Gender dynamics in referral-based hiring: A field experiment*

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Abstract

We explore gender dynamics in referral-based hiring, using a field experiment at one of Europe's leading business schools. In the experiment, 428 students are asked to refer another student at the school for a part-time job. We find strong evidence of same-gender bias in referrals among both male and female students. While the overall gender distribution of students at the school is fairly equal, 74 percent of male students refer another man and 71 percent of female students refer another woman. Roughly half of this same-gender bias can be accounted for by gender differences in social network composition at the school. These results are robust across different jobs with varying gender stereotypicality.

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1 Introduction

The convergence between male and female wages has slowed down considerably during the past decades (O'Neill 2003, Blau & Kahn 2006, Fortin 2008) and modern labor markets are characterized by a high degree of gender segregation. Women are underrepresented in high level management and boards of directors: while women represent 45 percent of the workforce in S&P 500 Companies, only 4 percent of CEOs, 19 percent of board members and 25 percent of senior level managers are women (Catalyst 2015). Moreover, women continue to be overrepresented in occupations with lower pay and status (Hegewisch & Hartmann 2014). In the US, occupations that are nontraditional[1] for women employ six percent of all women and 44 percent of all men while occupations that are nontraditional for men employ five percent of all men and 40 percent of all women (Hegewisch & Matite 2013). This occupational segregation explains a significant proportion of the gender wage gap (Anker 1998, Bayard et al. 2003, Levanon et al. 2009, Blau 2012). Thus, in order to understand the origins and persistence of the gender wage gap, it is crucial to understand the mechanisms behind occupational segregation by gender.

There have been numerous attempts to explain the persistence of occupational segregation through such channels as different returns on human capital investments (Schultz 1995) and elements of self-selection by which individuals of a certain gender systematically choose not to apply for certain types of jobs and sectors (Gaucher et al. 2011). This study focuses on a third mechanism: referral-based hiring and segregation of social networks by gender.

Referral-based hiring has likely been a key feature of even pre-industrial labor markets and most research indicates that it continues to be important as roughly 50 percent of jobs are obtained through family, friends, or other acquaintances (Loury 2006). Many companies are putting increasing weight on referrals from their current employees in their hiring processes. For instance, Deloitte has increased the share of experienced hires obtained through referrals from 43 to 49 percent during the past four years and Ernst & Young have set internal goals to increase the proportion of hiring that comes from internal referrals which currently accounts for 45 percent of non-entry-level placements (Schwartz

[1] A nontraditional occupation is defined as an occupation or field of work for which individuals of one gender comprise less than 25 percent of individuals employed.

2013).

Whilst referral-based hiring is likely to be advantageous for employers faced with asymmetrical information about job-seekers' abilities and likeliness to shirk, it also poses certain risks. As those that the employer asks are naturally limited to refer people that they know, the composition of the social networks of those that are asked becomes a determining factor in the type of referrals they will make. It is widely recognized that social networks are characterized by homophily: the tendency of individuals to associate and bond with people similar to themselves (McPherson et al. 2001). Employers can use homophily in worker networks to their advantage, as it imples that high ability employees will be more likely to refer high ability workers. However, homophily also implies that the use of networks in job search can have added risks in perpetuating inequalities between different groups. Thus, referral-based hiring may be a contributing factor behind the persistent gender segregation on the labor market.

A few previous studies indicate that those that refer individuals (the referrers) tend to be of the same gender as the individual(s) they refer (the referrals). Using data on applicants and hires at a mid-sized U.S. corporation, Brown et al. (2014) find that most referrals take place between a referrer and a referral with similar characteristics in terms of age, gender, ethnicity and education. In their data, the referrer and the referral are of the same gender 64 percent of the time. Similarly, Fernandez & Sosa (2005) use data on applicants for a job at a telephone customer service center in the U.S. and find that 75 percent of applicants referred by female employees, and 56 percent of applicants referred by male employees, were women. So far, the only experimental study on gender differences in referral-based hiring is by Beaman et al. (2015). They conduct a field experiment in Malawi, letting applicants for a job as enumerator at a research organization refer other candidates for the job, and find that women are disadvantaged by the use of job referrals. This effect is primarily driven by the fact that men tend to refer other men, despite being able to refer qualified women when explicitly asked to do so.

We conduct a field experiment at a top European business school in Sweden, letting 428 students refer another student at the school for a part-time job. Our experiment contributes to previous research on gender dynamics in referral-based hiring in several ways.

First, this is the first field experiment that elicits gender dynamics in referral-based hiring among highly educated individuals in a developed country. By conducting a field experiment we are able to elicit subjects' behavior when making referrals for a real job with high stakes, rather than relying on self-reported behavior or answers to hypothetical questions. Moreover, our subject pool consists of bachelor and master students in one of the most highly ranked countries in the world in terms of gender equality. Thus, observed gender differences in behavior are unlikely to be driven by different rates of educational attainment between men and women. The business school we study is highly ranked, competitive and prestigeous, and many students move on to top positions in the private sector.[2] Thus, the behavior of this subject pool is especially relevant for understanding the dynamics behind the much-debated "glass ceiling", i.e. the tendency of gender gaps to accelerate in the upper tail of the wage distribution and the underrepresentation of women at higher positions.

Second, we explore the role of social networks in generating gender differences in referral behavior. After subjects have made their referral, we ask them to list their closest friends at the school. Thus, we can provide some insights into whether any tendency to refer individuals of the same gender is driven by gender differences in social network composition.

Third, we randomly assign subjects to one of two job advertisements. One of the jobs is more stereotypically masculine than the other job. Thus, we can explore if gender differences in referral-based hiring are robust with respect to the gender stereotypicality of the job.

Fourth, our study elicits referral behavior directly: our sample consists of all individuals who were asked to provide a referral and our outcome variable is whether they referred a man or a woman. In contrast, previous empirical studies on gender dynamics in referral-based hiring (e.g.Brown et al. (2014), Fernandez & Sosa (2005), Beaman et al. (2015)) are restricted to data on applicants for a position or current employees at a firm. Thus,

[2] The Financial Times ranks the school as the best business school in the Nordic countries and the 26th best in the world, and the school's master's program in finance is ranked as no.12 in the world. Many students from the school move on to top positions within business or politics. For example, 30 percent of board members of listed companies in Sweden are graduates from the school. When the Swedish newspaper "Fokus" recently ranked the most powerful individuals in Sweden, 15 percent of the individuals on the list had attended the school.

the pattern observed in these studies - that female applicants or employees are more likely to have been referred by a woman - can be driven by either *referrer behavior* (female referrers are more prone to refer women) or *referral behavior* (female referrals who are referred by women are more prone to apply for the job or get hired). We contribute by directly eliciting the behavior of the referrers.

