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

Serena Canaan† Antoine Deeb‡ Pierre Mouganie§

This Version: October 30, 2019

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.

†Department of Economics, American University of Beirut, and IZA, e-mail: sc24@aub.edu.lb

‡Department of Economics, University of California Santa Barbara, e-mail: antoinedib@umail.ucsb.edu

§Department of Economics, American University of Beirut, and IZA, e-mail: pm10@aub.edu.lb

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. Indeed, only 41.6 and 60.4 percent of U.S. students at 4-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). Policymakers and researchers have been increasingly advocating for the use of academic support services such as college advising or mentoring in an effort to improve student outcomes.

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 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) 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 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

[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).

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 4-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 higher advisor 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 percent. Importantly, the benefits of having an effective freshman advisor do not fade out, as we document a 5.5 percent 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 both high-ability male and female students who respectively experience a 3.2 and 4.9 percentage points (or 7.8 and 16.3 percent) increase in the likelihood of enrolling in a STEM major, and comparable improvements in STEM graduation rates. 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. Finally, we show that students experience the largest gains from being matched to advisors in the top quartile of the VA distribution.

Our paper is related to several strands of literature. The first is a large literature that examines whether interventions such as mentoring or advising can be used to address educational barriers. Prior work evaluates counseling programs aimed at increasing *high school* students' access to college or financial aid (Bettinger et al., 2012; Avery, Howell and Page, 2014; Castleman, Page and Schooley, 2014; Carrell and Sacerdote, 2017; Barr and Castleman, 2018; Castleman and Goodman, 2018; Bird et al., 2019; Mulhern, 2019). Most of these studies show that providing students with one-on-one counseling or assistance significantly increases college enrollment, persistence, and financial aid receipt. In contrast, less is known about whether advising *during college* improves student outcomes and the existing evidence is mixed. Several studies find that access to advising has negligible impacts on college students' academic performance (Angrist, Lang and Oreopoulos, 2009; Scrivener and Weiss, 2009; Angrist, Oreopoulos and Williams, 2014; Oreopoulos and Petronijevic, 2019). On the other hand, some programs which offer personalized and proactive coaching or advising have shown to substantially increase academic performance (Kot, 2014; Oreopoulos and Petronijevic, 2019) and college persistence (Bettinger and Baker, 2014; Barr and Castleman, 2018).

We add to this literature in two ways. First, and to the best of our knowledge, no prior work has examined whether college advising *quality* matters for students' academic trajectories. Our paper is the first to show that higher advisor VA substantially improves college students' outcomes. Our finding that quality of advising is crucial for students' success may also potentially explain why some of the previously studied advising programs succeeded and others did not, as these papers have focused on advising at the extensive margin (i.e., having versus not having access to advising). Second, 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. Our paper offers a first look into the potential benefits of academic advising, which is important in and of itself, as it is an integral part of most U.S. colleges.[2] Our findings suggest that colleges can largely improve student outcomes by directing more resources towards enhancing the quality of academic advising.

Our results further complement 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; Castleman, Long and Mabel, 2018), differential pricing of academic programs (Stange, 2005), signals of ability (Avery et al., 2018) and timing of course-taking (Patterson, Pope and Feudo, 2019) in college major decisions. Our study is the first to highlight 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, 2010; Canaan and Mouganie, 2019; 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.

Finally, our findings relate to the extensive body of research on teacher and school value-

[2]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.

added. Prior studies have largely examined the extent to which VA measures are biased and whether teacher VA predicts students' subsequent outcomes (see Staiger and Rockoff, 2010; Jackson, Rockoff and Staiger, 2014; Koedel, Mihaly and Rockoff, 2015 for recent literature reviews). In particular, recent evidence highlights the importance of school teachers in improving students' adult outcomes (Chetty, Friedman, and Rockoff, 2014a and 2014b; Jackson, 2018). We complement this literature by assessing the impact of *advisor*—instead of teacher or school—quality, and by estimating VA at the postsecondary level.[3] In particular, we show that VA measures are a good tool for estimating college advisor quality by documenting that advisors who raise contemporaneous student achievement improve subsequent longer-term outcomes such as graduation. Our results suggest that academic advisors—an often overlooked input in the education production function—may be just as valuable as teachers or professors in predicting students' success.

