Gender Targeting before Civil Rights and Long-Run Employment

Enghin Atalay
Federal Reserve Bank
of Philadelphia

Lisa B. Kahn
University of Rochester
and NBER

Russell Weinstein*
Michigan State University
and IZA@LISER

July 21, 2026

WORK IN PROGRESS -
PLEASE DO NOT CITE/CIRCULATE WITHOUT PERMISSION

Abstract

We combine two different sources of job vacancies with firm-level employment records from 1966-1995 to understand whether explicit gender targeting in job ads – observed while the practice was still legal – predicts the evolution of female representation at work. We offer the first systematic characterization of gender targeting across our two sources: 1) digitized classifieds from 3 major U.S. newspapers from 1940-2000 and 2) a 1958 college recruiting directory. We then show that stated male preferences correlate with male employment shares at the firm-occupation level in the 1960s. Our preferred male targeting measure is expressed as a deviation from mean targeting within the detailed occupation, implying idiosyncratic firm preferences, rather than occupational norms, drive the result. After gender targeting was prohibited, the relationship between historical gender targeting and subsequent male employment share weakens modestly, but remains significant through 1995. Employer preferences over worker gender have remarkably persistent effects on female representation at work.

*Contact: Enghin Atalay at atalayecon@gmail.com, Lisa B. Kahn at lbkahn@gmail.com, Russell Weinstein at russellmweinstein@gmail.com. This work was supported (in part) by Grant #92-18-05 from the Russell Sage Foundation. We thank Claudia Goldin, and seminar participants at the University of Rochester and the Atlanta Federal Reserve for helpful comments. We thank Yulia Dudareva and Alice von Ende Becker for excellent research assistance. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

1 Introduction

The civil rights era fundamentally reshaped the United States labor market. Most notably, a substantial literature documents the importance of the 1964 Civil Rights Act and the establishment of the Equal Employment Opportunity Commission (EEOC) in contributing to Black-White progress in the labor market [Donohue and Heckman, 1991]. Impacts on women have been more difficult to pinpoint, partly because protections for women at work were only clarified via a series of influential court cases and EEOC guideline revisions over the next decade. The latter half of the 20th century saw unprecedented gender integration in the labor market. However, even today, barriers to women remain in many areas of work.

Up to the early 1970s, explicit gender targeting was not only legal, but a common feature of the U.S. labor market. Employers specified in job advertisements whether they wanted a man, a woman, or either for their position, alongside other desired worker characteristics. These ads offer a window into employers' hiring preferences at a time when such preferences could be openly stated. Following the expansion of anti-discrimination enforcement in the decade after the Civil Rights Act, explicit targeting in job ads did eventually fade. Evidence on modern day Austria and China suggest that the removal of gender targeting in job ads drove gender integration [Card et al., 2024; Kuhn and Shen, 2023]. However, little is known about whether the United States' own landmark anti-discrimination policies – including the prohibition of gender targeting – shaped firm-level gender equality during the civil rights era and beyond.

In this paper, we provide the first systematic analysis linking explicit gender targeting in the United States to the evolution of gender segregation in employment. We combine EEOC records for large firms and federal contractors (the EEO-1 filings) from 1966-1995 with two sources of job vacancies: classified ads from 3 major newspapers first used in Atalay et al. [2020] and a 1958 college placement directory [Zimmerman and Lavine, 1958]. We describe gender targeting in these prominent ad sources and then relate gender targeting at the firm-job title level to employment segregation by gender. We find a strong positive relationship between male employment shares and male targeting, focusing especially on targeting expressed as a deviation from occupational norms. A firm's idiosyncratic male targeting behavior meaningfully captures barriers to women in employment. The correlation between male targeting in the pre-civil rights era and higher male employment share persists through the 1990s. However, we also find evidence of some convergence starting in the mid-1970s, a period when anti-discrimination policy was solidified. We thereby provide new suggestive evidence on the role of these legal changes in reshaping the gender composition of the workforce.

