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ABSTRACT

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This paper provides new causal evidence on the effects of gender congruence in the student-adviser relationship on three key student outcomes: (i) retention; (ii) grades; and (iii) post-graduation career outcomes. In so doing, we use unique administrative data from a selective liberal arts university which includes detailed longitudinal records on all students. Our identification strategy is based on the University's first-year faculty adviser assignment policy which produces randomness in whether a student has a same-gender faculty adviser. First, we find that gender congruence in the student-adviser relationship has a positive and significant effect on the odds of retention (gender congruence effect on the extensive margin) and on cumulate GPA upon graduation (gender congruence effect on the intensive margin). Second, we uncover that much of the gender congruence effect on the extensive margin tends to be concentrated in the freshman and sophomore years, while the gender congruence effect on the intensive margin is less immediate and shows up only in cumulative GPA upon graduation. The results are found to change little when we account for unobserved adviser characteristics by using adviser fixed effects. Finally, student-adviser gender congruence is found to work differently for students with different backgrounds and interests. Most notably we find that gender congruence in the student-adviser relationship is particularly helpful for academically weak students and students without STEM-orientation.

JEL Classification: I21, I23

Keywords: higher education, gender congruence, advising, academic outcomes, labor market outcomes

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An Advisor Like Me: Does Gender Matter?

1. Introduction

A growing literature has investigated how gender and race impact the effectiveness of interactions between students and teachers, including teaching assistants and tutors, in achieving educational goals (Dee, 2005; Bettinger and Long, 2005; Hoffmann and Oreopoulos, 2009; Munley, et al., 2010; Carrell et al., 2010; Fairlie et al., 2014; Lusher et al., 2015).[1] Previous studies suggest that hiring more female faculty members in STEM fields, particularly to teach introductory STEM courses, can boost the female representation in STEM majors; moreover, minority students, especially African American students, can benefit from taking a class from a minority professor of the same race. However, the literature tends to focus on student-teacher interactions and ignore another set of potentially important relationships and interactions that students develop---the student-adviser interactions. The literature's neglect of the potentially important role that gender and race may play in affecting the efficacy of the student-adviser interaction is surprising, considering that advisers and counselors are found to contribute significantly to student success (Bettinger and Baker, 2013; Carrell and Hoekstra, 2014).

This paper is aimed at filling this important gap in the literature by studying the effects of gender on the efficacy of the student-adviser interactions in achieving educational goals (measured by student outcomes such as GPA). In so doing, we use unique administrative data from a selective liberal arts university (thereafter called LiberalArtsU) which includes detailed

[1] At the K-12 level, there are mixed findings (see for example: Carrington et al., 2008; Dee, 2007; Ehrenberg et al., 1995; Holmlund and Sund, 2008; Lahelma, 2000; Lavy and Schlosser, 2011; Nixon and Robinson, 1999). At the postsecondary level, evidence suggests that having a female instructor, especially for introductory courses, improves female students' performance and influences their subsequent course and major choices (Canes and Rosen, 1995; Rothstein, 1995; Neumark and Gardecki, 1998; Bettinger and Long, 2005; Hoffmann and Oreopoulos, 2009). Other papers have investigated the mechanisms of the gender congruence, such as expectation and teaching style (Gershenson et al., 2016; Gong et al., forthcoming).

longitudinal records (both academic and non-academic) on all students for their entire undergraduate years at LiberalArtsU.[2] Such data are available for twenty cohorts of students who entered LiberalArtsU between 1996 and 2015.

We take advantage of LiberalArtsU's first-year faculty adviser assignment policy, which produces randomness in whether a student has a same-gender faculty adviser for the first year. Specifically, in the summer before coming to LiberalArtsU, each incoming first-year student lists his/her preferred courses and the Registrar uses this information and assigns courses to him/her. One of these courses will be a first-year seminar, and the instructor of this course will automatically become the student's faculty adviser during the first year. Since each incoming first-year student is not aware of the gender of his/her possible first-year seminar instructor, the gender of his/her first-year adviser is randomly assigned to him/her. It is, however, possible that the odds of having a female first-year seminar instructor and hence a female first-year adviser are related to which first-year seminar courses he/she takes. For instance, the student who expresses his/her interest in economics and is therefore assigned to a first-year seminar in economics is more likely to have a male instructor than some other first-year seminar courses such as sociology. In other words, it is still possible that some students may express their interest in sociology rather than economics in part in order to avoid male advisers. To this end, we carry out our analysis, controlling for first-year seminar courses.

After confirming econometrically the random assignment of advisers with regard to gender, we first find that gender congruence in the student-adviser relationship has a positive and significant effect on the odds of retention (gender congruence effect on the extensive margin) and on cumulate GPA upon graduation (gender congruence effect on the intensive margin).

[2] Our confidentiality agreement with LiberalArtsU prohibits us from revealing the identity of the University.

Furthermore, we find that much of the gender congruence effect on the extensive margin tends to be concentrated during the freshman and sophomore years, while the gender congruence effect on the intensive margin is less immediate and shows up only in cumulative GPA upon graduation. We also find that our results change little even when we account for all unobserved adviser characteristics by using adviser fixed effects.

Finally, we find evidence that student-adviser gender congruence works differently for students with different backgrounds and interests. First, gender congruence helps students with below-median high school GPA (academic challenges) more than for students without academic challenges; and quantile regressions suggest that gender congruence raises cumulative college GPA only at the lower quantiles. Second, while overall gender congruence in the student-adviser relationship has no significant effect on post-graduation career outcomes, gender congruence raises the odds of moving on to graduate schools for students with academic challenges. Third, a further disaggregated analysis reveals that gender congruence in the student-adviser relationship helps students who are not STEM-oriented at the beginning of their freshman years, while students who are STEM-oriented are not influenced by gender congruence. Moreover, for students without STEM-orientation, gender congruence helps students with below-median high school GPA improve their student outcomes both on the extensive and intensive margins, whereas helping students with above-median high school GPA improve their outcomes only on the extensive margin.

Our contributions to the literature are twofold. First, we are the first to investigate how adviser-student gender congruence affects student outcomes in college. At the K-12 level, Carrell and Hoekstra (2014) show that school counselors play an important role. At the college level, Bettinger and Baker (2013) document the effectiveness of student advising on retention and

completion outcomes, while Thompson (2017) identifies gender biases in college advising and finds that college advisers tend to discount the ability of female students relative to males using a survey experiment. At the doctoral level, Neumark and Gardecki (1998) find that female students benefit from having a female adviser. Yet, to our knowledge, no one has looked at how gender congruence in the student-adviser relationship influences student outcomes. Second, a unique administrative data set that tracks students' first labor market outcomes six months after graduation allows us to look beyond college. Previous research has only focused on student course outcomes, course and major choices, and college GPA. However, we know little about the labor market impact. We are one of the first to examine such labor market outcome effects of gender congruence in college.

