ONLINE APPENDIX OF

GENERATIVE AI USAGE AND ACADEMIC PERFORMANCE

Completed Research Paper

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Variables	Definition	Rationale	Reference
Exam Score	Continuous measure of student performance in the final exam of the mandatory introductory accounting course indicating the percentage of points a student achieved in the final exam. The minimum is zero and the actual (achievable) maximum is 96.67 (100).	Exam scores reflect students' abilities to solve course-relevant problems, therefore approximating student performance. Consistent with related studies, we use it as the dependent variable.	Voshaar et al., (2024), Voshaar et al., (2023a), Cheng & Ding (2021), Eskew & Faley (1988), Hu et al., (2023), Lento (2018), Massoudi et al., (2017), Perera & Richardson (2010)
GenAI User	Indicator variable depicting student usage of GenAI applications for studying and crafting work that they intentionally should have written on their own. *GenAI User* is estimated by ZeroGPT, a GenAI detection system indicating the percentage of text identified as created by GenAI applications. *GenAI User* equals one if the estimate of ZeroGPT exceeds a threshold of 0.5 and is zero otherwise. In our robustness checks we use alternating thresholds of the ZeroGPT estimation (i.e., 0.4 and 0.6) to distinguish GenAI users from non-users.	Related studies document positive effects (e.g., simplification of complex topics and personalized learning) as well as negative effects (e.g., risk of superficial understanding and loss of independent problem-solving) of using GenAI applications in higher education. These factors can either enhance or impede students' performance. We use *GenAI User* as variable of interest in this study to examine the overall effect of GenAI usage on students' performance, which is unknown at present. We chose ZeroGPT over other GenAI detection due to three reasons. First, related studies rank ZeroGPT among the best GenAI detectors. Second, ZeroGPT is shown to minimize both false positive and false negative classifications texts created by GenAI applications and humans. Third, ZeroGPT is capable if correctly classify texts of German language.	Positive effects of GenAI usage: Fauzi et al., (2023), Gilson et al., (2023), AlAfnan et al., (2023), Pavlik (2023), Engelmann et al., (2023), Calderon et al., (2023), Sallam et al., (2023), Qadir (2023), Lund et al., (2023), Wu et al., (2023), Perkins (2023), Cotton et al., (2023), Ali et al., (2023), Sullivan et al., (2023) Negative effects of GenAI usage: Markauskaite et al., (2022), Eager & Brunton (2023), Jain & Kapoor (2013), Rasul et al., (2023), Crawford et al., (2023a), Sallam et al., (2023), Crawford et al., (2023b), Lund et al., (2023), Milano et al., (2023), Bangert-Drowns et al., (2004), Aremu (2023), Liang et al., (2023), Walters (2023), Weber-Wulff et al., (2023), Yeadon et al., (2024)
A-Level Grade	Continuous measure school performance prior to entering university, ranging from 4.0 (best grade) to 1.0 (worst grade).	*A-Level Grade* is used as proxy for general academic aptitude in this study. Related studies consistently document A-level grades to be predictive for exam performance.	Positive effect on exam performance: Azzali et al., (2023), Eskew & Faley (1988), Lento (2018), Massoudi et al., (2017), Papageorgiou & Halabi (2014), Tan & Laswad (2008)
Attempt	Continuous measure equals the number of times a student has registered for the final exam with a maximum value of five, as student must pass the examination within five semesters (i.e. five attempts) according to the regular examination regulations.	Students' academic behavior (e.g., the number of attempts) affect performance. We include *Attempt* into our analyses to control for prior academic performance and the level of general experience at university and particular course experience.	Positive effect on exam performance: Voshaar et al., (2023a), Dowling et al., (2003), Perera & Richardson (2010)