Our job advertisement datasets include classifieds from three major U.S. newspapers. These ads were originally published in the *Boston Globe*, *New York Times*, and *Wall Street Journal* between 1940 and 2000 and were first used by Atalay et al. [2020] to measure changes in demand for skill over the 20th century. We develop ad-level measures of gender targeting in this dataset. We supplement these advertisements with a college placement directory from 1958 [Zimmerman and Lavine, 1958] that was designed to help match recent college graduates to employers. The directory includes

detailed listings from nearly 1500 companies and offers a clean portrayal of the high-skilled labor market. From these sources, we identify ways in which employers signal a gender preference for their applicants and describe variation across jobs and firms over time.

In the classifieds, we find 7 percent of ads in the 1940s state an explicit preference for male applicants, while 5 percent target women. These rates gradually decline over subsequent decades but the practice does not fade completely until the mid 1970s.[1] A small fraction of ads in the early period express an explicit openness to either gender, and that propensity rises over our sample period, peaking in the 1980s. During the pre–civil rights era, when explicit targeting for a single gender was highest, we find that targeting is strongly correlated with census employment shares by gender at the detailed occupation level. Also, within occupations and job titles, male targeted ads had more skill requirements and higher posted salaries. Our second vacancy source, the 1958 directory, contains mostly professional positions, and every listing specifies a gender requirement: 72% target only men, 9% target only women, and the remainder are open to both. These rates are also strongly correlated with census employment shares by gender. Finally, ads targeting both men and women were more likely to require advanced degrees, even within occupations or job titles. Firms seem to cast a wider net across genders when the positions themselves are more specialized.

With the inception of the EEOC, all U.S. employers with at least 100 workers and federal contractors of at least 50 employees were required to submit employment counts across broad occupation categories by gender, race, and ethnicity. These data allow us to assess the extent to which stated gender preferences correlate with contemporaneous employment outcomes at the firm, as well as the evolution of gender representation over the remainder of the 20th century. We are able to link 2000 firms to at least one of the vacancy sources, representing 60% of our balanced panel of EEO-1 filers. We relate male targeting in the pre–civil rights era to male employment shares within firms and nine broad occupation categories. Our preferred male-targeting measure is expressed as a deviation from the average targeting rate within detailed (4-digit SOC) occupations, which adjusts for the fact that firms with greater targeting may be posting in job titles that are more stereotypically male.

We find a strong correlation between male targeting and male employment shares in the 1960s across both vacancy datasets. A firm with a 1 standard deviation higher idiosyncratic targeting rate in a given occupation has a roughly 7 percentage point (10%) higher male employment share in that occupation. This relationship between pre-civil rights male targeting and male employment share persists throughout the 20th century (1995 is the latest publicly available EEO-1 data). Male targeting may capture a workplace environment that poses barriers to women and these barriers are apparently persistent. Even so, starting in the mid-1970s we find some convergence in the male employment share between firms with more and less male targeting. This convergence is co-

[1]During this time period, newspapers also had segregated pages for female versus male help wanted ads. Ads on these pages could also include explicit targeting (which is based on the text of the ad itself), or not. We quantify the prevalence of segregated pages and find rates that are much higher than the rates of explicit targeting. This prevalence could be one reason why explicit targeting is less strong. We provide companion analyses of page targeting and reach similar conclusions. Still, we do not focus on page targeting since it may have been the norm in some instances and so less clearly reflects employer preferences.

timed with the resolution of uncertainty over how sex-based discrimination would be enforced. The modest convergence is consistent with these policies having greater impacts on firms that were more strongly targeting men relative to other firms recruiting the same occupation. It is also coincident with broader societal changes related to women such as delayed marriage, and increased educational attainment and participation [Goldin and Katz, 2002; Bailey, 2006; Blau and Kahn, 2007]. While these broader trends contributed to changes in gender composition in the labor market, they would not necessarily be expected to produce *greater* impacts among firms that had previously expressed strong male preferences. In fact, if these societal changes had stronger impacts on firms that had previously expressed less strong male preferences, this would bias us away from finding effects of the policies. Our findings therefore provide suggestive new evidence on the role of civil rights era anti-discrimination policies in female representation at work.