The rest of the paper is organized as follows. Section 2 gives some background and descriptive statistics of the student population we study and explains how advisors are assigned to students. Section 3 discusses the empirical strategies and presents results on advisers' impacts on student outcomes. Section 4 studies the heterogeneous effects, followed by concluding remarks.

2. Background and Data

The study uses administrative data from a selective liberal arts university (LiberalArtsU), with around 750 students each cohort. Our data contain information on student demographics before entering college, course outcomes, and advisers each term for every student enrolled at LiberalArtsU from the fall semester of 1996 to the spring semester of 2015. We supplemented the administrative data with biographical data on every teaching faculty member at LiberalArtsU who taught at least one course from the fall semester of 1996 to the spring semester of 2015, which we collected from his/her online home page and other websites.

All students are required to take a first-year seminar course (FSEM hereafter) during their first semester at LiberalArtsU. FSEMs are different from other classes and they are aimed at preparing students for their college learning experiences, such as training on time management, writing skills, proper citations, and so on. In other words, what is normally considered academic advising is an integral part of the course, and naturally the instructor of each FSEM course becomes the academic adviser for each student who is taking his/her FSEM at least during the freshman year.

LiberalArtsU's first-year faculty adviser assignment policy based on FSEM produces randomness in whether the student has a same-gender faculty adviser for the first year. Specifically, in the summer before coming to LiberalArtsU, each incoming first-year student lists his/her preferred courses and the Registrar uses this information and assigns courses to him/her. One of these courses is an FSEM course and its instructor automatically becomes the student's faculty adviser during the first year. Since each incoming first-year student is not aware of the gender of his/her possible first-year seminar instructor, the gender of his/her first-year adviser is randomly assigned to him/her. The odds of having a female FSEM instructor and hence a female first-year adviser can be related to which FSEM courses he/she takes. For instance, the student who expresses his/her interest in economics and is therefore assigned to an FSEM in economics is more likely to have a male instructor than other first-year students who express his/her interest in sociology and end up taking an FSEM by a sociology professor. In other words, it is still possible that some female students know that they will do better with female advisers and try to avoid male advisers by expressing their interest in sociology rather than in economics. Such self-selection will lead to an overestimation of the positive effect of gender congruence in the

student-adviser relationship. To this end, we include a set of FSEM course fixed effects to avoid such an overestimation.

We report descriptive statistics in Table 1. There are 14,678 students in total, 53% female. Unfortunately, data on race are only available for recent cohorts and we present the results without controlling for student race. The results change little though somewhat less precise even when we use much smaller data and control for student race.[3] Most importantly, the data include high school GPA for every student. The data set also includes SAT and ACT scores. However, our preferred measure of student pre-college academic potentials is high school GPA. First, Rask and Tiefenthaler (2009), Geiser and Santelices (2007), and others have argued GPA is a better predictor of ability and college success for students. Second, some students do not report SAT/ACT scores and hence the sample size will fall if we use SAT/ACT scores. On average, students have a high school GPA of 3.646. Close to 40 percent of them received financial aid. The retention rates of students at LiberalArtsU within 12 months, 24 months, and overall are 95%, 92.3%, and 90.7%. The cumulative college GPA in the sample is 3.2, with the maximum being 4.33. Students typically have somewhat slower start with the first semester GPA of 3.06, and receiving B- or better for 81 percent of all courses taken in the first semester. However, it is rare not to pass a course (receiving at least passing grades for 97 percent of all courses taken in the first semester.

Panel B of Table 1 reports some statistics on our key explanatory variables. There are 345 different first semester academic faculty advisers (advisers hereafter), 46.7% of them are female. When we turn to student-semester-level data, 40% of students are advised by a female adviser. This suggests that male faculty members have a higher share of students' academic advising.

[3] These and all other unreported results are available upon request from the corresponding author.

Only 23.8% of student-semester observations are comprised of a female student being advised by a female adviser.

Turning to labor market outcomes, we have information on the first destination within six months of graduation for the majority of graduates of eight cohorts, graduating classes of 2008 to 2015. The most important variable of interest here is a categorical outcome variable on whether a student is employed, enrolled in a graduate school, or neither. We also have some employer, industry, and salary information. However, we only observe around 77% of post-graduation first destination outcomes. Male, minority, and students with lower college cumulative GPA are more likely to be missing from the labor market data. As shown in Table 1, within six months of graduation, 74.4 percent of graduates were employed; and 15.6 percent were enrolled in graduate schools.

3. Empirical Strategy and Results

3.1 Random Assignment

Our identification strategy assumes that the assignment of academic advisers to first-year students at LiberalArtsU is random in gender, conditional on first-year students' selection of FSEM courses. In other words, among those who selected the same FSEM courses, whether or not each student has an academic adviser of the same gender is random. Should the random assignment assumption be violated, our estimates on the effect of gender congruence will be biased. For instance, suppose that female students with higher innate ability were disproportionately assigned to female first year academic advisers. The effect of gender congruence of female students (female students having female advisers) on student academic performance would be overestimated due to ability bias. Moreover, if female students who are

more likely to benefit from having female advisers self-selected into having female advisers, the estimated effect of gender congruence of female students on student outcomes would overstate the true effect due to self-selection bias.

As we described in the institutional background section, the institutional structure of first year adviser assignment at LiberalArtU provides a quasi-experimental setting which in principle eliminates the potential biases described above. As described above, it is still possible that the student manipulates his/her FSEM course preference (for example, switching his/her first-choice FSEM preference from "Current economic issues" to "Writing and Rhetoric" to avoid having a male FA). However, our interviews with multiple students at LiberalArtsU suggest that such a behavior is highly unlikely.

To confirm formally that gender of first year academic advisers is indeed random, we regress student characteristics on a binary variable for the gender of first year academic advisers. We also include cohort fixed effects, $\boldsymbol{\tau_j}$, to absorb differences across cohorts as well as FSEM course fixed effects, $\boldsymbol{\varphi_s}$, to control for student subject interests:

$$(1) \qquad F_{ijs} = \mathbf{X_i}\,\boldsymbol{\beta_1} + \boldsymbol{\tau_j} + \boldsymbol{\varphi_s} + \mu_{ijs}$$

where F_{ijs}=1 if student *i* in cohort *j* in FSEM course *s* has a female first-year adviser, 0 otherwise; $\boldsymbol{X_i}$ is a vector of student characteristics such as student gender, high school GPA, and whether or not the student receives financial aid.

Table 2 presents the OLS estimates of Eq. (1). Reassuringly, after controlling for FSEM course fixed effects, whether or not the student has a female adviser is found to be uncorrelated with the student's gender, high school GPA, and whether he/she receives financial aid, confirming our qualitative evidence that the assignment of first-year advisers to students is random in terms of gender.

