Gender and Race Sorting at the Application Interface

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Abstract

We document gender and race sorting of candidates into various jobs at the point of initial application to a company. At this step of the hiring process, the firm has implemented a policy whereby organizational screeners' discretion has been eliminated such that there is no opportunity for contact between hiring agents and applicants. Thus, the job choices studied here offer unique insight as they are uncontaminated by screeners' steering of candidates toward gender- or race-typed jobs. Even in the absence of steering, we find clear patterns of gendered job choices that line up with gender stereotypes of job roles. Moreover, these gendered patterns recur both within individuals and within race groups. Comparing our findings to the pattern of job sorting in the external local labor market, we find that supply-side factors do not fully account for the levels of race and gender segregation observed in the open labor market. Although probably not the entire story, it is clear that supply-side gender sorting processes cannot be ruled out as important factors contributing to job sex segregation.

Much recent scholarship has been devoted to documenting the patterns and trends of gender and race job segregation (Charles and Grusky 2004; Jacobs 1989; McCall 2001; Tomaskovic-Devey 1993). This attention is justified because gender and race segregation of jobs has important consequences for inequality in wages. Many studies have shown that men earn more than women, and that whites earn more than minorities, even after controlling for human capital factors. These wage differences, however, are significantly diminished once men and women, or whites and minorities, doing the same job are compared (e.g., England et al. 1994; Petersen and Morgan 1995; Tomaskovic-Devey 1993). As a consequence, understanding the mechanisms that lead to gender and race differences in job assignment has become a top priority in current labor market research.

A key debate in the research on job segregation has been the degree to which gender and race sorting is attributable to demand side factors—e.g., employers' actions and attitudes (e.g., Fernandez and Sosa 2005; Graves 1999; Kaufman 2002; Kmec 2005; Moss and Tilly 2001; Mun 2010)—or reflects a feature of labor supply, e.g., the skills and preferences of individual job seekers (England 1982; Grodsky and Pager 2001; Neal and Johnson 1996; O'Neill 1990; Okamoto and England 1999; Polachek 1981; Tam 1997). This issue is of substantial practical importance, since the idea that demographic groups differ in their degree of interest in jobs has emerged as an employer's legal defense against charges of discrimination (Nelson and Bridges 1999; see the discussion of the controversial "lack of interest" defense in Schultz and Peterson 1992).

Complicating inferences in this area is that fact that virtually all empirical research on gender and race sorting begins by studying *people who are already sorted into jobs.* For the purposes of identifying the factors contributing to race and gender segregation of jobs, these studies select on the dependent variable (for a detailed discussion of the limitations of “start with hire” studies, see Fernandez and Weinberg 1997). While this research may *describe* the net result of supply- and demand-side gender and race sorting processes, without pre-hire baseline information, these studies cannot isolate the supply-side processes at work at the hiring interface. While studies of hiring beginning with the pool of applicants (Fernandez and Weinberg 1997; Fernandez et al. 2000; Petersen et al. 2000; Fernandez and Sosa 2005; Petersen et al. 2005; Fernandez and Fernandez-Mateo 2006) and hiring audit studies (e.g., Riach and Rich 1987; Cross et al. 1989, 1990; Turner et al. 1991; Pager 2003; Bertand and Mullianathan 2004; Pager et al. 2009) avoid the selection on the dependent variable problem, these studies focus specifically on demand-side discrimination and screening processes and do not address supply side sorting processes.

In this paper, we focus on supply-side gender and race sorting as it contributes to job segregation. Our strategy is to examine the point where labor supply intersects the demand side screening process for this firm, namely, at the point of application. More specifically, we analyze unique pre-hire data on the expressed level of interest that male and female candidates show in two gender-typed jobs, the stereotypically female Receptionist job, and the stereotypically male Computer Programmer job. In addition, we examine how these gendered patterns of job choice differ by race (Browne and Misra 2003). Research on the demand-side origins of job segregation focuses on the gender or race biases of organizational screeners (e.g., Fernandez and Sosa 2005; Foschi and Valenzuela 2008; Glick et al. 1988; Steinpreis et al. 1999). Especially when examining job segregation for people who have already been hired (e.g., Kaufman 2002; Kmec 2005), the effects of such demand-side processes are confounded with supply-side factors. By assessing whether job choices are gendered *prior* to demand-side screening processes—i.e., at the point of initial application—we are able to isolate the role of supply-side factors in producing job segregation. While there is evidence that firms' hiring agents can influence the application process, sometimes steering job candidates from disfavored groups away from high status, higher paying jobs to lower status jobs (Pager and Western 2005; Pager et al. 2009; Turner et al. 1991; Fernandez and Mors 2008), in this setting, organizational screeners have no opportunity to steer candidates (see below). For this reason, we can be assured that candidates' job choices are uncontaminated by the actions of screeners. By instituting organizational procedures that limit screeners' discretion at this step of the process, the firm has enacted the suggestions of a number of scholars seeking to improve labor market outcomes for women and minorities (e.g., Bielby 2000; Nelson and Bridges 1999; Reskin and McBrier 2000). Thus, the special circumstances of this case serve as a fertile ground for studying the degree of job sex segregation when screeners' discretion has been significantly curtailed.

We begin by analyzing candidates' expressed job preferences at application, and show how candidates' ratings of jobs differ by gender. We find important gender differences in the ratings of gender typed jobs in the initial application pool. Although we find clear patterns of gender preferences, we find few race interactions with gender, i.e., the gender patterns of ratings are similarly ordered across race groups. In addition, we show that these gender and race patterns in job ratings do not simply reflect heterogeneity among candidates interested in different jobs, but recur within individuals as well. Moreover, these results are robust to some obvious alternative explanations for the observed job ratings (e.g., degree of urgency in finding a job, self-assessed skills). Even among the subset of applicants who self-report high interest in the stereotypically male Computer Programming job, females still rate the stereotypically female Receptionist job higher than do males. Also, among those applicants who rate the stereotypically female Receptionist job highly, males rate the stereotypically male Computer Programmer job more highly than do females. We also show that gender and race difference in wages in the external labor market, which might make these two jobs differentially attractive to men and women, are unlikely to explain the observed results. Finally, we compare our findings to the pattern of job sorting found in the external local labor market. While individual preferences play a significant role in the gender and race segregation of jobs, these cannot fully account for the levels of race and gender segregation observed in the open labor market. We conclude with a discussion of implications of these findings.

Data and Setting

The data analyzed here are taken from the records of applications to a call center located in the Western United States. A key feature of this study is that candidates for all jobs are required to apply to the company via telephone through a computer automated application system. Advertisements for job openings contain no street address or e-mail information; thus people cannot send resumes or other job inquiries directly to the company. Candidates for all job openings are directed to apply via the telephone. Similar to Yakubovich and Lup’s (2006) Internet-based recruitment setting, these highly formalized procedures mirror the suggestions of a number of scholars (e.g., Bielby 2000; Nelson and Bridges 1999; Reskin and McBrier 2000) about the diversity enhancing benefits of limiting screeners’ discretion. In this case, there is no opportunity for applicants to be steered to different jobs by company personnel during the application process. This is especially important in light of the Pager et al. (2009) study which showed that steering of minorities applying to low-wage jobs is commonplace. In contrast to Pager’s et al. (2009) and other settings (e.g., Fernandez and Mors 2008), in this context, the job choices that applicants express during the application process assuredly reflect the candidate's interest in the job at the point of application.

The company shared with us their data on their complete applicant pool for all jobs at the call center over the 13 month period from December, 1997 through December, 1998. These data are subject to two constraints, however. First, applicants may apply only once in a 12 month period (application data is kept in a database for consideration for job openings for 12 months). Early in the telephone application process, candidates are asked to provide their social security number as identifying information.[1] If an applicant is found to have applied during the previous 12 months, the telephone interview is terminated.[2] Consistent with this policy, we found no repeat applicants over the period we studied. Second, candidates are also asked to commit to work at least 15 hours per week and to stay with the company for at least six months. The telephone interview is also terminated for candidates responding negatively to this prompt. For these terminated interviews, only the identifying information used to screen for multiple application attempts is retained. A total of 5,315 people made it past these two screening criteria and successfully applied to the call center over the period of the study.

