Advisor Value-Added and Student Outcomes: Evidence from Randomly Assigned College Advisors*

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Abstract

This paper provides the first causal evidence on the impact of college advisor quality on student outcomes. To do so, we exploit a unique setting where students are randomly assigned to faculty advisors during their first year of college. We find that higher advisor value-added (VA) substantially improves freshman year GPA, time to complete freshman year and four-year graduation rates. Additionally, higher advisor VA increases high-ability students' likelihood of enrolling and graduating with a STEM degree. Our results indicate that allocating resources towards improving the quality of academic advising may play a key role in promoting college success.

JEL Classification: I23, I24, J16

Keywords: College Completion, STEM, Academic Advising, Value-Added

*We thank Andrew Barr, Clément de Chaisemartin, Joshua Goodman, Mark Hoekstra, Peter Kuhn, Jesse Rothstein, Dick Startz and Doug Steigerwald for helpful comments and suggestions. We also thank Zaher Bu Daher and Solange Constantine for assistance in providing us with the data used in this paper. All errors are our own.

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1 Introduction

College graduates earn significantly more than those with a high school diploma, and this gap has been widening over time (Oreopoulos and Petronijevic, 2013). The type of postsecondary degrees that students pursue is also a strong determinant of their future earnings. For example, earnings of graduates from the fields of science, technology, engineering and math (STEM) largely exceed those with degrees in non-STEM fields (Hastings, Neilson and Zimmerman, 2013; Kirkbøen, Leuven and Mogstad, 2016; Canaan and Mouganie, 2018). Despite these substantial labor market returns, college graduation and STEM enrollment rates remain relatively low. In the United States, only 41.6 and 60.4% of students at four-year colleges respectively graduate within 4 and 6 years of initial enrollment (National Center for Education Statistics, 2018). Additionally, only half of freshman college students who initially express interest in pursuing a STEM major eventually obtain a STEM bachelor's degree (Malcom and Feder, 2016). These issues have put the question of how to improve college students' outcomes at the center of ongoing policy debates in the U.S, but not many clear solutions have been put forth.

In an effort to understand how to boost postsecondary outcomes, we focus on an overlooked input in the education production function: the quality of academic advising. While academic advising is offered by most U.S. postsecondary institutions to help students navigate the complexities of college, little is known about whether quality of advising matters for students' academic trajectories. In general, the role of an academic advisor at four-year colleges is to provide students with high touch and personalized support throughout the academic year. Specifically, an advisor's duties are to monitor students' academic progress, provide personalized assistance with selecting courses and developing a plan of study, give information on academic programs and majors, and offer academic and career mentoring. Additionally, freshman or pre-major advisors help students select an appropriate field of study. Advising during the freshman year is particularly important since it is a critical period for both the recruitment of STEM majors (President's Council of Advisors on Science and Technology, 2012) and student retention.[1]

This paper provides the first causal evidence on the effects of college advisor quality on student outcomes. To do so, we first estimate freshman advisor value-added (VA), based on students' course grades, using rich administrative data linking students to faculty advisors at the American University of Beirut, a private 4-year university located in Lebanon. An important feature of the freshman advising system at AUB is that students are randomly

[1] The first-year retention rate is 73.9% among U.S. full-time students who entered college in the fall of 2016 (National Student Clearinghouse, 2018).

assigned to academic advisors. This enables us to compute VA estimates that are free from bias inherent to non-random settings (Rothstein, 2009 and 2010), where the student-advisor match is most likely correlated with unobservable factors. We then look at the impact of advisor VA on students' academic performance, retention, graduation and major choice. While the random assignment of students to advisors is unique to our setting, AUB is in many ways comparable to a private four-year university in the United States as we detail in section 2.

Our results indicate that being matched to a one standard deviation higher VA advisor increases freshman year GPA by 5.7 percent of a standard deviation. We further find that advisor grade VA has no significant impact on the likelihood that students persist after freshman year, but it does reduce time to complete the freshman year by 3.1%. Importantly, the benefits of having an effective freshman advisor do not fade out, as we document a 5.5% increase in 4-year graduation rates due to a one standard deviation higher freshman advisor VA. Effective freshman advisors also influence students' major choices. A one standard deviation higher advisor VA raises high-ability students' likelihood of enrolling and graduating with a STEM degree by around 4 percentage points. These effects are driven by high-ability male and female students who respectively experience a 3.2 and 4.9 percentage point (or 7.8 and 16.3%) increase in the likelihood of enrolling in a STEM major, and comparable improvements in STEM graduation rates. Advisor characteristics, such as gender or faculty rank, do not seem to predict advisor value-added. However, we do find evidence that gender match between advisors and advisees has positive effects on students' outcomes, especially for women.

Using detailed course-level data, we rule out that higher VA advisors push students to take "easier" courses, thereby inflating their freshman GPA and changing their subsequent outcomes. Instead, effective advisors seem to act as coaches or mentors, directly influencing students' grades without altering their course composition. We further construct alternative measures of advisor value-added based on non-grade outcomes and show that these measures of advisor quality also predict significant positive impacts on students' college outcomes. Results from this additional analysis suggests that our findings on the longer term impacts of advisors are, for the most part, driven by grade improvements in freshman year.

Finally, we conduct similar grade and non-grade VA analyses for a sample of students who first enroll at AUB as sophomores with a declared major and who are randomly assigned to faculty advisors within their chosen majors. As we detail in section 5.6, the way advising is conducted for these students is close to freshman advising. Notably, we show that our main freshmen results replicate using this new sample. Indeed, we find that sophomores experience a 3.7 percent of a standard deviation increase in their first-year GPA from having a one standard deviation higher grade VA advisor. Sophomore students are also 4.3% more likely to graduate on-time due to a one standard deviation higher advisor grade VA. These results highlight the importance of academic advisors for students at different stages of their postsecondary studies.

This paper is the first to document that effective college advisors largely improve students' academic outcomes. Our findings thus relate to a broad literature focused on how to address low college completion rates and increasing time to graduation in the U.S. A long body of work examines the role of financial aid in raising degree completion. While some need-based programs are promising (Dynarski, 2003; Bettinger et al., 2016; Castleman and Long, 2016; Barr, 2016; Angrist, Autor and Pallais, 2020), much of the research on financial aid has found limited impact on degree attainment (Deming, 2017). Another avenue for improving postsecondary outcomes is to increase per student spending and resources (Bound, Lovenheim, and Turner, 2010; Deming and Walters, 2017). Deming and Walters (2017) suggest that increased spending is effective because it can be directed towards academic support services such as advising. Our results corroborate this idea and provide a clear policy recommendation on how postsecondary institutions can promote student success. Specifically, our findings indicate that allocating resources towards improving the quality of academic advising may be an effective way to boost student outcomes.

Another related literature examines whether a variety of interventions can be used to address educational barriers. Programs which offer in-person, individualized and proactive college coaching or advising have shown to substantially increase academic performance (Kot, 2014; Oreopoulos and Petronijevic, 2019) and persistence (Bettinger and Baker, 2014; Carrell and Sacerdote, 2017; Barr and Castleman, 2018; Weiss et al., 2019).[2] On the other hand, light-touch interventions that omit the "personal" element have limited impact on student success. These include nudges, email or text message reminders (Dobronyi, Oreopoulos and Petronijevic, 2019; Bird et al., 2021), virtual advising (Oreopoulos and Petronijevic, 2019; Phillips and Reber, 2019; Sullivan, Castleman and Bettinger, 2019; Gurantz et al., 2020) and in-person but non proactive advising (Angrist, Lang and Oreopoulos, 2009; Scrivener and Weiss, 2009; Angrist, Oreopoulos and Williams, 2014).

To the best of our knowledge, no prior work has examined whether college advising quality matters for students' academic trajectories. Previous studies focus on access to advising (i.e., the extensive margin) and not on the quality of advising. Our finding that quality of

[2]Prior work also evaluates counseling programs aimed at increasing *high school* students' access to college or financial aid. These studies show that providing students with one-on-one counseling or assistance significantly increases college enrollment, persistence, and financial aid receipt (Bettinger et al., 2012; Avery, Howell and Page, 2014; Castleman, Page and Schooley, 2014; Castleman and Goodman, 2018; Mulhern, 2019).

advising matters for students' success may thus explain why some of the previously studied advising and coaching programs succeeded and others did not. More broadly, our results emphasize that a reason why some interventions have been successful at boosting college outcomes is because they give students access to high-quality advising. Indeed, programs that have shown the most promise at increasing college completion such as the Accelerated Study in Associates Program—which offers comprehensive student support—have repeated interactive advising as a key component (Weiss et al., 2019).

Our findings also relate to the extensive body of research on the education production function, and the role of school resources and teachers in determining student achievement. Recent studies highlight the importance of teacher value-added in predicting students' outcomes (Staiger and Rockoff, 2010; Jackson, Rockoff and Staiger, 2014; Koedel, Mihaly and Rockoff, 2015; Chetty, Friedman, and Rockoff, 2014a and 2014b; Jackson, 2018).[3] In line with the evidence on teacher VA, we find that advisors who raise contemporaneous student achievement improve subsequent longer-term outcomes such as graduation. Importantly, we add to this literature by offering a first look into the benefits of academic advising, which is an integral part of most U.S. colleges.[4] In particular, our paper is the first to show that college advisors are an important input in the education production function, and may be just as valuable as teachers in predicting students' success.

Our results further add to an emerging literature that evaluates whether a variety of policies influence students' major choice. Prior work has focused on the role of financial incentives (Sjoquist and Winters, 2015; Denning and Turley, 2017; Evans, 2017), differential pricing of academic programs (Stange, 2005) and timing of course-taking (Patterson, Pope and Feudo, 2019) in college major decisions. Our paper complements these studies by showing that advising quality largely influences students' major choice.

By showing that effective advisors increase female STEM degree attainment, we also join a growing literature aimed at identifying strategies to address women's persistent underrepresentation in the sciences. Previous work has highlighted that women are more likely to choose STEM majors and persist in STEM careers when they are exposed to female instructors, role models or advisors in the sciences (Blau et al., 2010; Carrell, Page and West,

[3]An exception is Carrell and West (2010) who show that U.S. Air Force Academy professors who are effective at increasing contemporaneous student achievement, harm subsequent academic performance. This is because teachers inflate their course grades—by for example, "teaching to the test"—in order to maximize student evaluations.

[4]Indeed, little is known about the role of academic advising in students' college trajectories. Previous studies have examined advising or coaching programs that are operated in partnership with universities but not by colleges themselves. A multitude of papers in the education literature have documented positive correlations between academic advising and students' college outcomes (see Tinto, 2010 for a review of the literature). However, these studies do not address the issue of selection bias and hence, cannot cleanly identify causal effects.

2010; Canaan and Mouganie, forthcoming; Porter and Serra, 2019). However, having a sufficient number of women take on the role of mentors might be difficult given the shortage of females in these fields and since on average, women in academia already allocate more time for service than men (Guarino and Borden, 2017; Buckles, 2019). Our findings suggest that investing in quality of academic advising can promote female STEM degree attainment, without requiring women to take on a disproportionate amount of service work compared to men.

The rest of this paper is organized as follows. Section 2 provides a detailed description of our institutional setting. Sections 3 and 4 outline our data and methodology, respectively. Section 5 presents our randomization tests and main results. We discuss our findings in section 6 and conclude in section 7.

2 Institutional Background

2.1 The University

To estimate the impacts of academic advisors' value-added, we exploit a unique feature of the advising system at the American University of Beirut (AUB), which randomly assigns students to faculty advisors. AUB is a small nonprofit private university located in the country of Lebanon. It provides a liberal arts education with an emphasis on undergraduate studies, although it does also offer numerous postgraduate degrees. In total, the university has approximately 50 degrees across a variety of disciplines such as humanities, social sciences, sciences, engineering and medicine. AUB is one of the oldest universities in the region and was established by American protestant missionaries in the year 1866. The sole language of instruction at AUB is English and degrees awarded by the university are officially registered with the New York Board of Regents. It is considered a selective university and has a total enrollment of around 7,000 students. Admission into the freshman year is based on a composite score that is a weighted average of SAT1 scores (50%) and high school GPA in grades 10 and 11 (50%). It is also relatively expensive with an average tuition of approximately \$14,000, which is large given the country's average yearly income of \$14,846.

Along many dimensions, AUB is comparable to an average private nonprofit 4-year college in the United States. The student to faculty ratio is 11 to 1 and the average class size is less than 25 students. Further, approximately 83% of full-time faculty have doctoral degrees and 50% of students and around 40% of full-time faculty are female. These statistics are similar to the average student to faculty ratio of 10 to 1 at private nonprofit 4-year colleges in the United States. Further, females account for around 55% of all undergraduate students and 44% of all full-time faculty at U.S. post-secondary institutions (National Center for Education Statistics, 2018). Additionally, AUB uses a credit hours system in line with the U.S. model of higher education whereby most courses are worth 3 credit hours and students take an average of 15 credits (5 courses) per semester. Starting with the freshman year, most bachelor's degrees require 120 credit hours or four years to completion.[5]

Our focus in this paper is on students who are initially enrolled at AUB as freshmen. Most students in Lebanon have to pass a national exam at the end of high school, upon which they are awarded a baccalaureate degree (or *Baccalauréat*). Those who pursue the baccalaureate track in high school are ineligible to enroll in university as freshmen, rather they enter as sophomore students with a declared major. Freshman students are those who attended Lebanese or foreign schools that follow the U.S. high school education system and curriculum. Students who initially enter AUB as freshmen are sometimes younger than those eligible to directly enroll as sophomores. Indeed freshman students are, on average, 17.8 years old when they first enroll compared to 18 years of age for sophomore students.[6] Students in our sample are thus academically and culturally more comparable to U.S. rather than Lebanese first-year college students. We should also note that although many freshman students in our sample come from foreign high schools, the role of academic advisors in our setting is *not* to facilitate students' transition into a new country (i.e., making them feel less stressed about moving to Lebanon, etc.). Instead, foreign students are assigned to another mentor whose main job is to help them transition into their new life in Lebanon. Furthermore, foreign school students at AUB are mostly Lebanese expatriates so they are likely already familiar with every day life in Lebanon and may not require much assistance with settling in the country.

2.2 Academic Advising

At the beginning of their freshman year, students are randomly assigned to academic advisors (or pre-major advisors). Advisors are full-time faculty of professorial rank (Assistant, Associate and Full Professors) chosen from various departments within the Faculty of Arts and Sciences. Preference is given to faculty who are not up for tenure the following year and who are not overloaded with service requirements. Academic advising is counted towards faculty members' service, but additional incentives are in place to encourage volunteering, such as extra research funds or a course release. Faculty commit to advising for the full

[5]The only exceptions are engineering and architecture which require five and six years to completion, respectively.

[6]We calculate students' ages using data on year of birth for both samples. We do not have data on month of birth, so these calculations are a rough approximation of their age.

academic year, and most advise for multiple years.

After deciding on the final pool of advisors, university administrators working within the Faculty of Arts and Sciences randomly assign freshman students to their respective advisors. This is done using a simple two step process. First, students are sorted by either their ID numbers or last names and placed on a list. The method of sorting varies by year, i.e. all freshman students are sorted either by name or by ID within the same academic year. Advisors are then randomly ordered and placed on a separate list. Administrators then pick the first name from the student list and match it to the first name on the advisor list. The second student is then matched to the second advisor and so on. This process continues until all students are matched to an advisor. Importantly, no characteristics of either the advisor or student—such as gender, prior academic performance, or even intended major, etc.—are taken into consideration throughout this process. In section 5.1, we confirm that this matching procedure is consistent with what we would expect from the random assignment of students to advisors. This unique institutional feature enables us to identify the causal effect of an academic advisor's VA on students' performance, major choice and graduation outcomes.

Students at AUB typically declare a major at the end of their freshman year, after having completed the requirements for admission into their intended majors. Academic advisors' main tasks are to monitor students' academic progress during the freshman year, help them choose a major and courses, as well as develop a plan of study that will allow them to meet the requirements for entry into their intended majors. Students are advised by the same advisor throughout the freshman year. They are required to meet with their advisors one-on-one at least once per semester and prior to course registration.[7] Advisors further have to hold weekly office hours throughout the semester, and students have the option of contacting them to set up additional out of office hours meetings. They are given access to students' full academic records, including their past high school grades and SAT scores, which allows them to tailor their advice to students' interests and abilities. Advisors are notified of any irregularity or change of status of their respective students—such as whenever students are placed on probation. Additionally, students are not allowed to withdraw from any course without first getting advisor approval.

A key part of an advisor's job is to help students decide on a major and importantly meet the requirements for entry into their intended major. Freshman students apply for a

[7]Students need a PIN code for course registration that can only be provided by their advisors during those one-on-one meetings, ensuring that they actually meet with their advisors. Furthermore, freshman advisors conduct a group advising session prior to the beginning of the academic year where they introduce students to university resources, the code of conduct and the general requirements for completing their first year and declaring a major.

major at the end of their first year of college giving them plenty of time to interact with their advisors before selecting a field of study. Admissions into different majors are granted based upon the fulfillment of credit and course requirements set by departments. Appendix Table A1 highlights an example of the requirements for four different majors—engineering, chemistry, business and history. Regardless of their intended majors, all students have to complete a total of 10 courses in a variety of disciplines (sciences, social sciences, humanities) in order to be eligible complete their freshman year and become sophomores. However, the emphasis on courses taken varies across intended majors. For example, students wishing to pursue science majors such as engineering and chemistry are required to take 2 math and 3 science courses during their freshman year. On the other hand, students who intend on enrolling in other majors such as business and history have to complete only one math and 2 science courses—but have to take more humanities and electives than science majors.

Further, some departments require students to take specific courses. In general, science majors—i.e., engineering, computer science, mathematics, physics, chemistry and biology—are the most restrictive as they require that students take a number of difficult science and math courses. For example, students wishing to pursue engineering have to take Calculus I and II, General Chemistry, and Introductory Physics. In contrast, those who plan on pursuing non-science majors have the option of enrolling in easier math and science courses.[8] Finally, some majors impose admission grade requirements. The most selective majors are engineering which require a minimum cumulative freshman-year GPA of 80 for admission.[9] In our analysis, students' final GPA in each freshman course is the main measure used to construct advisor value-added.[10]

2.3 Comparison to Academic Advising at Other Universities

In this section, we discuss how the different features of AUB's academic advising system compare to pre-major advising at 4-year colleges in the United States. First, advising at AUB is carried out by full-time faculty, and around 31 students are assigned to each advisor. A survey conducted by the College Board (2011) among U.S. 4-year colleges found that full-time faculty advise more than three-fourths of first-year students at 52.4% of responding institutions. This number however varies by type of institution. While 84.1% of surveyed baccalaureate-granting institutions reported that three-fourth of students are advised by

[8]For example, many of them take "Mathematics for Social Sciences" instead of Calculus.