Variables	Definition	Rationale	Reference
Attendance	Continuous measure indicating the number of tutorials a given student attended scaled by the total number of tutorials offered to the students. Information on students' attendance was collected by conducting short in-class quizzes on the LMS comprising three questions regarding the specific tutorial contents in each tutorial. To participate in the quizzes, the students had to sign in to the LMS utilizing a QR-code presented to them in the corresponding tutorial.	Related studies document a statistical association between student behavior (e.g., attendance) and their exam performance. The students' attendance reflects their effort and motivation they spend on the given course Byrne & Flood (2008). We therefore include *Attendance* into our analyses to control for characteristics of student behavior.	Positive effect on exam performance: Voshaar et al., (2023a), Aldamen et al., (2015), Cheng & Ding (2021), Massoudi et al., (2017), Romer (1993)
Vocational Training	Indicator variable equal to one if a given student completed vocational training before entering university, and zero otherwise.	Students that have completed a vocational training prior to entering university are more experienced, mature, and have higher knowledge, which positively affects their exam performance. Therefore, we integrate *Vocational Training* into our analyses to control for experience, maturity, and knowledge previously accumulated through completing a vocational training.	Positive effect on exam performance: Voshaar et al., (2023b), Guney (2009), Hartnett et al., (2004)
Voluntary Service	Indicator variable equal to one if a student completed a voluntary service or spent a gap year prior to entering university, and zero otherwise.	Completing a voluntary service or a gap year before entering the university is another source of experience, maturity, and knowledge for students. Voluntary Service reflects higher self-organization skills, supporting students to structure university life and thus improve exam performance. We include Voluntary Service to control for this potential impact.	Positive effect on exam performance: Voshaar et al., (2023b), Guney (2009), Hartnett et al., (2004)

Variables	Definition	Rationale	Reference
Female	Indicator variable equal to one if a student is female, and zero otherwise.	Related studies provide evidence for students' gender affecting their exam performance. The results of these studies are versatile, indicating a positive, negative, or no effect of gender on performance. We control for a potential influence by integrating *Female* into our analyses.	Positive effect on exam performance: Wecks et al., (2023), Aldamen et al., (2015), Gammie et al., (2003), Gracia & Jenkins (2003), Mutchier et al., (1987), Premuroso et al., (2011), Tan & Laswad (2008), Tyson (1989) Negative effect on exam performance: Johansson et al., (2022), Koh & Koh (1999), Massoudi et al., (2017), Tan & Laswad (2008) No significant effect on exam performance: Azzali et al., (2023), Byrne & Flood (2008), Hu et al., (2023), Papageorgiou & Halabi (2014)
LinkedIn User	Indicator variable equal to one if a student has a LinkedIn profile, and zero otherwise.	Having a LinkedIn profile potentially impacts exam performance and is therefore included in our analyses. Related studies document LinkedIn usage being correlated with exam performance. Moreover, (new) social media usage (e.g., LinkedIn usage) can be utilized as operationalization for personal innovativeness, which in turn affects GenAI acceptance among students.	Study documenting an effect on exam performance: Paul et al., (2012) Study documenting an effect on personal innovativeness: Strzelecki (2023) Studies documenting an effect on social media usage: Aldahdouh et al., (2020), Wijesundara & Sun (2018)
Course of Study	Categorial variable equal to one if a given student is registered for business studies, two for economics, three for economics in complementary subject, four for engineering and management - production engineering, five for electrical engineering with management, six for information systems and management, and seven for others, respectively. We integrate Course of Study as fixed effects in our analyses.	Student characteristics vary considerably across different courses of study as each attract certain student sub-populations. We consider that this potentially influences students' exam performance and therefore include Course of Study fixed effects into our analyses.	Studies documenting an effect on exam performance: Cheng & Ding (2021), Duff (2004), Jackson & Cossitt (2015), Tan & Laswad (2008), Tan & Laswad (2015)

Variables	Definition	Rationale	Reference
German Detector	Indicator variable alternatively deployed as *GenAI User* estimated by the detection system developed at the University of Applied Sciences Wedel. *German Detector* equals one if the estimate of Originality.AI exceeds a threshold of 0.1 and is zero otherwise.	The students' essays we use to estimate *GenAI User* are characterized by the morphological and semantic peculiarities of the German language. We therefore repeat the robustness check using an AI detector particularly designed for these aspects.	Tlok et al., (2023)
Originality.AI	Indicator variable alternatively deployed as *GenAI User* estimated by the detection system Originality.AI. *Originality.AI* equals one if the estimate of Originality.AI exceeds a threshold of 0.5 and is zero otherwise.	We ensure the robustness of our findings by using alternative detection tools. We utilize Originality.AI as it is prominent in literature and claims to be multi-language.	Walters (2023)
Manual Computation	Continuous measure indicating GenAI application usage for text generation. *Manual Computation* is extracted from principal component analysis comprising *Adjectives*, *Fog Index*, and *Herdan's C*. We use this GenAI detection as an alternative estimation of *GenAI User* in our robustness checks.	We deploy *Manual Computation* as an alternative measure to estimate *GenAI User* to test the robustness of our main analysis. Systems detecting GenAI applications typically rely on numerous determinants to classify, if a given text is created be GenAI or by humans. Related studies document three relevant categories of determinants for GenAI classification. First, GenAI texts show a higher number of adjectives compared to human texts. Second, based on various readability scores, GenAI texts are less readable than human texts. And finally, GenAI created texts provide higher lexical richness. Creating a legitimate variable that depicts GenAI usage requires to include determinants stemming from these categories.	Gunning (1952), Herdan (1960), Markowitz et al., (2023), Martínez et al., (2024), Muñoz-Ortiz et al., (2023), Shah et al., (2023), Deveci et al., (2023), Pehlivanoğlu et al., (2023)
Adjectives	Continuous measure indicating the number of adjectives scaled by the total number of words of a text.	We regard *Adjectives* as a determinant for GenAI usage to create texts and include it into the principal component analysis to extract *Manual Computation*. Related studied characterize GenAI texts to encompass more adjectives. By scaling the absolute number of adjectives by the total number of words of a given text, we avoid a biased measure due to the text length.	Markowitz et al., (2023)