We consider several alternative explanations for both the correlation between gender targeting and employment shares, as well as the modest convergence post-civil rights. A key issue is that EEO-1 occupations are reported only at a broad 1-digit level, so heterogeneity in job distributions within these broad groups could play a role. We leverage the greater detail available in the job ads data to rule out this heterogeneity as a driver of our results. Specifically, by using the firm's deviation from mean targeting in the detailed occupation, our results do not simply capture higher male targeting in traditionally-male occupations – where worker preferences and expectations, rather than firm preferences alone, could drive sorting. Our results are also robust to controls for a range of occupation characteristics, again using the detailed occupational ad distribution of firms to construct these measures. These controls help rule out that firms with greater male targeting have different production processes that favored males or production that evolved differently with technology or preferences in a way that affected gender integration. Finally, our results hold within industry and state, ruling out that firms with more male targeting are concentrated in certain locations or industries with different norms or labor supply and also higher male employment shares. Another explanation for the convergence is that preferences measured prior to the 1970s simply become out of date. However, this explanation seems less likely, as other variables measured in the vacancy datasets are predictive of employment throughout the sample period, with no convergence.

Our paper contributes to the extensive literature chronicling the declining, but still substantial, salience of gender in the labor market [Goldin, 2006, 2014; Blau and Kahn, 2017]. Women experienced especially rapid gains in employment and wage gaps during the 1980s and continued progress in the 1990s. We especially relate to the literature documenting women's increased entry into male-dominated occupations, which followed a similar time pattern [Pan, 2015; Blau et al., 2012; Cortes and Pan, 2018]. We find considerable heterogeneity across firms in gender segregation, which is systematically related to a firm's explicitly stated gender preferences. While our data allow us to measure occupational sorting within and across firms, a related literature shows that gender wage gaps are also impacted by sorting across firms [Blau, 1977; Groshen, 1991; Card et al., 2016].[2]

[2]See also a series of studies that measure sex and race segregation across employers, industries and occupations, and show the extent to which these measures account for wage gaps [Hellerstein and Neumark, 2008; Hellerstein et al., 2008; Bayard et al., 2003].

Several papers have evaluated the effect of the Civil Rights Act on Black-White convergence in the labor market, but its impact on gender gaps is less clear [Donohue and Heckman, 1991; Smith and Welch, 1989; Chay, 1998; Carrington et al., 2000]. Notably, Bailey et al. [2024] show the 1963 Equal Pay Act impacted gender pay gaps using cross-sectional variation in its incidence based on preexisting state laws and gender gaps across occupations and industries. A small literature beginning with Ashenfelter and Heckman [1976] uses EEO-1 filings and variation in federal contractor status to measure the impacts of affirmative action on workforce integration, typically finding positive impacts on Black-White convergence and little impact on women.[3] We gain traction by identifying firms that are more likely to impose sex-based barriers at work, based on their explicitly stated preferences.

Our paper also contributes to a smaller literature that quantifies the prevalence of gender targeting in job ads and its impact on labor market outcomes. As part of a larger survey on discrimination in the labor market, Darity and Mason [1998] present some examples of job ads from 1960 in which employers expressed gender- or race-based preferences. Goldin, in Goldin [1986] and other works, explores a 1940 Bureau of Labor Statistics survey of firms capturing personnel practices regarding occupational segregation among clerical workers. More recently, Kuhn and Shen [2013, 2020] quantify modern day gender targeting in Chinese and Mexican vacancy postings, drawing on large samples of ads from online job boards. Our paper is most closely related to Card et al. [2024] and Helleseter et al. [2020] who explore job applications and/or employment following legal rulings that outlawed gender targeting in modern day Austria and China, respectively. We provide the first evidence for the United States on how the correlation between gender targeting and female representation evolved following the major anti-discrimination measures of the 1960s and 70s.

While barriers facing women in firms with stronger gender targeting may have been worse absent civil rights era reforms, we find striking persistence in the relationship between pre–civil rights gender attitudes and female representation at the firm. Recent literature emphasizes the importance of gender-neutral policies – such as workplace flexibility – for closing remaining gender gaps, particularly in high-paying occupations [Goldin, 2014; Bertrand et al., 2010]. However, the persistence we uncover suggests that up until the 1990s – and possibly beyond – more work was necessary to undo the barriers to women in the labor market that were present decades early.