[9]Freshman students' applications are pooled with those entering directly to the sophomore year, and the admission rate for engineering averages around 17%.

[10]Importantly, courses are not graded on a curve at AUB and, unlike teachers, advisors cannot inflate or manipulate students' grades directly. Further, we standardize all course grades at the class-year level to account for differences in course grading across courses and years.

full-time faculty, this number is 50% at master's-granting institutions and 22.5% at research universities which mostly rely on professional advisors. Additionally, the National Academic Advising Association reports that in U.S. postsecondary institutions where faculty advise students, the median caseload for a faculty advisor is 25 for small institutions and 45 for medium-sized institutions.[11]

Second, the main goals of advising at AUB are to help students choose a major and courses, develop a plan of study and keep track of their academic progress during the freshman year. These tasks are in line with those emphasized in the U.S. 4-year college advising system. Indeed, according to a survey conducted by the National Academic Advising Association (NACADA, 2011), over 91% of 4-year public and private U.S. colleges stated that they have academic advisors whose responsibilities include helping students develop a plan of study, schedule and register in courses, and select a major. Third, AUB advisors are required to meet one-on-one with students at the beginning of each semester and prior to course registration. The College Board survey (2011) indicates that among U.S. 4-year colleges, 69% of responding institutions also required students to meet with their first-year advisor at least once per term.

To give a clearer idea about how AUB's advising system compares to other settings, we collected information on how pre-major advising is conducted at various selective private 4-year colleges in the United States. We chose 5 liberal arts colleges—Amherst College, Middlebury College, Swarthmore College, Wesleyan University and Williams College—and 5 research universities—Duke University, Harvard College, Princeton University, Vanderbilt University and Yale University. This information is summarized in Tables A2 and A3. Similar to AUB, advising at most of the liberal arts colleges is conducted exclusively by faculty (last column of Table A2). Research-intensive universities have faculty advisors but advising is also conducted by staff members or administrators.

Interestingly, the tasks of pre-major advisors at both liberal arts colleges and research intensive universities (second column of Table A2) are similar to those of AUB advisors. Specifically, advisors are responsible for helping students set academic and career goals, select courses and choose a program of study. The liberal arts colleges further emphasize that advisors should keep track of students' academic progress and problems. Furthermore, all colleges in Table A2 specify that advisors should meet one-on-one with students several times during the academic year and at least once before course registration—as one of the main goals of advising is to help students select courses.

Finally, AUB advisors have access to students' academic records, are notified when their

[11] Small institutions are defined as having an undergraduate enrollment head count of less than 5000 students, while medium-sized institutions have between 6000 to 23,999 students.

advisees are placed on academic probation and have to approve course withdrawals. We were unable to find aggregate statistics regarding whether U.S. advisors perform these tasks. However, we were able to find this information for some of the colleges that we collected data on. For example, Table A3 shows that advisors at Middlebury, Wesleyan and Swarthmore have access to their students' academic records. The latter two colleges as well as Williams College also notify advisors when students' academic standing is unsatisfactory. On the other hand, amongst colleges shown in Table A3, only Vanderbilt and Amherst require that advisors approve course withdrawals. In sum, evidence from this section indicates that AUB's academic advising system is comparable in many ways to advising at private 4-year colleges in the United States.

3 Data

3.1 Data Description

This paper uses student level administrative data acquired directly from the Registrar's office at the American University of Beirut (AUB). These data contain detailed student-level longitudinal information on course grades, credits accumulated, sex, semester GPA, class-year (Freshman, Sophomore, etc...) as well as major during every semester enrolled at university. Importantly, these data also contain information on each student's academic advisor including gender, faculty rank and department. These anonymized data were then matched, through an agreement between the registrar's office and the admissions office, to student baseline information. This enables us to also observe students' Verbal and Math SAT scores, year of birth, high school location as well as legacy status. Our data initially included 4,353 incoming freshmen students matched to 46 faculty advisors at AUB for the academic years 2003-2004 to 2015-2016.[12] We exclude all students who have missing baseline information and all advisors who advised for only one academic year.[13] This leaves us with a final sample of 3,857 freshman students matched to 38 academic advisors.

[12]Freshman students entering university before 2003-2004 had a different advising system in place. For results involving graduation outcomes, we also limit our sample to students entering AUB on or before 2012-2013 in order to observe graduation status for all students.

[13]As we discuss in detail in Section 4, our estimate of value-added (VA) for each advisor-year is computed using a leave one-year-out estimation strategy. Thus, we are unable to compute any VA estimate for advisors who served for one year.

3.2 Summary Statistics

Our main analysis involves 3,857 freshman students enrolled in 41,121 courses matched to 38 faculty advisors. Summary statistics for all students and advisors used in our analysis are shown in Table 1. In columns (1) and (2), we present means and standard deviations for key variables with the number of observations reported in column (3) throughout. We begin by summarizing student baseline characteristics in Panel A of Table 1. Female students constitute around 48% of individuals in our main sample, compared to 52% male. The average Mathematics and English SAT test scores for freshman students are 573 and 494 points respectively. Approximately 20% of all freshman students are legacy admits, defined as those with a close relative who attended AUB.

Next, we present summary statistics for our main student level outcomes in Panel B of Table 1. The average freshman GPA is 76.5 out of a possible 100 points with a standard deviation of 9. Relative to all students initially enrolled as freshmen, 79.4% complete the requirements of the freshman year and become sophomores. For students who enter sophomore year, the average time to do so is around 2.5 semesters. Approximately 46% of students initially enrolled as freshmen are able to graduate on-time, i.e., within 4 years of initial enrollment at AUB.[14] Further, around 57.5% of freshmen graduate within 6 years of enrollment.

In our analysis, we focus on the likelihood that students pursue science and business majors (henceforth, selective majors) for several reasons.[15] First, these majors impose more course and grade requirements than other fields and hence prospective students may require a great deal of guidance from their advisors in order to meet the admission requirements.[16] Second, from a policy perspective, these majors have been shown to have the highest labor market returns (Hastings et al., 2013; Kirkbøen et al., 2016), and governments have been increasingly investing in promoting STEM education. 43% of students in our sample enroll in a selective major and 35.5% of all students eventually graduate from a selective major.

In Panel C of Table 1, we report statistics for advisor level variables matched to our sample of students. In total, 38 unique faculty members served as freshman advisors for the academic years 2003-2004 to 2015-2016. On average, each advisor spends around 3.5 years advising resulting in 131 advisor-year observations. Around 39% of freshman advisors are female faculty members and 61% are male. This is in line with the overall proportion of

[14]For most majors, on-time graduation is defined as graduating within 4 years. The only exceptions are engineering and architecture which require 5 and 6 years to complete on-time.

[15]This includes all fields of engineering, architecture, Biology, Chemistry, Computer Science, Mathematics, Physics, Statistics and Business majors.

[16]While the business school does not require students to take specific courses, its does have a minimum admission freshman-GPA of 77—which is higher than most other majors.

female faculty at AUB which stands at approximately 40%. Further, 56.5% of advisors are in a science department and 43.5% are in a social sciences or humanities field within the faculty of arts and sciences. The majority of advisors are at the rank of assistant professor. Indeed, 28% are full professors, 22 are associate and 50% are lecturers or assistant professors. On average, each academic advisor has 31 students per academic year.

4 Identification Strategy

4.1 Methodology—Computing Value-Added Estimates

We construct advisor value-added (VA) following the methodology presented in Chetty, Friedman, and Rockoff (2014a) with slight modifications to fit our framework. During a given year, a typical student is enrolled in around 10 classes (5 during the fall semester, 5 during the spring semester). We predict value-added based on freshman course grades since one of the main roles of an advisor is to track and help improve students' performance during the freshman year. Given that advisors are randomly assigned to students each year, for the purpose of creating VA estimates, an advisor can be thought of as an instructor for multiple different classes in a given year. Accordingly, we define a classroom in this setting as an advisor-year-class cell.[17]

Let students be indexed by i, years by t, classes by c, and advisors by j. Then let student i's final freshman course grade, S_{itc}, in year t and class c be equal to:

$$S_{itc} = \boldsymbol{\beta X_{it}} + \eta_{itc}, \tag{1}$$

where:

$$\eta_{itc} = \mu_{jt} + \theta_{ict}, \tag{2}$$

and $\boldsymbol{X_{it}}$ is a set of student level covariates that includes math and verbal SAT scores, student gender, and whether the student was a legacy admit. The error term η_{itc} is decomposed into two parts, advisor VA: μ_{jt} (scaled such that the average advisor has a VA of zero and a one-unit increase in VA leads to a one-unit increase in course grades) and a student-class idiosyncratic shock θ_{ict} that is unrelated to advisor quality. As we detail in section 5.1, our data are consistent with what we would expect from the random matching of students to advisors. Importantly, under random assignment, $\boldsymbol{X_{it}}$ and θ_{ict} are balanced across advisors with different levels of VA and are thus uncorrelated with μ_{jt}.[18] Thus, one advantage of

[17] A class refers to all sections of a given course; for example, all students taking Calculus I. Additionally, our results are robust to running the analysis using advisor-year cells.

[18] We also assume that μ_{jt} and θ_{ict} are covariance stationary. This requires that mean advisor quality

our setting is that the average course grades of an advisor's students can be directly used to construct an unbiased estimate of advisor value added—without the need to impose any additional assumptions.[19]

Due to the random nature of advisor assignment, we do not directly estimate equation (1), rather we start by standardizing student course grades at the class-year level and running a regression of this standardized variable on year fixed effects:

$$S_{itc} = \alpha_t + \nu_{itc}. \tag{3}$$

We then create the residuals S^*_{itcj} from Equation (3) and collapse them to the advisor-year level $\bar{S}^*_{jt}$ using Chetty, Friedman, and Rockoff (2014a) precision weights which give more weight to classrooms with a lower variance of residual course grades.

The value-added $\hat{\mu}_{jt}$ of advisor j in year t is then constructed by predicting the average $\bar{S}^*_{jt}$ using $\bar{S}^*_{js}$ for all $s \neq 0$ where s is the separation between the years in which the classes were taught. Excluding the year $s = 0$ removes the endogeneity associated with using the same students to form both the treatment and the outcome. *This is equivalent to a leave one-year-out (jackknife) estimate*, where the data from different years are weighted using the method presented in Chetty, Friedman, and Rockoff (2014a) with weights only depending on the lag s:[20]

$$\hat{\mu}_{jt} = \sum_{s \neq 0} \hat{\phi}_s \bar{S}^*_{js}, \tag{4}$$

where $\hat{\phi}_s$ are obtained from OLS regressions of $\bar{S}^*_{jt}$ on $\bar{S}^*_{js}$ for each lag s.

Finally, our data include students who took more than one year to complete their freshman year. To account for concerns of mechanical correlations that might arise from these students being matched with the same advisor two years in a row, we compute the VA of advisors based only on the grades of freshman students in their first year of university schooling.

is constant over time and that the correlation between advisor quality and any shocks across years only depends on the amount of time elapsed between the years. We impose this assumption to be able to adjust our VA estimates for drift in advisor quality over time (Chetty, Friedman, and Rockoff, 2014a).

[19] Creating VA following the exact methodology of Chetty, Friedman, and Rockoff (2014a) where grades are first residualized using student covariates yields quantitatively similar estimates of VA. It does however lead to a small loss in precision of VA estimates due to a lower number of observations because of missing covariates for certain observations.

[20] We restrict the covariances for lags greater than 3 years to be equal to the covariance for a lag of 3.

4.2 Forecast Unbiasedness of VA estimates

Under the random assignment of students to advisors in a given year t, the average effect on final course GPA of a change in our estimated measure of VA is similar to the average effect of a change in actual VA. To see that, note that given random assignment we have that:

$$Cov(S^*_{itcj}, \hat{\mu}_{jt}) \equiv Cov(\mu_{jt}, \hat{\mu}_{jt}), \tag{5}$$

the covariance between residual course grade and estimated VA is equal to the covariance between true VA and estimated VA. This relationship holds because random assignment ensures that all observable and unobservable predictors of course performance are balanced across advisors. Following Chetty, Friedman, and Rockoff (2014a), we consider the following regression of residual course grades on estimated VA:

$$S^*_{itcj} = \alpha_t + \lambda\hat{\mu}_{jt} + \zeta_{itc} \tag{6}$$

In our setting we then have:

$$\lambda = \frac{Cov(S^*_{itcj}, \hat{\mu}_{jt})}{Var(\hat{\mu}_{jt})} = \frac{Cov(\mu_{jt}, \hat{\mu}_{jt})}{Var(\hat{\mu}_{jt})}, \tag{7}$$

and since $\hat{\mu}_{jt}$ is constructed to be the best linear predictor of S^*_{itcj} we have that $\lambda = 1$ and is the causal impact of being assigned an advisor with a one unit higher VA. We check that this holds in our setting by estimating the regression in Equation (6) and testing the hypothesis that $\lambda = 1$. The results presented in Table 2 show that a one unit increase in estimated freshman advisor course grade VA leads to a statistically significant 0.971 unit increase in freshman course grade. Importantly, we are unable to reject the null hypothesis of $\lambda = 1$. This indicates that a one unit change in our *out-of-sample* estimated VA has the same causal effect on course grades as a one unit change in true VA. This ensures that our estimated VA measure captures the true impact of advisor value-added on longer run outcomes. We also show that our measure of freshman advisor VA is forecast unbiased under different sample splits. Namely, we estimate VA in three other ways: 1) Leaving the current and two previous years out, 2) Leaving the current and two future years out, and 3) Randomly splitting the sample in half, estimating leave-year out VA in one half, and then checking for forecast unbiasedness in the second half of the sample. Appendix Table A4 presents results from this exercise. We are unable to reject the null hypothesis of $\lambda = 1$ in any specification, despite sample size reductions from this analysis.

4.3 Identifying Equation

Our empirical strategy exploits the random assignment of freshman students to academic advisors at the American University of Beirut. Our main focus involves estimating the causal impact of freshman advisor quality on students' academic outcomes. To capture these effects, we regress student outcomes on estimated advisor course grade VA ($\hat{\mu_{jt}}$) from Equation (4). Specifically, we standardize advisor VA by year ($\hat{m}_{jt}$), and run the following linear regression model for all freshman students matched to an academic advisor:[21]

$$Y_{ijt} = \alpha + \gamma \hat{m}_{jt} + \theta X'_{it} + \lambda_t + \epsilon_{ijt} \tag{8}$$

where Y_{ijt} refers to our outcomes of interest for student i matched to advisor j in academic year t. γ is our treatment parameter which captures the average impact of advisor value-added on student outcomes. Our simplest specification includes only these variables and λ_t an academic-year fixed effect that controls for unobserved changes across different years. Intuitively, with the inclusion of year fixed effects, we are comparing students during the same year that are matched with advisors having different VA measures. In alternate specifications, and to alleviate concerns over selection, we further add a set of student controls X'_{it} that should improve precision by reducing residual variation in the outcome variable, but should not significantly alter our VA effects. These controls include students' math and verbal SAT scores, gender and legacy admission status. Finally, ϵ_{ijt} represents our error term. Standard errors are clustered at the advisor-year (treatment) level throughout to account for correlations among students exposed to the same advisor in the same year.

5 Results

5.1 Tests of the Identifying Assumption

To identify the causal effect of an advisor, it is important that freshman students' characteristics are uncorrelated with their advisor's value-added. The ideal experiment to identify such effects free of bias would be to randomly assign advisors to students. While our institutional setting provides for random assignment of students to advisors, we perform a series of tests to confirm that our data are consistent with such a process. First, we show that students' predetermined baseline characteristics are uncorrelated with their advisor's VA estimate. To do so, we regress advisor grade VA on a host of student controls includ-

[21]The full distribution of the standardized advisor course grade VA measure $\hat{m}_{jt}$ is reported in appendix Figure A1.

ing Verbal and Math SAT scores, student gender and legacy status. We include year fixed effects in our regressions to account for any common shocks that vary by cohort. The results of this test are summarized in Table 3. We find no significant relationship between advisor VA and student ability, student gender or legacy status. Indeed, all coefficients on our student controls are statistically insignificant and reasonably precise. For example, we find that scoring 10 points higher on the math SAT test would lead to at most having an advisor with a 0.99 percent of a standard deviation (0.0099) higher VA. We also find that student characteristics are jointly insignificant, as indicated by a p-value of 0.25 from a test of joint significance. These results are in line with our institutional setting and indicate that students who are assigned to a lower or higher value-added advisor are similar in terms of observable characteristics, consistent with random student-advisor matching.

Second, we complement the above results with additional tests of randomization. Specifically, we use resampling techniques, analogous to those conducted in Carrell and West (2010), to empirically test if our data are consistent with what would be observed from a random process. To do so, we randomly draw 10,000 student samples of equal size for each advisor-year combination without replacement. For each randomly sampled advisor-year combination, we calculate the sums of both the verbal and math scores for all students in that sample. We then compute empirical p-values for each advisor-year based on the proportion of simulations with values less than that of the actual advisor-year sum. Under the random assignment of students to advisors, we would expect that any unique p-value is equally likely to be observed—i.e., that the distribution of empirical p-values should be uniform.

Accordingly, we test for the uniformity of this distribution using both a Kolomogrov-Smirnov one-sample of equality of distribution test and a χ^2 goodness of fit test. These results are summarized in Panel A of Table 4 and indicate that for all 13 years of our data, we fail to reject the null hypothesis of random assignment for all years based on either test of uniformity. These results hold regardless of whether we use the mathematics or verbal SAT test scores as a proxy for academic ability. In summary, we find no evidence of nonrandom assignment of students to advisors based on academic ability. As an additional test, we also regress these empirical p-values on advisor characteristics, such as value-added and academic rank. These results are reported in Panel B of Table 4 where we find no statistically significant relationship between our computed p-values and advisor characteristics. We must note however that estimates from Panel B are imprecise mostly because they involve regressions from 131 observations corresponding to the 131 advisor-year combinations in our data.

5.2 Freshman Year Academic Performance and Retention

As previously discussed, some of the main tasks of an advisor are to monitor students' academic progress and help them stay on track, with the ultimate goal of preparing students to enroll in a major by the end of their freshman year. Accordingly, we start by examining whether advising quality influences students' freshman year GPA. The corresponding regression estimates are reported in column (1) of Table 5, with and without the addition of student controls.[22] Throughout our analysis, both freshman GPA and advisor grade value-added (VA) are standardized, and all regressions involve the addition of academic year fixed effects. Results presented in Panel A indicate that a one standard deviation increase in advisor VA raises students' freshman-year GPA by 5.7 percent of a standard deviation. Consistent with the random assignment of students to advisors, the addition of student controls in Panel B does not alter this estimate in a meaningful way. Our estimates on GPA are comparable to professor VA estimates found in other university settings. Indeed, Carrell and West (2010) show that a one standard deviation change in professor quality leads to a 5 percent of a standard deviation increase in course grades at the U.S. Air Force Academy. Further, our estimate on academic performance is only slightly smaller than those found in teacher VA studies in school settings (For examples, see, Kane, Rockoff, and Staiger 2008; Chetty, Friedman, and Rockoff 2014). The fact that our estimates are comparable to those from teacher VA studies highlights that students can benefit from different types of interactions with educators. Specifically, while teachers may have more repeated interactions with students, advisors have the advantage of meeting with students one-on-one and providing them with high-touch personalized support.

