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Mind the Confidence Gap: Gender, Domain-Specific Self-Beliefs, and STEM Pathways

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Abstract

We examine how adolescents' domain-specific confidence shapes subsequent participation in Science, Technology, Engineering, and Mathematics (STEM) study and vocational training, using longitudinal data from a nationally representative cohort of German secondary school students. We show that domain-specific confidence measures provide markedly different predictions from composite confidence indices: in line with established models from educational psychology, higher confidence in mathematics and Information and Communications Technology (ICT) increase the likelihood of entering STEM pathways, whereas higher confidence in reading decreases it. These opposing patterns are obscured when confidence is aggregated into a single measure. Our findings demonstrate the importance of distinguishing between domains when studying non-cognitive determinants of STEM choices and suggest that broad confidence-building interventions may unintentionally reinforce existing gender disparities in STEM participation.

JEL classification

I24, I23, D91, J24, J16

Keywords

confidence, STEM, education, gender

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1 Introduction

Confidence is increasingly recognized as an important determinant of young people's educational decisions and later labor market outcomes. Adolescents with higher confidence, sometimes even overconfidence, are more likely to sort into high earning fields and enter top occupations (De Araujo and Lagos, 2013; Drago, 2011; Page and Ruebeck, 2022; Adamecz-Völgyi and Shure, 2022), even conditional on prior attainment, socio-demographic background, and other socio-emotional traits. By contrast, underconfidence is linked to avoidance of competition, lower test performance, and weaker labor-market outcomes (Niederle and Vesterlund, 2007; Douglas et al., 2023; Adamecz and Shure, 2024). These patterns have been attributed to mechanisms such as differences in motivation, effort, self-selection, and self-promotion (Bénabou and Tirole, 2002; Dohmen and Falk, 2011; Exley and Kessler, 2022). Yet economists typically conceptualize confidence using composite measures of mis-calibration (e.g. Adamecz-Völgyi and Shure, 2022) or focus narrowly on mathematics confidence (e.g. Page and Ruebeck, 2022), implicitly treating confidence as a single, general trait.

A large literature in educational psychology challenges this assumption. Psychologists and economists differ in how they define confidence. While the economic literature on confidence focuses on the mis-calibration between self-assessed performance and actual performance (Moore and Healy, 2008; Bandiera et al., 2022), psychologists focus on self-concept[1]. Research on academic self-concept (Shavelson et al., 1976; Marsh et al., 2012), and particularly Marsh's Internal/External Frame of Reference (I/E) model (Marsh, 1986), shows that young people form *domain-specific* beliefs about their ability through internal comparisons across subjects and external comparisons with peers. As a result, mathematics and reading self-concepts often diverge even when achievement levels in the two domains are similar. This framework implies that mathematics and reading confidence may push educational choices in opposite directions, an implication that composite confidence measures may obscure, especially in explaining gender differences in science, technology, engineering, and mathematics (STEM) participation.

This paper brings these insights into the economics literature by examining whether domain-specific confidence in mathematics, reading, science, and information and communication technology (ICT) at age 14/15 predicts subsequent entry into STEM study or vocational training more accurately, and more informatively, than composite confidence measures. Using longitudinal data from the German National Educational Panel Study (NEPS) (Blossfeld and Roßbach, 2019), we construct mis-calibration-based confidence measures that

[1] Defined as "self-perceptions that are formed through experience with and interpretations of one's environment [...] influenced especially by evaluations by significant others, reinforcements, and attributions for one's own behavior" (Marsh et al., 2012)

compare students' self-assessed performance with their actual test performance in four domains, allowing us to quantify domain-level confidence.

Our findings show that domain-specific confidence matters in distinct ways. While a composite measure is only weakly related to STEM entry, higher mathematics confidence substantially increases the probability of pursuing a STEM higher education pathway, whereas higher reading confidence reduces it. ICT confidence predicts STEM participation for boys, while science confidence predicts STEM entry for girls and sorting into a STEM field at university. These patterns are consistent with the predictions of the I/E model (Marsh, 1986) and help explain why girls, who typically report stronger reading confidence relative to mathematics confidence, are less likely to enter STEM even when they perform well in STEM subjects.

This paper makes three contributions to the literature on confidence and educational outcomes. First, we provide a conceptual contribution by introducing the I/E model from educational psychology into the economics of confidence. This framework clarifies why confidence should be understood as domain-specific and offers a theoretical basis for interpreting gendered patterns in STEM participation. We thereby contribute to previous literature that has used composite measures of confidence to explore gender gaps in labor market outcomes (Adamecz-Völgyi and Shure, 2022). Second, we show empirically that domain-specific confidence in mathematics, reading, science, and ICT yields substantially different predictions for STEM study and vocational training than composite or mathematics-only confidence measures. These findings reveal that composite indicators obscure opposing cross-domain mechanisms that are especially relevant for understanding gender differences in STEM entry. This builds on previous findings that highlighted the importance of mathematics confidence for entering STEM, but did not discuss the role of confidence in reading or other domains (Page and Ruebeck, 2022). Third, we contribute methodologically by modeling confidence as miscalibration by using residual score measures that compare subjective and objective performance rather than relying on broader self-concept scales (Guo et al., 2015).

The rest of this paper is structured as follows. In Section 2, we present the data, descriptive statistics, and our empirical strategy. In Section 3, we discuss our results. In Section 4, we conclude.

2 Data, Descriptive Statistics, and Empirical Strategy

2.1 Data

In this paper, we use a nationally representative study of German secondary school students: Starting Cohort 4 of the German National Educational Panel Study (NEPS) (NEPS Network, 2021).[2] Approximately 16,425 students were first surveyed in 2011, when they were in ninth grade (aged 14-15). The sample draws on students from all types of secondary schools in Germany and is nationally representative. The participants are followed throughout their upper secondary and post-secondary education, as well as during their entry into and participation in the labor market (Blossfeld et al., 2011). The data include detailed information on socio-demographic characteristics, educational and psychological characteristics, preferences, as well as education, training, and employment outcomes (Skopek et al., 2013). This allows us to observe whether participants pursue STEM study or vocational training conditional on a range of rich background characteristics.

The dataset is unique in its comprehensive testing of ability combined with questions on self-perceptions of ability. In the ninth grade, the respondents were tested in the domains of reading, scientific literacy, ICT literacy, and mathematics (Fuß et al., 2021). Crucially, after completing each competency test, the participants were asked to self-assess their performance on that test.

We restrict the sample to those participants who completed the competence tests in the ninth grade and remained in the survey until wave 12 in 2019/2020.[3] As not everyone starts university or vocational training, our sample is further restricted to individuals who do. This gives us a final estimation sample of 3,750 respondents, 1,829 men and 1,921 women. It is possible that some individuals start only vocational training or university, so for our pathway specific analyses, we have 2,307 individuals (1,246 women) who start university and 2,021 individuals (949 women) who start vocational training.

