IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

RESEARCH REPORT SERIES

IZA Research Report No. 87

Gender Differences in Student Dropout in STEM

Ingo E. Isphording (IZA)
Pamela Qendrai (IZA)

JANUARY 2019

GEFÖRDERT VOM

Bundesministerium
für Bildung
und Forschung

Gender Differences in Student Dropout in STEM

Ingo E. Isphording and Pamela Qendrai

Abstract. The misrepresentation of females among STEM graduates is believed to be an important driver behind the gender gap in labor market success. While barriers to entry into STEM for female students have gained strong attention by education researchers, subsequent gender differences in the persistence of pursuing STEM studies are less well understood. In this research note, we quantify the gender gap in dropout out of STEM using a representative student survey in Germany and apply a descriptive decomposition technique to differentiate between gender differences driven by differences in observed characteristics and behavioral differences. Our results point to a significant gap in dropout rates that cannot be explained by observable characteristics. Rather, female students in STEM appear to be positively selected in terms of the study capital, yet display higher dropout rates than their male counterparts. We discuss potential behavioral explanations and provide recommendations for policy interventions.

Disclaimer and acknowledgements: This note is part of the research project PIRanHa, funded by grant 01PX16013 from the German Ministry of Education and Research (Bundesministerium für Bildung und Forschung, BMBF). The sole responsibility for the report's contents lies with the authors. This paper uses data from the National Educational Panel Study (NEPS): Starting Cohort First-Year Students, doi:10.5157/NEPS:SC5:9.0.0. From 2008 to 2013, NEPS data was collected as part of the Framework Program for the Promotion of Empirical Educational Research funded by the German Federal Ministry of Education and Research (BMBF). As of 2014, NEPS is carried out by the Leibniz Institute for Educational Trajectories (LIfBi) at the University of Bamberg in cooperation with a nationwide network. We would like to thank Tobias Raabe, Arnim Seidlitz and Florian Wozny for support in the data preparation.

Corresponding author
Ingo Isphording, IZA - Institute of Labor Economics, Schaumburg-Lippe-Str. 5-9, 53113 Bonn, Germany.
Phone +49 (228) 3894-522, Fax +49 (228) 3894-510, E-mail isphording@iza.org

1. Introduction

Ongoing technological change has led to a steadily growing demand for graduates from Science, Technology, Engineering and Mathematics (STEM). Based on the newest available numbers for 2015, Germany is among the forefront of producing highly-talented graduates in these fields, with 37 percent of students enrolled in STEM-associated majors in 2015. Nonetheless, this leading role is not mirrored in its share of female students in STEM fields. Less than one out of three STEM students are female, even below the OECD average (OECD 2017).

The attempts to explain the persistent gender STEM gap range from earliest childhood determinants to labor-market-based explanations. Natural cognitive differences with boys being more capable in spatial vs verbal tasks (and vice versa) appear to be only moderate and weakly associated to STEM success (Spelke 2006). But despite the lack of inherent genetic gender differences, gaps start to arise in early development stages in childhood, when parents might engage in gender-specialized parenting. Such specialized parenting can lead to differentiated effects on STEM preferences, especially in the presence of opposite sex siblings (Brenøe 2018). As a result of such early influences, girls as early as 5th grade systematically under-estimate their math and science abilities (Weinhardt 2017). This development is then further reinforced by the prevalent lack in female STEM teachers acting as role models for successful STEM careers, which further deters girls from going into STEM tracks (Bottia et al. 2015). After school, women might anticipate gender pay gaps in STEM occupations (Osikominu and Pfeifer 2018).

Intervening policy measures typically focus on attracting women to STEM subjects, and on reducing barriers to enter STEM studies in the first place. Examples for such interventions are role model provision through female scientists visiting schools (Breda et al. 2018), gender-responsive teacher training in STEM-related subjects, and targeted scholarship programs (OECD 2014). But barriers to enter STEM studies are not the only driver of the gender STEM gap, and measures enhancing access to STEM studies won't suffice, if women further display a lower persistence in pursuing a degree, and are more likely to drop out of STEM education conditional on beginning their studies (Kugler et al. 2017).

In this report, we quantify and describe a significantly higher likelihood of female students to drop out of STEM education using data from the German National Educational Panel Study (NEPS). This gender difference is not observed in non-STEM fields. The gap cannot be explained by observable characteristics of students. Instead, female STEM students appear to be positively selected – they have better high-school degrees and possess a more conscientious personality than female non-STEM students have compared to their male counterparts.

