Gender Bias in Job Referrals: An Experimental Test

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Abstract

Employee referral programs, while efficient for the employer, have been shown to amplify sex-based occupational segregation in the labour markets. We present evidence from a laboratory experiment designed to shed light on same-gender bias in job referrals within gender-balanced networks. Our data suggest that women tend to favor women in their referral choice, whereas men do not attach much importance to the gender of potential candidates. Our experimental design allows us to disentangle between statistical discrimination, preferences, and pure same-gender bias. Our findings add to the existing literature by highlighting that gendered networks alone do not explain the observed gender homophily in referred-referrer pairs.

JEL Classification numbers: C91, J16, J71, J21, M51.

Keywords: Same-gender bias, job referral, laboratory experiment.

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1 Introduction

The importance of social networks in labour markets and particularly in job search is well established. Indeed, social networks can facilitate job search by providing information regarding vacancies to job seekers or by directing referrals to employers. Both in sociology and in labour economics, many studies highlight the prominent role of personal contacts in matching vacant jobs and job seekers (see Gorman and Marsden (2001) for a literature review in sociology and Topa (2011) for a literature review in economics). The use of social networks in referrals can be either informal through word-of-mouth communication or formal through employee referral programs. Nowadays firms widely recruit thanks to referrals, making it the first external source of hiring in the United States according to annual reports from the human resources think tank CarrerXRoad.

An employee referral program (ERP) is a recruiting strategy in which employers encourage current employees to refer possible candidates from both their personal and professional networks to fill current vacancies in the organization. The main difference with word-of-mouth referral is that the referrer employee gets monetary or non-monetary rewards if their referred applicant is ultimately hired. Employers use ERPs to reduce information asymmetry, which is inherent in the hiring process. Employees act as selection mechanism of potential candidates by making referrals (Montgomery, 1991; Beaman and Magruder, 2012; Dustmann et al., 2016). Consequently, as many empirical studies have shown, resulting matches are generally of higher quality than those resulting from usual recruitment processes in terms of wage, productivity and tenure (Castilla, 2005; Burks et al., 2015; Brown et al., 2016). In a field experiment investigating an online labour market, Pallais and Sands (2016) show that referred workers always perform better and have lower turnover rates than non-referred ones. Referrals are thereby efficient in revealing positive information, especially when made by high-quality workers. However, Calvo-Armengol and Jackson (2004) show theoretically that such hiring process can exacerbate labour market inequalities between groups in the long run. In their paper, the use of referrals disadvantages unemployed workers in job search because employed workers are out of their networks. Thus, employees' network composition appears as an essential factor in referral-based hiring outcomes.

Many empirical studies have shown that social networks tend to be gender homophilous[1] (see McPherson et al. (2001) for a literature review in sociology). Therefore, gendered networks and the increasing use of job referrals are involved in sex-based occupational seg-

[1] The homophily is the tendency of people to prefer interacting with similar others. In case of gender homophily, my social network is mainly made up of others of my gender.

regation and inequalities in the labour markets. Self-selection, discrimination and human capital investment are not the only ones at fault.

The tendency to refer someone of the same gender is empirically well-established. Brown et al. (2016) find that the extent of gender homophily in referred-referrer pairs is significant in a mid-sized US corporation. Among all of the hires observed from 2000 to the first half of 2011, 63.5% of referral matches are between people of the same gender. Similarly, using data from a call center in the U.S., Fernandez and Sosa (2005) find that 75% of referrals by female employees were women and only 44% of referrals by male workers were men. However, they cannot conclude to gender biased referral behavior for women because data do not pertain to referrals attempts. Indeed, such observations may result from gender differences in job preferences[2].

A few experimental investigations deal with gender bias in referrals. In a recruitment experiment run in Malawi, Beaman et al. (2018) investigate how the referral contract interacts with the gender and the quality of referred applicants and conclude that such hiring process disadvantages women. Indeed, they find that men tend to refer fewer women irrespective of the constraints and incentives associated to ERPs, whereas women refer women at approximately the same rate by which they apply traditionally. As women do not manage to refer high-quality women, hiring through referrals fails in identifying high-quality female workers. Unfortunately, having no information about subjects' network, Beaman et al. (2018) are not able to highlight exactly why men present a higher gender bias in selecting referrals than women or why women refer low-quality candidates. In a recruitment experiment run in a Business School in Stockholm, Hederos et al. (2015) ask to students to refer another student at the school for actual part-time jobs. Next, asking them the names of their closest friends, they assess whether networks are gender homophilous. They find strong evidence of same-gender bias in referrals for both genders. However, even though networks are gender homophilous, this propensity to refer someone of the same gender cannot be fully explained by network composition given that it remains unchanged when students refer someone outside of their own network. Last but not least, their findings hold irrespective of the gender stereotypes associated to the considered jobs.