Important for the goals of this research, applicants are also asked to respond to optional questions on demographic background: gender, race, and age (i.e., less than 40 years of age vs. 40 and older). While it is common to have data on demographic background for people who have been hired, it is quite rare to have this information on applicants (see discussion in Fernandez and Fernandez-Mateo 2006). The prompt for these items was: "We need to ask this information in order to comply with Federal law, and to ensure that our process does not have any

[1] The company did not share applicants' social security numbers. The dataset we were provided replaced the social security number with an internal code.
[2] Note that names are *not* asked and the social security number is the *only* identifying information that applicants are asked to provide at the application stage. Thus, as we discuss below, unless they voluntarily choose to divulge this information, the company's screeners are blind to the applicants' gender and race.

discriminatory impact. The … questions are optional and you are free to choose not to respond…”. Although voluntary, applicants provided responses to the gender, race and age items at very high rates (respectively, 99.4, 94.6, and 95.1 percent).

Also key for our purposes here, irrespective of whichever job might have induced the candidate to apply to the company, applicants are presented with a series of short descriptions of 16 jobs “that might be of interest to you” and asked to rate them on a 1-5 scale, where 1 = “Really not interested” and 5 = “Strong desire and the ability to do this job.”[3] Although it would be of theoretical interest to separate interest and ability (see the discussion of Correll [2001, 2004] below), applicants here are being asked to self-assess their levels of both for these jobs. The company does not screen on the responses to these questions, and there is nothing preventing people from rating all 16 jobs a 5, although only 2.8 percent (145 of 5,315) did so. There is, of course, wide variation in the levels of expressed interest across the 16 jobs. *All* applicants for *all* jobs are asked to perform these ratings, and at no prior time in the interview were the applicants asked to identify which job led them to apply to the company. Thus, these questions allow applicants to reveal their level of interest in these jobs, irrespective of which job applicants might be pursuing.

Two of these jobs are of particular interest for this paper: the stereotypically-male Computer Programmer job (described in the telephone interview as a job to “…create customized computer applications for a specific client”), and the stereotypically-female Receptionist job (described in the telephone interview as a job to “answer incoming phone calls…”). Indeed, both these jobs are highly sex-skewed in the PUMS data for the local labor

[3] For completeness: 2 = “You think you could do this job, even if it is sometimes boring”, 3 = “Not sure, but you think you could do this job for a while”, 4 = “…could do the job well, and it would be ok.”

market:[4] males constitute 72.4 percent of the Computer Programmers in the local area, while females are 93.8 percent of the local area Receptionists. Focusing on these two jobs allows us to examine job ratings for males and females for both gender typical (i.e., females rating the Receptionist job, and males rating the Computer Programming job) and gender atypical jobs (i.e., females rating the Computer Programmer job, and males rating the Receptionist job). As noted above, since these ratings are occurring in a context where steering by hiring agents is not possible, these analyses offer unique insight into the gendered nature of applicants' job choices for different race groups.[5]

The most popular job—i.e., the one with the highest percentage of '5' ratings—is the Telephone Interviewer job. Sixty three percent (3,309 of 5,252 non-missing cases) of the people who applied to the company during the 13 month study window rated the Telephone Interviewer job a '5'. In contrast to the Computer Programmer and Receptionist jobs, applicants for the Telephone Interviewer job are not significantly gender skewed: females 51.1 constitute percent of those rating the Telephone Interviewer job a '5'. Because it is attracting the modal applicant to the company, we will use the Telephone Interviewer job as a baseline of comparison in descriptive analyses assessing how individuals rate other jobs (see Tables 3 and 4 below).

[4] We obtained data on persons employed in the local MSA in the 5 percent 2000 Public Use Micro Sample (PUMS; Ruggles et al. 2009). The specific six digit occupation codes used are: Receptionist = 434171, and Computer Programmer = 151021).

[5] For several reasons, we limit our study to examining the gender and race composition of these two jobs. First, our strategy in this paper is to study jobs that are gender stereotyped, and these two job titles are the most clearly gender typed from among the sixteen job titles. Also, a number of the 16 titles are idiosyncratic to the firm, so their use would make it difficult to preserve the firm's confidentiality. However, we will use information on all sixteen jobs in an aggregated form to construct control variables (see below). Finally, because we will compare the gender and race composition of the applicant pool to information gleaned from the local labor, we have focused on jobs that facilitate such comparisons. For example, although it is a fairly generic job title, we have eliminated the job "Project Manager" ("Internal project coordination to ensure proper data collection…") because it is sufficiently vague that it does not generate a clear match in the PUMS. In contrast, the job titles we focus on here have clear matches to six digit occupation codes in the PUMS (see note 4).

In light of our decision to study this one setting, we can make no claims regarding generalizability. 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. Our main goal in adopting this empirically grounded, case-study approach is to gain insight into gender and race differences in job choices, a task which is normally very difficult due to the fact that it operates in the pre-hire phase of the recruitment process. Especially since these applications are occurring in a context where choices are uncontaminated by the actions of Human Resources personnel, the unique, fine-grained data we analyze here are exceptionally well suited to addressing these important questions.

Analysis

Table 1 shows the race distribution of all applicants to the call center over the 13 month study window by gender. Unlike many other call center settings (e.g., Fernandez et al. 2000; Fernandez and Mors 2008), the applicant pool for this call center is not highly feminized. The overall pool of applicants to the firm shows a slight skew toward males (52.0 percent); the left panel of the table shows that the race distribution within gender is quite similar. A slight majority of both males and females are non-Hispanic white (respectively, 51.3 and 51.8 percent). This is slightly less than the percentage white in the local area labor force (cf. the right panel of Table 1). For both sexes, African Americans are overrepresented, and Hispanics are underrepresented in the applicant pool as compared to the local labor force.

We explored whether these disparities between the applicant pool and the metro area labor force could be due to geographic differences in where various race groups live. We do not have addresses for the applicants, but we can get a sense of geographic patterns by varying the size of the catchment area around the call center. We used census block data from the Summary

Files 1 (i.e., SF1 files) of the 2000 census to define catchments areas of sizes varying from 1 to 25 kilometers (Table 2). We included data in the area if the geographic centroid of the census block fell within the distance specified.[6] Table 2 shows that the area immediately surrounding the company is clearly a majority white area: the population of the area within one km or less from the firm is 70.5 percent white. The overrepresentation of African Americans among the applicants cannot be explained by the racial distribution of the population at different distances from the firm. Whereas African Americans are 7.3 percent of the applicant pool, they are only 2.8 percent of those living in a distance of 1 km or less from the firm. The percentage of African American living in the catchment area decreases even further at longer distances. Thus, African Americans appear to be drawn to apply to this company at somewhat higher rates than one would expect on the basis of their representation in the local population. Although on occasion the numbers diverge slightly, the percentage of Asians roughly matches their proportion of the applicant pool. The same cannot be said for Hispanics, however. Except when compared to the 1 kilometer catchment area, Hispanics are clearly underrepresented in the applicant pool. Without other controls, we can only speculate as to why this should be the case.[7]

Table 3 shows the data for applicant ratings of the baseline Telephone Interviewer job, and the two focal jobs, i.e., Receptionist and Computer Programmer. Looking first at the total population (i.e., without regard to race), applicants of both sexes show the highest degree of interest in the Telephone Interviewer job (mean scores of 4.40 on the 5 point scale for both males

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[6] By using the centroid of the census block, some people will live farther than the stated distance. However, it is important to realize that the areas being aggregated are quite small (the median area for census blocks in this region is .011 square miles; the 90^{th} percentile is .30 square miles), so this source of error is slight.
[7] The research assistant who did on-site fieldwork in the company did not get any sense of it being a racially unwelcoming place. Perhaps telephone work is less comfortable for the area's Hispanics, some of whom are recent immigrants. But the same could be said of the local Asian population, and they seem to be well represented in the application pool.

and females). We see the same pattern replicated within racial groups: within each race, the highest scores are for the Telephone Interviewer job, with no significant gender differences.

The ratings for the Receptionist and Computer Programmer jobs, however, show strong and significant gender differences in the expected directions: on average, males rate the Computer Programmer job higher than do females, and females rate the Receptionist job more highly than do males. Also noteworthy is the fact that these gender patterns in job ratings recur *within* racial groups. The only exception to this pattern are the relatively small numbers of Native American applicants, for whom the gender differences in ratings for the Computer Programmer job are not statistically reliable. At least with respect to ratings of these jobs, race does not appear to interact with gender.