[2] This paper uses data from the National Educational Panel Study (NEPS, see Blossfeld and Roßbach (2019)). The NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi, Germany) in cooperation with a nationwide network.

[3] In order to correct for this possible self-selection into our final sample, we perform Heckman's two-step procedure (Heckman, 1976, 1979) for our outcomes. We use secondary school type as the main explanatory variable in the first stage as this has been found to be a strong predictor of attrition (Zinn et al., 2020) in the NEPS data. This is explained by both a change in interview type and an increased difficulty in tracking the individuals due to higher geographical mobility. This means that individuals in school types such as *Gymnasium*, which include upper secondary education and therefore take longer, might be less likely to drop out of the sample early compared to individuals in other school types. The estimation results in Online Appendix Table OA.7 suggest that controlling for selection in our sample does not alter our main results.

2.2 Confidence Measure

As mentioned, we measure objective performance in four domains using the NEPS ninth grade competence tests. These tests were administered in a paper-pencil format in classrooms. Depending on the domain, the test comprised 22 (mathematics), 28 (science), 33 (reading), and 40 (ICT) items. Items were randomized within booklets and booklets were randomly assigned to students. The tests in mathematics, science and ICT were administered during the first semester and the test in reading during the second semester of ninth grade.

Directly after completing each domain-specific test, participants were asked to assess their own performance in the respective test by estimating the number of correct answers they scored (Lockl, 2015). Both estimated and actual scores are divided by the number of items in each test to obtain measures for objective and subjective competence comparable across domains. Following Adamecz-Völgyi and Shure (2022) and Anderson et al. (2012), confidence is measured via a residual score. This residual score measure reflects variation in self-assessed performance after accounting for variance attributable to actual performance and is preferred because it is less prone to floor and ceiling issues (Belmi et al., 2019). We therefore construct confidence scores for each of the four domains by regressing the estimated performance on the actual performance in a specific test and predicting the residuals:

$$Subj\_Comp_d = \alpha + \beta * Obj\_Comp_d + \epsilon_d \tag{1}$$

$$ResidualScore_d = Subj\_Comp_d - \widehat{Subj\_Comp}_d \tag{2}$$

for domain d with $Obj\_Comp_d = \frac{TestScore_d}{NumberItems_d}$ and $Subj\_Comp_d = \frac{SelfAssessment_d}{NumberItems_d}$.

2.3 Outcomes

Our outcomes of interest are the first educational choices the participants make after finishing school. Specifically, we want to know whether they pursue STEM at either university or in vocational training. We capture whether the participants' first vocational training (KldB 2010, 5-digit) or first study program at university (destatis 2010/11, 1-digit) is in a STEM field using the following classifications. STEM vocational training participation is identified based on the specific STEM occupations aggregate of the Federal Employment Agency (KldB, 5-digit), which comprises all jobs that involve a high level of knowledge in STEM fields (Statistik der Bundesagentur für Arbeit, 2022). This is a broad definition and includes any type of vocational training (e.g., a dual program or a school-based program). Study programs are identified as STEM on a 1-digit level if they are in the categories mathematics, natural sciences, and engineering following Federal Statistical Office of Germany (2019). This definition is not limited to study programs at universities, but also includes programs at other types of tertiary education institutions such as universities of applied sciences or business academies.

We create our main outcome variable, $STEM\ education$, which combines these two outcomes by taking 1 if the first vocational training or first university program of an individual is in STEM and 0 if it is in another subject area. We also create additional outcome variables for $STEM\ University$ and $STEM\ Vocational\ Training$ in order to look at each higher education outcome separately. All the investigated outcomes focus on the choice to start a STEM education, not whether that specific education is finished.

We perform the heterogeneity analysis by university and vocational training as previous German research suggests a link between self-efficacy and pathway choice (Mohrenweiser and Pfeiffer, 2016), such that confidence might affect STEM participation differently across the two sub-samples. Since confidence is observed prior to entering vocational training or university, it constitutes a pre-determined characteristic, not an outcome of selection.

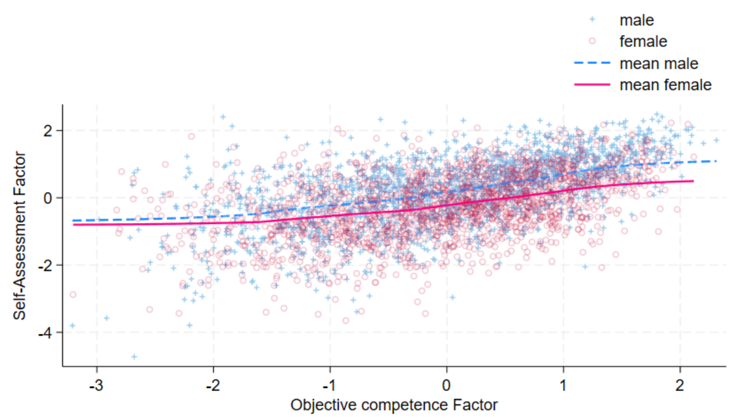
2.4 Descriptive Statistics

Aligning with official statistics on participation in STEM higher education Federal Statistical Office of Germany (2025b,a), Table OA.1 indicates a substantial gender gap in all STEM education outcomes. While more than half of men in our sample start a STEM study program or vocational training, only around 20% of women do so. This gap is even more pronounced for vocational training, where only 13% of women sort into STEM training.

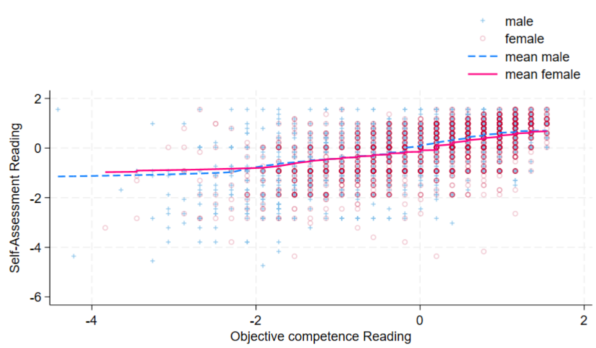
Our descriptive statistics also exhibit familiar patterns with respect to confidence and highlight the importance of differentiating between composite and domain-specific measures (full descriptive statistics by gender provided in Appendix Table OA.1). In Figure 1, we examine the relationship between objective and subjective competence both in a composite way and separately by domain. In line with other literature from economics and education, we see that boys assess themselves higher than girls along the competency distribution for mathematics, science, and ICT, but that for reading, girls assess themselves better at lower competency levels, similarly to boys in the middle of the distribution, and slightly lower at the top. This is different from the composite measure presented in Panel (a) of Figure 1, where we see that across the objective competency distribution, boys assess themselves to be better than girls. This is also true when examining the distribution of the residual scores of confidence by gender (see Online Appendix Figures OA.1 and OA.2). Again, gender differences are less pronounced for reading, while the remaining three domains show men being more confident than women.

