levels of self-competence and the cognitive requirement profile).

Occupation	*Self-Competence Level*	*Cognitive Requirement Profile*
Automotive Technician (in German, "Automobil-Fachfrau/-mann")	medium	0.54
Cook (in German, "Köchin/Koch")	high	-1.30
Commercial Employee (in German, "Kauffrau/-mann")	medium	0.35
Hairdresser (in German, "Coiffeuse/Coiffeur")	high	-1.81
Logistician (in German, "Logistiker/-in")	low	-1.42
Laboratory Assistant (in German, "Laborant")	high	1.05

Notes: Authors' calculations of their skill measures of six common VET occupations as examples. Self-competence measures are standardized on the labor market sample and then grouped into terciles (high level is the third tercile; medium, the second; and low, the third). The cognitive requirement profile stems from expert rating on the cognitive difficulty level in math and is standardized on the labor market sample.

The automotive technician—who maintains and repairs engines and cars—is at the second self-competence level, i.e., the share of self-competence in the curriculum is at a medium level relative to the entire labor market sample. The cognitive requirement profile is above the mean. In

[21] We derive the short descriptions of these occupations from the Swiss VET career counseling office (https://www.berufsberatung.ch/dyn/show/1893).

comparison, the cook has a cognitive requirement profile below the mean and a high level of self-competence.

The commercial employee—who handles administrative and organizational tasks—is at the medium self-competence level and has a cognitive requirement profile above the mean. In contrast, the hairdresser is at the highest level of self-competence, with a cognitive requirement profile below the mean.

An example of an occupation with a high self-competence level and a high cognitive requirement profile is the laboratory assistant. In contrast, the logistician—who primarily transports, stores, and distributes goods—is at a low level of self-competence, with a cognitive requirement profile below the mean, which may be due to highly standardized processes in this occupation in comparison to other occupations and thus may require only low levels of self-competence to act responsibly or interact with other people. These examples show how our measures can be interpreted in real-world examples and how our characterizations of self-competence and cognitive requirement profiles provide useful results.

4.2 Empirical Wage Analyses

Our following wage analyses test the first (nonlinear returns to self-competence) and the second hypotheses (nonlinear complementary returns between self-competence and the cognitive requirement profile) one after the other. We always use three levels (terciles) for self-competence to study whether the returns of the different levels increase in a nonlinear way. We also include the cognitive requirement profile and the interactions between the self-competence levels and the cognitive requirement profile. By using controls for the cognitive requirement profile in all of our estimations, we account, for example, for differences in occupational complexity across occupations.

For the main analysis, we conduct a Mincer-type OLS regression:

$$log\ (wage)_{\ i,t} = \beta_0 + \beta_1 MediumSelfCompetence_i +$$
$$\beta_2 HighSelfCompetence_i + \beta_3 CognitiveRequ_i +$$
$$\beta_4 MediumSelfCompetence_i * CognitiveRequ_i +$$
$$\beta_5 HighSelfCompetence_i * CognitiveRequ_i +$$
$$\beta_6 gender_i + \beta_7 age_{i,t} + \beta_8 age_{i,t}^2 + \beta_9 Swiss_i + \beta_{10-18} year_{i,t} + \varepsilon_{i,t}$$

, where $t = 2010, \dots, 2018;\ i = 1, \dots, N$.

The dependent variable is the log of annual wages. The main explanatory variables are dummies for the medium and high levels of self-competence (*MediumSelfCompetence*, *HighSelfCompetence, compared to LowSelfCompetence as reference category*) and the cognitive requirement profile (*CognitiveRequ*). We use these variables to test the first hypothesis. To test the second hypothesis, we examine the interaction of the dummies for the medium and high levels of self-competence with the cognitive requirement profile (*MediumSelfCompetence*CognitiveRequ, HighSelfCompetence*CognitiveRequ*). As all skill measures are at the level of the occupation in which the individual worker was trained, standard errors are clustered at the level of the training occupation. We also control for individual characteristics (*gender, age, age squared, Swiss nationality*) and *year*.[22]

Our main analyses focus on self-competence.[23] We do not incorporate social skills due to the high multicollinearity between self-competence and social skills (see correlation table C.1 in the appendix). But we analyze social skills separately and in line with previous research in appendix B (conducted the same way as our main analyses).[24]

The following paragraphs first explain our empirical results for our two hypotheses and second show the implications of our results by elaborating on the illustrative example occupations.

Our first hypothesis states that returns to self-competence are nonlinear. The regression results show that the wage returns to self-competence are indeed nonlinear: A medium level of self-competence, compared to low and high levels, is associated with the highest wage returns (in occupations with an average cognitive requirement profile). Table V shows that individuals trained in occupations at the *medium* self-competence level receive a positive wage premium of 10.9 percent relative to our baseline, the low self-competence level (see regression 2 in table V). However, those trained in occupations at the *high* self-competence level do not receive a positive wage premium relative to our baseline. Moreover, the positive wage return for the medium self-competence level is statistically different from those for the high self-competence level. Thus,

[22] Moreover, in the main analyses, we decided to only include controls that are not influenced by the training occupation, following the general rule of avoiding bald controls proposed by e.g., Angrist and Pischke (2009). Nonetheless, adding industry controls for robustness tests could lead to additional insights, which is why we include them as robustness tests but they do not change our main results (see appendix).

[23] In our main results tables, we also show results for a restricted sample of individuals below age 30. We do so to show that our results are robust for this restricted sample of younger individuals that are closer to their education.

[24] Similar to Albandea and Giret (2018), who used wage quantiles, we also conducted quantile wage regressions on the 25th, 50th, and 75th quantiles. These additional analyses show that our main results are robust across the different wage quantiles (cf. tables in the appendix C).

because the wage returns to self-competence first increase and then decrease across levels, they are nonlinear.[25]

Furthermore, the results show that the cognitive requirement profile is, *on average*, also important: a one-standard-deviation increase in the cognitive requirement profile is, on average, associated with 3.8 percent higher wages (regression 2 in table V).

Table V: Nonlinear wage returns to self-competence.

VARIABLES (Baseline: low self-competence)	**Full sample**			**Below age 30**
	(1)	(2)	(3)	(4)
	log wage	*log wage*	*log wage*	*log wage*
medium self-competence	0.113***	0.109***	0.113***	0.074***
	(0.031)	(0.029)	(0.029)	(0.026)
high self-competence	-0.065*	-0.044	-0.024	-0.011
	(0.038)	(0.037)	(0.039)	(0.023)
cognitive requirement profile		0.038***	0.023**	0.020**
		(0.012)	(0.011)	(0.009)
*medium self-competence*cognitive requirement profile*			-0.037	0.007
			(0.030)	(0.052)
*high self-competence*cognitive requirement profile*			0.073***	0.062***
			(0.028)	(0.020)
age, age²	Yes	Yes	Yes	Yes
gender	Yes	Yes	Yes	Yes
Swiss	Yes	Yes	Yes	Yes
years	Yes	Yes	Yes	Yes
Constant	9.691***	9.675***	9.679***	7.146***
	(0.053)	(0.057)	(0.054)	(0.325)
Observations	105,315	105,315	105,315	15,586
Number of individuals	65,349	65,349	65,349	10,793
R^2 overall	0.148	0.154	0.160	0.187
R^2 between individuals	0.155	0.160	0.167	0.195

Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. Standard errors in parentheses clustered on training occupation. * p<0.10, ** p<0.05, *** p<0.01. Reading example of the coefficient of the medium self-competence level in regression (1): "Compared to the low self-competence level, individuals trained in occupations at the medium self-competence level receive a positive wage premium of 11.3 percent."

