Applying to International Opportunity: Financial Assistance and Mentorship for Graduate School Applicants from Africa*

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Abstract

Students from lower-income countries face substantial barriers in accessing education abroad, shaping individual opportunity and global talent allocation. In a large sample of African prospective applicants, we document financial constraints, information gaps, and signaling frictions as first-order barriers in graduate school applications. Using a randomized controlled trial with high-achieving African candidates, we study whether application-stage financial assistance and mentorship relax these constraints. Overall, enrollment in Europe or North America nearly doubles from 16% in the control group. The program substantially reduces financial barriers to apply and increases applications on the level candidates are prepared for. PhD applications increase for candidates considered competitive for PhDs at baseline, who are then significantly more likely to obtain funded offers and enroll. Master's applications increase for those competitive at that level, but while they receive more admission offers, these are predominantly unfunded and there is no treatment effect on enrollment due to attendance costs. In terms of further mechanisms, the program does not strengthen the application profiles of candidates. Better mentor advice and advocacy positively correlate with enrollment, suggesting complementarities with financial support.

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Disclosure: All authors have been involved in leadership capacities at the organization studied (GAIN). Samira Adhar co-led the GAIN mentoring program from 2020–2022. Frank Odhiambo is a co-founder of the program, has been involved in mentor management in the past, and has led various webinars over recent years. Konstantin Poensgen co-led the GAIN mentoring program from 2021–23 and has led webinars on the GRE and graduate school options, and is currently a co-organizer of the Economics Mentoring Program (EMP). All authors are currently on the advisory board of GAIN. None of the authors have been involved in the active management of the program since the start of this study..

1 Introduction

International education promises large opportunities for students from developing countries. It provides access to high-quality tertiary education (Bound et al., 2021) and yields substantial income gains (Clemens, 2011). For instance, Gibson and McKenzie (2012) find that about two-thirds of high-achieving emigrants from Ghana obtained a graduate degree abroad and experience annual real income gains of about $34,000. Human capital accumulation, diaspora networks, knowledge diffusion, and return migration may also create large positive spillovers in the origin countries (Batista et al., 2025).[1] However, students from lower-income countries face prohibitive constraints to these opportunities, such as outsized application costs relative to local incomes, a lack of networks abroad to help navigate hidden information about the application process, and frictions in signaling their skills due to less developed or recognized education systems. In this paper, we study the role played by these constraints in shaping access to graduate education in Europe and North America through the lens of a comprehensive application-support program for high-achieving students from across Africa.

The focus of our paper is a randomized control trial in partnership with the *Graduate Applications International Network* (GAIN), which assists high-performing students from across Africa for international applications to graduate programs in economics. The program matches participants to a mentor, who accompanies them through the application process, and covers a range of application costs. By paying for application fees, the program could be effective if financial constraints restrict applications. Mentorship may increase admissions by shifting applications toward better matched schools or degrees, or by strengthening materials. Mentors may also use their networks to help overcome signaling frictions if applicants' home institutions are less recognized. On the other hand, if structural deficits in the education pipeline in lower-income countries, such as the quality of undergraduate education, lead to insufficient preparation and competitiveness, then a program at the application phase might be too late-stage to increase graduate school enrollment abroad. Moreover, high attendance costs may ultimately render increases in applications and admissions ineffective.

We proceed in three steps. First, using micro-level data on the census of US doctorates and cross-country data from the OECD, we establish that a small share of international doctoral students in North America and Europe come from Africa to date. We then document first-order barriers in the application stage in a large sample of prospective African applicants. Finally, based on random admission among a subset of high-performing candidates from across Africa, we study the effects and mechanisms of the GAIN mentoring program. A strength of our paper is extensive data on each step of the application-to-enrollment pipeline, including from multiple survey rounds, application materials, school-level information, administrative program data, and detailed mentor surveys.

To understand the scale of these representation gaps, we first document facts on doctoral education for international students. About one-third of US doctorates are awarded to international students across disciplines. Economics, the context of our study, is particularly international with about two-thirds of doctorates awarded to international students between 2000 and 2019, but only 2% awarded to Africans. This share is similar to that in most other fields in the US and doctorates awarded to African scholars across fields in Europe (2.5%). While disproportionately few doctorates are awarded to Africans compared to their population share, the number of doctorates awarded to Africans is consistent with

[1] International education may also generate large positive externalities for the destination country. As a major channel of high-skill international migration (Amornsiripanitch et al., 2021; Ganguli and MacGarvie, 2025), international education and mobility of scholars can promote innovation, entrepreneurship, and productivity in the destination country (Kerr et al., 2016; Chodavadia et al., 2025), including in the sciences (Borjas and Doran, 2012; Moser et al., 2014).

the cross-regional relationship between international doctorates and college-educated population. This may signify broader deficits in the education pipeline, which could contribute to limiting access to international graduate education. Amidst this, we ask whether a shorter-term and later-stage intervention can still meaningfully increase access to graduate opportunities abroad.

Next, we document substantial barriers in the graduate school application process for high-achieving African students. They align with barriers found in national settings, including financial constraints, informational gaps, and academic constraints (Long and Riley, 2007), and likely apply to other developing regions given their generality. First, we survey a large sample of aspiring graduate applicants in economics from across Africa. The financial cost of applying are first-order. Application costs—including standardized tests, application fees, and transcript evaluations—sum to about USD 2,400 at the average mentor recommendation of 15 applications, representing almost 85% of prospective applicants' annual income. Informational gaps are also meaningful, especially on nuanced topics that may be communicated informally, such as the relative importance of standardized test sections, or how many programs applicants often apply to. We also survey GAIN mentors, who underscore how structural deficits in undergraduate training result in weaker application profiles. For instance, prior degrees and research experience at African institutions tend to be less recognized, and admissions committees appear to be less familiar with African institutions and letter writers.

We then study the impact of a high-touch application-support program in partnership with GAIN. The organization offers a three-month webinar series on the graduate school application process in economics, implicitly focusing on programs in Europe and North America. This is followed by a mentoring program that bundles one-on-one mentorship, standardized test resources, and financial assistance for application costs. Mentors are graduate students, professors, or researchers, primarily in Europe or North America. Our evaluation is based on random admission to the mentoring program for a subset of applicants. Candidates who completed the organization's webinar series are eligible to apply to the competitive mentoring program, and GAIN directly admits the most outstanding candidates. In collaboration with us, GAIN then randomly admitted a set of highly qualified candidates in a "middle group" to fill remaining slots. These candidates are all above the high bar of the program, but have less application-related credentials than those admitted directly. The treatment and control group include 66 and 56 candidates, respectively, pooling program cycles in 2023-24 and 2024-25.

We look at the chain of events from submitting applications, receiving admission offers, accepting these offers, to attending a program. The program has large treatment effects across each of these steps. However, there is also a marked decline from receiving offers to actual enrollment. We dive into these two results next by discussing the outcomes in each step of the application-to-enrollment sequence, and the mechanisms driving these effects.

The effect on applications is the most direct impact of the program. Candidates in the treatment group have a 27 percentage point (pp) higher propensity to apply to at least one program anywhere in the world (including predocs). The total number of applications submitted globally increases by 3.9 from 5.6 in the control group. Consistent with the focus of the program, these effects are almost entirely driven by programs in Europe and North America. The propensity to apply to at least one program in these continents increases by 29 pp from a control mean of 0.60, and the number of applications increases by 3.7 from 4.9. Interestingly, there is neither crowd-out nor crowd-in of applications to other continents, including Africa. We thus limit our discussion to programs in North America and Europe.

Looking at applications by type of degree, the propensity of applying to at least one PhD program increases by 14 pp from a control mean of 0.35, and the number of PhD applications by 1.6 from 2.1 (p-value 0.104). There is no extensive margin effect for Master's programs overall, but the intervention still raises the number of Master's applications (by 1.8 from 1.9). This masks important heterogeneity across two types of candidates. As part of the admissions process, GAIN determines whether a candidate's profile is suitable (or "competitive") for Master's or PhD programs, which is then communicated to mentors but not to mentees, and is a non-binding assessment. Interestingly, the increase in PhD applications is fully driven by PhD-suitable mentees, whereas the converse holds for Master's applications. Fewer students apply to predoc programs (control mean 0.21) with no significant treatment effects. We match school-level information on submitted applications to a global ranking by *RePEc* and a US ranking by *US News*, and find that applications increase throughout the school-rank distribution.

The increase in applications shows the program effectively relaxes frictions at the stage of applying. However, constraints such as having a less competitive profile may limit the reach of these gains if applications do not translate into admission offers. Promisingly, the intervention more than doubles the propensity to receive at least one admission offer by 29 pp from a control mean of 0.28. The treatment group receives about one additional offer on average compared to a control mean of 1.15. The funding status of these offers is pivotal given the significant barriers posed by the cost of attendance (Dynarski et al., 2023b). On the one hand, treated candidates are 14 pp more likely to receive a fully-funded PhD offer compared to a control mean of just 0.02. On the other, there is no treatment effect on funded Master's offers, while unfunded Master's offers double from a control mean of 0.17. These effects can again be decomposed by the competitiveness assessment, with PhD-suitable candidates driving the effect on (funded and unfunded) PhD offers and Master's-suitable candidates explaining the effect on unfunded Master's offers. There is no effect on being offered a predoc position.

Barriers such as the cost of attendance, visa-related frictions, relocation costs, or commitments in the home country may still hinder applicants from enrolling abroad even after receiving admissions offers. Despite these constraints, the program nearly doubles attendance, with a treatment effect of 15 pp from a control mean of 0.16. This effect is driven by schools in the top 1-5% of the *RePEc* ranking. Moreover, the enrollment effect is almost entirely driven by fully-funded PhD programs, which increase by 12 pp from a control mean of just 0.02. In contrast, while 15% of the control group end up attending a Master's program, there is no treatment effect (neither positive nor negative) on attending Master's programs. Consistent with the previous heterogeneity, these treatment effects align with baseline program suitability, with attendance being almost entirely driven by the PhD-suitable candidates. There is no increase for predoc programs. To investigate how persistent these attendance effects are, we use participants' publicly posted information on LinkedIn and find that enrollment persists for at least one to two years into the start of the degree programs at the time of this study.

While we find large effects at each stage, the trends in treatment effects also reveal leakage from receiving an admission offer to enrollment, since a large share of offers does not convert into actual program attendance. While 67% in the treatment group receive at least one offer, 33% end up attending a program. This gap is driven by unfunded Master's offers, which participants accept and attend less often. When asked about why respondents are not attending programs despite having received an offer, the vast majority listed the prohibitive cost of attendance as the primary reason. This highlights the complementarity between application-stage support and financial aid for tertiary education.

What is driving these treatment effects from applications to enrollment? The increase in applications is likely a core contributor to the downstream impacts on offers and attendance. Further, the program increased admission chances conditional on applying, which could be due to strengthening application materials, improving application strategies, or using mentor networks to advocate for mentees. We combine different evidence to understand these mechanisms. First, our surveys included multiple questions on barriers experienced during the application season, first in an open-ended manner without framing, and then by outlining specific potential barriers and support received. We also collected application materials and asked several questions that allow us to directly measure whether certain barriers are alleviated. We complement this by correlating mentee outcomes with mentoring attributes obtained in the mentor survey to further speak to the role of mentors.

The program substantially lowers financial constraints; while 75% of control group respondents discuss this as an experienced barrier, the treatment group does this 44 pp less often. This is driven by application and standardized test fees. A majority of mentees identify the financial resources provided by the program as extremely important in reducing barriers, which is backed by self-reported measures on application expenses. The intervention lowers the cost per application by USD 56 from a control group mean of USD 78. Despite applying to significantly more programs, total expenses in the treatment group fell by about 45% from USD 366 in the control group.

In contrast, we find no evidence that the program increased the strength of applications. Analyzing the CVs and Statements of Purpose submitted by applicants using GAIN's grading rubric, we find that the quality of these materials is high in both the treatment and control group, and not statistically different. Treated candidates, however, are more likely to list GAIN on their CV, which admissions committees might perceive as a signal. The treatment group is not more likely to have a letter writer from Europe or North America.[2] While there are significant increases in taking standardized tests, there are no differences in GRE or language test scores conditional on test-taking. In terms of where students apply, the average application of a treated candidate targets a somewhat lower-ranked school. However, these differences are small and appear to be driven by increasing applications throughout the distribution. What appears to be more meaningful is the increase in and shift of applications towards degree types (PhD vs. Master's) that matches the right level given applicants' existing profiles.

Informational gaps on the application process, lack of peers, or missing role models are experienced as less important barriers, without statistical differences on these margins. This is consistent with both groups having completed the webinar series with information and exposure to peers and role models.

The analysis so far suggests a primary channel driving our effects is an increase in applications by lowering financial barriers. This should not be interpreted as evidence that mentors do not contribute to their mentees' success. For one, we observe a targeted increase in applications and offers for degrees candidates are considered to be competitive for, possibly due to mentors' advice. Further, it is possible that the financial support is so effective precisely *because* mentors are guiding them through the process and actively support their applications. For instance, according to the mentor survey, one in four put in a good word for their mentee at some institution, and some followed up at the institution where their mentee was waitlisted. This active support can be a very valuable signal given how admission committees might perceive their less familiar backgrounds.

We correlate various mentoring attributes with graduate school program attendance in both the impact evaluation sample as well as the sample of randomly and directly admitted mentees. While

[2]This may be because few mentors act as a letter writer for their mentees, most mentors in the randomization pool are PhD students rather than professors, or the short-term nature of the mentor relationship.

each of these correlations is noisy, consistent results emerge: proxies of higher quality advice (e.g., on the number of applications recommended, the important sections of the GRE, the importance of recommendation letters) and active support are all positively associated with eventual program attendance. In fact, combining mentors' application process related knowledge into a knowledge index is significantly positively correlated with mentee enrollment compared to the control group. These results suggest that mentors can positively shape their mentees' outcomes through the advice they give and by tapping into their networks. In contrast, mentoring characteristics such as PhD granting institution or years of mentoring experience are not statistically associated with mentee enrollment.

In summary, we find that the application-stage support significantly increases graduate program attendance, particularly at fully-funded PhD programs for candidates considered competitive for these programs at baseline. This is largely driven by lowering the financial constraints in the application process, potentially aided by mentor guidance and support, which appear to have a complementary role through their advice and advocacy for their mentee. These results have important implications for universities, which can reduce application costs through systematic fee waivers for students from lower-income countries, and delaying standardized test scores to be submitted through costly official channels at the time of enrollment. Our findings also show the limits of strengthening academic profiles through international Master's programs, especially when financial aid is extremely limited and credit constraints are exacerbated for many African students. Strengthening the pipeline into pre-doctoral fellowships can be a more efficient bridge, although it would require a willingness to train students on the job or at local institutions. The local research offices through networks such as J-PAL, IPA, and the IGC, however, can serve as a strong foundation in facilitating research experiences. These could also help address signaling frictions that mentors might otherwise need to help overcome.

Contributions to the literature. We view our paper as contributing to four strands of literature. First, we contribute to the largely absent literature on higher education for students in lower-income countries. To our knowledge, this paper provides the first experimental evidence on an intervention seeking to increase access to tertiary education in this setting. The closest paper to ours is Cosentino et al. (2019), who compare non-randomly selected beneficiaries of the Mastercard Foundation Scholars Program—mostly from Africa—to non-selected applicants with propensity score matching; they find large increases in undergraduate enrollment abroad. In Ghana, Duflo et al. (2021) find that scholarships which increased secondary high school enrollment let to increased tertiary education for female beneficiaries downstream. There is some causal evidence on access to higher education in middle-income countries, where baseline enrollment and institutional capacity are larger, especially on the effects of financial aid in Colombia (Londoño-Vélez et al., 2020; Laajaj et al., 2022).

Second, our evidence contributes to the literature on access to academia for underrepresented backgrounds, and we emphasize the understudied international dimension compared to minority groups as defined in the US context. Within economics, Bayer and Rouse (2016) discusses prior work on under-representation across several dimensions, such as gender (Dynan and Rouse, 1997; Rask and Tiefenthaler, 2008; Ginther and Kahn, 2021; Auriol et al., 2022), parental education (Stansbury and Schultz, 2023), and race (Price, 2009). Beyond access, Stansbury and Rodriguez (2025) show that first-generation college graduates face persistent disadvantages in their academic careers. Global imbalances in economics are also reflected in a lower representation of scholars from low-income countries in academic journals (Aigner et al., 2025). A few studies have evaluated efforts to increase representation for minority groups in economics in the US (Ginther et al., 2020; Ginther and Na, 2021; Antman et al., 2025). Most related to our study, based on a non-randomized evaluation, Becker et al. (2016) find that a summer training program for undergraduates from underrepresented groups increased PhD enrollment by 40 pp and completion by 26 pp compared to students who applied to the program but did not attend (including those not admitted to the training program).

Third, we draw parallels to the literature on access to tertiary education in high-income country settings, which has primarily focused on college education within the US. There is considerable evidence on the barriers students from disadvantaged backgrounds in high-income countries face applying to undergraduate programs nationally (see reviews in Avery et al., 2014; Page and Scott-Clayton, 2016; Dynarski et al., 2023a). The application stage has featured prominently in this work. For instance, Avery et al. (2014) argue that students submit too few applications, and weight them towards safety schools, which directly affects their chances of enrollment (Smith, 2014). Smith et al. (2015) find that high application fees discourage college applications, with a 10% increase in the fee corresponding to about a 1% decline in applications submitted. We show that students from lower-income countries face additional signaling frictions as universities in lower-income countries are less well-recognized, and applicants' competitiveness may thus be misperceived. There is also an extensive literature on interventions related to ours in higher-income countries, especially for college education in the US, including college-counseling, mentoring and preparation, targeted support for financial aid applications or standardized tests, information and nudges, and those addressing the cost of attendance (see reviews in Page and Scott-Clayton, 2016; Dynarski et al., 2023a,b).[3]

Finally, we document new descriptive facts on African students among doctoral recipients in the US and in Europe. This adds to a smaller literature on the internationalization of higher education. The US, in particular, has seen a large increase in international enrollment since the mid-1970s, driven by a large number of students from China and India, and especially in STEM fields (Bound et al., 2009), as have Australia, Canada and the UK since the 2000s (Bound et al., 2021). However, this literature is silent on students from Africa, likely reflecting their relatively smaller share of international student flows. In part, this small share might be due to demand drivers of international education, such as the college-educated population, the ability to afford education abroad, and policies around work opportunities upon degree completion (Bound et al., 2021).

The remainder of the paper is organized as follows. Section 2 presents new facts on African students among US doctorate recipients. Section 3 provides background on the GAIN program and discusses our overall methodology, including study samples and data sources. Section 4 documents evidence on application barriers. Section 5 presents the impact evaluation of the mentoring program, including empirical strategy, main outcomes, and mechanisms. Section 6 concludes.

2 Facts on African Students Among International Doctorate Recipients

This section contextualizes our study and provides new descriptive facts on African students among US doctorate recipients. The analysis is based on the *Survey of Earned Doctorates* (SED; NCSES, 2024),

[3]For instance, Bettinger et al. (2012) show that assistance with federal financial aid applications increased students' college enrollment by 8 pp. Hoxby et al. (2013) study the impact of providing application information and no-paperwork fee waivers targeted at high-achieving, low-income students, and find that they are 46% more likely to enroll in more selective colleges better suited to their academic background. Carrell and Sacerdote (2017) find that combined mentoring, application fee payments, help on financial aid forms, and a monetary participation incentive increases college enrollment among high school students in New Hampshire by 15 pp. Dynarski et al. (2021) find that providing high-achieving, low-income students in Michigan with explicit information on free tuition (that they are eligible for already) at the state's public flagship university has very similar effect magnitudes to our study on applications and enrollment. Barr and Castleman (2025) show how college advising during high school can increase degree attainment through improved college choice.

which provides an annual census of all research doctorates awarded by accredited institutions in the US. The SED contains information on the fields of research and characteristics of individuals, including on the country of citizenship. We report statistics for doctorates awarded between 2000 and 2019, the year in which the program we study was first initiated. The restricted-use micro data from the SED allows us to document facts on African international students by field, over time, and sub-region. While we do not have data on this granularity in other destination countries, we conclude the section by providing facts on doctorates awarded across fields in Europe based on data from the OECD (2025a) *Education at a Glance* on internationally mobile students.

A sizable share of doctorates in the US are awarded to international students. Across fields, somewhat more than one-third of US doctorates were awarded to international students between 2000–2019. Figure 1a breaks this down by broad fields as defined by the NSF with economics shown separately from the remaining social sciences. Economics stands out as one of the most international fields. About two-thirds of doctorates in economics were awarded to international students between 2000–2019. This share is very similar to the shares in engineering and the information and computer sciences.

African citizens account for a relatively small number of the doctorates awarded in the US. Combined across fields, about 1.6% of all US doctorates between 2000–2019 were awarded to Africans. Figure 1a shows that the share of African students ranges between roughly 1–2% across fields with the exception of psychology (0.3%) and agriculture (4.5%). A total of 2.1% of US doctorates were awarded to African citizens in economics between 2000–2019. Figure 1b shows that this share has been relatively stable during this period. Within Africa, during this period, the composition has shifted towards Sub-Saharan Africa away from Northern Africa.

The relatively small number of doctorates awarded to Africans stands out especially in comparison to the size of Africa's population (Figure 1c). Sub-Saharan Africa, for instance, accounts for about 14% of the non-US population, but only makes up about 3% of the international doctorates in economics. Other negative outliers are Southern Asia and South-Eastern Asia. A positive outlier with higher doctorate than population share is Eastern Asia, driven by US doctorates awarded to Chinese students. While striking and unambiguously showing an under-representation of Africans relative to its share of population, this can be viewed as an unfair benchmark given different extents of college education across regions. In fact, Figure 1d shows a strong positive association between the number of doctorates in economics and a region's college-educated population. This points toward a systematic issue in the pipeline leading up to graduate education, which requires preparation at the undergraduate level.

How do these numbers compare to doctorates awarded in Europe? Over 2013–2019,[4] about 24% of doctorates were awarded to international students, somewhat below the share in the US. This number differs substantially across countries within Europe; for instance, less than 2% of doctorates in Greece were awarded to international students, 11% in Germany, 19% in Belgium, 39% in France, and 56% in Switzerland, to name a few. Across Europe, about 2.5% of doctorates were awarded to Africans, which is in the same order of magnitude as the corresponding share in the US. Again, there is substantial heterogeneity across countries. For instance, about 3.9% of doctorates in the UK were awarded to African students, which is especially interesting since it might be the most comparable and international setting to the US in terms of the university system and language. An interesting outlier is France with almost 11% of doctorates awarded to Africans. This larger share may be explained by several co-operation agreements and partnerships that France has set up with African countries

[4]The OECD *Education at a Glance* data on internationally mobile students is available from 2013 onwards.

through an initiative called *Campus France* (OECD, 2025b).[5] This highlights the potential of increasing access to graduate education abroad through dedicated and targeted interventions.

The intervention we study attempts to increase the pipeline of students from across Africa into the economics profession. Given the small number of African students among US and European doctorates to date and its large share of global population, this appears highly relevant. The program we study focuses on a viable strategy in the short-term by supporting current graduates from across Africa in their graduate school application to programs in the Global North (primarily Europe and North America). The correlation between doctorates and college-educated population signifies it is non-trivial ex-ante how effective such support will be if underlying pre-application constraints are binding. However, as we document in section 4, there are substantial barriers in the graduate school application process, which suggest that application-support could be an effective tool to increase the number of doctorates even in the short-term.

3 Background and Methodology

This section begins by providing details on our study partner, and the program they run for prospective graduate students from across Africa. We then discuss our study samples and data.

3.1 Program Background

Our study is carried out in partnership with a comprehensive graduate application support program run by the *Graduate Applications International Network* (GAIN). The organization's goal is to strengthen the pipeline for African students into graduate economics, thereby improving the representation of African scholars in the profession. The organization's sequential three-part program offers qualified students (i) educational webinars, (ii) personalized mentoring coupled with targeted financial assistance to help them gain admission into competitive graduate programs in economics, and (iii) continued mentoring and peer support during graduate studies.

The program has grown substantially since its founding in 2019, with the number of registrants increasing every year. For instance, around 2,000 participants registered for the webinar series from countries across Africa in 2025; a smaller fraction of this group attends these webinars regularly. Participants are recruited through social media outreach, research networks and programs at African universities, and personal networks or word-of-mouth. Figure A.1a shows a map of the nationalities who registered for the webinars in 2025. While program participants are from countries across all of Africa, the program tends to attract large shares of applicants from Nigeria, Ghana, and Kenya.

Webinar Series

The first phase of the program is a 10-part webinar series that takes place in the spring and covers key aspects of graduate applications in economics, such as information about application components, scholarships and funding options, standardized test preparation, as well as balancing personal responsibilities during graduate school.[6] Featured speakers include professors, graduate students, GAIN alumni, and representatives from organizations such as *PREDOC.org* and standardized test preparation firms.

[5] Data from UNESCO Institute of Statistics (UIS) on international student flows on the tertiary level overall suggests that about half of the African students in France are from Northern Africa.

[6] Specifically, the ten webinars are: (1) information session and general application process; (2) graduate school options; (3) GRE session I; (4) statement of purpose and CV; (5) GRE session II; (6) scholarships; (7) chair-based PhD positions; (8) letter of recommendation; (9) predoctoral fellowships; (10) closing session.

The webinar series is designed to have a low barrier for entry and is open to anyone interested in applying to graduate programs in economics and related fields, regardless of their level of preparedness. Despite the low entry-barriers, the self-selected webinar participants are high-performing students from across Africa: In 2025, 43% of prospective applicants report having completed their degree in the top 5%, 26% in the top 5–10% range, 12% in the top 10–15%, and another 11% in the top 15–20%. Active participation in the webinar series includes regular attendance and submitting assignments associated with each webinar. Successful participants receive a certificate of completion.

Mentoring Program

The mentoring program pairs participants with a mentor, typically a doctoral student or faculty member experienced with the admissions process at their target universities, or an economics researcher at an international organization. The role of the mentor is to support them in choosing suitable programs, putting together a strong application package, and preparing for standardized tests. Mentors are advised to meet their mentees once a week, and GAIN offers regular support calls for both groups.

Mentees also benefit from a number of other resources such as financial support for application and standardized test expenses, access to a commercial online GRE study portal, office hours with the GAIN team, and a network of peers applying to graduate programs. The number of application and standardized test score submission fees covered by the GAIN program depends on the candidate's GRE score and range between 5 to 16. Every mentee is eligible for at least one GRE and TOEFL test to be covered, with GRE retakes being subject to approval. On an individual basis, the program also pays for official transcript evaluations which several universities require for African applicants.

To be eligible to apply to the competitive mentoring program, participants have to graduate within the top 20% of their programs and successfully complete the webinar series. The program application mirrors a graduate application, requiring applicants to submit their CV, a statement of purpose (SOP), and mock GRE scores (administered in partnership with a test preparation firm). The team screens applicants using a pre-determined grading scheme and categorizes them into three groups: eligible for direct admission, eligible for random admission, or not eligible for admission to the mentoring program. Each cohort is comprised of the first group and a random subset of the second, depending on the number of remaining slots. The program admits around 70 mentees every year. Applicants assigned direct admission are those with exceptionally strong profiles, who the organization wants to admit with certainty. For instance, as we discuss below, they are substantially more likely than other applicants to have studied outside the African continent. Since there remain too many highly qualified candidates beyond those admitted directly, the organization randomizes admission among the "middle group" in partnership with us. We discuss the randomization procedure in section 5.

In 2025, the structure of the mentoring program changed and was split into two phases. Eligible participants first apply to the *pre*-mentoring phase by submitting an application package in the same manner as before. Successful applicants are then enrolled in a three-month GRE boot camp with access to study materials and support from the team to prepare for the test. Admission into the pre-mentoring program continues to be randomized among the applicants eligible for random admission. At the end of the boot camp, participants take the GRE and their scores determine admission to the mentoring program. The mentoring phase in that program cycle featured two tiers with different application budgets and levels of standardized test support. Given the different admission and randomization procedure to earlier program cycles, this cohort is not included in our impact evaluation. As of early 2026, the pre-mentoring and mentoring program are undergoing further revisions.

Graduate School Support

Even after gaining admission to graduate school, students unfamiliar with the educational and cultural environment face several challenges when studying abroad. To help them have the best chance of success, GAIN offers continued support to ease the transition to life in Europe or North America. This includes frequent peer-organized webinars, guidance from experienced international students, and connections with networks such as the African Students Associations at their universities.