Next, we examine whether advisors impact students in ways that extend beyond grade improvements. In column (2) of Table 5, we look at the effect of advisor grade VA on the likelihood that students become sophomores. Since students typically become sophomores after completing all course and credit requirements for the freshman year, this outcome captures first-year retention—i.e., the likelihood that students remain at the university after their freshman year. We find that higher advisor VA has no significant impact on the likelihood that students persist until the sophomore year. On the other hand, column (3) reveals that effective advisors reduce the number of semesters that students take to complete the requirements of the freshman year and become sophomores. A one standard deviation improvement in advisor VA decreases the time to become sophomore by 0.078 semesters. This corresponds to an approximate 3.1% reduction from the baseline mean of 2.48 semesters. This finding is robust to the inclusion of student controls, as indicated by the statistically

[22]These controls include student gender, Math and Verbal SAT scores as well as legacy status.

significant -0.072 estimate reported in Panel B. Panels (a) and (b) of Figure 1 summarize the full distributional advisor grade VA effects for our two significant outcomes, where we display average effect sizes on the y-axis and standardized freshman advisor VA on the x-axis. Notably, advisor quality effect sizes (on student GPA) increase in a roughly linear manner across the whole VA distribution, whereas they decrease linearly with respect to students' time to reach sophomore status.

In Appendix Table A5, we conduct heterogeneity analysis for freshman GPA and retention. Overall estimates are restated in column (1) and heterogeneous effects by student ability and gender are reported in columns (2) through (5). We use mathematics SAT test scores as a measure of student ability. Specifically, low-ability students are those scoring below the median math SAT score of their cohort, while higher-ability students are those who score above the median of their cohort. Results presented in columns (2) and (3) of Panel A indicate that the effect of advisor VA on freshman GPA increases with student ability. A one standard deviation higher advisor VA increases low-ability students' GPA by 4.2 percent of a standard deviation, and by 7.2 percent of a standard deviation for higher-ability students. These estimates are robust to the inclusion of students controls. Results reported in columns (4) and (5) indicate that GPA effects do not differ by gender. Male and female students both experience a 5.4 and 5.8 percent of a standard deviation increase in GPA when exposed to a one standard deviation higher VA advisor, respectively.

In Panel B of Table A5, we examine heterogeneous effects for the likelihood that students declare sophomore status. Consistent with our result for the overall sample, we find that advisor grade VA has no significant impact on the probability that students of different abilities or genders complete the freshman year and become sophomores. On the other hand, Panel C reveals that the overall reduction in freshman year completion time is mostly driven by lower-ability students. Specifically, lower-ability students take 0.107 fewer semesters to become sophomores due to a one standard deviation higher advisor VA—i.e., a 4.1% decrease in time to enroll in the sophomore year. Furthermore, we find that exposure to a one standard deviation higher advisor VA reduces freshman completion time for both male and female students by 0.062 and 0.089 semesters (or 2.45 and 3.66%), respectively. Taken together, our findings indicate that advising quality is critical not only for students' academic performance, but also for improving time to complete the freshman year particularly among low-ability students.

5.3 College Completion

Findings from the previous section indicate that high quality advisors substantially improve students' academic performance and time to complete the freshman year. We next examine whether these documented gains persist in the long run and focus on whether freshman advisor grade VA influences college completion.[23] We first look at the likelihood of on-time or 4-year graduation in column (4) of Table 5. We find that a one standard deviation increase in advisor VA raises the probability of on-time graduation by 2.5 percentage points or 5.5%. The addition of student controls, as shown in Panel B, does not alter results in a meaningful way, as the estimate is slightly reduced to 2.2 percentage points and remains significant at the 1% level. Estimates from column (5) show that advisor VA has no statistically significant impact on 6-year graduation rates, albeit we cannot rule out large effects. These findings indicate that while higher quality advisors do not necessarily influence overall graduation rates, they do however have a large impact on the likelihood that students graduate from university on time. This is consistent with our finding that higher advisor VA does not affect the likelihood that students declare sophomore status, but significantly reduces time to complete the freshman year. Panels (c) and (d) of Figure 1 summarize these effects across the full VA distribution. Advisor VA effect sizes on four-year graduation rates exhibit an approximately linear increase with significantly negative effects for students matched to freshman advisors at the lower end of the VA distribution. On the other hand, we find no significant pattern of advisor VA effects on six-year graduation rates.

Heterogeneous effects for graduation outcomes are presented in Appendix Table A7. In columns (2) and (3), we report estimates for students with different levels of ability. For on-time graduation (Panel A), both low and higher-ability students are 2.4 and 2.3 percentage points (or 5.7 and 4.6%) more likely to graduate within 4 years when matched with a one standard deviation higher VA advisor. On the other hand, consistent with the effect for the overall sample, we detect no significant impacts on 6-year graduation rates for both low and higher-ability students (Panel B). In columns (4) and (5), we report heterogeneous effects by gender. We find that a one standard deviation improvement in freshman advisor VA increases men's likelihood of graduating on-time by 3 percentage points (or 6.2%) and no significant impact on 6-year graduation. We do not detect any statistically significant effects on female students' 4 and 6-year graduation rates, but reduced precision prevents us from drawing definitive conclusions regarding their graduation outcomes.

[23] We note that estimates from this section are based on a reduced sample size of freshman students initially enrolled at AUB from the 2003-2004 to 2012-2013 academic year since we cannot observe graduation for more recent cohorts. In Table A6 of the Appendix, we also report estimates of advisor VA on short run outcomes using the sample of freshman students entering AUB for the years 2003-2004 to 2012-2013. Our documented short run effects remain qualitatively similar using this reduced sample.

5.4 Major Choice

One of the main tasks of an academic advisor is to help students select a major and guide them on how to meet the requirements for admission into their preferred field of study. We therefore examine whether advising quality influences the likelihood that students enroll and eventually graduate from selective majors.[24] As discussed in section 2.2, selective majors have more stringent entry requirements compared to other fields of study. As a result, students wishing to enroll in these majors may require a lot of guidance from their freshman-year academic advisor. The different columns in Table 6 report estimates for the impact of advisor grade VA on students' major choice.[25] For our overall sample, results in Panel A and column (1) indicate that a one standard deviation increase in advisor VA raises the probability that students enroll in selective majors by 2.4 percentage points or 5.6%. The estimate for graduating from a selective major is on the order of 1.5 percentage points (or 4.2%) and is only statistically significant at the 10% level.

These overall effects may mask contextual heterogeneities, as selective majors are potentially more accessible to the highest-ability students. We therefore examine heterogeneous effects by student ability in columns (2) and (3). We define top students as those scoring in the top 75th percentile of the math SAT distribution (i.e., above 600), and non-top students as those with a score below 600. Estimates reported in columns (2) and (3) of Panel A confirm that the highest-ability students are indeed driving the overall effects on selective major enrollment. We find that a one standard deviation increase in freshman advisor VA raises top students' likelihood of enrolling in a selective major by a large and statistically significant 4.9 percentage points (or 8.6%). This is coupled with a similar and significant 3.9 percentage points (or 8.4%) increase in top students' probability of graduating from these majors, indicating that the initial enrollment effects persist in the long run and that virtually all students who are shifted into these majors end up graduating.[26]

Heterogeneous effects by gender, presented in columns (4) and (5) of Panel A, reveal that both top female and male students benefit from being matched to an effective advisor. Specifically, top male and female students with a one standard deviation higher advisor VA are 5.1 and 4.4 percentage points more likely to enroll in a selective major, respectively. Men are also 4.8 percentage points more likely to graduate from these majors. We do not detect

[24] Recall, we define selective majors as those in the sciences and engineering as well as business degrees. These degrees also happen to correspond to those with the highest earnings potential.

[25] All regressions in Table 6 include student controls and year fixed effects.

[26] All panels in Figure 2 summarize distributional VA effects on selective major enrollment and graduation for the overall and the top student. All figures indicate a roughly linear increase in the effects of advisor quality on students' enrollment and graduation rates across the whole VA distribution. Notably, the documented average positive effects on selective major enrollment for top students seem to be driven by the best set of advisors.

significant graduation effects for women, albeit estimates are fairly imprecise.

In Panels B and C of Table 6, we estimate effects separately for STEM and Business majors. For STEM majors, results are consistent with those for selective majors. Estimates in columns (2) through (5) of Panel B indicate that non-top students' STEM outcomes are not positively affected by a higher VA advisor. However, both top female and male students experience significant increases in the likelihood of enrolling and graduating from STEM fields. Indeed, a one standard deviation higher VA advisor increases top students' likelihood of enrolling and graduating from a STEM major by 3.8 and 4.2 percentage points, respectively. For top male students, this corresponds to a 3.8 percentage point (or 11.6%) increase in graduation with a STEM degree. For top female students, both STEM enrollment and graduation are statistically significant and on the order of 4.9 and 4.6 percentage points (or 16.3 and 19.8%), respectively.

Finally, estimates presented in Panel C of Table 6 show a 1.3 percentage point increase in the likelihood of majoring in Business for the overall sample, and that this effect is concentrated among non-top students and top male students. Put together, our findings indicate that effective advisors shift students toward selective majors, and that these effects are driven by an increase in STEM enrollment and graduation for top students and smaller increases in Business enrollment for non-top students.

5.5 Non-Grade Measures of Freshman Advisor Value-Added

We document that advisor value-added has a significant impact on students' college outcomes. Our constructed measure of VA is based on freshman course grades as tracking and helping improve student performance is one of the most important roles of an advisor. However, a good freshman advisor may also directly influence students' major choice and help them persist at university. Accordingly, we check whether non-grade measures of student outcomes are also good predictors of advisor quality and to what extent such VA measures correlate with our current measure of advisor VA. To do so, we introduce two new measures of advisor value-added based on student persistence and major choice indices. Specifically, using a principal component analysis (PCA) decomposition, we first create two student-level indices: a *Persistence Index* and a *Selective Index*. The *Persistence Index* is composed of five key university persistence measures: 4-year graduation, 6-year graduation, freshman drop-out, proportion of courses withdrawn and proportion of courses failed during freshman year. The *Selective Index*, which measures major selectivity, is computed using three key major choice variables: selective major enrollment, selective major graduation and proportion of key science and math courses taken during freshman year.[27] Following the Chetty, Friedman, and Rockoff (2014a) method introduced in Section 4.1, we then compute two separate leave one-year-out measures of advisor VA (i.e., a Persistence and a Selective VA) based on the *Persistence Index* and *Selective Index*, respectively.

We start by looking at how these two non-grade VA measures affect student outcomes. Appendix Table A8 summarizes results from this exercise. Estimates from column (1) indicate that a one standard deviation increase in persistence and selective advisor VA improves freshman GPA by a significant 4 and 5 percent of a standard deviation respectively. Additionally, columns (2) and (3) show that both advisor VA measures predict positive impacts on students' 4 and 6-year graduation rates, although not all estimates are statistically significant at conventional levels. We also find that having an advisor with a higher persistence or selective value-added lowers the likelihood of course withdrawal and failure for students. Finally, we show that being matched to an advisor with a higher persistence or selective VA increases students' chances of enrollment and graduation from selective majors (STEM + Business) as well as the likelihood of taking key science and mathematics courses during freshman year. Put together, these findings indicate that non-grade measures of advisor quality also predict significant positive impacts on students' college outcomes.

To better understand whether advisors who are skilled at raising student grades are also effective in promoting persistence and influencing major choice, we next report raw correlations between our previously constructed advisor VA measure (Grade VA) and our two new measures (Persistence and Selective VA) in Table A9. These results indicate a positive, but not strong, correlation between Grade VA and Persistence VA (ρ=0.17), as well as between Grade VA and Selective VA (ρ=0.29). Strikingly, the correlation between Persistence VA and Selective VA is quite high (ρ=0.80) suggesting overlapping advisor skills in affecting these outcomes.

To further understand these patterns, we conduct additional explanatory analysis in the spirit of Jackson (2018). Specifically, we separately regress students' Freshman GPA, *Persistence Index* and *Selective Index* (we also refer to these 3 outcomes as skill measures) on their respective advisor VA measures. We present coefficients from these regressions in Table 7 where both treatment (VA measure) and outcome are standardized. Estimates from columns (1), (7) and (10) indicate that advisors who raise a given skill measure out of sample have large and statistically significant effects on those same student skills. For instance, the 0.04 estimate from column (7) indicates that being matched to an advisor with a one standard deviation higher Persistence VA increases students' persistence index by 4 percent of a standard deviation. Next, we separately regress each of our skill measures on

[27] We standardize these indices to have a mean of zero and standard error of one.

advisor VA estimates computed using *other* skill measures. The results from this analysis are in line with the documented positive raw correlations across advisor VA measures. Indeed, columns (2) and (4) indicate that advisors who are skilled at increasing persistence and access to selective major positively and significantly affect students' GPA. Furthermore, estimates in columns (6) and (9) reveal that advisors who are effective at improving course grades also positively affect persistence and major choice.

Finally, we present estimates from regressions that simultaneously include grade and non-grade VA measures. Estimates from columns (3) and (8) of Table 7 indicate that, conditional on advisors' grade value-added, persistence VA is no longer statistically related to students' GPA (0.023) or *Persistence Index* (0.023). However, grade VA is still predictive of student GPA (0.055) and *Persistence Index* (0.052) even when controlling for advisors' persistence value-added. This suggests that advisors who improve persistence do so mainly through improving students' grades. On the other hand, regressions that simultaneously control for grade and selective VA result in statistically significant estimates for both VA measures as shown in columns (5) and (11). This suggests that advisors who influence students' major choice are not doing so solely through increasing their academic performance, rather advisor skills needed to improve grades and influence major choice, though correlated, seem to be somewhat complementary.

5.6 Additional Results Based on Major Advising

In this paper, we focus on pre-major advising conducted during the freshman year. However, an advantage of our data is that we are also able to look at the impacts of *major advisors*—i.e., advisors who mentor students after they declare a major—for a different sample of students. As discussed in section 2.1, most Lebanese students pursue a baccalaureate track in high school rendering them ineligible to enroll in college as freshmen. For these students, their final year in high school is considered equivalent to the U.S. college freshman year. Therefore, they enroll in college as sophomore students with a declared major immediately after finishing high school. We refer to students from this sample as the "sophomore sample". New enrolling sophomore students at AUB are randomly assigned to faculty advisors within their chosen major using a process similar to that used for freshmen. Specifically, all sophomore students are sorted by either their ID or last name within their respective departments. The chosen method of sorting is the same across all departments in the same year. Advisors within each department are then sorted randomly on a separate list. Students are then matched to advisors within their respective departments using the same matching process as the one used for freshman students. Each student has the same advisor for the entire academic year. Sophomore advisors' (henceforth major advisors) main tasks are to help students select courses and develop a plan of study that allows them to meet the requirements for graduating from their majors. They also monitor students' academic progress, have access to their academic records, are notified of their students' change of status, and are required to meet with students one-on-one at least once at the beginning of each semester.

In this section, we examine how major advisor VA impacts sophomore students' college outcomes. Extending our main analysis to the sophomore sample has several advantages. First, our main freshman sample includes 38 unique advisors. This limited number of advisors may render our results less generalizable to other settings thus potentially limiting their implications for policy discussions. In contrast, our sophomore sample allows us to observe a significantly larger number of unique advisors (194 unique advisors). Importantly, the sophomore advising system at AUB shares many similarities with freshman advising. Sophomores in our setting are comparable to freshmen in that they are both first-year college students and hence, we are essentially capturing the impacts of first-year college advising for both samples. Additionally, the tasks of a sophomore major advisor are similar to those of a pre-major advisor. The only difference between these two types of advising is their end-goal: while freshman advising is intended to keep students on track to declare a major, sophomore advisors help students stay on track to graduate from their chosen major. Second, our sophomore sample analysis provides new insights into the role of *major advising* which is important in and of itself, as it is offered by most U.S. private 4-year colleges. Indeed, all colleges shown in Table A2 offer one-on-one major advising that is comparable in its goals and the way it is conducted to the one in our setting.[28]

5.6.1 Sophomore Sample Summary Statistics

Before presenting our additional analysis, we describe the sophomore sample. Appendix Table A10 summarizes key statistics for the sample of 14,055 first-time enrolling sophomore students at AUB for the academic years 2003-2004 to 2015-2016.[29] Importantly, these students are matched to 194 distinct advisors during this time period, thus providing for a much larger number of student-advisor interactions than the freshman sample.[30] Students from this sample are approximately 48 percent female, similar to the freshman sample. Additionally, 25 percent of admissions are legacy students. Students score an average of 644 and 530

[28]Of course, this is with the exception that sophomores at AUB are first-year college students, while U.S. sophomores are second-year college students.

[29]Freshman students who eventually become sophomores at AUB are dropped from this analysis, since our focus here is on first-time advising effects.

[30]For the graduation sample, this number shrinks to 152 unique advisors.

points on the Math and Verbal SAT exams, respectively. Notably, these scores—particularly for the Math SAT—are significantly higher than those from the freshman sample. This is not surprising as students enrolling at AUB as sophomores spend an extra year in high school that is considered equivalent to the freshman university year.

Panel B of Appendix Table A10 shows means for the sophomore sample's main outcomes. Only 8.8 percent of students drop out after sophomore year. To examine the impacts of major advisor VA on longer-term outcomes, we focus on 4-year and 6-year graduation rates as in the freshman sample. However, since sophomore students enroll in college one year after freshmen, we slightly modify our definition of these variables. Specifically, for the sophomore sample, 4-year graduation—which is our measure of on-time degree completion—is defined as graduating within 3 years from initial enrollment at AUB. Similarly, 6-year graduation, our measure of overall degree completion, is defined in this case as graduating within 5 years from initial enrollment at AUB.[31] Appendix Table A10 reveals that 79.6 percent of students end up graduating overall, while only 52.9 percent complete their degree on time. We also look at whether major advisor VA influences the probability that students graduate from their initial major—i.e., their declared major in the first semester of their sophomore year. 40.5 percent of sophomore students graduate on-time and 55.4 percent graduate overall from their initial majors.

Finally, Panel C summarizes sophomore advisor level characteristics. 31 percent of major advisors are female and around half are in science departments. Additionally, advisors are well represented across all faculty ranks and each major advisor has an average of 19.1 sophomore students to advise per year.

