Institute for Policy Research
Northwestern University
Working Paper Series

WP-12-19

Do Job Networks Disadvantage Women? Evidence from a Recruitment Experiment in Malawi

Lori Beaman
Assistant Professor of Economics
Faculty Fellow, Institute for Policy Research
Northwestern University

Niall Keleher
Director of Research Methods and Training
Innovations for Poverty Action

Jeremy Magruder
Assistant Professor of Agricultural and Resource Economics
University of California, Berkeley

Version: December 2012

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2040 Sheridan Rd. ◆ Evanston, IL 60208-4100 ◆ Tel: 847-491-3395 Fax: 847-491-9916
www.ipr.northwestern.edu ◆ ipr@northwestern.edu

Abstract

Using a field experiment in Malawi where men and women apply for future surveyor positions with a local firm, Beaman and her co-authors find that highly skilled women are systematically disadvantaged through the use of referrals. This happens both because most men recommend other men, and because women refer fewer candidates who qualify for the position. The authors document that segregated networks do not cause this behavior. They develop a theoretical model of referral choice and exploit random variation in referral contract terms to find that that both men's and women's biases result from social incentives rather than expectations of performance. They also document that the screening potential of networks is maximized when men refer men, and the evidence points towards limited information about female candidates in men's networks. This paper suggests that the use of social networks in hiring is an additional channel through which women are disadvantaged in the labor market.

Do Job Networks Disadvantage Women?

Evidence from a Recruitment Experiment in Malawi *

Lori Beaman[†], Niall Keleher [‡], and Jeremy Magruder[§]

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Abstract

Using a field experiment in Malawi where men and women apply for future surveyor positions with a local firm, we find that highly skilled women are systematically disadvantaged through the use of referrals. This happens both because most men recommend other men, and because women refer fewer candidates who qualify for the position. We document that segregated networks do not cause this behavior. We develop a theoretical model of referral choice and exploit random variation in referral contract terms to find that that both men's and women's biases result from social incentives rather than expectations of performance. We also document that the screening potential of networks is maximized when men refer men, and the evidence points towards limited information about female candidates in men's networks. This paper suggests that the use of social networks in hiring is an additional channel through which women are disadvantaged in the labor market.

1 Introduction

While the gender gap in labor force participation has declined sharply in the last 30 years, women continue to earn less than men in countries around the world (World Bank Group and others, 2011). In Malawi, women are significantly under-represented in the formal sector (World Bank Group and others, 2010) as is common in many developing countries (Bell and Reich, 1988). A large portion of the literature in economics has focused on labor market discrimination

*We thank IPA-Malawi field staff and Sam Arenberg for research assistance. We also thank participants at numerous seminar and conference audiences for helpful comments. All errors are our own.

[†]Northwestern University. Email: l-beaman@northwestern.edu

[‡]Innovations for Poverty Action. Email: nkeleher@poverty-action.org

[§]University of California, Berkeley. Email: jmagruder@berkeley.edu

(taste-based or statistical) or differences in human capital accumulation as reasons for the gender gap in earnings (Altonji and Blank, 1999).[1] Another possibility is that hiring processes themselves disadvantage women. We conduct a field experiment recruiting employees for a job in which men and women regularly compete in order to ask whether the use of referrals inherently disadvantage women in the labor market.

A large fraction of jobs - up to 50% - are attained through informal channels, including employee referrals (Bewley, 1999; Ioannides and Loury, 2004). While there is relatively little empirical evidence on the distributional consequences of referral systems, the potential of referral systems to create inequality between groups has been described theoretically (Calvo-Armengol and Jackson, 2004).[2] Ioannides and Loury (2004) document stylized facts that women are less likely to be hired through a referral and that unemployed women are less likely than unemployed men to search using family and friends[3].

Of course, these stylized facts alone do not show that women are disadvantaged by the use of networks in the labor market: women may work in occupations where networks are less relevant, or they may be less likely to report network help for the same hiring procedure. Moreover, if individuals are able and willing to screen on hard-to-observe dimensions for their employers (Montgomery, 1991; Beaman and Magruder, 2012), then referral networks may be advantageous for disadvantaged groups including women. Labor market disadvantages may

[1] Additional explanations include the role of technology (Goldin and Katz, 2002), deregulation and globalization (Black and Strahan, 2001; Black and Brainerd, 2004), and differences in psychological attributes and preferences such as risk preferences, attitudes towards competition, other-regarding preferences, and negotiation (Niederle and Vesterlund, 2007; Bertrand, 2011).

[2] For the Calvo-Armengol and Jackson (2004) mechanism to be a relevant source of long-run inequality between men and women, job networks would need to be characterized by gender homophily. A large literature in Sociology (reviewed in McPherson, Smith-Lovin, and Cook, 2001) suggests that gender homophily in networks begins at early ages and is particularly strong in workforce networks. Mortensen and Vishwanath (1994) also show theoretically that network-based job information dissemination can disadvantage women, even if men and women are are equally productive but men have a higher contact probability.

[3] Moreover, occupational segregation is commonly cited as a source of income disparity across gender (Blau and Kahn, 2000; Arbache, Kolev, and Filipiak, 2010). The use of employee referrals may be one of the mechanisms creating this segregation (Fernandez and Sosa, 2005; Tassier and Menczer, 2008).

result in female applicants with weaker easily observable characteristics, like job experience, but network screening may succeed in identifying the women who have strong hard-to-observe but productive characteristics. We may also anticipate that informal information flows are particularly important for reaching women who are less likely to be employed in the formal sector. Therefore, it remains an open question whether women are made worse off by the use of employee referrals.

We used a competitive recruitment drive conducted by a research organization in Malawi, Innovations for Poverty Action (IPA-Malawi), as an opportunity to generate a database of male and female applicants[4] to test how job referrals affect the recruitment of men and women in an experimental setting. IPA-Malawi historically had struggled to hire female enumerators, and was interested in exploring whether referrals could reveal an otherwise untapped pool of qualified female applicants specifically, and qualified applicants in general[5]. The position was advertised using the traditional method of posting flyers. Initial applicants attended a half-day interview process which included a written exam and a mock interview, where the candidate surveyed an actor playing the role of a typical respondent. At the conclusion of the interview, candidates were asked to refer a friend or relative to apply for the position and were offered a finder's fee. The referral process was cross-randomized along two dimensions: candidates were either told that they must refer a woman, that they must refer a man, or that they may refer someone of either gender, and their finder's fee was randomly selected to be a fixed fee of either 1000 or 1500 Malawi Kwacha (MWK) or a performance incentive (a guaranteed 500 MWK with the potential to earn an additional 1300 MWK if the referral attained a certain threshold).

[4] Literally binders full of men and women.

[5] Often times the gender of the enumerator is important: for example, IPA-Malawi and many other survey firms prefer to use female enumerators when surveying women about sensitive questions, such as family planning practices. Therefore, IPA wanted to recruit both men and women, and historically had found that qualified women were particularly difficult to attract. Informal interviews with qualified female applicants suggest that one reason qualified female applicants were hard to find was that there are gender differences in willingness to travel regularly and for several weeks at a time in Malawi, which is necessary to work as a survey enumerator.

We find that qualified female candidates are strongly disadvantaged by the use of social networks in the hiring process. Among the conventional applicants (CAs) who were allowed to choose either gender for a referral, only 30% of referrals are women. This is significantly lower than the fraction of women who apply through traditional recruitment channels (38%). The low number of women referred is driven largely by male candidates. When given the choice, men systematically refer men; 77% of men's referrals are other men. Women refer women at approximately the same rate at which they apply through the traditional recruitment method. However, women systematically refer people who are less likely to qualify: a female candidate is nearly 20 percentage points less likely to refer someone who qualifies. These two effects combine to create a scenario where very few people ultimately refer qualified women when given a choice over which gender to refer: only 14% of men and 17% of women refer qualified women, which compares to 42% of men and 21% of women who refer qualified men. This disadvantage for women, however, does not appear due to men (or women) being unconnected to women that they deem suitable: men and women make referrals at identical rates when required to refer women as when they are required to refer men under all contracts.

Since men and women are capable of identifying suitable female referrals, this disadvantage for women appears due to some aspect of the referral choice problem. We propose a simple model of who individuals choose to refer under different types of referral contracts. The model provides a guide to interpreting our experimental variation and suggests empirical tests to provide evidence on the underlying reasons women are disadvantaged. In the model, individuals receive a social payment from referring a particular network member, in addition to any payment provided by the firm. The social payment may capture altruism, an actual financial transfer, or reduced future transfers if the two are in a repeated risk sharing arrangement Beaman and Magruder (2012). They also receive a noisy signal of each network members' quality. We allow there to be several key gender differences in this decision process, which could generate the main empirical finding that qualified women receive different opportunities from their networks: (i) for any type of CA, networks of men and women may differ in social payments; (ii) the quality of friends who provide the highest social payments; (iii) the extent of the tradeoffs between social payments and observable quality (this captures for example if high quality women are scarce in referral networks relative to high quality men); and (iv) the accuracy of the signal of observed quality relative to actual quality.

Because of random variation in the structure of the finder's fee, we are able to observe the characteristics of both potential referrals when CAs are motivated in their choice only by network incentives and when firms provide an additional incentive to find a person who is high ability. This facet allows several tests of the various sources of heterogeneity. First, the model suggests that referrals selected under fixed fee payments should reflect the people that give the highest social payments (net of recruitment costs) to CAs. From this framework, we identify that men systematically receive the highest social payments from other men. We also identify that both the men and women who are "preferred" in this way are of similar ability, which is slightly below the average CA's ability. Women are not systematically closer to one gender over the other, but women CAs receive the largest social payments from individuals who are significantly less likely to qualify than the average CA[6]. Overall, social incentives among both men and women's networks make it harder for qualified women to get job opportunities[7].

Other network characteristics may lead to disadvantages for qualified women if firms add additional incentives for workers to identify highly-skilled referrals[8]. Given our results

[6]This result comes from women who are allowed to refer either gender. From restricted-gender treatments, we also observe that the men who are closest to women outperform the women who are closest to other women.

[7]We discuss the possibility that CAs' referral choices are affected by the fact that CAs are competing with their referrals for the job in section 7.1.

[8]In other contexts, firms incentive workers both through actual cash incentives for making a high-performing referral and through reputational considerations.

on social payments and the quality of people referred under fixed fees, we derive that steeper tradeoffs or worse information could also put women at a disadvantage, and that either of these characteristics would manifest in a smaller change in referral qualification rates induced by performance pay. We note that this is additionally an important criterion for employers who use networks to screen: any gender disparities in performance premia will have direct implication for employer incentives to encourage or discourage women's disadvantage. We find that men exhibit a large performance premium when referring men, but no performance premium when referring women: this factor allows us to conclude that men's networks of women have either worse information or greater social tradeoffs than men's networks of men. These two concepts are highly related, which the model highlights, and accordingly difficult to disentangle. Nevertheless, several pieces of evidence all point towards men having poor information about women. Women CAs in performance pay treatments are not more likely to make referrals who qualify when referring men or women, but performance incentives do change women's referrals of both men and women in some productive dimensions.