While the gender gap in STEM drop out is not explained by observable characteristics in our data, we survey the existing literature on potentially unobservable behavioral explanations, such like gender differences in college preparation, gender differences in the willingness to compete and the role of teachers and teacher stereotypes.

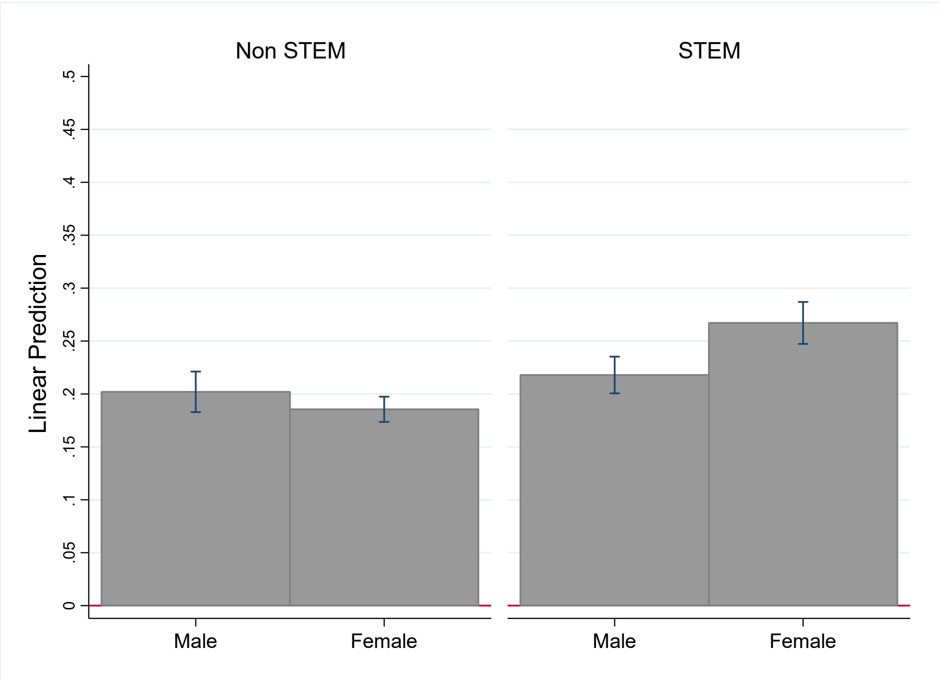
Enhancing STEM persistence asks for a different set of policy measures that have to complement initiatives aiming at attracting women to STEM. We therefore close our discussion with a summary of potential candidates for efficient interventions that take the behavioral reasons behind female dropout in STEM into account.

2. **Evidence from German STEM students**

We analyze the school dropout for university students in Germany using the nationally representative *National Education Panel Study*. This data tracks the students' persistence in tertiary education for ten semesters. We distinguish students by their field of study: In 2010, we observe 3703 students in the so-called STEM majors (Sciences, Technology, Engineering and Mathematics) and 6160 students in the remaining non-STEM-related fields. STEM and non-STEM fields differ distinctively in the share of female students. While about 72 percent of non-STEM students are female, it is only 43 percent for STEM students.

We focus on student dropout defined as leaving the tertiary education system entirely without achieving a degree or switching between STEM and non-STEM degree. This latter condition ensures that we include the significant group of students leaving the STEM field to commence their studies in a different field – we only observe very few students switching *into* STEM. Figure 1 demonstrates the strong difference in gender disparity in study persistence between STEM and non-STEM. Dropout rates are almost on par between male and female students in the non-STEM fields by about 18-20 percent. In STEM, dropout is in general higher, with female students displaying a 23 percent higher dropout rate than their male counterparts.

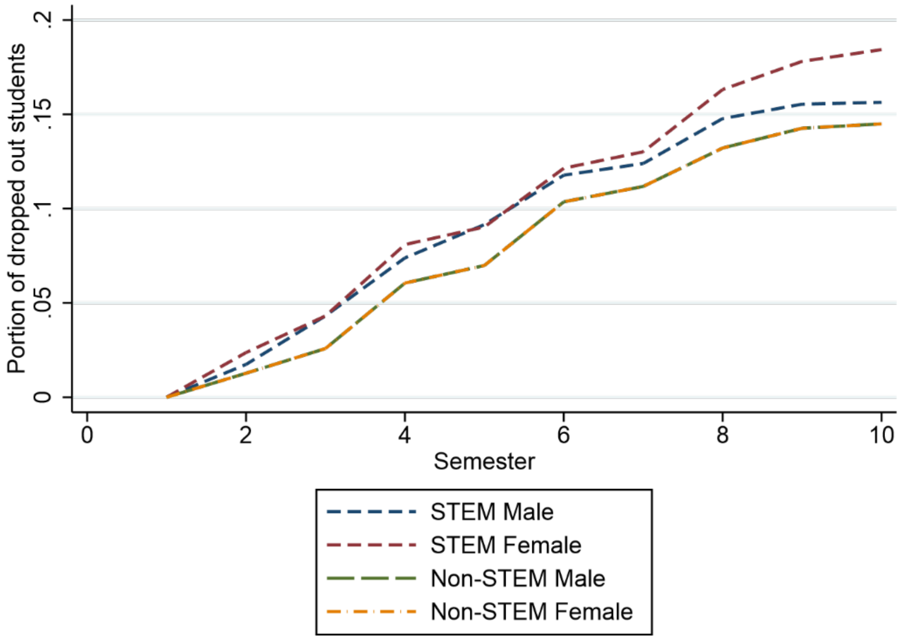
Figure 1: Differences in dropout by gender and subject