This paper proceeds as follows: we review the relevant historical and legal background for our study (section 2) and describe the data sources in section 3. We examine patterns in explicit gender targeting in section 4. In section 5, we examine the relationship between gender targeting and employment segregation by gender. We conclude in section 6.

[3]See Leonard [1984, 1989]; Miller [2017]; Kurtulus [2016], as well as Beller's time series analysis [Beller, 1983].

2 Legal and Institutional Background

In this section, we briefly review changes to the legal and regulatory environment related to gender-based discrimination in the labor market. We focus, in particular, on newspapers', employers', and employment agencies' discriminatory behavior in the course of placing and formatting newspaper job ads.[4]

Even before the introduction of federal legislation on employment discrimination in the 1960s, changes at the state level or by non-governmental entities eased restrictions on female and minority labor supply. Goldin [1991] chronicles the rise and fall of "marriage bars". Introduced in the late 1800s and concentrated in public schools and office environments, firms and school districts maintained policies of (i) refusing to hire married women, and/or (ii) firing already-employed women upon marriage. These marriage bars declined in frequency in the 1940s and were abandoned by the 1950s.

Furthermore, certain states enacted anti-discrimination legislation before the federal government, though with a greater emphasis on race-based rather than sex-based discrimination. Of particular relevance for this paper given that one of our job vacancy sources is concentrated in northeast newspapers, in 1945 New York state passed the Ives-Quinn Act. The first state-level legislation of its type, the law established a commission with the power "to eliminate and prevent discrimination because of race, creed, color or national origin either by employers, labor organizations, employment agencies or other persons" [Lichtash, 1945, p. 170].

The federal government instituted substantial legal restrictions on employment discrimination beginning in the 1960s with several acts enacted over that decade. Most notably, Title VII of the 1964 Civil Rights Act prohibited discrimination against individuals or segregation of employees on the basis of the individual's race, color, religion, sex, or national origin.[5]

The 1964 Civil Rights Act also provided for the creation of the Equal Employment Opportunity Commission (EEOC), an agency tasked with preventing unlawful employment practices. Founded the year following the Civil Rights Act, the EEOC initially had limited resources and power to enforce Title VII. Between 1965 and 1972 the EEOC's primary authorities were to "investigate, and conciliate charges of discrimination, to make technical studies and provide technical assistance to employers, but not the authority to sue employers who failed to comply with Title VII" [Occhialino and Vail, 2005, pp. 672-673]. Following the Equal Employment Opportunity Act of 1972, the EEOC had additional authority to litigate against discriminating employers. In an early victory for the EEOC, in 1973 AT&T agreed to file back pay to women it had previously been underpaying, reduce occupation-based gender segregation within its workforce, and alter its advertising and recruiting materials to include only gender-neutral language [Bem and Bem, 1973]. The EEOC also collected establishment-level reports on employment segregation (the EEO-1 filings), which we use in our

[4] For additional background, see Donohue III [1994] and Pedriana and Abraham [2006].

[5] Initial drafts of the 1964 Civil Rights Act did not include sex within this list. "Sex" was added in an amendment by civil rights opponent Howard W. Smith. While perhaps a simplification, the primary interpretation is that Smith introduced sex in an effort to scuttle the entire Civil Rights Act from passing. See Freeman [1991] for a more complete account.

analysis.

Newspapers were also subject to increased scrutiny beginning in the 1960s. As we will document, up to the 1960s newspapers commonly organized pages of job ads according to gender. Most pages would include as a header: "Help Wanted: Female," "Help Wanted: Male," "Situations Wanted: Female," or "Situations Wanted Male."[6] Even while the Civil Rights Act outlawed expressing a gender preference in advertisements for employment (704b), page targeting remained legal. Still, as we show below, the practice of expressing explicit gender preferences in individual job ads declined steadily in the years after the Civil Rights Act, but took about ten years before fading out.

In 1968, the National Organization of Women sued the EEOC, prompting it to issue revised guidelines that would prohibit these gender-segregated classifications of job ads [Endres, 2004].[7] Between 1968 and 1973 many newspapers desegregated pages of job ads as a result; the *New York Times* did so in December 1968. But segregation of job ads continued in certain newspapers until 1973, when the Supreme Court ruled — in Pittsburgh Press Co. v. Pittsburgh Commission on Human Relations [413 U.S. 376, 1973] — that newspapers' decisions on how to format job ads was not protected under the First Amendment's freedom of speech or freedom of the press clauses.