In this paper we investigate whether a 'pure' same-gender bias exists in job referrals. In other words, we attempt to identify whether a same-gender bias would persist irrespectively of network composition. For this purpose, we run a laboratory experiment in which we control the composition of the network from which subjects make referral

[2] Women can prefer such job and then apply more frequently when employees of the call center refer them.

choices[3], the set of available information about network members and the environment in which subjects are led to interact with referrals (cooperation or competition). We focus our analysis on the referrers' choice without considering the outcome of their referrals in term of hiring. Our contribution is manifold. First, running laboratory rather than field experiment allows controlling the network of referrers. Thus, an exogenous network rules out the social tie which may be present in the referrer-referred pairs. Moreover, the gender balance in the network eliminates the effect of social network composition on same-gender referrals, as highlighted by Hederos et al. (2015). We can thereby explore whether same-gender bias is robust when networks are exogenous and gender-balanced. Second, by comparing referral choices in cooperative and competitive environments, we can analyze whether gender bias changes with the nature of future interactions between the referrer and her/his referral. Third, by varying relevant displayed information, we can investigate to what extent same-gender bias persists when subjects have information regarding network members' productivity. In this way, we can distinguish statistical discrimination and preferences from 'pure' same-gender bias in job referral choices. Nowadays, organizations are especially concerned about workforce diversity. Understanding how employees make their referral choice seems essential to help them succeed.

Our findings allow us to rule out statistical discrimination in job referral decisions within our setting. Indeed, gender-biased choices are not influenced by the future interactions with the referrals. Moreover, we show that only women are concerned by the gender of referral candidates. Whereas men refer candidates from both genders at the same rate, women tend to refer more women in competitive environment, irrespective of information flows, and in cooperative environments when no other relevant information is available. Such behaviors suggest the existence of a 'pure' same-gender bias in job referral decisions of women mainly in case of future cooperation with referrals and support female preferences for same-gender competition.

2 Experimental design

2.1 Preliminary stages

We run a preliminary questionnaire to collect information about participants' characteristics. Participants provide information regarding their demographics (gender and age) and academic background (current year of study, specialization and school admission pro-

[3]As presented below, we provide gender-balanced networks with equal distribution of productivity between gender.

cess). The experiment is conducted in a business school, for which several specializations are available (International Business, Marketing & Business Development, Wine Tourism) [4]. The school admission process is divided in two categories : students who attended a preparatory class and students who accessed school from a parallel admission. The questionnaire is run beforehand, because most of the collected information is necessary in the referral game.

During the experiment, participants perform on multiple occasions in a real-effort task. We use a decoding task (Charness et al., 2014) where participants have to decode sets of two-digits numbers into letters from a grid of letters displayed on the screen (see screenshot in appendix A). This real-effort task is particularly suited to the context of our experiment as previous studies have found no gender differences in performance under this task (Charness et al., 2014; Kuhn and Villeval, 2015). After answering the preliminary questionnaire, participants are presented with the decoding task. They first take part to a trial period of two minutes with no monetary reward. This is intended to familiarize participants with the task. Then, all participants perform for four minutes under a piece-rate remuneration scheme. Participants earn €0.10 for each correctly solved task. Performance in this preliminary game is henceforth used as a measure of productivity.

2.2 The referral game

In the main game of our experiment, participants take one of two roles : *referrer* or *referral candidate*. Each experimental session includes N participants. Six participants (three females and three males) take the role of *referral candidate*, while the (N-6) remaining participants take the role of *referrer*. The attribution of these roles is not random, as the panel of *referral candidates* must meet certain criteria. The algorithm used to match participants in their respective roles is described in the next subsection.

In the first stage of the referral game, participants in the role of *referrer* face four independent decisions. Each decision consists in selecting one of the six *referral candidates* in the panel in a particular situation. Participants are informed that one of those four decisions will be randomly selected as effective for the second stage of the game. In this second stage, all participants perform in the decoding task. Payoffs in the referral

[4] As participant are in their first year of study and given that specialization is effective in the third year of study, participants express a wish only in the preliminary questionnaire.

game depend on the role, the referral choices and the performance of participants. We implement a 2×2 factorial design in a within-subject fashion, amounting to the four decisions undertaken by *referrers*. The selection process varies in two dimensions.

Competitive vs. cooperative environment

First, we vary the structure of the payoffs of participants. More precisely, we compare two types of remuneration schemes which induce two types of future interaction between the *referrer* and her/his *referral*. Indeed, when a worker refers another one for a position in the organization, she/he may have to work with her/him or compete against her/him for promotions in the future.

In the competitive environment, each *referrer* enter a competition with her/his *referral*. The participant who has the lowest performance receives a payoff of €0. The participant who performs the best receives a positive payoff, which is decreasing with the distance between her/his own performance and the performance of the opponent. We use such payoff structure to incite referring a high quality candidate despite the future competition with her/him[5]. Overall, *referrers* in this situation have a monetary incentive to select a *candidate* marginally less performing than them for referral.

Payoff structure in the competitive environment :
$\pi_i =$ €6 − €0.10 × (own performance-performance of opponent) *if the competition is won*
$\pi_i =$ €0 *if the competition is lost*

In the cooperative environment, each *referrer* enter a cooperation with her/his *referral*. Participants in both roles receive the same payoff, which is based on the average performance of the referrer/referred pair.

Payoff structure in the cooperative environment :
$\pi_i =$ €0.10 × [(own performance+performance of opponent)/2]

Low vs. high information

[5]In ERPs, only high quality referred candidates are recruited and referrers are better off referring such candidates even though they will compete with them for promotions. Consequently, in order to reduce threats to external validity, we use a payoff structure which avoids the ease of referring a low quality candidates in case of competition.

Second, we vary the information available to *referrers* when making their referral choices. In the low information treatments, *referrers* have access to information regarding the gender, the age, the specialization wish and the school admission process of the six *referral candidates*. In the high information treatments, *referrers* also get information regarding *referral candidates*' performance in the preliminary game. This information is given in the form of a noisy signal, that can take any integer value in a range from two units below to two units above the actual performance in the preliminary game. For instance, an actual performance of 50 will be associated to a signal lying between 48 and 52.

