Online Training Programs and (In)equality: Rewiring the Gender Distribution of Technical Jobs

ABSTRACT

Emerging technologies, such as machine learning and artificial intelligence are fundamentally changing the nature of work, leading to a technical skills gap between what mid-career professionals do and what they need to be effective in their jobs. Online programs in technical fields provide one promising avenue for addressing the growing skills gap. Yet given historical processes of gender inequality in the workplace, particularly in technical fields, one important question to ask is the extent that online technical training programs equally attract men and women to apply. We investigate this question using proprietary data on the multi-staged decision processes made by 180,186 prospects on whether to apply to an executive-level online technical training program in business analytics, augmented with communications data on the count and length of interactions between each prospect admissions counselor pair. We find that female prospects self-steer away from applying while admissions counselors screen-out female prospects by preferentially allocating resources to male prospects. Counter to theories of homophily, we find that gender congruity between female prospect-counselor pairs reduces the likelihood that females advance through the admissions process. Examining contextual features, we find that more gender-balanced workgroups and prior experience with female prospects may attenuate gender differences in application outcomes.

Keywords:

Gender inequality, training, technical fields, skills gap, future of work, labor market, online education

INTRODUCTION

In March 2018, AT&T announced a $1 billion massive retraining effort after discovering that nearly half of its 250,000 employees lacked the necessary skills needed to keep the company competitive (Caminiti, 2018). A few months later in July 2019, Amazon announced a $700 million effort to retrain a third or 100,000 of its workers due to the increase in new transformational technologies (Cutter, 2019). Meanwhile, JPMorgan is investing in a future of work platform called "skills passport" for workers to take assessments to measure their current skills and career options against a curated list of training resources to improve their readiness (Weber, 2019).

As these anecdotal examples suggest, the rapid growth in digitization and emerging technologies has created a need for widespread workforce retraining in new occupational categories, across industries and hierarchical chain of command (Illanes et al., 2018). A recent study by the MIT-IBM Watson AI Lab that analyzed 170 million online job postings in the US from 2010 to 2017, finds that new technologies are reorganizing tasks within occupations, replacing jobs that are more suitable for machine learning with redesigned job roles requiring workers to learn new skills—both technical and soft (Fleming et al., 2019). Yet only about three percent of organizations intend to increase their internal training spend to address the skills gap among workers (Shook & Knickrehm, 2018). Rather than risk career stagnation or obsolescence, workers are facing the need to supplement their skills with external training to adapt to recent developments in technology, such as robotics, artificial intelligence, data science, and machine learning (Illanes et al., 2018).

Against this backdrop, online and blended learning programs offer one promising avenue to obtain technical training. Digital delivery of content has enabled mid-career professionals or "adult learners" to take courses in a flexible learning format and schedule. Paralleling the improvements in digital content delivery is the growing demand among adult learners for online degree programs, short courses and professional certificates in technical fields, such as business analytics or data management (Grushka-Cockayne & Lakhani, 2019). According to a 2018 report by *Poet & Quants*, more than half of the top 100 business schools now offer a 9 to 18 month business analytics degree or certificate program, costing between $50,000-$75,000, to train mid-career professionals to synthesize data to make better managerial decisions and advance their careers (Ethier, 2018).

Although online technical training programs provide a promising avenue for mid-career professionals to seek technical training in new skills, one missing piece is the extent that they are able to equally attract male and female mid-career professionals to apply. Put differently, gender inequality related to occupation segregation, ascension to leadership positions and income inequality remain thorny and difficult to solve problems in contemporary labor markets (Barbulescu & Bidwell, 2013; Bertrand et al., 2010; Goldin, 2014; Reskin & Padavic, 1994), but online technical training programs offer a potential path to mitigate these systematic issues. Towards this end, there are three key features of online training programs that may aid with recruiting a more diverse pool of applicants. First, online platforms differ from traditional offline counterparts because their global reach enables people to access a larger and more diverse pool of prospective students or "prospects" (Brynjolfsson et al., 2003; Chan & Wang, 2017). Second, the admissions counselors or "decision-makers" on online platforms evaluate prospects mainly through the review of their credentials (e.g., undergraduate GPA, major, years of work experience) presented in textual form, and communicate with candidates via electronic communication media, such as phone and email, without conducting face-to-face interviews (Chan & Wang, 2017; Grushka-Cockayne & Lakhani, 2019). A rich literature indicates that electronic media reduces social context cues (e.g., status, gender, physical appearance, body gestures) (Daft et al., 1987) so that people may be less aware of social differences and communicate more across social boundaries (Dubrovsky et al., 1991), and under certain conditions, may promote positive relational effects that may be superior to traditional face-to-face settings (Walther, 1995). The status equalization phenomenon of electronic communication suggests that social cues, such as gender, may be less salient in the selection processes of demand-side screeners for online programs (Sproull & Kiesler, 1986). Third, prospects take many months to advance through the admissions process (Grushka-Cockayne & Lakhani, 2019), suggesting that prospects are less likely to be evaluated based on conscious taste-based or statistical discrimination-based preferences (Becker, 2010). During a lengthy process that can take many months or even years (Grushka-Cockayne & Lakhani, 2019), prospects and counselors engage in a relational process that is both selective *and* collaborative in the sense that both actors need to decide whether they are suitable program applicants and then subsequently work together cooperatively to complete an application; the duration and complexity of the admissions process means that admissions counselors use a variety of criteria to assess prospects, making it less likely that they will solely rely on heuristic cues or historical cognitive schemas (Becker, 2013; Bohnet et al., 2015; Chan & Wang, 2017). These factors suggest that the decision processes of whether to apply to online training programs may differ from traditional processes where application decisions have been studied (Coffman et al., 2019; Fernandez & Weinberg, 1997; Fernandez-Mateo & Fernandez, 2016; Hoisl & Mariani, 2016).

Despite these differences, there are several reasons why gender biases in application decisions to online technical training programs may still exist. Women and men tend to pursue different educational choices and lines of work (Barbulescu & Bidwell, 2013; Johns et al., 2005;

Reskin & Padavic, 1994). Among the women who choose STEM majors, there are fewer women at each career stage, suggesting higher exit rates and a leaky pipeline. While women represent roughly 35 percent of STEM degree recipients (National Science Board, 2018), they make up only 25 percent of the overall STEM workforce. This gap is particularly large in high-tech jobs, such as software developers, computer network architects, and aerospace engineers—in which U.S. women represent less than 20 percent of people employed in those positions (Bureau of Labor Statistics, 2018). Recent work suggests women tend to perceive that the "bar" is higher for the same job (Coffman et al., 2019), suggesting that women screen themselves out of a job even when they might be qualified for it (Abraham, 2019). These supply side issues only represent one side of the equation. Other research has focused on demand-side influences, and show that women face barriers in male-typed labor markets because decision-makers tend to hold unconscious stereotypes when evaluating candidates, or may be biased to maintain male privilege (Fernandez-Mateo & Fernandez, 2016; Gorman, 2005). Given the lengthy admissions process, relational factors, such as the gender congruity between prospects and admissions counselors can both enhance and hinder gender differences in application outcomes. Because of these opposing arguments, a critical gap remains in our understanding of whether and the extent that online technical training programs can equally attract male and female prospects to apply.

The objective of this paper is to address this gap in the literature by investigating the admissions process into a competitive online technical training program. We examine the decisions of men and women to apply to the program, and the extent that their decisions are influenced by the screening criteria used by demand-side decision-makers, and the exogenous matching process where prospects are assigned an admissions counselor of either the same or opposite gender—creating either gender congruity or incongruity in prospect-counselor pairs. Building on recent work on gender inequality in labor markets, we examine the decisions to apply as a process rather than a single event (Barbulescu, 2015; Fernandez-Mateo & Fernandez, 2016). This approach allows us to pinpoint the gender-sorting mechanisms that contribute to gender disparity at each stage of the admissions process, and sheds light on the decisions of individuals who both applied and did *not* apply to the program, prior to acceptance and enrollment into the program.

To advance understanding, we examine the admissions process into a competitive, executive-level online technical training certificate business analytics program, where the recruitment of prospective applicants into the program is managed by a third-party online program manager (OPM) provider. To scale and grow their online programs, many universities have chosen to partner with for-profit OPMs who bring their expertise on marketing, recruitment of students, online course design and management to the relationship with a non-profit university partner. We have data on the decisions made by 180,186 prospects to advance or drop out at each stage of the admissions pipeline, and whether each prospect was randomly assigned a gender congruent (or incongruent) admissions counselor. To gain deeper insight into potential gender biases, we complement the admissions pipeline data with count data on the frequency and duration of phone conversations and email exchanges between each prospect-counselor pair.