Variables	Definition	Rationale	Reference
Fog Index	Gunning (1952) readability index, calculated as: $\left(\frac{Total\ Words}{Total\ Sentences} + 100 * \frac{n_{wsy \geq 3}}{Total\ Words}\right) * 0.4$ where $n_{wsy} \geq 3$ is the number of words with three syllables or more. A higher (lower) *Fog Index* indicates an easier (a more difficult) read.	We include *Fog Index* into the principal component analysis to extract *Manual Computation*. Related studies have shown that GenAI texts are less readable. *Fog Index* is commonly used by numerous studies to approximate text readability.	Gunning (1952)
Herdan's C	Herdan (1960) lexical richness index, calculated as: $\frac{\log(Total\ Unique\ Terms)}{\log(Total\ Words)}$	*Herdan's C* is included into the principal component analysis to extract Detection Factor. Related studies provide evidence on lexical richness to be predictive for the use of GenAI applications to generate texts. We deploy *Herdan's C* to approximate lexical diversity and richness.	Herdan (1960)

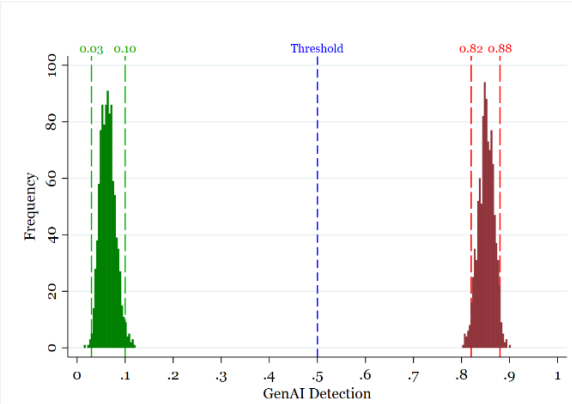
Appendix A. Variable Definitions.

Panel A: Descriptive Results of GenAI Detector Validation

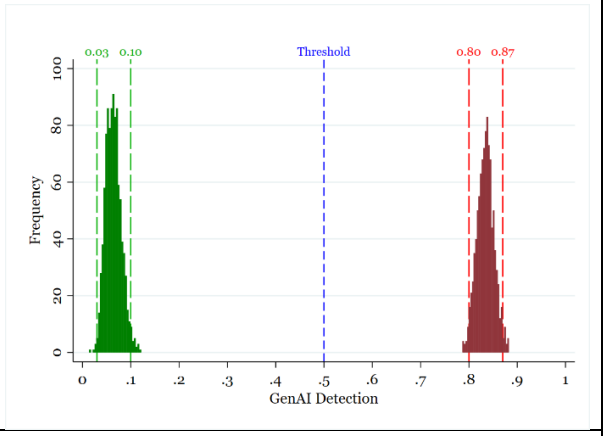
Variable	*N*	*Mean*	*Median*	*SD*	*P25*	*P75*	*Min*	*Max*
GenAI Detection Pre AI	30	0.0643	0.0364	0.0894	0.0000	0.0790	0.0000	0.3311
GenAI Detection AI Gen	30	0.8518	0.8629	0.0865	0.7739	0.9307	0.6689	0.9759
GenAI Detection AI Mod	30	0.8351	0.8548	0.0975	0.7482	0.8935	0.6420	0.9933