2.3 Panel formation

In our experiment, the panel of referral candidates from which referrers make referral choices is given but not random. Indeed, controlling environment is the main asset of laboratory experiments compared to field data and, as explained previously, controlling network composition is essential in our pure same-gender bias identification. Consequently, after the preliminary game, an algorithm selects three men and three women among all participants so that we obtain an equal gender performance distribution.[6] More precisely, the panel of candidates consists of three homogeneous female-male pairs. Within each pair, performances in the preliminary piece-rate task are either equal, or differ by one unit only. Thereby, referrers always have the choice between a low performer, a mid performer and a high performer of either gender. This information is particularly relevant in the high information treatments where a signal regarding performance is provided. Keep in mind that the panel of referral candidates stay unchanged between treatments, only the set of information changes between the low and the high information treatments.

2.4 Experimental procedure

The experiment was programmed using z-Tree (Fischbacher, 2007). In total, 211 participants (93 women and 118 men) took part in the experiment. The subject pool consisted of students from the Burgundy School of Business in Dijon (France). The sessions lasted approximately 45 minutes. Subjects' average earnings were €11.

[6]The panel formation algorithm is described in appendix B.

To control for potential order effects, the sequence of treatments was modified between sessions. Table 1 displays an overview of our experimental sessions.

Table 1: Characteristics of the experimental sessions

Session	Number of subjects	Number of females	Sequence of treatments[†]
1	36	10	Competiton - Cooperation
2	35	17	Cooperation - Competition
3	35	18	Competiton - Cooperation
4	36	19	Cooperation - Competition
5	35	17	Competiton - Cooperation
6	34	12	Cooperation - Competition
Total	211	93	

[†] *The low information treatments are always run before the high information ones. For instance, the treatment sequence in session 1 was: i) Competition/Low info - ii) Cooperation/Low info - iii) Competition/High info - iv) Cooperation/High info.*

3 Theoretical framework and predictions

Beaman et al. (2018) develop a theoretical model of referral choice to investigate which characteristics drive referral choices towards men rather than women. In our controlled environment, this theoretical framework is simplified so that theoretical predictions about referral choices can be tested. Each referrer i has a network $\mathcal{N}_i = \mathcal{F}_i \cup \mathcal{M}_i$, where $\mathcal{F}_i$ ($\mathcal{M}_i$) is the set of female (male) referral candidates, which consists of $|\mathcal{F}_i|$ females and $|\mathcal{M}_i|$ males. Given that $\mathcal{N}_i$ is exogenous, no idiosyncratic social benefit comes from making referrals. Moreover, as our experiment is an anonymous one-shot game, there is no ambient incentive to refer the more efficient worker so that no reputational effects plays. Consequently, in our intentionally simplified case, only direct financial incentives drive referral choices. These incentives change between the competitive and cooperative environment. In the high information treatments, the referrer i observes a signal Q_j about the quality Y_j of each referral candidate j of the network[7] such that: $Q_j = Y_j + \epsilon$, with $\epsilon \sim U[-2, 2]$. Thus, the *referrer i* chooses her/his optimal referral j^* both in cooperative

[7]Remind that the signal about quality of referral candidates is based on their performance in the preliminary game.

and competitive environment such that

$$j^* = \underset{j \in \mathcal{N}_i}{\arg\max} \quad E\left[P_i(Y_j)|Q_j\right], \tag{1}$$

where $P_i(Y_j)$ gives her/his payoff as a function of the quality of the referral j and depends on the environment in which the referrer and the referral interact[8]. As a consequence, only the quality of referrals matters, others characteristics are irrelevant. In our experiment, each network $\mathcal{N}_i$ (panel of referral candidates) consists of as many females as males, i.e. $|\mathcal{F}_i| = |\mathcal{M}_i|$. Moreover, the panel formation algorithm guarantees that the distributions of referral candidates quality are similar among genders, i.e. $E[Y_j|j \in \mathcal{M}_i] = E[Y_j|j \in \mathcal{F}_i]$, which implies that $E\left[P_i(Y_j)|Q_j\right]$ does not depend on the gender of $j \in \mathcal{N}_i$. As a consequence, we can make the following predictions.

Prediction 1 In treatments without signal about referral candidates quality (low information treatments), the probability to refer a female $p(j^* \in \mathcal{F}_i)$ or a male $p(j^* \in \mathcal{M}_i)$[9] equals to 50%, as $|\mathcal{F}_i| = |\mathcal{M}_i|$.

Prediction 2 In treatments with signal about referral candidates quality (high information treatments), referrers are concerned about signals of referral candidates only when making referral choices.

Prediction 3 In treatments with signal about quality (high information treatments), the probability to refer a female $p(j^* \in \mathcal{F}_i)$ or a male $p(j^* \in \mathcal{M}_i)$ equals to 50%, as $|\mathcal{F}_i| = |\mathcal{M}_i|$ and $E[Y_j|j \in \mathcal{M}_i] = E[Y_j|j \in \mathcal{F}_i]$.