Figure 1: The relationship between subjective and objective competency by domain

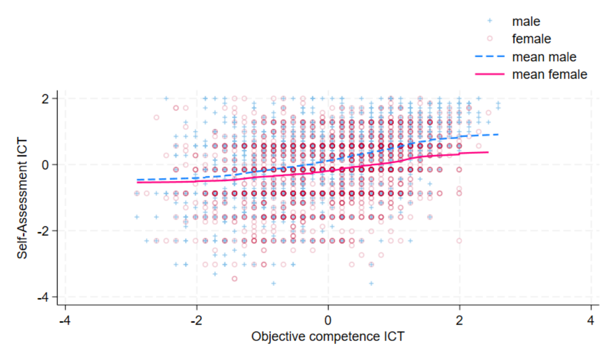
(a) Composite



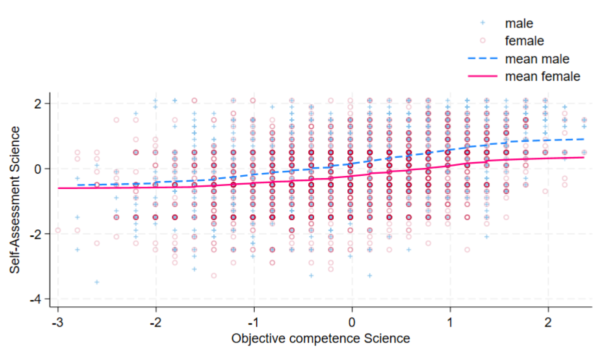
(b) Reading



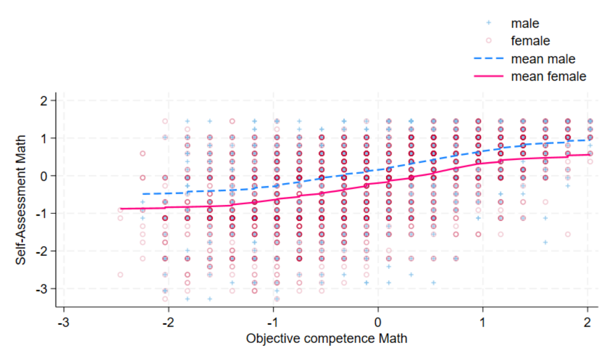
(c) ICT



(d) Science



(e) Math



Notes: Data from NEPS-SC4.
This figure depicts the relationship between subjective (self-assessed) competence and objective (actual) competence based on the competency tests.
All measures are standardized to mean 0, SD 1. Number of observations: 3,750

2.5 Empirical Strategy

Our goal is to understand how confidence is related to the probability of pursuing a STEM pathway, whether this changes between using a composite measure versus the four domains, and how this might explain the gender gap in pursuing these pathways. Our main estimation results are based on basic linear regression models, which take the following form:

$$Y_i = \alpha + \gamma Female_i + \beta_1 Confidence_i + \delta X_i + \epsilon_i \tag{3}$$

where Y_i is one of our binary STEM education outcome measures.

As explanatory variables, we include $Female_i$ which is the binary variable denoting the gender of an individual and $Confidence_i$, which captures the confidence residual scores, either composite or domain-specific, as explained in detail in Section 2.2. Lastly, X_i is a vector of controls covering individual and family background characteristics as well as several competence measure dummies.

We include binary controls for parental background indicating if a parent or parent's partner has a university degree (to capture socioeconomic status) and migration background (respondent or one of the parents migrated to Germany). Furthermore, we add the school leaving degree at the start of the respective post-secondary education spell using several dummies for the respective qualification to control for the (acquired) education of the individual.

Lastly, we control for competence in the four domains. Competence is assessed using the results from the previously mentioned NEPS administered competence tests. The included competence controls are based on the actual share of correct items. By construction of the residual score measures, these competence scores are orthogonal to the confidence measures. Nevertheless, we construct quintiles based on the competence distribution in the respective domain and include dummies for each quintile.

We present our main estimation results starting with one basic regression using only gender and individual characteristic controls. Afterwards we add only the competence controls. In the next model we add a composite confidence measure [4] and in the last model, we include the domain-specific confidence measures to demonstrate how a one-dimensional measure might not be able to fully capture the effects of confidence.

[4]Composite confidence is measured as a factor, which is formed by performing a principal component factor analysis for the four domain-specific confidence variables. The factor for confidence accounts for 49.52% of the total variance of the confidence measures. The composite confidence measure is then included as an explanatory variable in our main regressions instead of the domain-specific variables.

Robust standard errors are used in all specifications for each of the outcome variables. We use standardized confidence measures to allow for easier interpretation of the results. For heterogeneity analyses (e.g. gender or higher education type), we standardize by the respective groups.

3 Results

3.1 STEM Educational Pathways

Our main results are presented in Table 1. The first row is in line with findings from the previous literature and official statistics: girls are less likely to sort into STEM educational pathways than men (here about 35% less likely in the bivariate specification in Column (1)). Once we account for competence, however, in Column (2), the gender gap decreases by around 13.76%. This indicates that part of the gender gap can be explained by differences in competency scores, but not fully.

To probe the role of confidence, we begin by including a composite measure of confidence before turning to domain-specific measures. In Column (3) once we account for our composite confidence measure, the gender gap is further decreased by 4.56%. In Column (4), we see that the gender gap is further decreased to 29% with the inclusion of our domain-specific confidence measures. We take this as evidence that gender differences in confidence help explain sorting behavior in higher education pathways.

When we turn our attention to the coefficients on the confidence measures in Table 1, we see that composite confidence is associated with a greater likelihood of pursuing a STEM education. However, examining domain-specific confidence reveals that only higher confidence in mathematics and ICT is positively associated with STEM participation in a statistically significant manner. The significance of these two domains is expected given the direct relevance of these subjects to STEM fields. Conversely, greater confidence in reading is linked to a lower likelihood of pursuing STEM higher education, potentially reflecting a preference for non-STEM disciplines where reading skills are more central.

Interestingly, confidence in science does not significantly predict STEM participation, which is surprising considering the subject's close association with STEM. As this result warrants further investigation, we first explore whether there is a significant effect if the domains are added separately. The stepwise inclusion in Table 2 suggests a positive link between confidence in science and STEM participation. As the significance and magnitude of both confidence in science and ICT decreases once both are included, this suggests potential

Table 1: Confidence and STEM Education

Dependent Variable: STEM education	(1)	(2)	(3)	(4)
Female	-0.356***	-0.307***	-0.299***	-0.293***
	(0.015)	(0.016)	(0.016)	(0.016)
Composite confidence			0.019**	
			(0.008)	
Reading confidence				-0.031***
				(0.008)
ICT confidence				0.015*
				(0.008)
Science confidence				0.011
				(0.009)
Mathematics confidence				0.030***
				(0.008)
Adjusted R-squared	0.136	0.162	0.163	0.169
Individuals	3,750	3,750	3,750	3,750
Competence dummies	No	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

high correlation between these domains. As shown in Table OA.2, the highest positive correlation, though still moderate, is indeed between ICT and science.

