Gendering the Job:
Networks and Recruitment at a Call Center

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Abstract

Gender segregation of jobs plays a central role in current research on gender and labor markets, and understanding the mechanisms driving gender segregation has become a key focus of study. While the literature on gender segregation of jobs often invokes gender sorting mechanisms that operate *pre*-hire, the data that are used to empirically examine these processes are almost always collected on *post*-hire populations. This lack of fit between theory and data make it dangerous to conclude anything about the presence or absence of pre-hire gender sorting mechanisms on the basis of post-hire data. In this paper, we examine the workings of pre-hire mechanisms that are alleged to sort men and women into different jobs. Despite the theoretical importance of these mechanisms, very little empirical evidence has ever been offered on the pre-hire stages of the hiring process. We study a research setting that is unusually well suited for identifying and empirically isolating these social processes: we analyze unique data on the recruitment and hiring process starting with the pool of applicants for an entry-level customer service representative (CSR) job at a telephone customer service center of a large bank. We find that all of the factors we examined—pre-application choices, pre-application gender homophily of networks, and screeners' choices--played significant and distinct roles in the gender segregation of the CSR job. Furthermore, we demonstrate that making inferences about pre-hire processes on the basis of post-hire data can be misleading. We conclude with a discussion of the theoretical and methodological implications of our findings.

Gender segregation of jobs plays a central role in current research on gender and labor markets. Gender segregation of jobs is pervasive, and many studies have appeared documenting the patterns and trends of gender segregation across jobs (e.g., Jacobs 1989a; Jacobsen 1994; Tomaskovic-Devey 1993b; Tomaskovic-Devey et al. 1996). In addition, numerous studies have found that men earn more than women, even after controlling for human capital factors (e.g., England et al. 1994; Tomaskovic-Devey 1993a; Tomaskovic-Devey et al. 1996). This earnings gap, however, virtually disappears when men and women do the same job (Kilbourne et al. 1994; Petersen and Morgan 1995; Reskin and Padavic 1994; Tomaskovic-Devey 1993a; 1993b). For this reason, understanding the mechanisms driving gender segregation of jobs has become a key focus of research on gender inequality.

Virtually all research on gender segregation of jobs begins with data on job *incumbents*, i.e., people who have already been hired into a job. Such post-hire data, however, are limited in their ability to distinguish among various gender sorting mechanisms that are alleged to work *prior* to being hired. For example, arguments that men and women pursue different types of jobs because of gender differences in socialization (Subich et al. 1989) or stereotypical cultural beliefs about gender (Correll 2001; 2004; Cjeka and Eagly 1999) both imply that men and women self-select into gender-typical jobs. Others emphasize the role of *employers'* preferences and biases during pre-hire screening as the reason that men and women work in sex segregated jobs (e.g., Reskin and Roos [1990] on labor queues). Still other theories focus on gender differences in social networks that serve to direct men and women to different jobs (e.g., Drentea 1998). Despite the theoretical importance of these mechanisms, very little empirical evidence has ever been offered on the pre-hire stages of the hiring process.

In this paper, we explore the workings of these pre-hire mechanisms that are alleged to sort men and women into different jobs. We study a research setting that is unusually well suited for identifying and empirically isolating these social processes. We analyze unique data on the recruitment and hiring process starting with the pool of applicants for an entry-level job at a telephone customer service center of a large bank. We focus attention on a single entry-level job title—customer service representative (CSR)—that has remained constant in this setting over the period of our study, 1995-1996. While the duties and label of the CSR job remained constant, the gender distribution of job incumbents changed over this relatively short period. Although female-dominated at the start of our study (65.7 percent of CSRs were women as of December 31, 1994), the CSR job became even more female over this two year period: by the end of 1996, the percentage of women employed in the CSR job had increased to 72.5 percent. Indeed, as we discuss below, the composition of the set of new hires over this period is even more female, i.e., 77.7 percent. Our goal in this paper is to shed light on how various pre-hire processes contribute to the growing feminization of this job in this setting.

Gender and Job Segregation

At the most general level, accounts of gender segregation of jobs can be grouped into two sets: theories emphasizing labor supply factors, and theories stressing features of the demand side of the labor market. Supply side accounts argue that for various reasons men and women have different preferences, and consequently choose to work at different kinds of jobs (e.g., Polachek 1981). Some scholars have argued that men and women have different preferences for jobs due to gender differences in socialization (Betz and O'Connell 1989; Marini and Brinton 1984; Marini et al. 1996; O'Leary 1974; Subich et al. 1989; for a contrary view, see Jacobs [1989b]) or stereotypical cultural beliefs about gender job roles (Correll 2001; 2004; Cejka and Eagly 1999). Others emphasize differential constraints due to gender differences in family roles. For example, Becker (1981; 1985) argues that the gendered division of household labor leads women to be less committed to working outside the home than are men, resulting in poorer relative labor market performance (but see Bielby and Bielby 1984; 1988). Mincer and Polachek (1974; also see Polachek 1975a, 1975b, 1979) argue that the intermittent participation of women in the labor force (due to duties such as child rearing) make it rational for them to choose jobs whose skills do not atrophy over time. Zellner (1975) proposed that intermittent labor force participation leads women to choose jobs that allow them to earn better wages in the short run, although these jobs might offer worse prospects in the long term. England (1982; 1984) has challenged this line of reasoning. She showed empirical evidence that even in the short-run, women would still be better off in male-dominated jobs; thus, women's (alleged) needs for intermittent labor force participation could not explain job sex segregation.

Another set of supply side theories attempting to explain the gender segregation of jobs emphasize the role played by gender differences in social networks. A number of studies have appeared which show gender segregation of networks (e.g., Brass 1985; Campbell 1988; Ibarra 1992; Lincoln and Miller 1979; Marsden 1987; 1988; Moore 1990; Straits 1996). A number of scholars (e.g., Granovetter 1995) have argued that personal networks play an important role in job finding, so that gender homophily (i.e., the tendency for people to associate with same sex others; see McPherson, Smith-Lovin and Cook 2001:422-424) serves to channel men and women into different jobs during job search (Berger 1995; Corcoran et al. 1980; Drentea 1998; Hanson and Pratt 1991; 1995; Mencken and Winfield 1999; Reskin and Padavic 1994; Straits 1998; for contrary evidence, see Huffman and Torres [2001; 2002]).

In addition to the supply side approaches, several theories of gender segregation focus on the demand side of the labor market, specifically, employer's actions during screening. In particular, some theories stress the gender biasing effects of screeners' preferences. For example, Reskin and Roos' (1990) queuing theory posits that employers have definite preferences for men. Some have argued that discriminatory attitudes—whether conscious or unconscious—presumably affect employer screening, and the gender composition of candidates as they pass through the stages of the hiring process (Glick et al. 1988; Graves 1999; Heilman 1980; 1984; Marini 1989).

Another demand side mechanism focuses on how network factors affect screening. It is common for employers to use the networks of their current employees as part of their recruitment strategies, and many employers prefer to hire employee referrals (Fernandez and Weinberg 1997; Fernandez et al. 2000). To the extent that such networks are gender biased, then employers' preferences for employee referrals can also have gendering effects (e.g., Berger 1995; Reskin and Padavic 1994; Roos and Reskin 1984; Straits 1998). It is worth noting, however, that the most careful empirical study directed at this question (Petersen et al. 2000) found no evidence that their employer's preference for referrals affected the gender composition of candidates as they progress through the hiring process.

For our purposes, these theories of gender job segregation share one crucial feature: for all of them, the gender sorting actions are taking place *prior* to hire. Theories which emphasize men and women's differential job choices—whether they be due to gendered constraints or preferences—result in a self-selected pool of *applicants* for jobs. This is also true for supply side network theories, where women and men are channeled to different jobs through job contacts during job search. Similarly, for demand side theories of employers' preferences—whether the bias be for one gender over another, or for networked candidates—the gender sorting processes work during pre-hire screening. While all these theories are designed to explain the same outcome—the post-hire gender segregation of jobs—research strategies based on post-hire data alone cannot distinguish among these different gender sorting mechanisms. However, virtually all of the empirical research to date on the causes of gender segregation of jobs is based on job incumbents, i.e., people who have already found jobs.[1]

In this paper, we take a fresh approach to the study of gender based job segregation by studying a research setting that is unusually well suited to identifying and empirically isolating key processes alleged to be at work in the

[1] Although rare, there are some studies of *post*-hire gender job sorting mechanisms. Skuratowicz and Hunter (2004) study the reassignment of men and women to jobs during a bank reorganization. There are also a few studies which examine gender segregation processes occurring as organizational careers unfold (Yamagata et al. 1997; Barnett et al. 2000; Petersen and Saporta 2004). Our study is the first to empirically address the pre-hire mechanisms of job sex segregation (see below).

gender sorting of jobs. We open up the “black box” of pre-hire gender sorting mechanisms by examining unique data on recruitment and screening for an entry-level job at a telephone customer service center of a large bank. In order to control for the possibility that job titles are being defined on the basis of gender (e.g., Baron and Bielby 1986; Jacobs 1992), we focus attention on a single entry-level job title, the customer service representative (CSR).

Our strategy is to document the gender composition of the applicant pool, and examine how supply side pre-hire network factors affect the gender composition of the pool. By tracing the connections between referral applicants and the people who referred them, we study how gender homophily contributes to the gendering of the pool of candidates. In order to address theories about the role of screeners in the job gendering process, we track how the gender mix of candidates changes as they progress through the hiring pipeline. In addition, we engage the supply side network theory that employers' bias in favor of referrals might account for job segregation by studying the ways in which screeners' preferences for referrals affects the progression of men and women through the screening process. We conclude with a discussion of the theoretical and methodological implications of our findings.

Data

We studied the hiring process for an entry-level position at a phone center, within a large, globally diversified financial service institution. The job we study is the Customer Service Representative (CSR), which is a full-time, hourly position, paying a starting hourly wage of $8.25, and whose duties consist of answering telephone inquiries about customers' credit card accounts. New hires into this position are given two months of classroom and on-the-job training before being assigned to work on the phone. CSRs are trained in balancing the etiquette of customer service interactions with accuracy, speed and efficiency while processing phone calls. CSRs handle up to 5,000 phone calls per month per person; these calls are often monitored by managers to insure that courtesy and accuracy goals are being met.

The phone center offers a number of practical advantages for this research. The human resources department keeps virtually complete databases on recruitment for CSR jobs, which has allowed us to track applicants' movements through every phase of the hiring process. In addition to these computer databases, the human resources department keeps paper files on each applicant, including a standardized application form. From these paper files, we coded crucial data on applicants' education, work history, and other human capital characteristics. Particularly important for us is that, because we had access to the name and the handwritten signature of the applicant on the form, we were able to code the gender of the applicant for virtually all (i.e., 99.3 percent) of the cases.