From its inception, the Civil Rights Act outlawed expressing a preference related to a protected group in advertisements (704b). However, the early legal activity centered on litigating against newspapers for segregated help wanted pages, with less legal action against employers for ads that were discriminatory. This was likely because targeting individual employers would involve multiple lawsuits, whereas targeting newspapers could be very effective if it resulted in removal of segregated pages [Kerman, 1974]. Title VII also made an exception to outlawing gender preferences if there was a bona fide occupational qualification. However, this was not defined in the Act, and while the EEOC did issue guidelines, employers and newspapers could argue there was uncertainty over meaning and enforcement. As we show below, the practice of expressing explicit gender preferences in individual job ads took ten years to fade out after the passage of the Civil Rights Act. Likely the evolution of court cases related to segregated pages played a role in how employers and newspapers interpreted the legality of gendered language as a whole. Indeed, there are specific examples of courts or agencies holding newspapers responsible for ensuring the text of the ads they publish are not discriminatory.[8]

In sum, the 1964 Civil Rights Act and other Acts at that time, along with the 1965 establishment of the EEOC were key turning points in firms' and newspapers' ability to legally target workers on the basis of gender. However, (i) enforcement of these new pieces of legislation gradually and unevenly strengthened throughout the mid-to-late 1960s and early 1970s (this accords with

[6] "Help Wanted" refers to advertisements posted by employers or employment agencies, searching for potential employees. In contrast, the much less common phrase "Situations Wanted" refers to advertisements posted by individuals searching for employment opportunities.

[7] As Kerman [1974] recounts, Section 1604.5 of the EEOC guidelines was amended to indicate that "[t]he placement of an advertisement in columns classified by publishers on the basis of sex, such as columns headed "Male" or "Female," will be considered an expression of a preference, limitation, specification, or discrimination based on sex" and, as such, are a violation of Title VII of the Civil Rights Act [Equal Employment Opportunity Commission, 1968].

[8] This includes *Passaic Daily News vs. Blair* in the New Jersey Supreme Court in 1973, and the California Fair Employment Practices Commission letter to newspaper publishers in 1973. See Kerman [1974] for more details.

the EEOC's own characterization of the 1965-1971 period as one in which the commission was a "toothless tiger."[9]), and (ii) the legal and institutional environment was already evolving, towards greater equity in the labor market, in the 1940s and 1950s.

3 Data

This section introduces the main datasets used in this paper, explains how we merge them, and assesses representativeness.

3.1 EEO-1 Filings

Beginning in 1966, all firms with at least 100 employees and all federal contractors with at least 50 employees were required to file annual reports on their distribution of workers across gender, race, and ethnicity, within broad occupation classes. The EEOC's authority to collect these "EEO-1 filings" is based on Section 709(c) of Title VII of the Civil Rights Act and the subsequent executive order (#11246) covering affirmative action of government contractors [United States Congress, 1964; Office of the President of the United States, 1965]. We obtained reports for most years between 1966 and 1995 from the National Archives.[10]

Orley Ashenfelter conducted an independent analysis of the 1966 filings as part of an EEOC contract with the W.E. Upjohn Institute for Employment Research. He is quoted (via his report) in the first annual EEOC report:

> The most important conclusion of this report is that the data collected through the EEO-1 reporting system are a generally accurate and highly useful body of material for the investigation of the employment patterns of minority groups in the United States. The general accuracy of the data, and their inherent limitations, have been substantiated by comparing them with data from other sources.

[United States Equal Employment Opportunity Commission, 1966, p.viii]

Ashenfelter and Heckman [1976] offer an early economic analysis of the 1966 and 1970 EEO-1 filings to study the effect of the affirmative action executive order on Black-White gaps.[11]

The data consist of establishment-level reports on employment.[12] We use company names to match employers to their classifieds and directory listings but use Employer Identification Numbers

[9] See: https://www.eeoc.gov/eeoc/history/35th/1965-71/index.html , accessed May 14, 2018.