5.6.2 Sophomore Advisor Course Grade VA

We examine whether a higher value-added major advisor predicts improved outcomes for students entering AUB as sophomores. To do so, we first construct course grade value-added measures for major advisors following the Chetty, Friedman, and Rockoff (2014a) method introduced in section 4.1. One notable difference between this and our previous analysis involves the need to include department fixed effects to compute unbiased measures of VA. This is because sophomore students are randomly assigned to faculty advisors in the department corresponding to their declared major. Results presented in Appendix Table A11 confirm that this procedure results in a forecast unbiased measure of advisor grade value-added by showing that a one unit increase in estimated advisor course grade VA leads

[31] Compared to other majors, engineering and architecture require 1 and 2 more years to complete on-time, respectively. We accommodate for this in our definitions of 4 and 6-year graduation rates.

to a statistically significant 0.991 unit increase in sophomore course grade.[32] To analyze major advisor quality effects, we regress sophomore student outcomes on our constructed and standardized advisor course grade VA estimate ($\hat{\nu}_{jdt}$) using the following linear regression model:

$$Y_{ijdt} = \alpha + \beta\hat{\nu}_{jdt} + \theta X'_{it} + \zeta_d + \lambda_t + \epsilon_{ijdt} \tag{9}$$

Here, β captures the effect of major advisor VA on sophomore student i matched to advisor j in department d and cohort t. Our identifying equation now includes department fixed effects ζ_d since randomization of students to advisors occurs within departments.

Before presenting the main findings from this exercise, we show that our data are consistent with what we would expect from the random matching of sophomore students to advisors within departments. In Appendix Table A13, we show that advisor grade VA is unrelated to students' baseline characteristics. Results indicate that conditional on department fixed effects, students' Math and Verbal SAT scores, gender and legacy status are not statistically related to their advisors' value-added. Additionally, these variables are jointly unrelated to advisor grade VA, as the p-value from the test of joint significance is equal to 0.462.

Table 8 presents the main findings from our course grade VA analysis. Results in Panel A indicate that being matched to a major advisor with a one standard deviation higher grade value-added increases students' sophomore-year GPA by 3.7 percent of a standard deviation, but does not significantly affect their dropout rate one year after the start of their sophomore year. Column (3) further reveals that a one standard deviation higher quality major advisor increases the likelihood of on-time graduation by 2.3 percentage points, i.e. 4.3 percent. It also increases the overall graduation rate by 1.6 percentage points (column (4)), though this estimate is only significant at the 10 percent level. Estimates in columns (5) and (6) suggest that the documented effect for on-time degree completion is mostly due to students being more likely to graduate on time from their initial declared major. Specifically, we find that a one standard deviation higher advisor VA increases the probability that students graduate on time from their initial major by 2 percentage points, but we detect no statistically significant effects on ever graduating from initial major.

In our freshman sample analysis, we showed that higher advisor VA increases the probability that students enroll in STEM majors. Since sophomore students enroll at AUB with a

[32] We further check that our measure of sophomore advisor grade VA is forecast unbiased under different sample splits. Namely we estimate sophomore advisor VA in three other ways: 1) Leaving the current and two previous years out, 2) Leaving the current and two future years out, and 3) Randomly splitting the sample in half, estimating leave-year out VA in one half, and then checking for forecast unbiasedness in the second half of the sample. Appendix Table A12 presents results from this exercise. We are unable to reject the null hypothesis of $\lambda = 1$ in any specification, despite the reduced sample sizes from this analysis.

declared major, we cannot look at whether advisor VA impacts their STEM enrollment. An analogous analysis in this case is to examine whether effective advisors are most beneficial for sophomore students whose initial declared major is STEM—i.e., those who declared a STEM major in the first semester of their sophomore year. Indeed, students in these fields may require a great deal of assistance from their advisors since they are the most difficult and competitive majors at AUB. Panels B and C of Table 8 report estimates of the impact of advisor grade VA on students who initially enrolled in STEM and non-STEM majors. We find that a one standard deviation increase in major advisor's grade VA significantly improves both STEM and non-STEM students' sophomore-year GPA by 4.1 and 2.4 percent of a standard deviation, respectively. Nonetheless, the documented overall effects for all other outcomes are concentrated among STEM students. Columns (3) to (5) respectively show that a one standard deviation increase in advisor grade VA significantly raises STEM students' on-time degree completion by 3.4 percentage points, overall graduation by 2.6 percentage points and on-time graduation from their initial major by 3 percentage points. On the other hand, no statistically significant effects are detected for any of the non-STEM students' outcomes.[33]

Taken together, these results indicate that major advisor grade VA has significant impacts on sophomore students' outcomes. Importantly, while there are slight differences in magnitudes, findings from this exercise are consistent with those from the freshman sample. This further solidifies the importance of college advisors in the education production function.

5.6.3 Sophomore Advisor Persistence VA

The role of an effective major advisor is not restricted to improving students' academic performance. Effective advisors can also directly impact students' persistence in the major. As a result, we check whether non-grade measures of student outcomes are also good predictors of major advisor quality. To do so, we first construct a measure of advisor value-added based on a sophomore student persistence index. Specifically, using a principal component analysis (PCA) decomposition, we create a sophomore *Persistence Index* composed of five key university persistence measures related to sophomore students' success: 4-year graduation from initial major, 6-year graduation from initial major, dropout after sophomore year, proportion of courses withdrawn and proportion of courses failed during sophomore year. We then construct a non-grade measure of advisor value-added based on this index. Finally,

[33] The full distributional effects of sophomore advisor grade VA are summarized in Figure 3. Notably, the documented increase in average sophomore GPA seems to be driven by a decrease in the GPA of students matched to the worst set of sophomore advisors (Panel (a) of Figure 3). Additionally, the best set of sophomore advisors seem to significantly improve four and six-year graduation rates.

we regress all our outcomes of interest on this constructed sophomore advisor Persistence VA measure.

Findings from this exercise are summarized in Appendix Table A14. Strikingly, results presented in column (1) indicate that having an advisor with a one standard deviation higher persistence VA has no overall significant effect on students' sophomore GPA. Rather, higher persistence VA advisors only positively impact the GPA of students in STEM majors (0.025), while having no significant effect on those in non-STEM fields (0.003). Estimates from columns (2) through (6) of Table A14 indicate that persistence VA measures of advisor quality predict large and robust impacts on all student measures of persistence and graduation. Notably, these effects are significant and comparable for both STEM and non-STEM majors.

Our findings suggest that advising skills that improve students' persistence in their chosen majors are somewhat distinct from those that improve grade performance. We investigate this further by running additional regressions using our two measures of sophomore advisor value-added together. Specifically, we regress students' sophomore GPA and Persistence Index on their respective advisor VA measures separately and jointly. We present estimates from these regressions in Appendix Table A15. Notably, results presented in columns (2) and (3) indicate that advisors who are good at increasing students' persistence do not seem to increase their sophomore GPA. Additionally, estimates presented in columns (5) and (6) show that sophomore advisor persistence VA predicts higher student persistence even after controlling for advisors' grade VA. Taken together, results from this analysis indicate that sophomore advisors who increase students' grades have different skills than those who improve persistence. This provides further evidence that post-major advisor skills are distinct for these two measures of value-added. Overall, results presented in this section using the sophomore sample indicate that our documented findings on freshman advisor VA extend, and replicate, to a larger set of students and advisors.

6 Discussion

6.1 Discrete Treatment—High and Low Grade VA advisors

We have shown that higher grade VA academic advisors improve students' college outcomes. These positive effects could be masking some interesting treatment heterogeneity relevant for policy analysis. For example, how would students be affected if they were matched to a high-performing advisor rather than a low-performing one? Accordingly, we next estimate the impact of being matched to advisors in different quartiles of the grade VA distribution. These estimates are presented graphically in Appendix Figures A2 and A3 for the freshman sample and in Figure A4 for the sophomore sample. Specifically, the different panels plot point estimates and 95% confidence intervals representing the effects of being matched to advisors in the bottom and top two quartiles of the VA distribution—with the second quartile as our excluded baseline category.

Estimates presented in Figure A2a indicate that top quartile freshman advisors substantially improve students' first year GPA by approximately 10 percent of a standard deviation relative to advisors in the second quartile (omitted category). However, we must note that these estimates are relatively noisy which precludes us from making any definitive conclusions related to differences between top versus bottom advisors. Indeed, the top 95% confidence interval for bottom advisors overlaps with the bottom 95% confidence interval for top advisors. Estimates for time to declaring sophomore status mirror those for GPA, as shown in Figure A2b. Specifically, students matched to the lowest grade VA freshman advisors take approximately 0.12 more semesters to complete the freshman year compared to those in the second lowest quartile. However, these effects are relatively imprecise as we cannot rule out that effects are similar across the various VA quartiles. We next examine whether the impacts of top and low-performing advisors persist in the long run by focusing on graduation outcomes. One caveat to keep in mind when interpreting graduation effects is that they are based on a reduced sample of students, since we cannot observe graduation outcomes for more recent cohorts, resulting in a loss of precision. Estimates in Figure A2c and A2d suggest that being matched to a top rather than second quartile advisor results in an increase in on-time graduation and six-year graduation respectively, significant at the 10% level only. However, we are unable to determine that graduation estimates are statistically different across quartiles.

Panels (a) through (d) of Appendix Figure A3 show how freshman advisors in different quartiles of the VA distribution impact students' enrollment and graduation from selective majors. For both the overall sample (Figures A3a and A3b) and top students (Figures A3c and A3d), going from a second quartile to top advisor increases the likelihood of enrollment and graduation from selective majors, though these effects are not statistically significant for graduation. Taken together, results from the freshman sample suggest that students benefit the most from being matched to advisors in the top quartile of the VA distribution. However, we are unable to draw any strong conclusions from this exercise, particularly as it relates to differences between bottom and top advisors.

Finally, we run a similar analysis on the population of students entering AUB as sophomores, as they are matched to a larger number of advisors, which could help improve precision. Panels (a) through (d) of Appendix Figure A4 summarize findings from this analysis.

Notably, estimates for GPA are less noisy as we find that top versus bottom sophomore advisors have significantly different effects on students' first year GPA. These effects seem to be driven by bottom quartile advisors who reduce students' GPA by approximately 7.5 percent of a standard deviation relative to second quartile advisors. We also uncover evidence suggesting that bottom quartile advisors worsen students' four and six-year graduation rates, though effects similar to advisors in the top two VA quartiles cannot be ruled out.

6.2 Potential Mechanisms

In this paper, we find that academic advising quality substantially impacts students' college outcomes. In this section, we discuss the mechanisms that could explain the documented effects. Our first set of results show that effective advisors largely improve students' course performance. There are several potential explanations for this finding. First, it is possible that advisors directly improve students' academic performance by providing them with mentoring, coaching and affirmation effects—especially since they have the opportunity to continuously and repeatedly interact with students during their first year. Another possible explanation is that high quality advisors encourage students to enroll in a specific set of courses that maximize first-year grades (or "easy" courses). To understand which of these two explanations is more likely, we make full use of our data and look at the effects of advisor grade VA on students' course-level outcomes.

We start by looking at the impact of advisor VA on the likelihood that students take challenging courses during their first year. We focus on our main analysis sample which includes freshman students matched to pre-major advisors. We do not conduct this analysis for the sample of sophomores matched to post-major advisors, as sophomore students typically have to take courses that are required by their major during their first year and hence do not have much flexibility in terms of first-year course choice. The results from our freshman sample analysis are reported in Table 9 separately for the first (Panel A) and second (Panel B) semesters of the freshman year. The most challenging courses during the freshman year are math and science courses that are required for entry into selective majors.[34] Strikingly, estimates from column (1) of Table 9 reveal that advisors do not push students towards or away from core science and math courses. Importantly, estimates are small in magnitude and reasonably precise. This result is at odds with our second interpretation in which advisors may influence students' grades by changing their course composition.

While freshman advisors do not influence course choice, estimates presented in column (2) indicate that students are 0.9 percentage points less likely to fail courses due to a one

[34]These include Calculus I and II as well as Physics, Chemistry, Biology and Computer Science courses targeted for students intending to major in these fields.

standard deviation higher advisor VA. This corresponds to a 13.4 and 12.5 percent reduction in the likelihood of failing a course during the first and second semesters, respectively. A more telling result is that a one standard deviation improvement in advisor VA decreases the likelihood that students withdraw from a course by 0.5 percentage points or 9.4 percent during the first semester of the freshman year (column (3) and Panel A). Students can only withdraw from courses after meeting one-on-one with their pre-major advisors, and advisors have to approve course withdrawals. This suggests that effective advisors encourage students to persist in their courses, and provide positive affirmation and coaching directly influencing students' grades.[35] Interestingly, the estimate in Panel B reveals that advisor grade VA has no significant impact on course withdrawal during the second semester of the freshman year. This potentially indicates that with time, advisors (or students) acquire more information about their students' (own) abilities, pushing students in the second semester to take courses that match their interests and thereby reduce the chances of withdrawing from courses. Taken together, findings from columns (1) through (3) of Table 9 indicate that the documented improvement in overall Freshman GPA is most likely due to direct coaching and mentoring provided by advisors and not due to behavioral changes in course selection.

Our findings on the importance of academic advisors are not limited to grade improvements, rather they also extend to other college outcomes such as persistence and major choice. We cannot conclusively speak to the exact mechanism behind these longer run effects, but some of our previous analyses can help shed light on what is driving these effects. For freshman students, the effects we document on student persistence measures, such as time to complete the freshman year and 4-year graduation, are most likely explained by the documented improvement in academic performance during the freshman year. Indeed, higher grades and the lower likelihood of failing and withdrawing from courses increase the odds of successfully completing freshman year. This in turn can lead to a positive feedback loop where the documented increase in performance during freshman year enhances students' confidence and learning thus further bettering future academic outcomes such as on-time graduation. This interpretation is in line with estimates reported in column (8) of Table 7 which indicate that, conditional on being matched to an advisor who is good at improving students' grades, being matched to an advisor who is skilled at helping students persist no longer seems to meaningfully impact persistence at university.

On the other hand, our analysis using non-grade measures of VA for the sophomore sample yields different insights. Indeed, results presented in Table A15 reveal that even

[35]Sophomore students are not required to meet with their advisors or get their approval to withdraw from courses. As such, examining the relationship between post-major advisor VA and sophomore students' course withdrawal does not allow us to understand whether affirmation effects are at play.

after conditioning on having an advisor who is effective at raising students' grades, being assigned to an advisor who is good at improving persistence still significantly increases sophomore students' persistence in the major. Taken together, these results suggest that the main barrier for freshmen, i.e. pre-major, students' persistence is their first-year academic performance. However, students who already declared a major (i.e., sophomore students) may face other barriers to degree completion and require help from advisors who are skilled at improving both performance and persistence.

Finally, regarding the documented increase in STEM and business major enrollment for freshmen, findings from Table 9 suggest that it is not due to behavioral changes in terms of shifting away or towards certain classes to fulfill course requirements for these majors. Additionally, analysis reported in column (11) of Table 7 further suggests that this cannot be fully explained by grade improvements either. Rather, the most likely explanation for the documented increase in selective major enrollment is that it is driven by increased grade performance in addition to positive affirmation effects provided by freshman advisors.

6.3 Advisor Characteristics and Match Effects

We next examine whether advisors' observable characteristics predict their value-added. To do so, we regress all our constructed measures of advisor VA on advisor gender, rank and type of department. Results in Table A16 reveal no significant relationship between freshman advisors' faculty rank and their predicted grade or non-grade VA score. Specifically, being an associate or full professor as opposed to an assistant professor or lecturer does not predict a significantly higher or lower VA score, suggesting that faculty experience does not play a key role in predicting advisor quality. Additionally, we find that freshman advisor gender and department (i.e., whether the advisor is in a science versus non-science department) are also statistically unrelated to advisor VA. However, one caveat with these results is that they are based on regressions with a low number of observations—corresponding to the number of advisor-years in our freshman sample. For example, regressions involving the use of Grade VA are based on 131 advisor-year observations. Hence, results from Table A16 only provide suggestive evidence that advisors' observable characteristics are not related to VA. To strengthen conclusions from this analysis, we run the same regressions on a larger set of advisors, i.e. academic advisors matched to students from the sophomore sample. Importantly, results presented in Table A17 are all insignificant and in line with findings found in the freshman advisor sample, but more precise as they are based on 736 advisor-year observations. Overall, findings from both analyses are consistent with those from Barr and Castleman (2019) who show that counselor characteristics are not significantly related to student outcomes. This suggests that it is most likely unobservable characteristics, such as tone of voice, that may predict a large portion of what constitutes an effective advisor.

Results from the previous exercise indicate that advisors' observable characteristics, such as gender, do not predict advisor quality. Another interesting question is whether the match between advisor and student characteristics matters. Accordingly, we next check whether advisor-student gender match affects students' outcomes. To do so, we run the following reduced form regression:

$$Y_{iat} = \beta_0 + \beta_1 Femad_a + \beta_2 Femst_i + \beta_3 Femst_i * Femad_a + X_i'\gamma + \sigma_t + \epsilon_{iat} \tag{10}$$

where Y_{iat} is the outcome of interest for student i matched to advisor a in academic year t. $Femad_a$ is a dummy variable that is equal to 1 if advisor a is female and 0 otherwise. $Femst_i$ is another indicator variable for whether student i is female. We further interact both of these indicators. We also include student controls X_i' and year fixed effects σ_t throughout.[36] Our main coefficients of interest which we report in all our tables are β_1 (the effect of having a female versus male advisor for male students) and $\beta_1 + \beta_3$ (the effect of having a female versus male advisor for female students). Finally, standard errors are clustered at the advisor-year level throughout.

Table A18 summarizes the effects of student-advisor gender match for male and female students from our main freshman sample. Specifically, estimates from row 1 show impacts on male students who are matched with a female as opposed to male freshman advisor and estimates from row 2 present coefficients from own gender match for female students (being matched with a female rather than male advisor). Results presented in column (1) of Table A18 indicate that own gender match matters for female students in terms of academic performance but not for male students. Indeed, female students' freshman GPA increases by 7.7 percent of a standard deviation when they are matched with a female versus male advisor. Conversely, the gender of a freshman advisor does not have a significant impact on male students' grades. We also find that advisor gender does not affect the likelihood that men or women drop out after freshman year but gender match does increase female students' 4-year graduation rates by 6.4 percentage points. However, we uncover no significant gender-match effects on 6-year graduation rates. In terms of major choice, we find that gender congruence has no significant impact on the likelihood that men or women

[36] For regressions involving the sophomore sample, we also include department fixed effects since randomization occurs within department in that context.

enroll or graduate from a selective major. We also show that these effects are statistically insignificant for top-performing male and female students in columns (7) and (8).