We constructed a database of the hiring pipeline (i.e., application, interview, offer, and hire) for all 4,316 applications for the CSR job during 1995-1996. From information gleaned from the paper application forms, we have grouped the applicants into three recruitment sources: external non-referral (e.g., newspaper advertisements), external applicants who were referred by employees (hereafter, employee referrals) and candidates for internal transfers. Although this latter category is relatively small in number (N=151), internal applicants are an interesting comparison group since they are more likely than externals to be familiar with the CSR job. Note that the unit of analysis here is the *application*, and that some people applied multiple times during the period of our study. The maximum number of applications from individuals is three. Of the original 4,316 employment inquiries, 416 (9.6 percent) were from individuals who had applied twice, and only 15 (0.3 percent) applied three times. 60.7 percent (i.e., 2,618) of the 4,316 applications resulted in an interview with hiring managers; only 9.4 percent (406) of the applications led to the offer of a job, and 8.7 percent (376) of the original applications ended in a hire.

One of the most unique features of these data is the fact that we have been able to connect referrers with their referrals at the application phase. Unlike past research where data on the characteristics of the job contact are observed only among hires (e.g., Berger 1995; Corcoran et al. 1980), here referrers are linked to job applicants. Thus, for each external applicant, we are able to identify the presence or absence of a referral tie, as well as the gender of the referrer. There is a line on the employment application that explicitly asks the applicant to list the name of the referrer. Referring employees are paid $10 if the people they refer are interviewed, and $250 if the referral is hired and survives a 30-day probation period. This creates an important incentive for referring employees to ensure that applicants list them accurately as their referrer. This referral bonus also constitutes the firm’s social capital investment in the social networks of their employees (Fernandez et al. 2000; Fernandez and Castilla 2001).

More than one-third of the applications (35.8 percent, or 1,546) were external referrals, and slightly less than two-thirds were non-referrals (63.6 percent, or 2,745); we could not identify the recruitment source for 25 applications. 1,223 referrers produced 1,539 referrals; an additional 7 applications indicated that they were referred, but did not name an individual referrer. From company data sources, we located employment records for 97.5 percent (1,192) of the referrers who were identified. It is from these records that we coded the gender of the referrer. There were no limits on the number of applicants a person could refer, and the number of referrals per referrer varied between 1 and 6 (although 79.7 percent referred only one, and 15.8 percent referred two applicants).

Lastly, these data allow us to address gender differences in networking activities that lead people to apply. By comparing the gender distribution of those who refer applicants (i.e., the originators of network ties) to the gender distribution of the population of employees of the phone center (i.e., those at risk of referring), we can assess whether there are gender differences in the propensity to produce referral applications. We have assembled data on all workers employed at the site over the period of the study, and identified whether they participated in the company's referral program for customer service representatives. We were successful in coding such background data for 96.4 percent (3,968 of 4,114) of the workers employed at the phone center.

Although it is our sense that the firm is not particularly distinctive in its hiring practices, in light of our decision to study only one firm, we can make no claims regarding generalizability. Our main goal in adopting this empirically grounded, case-study approach is to elucidate the workings of the pre-hire mechanisms that are alleged to sort men and women into different jobs. Thus, our strategy has been to trade broad data across many settings, for very deep knowledge of this particular case. While we would expect that there will be some contingency in the ways the pre-hire processes contribute to gender segregation of jobs in different settings, it is impossible to distinguish among the different pre-hire mechanisms which might produce gender sorting without the unique, fine-grained data we analyze here. The need for this kind of detailed data is made even more acute by the fact that for many of these pre-hire mechanisms, no empirical evidence at all has ever been offered. The theoretical significance of this case is that it provides a window through which one can view the operations of a set of processes that are normally hidden from view. Thus, the insights gleaned from this case study can be used to guide broader-gauge research designed to represent wider populations of organizations.

Analyses

At the most general level, theoretical accounts of gender segregation of jobs can be grouped into two sets: theories emphasizing labor supply factors, and theories stressing features of the demand side of the labor market.

Supply Side Processes: Choice and Constraint

Supply side accounts of gender segregation argue that men and women have distinct preferences for different kinds of jobs due to gender differences in socialization (O'Leary 1974; Subich et al. 1989), gender role stereotypes (Correll 2001; 2004; Cjeka and Eagly 1999), and differential constraints due to gender differences in family roles (Zellner 1975). From the perspective of our study, all of these theories share a common prediction: pre-hire processes should result in a gender biased application pool. Indeed, the pool of applications over 1995-1996 for the CSR job is not gender neutral: 67.0 percent of the 4,286 applications for which we could code gender are from females. While this certainly departs from the 50/50 population sex ratio, it is interesting to compare this percentage against several other baselines.

A first baseline of comparison is the percentage of females employed at the call center just prior to the start of our study. As of the day prior to the start of the hiring window (i.e., December 31, 1994), 65.7 percent (69 of 105) of workers employed in the CSR position were women. Whatever processes were at work prior to our study, the net result of these processes was to produce a female dominated CSR job. Thus, the gender distribution of job incumbents at the beginning of the study closely matches the gender distribution of the pool of applicants obtained for this job over the subsequent two-year period (65.7 vs. 67.0 percent female).

There were, however, some interesting changes in the call center over the period of our study. During 1995-1996, the call center expanded its operations so that the number of CSRs would grow substantially (from 105 to 280). This expansion corresponded to an increase in the representation of women in the CSR job during this time: the percentage of CSRs that were women increased from 65.7 percent female before the study, to 72.5 percent female the day after the close of our hiring window (i.e., as of January 1, 1997).[2] Compared to this baseline, an application pool that is 67.0 percent underrepresents the gender composition of the CSR job at time 2. This suggests that women are more likely than men to survive the screening process and be hired (see below).

It is interesting to consider that "Customer Service Representative" appeared as an occupation for the first time in the 2000 census (code 524). We obtained the Public Use Micro Sample (PUMS) data for the Metropolitan Statistical Area (MSA) in which the call center was located. The percentage female among CSRs in these data was 74.2 percent, a figure that is quite close to the 72.5 percent figure reflecting CSR job holders at the end of our study. We have no way of eliminating the employees of our call center from the PUMS data. The local MSA does contain numerous call centers, however. This suggests that the gendered nature of the CSR job is a broader phenomenon in the labor market we are studying. We will use the PUMS data to further explore the gender distribution of the open labor market below.

[2] As we describe below, the percentage of females hired into the CSR job during our study is even higher, with 77.7 percent of the people hired during our study being female. Our data come from two sources that we cannot directly combine: applicants to the job, and a company database of job incumbents. The incumbents' database is anonymous, and we cannot reconcile these data with our hiring data, which we constructed ourselves with full access to the information on hires. The difference between 77.7 percent of CSR *hires* between time 1 and 2 being women, and 72.5 percent of CSR *incumbents* being female at time 2 is due to turnover, which we cannot study for incumbents. Due to these limitations, we use the incumbents' database only to define the before and after baselines of comparison.

It is important to consider that the 67.0 percent female figure combines applications from all sources. However, if there are gender differentiated network processes (e.g., gender differences in job information; see Campbell 1988) that also serve to bias the pool of applicants, then external referral applications would be affected by *both* the pre-hire preferences/constraints of the candidates, as well as the network processes. It is also likely that internals would have better information about the nature of the job than external candidates. To the extent that the job has characteristics that are differentially attractive for men and women, the gender distribution of internal candidates might differ from that of external candidates.

Table 1 shows that there is a significant relationship between the gender distribution of applications and recruitment source ($p < .001$, LR Chi-square 14.258, with 2 d.f.). The percentage of women is highest for internal candidates (74.2 percent), intermediate for referrals (69.9 percent), and lowest for external non-referrals (65.0 percent). Such a pattern is consistent with the idea that the CSR job becomes more attractive to women than men as more information is made available about the job. We found a similar pattern for a small number (169) of former employees of the call center, who are also likely to have good knowledge of the CSR job: the percent female among previous employees is 72.2 percent. Although a similar process could be at work for referrals if referrers were to be passing on information about the CSR job, our previous work shows little support for the idea that referrals have "extra information" compared with external non-referrals at this phone center (see Fernandez et al. [2000:1314-1322] tests of hypothesis 3). The results do suggest, however, that other network-related processes serve to raise the proportion of women who apply to this job via referrals (see below).

The analyses up to this point have been aimed at understanding the gender composition of the application pool for the CSR job. We have yet to address possible gender differences in the *quality* of the applicants. We interviewed the call center recruiters about the criteria they used when screening applicants. They said that they look for evidence of basic keyboarding and computer skills on the application form. In addition, they also place relatively high weight on an applicant's job history when screening applications. In light of the customer service aspects of the job, screeners also look for people with prior customer service experience. Recruiters said they are also quite concerned about work attitudes, and tend to look for applicants who they think will be reliable employees. This leads them to prefer applicants who are currently employed, and who have had some previous work experience. Because they are quite concerned about the cost of turnover, recruiters tend to avoid people who have changed jobs a lot during their work histories. Recruiters are also concerned about applicants who are "overqualified" for this entry-level position, so that candidates who report significantly higher wages in their previous job than the starting wage at the phone center ($8.25) are looked upon with some skepticism. Compared with work experience, the recruiters said that they place less weight on formal education for the entry-level CSR job. Recruiters are concerned, however, that highly educated people might be using these jobs as a platform to look for better employment and, consequently, that highly educated workers are more likely to turn over. The call center screeners thus consider very highly educated applicants as overqualified for the CSR job.[3]

From the original application forms, we coded each applicant's years of education, experience in the financial services industry, employment experience outside the banking industry, and customer service experience. We also coded a dummy variable for whether the person was employed at application, as well as the number of previous jobs listed on the application, years of tenure with the last firm, and wages of the last job. We looked for evidence of computer experience among the application materials, and created a dummy variable for the presence of these skills (the applications had a line specifically asking for such information). Similarly, based on the information provided on the application form, we also created a dummy variable for evidence of foreign language skills. In order to address recruiters' concerns about possible over-qualification for the CSR job, we distinguished applications from people with more than a college degree (i.e., greater than 16 years of education) with a dummy variable. For similar reasons, we coded a dummy variable for whether the applicant reported a wage on their last job as being greater than or equal to the starting wage for CSRs at the call center, $8.25 per hour.

Table 2 shows descriptive information on a number of background characteristics of the applicant pool by gender. In order to control for the network and information processes we address below, we focus here on the pool of non-referral applicants. We begin with tests of gender differences in individual variables. Univariate F tests show that male and female applications are not significantly different with respect to a number of background factors: computer and foreign language skills, number of previous jobs, whether the applicant was employed, and tenure on the last job. Female applications show superior qualifications compared to males with respect to customer service and financial services experience. Males have more experience in jobs outside financial services, and contain higher proportions of

[3] There is one criterion that absolutely disqualifies applicants, however. The application form asks whether the applicant has ever been convicted of a "breach of trust;" applicants responding 'yes' are eliminated from further consideration since regulatory agencies will not allow banks to hire such people into CSR positions. Breaches of trust include shoplifting, embezzlement, forgery, fraud, and writing checks with insufficient funds. All hires are required to undergo expensive fingerprinting and background checks. If these tests come back showing a conviction, the call center is required by law to let the new hire go. Only 0.6 percent (11 males and 14 females) of applications from all sources (external non-referrals, external referrals, and internals) indicated a breach of trust.

overqualified applicants than females. Although the median years of education are identical for males and females (i.e., 14 years), the proportion of applicants with greater than 16 years of education is significantly higher for males.

