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Supplementary Materials for

Reducing achievement gaps in undergraduate general chemistry could lift underrepresented students into a "hyperpersistent zone"

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- *Course grade*. We excluded students who took hardship withdrawals or exercised the credit/no-credit grading option.
- *Total SAT score*. When possible, we used SAT scores. However, 8.25% of students only took the ACT, in which case we converted ACT scores to SAT scores using concordance tables published by the College Board. If students took college entrance exams multiple times, we used the highest scores obtained.
- *Rank*. The University of Washington hires instructors of record in chemistry in one of three categories: 1) Tenure-track faculty who are hired and promoted primarily on the basis of their research productivity, 2) Lecturers who are not eligible for tenure but have full-time, often multi-year appointments and who are hired and promoted solely on the basis of teaching responsibilities, and 3) Temporary and often part-time instructors who are hired to teach one or two sections of a course in one or two quarters only.
- *Student evaluation of teaching scores (SETs)*. For each instructor in each section, we used the composite score calculated by the University's Office of Educational Assessment from four sub-scores recorded in the UW's standard end-of-course student evaluation of teaching form. This score is intended to be an overall indicator of students' assessment of the quality of the course and instruction.

Missing data and sample sizes

Of the 25,768 unique students included in our dataset, 1.15% were missing URM status, 0% were missing EOP status, 0.03% were missing binary gender status, and 0.6% were missing parental education information.

For calculations using binary gender status, there were 72,906 observations which constituted 24,800 unique students. For calculations using URM status, there were 70,542 observations

constituting 23,992 unique students. For calculations using FGN status, there were 71,696 observations constituting 24,382 unique students. For calculations using SES status, there were 72,965 observations constituting 24,821 unique students.

Supplementary analyses

Achievement gap models

Fig. S1 reports raw achievement gaps and achievement gaps controlled for SAT and high school GPA ("HSGPA" in the figure), for all four student subgroups and all six courses included in this study. A value of 0.0 indicates no difference in final course grade between the students of interest and the appropriate comparison group (e.g. women versus men). Notches in the box plots indicate 95% confidence intervals. The data in the "GenChem.1" panel of fig. S1 are also reported in Fig. 1. The means and standard deviations for all four student subgroups and six courses analyzed are reported in table S2A, with coefficients for models for all four student subgroups and all six courses reported in table S2B.

The data in Fig. S1 suggest that there is a fundamental change in the nature of the gendered gap in general chemistry versus organic chemistry. The two course series are considered conceptually distinct, with general chemistry being more quantitative and theory-driven and organic chemistry emphasizing the three-dimensional relationships of atoms and the impact of spatial relationships on reaction mechanisms. If so, then well-documented gendered differences in spatial reasoning performance may help explain why gendered gaps are higher in organic chemistry (40). In preliminary support of this hypothesis, we note that gendered gaps also widen in the third course in the general chemistry sequence, which features several topics that rely heavily on spatial reasoning: molecular orbital theory, hybrid orbital theory, and an introduction to organic chemistry. If the hypothesis is supported by additional work, the result would promote the use of interventions to boost spatial reasoning skills in women.

We can propose three non-mutually exclusive hypotheses to explain the observation that URM and EOP students underperform in general chemistry but perform at or above their predicted level in organic chemistry: 1) URM and EOP students have learned how to cope with

the emotional and psychological causes of underperformance by the time they get to organic chemistry; 2) the students who struggle the most with those emotional and psychological causes in general chemistry are no longer in the dataset by the time students get to organic; or 3) our indices of academic preparation in high school "decay" and become less predictive over time. All three hypotheses deserve testing.

In the legend, "SoI" stands for Student of Interest.

Table S2. Summary data from achievement gaps analyses.

A. Means and standard deviations (in parentheses) of achievement gaps shown in fig. S1. The

coefficients used to calculate these achievement gaps are shown in table S2b.