4 Results

In this section we report our findings. We start with an overview of the data we collected in the experiment. As a next step we show preliminary evidence of same-gender bias in the referral decision of female referrers. We finally confirm this finding through econometric analysis. We run Wilcoxon Mann-Whitney tests (henceforth *WMW*) and proportion tests (henceforth *prtest*) to support our analysis. When using non-parametric tests, we always

[8]As showed previously, profit functions are such that referrers always make a referral choice.

[9]For simplification and without loss of generality, we present proportions of same-gender referrals in the result section.

report two-sided $p - values$ throughout.

4.1 Descriptive statistics

Table 2: Descriptive Statistics

Referrers			
	All	Males	Females
Female	42.95%	-	-
Age (in years)	20.31	20.44	20.15
	(0.96)	(1.09)	(20.15)
Study level (in years)	2.30	2.32	2.29
	(0.56)	(0.60)	(0.51)
Preparatory class (school admission process)	55.43%	43.00%	72.00%
Performance (piece-rate)	58.73	58.73	56.93
	(10.62)	(10.13)	(11.16)
Payoff (in euros)	10.80	10.79	10.82
	(2.91)	(3.12)	(2.63)
# Participants	175	100	75
Referral candidates			
	All	Males	Females
Female	50%	-	-
Age (in years)	20.08	20.22	19.94
	(0.60)	(0.73)	(0.42)
Study level (in years)	2.14	2.17	2.11
	(0.35)	(0.38)	(0.32)
Preparatory class	55.55%	38.89%	72.22%
Performance (piece-rate)	59.64	59.56	59.72
	(9.06)	(9.26)	(9.12)
Payoff (in euros)	12.36	12.26	12.46
	(1.61)	(1.71)	(1.56)
# Participants	36	18	18

Note : Average values (standard deviations) are reported in this table.

Table 2 reports information regarding demographics and outcomes within our sample. The two subpopulations of *referrers* and *referral candidates* do not differ in age (WMW, p=0.2611), study level (WMW, p=0.3014) or proportion of students who attended preparatory classes (prtest, p=0.9889). The performance of referral candidates is not significantly different in average than the performance of referrers (WMW, p=0.5278). Participants in the role of referral candidate receive in average a higher payoff than participants in the role of referrer (WMW, p=0.0094). This is due to the structure of our experimental design; a participant in the role of referral candidate is paid according to the interaction which grants her/him the highest payoff.

As an important note, we observe that women and men do not differ in performance in the decoding task we implemented (WMW,p=0.4377). This is consistent with Charness et al. (2014) and Kuhn and Villeval (2015) that have shown that the decoding task does not entail any gender difference in performance. For this reason, a referrer has no monetary interest to discriminate against females (or males) when making her/him referral choice in the low information treatments, except in case of wrong beliefs.

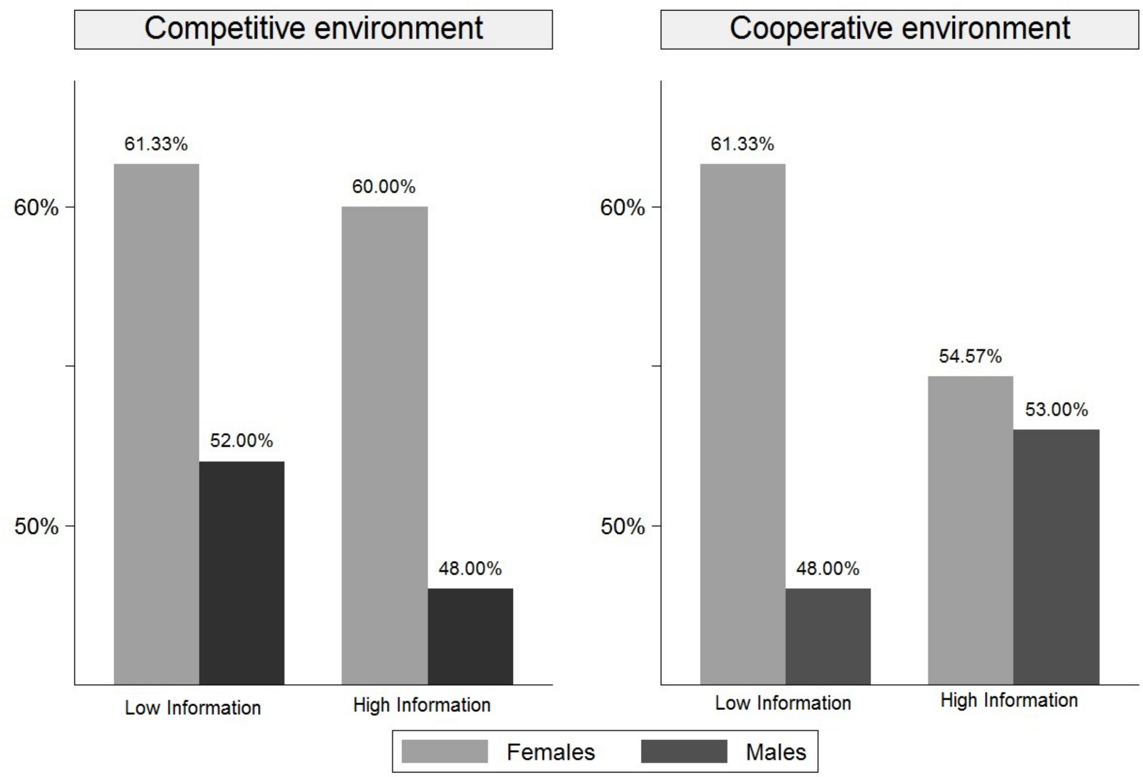
4.2 Gender bias in referral decisions

For each session, the panels of referral candidates have been constructed such that exactly three women and three men could be selected by the referrers. In the absence of gender bias, one would expect to observe a (close to) perfect gender balance among referrals. Furthermore, the probability to be selected should not be conditional on the gender of the decision-maker.