The ratings in Table 3 are simple aggregations of responses across individuals to the three job ratings. Table 4 shows that these gendered patterns of job ratings are happening within individuals as well. The first column shows the sex distribution of respondents who rate the Computer Programmer job strictly lower than (first row), strictly equal to (second row), and strictly greater than (third row) the Receptionist job. Females constitute 61.8 percent of those rating the Computer Programmer job lower than the Receptionist job. In contrast, the group of applicants rating the Computer Programmer job higher than the Receptionist job is 25 percent female. The population of those giving the same rating to the Computer Programmer and Receptionist jobs is also skewed male (62.9 percent male).[8] This gender pattern is even more pronounced when the degree of difference between the two job ratings is taken into account: The population simultaneously giving the Computer Programmer the lowest rating (i.e., ‘1’) and the

[8] In analyses not reported here, this same pattern of gender skew is evident and statistically reliable within each racial group. We did find evidence of one significant race x sex interaction, however. Asian females are 55.6 percent of the population rating the Computer Programmer job lower than the Receptionist job, 6.5 percentage points lower than the 63.1 percent female for the other racial groups.

Receptionist the highest rating ('5') is 73.7 percent female, while the group of people giving the Computer Programmer job their highest rating ('5') and the Receptionist job their lowest rating ('1') is 21.1 percent male. Here, too, with the exception of Asian females,[9] these patterns recur within race.

The analyses presented in column 1 combine candidates who might be seeking to apply to a heterogeneous set of jobs. Subsequent columns in Table 4 report the results for more focused sets of candidates. The second column shows the pattern of gendered job choices for the modal applicant to the call center, i.e., those rating the Interviewer job a '5.' These results are virtually identical to those presented for the general population of applicants in column 1. Similarly, the gender pattern is even more skewed when the degree of difference between the two job ratings is analyzed. The population simultaneously giving the Computer Programmer the lowest rating (i.e., '1') and the Receptionist the highest rating ('5') is 71.4 percent female, while the group of people giving the Computer Programmer job their highest rating ('5') and the Receptionist job their lowest rating ('1') is 82.2 percent male. Asian females remain an exception here as well.[10]

One possible explanation for these patterns is that men and women self-sort into different types of jobs because they expect employers to discriminate against them in the screening stage.[11] While it is possible that this can account for some of the gender stereotypical sorting observed, it is unlikely to be the whole story. We address this issue in the analyses presented in next two columns of Table 4. These report the gender distributions for candidates who give

[9] Among Asians, females are 60.2 percent of the population simultaneously giving the Computer Programmer the lowest rating (i.e., '1') and the Receptionist the highest rating ('5'), compared with 76.0 percent female for the non-Asian population.

[10] Among those in column 2, Asian females are 52 percent of the population rating the Computer Programmer job lower than the Receptionist job, compared 63.4 percent female for the other racial groups. Among Asians, females are 59.0 percent of the population simultaneously giving the Computer Programmer the lowest rating (i.e., '1') and the Receptionist the highest rating ('5'), compared with 73.4 percent female for the non-Asian population.

[11] We would like to thank a reviewer for pointing this out.

ratings of ‘5’ to either the Computer Programmer (column 3) or the Receptionist (column 4) job. If in general females anticipate that they will be discriminated against in screening for the Computer Programmer job, then the females shown in third column of Table 4 have overcome these concerns and wish to be considered for the Computer Programmer job anyway. Females are the clear minority of these candidates (34.2 percent; last row of column 3). Similarly, if in general males anticipate that they will be discriminated against in screening for the Receptionist job, then the males shown in column 4 have nevertheless have gone ahead and signaled their highest level of interest in the Receptionist job.

The findings in the last two columns of Table 4 show that even when the candidate pool is narrowed to those who have expressed the highest level of interest in jobs that are atypical for their gender, the sex distribution based on job ratings of the gender stereotypical jobs align tightly with the gender stereotype. Males are 75.6 percent of the applicants who rate the Computer Programmer job a ‘5,’ and rate the Receptionist job lower than a ‘5’ (column 3). Females are prevalent (70.4 percent; see column 4) among the subset of applicants who give the Receptionist job the highest rating, but who also rank the Computer Programmer below Receptionist (i.e., they rate the Computer Programmer job less than a ‘5’).[12] Male and female applicants sort themselves in ways that line up with stereotypical notions of job roles, even when the candidate pool is narrowed to those who have reported the highest level of interest in jobs that are atypical for their gender.

Multivariate Analyses

[12] Consistent with the other findings in the other columns, the gender distributions are even more extreme amongst the population of applicants with a maximal difference between the ratings of the two jobs. The population of applicants who simultaneously rate the Computer Programmer a ‘5’ and the Receptionist a ‘1’ is 78.9 percent male; for applicants who rate the Receptionist job a ‘5’ and the Computer Programmer job a ‘1’ are 73.7 percent female.

Although it is clear from the analyses up to this point that male and female applicants of all races self-sort in ways that line up with stereotypical notions of job roles at the point of initial application, it is possible that these patterns might be due to other factors that also break down along gender lines. While we are limited by the available information, we are able to control for a number of the most important alternative explanations for these observed sex differences in patterns of applicants' ratings in multivariate analyses.

One obvious alternative explanation for these patterns concerns the outside options available to these applicants. To the degree that labor market options vary by race and sex in the local area, these differences in job options should affect the relative attractiveness of these jobs for applicants from different sex and race backgrounds. These outside options should also affect the degree of urgency these job seekers have in finding *any* job, and not just the jobs on which we focus here. Similarly, hedging in anticipation of discrimination in screening could lead applicants to give higher ratings across the board for all 16 jobs. In addition, individuals might vary in their propensity to rate all jobs highly, and if race and gender groups differ in this tendency, not controlling for this factor can affect the substantive results. In order to account for these factors, for each of the jobs we study, a key control that we measure is the applicant's average rating on the other 15 jobs.

Another variable that is likely to affect the extent to which applicants hold stereotypical gender role attitudes is age. In national data, younger cohorts show more liberal gender role attitudes than do older cohorts (Brooks and Bolzendahl 2004). While it is rare to have age information for job applicants, these candidates were asked during the telephone interview whether they were less than or greater 40 years of age. While this question was optional in the interview protocol, 95.1 percent of applicants responded to this question. We control for age differences in ratings by entering a dummy variable for age (1= greater than 40 vs. 0=40 or less) in the analyses.

There is much research showing that people are willing to travel farther for higher paying than lower paying jobs and that such willingness to travel often differs by gender (for a review, see Fernandez and Su 2004). While the jobs' wages are not mentioned in the automated screening protocol, it is reasonable for applicants to infer that the Receptionist job is likely to pay less than the Computer Programmer job. Indeed, estimates based on the 2000 PUMS data for the local labor market show that the average hourly wages for Receptionists are $13.13 while Computer Programmers' average wages are $30.99. Consequently, when considered in relation to these wage differences, spatial considerations might also influence applicants' ratings of the desirability of these jobs. To address this question, we measured distance between the applicant's home and the location of the call center. To capture non-linear patterns (e.g., diminishing returns), we also entered distance-squared between the applicant's home and the location of the call center in the multivariate analyses.[13]

It is also possible that gender-stereotypical job choices might be explained by personality traits that might differ by gender. All applicants are asked to respond to a series 45 Likert-style items designed to measure a proprietary version of the "Big Five" personality traits (Wiggins 1996). While there is some variation in the way these factors are labeled, the five factors are "agreeableness," "negative emotionality," "openness to experience," "extraversion," and "conscientiousness." Recent research has found that the "Big Five" personality traits are related to women's labor force participation (Wichert and Pohlmeier 2010) and the male-female

[13] Since the company did not ask applicants for their home addresses, we geocoded each applicant to the only spatial information we could glean for them: the centroid of the area defined by the area code + exchange (first three digits) of the applicant's telephone number. Mobile telephones, of course, weaken this spatial link, but this is unlikely to be important for the field period for this site, 1997-1998.

earnings gap (Mueller and Plug 2006; Braakmann 2009). Most relevant for our purposes here, men and women have been shown to differ on two of these factors—“agreeableness” and “negative emotionality”—across a variety of studies and samples (e.g., Chapman et al. 2007; Costa et al. 2001; Mueller and Plug 2006). We will use these data to address the degree to which patterns of gender-stereotypical job choices might be explained by gender differences in measured personality.[14]

A final possibility we consider is that sex differences in patterns of job choices reflect sex differences in prior skills. Although the company does not ask any questions about education or experience at this stage of the screening process,[15] the firm does ask all applicants irrespective of which of the 16 jobs that attracted them to apply to the firm about knowledge of specific computer software. Following the interview questions about jobs, applicants are told “[this organization] has a number of employment opportunities that require knowledge of specific software.” Applicants are then asked a general question on whether or not they have computer “knowledge and interest.” We coded a dummy variable 1 if the respondent said “yes” to this question, and 0 if the reply was “no.” This step is not significantly gendered: males constitute 53.5 percent of those answering affirmatively to this question, and this is quite close to the percent male in the overall applicant pool (i.e., 52.0 percent).