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 Random Assignment of Students to Advisors

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 of-

[3]Indeed, the vast majority of the teacher value-added literature has focused on measuring VA in primary and secondary education. 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. In contrast, we find that advisors who increase contemporaneous student achievement *improve* subsequent longer-term outcomes. This is most likely because advisors cannot inflate their own VA since they do not directly control students' grades nor are they incentivized to do so. Additionally, in the context of secondary education, Mulhern (2019) shows that higher guidance counselor VA increases students' high school graduation, college attendance and persistence in first year.

ficially 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. postsecondary 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.[4]

Our focus in this paper is on students who are initially enrolled at AUB as freshmen. Students typically declare a major at the end of their freshman year, after having completed the requirements for admission into their intended majors. We should however note that freshman students are not typical Lebanese students. 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. Freshmen students are those who either attended foreign high schools or went to Lebanese schools that follow the U.S. high school education system.

At the beginning of their freshman year, students are randomly assigned to academic advisors (or pre-major advisors). Advisors are typically full-time faculty of professorial rank (Assistant, Associate and Full Professors) chosen from various departments within the Faculty of Arts and Sciences.[5] 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

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

[5]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 percent of responding institutions. This number however varies by type of institution. While 84.1 percent of surveyed baccalaureate-granting institutions reported that three-fourth of students are advised by full-time faculty, this number is 50 percent at master's-granting institutions and 22.5 percent at research universities which mostly rely on professional advisors.

volunteering, such as extra research funds or a course release. Faculty commit to advising for the full 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. 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.

2.2 Academic Advising

While the random assignment of students to advisors is unique to our setting, AUB's advising system is in general comparable to academic advising at private 4-year colleges in the United States. Freshman students at AUB are required to meet with their advisors one-on-one at least once per semester and prior to course registration.[6] In a survey conducted by the College Board (2011) among U.S. 4-year colleges, 69 percent of responding institutions also required students to meet with their first-year advisor at least once per term. Advisors at AUB 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 or fail a class. Additionally, students are not allowed to withdraw from any course without first getting advisor approval.

Academic advisors' main tasks at AUB 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

[6] 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.

that will allow them to meet the requirements for their intended majors. These tasks are in line with those emphasized in the U.S. college advising system. Indeed, according to a survey conducted by the National Academic Advising Association (NACADA, 2011), over 91 percent 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.

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 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.[7] 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.[8]

In our main analysis, we examine whether advising quality impacts students' major choice. We focus on the likelihood that students pursue science and business majors (henceforth, selective majors) for several reasons. 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.[9] Second, from

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

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

[9]While the business school does not require students to take specific courses, its does have a minimum

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.

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.[10] We exclude all students who have missing baseline information and all advisors who advised for only one academic year.[11] This leaves us with a final sample of 3,857 freshmen students matched to 38 academic advisors.

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 percent of individuals in our main sample, compared to 52 percent male. The average Mathematics and English SAT test scores for freshman students are 573

admission freshman-GPA of 77—which is higher than most other majors.

[10]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.

[11]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.

and 494 points respectively. Approximately 20 percent 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 percent 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 percent of students initially enrolled as freshmen are able to graduate on-time, i.e., within 4 years of initial enrollment at AUB.[12] Further, around 57.5 percent of freshmen graduate within 6 years of enrollment. Finally, 43 percent of students enroll in a selective major—i.e., STEM and business majors—and 35.5 percent of all students eventually graduate from a selective major. These majors also correspond to those with the highest earnings potential.[13]

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 percent of freshman advisors are female faculty members and 61 percent are male. This is in line with the overall proportion of female faculty at AUB which stands at approximately 40 percent. Further, 56.5 percent of advisors are in a science department and 43.5 percent 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 percent are full professors, 22 are associate and 50 percent 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). 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

[12]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.

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

for multiple different classes in a given year. Accordingly, we define a classroom in this setting as an advisor-year-class cell.

Let students be indexed by i, years by t, classes by c, and advisors by j. Then let student i's test score, 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 test scores) 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}.[14] Thus, one advantage of our setting is that the average test scores 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.[15]

We start by standardizing student test scores at the class-year level and running a regression of standardized test scores 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 test scores.

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

[15]Creating VA following the exact methodology of Chetty, Friedman, and Rockoff (2014a) where test scores 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.