The percentage of applications overqualified by virtue of past wages that are greater than the starting wage for the CSR job (i.e., \$8.25 per hour) is also significantly higher for males than females (37.0 vs. 21.7 percent; $p < .001$). Male applicants also earned higher wages on their last job than females when the difference is measured at the mean (\$8.15 vs. \$6.80; $p < .001$) or the median (\$7.25 vs. \$6.33). Indeed, with the exception of minimum wage applicants (i.e., \$4.25), male applicants have higher past wages than female applicants at every percentile point in the distribution. This is seen clearly in Figure 1, which plots the percentile distribution of wages the applicants' last job for females against the percentile distribution of wages on the last job for males. The 45-degree line shows a baseline of what the plot would look like if females and males were to have identical wage distributions. With the exception of the 5th percentile and below which consists of minimum wage applicants, the line for the observed data is always above the 45-degree line, showing that males had higher wages than females over virtually the entire distribution.

We checked whether applications could be classified into distinct profiles. Table 2 reports the multivariate test of whether gender is statistically independent of the joint distribution of the 10 measures of applicant quality. We find strong evidence that gender distinguishes applicants' profiles ($p < .0001$; Wilks' Lambda = .935, F-test = 13.327, d.f. = [10, 1,929]). In terms of the criteria that recruiters are seeking, on the whole, females are more qualified than males at application.

These latter findings suggest that the pool might be even *more* female if we were to adjust the pool of applicants by eliminating candidates who are not desirable according to the screeners. Human resource professionals refer to this as an "adjusted" application pool. Screeners often form adjusted pools as a way of judging how well they have targeted their recruitment effort. Screening from a pool which is composed of very few hirable people results in higher screening costs relative to a "richer pool" of applicants (see Fernandez et al. 2000). For example, eliminating from consideration "overeducated" and "overpaid" applicants—who tend to be male—increases the percentage of females in the remaining pool to 70.1 percent (1,177 of the surviving 1,668 candidates). Similarly, applying absolute cutoffs to eliminate candidates based on any of the criteria in Table 2 on which women are superior to men (e.g., customer service experience) would serve to increase the proportion of women in the adjusted pool. On the other hand, establishing a threshold for factors on which males dominate (e.g., months of non-bank experience) would decrease the percentage of women in the adjusted pool.

We have good reasons to think that recruiters do not rigidly apply such single variable thresholds, however. In our interviews, recruiters described the screening criteria as "things to look for" and "things to avoid." Moreover, analyzing the outcomes of their actual screening decisions shows that, with the exception of the "breaches of trust" mentioned earlier, they clearly did not apply any of these criteria as absolute "must haves" in their screening decisions, but rather allowed trade-offs among multiple factors. For example, among interviewees, the person with the highest hourly wage in their last job was $40.00, the same as it is in the original application pool. Thus, a $40.00 cutoff would exclude no one from the interview stage. Indeed, even among hires, only 0.6 percent of applicants would be excluded by applying the criterion of the highest paid person to be hired ($22.49) as a cutoff. By way of contrast, none of the 25 applications that cited a breach of trust were interviewed, offered the job, or hired.

Pool adjustment focuses on eliminating from consideration people who are inappropriate from among those who actually applied. However, this cannot address what the gender distribution of *potential* applicants to the CSR job might be. One reason that the CSR job might attract a predominantly female application pool is that the CSR job is relatively low wage, and given that women earn less in the open labor market, a low wage job is likely to be more attractive to women than men. Thus, the policy of having a fixed wage offer of $8.25 per hour is likely to skew the applicant pool in favor of females. We sought data on the external labor market in order to address this question. The most appropriate data we could locate was the 1999 wages reported in the 2000 PUMS for the MSA in which the call center was located. We then used the consumer price index (CPI) to adjust the wage data for inflation between January, 1996 (the midpoint of our study) and 1999. (None of the substantive findings we describe below change if we use unadjusted wage data.)

These data show that the female wage is 70.2 percent of the male wage in the open labor market. The mean hourly wage for males in 1996 dollars is $17.07 compared with $11.98 for females (the comparable figures in 1999 dollars are $18.36 and $12.89). Moreover, the $8.25 wage offer cuts off a bigger slice of the female than male local wage distribution. The call center's offered wage for CSRs falls at the 37th percentile of the local female wage distribution, compared with the 25th percentile of the local male wage distribution. Thus, wage inequality in the open labor market alone would serve to make the CSR job more attractive to females than males.

We used the inflation-adjusted wage data from the PUMS to get an idea of how much this factor might be contributing to the gendering of the application pool. Whereas females constitute 49 percent of those with positive earnings in the local labor market in 1999, they comprise 58.9 percent of those who earned $8.25 per hour or less. We repeated this exercise, varying the wage cutoff for eliminating people from the pool of potential applicants. Figure 2 tracks the percentage female in the labor pool as wage cutoffs are varied from \$5 to \$25 (\$25 falls at the 87th percentile of the male wage distribution, and the 95th percentile of the female wage distribution). With the exception of the jump from 58.5 percent at \$5 to 60.5 percent at \$6, the percentage female in the population declines as successively higher wages are used to adjust the pool of potential applicants. In separate analyses, we found that this exception is due to the fact that the lowest wage jobs are attracting male youth in greater proportion than female youth. The fact that males disappear from the pools as wages drop suggests that wage inequality in the open labor market is an important contributing factor to the gendered nature of the application pool for the CSR job. However, the highest percentage female occurs at \$6 per hour, 60.5 percent, and this figure is well short of the 67.0 percent figure observed for the call center. While certainly important, wages alone do not seem to account for females' greater attraction to the CSR job.

Supply Side Processes: Networks

Another set of supply side theories attempting to explain the gender segregation of jobs emphasize the role played by gender differences in social networks. A number of scholars have argued that gender segregation of networks leads men and women into different jobs (Corcoran et al. 1980; Drentea 1998; Hanson and Pratt 1991; 1995; Mencken and Winfield 1999; Reskin and Padavic 1994). As noted above, all of this research is based on job incumbents, i.e., people who have already found jobs. Thus, these studies cannot address the pre-hire network processes which are alleged to direct men and women to different jobs.[4] Here, we specifically focus on the pre-hire network factors that might differentially direct men and women to the CSR job.

In the context of our study, such network factors would manifest themselves by employee referral applicants being even more gender biased than the pool of non-referral applicants. As we showed in our discussion of Table 1 above, the data show just this pattern: 69.9 percent of referral applications are from women compared with 65.0 of non-referrals. The gender difference between the referral and non-referral application pools is statistically reliable ($p < .001$,

[4] We know of only one exception here. Petersen et al. (2000) provide an important study of the impact of employee referrals, gender and race in the pool of applicants for employment at a high tech firm over a ten year period. They found no evidence of females being disadvantaged as applicants progressed through the hiring process. From the perspective of our goals here, their study has two limitations. First, the firm they studied did not distinguish jobs or occupations, but instead hired people into broad functional areas (Petersen et al. 2000:774-775). For this reason, their study cannot, as we do, address the gender composition of a specific job, but only the gender composition of the firm as a whole. Second, they do not have access to the originators of the referral tie, i.e., they cannot identify who referred the applicant. Thus, they cannot address questions related to gender differences in the referring, or the gender homophily of the referral ties. We will examine both these issues below.

LR Chi-square 10.529, with 1 d.f.). Thus, the net impact of the network processes that produce applications[5] to this call center result in an applicant pool that is more female than the non-referral pool.

As with non-referrals, we explored whether there are gender differences in applicant quality among referrals (results available from the authors). Overall, the results for referrals are very similar to what we found for non-referrals: women are better qualified than males at application. The only difference is that for referrals, males and females do not differ with respect to years of experience in financial services, whereas females show significantly more financial services experience than males among non-referrals. Among referrals, too, we find strong evidence that gender distinguishes applicants' profiles ($p < .0001$; Wilks' Lambda = .936, F-test = 7.506, d.f. = [10, 1,104]).

As was the case for non-referrals, the male application pool also contains a higher proportion of overqualified applicants—both by virtue of education level and hourly wages on the last job—than the female application pool. Here too, a plot of the percentile distribution of wages on the last job for referrals shows that males had higher wages than females over virtually the entire distribution (available on request). This suggests that the referral pool might be even *more* female if we were to adjust the pool of applicants by eliminating candidates who are overqualified with respect to past wages. Since this pattern emerges *within* the population of referrals as well, the policy of having a fixed wage offer of $8.25 per hour and avoiding highly paid workers does not account for the observed referral/non-referral difference in the percentage of women. Moreover, the gaps between the percent female for referral applicants (69.9 percent) and the percent female expected in the various adjusted pools calculated from the PUMS data on the local labor (the maximum is 60.5 percent female; see Figure 2) are even larger than gaps observed for non-referrals. Among referrals as well, wages alone cannot account for females' greater attraction to the CSR job.

Who Refers?

At the beginning of the chain of the network processes leading people to apply to the CSR job are the call center employees, who form the pool of *potential referrers*. We assembled a dataset on all workers who were employed at the call center at any time during the two-year window of our study, and therefore, were at risk of referring CSR applicants. A total of 4,114 workers worked at the call center at some time during 1995-1996, and virtually all of these

[5] Note that we do not directly observe referrer's recruitment efforts in these data. Because we only observe recruitment attempts where the referral actually applies to the call center, we say "produce applications." We will explore the implications of this limitation of our data below.

workers were eligible to refer someone.[6] Women were much more prevalent than men among employees of any job title of the call center: women constitute 69.7 percent of workers.[7]

We next examined whether there are significant gender differences in the propensity to produce referral candidates to the CSR job. A little less than a quarter of the workers (i.e., 1,005) produced at least one referral applicant for the CSR job. 25.7 percent of women originated at least one referral, compared to 21.4 percent of men ($p < .003$, LR Chi-square 8.753, with 1 d.f.). Not only are women overrepresented among call center workers, they are also more prevalent among referring workers than are men: 73.4 percent of the referrers are women compared with 68.5 percent of non-referrers. Although there was no limit to the number of people that employees could refer, the vast majority of referrers (79.7 percent) produced only one referral candidate. The gender difference in producing multiple referrals among the subset who referred at least one candidate is negligible (women, 1.44 and men, 1.43). There are gender differences in overall "out-degree," however. Women produced an average of .371 referrals compared with an average of .308 referrals for men ($p < .012$, F-test 6.32 with 1 and 4,112 d.f.). Consequently, the gender difference in out-degree is driven by differences in the propensity to refer one candidate.

<u>Who is Referred</u>?

Thus far we have shown that women are more prevalent than men at the call center, and that women are more likely to produce referral applications than men. Taken alone or in concert, these factors could account for the observed results where there are more females among referral than non-referral applicants. However, the question of the *target* of referring remains. Specifically, we examine the data to see whether there is evidence of gender homophily for the referral applicants. As we noted above, a number of scholars assert that gender homophily is an important factor in job finding networks (e.g., Berger 1995; Reskin and Padavic 1994). To our knowledge, with only the exception of

[6] While the referral bonus program was widely available to employees working at the firm, a few (less than 10) of the 4,114 people employed at the phone center were barred from participating in the program. Managers who have hiring authority cannot claim a referral bonus for someone who winds up working for them (they could, however, refer people to other shifts or supervisors). Second, human resources personnel who screen applicants for the job cannot participate in the referral program. Due to data limitations, we could not identify these workers in order to exclude them from the set of people at risk for referring.