Applicants responding positively to the computer “knowledge and interest” question, were then asked to rate their knowledge of six specific software programs on a scale ranging

[14] We do not have access to the proprietary measurement formula that the company uses to score individuals on these 45 items. Our strategy then is to use the raw items as a set of controls in models predicting job choices as a way of assessing whether personality factors can explain gender patterns in job choices.

[15] They do inquire about these factors at the subsequent face to face interview step of the process. Unfortunately, the data we have for the subsequent steps are only for the people who were eventually hired into the Interviewer job. The gender distribution of hires for this job is 52.0 male and 48.0 percent female.

from 1 (“Beginner”) to 5 (“Expert”).[16] We constructed a spline for computer knowledge by taking the average rating across the six programs[17] for those responding “yes” to the “knowledge and interest” question, and 0 for those answering “no.” Thus, in the analyses below, the effect of computer knowledge is conditional on the respondent having expressed at least some computer “knowledge and interest.”

Table 5 shows means and standard deviations of the variables. The dependent variables are three different aspects of the ratings of the two gender stereotyped jobs, i.e., the Computer Programmer and Receptionist. In order to analyze the full range of these ratings, we analyze the raw (i.e., 1 – 5) scales for both the Computer Programmer and Receptionist ratings. In order to focus on those most interested in these jobs, we replicated the analyses predicting a dichotomized version of these variables coded 1 if the person rated the job a ‘5,’ and zero otherwise. Neither of these measures, however, capture individuals’ relative ranking of these two jobs. To address this issue, we standardized each individual’s ratings across all 16 jobs, producing variables that are within-individual z-scores (i.e., standard deviation units) for the Computer Programmer and Receptionist jobs.

The first and second columns of Table 5 show the means and standard deviations for all applicants, while the subsequent columns show the descriptive statistics for the subsets of applicants most interested in the Computer Programmer and Receptionist jobs, respectively (i.e., those applicants rating these jobs a ‘5’). The first two columns show that on average females rate the Computer Programmer job lower than do males (see the first row: 2.163 vs. 2.572). This is

[16] A reviewer asked for more information on the extent to which the computer programs are generic and in widespread use. We are limited in our ability to divulge the actual software titles. However, it is accurate to say that these titles are not in widespread use (e.g., none are Microsoft products), and that they operate as relatively low-level programming environments that might be used to build back-office call center applications. It is clear to us that these programs require considerable specialized training.

[17] In preliminary analyses, we also explored measures based on the average number of ratings of ‘5,’ of ‘4’ and ‘5,’ and ‘3,’ ‘4,’ and ‘5.’ These measures all yield the same substantive results as the average of the six ratings.

true within-person as well: the z-score for females is -.971 compared with -.687 for males. A similar result is seen when comparing the percentage rating the Computer Programmer a ‘5’: 9.6 percent of females 9.6 vs. 17.2 percent of males. Moreover, these patterns are hold for the subset of applicants rating the Receptionist job a ‘5’ (see rows 1-3 in columns 5 and 6).

The subsequent three rows show gender differences in the rating of the Receptionist job. Females rate this job higher than do males in absolute terms (3.800 vs. 2.971) and relative to the other jobs (z-scores of .297 vs. -.397). The percentage of females rating the Receptionist job ‘5’ is 47.5 percent, and this is considerably higher than the corresponding percentage for males, i.e., 24.1 percent. Here, too, this pattern of gender differences holds among those who rate the computer programmer a ‘5’.

Turning the multivariate analyses, we begin by analyzing the predictors of job ratings among all applicants (see Table 6). Model 1 shows the unstandardized coefficients from an OLS regression predicting applicants’ ratings of the Receptionist job using the 1 – 5 scale.[18] Consistent with the arguments discussed above, applicants who rate the other 15 jobs (i.e., excluding the Receptionist rating) highly are also likely to rate the Receptionist job highly. The magnitude of the effect is substantial: for a one point increase in the average ratings of the other jobs, the ratings of the Receptionist job increase by .856 points.

With respect to geographic distance, Model 1 shows positive linear and negative squared associations with distance measured by the natural-log of kilometers. The negative squared term, however, dominates the linear term so that the net relationship between distance and Receptionist job rating is negative above the 3rd percentile of the distance distribution (i.e., at 3 kilometers). As predicted, applicants’ ratings of the attractiveness of the low wage Receptionist job fall as

[18] We replicated Models 1 and 4 in Tables 6 and 7 using ordinal probit models. Those models yield substantively identical results to the simpler OLS regression models we present here.

distance increases. This effect is substantively small, however: the net effect of distance on the rating of the Receptionist job is -.06 points at the median (13 kms.), -.10 points at the 75th percentile (22 kms.), and -.13 points at the 90th percentile (32.0 kms.) of distance.[19]

Turning to the demographic variables, controlling other factors, applicants who are 40 years of age and older rate the Receptionist job .566 points lower on average than applicants under 40. The dummy variables for race show that net of other factors, Hispanics and Asians rate the Receptionist job more highly than do whites. Most important for our purposes here, females rate the Receptionist job significantly more highly than do males. While the addition of the 45 "Big Five" personality items tempers this relationship somewhat (without the 45 items, the gender effect is .950; cf. Model 1 in Table 6 with Model 1 in Appendix Table A1), the magnitude of the gender difference remains large even after controls: females rate the Receptionist job .863 points higher on average than do males.

Model 2 examines the within-person relative rankings for the Receptionist job. In contrast to the analyses of the raw scores in Model 1, which look at the absolute ratings, Model 2 shows that people who rate the other 15 jobs more highly, tend to rate the Receptionist job lower in relative terms. In this case, a one standard deviation unit increase in the average of the other 15 jobs is associated with a .163 standard deviation decrease in the relative rating of the Receptionist job. The other results follow the same pattern as in Model 1. Most noteworthy, however, females rate the Receptionist job .641 standard deviations higher than do males. At least among applicants to all positions, females show a higher preference than males for the Receptionist job gender both in absolute terms (Model 1) and relative to the other jobs (Model 2).

[19] In preliminary analyses, we found no evidence of significant interactions between distance and gender.

Model 3 replicates the analyses distinguishing applicants who are most interested in the Receptionist job (i.e., a rating of '5') from those rating the Receptionist job less than '5'.[20] Similar to the results in Model 1, the average rating of the other 15 jobs is strongly related to rating the Receptionist job a '5'. Compared to those with the average rating of the other 15 jobs, applicants with a one-point increase in the average rating of the other jobs are 2.7 times more likely to rate the Receptionist job a '5.' Applicants who are 40 years of age or older are about half as likely (odds ratio = .530) to rate the Receptionist job a '5' than are younger individuals. Black applicants are 1.3 times more likely to rate the Receptionist job a '5' than are white applicants. Consistent with Models 1 and 2, the effect for Hispanics are significantly more likely to rate the Receptionist job a '5.' However, in contrast with Models 1 and 2, the results for Asians are not statistically significant in Model 3. Most important for our purposes, however, there is a strong gender difference in the likelihood of rating the Receptionist highly: females are 3.9 times more likely to rate the Receptionist job a '5' than are males.

The rightmost panel of Table 6 replicates these analyses for the ratings of the Computer Programmer job. Like the models for the Receptionist ratings, older applicants rate the Computer Programmer job lower than younger applicants in both absolute (Model 4) and relative (Model 5) terms, and are less likely to rate the job a '5' (Model 6). Across all three models, the degree to which applicants rate the other 15 jobs highly is also strongly predictive of the applicant's Computer Programmer rating. Indeed, compared to those with the average rating of the other 15 jobs, applicants with a one-point increase in the average rating are 7.9 times more likely to rate the Computer Programmer job a '5.' Not surprisingly, the splines for computer skill are also associated with higher ratings of the Computer Programmer job. While the dummy variable for working knowledge of computer software is only statistically reliable in Model 4, the average of

[20] Combining scores of '4' and '5' yields very similar results.

the six items measuring knowledge of specific software programs is reliably associated with higher ratings of the Computer Programmer job. Most important, even after controlling for these other factors, female applicants rate the Computer Programmer job lower than do male applicants in both absolute (Model 4) and relative (Model 5) terms, and are less likely to rate the job a ‘5’ (Model 6). As was the case for the analyses of the Receptionist job, the addition of the 45 “Big Five” personality items only slightly tempers the relationship between gender and the ratings of the Computer Programmer job (cf. Models 4-6 in Table 6 with Models 4-6 in Appendix Table A1).