3.2 The Effects of Gender Congruence in the Student-Adviser Relationship

To provide causal evidence on the effects of the student-adviser gender congruence, we estimate:

(2) $Y_{ijs} = \beta_1 female_i + \beta_2 adviser\_female_i + \beta_3 female_i * adviser\_female_i + \mathbf{X_i\beta_4} + \boldsymbol{\varphi_s} + \boldsymbol{\tau_j} + \mu_{ijs}$

where Y_{ijs}: student outcomes of student *i* in cohort *j* taking his/her FSEM course *s*; $female_i$ = 1 if student *i* is female, 0 otherwise; $adviser\_female_i$ = 1 if student *i*'s first-year adviser is female, 0 otherwise; $\boldsymbol{X_i}$ = a vector of student characteristics of student *i* other than his/her gender; $\boldsymbol{\varphi_s}$ = a set of FSEM course fixed effects; $\boldsymbol{\tau_j}$ = a set of cohort fixed effects; and μ_{ijs} = error term.

For student outcomes, Y_{ijs}, our data are extensive and allow us to consider three kinds of outcomes: (i) extensive margin outcomes; (ii) intensive margin outcomes; and (iii) post-graduation career outcomes (for notational simplicity, we drop subscripts hereafter). Specifically, our main variable for the extensive margin outcomes is Retention (=1 if the student completes a Bachelor's degree at LiberalArtsU, 0 otherwise). Turning to the intensive margin outcomes, the key variable is Cumulative GPA which is the student's cumulative GPA upon his/her graduation (those with Retention = 0 are excluded from the intensive margin analysis). Finally, we use Employed (=1 if the student is employed six months after his/her graduation, 0 otherwise) and GradSchool (=1 if the student is enrolled in a graduate school six months after his/her graduation, 0 otherwise).

To understand the student-adviser gender congruence effect on student outcomes conceptually, consider a female student's cumulative GPA upon graduation. Her cumulative GPA will be higher with a female adviser than with a male adviser by $\beta_2 + \beta_3$. Now consider a male student's cumulative GPA. His GPA with a female adviser will differ from that with a male adviser by β_2. β_2 can be interpreted as the gender-neutral effect of having a female adviser. In

addition to this gender-neutral effect of a female adviser, there is an extra effect on GPA of a female adviser matched with a female student which is captured by β_3. We define β_3 as the student-adviser gender congruence effect on GPA.

Table 3 presents the OLS estimates of Eq. (2) with Retention as the dependent variable. We report the linear probability model results since the probit model yields very similar results and it is easier to interpret the coefficients on interaction terms in linear probability models than in probit models.

In column (2) of Table 3, the estimated coefficient on female*adviser female is positive and statistically significant at the 5 percent level, pointing to the presence of the student-adviser gender congruence effect on the extensive margin. The magnitude of the effect on Retention is modest yet meaningful. On average, as shown in Table 1, approximately 91 percent of all students complete their Bachelor's degrees at LiberalArtsU. Gender congruence in the student-adviser relationship is found to raise it to 93 percent.[4]

[4] In principle we can repeat the same analysis by focusing on male students rather than female students. Thus,substituting (1-malei) into femalei in Eq. (2),

(2)' $Y_{ijs} = \beta_1(1\text{-male}_i) + \beta_2(1\text{-adviser\_male}_i) + \beta_3(1\text{-male}_i)*(1\text{-adviser\_male}_i) + \mathbf{X_i\beta_4} + \mathbf{b_s} + \boldsymbol{\tau_j} + \mu_{ijs}$

(2)" $Y_{ijs} = (\beta_1+\beta_2+\beta_3) - (\beta_1+\beta_3)\text{male}_i - (\beta_2+\beta_3)\text{adviser\_male}_i + \beta_3\text{male}_i*\text{adviser\_male}_i + \mathbf{X_i\beta_4} + \mathbf{b_s} + \boldsymbol{\tau_j} + \mu_{ijs}$

Using the estimated coefficients in column (1) of Table 3, consider what will happen to a male student's overall retention rate when he is matched with a male adviser vs. a female adviser. His retention rate with a male adviser is given by $(\beta_1+\beta_2+\beta_3) - (\beta_1+\beta_3) - (\beta_2+\beta_3) +\beta_3=0$. His retention with a female adviser is given by $(\beta_1+\beta_2+\beta_3) - (\beta_1+\beta_3)= \beta_2$. As shown in Table 3, β_2 is 0.0121. Male student's retention rate when matched with a male adviser will be actually 1.21 percentage-point (0.0121) lower than when matched with a female adviser. The estimated coefficient of β2 is not precise, and hence we ought not to draw any definitive conclusion but at least there is no evidence that male student's outcome on the extensive margin is better when he and his adviser are of the same gender.

In contrast, as shown in Eq. (2), a female student's retention rate when matched with a female adviser will be higher than when matched with a male adviser by $(\beta_2+\beta_3)$. Note that the sum of β_2 and β_3= 0.0121+0.0204=0.0325 is statistically significant at the 5 percent level. A female student's retention rate is 3.25 percentage point (0.0325) higher when she and her adviser are of the same gender than when she and her adviser are of the opposite gender.

In sum, having a same-gender adviser is found to help a female student achieve a higher retention rate while there is no evidence that having a same-gender adviser helps a male student achieve a higher retention rate.

To shed light on the time profiles of the gender congruence effect, we further consider 1st year Retention (=1 if the student completes at least his/her freshman year, 0 otherwise); and 2nd year retention (=1 if the student completes at least his/her freshman and sophomore years, 0 otherwise). The estimated gender congruence effects are still positive and significant at the 10 percent level, suggesting that the gender congruence effect on the extensive margin is rather immediate. Moreover, the relative size of each coefficient suggests that much of the gender congruence effect on the extensive margin is concentrated in the first two years.

Though not our main focus, some of the estimated coefficients on other covariates warrant brief discussions. The estimated coefficients on financial aid are positive and statistically significant at the 1 percent level, while the estimated coefficients on high-school GPA are extremely small and not statistically significant even at the 10 percent level. Student outcomes on the extensive margin are strongly correlated with financial aid but not with high-school academic performance. Considering that LiberalArtsU is one of the most expensive schools in the nation, the positive and significant coefficient on financial aid and the insignificant coefficient on high-school GPA can be interpreted as indicating that student retention at an expensive private school such as LiberalArtsU has more to do with financial constraints than student preparedness.