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:[16]

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

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.

4.2 Forecast Unbiasedness of VA estimates

Under the random assignment of students to advisors in a given year t, the average effect on test scores 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 test scores 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 test scores are balanced across advisors. Following Chetty, Friedman, and Rockoff (2014a), we consider the following regression of residual test scores on estimated VA:

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

In our setting we then have:

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

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

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 VA leads to a statistically significant 0.971 unit increase in test scores. 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 test scores 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.

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 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:

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

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 VA on a host of student controls including 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.[17] Throughout our analysis, both freshman GPA and advisor 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).

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 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

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

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 percent reduction from the baseline mean of 2.48 semesters. This finding is robust to the inclusion of student controls, as indicated by the statistically significant -0.072 estimate reported in Panel B.

In Appendix Table A2, 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 A2, we examine heterogeneous effects for the likelihood that students declare sophomore status. Consistent with our result for the overall sample, we find that advisor 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 percent 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 percent), 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 effective 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 VA influences college completion.[18] 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 percent. 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 percent 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.

Heterogeneous effects for graduation outcomes are presented in Appendix Table A4. 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 percent) 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 (6.2 percent) 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.

[18]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 A3 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.[19] 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 VA on students' major choice.[20] 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 percent. The estimate for graduating from a selective major is on the order of 1.5 percentage points (or 4.2 percent) 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 (8.6 percent). This is coupled with a similar and significant 3.9 percentage points (or 8.4 percent) 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.

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 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

[19] 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.

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

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 percent) 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 percent), 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 Discrete Treatment—High and Low VA advisors

So far, we have shown that a higher VA academic advisor improves students' college outcomes both in the freshman year and in the long run. 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 or an average advisor rather than a low-performing one? Accordingly, we next estimate the impact of being matched to advisors in different quartiles of the VA distribution. These estimates are presented graphically in Figures 1 and 2 for our main outcomes of interest. Specifically, the different panels plot point estimates and 95% confidence intervals representing the effects of being matched to advisors in the top three quartiles of the VA distribution—with the bottom quartile as our excluded baseline category.

Estimates presented in Figure 1a indicate that moving from a bottom to top quartile advisor substantially improves students' freshman year GPA by approximately 14 percent of a standard deviation. Additionally, we find positive but insignificant effects from being matched to an advisor in the 2nd or 3rd quartile of the VA distribution, relative to the bottom quartile. Estimates for time to declaring sophomore status mirror those for GPA, as shown in Figure 1b. Indeed, students matched to top as opposed to bottom advisors take approximately 0.19 fewer semesters to complete the freshman year. We also find suggestive evidence of reduced time to completion for students matched to advisors in the 2nd and

3rd quartiles. This indicates that bottom performing advisors significantly delay students' academic progression.

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 1c show that being matched to a top rather than bottom advisor results in an approximate 5 percentage point increase in on-time graduation, significant at the 10 percent level. We also find suggestive evidence of a positive effect for those matched to an advisor in the 3rd quartile, but this estimate is statistically insignificant at conventional levels. On the other hand, advisors from different quartiles of the VA distribution seem to have no strong impact on 6-year graduation rates (Figure 1d), which is consistent with our main results for this outcome.

Panels (a) through (d) of Figure 2 show how advisors in different quartiles of the VA distribution impact students' enrollment and graduation from selective majors. For both the overall sample (Figures 2a and 2b) and top students (Figures 2c and 2d), going from a bottom to top advisor increases the likelihood of enrollment and graduation from selective majors, though these effects are not statistically significant for graduation. Specifically, students matched to a top rather than bottom advisor are approximately 6 percentage points more likely to enroll in a selective major, while this estimate is on the order of 11 percentage points for top students. Taken together, our results indicate that students benefit the most from being matched to advisors in the top quartile of the VA distribution, and that replacing the lowest-performing advisors with top advisors can lead to substantial gains for students both in the short and longer run.