3.2 Study Samples and Data

Our study focuses on the first two parts of the program, the webinar series and the mentoring program. Throughout the paper, we present results from four different samples of program participants across three cohorts; cohort 1 participated in the program from 2023 to 2024, cohort 2 from 2024 to 2025, and cohort 3 from 2025 to 2026. We outline them here in order of the GAIN program sequence, although the study period for the mentoring program evaluation predates the cohort of webinar participants surveyed for some of the analyses on barriers.

Prospective Applicants

We view webinar applicants as the relevant group of prospective graduate applicants who are both interested in applying to graduate school in Europe and North America and have an established academic track record. Since the threshold for initial registration may be too low to infer serious interest, we restrict the set of webinar applicants to those who have filled out a second form a few weeks later (after the first webinar) indicating their intent to participate actively. We surveyed this sample in cohort 3 at different stages of the webinars to collect information on the barriers they face in the graduate application process. A baseline survey for this group was conducted prior to the start of the webinars in January of 2025. Figure A.1a shows a map of the nationalities of this sample.

Pre-mentoring Applicants

A subset of prospective applicants applied to the newly established pre-mentoring phase in cohort 3. We surveyed these applicants in May during the application to the pre-mentoring program.[7] Seven of the ten webinars had been completed at the time, which enables us to assess how their application-related knowledge and preferences changed over that time. We surveyed them a second time in July to test their knowledge after the end of the webinar series.[8]

Mentoring Evaluation Sample

Our study sample for evaluating the impact of the mentoring program consists of participants who applied to the GAIN mentoring program in cohorts 1 and 2 and were assigned to the group eligible for random admission (the "middle group"). Those who were randomly admitted constitute the treatment group, while those randomly not admitted serve as the control group. All causal analyses on the impact of the mentoring program are based on this sample, and we report results for the directly admitted group for comparison where relevant. Unlike for the prospective applicant and pre-mentoring samples in cohort 3, we have less information on the characteristics and knowledge of this group prior to attending the webinar series.

[7] Our survey in the pre-mentoring application was marked as a separate and voluntary research survey. It was made very salient that participating in the study would have no influence on admission into the pre-mentoring program.

[8] This survey was conducted in conjunction with GAIN's own webinar evaluation form, which was voluntary and has lower response rates than the first survey.

Directly and randomly admitted candidates received the same admission messages for the mentoring program. In particular, the randomly admitted group was not informed about them being admitted randomly to avoid any differences to the directly admitted candidates and to not send signals that might be interpreted as lower ranking or fit for graduate school in comparison to the directly admitted candidates. In contrast, the randomly *not* admitted group (the control group) was informed that they were qualified for admission and were part of a randomization due to the program's capacity constraints; they were encouraged to continue applying to graduate school and were given several links to other mentoring programs that could provide support for applications and scholarships.

We administered midline and endline surveys in this sample for both cohorts.[9] The midline survey focuses on applications and preliminary offers and was carried out in April after application deadlines and when almost all admission offers should have been communicated. The endline survey was carried out in October/November to collect updated information on offers, funding, and importantly actual enrollment and attendance. For cohort 2, we administered a baseline survey at the end of the webinar series in May 2024. For cohort 1, however, the same set of "baseline" questions were included in the midline survey. Since the baseline survey covers socio-economic characteristics that are very unlikely to change due to the mentoring program, we still use these variables (such as gender, marital status, number of children) for testing balance of randomization. All surveys were compensated and participation was voluntary for any of the surveys; GAIN program eligibility, admission, and benefits were unaffected by survey participation, which was communicated to the study subjects throughout.

Mentors

Additionally, we surveyed mentors from program cycles spanning 2022 to 2025. Their responses provide a complementary perspective on the barriers to graduate education faced by students similar to their mentees, and offer deeper insights into the mechanisms through which the mentoring program operates. We also administer the set of knowledge questions asked to the prospective applicants and pre-mentoring applicants and use mentor responses to benchmark the answers and characterize mentors' application-related knowledge. Mentors for cohorts 1 and 2 were also asked specific questions about their respective mentees, including whether they actively supported them through recommendation letters, putting in a good word for them at some institution independent of writing a letter, and whether they followed up at an institution when their mentee was waitlisted.

We use administrative program data to supplement our surveys, such as participants' application materials for the webinar series, and pre-mentoring and mentoring programs. For applicants accepted to the mentoring program, we use administrative data on their graduate applications such as the number of paid applications for which they were eligible through the program.

Table 1 reports baseline characteristics for prospective applicants, pre-mentoring applicants, and the mentoring evaluation sample. The mentoring evaluation sample is further disaggregated into treated, control, and directly admitted participants. Notably, directly admitted mentees differ from those in the randomized group in two key dimensions: first, they report nearly double the annual income, and second, they are more likely to have studied abroad and completed a math course at a European or North American university. This second set of differences is expected, since GAIN considers these criteria in their selection process. We discuss balance of randomization in section 5.

Table A.1 provides descriptive statistics for the sample of mentors. The response rate of the mentor

[9] Figure B.1 provides a timeline of all surveys conducted.

survey is approximately 60%. About 40% of mentors are professors and about one-third are PhD students; the remaining mentors are researchers in non-university institutions (e.g., international organizations). About one-third of mentors have been on admissions committees previously, and about 40% hired a pre-doctoral fellow before. About 40% have 3 or more years of mentoring experience.

4 Barriers to Graduate Education

Section 2 documented that Africans make up a relatively small number of US and European doctorates. This section asks whether application-stage frictions could pose significant enough barriers to limit access to these education opportunities in Europe and North America for students from across Africa. These barriers are potentially manyfold and we primarily restrict our discussion to four sets of barriers: financial constraints, informational barriers, perceived competitiveness of candidate profiles, and a lack of role models and peers. Given the generality of the barriers, they likely apply to students from other developing regions that lack access to international education to date. The barriers we study parallel those uncovered in national settings, including financial constraints, academic constraints, and informational gaps and behavioral frictions (Long and Riley, 2007; Page and Scott-Clayton, 2016).

The evidence provided in this section is based on three sources of data. First, we ask program applicants about the barriers that students from their home country face in the graduate application process.[10] This includes an open-ended question prior to any prompting, followed by Likert questions about specific barriers in each of our categories. Second, we seek to substantiate these perceived barriers with additional evidence from survey and administrative data. For instance, a set of application process related knowledge questions allows us to quantify informational gaps. Third, we asked mentors about barriers faced by their mentees to draw on their experiences from the program. We can draw on the fact that many mentors have been on admissions committees before or have hired a pre-doctoral fellow in the past to ask about the perceived competitiveness of African scholars' applications.

To preview the subsequent discussion, we find that financial constraints in the application process are severe and first-order. Informational gaps are also prevalent, especially concerning more specific and potentially "hidden" information. Several pipeline issues affect applicants' perceived competitiveness, especially relating to the fact that their home institutions are less globally known or recognized. Finally, there is a lack of peers and role models, although participants perceive them to be of second-order.

4.1 Financial Constraints

Application costs can pose a substantial barrier to one's educational aspirations. In the US context, Avery et al. (2014) note that application fees can be prohibitive for students from low-income backgrounds. There is also evidence in the US setting that raising the number of free standardized test scores that can be sent to colleges increases enrollment among low-income students (Pallais, 2015; Hurwitz et al., 2017). These barriers extend to students from lower-income countries, who face similar types of costs to the national setting. Typical expenses include application fees, standardized test fees for taking the test and for submitting it to schools through the official provider, and official transcript certifications. Compared to the national setting, standardized language tests and transcript certifications provide additional barriers.

According to administrative data from GAIN in cohorts 1 and 2, the average application fee paid for by the organization for participants in the mentoring program is USD 84. The fee for taking the GRE—a

[10] We report answers from the prospective applicant sample, but results are qualitatively identical across all samples.

standardized test including quantitative reasoning, verbal reasoning, and analytical writing—is USD 220. Reporting a GRE score through the official test provider, which is required for almost all schools that ask for the GRE, costs USD 40 per school (beyond the free four score reports *at* the test center). The fee for taking the TOEFL test—a standardized English language test—varies by country around USD 200. A score report for the TOEFL test is USD 29 per school. A course-by-course transcript certification through WES costs USD 239, including sending the report to schools.[11]

Transcript certification is more often required for applicants from lower-income countries than their high income counterparts, which is a significant added expense. Since there are fewer testing sites for the GRE and TOEFL in lower-income countries, students may have to travel farther and pay for accommodation, all of which are additional costs in the application process. Evidence from the US suggests that the availability of testing sites affects test-taking and college enrollment (Bulman, 2015). Some schools provide application fee waivers, which can significantly lower expenses; however, international applicants may not know that they could request a waiver, and in the US, these are often limited to citizens, and have to be requested on a one-by-one basis. Hoxby et al. (2013) show that no-paperwork application fee waivers can be very effective in increasing applications. Similarly, the GRE fee reduction program is extended only to organizations or US citizens.

Mentors recommend applying to 15 programs on average, which brings the total cost of applications to about USD 2,400 with one attempt each at the GRE and TOEFL. This amounts to about 85% of the average *annual* income of prospective applicants (cf. Table 1). This calculation is conservative since it assumes the first four scores are sent from the GRE testing site for free. This is often not the case since the test taker may not yet know their list of schools or prefer to wait for their official score. It also does not account for any retakes, which are common among applicants from higher-income countries, and may increase scores and admission (Goodman et al., 2020). The calculation also neglects standardized test related travel. Even if applicants secure a number of application fee waivers, remaining costs for standardized tests and transcript certification are still substantial. Participants from the control group in our mentoring evaluation sample on average applied to much fewer schools and spent about USD 500 conditional on applying, largely financed through personal savings, and amounting to 16% of their annual income (see section 5 for a discussion of these results). This underscores the binding financial constraint and that most potential applicants from lower-income countries are far from being able to apply to the (on average) recommended number of schools financially.

Consistent with these large expenses, financial constraints emerge as the most important barrier identified by participants. Figure 2 reports that 80% and 82% of respondents state that fees for applications and standardized tests, respectively, are very or extremely important barriers in applying to graduate school. This narrative is reinforced by 80% identifying information on funding opportunities and scholarships as a very or extremely important barrier.

A potential concern might be that the financial constraints identified by participants are not limited to graduate programs in Europe or North America, but reflect more general liquidity constraints in this sample. Figure A.2 contrasts the extent to which potential applicants are constrained by barriers when applying to programs in Europe or North America as opposed to programs in Africa. While barriers exist for applications to African programs, financial barriers are much more pronounced for

[11] For GRE, see `https://www.ets.org/gre/test-takers/general-test/register/fees.html`. For TOEFL, see `https://www.ets.org/toefl/test-takers/ibt/register/fees.html`; for instance, test fees are USD 170 in Nigeria, USD 225 in Kenya, and USD 255 in Ghana. For WES, see ICAP course-by-course evaluation `https://www.wes.org/evaluations-and-fees/education/graduate-admissions/`. All links were last accessed on April 1, 2026.

applications to European and North American schools, and especially so for application fees. We also view this as an ex-post validation of the quality of the survey responses.

4.2 Informational Barriers

There could be several hurdles in the graduate application process such as knowing how to prepare strong application materials, the number and types of programs to apply to, or how to apply for scholarships, all of which we refer to as informational barriers. This parallels considerations in the national setting as Avery et al. (2014) discuss that students may fail to engage in applications optimally both quantitatively (how many applications to apply to) and qualitatively (where to apply). The prospective applicants we surveyed perceive a lack of information about the application process as the second most important barrier, as shown in Figure 2.

Before the webinars, we asked participants to rate the importance of various elements of graduate school applications. While there is substantial heterogeneity, Figure A.3 shows that respondents tend to understand the relative importance of application components. For instance, 73% and 83% of prospective applicants consider the quantitative section of the GRE and letters of recommendation, respectively, as very or extremely important. In contrast, only 38% and 45% view coding experience and the diversity statement as very or extremely important in a graduate school application.

However, there are still substantial knowledge gaps among both prospective and pre-mentoring applicants as documented in Table 2. Comparing answers indexed across components, the prospective applicants differ considerably from the modal mentor answer (column 1), and seem to be less aware of certain nuances. For instance, 62% believe that the verbal section of the GRE is very or extremely important, compared to 35% in the mentor survey.

We then probe their knowledge of aspects of the application process beyond its components. On average, prospective applicants answer 52% of several true/false questions correctly, compared to 81% for mentors (column 2). For example, 57% of the prospective applicants incorrectly think that a strong letter of recommendation for a PhD application *primarily* discusses classes taken and grades achieved in them (compared to 7% of mentors). They also underestimate the number of programs one may need to apply to in order to succeed in securing an offer of admission. While the average mentor recommendation is 14.9, prospective applicants report an average of 5.7 applications (column 4).

Thus, while applicants show an understanding of the broad strokes of the application process, they appear to lack knowledge of more specific or nuanced elements. This pattern lines up with the idea of there being a "hidden curriculum" for graduate applications, which is not explicitly taught and harder to obtain for students without prior access to academic spaces in higher-income countries.

4.3 Competitiveness

An applicant's academic background is another important factor that likely influences their chances of gaining admission to competitive graduate programs abroad. Several factors could negatively impact African candidates' competitiveness relative to their peers, such as academic institutions from their home countries being less recognized by admission committees abroad, having letter writers who may not be familiar with the norms for writing a recommendation, the letter writer being less able to send a credible signal, or lacking the coursework that adequately prepares them for graduate level economics.

Figure 3 shows that almost 80% of mentors agree with the statement that graduate admission committees disregard applicants from African institutions because they are personally unfamiliar with the institution, and that they perceive these institutions to be less recognized or prestigious. Mentors also highlight applicants' letters of recommendation as a potential obstacle, with 92% of mentors agreeing that letter writers from African institutions are less known to committees abroad, and 68% agree that they are not aware of the norms of writing strong recommendation letters for international programs.[12] Similarly, about 72% of mentors also believe that African applicants don't have as much recognized academic research experience, which could also affect the strength of their recommendations. Assessing African applicants' preparedness for coursework, however, only 39% view them as less prepared for graduate courses than applicants from Europe or North America.

Prospective applicants, however, view a feeling of not being competitive for schools abroad as a less important application barrier compared to financial and informational barriers (Figure 2). This could be due to overestimating their own application chances, or adequately targeting schools that match their profiles. Here, it also important to reiterate that the sample of prospective applicants consists of candidates who are self-selected on their interest in applying to graduate school, so we would not pick up if a self-perceived low competitiveness suppresses graduate school intentions altogether.

4.4 Role Models and Peers

Even highly qualified low-income students may not apply at the same rate to selective schools as their equally qualified, high-income peers (Pallais and Turner, 2006). One reason for this might be a lack of role models and peers at institutions abroad, in turn affecting their aspirations to apply to these graduate programs. In the US, peers have been found to be important in where students apply (Walton and Cohen, 2007; Hoxby et al., 2013) and network effects appear to contribute to locational decisions in international education (Beine et al., 2014).

Figure A.4 shows that 51% of prospective applicants report to not know anyone who applied to a program in Europe or North America within the last two years, and 54% have no one they know who studied there in the last 5 years. On average, prospective applicants have 1.7 contacts who, respectively, applied to or studied in Europe or the US recently. Further, at baseline, 62% of prospective applicants did not even know anyone else participating in the GAIN webinar series. This suggests that limited peer networks could negatively shape graduate school applications among African students.

At the same time, prospective applicants perceive these aspects as only moderately or less important obstacles to graduate applications (Figure 2). It is possible that these self-reported measures understate the extent of the barrier, especially in a sample of students that already expressed interest in applying to graduate school in Europe and North America. However, given the magnitude of the financial constraint, in particular, the self-reported relative ranking by the prospective applicants seems plausible.

5 Impacts of Financial Assistance and Mentorship

This section provides causal evidence on the impact of the comprehensive application-support program run by GAIN on participants' application outcomes. We begin by outlining our randomization and empirical strategy (section 5.1). We then present positive treatment effects on applications, admission offers, accepted admission offers, and attendance (section 5.2). Finally, we discuss the extent to which different mechanisms can help explain these positive effects (section 5.3).

[12] Participants of GAIN have reported challenges in securing letters at their home institutions, including non-personalized letters, being asked to draft the letter, or letter writers not being willing to send the letter to many schools.

5.1 Empirical Strategy

Once participants apply to the mentoring program, those who meet the selection criteria are assigned to groups eligible for either direct or randomized admission. Applicants in the latter group are admitted through a random selection process that is stratified by gender, degree competitiveness (PhD/MA), and baseline GRE score, forming our treated and control groups. The strata are cohort specific reflecting distinct randomization across program cycles. Appendix B.1 provides further details on the randomization protocol.

Balance of Randomization

We test for finite sample balance across baseline characteristics such as gender, age, marital status, number of children, income, and variables related to both graduate school and GAIN program participation, controlling for strata. Using administrative data on participants' application to the GAIN mentoring program, we assess whether baseline application components are balanced across groups. Table B.1 presents these results, confirming balance between randomly admitted and non-admitted respondents based on application data in column (1) and survey data in column (2). Specifically, the treatment and control groups appear balanced both for individual coefficients and in joint hypothesis tests assessing balance across *all* characteristics.

Survey Attrition

Table B.2 presents the balance of attrition across treatment and control groups. Column (1) reports attrition for the baseline characteristics survey, while columns (2)-(4) show results for the midline and endline surveys on applications data, both separately and combined. Survey participation is generally high with 86% of the mentoring evaluation sample completing the midline survey and 86% completing the endline survey. While treated participants are slightly less likely to respond to the baseline survey, attrition is balanced in the midline and endline surveys. Given the sequential application process and several repeated questions, we can also combine the midline and endline surveys on many of the outcomes.[13] Combining these two surveys, overall attrition is 6%.

In addition, Table B.3 checks for balance between attritors and non-attritors across several characteristics from the GAIN application data, such as their overall rank, mock test scores, and scores for their CV, statement of purpose, and transcript. There is generally no evidence of differential attrition based on these characteristics across groups in the midline or endline survey. The exception is that randomly admitted candidates who respond to neither the midline nor the endline survey have a one-point lower GRE verbal score, which is not a meaningful magnitude in practice.

Empirical Specification

Our main specification estimates the impacts of the mentoring program using the following equation:

$$Y_i = \alpha_0 + \alpha_1 Z_i + \lambda_i + e_i, \tag{1}$$

where Y_i denotes an outcome, $Z_i \in \{0,1\}$ is random admission to the GAIN mentoring program, and λ_i denotes the cohort specific strata (gender × MA/PhD competitiveness × above/below median GRE). The key coefficient of interest, α_1, captures the intent-to-treat (ITT) effect of the comprehensive

[13] Following our pre-analysis plan, when a respondent indicates not having submitted any applications in the midline survey (which takes place well after the main application season) and does not fill out the endline survey, we then infer that the respondent has also not accepted any application offers or is not attending a new program. Similarly, when a respondent indicates no offers in the midline, we infer no attendance for missing endline data.

application-support program conditional on strata.

We also test for heterogeneous treatment effects using the following specification:

$$Y_i = \beta_0 + \beta_1 Z_i + \beta_2 Z_i \times X_i + \beta_3 X_i + \lambda_i + e_i, \tag{2}$$

where X_i are different baseline characteristics. We report heteroskedasticity robust standard errors.

Compliance with random assignment is high. A subset of randomly admitted candidates ends their program participation during the course of the program, some of whom have received other opportunities and some who may no longer wish to apply to graduate programs. This is an outcome which we would expect to occur in the control group as well. In cohort 1, two randomly not-admitted candidates (who are in our control group) were added to the program by GAIN shortly after the randomization stage. In line with the actual randomization outcome, we code these as $Z_i = 0$; we note that they have submitted multiple applications paid for by the GAIN program, biasing our treatment effects downwards.

5.2 Effects on Main Outcomes

The ultimate goal of the program is to improve the pipeline into the academic economics profession. It attempts to do so through comprehensive support of graduate school applications. The immediate outcome of the program is thus applications. Ideally, applications then translate into admission offers, which students accept and eventually attend (enrollment). Figure 4 shows that the program has large positive treatment effects on each of these stages, ultimately almost doubling attendance. At the same time, there is a marked decline at each step in the pipeline, showing that a large number of admission offers does not materialize into attendance. The following discusses the impacts on each step in detail.

Submitted Applications

The program we evaluate provides high-touch support for graduate school applications leading up to and during the application phase. This includes one-on-one mentoring and payments of multiple application fees. How effective are these resources in increasing applications? In asking this, it is worth reiterating that both the treatment and control groups had participated in the preceding three-months webinar series (an information treatment) and have an almost complete application package prepared several months ahead of the first deadlines from the application to the GAIN mentoring program.

Table 3 shows the main treatment effects on submitted applications. The program raises the propensity to apply to at least one program anywhere in the world by 27 percentage points, or by 44% compared to the control group mean of 0.62 (column 1, panel A). The relatively high control group mean reflects their level of preparation and commitment to pursue graduate studies. The number of applications submitted increases by 3.8, compared to the control group mean of 5.6 applications (column 1, panel B). These effects are driven almost entirely by applications to schools in Europe and North America (column 2). Indeed, Appendix Table A.3 shows that there are no treatment effects on applications to any continent other than Europe and North America. This is consistent with an implicit focus of the application-support program on schools in Europe and North America.[14] Accordingly—and as pre-registered—we focus primarily on outcomes for schools in Europe and North America.

[14] The program could potentially shift applications from local institutions in Africa to those abroad. Appendix Table A.3 shows that this does not appear to be the case. While the point estimate of applying to at least one program in Africa is negative (β = -0.07), this estimate is noisy (p-value = 0.38, control mean of 24%), and the point estimate for the number of applications is small, positive, and noisy (β = 0.02, p-value = 0.89, control mean of 0.3).

Columns (3) to (5) of Table 3 break down application outcomes by degree types for Europe and North America. The program increases PhD applications both on the extensive margin (by 14 pp from a control mean of 0.35) and the intensive margin (by 1.60 from a control mean of 2.1; p-value of 0.104). A larger share of the control group is applying to MA programs than PhD programs and there is no treatment effect on the propensity to apply to MA programs. However, the program still doubles the number of applications submitted to MA programs. Finally, more participants in the treatment group apply to pre-doctoral positions, but this effect is not statistically significant. Appendix Table A.4 breaks down these results by Europe vs. North America with positive point estimates throughout.

These results mask important heterogeneity by whether the candidate was considered competitive for PhD or Master's applications at baseline. During the review of mentoring program applications, GAIN assessed the suitability of all applicants for either PhD or Master's programs based on the candidate's level of preparation. This is a non-binding assessment and was not communicated to the mentee. However, the degree suitability was communicated to the mentor.[15] Randomization was stratified on this variable (section 5.1). Figure 5 shows that treatment effects by degree type align strikingly with the initial assessment of PhD vs. Master's suitability.[16] For treated candidates viewed as competitive for a PhD, applications to PhD programs increase significantly whereas applications to MA programs decrease somewhat (not significant). In contrast, for treated candidates assessed as competitive for MA programs, applications to MA programs increase significantly whereas PhD programs decrease somewhat (not significant). This is consistent with mentors helping candidates identify and shift their applications towards the degree type they are most competitive for.

Appendix C discusses outcomes by school rank. The midline survey asked respondents to list the schools to which they have applied to. We match this information to the *RePEc* ranking on the *Top 10% Economic Institutions*, which provides percentiles for the top 10% of global institutions according to the *RePEc* criteria. For robustness, we compare results to the *US News* ranking on the *Best Economics Schools*. Table C.1, Panel A, columns (1) to (3) show that the program significantly raises applications across the school rank distribution. We further discuss in section 5.3 that there appears to be no substantial difference in where the treatment and control group apply to *conditional* on applying.

Admission Offers

The previous set of results showed large treatment effects on applications. However, the discussion on barriers in section 4 revealed significant barriers beyond the application itself, especially concerning candidates perceived competitiveness. A key question is thus whether the treatment group is actually competitive enough so that the additional applications also convert into additional applications.

Table 4 shows the main treatment effects on admission offers in Europe and North America.[17] The mentoring program significantly increases the likelihood of receiving an admission offer by 29 pp compared to a control mean of 28%. Overall, treated individuals receive on average 0.92 more offers than a participant in the control group (control mean of 1.15). Thus, on average, an additional application caused by the program leads to about 0.25 additional offers. While 68% of those who applied in the control group receive an offer, 77% of those in the treatment group do.[18] This is

[15]Specifically, the initial email to the mentor with the mentee's contact detail included information on the "[t]ype of degree GAIN believes they are best suitable for". Candidates had also stated a degree type in their application and this email also included information on the "[t]ype of degree the candidate listed in the application."

[16]Appendix Table A.5 shows the regression results in detail, including for the intensive margin.

[17]Appendix Table A.6 shows there are no treatment effects on admission offers outside of Europe and North America.

[18]The order of magnitude of this comparison depends on how we combine the midline and endline survey. The figures in

consistent with a positive impact of the program beyond simply raising the propensity of applying either through the increased number of applications or through strengthening aspects of the quality or fit of the applications.

The cost of attendance has been discussed extensively as a key barrier to higher education in the literature (Dynarski et al., 2023b). Promisingly, the mentoring program significantly increases the propensity to receive at least one fully funded PhD offer by 14 pp compared to a control mean of 2%. For Masters, in contrast, the treatment effect is almost entirely limited to unfunded offers. Figure 5, panel B corroborates these patterns: the increase in funded offers is fully driven by those candidates considered competitive for PhD applications at baseline, whereas those assessed as suitable for Master's only see increases in unfunded and partially funded offers.[19] Since Masters programs are typically unfunded these patterns may be expected. It does, however, require students to find other means of financing for these programs. This might prove especially difficult in our study sample. First, scholarships are much more limited than university admissions. Second, our study sample—and students from across Africa more general—most likely lack the resources to fund studies through family income or savings, and access to student loans is limited and subject to very high interest rates. We look into acceptances of admission offers and eventual attendance next.

Acceptances of Offers and Attendance

The comprehensive application-support program successfully increased both applications and admissions. This increase is for both PhD and MA programs and matches the initial assessment of MA vs. PhD suitability. Funded offers, however, only increase for PhD programs. The ultimate objective of the intervention is to increase actual attendance. The third bar in Figure 4 shows that the program substantially increases the propensity to accept at least one admission offers. Appendix Table A.7 shows that this holds for both PhD and MA programs. However, Figure 4 also reveals a decline from admission offers to candidates accepting such offers. Accepting an offer should be viewed as one's intent to pursue the degree several months before the program start. The final bar in Figure 4 shows that the treated group is almost twice as likely to actually attend the program a few months in. At the same time, the decline from offers to accepted offers continues, meaning a substantial share of admission offers does not convert into actual enrollment. As we discuss below, this is primarily driven by the cost of attendance for unfunded Master's programs admissions.

Table 5 provides details on the treatment effects on attendance. We measure enrollment a few months into the program, ensuring this reflects students' actual attendance. Overall, the application-support program raises the rate of attendance by 15 pp compared to a control mean of 0.16 (column 1, panel A). Panels B, C, and D further break this down by degree, and show that the treatment effect is entirely driven by PhD applications. Further, the effect on PhD applications comes from university funded admission offers, which group both fully funded admission offers and other scholarships provided by the university itself. In contrast, while the program had significantly increased admissions into and acceptance of MA programs, there is no impact on actually attending these programs compared to the control mean. Here, it is worth pointing out that attendance of MA programs (at 15%) is higher in the control group compared to PhD programs (at 2%).

the main text use the full information from both the midline and the endline survey. If, instead, we limit the information on offers to the endline survey as presented in Table 4 (due to data availability on the chosen breakdown), 47% of the control group participants who applied received an offer vs. 70% in the treatment group.

[19] Treated candidates with PhD suitability are 30 pp more likely to obtain a fully funded offer vs. 8% among the control group candidates with PhD suitability.

Figure 5, panel C confirms the PhD vs. MA results, showing the effect on attendance loads almost fully on the set of candidates considered competitive for PhD programs at baseline. Appendix Table A.8 shows that the program significantly raises overall attendance of programs in North America as well as to PhD programs in Europe. Appendix Table C.1 shows that the treatment effects on attendance are driven by schools in the top 1-5% of the *RePEc* ranking in particular.