The analyses to this point show the job ratings for candidates who might be seeking a heterogeneous set of jobs. In Table 7, we sharpen the analyses to focus on the subset of applicants targeting the two stereotypically male and female jobs. The analyses presented in columns 1-3 show the results of models predicting the ratings of the Receptionist job among the subset of applicants who rated the Computer programmer job a ‘5.’ Overall, the results are broadly parallel to the corresponding analyses presented in Table 6. Of most interest, however, are the coefficients for gender. While the effects are somewhat tempered compared to those for the broader population of applicants in Table 6, even among candidates who are very interested in being considered for the Computer Programmer job, males tend to rate the Receptionist job lower than do females. This is true even after controlling the factors in the model, including self-assessed computer skills. Here, too, the addition of the 45 “Big Five” personality items does not explain the relationship between gender and the ratings of the Computer Programmer job (cf. Models 1-3 in Table 7 with Models 1-3 in Appendix Table A2). Apparently, male Computer Programmers are less interested in working as a Receptionist than are female Computer Programmers.

Models 4-6 present the results of parallel analyses predicting the ratings of the Computer Programmer job among the subset of applicants who rate the Receptionist job a '5'. As in Table 6, males rate the Computer Programmer job more highly than do females. This result is not affected by the inclusion or omission of the 45 "Big Five" personality items (cf., Model 4-6 in Table 7 with Models 4-6 in Appendix Table A2). Even after controlling the other factors in the models, and even when considering candidates who have expressed a strong interest in jobs that are counter to the stereotype for their gender, the results in Table 7 show that males' and females' job ratings continue to reflect the gender stereotype of the job.

Discussion

Taken together, these results are consistent with Cjeka and Eagly's (1999) findings that gender-stereotypic images of occupations correspond to the sex segregation of employment. But the question remains: why do male and female applicants sort themselves in ways consistent with gender stereotypical notions of job roles? One possibility is that pre-existing gender inequalities in the open labor market affect how men and women choose jobs. In particular, gender inequalities in wages make different jobs more or less attractive to men and women and thereby can affect the composition of firms' applicant pools (Fernandez and Sosa 2005; Grams and Schwab 1985). To the extent that males earn more than females in the open labor market, the pool of potential applicants who might be interested in low paying jobs will tend to be more female.[21] Since job-seekers usually try to avoid wage cuts when seeking new jobs, external gender wage inequality in the local labor market will make lower wage jobs relatively unattractive to male applicants.

[21] A similar argument can be made for racial inequality. As we mentioned above with reference to Tables 1 and 2, one reason that whites might be underrepresented at application could be due to the relatively low wages the firm is likely to pay.

While the jobs' wages are not mentioned in the automated screening protocol, as we mentioned above, the local labor market data show that the average hourly wages for Receptionists are $13.13 while Computer Programmers' average wages are $30.99. Thus, it is reasonable for applicants to the call center to infer that the Receptionist job is likely to pay less than the Computer Programmer job. Based on the 2000 PUMS data for the local area, men constitute 55.5 percent of those in the labor force with positive wages, and men earn a higher hourly wage than do women ($25.53 vs. $19.54). The $13.13 average hourly wage for Receptionists falls at the 48th percentile of the local area wage distribution for females, and at the 41st percentile for males. As a consequence of their higher pay in the external labor market, fewer men than women would be interested in the relatively low pay Receptionist job. While this wage-based mechanism might be a contributing factor to the tendency for males to avoid the Receptionist job, it cannot explain why females would not be attracted to the higher paying Computer Programmer job. While 80 percent of the local area males earn less than the Computer Programmer's average $30.99 hourly wage, the percentage of females who would find such a wage attractive is even higher: 89 percent of females earn less than $30.99. Thus, sex differences in external wages *per se* can help to explain why men might avoid low paying Receptionist job, but external wage differences cannot explain why women would *avoid* the high paying Computer Programming job.

A second possible explanation for the observed gender-stereotypical patterns concerns people's hesitancy to apply for gender-atypical jobs for fear of being discriminated against.[22] Experimental research has shown evidence of employers having gendered judgments of desirable candidates for specific types of jobs. For example, Riach and Rich (2006) found that employers prefer women overall, but that their preference for women was particularly strong when filling

[22] We'd like to thank an anonymous reviewer for this suggestion.

secretarial jobs, and that they preferred men for engineering jobs.[23] Booth and Leigh (2010) also find that employers particularly prefer women for female-dominated jobs.

For this discrimination avoidance mechanism to work, however, applicants need to have accurate knowledge of an employer's tastes and preferences. Barbalescu and Bidwell (2010) demonstrate in the case of MBAs applying for jobs in finance that potential applicants' knowledge of employers' preferences are not always accurate, however. In their study, graduating female MBAs rate their chances of obtaining finance jobs lower than do graduating male MBAs, although conditional on applying, women are actually more likely than men to be offered finance jobs. To the degree that beliefs about employer discrimination are inaccurate, then application decisions based on those beliefs become hard to disentangle from other gendered beliefs that might affect job choices (e.g., "low perceived quality of work-life balance in finance jobs," see Barbalescu and Bidwell 2010: 7).

We do not have direct evidence on whether or not male and female applicants for gender non-stereotypical jobs anticipate being discriminated against by this employer. The gender and race questions on the standardized and automated screening protocol are optional. Nor are the names of the applicants asked for at this stage—the only identifying information kept is the social security number. Thus, unlike many other real-world settings, people can mask their ascriptive characteristics during this initial step of the hiring process. This firm's policy is particularly interesting in light of the results of Rudman and Farichild's (2004) lab study of gender stereotypes. They found that subjects' fear of backlash led them to hide their gender counterstereotypical behaviors. In this respect, the fact that very few of the applicants in this

[23] Interestingly, this same study showed that employers prefer females over males for computer analyst jobs.

setting chose to hide their gender or race suggests that, at least among those who choose to apply to the company, such concerns were not widespread.

While avoidance of discrimination cannot be completely ruled out, we think that it is unlikely to account for the patterns we report in Tables 4 and 7. Knowledge of whether an employer will discriminate is likely to vary considerably among potential candidates. Our strategy has been to look at variation among those who applied to the firm. Thus, it is difficult to see how such a mechanism could explain the stereotypically gendered choices we observe among the subset of candidates who—through either ignorance or perseverance—have expressed a strong interest in the counterstereotypically gendered jobs. Even among the subset of applicants who report high interest and ability in Computer Programming, females rate the stereotypically female Receptionist job higher than do males; for the subset of applicants who report high interest and ability in the Receptionist job, males rate the stereotypically male Computer Programmer job more highly than do females. Moreover, the analyses reported in Table 7 show that these patterns cannot be attributed to candidates' hedging their bets as they apply since the patterns hold even after controlling for candidates' ratings of the other jobs.

Rather, these results suggest that there are important supply-side processes affecting the gender sorting of job candidates. Indeed, a plethora of studies provide evidence that this result is over-determined. Past studies have documented gender differences in early role socialization (Corcoran and Courant 1985; Subich et al. 1989; Vella 1994), sex-role attitudes (Betz and O'Connell 1989; Bielby and Bielby 1984; Corrigall and Konrad 2007), gendered patterns of educational background and training (Brown and Corcoran 1997; Charles and Bradley 2009; Dickson 2010; Turner and Bowen 1999), and job values (Daymont and Andrisani 1984; Marini et al. 1996). Correll's (2001; 2004) research is also noteworthy in this regard. She shows that females often have biased self-assessments of their own ability. Thus, in a context like this one where applicants are asked to rate jobs based on both their "desire and ability," such biased assessments can also affect candidates' gendered self-sorting into jobs. While we cannot differentiate among the numerous pre-application factors that are behind the gendered application choices we observed here, in this setting, these patterns are not due to the actions of demand-side screeners.

While all of these processes are likely to reinforce gender sorting in the labor market, few studies have examined how these gendered processes work within race groups (an exception is Dickson [2010] which finds that gender differences in college major choice are much bigger than are race differences). Although we find clear patterns of gendered preferences, at least for the jobs analyzed here, we observe few race interactions with gender, as the gender patterns of job ratings are similarly ordered within race groups.