[7] There are slight gender differences in turnover among employees that make the 69.7 percent number a slight underestimate of the percent female at risk of referring. This is because 42.6 percent of the 4,114 workers were employed at the call center less than the entire two-year period of the study. If we limit attention to the 57.4 percent of people who were employed the entire two years, the percent female rises to 70.2. If we weight the cases by the amount of time they are exposed to the risk of referring (this is equivalent to conceiving of the unit of analysis as person-days employed over the two-year hiring window), females account for 70.1 percent of the population of potential referrers. The predictive models we present below include corrections for heterogeneity in exposure (see Table 4).

Fernandez et al. (2000), the evidence for gender homophily has been based on the job incumbents, and not on pre-hire data such as those we study here.

Table 3 tabulates the gender of the originator of the referral tie by the gender of the referral applicant. The correlation between the gender of the referrer and the gender of the referral is small (Pearson's correlation = .174), but statistically significant. Three quarters (75.1 percent) of the referral applications produced by female referrers are from women. What is interesting, however, is that the majority of referral applications produced by *male* referrers are also to women (56.3 percent).

We examined whether these results change after controlling for a number of facets of employee background. We include among the predictors two variables that measure knowledge of the job and referral practices at the company, i.e., dummy variables for whether the person had ever worked as a CSR at the company (1=yes) and whether the person was him- or herself hired as an employee referral (1=yes). In addition, we control for worker's age (in years), tenure (in years) with the firm, and annual salary (in thousands of dollars) at the start of the study (January 1, 1995). If the worker was hired after the start of the study, tenure is coded zero, and the salary is their starting salary with the company. From the employment records, we also code separate dummy variables for having a BA (1=yes) and an MA degree (1=yes).

Table 4 presents negative binomial regression analyses modeling the count of referrals made by each worker over the period of the study. We parameterized the count models to correct for differential exposure to the risk of referring associated with time employed during the hiring window (see note 7). For all three models presented in Table 4, there is evidence of overdispersion, i.e., that the variance of the dependent variable is greater than the mean. Thus, we opt for the negative binomial regression model, which corrects for the overdispersion when modeling the counts (Cameron and Trivedi 1998).

The first column shows the model predicting the number of referrals made by employees, irrespective of the gender of the target. As might be expected, controlling other factors, having been hired as an employee referral is strongly associated with producing referral applicants: the marginal effect shows that referrals have a conditional mean on referring that is .083 higher than non-referrals. Similarly, employees who have previously (or currently) worked as a CSR at the company produce substantially more referrals than non-CSRs (the marginal effect of CSR background on the conditional mean of referring is .100). Employee's tenure is a significant negative predictor of referring: longer-term employees produce fewer referrals compared with people hired during the period of the study (i.e., those hired most recently). Controlling tenure, older workers are also less likely to participate in referring than younger employees. The remaining control variables (salary, BA, and MA degrees) are also negatively associated with referring, although, with the exception of the dummy variable for having a BA degree, these effects are only significant at the .10 level.

Most important for our purposes, while the zero-order data showed that women tend to produce more referral applicants than men (the average number of referrals for females is .371 compared with .308 for males), this gender difference is explained by the other background factors. After controlling for other variables that are associated with referring, the gender difference is small and not statistically reliable. After controls, the marginal effect shows that the female-male difference in the conditional mean of referring is less than half of what it was without controls (.027 vs. .063).

Gender differences remain strong and significant, however, once we distinguish the gender of the target of referring (see the second and third models in Table 4). Consistent with the zero-order results in Table 3, females are more likely to produce same-sex (i.e., female) referrals than are males, even after controlling for the other background variables (Model 2). The pattern of the other effects in column 2 are similar to that we found in column 1. i.e., the count of referrals, irrespective of gender. Nor do the control variables explain the pattern for different-sex referrals (Model 3). As in Table 3, female employees are less likely to produce male referrals than are male workers to produce female referral applicants.

Before concluding that men are gender unbiased in their referring patterns, and that only women referrers show a tendency toward gender homophily, it is important to remember that these data pertain to referrals that actually go to the trouble of applying, rather than referral *attempts*. Even if males and females had no preference for one gender over the other when they contact people recommending that they apply to the CSR job (i.e., they show no tendency toward gender homophily in referral *attempts*), it is possible for gendered job preferences of the person contacted to lead to more women than men to ultimately apply. Indeed, referrers have an incentive to contact people who have a high chance of actually applying, getting hired, and succeeding at the CSR job, since referrers are paid bonuses for successful referrals.

Although we only observe the gender of referrals who end up applying, we can make an educated guess as to the size of the gender biasing effect of referring *per se* by comparing the referrer-referral gender homophily data in Table 3 to what the gender distribution of applications would be in the absence of referring, i.e., for the pool of external *non-referral* applicants. Female referrers produce applications that are about 10 percent more female than the external non-referral application pool (75.1 vs. 65.0 percent). A nearly similar biasing effect is evident for male referrers: males produce a referral application pool that is 8.7 percent more male than non-referrals (43.7 vs. 35.0 percent). When considered against the baseline of external non-referrals then, both male and female referrers do appear to produce referral applications from people of the same gender as themselves.[8]

Demand Side Processes: Screening

The net effect of the supply side processes discussed above is to deliver an application pool that is two-thirds female into the hiring pipeline. Several theories of gender segregation focus on how it is that male and female candidates differentially progress through the hiring pipeline. In particular, some demand side theories stress the gender biasing effects of screeners' preferences (e.g., Reskin and Roos' [1990] queuing theory). Others argue specifically that conscious or unconscious discriminatory attitudes affect employer screening, and thus the gender composition of candidates as they pass through the stages of the hiring pipeline (Glick et al. 1988; Heilman 1980; 1984). Virtually all extant studies of gender discrimination and prejudice in screening are done in simulated or laboratory settings (for a meta-analysis, see Olian et al. 1988). In the field setting we analyze here, we cannot directly distinguish among the various attitudinal and psychological processes at work in screeners' minds which might affect the ways men and women are selected to move on through the hiring pipeline.[9] We can, however, observe the impact of those decisions on the gender composition of candidates at each stage of hiring, and isolate where it is in the process that gendering is taking place in the hiring pipeline.

Table 5 shows the gender composition of candidates as they move through the hiring process by recruitment source. Considering first the data for all recruitment sources combined (see the fourth row of Table 5), we see that the percentage of women increases with each successive step in the process, i.e., from 67.1 percent for applicants to 77.7 percent of hires. The biggest jump in the percentage female occurs at the step between interview and offer (69.2 vs. 77.0

[8] Fernandez et al. (2000:1309-1314) tested whether the gendered job preferences of the person contacted alone could account for the observed degree of referrer-referral gender homophily. If gendered attraction to the job alone is leading to a spurious correlation between the gender of referrers and referrals, then gender homophily should also be observed when we randomly match referrers and referrals, and when referrers are randomly paired with *non-referrals*. The simulated data never met or exceeded the observed levels of gender homophily in 1,000 random pairings of each type (i.e., referrer-referral, and referrer-non-referral). Gendered attraction to the job alone cannot account for this result: the link between specific referrers and referrals needs to be maintained in order to reproduce the observed level of gender homophily.

[9] We only have data on who is interviewed by the hiring managers, who is offered the job (no one is ever offered a job without being interviewed by a hiring manager), and who accepts the job offer. Moreover, we have only limited information on the characteristics of the specific people involved in screening. We know that decisions on who should be brought in for an interview with hiring managers are based on a screen of the paper applications, and a brief interview, either in person or by telephone. This stage of the process is handled by one woman. Applicants who survive this phase of the screening are then sent on for another interview with two hiring managers, who have the final say about extending the candidate a job offer. We cannot identify which particular managers performed these interviews, although we know that they are a mixed gender group.

percent). Although we have not controlled for any background factors on which men and women might differ, this suggests that the screeners—and especially the hiring managers—are choosing women over men.

One possible explanation for this pattern of findings is that, for a variety of reasons, employers have a preference for hiring referrals (e.g., Mencken and Winfield 1999; Miller and Rosenbaum 1997; for a concise review, see Fernandez et al. 2000:1290-1298), who in this setting, are more likely to be females. Indeed, such an explanation is plausible: the percentage of referrals increases with each step in the process from 36.0 percent of applications, to 38.3 percent of interviewees, to 45.3 percent of offers, to 45.7 percent of hires.

The differential gender composition of the referral and non-referral pools, however, does not explain the tendency for females to progress in greater proportion through the screening steps. Table 5 shows that, except for the slight decline in female representation for internals (73.7 vs. 74.2) at the interview step, the female composition of candidates increases at each stage even *within* categories of recruitment source. When moving from the application to interview stage, these increases in the percentage female are modest (i.e., 1-3 percent). As we mentioned above (see note 9), the screening decisions for granting an interview are controlled by one woman. However, irrespective of recruitment source, a larger boost in the percentage female (5-9 percent) occurs at the next step of the process, where hiring managers extend job offers to interviewees. The vast majority of these offers are accepted, regardless of recruitment source (acceptance rates are 90 percent for referrals, 94 percent for non-referrals, and 100 percent for internal candidates). The gendering effect is again small (between 0-1 percent) at this last stage of the hiring process. This would seem to indicate that the men and women who have survived to this late phase of the recruitment process do not differ very much in their level of interest in the job, or the external options these job seekers might be considering. A suggestion of this latter point comes from the fact that the internal candidates, who are most likely to be limiting their job search to within the firm, accept 100 percent of the offers, regardless of gender.

A similar conclusion regarding gender differences in applicant's job alternatives or level of interest in the job is suggested by the limited data on applicant withdrawals at earlier stages in the hiring process.[10] The gender difference in

[10] In contrast to the situation with rejected job offers, there is some ambiguity about how to interpret withdrawn applications. Although we cannot be sure, we suspect that the majority of these withdrawals occurred when the screener called up the applicant to arrange an interview with the hiring manager. Screeners told us that it is very rare for applicants to call asking to have their names removed from consideration. The fact that *none* of the withdrawals were interviewed by hiring managers is also consistent with this scenario. If we are correct in our suspicion, then it is likely that there are many "undiscovered" withdrawals in the pool of people who the screener did not call up to offer an interview. This suggests that the pool of withdrawals does not simply reflect applicant's self-selected choices, but is biased by the actions of the screeners. Removing the small group of withdrawals (161) does not change any of the substantive results in Table 5: the corresponding percentages female are 64.8 percent for non-referrals, 69.6 percent for

the rate of application withdrawal prior to the offer stage is trivial (4.0 percent of females [116 cases] versus 3.8 percent of males [45 cases]) and not statistically reliable ($p < .156$; LR Chi-square 2.012, with 1 d.f.). *None* of the internal candidates withdraw from the application process.