Panel B: Distribution of Student vs. GenAI Texts

Pre AI (student) vs. AI-generated Essays



Pre AI (student) vs. AI-modified Essays



Panel C: *t*-test Results of Pre AI (student) vs. GenAI Essays

	Mean	*|Diff.|*
GenAI Detection Pre AI vs. *GenAI Detection AI Gen*	0.0643 0.8518	0.7870*** (-1,074.97)
GenAI Detection Pre AI vs. *GenAI Detection AI Mod*	0.0643 0.8351	0.7715*** (-999.83)

Panel D: Prompts for GenAI Texts

Prompt for AI-generated Essays (English)	You are a student at a German university and are enrolled in the Master's degree program “Business Administration”. You have chosen the specialization Accounting and are taking part in the module “Advanced Seminar: Advanced Problems in Accounting”. The examination of the module is a term paper on the topic “[title of student essay]”. Write a coherent text of about 1000 words for the term paper.
Prompt for AI-generated Essays (German)	Du bist ein Student an einer deutschen Universität und immatrikuliert im Masterstudiengang "Betriebswirtschaftslehre". Du hast den Schwerpunkt Rechnungswesen gewählt und nimmst am Modul "Hauptseminar: Fortgeschrittenenprobleme im Rechnungswesen" teil. Die Prüfungsleistung des Moduls ist eine Hausarbeit zum Thema "[Titel der Hausarbeit]". Verfasse einen zusammenhängenden Text mit einem Umfang von etwa 1000 Worten für die Hausarbeit.
Prompt for AI-modified Essays (English)	I am a student at a German university and enrolled in the Master's degree program “Business Administration”. I have chosen the specialization Accounting and am taking part in the module “Advanced Seminar: Advanced Problems in Accounting”. The module examination is a term paper on the topic “[title of student essay]”. This is my previous draft: “[text of student essay]” Revise and improve my draft. Write a coherent text of about 1000 words.

(Table continued)

Prompt for AI-modified Essays (German)	Ich bin ein Student an einer deutschen Universität und immatrikuliert im Masterstudiengang "Betriebswirtschaftslehre". Ich habe den Schwerpunkt Rechnungswesen gewählt und nehme am Modul "Hauptseminar: Fortgeschrittenenprobleme im Rechnungswesen" teil. Die Prüfungsleistung des Moduls ist eine Hausarbeit zum Thema "[Titel der Hausarbeit]". Dies ist mein bisheriger Entwurf: "[Text der Hausarbeit]" Überarbeite und verbessere meinen Entwurf. Verfasse einen zusammenhängenden Text mit einem Umfang von etwa 1000 Worten.
Appendix B presents the results from the GenAI detector validation study. Variables included in this study were constructed based 30 original student essays written before the availability of GenAI, thus without AI assistance (pre-AI), 30 AI-generated essays using the titles from the pre-AI essays, and 30 AI-modified texts based on the original student essays. ZeroGPT's detector scores for each essay were retrieved, resulting in three variables *GenAI Detection Pre AI*, *GenAI Detection AI Gen, and GenAI Detection AI Mod* representing these distinct sample groups. Panel A provides the descriptive results for the GenAI detections across the three groups. Panel B visualizes the distributions of detections through histograms. The left histogram compares detector values of original pre-AI student essays (green) against AI-generated essays (red), while the right histogram compares the original pre-AI student essays (green) to AI-modified essays (red). Due to the limited sample size, histogram observations were bootstrapped (1,000 replications) for visualization purposes. Green and red dashed vertical lines indicate upper and lower bounds of 95% confidence intervals, calculated from non-bootstrapped detector values. The blue dashed vertical line represents the detector threshold used to classify essays as AI-generated in the main analyses. In Panel C we report two-tailed *t*-test results for differences in mean detector values between original pre-AI student-written essays and their AI-generated and AI-modified counterparts. The *t*-values are presented in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. Panel D outlines the prompts used to generate both sets of AI-generated and AI-modified essays, presented in both German and English.	

Appendix B. Results of GenAI Detector Validation Study.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	VIF
(1) *GenAI User*	1.000								1.13
(2) *A-Level Grade*	-0.116 *	1.000							1.16
(3) *Attempt*	0.184 **	-0.152 **	1.000						1.19
(4) *Attendance*	-0.072	0.214 ***	-0.331 ***	1.000					1.29
(5) *Vocational Training*	-0.097	0.014	-0.100	0.049	1.000				1.20
(6) *Voluntary Service*	-0.056	0.057	-0.051	-0.066	-0.298 ***	1.000			1.16
(7) *Female*	-0.109	0.041	0.003	-0.001	-0.038	0.173 **	1.000		1.18
(8) *LinkedIn User*	0.048	0.106	0.057	-0.059	-0.038	0.071	0.067	1.000	1.05

Appendix C presents the pairwise Pearson correlations of the variable of interest *GenAI User* and the control variables. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively. The last column indicates the Variance Inflation Factor (VIF) for each variable. The mean VIF across all Variables (1.16) is below any conventional textbook threshold. All variables are defined in Appendix A.