	Raw				SAT+HSGPA					
Variable	Estimate	S.E.	$t-$ value	p -value	Estimate	S.E.	$t-$	$p-$ value		
value Gender Comparison										
Intercept	0.05	0.02	3.43	0.001	0.04	0.02	2.52	0.012		
Gender	-0.13	0.01		$< 2e-16$	-0.10	0.01	-7.91	$2.60e-$ 15		
	-0.18		-9.42	$< 2e-16$	-0.18	0.02	-7.89	2.28e-		
GenChem-2		0.02	-8.77					14		
GenChem-3	-0.23	0.02	10.34	$< 2e-16$	-0.23	0.02	-9.49	$<$ 2e- 16		
	-0.26			$< 2e-16$	-0.26	0.03	-9.99	$<$ 2e-		
OChem-1		0.02	10.54					16		
OChem-2	-0.34			$< 2e-16$	-0.34	0.03	-12.54	$<$ 2e-		
		0.03	13.37					16		
OChem-3	-0.40	0.02	15.84	$\sqrt{2e-16}$	-0.40	0.03	-14.77	$<$ 2e- 16		
Gender*GenChem-	0.09			1.54e-13	0.09	0.01	66.47	$<$ 2e-		
$\mathcal{D}_{\mathcal{L}}$		0.01	7.39					16		
Gender*GenChem- 3	-0.03	0.01	-2.23	0.026	-0.04	0.01	53.10	$<$ 2e- 16		
	-0.14			$< 2e-16$	-0.14	0.02	7.02	2.28e-		
Gender*OChem-1		0.02	-8.76					12		
Gender*OChem-2	-0.10	0.02	-5.66	1.51e-08	-0.10	$0.02\,$	-2.60	0.009		
Gender*OChem-3	-0.03			0.068	-0.04	0.02	-8.96	$<$ 2e-		
		0.02	-1.82					16		
SAT	NA	NA	NA	NA	0.002	0.0	-5.87	4.48e- 09		
HSGPA	NA	NA	NA	NA	0.29	0.0	-2.07	0.038		
URM Comparison										
Intercept	0.04	0.01	2.93	0.003	0.01	0.01	0.46	0.65		
URM	-0.56	0.02	24.74	$< 2e-16$	-0.16	0.02	-7.93	2.27e-		
	-0.13	0.02		1.69e-10	-0.13		-5.97	15 5.33e-		
GenChem-2			-6.58			0.02		09		
GenChem-3	-0.25	0.02		$< 2e-16$	-0.25	0.02	-11.00	$<$ 2e-		
			11.95					16		
OChem-1	-0.34	$0.02\,$	14.86	$< 2e-16$	-0.35	0.02	-13.91	$<$ 2e- 16		
OChem-2	-0.41	0.02		$< 2e-16$	-0.41	0.03	-15.68	$<$ 2e-		
			16.83					16		
OChem-3	-0.44	0.02	18.46	$< 2e-16$	-0.44	0.03	-17.13	$<$ 2e- 16		
URM*GenChem-2	0.03	0.02	1.34	0.179	0.02	0.02	1.15	0.252		
URM*GenChem-3	0.01	0.02	0.52	0.600	0.01	0.02	0.41	0.685		
URM*OChem-1	0.08	0.02	3.00	0.003	0.08	0.03	2.91	0.004		
URM*OChem-2	0.16	0.03	5.28	1.32e-07	0.16	0.03	5.22	1.82e- 07		
URM*OChem-3	0.23	0.03		4.98e-13	0.23	0.03	7.21	$5.5e-$		
			7.23					13		
SAT	NA	NA	NA	NA	0.002	0.0	66.03 $\overline{4}$	$<$ 2e- 16		

B. Coefficients for all achievement gap models. These coefficients were used to calculate the achievement gaps detailed above in Table S2a and are plotted in Fig 1.

Instructor characteristics as predictors of achievement gaps

Table S3A provides the regression coefficients for models where an instructor characteristic had a statistically significant impact on the size of achievement gaps. Table S3B provides model selection statistics for the instructor characteristics analysis.

Table S3. Summary data from instructor characteristics analyses.