The results suggest that women self-steer away from applying to online technical training programs at each stage of the admissions pipeline, while admissions counselors preferentially screen out female prospects by allocating resources to male prospects. On average, we find that 11.7% of male prospects start an application, compared to 10.6% of female prospects. This roughly one percent difference is accentuated depending on whether female prospects are assigned to male or female admissions counselors. By examining the gender congruity between prospect-counselor pairs, we find that gender congruity—i.e., when *female* prospects are assigned *female* counselors—reduces the likelihood that female prospects advance through the early-stages of the admissions pipeline by nearly 1%, corresponding to a roughly 7% decline in conversions to started applications compared to female prospects assigned to male counselors, and are nearly 2% less likely to advance than a gender congruent male-male prospect-counselor pair, corresponding to a roughly 14% decline in conversions to started applications. Overall, we find that gender discrepancies have greater economic impact at the early stages of the admissions pipeline, when prospects are deciding whether or not to start an application. The percentage differences have sizeable economic impact, contributing to roughly 750 fewer started applications by female prospects over the two-year study period, which have downstream effects that tilt the gender composition of completed and admitted applications by roughly 7 percentage points in the direction of more male-skewedness. We examine contextual factors to gain deeper insight into gender differences in conversion outcomes, and find that admissions counselors who are more experienced with female prospects, and admissions counselors in more gender-balanced workgroups, are more effective in converting female prospects through the admissions pipeline, suggesting both a direct and indirect learning effect. Because counselors are randomly assigned to prospects, our effects can be interpreted causally.

Our research is one of the first studies to examine how gender bias may affect the decisions of prospective students to apply to competitive online training programs in technical fields, and contributes to the nascent literature on the skills gap and the future of work. Our findings suggest that women in managerial and executive-level positions are less likely to pursue training, due to self-steering, unfavorable screening biases, and relational processes related to their interactions with their demand-side screeners. Given the importance of ongoing training to career advancement (Altonji & Spletzer, 1991; Becker, 2013; Bulte et al., 2016), inequality in access to online technical training programs may hinder the efficacy of ongoing top-down organizational initiatives to improve gender equity and female advancement. Our study also contributes to the literature on labor markets. By examining the application decisions as a process as opposed to an outcome, we contribute to the growing body of work that examines the gender-sorting mechanisms that occur prior to applying. We also have the rare opportunity to examine interactional processes, namely how gender congruity between supply-side and demand-side forces shapes people's decisions to apply. Towards this end, we show that homophilous forces do not necessarily shape the efficacy of interactions, but rather social context cues, such as the gender-stereotypically of screeners relative to the field or domain's gender-typed profile, and screeners' prior experience with atypical applicants, may be better suited to explain gender differences in application outcomes. We discuss implications for policy and managerial interventions aimed at mitigating gender inequality in online technical training programs.

Our paper proceeds as follows. We first review past literature and motivates possible links between supply-side, demand-side, and the intersection of supply- and demand-side factors in shaping application decisions. We then describe the research setting, data sources and variables. Next, we present the main results and conclude by discussing the implications of our findings.

ONLINE EDUCATION REWIRED: RISE IN ONLINE PROGRAM MANAGERS

Online degree and certificate programs are one of the fastest growing areas of education, particularly among the group of non-traditional "adult learners" who are seeking training in data management and business analytics to improve managerial decision making, career mobility and advancement (Rainie & Anderson, 2017). Online program manager (OPM) providers partner with universities to build, recruit and deliver online programs, and are for-profit organizations that offer a variety of services that traditional institutions historically do not have the expertise or capability to fully support, such as online digital content delivery and program offerings for non-traditional, adult student populations (Hill, 2018). OPM providers offer services that include marketing and admissions, enrollment management, curriculum development, online course design, and technology infrastructure to help universities scale and grow their online programs. These services typically require extensive upfront costs. To recoup their investments, OPMs enter revenue-sharing partnerships with universities, in an agreement that specifies for an OPM to foot the upfront cost to launch the program in return for a share in revenue per enrollment, usually around 60 or 70 percent of tuition revenue over a period of 10 to 15 years (Grushka-Cockayne & Lakhani, 2019).

A central aspect of an OPM's upfront investment is the admissions process of recruiting prospects to apply to the program. Because of its significance in shaping the students who enroll in the program, our study's focus is to better understand the dynamics of the admissions process. On average, schools spend \$38.53 for a prospect (for an individual's name and contact information), and more than \$380 to turn a prospect into someone who *starts* an application, and more than \$2,200 for every prospect that ends up enrolling (Newton, 2016). Because of the extensive upfront investments and high risks of drop-out, OPMs offer universities financial backing and recruitment expertise to attract and enroll students into online programs. Hence, the OPM serves as a buffer between the university and the pool of prospective applicants, meaning that any steering of prospects away from the admissions pipeline occurs indirectly through the OPM and their admissions counselors.

The OPM Admissions Process: Marketing, Recruiting and Admissions Counselors

OPMs use third party platforms, such as LinkedIn, Google, Facebook and Instagram to market the program (i.e., using advertisements or "ads") to prospects who may be interested in applying to the program. OPMs seek to optimize marketing spend, by monitoring the ratio of lifetime revenue to total cost of acquisition, and use sophisticated algorithms to tie every single prospect to a marketing event (Grushka-Cockayne & Lakhani, 2019).

When individuals click on an ad, they are redirected to the program's landing page or website where they can request more information about the program, by providing their name and contact information. After someone completes the intake information, he or she becomes a prospect. Prospects are assigned admissions counselors according to a workload scheduling algorithm, and are responsible for guiding and engaging with prospective students for enrollment into the program. Critical to an admissions counselor's success is the ability to establish rapport and build relationships with prospective students on the phone in a high-volume call environment or on email as needed, as well as the ability to achieve measurable results in a fast-paced metrics-driven environment.[1] The relational aspect of the job is particularly relevant because the admissions pipeline is a multi-staged multi-month process, with each stage corresponding to the amount of progress a prospect has made on an application. Prospects can search for up to two years before selecting a suitable program to apply to, and take on average, seven months to advance through the admissions process (Grushka-Cockayne & Lakhani, 2019). For every cohort of incoming students into a program, admissions counselors are assigned volume metrics for outbound phone calls and enrolled students, and ranked against cohort peers on their ability to meet or exceed these targets. It is only after an application is completed and submitted that the university's admissions team receives it and decides whether to admit, deny or conditionally accept an applicant into its program.

Gender Differences and Online Technical Training Programs

[1] Key skills selected from an admissions counselor job posting from a leading OPM; see https://boards.greenhouse.io/2u/jobs/4255173002

The literature on gender differences in application decision processes can be grouped into three classes of theories depending on whether they emphasize supply-side behavior (applicant's behavior), demand-side behavior (decision-maker's behavior), or the intersection of supply-side and demand-side behaviors (applicant and decision-maker's joint behaviors). Supply-side factors argue that men and women pursue different kinds of positions, thereby affecting the distribution of applicants for online technical training programs (Barbulescu, 2015; Barbulescu & Bidwell, 2013; Fernandez & Sosa, 2005). Women tend to be underrepresented in technical fields, such as STEM, representing a smaller fraction of the pipeline at each successive career stage (Cannady et al., 2014; Ellis et al., 2016). Related research finds that women shy away from competition (Flory et al., 2014; Samek, 2019), value money and leadership positions less highly than men and tend to value work that meshes well with child-rearing roles, even when they do not have children (Eccles, 1994). Women with children are more likely than men to experience work-life conflicts in their career due to gender-typed familial responsibilities (Bertrand et al., 2010; Goldin, 2014). Moreover, women tend to hold downward biased self-assessments of their own competencies and perceive that the "bar" of required qualifications is higher for a given position (Abraham, 2019); that is, vis-à-vis equal qualifications, women are less likely than equally qualified men to apply for a position (Buser et al., 2014; Coffman et al., 2019; Flory et al., 2019; Niederle & Vesterlund, 2007). These reasons suggest that gender-biasing effects that arise based on supply-side processes would manifest as female prospects being less likely than male prospects to advance through each stage of the admissions process.

In contrast to supply-side explanations, theories of demand-side biases focus on factors that prevent women from applying to competitive positions in technical fields. Demand-side screeners develop cognitive representations for jobs based on their observations of people holding these positions (Gorman, 2005). Gender stereotypes can be associated with screeners' cognitive schema, and the activation of these schemas would reinforce the notion that members of a certain gender are a better match for some fields than others. Technical fields, such as math and business, tend to be associated with male-typed domains (Moss-Racusin et al., 2012; Reuben et al., 2014), and screeners may use these cognitive schema to conclude that men are better suited for online training programs in technical fields. Using gender-based heuristics may reduce the cognitive load of in-depth screening for well-qualified applicants (Reuben et al., 2014) and help direct attention towards the incumbents who have demonstrated success in the past. Gender disparity that arises from demand-side processes would therefore be evidenced by the admissions counselors preferentially selecting men over women at each stage of the admissions process.

At the intersection of supply- and demand-side explanations is theories that account for how individuals' decisions are affected by the *expected* behaviors of screeners. Although gender-biasing effects from supply-side and demand-side processes would manifest in the behaviors of prospects and admissions counselors, acting independently, processes that lie at the intersection of supply-side and demand-side factors would be evidenced by different probabilities of advancing through each admissions stage that depend on the relational processes that manifest based on gender congruity between prospect-counselor pairs.