6 Discussion

In this paper, we document that academic advising quality substantially impacts students' college outcomes. A natural question that arises is what are the mechanisms through which these effects occur? Our first set of results show that effective advisors largely improve students' test scores during the freshman year. There are several potential explanations for this result. 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 the freshman year. Another possible explanation is that effective advisors encourage students to enroll in a specific set of courses that maximize freshman-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 VA on students' course-level outcomes. These results are reported in Table 7 separately for the first (Panel A) and second (Panel B) semesters of the freshman year. We start by looking at the impact of advisor VA on the likelihood that students take challenging courses during the freshman year. The most challenging courses during the freshman year are math and science courses that are required for entry into selective majors.[21] Strikingly, estimates from column (1) of Table 7 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 advisors do not influence course choice, column (2) indicates that students are 0.9 percentage points less likely to fail courses due to a one 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 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. Interestingly, Panel B reveals that advisor 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 7 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 time to complete the freshman year, graduating on time, and major choice. While we cannot conclusively speak to the exact mechanism driving these longer run effects, they are most likely explained by the documented improvement in academic performance during the freshman year. Indeed,

[21] 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.

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. Regarding the documented increase in STEM and business major enrollment, findings from Table 7 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. Rather effects seem to be mainly driven by increased grade performance causing students to be more likely to get accepted into these majors, which are more selective and have high grade requirements for admission.

Finally, we examine whether advisors' observable characteristics predict their value-added. To do so, we regress advisor VA on advisor gender, rank and type of department. Results in Table A5 reveal no significant relationship between advisors' faculty rank and their predicted VA score. Specifically, being an associate or full professor as opposed to an assistant professor or lecturer does not predict a higher or lower VA score, suggesting that faculty experience does not play a key role in predicting advisor quality. Additionally, we find that advisor gender and department (i.e., whether the advisor is in a science versus non-science department) are also statistically unrelated to VA score. However, one caveat with these results is that they are based on regressions with only 131 observations—corresponding to the number of advisor-years in our data. Hence, we can only provide suggestive evidence that advisors' observable characteristics are not related to VA. Strikingly though, our findings are consistent with those from Barr and Castelman (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 for example, that predict a large portion of what constitutes an effective advisor.

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 VA raises 4-year graduation rates by 5.5 percent. This finding is consonant with recent evaluations of multifaceted college support programs. Specifically, the programs that have shown the most promise in increasing college completion, such as the Accelerated Study in Associates Program (Weiss et al., 2019) and the Dell Scholars Program (Page et al., 2019), all have repeated interactive advising as a key component. Finally, we find that effective advisors have a strong impact on students' major choice. We document that exposure to higher-VA advisors largely increases both male and female 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 postsecondary institutions raises degree completion, through increased spending on academic support services such as advising. 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, 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, Oded Gurantz, Michael Hurwitz, and Jonathan Smith. 2018. Shifting college majors in response to advanced placement exam scores. *Journal of Human Resources* 53 (4): 918-956.

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, 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 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. 2019. Nudging at scale: Experimental evidence from FAFSA completion campaigns. *NBER Working Paper* No. 26158.

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.

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. 2019. Female science advisors and the STEM gender gap. *IZA DP* No. 12415.

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., Bridget Terry Long, and Zachary Mabel. 2018. Can Financial Aid Help to Address the Growing Need for STEM Education? The Effects of NeedBased Grants on the Completion of Science, Technology, Engineering, and Math Courses and Degrees. *Journal of Policy Analysis and Management* 37 (1): 136-166.

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 collegeintending, lowincome 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.

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., 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.

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.

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 nontest 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.

Page, Lindsay C., Stacy S. Kehoe, Benjamin L. Castleman, and Gumilang Aryo Sahadewo. 2019. More than dollars for scholars: The impact of the Dell Scholars Program on college access, persistence, and degree attainment. *Journal of Human Resources* 54 (3): 683-725.

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

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.

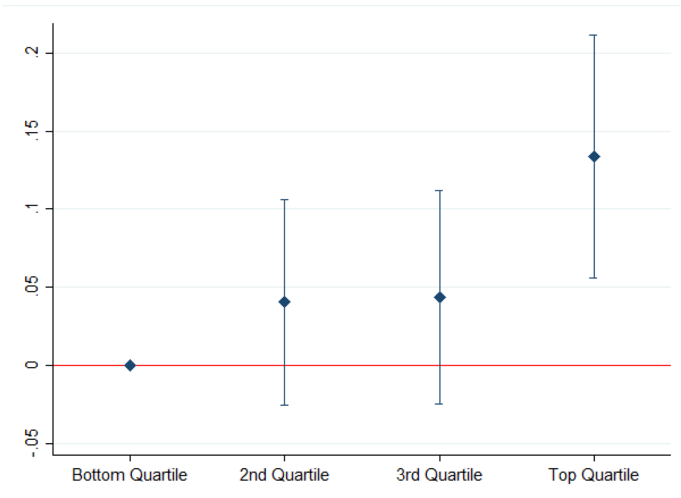
Stange, Kevin. 2015. Differential pricing in undergraduate education: Effects on degree production by field. *Journal of Policy Analysis and Management* 34 (1): 107-135.