Appendix C. Correlation Matrix.

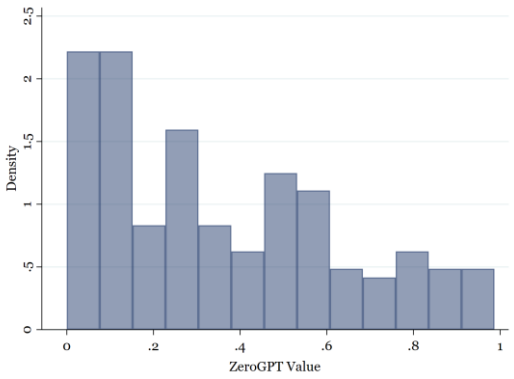
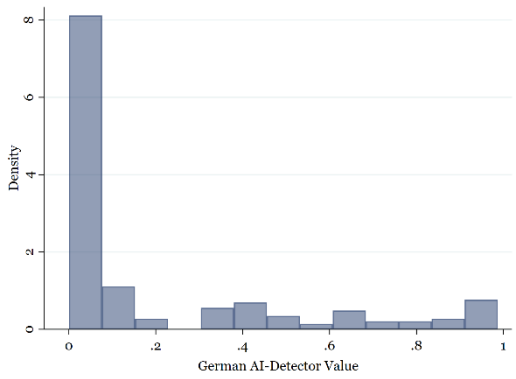
Panel A: Student Data by Essay Submission	*Essay submitter (within sample students)*		*Non-submitter (out of sample students)*		|*Diff.*|
Variables	*N*	*Mean*	*N*	*Mean*	
A-Level Grade	193	2.290	134	2.182	0.108
Attempt	193	1.441	134	2.388	-0.948 ***
Attendance (relative)	193	0.448	134	0.208	0.239 ***
Vocational Training	193	0.135	134	0.135	0.000
Voluntary Service	193	0.362	134	0.403	-0.041
Female	193	0.472	134	0.388	0.084
Panel B: Student Data by GenAI Usage	*GenAI User*		*Non-User*		|*Diff.*|
Variables	*N*	*Mean*	*N*	*Mean*	
A-Level Grade	59	2.184	134	2.337	0.152 *
Attempt	59	1.763	134	1.276	0.486 **
Attendance (relative)	59	0.413	134	0.463	0.051
Vocational Training	59	0.085	134	0.157	0.072
Voluntary Service	59	0.322	134	0.381	0.059
Female	59	0.390	134	0.508	0.118
LinkedIn User	59	0.221	134	0.179	0.041

Appendix D shows the results of two randomization tests two analyse potential sample selection biases. Panel A, shows students characteristics of essay submitting students (in our final sample) against those students, who do not submit an essay and are thus omitted in our further analyses. In Panel B, student characteristics disaggregated by GenAI usage. The last column presents the difference in mean values and the significance level of a two-tailed *t*-test (chi-squared test) for continuous (binary) variables. ***, **, * indicate statistical significance at the 1 %, 5 %, and 10 % level, respectively. Note that we cannot test for a difference in LinkedIn usage in Panel A as we only collected LinkedIn usage data for essay submitting students.

Appendix D. Randomization Test.

Students' GenAI usage	N	Yes	No
GenAI usage for general purposes within the course	30	8 (0.267)	22 (0.734)
GenAI usage for academic essay-writing within the course	30	9 (0.300)	21 (0.700)
Appendix E presents the student survey results on their GenAI usage.			

Appendix E. Survey Results.

ZeroGPT	German AI Detecot (FH Wedel)
	

Appendix F presents histogram plots for the AI Detector values of our main (ZeroGPT) as well as a tool specialized for German language (German AI Detector from FH Wedel).