Turning to the gender congruence effects on the intensive margin, the OLS estimates of Eq. (2) with Cumulative GPA as the dependent variable are presented in column (1) of Table 4. The estimated coefficient on female*adviser_female is positive and significant at the 5 percent level, again pointing to the presence of the positive student-adviser gender congruence effect on the intensive margin. The magnitude of the effect is comparable to prior studies. Fairlie et al (2010) and Carrell et al. (2010) find that race and gender congruence between introductory

course professors and students raise grade point by 5 to 8 percent standard deviations. In our case, the effect size of 0.034 amounts to about 8.7 percent standard deviation increase in cumulative GPA (cumulative GPA conditional on graduation has a mean of 3.23 and a standard deviation of 0.377). For those students who are on the fence of important cumulative GPA threshold, such as 3.0 for the employer screening or other thresholds for honors and high honors, this positive effect could have a consequential impact. Moreover, as shown below, the magnitude of the gender congruence effect on the intensive margin is larger for academically struggling students.

As in the case of the extensive margin effects, we test if gender congruence in the student-adviser relationship has an immediate effect on student grades by considering 1st semester GPA instead of cumulative GPA. The estimated coefficient on female*adviser_female is smaller and no longer significant even at the 10 percent level, suggesting that the gender congruence effect on the intensive margin may not be immediate. We further consider alternative academic performance measures during the first semester and continue to find no evidence for the immediate impact of gender congruence in the student-adviser relationship on the intensive margin.

Aside from the gender congruence effects, Table 4 also shows that the estimated coefficients on high-school GPA are positive and statistically significant at the 1 percent level except for % of passing grades in 1st semester which is significant at the 5 percent level. High-school GPA is, indeed, a strong predictor of college academic performance (student outcomes on the intensive margin).[5] In contrast, the estimated coefficients on financial aid are negative and statistically significant at least at the 5 percent level. We are not entirely sure about the negative correlation between financial aid and college GPA. One possibility is that many student athletes

[5] For the importance of high school GPA as a predictor of college academic performance, see, for instance, Geiser and Santelices (2005) and Rask and Tiefenthaler (2009).

in prominent sports come to LiberalArtsU with student aid and on average have lower college GPA. Another possibility is that students from disadvantaged backgrounds are more likely to receive financial aid and are, on average, not as prepared for college compared to their more privileged peers. Lastly, Table 4 confirms that female students perform better than male students, even after controlling for majors, cohorts, FSEM courses, high school GPA, and financial aid.

Table 5 presents the OLS estimates of Eq. (2) with post-graduation career outcomes as the dependent variable.[6] Though not precisely estimated, the gender congruence effect on post-graduation outcomes might be a shift from immediate employment to graduate school enrollment (the positive coefficient on female*adviser_female for Graduate School as the dependent variable and the negative coefficient on female*adviser_female for Employed as the dependent variable). As discussed below, when we divide the student sample into two groups: (i) students with below-median high-school GPA; and (ii) students with above-median high-school GPA, we find more precise estimates. Table 5 also shows that students with higher high school GPA and financial aid recipients are more likely to go on to graduate schools.

3.3 Adviser fixed effects

Adviser characteristics such as age, tenure, prior work experiences (e.g., types of schools he/she worked prior to joining LiberalArtsU), and educational backgrounds (e.g., types of undergraduate schools) may be correlated with adviser gender. For instance, it may be the case that female advisers are more likely to have their undergraduate degrees from liberal arts colleges than male advisers. If, as compared to male students, female students respond better to advisers with such a liberal arts educational background and hence perform better with such

[6] We also attempted to estimate a multinomial logit model with three outcomes: (i) employed; (ii) enrolled in a graduate school; and (iii) neither employed nor enrolled in a graduate school. Unfortunately the model failed to converge.

advisers, the observed gender congruence effects will be actually capturing the gender difference in the importance of adviser's liberal arts college background in the student-adviser interactions. There are multitudes of such adviser characteristics that may be correlated with adviser gender and play an important role in the student-adviser interactions differently for female and male students. To control for such adviser characteristics, we introduce adviser-fixed effects to our baseline model. Such adviser fixed effects will account for all adviser characteristics insofar as they are time-invariant, as in the case of holding an undergraduate degree from a liberal arts college.

Table 6 summarizes the OLS estimates of Eq. (2) augmented by adviser fixed effects. Note that adviser female is time-invariant and is therefore dropped as a result of the addition of adviser fixed effects. Reassuringly, our key results change little although the estimates are slightly less precise, which is expected, considering that we now rely only on variations within the same adviser. Thus, the estimated coefficients on female*adviser female remain positive and statistically significant at the 10 percent level for retention overall as well as for retention in 1st year as the dependent variables. The estimated coefficient for retention in the first two years as the dependent variable is also positive and close to being statistically significant. The estimated coefficient on female*adviser female for Cumulative GPA as the dependent variable is also positive and statistically significant at the 5 percent level. In sum, it is unlikely that the estimated effects of gender congruence are confounded by unobserved time-invariant adviser characteristics.[7]

3.4 An Alternative Interpretation: Introduction to the Field by a Same-Gender Instructor

[7] As in most fixed effect models, our estimates are still subject to time-variant confounders.

We interpret the estimated coefficients on female*adviser_female as the effects of gender congruence in the student-adviser relationship. However, each adviser is also an instructor of an introductory course (which happens to be an FSEM course in his/her field) taken by his/her advisee. For instance, consider a first-year female student taking an FSEM course in economics taught by a female instructor. The female student receives advising from this female instructor. We argue that the estimated coefficients on female*female_adviser measure the effects of gender congruence in the student-adviser relationship. However, the estimated coefficients on female*female_adviser might be capturing the effect of a female student being introduced to economics by a female instructor in an introductory economics course, and may have little to do with receiving advising by a female adviser.[8]

To see if we find evidence for such benefits for female students being introduced to their fields by female instructors, we focus on all first-year students who took non-FSEM introductory courses in economics, history, and mathematics, and estimate the effects of gender congruence in introductory courses in economics, history, and mathematics, excluding all FSEM courses. We selected introductory courses in these three fields, for they were the top three introductory courses with sufficient variations in gender congruence even after controlling for student cohorts.

Table 7 shows the OLS estimates of Eq. (2) that is modified to estimate the effects of gender congruence in the student-instructor relationship in introductory courses in economics, mathematics, and history. We focus on the effects on three retention measures and college GPA since we find evidence consistently for the significant effects of gender congruence in the student-adviser relationship on these measures. As shown in Table 7, none of the estimated

[8] A number of prior studies investigate the importance of female introductory instructor for female students. For instance, while Bettinger and Long (2005) use an instrumental variable approach and find mixed results for different majors, Carrell et al. (2010) exploit a natural experiment and find strong support for positive effects on high-achieving female students taking STEM courses with female instructors in introductory classes.

coefficients on Female*Instructor Female is significantly different from zero, and in fact the estimated coefficient is negative rather than positive. In sum, we find no evidence for the effects of gender congruence in the student-instructor relationship in introductory courses in economics, mathematics, and history, suggesting that a female student does not receive extra benefits from being introduced to a specific field through taking an introductory course taught by a female instructor. It is unlikely that we are misidentifying the effects of gender congruence in the student-adviser relationship by conflating gender congruence in the student-adviser relationship with gender congruence in the student-instructor relationship.