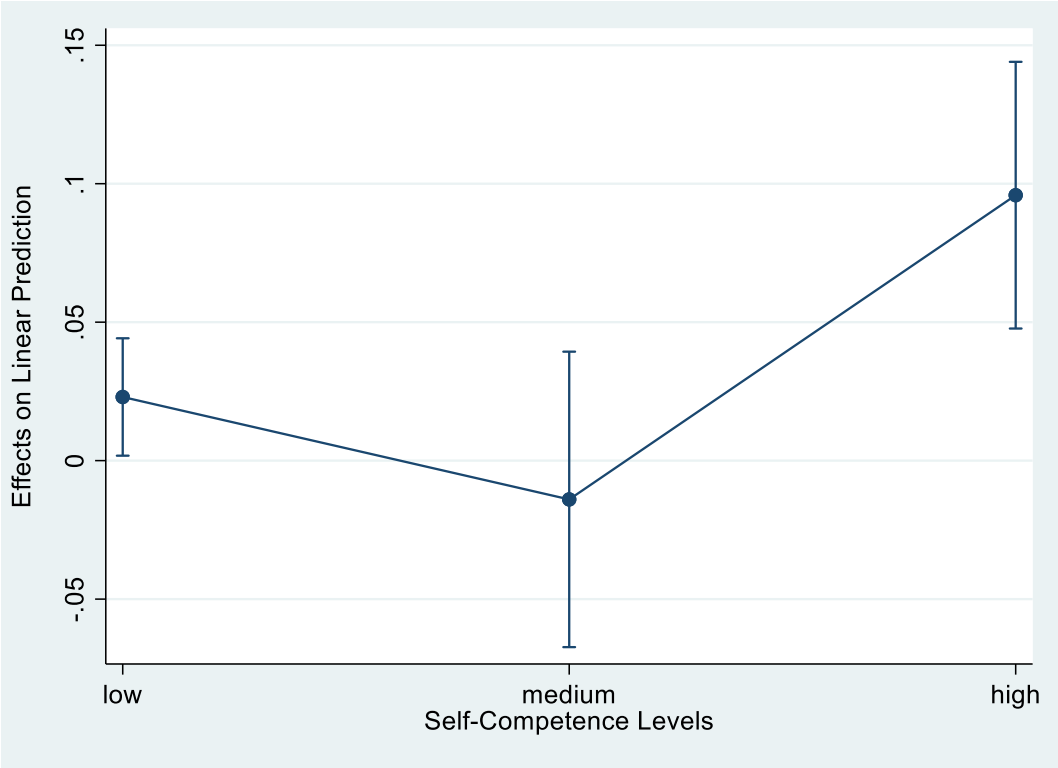
[25] This nonlinear pattern is so pronounced that average returns to self-competence would not be significantly positive.

Our second hypothesis states that complementary returns between self-competence levels and the cognitive requirement profile are also nonlinear. The regression results including interaction terms show that these complementary returns are indeed nonlinear (see regression 3 in table V). Looking at occupations with above-average cognitive requirement profiles: For the *high* self-competence level, the additional, complementary return is positive, but in contrast, for the *medium* self-competence level, the additional, complementary wage return is not significantly positive. Thus, for cognitively demanding occupations, the wage returns to self-competence are nonlinear: They primarily increase at the high self-competence level. Moreover, given the statistically significant difference between the coefficient of the high self-competence level and the coefficient of the interaction between the high self-competence level and the cognitive requirement profile, a high self-competence level is only worthwhile in occupations with a high cognitive requirement profile.

To further illustrate the nonlinear complementary returns between self-competence levels and the cognitive requirement profile, we plot the average marginal effect (dy/dx) of the cognitive requirement profile across different self-competence levels. While for the high (low) self-competence level, a one-standard-deviation increase of the cognitive requirement profile has a significant positive marginal wage return of 0.095 (0.023), the marginal wage return for the medium self-competence level and the one-standard-deviation increase in the cognitive requirement profile is not different from zero. Thus the figure further emphasizes that in occupations with a high cognitive requirement profile, a high self-competence level pays off.[26]

[26] Compared to the previous literature, our results on self-competence are novel as we are the first to examine self-competence and nonlinear returns. Nonetheless, when we compare our results with previous literature on nonlinear returns to conscientiousness (see literature section), we find similar patterns as Heineck (2011) and Le *et al.* (2011).

Figure 1: Marginal effects of the cognitive requirement profile across self-competence levels



Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. This figure is a margins plot after we run regression 3 in table V and calculate the marginal effects of self-competence levels with regard to the cognitive requirement profile.

We argue that the results are likely driven by a trade-off given that all curricula have fixed training time, i.e., the training time spent on increasing self-competence possibly reduces the time spent on technical and other important occupational skills, in combination with diminishing marginal returns for skills. Moreover, in occupations requiring a high cognitive profile, higher levels of self-competence have higher marginal returns.

To illustrate what these self-competence results mean in the context of particular occupations, we return to our earlier examples.[27] For a logistician, who is at a low level of self-competence, moving to a higher (medium) level of self-competence could lead to a wage increase because being more reliable, autonomous, or motivated would likely increase the individual's productivity. Moreover, an automotive technician with a medium self-competence level and a high cognitive requirement profile would receive an additional, complementary benefit if they would

[27] To illustrate our results, we focus on differences in occupational self-competence levels and see the cognitive requirement profile of an occupation as constant. Moreover, these illustrating examples are based on the assumption that the individual currently works in the training occupation.

have a high self-competence level because in such a cognitively demanding occupation, having a high self-competence level is additionally productive.