What explains the overall decline from admission offers to attendance? Financial constraints have consistently emerged as a major barrier to graduate education, and the total cost of attending a graduate program can be prohibitive for most individuals in our sample. Even accepting an offer typically comes with non-refundable costs regardless of eventual enrollment. Several pieces point to the cost of attendance as the main barrier explaining the decline from admission offers to attendance. First, as discussed, the treatment effect on attendance is almost entirely driven by funded PhD offers whereas the treatment effect magnitudes of unfunded Master's offers do not persist. Second, 79% of respondents who received an offer but ended up not attending listed the cost of attendance among the main reasons for being unable to attend. In contrast, other reasons such as not being able to meet administrative requirements were listed less frequently. Several students also listed not receiving a visa in addition to not having funding, but it is unclear from the survey to what extent students actually attempted to obtain a visa, or whether an actual denial was linked to the unfunded admissions status.

Further Heterogeneous Treatment Effects

To further understand potential factors driving the effects on applications, offers, acceptance, and attendance, Appendix Table A.9 explores heterogeneity across multiple dimensions. We include various characteristics: signals of application quality at baseline (columns 1 and 2), whether a respondent participated in the mentoring program in a previous cycle (column 3), whether they are from one of the countries most represented in the program (Ghana and Nigeria, column 4), gender (column 5), income (column 6), whether they already have a Masters degree (column 7), and their current occupation (columns 9-10). Generally, we do not find heterogeneous effects across these dimensions, although the sample size limits our statistical power.

There are some exceptions to these noisy null findings. First, current research assistants in the control group apply to fewer schools and receive fewer offers, which the program offsets. Income is negatively correlated with offers in the control group, which the program offsets (although the interaction is not statistically significant). The treatment effect for accepting an offer increases with income, but this does not persist for attendance. Finally, students with a higher score in the review of the mentoring program application are more likely to end up attending—which provides a high-level validation of the screening process—but there is no significant treatment effect heterogeneity along this dimension.

5.3 Mechanisms

The preceding exposition has shown large treatment effects on all margins of the application pipeline from submitting applications to attendance. What mechanisms could explain these effects? To answer this, we will explore a number of potential mechanisms broadly mirroring the barriers discussed in section 4. This analysis, however, will rely on information such as the types of schools applied to that are only observed conditional on having applied. We might expect those who submitted a graduate application in the control group to be systematically different from those in the randomly admitted group. For instance, applicants from the control group could have higher levels of income since they are not receiving any financial support for their applications. This kind of differential selection into graduate school applications would distort the subsequent mechanism analysis.

Table A.10 compares observable characteristics for applicants from the treated and control groups, testing for differences in the strength of their baseline materials, demographic characteristics, and prior participation in the GAIN program. Both groups are remarkably similar on average across these baseline characteristics, although there is a higher share of female applicants among randomly admitted candidates.[20] We also see a higher share of applicants from the control group that participated in previous iterations of the GAIN webinars, which might indicate that they are more dedicated to apply to graduate programs and can better utilize the information obtained in at least two webinar cycles.

In accordance with the barriers identified in section 4, we discuss how the program helps to overcome them to pin down the mechanisms driving our effects. We provide evidence from an open-ended question asking our mentoring evaluation sample about the obstacles they faced in their own applications before any explicit prompting, as well as Likert questions outlining specific barriers. To understand more about how the program works, we also ask program participants about the importance of different elements in aiding them through the application process. Complementing these self-reported measures, we use administrative data and other survey metrics to provide additional evidence wherever possible.

Financial Constraints

Section 4.1 documented the significant role of financial constraints in the graduate applications process. The program offers comprehensive financial support that explicitly targets this barrier, such as financial assistance to take standardized tests and covering the cost of application fees. We find that the program is highly effective in reducing application costs, consistent with lowering financial barriers being one of the key mechanisms of the main impacts on applications on the extensive and intensive margin.

When asked about the barriers faced during their own graduate applications in an open-ended question, randomly admitted program participants are significantly less likely by 44 pp to mention financial constraints compared to 75% of respondents in the control group, as reported in Table 6 Panel A.[21] Financial barriers are identified most often by the control group in this analysis, and the program has the largest and only statistically significant effect in lowering them compared to other application-stage constraints. Panel B shows the impact of the program in lowering specific barriers elicited in closed-form questions, and consistently, randomly admitted participants are 25 pp less likely to report application fees as an extremely or very important barrier relative to a control mean of 92%, with similar magnitudes for standardized test fees. Respondents also identify the financial resources provided by GAIN as extremely important in their graduate applications (Table A.11).

Table 7 shows that the mentoring program significantly reduces participants' total application related expenses, especially among respondents who applied to graduate programs. The table shows results for out of pocket expenditure on various application components, excluding costs paid for by the GAIN program. Randomly admitted participants who submitted at least one application spend about USD 256 less compared to the control group mean of USD 423 (column 3). The treated group spends about 24% less as a share of their annual income on their applications compared to the control group at 52% (column 4). This cost reduction is despite the higher number of applications submitted by

[20] There is a higher share of women in the treated group (Table 1) since randomization into the program is stratified by gender with a higher selection probability for women, and the gender differences in Table A.10 can be almost fully explained by the different gender composition in the treatment vs. control group.

[21] Here we specifically identify costs associated only with the applications stage, and do not include mentions of scholarships, funding, or other costs to *attend* graduate programs.

applicants in the treated group.[22] The program saves applicants about USD 56 per application, which is a sizable reduction. The cost savings primarily accrue to personal savings, which is the predominant source of financing for application expenses across groups (Table A.13). The results also highlight that the control group has considerable costs per application despite the availability of application fee waivers at some schools.

Interestingly, a number of mentoring program participants do not exhaust the application fee budget provided through GAIN. Figure A.5 compares the number of application payments mentees were eligible for with the number of fee payments they make through GAIN, and shows that many participants submit fewer applications than they could. One reason for this could be the fact that the program requires participants to request a fee waiver before they approve application fee payments. While the control group applies for fee waivers as well, randomly admitted participants apply at a 24 pp higher rate than them and receive 1.78 more fee waivers on average (Table A.14). However, conditional on applying, there are no differences in requesting or being granted fee waivers.

Information

Section 4.2 documented gaps in prospective applicants' knowledge about the application process before the webinar series took place. We test for improvements in information using the same knowledge measures for the pre-mentoring applicants recorded *after* the completion of the webinars. This is a comparable group to the mentoring evaluation sample since both groups consist of participants who completed the webinar series and submitted an application to be considered for the GAIN mentoring program, although in different years. The evidence in this section is suggestive at best since these differences are not causal estimates and could be explained as a function of time, but the improvements in information were tested in May, well before application deadlines later in the year.

There is evidence that the webinars improve their knowledge since participants' answers statistically significant move closer to the mentor responses for all our knowledge measures in Table 2 (panel B). For instance, the improvement in the application component index (column 1) is in part driven by participants perceiving the quantitative reasoning section of the GRE to be relatively more important than the verbal and essay sections (Figure A.3). They also improve on the true/false questions (see Table A.2 for all questions separately). Finally, they move closer to the mentor recommendation on the number of schools to apply to, increasing their answer from 6.8 to 9.7 on average. However, informational gaps still remain after the webinar series when benchmarked to mentors' answers.

When asked about this as a barrier experienced for their applications, 54% of participants in the control group report that not having information about the application process was an extremely or very important barrier to their graduate applications, and 67% say this about information on scholarships (Table 6 Panel B, columns 13–14). The mentoring program does not appear to reduce perceived information gaps since randomly admitted candidates do not significantly differ from the control group. These numbers appear somewhat high given everyone completed the webinar series, and the one-on-one mentoring in the treatment group. Reassuringly, a lack of information is identified less often by participants in both groups when asked in an open-ended question about the barriers faced

[22] Since these self-reported measures of expenses are noisy and imperfect, Table A.12 shows results from a separate question asking about application expenses paid from different sources, such as personal savings, loans from family or friends, or other similar application support programs. Consistent with the patterns in Table 7 (elicitation by expense category), respondents from the randomly admitted applicant pool spend a lot less on their applications in terms of amounts and share of the annual income. We report Table 7 in the main text with the more conservative numbers and given that recall is likely higher when asked to think about expenses in a specific category.

in their applications, and again treated and control group participants do not differ in their responses (Table 6, column 1). Given the null results on experienced barriers and the preceding extensive webinar series, we view information on the application process as less likely to be a major driver of the large treatment effects observed on applications, especially on the extensive margin of applying.

Application Strength

Section 4.3 discussed application-stage barriers related to applicants' competitiveness. Many of these, such as the institutions attended previously, cannot be addressed by the program. However, one avenue through which it might be having an effect is by making their application materials stronger or providing access to letter writers from more well-known institutions. Mentor support is largely targeted toward helping mentees prepare application materials and providing advice on application strategy, so we evaluate how the program affects participants' application components such as standardized tests, statements of intent, and letters of recommendation. Overall, as the following analysis reveals, the program does not seem to strengthen an applicant's profile, but participants perceive their competitiveness as less of a barrier.

The program increases the share of applicants that take standardized tests, as reported in column (1) of Table 8. Randomly admitted participants are 57 pp more likely to take the GRE at least once, compared to only 29% of the control group ever taking the test. This effect may be expected since the program provides financial support that covers test fees, and helps applicants broaden their set of schools since some require a GRE score to complete an application. Conditional on having taken the test, however, we do not see a statistically significant difference in how they perform on the test. Test takers from the control group have an average score of 153 (out of 170) on the quantitative reasoning section, and randomly admitted participants score about a point higher (column 2). Directly admitted candidates seem to do slightly better on average than the randomization sample, scoring four points higher than the control mean. This lack of effect is somewhat surprising since the program provides participants with study resources, including online test preparation tools, to prepare for the test. Differential selection into test-taking in the treatment and control group could explain this, making it a more complicated comparison. A similar pattern emerges for language tests, with more randomly admitted candidates taking the TOEFL at least once, but, if anything, scoring lower than the control group (columns 3–4).

We collect statements of purpose (SOPs) from our mentoring evaluation sample in the midline survey if they applied to graduate programs, and CVs from everyone, and then evaluate them in the same manner as the GAIN team does when they screen applications for their mentoring program. Conditional on having submitted an application, the quality of both SOPs and CVs of randomly admitted participants does not meaningfully differ from the control group (Table 8, columns 5–6). In fact, we observe a high quality in these materials in both the treatment and control group. A possible explanation for the null effect and the high quality materials is that both groups effectively used the resources and information on CVs and SOPs provided in the webinars, or used other resources available online. However, a difference emerges regarding whether participants list GAIN on their CV (column 8). A sizable share of randomly admitted participants mention being part of the GAIN program explicitly on their CV, which in itself might act as a signal to admissions committees.[23]

[23] We observe almost the same treatment effect magnitudes across the application-to-enrollment pipeline in cohorts 1 and 2 individually. We would expect the signal of GAIN to become stronger over time, which would suggest stronger treatment effects in cohort 2 everything else equal.

Mentors identified letters of recommendation as an important element of graduate applications where African applicants may be less competitive, since their letter writers might not be as well known abroad or unfamiliar with international norms. One way in which the program could overcome this barrier is by providing access to letter writers with experience at European or North American institutions. The bottom panel of Table 8 shows that about 30% of applicants from the control group have such a letter writer, but randomly admitted applicants do not differ significantly from them on that dimension. As an additional comparison, directly admitted applicants are more likely to have a letter writer from Europe or North America, with 54% of candidates reporting at least one such recommender. Corroborating this, very few participants in the treatment group appear to have a GAIN mentor as their letter writer, using information from both the mentee and mentor surveys.

Finally, participants could learn about other ways to strengthen their profile through the program, such as taking additional courses to bolster their transcript or gaining research experience. The final part of Table 8 shows that this is not the case; randomly admitted participants do not differ from the control group on math or economics courses, summer schools, or research and teaching experience.

In the open-ended question posed about barriers to graduate applications, the mentoring evaluation sample identifies several elements related to their application strength and competitiveness (Table 6 Panel A). 42% of respondents in the control group list components like test scores, the quality of their statements, and low grades (combined and reported in panel A column 3) and 21% specifically mention having trouble securing strong letters of recommendation (panel B column 2). Some also mention a lack of program alignment in terms of the courses they took during their undergraduate studies. Randomly admitted participants do not differ significantly from them along any of these margins. When explicitly asked about not being competitive as a barrier to graduate applications, randomly admitted candidates perceive this as less of a barrier compared to the control group (Table 6 in column 18 of panel B),[24] which could be due to the fact that mentor support is largely targeted at improving their application materials. The treatment group is less likely to state that feeling not to belong at target schools is an important barrier (column 19), which could be related to a stronger perception of one's own competitiveness.[25]

Role Models and Peers

Due to the structure of the program, all participants in our mentoring evaluation sample expand their network of peers applying to graduate programs as a result of participating in the webinar series. In line with this, participants in both treated and control groups do not list a lack of peers or role models as a major barrier in response to our unprompted question (Table 6, column 4).

We ask participants specifically about a lack of African professors or students at their target schools, as well as other applicants to these programs, and summarize their responses in column (18) of Table 6 Panel B. Randomly admitted participants are less likely to report a lack of role models as an extremely or very important barrier, although not statistically differently from the control group. The pattern is analogous when asked about the role of other applicants in the perceived barriers to their graduate applications, and conforms to the fact that many respondents in this group have already decided to

[24]The effect on perceiving oneself as not competitive is not statistically significant for the answer choices "extremely important" and "very important." The p-value is 0.108 when we code this as *not* perceiving oneself as not competitive using the answer choices "not at all important" or "slightly important". The middle category for these questions is "moderately important."

[25]The effect on not feeling competitive is again not statistically significant for the answer choices "extremely important" and "very important." However, the treatment group is statistically significant less likely to consider this as a barrier when we code this based on the answers "not at all important" or "slightly important."

apply to graduate programs.

Types of Schools Applied to

Since the program does not appear to have changed the composition of *who* applies, it is interesting to ask whether it has changed *where* candidates apply to conditional on applying. For instance, the mentorship program might shift applications towards lower-ranked schools if candidates are overoptimistic about their admission chances. Alternatively, if it improves the perceived application strength, it might shift applications towards higher-ranked schools. It is then relevant to ask whether a potential shift in the distribution of schools helps account for the treatment effects on attendance.

In short, we view the results from our analysis as not revealing major shifts in where candidates apply despite cautiously interpreting the somewhat lower-ranked average program applied to in the treatment group. Appendix C provides detail on this analysis, which we synthesize here. On *average*, applicants in the treatment group apply to somewhat lower-ranked programs than applicants in the control group. The average application in the treatment group is ranked 0.6 percentiles lower in the *RePEc* ranking and, for US schools only, ranks about 13 ranks lower in the US News ranking (Tables C.2 and C.3). Similarly, the modal rank of schools applied to by a treated applicant ranks 0.8 percentiles lower than the modal school of a control applicant. The difference in the average application appears to be driven by additional applications towards lower-ranked schools rather than differences in the highest-ranked program applied to, increasing the spread of applications (columns 7 to 9, Table C.2). This is consistent with the treatment-induced increase in applications allowing for additional applications that, possibly, in combination with the mentor are partially channeled to additional safety schools. When interpreting these magnitudes, however, it is also important to consider that these rankings are depending on their respective methodologies and are at best noisy in the first place. The somewhat lower averages are interesting, however, in that they allow us to rule out a noticeable shift toward higher-ranked programs. In the US context, Avery et al. (2014) note that many applicants tend to apply to too many "safety" schools, and thus have lower chances of admissions at higher-ranked "match" or "reach" schools.

Section 5.2 showed that the treatment effect on attendance is driven by schools in the top 1-5% of the *RePEc* distribution. Figure C.5, which shows the distribution of school ranks conditional on attending, further reveals that this is concentrated among the top 1-2% in particular. Thus, it seems unlikely that the main treatment effect on attendance is driven by the somewhat lower-ranked *average* application. We cannot rule out, of course, that it has contributed to the increase in offers. Moreover, our sample is too small and the baseline measures of application quality too noisy to test for a better match quality between the applicant and the school, and tests that we have conducted on this are inconclusive.

Role and Contribution of the Mentor

The analyses of mechanisms so far has revealed substantial impacts on lowering the financial barriers of applying, whereas the program does not appear to strengthen candidates' application profile in the short-run. It is unclear, however, to what extent the large treatment effects on the application outcomes presented in section 5.2 depend on the guidance and support provided by the mentor, or could be achieved through financial assistance alone. The heterogeneity in applications by baseline PhD vs. MA suitability already points toward a formative role of mentors in helping target degree types candidates are most competitive for. There are multiple further ways in which mentors can support their mentees during the application phase, and they might directly influence the outcomes of these applications, which we discuss next. Since mentors are not randomly assigned, the following analysis is suggestive and is an important avenue for future research. However, as argue next, a consistent picture still emerges in that better mentor advice and advocating at institutions appears to positively influence whether mentees end up attending a program. This suggests that mentors help overcome both information and signaling frictions. Appendix D contains more detail on the following discussions.

What support are mentors providing?

Mentors and mentees have frequent calls in addition to other forms of regular communication in which they discuss various aspects of the application process. On average, mentors report having about two calls per month during the program that last about 30 minutes each (Table D.1). These patterns do not differ by whether the mentee was randomly or directly admitted, a status that is unknown to mentors but still correlates with observable mentee characteristics. Both randomly and directly admitted mentees report often discussing application materials and strategy with their mentor and getting a lot of feedback on materials and schools (Table D.2). This stands out to much lower levels of feedback received from the letter writers, including in the control group, which suggests mentors are not simply substituting guidance from the letter writers, but provide additional feedback. We also find a positive correlation between what mentors report their mentees struggled with and how much support they have provided (Figure D.1), which we elicited in separate questions. Interestingly, mentors report providing relatively less support on finding scholarships, which mentees struggle with—consistent with the leakage from unfunded offers to eventual program attendance.

Mentors may also directly affect their mentees outcomes through additional support. For instance, 11% of mentors wrote a letter of recommendation for their mentee (Table D.1). Mentors write letters at a somewhat higher propensity for randomly admitted mentees compared to directly admitted mentees; this is consistent with a smaller number of randomly admitted mentees having studied abroad and mentors trying to fill a gap in their mentees' application portfolio. One in four mentors report putting in a good word for their mentee at some institution independent of writing a letter, which is more often the case among directly admitted mentees. Given admissions committee members likely lack familiarity with institutions in Africa (see section 4), this kind of mentor endorsement can significantly help mentees obtain offers conditional on applying. In addition, some mentors have followed up with an institution when their mentee was waitlisted there.

How is the mentor support affecting mentees' program outcomes?

We are interested in understanding how three types of mentoring attributes are associated with mentees' eventual graduate school attendance. First, we include proxies for the quality of advice given by mentors. This includes the number of applications they recommend submitting, their understanding of important and less important elements of the GRE, and their understanding of the importance of the letter of recommendation. Second, we include three types of actions they can take to directly support their mentee, including writing a recommendation letter, putting in a good word at some institution independent of writing a letter, and following up at a school when the mentee is waitlisted. Finally, we include mentor characteristics; whether they were a professor during the mentoring program, whether they had previously hired a predoctoral RA, the rank of their PhD granting institution, whether they have been on an admissions committee, and years of mentoring experience.

Since these results rely on mentor survey participation, we first test whether mentor survey participation is balanced across mentee characteristics. Table D.3 columns (1) and (6) show that this is the case for both baseline application strength and individual characteristics (with the exception of mentees' marital status and number of children). Second, since mentor assignment is non-random, we assess whether mentor assignment is balanced on observables after accounting for the matching process. Mentors from highly-ranked institutions are first assigned to the most promising mentees. We thus control for whether a mentee was directly admitted. Remaining mentors are primarily matched based on mutual field interests with the mentor. Overall, conditional on direct admission status, mentor assignment appears broadly balanced across baseline application strength and individual characteristics (columns 2-5 and 7-10). There are some imbalances along our measures of candidate strength, however, so we will also control for the baseline application measures in the following analyses.[26] Results are robust to adding the baseline individual characteristics as controls (which reduces the sample size).

We perform two types of tests of how mentoring attributes correlate with mentees' graduate program attendance. First, we ask how outcomes of randomly admitted mentees differ with the particular mentoring attribute relative to the control group. Formally, we estimate

$$\begin{aligned} \text{attending}_{ij} = \beta \text{ treatment group}_i + \gamma \text{ treatment group}_i \times \text{mentoring attribute}_j \\ + \eta \text{ mentor response}_j + \xi' \mathbf{X}_i + \lambda_i + \varepsilon_{ij}, \end{aligned}$$

where λ_i is the randomization strata and $\mathbf{X}_i$ is a vector of strength of the application to the mentoring program at baseline. Second, as a robustness check, within the sample of randomly and directly admitted mentees, we ask how program outcomes correlate with the mentoring attribute conditional on direct admission status and baseline application strength. Formally, we estimate

$$Y_{ij} = \alpha \text{ direct admission}_i + \gamma \text{ mentoring attribute}_j + \xi' \mathbf{X}_i + \varepsilon_{ij}.$$

Figure 6 shows results for the first specification and Figure A.6 for the robustness test. While the results are noisy given the combination of a small mentor sample size and variation in the outcome, consistent results emerge both across attributes and the two tests. First, better mentoring advice is positively associated with program attendance throughout. For the treatment vs. control comparison, combining the individual knowledge aspects into a joint Z-score index reveals a statistically significant relationship between mentors' application-related knowledge and mentee enrollment. This pattern is consistent with mentors' ability to positively steer their mentees' applications beyond the information provided in the webinars, and might be due to either filling in any remaining information gaps or helping to operationalize the information received through the webinars. Second, mentees are more likely to attend a graduate program when their mentor put in a good for them at some institution, independent of writing a letter, or followed up with an institution when waitlisted.[27] These results suggest that mentors can be an important part in overcoming signaling frictions when applicants lack the credentials from having studied abroad or having held a competitive research assistant position. The result for letter writers is more mixed, with a positive association in the impact evaluation sample,

[26] We view the imbalances as small in magnitude and partially offsetting each other. For instance, students with a higher CV score are more likely to have a professor as their mentor, but students with a higher transcript score have mentors from lower-ranked PhD institutions. Repeat mentees are more likely to have a professor as their mentor and from somewhat better ranked PhD institutions.

[27] We do not include the waitlist attribute for the impact evaluation sample in Figure 6 since there is only one such case in that sample.

but a somewhat negative correlation among the sample of randomly and directly admitted mentees. Third, certain type of mentor characteristics appear not to be relevant proxies of mentor quality; especially, the rank of the PhD granting institution, whether they were previously an admissions committee member, and years of mentoring experience are not associated with mentees' program attendance. In contrast, whether the mentor previously hired a pre-doctoral RA seems to be a positive predictor of attendance.

While descriptive and noisy, we interpret these combined results as suggestive of the positive roles mentors can play, complementing the financial support provided by the intervention. At the same time, given that we lack information on many mentors, we cannot quantify to what extent the results on attendance are driven by certain mentoring attributes. The results on direct mentor support provided would overestimate their influence if they are positively correlated with unobserved candidate strength, which our baseline application strength measures may not capture fully. Finally, since all mentees received both financial support and a mentor, we cannot answer the question of whether financial support or mentoring alone would have resulted in equally large treatment effects.

6 Discussion and Conclusion

This paper has documented several barriers for students from across Africa in applying to graduate programs abroad, which include financial constraints and a lack of information among the most pressing concerns, as well as pipeline issues that lower a candidate's competitiveness and a lack of role models and peers. We find that a comprehensive application-support program, which includes resources for standardized tests, financial support for application fee payments, and a one-on-one mentor, is effective in lowering these barriers, and as a result increases applications submitted, offers of admission received, and graduate program attendance. The generality of the barriers and mechanisms discussed suggests that the results likely inform barriers faced by applicants from other lower-income countries or underrepresented groups as well, and inform the effectiveness of similar application support programs.

An additional barrier that we have not yet discussed concerns international student policies. Participants from all cohorts note visa-related difficulties as a challenge to their graduate school aspirations. Issuing single-entry visas or imposing additional fees increases the financial burden on international students, provided they can apply for a visa among travel bans. Additional screening rules, increased denials, and long wait times for appointments make obtaining a visa in a timely manner an additional concern. While not explicitly tackled by the program, it seems to alleviate some of these issues for randomly admitted participants (Table 6), potentially through ad hoc support provided by the GAIN team.

The evidence provided speaks to a number of implementable measures that could help make the application process more equitable. To ease the financial burden on candidates, schools could adopt fee waivers more broadly and provide information on how to request them more clearly on their program websites. Admissions committees could allow for standardized test scores to be uploaded unofficially first and only submitted officially through the test provider if an applicant is accepted. Language test requirements are a disproportionate burden for international students, and could be relaxed for applicants from English-speaking countries beyond the Anglo-American world, or those with prior training with English as the medium of instruction.[28] Programs could state which application components carry more weight in their selection criteria more clearly, or provide typical minimum

[28]Many schools only consider undergraduate training, but not Masters programs, with English as the medium of instruction as evidence of fluency.

requirements for reference. Schools could also communicate funding opportunities better, and direct candidates to scholarships earlier in the application process. In terms of the transition to graduate school, relocation costs and visa fees pose an additional obstacle for low-income and international students. Schools could pay out part of their initial financial support up-front to to ease this burden.

The study also highlights the limitations of purely relying on an application-support program to improve access to higher education from lower-income countries. There are structural issues in the education pipeline that need to be addressed much sooner than the graduate applications phase. These include strengthening the undergraduate curriculum, facilitating research opportunities, and promoting exchanges and other connections to the frontier of academic research. These issues might be addressed in part by having more graduates with experience abroad returning to their home countries and bringing back cutting-edge research methods with them, and is an avenue for further research on the longer term impacts of such application-support programs on participants' home institutions.

As a result of these potential pipeline issues, international students aspiring to attend competitive doctoral programs often use recognized Masters' programs to build a stronger academic profile to improve their chances of admission. However, the cost to attend these programs, which largely come without attached funding, can be prohibitive. Thus, assistance in finding funded positions, fellowships, and scholarships remains vital. An alternative to this route is through pre-doctoral research positions, which allow candidates to gain research experience working with professors full-time, while also taking courses to bolster their transcript. These fellowships could tackle several barriers related to an applicant's competitiveness for PhD programs, and have the potential to democratize access to strong letters of recommendation. However, applications to pre-doctoral fellowships tend to be very competitive, highlighting the need to strengthen the research preparation of African students. At the same time, faculty may be willing to train students from less advantaged backgrounds through pre-doctoral positions, rather than requiring extensive prior research experience already.

The suggestive evidence on the role that mentors play in aiding graduate applications highlights another avenue for future research. While we have provided descriptive evidence on a positive correlation between proxies of mentor advice and advocacy at institutions and their mentee's outcomes, understanding the causal effects of mentors and the substitutability or complementarity between financial assistance and mentoring is an open question. Moreover, our study remains silent on how mentor attributes and their match with mentee characteristics—for example in terms of academic interest, gender, or country of citizenship—shape the causal effect of mentors. Beyond the study of mentors, our study opens up interesting future research on the longer-term effects of international education. This and similar settings are well-suited to study effects on individuals' economic outcomes as well the spillovers they generate for their origin and destination country more broadly.