Table 2: Confidence and STEM Education: Stepwise Inclusion

Dependent Variable: STEM education				
	(1)	(2)	(3)	(4)
Female	-0.309***	-0.300***	-0.300***	-0.297***
	(0.016)	(0.016)	(0.016)	(0.016)
Reading Confidence	-0.017**			
	(0.007)			
ICT Confidence		0.019**		
		(0.007)		
Science Confidence			0.018**	
			(0.007)	
Mathematics Confidence				0.030***
				(0.007)
Adjusted R-squared	0.163	0.164	0.163	0.166
Individuals	3,750	3,750	3,750	3,750
Competence dummies	Yes	Yes	Yes	Yes

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

We further break down our outcome variable by university and vocational training in Table 3. Here the results show a positive relationship between science confidence and STEM study at university and a positive (though insignificant) relationship between ICT confidence and both STEM vocational training and STEM study. The relationships between math and reading confidence remain similar as before regardless of the outcome measure. The fact that there is a positive relationship between science confidence and study at university and a negative (although insignificant) one with vocational training may also explain the lack of an overall relationship between science confidence and pursuing a STEM pathway.

Table 3: Confidence and STEM Education by Pathway

Dependent Variable:	STEM University				STEM Vocational Training			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Female	-0.304***	-0.243***	-0.224***	-0.217***	-0.379***	-0.347***	-0.342***	-0.338***
	(0.020)	(0.021)	(0.022)	(0.022)	(0.019)	(0.020)	(0.021)	(0.021)
Composite confidence			0.041***				0.012	
			(0.011)				(0.009)	
Reading confidence				-0.025**				-0.031***
				(0.010)				(0.011)
ICT confidence				0.016				0.017
				(0.011)				(0.011)
Science confidence				0.027**				-0.003
				(0.011)				(0.011)
Mathematics confidence				0.032***				0.033***
				(0.010)				(0.010)
Adjusted R-squared	0.098	0.132	0.138	0.142	0.180	0.189	0.189	0.195
Individuals	2,307	2,307	2,307	2,307	2,021	2,021	2,021	2,021
Competence dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1. STEM University captures whether the first started university program of an individual is in a STEM field, while STEM Vocational Training indicates whether the first started vocational training is in STEM.

3.2 Heterogeneity by Gender

Our previous results indicated that both composite and domain-specific confidence measures reduce the gender gap in pursuing a STEM pathway; however, the domain-specific measures revealed important differences in sign and magnitude. We probe this further in Table 4 by splitting the sample by gender and estimating our main models separately for men and women.

The first two columns of results show that the composite confidence measure is less important in magnitude and less statistically significant for women than for men (0.017 for women and 0.023 for men). Breaking this down by domain-specific confidence reveals important insights. Most of the coefficients for womenare smaller in magnitude than for men. This is especially pronounced in the case of ICT where higher ICT confidence is positively and strongly related to pursing a STEM pathway for men, but insignificant and negative for women. An exception is science confidence, where women have a positive and statistically significant relationship to pursing a STEM pathway, but men do not. This may be explained by women choosing university and vocational training programs in natural sciences, whereas men more often sort into mechanical or engineering occupations and programs. Interestingly, having higher confidence in reading decreases the likelihood of choosing a STEM education for both genders, but the aversion here is stronger for men.

Table 4: Confidence and STEM Education by Gender

Dependent Variable: STEM	(Women)	(Men)	(Women)	(Men)
Composite confidence	0.017*	0.023**		
	(0.009)	(0.012)		
Reading confidence			-0.021**	-0.039***
			(0.009)	(0.013)
ICT confidence			-0.003	0.036***
			(0.010)	(0.013)
Science confidence			0.021**	0.001
			(0.011)	(0.013)
Mathematics confidence			0.024**	0.033***
			(0.009)	(0.012)
Adjusted R-squared	0.045	0.040	0.049	0.050
Individuals	1,921	1,829	1,921	1,829
Competence dummies	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1 for each sub-sample separately. STEM education captures whether the first started vocational training or university program is in a STEM field.

3.3 Robustness Checks

We probe our results with several robustness checks. First, we add squared confidence measures to account for a possible nonlinear relationship between STEM educational and confidence such that our regression model takes the following form:

$$Y_i = \alpha + \gamma Female_i + \beta_1 Confidence_i + \beta_2 Confidence_i^2 + \delta X_i + \epsilon_i \tag{4}$$

Table OA.4 shows no indication for nonlinear effects between any of our confidence measures and beginning a STEM education. Adding the quadratic terms does also not improve the fit of the model, suggesting that the link between confidence and the investigated STEM education outcome is not nonlinear. Repeating this separately by STEM pathway or by gender (see Tables OA.5 and OA.6) also does not indicate a nonlinear relationship between confidence and pursuing STEM apart from a marginally significant effect of ICT for men, which we do not want to overinterpret.

Some existing literature suggests that the Big Five personality measures are significant predictors of confidence (Schaefer et al., 2004; Pulford and Sohal, 2006). This would pose a problem since previous research also finds a link between these personality measures and labor market outcomes such as earnings (Alderotti et al., 2023). We therefore include the Big 5 personality traits as additional controls. Unfortunately, the regressions controlling for the Big 5 contain slightly lower numbers of observations due to missing observations in these variables. Comparing the main regression results with those controlling for the Big 5 personality traits in Table OA.8 suggests that the results are mostly robust. While there is a small change in the significance of confidence in ICT and pursuing a STEM pathway, this can likely be attributed to the slightly smaller sample size. Given the reduced sample size for these regressions, we do not run the STEM pathway and gender specific regressions.

We further check whether our results are robust to different constructions of confidence scores regularly used in the existing economic literature on confidence (e.g. deviation scores, residual scores of ranks, and deviation scores of ranks). The main results regarding confidence in reading and mathematics are robust across all specifications. While confidence in ICT is insignificant in the full sample for these alternative measures, the effect is always positive, as for the residual score measure, and this effect still driven by men. For confidence in science, the positive effect is as before driven by university students and women. These results highlight that using either kind of deviation scores underscores the need for domain-specific measures. This is particularly true for uncovering gendered mechanisms, as the composite measure is only significant for men (see Online Appendix Tables OA.12, OA.20). The domain-specific analysis, however, reveals similar effects as before for women, where both science and math positively predict STEM participation, while reading negatively predicts it. A more detailed overview with descriptions of each measure and the corresponding tables can be found in Online Appendix Section A.2.

4 Conclusion

Recent literature in economics has highlighted the importance of non-cognitive skills or socio-emotional traits for a variety of life outcomes, including education and labor market outcomes such as pursuing STEM education or training (Almlund et al., 2011; Borghans et al., 2008). It has also flagged the importance of confidence captured in adolescence for labor market outcomes, including earnings and occupation (Adamecz-Völgyi and Shure, 2022; Page and Ruebeck, 2022). Yet, these findings ignore insights from educational psychology and obscure part of the picture because most studies either rely on broad, composite confidence measures or consider only mathematics confidence, overlooking cross-domain dynamics. Psychologists have long highlighted that "self-concept," especially academic self-concept in educational psychology, is to be investigated not globally but domain-specific (Shavelson et al., 1976; Marsh et al., 2012).