Table A19 summarizes these same gender match effects for our post-major advising sample (i.e. the sample of students directly enrolled as sophomores). We find that student-advisor gender match matters for both sexes in terms of first-year academic performance. Indeed, results presented in column (1) of Table A19 indicate that male students' first year GPA increases by 4.9 percent of a standard deviation when matched with a male as opposed to female advisor. Additionally, female students' GPA increases by around 5.4 percent of a standard deviation when matched with a same gender advisor. However, we find no statistically significant effect of own-gender match on any of our student persistence outcomes as shown in columns (2) through (6). Overall, results from this section indicate that even though observable advisor characteristics do not predict advisor VA, student-advisor gender match does seem to matter for some student outcomes; mainly students' GPA.

7 Conclusion

In this paper, we study the impact of academic advisor VA on student outcomes. To identify causal effects, we exploit a unique setting where college students are randomly assigned to faculty advisors at the beginning of their freshman year. Students interact with their advisors for the full academic year. Advisors assist students with academic planning, monitor their academic progress, and help them decide on a major. We find that improving advisor VA substantially increases students' first-year GPA and freshman year completion time. These effects are long-lasting, as we show that a one standard deviation increase in freshman advisor grade VA raises 4-year graduation rates by 5.5%. Finally, we find that effective advisors have a strong impact on students' major choice. We document that exposure to higher-VA advisors largely increases high-performing students' chances of enrolling and graduating with a STEM degree.

Our finding that college students substantially benefit from high-quality personalized and continuous support has important implications for current debates on how to increase the rates of college completion and STEM degree attainment. In particular, our results indicate that allocating resources towards improving the quality of academic advising may substantially improve such outcomes. This in line with a recent study by Deming and Walters (2017) who find that higher U.S. state funding for public post-secondary institutions raises degree completion, through increased spending on academic support services such as advising.

Our paper presents new evidence showing that advisor quality is an important determinant of students' college success. However, what exactly constitutes a good advisor remains an open question. Our results indicate that observable characteristics—such as advisor rank, gender or department—do not correlate with advisor VA. Further research is needed to identify which advisor attributes increase their VA. Doing so would allow colleges to improve the quality of academic advising through screening for or training faculty to become effective advisors. Importantly, since most colleges already offer some form of academic advising, policies geared towards improving advisor quality may be a scalable way to promote student success.

References

Angrist, Joshua, David Autor, and Amanda Pallais. 2020. Marginal effects of merit aid for low-income students. *NBER Working Paper* No. 27834.

Angrist, Joshua, Daniel Lang, and Philip Oreopoulos. 2009. Incentives and services for college achievement: Evidence from a randomized trial. *American Economic Journal: Applied Economics* 1 (1): 136-63.

Angrist, Joshua, Philip Oreopoulos, and Tyler Williams. 2014. When opportunity knocks, who answers? New evidence on college achievement awards. *Journal of Human Resources* 49 (3): 572-610.

Avery, Christopher, Jessica S. Howell, and Lindsay Page. 2014. A Review of the Role of College Counseling, Coaching, and Mentoring on Students' Postsecondary Outcomes. *College Board Research Brief.*

Barr, Andrew. 2016. Enlist or enroll: Credit constraints, college aid, and the military enlistment margin. *Economics of Education Review* 51: 61-78.

Barr, Andrew, and Benjamin Castleman. 2018. An engine of economic opportunity: Intensive advising, college success, and social mobility. *Texas A&M Working Paper.*

Barr, Andrew, and Benjamin Castleman. 2019. Exploring Variation in College Counselor Effectiveness. *AEA Papers and Proceedings* 109: 227-231.

Bettinger, Eric P., and Rachel B. Baker. 2014. The effects of student coaching: An evaluation of a randomized experiment in student advising. *Educational Evaluation and Policy Analysis* 36 (1): 3-19.

Bettinger, Eric, Oded Gurantz, Laura Kawano, and Bruce Sacerdote. 2016. The long run impacts of merit aid: Evidence from California's Cal Grant. *NBER Working Paper* No. 22347.

Bettinger, Eric P., Bridget Terry Long, Philip Oreopoulos, and Lisa Sanbonmatsu. 2012. The role of application assistance and information in college decisions: Results from the H&R Block FAFSA experiment. *The Quarterly Journal of Economics* 127 (3): 1205-1242.

Bird, Kelli A., Benjamin L. Castleman, Jeffrey T. Denning, Joshua Goodman, Cait Lamberton, and Kelly Ochs Rosinger. 2021. Nudging at scale: Experimental evidence from FAFSA completion campaigns. *Journal of Economic Behavior & Organization* 183: 105-128.

Blau, Francine D., Janet M. Currie, Rachel T.A. Croson, and Donna K. Ginther. 2010. Can mentoring help female assistant professors? Interim results from a randomized trial. *American Economic Review Papers & Proceedings* 100 (2): 348-352.

Bound, John, Michael F. Lovenheim, and Sarah Turner. 2010. Why have college completion rates declined? An analysis of changing student preparation and collegiate resources. *American Economic Journal: Applied Economics* 2 (3): 129-157.

Buckles, Kasey. 2019. Fixing the leaky pipeline: Strategies for making economics work for women at every stage. *Journal of Economic Perspectives* 33(1): 43-60.

Canaan, Serena, and Pierre Mouganie. 2018. Returns to education quality for low-skilled students: Evidence from a discontinuity. *Journal of Labor Economics* 36 (2): 395-436.

Canaan, Serena, and Pierre Mouganie. Forthcoming. The Impact of Advisor Gender on Female Students' STEM Enrollment and Persistence. *Journal of Human Resources.*

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

Carrell, Scott E., and Bruce I. Sacerdote. 2017. Why do college-going interventions work? *American Economic Journal: Applied Economics* 9 (3): 124-151.

Carrell, Scott E., and James E. West. 2010. Does professor quality matter? Evidence from random assignment of students to professors. *Journal of Political Economy* 118 (3): 409-432.

Castleman, Benjamin, and Joshua Goodman. 2018. Intensive college counseling and the enrollment and persistence of low-income students. *Education Finance and Policy* 13 (1): 19-41.

Castleman, Benjamin L., and Bridget Terry Long. 2016. Looking beyond enrollment: The causal effect of need-based grants on college access, persistence, and graduation. *Journal of Labor Economics* 34 (4): 1023-1073.

Castleman, Benjamin L., Lindsay C. Page, and Korynn Schooley. 2014. The forgotten summer: Does the offer of college counseling after high school mitigate summer melt among college-intending, low-income high school graduates? *Journal of Policy Analysis and Management* 33 (2): 320-344.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014a. Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates. *American Economic Review* 104 (9): 2593-2632.

Chetty, Raj, John N. Friedman, and Jonah E. Rockoff. 2014b. Measuring the impacts of teachers II: Teacher value-added and student outcomes in adulthood. *American Economic Review* 104 (9): 2633-2679.

Calonico, Sebastian, Matias D. Cattaneo, and Max H. Farrell. 2018. On the effect of bias estimation on coverage accuracy in nonparametric inference. *Journal of the American Statistical Association* 113, no. 522: 767-779.

College Board. 2011. How Four-Year Colleges and Universities Organize Themselves to Promote Student Persistence: The Emerging National Picture *College Board Advocacy & Policy Center.*

Deming, David J. 2017. Increasing college completion with a federal higher education matching grant. *The Hamilton Project, Policy Proposal* 2017-03.

Deming, David J., and Christopher R. Walters. 2017. The impact of price caps and spending cuts on US postsecondary attainment. *NBER Working Paper* No. 23736.

Denning, Jeffrey T., and Patrick Turley. 2017. Was that SMART? Institutional financial incentives and field of study. *Journal of Human Resources* 52 (1): 152-186.

Dobronyi, Christopher R., Philip Oreopoulos, and Uros Petronijevic. 2019. Goal setting, academic reminders, and college success: A large-scale field experiment. *Journal of Research on Educational Effectiveness* 12 (1): 38-66.

Dynarski, Susan. 2003. Does aid matter? Measuring the effect of student aid on college attendance and completion. *American Economic Review* 93 (1): 279-288.

Evans, Brent J. 2017. SMART money: Do financial incentives encourage college students to study science? *Education Finance and Policy* 12 (3): 342-368.

Guarino, Cassandra M., and Victor M. Borden. 2017. Faculty service loads and gender: Are women taking care of the academic family? *Research in Higher Education* 58 (6): 672-694.

Gurantz, Oded, Matea Pender, Zachary Mabel, Cassandra Larson, and Eric Bettinger. 2020. Virtual advising for high-achieving high school students. *Economics of Education Review* 75: 101974.

Hastings, Justine S., Christopher A. Neilson, and Seth D. Zimmerman. 2013. Are some degrees worth more than others? Evidence from college admission cutoffs in Chile. *NBER Working Paper* No. 19241.

Huber, Jo Anne, Marsha A. Miller. 2011. Chapter 11- Advisor Job Responsibilities – Four Year Institutions. 2011 NACADA National Survey of Academic Advising.

Jackson, C. Kirabo. 2018. What do test scores miss? The importance of teacher effects on non–test score outcomes. *Journal of Political Economy* 126 (5): 2072-2107.

Jackson, C. Kirabo, Jonah E. Rockoff, and Douglas O. Staiger. 2014. Teacher effects and teacher-related policies. *Annual Review of Economics* 26 (1): 801-825.

Kane, Thomas J., Jonah E. Rockoff, and Douglas O. Staiger. 2008. What does certification tell us about teacher effectiveness? Evidence from NewYork City. *Economics of Education* 27: 615-631.

Kirkebøen, Lars J., Edwin Leuven, and Magne Mogstad. 2016. Field of study, earnings, and self-selection. *The Quarterly Journal of Economics* 131 (3): 1057-1111.

Koedel, Corey, Kata Mihaly, and Jonah E. Rockoff. 2015. Value-added modeling: A review. *Economics of Education* 47: 180-195.

Kot, Felly Chiteng. 2014. The impact of centralized advising on first-year academic performance and second-year enrollment behavior. *Research in higher education* 55 (6): 527-563.

Malcom, Shirley, and Michael Feder. 2016. Barriers and opportunities for 2-year and 4-year STEM degrees: Systemic change to support students' diverse pathways. Washington, DC: National Academies Press.

Mulhern, Christine. 2019. Beyond teachers: Estimating individual guidance counselors' effects on educational attainment. *Working Paper*.

National Center for Education Statistics. 2018. Digest of Education Statistics. https://nces.ed.gov/programs/digest/d18/tables/dt18_326.10.asp

National Student Clearinghouse. First-year persistence and retention. Snapshot report. https://nscresearchcenter.org/wp-content/uploads/SnapshotReport33.pdf

Oreopoulos, Philip, and Uros Petronijevic. 2013. Making college worth it: A review of the returns to higher education. *The Future of children* 23 (1): 41-65.

Oreopoulos, Philip, and Uros Petronijevic. 2018. Student coaching: How far can technology go? *Journal of Human Resources* 53 (2): 299-329.

Oreopoulos, Philip, and Uros Petronijevic. 2019. The remarkable unresponsiveness of college students to nudging and what we can learn from it. *NBER Working Paper* No. 26059.

Patterson, Richard W., Nolan G. Pope, and Aaron Feudo. 2019. Timing is everything: Evidence from college major decisions. *IZA DP* No. 12069.

Phillips, Meredith, and Sarah J. Reber. 2019. Does virtual advising increase college enrollment? Evidence from a random assignment college access field experiment. *NBER Working Paper* No. 26509.

Porter, Catherine, and Danila Serra. 2019. Gender differences in the choice of major: The importance of female role models. *American Economic Journal: Applied Economics*. Forthcoming.

President's Council of Advisors on Science and Technology. 2012. Engage and excel: producing one million additional college graduates with degrees in science, technology, engineering, and mathematics. . Report to the President. Executive Office of the President. Washington, DC.

Rothstein, Jesse. 2009. Student sorting and bias in value-added estimation: Selection on observables and unobservables. *Education Finance and Policy* 4 (4): 537-571.

Rothstein, Jesse. 2010. Teacher quality in educational production: Tracking, decay, and student achievement. *The Quarterly Journal of Economics* 125 (1): 175-214.

Scrivener, Susan, and Michael J. Weiss. 2009. More guidance, better results? Three-year effects of an enhanced student services program at two community colleges. *New York: MDRC*

Sjoquist, David L., and John V. Winters. 2015. State merit aid programs and college major: A focus on STEM. *Journal of Labor Economics* 33 (4): 973-1006.

Staiger, Douglas O. and Jonah E. Rockoff. 2010. Searching for effective teachers with imperfect information. *Journal of Economic Perspectives* 24 (3): 97-118.

Stange, Kevin. 2015. Differential pricing in undergraduate education: Effects on degree production by field. *Journal of Policy Analysis and Management* 34 (1): 107-135.

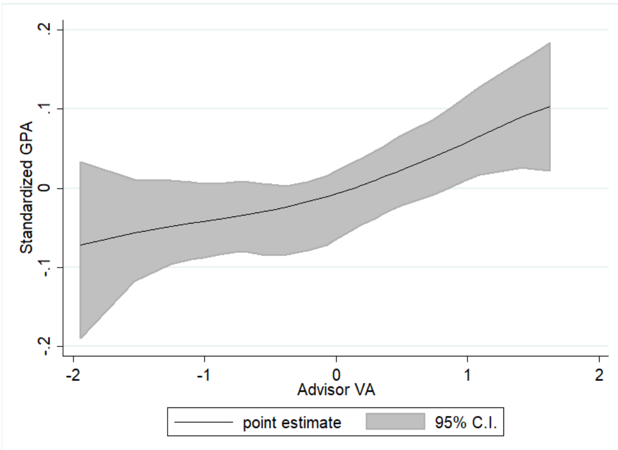
Sullivan, Zach, Ben Castleman, and Eric Bettinger. 2019. College advising at a national scale: Experimental evidence from the CollegePoint initiative. *Annenberg Ed Working Paper* No. 19-123.

Tinto, Vincent. 2010. From theory to action: Exploring the institutional conditions for student retention. *In Higher education: Handbook of Theory and Research*: 51-89. Springer, Dordrecht.

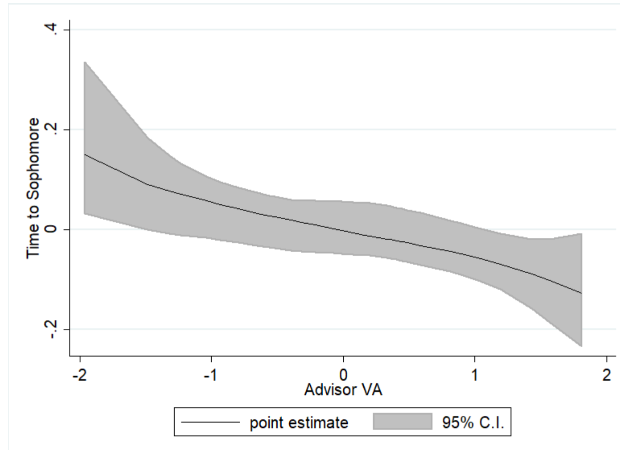
Weiss, Michael J., Alyssa Ratledge, Colleen Sommo, and Himani Gupta. 2019. Supporting community college students from start to degree completion: Long-term evidence from a randomized trial of CUNY's ASAP. *American Economic Journal: Applied Economics* 11 (3): 253-97.

A Figures

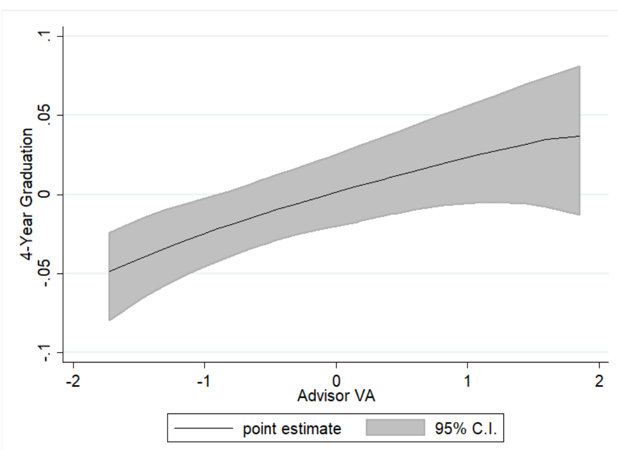
Figure 1: Distribution of Freshman Advisor Grade VA Effects on Academic Performance and College Completion



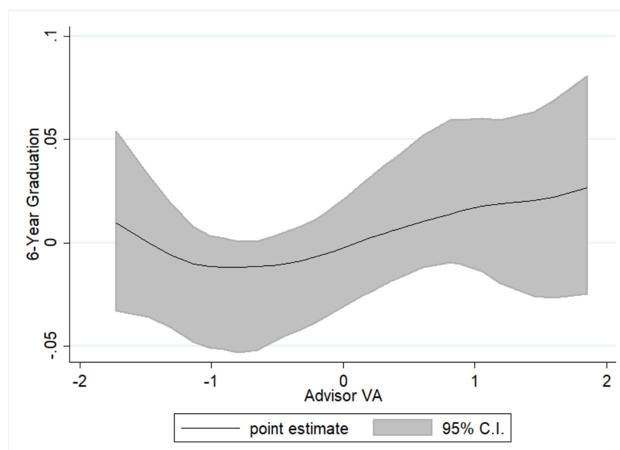
(a) Standardized GPA



(b) Time to Sophomore



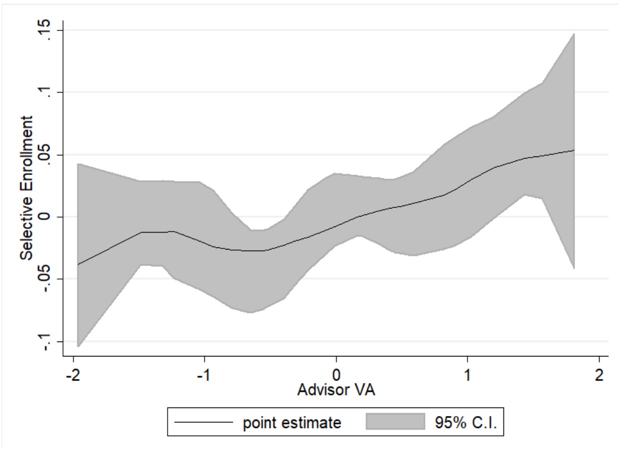
(c) 4-year Graduation



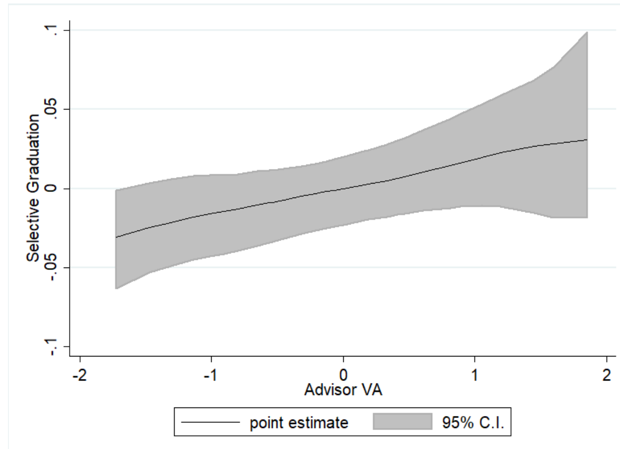
(d) 6-Year Graduation

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. The figures plot a nonparametric estimate of the conditional mean of outcomes (residualized with respect to a year fixed effect) on standardized VA (residualized with respect to a year fixed effect). Specifically, we estimate a nonparametric regression of residualized outcomes on residualized standardized VA using a local linear regression. We then plot the point-estimates from the nonparametric regression with the corresponding bias-corrected confidence intervals following Calonico, Cattaneo and Farrell (2018).