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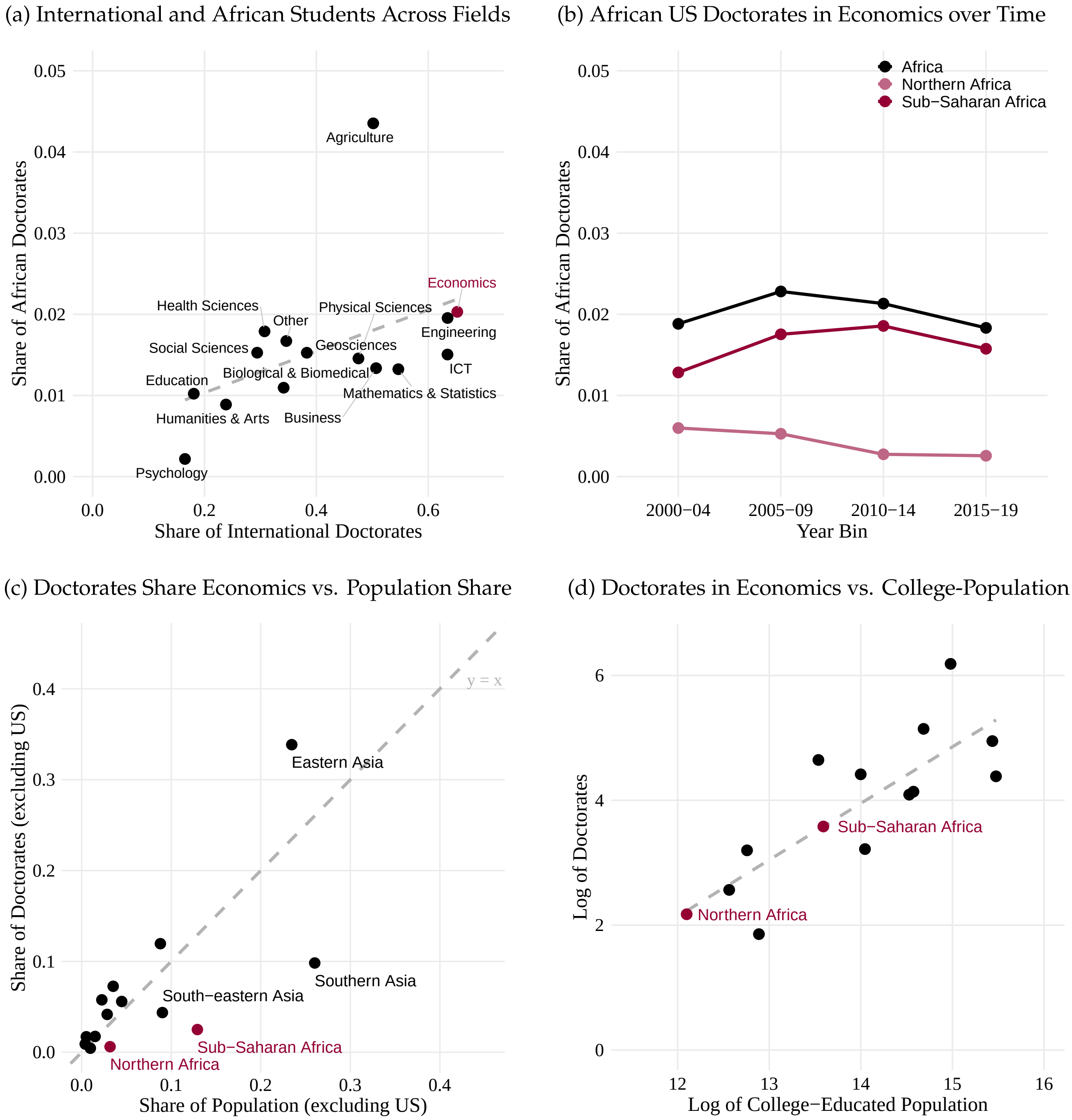
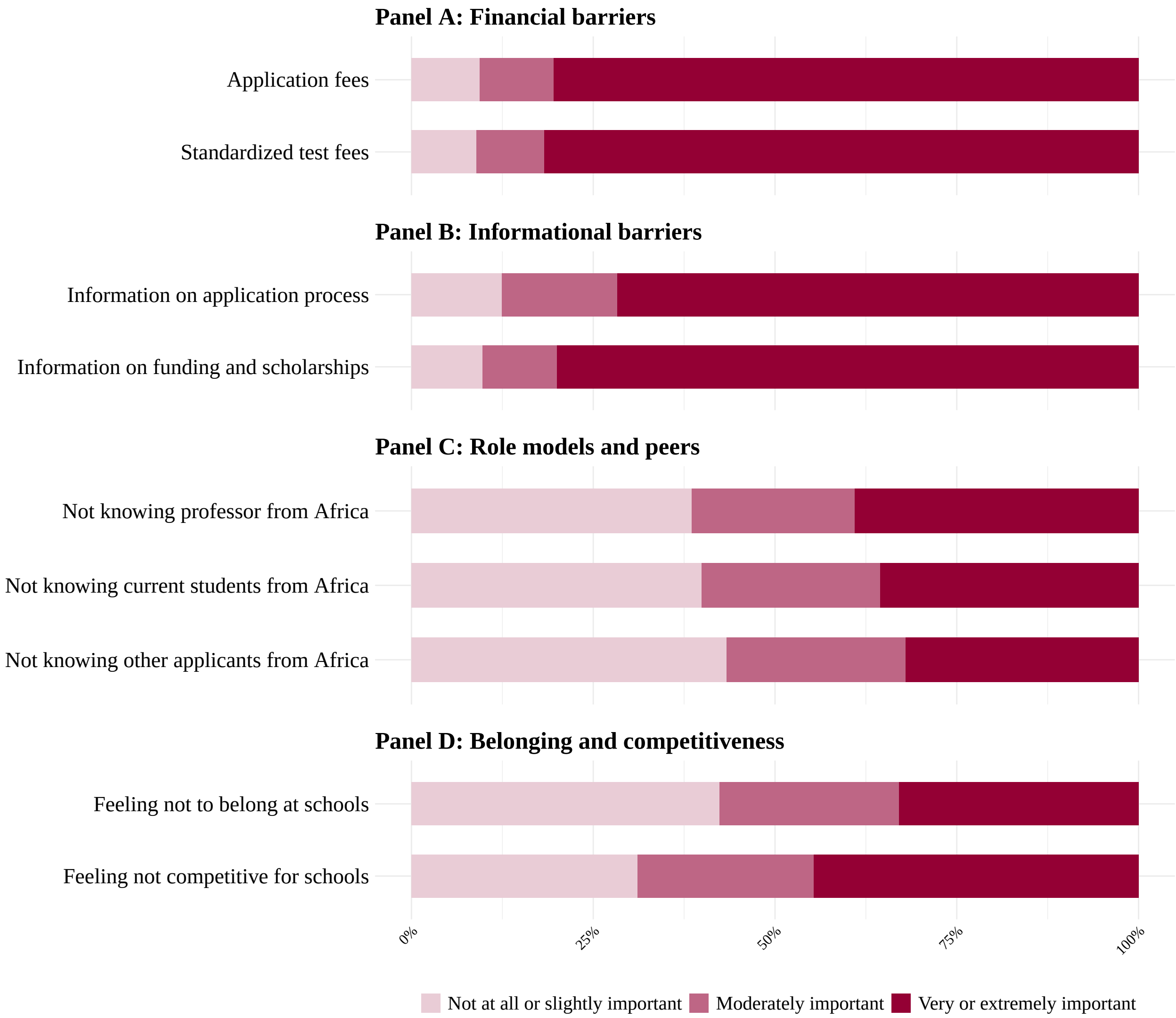
Figures

Figure 1: Representation of African Scholars Among US Doctorates in Economics



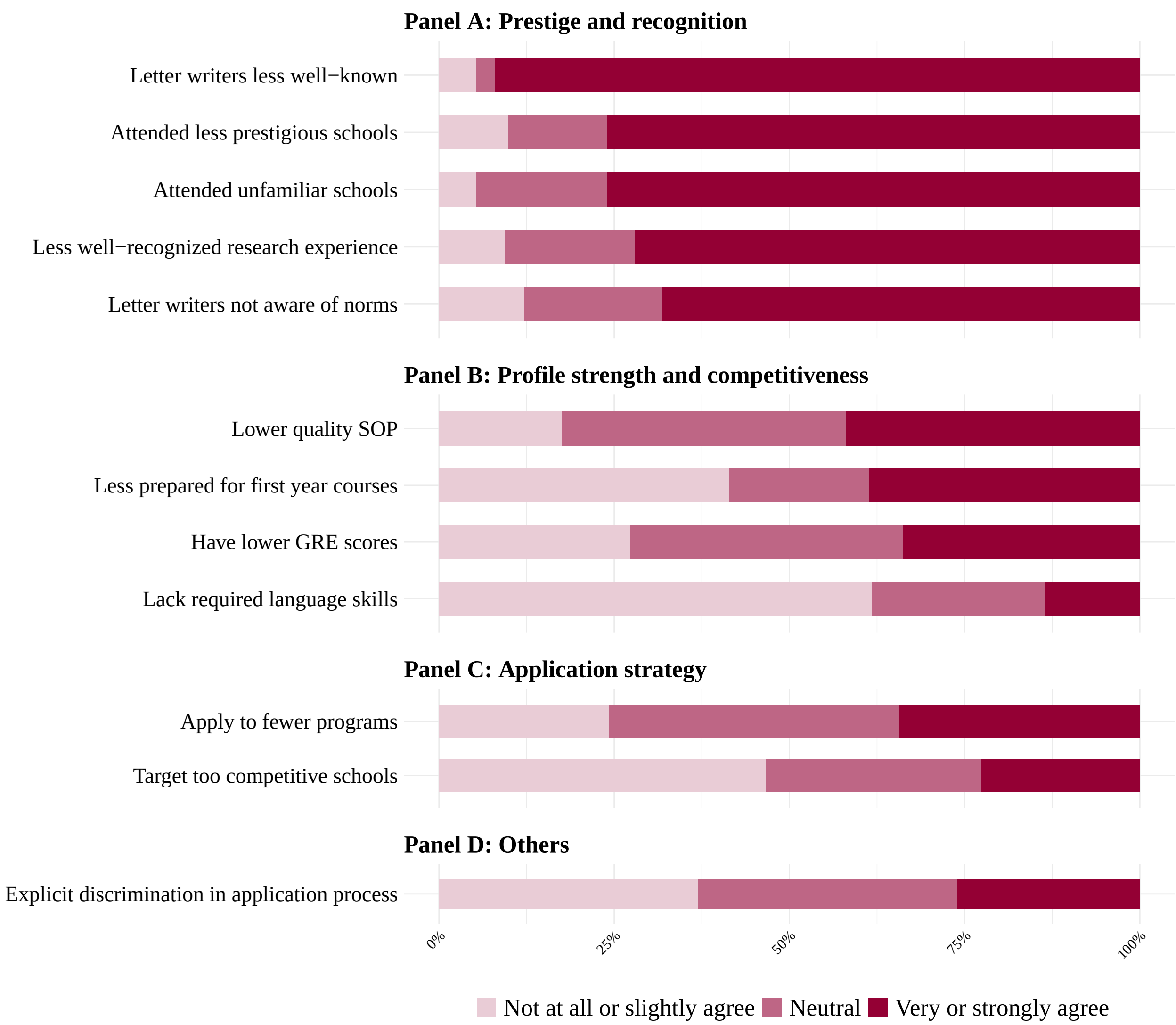
Notes: Shows statistics on African and international students among US doctorate recipients over 2000–2019. Panel (a) plots the share of Africans among all doctorates rewarded in the US between 2000–2019 vs. the share of US doctorates awarded to any international student in this period, grouped by broad fields as defined by the National Science Foundation (NSF) with the exception of showing Economics separately from the remaining social sciences. Panel (b) shows the share of US doctorates awarded to Africans in Economics over time in five-year bins and further decomposes this into doctorates awarded to citizens from Northern Africa and Sub-Saharan Africa, respectively. Panel (c) correlates the share of US doctorates awarded to international students in Economics between 2000–2019 by sub-region as defined by the UN M49 classification vs. the region's international doctorate population share in the US. Panel (d) correlates the log of the number of doctorates awarded by region to the region's log number of college-educated population. In panels (a) and (c), dashed lines are fitted values from a linear model (OLS). Data on US doctorates is from the NSF/NCSES Survey of Earned Doctorates; we define international students in the US to be respondents who are neither citizens nor permanent residents, and assign regions based on citizenship. Data on population is from the UN; data on college-educated population is from the World Bank.

Figure 2: Mentee Perceptions of Potential Application Barriers



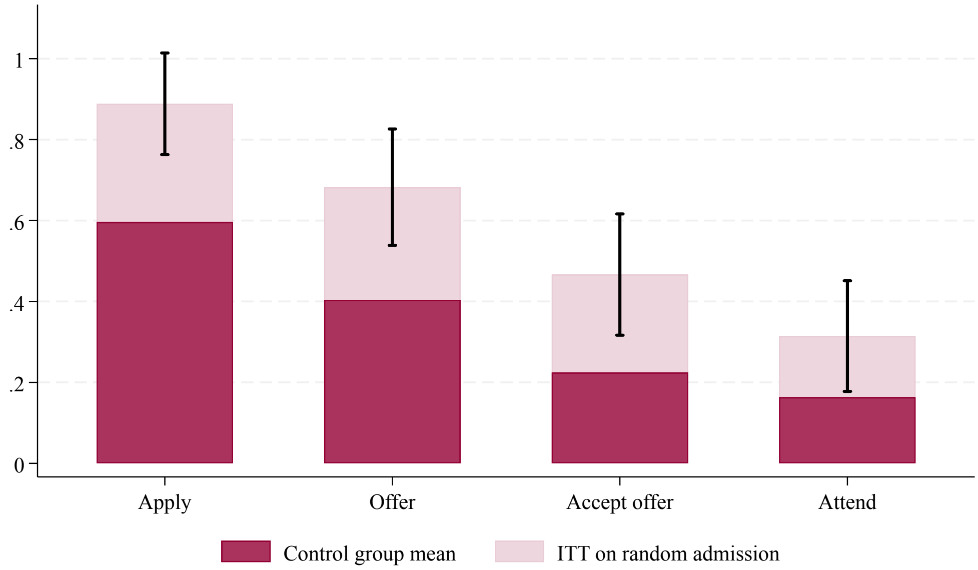
Notes: Shows responses from the prospective applicant sample ($N = 1,175$) to the question "For each of the following potential barriers, to what extent do you agree or disagree about their importance or relevance for students from your country of origin to successfully apply to graduate school (Masters or PhD) in Europe or North America?" Bars show the share of answers on a five-point Likert scale ranging from "not at all important" to "extremely important," grouping the bottom two and top two choices. The same set of questions were asked to the mentoring evaluation sample with quantitatively almost identical answers.

Figure 3: Mentor Perceptions of Potential Application Barriers



Notes: Shows perceptions of mentors on various potential barriers faced by graduate school applicants from across Africa. Mentors were shown several statements on these potential barriers and asked whether they agreed or disagreed with them on a five-point Likert scale. Respondents were shown a random subset of statements in a random order, and sample sizes across these questions range from 66 to 81. Each column reports the share of respondents that reported a given choice for the statement listed in the corresponding row.

Figure 4: Mentoring Program Treatment Effects on Applications, Offers, and Attendance

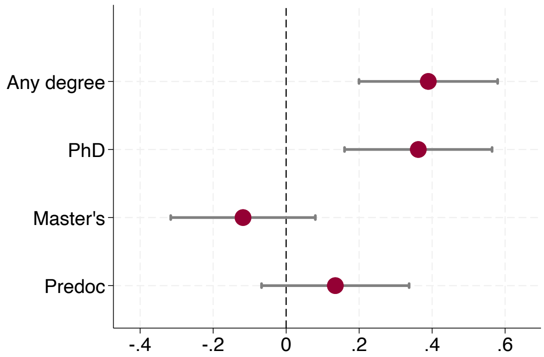


Notes: Shows intent-to-treat effects of the application-support program on the propensity of submitting at least one application, receiving at least one offer of admission, accepting at least one offer of admission, and attending a graduate program estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). The underlying data combines the midline and endline surveys for applications and offers, and is from the endline survey for the remaining outcomes. Table 3 shows detailed results for applications, Table 4 for admission offers, Table A.7 for accepting admission offers, and Table 5 for attending a graduate program. Vertical black lines show 90% confidence intervals.

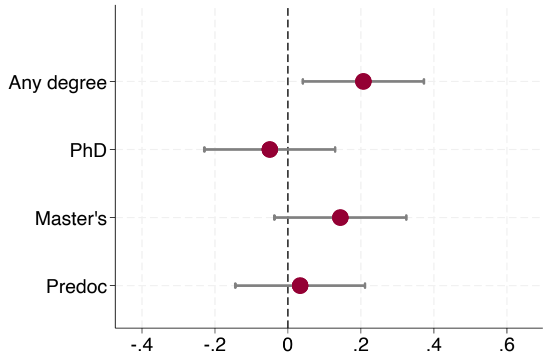
Figure 5: Treatment Effects on Primary Outcomes by PhD vs. MA suitability

Panel A: Propensity to Apply

(a) PhD Suitable Candidates

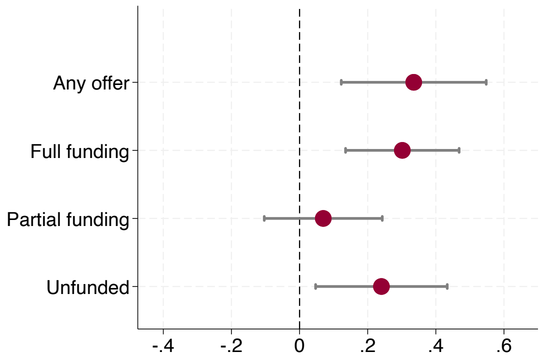


(b) MA Suitable Candidates

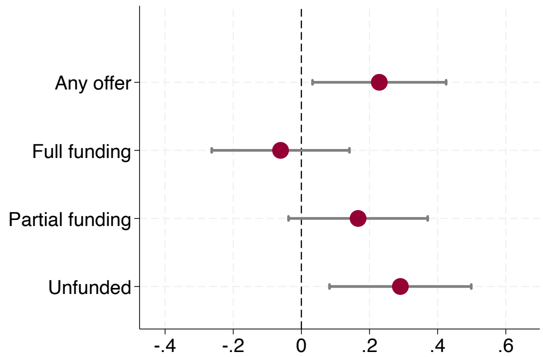


Panel B: Propensity to Receive at Least One Admissions Offer

(c) PhD Suitable Candidates

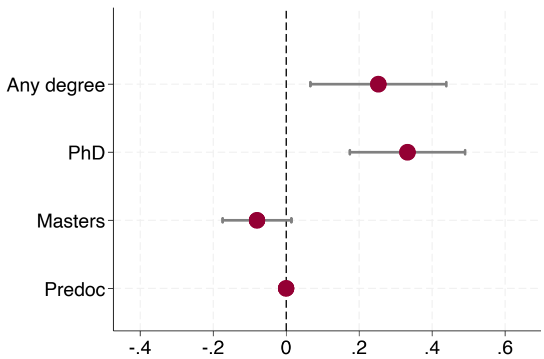


(d) MA Suitable Candidates

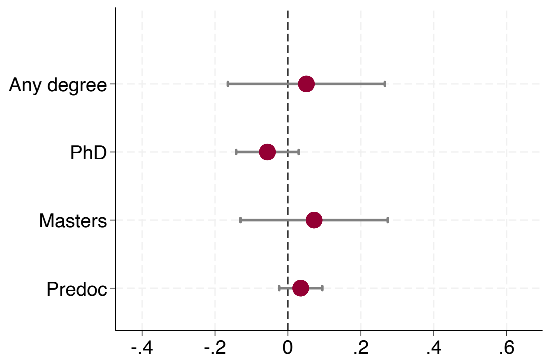


Panel C: Propensity to Attend

(e) PhD Suitable Candidates

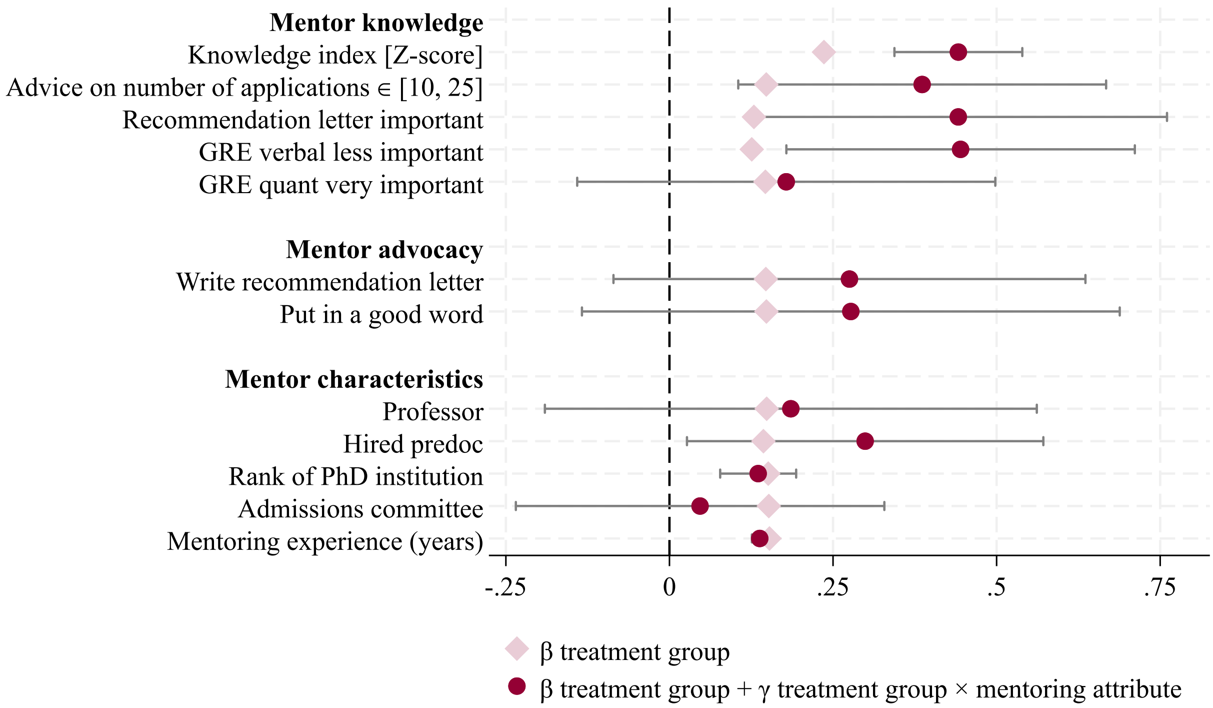


(f) MA Suitable Candidates



Notes: Shows intent-to-treat effects of the application-stage support program on the program outcomes by baseline assessment on whether the candidate is competitive for PhD or Master's programs. Coefficients are estimated using $y_i = \beta_{PhD} Z_i \times \mathbf{1}\{\text{PhD suitable}_i\} + \beta_{MA} Z_i \times \mathbf{1}\{\text{MA suitable}_i\} + \lambda_i$, where λ_i is the strata FE (gender $\times$ above GRE median $\times$ PhD/MA suitability), which controls for PhD vs. Master's assessment. The dark-colored horizontal lines show 90% CIs. Table A.5 show the corresponding regression results in table form, including outcomes on the intensive margin.

Figure 6: Heterogeneous Treatment Effects for Attendance by Mentoring Attributes



Notes: Shows heterogeneous treatment effects for mentees' graduate program attendance by different characteristics of their mentor. Each row shows coefficients from regressions of the form $Y_{ij} = \beta$ random admission$_i$ + γ random admission$_i$ × mentor attribute$_j$ + η mentor response$_j$ + $\xi'\mathbf{X}_i + \lambda_i + \varepsilon_{ij}$, where mentor attribute$_j$ is described in each row of the panel, λ_i is the randomization strata, and $\mathbf{X}_i$ is a vector of baseline application strength to the mentoring program. The light-colored diamonds show $\hat{\beta}$ whereas the dark-colored circles show $\hat{\beta} + \hat{\gamma}$ including 90%-CIs for $\hat{\gamma}$. The mentoring attributes include proxies for the quality of advice (number of applications recommended, whether the quantitative section of the GRE is considered very important, whether the verbal section of the GRE is considered as less important, and whether the letter of recommendation is considered to be very important), direct support of the application (writing a letter of recommendation and putting in a good word for the mentee at some institution independent of a letter), and mentor characteristics (is a current professor, hired a predoc in the past, REPEC rank of the PhD granting or attending institution, previously was on a graduate admissions committee, and years of mentoring experience). The knowledge index is the standardized mean of the individually standardized knowledge items. Figure A.6 shows correlations between attendance and mentoring attributes among both randomly and directly admitted mentees.

Tables

Table 1: Sample Summary Statistics

	Prospective Applicants (1)	Pre-mentoring Applicants (2)	Evaluation Sample: Control Group (3)	Evaluation Sample: Randomly Admitted (4)	Directly Admitted (5)
Female	0.37	0.39	0.23	0.32	0.37
	(0.48)	(0.49)	(0.43)	(0.47)	(0.49)
Married		0.15	0.14	0.17	0.21
		(0.35)	(0.35)	(0.38)	(0.41)
Age		28.25	28.23	28.05	28.19
		(5.68)	(4.88)	(4.48)	(3.67)
Children		0.27	0.23	0.27	0.19
		(0.78)	(0.61)	(0.61)	(0.52)
Annual income (USD)	2,812	3,708	3,014	2,702	6,267
	(6,950)	(10,327)	(4,981)	(4,595)	(8,054)
Master's degree	0.31	0.30	0.42	0.37	0.45
	(0.46)	(0.46)	(0.50)	(0.49)	(0.50)
MIT micromasters	0.06	0.12	0.14	0.10	0.10
	(0.24)	(0.33)	(0.35)	(0.30)	(0.30)
Studied abroad		0.16	0.12	0.12	0.42
		(0.37)	(0.32)	(0.38)	(0.52)
Math course from EU/NA		0.13	0.16	0.17	0.29
		(0.34)	(0.37)	(0.38)	(0.46)
Summer school		0.08	0.14	0.07	0.05
		(0.26)	(0.35)	(0.25)	(0.23)
Previous webinar participant		0.20	0.33	0.27	0.30
		(0.40)	(0.47)	(0.45)	(0.46)
Previous mentee		0.11	0.16	0.20	0.26
		(0.32)	(0.37)	(0.41)	(0.44)
Observations	1,175	332	56	66	83

Notes: Reports summary statistics for our three student samples: prospective applicants (column 1), pre-mentoring applicants (column 2), and the mentoring evaluation sample (columns 3–5). The mentoring evaluation sample is further split into those randomly not admitted [control group], those randomly admitted [treatment group], and those directly admitted. The mentoring evaluation sample comprises program cohorts 1 and 2, whereas the prospective applicants and pre-mentoring applicants are in cohort 3. The reported statistics show means and standard deviations (in parentheses) for selected baseline characteristics. Annual income is converted to USD using exchange rates as of September 2024 when reported in local currency units, and winsorized at the 1^{st} and 99^{th} percentiles. Table B.1 shows results from a formal balance of randomization tests for the control group vs. the randomly admitted.

Table 2: Knowledge Gaps Before and After Webinar Series

	Application Component Deviation Index (1)	True/False Score (2)	Application Number Advice (3)
Panel A: Prospective Applicants			
Pre-webinars	-1.04	0.48	5.71
	(0.32)	(0.23)	(6.72)
Panel B: Pre-mentoring Applicants			
Pre-webinars	-0.98	0.53	6.78
	(0.30)	(0.23)	(7.96)
Post-webinars	-0.88	0.61	9.65
	(0.27)	(0.21)	(11.12)
P-value $\bar{x}_{pre} = \bar{x}_{post}$	< 0.01	< 0.01	< 0.01
Panel C: Mentors			
Mentor survey	-0.77	0.80	14.90
	(0.25)	(0.20)	(8.61)

Notes: Shows descriptive results on application-related knowledge for the prospective applicants (panel A), the pre-mentoring applicants (panel B), and the mentors (panel C). For the pre-mentoring applicants, the table shows results from before the start of the webinars and at the time of the pre-mentoring application in cohort 3 (close to the end of the webinar series). The reported statistics are means and standard deviations (in parenthesis) for each sample. In Panel B, the p-values refer to two-sided unpaired tests of equality in the pre vs. post means. Higher numbers in columns (1) and (2) indicate more application-related knowledge. The outcome in column (1) measures how far *off* the perceived importance of multiple application elements is from the modal mentor survey answer. The index measure in column (1) is constructed as the negative average absolute deviation of the importance assigned to an application component, where the deviation is measured with respect to the modal mentor survey answer, and the Likert importance scale is converted into a numeric representation from 1 (not at all important) to 5 (extremely important). Column (2) summarizes the number of correct answers from a set of true/false questions about the application process. The index in column (2) is constructed as the average number of correct answers to true/false questions, where the correct answer is determined based on the modal mentor survey answer. The true/false index excludes a question on the statement of purpose, where the webinar program provided specific guidance that we (the research team) and the mentors disagree with; nevertheless, column (2) is robust to including this question. The outcome in column (3) reports the number of applications respondents would recommend applying to.