Note: This graph displays average dropout rates by gender and STEM/non-STEM subject. Coefficients with 95 % confidence interval. The sample size is 6160 individuals for non-STEM majors and 3703 individuals for STEM majors.

If we look at this difference over time in Figure 2, we observe that gender differences mainly emerge at later stages of the STEM studies following the 7^{th} semester. Thus, this divergence occurs in the final stages of the studies, where students start to orientate themselves towards labor market opportunities.

Figure 2: The dropout semester by field of study and gender



Note: This graph describes the portion of students that have dropped out of tertiary education from Winter Semester 2010 until Summer Semester 2015 based on longitudinal data of 9863 individuals studying in either a STEM or Non-STEM major.

3. **Are women in STEM any different?**

This strong difference in dropout rates is worrisome, as it severely counteracts endeavors to increase STEM participation among female students. It is therefore crucial to understand the sources of this difference. Comparing students by field of study and gender indeed points to significant differences in observed gender disparities between STEM and non-STEM students. Table 1 lists average levels of observable characteristics divided by gender and field of study. Numbers in the first column list *differences in differences*, i.e. the difference in gender disparities between STEM and non-STEM.

Table 1: Gender differences by subject and gender

			Non-STEM				**STEM**			
	DiD		Males		Females		Males		Females	
A. Social Background										
Age	-0.283**	0.134)	21.53	[3.37]	21.10	[3.83]	21.04	[2.82]	20.33	[2.60]
Migrant	-0.002	(0.018)	0.20	[0.40]	0.20	[0.40]	0.21	[0.41]	0.21	[0.41]
Parents' education	0.004	(0.021)	0.62	[0.48]	0.62	[0.49]	0.62	[0.49]	0.62	[0.49]
B. Studies										
High School										
No retention	-0.007	(0.015)	0.82	[0.39]	0.89	[0.32]	0.83	[0.38]	0.89	[0.31]
Non traditional	-0.002	(0.008)	0.05	[0.22]	0.03	[0.18]	0.03	[0.18]	0.01	[0.12]
School Grade	-0.030	(0.027)	2.28	[0.65]	2.17	[0.60]	2.30	[0.64]	2.16	[0.59]
Environment										
Preferred Subject	-0.051***	(0.017)	0.80	[0.40]	0.82	[0.39]	0.83	[0.38]	0.80	[0.40]
Preferred Institution	-0.062***	(0.018)	0.73	[0.45]	0.72	[0.45]	0.83	[0.38]	0.77	[0.42]
Live at home	-0.010	(0.021)	0.35	[0.48]	0.36	[0.48]	0.46	[0.50]	0.47	[0.50]
C. Personality										
Extraversion	0.116***	(0.036)	3.76	[0.82]	3.81	[0.82]	3.49	[0.84]	3.66	[0.84]
Agreeableness	0.000	(0.024)	3.48	[0.57]	3.67	[0.53]	3.47	[0.56]	3.67	[0.52]
Conscientiousness	0.065**	(0.032)	3.65	[0.76]	3.95	[0.72]	3.52	[0.76]	3.88	[0.72]
Neuroticism	-0.008	(0.034)	2.40	[0.77]	2.90	[0.78]	2.43	[0.74]	2.93	[0.80]
Openness	-0.012	(0.039)	3.48	[0.95]	3.76	[0.89]	3.37	[0.88]	3.63	[0.87]
D. Labor Market										
Unemployed	-0.025	(0.021)	0.48	[0.50]	0.33	[0.47]	0.47	[0.50]	0.30	[0.46]
Employed	-0.093***	(0.021)	0.45	[0.50]	0.48	[0.50]	0.42	[0.49]	0.36	[0.48]
Internship	0.005	(0.020)	0.30	[0.46]	0.38	[0.49]	0.29	[0.45]	0.38	[0.49]

***Note**:* Column named DiD (difference in difference) displays the coefficients of the difference in gender difference between the students enrolled in STEM majors and non-STEM majors. Robust standard errors in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.001$

A first difference appears in the age composition, with women in general being younger than males, but with an age gap in STEM more than two times as large as in non-STEM. In line with this age difference, females in STEM possess less labor market experience compared to male STEM-students and their female counterparts in non-STEM. Previous research on these age-related determinants of student dropout has turned out to be inconclusive (Larsen et al. 2013), so the effect of this age disparity is a priori unclear.