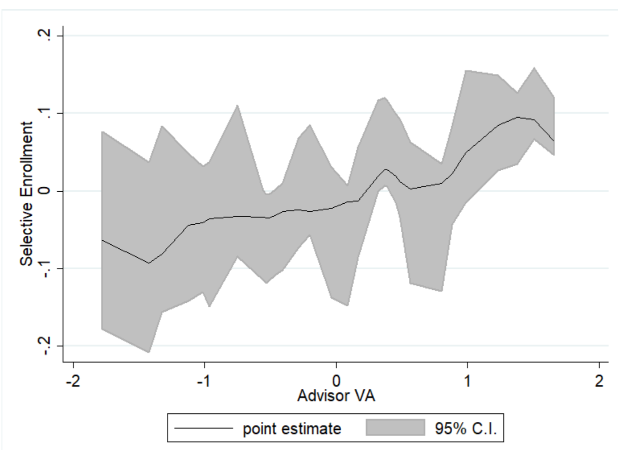
Figure 2: Distribution of Freshman Advisor Grade VA Effects on Selective Major Enrollment and Graduation



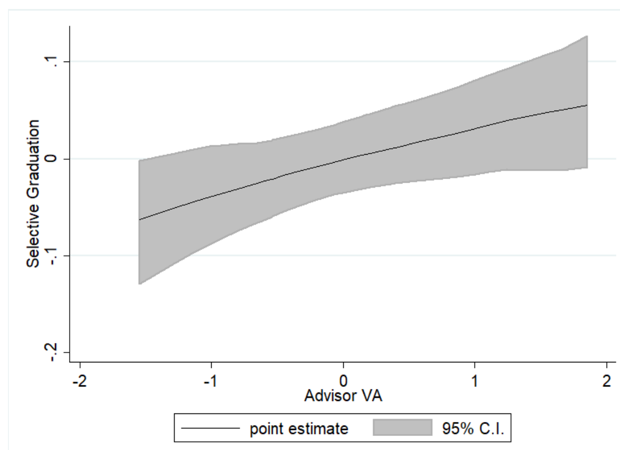
(a) Selective Major Enrollment



(b) Selective Major Graduation



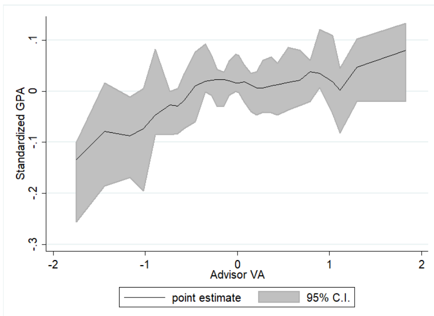
(c) Top Students' Selective Major Enrollment



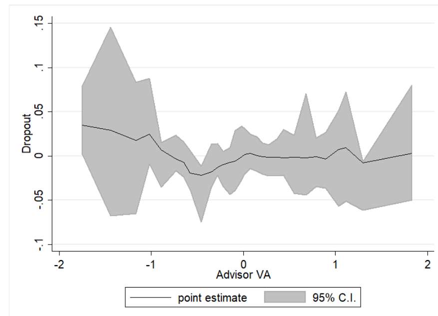
(d) Top Students' Selective Major Graduation

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. The figures plot a nonparametric estimate of the conditional mean of outcomes (residualized with respect to a year fixed effect) on standardized VA (residualized with respect to a year fixed). Specifically, we estimate a nonparametric regression of residualized outcomes on residualized standardized VA using a local linear regression. We then plot the point-estimates from the nonparametric regression with the corresponding bias-corrected confidence intervals following Calonico, Cattaneo and Farrell (2018).

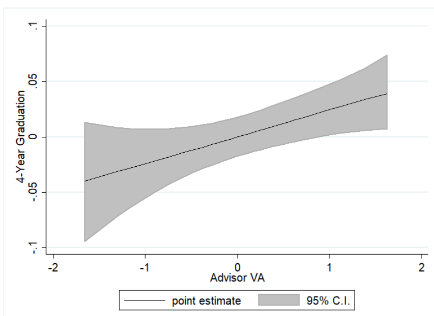
Figure 3: Distribution of Sophomore Advisor Grade VA Effects on Academic Performance and College Completion



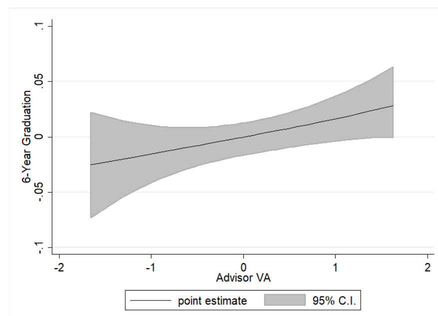
(a) Standardized GPA



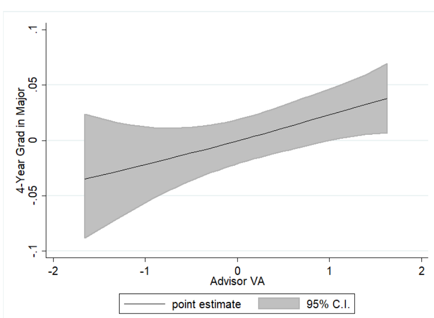
(b) Dropout after Sophomore



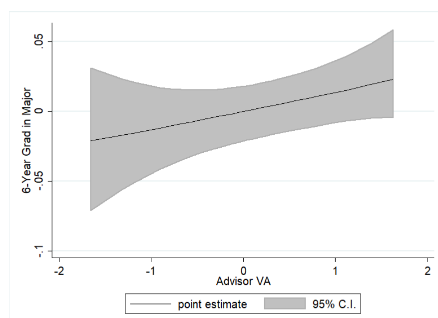
(c) 4-year Graduation



(d) 6-Year Graduation



(e) 4-year In-Major Graduation



(f) 6-Year In-Major Graduation

Notes: The sample includes first-time enrolling sophomore students from the academic years 2003-2004 to 2015-2016. The sample is restricted to the yeas 2003-2004 to 2012-2013 for graduation outcomes. The figures plot a nonparametric estimate of the conditional mean of outcomes (residualized with respect to year and department fixed effects) on standardized VA (residualized with respect to year and department fixed effects). Specifically, we estimate a nonparametric regression of residualized outcomes on residualized standardized VA using a local linear regression. We then plot the point-estimates from the nonparametric regression with the corresponding bias-corrected confidence intervals following Calonico, Cattaneo and Farrell (2018).

B Tables

Table 1: Summary Statistics

	Mean (1)	S.D. (2)	Obs. (3)
A. Student Level Covariates			
Female	0.478	0.500	3,857
Math SAT	573	75.5	3,857
Verbal SAT	494	90.0	3,857
Legacy Status	0.202	0.402	3,857
B. Student Level Outcomes			
Freshman GPA	76.5	9.15	3,857
Become a Sophomore	0.794	0.405	3,857
Time to Sophomore	2.480	1.159	3,047
Graduate in 4 years	0.458	0.498	2,952
Graduate in 6 Years	0.575	0.494	2,952
Enroll in Selective Major	0.429	0.495	3,857
Graduate from Selective Major	0.355	0.478	2,952
C. Advisor-Year Level Characteristics			
Female	0.389	0.489	131
Science Department	0.565	0.498	131
Lecturer and Other	0.100	0.300	131
Assistant Professor	0.400	0.491	131
Associate Professor	0.221	0.417	131
Professor	0.282	0.452	131
Number of Students	31.1	7.54	131

Notes: Our main sample includes freshman students who first enrolled in AUB in the academic years 2003-2004 to 2015-2016. Data from these years comprise 38 unique advisors. Our graduation sample includes students who first enrolled in AUB in the academic years 2003-2004 to 2012-2013.

Table 2: Estimate of Forecast Bias of Advisor Grade VA Measure

	Freshman Course Grade
Advisor VA	0.971***
	(0.253)
Mean of VA	-0.005
S.D of VA	0.055
N	39,369

Notes: Standard errors in parentheses are clustered at the advisor-year level. Regression includes year fixed effects. Freshman advisor VA is constructed using a leave-year out estimate as described in the methodology section. *** p <0.01 ** p <0.05 * p <0.1.

Table 3: Test of Random Assignment

	Advisor Grade VA
Math SAT	0.0004
	(0.0003)
Verbal SAT	0.0001
	(0.0003)
Female	0.0216
	(0.0320)
Legacy	-0.0354
	(0.0402)
N	3,857
P-Value Joint Significance	0.25

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. Standard errors in parentheses are clustered at the advisor-year level. Regression includes year fixed effects. Advisor VA is standardized by year. *** p <0.01 ** p <0.05 * p <0.1.

Table 4: Random Assignment Check

	Math SAT Empirical P-Value (1)	Verbal SAT Empirical P-Value (2)
A. Test for Student Characteristics		
Kolmogorov-Smirnow test (no. failed/total tests)	0/13	0/13
χ^2 goodness of fit test (no. failed/total tests)	0/13	0/13
B. Test for Advisor Characteristics		
Advisor Grade VA	0.021	0.033
	(0.025)	(0.021)
Associate/Full Professor	-0.044	0.004
	(0.060)	(0.056)
N	131	131

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. Standard errors in parentheses are clustered at the advisor level. All regressions include year fixed effects. The empirical p-value of each advisor represents the proportion of the 10,000 simulated groups of students with a summed value less than that of the observed group. Advisor VA is standardized by year. The Kolmogorov-Smirnov and χ^2 goodness of fit test results indicate the number of tests of the uniformity of the distribution of p-values that failed at the 5 percent level. *** p <0.01 ** p <0.05 * p <0.1.

Table 5: Effect of Advisor Grade VA on Academic Performance, Retention and College Completion

	Standardized GPA (1)	Becoming Sophomore (2)	Time to Sophomore (3)	4-Year Graduation (4)	6-Year Graduation (5)
A. No Controls					
Advisor Grade VA	0.057***	0.008	-0.078**	0.025***	0.015
	(0.016)	(0.006)	(0.026)	(0.008)	(0.010)
B. With Controls					
Advisor Grade VA	0.048***	0.007	-0.072**	0.022***	0.013
	(0.014)	(0.006)	(0.025)	(0.008)	(0.010)
Mean Dep Var	0.038	0.794	2.480	0.458	0.575
R^2 No Controls	0.010	0.014	0.060	0.017	0.014
R^2 with Controls	0.149	0.024	0.080	0.058	0.042
N	3,857	3,857	3,047	2,952	2,952

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. Standard errors in parentheses are clustered at the advisor-year level. All regressions include year fixed effects and advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student.
*** p <0.01 ** p <0.05 * p <0.1.

Table 6: Effect of Advisor Grade VA on Student Major Choice

	Overall Sample (1)	Non-top Students (2)	Top Students (3)	Top Male (4)	Top Female (5)
A. Selective Major					
Enrollment	0.024***	0.013	0.049***	0.051***	0.044**
	(0.008)	(0.009)	(0.011)	(0.018)	(0.020)
Graduation	0.015*	0.006	0.039**	0.048**	0.017
	(0.009)	(0.010)	(0.015)	(0.021)	(0.025)
Mean Enrollment	0.429	0.357	0.567	0.586	0.537
Mean Graduation	0.355	0.299	0.464	0.469	0.456
B. STEM Major					
Enrollment	0.010	-0.006	0.038***	0.032*	0.049**
	(0.007)	(0.008)	(0.014)	(0.018)	(0.022)
Graduation	0.010	-0.007	0.042***	0.038*	0.046*
	(0.007)	(0.008)	(0.014)	(0.020)	(0.024)
Mean Enrollment	0.216	0.138	0.368	0.410	0.300
Mean Graduation	0.163	0.098	0.290	0.326	0.232
C. Business Major					
Enrollment	0.013**	0.019**	0.010	0.019*	-0.005
	(0.006)	(0.008)	(0.010)	(0.011)	(0.019)
Graduation	0.005	0.012	-0.004	0.010	-0.029
	(0.006)	(0.007)	(0.012)	(0.014)	(0.020)
Mean Enrollment	0.212	0.219	0.190	0.175	0.238
Mean Graduation	0.191	0.200	0.174	0.143	0.224
N Enrollment	3,857	2,540	1,317	816	501
N Graduation	2,952	1,957	995	616	379

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. Standard errors in parentheses are clustered at the advisor-year level. All regressions include year fixed effects and advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. *** p <0.01 ** p <0.05 * p <0.1

Table 7: Effect of Various VA Skill Measures on the Corresponding Skills

	Standardized GPA					Persistence Index			Selective Index		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Grade VA	0.058***		0.055***		0.049***	0.054***		0.052***	0.042**		0.032*
	(0.016)		(0.015)		(0.016)	(0.019)		(0.018)	(0.019)		(0.018)
Persistence VA		0.040**	0.023				0.040**	0.023			
		(0.019)	(0.016)				(0.019)	(0.017)			
Selective VA				0.050***	0.033**					0.060***	0.045**
				(0.018)	(0.016)					(0.019)	(0.020)
N	2,949	2,984	2,917	2,984	2,917	2,952	2,987	2,920	2,952	2,987	2,920

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2012-2013 to be able to create graduation outcomes. Standard errors in parentheses are clustered at the advisor-year level. All regressions include year fixed effects and VA is standardized by year. Each column represents estimates from a separate regression. Controls included are math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. The slight difference in number of observations across columns is due to missing data points for some VA measures. *** p <0.01 ** p <0.05 * p <0.1.

Table 8: Effect of Sophomore Advisor Grade VA on Academic Performance, Retention and College Completion

	Standardized GPA (1)	Dropout after Sophomore (2)	4-Year Graduation (3)	6-Year Graduation (4)	4-Year Graduation in Major (5)	6-Year Graduation in Major (6)
A. Overall Sample						
Grade VA	0.037***	-0.003	0.023**	0.016*	0.020*	0.013
	(0.007)	(0.005)	(0.010)	(0.009)	(0.011)	(0.010)
Mean Dep Var	0.004	0.088	0.527	0.791	0.403	0.549
N	14,055	14,055	9,120	9,120	9,120	9,120
B. STEM Majors						
Grade VA	0.041***	-0.010***	0.034***	0.026***	0.030*	0.019
	(0.010)	(0.003)	(0.011)	(0.008)	(0.015)	(0.014)
Mean Dep Var	0.081	0.070	0.579	0.814	0.417	0.528
N	7,859	7,859	4,985	4,985	4,985	4,985
C. Non-STEM Majors						
Grade VA	0.024***	0.006	0.08	0.001	0.012	0.008
	(0.008)	(0.009)	(0.013)	(0.012)	(0.012)	(0.012)
Mean Dep Var	-0.092	0.109	0.466	0.765	0.386	0.574
N	6,196	6,196	4,135	4,135	4,135	4,135

Notes: Sample includes first-time enrolling sophomore students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. Standard errors in parentheses are clustered at the advisor-year level. Regressions includes department and year fixed effects. Advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. SAT scores are standardized within department and year.
*** p <0.01 ** p <0.05 * p <0.1.

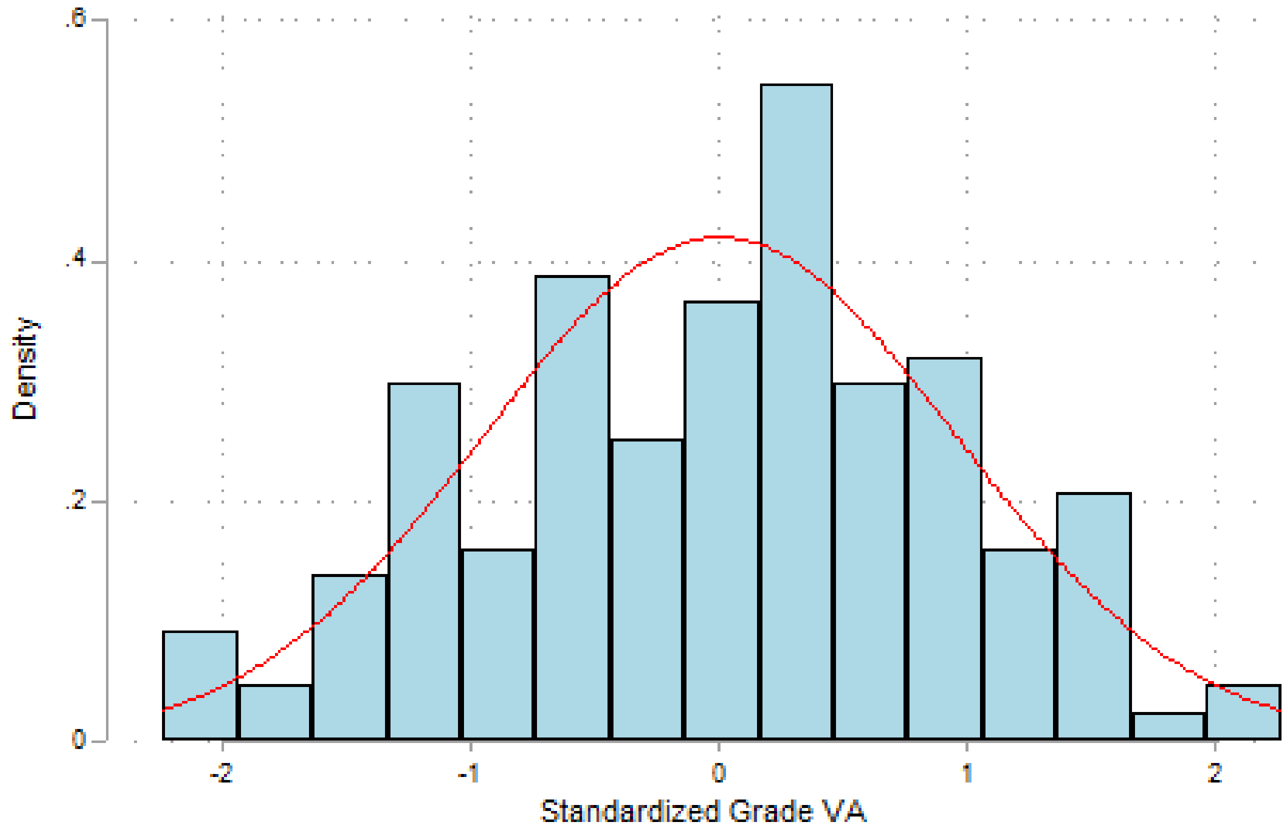
Table 9: Effect of Advisor Grade VA on Course-Level Freshman Student Outcomes

	Take Science or Maths Course (1)	Fail Course (2)	Withdraw from Course (3)
A. First Semester			
Advisor Grade VA	-0.002	-0.009***	-0.005**
	(0.004)	(0.003)	(0.002)
Mean Dep. Var.	0.317	0.067	0.053
Course-Term FE	No	Yes	Yes
N	19,371	19,371	19,371
B. Second Semester			
Advisor Grade VA	-0.002	-0.009***	0.000
	(0.004)	(0.003)	(0.002)
Mean Dep. Var.	0.305	0.072	0.048
Course-Term FE	No	Yes	Yes
N	16,092	16,092	16,092

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. Standard errors in parentheses clustered two-ways at the advisor-year and individual level. All regressions include year fixed effects and advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. Sample includes students from academic years 2003-2004 till 2015-2016. *** p <0.01 ** p <0.05 * p <0.1.