This paper suggests that an additional factor leading to the observed gender gap in women's earnings is the way employees are recruited. As we discuss below, this experiment suggests that gender differences in network characteristics create several profitable motivations for firms to permit this disadvantage, even in the absence of any intended (taste-based or statistical) discrimination on the part of the firm. The results also highlight that the screening potential of networks must be bought: firms must be willing to generate incentives to refer only the best people within their employees' networks in order to find high quality referrals.

The paper is organized as follows. The experiment design and data are described in section 2. The main results are discussed in section 3. The theoretical framework which highlights potential mechanisms for why women are disadvantaged by referral hires is elaborated in section 5. The empirical evidence for each of the three hypotheses are presented in sections 6 and 7, followed by discussion of an alternative explanation in 8 and then the conclusion.

2 Experimental Design

2.1 Setting and Overview

Gender-based difference in employment is common in many developing countries (Bell and Reich, 1988). Women in Africa are more likely to be in the informal sector and the proportion of women in the formal employment is less than half that of men. A survey of 14 African countries found that women are more likely to be employed (formally or informally) in agricultural jobs and less likely to hold jobs is the manufacturing and services (Arbache, Kolev, and Filipiak, 2010).

Malawi is not an exception to this trend. A recent survey of Malawian households suggests that less than one-third of women participate in the formal labor force, while nearly 58% of men do so (World Bank Group and others, 2010). Among urban women, 38.2% had not been employed in the preceding twelve months; this rate is more than double that found among urban men (18.6%) (National Statistics Office (NSO) and ICF Macro, 2011).

IPA-Malawi hires enumerators to conduct interviews of farmers, business owners, and households in rural and urban Malawi. In the 12 months following the recruitment drive (our experiment), IPA-Malawi projected hiring a minimum of 200 enumerators for its survey activities. IPA-Malawi had an explicit motivation to hire more female enumerators than their usual recruitment methods allow. Typically, only 15 to 20 percent of enumerators hired by IPA-Malawi are women, and some survey tasks require same-gendered enumerators (for example, same-gendered enumerators are sometimes important for sensitive questionnaires). For this experiment, we introduced incentives for job applicants to make referrals during IPA's recruitment sessions in the two main Malawian cities, Blantyre and Lilongwe.

The standard method for recruiting enumerators is to post announcements at community centers, technical schools, and government offices. An initial screening session is open to all applicants with minimum qualifications. Minimum requirements to be hired for an enumerator position are: a secondary certificate, fluency in the local language (Chichewa), and English reading and oral comprehension. Candidates with data collection experience, good math skills, and basic computer skills are given preferential review.

The standard IPA-Malawi screening session consists of submitting a CV to IPA and sitting for a written test. The written test assesses reading comprehension, hand writing, math ability, and computer literacy (via self-assessment). Following the screening session, applicants deemed to be qualified may be invited for a survey-specific training of enumerators.[9] At the end of the training, job offers are made to a group of individuals deemed to be adequate for work on the survey.

In this experiment, IPA posted fliers indicating a hiring drive at a number of visible places in urban areas. The posters included information on the minimum requirements for IPA enumerators, the dates and times of the recruitment sessions, and a solicitation to bring a CV and certificate of secondary school completion (MSCE). Participants then attended an interview session, where they submitted their CV and were registered with a unique applicant number. Participants were limited to those individuals who had never worked for IPA. Each day, two sessions were conducted by IPA staff. At the start of each session, participants were introduced to IPA and the role of an enumerator was described.

[9]These trainings consist of a multiple-day workshop on proper technique and procedures for conducting paper-assisted or computer-assisted personal interviews. Each training is tailored to a specific survey; however, interview techniques for facilitating and documenting interviews is rather standardized. Also, during a training workshop, practical skills are assessed through a field pilot of the given survey.

2.2 Quality Assessment

The screening session included a written test similar to the one IPA had previously used, and a practical test which served as a condensed version of the training that IPA had previously used to select enumerators. Participants were given one of two distinct written tests[10]. Each test consisted of several math problems, ravens matrices, English skills assessment, job comprehension component, and a computer skills assessment. Our screening session integrated a practical test to obtain information on otherwise hard to observe qualities that are important for the work of an enumerator.

For the practical test, the participant played the role of the enumerator for a computer assisted personal interview.[11] An experienced IPA enumerator played a scripted role of the interview respondent. The respondent scripts included implausible or inconsistent answers (i.e. age, household size, household acreage) to survey questions. These false answers were used as checks on the participant's ability to pay attention to detail and verify inaccuracies in responses. When the participant pressed the respondent for a correction, the respondent gave a plausible answer. Among the respondents, two sets of implausible answers were used in order to limit any ability to predict the practical test.

Scores were calculated for all participants on a 0-to-100 scale. The total score was a combination of the CV score, written test score and practical test score.

2.3 Referral Instructions

The setting offered an opportunity to test several potential channels through which a firm can influence the type and quality of applicants generated through a referral process. Prior to

[10]The two tests were distributed at random to limit cheating.

[11]All participants were required to go through a short self-administered training with a computer-assisted personal interviewing (CAPI) software in order to ensure a consistent level of familiarity with the computer program. Once finished with the self-administered CAPI training, participants moved to the practical test.

leaving the recruitment session, participants had a one-on-one conversation with the recruitment manager. During this conversation, a letter was provided to the applicant inviting the applicant to identify another individual to refer to IPA for consideration as an enumerator. The message provided to the participant was the crux of this experiment. All original participant letters described a specific set of instructions about the referral process. We randomly varied the content of the letters.

Each letter included an instruction about the gender requirement of the referral who could be invited to attend a future recruitment session. The letter instructed the original participants that their referral had to be male, had to be female, or could be either gender. The referral needed to be someone who had not worked for or been tested by IPA in the past. The letter also said that the referral should be highly qualified for the enumerator position and given a suggestive guide about what this would entail. Namely, the letters stated that a strong enumerator should have a secondary school certificate, fluency in Chichewa, excellent comprehension of English, data collection experience, and good math and computer skills. The CA was told that the referral would need to complete the same written and practical assessments as done by the CA.

Conventional applicants were randomly assigned into one of three pay categories (cross randomized with the gender treatments): a fixed fee of 1000 Malawi Kwacha, a fixed fee of 1500 MWK, or a performance incentive of 500 MWK if their referral does not qualify or 1800 MWK if their referral does qualify. All treatments were fully blind from the perspective of all evaluators. All conventional applicants were eligible to receive payment (fixed fee or base pay, if in the incentive group) if their referral attended and completed a recruitment session.

Referrals typically participated in recruitment sessions 3 to 4 days after the conventional applicant's session. The screening session, including the written and practical test components, were the same as for conventional applicants.Conventional applicants were asked to complete an anonymous questionnaire as an assessment of their referral's quality and whether or not they shared any of their payment with the referral. In addition, CAs were contacted by an IPA staff member to ask how the conventional applicant identified the referral and how the payment was used.

Each week, a list of qualified applicants was posted at the recruitment venue, and qualified applicants were told that they would be considered for future job opportunities with IPA-Malawi. Any original applicant who qualified for a payment was informed and given payment in a sealed envelope.[12]

Appendix Table A1 displays summary statistics for the sample of CAs, for men and women separately. It also shows that the randomization lead to balance along most characteristics. The p value for the joint test of all the treatment variables, and their interactions, is displayed in column (2) for male CAs and column (5) for female CAs. Among male CAs, only the number of feedback points for male CAs is significant 5% level (though the Practical Component Z-score is almost significant at the 10% level for both men and women CAs). For women CAs, there is a baseline difference in test scores at the 10% level. This is driven by women CAs who were in the male-fixed fee treatments performing slightly worse on average than other women CAs in either unrestricted or women-only fixed fee treatments.

3 Are Qualified Women Disadvantaged?

Figure 1 plots kernel densities of CA overall test score separately for men and women, and confirms that men and women who respond to the traditional recruitment method on average

[12]To maintain a quick turn-around in notifying applicants of qualifying, real-time test-scoring and data entry was necessary. This led to a few misenterred values which slightly affected the identities of qualifying people. In this paper, we use corrected scores and qualifying dummies which do not reflect these typos in all main analysis, though results are robust to using the actual qualification status.

have similar distributions of test scores. There is some evidence that male CAs outperform female CAs on the assessment, which can be seen in a small rightward shift in men's performance across the distribution of the referral test scores. Panel A of Table 1 confirms that this difference is statistically significant. However, there is much more variation within CA gender than there is between CA genders, and nearly all of the support of men's and women's test scores is common. As such, men and women are in true competition for these jobs. Nonetheless, we may be concerned over whether the distribution of quality of potential referrals is different in networks of men and women. In section 5 we will develop and test a model to evaluate whether there are gender differences in the quality of potential referrals.

Panels A through C of Table 2 document the primary result of this paper. While 38% of applicants themselves were women (and 39% of applicants who could refer either gender), only 30% of referrals are women when we allow CAs to choose which gender to refer (difference significant at the 5% level). This difference in application rates happens entirely because men systematically do not refer women: women refer women at approximately the rate by which women apply themselves (43% of the time), while men refer women only 23% of the time when given the choice. The difference between male and female CAs is significant at the 1% level, as shown in column (4). Moreover, these difference persist across the range of CA performance: Figure 2 presents local polynomial regressions of the gender choice of referral on CA overall test score, disaggregated by men and women[13]. Across the distribution of potential test scores, CA women are more likely to refer women than CA men, with particularly large differences at the top and bottom of the distribution of CA test scores.

However, qualified women can also be disadvantaged if unqualified people are being referred more than qualified people regardless of any gender preference. Table 1 also shows

[13] In both cases, the sample is restricted to CAs who have the choice of which gender to refer.

that there is a large gender difference in the qualification rate of referrals: while men make references who are about as likely to qualify as CAs are on average, women make references who are eighteen percentage points less likely to qualify (38% versus 56%) when given an unrestricted choice of genders. Rows 3 and 4 reveal that these two results together combine to create a scenario where very few CAs - either men or women - refer qualified women, as only 13% of men and 17% of women refer qualified women (in contrast to 43% of men and 22% of women who refer qualified men). Women's references are much less likely to qualify irrespective of the gender of the referral. When women choose to refer men, those men qualify at a 38% rate (22% make a male referral who qualifies/57% who make a male referral) while the women they choose to refer qualify 39% of the time. Men's male referrals have a 55% qualification rate while men's female references have a 57% qualification rate. In Figure 3, we again verify that this difference persists across the range of CA test scores. In this case, the qualification difference is most notable at the top of the distribution, as male CAs make referrals who are more likely to qualify in a way which increases monotonically with their test scores, while women's referral quality faces an inverted-u shape, so that the most-skilled and least-skilled women make referrals who are similarly unlikely to qualify.