We find strong evidence of same-gender bias in referrals among both male and female students. While the overall gender distribution of students at the school is fairly equal, 74 percent of male students refer another man and 71 percent of female students refer another woman. Roughly half of this same-gender bias can be accounted for by gender differences in social network composition at the school. The gender sterotypicality of the job description does not significantly affect the degree of same-gender bias in referrals.

In the next section, we outline the institutional setting and experimental design. This is followed, in Section 3, by descriptive statistics. In Section 4, we present the results and Section 5 concludes.

2 Experiment

2.1 Institutional environment

The experiment took place at the Stockholm School of Economics (SSE) in spring 2015. The SSE is a highly ranked business school in Stockholm with a competitive admissions process.[3] The Financial Times ranks the SSE as the best business school in the Nordic countries and the 26th best in the world, and the school's master's program in finance is ranked as no. 12 in the world.[4] Many students from the school move on to top positions within business or politics. For example, despite the small size of the school (currently, around 1650 full-time students are enrolled), 30 percent of board members of listed companies in Sweden are SSE graduates.[5] Moreover, when a Swedish business magazine recently ranked the most powerful individuals in Sweden, 15 percent of the individuals on the list had attended the SSE.[6]

[3] In 2012 the master's programs at the school received 3261 applications for 150 available slots.

[4] http://rankings.ft.com/

[5] http://allbright.se/wp-content/uploads/2013/11/Lika-barn-leka-b%C3%A4st.pdf

[6] http://www.fokus.se/2014/04/maktens-hogre-skolor/

The most common industries of employment for SSE graduates are finance and consultancy, and referral-based hiring is a common way for students at the school to find employment. A recent survey at the school reports that more than half of bachelor students, and more than one fourth of master students, used friends or other contacts to find their first job after graduation.

The SSE provides a three-year *bachelor program in business and economics*, consisting of two years of mandatory courses and one year of specialization in two of five areas. The school also provides two-year *master programs* in accounting & financial management, economics, finance, business & management and international business. Moreover, the school's affiliate campus in Norrtälje, outside of Stockholm, offers a three-year *bachelor program in retail management.*[7] Compared to the main campus, the bachelor program at the Norrtälje campus requires a slightly lower high school GPA for admission and enrolls a higher share of female students.

All subjects in the experiment were either bachelor or master students at the SSE at the time of the study.

2.2 Experimental procedure

We recruited the majority of subjects during lectures at the SSE, asking all students in the classroom to participate either in conjunction with a break or at the end of the lecture. We recruited the remaining subjects by approaching students in common seating areas at the main campus and during a student association choir training session.Table A.1 in the Appendix displays a list of all experimental sessions.

We asked all subjects to refer another student at the SSE for a part-time position at a public relations and media company. The company is fairly well known among students at the school and subjects were aware that they were referring someone for a real job. The SSE is characterized by a strong connection to the business-community and recruiters from various companies and organizations are frequently present at the school. Thus, being approached by a company regarding a job opportunity is not likely to feel like an unnatural situation for the subjects.

Subjects were instructed to fill out a three-page form (see Appendix B for a translated

[7]After our study was conducted, in fall 2015, the affiliate campus was relocated to Stockholm.

copy of the form). Upon handing in a completed form, each subject was awarded a lottery ticket worth 10 SEK ($\approx$ \$1.19 USD). The first page of the form contained instructions, while the second page contained a job advertisement along with a request to refer another student for the advertised position. After the experiment, we emailed all individuals who had been referred, notifying them that they had been referred for a job and providing instructions for how to apply.

The final page of the form included questions regarding the subject, their background, and their network at the school. To elicit the gender distribution of the subject's social network, we asked them to name five students at the school with whom they socialize frequently. We also asked subjects to indicate their grade point average (GPA) at the school. Due to the high degree of circularity in the data (62 percent of subjects were also referred by another subject), we can use this GPA measure as a proxy for referral quality whilst maintaining two thirds of our sample. The job advertisement specifies that the job is especially suited for top students. Consequently, whilst GPA is only one dimension that the firm uses to judge the quality of an applicant, subjects could reasonably be argued to consider the GPA of the referral in selecting whom to refer.

One potential concern is that subjects who wanted the job for themselves may have had an incentive to refer a less qualified person. To mitigate this concern, the advertisement states that the company is seeking 1-2 people for the position. This should have lessened the incentive to strategically refer unsuitable candidates. Moreover, to explore this concern in the empirical analysis, we will control for whether the referrer applied for the job. Finally, to further incentivize subjects to refer someone qualified, we introduced a finder's fee. In the instructions, subjects were informed that they would receive a cash bonus of 5000 SEK ($\approx$ \$580 USD) if the person they referred was hired.

Providing cash bonuses for referrals is an established practice in many firms (Castilla 2005). One important difference between our experimental setting and the practices of many companies is that finder's fees are usually awarded to current employees. By using referrers within the organization, employers can hold the referrer responsible if the referral ends up performing badly after being hired. While we do not capture this important dimension of referral-based hiring, our design resembles another common recruiting method: the practice of employing third-party agents who are paid a fee for finding job candidates

(Finlay & Coverdill 2007). In such headhunting procedures, the referrer is only paid if their referral ends up getting the job.

2.3 Job advertisements

We randomly assigned subjects to one of two different job advertisements within the same company: *analyst* or *creative content manager (CCM).* The purpose of this treatment was to explore the effect of the gender stereotypicality of the job. The analyst position is more stereotypically masculine, while the CCM position is more stereotypically feminine. For instance, the advertisement for the analyst position calls for someone business minded and analytical to perform quantitative tasks, while the advertisement for the CCM position calls for someone creative and passionate to oversee community management and other creative content. Appendix C contains the two job advertisements (translated from Swedish), and Table 1 summarizes the main differences between them.

The company confirmed that, historically, men have been more prone to apply for positions as analysts while women have been more prone to apply for CCM positions. To further verify that the analyst job was perceived as more stereotypically male than the CCM job, we conducted a follow-up online survey on a separate but similar sample of economics students at Stockholm University. Subjects were notified of the survey via email, and no monetary incentives were provided. Each subject was randomly allocated to read one of the two job advertisements and then rate how masculine they perceived the job to be on a 1-9 scale (1 being very feminine and 9 being very masculine) In total, 93 students participated in the online survey. Results from the survey confirm that the analyst job was perceived to be more masculine than the CCM job ($t=-2.08$, $p=0.04$). However, the size of this difference is quite small: the average masculinity rating was 5.14 for the analyst job and 4.59 for the CCM job.