In the appendix. we also study social skills to compare our results to previous literature and to our self-competence results (see appendix B for the detailed analyses). Our findings are twofold: First, we find nonlinearities in the returns to social skills: The point estimates for the difference between low and medium levels of social skills are higher than the differences between medium and high levels (however, they are not significantly different and we cannot reject a null hypothesis of linear returns to social skills). Second, for complementary returns, our results indicate a nonlinear pattern: A high level of social skills combined with a high cognitive requirement profile has a higher positive return than that of a medium level of social skills combined with a high cognitive requirement profile.[28] Thus, adding to previous literature, our results indicate that nonlinearity is also important with respect to social skills. Previous studies also investigated social skills and complementarities between social skills and cognitive skills (Deming, 2017; Deming and Kahn, 2017; Palczyńska, 2021; Weinberger, 2014). Primarily, these studies find positive complementary returns, but Palczyńska (2021) finds—for Poland—no complementary returns (see literature section). In additional analyses, we also show—*at the mean*—positive individual returns of both social skills and the cognitive requirement profile and a complementary return of social skills and the cognitive requirement profile (see table C.II in the appendix). As our results are broadly in line with previous results, this also indirectly confirms the validity of our methods for measuring noncognitive skills from occupational curricula texts (as well as of our proxy for cognitive skills).

5. Conclusion

5.1 Concluding Remarks

In this paper, we investigate self-competence as one important dimension of noncognitive skills that is required in the workplace in modern economies. We draw on a socio-psychological concept (Salvisberg, 2010; Roth, 1971) when introducing self-competence to economics research and extend recent economics studies focusing mainly on social skills (Deming, 2017; Weinberger, 2014; Deming and Kahn, 2017). Similar to these recent economics studies, we build on the skill perspective in the sense that skills can be acquired by workers (i.e., skills are not innate). However,

[28] Beyond these two important results on nonlinear returns to social skills, we also find significantly positive average returns to social skills—a finding in line with most of the previous literature on social skills.

one challenge of previous studies of noncognitive labor-market relevant skills was that measuring these skills was difficult because they cannot be proxied by years of education or by test scores (measures that have been readily available so far). To overcome this problem, we use the content of occupational training curricula. We take the vast quantity of curriculum texts and apply advanced machine-learning methods to identify noncognitive skills, particularly self-competence (as well as social skills, which are also used in a new study by Kiener *et al.*, 2022a), that are taught in an occupational training program. We contribute methodologically to the economics literature on skills because we introduce a method that can also be used in other training contexts and to measure other skills of interest that we have not been addressing in this paper.

Another major contribution of our paper is to show that analyzing nonlinearities in returns to labor market-relevant noncognitive skills is crucial.[29] For self-competence, we find the highest wage returns when teaching a medium level of self-competence in a given time, compared to a low or a high level. We also find complementarities between the cognitive requirement profile and the returns to self-competence. Here again, we find nonlinear returns: teaching a high level of self-competence only increases wages in occupations with a high cognitive requirement profile.

Our results on the nonlinearity of returns to noncognitive skills such as self-competence also lead to important insights for designing occupational training curricula because these results point to essential trade-offs in curricula. Teaching self-competence, i.e., encouraging individuals to act responsibly on one's own, is a very important part of occupational training curricula, but it has to be at the right level in comparison to other skills taught in the same curriculum: A medium level of self-competence in training curricula is generally most valuable in comparison to occupational curricula that spend almost no time or an excessive amount of time on self-competence.

To incorporate self-competence, curricula could be improved by better combining the learning of occupational skills with simultaneously acquiring noncognitive skills such as self-competence (especially in occupations with a low level of self-competence and with average or below-average cognitive requirement profiles). For example, technical and other occupational skills could be better connected with self-competence by fostering more independent learning projects, for which a strong foundation of technical skills also needs to be applied. Only in occupations with a high cognitive requirement profile, fostering very high levels of self-

[29] As shown in the introduction and literature section, research on personality traits already dealt with nonlinearities in returns, while research on social skills primarily investigates returns at the mean.

competence pays off because these occupations have high levels of discretion that need to be combined with high levels of self-competence. Thus our findings on nonlinear returns to noncognitive skills provide important policy lessons for curricula design. Adjusting the design of curricula may likely contribute to higher returns for workers and thereby possibly reduce labor market inequalities.

5.2 Limitations and Avenues for Future Work

While our paper makes several important contributions on nonlinear returns to noncognitive skills taught in training curricula, future research could address three key limitations of our approach. First, when studying the relationship between the skill composition of workers and their wages, we cannot distinguish whether our results originate from a selection effect, in line with Borghans *et al.* (2008b), or from a causal effect, in line with Heckman and Kautz (2012). A causal effect would occur if workers acquire or substantially strengthen their skills during training. A selection effect would occur if workers with high self-competence choose occupations that strongly emphasize the need for self-competence. Both mechanisms together could drive our results, as shown by Hoeschler *et al.* (2018) for "grit," so a causal effect is likely to be lower than the coefficients that we estimate in our analysis. In other words, our results are driven by (a) VET curricula prescribing the teaching of large amounts of self-competence, thereby increasing individuals' self-competence and (b) individuals with already comparatively higher levels of self-competent selecting into occupations that prescribe the teaching of larger amounts of self-competence. If future research would want to disentangle these effects, it should try to use either quasi-experimental settings or randomized control trials.[30] However, these approaches cannot be used for regulated national curricula, like in our case of VET occupations, because they have to be taught in the same manner everywhere. However, such a research design may be possible in short-term training settings or any type of unregulated educational program or continuous training measures (as in Barrera-Osorio *et al.*, 2020, for example).

Second, future work could improve the econometric analyses in two ways: through datasets with further controls and through novel econometric methods accounting for multidimensional skills. Regarding further controls, future studies could integrate more controls on the background, such as the economic circumstances within a training firm or the educational background (own or

[30] In a hypothetical experimental design, we would measure first how self-competent an individual performs specific tasks in the work environment and second, randomly assign individuals in the same occupation to three different levels of self-competence training, and third, we would conduct the measurement again.

parental background). As our dataset with its focus on the labor market does not include such variables, we cannot exclude that such factors may affect our results. Future research could use new administrative educational datasets that can be matched to labor market outcomes and that allow using additional controls such as school grades or parental education. Regarding new methods, future research could, e.g., use econometric machine-learning methods to provide new solutions for analyzing multidimensional skills.

Third, future work could try to measure self-competence at the individual level, for example by socio-psychological test batteries, instead of the level of the occupational training program. In this paper, we only have information at the occupational level, therefore, we need to build on simplifying assumptions. One important assumption, for example, is that the amount of technical and occupational skills in curricula are constant across our VET occupations. However, if differences would exist, they are not accounted for in our analyses and may distort our results. So future research could try to measure all skills in a more direct way. Our paper contributes a novel methodology for using training curricula as data source to do so and future research could explore more skills in more detail.

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Appendices

Appendix A: Measuring Noncognitive Skills in VET Curricula

This appendix explains in detail our methodology to measure noncognitive skills in VET curricula. We identify self-competence with a two-step procedure. First, we identify any text passages in a curriculum that contains any type of noncognitive skill. Second, we identify which parts describe self-competence (and, likewise, social skills) using keywords found in these text passages. Both steps are explained in the following subsections.