4. Heterogeneous Effects

Our extensive interviews at LiberalArtsU suggest that the impact of advisers on students may differ significantly for different groups of students. Advisers may play an important role when students are struggling academically. Furthermore, advisers may help students in different areas of their academic life, depending on their backgrounds and interests. In short, the impact of advisers in general and gender congruence in the student-adviser relationship in particular may have heterogeneous effects for different groups of students. To this end, we conduct two additional sets of analysis. First, we investigate whether the effects of the student-adviser gender congruence are stronger for students with academic challenges. Second, we explore if gender congruence in the student-adviser relationship play out differently, depending on whether or not students select their FSEM courses in STEM. Our focus on STEM is largely motivated by the growing interest in the interplay between gender and STEM (see, for instance, Rose and Betts, 2004).

Regarding the heterogeneous effects on students with different degrees of academic challenges, we first estimated quantile regressions and produced Figure 1 in which we plotted the estimated quantile effects of the student-adviser gender congruence on cumulative GPA upon graduation. As shown in the figure, the estimated gender congruence effects are larger for lower quantiles and reach close to 0.1 at the 15^{th} percentile. In fact, the 95 percent confidence interval indicates that the gender congruence effects are statistically different from zero for those who are below the 40^{th} percentile.

Second, instead of grouping students based on college GPA, we group students by their high school GPA and see if the effects of gender congruence vary by the degree of college preparedness. Specifically, we split all students into two groups, those with below-median high school GPA and those with above-median high school GPA, and estimate Eq. (2) separately. Tables 8 and 9 summarize the results. To be consistent with our interviews with personnel at LiberalArtsU, as shown in the two tables, the gender congruence effects both on the extensive and intensive margins are larger and more significant for students with below-median high school GPA than for students with above-median high school GPA. Especially the gender congruence effect on the intensive margin (cumulative GPA) is statistically significant only for students with below-median high school GPA. In addition, for those with below-median high school GPA, gender matching in the student-adviser relationship is now found to affect post-graduation career choice significantly—raising the odds of pursuing graduate schools. Again, no such effect is found for those with above-median high school GPA.

Finally, we conduct a similar analysis for those with FSEM courses in STEM subjects (STEM orientation) and those with FSEM courses in non-STEM subjects (non-STEM orientation). On the one hand, our data show that mean high school GPA is significantly higher

for students with STEM orientation than for other students. On the other hand, the above results on high school GPA indicate that the gender congruence effects differ, depending on high school GPA. As such, any observed differences in the gender congruence effects between students with and without STEM orientation will be confounded by the aforementioned differences in the gender congruence effects between students with above and below-median high school GPAs. Thus, we estimate Eq. (2) for four different groups of students: (i) STEM-oriented students with below-median high school GPA; (ii) STEM-oriented students with above-median high school GPA; (iii) non-STEM-oriented students with below-median high school GPA; and (iv) non-STEM-oriented students with above-median high school GPA. Tables 10-13 summarize the OLS estimates of Eq. (2) for the four groups.

Two noteworthy findings emerge. First, as shown in Tables 10 and 11, gender congruence has no significant impact on students with STEM-orientation regardless of whether their high-school GPAs are below or above the median. Second, for students without STEM-orientation, gender congruence helps students with below-median high school GPA improve their student outcomes both on the extensive and intensive margins, while helping students with above-median high school GPA improve their outcomes only on the extensive margin.

5. Conclusions

We have filled an important gap in the literature by studying the effects of gender congruence in the student-adviser relationship on three key student outcomes: (i) retention; (ii) grades; and (iii) post-graduation career outcomes. In so doing, we have used unique administrative data from a selective liberal arts university (LiberalArtsU) which includes detailed

longitudinal records (both academic and non-academic) on all students for their entire undergraduate years at LiberalArtsU.

We have provided new causal evidence on the gender congruence effects by taking advantage of LiberalArtsU's first-year faculty adviser assignment policy, which produces randomness in whether the student has a same-gender faculty adviser for the first year. First, we have found that gender congruence in the student-adviser relationship has a positive and significant effect on the odds of retention (gender congruence effect on the extensive margin) and on cumulate GPA upon graduation (gender congruence effect on the intensive margin). Second, we have uncovered that much of the gender congruence effect on the extensive margin tends to be concentrated during the freshman and sophomore years, while the gender congruence effect on the intensive margin is less immediate and shows up only in cumulative GPA upon graduation. We have also confirmed that our results change little even when we account for all unobserved adviser characteristics by using adviser fixed effects. Furthermore, we have provided evidence that we are not likely to be misidentifying the observed effects of gender congruence in the student-adviser relationship by conflating gender congruence in the student-adviser relationship with gender congruence in the student-instructor relationship.

Finally, student-adviser gender congruence has been found to work differently for students with different backgrounds and interests.

1. Gender congruence has been found to help students with below-median high school GPA both on the extensive and intensive margin yet for students with above-median high school GPA, gender congruence affects their outcomes only on the extensive mragin; and quantile regressions have also yielded a complementary finding that gender congruence raises cumulative college GPA only at the lower quantiles.

2. Moreover, while overall gender congruence in the student-adviser relationship has been found to have no significant effect on post-graduation career outcomes, for students with below-median high school GPA, we have found that gender congruence raises the odds of moving on to graduate schools.
3. Gender congruence in the student-adviser relationship has been found to help students who are not STEM-oriented at the beginning of their freshman years, while students who are STEM-oriented are not influenced by gender congruence.
4. Moreover, for students without STEM-orientation, gender congruence has been found to help students with below-median high school GPA improve their student outcomes both on the extensive and intensive margins, whereas helping students with above-median high school GPA improve their outcomes only on the extensive margin.

Our methodology is an econometric case study. The econometric case study approach compares favorably to more traditional competing approaches (large scale surveys) in terms of construct validity (or minimum measurement error) and internal validity (or causal inference). However, external validity is an obvious concern for any econometric case study. There is a need for similar econometric case studies of other schools, especially those schools that fall into different categories of schools (e.g., large public universities) to test the generalizability of our findings.