3 Descriptive Statistics

A total of 432 students participated in the study between March 26th and April 9th 2015. We drop four observations (1 woman and 3 men) from the analysis since these subjects acted against the instructions and referred themselves for the job. Thus, our final sample consists of 428 subjects (206 women and 222 men). The majority of subjects were enrolled at the main campus of the Stockholm School of Economics (N=368), and the rest were enrolled at the school's affiliate campus outside of Stockholm in Norrtälje (N=60).

We show descriptive statistics in Table 2. 52 percent of the referrers are men, and the mean age is 23 years. The mean value of the self-reported GPA measure (on a scale from 1=E to 5=A) is 3.8 and the mean school year (on a scale from 1=first year of bachelor studies to 5=second year of master studies) is 2.4. The variable *Prop. men in class of referrer* indicates the enrolling proportion of men in each specific cohort and program of study. Overall, the average share of men in the referrer's class is 53 percent. The minimum share is 24 percent (the first year of the master's program in marketing) and the maximum share is 79 percent (the second year of the master's program in finance). Although the difference between the minimum and maximum shares is quite large, the variation in this variable is quite small as the majority of our sample comes from classes with a fairly even gender distribution. The average value of the variable is mostly driven by the large classes in the first two years of the bachelor program in business and economics, for which the average share of male students is approximately 60 percent.

The variable *Network size of referrer* indicates the number of names that the referrer reported when asked to name five students at the school with whom they socialize frequently. The vast majority of subjects reported five names, and the average number of names reported is 4.5. Henceforth, we refer to these names as the referrer's *network*. 44 percent of subjects referred someone in their network for the job. The average share of men in the referrers' networks is 54 percent, and 53 percent of subjects referred a man for the job. Out of the 428 referrals made, 297 unique individuals were referred. Thus, many individuals were referred more than once. The variable *Total no. of referrals received by referral* indicates how many times each referral has been referred. The most referred individual received 7 referrals and the average number is 2.

Table 3 displays descriptive statistics by the gender of the referrer. The referrers' networks are strongly gender homophilous, with men reporting on average 81 percent men in their network and women reporting on average 76 percent women in their network. As shown in Figure 1, a large share of referrers (48 percent of men and 40 percent of women) have only same-gender individuals in their network. On average, male referrers report to have a slightly higher GPA than female referrers (3.9 vs. 3.7). There is no significant gender difference in the school year, the network size or the propensity to refer someone within their own network. Moreover, there is no significant difference between female and male referrers in the self-reported GPA of the referred student.

Table 4 displays descriptive statistics separated by the different jobs. The only statistically significant differences between the two job advertisements is that, for the analyst job, referrers are more prone to refer candidates within their own network (50 % vs. 37%) and candidates with a higher self-reported GPA (4.0 vs. 3.8).

4 Results

4.1 Gender of referral

As shown in Figure 2, both men and women are more prone to refer candidates of their own gender than candidates of the opposite gender. 75.2 percent of men referred another man while 71.2 percent of women referred another woman. Thus, men are 2.6 times more likely than women to refer a man and women are 2.9 times more likely than men to refer a woman (χ^2=92.28, p<0.00).

The dotted lines in Figure 2 represent the average share of men in the referrers' classes. By comparing the gender distribution of referrals to this benchmark, we can asses whether men are over- or under-referred in relation to the share of men among the referrers' peers. Overall, the average share of men in the class is 53.5 percent and the average share of men referred is 53.0 percent. Thus, on the aggregate, the gender composition of referrals follows the gender composition of the underlying subject population very closely. However, among male subjects the share of men referred is 18.1 percentage points higher than the average share of men in their class (two-sided binomial test: p<0.00) while among female subjects the share of men referred is 20.9 percentage points lower than the average share of men in their class (two-sided binomial test: p<0.00). Thus, compared to this benchmark, both men and women over-refer individuals of their own gender to a similar extent.

4.2 Propensity to refer within network

As discussed in Section 3, and illustrated in Figure 1, the referrers' networks are highly gender homophilous. On average, the share of men in male referrers' networks is 24.2 percentage points higher than the share of men in their class (t=-14.70: $p<0.00$), while the average share of men in female referrers' networks is 25.1 percentage points lower than the average share of men in their class (t=12.69: $p<0.00$). To account for these differences in network composition, in Table 5 we run regressions controlling for the share of men in the referrer's network. The dependent variable is an indicator variable taking the value 1 for male referrals. The size of the coefficient of *Prop. men in network of referrer* is 0.430, indicating that, on average, going from an all-female to an all-male network increases a referrer's propensity to refer a man by 43.0 percentage points. When controlling for the network gender composition, the gender difference in the propensity to refer a man, indicated by the coefficient of *Male referrer*, decreases from 46.4 percentage points to 22.2 percentage points. This means that approximately half of the propensity to refer someone of the same gender can be accounted for by the fact that students at the school tend to socialize frequently with students of the same gender.[8] These results do not change much when controlling for the proportion of men in the class of the referrer and the referrer's GPA, school year and age in the third column of Table 5. Thus, the gender composition of the referrers' networks cannot, in itself, fully explain the same-gender bias in referrals. This finding is further illustrated in Table 6 and Figure 3, comparing the share of male referrals between male and female referrers with identical network gender compositions.

Recall that the majority of referrers (55 percent of women and 58 percent of men) refer someone outside their network. To explore whether the same-gender bias that remains after controlling for network composition is driven by these individuals, we split the sample by whether the referral is in the referrer's network or not. We show these results in the final two columns of Table 5. Among subjects who refer someone in their network, controlling for the proportion of men in the network, men are 19.5 percentage points more likely than women to refer a man. For subjects who referred outside of their network, the equivalent

[8]In Table 5 we control for a linear effect of the proportion of men in the referrer's network. The results remain largely unchanged when instead controlling for dummy variables indicating the different proportions of men in the network. We show these results in Table A.2 in the Appendix.

number is 23.0 percentage points. This points to the existence of a same-gender bias above and beyond gender differences in in network composition regardless of whether individuals refer within or outside their network.

4.3 Job type

In Table 7, we regress the gender of the referral on the job type. As indicated by the coefficient of *Analyst*, subjects are 8.7 percentage points more prone to refer men for the analyst job, which is more stereotypically male, than for the CCM job. However, as shown in Figure 4 and the final columns of Table 7, the gender difference in the propensity to refer a man does not differ significantly across the two jobs. For the job as analyst, men are 42.7 percentage points more likely than women to refer a man, while for the job as CCM, men are 49.5 percentage points more likely than women to refer a man.

4.4 Quality of referrals

In Table 9, we regress the self-reported GPA of the referral on various referrer and referral characteristics. The purpose of this analysis is to explore how the propensity to refer same-gender individuals affects the quality of referrals. However, these results should be interpreted with caution. First, we only have the self-reported GPA measure for the 286 referrals who were also subjects in the experiment. Thus, we are forced to drop 33 percent of our sample. Second, since the measure is self-reported there may be systematic gender-differences among students in the propensity to over-report their GPA. Third, overall GPA is a not a perfect proxy for referral quality. A better proxy would be the average grade in the courses that are particularly relevant for the available position.