Table 3: Submitted Applications by Degree

		North America or Europe			
	Anywhere	Any Degree	PhD	MA	Predoc
	(1)	(2)	(3)	(4)	(5)
Panel A: Propensity to Apply					
Treatment group	0.27***	0.29***	0.14*	0.02	0.08
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Observations	116	116	116	116	116
Control group mean	0.62	0.60	0.35	0.50	0.21
Directly admitted mean	0.80	0.84	0.56	0.39	0.28
Panel B: Number of Applications					
Treatment group	3.86**	3.74**	1.60	1.81***	0.32
	(1.63)	(1.52)	(0.98)	(0.65)	(0.60)
Observations	116	116	116	116	116
Control group mean	5.58	4.92	2.06	1.87	1.00
Directly admitted mean	11.59	11.20	6.97	1.77	2.46

Notes: Shows intent-to-treat effects of the application-support program on submitted applications estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel A shows the propensity to apply, panel B shows the number of applications. Column (1) considers applications globally, whereas columns (2) to (5) restrict to applications to institutions in North America or Europe; this follows both the pre-analysis plan and the implicit focus of the application-support program. Appendix Table A.3 breaks down column (1) across the different continents. Appendix Table A.4 breaks down the analysis by degree into North America and Europe. The underlying data combines the midline and endline surveys. We only collected information on applications outside of Europe and North America in the midline survey; thus, for 10 respondents who filled out the endline but not the midline survey, column (1) includes information on North America or Europe only (results are quantitatively very similar to using only midline data). * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table 4: Admission Offers by Degree and Funding Status

	Any Degree	PhD			MA			Predoc
		Full Funding	Partial Funding	Unfunded	Full Funding	Partial Funding	Unfunded	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Propensity to Receive at Least One Offer								
Treatment group	0.29***	0.14**	0.01	0.13**	−0.02	0.03	0.17**	−0.04
	(0.09)	(0.06)	(0.06)	(0.06)	(0.05)	(0.08)	(0.08)	(0.05)
Observations	105	105	105	105	105	105	105	105
Control group mean	0.28	0.02	0.07	0.02	0.09	0.17	0.17	0.07
Directly admitted mean	0.67	0.35	0.08	0.27	0.12	0.19	0.20	0.12
Panel B: Number of Offers								
Treatment group	0.92*	0.17	−0.05	0.27**	−0.11	0.07	0.67**	−0.10
	(0.47)	(0.13)	(0.08)	(0.13)	(0.13)	(0.13)	(0.30)	(0.09)
Observations	105	105	105	105	105	105	105	105
Control group mean	1.15	0.07	0.11	0.02	0.22	0.26	0.37	0.11
Directly admitted mean	3.04	1.12	0.09	0.56	0.27	0.25	0.52	0.23

Notes: Shows intent-to-treat effects of the application-support program on admission offers in North America or Europe estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel A shows the propensity to receive at least one offer, Panel B shows the number of offers. Column (1) shows results on admission offers in any of PhD, MA, or predoc irrespective of funding. Columns (2)–(4) break down PhD offers by funding status. Columns (5)–(7) break down MA offers by funding status. Column (8) shows predoc offers, which are full-time paid research assistant positions. The underlying data is from the endline survey. Appendix Table A.6 shows admission offers by continent. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table 5: Attendance by Degree and Funding

	Combined (1)	University Funding (2)	External Scholarship (3)	Savings (4)	Loan (5)
Panel A: Any Degree					
Treatment group	0.15*	0.16**	0.01	0.03	0.02
	(0.09)	(0.08)	(0.04)	(0.05)	(0.02)
Observations	105	105	105	105	105
Control group mean	0.16	0.11	0.04	0.04	0.00
Directly admitted mean	0.47	0.43	0.01	0.03	0.04
Panel B: PhD					
Treatment group	0.14**	0.12**	0.02	0.02	0.00
	(0.06)	(0.06)	(0.02)	(0.02)	(0.00)
Observations	105	105	105	105	105
Control group mean	0.02	0.02	0.00	0.00	0.00
Directly admitted mean	0.24	0.24	0.00	0.00	0.00
Panel C: MA					
Treatment group	−0.00	0.04	−0.01	0.03	0.02
	(0.07)	(0.06)	(0.04)	(0.04)	(0.02)
Observations	105	105	105	105	105
Control group mean	0.15	0.09	0.04	0.02	0.00
Directly admitted mean	0.17	0.15	0.01	0.03	0.04
Panel D: Predoc					
Treatment group	0.02				
	(0.02)				
Observations	105				
Control group mean	0.00				
Directly admitted mean	0.05				

Notes: Shows intent-to-treat effects of the application-support program on graduate school attendance estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel A combines degree types, Panel B shows attendance for PhD degrees, Panel C for MA degrees, and Panel D for predoctoral RA positions. Column (1) pools across funding types. Column (2) shows attendance with university funding (fully funded offer or scholarship provided by the university). Column (3) shows attendance with an external scholarship, i.e., a scholarship not provided by the university itself. Columns (4) and (5) show attendance funded through savings or loans, respectively. The financing categories are not mutually exclusive. Appendix Table A.8 shows attendance by continent and degree. The underlying data is from the endline survey. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table 6: Barriers Experienced During Application Season

Panel A: Open-Text Responses

	Information	Financial Costs	Application Strength	Peers and Role Models	Self-perception	GAIN Overcome
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment group	−0.07	−0.44***	−0.00	0.02	−0.07	0.10**
	(0.06)	(0.09)	(0.10)	(0.03)	(0.05)	(0.05)
Observations	106	106	106	106	106	106
Control group mean	0.15	0.75	0.42	0.02	0.10	0.02
Directly admitted mean	0.12	0.30	0.51	0.01	0.13	0.14

Panel A continued

	Scholarships	Letter Writers	Program Alignment	Lack of Mentors	Lack of Supervisors	Visa Bureaucracy
	(7)	(8)	(9)	(10)	(11)	(12)
Treatment group	0.04	0.07	0.02	−0.06	−0.05	−0.06*
	(0.05)	(0.09)	(0.04)	(0.06)	(0.03)	(0.04)
Observations	106	106	106	106	106	106
Control group mean	0.06	0.21	0.04	0.12	0.04	0.06
Directly admitted mean	0.14	0.24	0.17	0.11	0.04	0.00

Panel B: Closed-Form Responses

	Information Process	Information Scholarships	Application Fees	Standardized Test Fees	Role Models Peers [Index]	Not Competive	Feeling Not to Belong
	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Treatment group	−0.01	−0.03	−0.25***	−0.23***	−0.18	−0.12	−0.09
	(0.09)	(0.09)	(0.07)	(0.07)	(0.21)	(0.10)	(0.09)
Observations	105	105	105	105	105	105	105
Control group mean	0.54	0.67	0.92	0.92	0.15	0.46	0.29
Direct admission mean	0.53	0.51	0.72	0.67	-0.06	0.41	0.24

Notes: Shows intent-to-treat effects of the application-support program on barriers experienced during the application season estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). **Panel A** shows answers from the following open-ended question prior to the closed-form question: *"In your own experience, what were the main barriers that YOU faced when applying to graduate programs in Europe or the US? If you have not applied to any program in Europe or the US, please describe the main barriers that have prevented you from applying."* The responses were analyzed by Gemini 3 to create dummies for whether the responses mentioned a lack of information, application strength, financial costs, peers and role models, and self-perceived barriers to graduate applications, and whether GAIN helped overcome any barriers. Other barriers that were identified in the responses were lack of scholarships, difficulties with letter writers, lack of program alignment, lack of mentors or supervisors, and bureaucratic hurdles regarding visas. These variables were then manually checked for errors. **Panel B** shows answers from closed-form questions asking about specific barriers. Each column refers to separate prompted items and the main question *"For each of the following barriers, to what extent do you agree or disagree about their importance in YOUR ability to successfully apply to graduate school in Europe or the US? If you have not applied to any program in Europe or the US, please think about the barriers that have prevented you from applying."* The answer options for each item are on a Likert importance scale. The outcome is a binary variable if the respondent selected "extremely important" or "very important." Column (18) combines the following individual items into a single index: not knowing of African professors at schools in Europe or North America, not knowing of African students at schools in Europe or North America, and not knowing of other African students currently applying to schools in Europe or North America. This index is the standardized average of the responses to each of these item, all standardized prior to averaging. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table 7: Effect on Application Related Expenses

	Full Sample		Conditional on Applying		
	Total Amount (1)	% Annual Income (2)	Total Amount (3)	% Annual Income (4)	Amount Per Application (5)
Treatment group	−164.80**	−0.15	−255.97***	−0.24	−55.98***
	(75.46)	(0.12)	(93.64)	(0.15)	(19.04)
Observations	105	81	80	63	80
Control group mean	365.89	0.44	422.68	0.52	78.33
Direct admission mean	274.07	0.24	298.51	0.23	30.40

Notes: Shows intent-to-treat effects of the application-support program on application expenses estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Columns (1) and (2) show results for the full mentoring evaluation sample, whereas columns (3) to (5) restrict the sample to those who applied to at least one graduate program in Europe or North America. Columns (1) and (3) show total amounts spent, (2) and (4) show these amounts as a percentage of reported annual income if income was reported as non-zero, and column (5) divides the total amount by the number of applications submitted. All amounts are converted to USD using exchange rates as of September 2024 and winsorized at the 95^{th} percentile. The data comes from eliciting application-related expenses by category (e.g., application fees, standardized tests, etc.). Table A.12 shows robustness using a separate question where application-related expenses were elicited by source of expenses (e.g., income, savings, loans, etc.). * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table 8: Treatment Effect on Dimensions of Application Strength

	Standardized Tests				Application Materials			
	GRE Taken (1)	GRE Quant Score (2)	TOEFL Taken (3)	TOEFL Score (4)	SOP Score (5)	CV Score (6)	CV Math (7)	CV GAIN (8)
Treatment group	0.57***	1.32	0.20**	−4.22	−0.43	−0.22	0.01	0.22***
	(0.07)	(2.14)	(0.08)	(7.81)	(0.28)	(0.18)	(0.06)	(0.07)
Observations	106	65	106	28	68	74	74	74
Control group mean	0.29	153.64	0.15	86.86	0.13	-0.19	0.09	0.00
Direct admission mean	0.95	157.68	0.28	87.43	0.20	0.40	0.22	0.15

	Letter Writers		Additional Credentials			
	Info Available	Europe North America	Math Course	MIT Micromaster	Summer School	RA or TA Experience
Treatment group	0.06	−0.11	−0.00	−0.12*	−0.03	−0.07
	(0.08)	(0.12)	(0.06)	(0.07)	(0.07)	(0.09)
Observations	75	68	48	48	48	48
Control group mean	0.88	0.29	0.04	0.12	0.08	0.92
Direct admission mean	0.87	0.54	0.11	0.03	0.00	0.92

Notes: Shows intent-to-treat effects of the application-support program on various dimensions of application strength estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Columns (1) and (3) refer to whether the respective standardized test was taken at least once. Test scores in columns (2) and (4) are reported conditional on taking the respective standardized test. Outcomes for the SOP and CV score are conditional on respondents uploading the respective document, which is balanced across the treatment and control group. SOPs are collected only from those who applied to graduate programs in the mentoring evaluation sample. Scores for SOP and CV are computed based on the methodology used by GAIN in the mentorship application. The outcomes for recommendation letter writers show whether information on letter writers is provided (conditional on applying) and for whether at least one letter writer is from an institution in Europe or North America. Results for additional application-related credentials are based on cohort 1 only (due to data availability) and show whether the respective credentials was obtained since the beginning of the mentorship program. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Appendix Figures

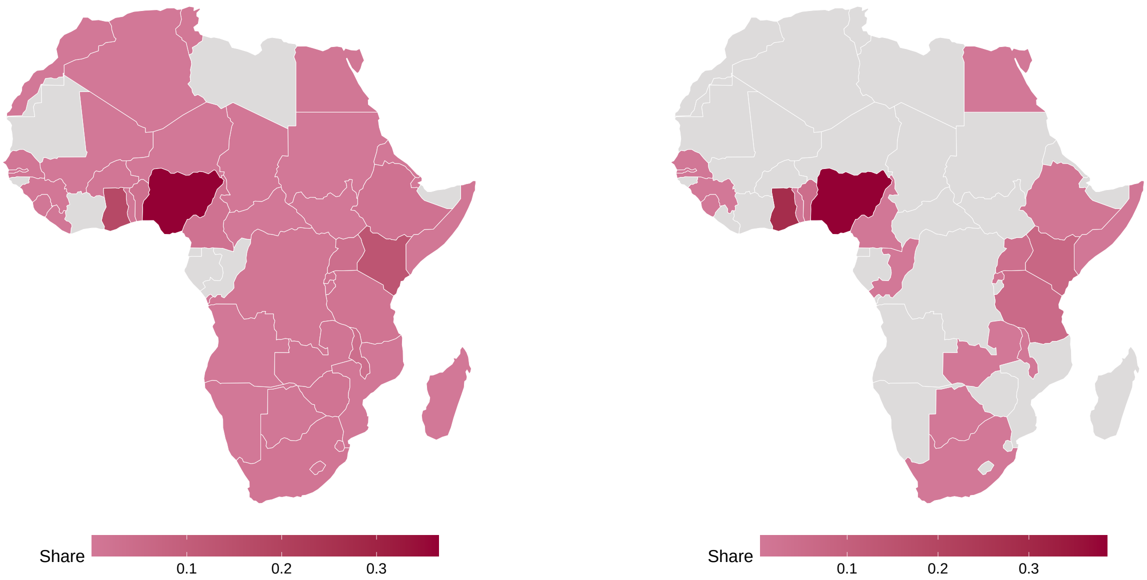
Figure A.1: Sample Distribution across Africa

(a) Prospective Applicants

[2025-26 program cycle]

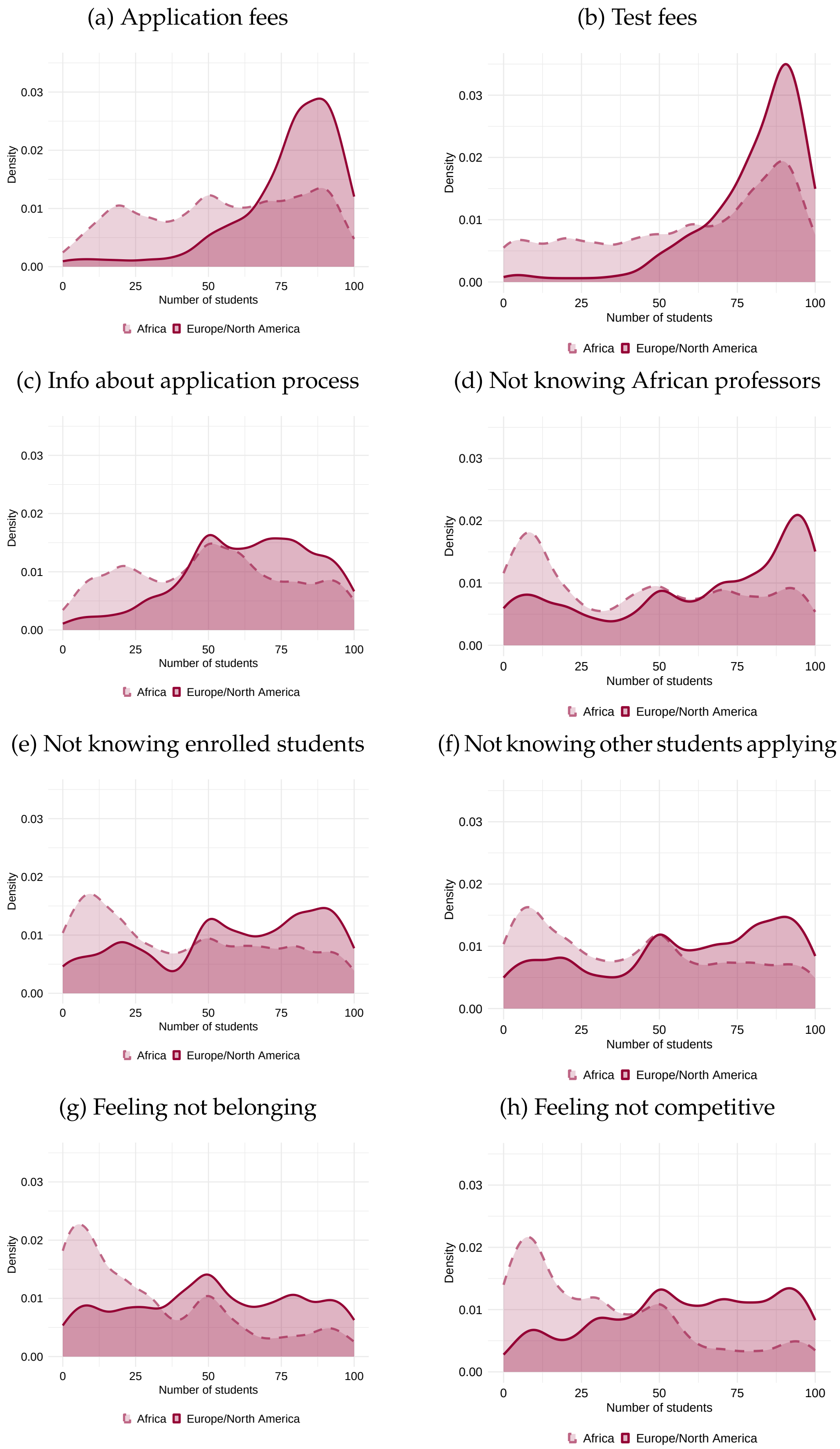
(b) Mentoring Evaluation Sample

[2023-24, 2024-25 program cycles]



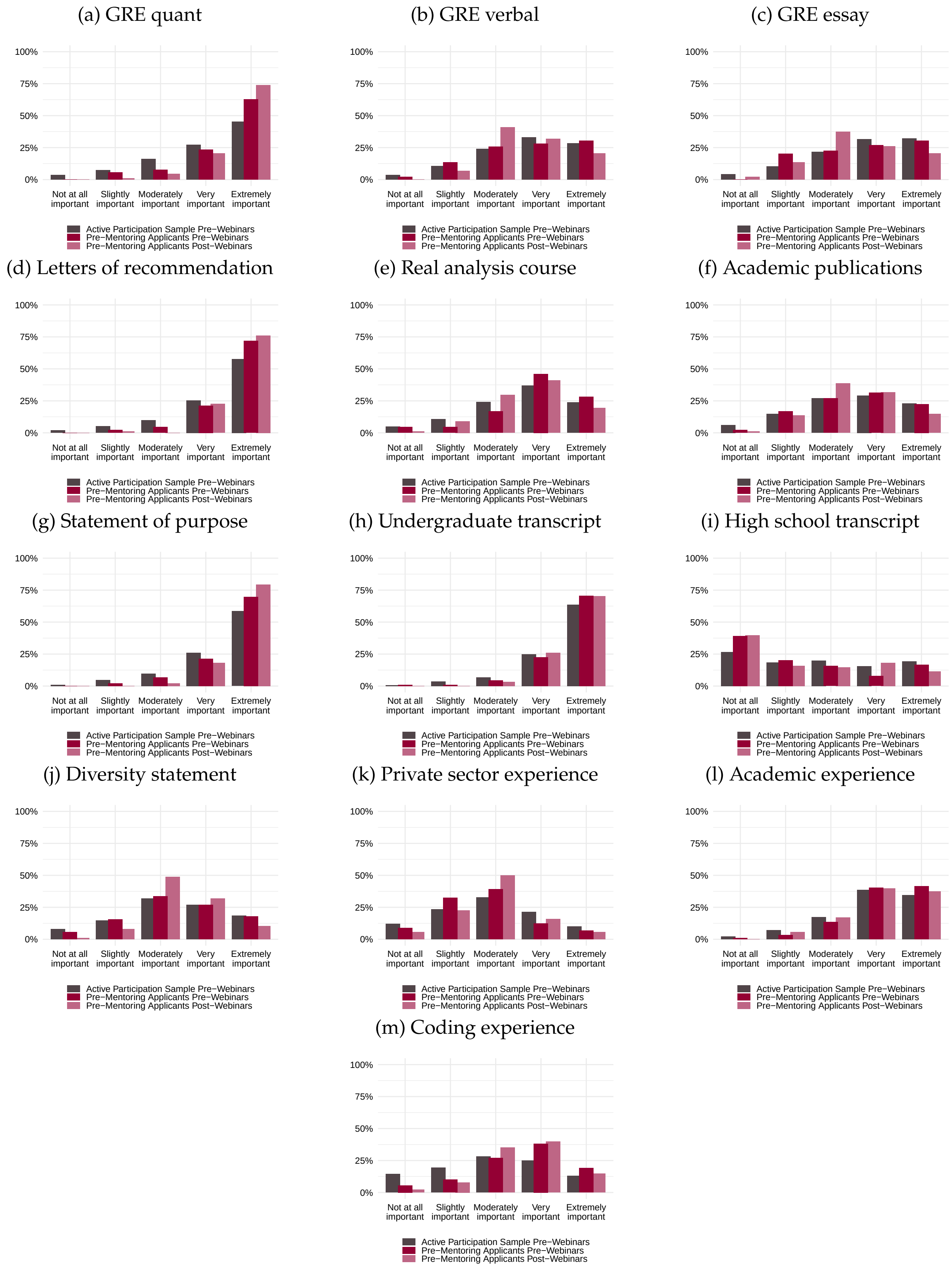
Notes: Shows the distribution of the nationalities of our two main samples across countries in Africa. Panel A shows the prospective applicants, that is, the initial participants of the GAIN webinar program (for cohort 3). Panel B shows the mentoring evaluation sample, that is, those participating in the mentoring program (both randomly and directly admitted) and those randomly not admitted into the program (cohorts 1 and 2).

Figure A.2: Perceived Number of Students Constraint by Potential Application Barriers



Notes: Shows the extent to which pre-mentoring applicants perceive different potential barriers as a constraint for applications to (i) Europe and North America and (ii) Africa, respectively, considering applicants from their home country. Specifically, respondents were asked "Out of 100 students interested in applying to graduate school, for applications to programs in the US or Europe (Africa), how many students will be constrained by..." The underlying data is from the pre-mentoring application survey. Shows flexible polynomial kernel density plots of the distribution of answers.

Figure A.3: Perceived Importance of Application Components Before and After the Webinars

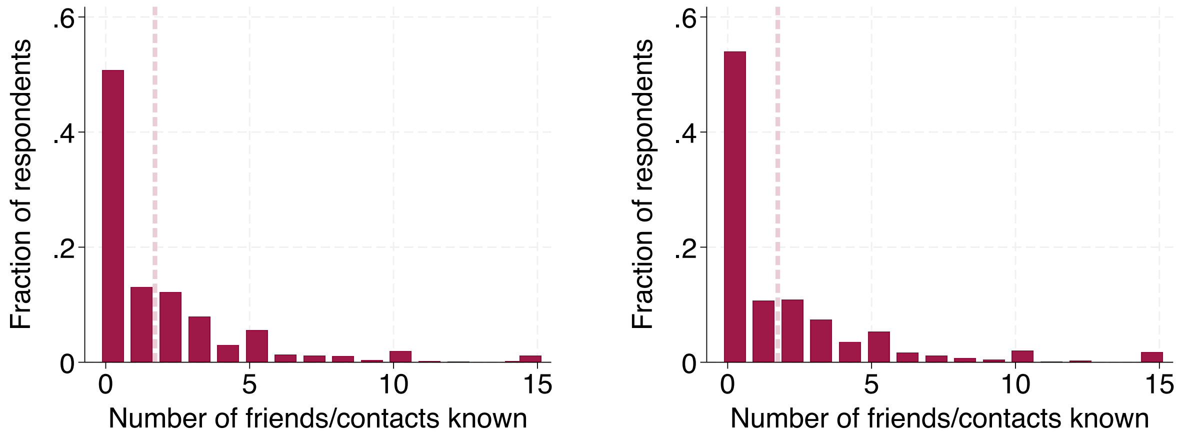


Notes: Shows the perceived importance of various application elements for the prospective applicants prior to the webinars (gray bars), the pre-mentoring applicants prior to the webinars (dark red bars), and the pre-mentoring applicants after the webinars (light red bars). Answer choices reached from "not at all important" to "extremely important" on a five-point Likert scale.

Figure A.4: Number of Known Contacts Who Studied in or Applied to Grad School in NA/EU

(a) Applied within last 2 years or in 2025

(b) Studied within last 5 years

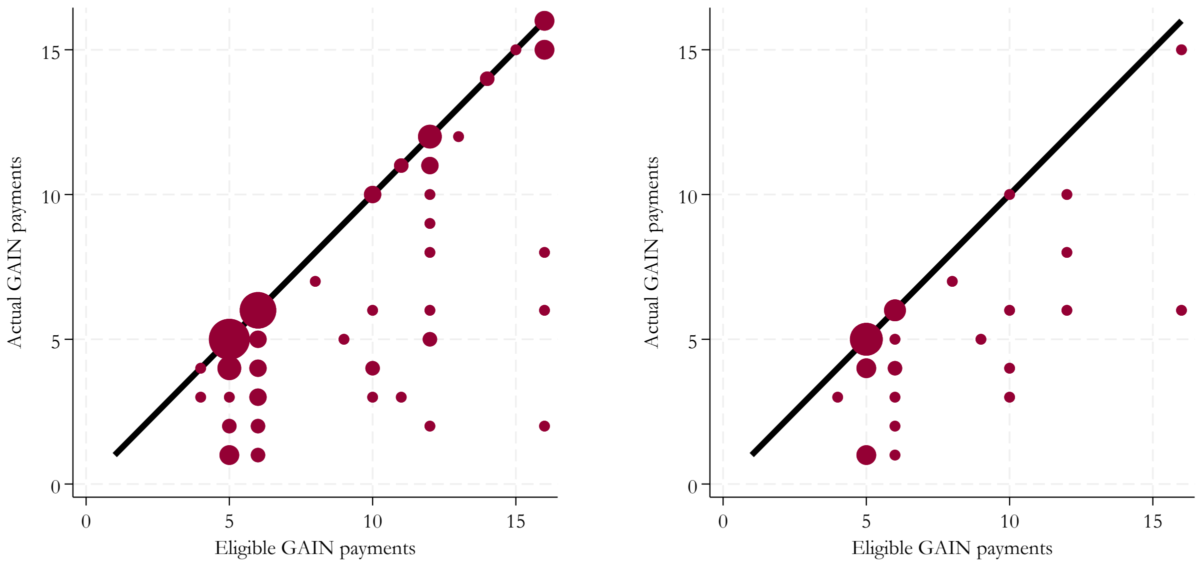


Notes: Shows the distribution of the network of prospective applicants with respect to people who applied to a graduate school program in Europe or North America in the past two years (panel a) and with respect to people who studied in Europe or North America in the past two years (panel b).

Figure A.5: Actual vs. Eligible GAIN Application Fee Payments

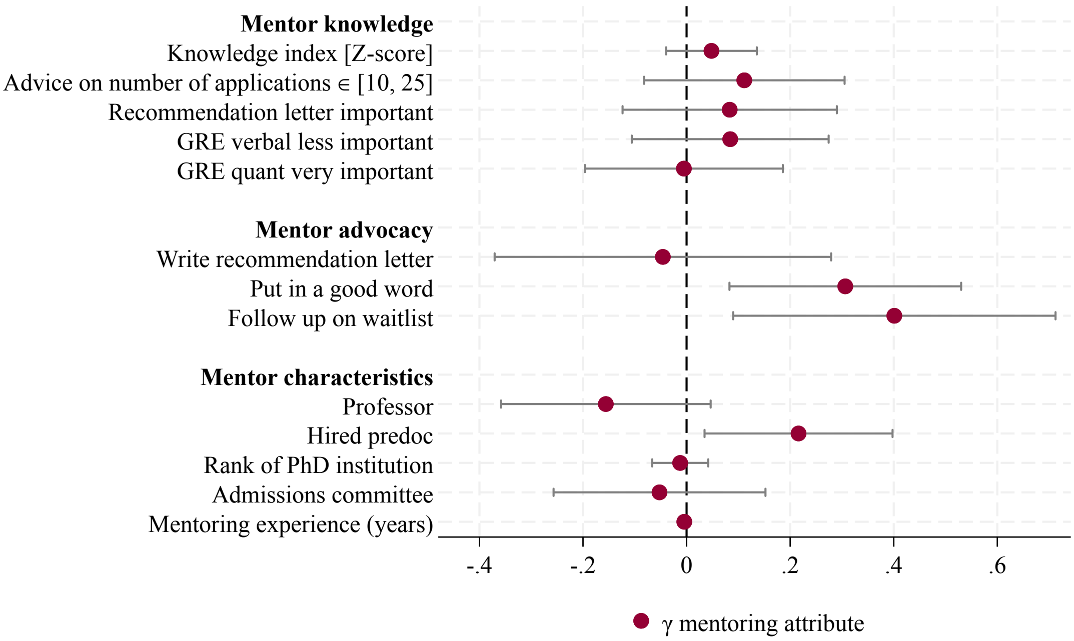
(a) All mentees

(b) Randomly admitted



Notes: Shows the number of actual application fee payments paid for by the GAIN program vs. the number of eligible payments. The size of the dots indicates the number of participants at a given (x, y) pair. Panel (a) shows both randomly and directly admitted mentees in cohorts 1 and 2, whereas panel (b) restricts the analysis to randomly admitted mentees. The number of eligible payments depends on the GRE score. Students can trade-in application fee payments with other support such as sending test scores.