These two differences together put qualified women at a substantial disadvantage: most men seem to respond to an unrestricted referral situation by identifying men, while most women seem to respond to such a situation by referring unqualified people of either gender. This is consistent with the finding from observational data from a call-center in Fernandez and Sosa (2005)[14] and is the first experimental evidence that we know of that supports the large literature in sociology arguing that informal referral processes are one of the drivers of segregation of jobs (Doeringer and Piore, 1971; Mouw, 2006; Rubineau and Fernandez, 2010). Overall, we conclude

[14] In that context, men are the disadvantaged group, who are similarly less likely to receive referrals.

that the use of referral systems strongly disadvantages qualified women in this context.

4 Are Men and Women Connected?

One explanation for why men refer so few women is that it may not be a choice: men may simply not be connected to women. Indeed, one proposed cause of gender segregation in the labor market is segregated social networks (Tassier and Menczer, 2008). Based on this explanation, referrals serve to perpetuate job segregation due to the limited overlap of groups from which referrals are drawn.

Our view is that a sensible definition of connectedness would reflect contract terms: clearly, any of our male CAs would be successful at finding a female referral at a sufficiently high price, particularly in fixed fee treatments where the CA need not be concerned with referral quality. For now, suppose simply that each CA i receives a number of draws of friends, who may be male or female. Each friend j is characterized by two characteristics: a social payment α_j (net of costs of recruiting that person) which (s)he will give to i if (s)he is offered the referral, and some probability of qualifying, λ_j, as well as their gender. The social payment is meant to include ideas like altruism or expected future reciprocity as well as the costs of notifying friend j about the opportunity. Thus, when CA i is offered a contract with fixed component F_i and performance component P_i, if i refers j, then i receives in expectation

$$F_i + \alpha_j + \lambda_j P_i \tag{1}$$

Assuming that CAs do not make referrals if they cannot receive positive payments in expectation suggests a straightforward definition of connectedness.

Definition 1 *CA i is* ***connected*** *to gender g at contract (F_i, P_i) if $max_{j \in g} F_i + \alpha_j + \lambda_j P_i > 0$*

Under this definition of connectedness, CAs are unconnected under fixed fees if the largest possible social payment is less than $-F_i$, and they are unconnected under performance pay if referrals share a low α_j and a low probability of qualifying. Clearly, if male CAs are less connected to women at our contracting terms, it could generate the disadvantage that women face in referral systems.

We can analyze this in a straightforward way: define an indicator $R_i = 1$ if the CA makes a referral, and $R_i = 0$ if the CA does not. Since we randomly restricted some CAs to referring only women, and other CAs to referring only men, we can test whether CAs are more or less likely to be connected to women or men at our contracting terms. Moreover, because some CAs were allowed to refer either women or men, we will additionally be able to test whether CAs who are unconnected to men at a particular contract are likely to be connected to women at that contract: if so, it would suggest that CAs are receiving a number of draws of both men and women, so that even if all the draws of an CA's own gender fail to make the participation threshold, there is a strong chance that the other gender exceeds it. As a test, then, we simply regress

$$R_i = \sum_k \alpha_k T_{ik} + \delta_t + u_i$$

Where T_{ik} is the exogenously assigned treatment in terms of referral gender and contract payment and δ_t are time trends. Table 2 presents this analysis, where restricted male treatments (or male fixed fee treatments in specifications which disaggregate by contract terms) are the excluded group. Overall, neither men nor women are significantly less likely to make a reference when assigned to refer women than when assigned to refer men, and point estimates on any gender differences are small in magnitude. When we disaggregate by treatment, we observe that men are statistically significantly less likely to make a reference when they are given performance pay than when they are given fixed fees if they are required to refer either men or women. The mean referral rate under fixed fees for men in restricted treatments is 90%; point estimates suggest that if these men are instead given the performance contract return rates fall to 75%. However, if men are given the choice of referring either men or women, the return rate rises back to 90% - this suggests that there are 15% of men who only know a man who is worth referring under performance pay, but also 15% who only know a woman who is worth referring. For female CAs, there is a similar trend, though the point estimate is smaller and not statistically significant.

We find these results striking in several ways. First, they reject the hypothesis that the trend of men referring men noted in section 3 occurs because of men being unconnected to women. Most male applicants are connected to suitable women, and they are as likely to be connected to women as they are to be connected to men under either contract structure. There are also a sizeable number of men who are only connected to women, when the performance of the referral matters. Second, they suggest that mean returns under performance pay are lower than under fixed fees. CA return rates under fixed fees remain at 90% for both genders of CAs assigned to both levels of fixed fees; this suggests that the expected return to performance pay is lower than 1000 MWK, the lower fixed fee level. Given that the performance pay contract featured a guaranteed fee of 500 MWK and a performance premium of 1300 MWK, this suggests that the person they choose to refer under fixed fees (who they could have also referred under performance pay) has an expected qualification likelihood below 5/13, which we return to below. Finally, there are no differences in referral rates for CAs of either gender when we restrict them to men versus when we restrict them to women. There are, however, differences in return rates between contract terms for gender-restricted referrals. Given that attrition rates are in any event low relative to most panel studies and uncorrelated with the gender treatments which are the focus of this study, we abstract from them in the main analysis, though when we analyze performance premia we will discuss the potential role of attrition in biasing our estimates.

Given that CAs are connected to both men and women, it seems likely that some other factor leads to the disadvantage women face from referral systems. In the next section, we further develop the model in the interest of identifying key differences between an individual CA's networks of men and women.

5 Model and Mechanisms

Building on equation 1, retain the notation α_j as a social incentive supplied by friend j and now suppose that CA i expects j to score Q_j points on the skills assessment. If j belongs to gender g, suppose that his (her) actual performance is $Y_j = Q_j + \varepsilon_j$, where ε_j is distributed $N\left(0, (\sigma_\varepsilon^g)^2\right)$, and the referral qualifies if $Y_j > 60$. Note that σ_ε^g may be different between men and women. Using the language from the previous section, this suggests that $\lambda_j = \left(1 - \Phi\left(\frac{60-Q_j}{\sigma_\varepsilon^g}\right)\right)$ where $\Phi(\cdot)$ is the cdf of the standard normal distribution. As before, CA i is given a contract (F_i, P_i) and is restricted to make a referral out of individuals who belong to set $\mathcal{G}$, where $\mathcal{G}$ could be $\{male\}, \{female\}$ or $\{everyone\}$.

While i knows a number of people in each gender specific network, we focus on the subset of those draws who could be optimal referrals under various contracting conditions. In particular, individual j will only get chosen under some contract (F_i, P_i) if $Q_j \in \arg\max_{k \in \mathcal{G}} Q_k | \alpha_k \geq \alpha_j$, that is, j will only get chosen if his or her observed quality is the best among eligible referrals who offer at least as much in social payments. For each gender g, define $h^g(\alpha_j) = Q_j$ to be the mapping between α_j and Q_j in this set, where $h^g(\alpha_j)$ is decreasing in α_j by the selection rule. Denote $\alpha_1^g = \max_{j \in g} \alpha_j$, where $j \in g$ if j is of gender g. To make analysis tractable, approximate $h^g(\alpha_j) = Q_1^g + \gamma^g(\alpha_1^g - \alpha_j)$. CA i therefore solves

$$\pi_i(\alpha_j, P_i, F_i) = \max_{j \in \mathcal{G}} P_i \left(1 - \Phi\left(\frac{60 - Q_1^g - \gamma^g(\alpha_1^g - \alpha_j)}{\sigma_\varepsilon^g}\right)\right) + F_i + \alpha_j \tag{2}$$

Gender-specific networks can be heterogeneous, therefore, in 4 different ways: they may differ in $\alpha_1^g, Q_1^g, \gamma^g$, and σ_ε^g. The following set of definitions characterize these differences

Definition 2 *CA i is **closer** to gender g than to gender g' if $\alpha_1^g > \alpha_1^{g'}$*

Definition 3 *CA i's network of gender g is **higher quality** than his network of gender g' if $Q_1^g > Q_1^{g'}$*[15]

Definition 4 *CA i faces a **shallower** network of gender g' than of gender g if $\gamma^g > \gamma^{g'}$*

Definition 5 *CA i has **better information** about gender g than about gender g' if $\sigma_\varepsilon^g < \sigma_\varepsilon^{g'}$*

These four types of heterogeneity allow networks of men and women to be different in the degree of social payments possible, in quality of key individuals, in the tradeoff between social payments and quality, and in the usefulness of referral networks for screening. Our interest is to test whether gender differences in these four characteristics can contribute to the observed differences in referral choices. We consider separately optimal behavior under fixed fee contracts of the form $(F_i, 0)$ and performance pay contracts of the form (F_i', P_i) where $P_i > 0$.

5.1 Fixed Fees and Social Incentives

In interpreting our data in the context of the model, we start with a description of what happens when we provide contracts of the form $(F_i, 0)$.

[15] This is a rather special definition of higher quality and does not indicate that all members of gender g are higher quality than gender g' or even that members of gender g are on average higher quality than members of gender g'.

Proposition 1 *Under fixed fee contracts of the form* $(F_i, 0)$*, CAs always refer the closest person of the eligible gender, friend 1. Differences in* α_1^g *can lead to different return rates between genders, but differences in* Q_1^g*,* γ^g*, and* σ_ε^g *will not result in different return rates between genders. Characteristics of referrals under fixed fees will therefore be characteristics of the closest person, including gender and quality.*

Proposition 1 shows that a referral recruited under fixed fees, and restricted to a particular gender, is friend 1 of the designated gender. A first implication of this proposition is that the fraction of CAs who refer men when allowed a choice of genders can be interpreted as the fraction of CAs for whom $\alpha_1^1 > \alpha_1^2$. If CAs systematically refer men under fixed fee treatments, proposition 1 suggests that this is because men are systematically closer to CAs. A similar logic applies for the trend by which women are making referrals who are unlikely to qualify: if they make these referrals under social payments, then we can conclude that women are closest to potential enumerators with poor skills. Our empirical analysis in section 6 therefore begins by examining fixed fee treatments to test whether gender differences in network quality or in closeness could affect the opportunities available to women.

5.2 Performance Payments

Only one parameter of network heterogeneity, social payments, could lead to womens' disadvantage under fixed fees. However, heterogeneity of any of the four parameters could lead to biases in referral behavior under performance pay contracts, or more generally if the employee making the referral perceives a benefit to referring a more highly skilled workers[16]. In particular, the returns to making a referral under performance pay are increasing in α_1^g and Q_1^g, decreasing in

[16]This includes the possibility that social payments in the ambient network are related to referral qualification rates. While we noted above that a negative relationship would necessarily occur among the subset of referrals who are not dominated in the CA's overall network, there is no such guarantee on undominated referrals and there could in principle be a positive relationship between referral qualification and social payments. We return to this explanation in section 8.