The first column of Table 9 shows that, on a scale from 1=E to 5=A, the GPA of male referrals is on average 0.17 higher than that of female referrals ($p<0.00$). However, as shown in the second column, there is no significant difference in the GPA of referrals made by male and female referrers ($\beta_{Male\,referrer} = 0.061$, p=0.22). At first glance, this seems contradictory: Even though male referrers are more prone than female referrers to refer men, and men report higher GPA than women, male referrers do not refer individuals with higher GPA than do female referrers. However, as illustrated in Figure 5 and the third column of Table 9, this pattern can be explained by the fact that women refer men with especially high GPA. Among female referrers, the average GPA of male referrals is 0.238 points higher than that of female referrals ($\beta_{Male\,referral} = 0.238$, p=0.002). Among male referrers, the equivalent number is 0.123 ($\beta_{Male\,referral} + \beta_{Male\,referral\;X\;male\,referrer} = 0.123$, p=0.138).

The fourth column of Table 9 shows that referrals for the analyst job have significantly higher GPA than referrals for the CCM job. The fifth column shows that the GPA of the referrer is positively correlated with the GPA of the referral, although this correlation is rendered insignificant when adding control variables in the sixth column.

5 Conclusions

We conduct a field experiment at a leading European business school to explore gender dynamics in referral-based hiring. We find a strong interaction between the gender of the referrer and the gender of the referral: Women are 2.9 times more likely than men to refer a woman for the position. Comparing the gender composition of referrals to the gender composition of the students' classes, we find that men and women are roughly equally prone to over-refer someone of their own gender: women over-refer women by 21 percentage points and men over-refer men by 18 percentage points. We also find substantial gender differences in network composition: compared to the share of women in their class, women have on average 25 percentage points more women in their network while men have on average 24 percentage points fewer women in their network. Nevertheless, even when accounting for these differences in network composition, approximately half of the same-gender bias in referral behavior remains.

Randomizing subjects to one of two different job advertisements, we find that subjects are slightly more prone to refer men for the more stereotypically masculine job as analyst than for the more stereotypically feminine job as creative content manager. However, the same-gender bias in referrals is robust across job types: there is no significant difference in subjects' likelihood of referring someone of their own gender between the two jobs.

We find no difference in the quality of referrals made by men and women. This finding is in contrast to Beaman et al. (2013) who find that, on average, men provide higher quality referrals than women. One potential explanation for these diverging findings may be that gender differences in education, and thus gender differences in the education of network members, are larger in Malawi than in Sweden.

Our findings indicate that the gender of the referrer is a crucial determinant of the gender or the referral. This implies that if an employer asks current employees to refer candidates for job openings, the gender composition of the applicant pool is likely to reflect the current gender composition of the organization. Thus, the prevalence of referral-based hiring is likely to contribute to the persistent gender segregation on the labor market. However, our results also suggest that employers can use referral-based hiring to increase diversity, by asking individuals of the underrepresented gender to make referrals. An organiziation that aims to increase the number of female (male) hires should simply ask their female (male) employees to make a referral.

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Table 1: Differences between job advertisements

Analyst	**Creative Content Manager (CCM)**
Characteristics	*Characteristics*
-Business-minded and analytical	-Creative and passionate
-Interest in measurement and analysis	-Understanding for social media and digital platforms
-Structured	-Enjoys working with several projects simultaneously and coming up with new creative input
	-Prior experience in client facing activities is viewed favorably
	-Enjoys working with several projects simultaneously and coming up with new creative input
Tasks & responsibilities	*Tasks & responsibilities*
-Quantitative and qualitative analysis	-Community management and other creative activities
-Judging, evaluating and summarizing clients' and their stakeholders' portrayal in the media and other public relations related activities	-Follow up projects and present results
	-Image and website management

Table 2: Descriptive statistics

VARIABLES	N	mean	sd	min	max
Analyst	428	0.50	0.50	0	1
Referrer characteristics					
Male referrer	428	0.52	0.50	0	1
Age of referrer	428	22.94	2.74	17	42
GPA of referrer (1-5)	416	3.81	0.42	2.88	4.50
School year of referrer (1-5)	427	2.38	1.23	1	5
Prop. men in class of referrer	428	0.53	0.14	0.24	0.79
Norrtälje Campus	428	0.14	0.35	0	1
Network size of referrer	428	4.51	1.12	0	6
Referral within network of referrer	415	0.44	0.50	0	1
Prop. men in network of referrer	415	0.54	0.37	0	1
Referral characteristics					
Male referral	428	0.53	0.50	0	1
GPA of referral (1-5)	287	3.90	0.43	2.88	4.50
Total no. of referrals received by referral	428	1.98	1.31	1	7

Table 3: Gender differences among referrers

	Female referrer	Male referrer	Difference	p-value
Analyst	0.473	0.523	-0.049	0.309
	(0.501)	(0.501)		
Age of referrer	23.068	22.842	0.226	0.396
	(2.871)	(2.622)		
GPA of referrer	3.737	3.885	-0.149	0.000
	(0.422)	(0.414)		
School year (1-5) of referrer	2.429	2.335	0.094	0.429
	(1.261)	(1.201)		
Prop. men in class of referrer	0.497	0.571	-0.075	0.000
	(0.153)	(0.117)		
Network size of referrer	4.512	4.509	0.003	0.977
	(1.037)	(1.187)		
Prop. men in network of referrer	0.244	0.813	-0.570	0.000
	(0.251)	(0.233)		
Referral within network of referrer	0.453	0.423	0.030	0.537
	(0.499)	(0.495)		
GPA of referral	3.874	3.935	-0.061	0.229
	(0.453)	(0.395)		
Norrtalje Campus	0.200	0.081	0.119	0.000
	(0.401)	(0.274)		

Note: Standard deviations in parentheses. P-values are obtained using a ttest.

Table 4: Differences between job types

	CCM	Analyst	Difference	p-value
Male referrer	0.495	0.545	-0.049	0.309
	(0.501)	(0.499)		
Age of referrer	22.958	22.944	0.014	0.957
	(2.564)	(2.918)		
GPA of referrer	3.830	3.799	0.031	0.456
	(0.424)	(0.424)		
School year (1-5) of referrer	2.432	2.329	0.103	0.387
	(1.225)	(1.234)		
Prop. men in class of referrer	0.530	0.541	-0.012	0.388
	(0.143)	(0.138)		
Network size of referrer	4.481	4.540	-0.059	0.588
	(1.158)	(1.075)		
Prop. men in network of referrer	0.516	0.557	-0.041	0.260
	(0.388)	(0.359)		
Referral within network of referrer	0.372	0.502	-0.130	0.007
	(0.485)	(0.501)		
GPA of referral	3.832	3.982	-0.150	0.003
	(0.399)	(0.442)		
Norrtalje Campus	0.131	0.146	-0.015	0.661
	(0.338)	(0.353)		

Note: Standard deviations in parentheses. P-values are obtained using a ttest.