In terms of high school performance, female students in STEM display a stronger advantage compared to STEM males than non-STEM females when compared to non-STEM males. With a better high school grade being one of the most powerful predictors for college success, this observation runs counter the observed differences in dropout rates. The same is true for observed differences in personality. Female STEM students possess higher scores in personality dimensions of extraversion and conscientiousness, both of which have been demonstrated to be beneficial for the stability of educational careers.

A potentially better candidate in explaining the observed differences in persistence is found when looking at the match quality between students, institution and subject. Females in STEM lack behind their male counterparts in terms of reported match to preferred institution and subject, while no such gender difference in matching quality can be observed for non-STEM students. If match quality indeed drives the likelihood in dropout rates, adjusting the matching mechanism of students to programs could be a potential remedy.

Taken together, females in STEM and non-STEM do indeed differ in a number of characteristics, leading to observed differences in gender gaps. Still, the observed differences do not paint a clear picture of why female STEM students display a lower persistence. Rather, some characteristics, such like beneficial personality traits and better high school grades, point to advantages through a better endowment of *study capital* of female STEM students.

4. **Persistent gender differences remain unexplained**

To assess the joint explanatory power of the observed differences in student characteristics on the observed gender gap in persistence, we focus from now on STEM students only and relate the dropout out of STEM fields (either by leaving tertiary education or switching fields) to the observed characteristics in a multivariate regression model.

By doing so, we make students statistically comparable, i.e. we intuitively compare students that are similar in the characteristics we *statistically control* for. Table 2 summarizes the according results. From left to right, the displayed coefficients stem from increasingly comprehensive specifications controlling for a larger set of characteristics, making students more and more statistically similar.

Table 2: Gender Differences in the Dropout Probability of STEM Majors' Students

	I	II	III	IV	V	VI	VII
Gender Gap	-0.049***	-0.053***	-0.070***	-0.060***	-0.069***	-0.067***	-0.037**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.017)
Social Background	No	Yes	Yes	Yes	Yes	Yes	Yes
High School Performance	No	No	Yes	Yes	Yes	Yes	Yes
Study Environment	No	No	No	Yes	Yes	Yes	Yes
Personality Traits	No	No	No	No	Yes	Yes	Yes
Labor Market Experience	No	No	No	No	No	Yes	Yes
Institutional Fixed Effects	No	No	No	No	No	No	Yes

***Note**:* Robust standard errors in parenthesis. The number of observations is 3703 for each specification. The dependent variable is the dropout indicator. Detailed estimations of this table are presented in Table A1 in the Appendix. * $p<0.1$, ** $p<0.05$, *** $p<0.001$

Specification I) mostly resembles the raw gap already indicated in Figure 1. Female students have on average a 4.9 percentage points larger probability of leaving STEM studies compared to their male counterparts. Keeping constant basic variables of the social background (age, migration status and parent's education, specification II) does not distinctively change the observed gap. Adding highly explanatory variables of high school performance (high school grade, retention experience, traditional university entrance qualification, spec. III) even increases the observed gap, i.e. making students more comparable indicates an even larger gap in persistence. Keeping match quality, personality traits and labor market experience constant does not further change the observed gender gap.