Our data suggest however that women tend to favor women in their referral decision. Over our four treatments, female referrers choose a female candidate in 59.33% of the cases. This is significantly higher than the 50% share predicted by our model (prtest, p=0.0012). In sharp contrast, men do not appear to attach particular importance to the gender of candidates when making their referral decision. Male referrers select a male candidate in 50.25% of the cases. This figure is not significantly different than a perfect gender balance (prtest, p=0.9203).

Figure 1 reports the proportion of same-gender referrals across treatments and according to the gender of the referrer who makes the referral choice. In all four treatments of the experiment, male referrers do not exhibit differential treatment between women and men in their referral choice (prtest, p>0.10 in each treatment). Thus, the theoretical predictions 1 and 3 are verified for male referrers in all our treatments, whereas this is not the case for female referrers. Indeed, female referrers tend to refer more women in the Competitive/Low information treatment (prtest, p=0.0496), the Competitive/High information treatment (prtest, p=0.0833), and the Cooperative/Low information treatment (prtest, p=0.0496). However, this tendency to refer more women than men does not appear in the Cooperative/High information treatment (prtest, p=0.4189).

Figure 1: Proportion of same-gender referrals across treatments



4.3 Robustness check

To ensure that the observed inclination of women to refer female candidates is not driven by other observable characteristics, we run additional econometric regressions. We choose to use conditional logit models due to the structure of our data. Developed by McFadden (1973), the conditional logit model is an extension of the multinomial logit model and is particularly appropriate in discrete choice situations. In this model, explanatory variables include attributes of the choice alternatives (here, the characteristics of referral candidates) and characteristics of the individuals making the choices (here, the referrers).

Participants in the role of referrer face a panel of six candidates from which only one candidate should be selected. The decision to refer or not a candidate therefore depends on the other choices available in the panel and on their own characteristics. Such effects on choice can be captured with a conditional logit model.

Results are presented in table 3. As our purpose is to identify a pure same-gender bias in referral choice, we run econometric regressions from this perspective. Same-gender bias reveals the existence of in-group favoritism, but others shared characteristics can lead to such behavior, as the school admission process in our case. Indeed, in business schools, school admission processes can divide students. Moreover, as showed in Table 2, this characteristic is not perfectly balanced among gender, women are more frequently from preparatory classes. Due to implementation issues, our panels of referral candidates were not perfectly balanced among gender concerning this observable characteristic. Consequently, our econometric analysis allows to distinguish a same-gender bias from a likely same-admission bias.

As expected, the signal about referral candidates' quality significantly affects participants' decisions when available. In competitive environment, referrers choose referral candidates of lower quality and do the opposite in cooperative environment. Moreover, the theoretical prediction 2 is always verified except with female referrers in competitive environment. Although they are informed that females and males do not differ in performance within the panel, women are more willing to choose a female candidate in competitive environment whereas they do not exhibit gender bias in cooperative environment.
Regressions confirm that men do not exhibit favoritism toward male referral candidates. Indeed, male referrers do not choose significantly more male referral candidates. However, they choose significantly more referral candidates from the same admission process in the cooperative/low information treatment. Although this may be viewed as evidence for in-group favoritism among males, this finding is not supported through other treatments and may not be over interpreted.

Finally, our regressions show that women are not willing to refer more candidates from the same admission process in any of our treatments, whereas they are willing to refer more candidates of the same gender in all but the cooperative/high information treatment. As a consequence, we confirm that their inclination to refer more female referral candidates is not driven by the composition of our pool of participants (i.e. by the fact that more than 70% of female participants comes from preparatory classes). Furthermore, as the bias remains the same in cooperative and competitive environments without signal about candidates' quality, we conclude that it does not reflect statistical discrimination. Indeed, if beliefs regarding candidates' quality were related to gender, we would have observed opposite behaviors in cooperative and competitive environments. Finally, when information regarding candidates' quality is provided, females' tendency to refer females is observed in the competitive treatment only. One interpretation would be that the same-gender bias we observe in the absence of information does not reflect strong preferences from women for women, and that the persistence of this same-gender bias in the competitive setting with information is due to preference of women for same-gender competition.[10]

[10] Such preferences have been documented in the experimental literature (e.g. Datta Gupta et al. (2013), ?)