While this paper provides strong evidence of gender sorting at the point of initial application, we do not think that is likely to be a complete explanation of occupational sex segregation. Table 8 provides some indirect evidence in this regard. As noted above, we do not have access to the demand side of the screening process here. However, we can study the gender and race distributions of people working in labor market in the local area from the PUMS data. Although the numbers of cases are small for some of the race groups, these figures in Table 8 yield an important lesson. Compared to the percentage of applicants rating the Receptionist and Computer Programmer jobs '5' at the company, the gender distributions of these jobs in the open labor market are more extreme. Across racial groups, the self-sorted applicants with the highest interest in the Receptionist job are 2/3rds female, but over 90 percent of Receptionists in the area are female. Although less dramatically for some of the race groups, the gender split also grows at the male end of the continuum. About 2/3rds of applicants rating Computer Programmers '5' are male, compared with 73-80 percent male among people working as Computer Programmers in the local area. The fact that the post-hire data yield more extreme gender distributions suggest that, in addition to the supply-side job rankings we have isolated here, demand-side screening and post-hire processes (e.g., gender differences in turnover and promotions) are also likely to be important contributors to job segregation by sex.

Summary and Conclusion

These findings have important implications for our understanding of supply-side gender and race sorting. While Reskin and Roos (1990) developed the idea of a job queue to capture the idea that different job seekers might rank order various job opportunities differently, extant research on how gender and race are related to job queues has been limited. In this conceptualization, the actions of job seekers are occurring *prior* to anyone being hired. But with few exceptions, analyses of job segregation have been based on data collected on people *after* they have been hired. As a consequence, such studies conflate the effects of supply-side job queues with demand-side screening processes. By studying choices made at the point of application to this company, however, we have been able to isolate the sex segregating consequences of the actions of supply-side actors at this labor market interface. Since the company's application procedures do not allow for any contact between the recruiters and the applicants at this initial stage, the pattern of applicants' job choices made here is not contaminated by the influence of screeners who might steer applicants toward gender stereotypical choices.

Men and women express different job preferences, with more men preferring the Computer Programmer job, and more women interested in the Receptionist job. Gender patterns of ratings are similarly ordered across race groups, and recur within individuals as well. Moreover, introducing control variables into the analyses shows that these patterns are robust to some obvious alternative explanations for the observed job ratings (e.g., degree of urgency in finding a job, self-assessed computer skills). Thus, at least in this setting, the answer to Okamoto and England's (1999) question—is there a supply side to occupational sex segregation?—appears to be yes.

Finally, this paper offers valuable lessons for our understanding of policies designed to reduce job sex segregation. In particular, the special features of this case shed valuable light on what the likely effect of removing managerial discretion from the demand-side screening process is likely to be (e.g., Bielby 2000; Reskin and McBrier 2000). The fact is that significant gendering is evident even at a step *prior* to screening. While the data reported in Table 8 suggest that there is considerable room for demand-side factors to also affect job sex segregation, even in a setting where there is no contact between the candidate and the screener, we still observe substantial levels of job sex segregation. Thus, the main lesson of this paper is that job segregation by gender and race are not the exclusive product of the demand-side actions of organizational screeners. Although probably not the entire story, the supply-side processes documented here should not be ruled out as important contributing factors to job segregation by race and gender.

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Table 1: Racial Distributions of Applicant Pool (December, 1997-December, 1998) and Persons in the Metropolitan Area Labor Force

	Applicant Pool		Metro Area From 2000 PUMS [a]	
	Male Applicants	Female Applicants	Male Workers	Female Workers
Non-Hispanic White	51.3	51.8	55.6	57.5
African American	6.8	8.0	1.6	1.6
Hispanic	14.7	13.0	25.8	22.7
Asian American	16.3	16.1	12.9	14.0
Native American	2.5	1.8	0.4	0.4
Other, Multirace	8.5	9.3	3.7	3.9
Total	100.0	100.0	100.0	100.0
Total N	2,733	2,522	40,345	32,369

[a] Persons in the local area 5 percent 2000 PUMS who are in the labor force. PUMS data are weighted to reflect the population; Ns are unweighted.

Table 2. Racial Distribution of Applicant Pool and Population Residing in Labor Catchment Areas

	Applicant Pool	Catchment Area Based on 2000 Census Data [a]					
		1 km.	5 km.	10 km.	15 km.	20 km.	25 km.
Non-Hispanic White	51.2	70.5	46.6	40.7	44.1	46.8	49.9
African American	7.3	2.8	1.6	1.3	1.2	1.3	1.5
Hispanic	13.8	5.5	26.1	42.9	36.8	34.5	31.7
Asian American	16.1	13.5	22.1	12.7	15.4	14.8	14.1
Native American	2.2	0.0	0.2	0.2	0.3	0.3	0.3
Other, Multirace	9.3	7.7	3.5	2.2	2.2	2.3	2.4
Total N	5,286	325	129,975	715,619	1,259,887	1,895,220	2,507,052

[a] Population of 2000 census blocks (based on SF1 files) whose geographic centroids falls within the specified distance from the firm (in kilometers).

Table 3. Mean Levels of Interest/Ability in Receptionist, Telephone Interviewer, and Computer Programmer Jobs by Gender and Race (1=Really not interested, 5=Strong desire and the ability to do this job)

	Receptionist			**Telephone Interviewer**			**Computer Programmer**			**Minimum Valid N**	
	Male		Female	Male		Female	Male		Female	Male	Female
White	2.73	*	3.63	4.46	*n.s.*	4.49	2.36	*	1.98	1,397	1,302
Black	2.92	*	3.93	4.43	*n.s.*	4.35	2.85	*	2.19	184	201
Hispanic	3.20	*	4.10	4.34	*n.s.*	4.35	2.70	*	2.19	395	327
Asian	3.51	*	3.91	4.35	*n.s.*	4.30	2.96	*	2.64	446	405
Nat. Amer.	2.97	*	3.69	4.29	*n.s.*	4.38	2.35	*n.s.*	2.18	68	44
Other	2.75	*	3.67	4.18	*n.s.*	4.22	2.66	*	2.18	209	206
Total	2.95	*	3.77	4.40	*n.s.*	4.40	2.57	*	2.15	2,711	2,497

Note: * = p – value of gender difference < .001

Table 4. Percent Female by Within-Person Ranking of Receptionist and Computer Programmer Jobs for Various Populations of Applicants (Number of cases in parentheses)

Ranking:	All Applicants **Percent Female**	Applicants for Telephone Interviewer (Scores of '5') **Percent Female**	Applicants for Computer Programmer (Scores of '5') **Percent Female**	Applicants for Receptionist (Scores of '5') **Percent Female**
Comp. Prog. < Receptionist	61.8 (2,722)	61.8 (1,747)	--	70.4 (1,401)
Comp. Prog. = Receptionist	37.1 (1,582)	37.6 (1,046)	42.1 (392)	42.1 (392)
Comp. Prog. > Receptionist	25.0 (903)	27.1 (494)	24.4 (315)	--
Total	47.9 (5,207)	48.9 (3,287)	34.2 (707)	64.2 (1,793)
LR X^2 =	487.0	268.5	24.6	103.5
Degrees of Freedom	2	2	1	1

Table 5. Means (and Standard Deviations) for Predictor and Dependent Variables by Sex for All Applicants, and Applicants Rating the Receptionist and Computer Programmer Jobs a '5' (5=Strong desire and the ability to do this job)