A. Regression coefficients.

B. Model selection statistics. "Step" refers to the sequence in stepwise selection. SoI stands for Students of Interest. In the columns that specify models, variables that follow the form (1|StudentNo) indicate a random effect, with all other terms being fixed effects. "AICc" is the value of the Akaike Information Criterion with the small-sample size correction; "delta" indicates the magnitude of the difference between the model in the row and the model with the smallest AICc. Other terms are explained in the text.

The small-to-negligible impact of instructor gender on achievement gaps reported here was surprising, as other work in STEM has shown a slight but significant impact of instructor gender on gendered gaps. The lack of correspondence between SETs and achievement gaps that we

observed has been well-documented in the literature, however (*33*). Extensive data on bias in SETs based on instructor gender and lack of correlation with student learning have inspired calls to abandon student evaluations of teaching in favor of evidence-based approaches (*33*).

Risk and attrition models

The risk of not continuing for each course in GenChem and OChem, along with attrition over time, are reported for each student subgroup in Fig. 2. Fig. S2 plots the same results, but from models that do not control for indices of academic preparation and ability (SAT and high school GPA). Table S4 provides fitted hazard and survival probability estimates without and with controls for student preparation and ability, along with regression coefficients for both models.

Fig. S2. Risk by course and survival over time, not controlling for academic preparation. The top graph shows the actual or raw proportion of students at the beginning of each general chemistry (GC) or organic chemistry (OC) course who did not advance to the subsequent course. The bottom graph shows the actual or raw proportion of original students retained at the end of each course. In both panels, underrepresented students are represented by bold lines and wellrepresented students by grayed lines.

Table S4. Summary data from risk and survival analyses.

A. Fitted hazard and survival probability estimates with 95% confidence intervals, in brackets.

B. Fitted hazard and survival probability estimates, adjusted for indices of academic preparation and ability.

D. Coefficients for risk and attrition models, without controls for academic preparation and ability. SoI stands for Students of Interest.

E. Coefficients for risk and attrition models, with controls for academic preparation and ability.

Consequences of achievement gaps: "Next steps" after GenChem 1

Fig. S3 plots data on what students did after taking the initial course in general chemistry as a function of their grade in that course, without controlling for indices of academic preparation. A dashed line represents the underrepresented group identified on the right margin; a solid line represents the relevant comparison group (e.g. men in the top panel). "Drop" (in red) represents the probability that the student never reappeared in the dataset; "retake" (blue) indicates the probability that the student took the initial course in the series again; "persist" is the probability that the student took the second course in the series at some point during the study period. The vertical dashed line on the graph indicates the 1.7 grade threshold for moving on in the series; the vertical dotted line on the graph indicates the typical median grade of 2.6 in each section. The data in this figure are analogous to the analysis presented in Fig. 4, but the estimated probabilities in this figure are not controlled for indices of student academic preparation and ability.

Table S5 presents the coefficients from the models on the next steps taken by students after enrolling in GenChem 1. Part A reports the values from models that do not control for indices of student academic preparation and ability; part B reports the values from models that do control for indices of student academic preparation and ability.

Fig. S3. **Consequences of GenChem 1 grades for four student subgroups, not controlled for indices of academic preparation.**

Table S5. Model coefficients for "next-steps" analyses.

A. Coefficients and standard errors for "Drop" and "Persist" outcomes relative to "Retake"

without adjusting for student academic preparation (see Fig. 4).

** p* < .05; ** *p* < .01; ****p* < .001

B. Coefficients and standard errors for "Drop" and "Persist" outcomes relative to "Retake" with controls for student academic preparation and ability (see fig. S3).