The central contribution of this paper is to show that failing to differentiate confidence by domain masks gendered mechanisms that drive STEM participation. We do this by bringing insights from educational psychology to economics to show that domain-specific confidence matters. When we use composite measure of confidence, our results are weaker and mask domain-specific dynamics. Composite confidence has a small and positive relationship with pursuing STEM. Consistent with the I/E model proposed by Marsh (1986), our results show that mathematics confidence and reading confidence work in opposing directions for STEM participation in more economically meaningful ways. Because women tend to report higher confidence in reading relative to mathematics, their internal subject comparisons may strengthen a perceived comparative advantage outside STEM, thereby reducing STEM participation even when their absolute math attainment is moderate or high. This helps explain why earlier studies using composite confidence measures or mathematics confidence alone have produced incomplete results: they miss the countervailing influence of reading confidence and thus mischaracterize gender differences in STEM entry. This is especially important from a policy perspective given the high lifetime earnings of STEM occupations (Andrews et al., 2024; Kugler et al., 2017) and the "leaky" gender pipeline in STEM (Speer, 2023).

Our work is not without limitations. Germany has a specific educational system with early tracking, which may amplify domain-specific perceptions and comparative advantage considerations, so our results may not fully extrapolate to all educational contexts. The NEPS includes students from all school tracks and they all take the same competence tests and are asked to assess their ability. We try to use the tracked school system to our advantage to include vocational training as an additional outcome; nevertheless, our results may lack external validity.

More broadly, our findings point to the need for a multi-dimensional understanding of confidence. We should treat confidence not as a monolithic trait, but as a portfolio of domain-specific signals that interact with the educational system and labor market opportunities. The fact that we capture science and ICT confidence and that they behave differently than mathematics and reading confidence in our models highlights this. This further emphasizes the need to move away from general confidence-building interventions and instead keep domains in mind. Interventions to increase girls' participation in STEM must be focused on mathematics or science, otherwise they risk disproportionately steering girls away from STEM. Recognizing confidence as multi-dimensional can help reconcile gender differences in educational choices and provide a clearer framework for designing targeted interventions.

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Online Appendix

A Additional Descriptives

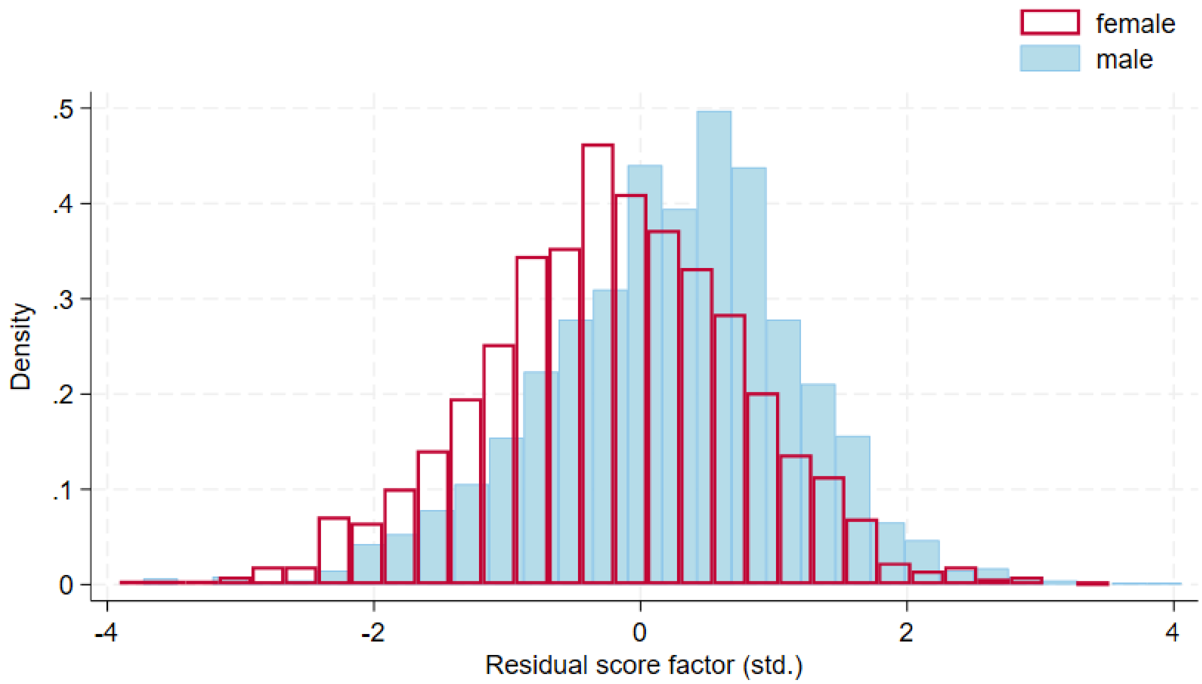

Figure OA.1: Histograms of residual scores by gender using data from NEPS-SC4. Number of observations: 3,750

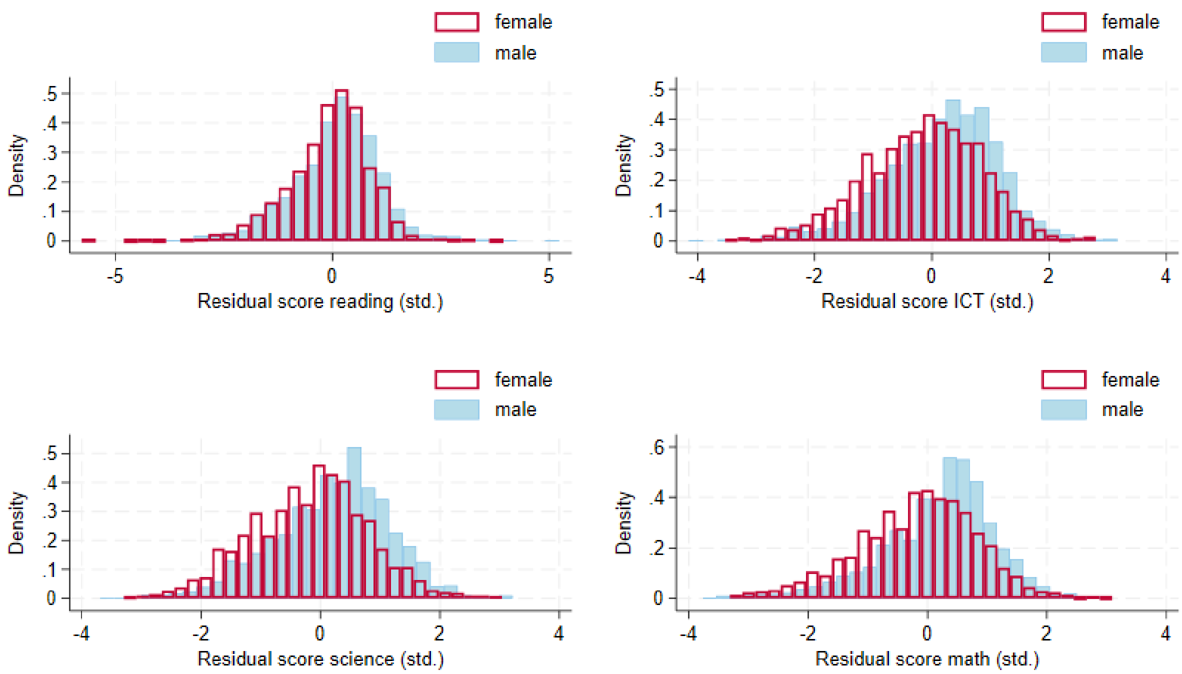

Figure OA.2: Histograms of residual scores by gender and domain using data from NEPS-SC4. Number of observations: 3,750