First Step: Identifying Text Passages with Noncognitive Skills

The first step, identifying curriculum text passages describing noncognitive skills, uses deep learning, which comprises complex, nonlinear learning and neural networks, and is similar to human thinking through learning from experience and breaking down concepts into simpler ones (Goodfellow *et al.*, 2016). As deep learning most closely approximates human thought processes, the method constitutes a highly useful approach for analyzing large quantities of unstructured texts (Meng *et al.*, 2018), such as our VET training curricula.

The principle of the deep-learning method follows typical supervised machine-learning processes: a deep neural network uses input data (unstructured) and training data (structured and labeled) to generate the output data (structured and labeled). Our deep-learning method for measuring noncognitive skills was developed by Gnehm (2018), who segments job postings into different text passages called “text zones.” One of these text zones identifies noncognitive skills

(see Schultheiss *et al.*, 2018, or Schoen and Gnehm, 2019, for two studies using Gnehm's text zones).[31] Applying the same method as Gnehm (2018), we use curriculum texts as our input data.

Figure A.1 graphically shows the different parts of the method and includes text examples as illustrations. As training data, first, we use job postings because the model developed by Gnehm (2018) is trained on job postings data (example 1).

> **Example 1: Training data for noncognitive skills from a SJMM job posting for a carpenter**, which describes the prerequisites of a potential applicant as follows (italicized words are those labeled as noncognitive skills): "Successfully completed apprenticeship as a carpenter with at least two years of work experience; *reliable, flexible, quality-conscious and on schedule; precise and clean work; punctuality and good manners*."

The training data covers approximately 25,000 job postings from the Swiss Job Market Monitor (SJMM).[32] SJMM experts have categorized these job postings into text zones, with one text zone capturing noncognitive skills. The SJMM experts' definition of noncognitive skills follows Salvisberg's (2010) sociological concept, which includes social skills and self-competence as two important dimensions. Given that job postings constitute a type of text similar to curricula, they are highly suitable for using as training data in a model applied to curricula. The main advantages of using this training data are the large size of *labeled* text data (in contrast to the lack of labeled curricula text data) and manual labeling that follows Salvisberg's (2010) well-established theoretical concept.

Second, we feed a set of eight occupational curricula into the training data to fine-tune the model for our purpose. To ensure that the specific language used in curricula is also well represented in our training dataset, we manually labeled the noncognitive skills in the eight curricula ourselves (example 2).

[31] Gnehm (2018) uses recurrent neural networks, a subclass of neural networks, that are suitable for sequence labeling, because they are flexible in the use of the context information: They easily recognize what information to store and what to forget. In particular, Gnehm uses bidirectional long short-term memories (BiLSTMs), a class of recurrent neural networks that considers the context before and after a labeled text passage.
[32] The SJMM corpus is available at forsbase.unil.ch (Buchmann *et al.* (2020).

Example 2: Training data for noncognitive skills from a VET curriculum using a "Florist" as an example (italicized words are those labeled as noncognitive skills): "Florists are able to *independently* and *autonomously advise* and *serve customers with different needs*."

Third, following the same reasoning, we feed twelve definitions of noncognitive skills, provided in the introductory parts of the curricula, into the training data (example 3).

Example 3: Training data from the introductory part of a VET curriculum using a "Cooling System Technician" as an example for a definition of their required noncognitive skills (italicized words are those labeled as noncognitive skills): *"Creative thinking and acting, openness to new ideas and unconventional solutions* are important skills of cooling system technicians.… They *assess themselves realistically* and *seek support* if necessary."

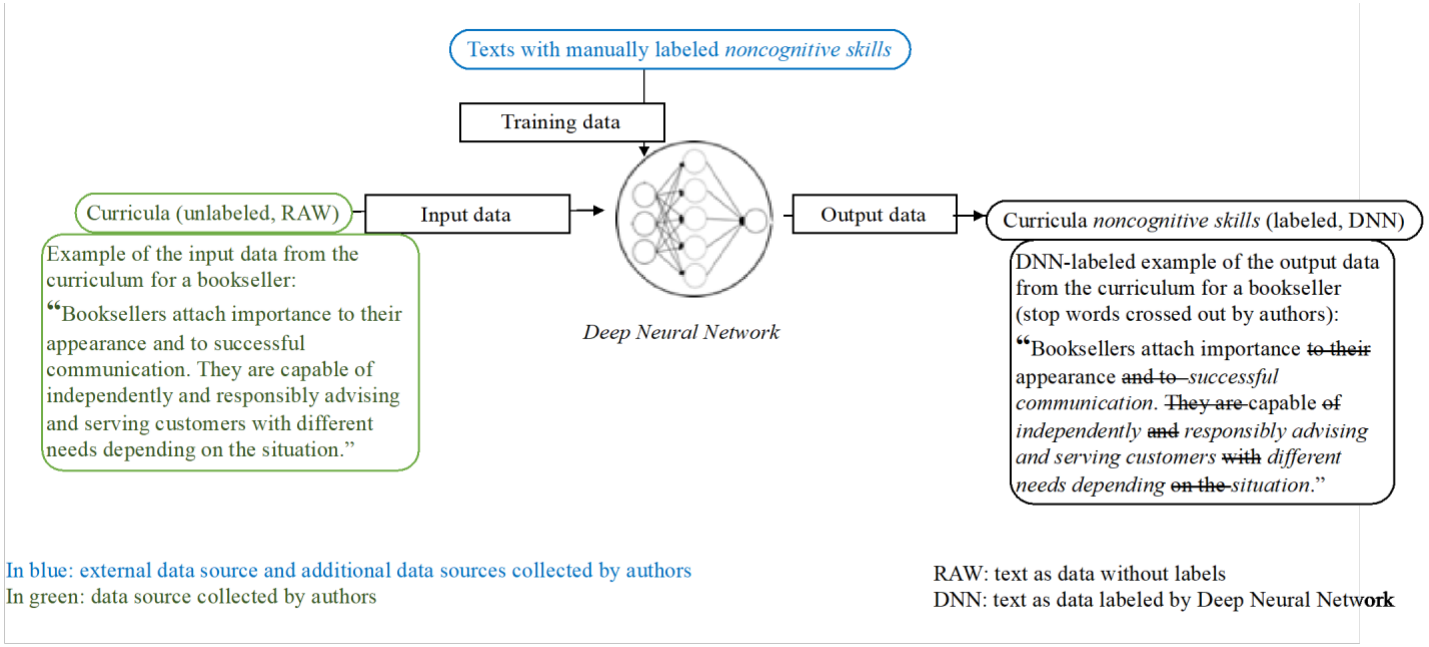
This training data provides a solid foundation that we can use to apply a deep-learning method to VET curricula (input data) and thus produce labeled texts marked for noncognitive skills in occupations (example 4).