The analyses to this point, however, do not adjust for any background factors on which men and women might differ, and that could form the basis of screeners' judgments. In order to control for such background factors, we developed a set of predictive models of the interview and job offer stages of the hiring process. Table 6 shows the means and standard deviations of the background variables for the interview and job offer analyses. As we discussed above, we coded the background information from the original application forms, making sure to include the criteria that the call center screeners look for when reviewing applications. In addition, we included a squared term for non-bank experience in order to capture decay in the value of work experience over time (see Mincer 1974). In preliminary analyses, we examined a number of specifications of the experience variables and found no evidence of diminishing returns to months of banking or customer service experience. Because the unit of analysis is the application (see above) and some people applied multiple times, we also coded a dummy variable to distinguish repeat applicants from first time applicants (1 for repeat applicants, and 0 otherwise). We also control for the state of the market in these analyses by including the number of job openings and the number of applications on the date the candidate applied. Finally, as we mentioned above (see note 3), 25 cases indicated they had been convicted of a breach of trust. None of these cases were ever interviewed or offered a job. Since it is impossible for these people to get hired at the company, we have deleted them from the predictive models.

In Table 7, we present predictive models of the interview stage of the hiring process. Model 1 shows that women are 6.2 percent more likely to be granted an interview than are men (see the marginal effect in column 3). Model 2 introduces the control variables into the model predicting interview. A number of these factors are significantly related to being granted an interview. Controlling the other factors, applicants with computer experience are more likely to be interviewed than applicants without such experience, while foreign language experience is negatively related to being interviewed. This latter effect could be due to screeners avoiding applicants with accents.

However, contrary to what we would expect in light of our interviews with screeners, overeducated applicants are *more* likely to be interviewed, although the effect is not statistically reliable. In preliminary analyses, we found that

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referrals, 74.2 for internals, and 67.0 percent overall. Because we have no way of identifying the "undiscovered" withdrawals, and the "discovered" withdrawals might be endogenous with respect to the interview decision, we have chosen to combine withdrawals and non-withdrawals in the analyses predicting interview (Table 7, and the selection stage of the offer model in Table 8). Here too, the results do not change if we exclude the withdrawals.

years of education is a positive and statistically significant predictor of being interviewed. Contrary to interviewer's stated concerns about overeducated candidates (see above), we could find no statistically reliable evidence of highly educated candidates being avoided by screeners. Nor does replacing the overeducation dummy variable with a continuous measure of education change the other substantive results. Applicants with more customer service experience and more non-bank experience are more likely to be interviewed than candidates without such experience. As predicted by human capital theory, the squared term on non-bank experience is negative indicating that screeners place less value on very high levels of labor market experience when making decisions about who to interview. Consistent with our expectations, applicants who are employed at the time of application, and candidates who have longer tenures on their last job are significantly more likely to be interviewed than unemployed applicants or people with shorter tenure on their last job. Screeners are less likely, however, to grant interviews to candidates with high wages on their last job. Entering the last wage variable as a continuous variable measured in dollars shows a significant negative effect on the chances of being interviewed. Here, too, the substantive results do not change if we substitute the continuous measure of wage for the high wage dummy variable. The state of the market also affects the propensity of the candidate to be interviewed. Although the number of applications received on the same day as the candidate applied is not a significant predictor of being interviewed, candidates applying when there are many openings are more likely to be interviewed.

For our purposes, the most important finding is that, even after controlling for this impressive array of background factors, the coefficient for gender is strong and statistically reliable in Model 2. After controls, women are 4.7 percent more likely to be interviewed than are males. This 4.7 percent figure is 76 percent of the 6.2 percent advantage that females enjoy before controls are added. Thus, only a small part of the preference that recruiters demonstrate for females is explained by the background factors in model 2.

Nor does recruitment source account for the advantage that females have in being granted interviews. Model 3 adds dummy variables distinguishing external referrals and internals from external non-referrals. Controlling other factors, referrals are 7 percent more likely to advance to the interview phase than are non-referrals. While substantial, the apparent preference that recruiters give to internals is more than double the referral advantage: internal candidates are 17.8 percent more likely to be granted interviews than external non-referrals. Although women are overrepresented among applicants from both these recruitment sources (see Table 6), the results of model 3 show that females are 4.6 percent more likely to advance to the interview stage even after controlling for recruitment source.[11]

Table 8 presents the models for the job offer stage. Since no one was ever hired without an interview, it is possible that selection bias may affect our estimates of the job offer stage model. For this reason, we control for selection bias using a bivariate probit model with selection, which is the appropriate statistical procedure when both the ultimate dependent variable (job offer) and the selection criterion (interview) are dichotomous (Fernandez and Weinberg 1997).[12]

Model 1 presents the results of a bivariate probit model which includes all the regressors from the interview stage (Table 7, Model 3) in the interview selection step, and just the dummy variable for gender in the equation predicting job offer. As would be expected, the results of the interview selection step are very similar to those in Table 7. The *rho* parameter—the correlation between the errors of the two stages—is statistically significant, indicating that there is evidence of selection bias. Even after controlling for the interview selection factors, however, the marginal effect for gender in the offer stage shows that females are 4.9 percent more likely to be offered a job than are males.

Model 2 adds a number of regressors to the offer stage of the model. Comparing the log likelihoods (c.f. Models 1 and 2) shows that adding these factors significantly improve the fit of the model ($p < .01$, LR $X^2 = 26.686$, with 12 d.f.). Also, the *rho* parameter is no longer significant. Most important for our purposes, however, females appear to be preferred over males, even after controlling for other factors on which hiring managers are screening (marginal effect 5.9 percent).

[11] We examined whether there were interactions between gender and recruitment source. We found no such interactions with respect to referrals: gender and referral effects worked in an additive fashion. With respect to internals, the story is more complicated. Adding gender x internal and gender x referral interaction terms to model 3 shows no significant effect for gender x referral, but a significant negative effect for gender x internal. In analysis not presented here, we found that this effect is not substantive and is entirely accounted for by the changing of the case base due to listwise deletion of missing cases (results available from the author).

[12] The hiring process at the phone center is organized in such a way as to make it very difficult to identify selection bias. To the extent that recruiters are successful in mimicking the behavior of the hiring managers, the recruiters' actions become indistinguishable from those of the hiring managers. In the limit, one can consider them *becoming* hiring managers. Indeed, recruiters were granted such hiring authority after our field period ended. Our main strategy for addressing the challenge of selection bias in this setting is to define instrumental variables for the analyses (see note 13 below). The net result of these analyses, however, is that our central findings are robust to whether or not we control for selection bias.

Model 3 adds dummy variables for recruitment source to the offer stage of the equation.[13] Here, too, *rho* is not significantly different from zero indicating little evidence of selection bias. The log-likelihoods (c.f. Models 2 and 3) show that adding these dummy variables improves the fit of the model over and above the other background factors ($p < .0001$, LR $X^2 = 58.850$, with 2 d.f.). The marginal effects for recruitment source show an interesting pattern. Hiring managers and HR recruiters express roughly similar degrees of preference for referrals over non-referrals. Recruiters show a 7.0 percent marginal effect for referrals at the interview stage, while the hiring managers' preference for referrals at the job offer step is 7.7 percent. The contrast between the recruiters' and the hiring managers' behavior with respect to internal candidates is huge, however. Controlling other factors, internals are 17.6 percent more likely than external non-referrals to be sent on for an interview with hiring managers. However, the marginal effect for internals at the job offer stage is more than double this rate: hiring managers are 37.2 percent more likely to extend job offers to internals than external non-referrals. None of these factors, however, explain the tendency for more females than males to advance through the hiring stages. Consistent with the descriptive analyses in Table 5, hiring managers' preference for females is over and above their bias in favor of referrals and internals: females are 4.2 percent more likely to be offered jobs than are males even after controlling applicant background factors and recruitment source. Here, too, we found no evidence of interactions between gender and recruitment source.

The final step of the hiring process is offer acceptance (see last column of Table 5). In contrast to the interview and offer decisions which are made by company personnel, the decision to accept or reject the offer is made by the candidate. The company has a policy of not negotiating wage offers for the CSR job. For all candidates, the wage being offered is a constant $8.25 per hour. Therefore, gender differences at this final stage are more likely to reflect candidates' feelings of fit for the job or other employment options than screeners' preferences for one gender over another.

Unfortunately, due to the small number of cases that have survived to this stage, we lack sufficient statistical power to reliably say anything about gender differences in offer acceptance rates. Overall, females show a higher acceptance rate of offers: 93.6 percent for females vs. 89.4 for males, but this difference is not statistically reliable ($p <$

[13] Note that we have excluded the application behavior variables (number of applications and number of job openings) from the offer stage of Models 2 and 3 in Table 8. In so doing, we are treating these variables as instruments—variables that, by assumption, affect the selection stage, but not the substantive stage. Without instruments, the bivariate probit model with selection is only weakly-identified off of the non-linearity of the selection effect. In this setting, this is tantamount to arguing that the recruiters worry about the state of the market when deciding who to interview, but that line managers have delegated concerns about the state of the market to the HR department when deciding job offers. Relaxing this assumption (analyses available from the author) does not change our central conclusions with respect to gender.

.170, LR X 2 = 1.887, with 1 d.f.). Looking within recruitment source, we find that, regardless of gender, 100 percent of the offers to internals (10 males and 39 females) were accepted. For external non-referrals, the gender difference in acceptance rates is only one percentage point (89.4 percent of males and 90.4 percent of females accept the job). The largest gender difference in the rate of offer acceptance is for the external referrals, where 95.2 percent of females and 88.9 percent of males accept offers. But this difference, too, is not statistically significant ($p < .182$, LR X 2 = 1.780, with 1 d.f.). The lack of significant gender differences also does not appear to be due to suppressor effects of other control variables. We estimated a series of predictive models of offer acceptance using various combinations of the variables listed in Table 6. Gender is never significant in any of these predictive models; for that matter, neither are any of the control variables. Thus, we are clearly at the limits of our data.

Discussion

Although we can never be certain that we have controlled for all the relevant gender differences in background factors, the analyses in the previous section suggest that in this setting recruiters' and hiring managers' preferences—perhaps unconscious—significantly contribute to the gendering of the CSR job. In this respect, the latter findings are consistent with statistical discrimination mechanisms (e.g., Phelps 1972; Aigner and Cain 1977). In the absence of cheaply available information about the quality of the person being screened, statistically discriminating employers treat each applicant like the average applicant from their gender group. While we think this process may well be going on, it is also possible that these screening decisions may reflect gender differences in CSR performance.