Table OA.1: Descriptives by Gender

	Male		Female		Male-Female		
	Mean	Observations	Mean	Observations	Mean	p	se
Outcomes							
first study program or first voc. train is in STEM	0.556	1829	0.201	1921	0.355	0.000	0.015
first study program is in STEM	0.545	1061	0.238	1246	0.306	0.000	0.019
first voc. training is in STEM	0.519	1072	0.130	949	0.389	0.000	0.019
Confidence Measures							
Reading Confidence	0.080	1829	-0.076	1921	0.156	0.000	0.033
ICT Confidence	0.171	1829	-0.163	1921	0.335	0.000	0.032
Science Confidence	0.196	1829	-0.186	1921	0.382	0.000	0.032
Math Confidence	0.186	1829	-0.177	1921	0.363	0.000	0.032
Actual and estimated prop. correct items							
Proportion correct items reading	-0.154	1829	0.146	1921	-0.300	0.000	0.032
Proportion correct items ICT	-0.005	1829	0.005	1921	-0.009	0.773	0.033
Proportion correct items science	0.076	1829	-0.072	1921	0.148	0.000	0.033
Proportion correct items math	0.171	1829	-0.163	1921	0.333	0.000	0.032
Self-assessed proportion correct items reading	-0.028	1829	0.026	1921	-0.054	0.097	0.033
Self-assessed proportion correct items ICT	0.157	1829	-0.149	1921	0.306	0.000	0.032
Self-assessed proportion correct items science	0.209	1829	-0.199	1921	0.408	0.000	0.032
Self-assessed proportion correct items math	0.249	1829	-0.237	1921	0.487	0.000	0.032
Controls							
Migrant	0.112	1829	0.098	1921	0.014	0.155	0.010
Parent University	0.366	1829	0.368	1921	-0.002	0.913	0.016
Parent (incl. partner) University	0.384	1829	0.379	1921	0.005	0.734	0.016
School leaving degree							
No degree/Primary Educ.	0.009	1829	0.004	1921	0.005	0.079	0.003
Haupt-/Volksschulabschluss	0.085	1829	0.050	1921	0.035	0.000	0.008
Mittlere Reife/Realschulabschluss	0.281	1829	0.198	1921	0.083	0.000	0.014
(Fach-)Hochschulreife	0.619	1829	0.744	1921	-0.125	0.000	0.015
(Fach-)Hochschulreife (second cycle)	0.005	1829	0.003	1921	0.003	0.165	0.002
School type							
Hauptschule	0.163	1829	0.116	1921	0.047	0.000	0.011
Comprehensive School	0.055	1829	0.044	1921	0.011	0.121	0.007
Realschule	0.233	1829	0.195	1921	0.038	0.004	0.013
Integrated School	0.101	1829	0.096	1921	0.005	0.582	0.010
Gymnasium	0.448	1829	0.550	1921	-0.102	0.000	0.016

Notes: Data source: NEPS-SC4. All (self-assessed and actual) competence and confidence measures standardized to mean 0, SD 1 based on full sample.

Table OA.2: Correlation between confidence measures

	Reading confidence	ICT confidence	Science confidence	Math confidence
Reading confidence	1.0000			
ICT confidence	0.2882	1.0000		
Science confidence	0.3069	0.4399	1.0000	
Math confidence	0.2444	0.3110	0.3541	1.0000

Notes: Data source: NEPS-SC4. All confidence measures standardized to mean 0, SD 1.

Table OA.3: Correlation between competency measures

	obj. comp. reading	obj. comp. ict	obj. comp. science	obj. comp. math
obj. comp. reading	1.0000			
obj. comp. ict	0.6519	1.0000		
obj. comp. science	0.6407	0.6760	1.0000	
obj. comp. math	0.5047	0.5668	0.6377	1.0000

Notes: Data source: NEPS-SC4. All competence measures standardized to mean 0, SD 1.

A.1 Robustness Checks

A.1.1 Nonlinear Effects

Table OA.4: Nonlinear Effects

Dependent Variable: STEM education				
	(1)	(2)	(3)	(4)
Female	-0.356***	-0.307***	-0.293***	-0.292***
	(0.015)	(0.016)	(0.016)	(0.016)
Reading Confidence			-0.031***	-0.032***
			(0.008)	(0.008)
ICT Confidence			0.015*	0.014
			(0.008)	(0.009)
Science Confidence			0.011	0.013
			(0.009)	(0.009)
Math Confidence			0.030***	0.033***
			(0.008)	(0.008)
Reading Confidence squared				0.000
				(0.004)
ICT Confidence squared				0.000
				(0.006)
Science Confidence squared				0.006
				(0.005)
Math Confidence squared				0.006
				(0.005)
Adjusted R-squared	0.136	0.162	0.169	0.169
Individuals	3,750	3,750	3,750	3,750

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

Table OA.5: Nonlinear Effects by Type

Dependent Variable:								
	STEM University				STEM Vocational Training			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Female	-0.304***	-0.243***	-0.217***	-0.215***	-0.379***	-0.347***	-0.338***	-0.337***
	(0.020)	(0.021)	(0.022)	(0.022)	(0.019)	(0.020)	(0.021)	(0.021)
Reading Confidence			-0.025**	-0.028**			-0.031***	-0.032***
			(0.010)	(0.012)			(0.011)	(0.011)
ICT Confidence			0.016	0.019			0.017	0.016
			(0.011)	(0.012)			(0.011)	(0.012)
Science Confidence			0.027**	0.029**			-0.003	-0.002
			(0.011)	(0.012)			(0.011)	(0.012)
Math Confidence			0.032***	0.038***			0.033***	0.036***
			(0.010)	(0.012)			(0.010)	(0.011)
Reading Confidence squared				-0.001				0.001
				(0.005)				(0.006)
ICT Confidence squared				0.006				0.000
				(0.007)				(0.007)
Science Confidence squared				0.010				0.004
				(0.007)				(0.007)
Math Confidence squared				0.007				0.005
				(0.006)				(0.007)
Adjusted R-squared	0.098	0.132	0.142	0.143	0.180	0.189	0.195	0.194
Individuals	2,307	2,307	2,307	2,307	2,021	2,021	2,021	2,021

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1. STEM University captures whether the first started university program of an individual is in a STEM field, while STEM Vocational Training indicates whether the first started vocational training is in STEM.