Figure A.6: Correlating Attendance and Mentoring Attributes for Randomly + Directly Mentees



Notes: Shows correlations between mentees' graduate program attendance and different characteristics of their mentor in the sample of all mentoring program participants, that is, randomly and directly admitted mentees. Each row shows coefficients from regressions of the form $Y_{ij} = \alpha$ direct admission$_i + \gamma$ mentoring attribute$_j + \xi' \mathbf{X}_i + \varepsilon_{ij}$. The dark-colored circles show $\hat{\gamma}$ and its 90%-CI. The mentoring attributes include proxies for the quality of advice (number of applications recommended, whether the quantitative section of the GRE is considered very important, whether the verbal section of the GRE is considered as less important, and whether the letter of recommendation is considered to be very important), direct support of the application (writing a letter of recommendation, putting in a good word for the mentee at some institution independent of a letter, and following up on a waitlist), and mentor characteristics (is a current professor, hired a predoc in the past, REPEC rank of the PhD granting or attending institution, previously was on a graduate admissions committee, and years of mentoring experience). Figure 6 shows the main specification, showing heterogeneous treatment effects among the mentoring attributes in the impact evaluation sample.

Appendix Tables

Table A.1: Sample Summary Statistics of Mentor Survey

	Full Sample [2022-2026] (1)	Randomly Admitted [2023-2025] (2)	Directly Admitted [2023-2025] (3)
Female	0.43	0.42	0.46
	(0.50)	(0.50)	(0.50)
Non-binary	0.01	0.03	0.00
	(0.10)	(0.17)	(0.00)
No previous mentoring experience	0.19	0.24	0.17
	(0.40)	(0.44)	(0.38)
1-2 years of mentoring experience	0.26	0.27	0.35
	(0.44)	(0.45)	(0.48)
3+ years of mentoring experience	0.44	0.48	0.48
	(0.50)	(0.51)	(0.51)
Graduate admissions committee before	0.34	0.30	0.35
	(0.48)	(0.47)	(0.48)
Hired predoc in the past	0.41	0.39	0.52
	(0.49)	(0.50)	(0.51)
Current PhD student	0.31	0.42	0.24
	(0.46)	(0.50)	(0.43)
Current Professor	0.39	0.19	0.51
	(0.49)	(0.40)	(0.51)
Observations	109	33	46

Notes: Reports summary statistics for the mentor survey sample. Column (1) includes the full sample of mentor respondents, including mentors of the program cycles from 2022/23 to 2025/26. Column (2) limits this to mentors of randomly admitted mentees in our mentoring evaluation sample; column (3) restricts this to mentors of directly admitted mentees in our mentoring evaluation sample. Columns (2) and (3) are not mutually exclusive since repeat mentors can be in different categories in different years. The reported statistics show means and standard deviations (in parentheses) for selected characteristics.

Table A.2: Knowledge True/False Questions Before and After the Webinars

	GRE		Paper		Funding		SOP		Predoc		Letter		
	True	False	True	False	True	False	True	False	True	False	True	False	N
Panel A: Prior to webinars (baseline)													
Webinar participation form	0.55	0.45	0.77	0.23	0.52	0.48	0.29	0.71	0.75	0.25	0.57	0.43	1131
Prementoring application sample	0.47	0.53	0.74	0.26	0.59	0.41	0.25	0.75	0.79	0.21	0.53	0.47	318
Panel B: Surveys after webinar series (endline)													
Prementoring application	0.35	0.65	0.74	0.26	0.83	0.17	0.58	0.42	0.77	0.23	0.47	0.53	318
Panel C: Mentor survey (benchmark)													
Mentor survey	0.17	0.83	0.35	0.65	0.88	0.12	0.14	0.86	0.73	0.27	0.11	0.89	66

Notes: Shows the disaggregated answers of the True/False Score in column (2) of Table 2. Pre-mentoring applicants are a *strict* subset of the prospective applicants. The true/false statements are: **GRE** "The total GRE score which combines the test's verbal and quantitative section matters more than a score in the test's individual components"; **Paper** "A published paper on your CV is very important for getting into a competitive graduate program"; **Funding** "MA programs generally do not come with funding from the school, while PhD programs usually do"; **SOP** "In the statement of purpose (SOP) of a PhD application, one should not describe a specific research idea because one might not want to carry it out later in the dissertation"; **Predoc** "Two-year predoc positions increase admission chances to competitive PhD programs, but are unnecessary if you have already completed a master's program at a well-ranked school"; **Letter** "A strong letter of recommendation for a PhD application will primarily discuss the classes you took and the grades you achieved in them." Note that the letter of recommendation webinar was *after* the pre-mentoring application, but was touched upon in previous webinars.

Table A.3: Submitted Applications by Continent

	Africa (1)	Asia (2)	Europe (3)	Oceania (4)	North America (5)	South America (6)
Panel A: Propensity to Apply						
Treatment group	−0.07	0.04	0.43^{***}	0.03	0.42^{***}	0.02
	(0.08)	(0.05)	(0.09)	(0.05)	(0.08)	(0.05)
Observations	108	108	108	108	108	108
Control group mean	0.24	0.04	0.35	0.06	0.41	0.04
Directly admitted mean	0.12	0.04	0.70	0.04	0.86	0.03
Panel B: Number of Applications						
Treatment group	0.02	0.15	2.45^{***}	−0.07	2.46^{**}	0.04
	(0.16)	(0.20)	(0.74)	(0.12)	(1.00)	(0.13)
Observations	108	108	108	108	108	108
Control group mean	0.33	0.10	1.33	0.16	2.71	0.10
Directly admitted mean	0.26	0.04	1.62	0.06	11.29	0.04

Notes: Shows intent-to-treat effects of the application-support program on submitted applications by continent estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). The underlying data is from the midline survey only since the endline survey did not ask about the application breakdown outside of Europe and North America. Table 3 shows submitted applications by degree. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table A.4: Submitted Applications by Continent and Degree

	Any degree			PhD			MA			Predoc		
	N. America or Europe	North America	Europe	N. America or Europe	North America	Europe	N. America or Europe	North America	Europe	N. America or Europe	North America	Europe
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Propensity to Apply												
Treatment group	0.29***	0.31***	0.35***	0.14*	0.16*	0.21***	0.02	0.09	0.10	0.08	0.04	0.10
	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.07)	(0.08)	(0.08)	(0.09)	(0.08)	(0.07)	(0.07)
Observations	116	116	116	116	116	116	116	116	116	116	116	116
Control group mean	0.60	0.48	0.38	0.35	0.25	0.12	0.50	0.35	0.35	0.21	0.17	0.10
Directly admitted mean	0.84	0.75	0.61	0.56	0.54	0.41	0.39	0.34	0.23	0.28	0.23	0.13
Panel B: Number of Applications												
Treatment group	3.74**	1.67	2.07***	1.60	0.33	1.27***	1.81***	1.29***	0.52	0.32	0.05	0.27
	(1.52)	(1.17)	(0.75)	(0.98)	(0.83)	(0.47)	(0.65)	(0.44)	(0.43)	(0.60)	(0.49)	(0.17)
Observations	116	116	116	116	116	116	116	116	116	116	116	116
Control group mean	4.92	3.54	1.38	2.06	1.83	0.23	1.87	0.90	0.96	1.00	0.81	0.19
Directly admitted mean	11.20	9.67	1.53	6.97	6.24	0.73	1.77	1.35	0.42	2.46	2.08	0.38

Notes: Shows intent-to-treat effects of the application-support program on submitted applications by continent and degree estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel A shows the propensity to apply, panel B shows the number of applications. The underlying data is from the midline and endline surveys. Extends Table 3 by showing results for Europe and North America separately. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table A.5: Primary Mentoring Program Outcomes by PhD vs. Master's Suitability

	Extensive Margin (Propensity)				Intensive Margin (Number)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Applications								
	Any Degree	PhD	MA	Predoc	Any Degree	PhD	MA	Predoc
Treatment group × MA-suitability	0.21**	−0.05	0.14	0.03	3.31**	−0.87	3.76***	0.42
	(0.10)	(0.11)	(0.11)	(0.11)	(1.50)	(0.90)	(1.04)	(0.44)
Treatment group × PhD-suitability	0.39***	0.36***	−0.12	0.13	4.22	4.42**	−0.40	0.21
	(0.12)	(0.12)	(0.12)	(0.12)	(2.77)	(1.72)	(0.57)	(1.19)
Observations	116	116	116	116	116	116	116	116
Control group MA-suitability mean	0.70	0.26	0.70	0.19	4.30	1.33	2.59	0.37
Control group PhD-suitability mean	0.50	0.46	0.29	0.25	5.83	2.96	1.12	1.75
Directly admitted MA-suitability mean	0.92	0.29	0.71	0.33	7.42	1.46	4.29	1.67
Directly admitted PhD-suitability mean	0.80	0.67	0.25	0.25	12.85	9.38	0.67	2.80
Panel B: Admission Offers								
	Any Offer	Full Funding	Partial Funding	Unfunded	Any Offer	Full Funding	Partial Funding	Unfunded
Treatment group × MA-suitability	0.23*	−0.06	0.17	0.29**	1.13	−0.28	0.11	1.19**
	(0.12)	(0.12)	(0.12)	(0.13)	(0.78)	(0.26)	(0.38)	(0.52)
Treatment group × PhD-suitability	0.34**	0.30***	0.07	0.24**	0.94*	0.47***	0.02	0.56**
	(0.13)	(0.10)	(0.11)	(0.12)	(0.52)	(0.17)	(0.16)	(0.26)
Observations	116	116	116	116	116	116	116	116
Control group MA-suitability mean	0.59	0.30	0.33	0.37	2.30	0.63	0.81	0.81
Control group PhD-suitability mean	0.21	0.08	0.12	0.12	0.62	0.08	0.21	0.17
Directly admitted MA-suitability mean	0.67	0.33	0.50	0.50	3.50	1.08	0.75	1.46
Directly admitted PhD-suitability mean	0.69	0.53	0.18	0.40	3.00	1.76	0.22	0.93
Panel C: Attendance								
	Any Degree	PhD	MA	Predoc				
Treatment group × MA-suitability	0.05	−0.06	0.07	0.04				
	(0.13)	(0.05)	(0.12)	(0.04)				
Treatment group × PhD-suitability	0.25**	0.33***	−0.08	−0.00				
	(0.11)	(0.10)	(0.06)	(0.00)				
Observations	105	105	105	105				
Control group MA-suitability mean	0.29	0.05	0.24	0.00				
Control group PhD-suitability mean	0.08	0.00	0.08	0.00				
Directly admitted MA-suitability mean	0.41	0.05	0.36	0.00				
Directly admitted PhD-suitability mean	0.49	0.32	0.09	0.08				

Notes: Shows intent-to-treat effect heterogeneity by the non-binding baseline assessment of whether candidates where considered competitive for PhD applications (PhD Suitable) or competitive for Master's applications (MA Suitable), estimated using equation (2) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel A shows results for applications, panel B for admission offers, and panel C for attendance. Across panels, columns (1) to (4) show the extensive margin, that is, the propensity to apply, receive at least one offer, and attend; columns (5) to (8) show the number of applications and offers. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table A.6: Admission Offers by Continent

	Anywhere (1)	Africa (2)	Asia (3)	Europe (4)	Oceania (5)	North America (6)	South America (7)
Panel A: Propensity to Receive at Least One Offer							
Treatment group	0.29***	−0.04	0.02	0.22**	−0.01	0.23**	−0.01
	(0.09)	(0.04)	(0.02)	(0.08)	(0.04)	(0.09)	(0.04)
Observations	108	108	108	108	108	108	108
Control group mean	0.41	0.08	0.00	0.16	0.04	0.27	0.04
Directly admitted mean	0.82	0.04	0.00	0.26	0.00	0.74	0.03
Panel B: Number of Offers							
Treatment group	0.39	−0.08	0.02	0.63	−0.11	0.25	−0.32
	(0.90)	(0.06)	(0.02)	(0.46)	(0.12)	(0.42)	(0.22)
Observations	108	108	108	108	108	108	108
Control group mean	2.22	0.12	0.00	0.65	0.12	1.02	0.31
Directly admitted mean	3.79	0.05	0.00	0.37	0.00	3.30	0.07

Notes: Shows intent-to-treat effects of the application-support program on admission offers by continent estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel A shows the propensity to receive at least one offer, Panel B shows the number of offers. The underlying data is from the midline survey. Table 4 shows admission offers by degree and funding status. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table A.7: Accepted Offers by Degree

	Any degree (1)	PhD (2)	MA/MSc (3)	RA (4)
Panel A: Acceptance (Irrespective of Eventual Attendance)				
Treatment group	0.24***	0.11*	0.14*	0.02
	(0.09)	(0.06)	(0.08)	(0.02)
Observations	105	105	105	105
Control group mean	0.24	0.04	0.15	0.00
Directly admitted mean	0.55	0.32	0.23	0.04
Panel B: Acceptance × Attendance				
Treatment group	0.14*	0.14**	0.07	0.00
	(0.08)	(0.06)	(0.06)	(0.00)
Observations	105	105	105	105
Control group mean	0.15	0.02	0.09	0.00
Directly admitted mean	0.45	0.27	0.17	0.04

Notes: Shows intent-to-treat effects of the application-support program on accepted admission offers by degree estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel A shows results for accepted offers regardless of whether the respondent ends up attending eventually. Panel B shows results interacting the outcome variable (acceptance) with whether the respondent ends up attending (attendance) eventually. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table A.8: Attendance by Continent and Degree

	Combined	PhD	MA	Predoc
	(1)	(2)	(3)	(4)
Panel A: Europe				
Treatment group	0.03	0.08**	−0.06	0.02
	(0.07)	(0.04)	(0.05)	(0.02)
Strata FE	Yes	Yes	Yes	Yes
Observations	105	105	105	105
Control group mean	0.10	0.00	0.10	0.00
Directly admitted mean	0.04	0.00	0.03	0.01
Panel B: North America				
Treatment group	0.12*	0.06	0.06	0.00
	(0.07)	(0.05)	(0.05)	(0.00)
Strata FE	Yes	Yes	Yes	Yes
Observations	105	105	105	105
Control group mean	0.06	0.02	0.04	0.00
Directly admitted mean	0.43	0.24	0.15	0.04

Notes: Shows intent-to-treat effects of the application-support program on graduate school attendance by continent and degree estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel B shows results for attendance in Europe, whereas Panel B shows results for attendance in North America. Column (1) combines attendance of either a PhD program, a MA program, or a predoc program; these are shown separately across columns (2) to (4). Table 5 shows results for attendance by degree and funding status. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table A.9: Heterogeneous Treatment Effects for Main Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Covariate	App. score (Z-score)	GRE quant (Z-score)	Prior mentee	From Ghana or Nigeria	Female	Income (Z-score)	Has MA/MSc degree	Current student	Full-time employed	Is research assistant
Applications (extensive margin)										
Treatment group	0.28^{***}	0.33^{***}	0.33^{***}	0.27^{*}	0.23^{***}	0.26^{***}	0.23^{**}	0.22^{**}	0.23^{***}	0.26^{***}
	(0.08)	(0.08)	(0.09)	(0.15)	(0.09)	(0.08)	(0.11)	(0.09)	(0.09)	(0.09)
Interaction	0.07	0.10	−0.19	0.03	0.18	0.01	0.08	0.24	0.16	0.02
	(0.09)	(0.07)	(0.26)	(0.18)	(0.17)	(0.10)	(0.19)	(0.17)	(0.24)	(0.19)
Covariate	−0.03	−0.03	0.02	−0.00		−0.04	−0.04	−0.17	−0.03	−0.05
	(0.07)	(0.08)	(0.18)	(0.14)		(0.09)	(0.17)	(0.14)	(0.21)	(0.17)
Observations	112	105	116	116	116	101	101	116	101	101
Control mean	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.75
Number of applications										
Treatment group	3.69^{**}	3.87^{**}	4.98^{***}	6.97^{**}	3.22	3.78^{**}	3.67^{*}	3.30^{*}	4.47^{**}	1.47
	(1.59)	(1.68)	(1.70)	(2.70)	(2.10)	(1.75)	(1.90)	(1.99)	(1.93)	(2.28)
Interaction	0.68	0.40	−6.45	−5.00	1.58	−2.28	0.14	1.50	−3.64	6.58
	(1.63)	(1.55)	(4.99)	(3.12)	(2.71)	(1.93)	(4.31)	(3.37)	(4.84)	(3.96)
Covariate	0.66	0.40	5.38	3.13^{*}		0.72	0.85	−1.08	1.66	-6.47^{**}
	(1.37)	(1.22)	(4.19)	(1.78)		(1.74)	(2.84)	(2.65)	(4.51)	(2.81)
Observations	112	105	116	116	116	101	101	116	101	101
Control mean	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92	6.92
Offers (extensive margin)										
Treatment group	0.28^{***}	0.31^{***}	0.28^{***}	0.16	0.30^{***}	0.30^{***}	0.36^{***}	0.20^{*}	0.27^{***}	0.29^{***}
	(0.09)	(0.09)	(0.10)	(0.17)	(0.11)	(0.09)	(0.12)	(0.11)	(0.10)	(0.11)
Interaction	0.13	0.08	0.02	0.19	−0.05	0.14	−0.12	0.29	0.17	0.04
	(0.10)	(0.09)	(0.24)	(0.20)	(0.19)	(0.08)	(0.22)	(0.19)	(0.26)	(0.22)
Covariate	−0.02	−0.08	−0.03	−0.10		-0.11^{*}	0.11	−0.09	0.13	−0.00
	(0.09)	(0.09)	(0.17)	(0.15)		(0.07)	(0.17)	(0.14)	(0.22)	(0.19)
Observations	112	105	116	116	116	101	101	116	101	101
Control mean	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55
Number of offers										
Treatment group	1.12^{**}	1.30^{**}	1.16^{**}	1.20^{*}	1.02^{*}	1.24^{**}	1.56^{*}	0.79	1.23^{*}	0.95
	(0.49)	(0.51)	(0.53)	(0.62)	(0.55)	(0.53)	(0.83)	(0.61)	(0.64)	(0.67)
Interaction	0.22	0.29	−0.60	−0.30	0.06	0.37	−0.79	0.97	−0.00	0.69
	(0.55)	(0.66)	(1.34)	(0.85)	(1.09)	(0.51)	(1.17)	(0.99)	(1.08)	(0.94)
Covariate	0.37	−0.60	0.49	0.86		−0.62	0.37	−0.05	−0.18	-1.72^{**}
	(0.48)	(0.47)	(0.90)	(0.58)		(0.48)	(0.66)	(0.59)	(0.87)	(0.84)
Observations	112	105	116	116	116	101	101	116	101	101
Control mean	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03
Accepted offers (extensive margin)										
Treatment group	0.25^{***}	0.29^{***}	0.25^{**}	0.29^{*}	0.25^{**}	0.27^{***}	0.34^{**}	0.22^{*}	0.29^{**}	0.34^{***}
	(0.09)	(0.10)	(0.11)	(0.16)	(0.11)	(0.10)	(0.14)	(0.11)	(0.11)	(0.12)
Interaction	−0.08	−0.03	−0.01	−0.07	−0.04	0.15^{*}	−0.14	0.09	−0.03	−0.21
	(0.10)	(0.11)	(0.23)	(0.20)	(0.19)	(0.09)	(0.21)	(0.20)	(0.25)	(0.23)
Covariate	0.14^{*}	−0.01	−0.09	0.02		−0.08	0.11	0.04	0.24	0.03
	(0.07)	(0.10)	(0.15)	(0.14)		(0.07)	(0.15)	(0.14)	(0.20)	(0.18)
Observations	106	100	110	110	110	95	95	110	95	95
Control mean	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36
Attendance (extensive margin)										
Treatment group	0.16^{*}	0.20^{**}	0.09	0.23	0.23^{**}	0.17^{*}	0.11	0.14	0.20^{*}	0.21^{*}
	(0.08)	(0.08)	(0.09)	(0.14)	(0.10)	(0.09)	(0.13)	(0.10)	(0.10)	(0.11)
Interaction	−0.12	0.01	0.29	−0.11	−0.24	0.07	0.15	0.04	−0.10	−0.14
	(0.09)	(0.10)	(0.24)	(0.19)	(0.18)	(0.07)	(0.20)	(0.18)	(0.24)	(0.21)
Covariate	0.15^{**}	−0.03	−0.13	0.01		−0.07	−0.05	−0.00	0.13	0.01
	(0.06)	(0.07)	(0.16)	(0.11)		(0.05)	(0.12)	(0.12)	(0.17)	(0.15)
Observations	106	100	110	110	110	95	95	110	95	95
Control mean	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25

Notes: Shows heterogeneous intent-to-treat effects of the application-support program on the four application process margins estimated using equation (2) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel titles list the respective outcome variable. Column headers indicate the baseline co-variate X for which heterogeneity is tested. In Column (1), X is the baseline application score to the GAIN mentoring program; column (2) the GRE quantitative score from the GAIN mentoring application; column (3) a dummy for whether the respondent was a mentee in a previous cycle; column (4) whether the respondent is from Ghana or Nigeria; column (5) a dummy whether the respondent's gender is female; column (6) is income; column (7) whether has a MA degree; column (8) whether is a current student; column (9) whether full-time employed currently; column (10) whether currently a research assistant. Table 3 shows average results for applications. Table 4 shows average results for admission offers. Table A.7 shows average results for accepted offers. Table 5 shows average results for attendance. Statistical significance indicated with * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$.

Table A.10: Selection Into Application

	Randomization sample			
	Control group (1)	Treatment group (2)	p-value t-test (3)	Directly admitted (4)
Application rank	79.23	75.38	0.53	30.11
	(27.42)	(27.59)		(25.97)
	[82.20]	[78.74]		[31.73]
GRE quant	154.63	155.65	0.33	159.36
	(5.63)	(4.09)		(5.31)
	[146.86]	[153.17]		[159.45]
GRE verbal	150.00	151.36	0.50	155.91
	(8.39)	(9.17)		(6.46)
	[145.75]	[151.23]		[155.73]
CV score	5.05	4.96	0.71	6.27
	(0.98)	(1.16)		(1.70)
	[4.96]	[4.94]		[6.36]
SOP score	7.80	7.88	0.80	8.97
	(1.22)	(1.52)		(0.94)
	[7.90]	[7.86]		[8.90]
Transcript score	7.69	7.65	0.92	8.36
	(1.40)	(1.65)		(1.88)
	[7.80]	[7.59]		[8.24]
Female student	0.18	0.33	0.16	0.37
	(0.39)	(0.47)		(0.49)
	[0.23]	[0.32]		[0.38]
Marital status	0.11	0.15	0.57	0.17
	(0.31)	(0.36)		(0.38)
	[0.14]	[0.17]		[0.21]
Age	27.39	27.79	0.71	27.93
	(4.95)	(4.29)		(3.54)
	[28.23]	[28.05]		[28.11]
Children	0.18	0.25	0.60	0.17
	(0.55)	(0.59)		(0.49)
	[0.23]	[0.27]		[0.20]
Income (wins)	2,938.23	2,387.76	0.59	5,303.27
	(5,052.15)	(3,961.24)		(7,285.76)
	[3,013.97]	[2,702.50]		[6,062.03]
Master	0.36	0.37	0.94	0.42
	(0.49)	(0.49)		(0.50)
	[0.42]	[0.37]		[0.44]
Prior webinar	0.36	0.27	0.42	0.28
	(0.49)	(0.45)		(0.45)
	[0.33]	[0.27]		[0.30]
Prior mentoring	0.18	0.17	0.95	0.23
	(0.39)	(0.38)		(0.43)
	[0.16]	[0.20]		[0.24]
Number of applicants	31	56		66

Notes: Compares the set of applicants in the treatment vs. control groups based on observable characteristics. Applicants are those who have submitted at least one application to a program in Europe or North America. The first row for each variables in columns (1), (2) and (4) show sample means for various *baseline* characteristics of applicants in the control group, treatment group, and directly admitted group, respectively. Column (3) shows the p-value from a difference in means t-test between the control and treatment group. Numbers in parentheses show the standard deviation. Numbers in brackets show the unconditional mean in the respective group irrespective of application status.

Table A.11: Importance of GAIN Program Elements in Reducing Barriers

	Not at all important	Slightly important	Moderately important	Very important	Extremely important
Webinar series	0.0	0.8	8.4	21.4	69.5
One-on-one mentoring	3.2	4.8	7.2	13.6	71.2
Funding for application fees	0.0	0.0	0.8	8.7	90.6
Funding for standardized tests	0.8	0.8	1.6	6.5	90.3
Resources for standardized tests	0.0	0.0	7.1	18.9	74.0
Info about application process	0.0	0.8	10.2	18.0	71.1
Info on funding & scholarships	0.8	2.3	11.5	24.4	61.1
Info & resources about predocs	0.8	9.3	14.4	26.3	49.2
List of grad school programs	0.8	5.4	10.0	28.5	55.4
Connection to peers	3.9	12.4	24.0	22.5	37.2

Notes: Shows responses of non-admitted as well as randomly and directly admitted participants combined for importance of GAIN elements in reducing barriers to graduate applications on a five-point Likert scale. Each column reports the share of respondents that reported a given choice for the barrier listed in the corresponding row.

Table A.12: Effect on Application Related Expenses (Elicitation by Source of Expense)

	Full Sample		Conditional on Applying		
	Total Amount (1)	% Annual Income (2)	Total Amount (3)	% Annual Income (4)	Amount Per Application (5)
Treatment group	−248.39**	−0.54*	−430.60***	−0.81**	−60.98***
	(105.37)	(0.30)	(145.33)	(0.36)	(20.45)
Observations	105	81	80	63	80
Control group mean	434.39	0.89	571.31	1.05	79.89
Direct admission mean	357.77	0.64	375.97	0.53	36.40

Notes: Shows intent-to-treat effects of the application-support program on application expenses estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Columns (1) and (2) show results for the full mentoring evaluation sample, whereas columns (3) to (5) restrict the sample to those who applied to at least one graduate program in Europe or North America. Columns (1) and (3) show total amounts spent, (2) and (4) show these amounts as a percentage of reported annual income if income was reported as non-zero, and column (5) divides the total amount by the number of applications submitted. All amounts are converted to USD using exchange rates as of September 2024 and winsorized at the 95^{th} percentile. The data in this table is from eliciting application-related expenses by source of expenses (e.g., income, savings, loans, etc.). Table 7 shows the main version using a separate question where application-related expenses were elicited by category (e.g., application fees, standardized tests, transcript fees, etc.). * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

Table A.13: Source of Application-Related Expenses

Average expense share across respondents					
Personal savings	Family savings	Credit/ loan	Non-GAIN mentoring	Other	No. of observations
Panel A: Control group					
0.72	0.18	0.07	0.01	0.01	26
[0.83]	[0.00]	[0.00]	[0.00]	[0.00]	
Panel B: Treatment group					
0.82	0.07	0.05	0.02	0.04	35
[1.00]	[0.00]	[0.00]	[0.00]	[0.00]	
Panel C: Directly admitted mentees					
0.84	0.08	0.05	0.02	0.01	48
[1.00]	[0.00]	[0.00]	[0.00]	[0.00]	

Notes: Shows descriptive statistics on the source of application-related expenses by group. The first row in each panel shows sample averages; numbers in square brackets show the median response.

Table A.14: Application fee waivers

	Fee waivers requested		Fee waivers granted	
	(1) Extensive margin	(2) Intensive margin	(3) Extensive margin	(4) Intensive margin
Panel A: Full sample				
Treatment group	0.24**	1.78*	0.10	0.03
	(0.10)	(1.01)	(0.09)	(0.51)
Strata FE	Yes	Yes	Yes	Yes
Observations	106	106	106	106
Control group mean	0.38	2.62	0.21	1.25
Panel B: Conditional on applying				
Treatment group	0.09	0.44	−0.05	−0.81
	(0.12)	(1.43)	(0.12)	(0.80)
Strata FE	Yes	Yes	Yes	Yes
Observations	82	82	82	82
Control group mean	0.55	4.03	0.34	2.07

Notes: Shows intent-to-treat effects of the application-support program on requested and granted application fee waivers estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Panel A includes the full set of treatment and control individuals, whereas Panel B restricts it to those who submitted at least one application to a graduate program in Europe or North America. The outcome in column (1) is whether at least one application fee waiver was requested; the outcome in column (2) is the number of application fee waivers requested. The outcome in column (3) is whether at least one application fee waiver was granted; the outcome in column (4) is the number of fee waivers granted. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

B Details on Empirical Strategy

This appendix first describes the details of the procedure for admitting candidates eligible for random admission, and then discusses survey attrition.