Table 3: Determinants of referral choice (conditional logit estimates)

	Competitive environment			
	Low information		High information	
	i is a female	i is a male	i is a female	i is a male
i and j are from the same gender	0.476**	0.083	0.432*	-0.103
	(0.241)	(0.202)	(0.236)	(0.202)
i and j are from the same admission	-0.104	0.050	-0.192	-0.008
	(0.387)	(0.266)	(0.372)	(0.270)
Signal of j	-0.001	0.013	-0.073***	-0.053***
	(0.013)	(0.012)	(0.016)	(0.014)
# Obs	450	600	450	600
# Participant i	75	100	75	100
	Cooperative environment			
	Low information		High information	
	i is a female	i is a male	i is a female	i is a male
i and j are from the same gender	0.408*	-0.105	0.113	0.170
	(0.240)	(0.203)	(0.233)	(0.196)
i and j are from the same admission	0.412	0.610**	0.0415	-0.0219
	(0.341)	(0.307)	(0.265)	(0.236)
Signal of j	0.00219	-0.0111	0.114***	0.105***
	(0.0124)	(0.0133)	(0.0243)	(0.0233)
# Observations	450	600	450	600
# Participants i	75	100	75	100

Note: Robust standard errors are displayed in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

5 Discussion and conclusion

We conduct a laboratory experiment in an attempt to identify gender bias in job referral choices. The choice of using a laboratory experiment enables us to exogeneize and control the network composition from which referrers make their choice. Thereby, we neutralize the network composition effect which has been highlighted in the existing literature as a probable cause for gender homophily in job referral. Furthermore, our various treatments enable us to disentangle statistical discrimination, preferences and 'pure' same-gender bias.

We observe that females exhibit same-gender favoritism in their referral choices in several instances. First, females tend to favor females for positions that lead to future cooperation only when no information regarding productivity is available. Second, females tend to favor females for positions that lead to future competition, even when they are informed that there is no productivity difference between both gender. If participants' discriminatory practices would be statistically driven, we would not observe that females favor females in both competitive and cooperative environments. Furthermore, if females had strong preferences for interacting with other females, the presence of same-gender favoritism would hold in the cooperative environment with information. As such, we believe that the observed same-gender favoritism is mainly driven by (cognitive) bias in cooperative environment and preferences for competing against an other female in competitive environment. In contrast, male referrers do not seem to be concerned about gender in their referral choices. We observe however, in one treatment only, that males' choices might be biased towards candidates who have similar curriculum, suggesting that males are not exempt from in-group favoritism.

We acknowledge that the referral game we implement is simple, and several dimensions of the job referral environment, such as ambient incentives or social benefit, are absent from our design. This absence is however intended, as our research question is precisely to investigate the existence of 'pure' gender bias, independent of all those dimensions. It may be interesting for future research to extend this experimental framework.

Our study does not aim at minimizing the role of the network composition effect. Gender bias can be indirectly related to the gender composition of our participants' actual networks, as they may form with one's social environment. However, we demonstrate through this experiment that (artificially) neutralizing the network composition effect is not sufficient to ensure gender parity in referral choices. Furthermore, our findings suggest that the response of referrers to such an environment depends on the referrer's own gender. Those results are potentially relevant to managers who are interested in promoting workforce diversity while using Employee Referral Programs.

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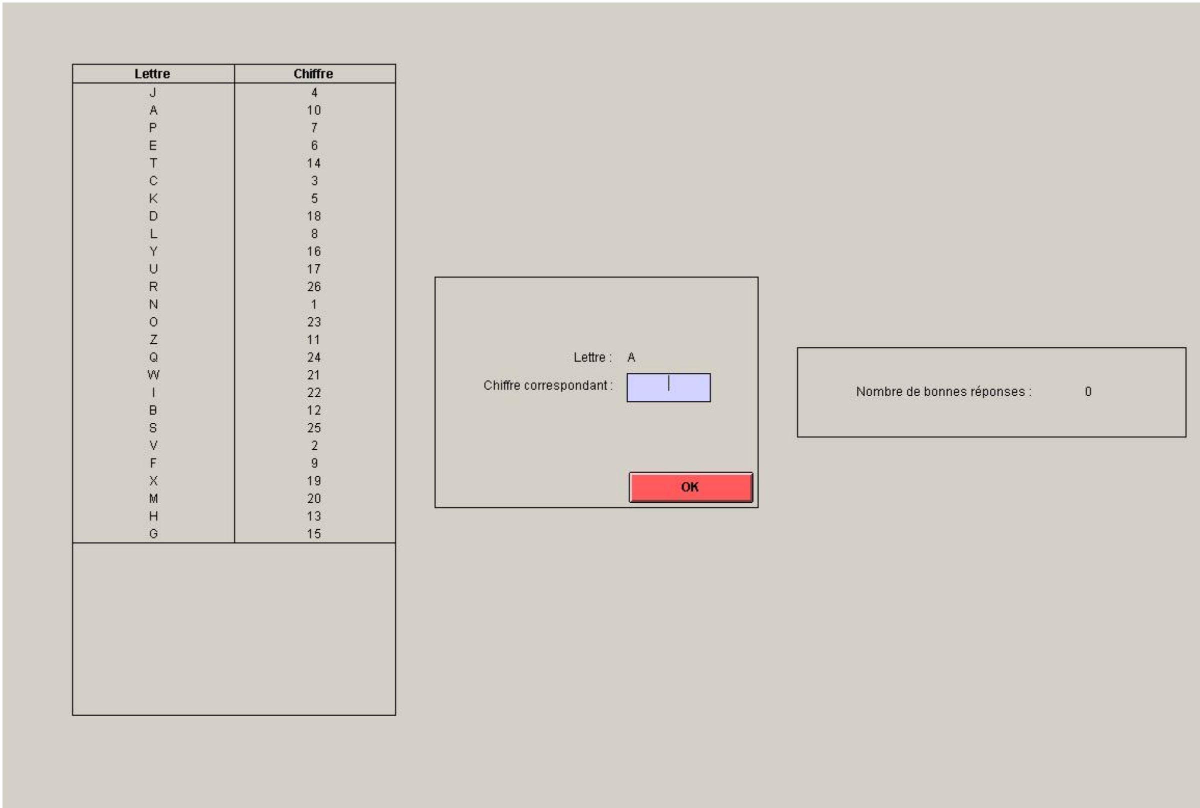
Appendix A: Instructions

Experiment instructions (first part)

The experimental session entails three stages. In stage one and three, you will perform in a task. In stage two, you will take a series of decisions.
During stage 1, you perform for four minutes in the task that is described below. At the end of this stage, you will be informed of your performance. This performance determines the first component of your earnings. Only at the end of stage 1 will you receive the instructions for the following of the experiment.