Gender can affect people's application decisions through its effect on men and women's expectations of success (e.g., their beliefs on how likely they are to be admitted) (Barbulescu, 2015). For example, experiments show that women tend to underperform on tests in technical domains (such as math, engineering, leadership) when they are told that the test revealed gender differences in the past (Correll, 2001; Johns et al., 2005; Shapiro & Williams, 2012). Other studies show that women may feel anxious and underperform on tests when they believe that others (e.g., screeners) expect women to perform poorly on a task (Shapiro & Williams, 2012). During the admissions process into online programs, men and women's expectations of about whether they will get in are shaped by social processes—in particular, their interactions with admissions counselors. A critical difference between screeners in typical demand-side processes, such as hiring, and the admissions counselors for online programs, is that a key part of a counselor's job is to interact, advise and work cooperatively with prospects to encourage them to apply. Hence, the process involves both selection *and* collaboration. That said, certain socially constructed characteristics, such as the counselor's gender, may affect their ability to convert male and female prospects through the admissions pipeline. Prior research suggests that women tend to process information more subjectively than men, and may be more likely to consider tangential and subtle cues, such as gender, in addition to more focal cues (Darley & Smith, 1995). This suggests that female prospects may be more sensitive to their admissions counselor's gender, and their likelihood of advancing through the admissions pipeline may depend on whether they are assigned male or female counselors.

On one hand, when people face uncertainty, such as when prospects are initially deciding whether or not to apply, they are more likely to prefer homophilous interactions with similar others from their in-group, such as other members of the same gender (Ibarra 1993; Kanter 1977). Gender is an observable characteristic that can be detected among strangers without a face-to-face meeting, because of differences in voice pitch and intonation (Klofstad et al., 2012). Based on these reasons, interactions between gender congruent female prospects and female admissions counselors are more rewarding, and female prospects may be more willing to trust their counselors' judgments and guidance. That being said, trust tends to be difficult to develop in online settings because of limited social presence and face-to-face interactions (Cramton, 2001; Hinds & Bailey, 2003). For example, individuals develop schemas or cognitive knowledge structures, often from their prior experiences—that help them encode and represent incoming information efficiently (Markus, 1977). Prospective female applicants may have cognitive schemas of whose admissions advice they are more willing to trust, and these schemas may be associated with their representations of particular domains as being male- or female-typed (Gorman, 2005). When these schemas are activated, female prospects may perceive that members of a particular gender are more trustworthy and competent (Chan & Wang, 2017; Flory et al., 2014). Because technical fields tend to be male-typed domains (Gorman, 2005; Moss-Racusin et al., 2012; Reuben et al., 2014), female prospects may perceive that male admissions counselors are more competent, and be more trusting of their advice.

In addition to the admissions counselors' gender and their relative effectiveness in advancing female prospects through the pipeline, it is also meaningful to consider the conditions under which these gendered outcomes may be attenuated or amplified. Prior literature shows that diverse experience can improve an individual's ability to learn and translate knowledge so that it can be applied to different settings (Cohen & Levinthal, 1990; Grant, 1996; Levinthal & March, 1993). A significant portion of an admissions counselors' knowledge is tacit, meaning that it is difficult to articulate, developed from direct experience, and hard to remove from its original context of creation or use (Grant, 1996). In online training programs, admissions counselors learn through their interactions and direct experiences advising and guiding prospects through the admissions process. Because learning involves developing new understanding, admissions counselors who have been assigned more female prospects gain a greater diversity of experiences, and have more opportunities to learn from these interactions, expanding the range of one's potential behaviors and interpretations of events (Fiol, 1994; Greenwood et al., 2018). This suggests that gendered outcomes in the admissions process may be attenuated among counselors with greater prior experiences working with female prospects, suggesting an individual learning effect.

Aside from individual learning through different experiences, admissions counselors also have the opportunity to learn from each other (Fiol, 1994). Organizational capabilities are not embedded within a single person, but as links across different individuals (Cohen & Levinthal, 1990), through collective learning. As admissions counselors share their own prior experiences with one another, they may develop common understandings that pool the diversity of their collective knowledge together. Therefore, admissions counselors may not only learn through their direct experiences advising female prospects but also through the indirect experiences of their colleagues (Gino et al., 2010), such as through the transfer of best practices from prior successes and failures (Jensen & Szulanski, 2007), and through vicarious learning where they absorb the experiences of others (Bandura & Walters, 1977). That said, not all indirect experiences are likely to be beneficial, and the relative value of learning through indirect experiences will likely depend on the diversity in the composition of the admissions counselor cohorts, such as the extent that they are gender-balanced or skewed. Compared with homogeneous groups, heterogenous groups are more likely to share more information and may demonstrate increased group performance. However, heterogenous groups are also prone to less cohesiveness and more conflict (Loyd et al., 2013). These opposing arguments comparing the benefits and downsides of group diversity may be reflected in the ability of admissions counselors to indirectly learn and benefit from more homogenous versus more heterogenous groups of colleagues.

Studying the admissions process into online technical training programs provides a strategic research site for making theoretical and empirical progress on supply-side, demand-side, and intersection of supply- and demand-side factors that affect the gender distribution of program applicants in technical fields. We can isolate supply-side processes, such as biased self-assessments or self-steering by female prospects' decisions to drop out of the admissions process at each stage. We can separate demand-side discriminatory behaviors by examining whether the admissions counselors preferentially select male prospects, such as by contacting them more frequently. Finally, we can examine interaction effects of supply- and demand-side processes by examining how any potential gendered outcomes are attenuated or amplified by gender congruity between prospect-counselor pairs, and contextual features, such as diversity of prior experiences. In the next section, we describe how we investigate these important theoretical questions from the supply-side, demand-side and intersection of supply- and demand-side forces.

RESEARCH SETTING

Our empirical investigation draws on the admissions process to a competitive, executive-level blended learning program that incorporates asynchronous interactive online lectures, weekly live video classes, in-person immersions and an online peer-to-peer learning community—all managed by the university's OPM partner, *OnlineEdCo*. The program is a nine-month executive certificate program designed for business leaders, including MBA graduates who are seeking to learn new ways to analyze, interpret and take advantage of increasingly complex data across industries. The courses are aimed to help students develop core skills in analytics, software design, architecture and data science. Sample courses in the curriculum included data-driven marketing, data collection, programming, statistics, data science, and people analytics. The program's student population had an average of 17.5 years of work experience, an average age of 42, a majority with advanced degrees, each paying $50,000 for the certificate.

OnlineEdCo manages the admissions process of recruiting prospects to apply to the program. Prospects refer to individuals who have visited the landing page or online program's website, completed an intake form with their name, demographic information (years of work experience, highest level of education, undergraduate GPA, undergraduate business or non-business major) and contact details, and requested more information about the program. Figure 1 depicts the complete multi-stage admissions pipeline—from lead stage to registered stage. The *lead* stage is the pre-application stage, after someone becomes a prospect but before he or she starts an application. There are two important features of the lead stage: first, admissions counselors are randomly assigned to prospects at the lead stage; second, a prospect's gender is revealed to the admissions counselor from the prospect's first name on the intake form. After the lead stage, there are three critical stages that describe the extent of progress made on the application. The *started* stage means that the prospect has *started* an application, and has begun filling out the personal information section of the application. The *engaged* stage means that the prospect has become a committed applicant, moving beyond the personal information to the program information section, which requests details about the potential applicant's intended program start date and source of funds. The *completed* stage means that the applicant has filled out the remainder of the application, which includes details on his or her academic background, professional experience, essays, transcripts and letters of recommendation and submitted a completed application for consideration into the program. Once an application is completed, the application materials are sent in electronic form to the university's admissions team via the OPM's application management system. Based on the application materials, the university's admissions team makes the decision on whether to admit, deny or conditionally accept an applicant into the program. This decision occurs at the *admitted stage.* Lastly, once admitted, the *registered stage* refers to whether a prospect decides to put down a deposit and secure their spot in the incoming cohort, defer or decline admission. Because the university only becomes involved at the entry decision stage, the admissions counselors are the buffers between prospective students and the university's admissions team, and play a critical role in recruiting and managing the potential pool of prospects from the lead to completed application stage.

Insert Figure 1 about here.

SOURCES OF DATA AND VARIABLES

Admissions Pipeline Data

Our dataset includes 198,522 U.S. prospects (both U.S. citizens and residing in the U.S.) between 10/17/2017 to 11/6/2019 and 44 admissions counselors that were randomly assigned to each prospect at the lead stage. The gender of the prospects and admissions counselors are inferred using first names (from the prospect intake form) using the R 'gender' package, which imputed the gender of 182,299 prospects, and 42 of the 44 admissions counselors (AC). Because we are interested in analyzing gendered outcomes in the admissions process, our analyses are based on 180,299 prospects for which the gender of the prospect-admissions counselor pair could be imputed.

For each prospect, we have details on his or her undergraduate major (business or non-business), undergraduate GPA, military affiliation, and years of work experience. In addition to this information, we have data on the month that the prospect requested more information about the program, the lead source or platform (e.g., LinkedIn, Instagram, Facebook, Google search) that the individual saw and clicked on an ad to land on the program website, and the landing page version that appeared when the prospect first entered the program's website.