γ^g, and ambiguously related to σ_ε^g, depending on whether the optimal referral under performance pay is expected to qualify or not. As a result, if (for example) men's networks of women feature lower social payments, are lower quality, are more shallow, or have different information, this could lead to a preference in referring men under performance pay contracts. Fortunately, we can use random referral contract variation to learn more about whether heterogeneity in key parameters other than α_1^g can contribute to womens' disadvantage in the case where CAs face an incentive to make highly skilled references.

First, Proposition 1 suggests that differences in quality can be directly estimated through the quality of referrals made under fixed fees. Since quality, defined as Q_1^g is the quality of the closest member of gender g, we can directly estimate the quality distribution of referrals from male and female CAs who are restricted to refer only men or only women, and conclude whether quality differences may lead to differences in referral choices.

To test differences in other parameters, we need to return to the referral choice problem under performance payments. Recall that λ_j^g denoted the probability that referral j was hired. Suppose person p is the optimal referral when performance pay is positive $(P_i > 0)$. In keeping with the modelling and results on fixed fees, we will be careful to separate the roles of marginal changes within internal solutions and the minimum performance pay necessary to generate an internal solution.

Definition 6 *Define the performance premium,* $\Psi^g = \lambda_p^g - \lambda_1^g$, *the difference in qualification rates between the optimal referral under performance pay,* λ_p^g *and the optimal referral under fixed fees* λ_1^g.

A consequence of proposition 1 is that the only two network characteristics related to λ_1^g are quality, Q_1^g and information, σ_ε^g.

Proposition 2 *For $P_i > 0$, except because of the network constraint that $\max_j \left(\alpha_j^g\right) = \alpha_1^g$, CAs choose an optimal qualification probability, defined as λ_p^{g*}, which is a monotonically decreasing function of $\sigma_\varepsilon^g / P_i \gamma^g$ and unrelated to other characteristics.*

Proposition 3 *Suppose that $\gamma^g > 0$ (networks are not infinitely shallow), that $\sigma_\varepsilon^g < \infty$ (there is some useful information), and that quality is low enough so that $\lambda_1^g < \lambda_p^{g*}$. Then*

i): The performance premium is decreasing in shallowness ($\partial \Psi^g / \partial \gamma^g \geq 0$) and increasing in information ($\partial \Psi^g / \partial \sigma_\varepsilon^g \leq 0$) so long as λ_1^g and λ_p^{g*} are not too close to 1[17].

ii): The performance premium is unrelated to closeness ($\partial \Psi^g / \partial \alpha_1^g = 0$).

iii): For a given γ, σ, α, and P,there is a threshold level of quality $\widetilde{Q}_1^g$ such that $\Psi^g = 0$ for $Q_1^g < \widetilde{Q}_1^g$ and there is a positive performance premium for $Q_1^g > \widetilde{Q}_1^g$. If there is a positive performance premium, that premium is decreasing in Q_1^g for $Q_1^g > \widetilde{Q}_1^g$.

iv): If any of the network conditions fail $\left(\gamma^g = 0; \sigma_\varepsilon^g \to \infty; \lambda_1^g > \lambda_p^{g*}\right)$ then $\Psi^g = 0$.

When CAs face an incentive to make a reference who qualifies, quality (which can be directly estimated), information, and shallowness can all affect the optimal referral ability. Propositions 2 and 3 highlight symmetric roles of information and shallowness in the choice of referral ability. Intuitively, this makes sense: when individuals have high information but shallow networks, they have networks where they receive accurate signals of potential referrals, and know that they must give up large amounts of social payments to get a referral who is more likely to qualify. When CAs have networks which are not shallow but have poor information, they can find potential referrals with higher expected performance levels at relatively low cost; but poor information levels means that even a large increase in expected performance is

[17]The information result holds so long as either $Q_1^g < 60$ ($\lambda_1^g < 0.5$) or $Q_p^{g*} < 60 + \sigma_\varepsilon^g$ $\left(\lambda_p^{g*} < 0.84\right)$. In our data, both of these conditions appear to hold for most CAs, and no groups that we can identify seem to surpass an 84% qualification rate at any time suggesting that the second condition almost certainly holds. For $Q_1^g > 0.5$ and $Q_p^{g*} > 60 + \sigma_\varepsilon^g$, there is a function $\chi\left(Q_1^g\right) \in \left(60 + \sigma_\varepsilon^g, 1\right)$ such that the information result holds whenever $Q_p^{g*} < \chi\left(Q_1^g\right)$.

associated with only a small increase in the likelihood of qualification. Both conditions result in CAs making referrals without a substantial performance premium.

5.3 Distinguishing shallowness from poor information

To consider which network characteristics can lead to women's disadvantage, it is desirable to separate these two (empirically similar) concepts. One way in which information and shallowness can be distinguished in some networks is that poor information imposes that the likelihood of any referral qualifying is close to one-half, as individuals with low quality signals still face a strong chance of qualifying (as the signal is likely far from the truth, at any rate), and individuals with high quality signals are still not tremendously likely to qualify. In other words, a network with poor information looks much like a very shallow network with $\lambda_1^g \cong 1/2$ in terms of the tradeoffs between social payments and likelihood of qualification. In contrast, a network can be highly shallow with any value of λ_1^g. If we find a larger performance premium in networks of one gender than the other, then this distinction can lead to a test of the relative contribution of shallowness versus information to the lower premium gender.

More specifically, note that CAs who are unrestricted in their choice of gender may pull from their network of gender g or g'. We note that even under performance contracts, CA incentives are not perfectly aligned with the employers, as they must still weigh their social incentives against expected performance pay. However, if we see a larger performance premium in the same gender which gives higher social payments, then allowing the option to refer either gender may have different effects if a network is more shallow or if it has worse information, for some levels of relative quality.

Proposition 4 *Allowing the choice of either gender under performance pay leads to an unambiguously higher return rate. However, the effect of allowing either gender on referral* *performance is ambiguous if the performance premium is larger for gender g than for gender g'. Suppose that gender g is closer than gender g' $\left(\alpha_1^g \geq \alpha_1^{g'}\right)$ and the quality of gender g' networks is weakly lower than the quality of gender g $\left(Q_1^g \geq Q_1^{g'}\right)$. If the network of gender g' is more shallow than the network of gender g' but has similar information, then the unrestricted performance premium (Ψ^u) is equal to Ψ^g. If in contrast, information is better about gender g than about gender g' $\left(\sigma_\varepsilon^g < \sigma_\varepsilon^{g'}\right)$, then $\Psi^u \leq \Psi^g$. However, if quality of gender g' is greater than quality of gender g, $\left(Q_1^g < Q_1^{g'}\right)$ no sharp distinction can be drawn.*

The intuition behind Proposition 4 is straightforward: under performance pay, individuals are maximizing a weighted sum of expected performance pay and social incentives. Suppose the performance premium is larger in gender g than in gender g'. When CAs are allowed the choice between gender g and gender g', the optimal choice may be the gender g performance pay referral, who is higher ability, or it may be the gender g' performance pay referral, if that referral gives enough social payments to compensate for the loss in expected performance pay. Given that the performance premium is lower for network g', it must be the case that either quality is lower, information is worse, or the network is more shallow. However, if gender g contributes higher social payments, is similar or higher quality, and is also less shallow, then the network of gender g dominates, and allowing the option to refer gender g' does not change referral choices. For the unrestricted CA to choose from the lower performance premium network, it must be the case that there is some additional return from that network, which can happen simultaneously with a lower performance premium if the CA has worse information (so that high social payment, but poor signal individuals have a greater chance of qualifying) or that network is both higher quality and more shallow. As we noted above, these two types of networks are extraordinarily similar from the perspective of who qualifies.

Finally, we note that while the performance premium leads to a clear test on differences in underlying parameter distributions, it also represents a useful piece of information for firms: if there are gender differences in the performance premium, then firms who use referrals to maximize screening may encourage those differences.

6 Do Social Payments disadvantage women?

As we discuss above, referrals under fixed fee treatments provide consistent estimates of characteristics of the index partner of each gender, partner 1. This allows us to draw several inferences: first, if we repeat Panel B of Table 1 using only CAs in fixed fee treatments, we can infer whether male and female CAs are closer to men or women. That analysis is presented in Panel D of Table 1, which indicates that 75% of male CAs are closest to men, which contrasts to 57% of female CAs. From proposition 1, we can conclude directly that male CAs get their highest social payments from other men, which can lead to across the board disadvantages to women coming from male referrals. Thus, while we rejected the idea that networks were sufficiently homophilic so that men were unconnected to women (and vice versa), we can conclude that there is homophily in the social incentives which live over the network, at least for men: the closest people for men tend to be men.

Panel D of Table 1 also indicates that, under fixed fees, women remain much more likely to make references who will not qualify than men, with 60% of men's fixed fee references qualifying against 37% of women's. Once again, this difference is highly significant, and these numbers are very similar to the overall performance gap between men's and women's referrals. Since only closeness directly affects referral choice under fixed fees, we can conclude that for women, social payments are maximized by referring low ability people. Given that the two sources of women's disadvantage that we highlighted earlier are both present when we introduce no direct financial incentives to make a qualified referral, we conclude that differences in social payments contribute to women's disadvantage both because men experience higher social payments by referring men and because women experience higher social payments by referring the unqualified. The potential of CA concerns about competing with their referrals affecting these results is discussed in section 7.1.

7 The role of quality, shallowness and information

Proposition 3 suggests that three main factors could affect women's opportunities when an employee has a stake in the referral's performance (our performance pay contracts): quality (of the person who gives the largest social payments), information and the extent of the tradeoff between social payments and network quality (network shallowness). If CAs have more information about men than about women, or if CAs have less shallow networks of men than of women, then that should be reflected in a larger performance premium. Gender differences in quality may also affect the performance premium; in particular, corner solutions (where the index partner is selected) exist for a wider range of performance incentives when quality is low than when it is relatively high. Of these three factors, quality can be directly measured using the fixed fee treatments. Therefore before discussing the empirical evidence on performance premia, we first ask whether there are quality differences across networks.

7.1 Are there quality differences across networks?

Figure 4 presents kernel densities of the ability of men's male and female networks recruited under fixed fees. The two distributions overlap, and a Kolmogorov-Smirnov test does not statistically differentiate them. If anything, it appears that the quality of men's networks of women dominates that of men's networks of men. We conclude, therefore, that differences of the quality of women in men's networks as opposed to men in men's networks does not contribute to men's preference for referring men.