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Table 1. Summary Statistics

Panel A. Student Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample		All			Female			Male	
VARIABLES	mean	sd	N	mean	sd	N	mean	sd	N
female	0.529296	0.499158	14678						
high school GPA	3.645749	2.374345	13882	3.6996	1.968713	7,398	3.584306	2.764299	6,484
received financial aid (0/1)	0.388336	0.487388	14678	.39619	.4891363	7,769	.379505	.4852989	6,909
retention overall	0.909593	0.286774	14678	.9147895	.2792126	7,769	.9037487	.2949569	6,909
retention in 1st year	0.949721	0.218528	14678	.9478697	.222304	7,769	.951802	.2141999	6,909
retention in the first two years	0.922469	0.267441	14678	.9217402	.2685972	7,769	.9232885	.2661525	6,909
Cumulative GPA	3.200557	0.444415	14675	3.2938	.3750404	7,769	3.095662	.490613	6,906
1st semester GPA	3.058888	0.558037	14678	3.137595	.5037301	7,769	2.970383	.6012392	6,909
% of B- or above in 1st semester	0.811661	0.251529	14678	.8458498	.2187793	7,769	.7732175	.278932	6,909
% of passing grades in 1st semester	0.973624	0.095785	14678	.9808984	.0798041	7,769	.9654436	.1104763	6,909
Employed (0/1)	.7440663	.4364471	3,497	.740186	.4386458	1,936	.7488789	.433797	1,561
Graduate School (0/1)	.1555619	.3624913	3,497	.1627066	.3691931	1,936	.1467008	.3539208	1,561
Employed or Graduate Study (0/1)	.8996283	.300538	3,497	.9028926	.2961805	1,936	.8955798	.3059029	1,561

Panel B. Gender of Advisers

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	Student-Semester Level			Adviser Level		
VARIABLES	mean	sd	N	mean	sd	N
Adviser female	0.401	0.490	98,739	0.467	0.5	345
Female*Adviser female	0.238	0.426	98,739			

Source: Administrative data provided by LiberalArtsU.

Note: Most variables are available for twenty cohorts of students, while post-graduation outcomes are available for only six cohorts.

Table 2. Random Assignment

	(1)	(2)	(3)
VARIABLES	female adviser		
female	0.00479	0.00658	0.00846
	(0.00527)	(0.00538)	(0.00612)
high school GPA		-0.00116	-0.00134
		(0.000755)	(0.000862)
financial aid (0/1)		-0.00215	0.00215
		(0.00536)	(0.00606)
Observations	14,628	13,859	10,448
R-squared	0.652	0.655	0.671
Graduates Only	N	N	Y
FSEM Course FE	Y	Y	Y
Cohort FE	Y	Y	Y

Source: Administrative data provided by LiberalArtsU
Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 The OLS Estimates on the Effect of Gender Congruence on the Extensive Margin

VARIABLES	(1) Retention overall	(2) Retention in 1st year	(3) Retention in the first 2 years
female	0.00111	-0.0107**	-0.00859
	(0.00661)	(0.00503)	(0.00619)
adviser female	0.0121	0.00460	0.00638
	(0.00991)	(0.00747)	(0.00913)
female*adviser female	0.0204**	0.0143*	0.0158*
	(0.0102)	(0.00777)	(0.00951)
high school GPA	0.000926	-4.73e-05	0.000257
	(0.00120)	(0.00119)	(0.00118)
financial aid (0/1)	0.0148***	0.0177***	0.0201***
	(0.00512)	(0.00387)	(0.00474)
Observations	13,859	13,859	13,859
R-squared	0.031	0.029	0.028
FSEM Course FE	Y	Y	Y
Cohort FE	Y	Y	Y

Source: Administrative data provided by LiberalArtsU

Note: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4 The OLS Estimates on the Effect of Gender Congruence on the Intensive Margin

VARIABLES	(1) Cumulative GPA	(2) 1st semester GPA	(3) % of B- or above in 1st semester	(4) % of passing grades in 1st semester
female	0.166***	0.154***	0.0707***	0.0144***
	(0.00974)	(0.0125)	(0.00569)	(0.00209)
adviser female	-0.0164	-0.0314	-0.0115	-0.00308
	(0.0151)	(0.0199)	(0.00904)	(0.00352)
female*adviser female	0.0361**	0.0282	0.00423	0.00159
	(0.0146)	(0.0195)	(0.00889)	(0.00346)
high school GPA	0.0119***	0.0174***	0.00704***	0.00111**
	(0.00298)	(0.00495)	(0.00195)	(0.000473)
financial aid (0/1)	-0.0157**	-0.0202**	-0.0232***	-0.0135***
	(0.00760)	(0.0101)	(0.00448)	(0.00177)
Observations	10,448	13,859	13,859	13,859
R-squared	0.181	0.093	0.087	0.052
FSEM Course FE	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y
Major FE	Y	N	N	N

Source: Administrative data provided by LiberalArtsU

Note: Robust standard errors in parentheses. Column (1) uses only graduated students sample to look at cumulative GPA at graduation, while other columns include all students.

*** p<0.01, ** p<0.05, * p<0.1

Table 5 The OLS Estimates on the Effect of Gender Congruence on Post-graduation Outcomes

VARIABLES	(1) Employed (0/1)	(2) Graduate School (0/1)	(3) Employed or Graduate School (0/1)
female	0.0238	-0.00755	0.0163
	(0.0190)	(0.0159)	(0.0135)
adviser female	7.33e-05	-0.0107	-0.0106
	(0.0168)	(0.0138)	(0.0120)
female*adviser female	-0.0247	0.0205	-0.00413
	(0.0262)	(0.0215)	(0.0186)
high school GPA	-0.106***	0.104***	-0.00107
	(0.0240)	(0.0197)	(0.0167)
financial aid (0/1)	-0.0699***	0.0431***	-0.0268**
	(0.0166)	(0.0140)	(0.0116)
Observations	3,483	3,483	3,483
R-squared	0.149	0.159	0.107
FSEM Course FE	Y	Y	Y
Cohort FE	Y	Y	Y
Major FE	Y	Y	Y

Source: Administrative data provided by LiberalArtsU

Note: Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6 Controlling for Adviser Fixed Effects

VARIABLES	(1) Retention overall	(2) Retention in 1st year	(3) Retention in the first 2 years	(4) Cumulative GPA	(5) 1st semester GPA	(6) % of B- or above in 1st semester	(7) % of passing grades in 1st semester	(8) Employed (0/1)	(9) Graduate School (0/1)	(10) Employed or Graduate School (0/1)
female	0.00160	-0.0103**	-0.00798	0.167***	0.155***	0.0712***	0.0143***	0.0310	-0.0107	0.0203
	(0.00668)	(0.00508)	(0.00625)	(0.00985)	(0.0127)	(0.00576)	(0.00213)	(0.0204)	(0.0171)	(0.0145)
female* adviser female	0.0186*	0.0130*	0.0136	0.0317**	0.0280	0.00363	0.00150	-0.0448	0.0238	-0.0211
	(0.0104)	(0.00790)	(0.00971)	(0.0148)	(0.0198)	(0.00905)	(0.00349)	(0.0313)	(0.0255)	(0.0223)
Observations	13,859	13,859	13,859	10,448	13,859	13,859	13,859	3,483	3,483	3,483
R-squared	0.050	0.052	0.047	0.198	0.108	0.100	0.065	0.166	0.173	0.126
FSEM Course FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Major FE	N	N	N	Y	N	N	N	Y	Y	Y
Adviser FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Source: Administrative data provided by LiberalArtsU.