B.1 Randomization Protocol

GAIN has seen a steady increase in registrations to its webinar series and applications to its subsequent mentoring program. Due to financial and staff resource constraints, they only admit a subset of the qualified candidates applying each year. In collaboration with us, they decided to introduce an element of random admissions for a subset of applicants.

Mentoring program applicants are first screened by GAIN using a rubric to evaluate their comprehensive application package. Based on this evaluation, the team directly admits the most outstanding candidates into the mentoring program. Candidates falling below the eligibility threshold are not considered for admission. However, there is a sizeable number of applicants that meet the required qualifications to be admitted, but they do not stand out compared to the candidates directly admitted. Deciding who to admit among these qualified applicants is notoriously difficult and quite subjective. For this reason, admission to the mentoring program is random among this set of applicants.

Stratification

Randomization is stratified at the gender–PhD/MA competitiveness–GRE score level. Specifically, we assign individuals into strata based on their self-reported gender, whether the team considers them fit for PhD or MA/MSc applications, and whether their GRE application score is above or below the median in the respective gender–PhD/MA competitiveness group.[29] We stratify on this level since we believe these variables to have a predictive power for the outcomes of interest, and stratification ensures balance of randomization along these criteria.

Admission probabilities

The GAIN program goals of increasing representation are intersectional, and the team actively seeks to promote gender equality. Among the applicants to its mentoring program, women tend to be underrepresented, reflecting the status quo in economics worldwide. The team therefore aims to admit a somewhat higher proportion of female applicants to the mentoring program. This has already been in practice for the years prior to our study, and in line with this objective the randomization mechanism assigns a higher probability to be selected into the mentoring program for women than for men. This share of female participants in the mentoring program is determined by the GAIN team, thus, we aim to keep the share of women admitted as what GAIN would have done in the absence of the study.[30]

We calculate the number of candidates assigned to the treatment group in each strata as follows. Let g index gender, t PhD or MA/MSc competitiveness, and s above or below GRE score relative to candidates in the same gt cell. We seek to calculate a target number of treated individuals per strata, n^*_{gts}. Let n^*_g denote the targeted number of randomly admitted participants into the mentoring program of self-reported gender g; this number is set by the GAIN team. For each strata, we then

[29]The GRE score refers to a GRE quantitative reasoning score submitted from a mock test administered online through a GRE preparation firm at the end of the webinar series.

[30]The specific target may vary from year to year depending on the share of female applicants. For cohort 1, GAIN targeted a female share of 40%, implying an admissions probability of 60% of female candidates and a 40% admission probability for male applicants.

calculate the number of admitted candidates proportional to strata size. That is,

$$n^*_{gts} = n^*_g \times \frac{n_{gts}}{n_g},$$

where n_{gts} is the number of individuals in strata gts and n_g the total number of individuals of gender g. Note that

$$\sum_s \sum_t \frac{n_{gts}}{n_g} = 1.$$

We assign each individual a pseudo-random number drawing from a uniform distribution between 0 and 10 with no duplicate numbers. Within strata, we then assign the n^*_{gts} individuals with highest pseudo-random number to the treatment group.

Balance of randomization

Table B.1 tests for finite sample balance across baseline characteristics, both using survey and administrative data.

Table B.1: Balance of Randomization

Application Data	(1)	Baseline Characteristics	(2)
Application rank	−0.090	Marital status	0.037
	(0.180)		(0.077)
GRE quant	0.058	Age	0.044
	(0.136)		(0.198)
GRE verbal	0.229	Children	0.128
	(0.175)		(0.218)
CV score	−0.024	Income (wins)	−0.038
	(0.178)		(0.227)
SOP score	−0.014	Master	−0.031
	(0.183)		(0.093)
Transcript score	−0.139	Prior webinar	−0.076
	(0.181)		(0.095)
		Prior mentoring	0.025
			(0.080)
Strata FE	Yes	Strata FE	Yes
Observations	122	Observations	102
F-test $H_0 : \beta_k = 0\ \forall k$ (p-value)	0.875	F-test $H_0 : \beta_k = 0\ \forall k$ (p-value)	0.979

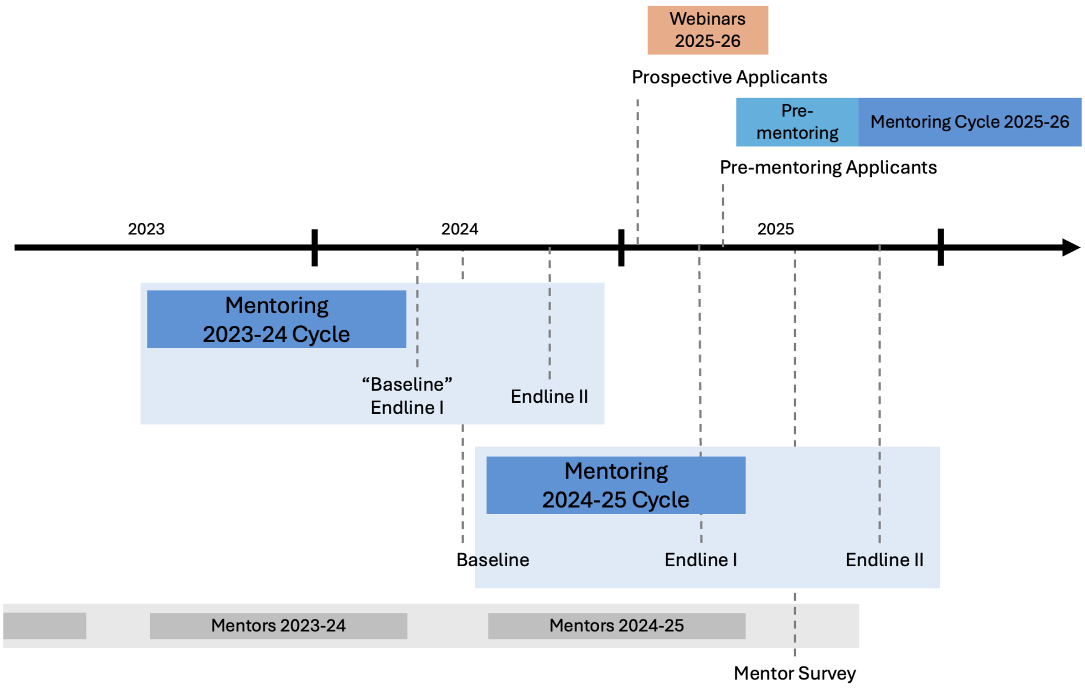
Notes: Shows estimation results from a test for balanced randomization using data from the mentoring program application (column 1) and from the baseline survey (column 2). Each coefficient is from a separate regression of the form $X_i = \beta Z_i + \lambda_i + \varepsilon_i$, where X_i is the co-variate of interest, $Z_i = 1$ if randomly admitted and $Z_i = 0$ if randomly not admitted, and λ_i captures the Strata. The F-test in the bottom row shows the p-value from a joint hypothesis test whether all coefficients are equal to zero, implemented through a stacked regression balance test. * for $p \leq 0.1$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$.

B.2 Surveys

Our study combines administrative data from the GAIN program with primary survey data. We surveyed the including cohorts at different points during the webinar and mentoring programs. Figure

B.1 outlines the survey timing across the different program cycles.

Figure B.1: Timeline of Surveys



B.3 Survey Attrition

Table B.2 presents the balance of attrition across treatment and control groups. Column 1 reports attrition for the baseline characteristics survey, while columns 2-4 show results for the midline and endline surveys on applications data, both separately and combined. Survey participation is generally high with 86% of the mentoring evaluation sample completing the midline survey and 86% completing the endline survey. While treated participants are slightly less likely to respond to the baseline, attrition is balanced in the midline and endline surveys are combined.[31]

In addition, Table B.3 checks for balance between attritors and non-attritors across several characteristics from the GAIN application data, such as their overall rank, practice test scores, and scores for their CV, statement of purpose, and transcript. There is generally no evidence of differential attrition based on these characteristics across groups in the midline or endline survey. The exception is that randomly admitted candidates who respond to neither the midline nor the endline survey have a one-point lower GRE verbal score, which is a not a meaningful magnitude in practice.

[31]We combine the midline and endline survey according to the sequential application process. That is—following our pre-analysis plan—when a respondent indicates not having submitted any applications in the midline survey (which takes place well after the main application season) and does not fill out the endline survey, we then infer that the respondent has also not accepted any application offers or is not attending a new program.

Table B.2: Attrition across treatment groups

	Baseline (1)	Midline (2)	Endline (3)	Midline or Endline (4)
Treatment group	−0.127*	0.003	−0.080	−0.061
	(0.070)	(0.064)	(0.063)	(0.046)
Strata FE	Yes	Yes	Yes	Yes
Observations	122	122	122	122
Control group mean	0.232	0.143	0.179	0.089
Sample mean	0.164	0.139	0.139	0.057

Notes: Shows estimation results from a test for balanced attrition in the different surveys (columns 1 to 3) and the midline and endline survey combined. Each column is a separate regression of the form $A_i = \beta Z_i + \lambda_i + \varepsilon_i$, where $A_i \in \{0, 1\}$ captures survey non-response (attrition). The sample mean is the average non-response rate among randomly admitted [treatment group] and randomly non-admitted candidates [control group]. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$.

Table B.3: Characteristics Associated with Attrition

	(1) Application Rank	(2) GRE Quant	(3) GRE Verbal	(4) CV Score	(5) SOP score	(6) Transcript Score
Panel A: Midline survey						
Attrition	−0.249	−0.470	−0.749	0.710*	0.406	0.579*
	(0.510)	(0.693)	(0.844)	(0.416)	(0.299)	(0.300)
Attrition × Treatment group	0.692	−0.151	0.548	−0.538	−0.786	−0.497
	(0.624)	(0.819)	(0.783)	(0.546)	(0.576)	(0.512)
Treatment group	−0.191	0.216	0.151	0.052	0.099	−0.068
	(0.186)	(0.154)	(0.159)	(0.191)	(0.192)	(0.193)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122	122	122	122	122	122
Panel B: Endline survey						
Attrition	−0.517	0.355	0.185	0.100	0.400	0.018
	(0.363)	(0.230)	(0.179)	(0.395)	(0.273)	(0.317)
Attrition × Treatment group	0.798	−0.465	−0.455	−0.433	−0.390	−0.119
	(0.532)	(0.299)	(0.323)	(0.489)	(0.414)	(0.507)
Treatment group	−0.210	0.266	0.288	0.026	0.056	−0.126
	(0.206)	(0.214)	(0.207)	(0.195)	(0.197)	(0.205)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122	122	122	122	122	122
Panel C: Midline and endline survey combined						
Attrition	−0.719*	0.315	0.332*	0.529	0.362	0.196
	(0.376)	(0.317)	(0.170)	(0.549)	(0.362)	(0.296)
Attrition × Treatment group	0.245	−0.461	−1.073***	−0.758	0.516	0.209
	(0.478)	(0.406)	(0.389)	(0.776)	(0.444)	(0.431)
Treatment group	−0.142	0.226	0.283	0.032	−0.008	−0.134
	(0.193)	(0.202)	(0.190)	(0.184)	(0.189)	(0.196)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122	122	122	122	122	122

Notes: Shows estimation results from a test for differential attrition by respondent characteristics in the treatment vs. control group. Each panel-column combination shows results from a separate regression of the form $X_i = \beta_1 A_i + \beta_2 A_i \times Z_i + \beta_3 Z_i + \lambda_i + \varepsilon_i$, where X_i is the co-variate expressed in the column title, A_i captures survey non-response (attrition), Z_i is random admission outcome, and λ_i is the strata. All outcomes are expressed in Z-scores. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$.

C Outcomes by School Rank

C.1 Methodology

Our midline and endline survey included questions on programs, which allow us to analyze treatment effects across the school rank distribution. Specifically, our midline survey asked about the schools participants applied to conditional on applying. The midline survey for cohort 2 also included questions on the programs where offers were received. Our endline survey asked about the schools where they have accepted admission offers and the school and program they are attending, if any.

We then match the schools with the *REPEC* ranking on the *Top 10% Economic Institutions, as of December 2024 (with details)*.[32] This ranking includes institutions globally. For each school in the top 1-5%, the ranking includes a score as well as a rank. For schools outside of the top 5%, the ranking includes the percentile (e.g., top 6%). The ranking lists some institutions more than once (for instance listing separate departments); we include the highest-ranked position. We carefully review each unmatched survey record (after cleaning school names) and assign it to be outside the top 10% if it is not included in the REPEC ranking. For robustness, we also match our survey data to the 2025 *US News* ranking on the *Best Economics Schools* in the US.[33]

We test the coverage of the self-reported information on schools in columns (1) to (3) of Table C.2. Reassuringly, listing at least one school—conditional on applying—is balanced across treatment and control (column 1). We can also compare the number of schools listed to the stated number of applications; this test is not only balanced, but coverage is high at 90% in the control group (column 2). While this is in part an outcome rather than a balance test, the treatment and control group are equally likely to list at least one school outside of the REPEC ranking (column 3).

C.2 Treatment Effects by School Rank

This section discusses the primary outcomes by school rank. Table C.1 shows effects on applications, accepted offers, and attendance by range of percentiles of the REPEC ranking. To increase power, we group programs in the top 1-5%, top 6-10%, and those outside of the ranking. Figure C.1 shows the results for the pooled cohorts by individual percentile in the REPEC ranking for completeness.[34]

Table C.1 columns (1) to (3) show that the program increased the propensity to apply across the school distribution. It is worth pointing out that the control mean is substantially higher for programs in the top 1-5% compared to lower ranks, so the program's treatment effect is on top of a relatively higher baseline. Individuals in the treatment group appear similarly likely to apply to a school in the top 1-5% like participants who were directly admitted into the mentoring program.

The effect on accepting an offer of admission (columns 4 to 6) and attendance (columns 7 to 9) is limited to school in the top 1-5%. The magnitudes are large compared to the control group mean. For attendance, in particular, the program increases the propensity to attend a graduate program by almost four times. Looking at the two cohorts separately, it is interesting to note that this treatment effect is driven by cohort 1, whereas admissions go up in the top 6-10% range for cohort 2 (this effect is not statistically significant; the treatment effect on attendance across school ranks *is* significant in

[32]Source: https://ideas.repec.org/top/top.inst.alldetail.html (downloaded on 2025-01-09).

[33]Source: https://www.usnews.com/best-graduate-schools/top-humanities-schools/economics-rankings (downloaded on 2025-07-30).

[34]We only have program-level data on offers for cohort 2, so we omit this outcome from the table. In this cohort, admission offers go up in both the top 1-5% range and the top 6-10%, following an increase in applications across the school-rank distribution.

cohort 2 alone).

Panels (e) to (g) of Figure C.1 reveal a shift in the distribution of attendance towards higher-ranked programs when moving from the control group (panel g) to the randomly admitted group (panel f) and finally to the directly admitted participants (panel e). This likely reflects (i) the positive treatment effect of the application-support program on all outcomes from applications to attendance and (ii) the relatively stronger application profiles in the directly admitted group vs. those randomly admitted.

C.3 Treatment Effects by School Rank Conditional on Applying

This section discusses the primary outcomes by school rank conditional on applying. Recall from section 5.3 that those who submit applications in the treatment group appear to not differ systematically on observables from those who submit applications in the control group. Thus, it is interesting to ask whether the mentorship program has, for instance, shifted applications towards higher or lower-ranked schools, and whether this can help explain the treatment effect on attendance.

In short, we interpret the following analyses as not revealing significant shifts in where candidates apply conditional on applying. While there are some results that could suggest applicants in the treatment group apply to somewhat lower ranked schools *on average*, driven by an increase in additional lower-ranked schools rather than a substitution away from higher-ranked schools, this interpretation is somewhat more speculative and subject to future research with larger sample sizes.

Table C.2 conducts an analysis of applications on the respondent-level. Columns (4) and (5) of Table C.2 suggest treatment group applications apply to somewhat lower ranked schools on average, but this effect is not statistically significant. Column (6) suggest the modal application for the treatment group is to lower-ranked schools. Columns (7) to (9) suggest that there are less differences for the highest-ranked school applied to compared to the lowest-ranked one, leading to an increase in the spread between the lowest and highest-ranked school for treatment group applicants. This is consistent with the treatment-induced increase in applications allowing treatment group applicants to diversify their applications and apply to a broader set of schools. However, these results are not statistically significant and column (10) reveals no significant difference in the standard deviation of school ranks applied to. Figure C.2 shows the distributions of the percentiles for the average, median, highest ranked, and lowest ranked school applied to; they are similar for the treatment and control group.

Table C.3 performs an analysis of applications on the respondent-applicant level. There is no difference in the propensity to apply to schools outside of the REPEC ranking (column 1). However, the average percentile is 0.6 points higher in the treatment vs. the control group (column 2). This is consistent with a lower propensity that an application is in the top 5% and slightly lower-ranked schools *within* the top 5%, where precise ranks—rather than broader percentiles—are available. These results are consistent with the US News ranking; the average application for the treatment group is to a school ranked 13 positions below that of the control group. Figure C.3 shows the application-level distributions of the REPEC percentiles, the REPEC ranks (within the top 5%), and the US News ranks.

Figure C.4 shows the distributions of the best accepted offer within the top 10% of REPEC schools. The figure shows the general increase in the number of accepted offers in the treatment vs. control group as well as the skewness toward higher ranked programs. This is even more the case for directly admitted candidates. Figure C.5 shows the same for the attending schools.

Table C.1: Primary Outcomes by REPEC Percentile Ranges

	Applied			Accept			Attend		
	(1) [1 – 5]	(2) [6 – 10]	(3) > 10	(4) [1 – 5]	(5) [6 – 10]	(6) > 10	(7) [1 – 5]	(8) [6 – 10]	(9) > 10
Treatment group	0.39***	0.37***	0.23**	0.13*	0.06	0.02	0.11*	0.03	0.02
	(0.08)	(0.09)	(0.09)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.04)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111	111	111	110	110	110	110	110	110
Control group mean	0.44	0.26	0.28	0.10	0.12	0.12	0.04	0.08	0.04
Direct admit mean	0.83	0.58	0.38	0.39	0.20	0.05	0.36	0.08	0.03

Notes: Shows intent-to-treat effects of the application-support program on applications, accepting admission offers, and attendance, by percentile bins of the REPEC Top 10% Institution Ranking, estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). Figure C.1 shows the disaggregated results for each percentile of the REPEC distribution. Table 3 shows the main results for applications, Table 4 for offers, Table A.7 for accepting admission offers, and Table 5 for attendance. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$.

Table C.2: REPEC Top X% of Schools Applied to on Respondent-Revel

	Coverage			Average			Distribution			
	(1) Lists any	(2) Share covered	(3) Outside Top 10%	(4) Average top X%	(5) Median top X%	(6) Modal top X%	(7) Highest ranked	(8) Lowest ranked	(9) Spread low – high	(10) Standard deviation
Treatment group	0.04	0.05	0.00	0.47	0.56	0.79*	0.16	0.83	0.67	−0.03
	(0.04)	(0.06)	(0.13)	(0.41)	(0.47)	(0.46)	(0.24)	(0.84)	(0.87)	(0.36)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74	73	73	72	72	72	72	72	72	72
Control group mean	0.96	0.90	0.61	3.37	2.89	1.68	1.30	6.61	5.32	2.39

Notes: Shows estimation results on the rankings of schools applied to conditional on submitting at least one application and estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). The data in this table is aggregated to the respondent-level, Table C.3 provides results using the respondent-application level. Columns (1) to (3) test for balance of the reported school-level information on applications. Share covered (column 2) is the number of specific schools listed to the number of applications stated. An exact match only possible for schools included in REPEC top 10% institutions. Whenever possible, for schools that are not listed, we impute a REPEC top 10% prediction using US news ranking. This is to increase the match; results are robust to only using original REPEC scores. Percentiles are recorded in 0.5 intervals for top 0.5-5.0%, and in 1.0 intervals for top 5.0-10% (based on data availability from REPEC). A higher top X% represents a lower ranking (e.g., the highest ranked schools are in the top 0.5% of schools). Figure C.2 shows non-parametric distributions of the outcomes analyzed in this table. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$.

Table C.3: REPEC and US News Ranks of Schools Applied to on Respondent-Application Level

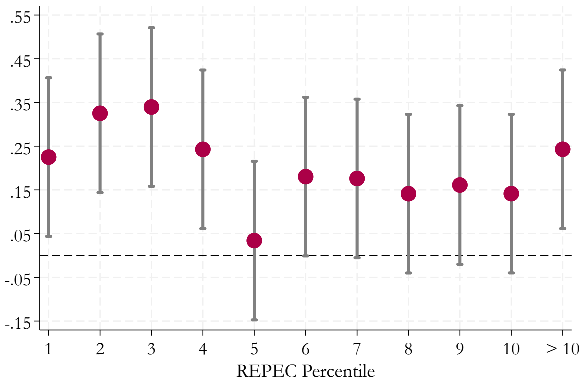
	Percentiles (top 10%)		Ranks (top 5%)		
	(1) Outside top 10%	(2) Top X% (top 10%)	(3) Applied top 5%	(4) Rank (top 5%)	(5) US News Rank
Treatment group	0.04	0.50	-0.08^{*}	9.58	13.4^{**}
	(0.04)	(0.30)	(0.05)	(14.3)	(6.42)
Strata FE	Yes	Yes	Yes	Yes	Yes
Observations	649	552	649	418	301
Control group mean	0.14	3.30	0.68	155.66	56.99

Notes: Shows estimation results on the rankings of schools applied to conditional on submitting at least one application and estimated using equation (1) and including strata FE (gender × above GRE median × PhD/MA competitiveness). The data in this table is on the application-respondent level, Table C.2 provides results aggregated to the respondent-level. Figure C.3 provides non-parametric distributions. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$

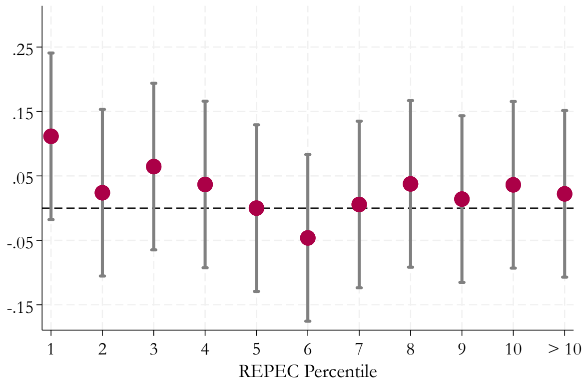
Figure C.1: Application Outcomes by REPEC Percentiles

Treatment Effects on Application Outcomes

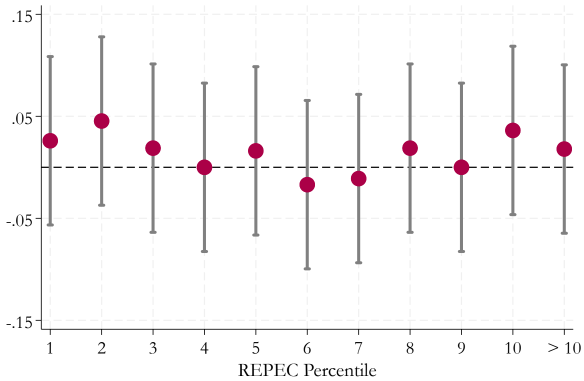
(a) Propensity to Apply



(b) Propensity to Accept Offer

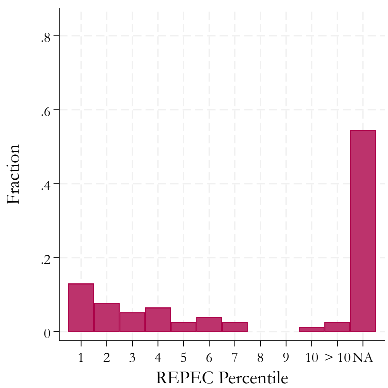


(c) Propensity to Attend

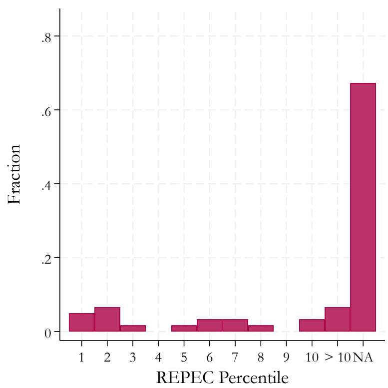


Distribution of Attending Program

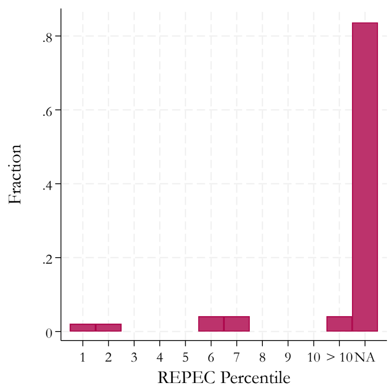
(d) Directly Admitted Participants



(e) Randomly Admitted Participants



(f) Control Group

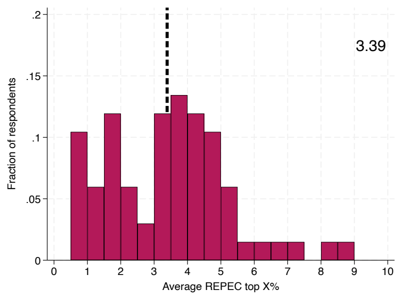


Notes: Panels (a) to (c) show the disaggregated results corresponding to the results in Table C.1. Panels (d) to (f) show the distribution of attending program in the full sample with "NA" referring to non-attending. Figure C.5 shows the distributions conditional on attending.