For women's networks, in contrast, there is a sharp difference. Figure 5 also presents kernel densities for the women and men who are closest to female CAs. The ability distribution of men who are closest to women clearly stochastically dominates the distribution of women who are closest to women, with the Kolmogorov-Smirnov test rejecting the distributions being the same at the 5% level. In terms of means, women who are closest to women perform 0.42 of a standard deviation below the CA mean, on average, while men who are closest to women perform 0.08 standard deviations below the CA mean, which is higher than the men (or women) who are closest to men though not statistically different. Our results therefore indicate that women are closest to women who are particularly low ability.

An alternative mechanism behind women's tendency to refer low ability individuals is that women in particular are more averse to competition than men (despite the firm's motivation of wanting to hire more women)[18]. Competition is likely more salient in the context of this experiment than in other employment contexts where existing employees make referrals - though we note that competition is certainly present there as well. Existing employees may fear the referral will perform better and make the CA look bad, or compete with the CA over promotions. Compared to our setting where the referral only marginally affects the likelihood of qualifying or getting called for a job (given the large number of recruits), competition on the job may actually be stronger.

Nevertheless, if women CAs are concerned about the competitive threat their referrals pose, they may choose to either forgo the finder's fee (and not make a referral) or refer someone who is unlikely to qualify. We do not observe the former, since the referral rate is almost identical among women CAs and male CAs. However, the the latter is consistent with the results

[18]Niederle and Vesterlund (2007) find that women shy away from competition in particular when competing with men. In our context, this would lead women to either not make a referral or refer poorly qualified men. This is not what we observe.

presented in Table 1: in unrestricted treatments, women refer poor quality men and women. However, Figure 5 shows that women in the restricted-men treatment refer high quality men. This is not consistent with competition. If competition was driving behavior, women in those treatments who did not know a low quality man would not make a referral. Recall from Table 2 that we do not observe any differential attrition rate among women in different treatments. Instead, it suggests that the women whose closest men are high quality - those leading to better quality male referrals in Figure 5 - would get higher social payments from women who are low quality, and hence refer women who are less likely to qualify in the unrestricted treatment.

Figure 3 is also inconsistent with the competition hypothesis: women who are on the margin of qualification (near a score of 60) are if anything more likely to refer someone who is qualified. Finally, we also discuss a direct test of the role of competition in the Appendix: in an additional cross-randomized treatment, we experimentally varied whether the CA was directly competing with their referral and find no differences in the quality of the referrals. Taken together, these pieces of evidence all point towards strong social payments within women's networks, and not women having a pronounced fear of competition driving women's referral choices.

Figures 4 and 5 are about the quality of closest people, rather than the full distribution of network quality. It is also possible that quality is different across the range of the network: this could make the tradeoff between social payments and quality more steep, which is captured by the model's concept of shallowness and is investigated in the next section.

7.2 Are there gender differences in information or shallowness?

The above section indicates that the closest women in men's networks are similar in ability than the closest men in their networks. This implies that if we observe a performance premium among male CAs referring men but not women, this must be due to either worse information or more shallow networks of women.

The ability to identify good potential workers from among individuals in their social network is also directlyy of interest to employers. To test whether men and women are willing and able to identify high quality men and women, we regress

$$Y_i = \sum_k \alpha_k T_k + \delta_t + v_i$$

as before, where Y_i is an indicator for referring a qualified referral, T_k are the treatment categories in terms of gender and contract structure, and δ_t are time trends. Once again, CAs in restricted male, fixed fee treatments are used as the excluded group.

7.2.1 Male CAs' response to performance pay

Table 3 presents the results of this analysis in column (3) for male CAs. Male CAs experience a substantial performance premium when referring men: when restricted to refer men, male CAs refer someone who is about 27 percentage points more likely to qualify when assigned to the performance pay treatment. However, they do not experience any performance premium when restricted to refer women. Female CAs show positive coefficients on performance pay for all gender treatments, but they are never significant and always small in magnitude. We therefore conclude that male CAs have useful information for employers about men, and that tradeoffs are not too high to prohibit using it.

Men do not, however, choose female referrals with a positive performance premium. The evidence of a performance premium when referring men but not women is consistent with either worse information about women or a more shallow network of women. As we discuss above, information and shallowness are actually quite similar in principle, as both act to make the slope between likelihood of qualification and social payments more steep.

A striking result from Table 3 is that performance premia are in fact lower for men under unrestricted treatments than under male restricted treatments. Returning to proposition 4, this result is indicative of poor information about womens' capabilities contributing to the lower performance premium if we interpret the estimates in section 7.1 as stating that mens' female referrals are similar in quality to their male referrals. Indeed there is no significant difference in their performance, and point estimates of the difference are fairly small. However, if we take the point estimates at face value, then there is the possibility that women network members are higher quality than male network members. This is the one scenario in which we can not disentangle shallowness from information in the model.

An additional test we can run compares the quality distributions of mens' referrals of women under fixed fees with the distribution of mens' referrals of women under performance pay. The motivation for such a test is that we know that some men are choosing not to make a referral when restricted to refer either men or women under performance pay. If men have good information, but shallow networks of women, we may anticipate that the men who choose not to make a referral are those who are closest to particularly low quality women. In contrast, if men have poor information about women, then return rates should be similar for men who are closest to women who are actually low quality. Figure 6 presents this result, and we see that the left tail of the distribution of female quality is at least as heavy in the performance pay treatment as in the fixed fee treatment, suggesting that there is not a correlation between womens' likelihood of qualification and whether the male CA finds it worthwhile to refer them. Together, we interpret these two pieces of evidence as indicating that poor information about women is likely to be at least part of the answer. We note also that this result is particularly problematic for women if networks are utilized for screening: not only do employers maximize screening by having men refer men, they do better by discouraging them from even considering female referrals.

Table 4 explores further the differences how performance pay affects the way men choose to refer men and women by asking how men's referrals perform on various components of the test. Table 4 finds that men referred be men under performance pay do statistically significantly better on the computer knowledge part of the exam and better (though not significantly) on most of the other components, whereas the women they refer under performance pay behave quite similarly on all components as the women they refer under fixed fees. Following the model, this is very consistent with the hypothesis that men are referring their index female partner under both contracts.

7.2.2 Female CAs' response to performance pay

Women do not demonstrate an overall performance premium under any treatments as seen in column (4) of Table 3. However, they are nonetheless changing their referral choices. Table 5 again disaggregates referral performance by component for women CAs, and finds that women are changing their optimal referral choices of both men and women. When we provide performance pay, women refer women with better English skills and who solve more ravens matrices correctly (though the latter is insignficant), and they refer men who are more likely to have worked for a survey firm in the past and who perform better on the practical exam. However, neither of these improvements translate to higher qualification rates because they are also associated with worse scores on other components. The more experienced men also have worse math skills than the men being referred under fixed fees, while the women with better language skills perform weakly worse on a number of characteristics[19]. These suggest that

[19]The total effect on women referred under performance pay is the sum of the performance pay component and the interaction between performance pay and female restricted treatment; this is never significantly different from zero though often negative in point value.

women are responding to performance pay and do have some useful information for employers, particularly about other women (as cognitive ability is likely harder to observe in a resume than past experience) but that they do not have enough information or face networks which are too shallow overall to choose women or men who are likely to qualify.[20]

7.2.3 Attrition

In section 4, we made note of the fact that there was strong evidence that male CAs were more likely to make a referral in the presence of fixed fees than performance pay, and weaker evidence that female CAs responded similarly. In principle, these differential return rates could influence our estimates of the performance premium, though the fact that we rely on differences between restricted-gender treatments (where return rates were identical) does ameliorate this concern. Still, for example, one interpretation which would be consistent with presented results is that all CAs will only refer person 1, but CAs will just attrit rather than refer person 1 under performance pay if they are in a restricted male treatment and person 1 is low quality. Interestingly, the gender differences here still require differences in information: clearly CAs have good information if they attrit because they know that their optimal referral is low quality, and so they would have to have poor information about women's capabilities if they do not attrit in the same way when required to refer women[21]. Figure 7 suggests that among men, there is assortative matching in ability between the CA and their referral under fixed fees. This presents an additional concern for interpreting the results in Table 3: if performance pay reduces the likelihood of high ability CAs making referrals, and ability is correlated within

[20] Note also that this makes the competition hypothesis also less likely: if women have a hard time anticipating who will qualify, referring low quality people instead of just not making a referral is a very risky strategy.

[21] This explanation is, however, inconsistent with the fact that male CAs decline to make a referral at the same rate whether they are required to refer men or women under performance pay. Together with the evidence on poor information about women, it suggests that male CAs are indeed making different optimal male referrals under performance pay.

networks, then Table 3 could be biased. However, figure 7 also shows that the performance premium exists throughout the entire distribution of CA test scores, which make attrition bias less likely to be driving the results on information / shallowness[22]. Figure 8 shows analogously that there is little evidence of female CAs responding to the performance pay incentive at any point in the CA performance distribution.

8 Quality expectations and social payments

While Table 1 established that social payments contribute to women's disadvantage, could expectations of quality be a contributing factor even if fixed fee treatments? In particular, CAs may receive higher social payments when their referrals qualify than when they do not[23], creating a relationship between the CA's expectations of quality of men versus women and social payments.

In the model, expectations of referral quality are unbiased as ε_j^g is mean zero for both men and women. Recall that the quality of men and women are similar in men's networks (Figure 4), and that women's (low quality) fixed fee referrals are also not the highest quality people they know, since they know high quality men (documented in Figure 5). If social payments were a function of qualification, with unbiased expectations we would see - in contrast to our findings - that women systematically refer men, and men refer similar numbers of men and women.

However, CA expectations of referral quality may be biased. In that case, ε_j^g is not mean zero, and differences in CA i's expectations over quality $(E_i\left[Q_1^g + \varepsilon_1^g\right])$ would have similar

[22]This also demonstrates that in this setting, the problem of social payments generating incentives for employees not to refer the best person to the firm takes place across the ability distribution. We therefore have more confidence that the results extrapolate to other contexts where only existing employees make referrals.

[23]This could occur because referrals who actually get the job give higher transfers to the references who helped them than referrals who only get the opportunity to apply, or because CAs believe that they will receive a reputational premium from IPA for making a highly skilled referral.

implications in the model to actual differences in quality (Q_1^g). Therefore, biased expectations of referral quality may be able to explain our results if social incentives are positively related to referral quality in the overall network.

We can point to several pieces of evidence that biased expectations are not driving the behavior that leads to few qualified women getting referred. First, recall that table 3 showed that men did not refer the highest ability men in their network under fixed fees, since the performance pay lead to more qualified male referrals. Therefore it can not be the case that social payments are completely indexed to qualification: if they were, there would be no additional impact of the performance pay. This intuition - that social incentives indexed to qualification in essence acts as performance pay - also leads to two additional insights.