While exceptionally accurate and objective performance measures are kept for CSRs at the phone center,[14] there is no evidence of significant male-female differences in the key performance measures used at the phone center (Castilla 2004). While the small number of cases (N=290) for whom these various measures are available for study might be hindering this assessment, there is no reliable evidence of gender differences in the performance measures they collect in these analyses. Castilla (2004) reports analyses of both raw and quality adjusted handletime and turnover. He presents numerous models predicting various aspects of performance, including initial performance after the two-month

[14] CSRs receive up to 5,000 customer inquiries from incoming phone calls per month, and a computer system randomly routes these phone calls to the next available CSR. This latter feature of the system means that the difficulty of the inquiries has been randomized across CSRs. Supervisors often monitor employee's phone conversations in order to ensure that courtesy and accuracy goals are being met. In addition, the computer system automatically records extensive information on each CSR's "handletime," i.e., how much time a CSR takes to complete each phone call. Conditional on a sufficient level of accuracy and courtesy, in this setting, employees who can get off the phone more quickly (i.e., have lower average handletimes) are more productive than CSRs who dispatch customers more slowly. This is because the longer the handletime, the fewer calls the CSR is available to receive, the more staff is required to handle a given volume of phone calls, and the more time customers will be made to wait on hold. For more detail about the performance measurement system at the phone center, see Castilla (2004).

training period, initial performance controlling for selection, turnover during training, post-training turnover, performance growth, and performance growth controlling for selection due to turnover. Gender is never significant in any of these models. The insignificant differences that do appear (e.g., 0.5 calls per hour against a mean of 20 calls per hour) virtually always favor males over females. At least by these relatively objective criteria, we cannot explain the preference that screeners in this setting show for females by a simple appeal to females' performance advantages in this job.

We explicitly asked HR screeners and hiring managers whether men or women are better suited to the CSR job. Although their responses might be constrained by desirability bias, they all claimed that both men and women do equally good jobs as CSRs. These people would often provide anecdotal examples of good male and female CSRs. We pointed out that there were a lot of women employed as CSRs; the supervisor of the screeners responded that she had noticed that, and she hoped that we would be able to shed some light on why this is the case.

Although we can only speculate, our fieldwork in the call center has led us to think that the observed preference for females that we have documented might have its roots in subtle processes of the gender encoding of what screeners think of as good job performance for customer service interactions (for a review of the role of gender in service delivery, see Gutek et al. 1999). When we asked the call center managers who they considered ideal performers on the job, they suggested that we monitor the phone calls of "two of their best CSRs," who they described as "both excellent, but for different reasons." With the workers' permission, we listened in on a number of calls handled by each of them.

These workers—one male and one female—had dramatically contrasting styles of interaction on the phone. While both workers spoke very clearly and succinctly, the male CSR spoke very quickly. Although he was polite in his interactions (e.g., not interrupting the customer as they spoke), his quick, focused responses left the impression that he was a very busy person, and did not have time to waste. At least in our reading of these interactions, while this CSR did not go to the point of seeming impatient with customers, he was definitely leaning in that direction. Customers appeared to pick up on these cues, and seemed to speak more quickly themselves over the course of their phone calls. The net result appeared to us to be a series of clear, efficient, but somewhat curt interactions.

In contrast, the female CSR spoke much more slowly, and we did not sense the customer speeding up as her calls progressed. She spoke distinctly, and precisely, but was relatively leisurely in her style. Customers seemed to sense her as a warm person, and would often open ancillary lines of discussion that were not immediately relevant to the topic at hand. In a particularly dramatic example of this, one female customer who had recently been widowed and was calling to clear up questions about her husband's financial affairs, began confiding her feelings of despair and loneliness to the female CSR. Her reaction to this customer was to be kind and gentle in her tone of speaking. She went further to encourage the customer to place her faith in God, that He would help her through this trying time.

The call center managers were certainly aware of this dramatic contrast in styles, and indeed, were ambivalent about which was the superior style between them. They said that the ideal CSR was a combination of these two, but they recognized that they were probably impossible to combine. They described the male CSR as having an excellent handletime, while still meeting or exceeding the phone center's customer courtesy and accuracy goals. While the managers were concerned that the female CSR's handletime was not as fast as they would like, they praised her for being someone who could foster customer loyalty, even within the difficult limits of a fleeting call center interaction. The managers saw that the emotional work that the female CSR was doing was a key part of customer courtesy, and that was likely to take time. In contrast, the "on-the-edge-of-impatient" style of the male CSR might run the risk of seeming officious to customers. We think that managers are correct in this interpretation: we do not imagine that the same widow, who felt so comfortable with the female CSR, would even be tempted to open up to the male CSR in the same way.[15]

As much research has shown (Hochschild 1983; Leidner 1991, 1993), the contrast in the emotional work between the two styles typified by these two CSRs evoke sex-role stereotypes that spillover from domains other than work. Another factor that would serve to invite such spillovers is that there is considerable uncertainty with respect to how to screen for these workers. Indeed, the screeners freely admitted to us that they found it quite difficult to discern who is likely to be a good CSR. Much research shows that in the face of uncertainty, stereotypes become more salient in decisionmaking (e.g., Fiske and Taylor 1991; Hilton and von Hippel 1996). The screeners at the firm seem unlikely to be immune to the gender stereotype of the "nurturing" female (see Glick and Fiske [2001] on benevolent sexism). The fact that the interviewing process seems to produce the largest boost in the percentage of women is consistent with the idea that it is the interaction with the candidate that seems to activate the stereotypical conception of gender (Correll 2001; 2004; Ridgeway 1997). If we are correct in these speculations, then it is not simple coincidence that the CSRs we

[15] In this setting, the entry-level CSRs we have studied are exclusively assigned to inbound calls, and cannot dial phone calls out. Consequently, they have no way of reestablishing a contact with a specific client. Nor do customers have any way of asking to be served by a specific CSR. In Gutek et al.'s (2000) useful terms, these features of the technology make these customer service interactions much closer to "encounters" than "relationships." Seen in this light, the male CSR's style is much closer to an encounter, while the female CSR stretches toward the relationship end of the continuum (in Gutek et al. [2000] vocabulary, a "pseudo-relationship") despite the strictures of the technology.

were directed to monitor as exemplars of the two ways of being excellent CSRs were of different genders. While they may feel genuinely ambivalent about choosing between the efficient ("male") and supportive ("female") styles, our findings suggest that, on the ground, they may in fact be shading their choices toward the more supportive definition of CSR performance. If this interpretation is right, then screeners would have to be deemphasizing the importance of handletime "efficiency" at the margin as they screen candidates. Although the differences are never statistically significant, the fact that the handletime performance measures were generally better for males, is consistent with the idea that the handletime constraint might be being relaxed for females during screening. In so doing, they would be giving the benefit of the doubt to female candidates, who they view as more likely to deliver on the more difficult to measure dimension of performance. With these actions, they have subtly, and probably unwittingly, contributed to the gendering of the CSR job in this setting.

Screeners' behavior after application cannot account for why the application pool is two-thirds female at the beginning of the hiring pipeline, however. As we discussed above, the call center's policy of paying relatively low wages is likely to be part of the explanation. But it is also possible that screeners' gender stereotypes about job roles extends to the stage of initial contact with the company (see Fernandez and Mors 2005). The human resources screener says that she does steer people to apply to jobs which she thinks they would be best suited for and most interested in during pre-application inquiries. However, she denies using gender as the basis for such suggestions. To the extent that such steering is along gender stereotypical lines, this would manifest itself in more women than men applying for CSR jobs. Although we are limited in our ability to address this issue in this setting (Fernandez and Mors 2005), we have been able to locate data which speak to this issue in another firm's call center, located in a different state.

Between April, 1996 and December, 1998, 8,323 applications were filed by job seekers at this second call center. In contrast to the call center that has been the focus of our study, this firm screens for fit with the company overall via an automated phone system, irrespective of the job in which the person might be interested. In addition to a battery of test items designed to measure fit with the company, all applicants to the call center are then presented with a short description of jobs "…that might be of interest to you in the future," and asked to rate their level of interest in these jobs on a 5 point Likert scale. The ratings range from a low of 1 "really not interested" to 5 "it is a job you really want and have the ability to do it at excellence." Because the wording of the 5 category confounds interest in the job with perceived ability to do the job, we will not calculate means on these items, but will focus instead in the gender distributions of those choosing 1 and those choosing 5 separately.

These data also allow us to measure the gender distribution of people who are choosing or avoiding jobs, even if they were looking to apply to some other job, prior to any opportunity to be steered by the human resources department personnel. Also important for our purposes is the fact that Customer Service Representative was included among the job titles. The exact wording of the job description for the "customer service representative" was: "Finding out what customers need and providing services that lead to a high level of satisfaction. Answering complaints when necessary." Since people in this setting are free to express interest in a number of gendered job titles—we will focus particularly on receptionist and computer programmer—these data can also be used to explore gender stereotypes operating among applicants on the supply side of the labor market.

Fifty five percent of the applications to the company overall were from females. The representation of women among the pool of people very interested in the receptionist job is 20 points higher: women comprise 75 percent of those saying "5" to the receptionist job. In contrast, females are underrepresented by 30 points among those who are avoiding the receptionist job: females constitute 25 percent of those who code the reception job a "1." Considering the computer programmer job, while females are 55 percent of the applicants to the firm overall, women represent only 40 percent of those who choose a "5" for the computer programmer job. But women are found in overabundance among those avoiding the computer programmer job: women are 65 percent of those giving the computer programmer job a "1." The results for customer service representative are intermediate between these two extremes. Women are underrepresented by 4 points among those choosing 1: while women are 55 percent of those applying to the company overall, females are 51 percent of those responding that they "really are not interested" in the CSR job. Women's representation in the group of people who are choosing a 5 for customer service representative is 60 percent, a 5 point boost over the female composition in the pool of applicants for the company overall.

The gender distributions of the choices being given by applicants to this call center align starkly for the two most clearly gendered job titles. At least in this setting, the customer service representative job title is not as stereotypically female in the minds of the applicants as is the receptionist job. Of course, in line with our analyses of the gender biasing effects of the open labor market above, these patterns of choice and avoidance are probably affected by applicants' expectations that computer programmer is likely to pay more than the other two jobs. Here, too, some part of the gender differences in these patterns reflect extant gender inequality in the local labor market.

However, pre-application steering by firm recruiters is not available as an explanation for these patterns in this setting. Even in the absence of steering, men and women show different levels of interest in the customer service representative job title. Although we cannot similarly remove the influence of pre-application steering in the focal call center, the findings from the alternative site suggest that steering is not required to produce gender biasing in the application pool. This implies that there is likely to be some gendering even at the pre-application inquiry phase of the hiring process. This further suggests supply side gender differences in preferences for jobs—affected at least in part by extant gender inequalities in the labor market—cannot be eliminated as a contributing factor to the gendering of the CSR job.

Summary and Conclusions

The patterns we have documented here have several important implications for our understanding of the gender segregation of jobs. This work is unusual in its ability to distinguish among various gender segregating processes that are alleged to occur in the hiring pipeline. Starting with the pre-application phase, while we cannot rule out that gender differences in preferences may be playing some part in the skewed nature of the initial application pool, our analyses suggest that gender wage inequality in the open labor market is likely to be a contributing factor. The male distribution of applicants' past wages dominates the female distribution over virtually the entire range (Figure 1). The "adjusted pool" simulations (Figure 2) suggest that the firm's policy of offering a fixed wage of $8.25 per hour likely has the effect of attracting proportionately more women than men to apply.