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.

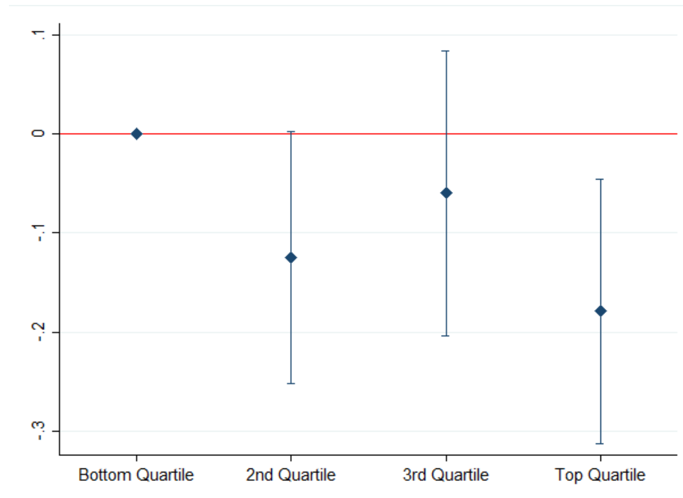
Weiss, Michael J., Alyssa Ratledge, Colleen Sommo, and Himani Gupta. 2019. Supporting community college students from start to degree completion: Long-term evidence from a randomized trial of CUNY's ASAP. *American Economic Journal: Applied Economics* 11 (3): 253-97.

A Figures

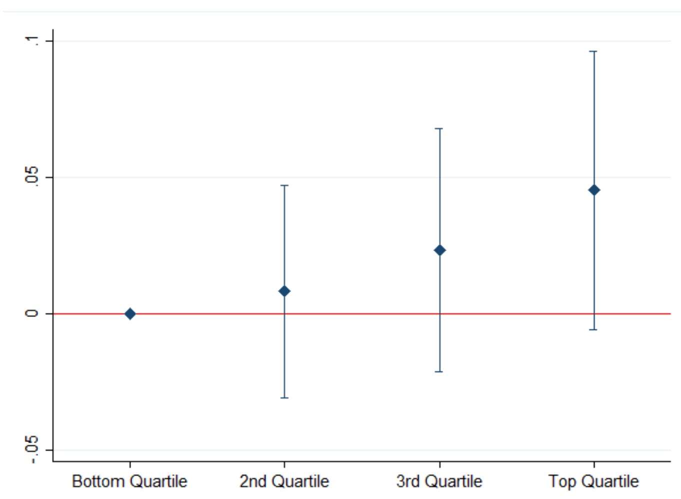
Figure 1: Discrete Treatment on Academic Performance and College Completion