Pairwise Communications Data

For each stage of the admissions process, we have count data on the directionality—i.e., inbound or outbound data on the phone and email communications between each counselor-prospect pair. The outbound data refers to the number of call attempts and emails from the counselor to the prospect, and the inbound data refers to the number of call attempts and emails from the prospect to the counselor. For the phone data, we also have the breakdown of outbound call attempts that resulted in *meaningful* conversations of at least one minute in duration, as well as the duration of the first phone conversation between the prospect-counselor pair. Notably, 97.65 percent of prospects who submitted a complete application had at least one meaningful conversation with their admissions counselor. Using the inbound and outbound emails, we define *meaningful* email as the count of two-way or reciprocated emails between the prospect-counselor pair. Moreover, the communications data between the prospects and counselors is automatically recorded in the OPM's data anytime a counselor makes an outbound or inbound contact attempt with a prospect. This is an advantageous feature of our setting because it means that the communications data is not subject to self-reporting differences among counselors.

Table 1 provides the descriptive statistics for the admissions pipeline data and the pairwise communications data.

Dependent Variables

Admissions Pipeline. We use dummy variables corresponding to whether a prospect advanced to the *started*, *engaged*, *completed*, *admitted*, and *registered* stages, respectively.

Communication data. We use the dummy variable, *lead meaningful call* to measure whether a prospect-counselor pair have one or more phone calls of at least one-minute long during the lead stage, and the dummy variable, *lead meaningful email* to measure whether a prospect-counselor pair have at one two-way (reciprocated) email exchange during the lead stage. We use *lead outbound calls* and *lead inbound calls* to measure the count of outbound and inbound call attempts between a prospect-counselor pair. Similarly, we use *lead outbound emails* and *lead inbound emails* to measure the count of outbound and inbound email attempts between a prospect-counselor pair. Lastly, we use *first meaningful call duration* to measure the duration (in minutes) of the first call duration between a prospect-counselor pair.

Independent Variables

Female prospect. We use the dummy variable*, female prospect* to measure whether a prospect is female.

Female counselor. We use the dummy variable, *female counselor* to measure whether a prospect is assigned a female admissions counselor.

Gender congruity. We use the categorical variable, *gender congruity* to measure the specific pairwise gender configuration (male prospect and male counselor, male prospect and female counselor, female prospect and male counselor, and female prospect and female counselor) between the prospect-counselor pairs.

Prior female experience. We use the continuous variable, *prior female experience* to measure the fraction of female prospects in an admissions counselor's prospect pipeline, using their trailing history of assignments to either male or female prospects. To ensure that we only captured actual and meaningful interactions between prospect-counselor pairs, we excluded any cases for which the prospect-counselor pair did not have at least one phone conversation of at least one minute in duration.[2] The resulting variable ranges from 0 to 1, where 0 represents no female

[2] The OPM considers a phone conversation of one minute to be the threshold for a meaningful conversation.

prospect assignments, and 1 representing only female prospect assignments, updated for each counselor according to his or her unique sequence of male and female prospect assignments.

Workgroup diversity. We use the continuous variable, *Workgroup diversity* to measure the fraction of female colleagues in an admissions counselor's workgroup. The variable ranges from 0 to 1, where 0 represents no female colleagues, and 1 representing only female colleagues. Because the admissions counselors were majority male, the variable ranged from 0.34 to 0.46, corresponding to more gender- or male-skewed and more gender-balanced counselor workgroups, respectively.

Control Variables

We control for a variety of prospect characteristics using categorical variables: *undergraduate GPA*, *undergraduate major*, *military affiliation*, *years of work experience*, *lead source* (e.g., Facebook, LinkedIn, Instagram, Twitter, Google search), and *splash creative* (e.g., desktop or mobile version of landing page, organic search vs. paid search version of landing page). In addition, we control for *lead meaningful call* and *lead meaningful email* to measure whether the prospect-counselor pair had a meaningful exchange, either by phone or by email at the lead stage.

Analytical Strategy

Our analyses is based on the likelihood that prospects at the lead stage convert to the started, engaged, and completed application stages, respectively. Towards this end, we perform three sets of analyses. First, we analyze the likelihood that prospects advance or drop-out at each stage to determine whether there is evidence that female prospects self-steer away from consideration for the program. We perform a series of multivariate regressions to predict the probability that prospects convert from the lead stage to each subsequent stage of the admissions process (started, engaged, completed, admitted and registered). Second, we analyze communication data to determine whether and the extent that admissions counselors screen out female prospects. This analysis is made possible by the communications data. We perform a series of multivariate regressions to examine the outbound and inbound phone and email communication count and duration data between the prospect-counselor pairs, to see if there are gender differences in the likelihood of being contacted. Third, we examine interactional processes between the gender of the prospect-counselor pairs to determine how gender congruity (i.e., same-gender, mixed-gender assignments) affects the likelihood that female prospects advance through the admissions pipeline, from lead stage to started, engaged, completed, admitted and registered stages, respectively. We perform a series of multivariate regressions that examine the interaction effect between the prospect gender and admissions counselor gender. We first examine differences in conversion outcomes when there is gender congruity between the prospect-counselor pair. We then examine differences in conversion outcomes according to each specific pairwise gender configuration (female prospect and male counselor, and female prospect and female counselor) relative to the male prospect and male counselor configuration. Lastly, we examine contextual factors, related to the admissions counselors' diversity of prior direct and indirect experiences in working with female prospects—which may attenuate or amplify the effects, to gain a deeper understanding of the relationships between gender congruity and decisions to advance through the pipeline.

We use linear probability models (LPMs) in all regressions. Although non-linear models, such as logit may be used to model dichotomous outcomes, the LPM is easier to interpret particularly for interaction terms. We use counselor fixed effects in all regression analyses to control for differences (e.g., quality, tenure, personality) between counselors, as well as fixed effects for the year and month that the prospect requested more information about the program.

RESULTS

Descriptives: Likelihood of Advancing Through the Admissions Pipeline

Figure 2 illustrates the observed gender composition at each stage of the admissions pipeline, indicating that the percentage of female prospects drops from 36.9% at the lead stage to 30.3% at the completed application stage, before increasing slightly to 34% at the registered stage, due to a greater percentage of admitted women registering for the program, *after* being admitted. Table 1 presents the descriptive summary statistics for the admissions pipeline data and communications data for all prospects, and by male and female prospects. Table 2 presents OLS regressions results of the likelihood of a prospect being female according to observed prospect features. Compared to male prospects, female prospects have more varied GPAs, are more likely to be non-business majors, have fewer years of work experience, and are less likely to have a military affiliation.

Insert Figure 2 about here.

Insert Table 1 about here.

Insert Table 2 about here.

Table 3 presents the OLS regressions predicting the likelihood that a prospect advances through the admissions pipeline from lead to started stage (Model 1), from lead to engaged stage (Model 2), and from lead to completed stage (Model 3), with all controls and counselor fixed effects. Models 1-5 show that female prospects are significantly less likely to advance through the admissions pipeline at each stage: started (-1.13%), engaged (-0.99%), completed (-0.18%), and admitted (-0.13%). Although females are less likely to advance through the admissions pipeline, from lead to admitted stage, the effect sizes indicate that the negative female effect has greater economic significance during the early stages of the admissions process—suggesting that female prospects are more difficult to convert from leads to applicants.

Insert Table 3 about here.

Supply-Side and Interactional Processes: Self-Steering and Gender Congruity

Table 4 presents our main regression results on the effects of interactional processes and gender congruity on the likelihood of advancing through the admissions pipeline. These regression results unpack the negative effect of being a female prospect on advancing through the admissions pipeline by differentiating between female self-steering (supply-side) and female gender congruity between prospect-counselor pairs (interactional processes), while controlling for demand-side differences with counselor fixed effects. Models 1-5 presents differences in started, engaged, completed, admitted, and registered application outcomes when there is gender congruity between female prospects and female admissions counselors. Models 6-10 then presents differences in application outcomes for each gender configuration against the male prospect, male counselor configuration. The effect sizes in Models 1-5 show that female prospects are less likely to advance through the admissions pipeline, from lead to admitted stage. Examining the interaction effect between *female prospect* x *female counselor* in Models 1-5, shows that compared to female prospect and male counselor pairs, female prospects assigned female counselors (i.e., gender congruent pairs) are 0.77% less likely to convert from lead to started application, which is a 7.2% (0.00773/0.1074) decline in the rate of started applications compared to female prospects assigned to male counselors (i.e., gender incongruent pairs), and 0.65% less likely to convert from lead to engaged application or a 9.8% (0.0065/0.0667) decline in the rate of engaged applications compared to female prospects assigned to male counselors (i.e., gender incongruent pairs). There are no significant interaction effects between female prospect and female counselor pairs at the completed, admitted, and registered stages, suggesting that interactional processes are more likely to occur during the early stages of the admissions pipeline.

Models 6-10 present the same coefficients, but for each gender congruity configuration. We observe that compared to male-male prospect-counselor gender congruent pairs, both the female-female prospect-counselor gender congruent pairs and female-male prospect-counselor gender incongruent pairs are significantly less likely to advance through the admissions pipeline, from started to admitted stage, but the leakage is roughly two-fold larger for female-female prospect-counselor pairs.