Table 1 indicates that men systematically refer men under fixed fees. In principle, this could be explained by expectations about women's relative quality if men expect their closest male connections to outperform their closest female connections. In that case, however, men have even greater incentives to refer men under performance pay than under fixed fees, and so we should expect men to refer men even more frequently under performance pay than under fixed fees unless they also know women who are much better (by more than their bias) than the men they know. However, as Table 1 Panel E indicates, men refer men at the same rate under performance pay as under fixed fees, and those men qualify more frequently than the women they (endogenously) choose to refer (though not significantly so, owing in part to the still small fraction of women referred), which is inconsistent with women's disadvantage resulting from expectations over quality. A similar argument suggests that women are not referring low quality people due to biased expectations of performance (in particular, the people they refer under performance pay are at least as good as those referred under fixed fees).

Finally, with this explanation we would expect men, who incorrectly anticipate women being less likely to qualify and receive higher social payments when referrals qualify, to differentially attrit when they are required to refer a woman. In table 2 we see that is neither the case in fixed or in performance pay treatments. Taken together, quality expectations appear to play a minimal role in explaining why so few qualified women get recruited through referrals.

9 Conclusion

There is a large literature in economics and sociology which has used observational data to suggest that women benefit less from job networks than men do Ioannides and Loury (2004). Using an experiment designed around a recruitment drive for real-world jobs, we provide direct evidence that the use of referral systems puts women at a disadvantage. We find that qualified women tend not to be referred by networks for two reasons: first, men exhibit a preference for referring men, and second, women exhibit a preference for referring unsuitable candidates. This result suggests that the ubiquity of job networks as a hiring system could contribute to persistent gender gaps in wages. As with any experiment, our results are only internally valid for our sample, enumerator applicants in Malawi. However, given that they closely mirror stylized facts about gender and networks which are based on a wealth of observational studies primarily in the US and Europe[24], there is reason to believe that our findings may generalize to many other contexts.

Our experiment allows us to say several additional things about the structure of networks which could be driving the observed disadvantage for women. Social incentives within both men's and women's networks lead to fewer qualified women being referred for a job. Employers are faced with a choice of using male employees to make referrals, in which case social incentives are maximized by permitting women's disadvantage; or using female employees to make a

[24]Most recently, Lalanne and Seabright (2011) find that male executives in the US and Europe have salaries which increase in numbers of executive contacts, while female executives do not receive this benefit.

referral, in which case relatively few of the people referred are qualified. This suggests that unless employers design referral contracts to contradict these incentives (at additional cost), women are disadvantaged by social network-based recruitment.

We also find that men have a greater potential to screen men than to screen women, and some weaker evidence that women may be able to screen both genders in different ways. If employers use referral systems because they hope to screen, then this result suggests that employers have the incentive to encourage only men to refer only men when hiring through networks. This result suggests that in order to prevent discrimination against women, careful hiring procedures may need to be followed. One such procedure which these results suggest may work well is a quota-based referral system, where people making references are required to make references of either gender - given that male CAs can both screen men and tend to be close to high quality women, these estimates suggest that a quota based system may be effective at identifying high quality workers of both genders.

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Table 1: Gender Distributions of CAs and Referrals

	(1) All CAs	(2) Male CAs	(3) Female CAs	(4) Diff: *p* value
A. CA Characteristics				
Fraction of CAs	100%	62%	38%	
CA is qualified	53%	56%	48%	0.047
N	767	480	287	
B. CA Characteristics: Made Referral, Either Gender Treatments				
Fraction of CAs	100%	61%	39%	
CA is qualified	57%	62%	49%	0.061
N	217	130	87	
C. Referral Characteristics: Made Referral, Either Gender Treatments				
Referral is Female	30%	23%	43%	0.002
Referral is Qualified	49%	56%	38%	0.019
Referral is Qualified Male	34%	43%	22%	0.002
Referral is Qualified Female	14%	13%	17%	0.456
N	195	117	78	
D. Referral Characteristics: Made Referral, Either Gender, Fixed Fee Treatments				
Referral is Female	32%	25%	43%	0.042
Referral is Qualified	50%	60%	37%	0.012
Referral is Qualified Male	34%	44%	20%	0.007
Referral is Qualified Female	16%	16%	16%	0.983
N	117	68	49	
E. Referral Characteristics: Made Referral, Either Gender, Perf Treatments				
Referral is Female	31%	22%	45%	0.039
Referral is Qualified	46%	49%	41%	0.521
Referral is Qualified Male	35%	41%	24%	0.138
Referral is Qualified Female	12%	8%	17%	0.231
N	78	49	29	

Table 2: Probability of Making a Referral

	(1)	(2)	(3)		(4)
Female Treatment	-0.004	-0.055	-0.004		-0.042
	(0.038)	(0.054)	(0.050)		(0.074)
Either Gender Treatment	0.014	0.017	-0.052		-0.024
	(0.040)	(0.055)	(0.052)		(0.071)
Performance Pay			-0.148	***	-0.113
			(0.056)		(0.080)
Perf Pay * Female Treatment			0.004		-0.013
			(0.076)		(0.111)
Perf Pay * Either Treatment			0.152	*	0.086
			(0.079)		(0.110)
Observations	506	310	506		310
CA Gender	Men	Women	Men		Women

Notes

1 The dependent variable is an indicator for whether the CA makes a referral.

2 All specifications include CA visit day dummies.

Table 3: Referral Performance

	Referral Qualifies							
	(1)	(2)		(3)		(4)	
Female Referral Treatment	-0.030	-0.190	**	0.068		-0.181	
	(0.062)	(0.083)		(0.081)		(0.113)	
Either Gender Treatment	0.071	-0.231	***	0.227	***	-0.242	**
	(0.066)	(0.082)		(0.084)		(0.107)	
Performance Pay				0.267	***	0.021	
				(0.093)		(0.122)	
Perf Pay * Female Treatment				-0.248	*	-0.022	
				(0.127)		(0.171)	
Perf Pay * Either Treatment				-0.383	***	0.032	
				(0.132)		(0.169)	
Observations	390	227		390		227	
CA Gender	Men	Women		Men		Women	

Notes

1 The dependent variable is an indicator for the referral qualifying.

2 All specifications include CA visit day dummies.

Table 4: Screening of Male CAs on Different Characteristics

	Survey Experience	Tertiary Education	Math Score	Language Score	Ravens score	Computer Score	Practical Exam Score	Feedback points
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female Referral Treatment	-0.033	0.045	-0.017	-0.115	-0.092	0.062	1.033	3.003 ***
	(0.069)	(0.074)	(0.142)	(0.207)	(0.194)	(0.371)	(0.661)	(1.044)
Either Gender Treatment	0.040	0.072	0.009	0.087	0.089	0.623	1.378 **	1.856 *
	(0.072)	(0.077)	(0.148)	(0.215)	(0.203)	(0.387)	(0.689)	(1.089)
Performance Pay	0.080	0.067	0.134	-0.005	0.230	0.943 **	0.496	1.883
	(0.080)	(0.085)	(0.164)	(0.238)	(0.224)	(0.428)	(0.757)	(1.197)
Perf Pay * Female Treatment	-0.075	0.025	-0.259	-0.027	-0.293	-0.915	-0.950	-2.443
	(0.108)	(0.116)	(0.223)	(0.325)	(0.305)	(0.583)	(1.026)	(1.622)
Perf Pay * Either Treatment	-0.165	-0.083	-0.065	-0.169	-0.367	-0.856	-1.768 *	-3.371 **
	(0.113)	(0.121)	(0.232)	(0.338)	(0.318)	(0.607)	(1.069)	(1.696)
Observations	386	390	390	390	390	390	383	382

Notes

1 The dependent variable is an indicator for the referral qualifying.

2 All specifications include CA visit day dummies.

Table 5: Screening of Female CAs on Different Characteristics

	Survey experience	Tertiary Education	Math Score	Language Score	Ravens score	Computer Score	Practical Exam Score	Feedback points
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female Referral Treatment	0.032	0.151	-0.332	-1.140 ***	-0.435	-0.627	0.972	2.152
	(0.091)	(0.110)	(0.216)	(0.342)	(0.270)	(0.538)	(0.963)	(1.349)
Either Gender Treatment	0.040	0.017	-0.189	-0.246	-0.172	-0.139	0.015	0.879
	(0.086)	(0.104)	(0.205)	(0.324)	(0.256)	(0.509)	(0.910)	(1.274)
Performance Pay	0.264 ***	0.143	-0.400 *	-0.465	-0.175	0.419	1.832 *	1.604
	(0.098)	(0.119)	(0.234)	(0.370)	(0.293)	(0.582)	(1.056)	(1.479)
Perf Pay * Female Treatment	-0.320 **	-0.292 *	0.402	1.330 **	0.551	0.232	-2.164	-2.134
	(0.138)	(0.166)	(0.326)	(0.515)	(0.408)	(0.811)	(1.468)	(2.055)
Perf Pay * Either Treatment	-0.270 **	-0.052	0.368	0.500	-0.260	-0.372	-1.625	-4.511 **
	(0.136)	(0.164)	(0.323)	(0.510)	(0.403)	(0.802)	(1.448)	(2.027)
Observations	226	227	227	227	227	227	222	222