[10] Accessed here `https://catalog.archives.gov/id/600965` on February 28, 2025. Establishment-level reports are made publicly available after 30 years but reports are not available for 1976, and odd years between 1977 and 1989; we do not know why reports are unavailable for these years. Reports were available for 1978 but we deem these to be anomalous, as they severely under count female employees, so we exclude them from our analysis.

[11] See also later studies on affirmative action using EEOC data including: Leonard [1984, 1989]; Miller [2017]; Kurtulus [2016]. These studies leverage variation in federal contractor status across filers over time to study the impact of the affirmative action executive order on race and/or gender integration.

[12] Starting in 1970, multi-establishment companies were instructed to file an EEO report for each establishment, as well as a consolidated report for the entire company. We evaluate these alternative data for robustness.

(EINs) as our main unit of analysis by summing employment in each category across all establishment reports. It would be difficult to distinguish establishments within the company-name match because of limited geographic information in the ad sources. It is the case that national companies can have more than one EIN, that a single EIN can match to many different company names, and EINs can change over time. We also explored defining employers based on a regularized company name. However, EINs provide a cleaner and more transparent approach than string-based matching.[13]

At the EIN level, we have good coverage over time. Because we are interested in changes in gender composition after the 1964 Civil Rights Act and subsequent court rulings, we include only EINs that have at least some employment data in the years 1966-69. While this period falls after the 1964 Civil Rights Act, it is before the 1973 Supreme Court ruling prohibiting job advertisements segregated by sex. Of the 72,944 companies (EINs) that appear in the filings in the 1960s, 33% are observed as well in both the 1970's and 1980's, reflecting 71% of 1960s employment. Hereafter, we focus on this balanced panel of EINs, but assess representativeness in appendix B.

Occupation detail is limited to nine groups that are consistently observed over our sample period: managers & officials, professionals, technicians, sales workers, clerical workers, craftsmen, production workers, laborers, and service workers.

3.2 Classified ads in 3 major U.S. Newspapers: 1940-2000

Data Details

The classifieds dataset is constructed from a sample of 9.3 million job ads which were published in the *Boston Globe, New York Times,* and *Wall Street Journal*; see Atalay et al. [2018, 2020]; Atalay and Sarada [2020]. The *Times* ads are available from 1940 to 2000; the *Journal* from 1940 to 1998, and the *Globe* from 1960 to 1983. In those earlier papers, the authors obtained raw text files from ProQuest, identified which pieces of text constituted job ads, and defined the boundaries between ads. They used both display ads and regular classifieds sections, which we pool for the most part.

As in the original papers, we limit our attention to ads meeting a length requirement and a cutoff for the percentage of correctly-spelled words. This restriction helps somewhat in limiting noise generated by the fact that the text scraping is imperfect and many ads are abbreviated or incomplete due to space constraints. We use their codings for education and experience requirements, as well as tasks, skills, and technology used on the job. We also use their imputed occupations.[14] See appendix A.2 for additional details.

Compared to those papers, we focus on the content of these ads as they pertain to gender

[13]To further validate, we examined year-to-year variation in total employment at the EIN level to see whether measurement issues (such as adding, dropping, or changing establishment links to EINs) were common but the distribution looks reasonable, with very few outliers.

[14]The earlier papers extracted the job title for each ad and mapped these to detailed SOC occupation codes using a *continuous bag of words* model. The method associates job titles together that tend to be found nearby similar sets of words using the full text of the job ads plus supplemental corpora, and in so doing, matches each job title to the closest in a list of O*NET titles, which then yields an O*NET SOC occupation code.

preferences. We also merge the data with the EEO-1 records (detailed below) and map 6-digit SOC codes to broad EEO occupation categories using an EEOC provided crosswalk [U.S. Equal Employment Opportunity Commission, 2006].