Using the coefficients from Table 4, Figure 3 examines the economic impact of female leakage, by presenting the total number of female prospects that are leaked at each stage due to self-steering (Figure 3a), gender congruity in female prospect-counselor pairs (Figure 3b), and the aggregated effect of both self-steering and gender congruity (Figure 3c) with 95 percent confidence intervals (CIs). Figure 3c shows that the combined gendered processes contributed to an estimated 753 fewer started applications, 659 fewer engaged applications, and 117 fewer completed applications, 85 fewer admitted applications, and 19 fewer registered applications by female prospects over our study period, on average. The effect sizes at the started, engaged and completed application stages are statistically significant. Figure 4 then shows the projected change in the gender composition of the prospect pool by eliminating the self-steering and the female prospect-counselor gender congruity penalty, assuming that the total number of male prospects at each admissions stage remains unchanged. Examining the percentages of female prospects at each stage shows that female self-steering is the larger contributor to gendered outcomes in the admissions pipeline, followed by gender congruity between prospect-counselor pairs. This suggests

In supplementary analyses, we interact all measures of quality (i.e., undergraduate GPA, undergraduate major, and years of work experience) with counselor gender, and the negative interaction effect of female prospect and female counselor remains significant at all stages. This suggests that the observed self-steering of female prospects away from applying (Table 3) is amplified when female prospects are assigned female counselors—with the negative effects on conversion outcomes being larger in the earlier stages of the pipeline.

Insert Table 4 about here.

Demand-Side Processes: Likelihood of Contact By Admissions Counselors

Next, we examine the likelihood that admissions counselors equally contact and interact with male and female prospects. Turning to the communication log data, Table 5 presents the regression results on the probability and frequency of having phone and email communication at the lead stage. Model 1 shows that female prospects are 3.27% less likely to have a meaningful phone call with an admissions counselor, while Model 2 indicates no gender differences in the likelihood of having a meaningful email. Models 3 and 4 examine the count of outbound phone calls and count of outbound calls that resulted in a meaningful conversation of at least 1 minute. Although there is no difference in outbound calls, female prospects had fewer outbound calls that resulted in a meaningful conversation. Similarly, Model 5 shows that female prospects received fewer outbound emails.[3] Model 6 shows the duration of the first meaningful phone interaction, and indicates that female prospects have shorter phone interactions by roughly 0.23 minutes (or 14

[3] Admissions counselors are required, as part of their job, to contact all prospects but retain flexibility on how they manage and allocate their outbound phone calls among prospects.

seconds). The results indicate that admissions counselors preferentially contact and have more meaningful and longer interactions with male prospects; put differently, female prospects are being screened out of the admissions pipeline. In supplementary analyses, we add the interaction term between *female prospect* x *female counselor* in Models 1-6. None of the interaction terms is significant suggesting that the preferential bias for male prospects exists for both male and female admissions counselors.

Finally, in Models 7 and 8, we turn to the inbound communication data to gain deeper insight into potential self-steering or anticipatory behaviors, with the results showing that admissions counselors receive 0.23 fewer inbound emails from female prospects but no difference in inbound calls from male and female prospects.

Insert Table 5 about here.

Contextual Factors: Prior Female Experience and Workgroup Diversity

Turning to contextual factors, Table 6 presents the regression results examining how prior female experience and workgroup diversity affect the likelihood of advancing through the admissions pipeline. Models 1-5 examine how prior female experience affects the likelihood of converting a female prospect through the admissions pipeline, while Models 6-10 examine how the workgroup gender diversity (i.e., male-skewed versus gender-balanced teams) affects the likelihood of converting a female prospect through the admissions pipeline. The interaction effect between *female prospect* x *prior female experience* in Models 3 and 4 suggest that female prospects are more likely to advance to the completed and admitted stages when assigned an admissions counselor with more experience with female prospects. The coefficients in Models 3 and 4 can be interpreted it as follows: a 0.10 or 10 percent increase in prior female experience (i.e., equivalent to being assigned one additional female prospect for every 10 prospects) has a 0.0018 and 0.00196 increase on the likelihood of female prospects completing and being admitted into the program, respectively—corresponding to a 34.8% (0.0018/0.0052) and 42.5% (0.00196/0.0046) increase over the observed completed and admitted conversion rates for female prospects (see Table 1). Turning next to workgroup diversity, we find a positive interaction effect between *female prospect* x *workgroup diversity* in Models 8-10, suggesting that the indirect experiences shared among a more gender-balanced workgroup may have a positive learning effect on the likelihood on female prospects completing, admitting and registering, respectively. The coefficients in Models 8-10 can be interpreted as follows: a 0.10 or 10 percent increase in workgroup diversity has a 0.00395, 0.00392 and 0.00274 increase on the likelihood of female prospects completing, being admitted and registering to the program, corresponding to a 76.4% (0.00395/0.00517), 85.0% (0.00392/0.00461) and 125.8% (0.00274/0.00218) increase over the observed average completed, admitted and registered conversion rates for female prospects, respectively.

Table 7 presents both interaction effects in the same model for each stage of the admissions pipeline, and shows that the interaction effects for *female prospect* x *female prior experience* and *female prospect* x *workgroup diversity* remain significant and positive. Lastly, Table 8 presents the models for each admissions stage separately for male counselors (Models 1-5) and female counselors (Models 6-10). The results indicate that although the effect of workgroup diversity has a positive effect on both male and female counselors in converting female prospects to the completed, admitted and registered stages, respectively, prior female experience only improves the performance of male counselors. In Models 6-10, there is no evidence that prior experience with female prospects improves the likelihood of converting female prospects at any stage. These results confirm that although prior female experience may improve the conversion outcomes of female prospects, this learning effect is more applicable to male counselors, and also at the later stages of the admissions pipeline.

Insert Table 6 about here.

DISCUSSION

We began this study with a simple question: *do online technical training programs equally attract men and women to apply?* Given that emerging technologies and machine learning are changing the nature of jobs across most industries, mid-career professionals are facing the need to undergo additional training to improve their technical and quantitative skills. Many professionals are turning to online technical training programs to address this skills gap—which has been met by a growing plethora of online program and certificate offerings to meet the growing demand. A promising aspect of technical online programs is that they offer a potential pathway to reduce gender inequality in labor markets by preparing men and women to take on managerial and executive-level positions in technical fields within their organizations. Despite their promise, past research on gender inequality in a variety of settings, such as education (in technical fields) (Cannady et al., 2014; Moss-Racusin et al., 2012; Reuben et al., 2014), hiring for managerial and (Barbulescu, 2015; Barbulescu & Bidwell, 2013) and executive-level positions (Fernandez-Mateo & Fernandez, 2016) as well as venture capital funding (Ewens & Townsend, 2019; Kanze et al., 2018; Lee & Huang, 2018) indicates that gendered outcomes may also be applicable to people's decisions to apply for online technical training programs.

We explore this critical question using a unique and proprietary dataset from the admissions process into a competitive, executive-level online training program, which is managed by a third-party OPM. We make three key findings. First, there is evidence that women self-steer away from applying to technical programs, particularly during the early stages of the admissions process (for example, deciding whether to start an application). Second, we find that demand-side screeners, or the admissions counselors contribute to the female gender disadvantage by preferentially selecting to engage with men over women. We are able to distinguish the demand-side sources of gender disparity from the supply-side by analyzing the outbound communications made by admissions counselors to male and female prospects. Third, we show that gender congruity between prospect and counselor pairs affects the magnitude of gender differences in application decisions. Contrary to homophily preferences, we find that female prospects are more likely to advance through the admissions pipeline when assigned to male counselors. Examining contextual factors, namely the counselors' prior experience with female prospects and counselor workgroup diversity, we find that admissions counselors who have had more prior female experience, and counselors whose workgroups are more gender-balanced, are more effective at converting prospects. Although this suggests a learning effect on performance, our analysis further reveals that impact of prior female experience is only relevant for male counselors, as we find no evidence that greater female experience improves the performance of female counselors in converting female prospects. Because the counselor workgroups were majority male, it is possible that counselors may benefit from the increased diversity of perspectives of more gender-balanced workgroups. Also, our findings suggest that the effect on learning tends to affect the later stages of the admissions pipeline, whereas gender differences in application decisions tend to be magnified in the early stages of the admissions pipeline. Because of random assignment of admissions counselors to prospects, we have exogenous variation in gender congruity among prospect-counselor pairs that enables us to overcome the endogeneity and selection problems of relational data; accordingly, our results can be interpreted causally.

Our study aims to make several important contributions. This study is among the first empirical efforts to investigate the presence and directionality of gender-related admissions bias in online technical training programs. Given the growing skills gap and the inability of employers to meet training needs, online training programs are becoming an increasingly important factor in preparing workers for the future of work (Illanes et al., 2018). Our study suggests that entry into these programs may perpetuate gender inequality in labor markets, because women are less likely to apply for training and are subsequently less likely to receive training that may have remunerative benefits on career mobility and advancement.