Notes

1 The dependent variable is indicated in the column heading.

2 All specifications include CA visit day dummies.

Figure 1: CA Ability by Gender

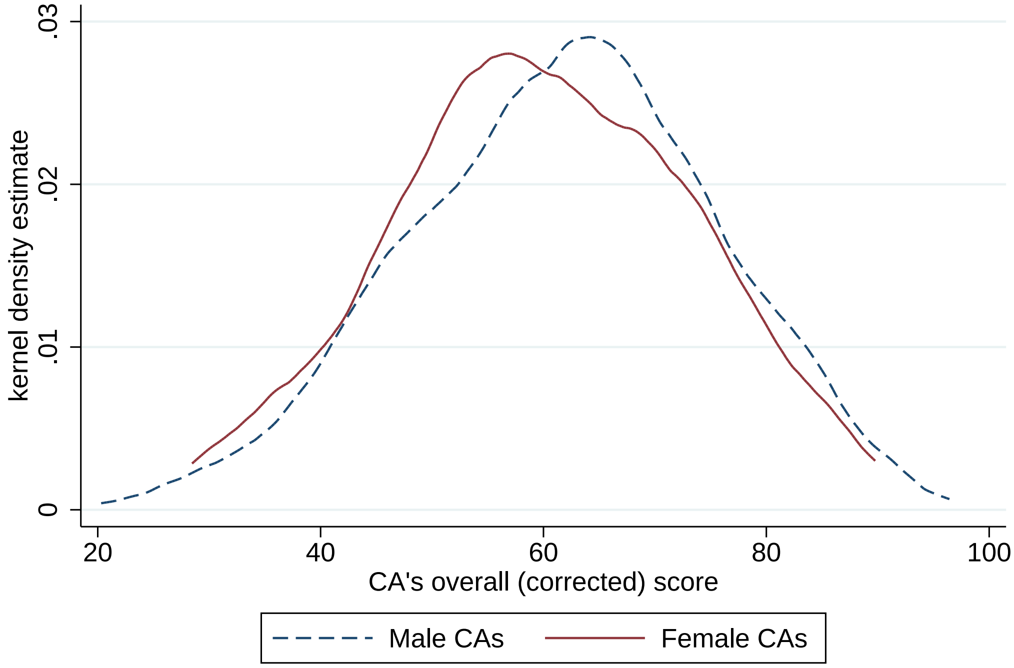


Figure 2: Gender choice in referrals, by CA performance

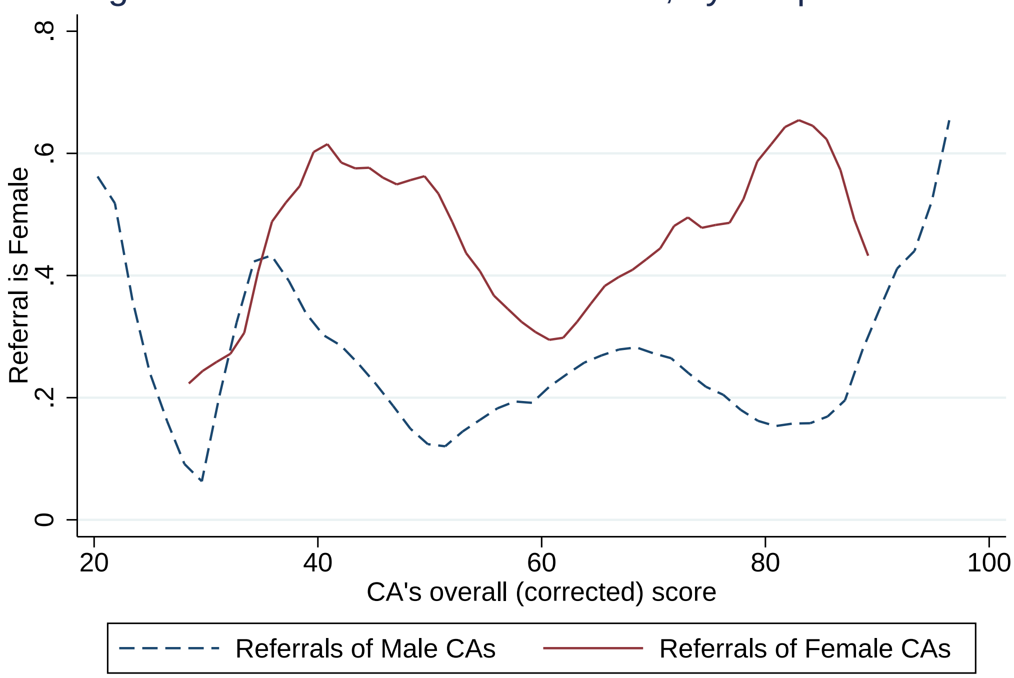


Figure 3: Referral qualification rate, by CA performance

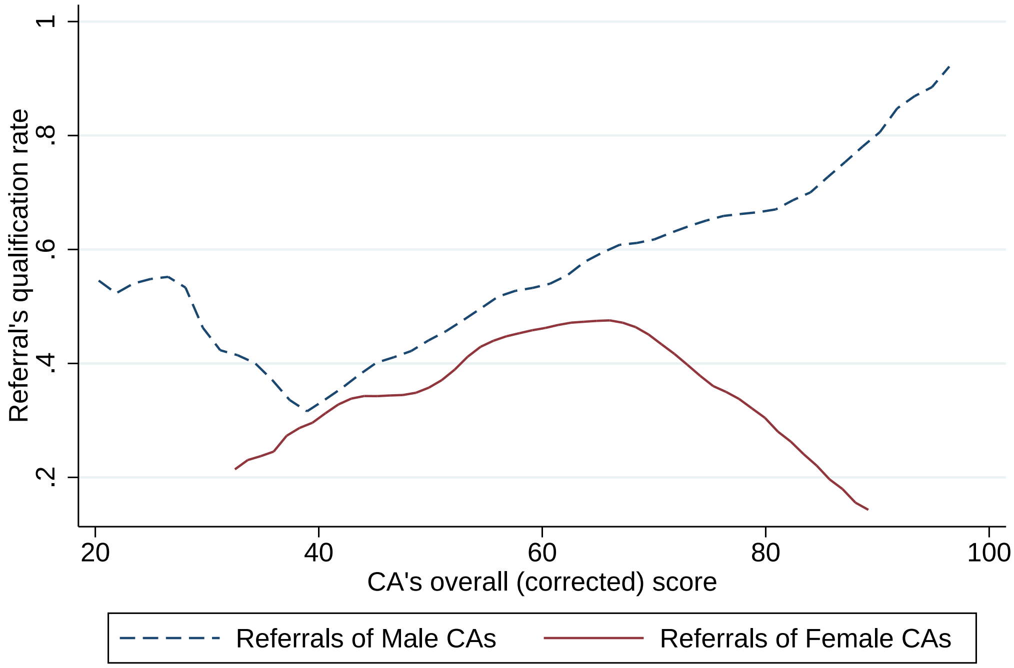


Figure 4: Men's Fixed Fee Referrals

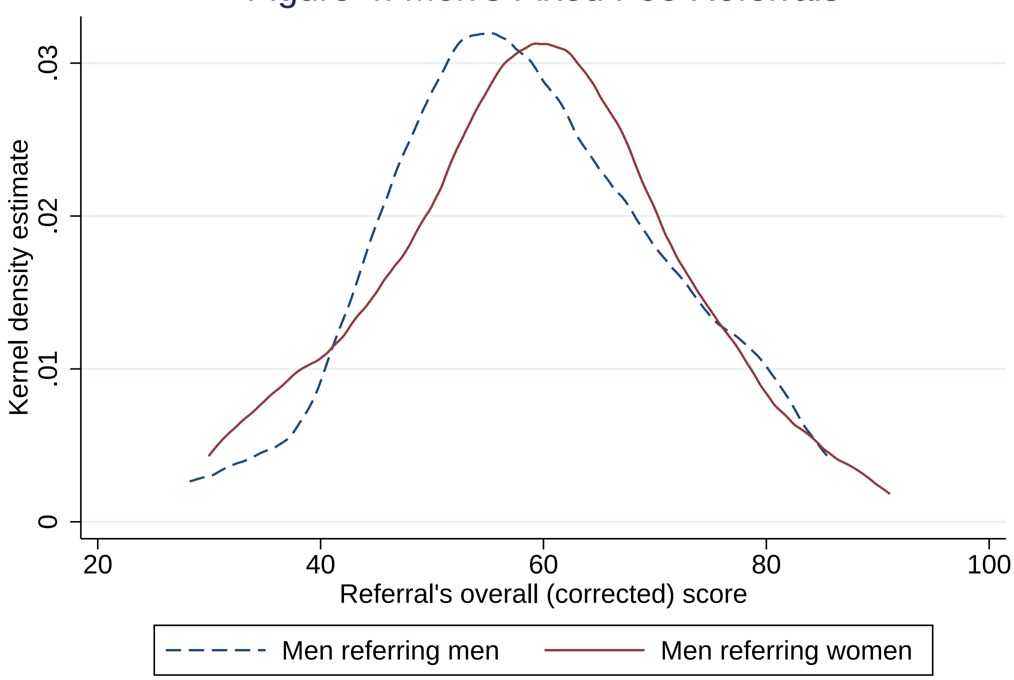


Figure 5: Women's Fixed Fee Referrals

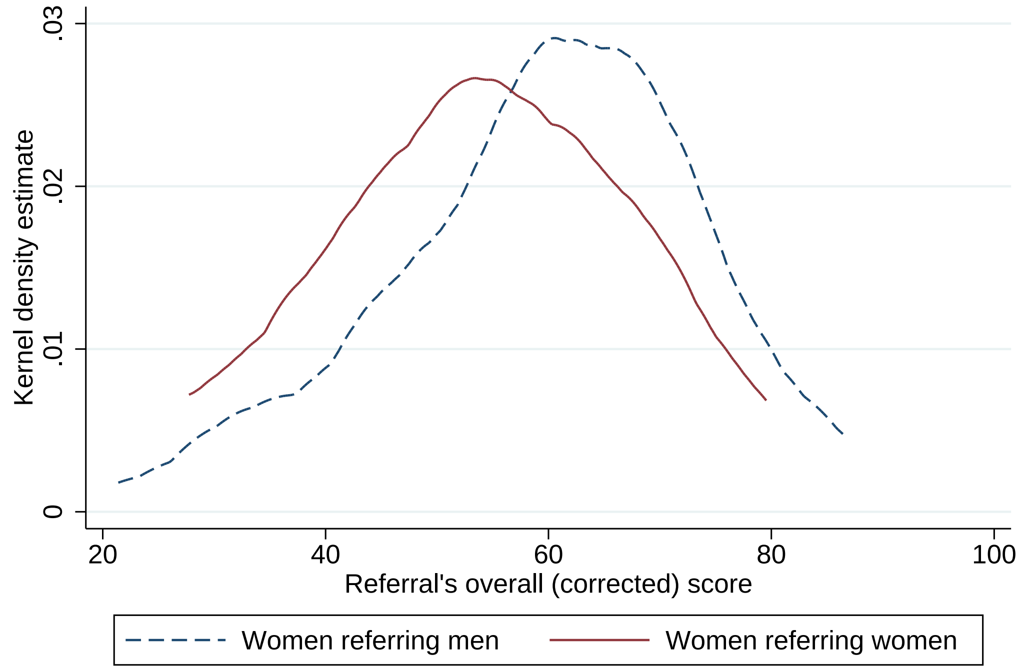
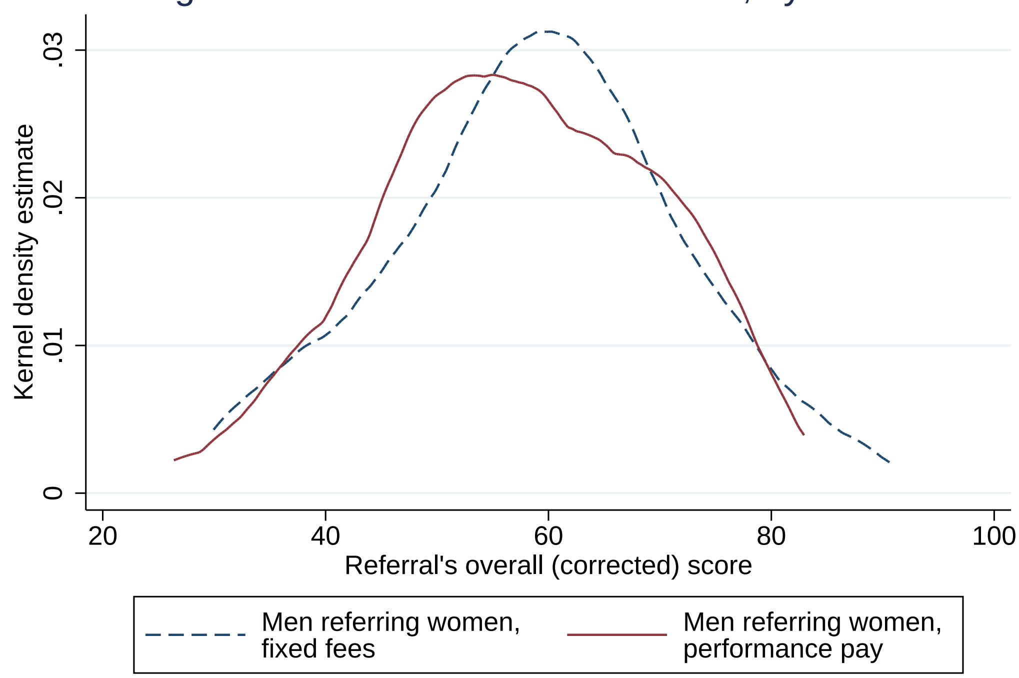