Measuring Gender Targeting

We search ad text for words and phrases indicating an explicit preference for men or women. To do so, we construct three lists: one indicating a preference for a male candidate, a second indicating a preference for a female candidate, and a third explicitly indicating no preference for male or female candidates. Examples from the first list include: "young man", "right man", "for men", "experienced man", and "man fri".[15] Examples from the second list include "gal fri", "young lady", "girl office", "young woman', and "for women". The third list includes strings like "man or woman", "men or women", "guy gal", and"housewives or men". We present the exhaustive lists in Appendix A.2 along with more details. We assign a job ad as explicitly targeting male candidates if it includes a string match from the first list but not the second or third. We assign a job ad as explicitly targeting female candidates if it includes a string match from the second list but not the first or third. We assign a job ad as explicitly open to either gender if it includes a mention from the third list. We exclude the job title from the text being searched for keywords to avoid ambiguous cases where the job title itself is gendered (e.g., "salesman").

Appendix table D.2 provides summary statistics of the job ads by whether the ad had an explicit gender preference. For this table and in most of our analyses, we focus on the 1946-1970 period as it is 1) overlapping with the directory, 2) focuses on the period when gender targeting was most active, 3) comes mainly before the major legal precedents for gender discrimination in job advertising were set, and 4) avoids World War II, which might have driven unusual (and interesting in their own right) hiring preferences. We also evaluate gender targeting over time in section 4.2.

Gender targeting is fairly uncommon with 5% of ads specifying a male preference, 4% targeting women, and 1.5% expressing explicit openness to either gender.[16] Most types of classifieds were typically quite abbreviated, since authors paid for space. Ads generally have many missing characteristics and the same is true of the gender categorizations. For instance, only about 10% of ads have an identifiable education requirement. Still, we find a great deal of signal in the gender preferences, despite the noise. Explicitly listing gender in the ad may reflect strong employer preferences, given that ads are brief and employers are paying for space.

Appendix table D.2 also shows that ads with gender preferences are wordier than ads without. Male ads have more skill requirements, are more likely to prefer a married worker, and are more

[15] "Fri" is the first three characters of Friday. "Man Friday" and "Gal Friday" were positions akin to today's administrative assistant roles.

[16] We considered a much broader classification that triggered a gender target for any male or female noun. This definition results in a more than doubling of gender targeted ads, but we are concerned about false positives. For instance, the alternative definition would trigger "come work in a men's clothing store" as targeting men and "nanny for our baby girl" as targeting women. These targeting rates remained non-trivially elevated throughout the sample period (ending in 2000), even after targeting was outlawed, in principle and in practice. Still, we find consistent results with these alternative measures, compared to the preferred ones presented here.

likely to indicate an irregular schedule, relative to ads targeting women, both men and women, or non-targeted ads. Female ads are more likely to prefer an attractive worker and indicate a regular schedule. Finally, our sample is dominated by the *New York Times* and by classifieds, even though we also make use of larger display ads.

One reason why our measures of explicit gender targeting may understate employers' underlying preferences is that newspapers (excluding the *Wall Street Journal*) often segregated advertisements onto pages targeted at either Male or Female job seekers. We code this information as well. Appendix Figure D.1 plots trends in page targeting and shows a sharp declining following the 1968 ruling in the National Organization of Women lawsuit. We focus on the explicit targeting measures discussed above both because the language itself more likely reflects the choice of the firm posting the ad, since many ads likely defaulted to targeted pages – though we also present companion results for page targeting and reach similar conclusions (see appendix C). The two measures are correlated. From table D.2, 41% of male targeted ads are on a male page; 45% of female targeted ads are on a female page. At the same time, half of ads that are not explicitly targeted fall on a targeted page. Our explicit targeting measures likely understate gender preferences, since firms advertising on a gender-specific page may have less reason to state those preferences explicitly.

3.3 The 1958 College Placement Directory

Data Details

The *College Placement Directory* series was first published in 1953 to help match college students with employers. The volume was deemed so successful (by the authors) that it was updated in 1955, 1958, and 1965. We access the third edition, published in 1958, as it is the closest one to the beginning of the EEO employment data in 1966, that still had gender targeting. From the preface:

> COLLEGE PLACEMENT DIRECTORY, therefore, was designed to serve several groups. It will point out to college graduates–both men and women–many job opportunities they did not know existed. And it will thus increase each one's chance of obtaining the type of job he wants with the type of company for whom he would like to work. It will help the companies by making it possible for them to learn about outstanding men and women whom they would ordinarily not reach through their recruiting services. And it will be of inestimable value to our busy professors and college placement officers who are constantly asked for answers to the questions: "Where Can I Get A Job?" and "What Can You Tell Me About the Such-and-Such Company?"