Table OA.6: Nonlinear Effects by Gender

Dependent Variable: STEM				
	(Women)	(Men)	(Women)	(Men)
Reading Confidence	-0.021**	-0.039***	-0.024**	-0.038***
	(0.009)	(0.013)	(0.010)	(0.013)
ICT Confidence	-0.003	0.036***	0.000	0.026*
	(0.010)	(0.013)	(0.011)	(0.014)
Science Confidence	0.021**	0.001	0.021*	0.005
	(0.011)	(0.013)	(0.011)	(0.014)
Math Confidence	0.024**	0.033***	0.025**	0.041***
	(0.009)	(0.012)	(0.010)	(0.014)
Reading Confidence squared			-0.001	0.003
			(0.004)	(0.007)
ICT Confidence squared			0.010	-0.014*
			(0.007)	(0.008)
Science Confidence squared			0.008	0.002
			(0.007)	(0.008)
Math Confidence squared			0.002	0.008
			(0.006)	(0.008)
Adjusted R-squared	0.049	0.050	0.050	0.050
Individuals	1,921	1,829	1,921	1,829

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

A.1.2 Selection

Table OA.7: NEPS education all: Selection

Dependent Variable: STEM education		
	(without)	(with)
Female	-0.293***	-0.294***
	(0.016)	(0.016)
Standardized rsc_reading	-0.031***	-0.031***
	(0.008)	(0.008)
Standardized rsc_ict	0.015*	0.015*
	(0.008)	(0.008)
Standardized rsc_science	0.011	0.011
	(0.009)	(0.009)
Standardized rsc_math	0.030***	0.030***
	(0.008)	(0.008)
imr		-0.040
		(0.088)
Adjusted R-squared	0.169	0.169
Individuals	3,750	3,750

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

A.1.3 Big 5

Table OA.8: NEPS Education all Big5

Dependent Variable: STEM Education		
	(1)	(2)
Female	-0.293***	-0.288***
	(0.016)	(0.018)
Reading Confidence	-0.031***	-0.032***
	(0.008)	(0.008)
ICT Confidence	0.015*	0.014
	(0.008)	(0.009)
Science Confidence	0.011	0.008
	(0.009)	(0.009)
Math Confidence	0.030***	0.030***
	(0.008)	(0.008)
Big 5	No	Yes
Adjusted R-squared	0.169	0.172
Individuals	3,750	3,584

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

A.2 Alternative Confidence Measures

A.2.1 Deviation Scores

Another way of measuring self-confidence is via deviation scores, which measure how the respondents' self-assessments and actual performance differ. Deviation scores are calculated as the difference between the estimated proportion of correctly answered items (subjective competence) and the proportion of items that were actually correct (objective competence) (Lockl, 2015):

$$\text{dev} = \frac{\#\ \text{self-assessed correct answers}}{\#\ \text{items}} - \frac{\#\ \text{correct answers}}{\#\ \text{items}}\ \ ;\ \text{with dev} \in [-1, 1]$$

A deviation score of zero indicates perfect estimation of one's performance while scores above (below) 0 indicate overestimation (underestimation).

Table OA.9: Deviation Scores 1

Dependent Variable: STEM education	(1)	(2)	(3)	(4)
Female	-0.356***	-0.307***	-0.301***	-0.297***
	(0.015)	(0.016)	(0.016)	(0.016)
Composite Confidence			0.019**	
			(0.009)	
Reading Confidence				-0.030***
				(0.009)
ICT Confidence				0.016
				(0.010)
Science Confidence				0.008
				(0.010)
Math Confidence				0.030***
				(0.009)
Adjusted R-squared	0.136	0.162	0.163	0.167
Individuals	3,750	3,750	3,750	3,750
Competence dummies	No	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All competence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

Table OA.10: Deviation Scores 2

Dependent Variable:	STEM University				STEM Vocational Training			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Female	-0.304***	-0.243***	-0.226***	-0.221***	-0.379***	-0.347***	-0.343***	-0.341***
	(0.020)	(0.021)	(0.021)	(0.022)	(0.019)	(0.020)	(0.021)	(0.021)
Composite Confidence			0.040***				0.012	
			(0.011)				(0.012)	
Reading Confidence				-0.022**				-0.031***
				(0.011)				(0.012)
ICT Confidence				0.017				0.020
				(0.012)				(0.013)
Science Confidence				0.027**				-0.009
				(0.012)				(0.013)
Math Confidence				0.032***				0.036***
				(0.011)				(0.011)
Adjusted R-squared	0.098	0.132	0.137	0.140	0.180	0.189	0.189	0.194
Individuals	2,307	2,307	2,307	2,307	2,021	2,021	2,021	2,021
Competence dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1 for each sub-sample separately. STEM University captures whether the first started university program of an individual is in a STEM field, while STEM Vocational Training indicates whether the first started vocational training is in STEM.

Table OA.11: Deviation Scores 3

Dependent Variable: STEM education	(1)	(2)	(3)	(4)
Female	-0.310***	-0.301***	-0.302***	-0.299***
	(0.016)	(0.016)	(0.016)	(0.016)
Reading Confidence	-0.017**			
	(0.008)			
ICT Confidence		0.020**		
		(0.009)		
Science Confidence			0.015*	
			(0.009)	
Math Confidence				0.030***
				(0.008)
Adjusted R-squared	0.163	0.163	0.163	0.165
Individuals	3,750	3,750	3,750	3,750
Competence dummies	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All competence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

Table OA.12: Deviation Scores 4

Dependent Variable: STEM	(Women)	(Men)	(Women)	(Men)
Composite Confidence	0.016	0.024*		
	(0.011)	(0.014)		
Reading Confidence			-0.020**	-0.040***
			(0.010)	(0.014)
ICT Confidence			-0.005	0.041***
			(0.012)	(0.015)
Science Confidence			0.021*	-0.003
			(0.013)	(0.015)
Math Confidence			0.024**	0.036**
			(0.010)	(0.014)
Adjusted R-squared	0.044	0.040	0.047	0.048
Individuals	1,921	1,829	1,921	1,829
Competence dummies	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1 for each sub-sample separately. STEM education captures whether the first started vocational training or university program is in a STEM field.

A.2.2 Residual Scores of Ranks

We further try a measure of confidence based on rank measures. We split both the objective and subjective competence scores into percentiles and proceed to residualize these ranked measures in the same way as in the baseline specification.