Figure 6: Men's Referrals of Women, by Contract



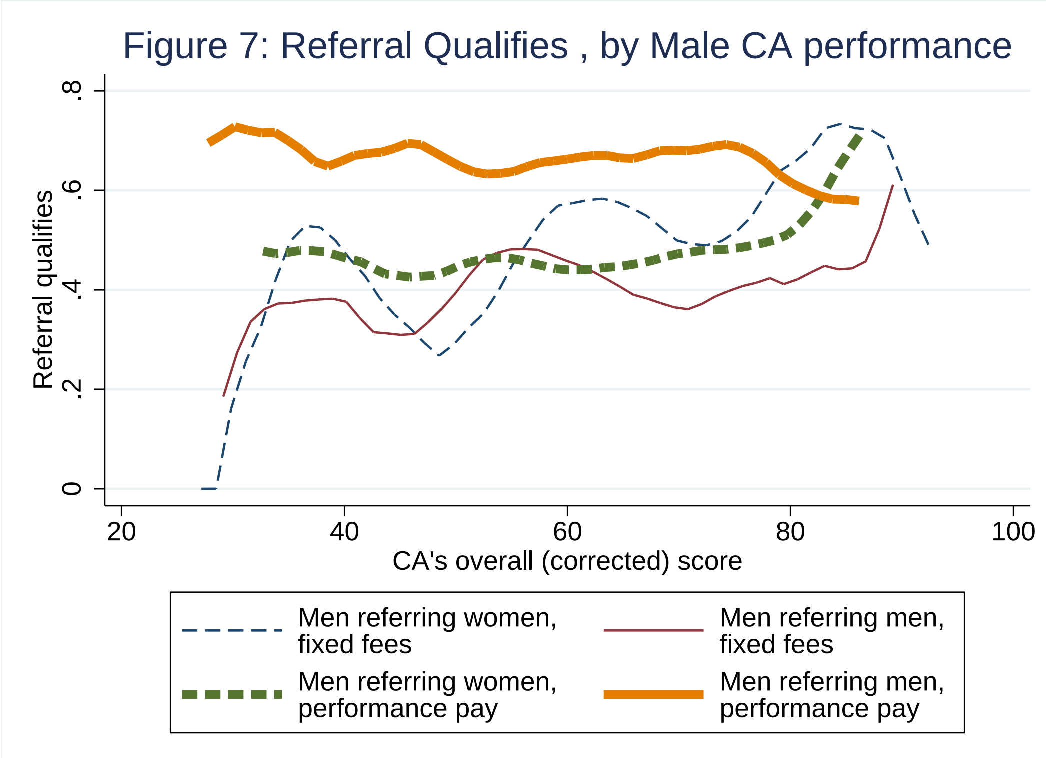


Figure 7: Referral Qualifies , by Male CA performance
Referral qualifies
0
.2
.4
.6
.8
20
40
60
80
100
CA's overall (corrected) score
Men referring women, fixed fees
Men referring men, fixed fees
Men referring women, performance pay
Men referring men, performance pay

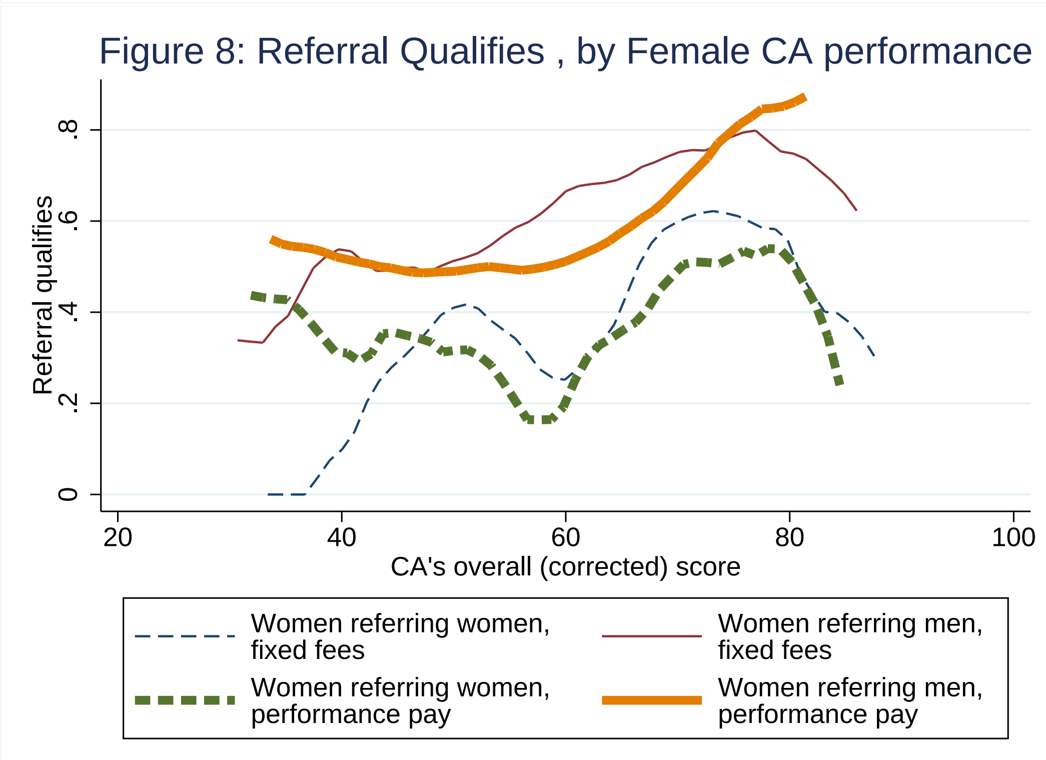


Figure 8: Referral Qualifies , by Female CA performance
Referral qualifies
0
.2
.4
.6
.8
20
40
60
80
100
CA's overall (corrected) score
Women referring women, fixed fees
Women referring men, fixed fees
Women referring women, performance pay
Women referring men, performance pay

A Appendix

A.1 Competition

In order to directly look at the role of competition in referral decisions, we experimentally varied how salient competition was to CAs. CAs were told the qualification threshold was either (i) determined using an absolute standard: receiving a score greater than 60 or (ii) in relative terms: scoring in the top half of applicants. Table A2 shows that referrals, both men and women, are not statistically less likely to qualify when CAs are directly competing with their referrals to become qualified. While this treatment should not alter perceptions of competition in the post-qualification phase, and is therefore a fairly weak test, it provides suggestive evidence that, on average, competition is unlikely to be driving our main results.

A.2 Appendix Tables

Appendix Table 1: Summary Statistics and Randomization Check

Dependent Variable	Mean and SD: Male	p value of joint test of treatments	N	Mean and SD: Female	p value of joint test of treatments	N
	(1)	(2)	(3)	(4)	(5)	(6)
CA Age	25.52	0.441	445	24.61	0.787	271
	[3.88]			[4.62]		
CA qualified	0.56	0.188	480	0.48	0.390	287
	[0.50]			[0.50]		
CA Overall Test Score (corrected)	61.66	0.373	480	59.98	0.085	287
	[13.59]			[13.22]		
CA Has Previous Survey Experience	0.31	0.410	480	0.26	0.189	288
	[0.46]			[0.44]		
CA Has Tertiary Education	0.69	0.367	480	0.78	0.186	287
	[0.46]			[0.42]		
CA MSCE Math Score	5.65	0.867	419	6.84	0.061	242
	[2.30]			[1.80]		
CA MSCE English Score	5.68	0.651	435	5.75	0.594	256
	[1.49]			[1.41]		
CA Job Comprehension Score	0.80	0.894	480	0.81	0.573	288
	[0.40]			[0.39]		
CA Math Score	0.21	0.245	480	0.18	0.351	288
	[0.10]			[0.09]		
CA Ravens Score	0.61	0.146	480	0.56	0.460	288
	[0.40]			[0.39]		
CA Language Score	0.15	0.302	480	0.14	0.602	288
	[0.03]			[0.03]		
CA Practical Component Z-score	-0.10	0.102	476	0.17	0.101	284
	[1.03]			[0.90]		
CA Computer Score	0.44	0.533	480	0.43	0.523	288
	[0.21]			[0.20]		
CA Feedback Points	25.90	0.037	474	27.92	0.252	284
	[7.28]			[6.31]		

Notes

1 The displayed p value is from the joint test of all the treatment variables and their interactions from a regression of the dependent variable listed at left on indicators for each treatment and CA visit day controls. The regressions are done separately for men and women.

2 All specifications include CA visit day dummies.

Appendix Table 2: Competition incentives in the fixed fee treatments

	CA Qualifies	Referral Qualifies	Referral Qualifies			
	(1)	(2)	(3)	(4)	(5)	(6)
Competitive Treatment	-0.055	0.072	0.052	0.014	0.090	0.227
	(0.062)	(0.069)	(0.121)	(0.086)	(0.095)	(0.165)
Female Treatment			0.094			-0.024
			(0.116)			(0.177)
Either Treatment			0.175			-0.160
			(0.123)			(0.169)
Competitive * Female Treatment			0.007			-0.263
			(0.166)			(0.236)
Competitive * Either Treatment			0.103			-0.142
			(0.176)			(0.236)
Observations	276	232	232	166	133	133
CA Gender	Men	Men	Men	Women	Women	Women

Notes

1 The dependent variable is indicated in the column heading.

2 All specifications include CA visit day dummies.