Example 4: Output data from a VET curriculum with labeled noncognitive skills text passages (italicized parts of the text; "stop words"[33] are crossed out by the authors): "Booksellers attach importance ~~to their~~ appearance ~~and to~~ *successful communication*. ~~They are~~ capable ~~of~~ *independently* ~~and~~ *responsibly advising* ~~*and*~~ *serving customers* ~~with~~ *different needs depending* ~~on the~~ *situation*… Booksellers demonstrate how to add new products to the product range and to attract new customer groups."

Figure A.1 graphically illustrates the different parts of the method. The labeled curricula text passages of noncognitive skills form the backbone for identifying self-competence and social skills in the second step.

[33] A "stop word" is a very commonly used word that adds no real value regarding the content of a sentence (e.g., "the" or "as").

Figure A.1: Method for labeling curricula text passages describing noncognitive skills.



Notes: Authors' illustration of the method used for labeling curricula text passages describing noncognitive skills.

Second Step: Identifying Self-Competence and Social Skills in Text Passages with Noncognitive Skills

In the second step, after recognizing any text passages describing any type of noncognitive skills, we specifically identify text with words describing self-competence and social skills by applying further machine-learning techniques. We do so by proceeding in three substeps. First, we select typical words of self-competence and social skills according to Salvisberg's (2010) concept from a list of the 300 most frequent noncognitive skill words in the SJMM corpus.[34] Second, we use a word-embedding technique that uses contextual information to find synonyms of and similar words for the selected "typical" words.[35] Third, we apply the typical words for social skills and self-competence (from substep one) and similar words (from substep two) to analyze which ones occur in text passages mentioning the noncognitive skills of each curriculum.

Examples of the most frequently occurring words that indicate self-competence and social skills in the curricula appear in table A.I. We use them and all less frequent words to calculate the proportions of social skills and self-competence within each occupational curriculum. The proportions constitute the words labeled as self-competence or social skills over all words in the curriculum (excluding stop words). The proportions reflect our intensity measure of self-competence and social skills.

[34] A possible concern is that we fixed the threshold at 300 words. However, from a natural language processing (NLP, i.e., machine-learning applied to texts) perspective, such thresholds are very common. Moreover, we use the list for synonyms and similar words, and because words around the threshold would most likely be synonyms for words mentioned earlier in the list, the threshold is a "soft" (not absolute) limit.

[35] We use word2vec embeddings Mikolov *et al.* (2013) trained on the online job postings corpus of 9 million job postings. We set the default parameters as specified by Mikolov et al. (2013), and we train embeddings over lemmatized and lower-case words belonging to the skills and task descriptions in the job postings. We use a cosine similarity threshold of 0.6 for suggesting similar words; for example, for the original word "curiosity," we find the similar word "creativity."

Table A.I: Examples of the most frequent words for self-competence and social skills within the curricula.

Self-competence	autonomous, resilience, dutifully, independent, sense of responsibility, motivated, readiness to perform, reliability, accuracy
Social skills	communication skills, team spirit, manners, ability to deal with conflicts, ability to work in a team, convincing, friendly, empathy

Notes: Examples are the results of the NLP methods, as described in this section.

Appendix B: Empirical Results for Returns to Social Skills

This appendix contains our additional empirical results for returns to social skills that are not in the main paper because the analysis of social skills is not the main focus of the paper. However, they show that self-competence and social skills follow similar—but not identical—patterns, and importantly, the results on social skills are consistent with results from previous literature, which indirectly confirms the suitability of our measuring methodology. In describing our results, we follow the exact same structure of estimations and tables as in the main document. Before we present our results, we provide the summary statistics for our social skills measure.

Summary statistics of social skills[36]

Table B.I: Summary statistics of social skills across levels (proportion).

Variable	*Mean*	*St. dev.*	*Min*	*Max*	*N*
low social skills level	0.11%	0.09%	0%	0.29%	35,333
medium social skills level	0.78%	0.33%	0.30%	1.09%	55,563
high social skills level	1.67%	0.55%	1.12%	2.81%	14,419

Notes: Authors' calculations of the summary statistics from their sample (a representative sample of VET workers in Switzerland from SESAM, 2010–2018, matched to their skills measures, without observations with missing values of the needed variables, without the first and last percentile of wages). The values cover overall observations. Social skills are standardized on the sample and then grouped into three levels (terciles). The number of observations across social skills terciles is not equally distributed because the social skills measure of the largest occupation (commercial employee) falls directly in the second tercile, not the third.

[36] In the summary statistics in the main text, the number of observations across self-competence levels is evenly distributed. However, the number of observations across social skills levels is not equally distributed, because the social skills measure of the largest occupation (commercial employee) falls directly in the medium level (second tercile), not the high one (third tercile).

Table B.II: Summary statistics of social skills across levels (values standardized on the sample).

Variable	*Mean*	*St. dev.*	*Min*	*Max*	*N*
low social skills level	-0.96	0.16	-1.14	-0.64	35,333
medium social skills level	0.18	0.55	-0.64	0.71	55,563
high social skills level	1.68	0.93	0.75	3.61	14,419

Notes: Authors' calculations of the summary statistics from their sample (a representative sample of VET workers in Switzerland from SESAM, 2010–2018, matched to their skills measures, without observations with missing values for the required variables, without the first and last percentile of wages). The values relate to overall observations. Social skills are standardized on the wage sample and then grouped into three levels (terciles). This table displays the standardized values of each level of social skills. As in the previous table, the number of observations across social skills terciles is not equally distributed because the social skills measure of the largest occupation (commercial employee) falls directly in the second tercile, not the third.

Empirical results for social skills

We test the same hypotheses as for self-competence but now replace self-competence with social skills. The results on the first hypothesis (nonlinear returns to social skills) indicate that wage returns to social skills are likely nonlinear: Individuals trained in occupations at the *medium* level of social skills receive a positive wage premium of 12.2 percent relative to our baseline, the low social skills level (see regression 2 in table B.III). Those trained in occupations at the *high* social skills level also receive a positive wage premium relative to our low-level baseline (see regression 2, the coefficient of 9.1 percent).

Given that the coefficients of the medium and high social skills levels do not significantly differ, we do not interpret this difference. We cannot reject the possibility that returns to social skills are linear; in other words, the results on social skills are not as conclusive as those for self-competence. However, the patterns still point to our hypothesis that the returns to social skills are nonlinear because they do not proportionally increase across the social skills levels (i.e., the increase between the low and medium levels is smaller than that between the medium and the high levels).

Table B.III: Nonlinear wage returns to social skills.