Table OA.13: Residual Scores of Ranks 1

Dependent Variable: STEM education				
	(1)	(2)	(3)	(4)
Female	-0.356***	-0.307***	-0.297***	-0.289***
	(0.015)	(0.016)	(0.016)	(0.016)
Composite Confidence			0.022***	
			(0.008)	
Reading Confidence				-0.031***
				(0.008)
ICT Confidence				0.010
				(0.008)
Science Confidence				0.016*
				(0.009)
Math Confidence				0.034***
				(0.008)
Adjusted R-squared	0.136	0.162	0.164	0.170
Individuals	3,750	3,750	3,750	3,750
Competence dummies	No	Yes	Yes	Yes

Standard errors in parentheses
Controls: SES background, migrant, school leaving degree, competences
*** p<0.01, ** p<0.05, * p<0.1

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All competence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

Table OA.14: Residual Scores of Ranks 2

Dependent Variable:								
	STEM University				STEM Vocational Training			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Female	-0.304***	-0.243***	-0.223***	-0.214***	-0.379***	-0.347***	-0.340***	-0.336***
	(0.020)	(0.021)	(0.022)	(0.022)	(0.019)	(0.020)	(0.021)	(0.021)
Composite Confidence			0.039***				0.015	
			(0.010)				(0.010)	
Reading Confidence				-0.024**				-0.035***
				(0.010)				(0.010)
ICT Confidence				0.012				0.014
				(0.011)				(0.011)
Science Confidence				0.026**				0.006
				(0.011)				(0.012)
Math Confidence				0.039***				0.033***
				(0.011)				(0.011)
Adjusted R-squared	0.098	0.132	0.138	0.143	0.180	0.189	0.189	0.196
Individuals	2,307	2,307	2,307	2,307	2,021	2,021	2,021	2,021
Competence dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Standard errors in parentheses
Controls: SES background, migrant, school leaving degree, competences
*** p<0.01, ** p<0.05, * p<0.1

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1 for each sub-sample separately. STEM University captures whether the first started university program of an individual is in a STEM field, while STEM Vocational Training indicates whether the first started vocational training is in STEM.

Table OA.15: Residual Scores of Ranks 3

Dependent Variable: STEM education				
	(1)	(2)	(3)	(4)
Female	-0.310***	-0.300***	-0.298***	-0.294***
	(0.016)	(0.016)	(0.016)	(0.016)
Reading Confidence	-0.016**			
	(0.007)			
ICT Confidence		0.017**		
		(0.008)		
Science Confidence			0.021***	
			(0.008)	
Math Confidence				0.035***
				(0.008)
Adjusted R-squared	0.163	0.163	0.164	0.167
Individuals	3,750	3,750	3,750	3,750
Competence dummies	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All competence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

Table OA.16: Residual Scores of Ranks 4

Dependent Variable: STEM				
	(Women)	(Men)	(Women)	(Men)
Composite Confidence	0.017*	0.027**		
	(0.009)	(0.012)		
Reading Confidence			-0.028***	-0.034***
			(0.010)	(0.012)
ICT Confidence			0.001	0.022*
			(0.010)	(0.013)
Science Confidence			0.022**	0.010
			(0.011)	(0.013)
Math Confidence			0.027***	0.039***
			(0.010)	(0.012)
Adjusted R-squared	0.045	0.041	0.052	0.048
Individuals	1,921	1,829	1,921	1,829
Competence dummies	Yes	Yes	Yes	Yes

Standard errors in parentheses; Standardization by gender subsample
Controls: SES background, migrant, school leaving degree, competences
*** p<0.01, ** p<0.05, * p<0.1

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1 for each sub-sample separately. STEM education captures whether the first started vocational training or university program is in a STEM field.

A.2.3 Deviation Scores of Ranks

Lastly, we consider deviation scores based on rank measures. Again using the percentile ranks, we compute deviation scores as the difference between the percentile of estimated score and the percentile of the actual score.

Table OA.17: Deviation Scores of Ranks 1

Dependent Variable: STEM education	(1)	(2)	(3)	(4)
Female	-0.356***	-0.307***	-0.298***	-0.292***
	(0.015)	(0.016)	(0.016)	(0.016)
Composite Confidence			0.024**	
			(0.010)	
Reading Confidence				-0.032***
				(0.009)
ICT Confidence				0.011
				(0.010)
Science Confidence				0.016
				(0.010)
Math Confidence				0.037***
				(0.009)
Adjusted R-squared	0.136	0.162	0.163	0.169
Individuals	3,750	3,750	3,750	3,750
Competence dummies	No	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All competence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

Table OA.18: Deviation Scores of Ranks 2

Dependent Variable:								
	STEM University				STEM Vocational Training			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Female	-0.304***	-0.243***	-0.224***	-0.217***	-0.379***	-0.347***	-0.341***	-0.338***
	(0.020)	(0.021)	(0.022)	(0.022)	(0.019)	(0.020)	(0.021)	(0.021)
Composite Confidence			0.043***				0.015	
			(0.012)				(0.012)	
Reading Confidence				-0.023**				-0.037***
				(0.011)				(0.011)
ICT Confidence				0.012				0.016
				(0.012)				(0.013)
Science Confidence				0.028**				0.004
				(0.013)				(0.013)
Math Confidence				0.041***				0.037***
				(0.012)				(0.012)
Adjusted R-squared	0.098	0.132	0.137	0.142	0.180	0.189	0.189	0.195
Individuals	2,307	2,307	2,307	2,307	2,021	2,021	2,021	2,021
Competence dummies	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1 for each sub-sample separately. STEM University captures whether the first started university program of an individual is in a STEM field, while STEM Vocational Training indicates whether the first started vocational training is in STEM.

Table OA.19: Deviation Scores of Ranks 3

Dependent Variable: STEM education				
	(1)	(2)	(3)	(4)
Female	-0.310***	-0.301***	-0.300***	-0.296***
	(0.016)	(0.016)	(0.016)	(0.016)
Reading Confidence	-0.017**			
	(0.008)			
ICT Confidence		0.018**		
		(0.009)		
Science Confidence			0.022**	
			(0.009)	
Math Confidence				0.037***
				(0.009)
Adjusted R-squared	0.163	0.163	0.163	0.166
Individuals	3,750	3,750	3,750	3,750
Competence dummies	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All competence measures standardized to mean 0, SD 1. STEM education captures whether the first started vocational training or university program is in a STEM field.

Table OA.20: Deviation Scores of Ranks 4

Dependent Variable: STEM				
	(Women)	(Men)	(Women)	(Men)
Composite Confidence	0.019	0.031**		
	(0.012)	(0.014)		
Reading Confidence			-0.028***	-0.035***
			(0.011)	(0.013)
ICT Confidence			-0.001	0.024
			(0.013)	(0.015)
Science Confidence			0.024*	0.010
			(0.013)	(0.015)
Math Confidence			0.030**	0.043***
			(0.012)	(0.014)
Adjusted R-squared	0.045	0.041	0.050	0.047
Individuals	1,921	1,829	1,921	1,829
Competence dummies	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Data source: NEPS-SC4. Controls: SES background, migrant, school leaving degree. All confidence measures standardized to mean 0, SD 1 for each sub-sample separately. STEM education captures whether the first started vocational training or university program is in a STEM field.