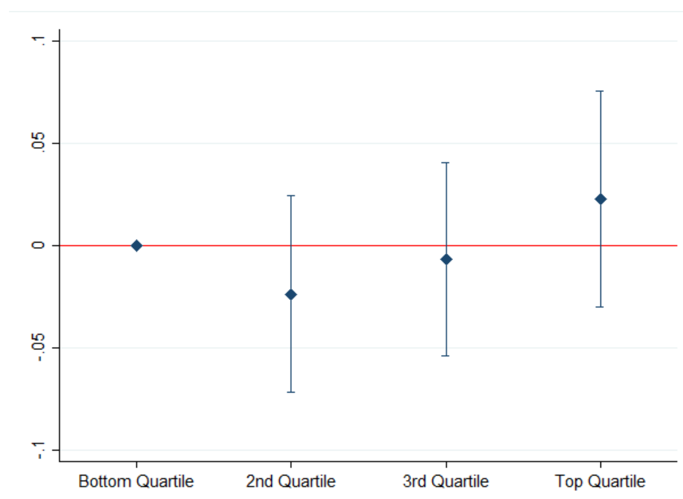
(a) Standardized GPA



(b) Time to Sophomore



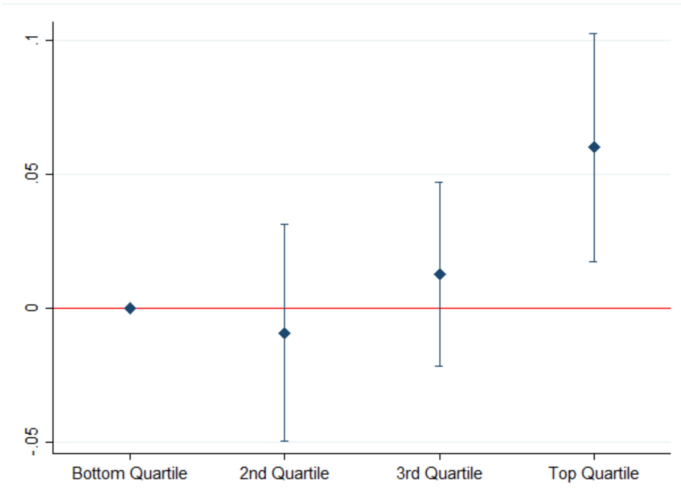
(c) 4-year Graduation



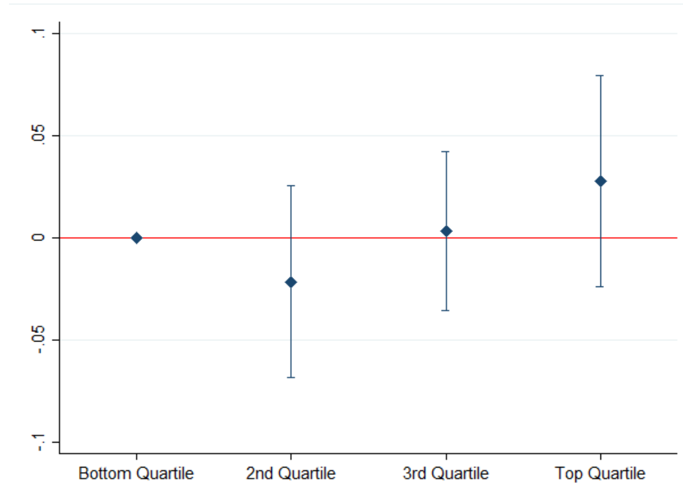
(d) 6-Year Graduation

Notes: The different panels show the impacts of being matched to advisors from different quartiles of the VA distribution. Point estimates represent coefficients from regressions of advisor VA quartile (with the bottom quartile as the baseline excluded category) on student outcomes for the academic years 2003-2004 till 2015-2016. All regression include year fixed effects and students controls. All bars represent 95% confidence intervals with standard errors clustered at the advisor-year level.

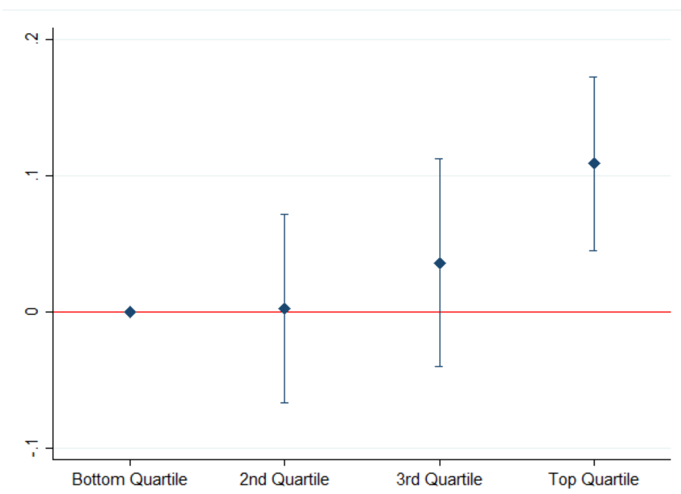
Figure 2: Discrete Treatment on Selective Major Enrollment and Graduation