VARIABLES (Baseline: low social skills)	Full sample			Below age 30
	(1)	(2)	(3)	(4)
	log wage	*log wage*	*log wage*	*log wage*
medium social skills	0.077**	0.122***	0.094***	0.031*
	(0.035)	(0.033)	(0.034)	(0.017)
high social skills	0.024	0.091*	0.104***	0.038
	(0.058)	(0.051)	(0.040)	(0.028)
cognitive requirement profile		0.072***	0.037**	0.015
		(0.016)	(0.017)	(0.010)
*medium social skills * cognitive requirement profile*			0.030	0.055**
			(0.036)	(0.024)
*high social skills * cognitive requirement profile*			0.116***	0.104***
			(0.027)	(0.022)
age, age^2	Yes	Yes	Yes	Yes
gender	Yes	Yes	Yes	Yes
Swiss	Yes	Yes	Yes	Yes
years	Yes	Yes	Yes	Yes
Constant	9.668***	9.629***	9.652***	7.134***
	(0.052)	(0.055)	(0.057)	(0.332)
Observations	105,315	105,315	105,315	15,586
Number of individuals	65,349	65,349	65,349	10,793
R^2 overall	0.128	0.146	0.154	0.184
R^2 between individuals	0.135	0.152	0.160	0.191

Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. Standard errors in parentheses clustered on training occupation. * p<0.10, ** p<0.05, *** p<0.01. Reading example of the coefficient of the medium social skills level in regression (1): "Compared to the low social skills level, individuals trained in occupations at the medium social skills level receive a positive wage premium of 7.7 percent."

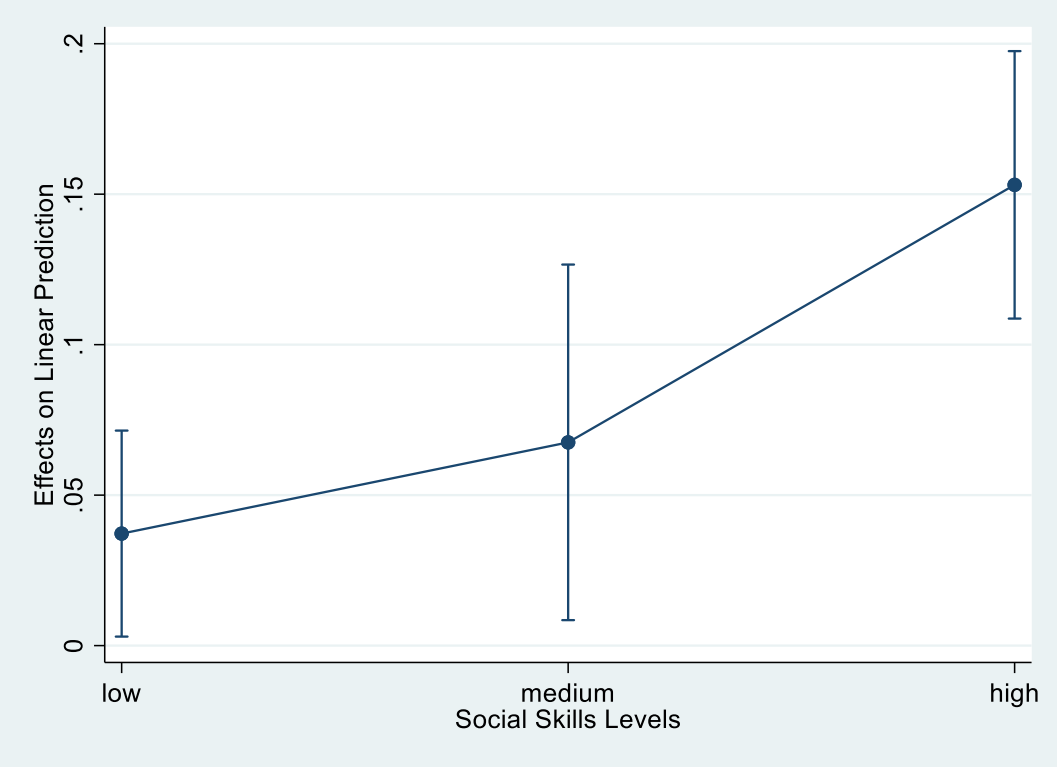
The second hypothesis states that complementary returns between social skills and the cognitive requirement profile are nonlinear. The results show that the return is positive for the *high* social skills level when the cognitive requirement profile is high (see regression 3 in table B.III). Looking at occupations with above-average cognitive requirement profiles: For the *high* social skill level, the additional, complementary return is positive, but in contrast, for the *medium* self-competence level, the additional,

complementary wage return is not significantly positive (see regression 3 in table B.III). Thus for occupations with a high cognitive requirement profile, the wage returns to social skills are nonlinear: They primarily increase at the highest level, showing patterns similar to those of self-competence.[37]

To further shed light on the nonlinear complementary returns between social skills levels and the cognitive requirement profile, we plot the marginal effect (dy/dx) of the cognitive requirement profile across social skills levels. For the high social skills level, a one-standard-deviation increase of the cognitive requirement profile has a significant positive marginal wage return of 0.153. In comparison, the marginal wage return for the medium social skills level and a one-standard-deviation increase in the cognitive requirement profile is also significantly positive but disproportionately lower—and the same holds for the low social skills level. Given that the confidence intervals of the marginal returns for medium and high social skills levels regarding a one-standard-deviation increase in the cognitive requirement profile overlap, we do not further interpret their difference.

[37] For individuals below age 30, the complementary returns seem to increase linearly across social skills levels (with a one-standard-deviation increase in the cognitive requirement profile).

Figure B.1: Marginal effects of the cognitive requirement profile across social skills levels.



Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. This figure is a margins plot after we run regression 3 in table BIII and calculate marginal effects of social skills levels with regard to the cognitive requirement profile.

To again illustrate what these social skills results mean for particular occupations, we return to the earlier examples.[38] For automotive technicians at the low social skills level, moving to a higher (medium) level of social skills could lead to a wage increase, because being friendly, communicative, and able to work in a team could increase their productivity.

A hairdresser at the highest social skills level but with a cognitive requirement profile below the mean receives a wage premium for the high social skills level. The laboratory assistant, who has a high social skills level and a high cognitive requirement profile, receives an additional wage premium for the complementarity—so more than only the sum of the wage premium for social skills and the cognitive requirement profile, because they can use their social skills even more productively.

[38] In our examples, we still follow the assumption that the individual works in the training occupation.

Appendix C: Further analyses

Correlation Table and Analyses of Social Skills at the Mean

Table C.I: Correlations between wages, self-competence, social skills and the cognitive requirement profile

	wages	*cognitive requirement profile*	*low self-competence*	*medium self-competence*	*high self-competence*	*low social skills*	*medium social skills*
wages							
cognitive requirement profile	0.1940*						
low self-competence	-0.0123	0.1864*					
medium self-competence	0.1263*	0.0800*	-0.5468*				
high self-competence	-0.1198*	-0.2797*	-0.4740*	-0.4780*			
low social skills	0.0377*	0.4784*	**0.5194***	-0.2489*	-0.2831*		
medium social skills	-0.0088	-0.2987*	-0.2826*	**0.4449***	-0.1714*	-0.7445*	
high social skills	-0.0384*	-0.2197*	-0.2984*	-0.3009*	**0.6296***	-0.2871*	-0.4259*

Notes: Authors' calculations, based on their skills measures and the SESAM, 2013. Pairwise correlations with a Bonferroni correction. Only data on 2013 (year randomly chosen) included, because some individuals in more than one year observed. The values in bold show the correlations between the same levels of self-competence and social skills. * means statistical significance on the 0.01 significance level.