Table 5: Effect of gender of referrer on propensity to refer a man

	All	All	All	Ref. within network	Ref. outside network
Male referrer	0.464	0.222	0.208	0.195	0.230
	(0.043)***	(0.065)***	(0.065)***	(0.074)***	(0.094)**
Prop. men in network of referrer		0.430	0.476	0.825	0.118
		(0.088)***	(0.087)***	(0.098)***	(0.127)
Constant	0.288	0.184	0.536	-0.009	0.343
	(0.031)***	(0.037)***	(0.306)*	(0.040)	(0.056)***
R^2	0.216	0.262	0.310	0.628	0.090
N	427	414	404	181	233
Controls	No	No	Yes	No	No

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note: Dependent variable: Man Referred = 1 if the referral was a man, =0 otherwise. OLS regressions. Robust standard errors in parentheses. Controls include the following referrer characteristics: proportion men in class, self-reported GPA, school year, and age.

Table 6: Share male referrals, by proportion men in network.

% men in network	female referrer	male referrer	Difference	p-value
0%	0.228	0.000	0.228	0.044
	(0.422)	(0.000)		
	[79]	[5]		
20-33%	0.271	0.500	-0.229	0.216
	(0.449)	(0.707)		
	[48]	[2]		
40-50%	0.364	0.500	-0.136	0.250
	(0.487)	(0.516)		
	[44]	[16]		
60-75%	0.400	0.750	-0.350	0.301
	(0.503)	(0.439)		
	[20]	[36]		
80%	0.429	0.673	-0.245	0.205
	(0.535)	(0.474)		
	[7]	[52]		
100%	0.000	0.882	-0.882	0.051
	(0.000)	(0.324)		
	[3]	[102]		

Note: Standard deviations in parentheses and number of observations in brackets. P-values are obtained using a chi2 test.

Table 7: Effect of gender of referrer and job type on propensity to refer a man

	(1)	(2)	(3)	(4)
Analyst	0.087	0.099	0.078	0.083
	(0.048)*	(0.062)	(0.061)	(0.060)
Male referrer		0.495	0.237	0.228
		(0.061)***	(0.079)***	(0.078)***
Male Referrer X Analyst		-0.068	-0.030	-0.041
		(0.086)	(0.085)	(0.084)
Prop. men in network of referrer			0.426	0.472
			(0.088)***	(0.087)***
Constant	0.486	0.241	0.148	0.511
	(0.034)***	(0.043)***	(0.046)***	(0.306)*
R^2	0.008	0.221	0.266	0.314
N	427	427	414	404
Controls	No	No	No	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note: Dependent variable: Man Referred = 1 if the referral was a man, =0 otherwise. OLS regressions. Robust standard errors in parentheses. Controls include the following referrer characteristics: proportion men in class, self-reported GPA, school year, and age.

Table 8: Effect of gender of referrer on propensity to refer a man, by job type

	Analyst	CCM	Analyst	CCM	Analyst	CCM
Male referrer	0.427	0.495	0.107	0.328	0.061	0.345
	(0.062)***	(0.060)***	(0.091)	(0.093)***	(0.092)	(0.089)***
Prop. men in network of referrer			0.607	0.271	0.649	0.310
			(0.127)***	(0.120)**	(0.128)***	(0.116)***
Constant	0.340	0.241	0.179	0.183	0.586	0.375
	(0.046)***	(0.042)***	(0.055)***	(0.050)***	(0.441)	(0.422)
R^2	0.185	0.245	0.277	0.256	0.311	0.358
N	213	214	207	207	205	199
Controls	No	No	No	No	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note: Dependent variable: Man Referred = 1 if the referral was a man, =0 otherwise. OLS regressions. Robust standard errors in parentheses. Controls include the following referrer characteristics: proportion men in class, self-reported GPA, school year, and age.

Table 9: Determinants of quality of referral

	(1)	(2)	(3)	(4)	(5)	(6)
Male referral	0.170		0.238			0.216
	(0.049)***		(0.078)***			(0.075)***
Male referrer		0.061	0.033			0.053
		(0.050)	(0.083)			(0.081)
Male referral X male referrer			-0.115			-0.168
			(0.113)			(0.111)
Analyst				0.150		0.136
				(0.050)***		(0.048)***
GPA of referrer					0.146	0.084
					(0.060)**	(0.059)
School year (1-5) of referrer						-0.121
						(0.025)***
Age of referrer						0.032
						(0.013)**
Constant	3.817	3.874	3.809	3.832	3.347	3.001
	(0.035)***	(0.035)***	(0.041)***	(0.034)***	(0.232)***	(0.341)***
R^2	0.040	0.005	0.044	0.031	0.021	0.161
N	286	286	286	286	279	278

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note: Dependent variable: Self-reproted GPA of referral. OLS regressions. Robust standard errors in parentheses.