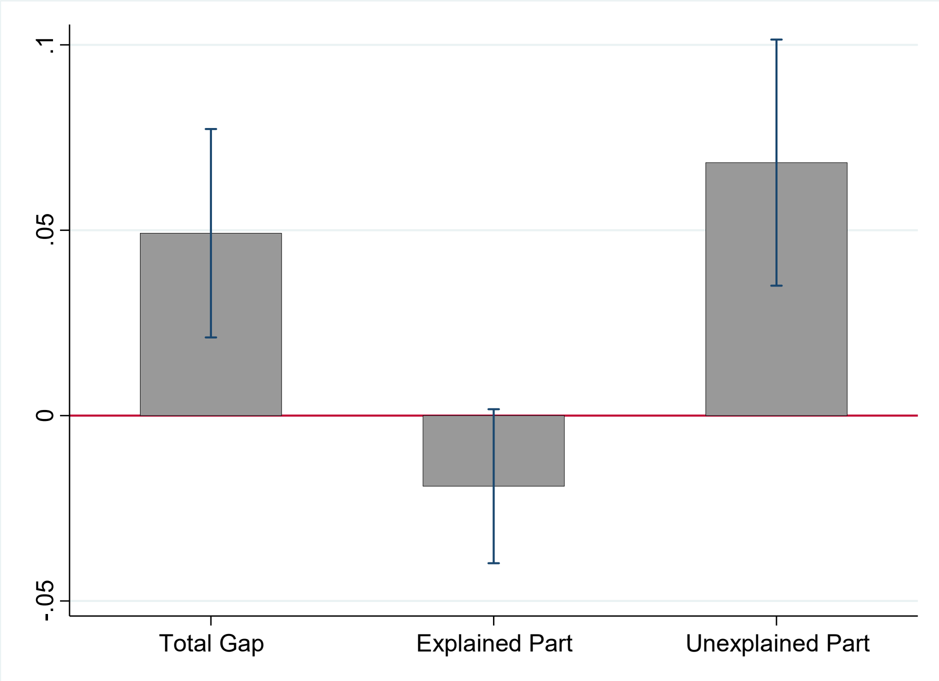
Only if we use an alternative empirical approach by only comparing students who study at the same university by using *institution-fixed effects* (specification VII), the gender gap becomes smaller, but remains statistically significant accounting for about 4 percentage points. This points to a certain role of sorting by gender into institutions with on average different dropout rates.

We conclude from these regressions that the strong gender gap in persistence in STEM fields cannot be explained by observed differences in student characteristics on the contrary, the results highlight the importance of comparing statistically similar students to uncover the actual magnitude of the gender difference.

5. **Individual characteristics would predict *higher* persistence**

A similar picture can be drawn by an empirical exercise using a so-called *Blinder-Oaxaca* decomposition. This statistical technique answers the questions what the dropout rate of female STEM students would be if their characteristics were to be evaluated with the model parameters of their male counterparts.

Figure 3: Blinder-Oaxaca Decomposition of Gender Gap in School Dropout in STEM



Note: Coefficients with 95 % confidence interval of the total gap, explained and unexplained part from the last model specification of Table 2. Sample size is 3703. Oaxaca command with females intercepts used for the decomposition. Robustness checks conducted with males and pooled regression coefficients and no substantial changes were found. Detailed decomposition results are presented in table A2 in the Appendix.

Figure 3 displays the results of the decomposition. The first bar again displays the raw gap in dropout rates. The second bar displays the *explained part* of this gap: given the observed characteristics, but evaluated with male model parameters, female STEM students should display a lower dropout rate by about 2 percentage points.

The third bar displays the *unexplained part*. Women differ in estimated model parameters in a way that counteracts the advantage in endowments of beneficial characteristics, leading the higher dropout rate. These unexplained differences may consist of differences in behavior, discrimination or differences in character traits and individual characteristics not covered by the data. In the following, we survey the literature with regard to potential alternative explanations.

6. **Alternative explanations: high-school preparation, teachers and the willingness to compete**

Empirically, it remains challenging to disentangle the actual sources of the gap in STEM persistence, as female selection on observed characteristics would predict lower dropout rates. We therefore take a detour into the recent economic literature on gender differences in persistence to gain some insights about potential explanatory factors that are unobservable in our data.

College preparation. First decisions towards STEM fields are already taken during middle school, when students decide for or against areas of specialization with STEM content, e.g. advanced courses in math and physics. Females' comparatively lower participation rates in these courses, and the accordingly weaker foundations in mathematics and science prior to tertiary education are found to be a mechanism behind the low female persistence in STEM during university studies. Speer (2017) using ASVAB data concludes that college preparation accounts for two-thirds of the gender differences in science major choices, and that it explains about a quarter of differences in switching out of science majors.

The role of teachers and professors. Teachers play a twofold role in shaping their students' career decisions: they act as powerful role models for their students, but their teaching style might reflect underlying gender-biased stereotypes. Professor's gender has a powerful causal effect on not only females' performance in STEM intensive courses but also endurance and graduation in STEM majors (Carrell et al. 2010). Apparently, females seem to exhibit a self-perception of belonging in STEM culture and are more motivated to pursue studies in the presence of female role models/professors/experts (Dasgupta et al. 2011). This self-perception might be further enhanced by teachers' gender stereotypes. Carlana (2017) finds that teachers with experimentally measured stronger gender stereotypes generate larger gender gaps in students' performance in mathematics, which then in turn affects the choice of majors.