Notes: Robust standard errors in parentheses. All regressions include high school GPA and financial aid (0/1) as controls.

*** p<0.01, ** p<0.05, * p<0.1

Table 7 The OLS Estimates on the Effect of Gender Congruence in the Student-Instructor Relationship in Introductory Courses in Economics, Mathematics, and History

	(1)	(2)	(3)	(5)
Dependent Variable	Retention within 12 months	Retention within 24 months	Retention	college GPA
Female	-0.00810	-0.0104	0.00290	0.224***
	(0.00738)	(0.00903)	(0.00948)	(0.0142)
Instructor Female	0.00739	0.00563	0.00219	-0.00708
	(0.00857)	(0.0107)	(0.0119)	(0.0192)
Female* Instructor Female	0.00657	0.0172	0.0125	-0.0195
	(0.0126)	(0.0155)	(0.0168)	(0.0264)
Observations	5,186	5,186	5,186	4,538
R-squared	0.005	0.007	0.006	0.206
Course FE	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y
Major FE	N	N	N	Y

Source: Administrative data provided by LiberalArtsU.

Notes: Robust standard errors in parentheses. All regressions include high school GPA and financial aid (0/1) as controls.

*** p<0.01, ** p<0.05, * p<0.1

Table 8 The OLS Estimates on the Effects of Gender Congruence for Students with Below-Median High School GPA

VARIABLES	(1) Retention overall	(2) Retention in 1st year	(3) Retention in the first 2 years	(4) Cumulative GPA	(5) 1st semester GPA	(6) % of B- or above in 1st semester	(7) % of passing grades in 1st semester	(8) Employed (0/1)	(9) Graduate School (0/1)	(10) Employed or Graduate School (0/1)
female	-0.0127	-0.0113	-0.0187**	0.126***	0.0940***	0.0526***	0.00747**	0.0172	0.000159	0.0173
	(0.00969)	(0.00730)	(0.00907)	(0.0120)	(0.0163)	(0.00810)	(0.00338)	(0.0273)	(0.0198)	(0.0214)
adviser female	-0.0134*	-0.00775	-0.00990	-0.00930	-0.0167	-0.00434	-0.00305	-0.00795	-0.0105	-0.0185
	(0.00735)	(0.00520)	(0.00651)	(0.0102)	(0.0144)	(0.00732)	(0.00305)	(0.0230)	(0.0160)	(0.0190)
female* adviser female	0.0382***	0.0164	0.0263**	0.0283*	-0.00523	-0.0106	-0.000778	-0.0598	0.0727**	0.0129
	(0.0129)	(0.0101)	(0.0122)	(0.0158)	(0.0221)	(0.0110)	(0.00470)	(0.0381)	(0.0299)	(0.0285)
Observations	6,920	6,920	6,920	5,391	6,920	6,920	6,920	1,644	1,644	1,644
R-squared	0.059	0.055	0.053	0.308	0.220	0.197	0.110	0.223	0.207	0.193
FSEM Course FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Student Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Major FE	N	N	N	Y	N	N	N	Y	Y	Y

Source: Administrative data provided by LiberalArtsU.

Notes: Robust standard errors in parentheses. All regressions include high school GPA and financial aid (0/1) as controls.

*** p<0.01, ** p<0.05, * p<0.1

Table 9 The OLS Estimates on the Effects of Gender Congruence for Students with Above-Median High School GPA

VARIABLES	(1) Retention overall	(2) Retention in 1st year	(3) Retention in the first 2 years	(4) Cumulative GPA	(5) 1st semester GPA	(6) % of B- or above in 1st semester	(7) % of passing grades in 1st semester	(8) Employed (0/1)	(9) Graduate School (0/1)	(10) Employed or Graduate School (0/1)
female	-0.00359	-0.0182***	-0.0101	0.0966***	0.0713***	0.0317***	0.0102***	-0.0149	-0.0106	-0.0255
	(0.00844)	(0.00647)	(0.00799)	(0.0126)	(0.0151)	(0.00614)	(0.00199)	(0.113)	(0.101)	(0.0715)
adviser female	-0.00775	-0.00516	-0.00676	0.00491	-0.0231*	-0.00310	-0.000721	0.0104	-0.0251	-0.0147
	(0.00688)	(0.00505)	(0.00644)	(0.0107)	(0.0132)	(0.00528)	(0.00185)	(0.0275)	(0.0239)	(0.0178)
female* adviser female	0.0234**	0.0223**	0.0198*	0.0124	0.00489	-0.00557	-0.00178	0.0286	-0.0360	-0.00742
	(0.0113)	(0.00894)	(0.0107)	(0.0157)	(0.0197)	(0.00785)	(0.00268)	(0.0413)	(0.0359)	(0.0278)
Observations	6,934	6,934	6,934	5,052	6,934	6,934	6,934	1,591	1,591	1,591
R-squared	0.062	0.056	0.060	0.140	0.087	0.080	0.073	0.202	0.202	0.167
FSEM Course FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Student Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Major FE	N	N	N	Y	N	N	N	Y	Y	Y

Source: Administrative data provided by LiberalArtsU.

Notes: Robust standard errors in parentheses. All regressions include high school GPA and financial aid (0/1) as controls.

*** p<0.01, ** p<0.05, * p<0.1

Table 10 The OLS Estimates on the Effects of Gender Congruence for Students with STEM-orientation and Below-Median High School GPA

VARIABLES	(1) Retention overall	(2) Retention in 1st year	(3) Retention in the first 2 years	(4) Cumulative GPA	(5) 1st semester GPA	(6) % of B- or above in 1st semester	(7) % of passing grades in 1st semester	(8) Employed (0/1)	(9) Graduate School (0/1)	(10) Employed or Graduate School (0/1)
female	-0.0437*	-0.0136	-0.0433*	0.0750***	0.0554	0.0375**	0.0132	0.0261	-0.0466	-0.0205
	(0.0244)	(0.0189)	(0.0233)	(0.0276)	(0.0375)	(0.0180)	(0.00839)	(0.0805)	(0.0610)	(0.0526)
adviser female	0.00271	-0.00189	0.00444	-0.0333	-0.0687*	-0.0336*	-0.0132*	0.0537	-0.0684	-0.0147
	(0.0175)	(0.0133)	(0.0147)	(0.0278)	(0.0381)	(0.0187)	(0.00747)	(0.0921)	(0.0657)	(0.0713)
female* adviser female	0.0441	0.00769	0.0164	0.0213	-0.00439	-0.0233	0.00219	-0.172	0.159	-0.0132
	(0.0311)	(0.0246)	(0.0292)	(0.0377)	(0.0552)	(0.0261)	(0.0118)	(0.122)	(0.101)	(0.0761)
Observations	1,577	1,577	1,577	1,215	1,577	1,577	1,577	355	355	355
R-squared	0.158	0.129	0.146	0.456	0.332	0.331	0.190	0.436	0.514	0.376
FSEM Course FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Student Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Major FE	N	N	N	Y	N	N	N	Y	Y	Y

Source: Administrative data provided by LiberalArtsU.