We contribute to the literature on gender inequality in labor markets by being one of the few studies that views admissions decisions as a process rather than an outcome (Barbulescu, 2015; Fernandez-Mateo & Fernandez, 2016). For example, most studies tend to focus on the individuals who have chosen to apply rather than the multi-staged process of individuals who choose whether or not to apply and the factors that influence these decisions. Distinguishing between the admissions process and admissions outcomes makes important progress towards understanding what gender-sorting mechanisms exist prior to applying (Fernandez & Sosa, 2005). Another advantage to viewing the admissions pipeline as a process is that we are able to pinpoint the stage(s) where gendered outcomes are most likely to exist. In particular, we find that gender differences in conversion outcomes are largest at the early stages of the admissions pipeline—which is impactful because of the significant number of prospects and greater potential to make policy changes that target these stages of the pipeline. Our ability to make progress is facilitated by the granularity of our data, which includes prospective students' decisions at each stage of the admissions process, as well as communications data on the frequency and duration of interactions between prospect-counselor pairs. This granular data enables us to understand how the pool of potential applicants changes through the process, to distinguish between supply-side self-steering and demand-side screening behaviors, as well as the intersection of supply-side and demand-side influences. Prior work has had limited ability to study these relational processes and the impact of gender congruity in shaping admissions outcomes. The unique admissions process into online training programs, which involves both selection and collaboration between prospects and admissions counselors, provides us with a rare opportunity to make theoretical and empirical progress on these relational processes.

We also make progress on understanding the conditions when gender differences are amplified and attenuated. By examining features of the social context, we are able to shed some light on actionable ways to mitigate gender differences. To this end, we explore how prior female experience impacts the likelihood of female prospects advancing through the admissions pipeline, and observe that gender differences in conversion outcomes can be explained in part by lack of exposure to female prospects. Given that the prospect pool is majority male, admissions counselors have more experience advising male prospects. This is supported by the finding that admissions counselors (particularly male counselors) who have been assigned more female prospects are more effective in converting female prospects into completed applications. Similarly, we find that counselors with more diverse, gender-balanced workgroups are also more effective in advancing female prospects through the later stages of the admissions pipeline. This suggests that admissions counselors benefit from sharing information with one another—potentially about their experiences interacting with female prospects, highlighting not only the importance of direct experience with female prospects but also indirect experiences that are shared by through interactions with colleagues.

Policy Implications

Our research has a number of policy implications for improving the ability for technical online training programs to attract equal numbers of men and women to apply. Our analyses have three potential implications for policy. First, targeted interventions are likely to have the most economic significance on changing the gender composition of the prospect pool at the early stages of the admissions pipeline, due to the large number of prospects that have the potential to be converted at the beginning of the admissions process. For example, our findings show that there were over 750 potential female applicants who dropped out of starting an application over our two-year study period because of either self-steering or penalizing prospect-counselor gender congruity. Although the effect sizes (percentage-wise) of self-steering and gender congruity related leakage are similar in the early stages of the pipeline, we find that self-steering is more likely persist through the later stages of the admissions process. Therefore, policies that target female self-steering behaviors at the earliest stages of the admissions pipeline, such as female role models and diversity promoting communications are likely to have greater impactful economic significance (Del Carpio & Guadalupe, 2018; Flory et al., 2019). Second, although gendered outcomes tend to be more prevalent in the early stages of the admissions pipeline, the learning effect tends to improve conversion outcomes at the later stages of the admissions pipeline. It is critical to understand why these learning effects tend to appear at the later stages of the admissions pipeline to design interventions that may promote greater communication and information sharing in the early stages. Third, our findings suggest that the admissions counselors also contribute to gender biases in conversion outcomes. Although we find a small but significant effect that female prospects are less likely to be contacted, these gender discrepancies exist even though admissions counselors are required as part of their job description, to call every prospect assigned to their workflow. We highlight this detail as although it is a unique feature of our setting, it is suggestive that demand-side screening (i.e., by executive search firms, human resources recruiting, algorithmic screening) could be magnified if such stringent policies were not already in place. Even then, there may be additional interventions that could increase the number and duration of outbound calls to female prospects to help compensate for self-steering behaviors.

Limitations and Future Directions

Although we make a number of empirical and theoretical contributions, our study is not without limitations that point to fruitful avenues for future work. First, our study represents a trade-off between broad data across many programs and detailed information on one particular program. Although we chose to focus on one specific program, the admissions process is representative of the partnerships that universities often enter with third-party OPM's to manage the recruitment of applicants into the program. Therefore, our findings are generalizable in the sense that the admissions process studied in our context is similar to processes at other universities who have partnered with OPMs to scale efficiently into online training programs. Future work could aim to collect a representative sample of technical online programs to draw more extensive insights.

Second, we do not have the ability to observe the selection processes that convert men and women into prospects. We control for the lead source or ad platform that resulted in a click through to the landing page, as well as the landing page version, but we are not able to observe the entire path-dependent process *before* an individual became a prospect. That said, future research can explore how the content, imagery and sequence of ads may have influenced people's decisions to click on an ad for the program and their downstream decisions of whether to become a prospect and an applicant of the program. Similarly, we do not observe external factors and interactions that occur during the admissions process (e.g., interactions with former students and mentors) that may have influenced prospects' decisions to apply. Given the growing popularity of online training programs, referrals may be an important next step to explore in the admissions process and likelihood of advancing (Fernandez & Sosa, 2005).

Third, we rely most heavily on behavioral measures of what people do, rather than the reasons for what they do. Given the proprietary nature of the data, we are unable to access the transcripts of prospect and counselor interactions to interpret why gender congruity *amplifies* gender differences in conversion outcomes through the admissions pipeline. Similarly, we are not able to interview admissions counselors to understand why they are more likely to contact male prospects. Possible explanations could be that women may represent a riskier choice because they involve more difficult conversations, or because they appear to be atypical in the prospect pool in a male-typed domain. Absent interviews and transcripts, and costly learning processes (i.e., the opportunity cost of "leaked" prospects due to counselor on the job learning), natural field experiments present a promising way to address these outstanding issues. For example, future research could examine how diversity-promoting experiments targeted at altering the potential pool of prospects (Flory et al., 2019) may have downstream implications on self-steering and screening behaviors. Similarly, future work could adopt "blinding" procedures (Goldin & Rouse, 2000) to hide the gender of supply-side prospects from their demand-side admissions counselors, or to hide the gender of demand-side counselors from supply-side prospects. Such experiments point to promising avenues of future work to tackle this important problem of gender inequality in competitive, technical jobs.

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TABLE 1

Summary of Descriptive Statistics of Admissions Pipeline

Variable	All Prospects (N = 180,186)	Male Prospects (N = 113,609)	Female Prospects (N = 66,577)	Difference M-F (two-tailed t-test)
Application started	0.113	0.117	0.106	0.012***
Application engaged	0.071	0.075	0.065	0.010***
Application completed	0.006	0.007	0.005	0.002***
Admitted	0.005	0.006	0.005	0.001***
Registered	0.002	0.002	0.002	0.000
Female AC (admissions counselor)	0.360	0.361	0.359	0.002
Prior female experience	0.369	0.366	0.376	0.002***
Female counselor ratio	0.360	0.361	0.358	0.003***
Any lead meaningful call (0/1)	0.196	0.210	0.173	0.037***
Any lead meaningful email (0/1)	0.068	0.068	0.067	0.001
# of lead outbound calls	1.468	1.470	1.463	0.007
# of lead outbound calls (> 1 min.)	0.229	0.246	0.201	0.045***
# of lead outbound emails	0.728	0.729	0.725	0.004
Lead call length (mins.)	1.067	1.168	0.893	0.275***
# of lead inbound calls	0.082	0.088	0.071	0.018***
# of lead inbound emails	0.112	0.113	0.110	0.004

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

TABLE 2

Probability of prospects being female (linear probability model – 0 is male; 1 is female)

VARIABLES	Model 1
Baseline GPA: < 2.49 and below	
GPA: 2.99-2.50	0.0328***
	(0.00741)
GPA: 3.49-3.00	0.0983***
	(0.00728)
GPA: 3.99-3.50	0.191***
	(0.00741)
GPA: 4.00 and above	0.218***
	(0.00885)
Baseline undergraduate major: Business	
Undergraduate major: N/A	-0.0286
	(0.0248)
Undergraduate major: Non-business	0.0370***
	(0.00271)
Baseline work experience: 0-4 years	
Work experience: 5-10 years	-0.0284***
	(0.00506)
Work experience: >10 years	-0.0425***
	(0.00384)
Work experience: N/A	-0.322***
	(0.0364)
Military	-0.157***
	(0.00383)
Constant	0.201***
	(0.0158)
Year FE	Y
Month FE	Y
AC FE	Y
Observations	180,186
R-squared	0.033

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 3

Probability of Advancing Through the Admissions Pipeline (Linear Probability Models)