We also found stark evidence that clearly supports arguments that pre-hire network processes add to the gender skewing of jobs. In these data, the pool of employee referral applicants is even more female than the pool of non-referrals. Examining the origins of these ties, we found that women are overrepresented among the potential initiators of referral ties (i.e., employees working at the call center), as well as the population originating referral applications to the CSR job. Moreover, we found clear evidence of gender homophily in the referring process: referrers of both genders tend to produce same sex referrals.

While these network factors certainly play a role in the gendering of the early phase of the recruitment process (specifically, the formation of the application pool), the network mechanisms cannot provide a complete explanation of the gendering of the CSR job. In order to complete the picture, we need to consider the behavior of the actors on the demand side of this market interface. We found that in making their screening decisions, screeners and hiring managers appeared to prefer internals and employee referrals, categories which were both composed of a higher proportion of women than external non-referrals. Even within categories of recruitment source, females seem to have been given the benefit of the doubt in screening decisions, resulting in a further skewing of the population of candidates toward females. Apparently, being a referral did not *substitute* for whatever advantages screeners were attributing to females in this setting: on the contrary, referral background and the screens *combined* additively, such that among hires, the highest percentage of females is found among referrals (81.4 percent). As a final point, although we can only speculate, our interviews with screeners suggest to us that managers at the company might have been enacting gendered notions of what makes for good customer service interactions when making these screening decisions.

As we see it, our study has important methodological implications for studies of gender based job segregation. While the literature on gender segregation of jobs often invokes gender sorting mechanisms that operate *pre*-hire, the data that are used to empirically examine these processes are almost always collected on *post*-hire populations. Consequently, it has been difficult to distinguish the various processes that may be at work in producing gender segregation. This lack of fit between theory and data make it dangerous to conclude anything about the presence or absence of pre-hire gender sorting mechanisms on the basis of post-hire data, which reflect the net effects of various pre-hire processes.

As an illustration, we offer Table 9, which is a cross-tabulation of the gender of referrers and referrals based solely on post-hire data. In sharp contrast to Table 3, where we saw ample evidence of one of the key network mechanisms that is cited as a source of gender segregation of jobs—gender homophily in the employee referral process—Table 9 shows *no evidence whatsoever* in support of gender homophily. Although gender homophily in the referral process has clearly contributed to the early stages of the process by which this job has become gender segregated, a research strategy which starts with hires (e.g., Leicht and Marx 1997; Mencken and Winfield 2000), would miss this fact in this setting. Since it is quite common for researchers to invoke gender homophily of job finding networks as an explanation for gender segregation, the comparison of Tables 3 and 9 should strike a cautionary note for researchers in this area.

We see this paper as contributing in significant ways to the conceptual grounding and clarification of the theoretical mechanisms at work in theories of job segregation by gender. The story we have told is necessarily multifaceted, and in this respect, bears some resemblance to the *dénouement* of the murder mystery novel *Murder on the Orient Express* where *all* the suspects did it. In this setting, we can say with assurance that all of the factors we examined—pre-application choices, pre-application gender homophily of networks, and screeners' actions—played a role in the gender segregation of the CSR job in this setting. Not only have we been able to isolate the processes, but close analyses of these very special data have yielded important insights on how these factors work across the many links in the hiring process. Especially in light of the complicated and overlapping nature of the predictions of theories of job segregation by gender, our ability to empirically distinguish among these mechanisms constitutes an important step forward for this literature. If we are to attain a deep understanding of the social processes that sort men and women into distinct jobs, we suggest that future research in this area needs to move beyond the post-hire, “black box” treatment of the core pre-hire processes that produce the gender segregation of jobs.

Finally, the results of our analyses suggest an important new direction for research on gender segregation. While this paper has identified and empirically documented the various separate mechanisms that contribute to the gender segregation of jobs, we have been careful not to apportion variation in gender segregation of the job with particular mechanisms. As pointed out by an anonymous reviewer, such a variance partitioning exercise holds much theoretical appeal. It is important to note, however, that the structure of the hiring pipeline suggests that the various mechanisms we have documented here potentially feed back on one another, vastly complicating any attempts at a linear partitioning of effects. Developing such a decomposition is a high priority for our future research. In pursuing this goal, we have opted for an agent-based simulation framework in order to do justice to potential feedbacks and non-linearities in the hiring pipeline (Rubineau and Fernandez 2005). In addition to identifying key leverage points in the system, agent-based models provide a way to decompose effects even in the presence of complex interdependencies. Moreover, the agent-based approach allows us to vary the empirical parameters of the processes that we observed in this setting. In this manner, we expect that the painstaking work of identifying the numerous gender sorting mechanisms documented here will pay dividends in furthering our understanding how the various mechanisms combine to produce job sex segregation in settings beyond the call center.

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Table 1. Gender Distribution of Applications by Recruitment Source

	Female	Male	Total N
External Non-Referral	65.0 %	35.0 %	2,578
External Referral	69.9 %	30.1 %	1,534
Internal	74.2 %	25.8 %	151
All Sources	67.1 %	32.9 %	4,263

Table 2. Means and Standard Deviations of Background Variables by Gender for External Non-Referral Applicants

	Female		**Male**		**Univariate F Tests**
	Mean	SD	Mean	SD	*p* <
Skills:					
Computer (1=Yes)	.786	.410	.786	.412	*ns*
Language (1=Yes)	.190	.392	.193	.395	*ns*
Overeducated (> 16 yrs)	.026	.160	.049	.215	.009
Experience:					
Bank exp (in years)	.216	1.338	.101	.781	.040
Nonbank exp. (in years)	5.053	4.438	6.162	5.707	.001
Cust. Serv. exp. (in years)	2.952	3.766	2.231	3.515	.001
No. of previous jobs	3.297	1.038	3.314	1.024	*ns*
Works at time of app.	.480	.500	.437	.496	*ns*
Tenure on last job (in years)	1.848	2.709	1.865	3.030	*ns*
High wages last job (> $8.25)	.217	.412	.370	.483	.001
Number of Cases:	1,262		678		
Multivariate Test of Gender Difference in Profiles:					
Wilks' Lambda = .935					
$F_{(10,\ 1929\ \text{d.f.})} = 13.327$					.001

NOTE: 2.3% of applications report never having had a job. Tenure on last job and last wage are coded zero for those who have never had a previous job. The results do not change if we exclude those who have never had a job.

Table 3. Gender Distribution of Referral Applicants By Gender of the Referrer, Compared With Gender Distribution Of Non-Referral Applicants.

		Gender of Applicants		
		Male	**Female**	Total
Referral Applicants	**Referrer Male**	43.7%	56.3%	N=375
	Referrer Female	24.9%	75.1%	N=1,056
External Non-Referral Applicants		35.0%	65.0%	N=2,578
All External Applicants		33.2%	66.8%	N=4,112

Table 4. Negative Binomial Regression Models Predicting the Count of All Referrals, Same Sex Referrals, and Different Sex Referrals Made by Company Employees (Z-values in parentheses)

	Count of Referrals		**Count of Same Sex Referrals**		**Count of Different Sex Referrals**	
	Coeff.	Marginal Effect[a]	Coeff.	Marginal Effect[a]	Coeff.	Marginal Effect[a]
Gender (1=Female)	.093	.027 (1.22)	.635	.101 *** (6.50)	-.703	-.086 *** (-5.32)
Employee Referral	.238	.083 * (2.33)	.265	.065 * (2.15)	.142	.013 (.94)
Ever Worked As a CSR	.282	.100 *** (4.12)	.339	.086 *** (4.10)	.129	.012 (1.23)
Tenure (in years)	-.045	-.014 *** (-4.03)	-.044	-.009 *** (-3.24)	-.053	-.004 ** (-2.98)
Annual Salary (in 1,000's $)	-.007	-.002 (-1.74)	-.006	-.001 (-1.02)	-.011	-.00009 (-1.85)
BA Degree	-.242	-.066 * (-2.38)	-.014	-.039 (-1.56)	-.266	-.020 (-1.77)
MA Degree	-.881	-.180 * (-2.51)	-1.780	-.178 *** (-4.44)	-.146	-.011 (-.25)
Age	-.013	-.004 *** (-3.38)	-.199	-.003 ** (-2.94)	-.011	-.0009 (-1.78)
Constant	-.493 ***		-1.416 ***		-1.416 ***	
LR Chi-square	160.93 with 8 d.f.		166.24 with 8 d.f.		93.81 with 8 d.f.	
p <	.00001		.00001		.00001	

Note: Number of cases = 4,051. Exposure is set to the length of time employed during the hiring window.

[a] Change in the conditional mean of the dependent variable associated with a unit change in the independent variable, evaluated at the means of tenure, salary, age, days of exposure, and for the modal categories of the other independent variables (i.e., females, not employee referrals, not CSRs, not BA, and not MA degrees).

*** = $p < .001$; ** = $p < .01$; * = $p < .05$

Table 5. Percent Female By Hiring Stage For Internals, External Referrals and External Non-Referrals (Number of cases in parentheses)

	Applications	Interviews	Offers	Hires
External Non-Referral	65.0 % (2,578)	67.6% (1,476)	72.7 % (172)	72.9 % (155)
External Referral	69.9 % (1,534)	71.2 % (989)	80.3 % (183)	81.4 % (172)
Internal	74.2 % (151)	73.7 % (114)	79.6 % (49)	79.6 % (49)
All Sources	67.1 % (4,263)	69.2 % (2,579)	77.0 % (404)	77.7 % (376)

Table 6. Means and Standard Deviations for Variables in the Interview and Job-Offer Models

	Interview Model		Job-Offer Model	
Independent Variables:	Mean	s.d.	Mean	s.d.
Gender (1=Female)	.671	.470	.693	.461
Repeat application (1=Yes)	.101	.302	.099	.299
Skills				
Computer	.784	.412	.813	.390
Language	.201	.401	.188	.391
Overeducated (> 16 yrs)	.029	.168	.032	.177
Experience				
Years of bank experience	.195	1.259	.239	1.391
Years of non-bank experience	5.474	5.190	5.851	5.121
Non-bank exp.-squared	56.895	216.776	60.448	131.975
Years of customer service	2.796	3.741	3.099	4.038
Number of previous jobs	3.277	1.054	3.292	1.068
Works at time of application	.536	0.499	.572	.495
Tenure in last Job (in years)	1.936	2.863	2.161	3.117
High wage on last job (> $8.25)	.247	.431	.250	.433
Application Behavior				
Number of applications	18.780	15.463	18.510	14.797
Number of job openings	19.164	10.986	21.125	11.851
Application Source				
External Referral	.354	.478	.379	.485
Internal	.032	.175	.148	.355
Dependent Variables				
Interviewed	0.624	0.484	--	--
Received job offer	--	--	0.148	0.355
Number of cases	3,134		1,955	

Table 7. Coefficients for the Probit Regression Predicting Job Interview for Customer Service Representative Job on Selected Independent Variables.