Figure 1: Distribution of proportion of men in network

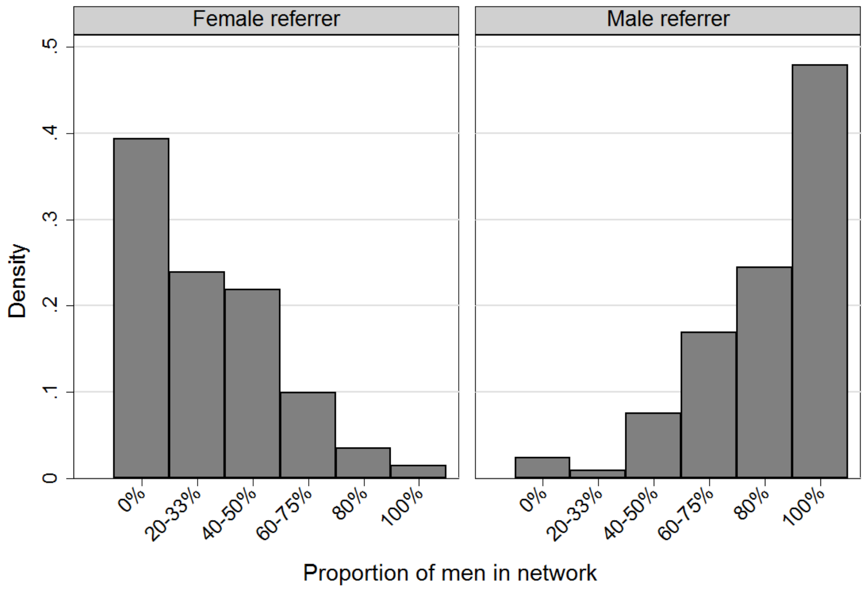
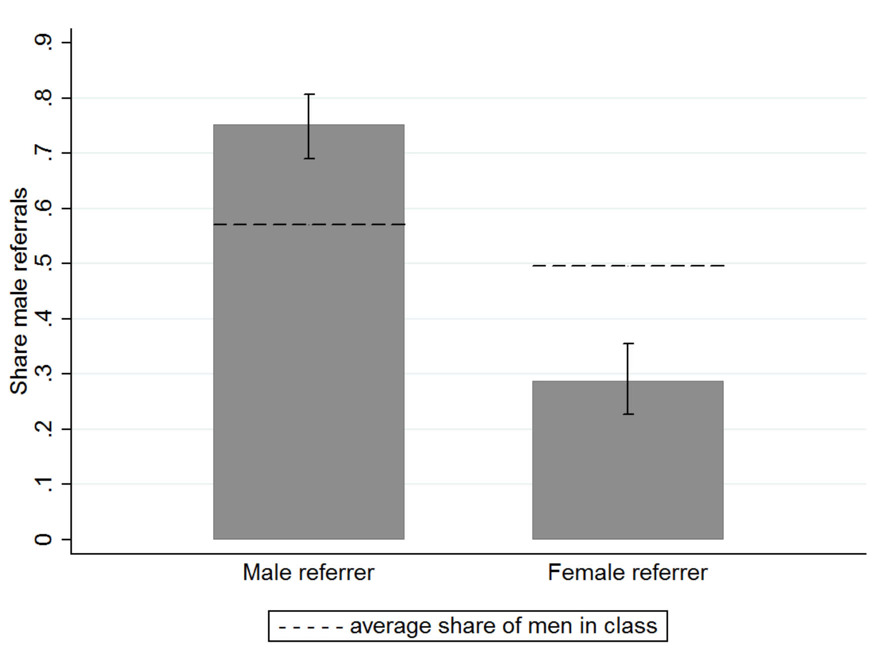
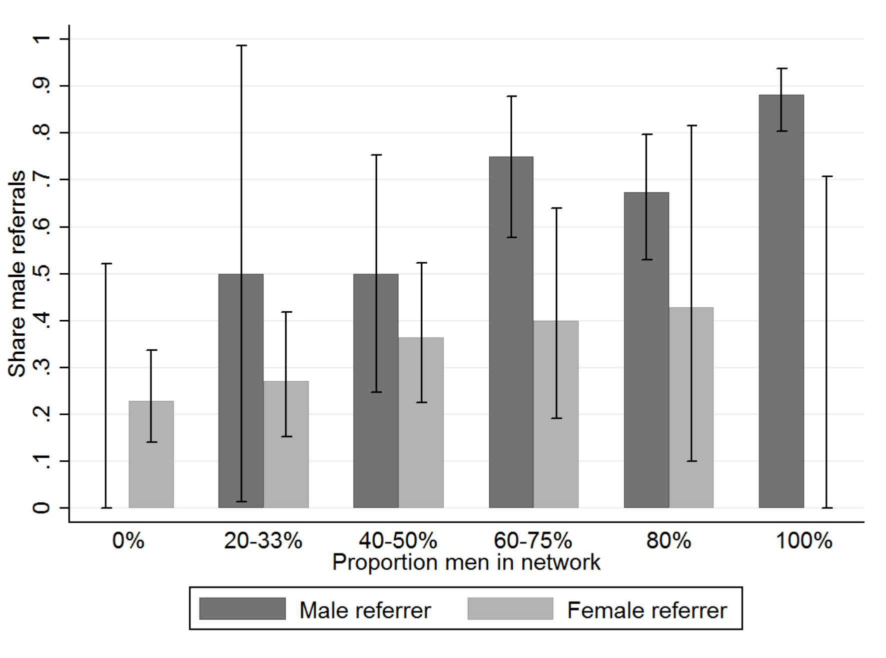


Figure 2: Gender differences in referrals, by gender of referrer



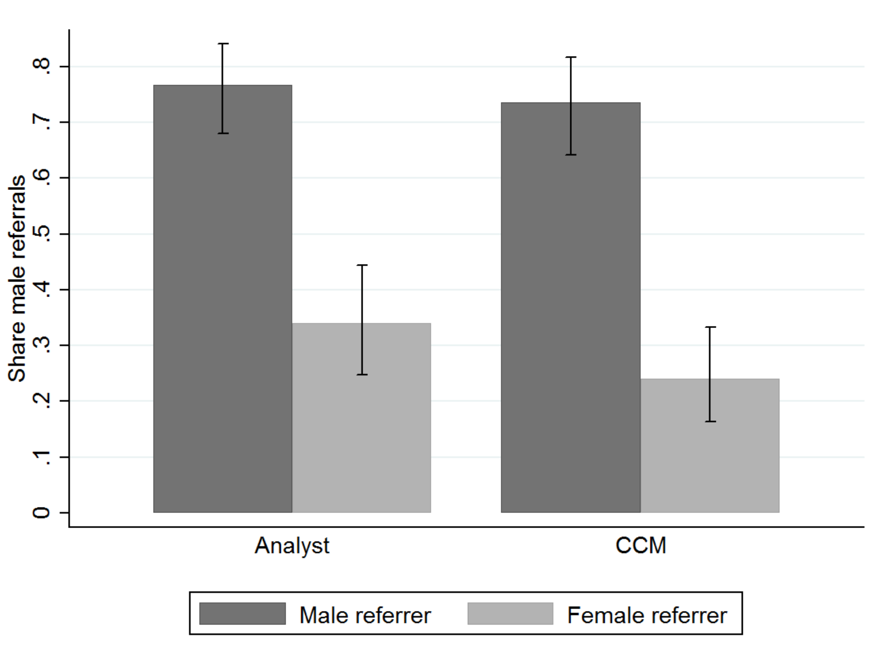
Note:The bars indicate 95 % confidence intervals.

Figure 3: Share male referrals, by proportion men in network.