Gender differences in the willingness to compete. A considerable body of research has demonstrated early in life arising and persistent gender differences in the willingness to compete. Women are more likely to shy away from competition and have higher levels of personal traits such like risk and feedback aversion (Niederle and Vesterlund 2007). Such gaps in competitive behavior arise very early in life and are persistent (Sutter and Glätzle-Rützler 2015). If study environments in STEM are more competitive or are perceived as more competitive through a higher share of male students, this might indeed lead to the observed differential persistence of females in STEM compared to non-STEM. Using data of a large US university, Kugler et al. (2017) indeed demonstrate that women especially in male-dominated STEM fields are more likely to be discouraged by low relative performance (compared to males) and to switch fields in response. Overwhelmingly, females seem to avoid the culture of STEM rather than science itself, choosing thus more female "intensive" subjects (Astorne-Figari and Speer 2018).

Promising interventions. In this context intervening measures become a necessary tool. Career-counselling, information provision and learning communities could be some of the promising intervention scenarios. Although learning communities are in general found to not be useful for the persistence of all students, they are found to significantly help females in STEM majors' performance (Russell, 2017). More specifically, the author uses a lottery-based admission system into learning communities of MIT freshman students, to provide evidence that the participation in learning communities help women and minorities in STEM fields to get higher grades and complete more courses. Additionally, information provision regarding the study costs is found to be another helpful channel of intervention. Schmeiser et al. (2016) find that providing students with information regarding their ability to repay the study loans makes students in general to switch more into majors with high return and more high-performing students to choose STEM fields. Another promising, though more costly way is to provide female students with a more senior student as mentor who guides through first year obstacles and acts as a role model. Such a mentoring intervention has been positively evaluated in field experiment by Dennehy and Dasgupta (2017). Women in engineering who were assigned a female mentor were less likely to drop out and reported higher levels of belonging and confidence into their skills.

To sum up, females persistence in STEM majors seem to prevail from early childhood and develop further during the educational path as a result of comparatively weaker foundations in college, absence of female role models and willingness to compete. While we are not able to pinpoint these mechanisms in our own data, a number of studies have utilized these newer insights to design and to evaluate according interventions aiming at raising the STEM orientation of female students.

7. **Conclusion and policy recommendations**

The under-representation of women in STEM education and later STEM careers is a worrisome and persistent phenomenon. While barriers to entry have received ample attention by policy makers and researchers, less focus has been put on gender differences in the persistence of pursuing a STEM career after entering tertiary education. In this regard, we have shown a substantial gender gap in STEM persistence, with female STEM students being more likely to drop out of their studies by about 23 percent.

Differences in demographic compositions between male and female students, as well as differences in personality profiles, high school performance or labor market experience do not explain this observed gender gap in persistence. Instead, female STEM students appear to be positively selected on observable characteristics and statistically more comparable students exhibit a stronger gender difference.

We drew from recent literature on behavioral differences, especially a stronger responsiveness of female students to negative feedback in competitive environments, differences in college preparation and the role of teachers in encouraging female students to gain insights into potential alternative mechanisms.

Our results imply that traditional intervening measures such like tougher selection processes might not necessarily but could even counteract the target of reducing gender gaps in STEM persistence by inducing even stronger competitive environments.

More promising alternatives might be found in gender-specific mentoring and counselling programs, as well as teacher trainings raising the awareness and sensitivity towards gender differences persistence-affecting behavior, which might not be given among still male-dominated faculties.

A number of promising initiatives have already implemented such insights into the German STEM faculties. The *Bundesverband Mentoring in der Wissenschaft* (Federal Association of Mentoring in the Sciences) lists 65 mostly faculty-specific mentoring programs aimed at female STEM students. Long-term evaluations of such programs will be needed to assess their efficiency in increasing female STEM persistence as a step to close the gender gap in STEM degrees to mitigate the pressing issue of skills shortage.

References

Astorne-Figari, C., & Speer, J. D. (2018). Drop out, switch majors, or persist? The contrasting gender gaps. *Economics Letters*, *164*, 82-85.

Marianne, B. (2011). New perspectives on gender. In Handbook of labor economics (Vol. 4, pp. 1543-1590). Elsevier.

Bottia, M. C. and Stearns, E. and Mickelson, R. A. and Moller, S. and Valentino, L., (2015). Growing the roots of STEM majors: Female math and science high school faculty and the participation of students in STEM. Economics of Education Review, Elsevier, vol. 45(C), pages 14-27.