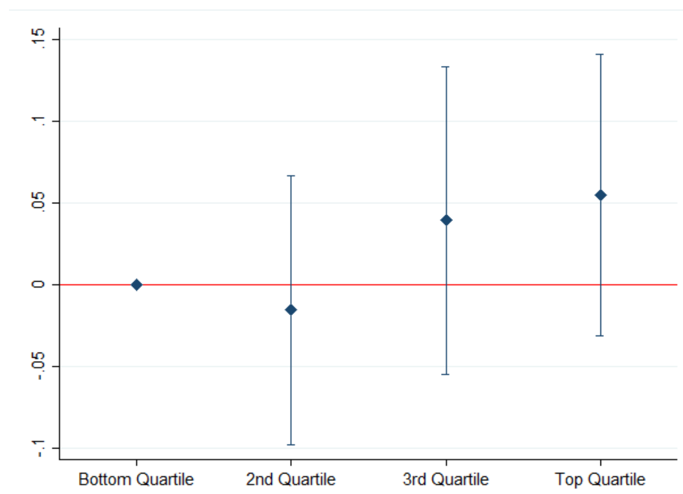
(a) Selective Major Enrollment



(b) Selective Major Graduation



(c) Top Students' Selective Major Enrollment



(d) Top Students' Selective Major Graduation

Notes: The different panels show the impacts of being matched to advisors from different quartiles of the VA distribution. Point estimates represent coefficients from regressions of advisor VA quartile (with the bottom quartile as the baseline excluded category) on student outcomes for the academic years 2003-2004 till 2015-2016. All regression include year fixed effects and students controls. All bars represent 95% confidence intervals with standard errors clustered at the advisor-year level.

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 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

	Test Score
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. 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 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: 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 VA	0.021	0.033
	(0.025)	(0.021)
Associate/Full Professor	-0.044	0.004
	(0.060)	(0.056)
N	131	131

Notes: 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. Sample includes students from academic years 2003-2004 till 2015-2016. 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 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 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 VA	0.048***	0.007	-0.072**	0.022***	0.013
	(0.014)	(0.006)	(0.051)	(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: Standard errors in parentheses are clustered at the advisor-year level. For graduation outcomes, the number of observations decreases as we restrict our sample to students who first enrolled in AUB prior to the academic year 2013-14. 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 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: 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. Enrollment sample includes students from academic years 2003-2004 till 2015-2016. Graduation sample includes students from academic years 2003-2004 till 2012-2013. *** p <0.01 ** p <0.05 * p <0.1.

Table 7: Effect of Advisor VA on Course-Level Student Outcomes

	Take Science Course (1)	Fail Course (2)	Withdraw from Course (3)
A. First Semester			
Advisor VA	-0.002	-0.009***	-0.005**
	(0.004)	(0.003)	(0.002)
Mean Dep. Var.	0.314	0.067	0.053
Course-Term FE	No	Yes	Yes
N	19,669	19,372	19,371
B. Second Semester			
Advisor VA	-0.002	-0.009***	0.000
	(0.004)	(0.003)	(0.002)
Mean Dep. Var.	0.300	0.072	0.048
Course-Term FE	No	Yes	Yes
N	16,523	16,097	16,092

Notes: 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 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: Heterogeneous Effects of Advisor 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: 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. Sample includes students from academic years 2003-2004 till 2015-2016. *** p <0.01 ** p <0.05 * p <0.1.

Table A3: Effect of Advisor 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 VA	0.070***	0.007	-0.081***	0.022**
	(0.018)	(0.008)	(0.028)	(0.009)
B. With Controls				
Advisor 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: 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 A4: Heterogeneous Effects of Advisor VA on College Completion

	Overall Sample	Below Median Math SAT	Above Median Math SAT	Male	Female
	(1)	(2)	(3)	(4)	(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: 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. Sample includes students from academic years 2003-2004 till 2012-2013. *** p <0.01 ** p <0.05 * p <0.1.

Table A5: Observable Characteristics Effect on VA

	Advisor VA
Professor	-0.004
	(0.018)
Associate Professor	0.006
	(0.015)
Female Advisor	0.016
	(0.012)
Science Department	0.005
	(0.010)
N	131

Notes: Standard errors in parentheses are clustered at the advisor level. Regression includes year fixed effects. *** p <0.01 ** p <0.05 * p <0.1.