VARIABLES	(1) Model 1 Started	(2) Model 2 Engaged	(3) Model 3 Completed	(4) Model 4 Admitted	(5) Model 5 Registered
Female prospect	-0.0113***	-0.00991***	-0.00176***	-0.00128***	-0.000286
	(0.00193)	(0.00128)	(0.000428)	(0.000393)	(0.000260)
Constant	0.254***	0.160***	0.0297***	0.0172**	0.00928*
	(0.0255)	(0.0172)	(0.00915)	(0.00708)	(0.00505)
Controls	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
AC FE	Y	Y	Y	Y	Y
Observations	180,186	180,186	180,186	180,186	180,186
R-squared	0.028	0.016	0.005	0.005	0.003
Number of ACs	42	42	42	42	42

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 4

Relationship Between Gender Congruity and Advancing Through Admissions Pipeline

VARIABLES	(1) Model 1 Started	(2) Model 2 Engaged	(3) Model 3 Completed	(4) Model 4 Admitted	(5) Model 5 Registered	(1) Model 1 Started	(2) Model 2 Engaged	(3) Model 3 Completed	(4) Model 4 Admitted	(5) Model 5 Registered
Female prospect	-0.00854***	-0.00756***	-0.00136**	-0.000928*	-9.89e-05					
	(0.00209)	(0.00136)	(0.000551)	(0.000519)	(0.000321)					
F. prospect x F. counselor	-0.00773**	-0.00653***	-0.00110	-0.000979	-0.000520					
	(0.00349)	(0.00227)	(0.000785)	(0.000701)	(0.000481)					
Baseline gender congruity = M. prospect, M. counselor										
F. prospect, F. counselor						-0.0163***	-0.0141***	-0.00246***	-0.00191***	-0.000619
						(0.00291)	(0.00183)	(0.000567)	(0.000486)	(0.000384)
F. prospect, M. counselor						-0.00854***	-0.00756***	-0.00136**	-0.000928*	-9.89e-05
						(0.00209)	(0.00136)	(0.000551)	(0.000519)	(0.000321)
Constant	0.254***	0.160***	0.0297***	0.0172**	0.00928*	0.254***	0.160***	0.0297***	0.0172**	0.00928*
	(0.0254)	(0.0172)	(0.00914)	(0.00709)	(0.00505)	(0.0254)	(0.0172)	(0.00914)	(0.00709)	(0.00505)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Counselor FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	180,186	180,186	180,186	180,186	180,186	180,186	180,186	180,186	180,186	180,186
R-squared	0.028	0.016	0.005	0.005	0.003	0.028	0.016	0.005	0.005	0.003
Number of AC	42	42	42	42	42	42	42	42	42	42

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 5

Likelihood and Frequency of Phone and Email Communication at Lead Stage

VARIABLES	Model 1 Meaningful call	Model 2 Meaningful email	Model 3 Outbound calls	Model 4 Outbound meaningful calls	Model 5 Outbound emails	Model 6 Duration 1st call (min.)	Model 7 Inbound calls	Model 8 Inbound emails
Female prospect	-0.0327***	-0.000646	0.0112	-0.0385***	-0.0340***	-0.232***	-0.00165	-0.232***
	(0.00180)	(0.00105)	(0.00676)	(0.00274)	(0.00670)	(0.0203)	(0.00187)	(0.0203)
Constant	0.174***	-0.00707	0.422**	0.246***	-0.256	1.003***	0.0895	1.003***
	(0.0278)	(0.0229)	(0.202)	(0.0475)	(0.165)	(0.242)	(0.0632)	(0.242)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
AC FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	180,186	180,186	180,186	180,186	180,186	180,186	180,186	180,186
R-squared	0.016	0.008	0.079	0.018	0.026	0.003	0.008	0.011

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 6

Relationship Between Each Social Context Factor and Advancing Through Admissions Pipeline

VARIABLES	(1) Model 1 Started	(2) Model 2 Engaged	(3) Model 3 Completed	(4) Model 4 Admitted	(5) Model 5 Registered	(6) Model 6 Started	(7) Model 7 Engaged	(8) Model 8 Completed	(9) Model 9 Admitted	(10) Model 10 Registered
Female prospect	-0.0172*	-0.0213***	-0.00748***	-0.00755**	-0.000951	-0.0475*	-0.0453**	-0.0178***	-0.0172***	-0.0114***
	(0.0100)	(0.00650)	(0.00270)	(0.00306)	(0.00171)	(0.0246)	(0.0186)	(0.00493)	(0.00475)	(0.00322)
Prior F. experience	0.0199	0.0140	-0.0133	-0.00583	0.000436					
	(0.0277)	(0.0250)	(0.00987)	(0.00959)	(0.00455)					
F. prospect x Prior F. experience	0.0150	0.0337	0.0180**	0.0196**	0.00212					
	(0.0314)	(0.0207)	(0.00819)	(0.00960)	(0.00539)					
Workgroup diversity						-0.285***	-0.202***	-0.0246**	-0.0186*	-0.00777
						(0.0548)	(0.0442)	(0.00914)	(0.00984)	(0.00708)
F. prospect x Workgroup diversity						0.0864	0.0856*	0.0395***	0.0392***	0.0274***
						(0.0592)	(0.0453)	(0.0123)	(0.0117)	(0.00797)
Constant	0.243***	0.148***	0.0247***	0.0124**	0.00500	0.344***	0.219***	0.0296***	0.0172**	0.00827*
	(0.0250)	(0.0168)	(0.00790)	(0.00548)	(0.00385)	(0.0317)	(0.0232)	(0.00858)	(0.00638)	(0.00479)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
AC FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	173,158	173,158	173,158	173,158	173,158	173,763	173,763	173,763	173,763	173,763
R-squared	0.027	0.015	0.005	0.005	0.003	0.027	0.015	0.005	0.005	0.003
Number of AC	42	42	42	42	42	42	42	42	42	42

Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 7

Relationship Between Social Context Factors and Advancing Through Admissions Pipeline

VARIABLES	(1) Model 1 Started	(2) Model 2 Engaged	(3) Model 3 Completed	(4) Model 4 Admitted	(5) Model 5 Registered
Female prospect	-0.0495*	-0.0560***	-0.0213***	-0.0221***	-0.0117***
	(0.0285)	(0.0184)	(0.00529)	(0.00585)	(0.00327)
Prior F. experience	0.0148	0.0111	-0.0131	-0.00549	0.000829
	(0.0281)	(0.0251)	(0.00971)	(0.00931)	(0.00447)
F. prospect x Prior F. experience	0.0107	0.0292	0.0163**	0.0179*	0.000829
	(0.0305)	(0.0211)	(0.00783)	(0.00908)	(0.00531)
Workgroup diversity	-0.281***	-0.197***	-0.0244**	-0.0193*	-0.00882
	(0.0573)	(0.0462)	(0.00964)	(0.0103)	(0.00735)
F. prospect x Workgroup diversity	0.0833	0.0892*	0.0356***	0.0374***	0.0277***
	(0.0620)	(0.0460)	(0.0123)	(0.0114)	(0.00836)
Constant	-0.0495*	-0.0560***	-0.0213***	-0.0221***	-0.0117***
	(0.0285)	(0.0184)	(0.00529)	(0.00585)	(0.00327)
Controls	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
AC FE	Y	Y	Y	Y	Y
Observations	173,158	173,158	173,158	173,158	173,158
R-squared	0.027	0.015	0.005	0.005	0.003
Number of AC	42	42	42	42	42

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

TABLE 8

Relationship Between Social Context Factors and Advancing Through Admissions Pipeline for Male and Female Counselors

VARIABLES	(1) Model 1 Started Male	(2) Model 2 Engaged Male	(3) Model 3 Completed Male	(4) Model 4 Admitted Male	(5) Model 5 Registered Male	(6) Model 6 Started Female	(7) Model 7 Engaged Female	(8) Model 8 Completed Female	(9) Model 9 Admitted Female	(10) Model 10 Registered Female
Female prospect	-0.0583	-0.0675**	-0.0232***	-0.0270***	-0.0126***	-0.0333	-0.0345	-0.0187***	-0.0138**	-0.0111*
	(0.0375)	(0.0243)	(0.00734)	(0.00813)	(0.00396)	(0.0423)	(0.0268)	(0.00617)	(0.00584)	(0.00626)
Prior F. experience	-0.300***	-0.234***	-0.0284**	-0.0211*	-0.00270	-0.227**	-0.134	-0.0213	-0.0216	-0.0238
	(0.0653)	(0.0529)	(0.0116)	(0.0119)	(0.00648)	(0.106)	(0.0781)	(0.0160)	(0.0177)	(0.0156)
F. prospect x Prior F. experience	0.00561	0.0362	0.0193*	0.0269**	0.00499	0.00567	-0.00106	0.00749	-0.00311	-0.00972
	(0.0366)	(0.0262)	(0.0103)	(0.0120)	(0.00646)	(0.0558)	(0.0395)	(0.0128)	(0.0116)	(0.00902)
Workgroup diversity	-0.300***	-0.234***	-0.0284**	-0.0211*	-0.00270	-0.227**	-0.134	-0.0213	-0.0216	-0.0238
	(0.0653)	(0.0529)	(0.0116)	(0.0119)	(0.00648)	(0.106)	(0.0781)	(0.0160)	(0.0177)	(0.0156)
F. prospect x Workgroup diversity	0.117	0.119*	0.0389**	0.0433***	0.0270**	0.0335	0.0482	0.0341**	0.0315**	0.0334*
	(0.0832)	(0.0595)	(0.0163)	(0.0152)	(0.00969)	(0.0785)	(0.0625)	(0.0152)	(0.0142)	(0.0174)
Constant	0.311***	0.221***	0.0333**	0.0189**	0.00335	0.372***	0.191***	0.0339**	0.0213*	0.0185
	(0.0400)	(0.0290)	(0.0120)	(0.00840)	(0.00307)	(0.0514)	(0.0363)	(0.0145)	(0.0112)	(0.0110)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
AC FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	110,656	110,656	110,656	110,656	110,656	62,502	62,502	62,502	62,502	62,502
R-squared	0.026	0.015	0.006	0.005	0.003	0.029	0.017	0.006	0.006	0.003
Number of lead_owner_id	24	24	24	24	24	18	18	18	18	18