Notes: Robust standard errors in parentheses. All regressions include high school GPA and financial aid (0/1) as controls.

*** p<0.01, ** p<0.05, * p<0.1

Table 11 The OLS Estimates on the Effects of Gender Congruence for Students with STEM-orientation and Above-Median High School GPA

VARIABLES	(1) Retention overall	(2) Retention in 1st year	(3) Retention in the first 2 years	(4) Cumulative GPA	(5) 1st semester GPA	(6) % of B- or above in 1st semester	(7) % of passing grades in 1st semester	(8) Employed (0/1)	(9) Graduate School (0/1)	(10) Employed or Graduate School (0/1)
female	-0.000409	-0.0183*	-0.00980	0.0890***	0.0813***	0.0309***	0.0129***	-0.000376	0.00755	0.00718
	(0.0145)	(0.0106)	(0.0137)	(0.0245)	(0.0294)	(0.0115)	(0.00374)	(0.0560)	(0.0507)	(0.0369)
adviser female	0.00400	0.00927	0.00366	-0.0146	-0.0736***	-0.00501	0.00122	0.0218	-0.0451	-0.0233
	(0.0115)	(0.00748)	(0.0108)	(0.0232)	(0.0268)	(0.0106)	(0.00351)	(0.0635)	(0.0595)	(0.0382)
female* adviser female	0.00157	0.0209	0.00366	0.0203	-0.0137	-0.0122	-0.00241	0.120	-0.115	0.00542
	(0.0191)	(0.0133)	(0.0174)	(0.0327)	(0.0387)	(0.0148)	(0.00529)	(0.0856)	(0.0759)	(0.0621)
Observations	2,320	2,320	2,320	1,756	2,320	2,320	2,320	635	635	635
R-squared	0.166	0.139	0.150	0.235	0.159	0.165	0.133	0.356	0.360	0.337
FSEM Course FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Student Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Major FE	N	N	N	Y	N	N	N	Y	Y	Y

Source: Administrative data provided by LiberalArtsU.

Notes: Robust standard errors in parentheses. All regressions include high school GPA and financial aid (0/1) as controls.

*** p<0.01, ** p<0.05, * p<0.1

Table 12 The OLS Estimates on the Effects of Gender Congruence for Students with no STEM-orientation and Below-Median High School GPA

VARIABLES	(1) Retention overall	(2) Retention in 1st year	(3) Retention in the first 2 years	(4) Cumulative GPA	(5) 1st semester GPA	(6) % of B- or above in 1st semester	(7) % of passing grades in 1st semester	(8) Employed (0/1)	(9) Graduate School (0/1)	(10) Employed or Graduate School (0/1)
female	-0.00569	-0.0113	-0.0133	0.139***	0.104***	0.0573***	0.00542	0.0141	0.0162	0.0303
	(0.0112)	(0.00835)	(0.0104)	(0.0139)	(0.0188)	(0.00946)	(0.00389)	(0.0313)	(0.0223)	(0.0255)
adviser female	-0.0148*	-0.00696	-0.00953	-0.00933	-0.00237	0.00309	-0.00249	-0.0162	0.00410	-0.0121
	(0.00847)	(0.00595)	(0.00758)	(0.0117)	(0.0163)	(0.00838)	(0.00354)	(0.0260)	(0.0177)	(0.0216)
female* adviser female	0.0374**	0.0191*	0.0286**	0.0349*	-0.00976	-0.0106	-0.000630	-0.0405	0.0564*	0.0158
	(0.0148)	(0.0114)	(0.0139)	(0.0181)	(0.0249)	(0.0124)	(0.00531)	(0.0424)	(0.0321)	(0.0327)
Observations	5,343	5,343	5,343	4,176	5,343	5,343	5,343	1,289	1,289	1,289
R-squared	0.075	0.066	0.067	0.327	0.233	0.205	0.123	0.262	0.219	0.253
FSEM Course FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Student Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Major FE	N	N	N	Y	N	N	N	Y	Y	Y

Source: Administrative data provided by LiberalArtsU.

Notes: Robust standard errors in parentheses. All regressions include high school GPA and financial aid (0/1) as controls.

*** p<0.01, ** p<0.05, * p<0.1

Table 13 The OLS Estimates on the Effects of Gender Congruence for Students with no STEM-orientation and Above-median High School GPA

VARIABLES	(1) Retention overall	(2) Retention in 1st year	(3) Retention in the first 2 years	(4) Cumulative GPA	(5) 1st semester GPA	(6) % of B- or above in 1st semester	(7) % of passing grades in 1st semester	(8) Employed (0/1)	(9) Graduate School (0/1)	(10) Employed or Graduate School (0/1)
female	-0.00681	-0.0210**	-0.0127	0.112***	0.0792***	0.0344***	0.0100***	0.0509	-0.0233	0.0276
	(0.0110)	(0.00863)	(0.0105)	(0.0159)	(0.0186)	(0.00758)	(0.00259)	(0.0344)	(0.0311)	(0.0235)
adviser female	-0.00112	-0.00492	-0.00108	0.00549	-0.00117	0.000763	-0.000395	0.0142	-0.0128	0.00138
	(0.00891)	(0.00676)	(0.00846)	(0.0134)	(0.0164)	(0.00663)	(0.00228)	(0.0302)	(0.0261)	(0.0198)
female* adviser female	0.0315**	0.0231*	0.0259*	0.00971	0.0102	-0.00222	-0.00222	-0.0247	0.000634	-0.0241
	(0.0145)	(0.0119)	(0.0140)	(0.0191)	(0.0239)	(0.00958)	(0.00322)	(0.0450)	(0.0382)	(0.0308)
Observations	4,614	4,614	4,614	3,296	4,614	4,614	4,614	1,204	1,204	1,204
R-squared	0.080	0.061	0.077	0.169	0.112	0.104	0.091	0.231	0.225	0.186
FSEM Course FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Student Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cohort FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Major FE	N	N	N	Y	N	N	N	Y	Y	Y

Source: Administrative data provided by LiberalArtsU.

Notes: Robust standard errors in parentheses. All regressions include high school GPA and financial aid (0/1) as controls.

*** p<0.01, ** p<0.05, * p<0.1

Figure 1 The Quantile Effects of Gender Congruence in the Student-adviser Relationship on Cumulative GPA upon Graduation