The task

During this experiment, you will have to perform a particular task. This task consists of converting letters into numbers. The screen is divided into three parts (see screenshot below).



The left part of the screen displays a two-column table. The first column includes all letters of the alphabet, in no particular order. The second column reports for each letter a corresponding number. Your task is to find the number corresponding to an instructed letter.

You can find the instructed letter in **the central part of the screen**. To provide your answer, you must type it in the central field and confirm your choice by clicking the ≪ok ≫button. If the answer you provide is correct, your score increases by one unit. A new letter appears, and you have to find again the new number that matches this letter. If the answer you provide is incorrect, a warning message appears, and you are invited to provide a new answer for the same letter.

The number of correct answers you have provided is displayed in **the right part of the screen**. This is your score. Anytime you provide a correct answer, your score increases by one unit.

To familiarize with the task, we offer you to perform for two minutes. Your earnings will not be affected by the performance in this familiarization stage. Once all participants have performed for two minutes, you will be asked to answer a short questionnaire. Once all participants have answered this questionnaire, stage 1 of the experiment will start.

Payoffs

Your earnings for the whole experiment are calculated as the sum of what you earn in stage 1 and what you earn in stage 3. You will be paid in cash at the end of the experimental session.

In stage 1, you will take part in the decoding task for four minutes. Every problem that you solve correctly will grant you €0.10. Your earnings for the stage 1 of the experiment are computed as follows:

$$\boxed{\textit{Earnings for stage 1} = \text{€}0.10 \times \textit{Problems correctly solved}}$$

Incorrect answers are not considered in the calculation of your payoff. When the four minutes of stage 1 have elapsed, an information screen will provide you feedback on your performance and your earnings for this stage. We will then hand you new instructions, to continue the experiment.

Experiment instructions (second part)

These new instructions explain the proceedings of stage 2 and stage 3 of the experiment. In the following of the experiment, we place ourselves in the context of an employee referral system. Employee referral is an internal recruitment system which encourage a company's existing employees to select and recruit potential candidates to a position. You will participate either in the role of referrer, or in the role of candidate.
Participants in the role of referrer choose a candidate for the position.
Participants in the role of referral candidate can be chosen by referrers for the position.

Stage 2

At the beginning of stage 2, six participants in the room will be assigned the role of referral candidate by the computer. Those six participants will form the group of candidates who can be selected by referrers. You are informed of your role at the beginning of stage 2. The actions you can undertake in stage 2 depend on your role.

If you are a referral candidate
You do not take any decision in stage 2.

If you are a referrer
The group of six referral candidates will be displayed to you. This group will remain unchanged for the whole experiment. During stage 2, you will have to select a candidate with whom you will participate in stage 3 in four different situations. Those four situations vary in both the information you receive regarding potential referral candidates, and the environment in which you will participate with the referral candidate you select for stage 3.

Please note that your selection decision will influence your earnings in the stage 3 of the experiment. Furthermore, the calculation of your earnings in stage 3 will be affected by the environment you will take part in. One of the four situations will be randomly drawn and made effective. The four situations are described as below:

- ***Situation 1*** : *partial information + competitive environment*

You are provided with information regarding personal characteristics of all potential candidates. During stage 3, you will be competing against the candidate that you selected.

- ***Situation 2*** : *partial information + cooperative environment*

You are provided with information regarding personal characteristics of all potential candidates. During stage 3, you will be cooperating with the candidate that you selected.

- ***Situation 3*** : *complete information + competitive environment*

You are provided with additional information regarding the ability of all potential candidates. During stage 3, you will be competing against the candidate that you selected.

- ***Situation 4*** : *complete information + cooperative environment*

You are provided with additional information regarding the ability of all potential candidates. During stage 3, you will be cooperating with the candidate that you selected.

In situation 3 and 4, you receive additional information regarding the ability of potential candidates. This information takes the form of a performance signal S, that is calculated as follows :

$$S = P + K$$

Where P is the exact performance of the individual during stage 1 et K is a number that takes value in $[-2; -1; 0; 1; 2]$.
Therefore, two participants with identical stage 1 performance can have different signal. Two participants with the same signal did not necessarily perform the same in stage 1.

Stage 3

The situation made effective in stage 3 is randomly chosen by the computer at the end of stage 2. Before starting stage 3, you will be reminded your candidate choice for this situation. During this last stage, all participants will perform again in the decoding task for four minutes.

Payoffs

The calculation of your payoff for stage 3 depends on your role, your performance, potentially the performance of the other participant, and the environment you enter (competitive or cooperative).