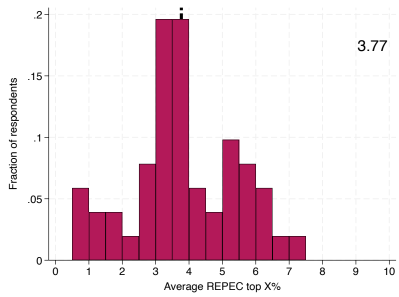
Figure C.2: Distribution of REPEC Top X% Applied to on Respondent-Level

Average

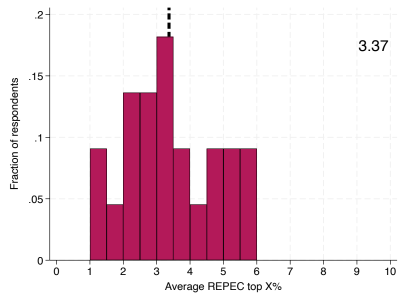
(a) Direct admissions



(b) Treatment group

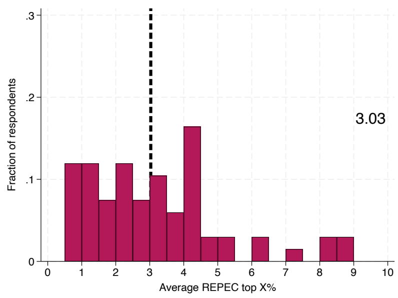


(c) Control group

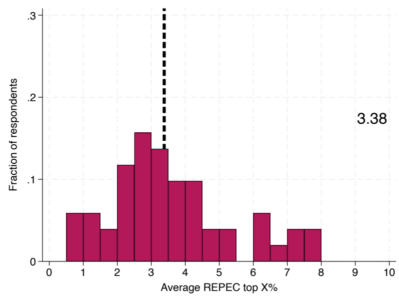


Median

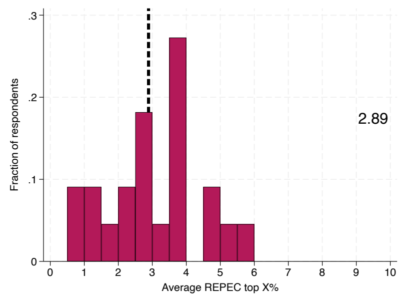
(d) Direct admissions



(e) Treatment group

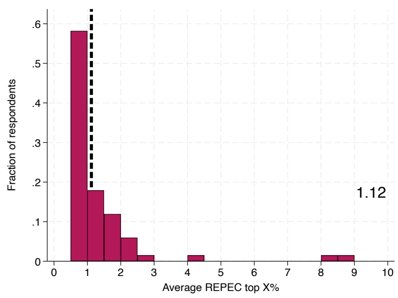


(f) Control group

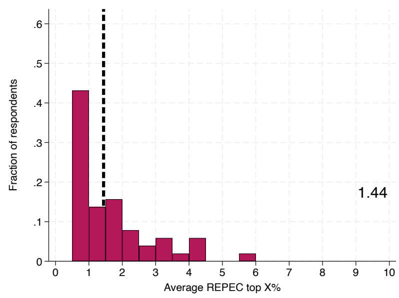


Highest ranked

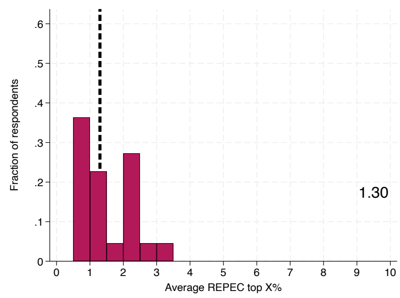
(g) Direct admissions



(h) Treatment group

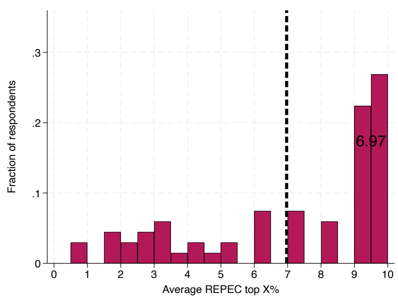


(i) Control group

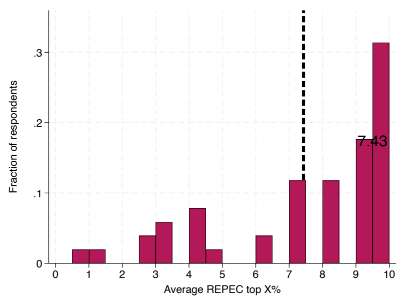


Lowest ranked

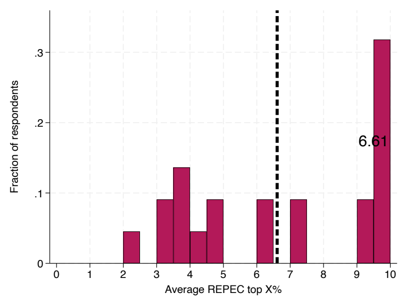
(j) Direct admissions



(k) Treatment group



(l) Control group

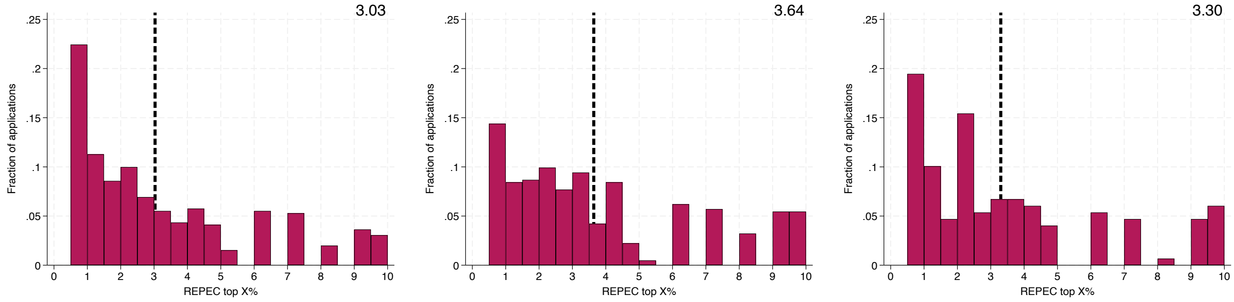


Notes: Shows the distribution of various statistics on submitted applications on the respondent-level. Table C.3 provides regression results.

Figure C.3: Distribution of REPEC and US news ranking applied to on respondent-application level

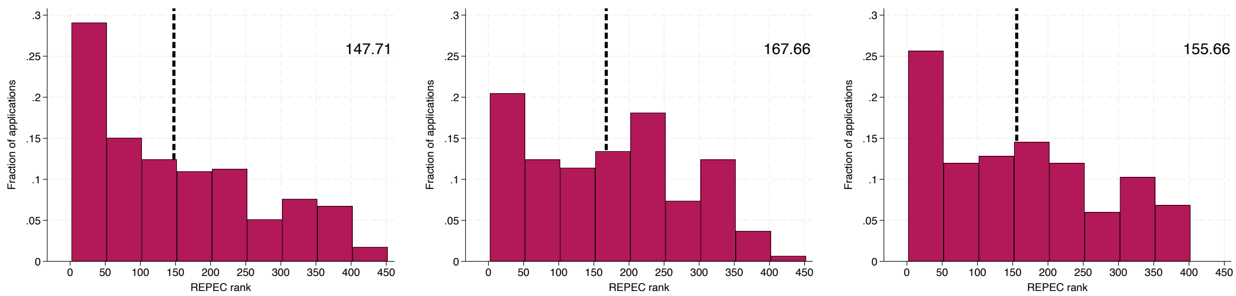
REPEC top X% within top 10%

(a) Direct admissions (b) Treatment group (c) Control group



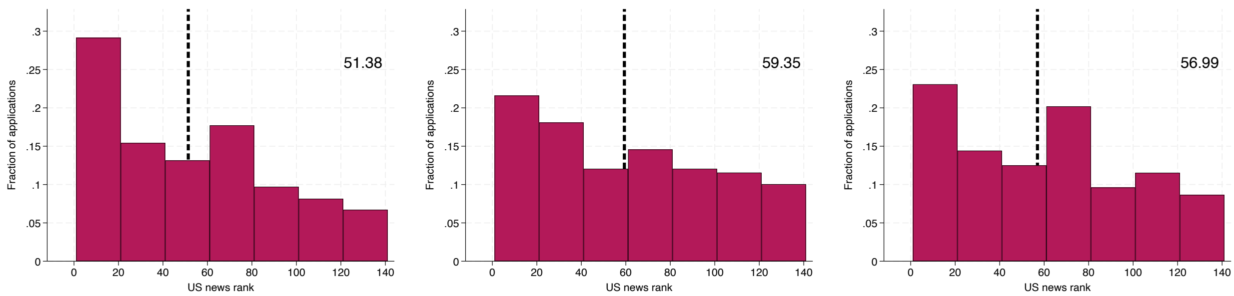
REPEC rank within top 5%

(d) Direct admissions (e) Treatment group (f) Control group



US News rank

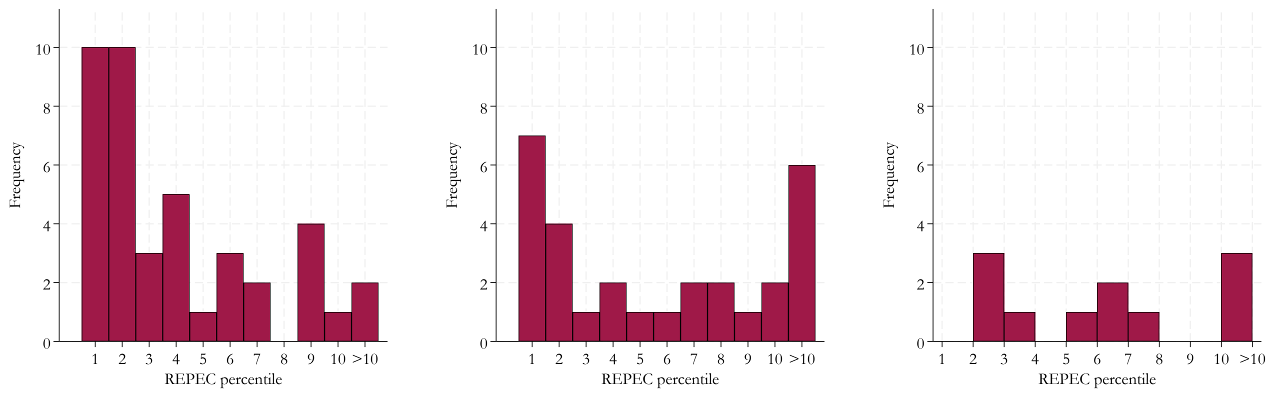
(g) Direct admissions (h) Treatment group (i) Control group



Notes: Shows the distribution of various statistics on submitted applications on the respondent-application level. Table C.2 provides regression results.

Figure C.4: Distribution of REPEC Top X% of Best Accepted Offers

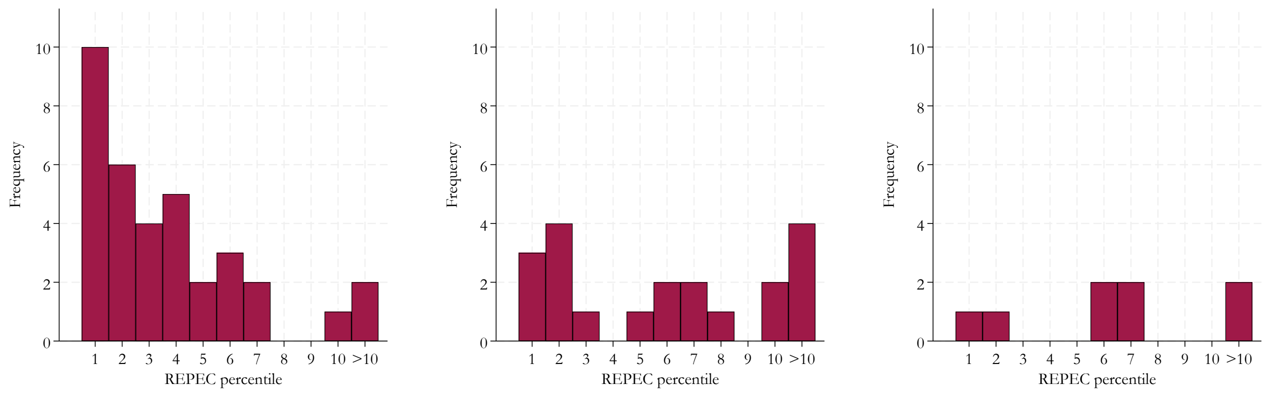
(a) Direct admission (b) Randomly admitted (c) Control group



Notes: Shows the distribution of accepted admissions offers by REPEC school rank conditional on accepting an offer.

Figure C.5: Distribution of REPEC Top X% of Attending Schools

(a) Direct admission (b) Randomly admitted (c) Control group



Notes: Shows the distribution of attendance by REPEC school rank conditional on attending a program.

D Role and Contribution of the Mentor

This section provides details on how the mentors shape their mentees' application outcomes. We interpret this analysis as suggestive given that mentors are not randomly assigned. We view unpacking the mentor role and causal contribution as fertile ground for future research.

The information discussed in this section is subject to the voluntary survey participation of mentors. We describe the mentor survey and sample in section 3.2 of the main text. The analyses use information on all mentors, including those for directly admitted mentees.

D.1 Characteristics of mentor support

Mentors and mentees have frequent communication in which they discuss various aspects of the application process. Table D.1 shows characteristics on the mentor-mentee level describing different aspects of mentor support. On average, mentors have about two calls with their mentee per month during the application season. These calls last about 30 minutes on average. In addition, mentors report interacting about three times per month through email, WhatsApp, or another messaging service with their mentee. These communication patterns do not differ systematically by whether the mentee was admitted randomly or directly. While the admission status was not known to mentors, it is correlated with observable mentee characteristics. The observation that mentors spend similar amounts of time communicating with their mentee across direct and random admission is indicative of their general availability and willingness to support not being a function of the mentees' baseline application strength.

Table D.2 summarizes mentees' responses to how often they discussed different application aspects with their mentor and letter writers. Randomly and directly admitted mentees report often discussing application materials and strategy with their mentor. They also report receiving a lot of feedback from their mentor on their application materials and the list of schools they intend to apply to. The support received from mentors stands out in particular to those from letter writers, possibly suggesting that mentors are complementing letter writers in guiding applicants through the application process, especially since the control group is very similar in how they interact with their letter writers.

To get a further sense of how mentors supported their mentees, we asked them to rate on a scale from 0 (none) to 10 (a lot) how much advice they have given their mentee on various items. We separately inquired with the mentor to what extent their mentee struggled with each of these items; these questions were shown on different pages with no "back buttons" trying to elicit independent evaluations on these two kinds of questions. While suggestive, the average mentee struggle is positively correlated with the average support provided by mentors (Figure D.1). It is interesting that mentors perceived their mentees to struggle a lot with the SOP and that they provided the most support on the SOP, while we find no differences in the SOP quality according to the GAIN grading criteria (Table 8). The answer on mentor support and mentee struggle on the SOP are in line with mentees' reporting discussing these materials a lot with their mentor. To some extent, this might also reflect that mentors felt their mentee had a hard time incorporating the mentors feedback or simply large differences between the first SOP draft and the final version. Importantly, we find the quality of SOPs is generally "high" for all groups (directly admitted mentees, randomly admitted mentees, and the control group). Another noteworthy observation is that mentees struggled a lot with scholarships, yet mentors were less able to provide support on this compared to application materials. This is consistent with the leakage from unfunded offers to attendance. Finally, these responses highlight how committed the mentees are to applying to graduate school. That is, mentees struggled very little with whether they wanted to pursue graduate school according to mentors' survey answers.

Mentors may also directly support applications by acting as a letter writer. Indeed, Table D.1 shows that the GAIN mentor acts as a letter writer in 11% of the observed mentor-mentee pairs. This is the case in both the randonly and directly admitted sample. Interestingly, there is a higher share of GAIN mentor letter writers among randomly admitted mentees (17%) than directly admitted mentees (10%). Given the already stronger application profile of the directly admitted mentees and their higher propensity to have studied abroad already, this is consistent with mentors filling a gap in mentees' application strength, possibly to strengthen the application signal.

Finally, mentors can also shape outcomes conditional on applications by putting in a good word for their mentee at a particular institution, which one in four mentor reports having done. This can be a strong signal, especially when letter writers are less well-known or from less recognized institutions. Mentors in the directly admitted groups are more likely to put in a good word at an institution than mentors of randomly admitted mentees; this could either be due to the directly admitted candidates having a stronger profile or—possibly more likely—a smaller share of professors among the randomly admitted mentees' mentors and it being difficult for a PhD student to put in a good word at some (especially other) institution. In addition, for 7% of mentor-mentee pairs, the mentor reports following up with someone at the institution on a waitlisted offer (however, only in one case for the randomly admitted group).

D.2 Correlation of mentor assessment and mentee outcomes

How much of this support is leading to higher attendance among mentees? We try to answer this in a descriptive sense since mentors are not randomized. However, we still find a consistent picture emerging in that better mentor advice and direct support of the application is positively associate with graduate program attendance. Probing these conclusions in causal analysis is a promising direction for future research.

Since the analysis is limited to the available mentor information, Table D.3 first tests for balance of mentor survey participation and balance of mentor assignment. For background, mentors are primarily matched in a two-way process. First, mentors from highly-ranked institutions are assigned to the most promising mentees. We thus control for whether a mentee was directly admitted (signal for their application strength). Second, outside of the seemingly strongest candidates, mentors are primarily matched based on mutual field interests with the mentor. Generally, they are not matched on other characteristics such as gender. We thus argue that—conditional on direct admission status—various assessments of the mentor are uncorrelated with mentee attributes.

Columns (1) and (6) of Table D.3 show that mentor survey participation is balanced across baseline application strength to the mentoring program and based on individual characteristics. The only exceptions are that mentors of mentees with more children are less likely to respond to the survey and that mentors whose mentee is married are more likely to respond. The balance test suggests that mentor assignment, conditional on direct admission status, is generally balanced across baseline application strength and individual characteristics (columns 2-5 and 7-10). As expected, there are some imbalances, but they appear small in magnitude, go in different directions in terms of candidate strength, and crucially are with respect to mentor attributes that we find to be uncorrelated with program outcomes (professor status, PhD rank, years of mentoring experience). Further, we will control for both direct admission status and the baseline application strength in the following analyses. Results are also robust to adding the baseline individual characteristics as controls; however, this reduces the sample size due to baseline survey non-responses, so we report the specification with the larger sample size.

We perform two type of tests of how mentoring attributes correlate with mentees' graduate program attendance. We include three type of mentoring attributes. First, we include proxies for the quality of advice given by mentors. This includes the number of applications they recommend, their understanding of the important and less important elements of the GRE, and their understanding of the importance of the letter of recommendation. Second, we include three types of actions they can take to directly support their mentee, including writing a recommendation letter, putting in a good word at some institution independent of writing a letter, and following up on a waitlist. Finally, we include mentor characteristics; whether they were a professor at the time of the mentoring program, whether they had hired a predoc before, the rank of their PhD granting institution, whether they were an admissions committee member before, and the years of their mentoring experience. Figure 6

The first test is within the sample of randomly admitted and randomly non-admitted mentees. The test asks how outcomes of randomly admitted mentees correlate with the particular mentoring attribute. We define the mentoring attributes based on the available data and code them to equal 0 when no data is available. For instance, when we have no information on whether the mentor wrote a letter of recommendation, we code up mentor attribute$_j$ = 0. Formally, then, we estimate

$$\begin{aligned}\text{attending}_{ij} = \beta \text{ random admission}_i + \gamma \text{ random admission}_i \times \text{mentor attribute}_j \\ + \eta \text{mentor response}_j + \xi' \mathbf{X}_i + \lambda_i + \varepsilon_{ij},\end{aligned}$$

where λ_i is the randomization strata and $\mathbf{X}_i$ is a vector of baseline application strength to the mentoring program. We are interested particularly in γ, which tells us the difference in mentee program attendance as a function of the mentoring attribute. In principle, we are also interested in how β changes compared to the ITT specification in equation XX; however, since we do not have information on all mentees, mentor attribute$_j$ = 0 in many cases even when the mentor might have provided the support.

The second test is within the sample of randomly and directly admitted mentees. Here, we ask how program outcomes depend on the mentoring attribute conditional on direct admission status and baseline application strength. Formally, we estimate

$$Y_{ij} = \alpha \text{ direct admission}_i + \gamma \text{ mentoring attribute}_j + \xi' \mathbf{X}_i + \varepsilon_{ij}.$$

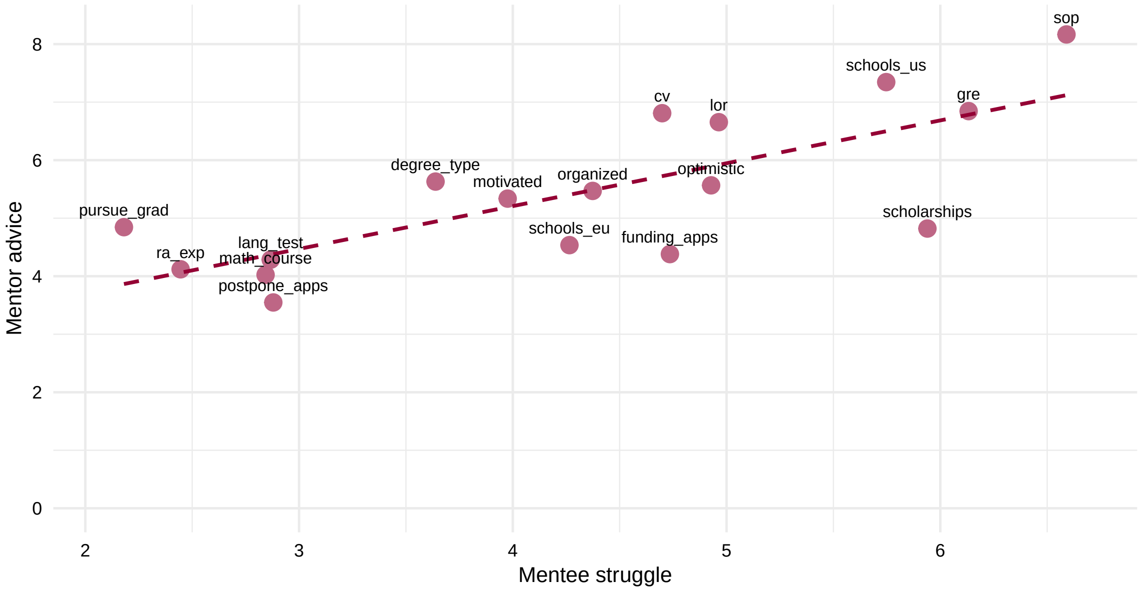
Figure 6 shows results for both of these tests, which we also discuss in the main text. All of the results are noisy given the combination of small mentor sample size and infrequent outcome (program attendance). First, better mentoring advice is positively associated with program attendance in both tests. This is consistent with persistent information frictions after the webinar program or mentors directly influencing the application strategy of their mentees. Second, mentees are more likely to attend a graduate program when their mentor put in a good for them at some institution independent of writing a letter or followed up with an institution when waitlisted.[35] The result for letter writers is

[35]We do not include the waitlist attribute for the impact evaluation sample since there is only one case when the mentor followed up on a waitlist in this sample and we are not comfortable interpreting results based on one data point.

more mixed with a positive association in the impact evaluation sample, but a somewhat negative correlation among the sample of randomly + directly admitted mentees. Third, certain type of mentor characteristics appear not to be good proxies of mentor quality; especially, the rank of the PhD granting institution, whether they were an admissions committee member before, or the years of their mentoring experience are not associated with program attendance. In contrast, whether the mentor hired a predoc before seems to be a better and positive predictor of attendance.

While each of the individual estimates is noisy, the combined evidence still portrays a fairly clear picture. Proxies of higher quality advice and directly supporting the application by reaching out to institutions are positively associated with mentees' program outcome in both specifications. This suggests that mentors can positively influence their mentees' outcome through the advice they give (possibly overcoming information frictions) and by using their connections to institutions (possibly overcoming signaling frictions).

Figure D.1: Correlation between Mentee Struggle and Mentor Advice



Notes: Shows the correlation between the amount of advice mentors have given on a particular application-related aspect (y-axis) and the extent to which mentors perceive the mentee struggled with a particular aspect (x-axis). Mentors were asked about advice given and mentee struggle in separate questions (and after two page breaks). Specifically, on advice, mentors were asked *On a scale from 0 (none) to 10 (a lot), how much advice have you given [mentee name] on each of the following?* On mentee struggle, mentors were asked *On a scale from 0 (none) to 10 (a lot), to what extent did [mentee name] struggle with each of the following in the application process?* Each (x,y) combination shown in the scatter plot represents the average across mentor answers on the particular aspect.

Table D.1: Descriptive Statistics on Mentor Support on the Mentor-Mentee Level

	Full Sample [2022-2025] (1)	Randomly Admitted [2023-2025] (2)	Directly Admitted [2023-2025] (3)
Monthly call frequency	2.02	1.91	1.93
	(1.31)	(1.23)	(1.23)
Average call length [in minutes]	35.69	36.33	34.88
	(16.81)	(18.10)	(16.59)
Monthly Email/WhatsApp frequency	2.81	3.03	2.52
	(1.65)	(1.87)	(1.40)
Wrote letter of recommendation	0.11	0.16	0.09
	(0.31)	(0.37)	(0.29)
Hired as a research assistant	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Put in good word at some institution	0.25	0.17	0.31
	(0.44)	(0.38)	(0.47)
Followed-up on waitlisted offer	0.07	0.03	0.09
	(0.25)	(0.18)	(0.29)
Self-assessed mentor contribution [0 to 10]	4.96	4.53	4.93
	(2.33)	(2.30)	(2.29)
Observations	92	31	45

Notes: Shows descriptive statistics on the support provided by mentors on the mentor-mentee level. Each row reports means and standard deviations (in parentheses) for selected characteristics for mentors across cohorts from 2022-25. Column (1) shows answers in the full sample of mentors who replied to the mentor survey covering the GAIN program cycles 2022/23, 2023/24, and 2024/25. Column (2) shows answers for the subset of mentors whose mentee is randomly admitted in our study cohorts. Column (3) shows answers for the subset of mentors whose mentee is directly admitted in our study cohorts.

Table D.2: Discuss application with letter writer and mentor

	(1) Never / None at all	(2) Rarely / A little	(3) Sometimes / A moderate amount	(4) Often A lot
Panel A: Randomly admitted mentees				
GAIN mentor				
Discuss application materials and strategy	0.06	0.10	0.19	0.65
Get feedback on application materials	0.04	0.12	0.27	0.58
Get feedback on list of schools	0.12	0.12	0.29	0.48
Letter writer				
Discuss application materials and strategy	0.02	0.27	0.31	0.40
Get feedback on application materials	0.23	0.27	0.27	0.23
Get feedback on list of schools	0.23	0.37	0.19	0.21
Panel B: Directly admitted mentees				
GAIN mentor				
Discuss application materials and strategy	0.06	0.08	0.15	0.71
Get feedback on application materials	0.06	0.13	0.16	0.65
Get feedback on list of schools	0.10	0.16	0.16	0.58
Letter writer				
Discuss application materials and strategy	0.17	0.11	0.48	0.23
Get feedback on application materials	0.23	0.28	0.25	0.23
Get feedback on list of schools	0.30	0.27	0.20	0.23
Panel C: Control group				
Letter writer				
Discuss application materials and strategy	0.17	0.10	0.48	0.24
Get feedback on application materials	0.31	0.31	0.24	0.14
Get feedback on list of schools	0.28	0.34	0.21	0.17

Notes: Shows descriptive statistics on the extent to which GAIN mentors and letter writers, respectively, discussed application materials and strategy, provided feedback on application materials, and provided feedback on the list of schools where one seeks to apply to. The control group did not have a GAIN mentor. Includes only respondents who applied to at least one program in Europe or North America.

Table D.3: Balance of Mentor Response and Assignment

Mentoring Application Data	(1) Mentor Survey Response	(2) Mentor PhD Top X%	(3) Mentor Current Professor	(4) Mentor Advice Programs	(5) Mentor Experience Years	Baseline Survey Data	(6) Mentor Survey Response	(7) Mentor PhD Top X%	(8) Mentor Current Professor	(9) Mentor Advice Programs	(10) Mentor Experience Years
GRE Quant	0.01	0.23	0.16	0.34	0.07	Marital status	0.22*	−0.26	0.27*	0.25	2.48*
	(0.03)	(0.65)	(0.19)	(0.54)	(1.63)		(0.12)	(0.49)	(0.15)	(0.43)	(1.48)
GRE Verbal	−0.04	0.07	−0.04	0.05	−0.43	Age	0.06	0.12	0.02	−0.02	−0.98
	(0.04)	(0.20)	(0.05)	(0.15)	(0.53)		(0.06)	(0.23)	(0.07)	(0.15)	(0.59)
CV Score	−0.02	−0.22	0.16***	−0.19	1.04**	Children	−0.12**	0.05	−0.10	−0.45*	0.11
	(0.04)	(0.18)	(0.04)	(0.15)	(0.48)		(0.06)	(0.18)	(0.08)	(0.25)	(0.65)
SOP Score	0.02	0.00	0.02	0.07	0.67*	Income (wins.)	−0.08	−0.03	0.03	0.16	0.28
	(0.04)	(0.21)	(0.05)	(0.15)	(0.39)		(0.05)	(0.17)	(0.05)	(0.11)	(0.50)
Transcript Score	−0.05	−0.39*	−0.04	0.26*	0.01	Has MA/MSc	0.09	−0.30	0.08	−0.18	1.80
	(0.04)	(0.20)	(0.04)	(0.14)	(0.41)		(0.11)	(0.42)	(0.13)	(0.38)	(1.13)
						Prior Webinar	0.09	0.36	−0.00	−0.79**	−0.44
							(0.10)	(0.43)	(0.11)	(0.34)	(0.97)
						Prior mentoring	0.01	−0.79**	0.37***	0.36	1.21
							(0.11)	(0.36)	(0.12)	(0.39)	(1.11)
Direct admission	0.16	−0.65	0.22*	0.21	−1.00	Direct admission	0.09	−0.91**	0.34***	0.14	0.07
	(0.10)	(0.44)	(0.13)	(0.33)	(1.08)		(0.09)	(0.44)	(0.10)	(0.28)	(0.75)
Observations	149	79	88	53	89		134	74	82	49	82
F-test covariates	0.61	0.36	0.03	0.55	0.15		0.23	0.46	0.01	0.07	0.16
Sample mean	0.60	1.54	0.39	-0.00	3.53		0.60	1.54	0.39	-0.00	3.53

Notes: Shows results from a test of balanced mentor assignment along baseline mentee co-variates conditional on direct admission status. Each column shows results from a regression of the form $M_{j(i)} = \boldsymbol{\beta}\mathbf{X}_i' + \sigma$ direct admission$_i$ + ε_i, where $M_{j(i)}$ is an attribute of mentor j assigned to mentee i as outlined in the column header, $\mathbf{X}_i$ is a vector of mentee baseline characteristics as outlined in the rows, and direct admission$_i = 1$ if the mentee was directly admitted. The *F-test covariates* shows the p-value from a joint F-test whether $\boldsymbol{\beta} = \mathbf{0}$. The sample mean shows the mean outcome variable among mentors. * for $p \leq 0.10$, ** for $p \leq 0.05$ and *** for $p \leq 0.01$