Table C.II: Wage returns to social skills at the mean.

VARIABLES	(1)	(2)
	log wage	*log wage*
Social skills	0.049***	0.041***
	(0.013)	(0.012)
Cognitive requirement profile	0.060***	0.068***
	(0.015)	(0.012)
*Social skills*Cognitive requirement profile*		0.045***
		(0.010)
age, age^2	Yes	Yes
gender	Yes	Yes
Swiss	Yes	Yes
years	Yes	Yes
Constant	9.704***	9.716***
	(0.057)	(0.055)
Observations	105,315	105,315
Number of individuals	65,349	65,349
R^2 *overall*	0.147	0.157
R^2 *between individuals*	0.152	0.163

Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. Standard errors in parentheses clustered on training occupation. * p<0.10, ** p<0.05, *** p<0.01. Reading example coefficient of the coefficient of social skills in regression (1): "An increase of one standard deviation of social skills is associated with a 4.9 percent increase in wages at the mean."

Robustness Test 1: Quantile Regressions

In line with Albandea and Giret (2018), we conducted additional quantile wage regressions (0.25, 0.5, 0.75). For these new analyses, we combined quantile regressions with the same estimation model (outcome, explanatory variables, and controls) that we used in the analyses. In contrast to the dataset that we used in those original analyses, for the new quantile analyses we restrict our dataset to only one observation per individual (i.e., the first observation of each individual).

Table C.III: Quantile regressions (0.25, 0.5, 0.75) for nonlinear returns to self-competence

VARIABLES (Baseline: low self-competence)	(1) **Q(0.25)** *log wage*	(2) **Q(0.5)** *log wage*	(3) **Q(0.75)** *log wage*
medium self-competence	0.120*** (0.031)	0.122*** (0.033)	0.120*** (0.030)
high self-competence	-0.039 (0.037)	-0.007 (0.035)	0.025 (0.041)
cognitive requirement profile	0.040*** (0.011)	0.026** (0.012)	0.010 (0.010)
*medium self-competence*cognitive requirement profile*	-0.068 (0.043)	-0.058* (0.031)	-0.021 (0.023)
*high self-competence*cognitive requirement profile*	0.053* (0.029)	0.066** (0.028)	0.095*** (0.033)
age, age^2	Yes	Yes	Yes
gender	Yes	Yes	Yes
Swiss	Yes	Yes	Yes
years	Yes	Yes	Yes
Constant	9.455*** (0.065)	9.936*** (0.042)	9.956*** (0.054)
Observations (=Number of individuals)	65,349	65,349	65,349
R^2	0.161	0.162	0.158

Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. See details on dataset for quantile regressions in the text above. Standard errors in parentheses clustered on training occupation. * p<0.10, ** p<0.05, *** p<0.01.

Table C.IV: Quantile regressions (0.25, 0.5, 0.75) for nonlinear returns to social skills

VARIABLES (Baseline: low social skills)	(1) **Q(0.25)** *log wage*	(2) **Q(0.5)** *log wage*	(3) **Q(0.75)** *log wage*
medium social skills	0.064*	0.079***	0.106***
	(0.037)	(0.028)	(0.028)
high social skills	0.072	0.091**	0.131***
	(0.044)	(0.039)	(0.034)
cognitive requirement profile	0.045**	0.032***	0.021**
	(0.019)	(0.011)	(0.010)
*medium social skills * cognitive requirement profile*	0.031	0.031	0.033
	(0.037)	(0.043)	(0.037)
*high social skills * cognitive requirement profile*	0.126***	0.123***	0.133***
	(0.033)	(0.028)	(0.026)
age, age^2	Yes	Yes	Yes
gender	Yes	Yes	Yes
Swiss	Yes	Yes	Yes
years	Yes	Yes	Yes
Constant	9.471***	9.907***	9.926***
	(0.077)	(0.051)	(0.051)
Observations (=Number of individuals)	65,349	65,349	65,349
R^2	(0.077)	(0.051)	(0.051)

Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. See details on dataset for quantile regressions in the text above. Standard errors in parentheses clustered on training occupation. * p<0.10, ** p<0.05, *** p<0.01.

Robustness Test 2: Analyses including industry controls

As a further robustness test, we conduct analyses in including industry controls. To do so, we use the same dataset as in our main analyses. For 55 observations, we do not have any industry data thus these observations are not included here. The additional analyses include industry controls as available in the SESAM dataset, i.e., 21 industries. These additional analyses consist of four parts. First, we show the table for our main regression on self-competence, controlling for industries (Table C.V). Second, for the interaction effects, we also add the marginal effects of having one-unit increase in the cognitive requirement profile across all self-competence levels,

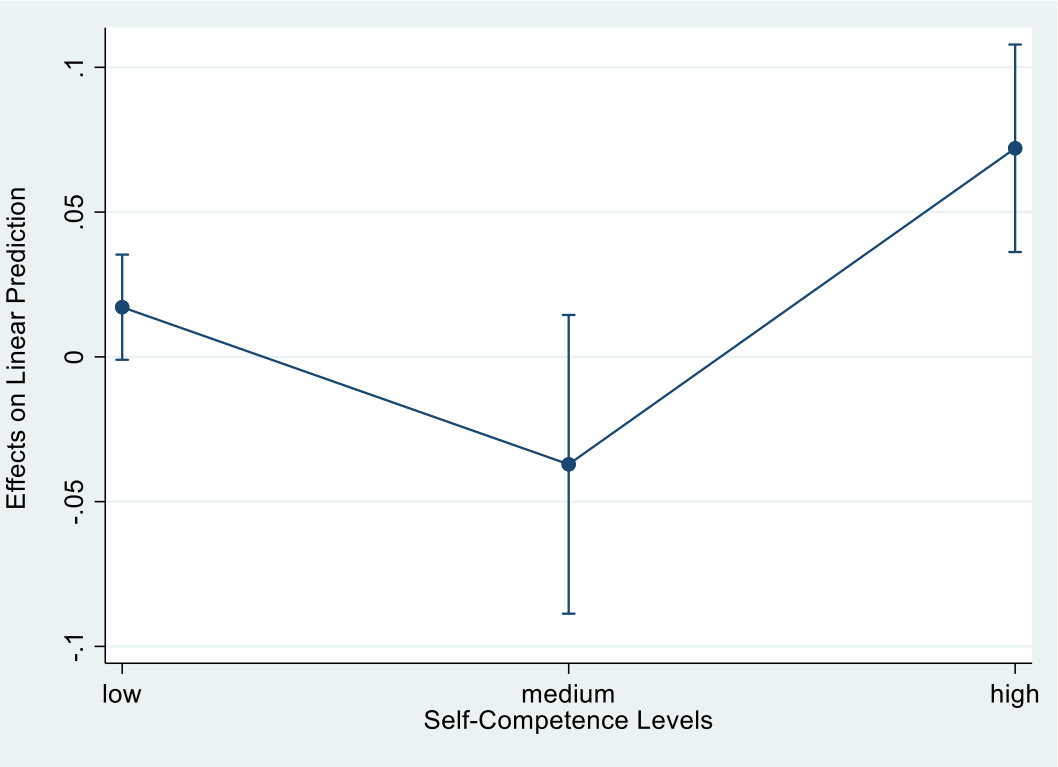
controlling for industries (Figure C.1). Third, we show the table for our main regression on social skills, controlling for industries (Table C.VI). Fourth, for the interaction effects, we also add the marginal effects of having one-unit increase in the cognitive requirement profile across all social skills levels, controlling for industries (Figure C.2).