If you are a candidate who did not get selected in stage 2
Regardless of the randomly drawn situation, your payoff depends only on your performance.

$$\boxed{\textit{Earnings for stage 3} = \text{€}0.10 \times \textit{Problems correctly solved}}$$

If you are a candidate who got selected in stage 2
Your payoff depends on your performance and on the performance of the referrer who selected you. If you have been selected by several referrers, the most favorable situation will be considered. In other words, we assign you the referrer for whom your payoff would be maximum. Note that you receive no information on the referrers who have selected you.

- **Competitive environment:**

In the competitive environment, your payoff is positive only if your score in stage 3 is higher or equal to the score of the referrer who has selected you.

Earnings for stage 3 = *€6 - €0.10* × *(your score - score of referrer)*	if you win
= *0€*	otherwise

- **Cooperative environment:**

Earnings for stage 3 = €0.10 × [(your score + score of referrer)/2]

If you are a referrer
Your payoff depends on your performance and on the performance of the candidate you have selected in stage 2 for the situation randomly drawn.

- **Competitive environment:**

In the competitive environment, your payoff is positive only if your score in stage 3 is higher or equal to the score of the referrer who has selected you, and if the score of the candidate is positive.

Earnings for stage 3 = *€6 - €0.10* × *(your score - score of candidate)*	if you win
= *0€*	otherwise

- **Cooperative environment:**

Earnings for stage 3 = €0.10 × [(your score + score of candidate)/2]

Appendix B: Panel formation algorithm

Two-step matching protocol

Lets consider a population Ω of size n, divided into two subpopulations $\mathcal{F}$ and $\mathcal{M}$ of respective sizes $|\mathcal{F}|$ and $|\mathcal{M}|$: $\Omega = \{\mathcal{F}; \mathcal{M}\}$.
Each individual $i \in \Omega$ is associated with a performance $y_i \in \mathbb{N}$ and a group membership $s_i \in \{f, m\}$.

$$\{i|s_i = f\} \in \mathcal{F} \quad \text{and} \quad \{i|s_i = m\} \in \mathcal{M}$$

We want to build a panel of six individuals from the population Ω, satisfying the following conditions:

- **Parity**: The panel includes three individuals from group $\mathcal{F}$ and three individuals from group $\mathcal{M}$.

- **Inter-group balance**: No significant difference in performance appears between individuals from group $\mathcal{F}$ and individuals from group $\mathcal{M}$. More precisely, for each individual i_k from group $\mathcal{F}$ with performance $y_{(i_k)}$, the panel includes an individual j_k from group $\mathcal{M}$ with performance $y_{(j_k)}$ such that $|y_{(j_k)} - y_{(i_k)}| \leqslant \epsilon, \forall k = \{1; 2; 3\}$. We thereby minimize intergroup variance of performance.

- **Intra-group heterogeneity**: We aim at achieving sufficiently high intra-group variance of performance under the aforementioned constraints of *parity* and *inter-group balance*. In other words, if more than three female-male pairs could be selected to achieve inter-group balance, we select three pairs to maximize intra-group variances $V_{\mathcal{F}}$ and $V_{\mathcal{M}}$:

$$V_{\mathcal{F}} = \frac{1}{3}\sum_{k=1}^{3}(y_{i_k} - \overline{y}_f)^2, \quad \overline{y}_f = \frac{1}{3}\sum_{k=1}^{3} y_{i_k} \quad \text{with} \quad i_k \in \mathcal{F}$$

$$V_{\mathcal{M}} = \frac{1}{3}\sum_{k=1}^{3}(y_{j_k} - \overline{y}_m)^2, \quad \overline{y}_m = \frac{1}{3}\sum_{k=1}^{3} y_{j_k} \quad \text{with} \quad j_k \in \mathcal{M}$$

Step one: Eligibility

The first step of the matching procedure aims at identifying all pairs $\{i; j\}$, $i \neq j$, $i \in \mathcal{F}$, $j \in \mathcal{M}$ that satisfy the condition:

$$|y_i - y_j| \leq \epsilon$$

In other words, we identify each pair including a member of group $\mathcal{F}$ and a member of group $\mathcal{M}$ whose performance do not differ more than ϵ units. These pairs are defined as eligible and are the ones considered in the second step of the procedure. This step ensures the satisfaction of the parity and inter-group balance conditions.

For $\epsilon = 0$, inter-group variance would be set to 0. Although this would be an ideal situation, it may not be always possible to identify three exclusive pairs that satisfy this condition. Step one proceeds therefore sequentially through a simple algorithm. Starting from an initial value of $\epsilon = 0$, if the protocol cannot identify three exclusive pairs, it considers a value of $\epsilon = 1$, and so on until the number of eligible pairs of candidates reaches the lower limit of three.

Step two: Panel formation

The second step builds on the set of eligible pairs that have been identified in step one. To ensure the condition on intra-group heterogeneity, three pairs out of the eligible pairs are selected based on a variance criterion. Each pair is exclusive, i.e. an individual cannot appear in more than one selected pairs.

The condition of inter-group balance is given priority over intra-group heterogeneity. Therefore, if there are more than three female-male pairs that could be selected to achieve inter-group balance, we build our final panel with the three pairs which maximize intra-group variances $V_{\mathcal{F}}$ and $V_{\mathcal{M}}$.

Following this matching protocol ensures the formation of a panel of six participants that respects the desired properties:

- The panel includes three female-male pairs.
- Each pair is homogeneous in performance, i.e. the female and the male do not significantly differ in performance.
- Pairs are different and can be ranked by referrers: the panel includes a low-performing, a middle-performing and a high-performing pair.