Breda, T. and van Effenterre, C. and Grenet, J. and Monnet, M. (2018). Can female role models reduce the gender gap in science? Evidence from classroom interventions in French high-schools. PSE Working Papers No. 2018-06.

Brenøe, A. (2018). Sibling Gender Composition and Participation in STEM Education. Mimeo.

Carlana, M. (2017). Stereotypes and Self-Stereotypes: Evidence from Teachers' Gender Bias. Working Paper.

Carrell, S. E., Page, M. E., and West, J. E. (2010). Sex and science: How professor gender perpetuates the gender gap. The Quarterly Journal of Economics, 125(3), 1101-1144.

Dennehy, T. C., & Dasgupta, N. (2017). Female peer mentors early in college increase women's positive academic experiences and retention in engineering. Proceedings of the National Academy of Sciences of the United States of America, 114(23), 5964-5969.

Francis, B., L. Archer, J. Moote, J. DeWitt, E. MacLeod, and L. Yeomans (2017). The construction of physics as a quintessentially masculine subject: Young people's perceptions of gender issues in access to physics. Sex Roles 76 (3-4), 156-174.

Griffith, A. L. (2010). Persistence of women and minorities in STEM field majors: Is it the school that matters? Economics of Education Review, 29(6), 911-922.

Hoffman, M., Gneezy, U., and List, J. A. (2011). Nurture affects gender differences in spatial abilities. Proceedings of the National Academy of Sciences, 108(36), 14786-14788.

Humphreys, L. G., Lubinski, D., and Yao, G. (1993). Utility of predicting group membership and the role of spatial visualization in becoming an engineer, physical scientist, or artist. Journal of Applied Psychology, 78(2), 250.

Jann, B. (2008). A Stata implementation of the Blinder-Oaxaca decomposition. Stata journal, 8(4), 453-479.

Kahn, S., and Ginther, D. (2017). Women and STEM (No. w23525). National Bureau of Economic Research.

Kugler, A. and Tinsley, C. and Ukhaneva, O. (2017). Choice of Majors: Are women really different from men? National Bureau of Economic Research. No. w23735

Larsen, M. R., Sommersel, H. B. and Larsen, M. S. (2013). Evidence on Dropout Phenomena at Universities. Danish Clearinghouse for educational research

Niederle, M., Vesterlund, L. (2007) Do Women Shy Away From Competition? Do Men Compete Too Much? The Quarterly Journal of Economics, Volume 122, Issue 3, 1 August 2007, Pages 1067–1101.

OECD (2014). Promoting female participation in STEM. Compendium of Practical Case Studies. OECD Higher Education Programme IMHE.

OECD (2017), Education at a Glance 2017: OECD Indicators, OECD Publishing, Paris.

Osikominu, A. and Pfeifer, G. (2018). Perceived Wages and the Gender Gap in STEM Fields. IZA Discussion Paper 11321

Russell, L. (2017). Can learning communities boost success of women and minorities in STEM? Evidence from the Massachusetts Institute of Technology. *Economics of Education Review*, *61*, 98-111.

Schmeiser, M., Christiana S., and Carly U. (2016). "Student Loan Information Provision and Academic Choices." *American Economic Review, 106 (5): 324-28.*

Spelke, E. (2006). Sex Differences in Intrinsic Aptitude for Mathematics and Science?: A Critical Review. The American psychologist. 60. 950-8.

Speer, J. D. (2017). The gender gap in college major: Revisiting the role of pre-college factors. *Labour Economics*, *44*, 69-88.

Stout, J. G., Dasgupta, N., Hunsinger, M., and McManus, M. A. (2011). STEMing the tide: using ingroup experts to inoculate women's self-concept in science, technology, engineering, and mathematics (STEM). Journal of personality and social psychology, 100(2), 255.

Sutter, M., Glätzle-Rützler,D. (2015). Gender Differences in the Willingness to Compete Emerge Early in Life and Persist. Management Science, INFORMS, vol. 61(10), pages 2339-23354, October.

Wang, M. T., Eccles, J. S., and Kenny, S. (2013). Not lack of ability but more choice: Individual and gender differences in choice of careers in science, technology, engineering, and mathematics. Psychological science, 24(5), 770-775.

Weinhardt, F. (2017). Ursache für Frauenmangel in MINT-Berufen? Mädchen unterschätzen schon in der fünften Klasse ihre Fähigkeiten in Mathematik. DIW-Wochenbericht.