	All Applicants		Among Computer Programmer Applicants (Scores of '5' for Computer Programmer)		Among Receptionist Applicants (Scores of '5' for Receptionist)	
	Female	**Male**	**Female**	**Male**	**Female**	**Male**
Dependent Variables:						
Rating of Computer Programmer Job	2.163 (1.348)	2.572 (1.488)	--	--	2.350 (1.455)	3.135 (1.641)
Z-Score of Computer Programmer Rating	-.971 (.865)	-.687 (.964)	.601 (.478)	.690 (.487)	-1.028 (.899)	-.714 (1.031)
Rating of '5' for Computer Programmer vs. 0	.096 (.295)	.172 (.378)	--	--	.139 (.346)	.346 (.476)
Rating of Receptionist Job	3.800 (1.419)	2.971 (1.525)	4.414 (1.068)	3.812 (1.419)	--	--
Z-Score of Receptionist Rating	.297 (.975)	-.397 (1.018)	.035 (.833)	-.453 (1.059)	1.012 (.445)	.797 (.482)
Rating of '5' for Receptionist vs. 0	.475 (.499)	.241 (.428)	.688 (.464)	.483 (.500)	--	--
Independent Variables:						
Age (1=GT 40)	.220 (.414)	.173 (.378)	.088 (.284)	.067 (.250)	.135 (.341)	.054 (.227)
African American	.077 (.267)	.067 (.250)	.079 (.270)	.090 (.287)	.095 (.293)	.063 (.243)
Hispanic	.133 (.339)	.147 (.354)	.130 (.337)	.155 (.362)	.168 (.374)	.177 (.382)
Asian American	.169 (.375)	.174 (.379)	.298 (.458)	.236 (.425)	.164 (.370)	.259 (.438)
Native American	.018 (.134)	.023 (.151)	.023 (.151)	.019 (.137)	.016 (.126)	.024 (.153)
Other Race	.071 (.256)	.062 (.242)	.070 (.255)	.069 (.254)	.076 (.266)	.053 (.224)
Mean Rating of Other Jobs (Comp. Prog. Job Omitted)	3.415 (.647)	3.438 (669)	4.164 (.623)	4.095 (.603)	3.653 (.647)	3.967 (.631)
Mean Rating of Other Jobs (Receptionist Job Omitted)	3.312 (.665)	3.413 (.675)	4.201 (.596)	4.169 (.550)	3.487 (.702)	3.850 (.699)
Any Computer Skill (1=Yes)	.319 (.466)	.303 (.459)	.591 (.493)	.500 (.501)	.358 (.479)	.419 (.494)
Average Computer Skill	.628 (1.112)	.663 (1.204)	1.467 (1.649)	1.341 (1.680)	.743 (1.232)	1.030 (1.535)
Ln(Distance in kms)	2.602 (.932)	2.576 (.922)	2.505 (.967)	2.494 (.923)	2.572 (.859)	2.557 (.930)
Ln(Distance in kms) - squared	7.637 (6.365)	7.484 (6.042)	7.207 (7.169)	7.072 (6.441)	7.351 (5.438)	7.403 (6.543)
Number of cases:	2,234	2,435	215	420	1,062	587

Table 6. Models Predicting Ratings of Receptionist and Computer Programmer Jobs for all Applicants (N = 4,669)

	Models Predicting Receptionist Rating for All Applicants			**Models Predicting Computer Programmer Rating for All Applicants**		
	[1] OLS Predicting 1 -5 Ratings [a]	**[2] OLS Predicting Z-Score of Ratings [a]**	**[3] Logit Model Predicting Rating of ‘5’ [b]**	**[4] OLS Predicting 1 -5 Ratings [a]**	**[5] OLS Predicting Z-Score of Ratings [a]**	**[6] Logit Model Predicting Rating of ‘5’ [b]**
Gender (Female=1)	0.863*** (22.01)	0.641*** (22.32)	3.941*** (17.60)	-0.358*** (-9.99)	-0.262*** (-9.52)	0.457*** (-6.98)
Age (1=GT 40)	-0.566*** (-10.69)	-0.039*** (-9.98)	0.530*** (-5.71)	-0.186*** (-3.86)	-0.070 (-1.89)	0.645* (-2.30)
Black	0.091 (1.21)	0.092 (1.67)	1.327* (1.96)	0.125 (1.82)	0.124* (2.35)	1.209 (0.94)
Hispanic	0.226*** (3.93)	0.140*** (3.33)	1.507*** (3.83)	0.070 (1.33)	0.054 (1.34)	0.996 (-0.03)
Asian	0.115* (2.08)	0.092* (2.27)	1.148 (1.34)	0.218*** (4.34)	0.169*** (4.38)	1.408* (2.45)
Native American	-0.040 (-0.30)	-0.000 (-0.00)	0.964 (-0.14)	-0.038 (-0.32)	-0.007 (-0.08)	0.966 (-0.09)
Other Race	-0.012 (-0.16)	-0.015 (-0.27)	1.071 (0.46)	0.130 (1.84)	0.084 (1.56)	1.127 (0.55)
Mean Rating of Other 15 Jobs	0.856*** (24.91)	-0.163*** (-6.48)	2.739*** (14.46)	1.078*** (34.01)	-0.157*** (-6.44)	7.888*** (17.11)
Working Software Knowledge	-0.067 (-0.92)	-0.041 (-0.78)	0.974 (-0.20)	0.134* (2.04)	0.076 (1.49)	1.138 (0.73)

Average Computer Skill	0.037 (1.27)	0.020 (0.96)	1.104* (1.84)	0.123*** (4.65)	0.106*** (5.22)	1.201** (2.84)
Ln(Distance in kms)	0.011* (2.03)	0.077* (2.00)	1.148 (1.36)	-0.076 (-1.59)	-0.071 (-1.93)	0.854 (-1.15)
Ln(Distance in kms)^2	-0.014 (-1.79)	-0.010 (-1.74)	0.978 (-1.43)	0.006 (0.86)	0.007 (1.33)	1.014 (0.65)
+ 45 "Big Five" Personality items [c]	$p < .0001$ LR X^2 = 508.74 (with 45 d.f.)	$p < .0001$ LR X^2 = 459.15 (with 45 d.f.)	$p < .0001$ LR X^2 = 369.59 (with 45 d.f.)	$p < .0001$ LR X^2 = 243.04 (with 45 d.f.)	$p < .0001$ LR X^2 = 188.08 (with 45 d.f.)	$p < .0001$ LR X^2 = 127.61 (with 45 d.f.)
Pseudo R-square	--	--	.206	--	--	.315
LR X^2 = (with 57 d.f.)	--	--	1,251.82	--	--	1,170.09
Adjusted R-square	.328	.242	--	.365	.098	--

[a] t-values in parentheses.
[b] Coefficients are odds ratios; z-values in parentheses.
[c] Joint test of statistical significance based on Likelihood-ratio test.

Table 7. Models Predicting Ratings of Receptionist Job for Applicants with High Levels of Interest in the Computer Programmer Job, and Models Predicting Ratings of Computer Programmer Job for Applicants with High Levels of Interest in the Receptionist Job

	Models Predicting Receptionist Rating for Applicants Rating Computer Programmer '5'			**Models Predicting Computer Programmer Rating for Applicants Rating Receptionist '5'**		
	[1] OLS Predicting 1 -5 Ratings [a]	**[2] OLS Predicting Z-Score of Ratings [a]**	**[3] Logit Model Predicting Rating of '5' [b]**	**[4] OLS Predicting 1 -5 Ratings [a]**	**[5] OLS Predicting Z-Score of Ratings [a]**	**[6] Logit Model Predicting Rating of '5' [b]**
Gender (Female=1)	0.503*** (4.93)	0.447*** (5.08)	2.751*** (4.10)	-0.301*** (-4.53)	-0.264*** (-5.14)	0.470*** (-4.42)
Age (1=GT 40)	-0.198 (-1.06)	-0.170 (-1.05)	0.853 (-0.36)	-0.181 (-1.69)	-0.047 (-0.57)	0.862 (-0.42)
Black	0.940 (0.53)	0.109 (0.72)	1.608 (1.15)	0.244* (2.14)	0.213* (2.42)	1.591 (1.52)
Hispanic	0.086 (0.60)	-0.047 (-0.38)	1.122 (0.36)	0.206* (2.34)	0.130 (1.92)	1.057 (0.21)
Asian	0.175 (1.45)	0.160 (1.53)	1.567 (1.62)	0.223** (2.65)	0.162* (2.50)	1.665* (2.37)
Native American	0.354 (1.07)	0.358 (1.25)	5.568 (1.87)	0.087 (0.40)	0.147 (0.86)	1.404 (0.62)
Other Race	0.256 (1.32)	0.204 (1.22)	2.710* (2.00)	0.205* (1.67)	0.149 (1.57)	1.350 (0.89)
Mean Rating of Other 15 Jobs	0.968*** (9.05)	-0.127 (-1.37)	6.998*** (7.39)	1.317*** (21.81)	-0.071 (-1.53)	13.362*** (11.67)
Working Software Knowledge	0.145 (0.98)	0.114 (0.89)	1.262 (0.68)	0.147 (1.44)	0.054 (0.69)	1.242 (0.84)

Average Computer Skill	-0.001 (-0.03)	0.014 (0.36)	1.049 (0.43)	0.100** (2.67)	0.106*** (3.70)	1.183 (1.93)
Ln(Distance in kms)	0.008 (0.07)	-0.010 (-0.09)	0.947 (-0.19)	-0.182* (-2.12)	-0.170* (-2.57)	0.603* (-2.34)
Ln(Distance in kms)^2	0.004 (0.21)	0.008 (0.51)	1.021 (0.50)	0.021 (1.64)	0.021* (2.16)	1.071* (2.14)
+ 45 "Big Five" Personality items	$p < .0001$ LR X^2 = 90.08 (with 45 d.f.)	$p < .0002$ LR X^2 = 85.61 (with 45 d.f.)	$p < .0003$ LR X^2 = 84.97 (with 45 d.f.)	$p < .0001$ LR X^2 = 116.43 (with 45 d.f.)	$p < .0001$ LR X^2 = 106.28 (with 45 d.f.)	$p < .0001$ LR X^2 = 87.21 (with 45 d.f.)
Pseudo R-square	--	--	.304	--	--	.403
LR X^2 = (with 57 d.f.)	--	--	265.90	--	--	688.54
Adjusted R-square	.320	.113	--	.435	.101	--
Number of cases	635	635	635	1,649	1,649	1,649

[a] t-values in parentheses.
[b] Coefficients are odds ratios; z-values in parentheses.
[c] Joint test of statistical significance based on Likelihood-ratio test.