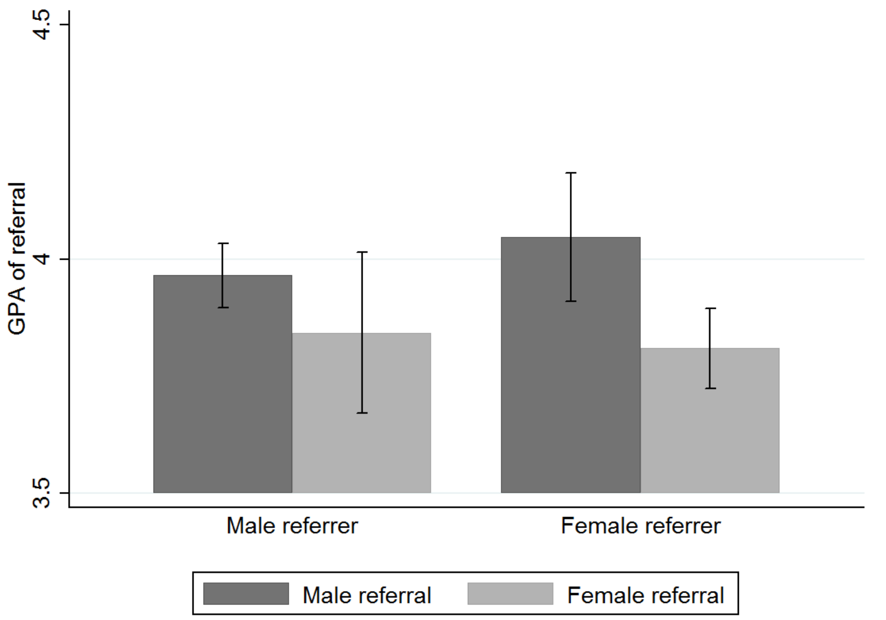
Note:The bars indicate 95 % confidence intervals.

Figure 4: Gender differences in referrals, by job type and gender of referrer



Note:The bars indicate 95 % confidence intervals.

Figure 5: Quality of referral



Note:The bars indicate 95 % confidence intervals.

Appendix A Additional tables and figures

Table A.1: Experimental sessions

Session	**Campus**	**Date**	**Setting**	**School year**	**MSc or BSc**	**# obs.**	**% men**
1	Main	March 26 4 pm	Classroom	2	BSc	86	62%
2	Main	March 27 11 am	Classroom	1	BSc	105	53%
3	Main	March 27 2 pm	Classroom	4	Msc	34	21%
4	Norrtalje	March 30 11 am	Classroom	1	BSc	22	36%
5	Norrtalje	March 30 2 pm	Classroom	2	BSc	36	31%
6	Main	March 31 11 am	Classroom	4-5	MSc	25	48%
7	Main	March 31 5 pm	Classroom	3	BSc	4	50%
8	Main	March 31 7.30 pm	Choir training	Various	Both	10	70%
9	Main	April 9 9 am	Classroom	4	MSc	15	60%
10	Main	April 9 11 am	Classroom	3	BSc	30	50%
11	Main	April 9 3 pm	Classroom	3	BSc	16	75%
12	Main	April 9 5 pm	Classroom	3	BSc	16	81%
13	Main	March 26 -April 9	Common areas at campus	Various	Both	29	59%

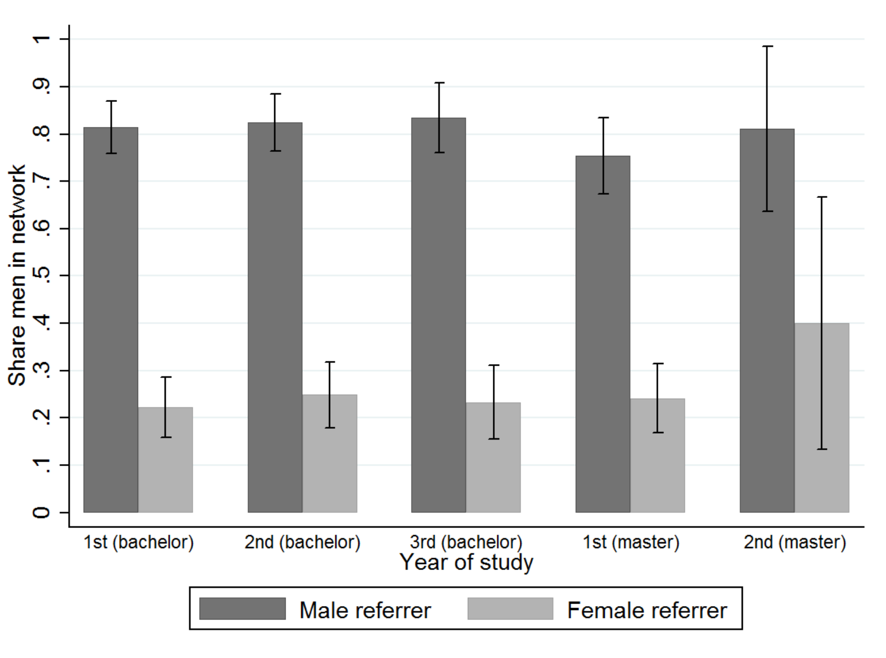
Table A.2: Robustness: Effect of gender of referrer on propensity to refer a man, controlling for proportion of men in network as indicator variables.

	All	All	All	Ref. within network	Ref. outside network
Male referrer	0.464	0.237	0.232	0.252	0.236
	(0.043)***	(0.068)***	(0.068)***	(0.083)***	(0.095)**
Indicator: 0% men in network		-0.427	-0.466	-0.767	-0.110
		(0.089)***	(0.088)***	(0.101)***	(0.129)
Indicator: 20-33% men in network		-0.356	-0.355	-0.637	-0.148
		(0.098)***	(0.097)***	(0.119)***	(0.136)
Indicator: 40-50% men in network		-0.290	-0.294	-0.356	-0.228
		(0.085)***	(0.084)***	(0.100)***	(0.122)*
Indicator: 60-75% men in network		-0.154	-0.163	-0.210	-0.074
		(0.075)**	(0.075)**	(0.091)**	(0.105)
Indicator: 80% men in network		-0.192	-0.186	-0.210	-0.158
		(0.071)***	(0.070)***	(0.077)***	(0.104)
Constant	0.288	0.627	0.971	0.748	0.508
	(0.031)***	(0.078)***	(0.318)***	(0.094)***	(0.111)***
R^2	0.216	0.265	0.309	0.625	0.105
N	427	414	404	181	233
Controls	No	No	Yes	No	No