		Drop	Persist						
Variable	Estimate	S.E.	Estimate	S.E.					
Gender Comparison									
Intercept	0.79	0.024	-2.16	0.063					
Gender	0.43	0.036	0.56	0.083					
Grade	0.66	0.027	-0.29	0.046					
Gender*Grade	0.24	0.036	0.32	0.06					
SAT	0.00	0.0	0.00	0.0					
HSGPA	-0.02	0.018	-0.26	0.03					
URM Comparison									
Intercept	0.95	0.018	-1.96	0.045					
URM	0.44	0.07	0.81	0.12					
Grade	0.73	0.021	-0.22	0.036					
URM*Grade	0.37	0.06	0.37	0.08					
SAT	0.00	0.0	0.00	0.0					
HSGPA	0.02	0.017	-0.21	0.03					
SES Comparison									
Intercept	0.94	0.019	-2.01	0.048					
SES	0.40	0.054	0.72	0.098					
Grade	0.71	0.022	-0.23	0.039					
SES*Grade	0.29	0.049	0.35	0.067					
SAT	0.00	0.0	0.00	0.0					
HSGPA	0.02	0.018	-0.21	0.03					
FGN Comparison									
Intercept	1.03	0.022	-1.93	0.055					
FGN	-0.08	0.037	0.13	0.084					
Grade	0.72	0.026	-0.20	0.047					
FGN*Grade	0.09	0.037	0.11	0.062					
SAT	0.00	0.0	0.00	0.0					
HSGPA	0.02	0.017	-0.22	0.030					

Model selection for grade gap, hazard/attrition, and "next steps" analyses

Table S6 reports the full models, assessed models, and regression statistics used in model selection for analyzing A) achievement gaps, B) risk of not advancing, and C) what students did after the first time they took GenChem 1—their "next step" in terms of continuing in STEM majors that require the full general chemistry sequence, where "status" refers to whether the student re-took the course, never again appeared in the dataset ("dropped"), or went on to the next course in the series during the study period ("persisted"). In this table, "Step" refers to the sequence in stepwise selection. In the "Model" column, variables that follow the form "Women * course" specify a two-way interaction term; variables that follow the form (1|StudentNo) indicate a random effect, with all other terms being fixed effects. "AICc" is the value of the Akaike Information Criterion with the small-sample size correction; "delta" indicates the magnitude of the difference between the model in the row and the model with the smallest AICc. "Weight" is the model weighting.

To analyze the risk of not advancing for each student subgroup in each course in the GenChem and OChem series, and attrition over time, we conducted a two-phase model selection procedure. First we selected the optimal random-effect structure in the presence of all fixed effects based on AIC. Then, with the optimal random-effect structure, fixed effects were retained based on AIC. We repeated this analysis with a second model adjusted for academic preparation and ability. Hazard probability estimates $(\hat{h}_i(t_i))$ and standard errors for each group, *j*, and at each time point, *i*, were estimated by applying an inverse transformation to the logithazard model:

$$
\hat{h}_j(t_i) = \frac{1}{1 + e^{-logit_{ij}}}
$$

Survival probabilities, $\widehat{\delta_i(t_i)}$ were then estimated as:

$$
\hat{S}_i(t_i) = \hat{S}_i(t_{i-1})[1 - \hat{h}_i(t_i)]
$$

Table S6. Model selection and regression statistics

A. Gap models.

^aFull model: $logit(h) \sim Course*Gender + (1|StudentID) + (1|Year) + (1|Term) + (1|SectionID)$

^bFull model: logit(h) ~ Course*URM + (1|StudentID) + (1|Year) + (1|Term) + (1|SectionID)

c Full model: logit(h) ~ Course*SES + (1|StudentID) + (1|Year) + (1|Term) + (1|SectionID) d Full model: logit(h) ~ Course*FGN+ (1|StudentID) + (1|Year) + (1|Term) + (1|SectionID)

e Full model: logit(h) ~ Course*Gender + SAT + HSGPA + (1|StudentID) + (1|SectionID); only model to converge

f Full model: logit(h) ~ Course*URM + SAT + HSGPA + (1|StudentID) + (1|SectionID); only model to converge

g Full model: logit(h) ~ Course*SES + SAT + HSGPA + (1|StudentID) + (1|SectionID); only model to converge h Full model: logit(h) ~ Course*FGN + SAT + HSGPA + (1|StudentID) + (1|SectionID); only model to converge

C. "Next steps after GenChem 1" plots.

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