Appendix F. Distribution of AI Detector

Variables	(1) Threshold 0.4	(2) Threshold 0.6	(3) Continuous Detection Score	(4) German Detector	(5) Manual Computation	(6) Balanced Sample
GenAI User	**-7.10 ****	**-7.17 ****	**-14.67** ***	**-8.53 *****	**-2.66 *****	**-6.51 ****
	(-2.43)	**(-2.02)**	**(-2.82)**	**(-2.90)**	**(-2.70)**	**(-2.07)**
A-Level Grade	11.64 ***	11.42 ***	11.46 ***	11.21 ***	11.62 ***	8.88 ***
	(4.92)	(4.78)	(4.81)	(4.75)	(4.87)	(3.03)
Attempt	0.89	0.84	0.96	0.94	0.79	2.05 **
	(0.74)	(0.69)	(0.79)	(0.79)	(0.66)	(1.98)
Attendance (relative)	17.70 ***	18.38 ***	14.85 ***	16.81 ***	15.55 ***	17.75 ***
	(3.75)	(3.87)	(3.78)	(3.58)	(3.25)	(2.95)
Vocational Training	10.37 **	11.25 ***	10.92 **	10.93 **	12.09 ***	8.75
	(2.41)	(2.63)	(2.57)	(2.58)	(2.86)	(1.65)
Voluntary Service	1.81	2.07	2.60	1.57	1.24	1.52
	(0.60)	(0.69)	(0.87)	(0.53)	(0.41)	(0.45)
Female	-10.14 ***	-9.29 ***	-9.40 ***	-10.20 ***	-10.18 ***	-10.49 ***
	(-3.50)	(-3.18)	(-3.24)	(-3.54)	(-3.50)	(-3.22)
LinkedIn User	10.75 ***	9.25 ***	9.34 ***	10.26 ***	7.89 **	10.53 ***
	(3.05)	(2.65)	(6.66)	(2.96)	(2.25)	(2.82)
Constant	Included	Included	Included	Included	Included	Included
Course of Study-FE	Included	Included	Included	Included	Included	Included
N	193	193	193	193	193	193
Adj. R^2	0.31	0.30	0.41	0.32	0.31	0.20

Appendix G presents the results of the robustness checks. In columns (1) and (2), we reduced (> 0.4) or increased (> 0.6) the threshold of the AI detector value to be classified in the *GenAI User* group. In column (3) we include the continuous detection score from ZeroGPT as our independent variable *GenAI User*. Column (4) uses alternative AI detectors. Column (5) includes a manual computed score that represents AI detection. In column (6), we again present our main results but with an entropy-balanced sample. Bold font indicates the variable of interest. ***, **, * indicate statistical significance at the 1 %, 5 %, and 10 % level (two-tailed), respectively. *t*-values are presented in parentheses. All variables are defined in Appendix A (https://tinyurl.com/zjehfa3n).

Appendix G. Results of Robustness Checks

Variables	(1) Higher A-Level Grade	(2) Lower A-Level Grade	(3) Higher Attendance	(4) Lower Attendance
ChatGPT User	-12.27 *******	2.09	-11.90 *******	-2.92
	(-2.73)	(0.46)	(-2.74)	(-0.64)
A-Level Grade	11.96 **	24.13 ***	11.58 ***	12.64 ***
	(2.37)	(3.25)	(3.60)	(3.31)
Attempt	-2.03	1.21	-1.78	2.27
	(-0.87)	(0.87)	(-0.71)	(1.44)
Attendance (relative)	17.18 **	12.07 *	18.62	34.93 *
	(2.24)	(1.89)	(1.65)	(1.83)
Vocational Training	4.41	24.40 ***	10.33 *	11.93 *
	(0.76)	(3.80)	(1.77)	(1.76)
Voluntary Service	-1.17	3.97	-2.80	8.47 *
	(-0.27)	(0.94)	(-0.67)	(1.83)
Female	-9.65 **	-9.44 **	-11.07 ***	-8.22 *
	(-2.25)	(-2.30)	(-2.76)	(-1.71)
LinkedIn User	9.87 **	6.00	16.44 ***	0.81
	(2.12)	(1.12)	(3.37)	(0.15)
Constant	Included	Included	Included	Included
Course of Study-FE	Included	Included	Included	Included
N	103	90	104	89
Adj. R^2	0.27	0.28	0.30	0.12

Appendix H presents the regression results using split samples. In columns (1) and (2), we repeat our main regression analysis on a restricted sample only containing students with above- (below-)median *A-Level Grade*. Columns (3) and (4) present the main regression separately for students with above- and below-median attendance. Bold font indicates the variable of interest. ***, **, * indicate statistical significance at the 1 %, 5 %, and 10 % level (two-tailed), respectively. *t*-values are presented in parentheses. All variables are defined in Appendix A (https://tinyurl.com/zjehfa3n).

Appendix H. Results of Split Sample Regressions

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