Appendix

Table A1: Gender Differences in STEM Majors

	I	II	III	IV	V	VI	VII
Male	0.0492***	0.0532***	0.0702***	0.0604***	0.0691***	0.0669***	-0.0372**
	(0.0143)	(0.0144)	(0.0142)	(0.0141)	(0.0156)	(0.0158)	(0.0172)
Age		0.00544*	-0.00225	-0.000749	-0.000281	0.00131	0.00479
		(0.00279)	(0.00315)	(0.00323)	(0.00316)	(0.00329)	(0.00346)
Migration bckg		0.0566***	0.0356**	0.0291	0.0286	0.0279	0.0302*
		(0.0180)	(0.0179)	(0.0177)	(0.0177)	(0.0177)	(0.0180)
Parents educ		-0.0366**	-0.0149	-0.0104	-0.0131	-0.0128	-0.0121
		(0.0147)	(0.0146)	(0.0145)	(0.0145)	(0.0145)	(0.0149)
No Retention			0.0824***	0.0765***	0.0744***	0.0724***	0.0732***
			(0.0233)	(0.0230)	(0.0230)	(0.0230)	(0.0235)
Non Traditnl			0.0397	0.0335	0.0352	0.0309	0.0458
			(0.0498)	(0.0501)	(0.0494)	(0.0499)	(0.0545)
School Grade			0.119***	0.101***	0.0947***	0.0961***	0.108***
			(0.0118)	(0.0120)	(0.0123)	(0.0123)	(0.0132)
Preferred Subj				-0.131***	-0.128***	-0.127***	-0.129***
				(0.0201)	(0.0201)	(0.0201)	(0.0204)
Preferred Inst				0.0591***	0.0591***	0.0592***	0.0574***
				(0.0190)	(0.0190)	(0.0190)	(0.0196)
Live at home				0.0356**	0.0378***	0.0347**	0.0432***
				(0.0140)	(0.0140)	(0.0140)	(0.0148)
Extraversion					0.0134	0.0147*	0.0111
					(0.00864)	(0.00871)	(0.00893)
Agreeableness					0.0176	0.0168	0.0163
					(0.0128)	(0.0128)	(0.0133)
Conscientiousness					-0.0216**	-0.0217**	-0.0168*
					(0.00978)	(0.00977)	(0.01000)
Neuroticism					-0.0227**	-0.0224**	-0.0229**
					(0.00942)	(0.00942)	(0.00951)
Openness					0.0158**	0.0158**	0.0172**
					(0.00792)	(0.00792)	(0.00812)
Unemployed						-0.0168	-0.0117
						(0.0143)	(0.0148)
Employed						-0.0230	-0.0101
						(0.0147)	(0.0150)
Internship						-0.0130	-0.0168
						(0.0144)	(0.0154)
Constant	0.267***	0.168***	0.132*	0.267***	0.246**	0.225**	0.0928
	(0.0110)	(0.0594)	(0.0763)	(0.0820)	(0.110)	(0.111)	(0.115)
Observations	3,703	3,703	3,703	3,703	3,703	3,703	3,703
R-squared	0.003	0.010	0.047	0.068	0.073	0.074	0.115
Institutional FE	No	No	No	No	No	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A2: Blinder-Oaxaca Detailed Decomposition

	Model I		Model II	
Males	0.267***	(0.0111)	0.267***	(0.0111)
Females	0.218***	(0.00905)	0.218***	(0.00904)
Total Gap	0.0492***	(0.0143)	0.0492***	(0.0143)
Explained Part	-0.0157	(0.0101)	-0.0190	(0.0106)
Unexplained Part	0.0649***	(0.0168)	0.0682***	(0.0169)
Explained Part				
Social background	0.00153	(0.00280)	-0.00128	(0.00309)
High School Performance	-0.0175***	(0.00342)	-0.0199***	(0.00377)
Studies Environment	0.00776**	(0.00257)	0.00876**	(0.00271)
Personality Traits	-0.0124	(0.00845)	-0.00903	(0.00863)
Labor Market Experience	0.00481	(0.00385)	0.00243	(0.00398)
Unexplained part				
Social background	0.158	(0.128)	0.153	(0.142)
High School Performance	0.0464	(0.0733)	0.0557	(0.0781)
Studies Environment	0.0216	(0.0388)	0.0378	(0.0409)
Personality Traits	0.271	(0.154)	0.212	(0.158)
Labor Market Experience	0.0339	(0.0182)	0.0234	(0.0191)
Intercept	-0.465*	(0.212)	-0.414	(0.227)
Observations	3703		3703	

Note: Model I presents the detailed decomposition without controlling for sorting into institutions. Whereas Model II presents the decomposition results having controlled for sorting into institutions. Robust standard errors in parenthesis. p<0.1, ** p<0.05, ***p<0.001