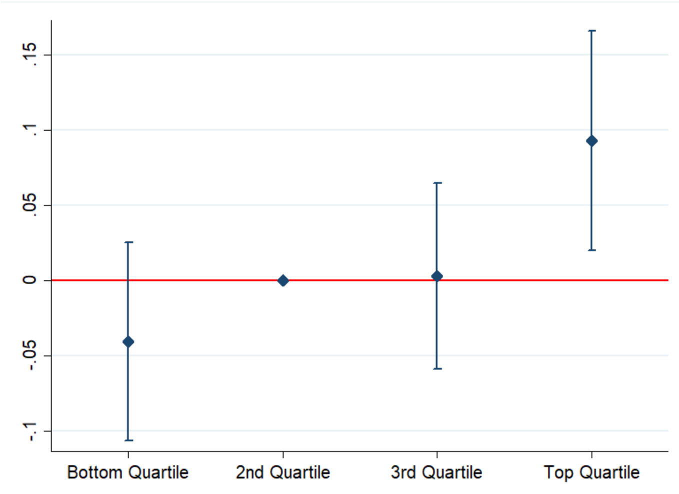
C Appendix Figures

Figure A1: Standardized distribution of advisor VA measure

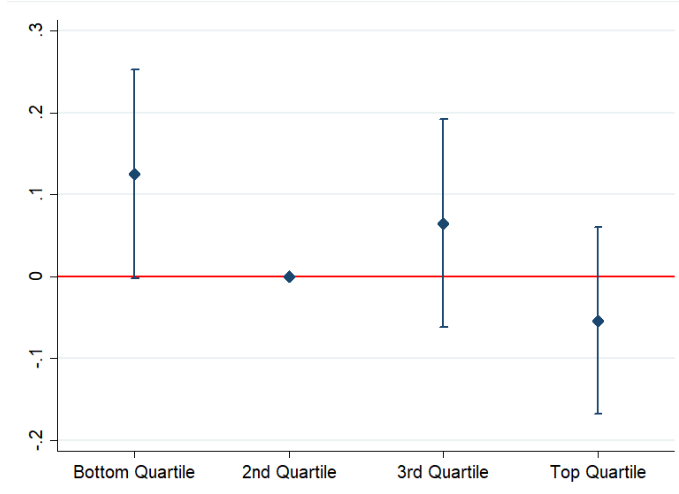


Notes: The above figure shows the standardized distribution of our constructed advisor value-added measure—based on student course grades. Freshman advisor VA is standardized by year and the sample includes students matched to a freshman advisor who initially enrolled at AUB from academic years 2003-2004 till 2015-2016.

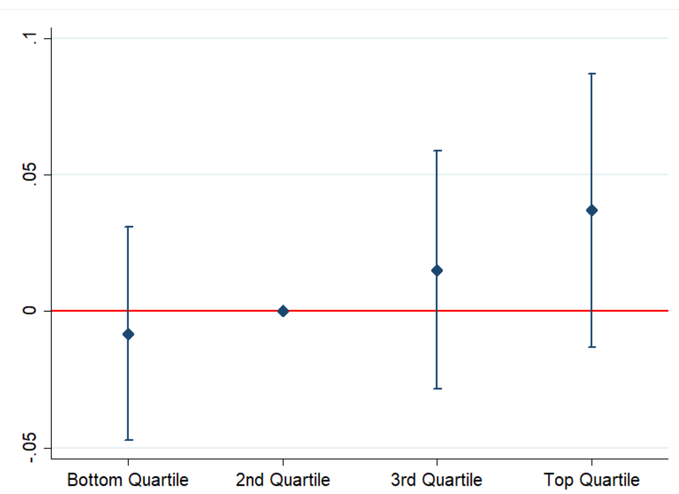
Figure A2: Discrete Treatment on Freshman Academic Performance and College Completion



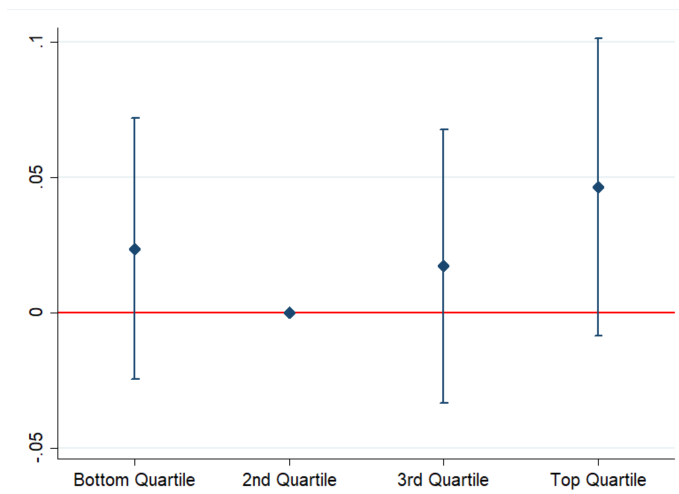
(a) Standardized GPA



(b) Time to Sophomore



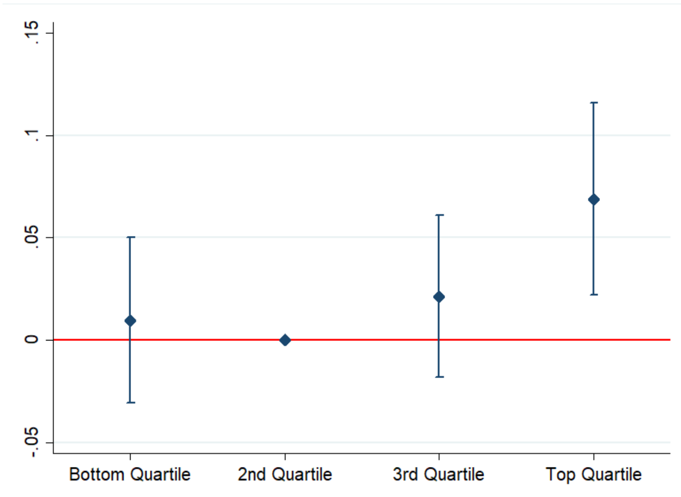
(c) 4-year Graduation



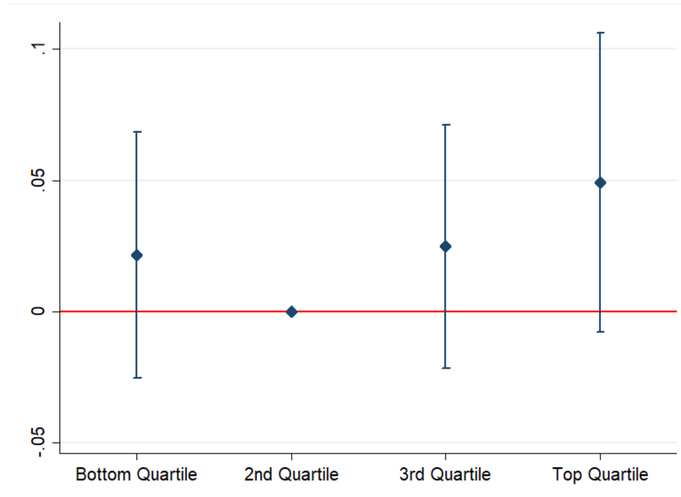
(d) 6-Year Graduation

Notes: The different panels show the impacts of being matched to freshman advisors from different quartiles of the grade VA distribution. Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. Point estimates represent coefficients from regressions of advisor VA quartile (with the second quartile as the baseline excluded category) on student outcomes. All regression include year fixed effects and students controls. All bars represent 95% confidence intervals with standard errors clustered at the advisor-year level.

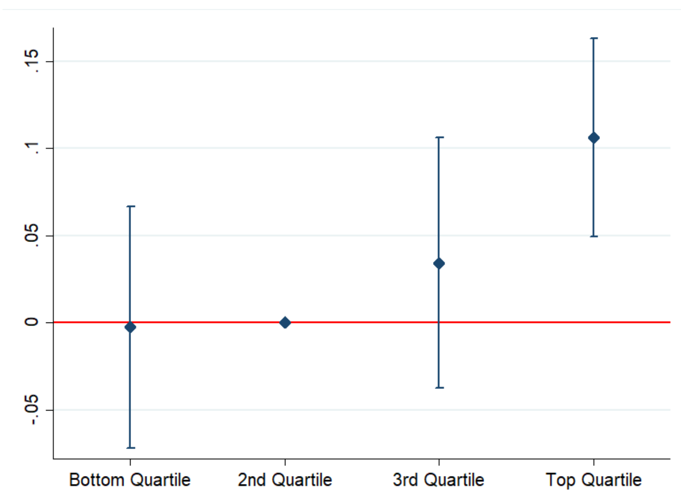
Figure A3: Discrete Treatment on Freshman Selective Major Enrollment and Graduation



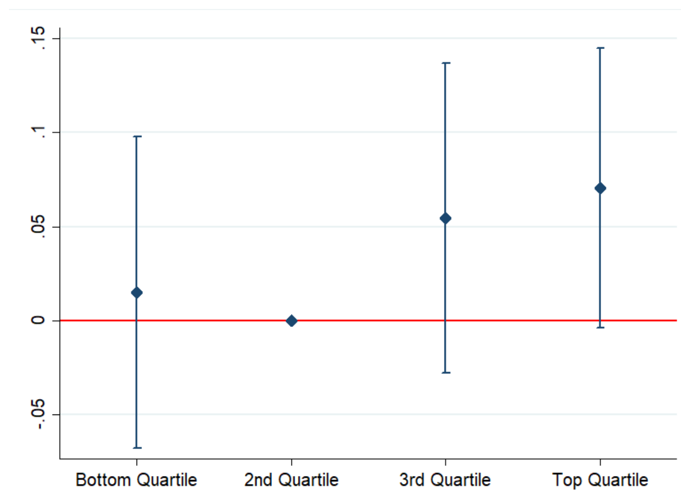
(a) Selective Major Enrollment



(b) Selective Major Graduation



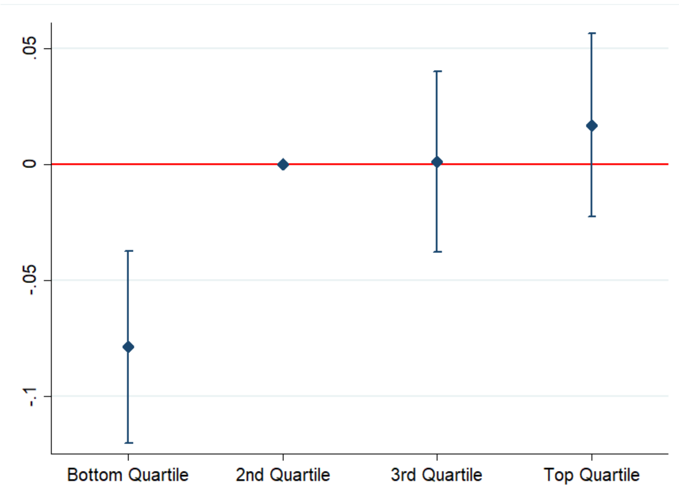
(c) Top Students' Selective Major Enrollment



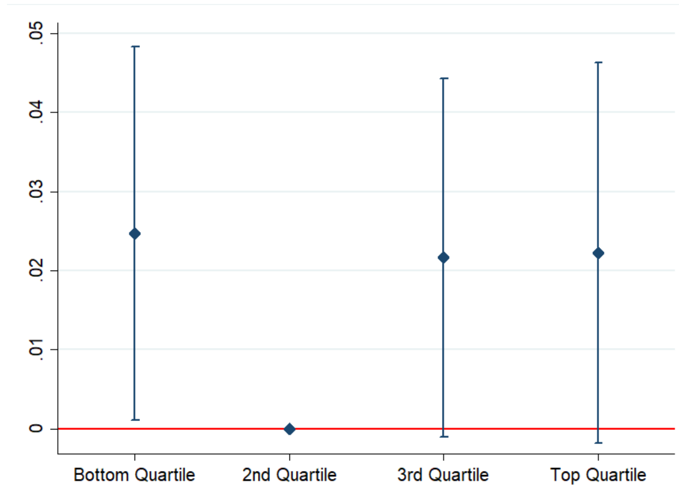
(d) Top Students' Selective Major Graduation

Notes: The different panels show the impacts of being matched to freshman advisors from different quartiles of the grade VA distribution. Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. Point estimates represent coefficients from regressions of advisor VA quartile (with the second quartile as the baseline excluded category) on student outcomes. All regression include year fixed effects and students controls. All bars represent 95% confidence intervals with standard errors clustered at the advisor-year level.

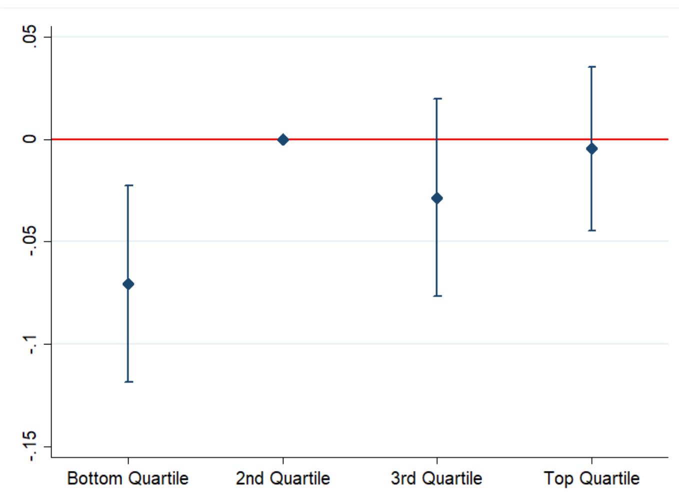
Figure A4: Discrete Treatment on Sophomore Academic Performance and College Completion



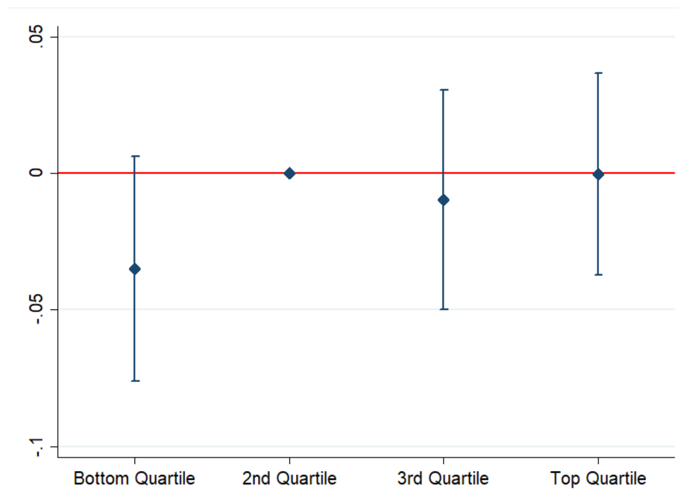
(a) Standardized GPA



(b) Dropout after Sophomore



(c) 4-year Graduation



(d) 6-Year Graduation

Notes: The different panels show the impacts of being matched to sophomore advisors from different quartiles of the grade VA distribution. Sample includes first-time enrolling sophomore students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. Point estimates represent coefficients from regressions of advisor VA quartile (with the second quartile as the baseline excluded category) on student outcomes. All regression include year and department fixed effects and students controls. All bars represent 95% confidence intervals with standard errors clustered at the advisor-year level.

D Appendix Tables

Table A1: Requirements for admission in different majors

Number of credits required in each discipline by major

Major	English Level 200	Arabic	Humanities	Math	Natural Sciences	Social Sciences	Electives
Engineering	3	3	3	6	9	3	3
Physics	3	3	3	6	9	3	3
Business	3	3	6	3	6	3	6
History	3	3	6	3	6	3	6

Notes: The above table shows the number of credits that a student must pass during the freshman year within each discipline in order to be eligible for admission into engineering, physics, business and history. Each course is typically equivalent to 3 credits.

Additional course and grade requirements by major

Engineering	completion of MATH 101 and 102, CHEM 101, 101L, PHYS 101, and PHYS 101 L, and a cumulative average of at least 80 in the freshman year
Physics	a minimum cumulative average of 70 in PHYS 101 and 101L, and a minimum cumulative average of 70 in MATH 101 and 102
Business	a minimum cumulative average of 77 in at least 24 credits during the freshman year, and a minimum grade of 70 in any one of the following courses: MATH 101, MATH 102, MATH 203 (Refer to Mathematics Department for course requirements).
History	a minimum cumulative average of 70 in English courses taken in the freshman year

Notes: The above table shows specific courses and grades that students must obtain during the freshman year to be eligible for admission into engineering, physics, business and history. For example, the engineering department requires that students take Math 101 (Calculus I), Math 102 (Calculus II), CHEM 101 and 101L (General Chemistry) and PHYS 101 and 101L (Introductory Physics). By passing these courses, students receive enough credits to fulfill the math and science credit requirements for admission into engineering (the first table shows that students need 6 credits in math and 9 credits in sciences).