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

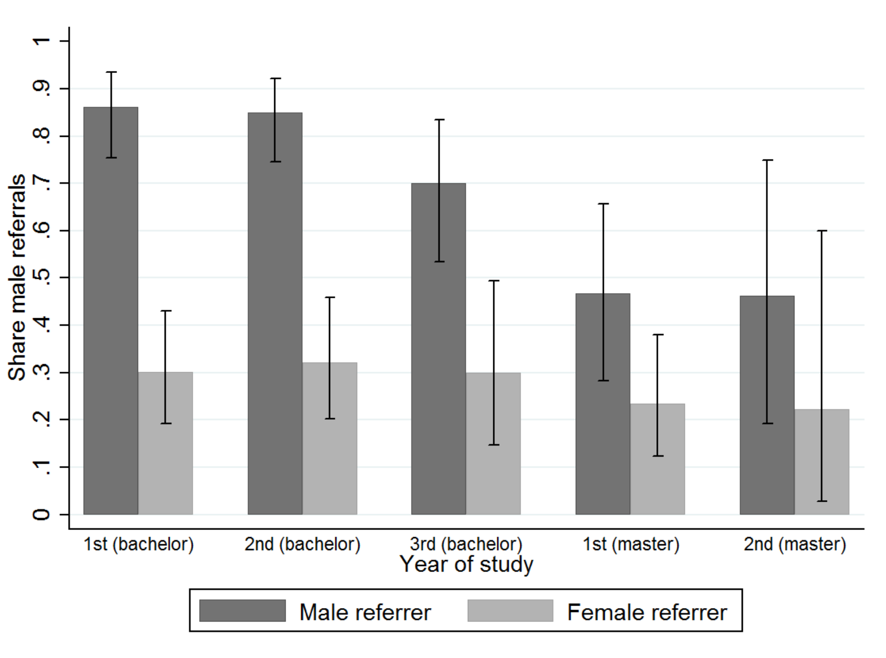
Note: Dependent variable: Man Referred = 1 if the referral was a man, =0 otherwise. OLS regressions. Robust standard errors in parentheses. Controls include the following referrer characteristics: proportion men in class, self-reported GPA, school year, and age.

Figure A.1: Proportion men in network by year of study



Note:The bars indicate 95 % confidence intervals.

Figure A.2: Share male referrals by year of study



Note:The bars indicate 95 % confidence intervals.

Appendix B Instructions

Page 1

On the next page you will find a job advertisement for a part-time position at the company [**Name of company**]. Your task is to read the ad and thereafter *refer another student at the SSE* that you think is well suited for the position. If you complete this tas, you will receive a lottery ticket, and *additionally*, if the student that you refer gets the job you will receive 5 000 SEK as a finder's fee.

This survey is anonymous. The name of the student you refer, and other details you provide, will not be shown to other students.

(If the student who gets the job has been referred by several people, these people will share the fee, but 5 000 SEK is given out per student hired).

Page 2

[JOB ADVERTISEMENT]

I would like to refer the following SSE student for the above position:

Name: ____

In what year is this student? (circle)

Bachelor			*Master*	
Year 1	*Year 2*	*Year 3*	*Year 1*	*Year 2*

Please circle three qualities that distinguish this student.

responsible decisive co-operative logical good leadership potential
dedicated confident reliable analytical communicative perseverant
modest independent considerate

How well do you know this student?
Not at all 1 2 3 4 5 6 7 *Very well*

(Referred students will be contacted through their school e-mail.)

Page 3

DETAILS ABOUT YOU

Name: ______________________________

Registration number: ______________________________

Year of birth: ______________________________

In what year are you? (circle)

Bachelor			*Master*	
Year 1	*Year 2*	*Year 3*	*Year 1*	*Year 2*

What high school did you attend? ______________________________

What high school program did you attend? ______________________________

In what city was your high school located? ______________________________

In what city did you grow up (mainly)? ______________________________

Within what range does your bachelor grade point average lie? (circle)
(1=E, 2=D, 3=C, 4=B, 5=A)

1-2.75   2.75-3   3-3.25   3.25-3.5   3.5-3.75   3.75-4   4-4.25   4.25-5

Name five people at the SSE with whom you socialize frequently (first and last name).
(*preferably* five, but if you are unable to name five, name fewer.)

____

____

____

____

____

(In the event of you being allocated a finder's fee, you will be contacted through the school e-mail.)

Appendix C Job advertisements

C.1 Creative Content Manager

*[**Name of company**] is a Swedish analytics company that helps companies like Tele2, Trygg-Hansa, McDonald's, CocaCola, Spotify and Ferrari to evaluate, analyze and improve their communication and Public Relations activities. From our offices in Sweden, Norway and USA, we work with global assignments in both editorial and social media, by providing a unique mix of specialist analysis and innovative IT-systems. We have received several international awards and place a heavy emphasis on business development and profitable expansion.*

We are looking for 1-2 Creative Content Managers on a part-time basis. The person we are looking for...

- ... is creative and passionate.
- ... likes to work in a growing company, where both employees and the company are constantly. developing
- ... recognizes themselves in our values positive, efficient and innovative.
- ... has a strong interest in and understanding of social media and digital platforms.
- ... likes working with several projects simultaneously.
- ... is considerate and likes to come up with creative input and new ideas.

As a Creative Content Manager your responsibilities will include...

- ... community management and other creative content for our clients (e.g. on Facebook and Instagram).
- ... web.
- ... image management.
- ... to follow up and present the results of different projects.
- ... presentations and reports.

We would prefer for you to have worked with client facing tasks before. You should also have very strong language skills in both Swedish and English, and it is a big bonus if you speak additional languages. You are mindful of correct spelling and find it easy to communicate with others.

You will be working in a focused environment with a fast pace where it is very important that you take responsibility and keep to deadlines.

The position is on a part-time basis at our head office in Stockholm. The job can however often be done at times and places that are suitable for you, which makes it perfect for you if you are a top student.

C.2 Analyst

*[**Name of company**] is a Swedish analytics company that helps companies like Tele2, Trygg-Hansa, McDonald's, CocaCola, Spotify and Ferrari to evaluate, analyze and improve their communication and Public Relations activities. From our offices in Sweden, Norway and USA, we work with global assignments in both editorial and social media, by providing a unique mix of specialist analysis and innovative IT-systems. We have received several international awards and place a heavy emphasis on business development and profitable expansion.*

We are looking for 1-2 analysts on a part-time basis. The person we are looking for...

- ... is business minded and analytical.
- ... likes to work in a growing company, where both employees and the company are constantly developing.
- ... recognizes themselves in our values positive, efficient and innovative.
- ... has a strong interest in measurement and analysis.
- ... is considerate and efficient.

As a junior analyst you will work with assessing, evaluating and summarizing our clients' and their stakeholders' media portrayals and communication related activities. The position involves both quantitative and qualitative tasks, but prior knowledge of SPSS and related skills is not necessary.

We would prefer for you to have worked with client facing tasks before. You should also have very strong language skills in both Swedish and English, and it is a big bonus if you speak additional languages. You are mindful of correct spelling and find it easy to communicate with others.

You will be working in a focused environment with a fast pace where it is very important that you take responsibility and keep to deadlines.

The position is on a part-time basis at our head office in Stockholm. The job can however often be done at times and places that are suitable for you, which makes it perfect for you if you are a top student.