Table C.V: Additional analyses including industry controls—nonlinear returns to self-competence

VARIABLES (Baseline: low self-competence)	(1) *log wage*	(2) *log wage*
medium self-competence	0.113***	0.084***
	(0.029)	(0.025)
high self-competence	-0.024	-0.010
	(0.039)	(0.027)
cognitive requirement profile	0.023**	0.017*
	(0.011)	(0.009)
*medium self-competence*cognitive requirement profile*	-0.037	-0.054*
	(0.030)	(0.029)
*high self-competence*cognitive requirement profile*	0.073***	0.055***
	(0.028)	(0.021)
age, age^2	Yes	Yes
Gender	Yes	Yes
Swiss	Yes	Yes
Years	Yes	Yes
Industry	**NO**	**YES**
Constant	9.679***	9.418***
	(0.054)	(0.076)
Observations	105,260	105,260
Number of individuals	65,321	65,321
R^2 overall	0.160	0.219
R^2 between individuals	0.166	0.227

Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. See details on dataset for these additional analyses including industry controls in the text above. Standard errors in parentheses clustered on training occupation. * p<0.10, ** p<0.05, *** p<0.01.

Figure C.1: Additional analyses including industry controls—Marginal effects of the cognitive requirement profile across self-competence levels.



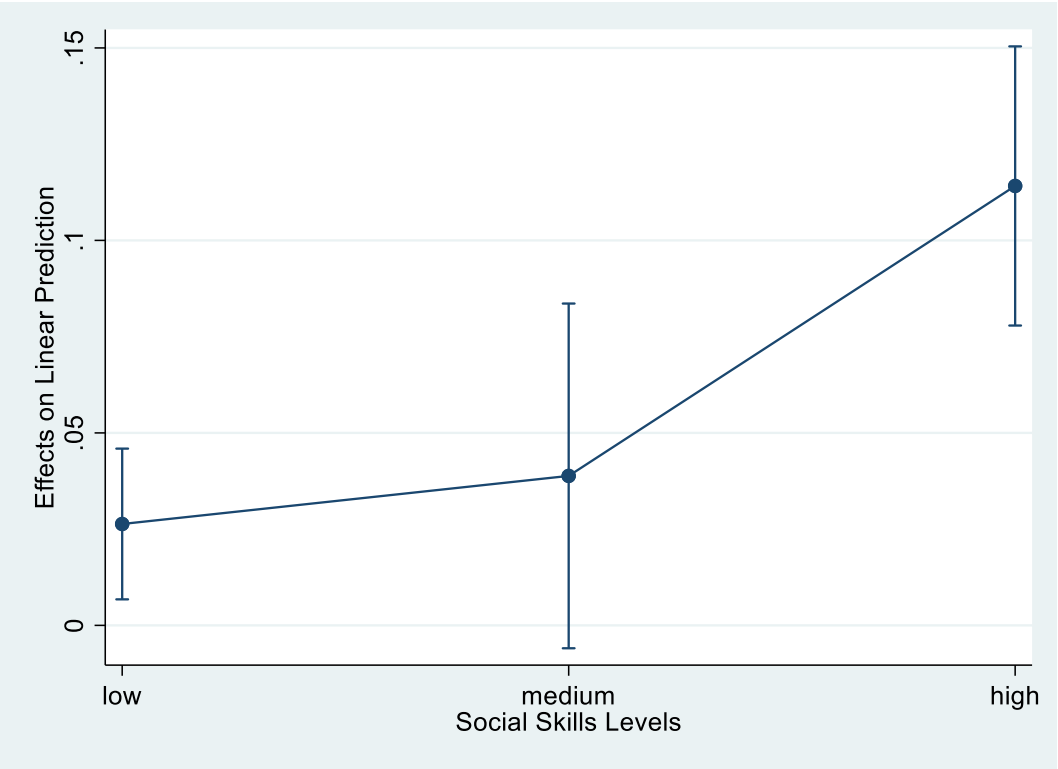
Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. This figure is a margins plot after we run regression 2 in table C.V, which includes industry controls, and calculate the marginal effects of self-competence levels with regard to the cognitive requirement profile. See details on the dataset for these additional analyses including industry controls in the text above.

Table C.VI: Additional analyses including industry controls—nonlinear returns to social skills

VARIABLES (Baseline: low social skills)	(1) *log wage*	(2) *log wage*
medium social skills	0.094***	0.053***
	(0.034)	(0.020)
high social skills	0.104***	0.073***
	(0.040)	(0.026)
cognitive requirement profile	0.037**	0.026***
	(0.017)	(0.010)
*medium social skills * cognitive requirement profile*	0.030	0.012
	(0.036)	(0.027)
*high social skills * cognitive requirement profile*	0.116***	0.088***
	(0.027)	(0.020)
age, age^2	Yes	Yes
gender	Yes	Yes
Swiss	Yes	Yes
years	Yes	Yes
Industry	**NO**	**YES**
Constant	9.668***	9.629***
	(0.052)	(0.055)
Observations	105,260	105,260
Number of individuals	65,321	65,321
R^2 overall	0.154	0.215
R^2 between individuals	0.160	0.222

Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. See details on the dataset for these additional analyses including industry controls in the text above. Standard errors in parentheses clustered on training occupation. * p<0.10, ** p<0.05, *** p<0.01.

Figure C.2: Additional analyses including industry controls—marginal effects of the cognitive requirement profile across social skills levels.



Notes: Authors' calculations, based on their skills measures and the SESAM, 2010–2018. This figure is a margins plot after we run regression 2 in table C.VI, which includes industry controls, and calculate marginal effects of social skills levels with regard to the cognitive requirement profile. See details on the dataset for these additional analyses including industry controls in the text above.

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