Table A2: Pre-major academic advising at other private 4-year colleges and universities

College/University	Advisors help students with	Meetings	Advisors are
Amherst College	defining academic goals, improving academic skills, selecting courses, exploring new areas of study and declaring a major	One-on-one meetings prior to course registration	Faculty
Duke University	selecting courses, setting academic goals, deciding on field of study, finding co-curricular opportunities	One-one meeting during orientation week and prior to course registration	Faculty or staff members
Harvard College	choosing courses, meeting degree requirements, considering concentration options, or planning for the summer	One-on-one meetings during course selection week and every 3 or 4 weeks during semester	Faculty, administrators or graduate students
Middlebury College	choosing courses and major keeping tabs on academic problems	One-on-one meetings prior to course registration	Faculty
Princeton University	setting long-term academic goals, selecting courses, discovering academic interests	One-on-one meetings each semester	Faculty
Swarthmore College	selecting courses and program of study; maintaining academic success; discuss setting goals, time management, balancing academics with other parts of life	One-on-one meetings during pre-registration period or when students have academic difficulties	Faculty, deans, administrators, or staff members
Vanderbilt University	creating course schedule; discuss academic goals and progress towards fulfilling curriculum requirements	Phone meeting prior to Fall semester and one-on-one meeting later on	Faculty
Wesleyan University	academic planning, setting long-term academic and career goals, selecting courses and program of study	One-on-one meetings	Faculty
Williams College	choosing a major and courses, setting long-term career goals; check in on students' well-being and academic progress	One-one meetings prior to each course registration period	Faculty
Yale University	selecting courses, setting academic goals, deciding on program of study	Advisors set up one-on-one meetings	Faculty, administrators or staff members

Notes: This table shows the organization of pre-major academic advising at various U.S. private 4-year colleges or universities. The information is taken from each college or university's website.

Table A3: Pre-major academic advising at other private 4-year colleges and universities (continued)

College/University	Advisors have access to students' academic records	Advisors notified of students' academic standing	Advisors approve course withdrawals
Amherst College	N/A	N/A	Yes
Duke University	N/A	N/A but students urged to talk to advisor in case of academic probation	No but students encouraged to discuss course withdrawal with advisors
Harvard College	N/A	N/A	N/A
Middlebury College	Yes	Advisors emailed when students receive course warning (i.e., expected to earn a final grade of "D" or "F")	No but students should discuss course withdrawal with advisors
Princeton University	N/A	N/A	Required approval of Residential dean, director of studies, or academic advisor
Swarthmore College	Yes	Advisors receive copies of all official correspondence concerning advisees' academic standing	No
Vanderbilt University	N/A	N/A	Yes
Wesleyan University	Yes	Advisors notified of students' Unsatisfactory Progress Report and required to schedule one-on-one meeting in that case	No
Williams College	N/A	Advisors notified of students' unsatisfactory grades	No
Yale University	N/A	N/A	No

Notes: This table reports whether pre-major advisors at various U.S. private 4-year colleges or universities perform certain tasks. Each task is shown in a different column. The information is taken from each college or university's website. Information is reported as unavailable (N/A) in case we could not find it on the corresponding university/college's website.

Table A4: Estimate of Forecast Bias of Freshman Advisor Grade VA Measure with Different Sample Splits

A. Leave Current Year and 2 Lags Out

	Freshman Course Grade
Advisor VA	0.950***
	(0.333)
N	33,981

B. Leave Current Year and 2 Leads Out

	Freshman Course Grade
Advisor VA	1.052***
	(0.301)
N	33,696

C. Random Sample Split

	Freshman Course Grade
Advisor VA	0.811***
	(0.343)
N	17,749

Notes: Standard errors in parentheses are clustered at the advisor-year level. All regressions include year fixed effects. Freshman advisor VA is constructed using a leave-year out estimate as described in the methodology section. In Panel C, the random sample split is done by randomly dropping half of the observations in a each year, estimating leave-year out VA, then checking for forecast unbiasedness using the dropped observations. *** p <0.01 ** p <0.05 * p <0.1.

Table A5: Heterogeneous Effects of Advisor Grade VA on Academic Performance and Retention

	Overall Sample (1)	Below Median Math SAT (2)	Above Median Math SAT (3)	Male (4)	Female (5)
A. Standardized GPA					
No Controls	0.057***	0.042**	0.072***	0.054**	0.058***
	(0.016)	(0.017)	(0.023)	(0.024)	(0.014)
Controls	0.048***	0.041**	0.054***	0.047**	0.047***
	(0.014)	(0.016)	(0.020)	(0.023)	(0.013)
Mean Dep. Var.	0.038	-0.111	0.202	-0.094	0.182
N	3,857	2,019	1,838	2,014	1,843
B. Likelihood of Becoming Sophomore					
No Controls	0.008	0.001	0.013	0.003	0.012
	(0.006)	(0.009)	(0.008)	(0.009)	(0.008)
Controls	0.007	0.001	0.012	0.003	0.011
	(0.006)	(0.009)	(0.008)	(0.009)	(0.008)
Mean Dep. Var.	0.793	0.772	0.817	0.773	0.816
N	3,857	2,019	1,838	2,014	1,843
C. Time to Sophomore					
No Controls	-0.078***	-0.107***	-0.049	-0.062*	-0.089***
	(0.026)	(0.032)	(0.032)	(0.033)	(0.030)
Controls	-0.072***	-0.103***	-0.041	-0.056*	-0.086***
	(0.025)	(0.031)	(0.031)	(0.032)	(0.029)
Mean Dep. Var.	2.480	2.587	2.373	2.527	2.433
N	3,047	1,526	1,521	1,525	1,522

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. Standard errors in parentheses are clustered at the advisor-year level. All regressions include year fixed effects and advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$.

Table A6: Effect of Advisor Grade VA on Student Outcomes Using Graduation Sample

	Standardized GPA (1)	Become a Sophomore (2)	Time to Sophomore (3)	Enroll in a Selective Major (3)
A. No Controls				
Advisor Grade VA	0.070***	0.007	-0.081***	0.022**
	(0.018)	(0.008)	(0.028)	(0.009)
B. With Controls				
Advisor Grade VA	0.056***	0.006	-0.075***	0.023**
	(0.016)	(0.008)	(0.026)	(0.009)
Mean Dep Var	0.035	0.776	2.575	0.434
N	2,952	2,952	2,287	2,952

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2012-2013. Standard errors in parentheses are clustered at the advisor-year level. All regressions include year fixed effects. Advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. Sample includes students from academic years 2003-2004 till 2012-2013. *** p <0.01 ** p <0.05 * p <0.1.

Table A7: Heterogeneous Effects of Advisor Grade VA on College Completion

	Overall Sample (1)	Below Median Math SAT (2)	Above Median Math SAT (3)	Male (4)	Female (5)
A. 4-Year Graduation					
No Controls	0.025***	0.024**	0.023*	0.030**	0.017
	(0.008)	(0.011)	(0.013)	(0.012)	(0.012)
Controls	0.022***	0.025**	0.020	0.028**	0.014
	(0.008)	(0.010)	(0.013)	(0.012)	(0.012)
Mean Dep. Var.	0.458	0.422	0.500	0.480	0.575
B. 6-Year Graduation					
No Controls	0.015	0.008	0.020	0.019	0.010
	(0.009)	(0.011)	(0.015)	(0.014)	(0.010)
Controls	0.013	0.010	0.018	0.018	0.008
	(0.010)	(0.011)	(0.015)	(0.014)	(0.010)
Mean Dep. Var.	0.575	0.547	0.606	0.600	0.687
N	2,952	1,551	1,401	1,551	1,401

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2012-2013. Standard errors in parentheses clustered at the advisor-year level. All regressions include year fixed effects and advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. *** p <0.01 ** p <0.05 * p <0.1.

Table A8: Effect of Non-Grade VA on Academic Performance, College Completion, and Major Choice

	Standardized GPA	4-Year Graduation	6-Year Graduation	Proportion of Courses Withdrawn	Proportion of Courses Failed	Enroll in Selective Major	Graduate from Selective Major	Proportion of Courses Science
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Persistence VA	0.040**	0.018**	0.014	-0.004**	-0.005	0.020**	0.024***	0.010**
	(0.019)	(0.008)	(0.009)	(0.002)	(0.004)	(0.008)	(0.008)	(0.004)
Selective VA	0.050***	0.018**	0.016*	-0.005***	-0.007*	0.024***	0.028***	0.008**
	(0.018)	(0.008)	(0.010)	(0.002)	(0.004)	(0.009)	(0.009)	(0.004)
N	2,984	2,987	2,987	2,987	2,987	2,987	2,987	2,987

Notes: Sample includes first-time enrolling freshman students from the academic years 2003-2004 to 2012-2013 to be able to create graduation outcomes. Standard errors in parentheses are clustered at the advisor-year level. All regressions include year fixed effects and VA is standardized by year. Controls included are math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. *** p <0.01 ** p <0.05 * p <0.1.

Table A9: Correlations Between Different VA measures

	Grade VA	Persistence VA	Selective VA
Grade VA	1.00		
Persistence VA	0.17	1.00	
Selective VA	0.29	0.80	1.00

Notes: This table presents the two-way correlation coefficient between the estimated VA on Grades, the Persistence Index, and the Selectiveness Index.

Table A10: Summary Statistics for Sophomore Sample

	Mean (1)	S.D. (2)	Obs. (3)
A. Student Level Covariates			
Female	0.480	0.500	14,055
Math SAT	644	72.2	14,055
Verbal SAT	530	106.2	14,055
Legacy Status	0.249	0.432	14,055
B. Student Level Outcomes			
Sophomore GPA	77.5	7.84	14,055
Dropout after Sophomore	0.088	0.283	14,055
Graduate in 4 years	0.529	0.499	9,120
Graduate in 6 Years	0.796	0.403	9,120
Graduate in 4 years in major	0.405	0.491	9,120
Graduate in 6 Years in major	0.554	0.497	9,120
C. Advisor-Year Level Characteristics			
Female	0.310	0.463	736
Science Department	0.484	0.500	736
Lecturer and Other	0.240	0.428	736
Assistant Professor	0.352	0.478	736
Associate Professor	0.174	0.379	736
Professor	0.234	0.423	736
Number of Students	19.1	19.5	736

Notes: Our main sample includes sophomore students who first enrolled in AUB in the academic years 2003-2004 to 2015-2016. Data from these years comprise 194 unique advisors. Our graduation sample includes students who first enrolled in AUB in the academic years 2003-2004 to 2012-2013. Data from these years comprise 152 unique advisors.

Table A11: Estimate of Forecast Bias of Advisor Grade VA Measure for Sophomore Sample

	Sophomore Course Grade
Advisor Grade VA	0.991***
	(0.163)
Mean of VA	0.0004
S.D of VA	0.043
N	144,093

Notes: Standard errors in parentheses are clustered at the advisor-year level. Regressions includes department and year fixed effects. Sophomore advisor VA is constructed using a leave-year out estimate as described in the methodology section. *** p <0.01 ** p <0.05 * p <0.1.

Table A12: Estimate of Forecast Bias of Sophomore Advisor Grade VA Measure with Different Sample Splits

A. Leave Current Year and 2 Lags Out	
	Sophomore Course Grade
Advisor VA	1.017***
	(0.164)
N	141,305
B. Leave Current Year and 2 Leads Out	
	Sophomore Course Grade
Advisor VA	1.060***
	(0.164)
N	139,181
C. Random Sample Split	
	Sophomore Course Grade
Advisor VA	0.891***
	(0.192)
N	71,939

Notes: Standard errors in parentheses are clustered at the advisor-year level. Regressions include department, and year fixed effects. Sophomore advisor VA is constructed using a leave-year out estimate as described in the methodology section. In Panel C, the random sample split is done by randomly dropping half of the observations in a each year-department, estimating leave-year out VA, then checking for forecast unbiasedness using the dropped observations. *** p <0.01 ** p <0.05 * p <0.1.

Table A13: Test of Random Assignment for Sophomore Sample

	Advisor Grade VA
Math SAT	0.010
	(0.009)
Verbal SAT	0.002
	(0.008)
Female	0.029
	(0.022)
Legacy	-0.015
	(0.020)
N	14,055
P-Value Joint Significance	0.462

Notes: Sample includes first-time enrolling sophomore students from the academic years 2003-2004 to 2015-2016. Standard errors in parentheses are clustered at the advisor-year level. Regression includes department and year fixed effects. Advisor VA is standardized by year. SAT scores are standardized within department and year. *** p <0.01 ** p <0.05 * p <0.1.

Table A14: Effect of Sophomore Advisor Persistence VA on Academic Performance, Retention and College Completion

	Standardized GPA (1)	Dropout after Sophomore (2)	4-Year Graduation (3)	6-Year Graduation (4)	4-Year Graduation in Major (5)	6-Year Graduation in Major (6)
A. Overall Sample						
Persistence VA	0.003	-0.022***	0.030***	0.025***	0.035***	0.036***
	(0.007)	(0.006)	(0.009)	(0.008)	(0.010)	(0.009)
Mean Dep Var	0.006	0.085	0.527	0.791	0.403	0.549
N	8,761	8,761	8,761	8,761	8,761	8,761
B. STEM Majors						
Persistence VA	0.025*	-0.016***	0.026**	0.016*	0.037**	0.036***
	(0.013)	(0.004)	(0.011)	(0.008)	(0.015)	(0.014)
Mean Dep Var	0.083	0.067	0.579	0.814	0.417	0.528
N	4,747	4,747	4,747	4,747	4,747	4,747
C. Non-STEM Majors						
Persistence VA	0.001	-0.022**	0.038***	0.027***	0.037***	0.035***
	(0.008)	(0.009)	(0.011)	(0.010)	(0.011)	(0.011)
Mean Dep Var	-0.086	0.108	0.466	0.765	0.386	0.574
N	4,014	4,014	4,014	4,014	4,014	4,014

Notes: The sample includes first-time enrolling sophomore students from the academic years 2003-2004 to 2012-2013. Standard errors in parentheses are clustered at the advisor-year level. Regressions includes department and year fixed effects. Advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. SAT scores are standardized within department and year.
*** p <0.01 ** p <0.05 * p <0.1.

Table A15: Effect of Various VA Skill Measures on the Corresponding Skills Sophomore Sample

	Standardized GPA			Persistence Index		
	(1)	(2)	(3)	(4)	(5)	(6)
Grade VA	0.027***		0.027***	0.038*		0.033*
	(0.009)		(0.009)	(0.021)		(0.018)
Persistence VA		0.003	0.001		0.075***	0.073***
		(0.007)	(0.008)		(0.019)	(0.018)
N	8,761	8,761	8,761	8,761	8,761	8,761

Notes: The sample includes first-time enrolling sophomore students from the academic years 2003-2004 to 2012-2013. Standard errors in parentheses are clustered at the advisor-year level. Regressions includes department and year fixed effects. Advisor VA is standardized by year. Controls include math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. SAT scores are standardized within department and year. Each column represents estimates from a separate regression. Controls included are math and verbal SAT scores, a dummy variable for being a female, and a dummy variable for being a legacy student. *** p <0.01 ** p <0.05 * p <0.1.

Table A16: Observable Characteristics Effect on Freshman Advisor VA Measures

	Grade VA	Persistence VA	Selective VA
Professor	-0.004	0.019	0.014
	(0.018)	(0.023)	(0.020)
Associate Professor	0.006	0.023	0.013
	(0.015)	(0.024)	(0.019)
Female Advisor	0.016	0.012	0.014
	(0.012)	(0.022)	(0.017)
Science Department	0.005	0.021	0.021
	(0.010)	(0.027)	(0.022)
N	131	115	115

Notes: Sample includes academic advisors matched to first-time enrolling freshman students for academic years 2003-2004 to 2015-2016. Standard errors in parentheses are clustered at the advisor level. All regressions include year fixed effects. The number of observations drops for Persistence and Selective VA measures because they are constructed using the sample of students we can observe graduation for (2003-2004 till 2012-2013 freshman entering cohorts). *** p <0.01 ** p <0.05 * p <0.1.

Table A17: Observable Characteristics Effect on Sophomore Advisor VA Measures

	Grade VA	Persistence VA
Professor	-0.008	-0.002
	(0.006)	(0.007)
Associate Professor	-0.003	0.001
	(0.005)	(0.007)
Female Advisor	-0.004	0.008
	(0.005)	(0.007)
Science Department	0.006	0.002
	(0.004)	(0.007)
N	736	646

Notes: Sample includes academic advisors matched to first-time enrolling sophomore students for academic years 2003-2004 to 2015-2016. Standard errors in parentheses are clustered at the advisor level. All regressions include year fixed effects. The number of observations drops for Persistence VA because it is constructed using the sample of students we can observe graduation for (2003-2004 till 2012-2013). *** p <0.01 ** p <0.05 * p <0.1.

Table A18: Effect of Being Matched with a Female Rather than Male Advisor on Freshman Student Outcomes

	Standardized GPA (1)	Becoming Sophomore (2)	4-Year Graduation (3)	6-Year Graduation (4)	Selective Major Enroll (5)	Selective Major Grad (6)	Selective Major Enroll Top (7)	Selective Major Grad Top (8)
Effect on Male Students (β_1)	-0.012	-0.023	-0.036	-0.020	-0.016	-0.009	-0.045	-0.007
	(0.037)	(0.018)	(0.023)	(0.025)	(0.022)	(0.025)	(0.035)	(0.040)
Effect on Female Students ($\beta_1 + \beta_3$)	0.077**	0.009	0.064***	0.024	0.017	0.032	0.006	0.025
	(0.032)	(0.017)	(0.024)	(0.023)	(0.024)	(0.024)	(0.049)	(0.055)
Mean Dep Var	0.038	0.794	0.458	0.575	0.429	0.355	0.567	0.464
N	3,857	3,857	2,952	2,952	3,857	2,952	1,317	995

Notes: Sample includes advisors matched to first-time enrolling freshman students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. Standard errors are clustered at the advisor-year level and reported in parentheses. All regressions include year fixed effects. Controls include math and verbal SAT scores and a dummy variable for being a legacy student. *** p <0.01 ** p <0.05 * p <0.1.

Table A19: Effect of Being Matched with a Female Rather than Male Advisor on Sophomore Student Outcomes

	Standardized GPA (1)	Dropout after Sophomore (2)	4-Year Graduation (3)	6-Year Graduation (4)	4-Year Graduation in Major (5)	6-Year Graduation in Major (6)
Effect on Male Students (β_1)	-0.049*	-0.003	-0.043	-0.041	-0.009	-0.011
	(0.030)	(0.015)	(0.026)	(0.025)	(0.025)	(0.026)
Effect on Female Students ($\beta_1 + \beta_3$)	0.054**	-0.012	0.003	0.011	0.025	0.031
	(0.021)	(0.017)	(0.028)	(0.025)	(0.028)	(0.026)
Mean Dep Var	0.004	0.088	0.527	0.791	0.403	0.549
N	14,055	14,055	9,120	9,120	9,120	9,120

Notes: Sample includes advisors matched to first-time enrolling sophomore students from the academic years 2003-2004 to 2015-2016. The sample is restricted to 2003-2004 to 2012-2013 for graduation outcomes. Standard errors are clustered at the advisor-year level and reported in parentheses. All regressions include year and department fixed effects. Controls include math and verbal SAT scores and a dummy variable for being a legacy student. SAT scores are standardized within department and year. *** p <0.01 ** p <0.05 * p <0.1.