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

FIGURE 1

Admissions Pipeline at *OnlineEdCo*

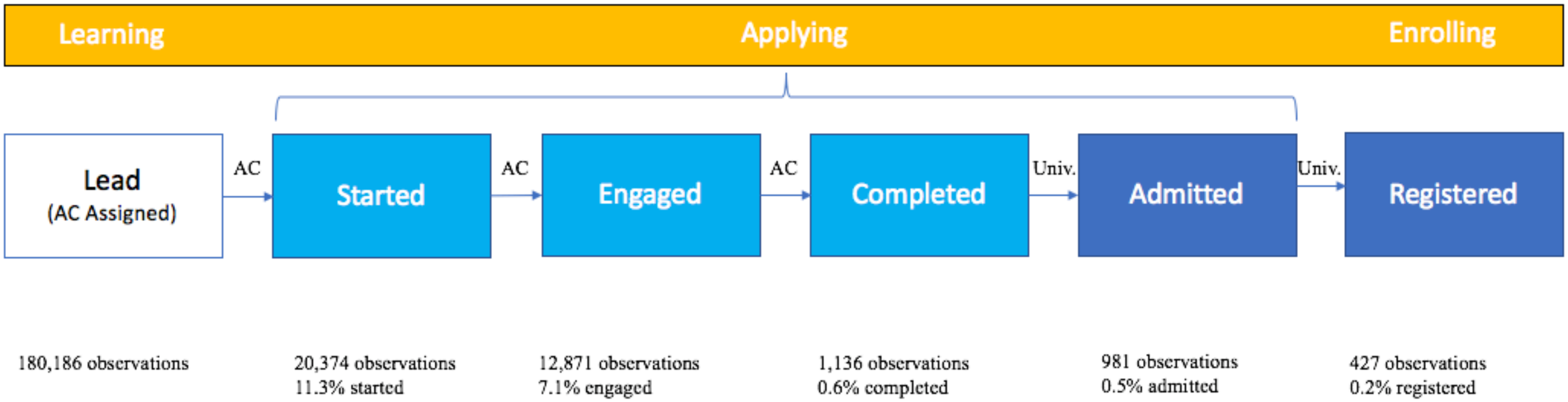

FIGURE 2

Gender Composition Across Stages of the Admissions Pipeline

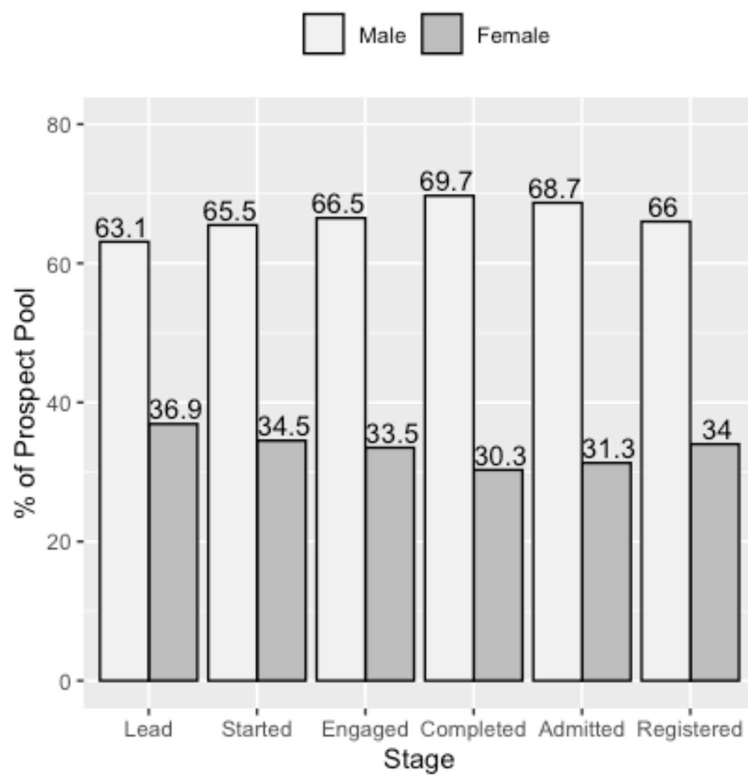

FIGURE 3

Estimated Economic Impact of Leaked Female Prospects Across Admissions Pipeline

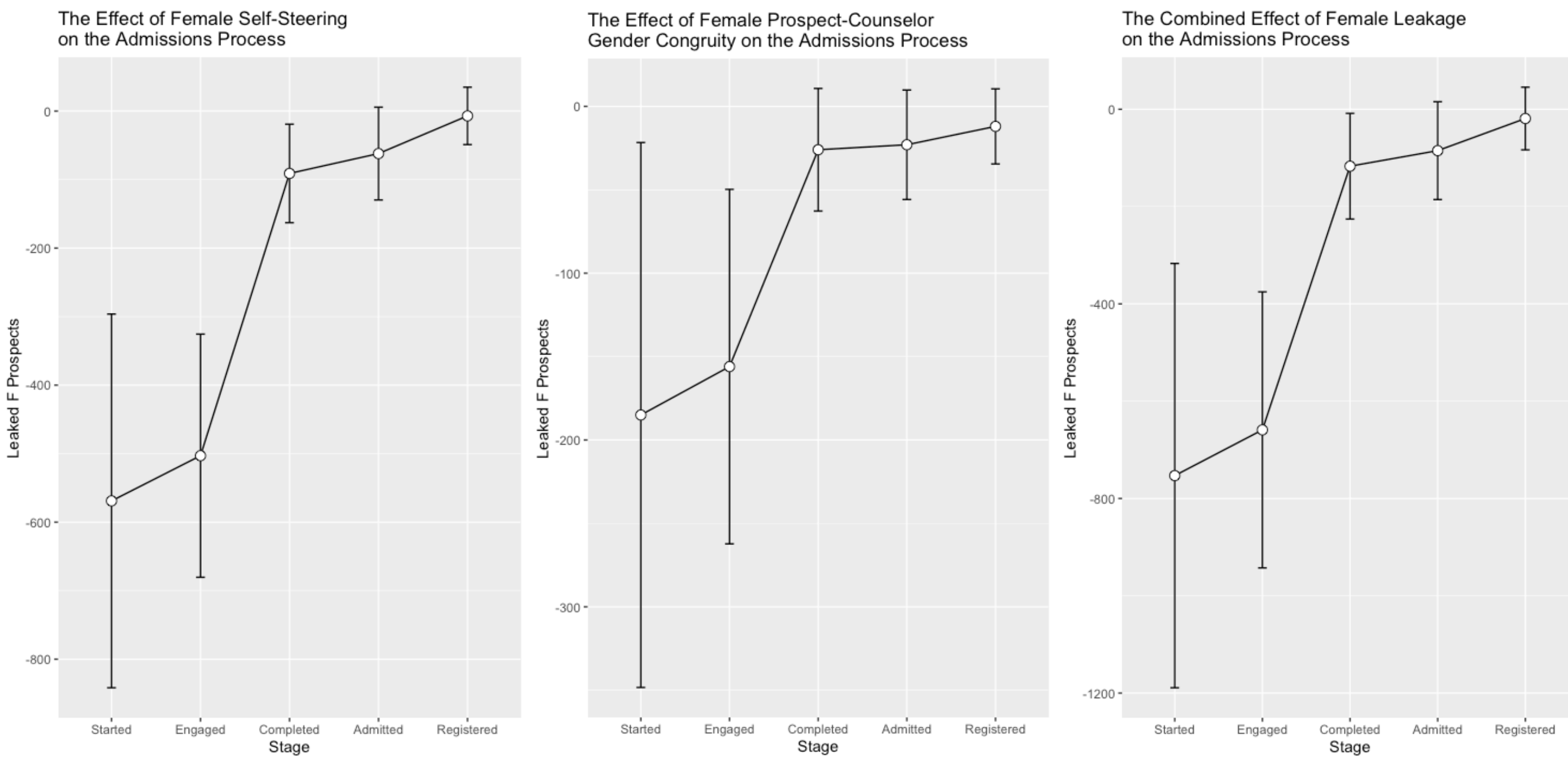

FIGURE 4

Projected Change in Gender Composition From Eliminating Female Leakage Across Admissions Pipeline