INDEPENDENT VARIABLES	Model 1			Model 2			Model 3		
	Coefficient	Marginal Effect [a]	Z-value	Coefficient	Marginal Effect [a]	Z-value	Coefficient	Marginal Effect [a]	Z-value
Constant	.207***			-.893***			-.985***		
Gender (1 = female)	.163	.062***	3.36	.135	.047**	2.57	.126	.046*	2.41
Repeat application (1= yes)				-.031	-.010	-.40	-.064	-.023	-.81
Skills:									
Computer				.292	.104***	4.94	.300	.112***	5.09
Language				-.132	-.046*	-2.20	-.137	-.050*	-2.27
Overeducated (> 16 yrs)				.165	.052	1.21	.185	.062	1.35
Experience:									
Bank experience				.036	.012	1.52	.030	.011	1.26
Nonbank experience				.046	.015***	3.55	.047	.017***	3.61
Nonbank experience squared				-.001	-.0005**	-2.98	-.001	-.0005**	-3.00
Customer service experience				.023	.008**	2.84	.023	.008**	2.81
No. of previous jobs				.007	.002	.28	.009	.003	.38
Works at time of application				.183	.064***	3.81	.141	.052**	2.93
Tenure on last job				.039	.013***	3.41	.037	.013***	3.23
High wage on last job (> $8.25)				-.155	-.054*	-2.49	-.140	-.051*	-2.25
Application behavior:									
No. of applications				.0003	.0001	.19	.0009	.0003	.56
No. of job openings				.028	.009***	11.53	.028	.010***	11.60
Application source:									
External referral applicant							.20	.070***	4.12
Internal applicant							.597	.173***	4.87
Log Likelihood		-2069.549			-1925.193			-1910.690	
Improvement LR X^2 (*df*)					288.71*** (14)			29.01*** (2)	

NOTE. No. of cases = 3,134; * $p < .05$; ** $p < .01$; *** $p < .001$, two-tailed test.

[a] Change in the conditional probability of being interviewed associated with a unit change in the independent variable, evaluated at the means of bank experience, nonbank experience, nonbank experience squared, customer service experience, number of previous jobs, tenure, number of applications, number of openings, and for the modal categories of the other independent variables (i.e., females, not a repeat applicant, with computer skills, no language skills, not overeducated, working at application, not high wage, not employee referrals, and not an internal).

Table 8. Coefficients for the Bivariate Probit Regression Model With Selection Predicting Job Offer for Customer Service Representative Job on Selected Independent Variables

Offer Model	Model 1			Model 2			Model 3		
	Coefficient	Marginal Effect [a]	Z-value	Coefficient	Marginal Effect [a]	Z-value	Coefficient	Marginal Effect [a]	Z-value
Constant	-.623***			-1.242***			-2.176***		
Gender (1 = female)	.142	.049*	2.04	.202	.059*	2.57	.261	.042**	3.27
Repeat application (1= yes)				-.103	-.031	-.88	-..213	-.035	-1.91
Skills:									
Computer				.033	.010	.34	.231	.038**	2.71
Language				-.056	-.017	-.60	-.106	-.019	-1.20
Overeducated (> 16 yrs)				.108	.035	.53	.215	.046	.98
Experience:									
Bank experience				-.010	-.003	-.39	-.020	-.004	-.73
Nonbank experience				.039	.012*	2.09	.059	.011**	3.19
Nonbank experience squared				-.001	-.0004	-1.92	-.002	-.0004**	-2.78
Customer service experience				.016	.005	1.61	.020	.004*	2.04
No. of previous jobs				-.060	-.019	-.170	-.049	-.009	-1.35
Works at time of application				.320	.090***	4.47	.303	.047***	3.77
Tenure on last job				.013	.004***	.90	.025	.005	1.76
High wage on last job (> $8.25)				-.053	-.016	-.59	-.056	-.010*	-.66
Application source:									
External referral applicant							.336	.077***	4.31
Internal applicant							1.181	.372***	6.24
Selection Model: Interview									
Constant	-.871***			-.969***			-.993***		
Gender (1 = female)	.121	.044*	2.33	.125	.046*	2.39	.126	.046*	2.41
Repeat application (1= yes)	-.091	-.033	-.1.21	-.069	-.025	-.87	-.067	-.024	-.85
Skills:									
Computer	.291	.109***	5.18	.301	.113***	5.11	.303	.114***	5.14
Language	-.139	-.051*	-2.44	-.137	-.050*	-2.27	-.136	-.049*	-2.25
Overeducated (> 16 yrs)	.214	.072	1.68	.191	.065	1.40	.179	.060	1.31
Experience:									
Bank experience	.033	.012	1.43	.032	.011	1.34	.026	.009	1.10
Nonbank experience	.052	.018***	4.34	.048	.017***	3.68	.047	.016**	3.50
Nonbank experience squared	-.002	-.0006***	-3.73	-.001	-.0005**	-3.07	-.001	-.0005**	-2.87

Table 8 (continued). Coefficients for the Bivariate Probit Regression Model With Selection Predicting Job Offer for Customer Service Representative Job on Selected Independent Variables

	Model 1			**Model 2**			**Model 3**		
Selection Equation: (Continued) Interview	Coefficient	Marginal Effect [a]	Z-value	Coefficient	Marginal Effect [a]	Z-value	Coefficient	Marginal Effect [a]	Z-value
Customer service experience	.026	.009**	3.42	.023	.008**	2.85	.022	.008**	2.74
No. of previous jobs	-.004	-.001	-.16	.010	.003	.40	.009	.003	.38
Works at time of application	.183	.068***	4.01	.137	.050**	2.83	.142	.052**	2.93
Tenure on last job	.037	.013**	3.42	.037	.013**	3.21	.037	.013**	3.22
High wage on last job (> $8.25)	-.124	-.045*	-2.12	-.135	-.049*	-2.17	-.138	-.050*	-2.22
Application behavior :									
No. of applications	-.0003	-.0001	-.23	.0005	.0002	.31	.001	.0005	.85
No. of job openings	.023	.008***	8.34	.027	.010***	10.42	.028	.010***	11.67
Application source:									
External referral applicant	.244	.081***	5.14	.226	.076***	4.39	.209	.070***	4.14
Internal applicant	.831	.221***	8.24	.705	.198***	5.54	.608	.176***	4.98
Rho		-.700**			-.291			.562	
Log Likelihood		-2711.642			-2698.299			-2668.874	
Improvement LR X^2 (*df*)					26.686** (12)			58.850*** (2)	
Number of cases Offer stage		1,955			1,955			1,955	
Number of cases Interview stage		3,134			3,134			3,134	

NOTE: * $p < .05$; ** $p < .01$; *** $p < .001$, two-tailed test.

[a] Change in the conditional probability of job offer associated with a unit change in the independent variable, evaluated at the means of bank experience, nonbank experience, nonbank experience squared, customer service experience, number of previous jobs, tenure, number of applications, number of openings, and for the modal categories of the other independent variables (i.e., females, not a repeat applicant, with computer skills, no language skills, not overeducated, working at application, not high wage, not employee referrals, and not an internal). For the selection equation, marginal effects refer to the probability of surviving selection.

Table 9. Gender Distribution of Referral Hires By Gender of the Referrer, Compared With Gender Distribution Of Non-Referral Hires

		Gender of Hires		
		Male	**Female**	Total
Referral Hires	**Referrer Male**	15.0%	85.0%	N=40
	Referrer Female	20.0%	80.0%	N=125
External Non-Referral Hires		27.1%	72.9%	N=155
All External Hires		22.7%	77.3%	N=327

Figure 1. Percentile Distribution of Non-Referral Applicants' Wages on Their Last Job By Gender

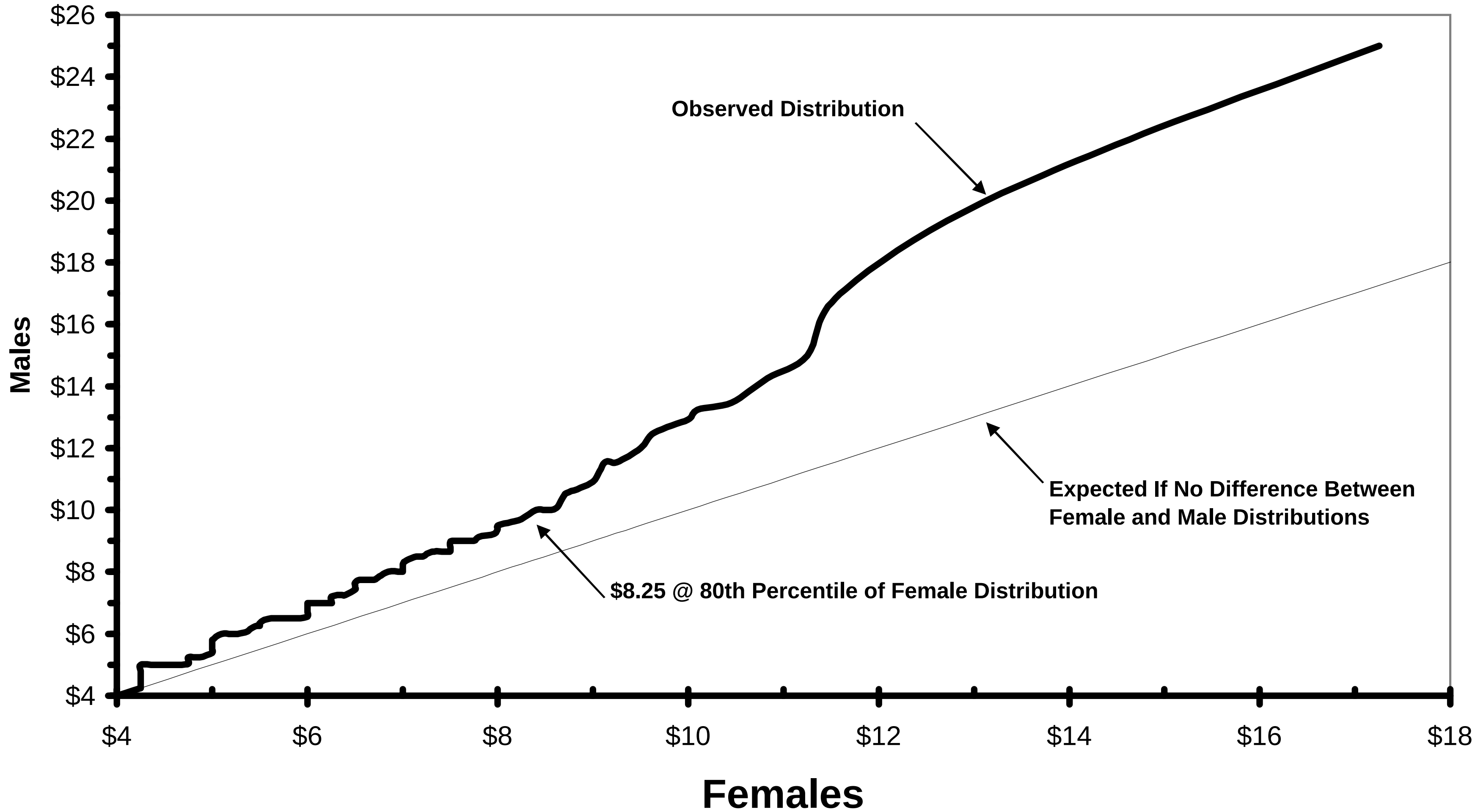

Figure 2. Percent Female in Local Labor Pools Adjusted by Hourly Wage