Table 8. Percent Female Among Job Incumbents in Local Labor Market [a] and Applicants Who Rate Jobs "Very interested in the job and have the ability" ('5')

	Receptionist		**Computer Programmer**	
	Job Incumbents	Applicants	Job Incumbents	Applicants
White	94.9 (448)	67.3 (813)	19.6 (250)	32.8 (296)
Black	83.3 (6)	71.6 (155)	57.1 (7)	31.1 (61)
Hispanic	92.7 (220)	63.5 (299)	27.5 (51)	29.3 (99)
Asian	89.6 (67)	53.8 (346)	41.0 (144)	39.3 (173)
Other[b]	97.1 (35)	67.4 (169)	22.7 (22)	36.2 (69)
Total	93.8 (777)	64.4 (1,782)	27.6 (474)	34.1 (698)

[a] Data are persons in the local area 5 percent sample of the 2000 PUMS who are in the labor force. PUMS data are weighted to reflect the population; Ns are unweighted.
[b] Native Americans are included in the "Other" category

Table A1. Models Predicting Ratings of Receptionist and Computer Programmer Jobs for all Applicants Omitting 45 "Big Five" Personality Items (N = 4,669)

	Models Predicting Receptionist Rating for All Applicants			**Models Predicting Computer Programmer Rating for All Applicants**		
	[1] OLS Predicting 1 -5 Ratings [a]	**[2] OLS Predicting Z-Score of Ratings [a]**	**[3] Logit Model Predicting Rating of '5' [b]**	**[4] OLS Predicting 1 -5 Ratings [a]**	**[5] OLS Predicting Z-Score of Ratings [a]**	**[6] Logit Model Predicting Rating of '5' [b]**
Gender (Female=1)	0.950*** [c] (24.39)	0.702*** (24.75)	3.863*** (19.11)	-0.370*** (-10.74)	-0.279*** (-10.58)	0.463*** (-7.40)
Age (1=GT 40)	-0.793*** (-15.59)	-0.544*** (-14.70)	0.410*** (-8.97)	-0.256*** (-5.66)	-0.125*** (-3.61)	0.572** (-3.20)
Black	0.075 (0.97)	0.072* (1.28)	1.281* (1.88)	0.162** (2.37)	0.148*** (2.84)	1.214 (1.02)
Hispanic	0.310*** (5.28)	0.195*** (4.56)	1.604*** (4.75)	0.154*** (2.95)	0.114*** (2.87)	1.130 (0.82)
Asian	0.215*** (3.90)	0.165*** (4.12)	1.177* (1.74)	0.353*** (7.24)	0.256*** (6.86)	1.687*** (4.06)
Native American	0.063 (0.46)	-0.071 (0.099)	1.010 (0.04)	-0.016 (-0.13)	0.003 (0.03)	0.982 (-0.05)
Other Race	0.034 (0.43)	0.02 (0.32)	1.048 (0.33)	0.224** (3.15)	0.137** (2.51)	1.192 (0.85)
Mean Rating of Other 15 Jobs	0.754*** (24.47)	-0.230*** (-10.24)	2.692*** (17.12)	1.015*** (36.67)	-0.166*** (-7.85)	8.739*** (22.15)
Working Software Knowledge	-0.131* (-1.75)	-0.085 (-1.55)	0.904 (-0.78)	0.141** (2.12)	0.090* (1.76)	1.144 (0.78)

Average Computer Skill	0.035 (1.17)	0.020 (0.92)	1.101* (1.87)	0.129*** (4.82)	0.108*** (5.27)	1.203*** (2.97)
Distance in kms	0.108** (1.98)	0.076* (1.92)	1.145 (1.39)	-0.077 (-1.60)	-0.074** (-2.01)	0.813 (-1.57)
Distance in kms^2	-0.016** (-2.00)	0.006* (-1.91)	0.976 (-1.62)	0.006 (0.77)	0.007 (1.29)	1.023 (1.16)
Pseudo R-square	--	--	.145	--	--	.281
LR X^2 = (with 12 d.f.)	--	--	882.23	--	--	1042.47
Adjusted R-square	.257	.171	--	.337	.070	--

[a] t-values in parentheses.
[b] Coefficients are odds ratios; z-values in parentheses.
[c] Joint test of statistical significance based on Likelihood-ratio test.

Table A2. Models Predicting Ratings of Receptionist Job for Applicants with High Levels of Interest in the Computer Programmer Job, and Models Predicting Ratings of Computer Programmer Job for Applicants with High Levels of Interest in the Receptionist Job (Models Omit 45 "Big Five" Personality Items)

	Models Predicting Receptionist Rating for Applicants Rating Computer Programmer '5'			**Models Predicting Computer Programmer Rating for Applicants Rating Receptionist '5'**		
	[1] OLS Predicting 1 -5 Ratings [a]	**[2] OLS Predicting Z-Score of Ratings [a]**	**[3] Logit Model Predicting Rating of '5' [b]**	**[4] OLS Predicting 1 -5 Ratings [a]**	**[5] OLS Predicting Z-Score of Ratings [a]**	**[6] Logit Model Predicting Rating of '5' [b]**
Gender (Female=1)	0.556*** [c] (5.74)	0.474*** (5.69)	2.799*** (4.94)	-0.309*** (-4.80)	-0.282*** (-5.69)	0.448*** (-5.26)
Age (1=GT 40)	-0.347* (-1.94)	-0.283 (-1.84)	0.715 (-0.93)	-0.216** (-2.16)	-0.078 (-1.01)	0.799 (-0.73)
Black	0.130 (0.76)	0.118 (0.81)	1.495 (1.07)	0.277** (2.46)	0.234*** (2.71)	1.615* (1.74)
Hispanic	0.192 (1.39)	0.058 (0.49)	1.139 (0.46)	0.299*** (3.51)	0.204*** (3.13)	1.249 (0.96)
Asian	0.240** (2.08)	0.222** (2.24)	1.434 (1.54)	0.284** (3.48)	0.204*** (3.26)	1.699*** (2.74)
Native American	0.292 (0.90)	0.342 (1.22)	2.624 (1.37)	0.118 (0.53)	0.155 (0.91)	1.422 (0.68)
Other Race	0.298 (1.58)	0.213 (1.32)	1.907 (1.55)	0.230* (1.87)	0.162* (1.71)	1.374 (1.02)
Mean Rating of Other 15 Jobs	1.079*** (12.51)	-0.083 (-1.11)	6.840*** (9.56)	1.262*** (25.24)	-0.084** (-2.18)	14.212*** (15.01)

Working Software Knowledge	0.055 (0.37)	0.065 (0.51)	1.102 (0.32)	0.171* (1.67)	0.067 (0.85)	1.199 (0.75)
Average Computer Skill	0.033 (0.73)	0.034 (0.85)	1.092 (0.89)	0.107*** (2.86)	0.114*** (3.95)	1.208** (2.31)
Distance in kms	-0.010 (-0.08)	-0.039 (-0.36)	0.815 (-0.80)	-0.193** (-2.23)	-0.181*** (-2.72)	0.584*** (-2.73)
Distance in kms^2	0.005 (0.31)	0.011 (0.71)	1.037 (1.02)	0.021 (1.61)	0.022** (2.16)	1.075* (2.57)
Pseudo R-square	--	--	.207	--	--	.352
LR X^2 = (with 12 d.f.)	--	--	180.93	--	--	601.33
Adjusted R-square	.273	.059	--	.410	.068	--
Number of cases	635	635	635	1,649	1,649	1,649

[a] t-values in parentheses.
[b] Coefficients are odds ratios; z-values in parentheses.
[c] Joint test of statistical significance based on Likelihood-ratio test.