[Zimmerman and Lavine, 1958, p.vii]

The authors of this volume surveyed employers about the jobs for which they were recruiting, and surveyed colleges about their enrollment and placement office contact information. We focus on the section of company listings. Appendix figure D.2 gives an example of an entry for Eastman Kodak. Entries are highly regularized in this volume and include the company name, location,

nature of business, size, approximate number of graduates hired per year, and contact information. The volume has 1468 unique entries. Within an entry, a company will list several job titles along with gender and education preferences. The volume includes over 11 thousand job title listings within company entries. For instance, Kodak seeks accountants who are male with either bachelor's or master's degrees. For chemists, they hire both men and women; librarians are exclusively women, etc.

Appendix A.3 describes how we extract the information contained in the listings from an already-available OCR version of the directory.[17]

We regularize job titles across listings with a series of text cleanings. We then use the OpenAI GPT-5 language model (OpenAI [2025]; accessed through ChatGPT) to assign job titles to EEO occupation categories. The prompt includes a description of the nine EEO occupational categories that was included in the EEO's earliest documentation given to firms to help them fill out the forms (United States Equal Employment Opportunity Commission [1966], p.xv). We manually reviewed the resulting crosswalk, and made minor changes for consistency. In addition, we map the regularized job titles into SOC occupation codes following the same method as in Atalay et al. [2020].

Measuring Gender Targeting

Compared to the classifieds, these listings are much cleaner and more complete. Each job title within an entry includes education and gender preferences, which are readily extracted in our pdf scraping. Every position lists a gender preference: M for only men, W for only women, and MW for both.[18] Appendix table D.3 provides summary statistics for listings in the directories by gender preference. 72% of listings are for only men, 8.6% are for only women, and 19% are for both. We have a much more limited set of covariates in the directory, but the ones we do have are complete. All ads require at least a Bachelor's degree. Firms hiring men also are more likely to be searching for workers with advanced degrees, as are firms with an openness to both genders. Firms with ads targeting men only are also larger.

3.4 Census and Current Population Survey Data

We also bring in population-level data from the decennial censuses and Current Population Survey March Supplement for the periods of overlap with our data. We map 1990 census occupation codes to broad EEO categories using an EEOC provided crosswalk [U.S. Equal Employment Opportunity Commission, 1994]. See appendix A.4 for details.

[17] Accessed via the HathiTrust Digital Library in April 2025 `https://catalog.hathitrust.org/Record/006106244`.

[18] There were two company entries out of 1468 that did not contain gender preferences and we drop these from our analysis.

3.5 Merges

We merge each job vacancy dataset to EEO-1 filings using company name. As detailed in the data appendices (A.2 and A.3), we regularize company names across all datasets and identify both exact matches and close string matches. We use manual checks to ensure match quality and also perform manual searches for large firms that did not match.

We then must aggregate company-level gender preferences to the EIN level, which serves as our primary unit of analysis. The same company name can match to more than one EIN and multiple company names can match to the same EIN, so the vacancy-EEO linkage is many-to-many. In order to aggregate gender preferences to the EIN level, we average gender preference indicators across all listings associated with a given EIN. When a vacancy matches to multiple EINs, we allow it to contribute to the gender-targeting measure of each EIN. This approach reflects our view that individual vacancy listings provide noisy signals of an employer's underlying hiring preferences, so all credible matches contain useful information.

We also construct gender targeting measures at the EIN-by-EEO occupation level. In this case, we restrict the aggregation to vacancies whose job titles map to the corresponding broad EEO occupational category.

We match 2000 firms in the EEO to at least one of the vacancies datasets. This match reflects 10% of firms and 60% of employment in the EEO balanced panel (46% of employment matches to the classifieds and 45% to the directories; 33% of employment match to both). For the classifieds, the majority of ads are missing information on firm name. Of the 5000 identifiable names, we can match about 1,000 to the EEO, reflecting 20% of ads. In the directory, we can also match about 1000 firms (out of 1500) to the EEO, reflecting 70% of listings.

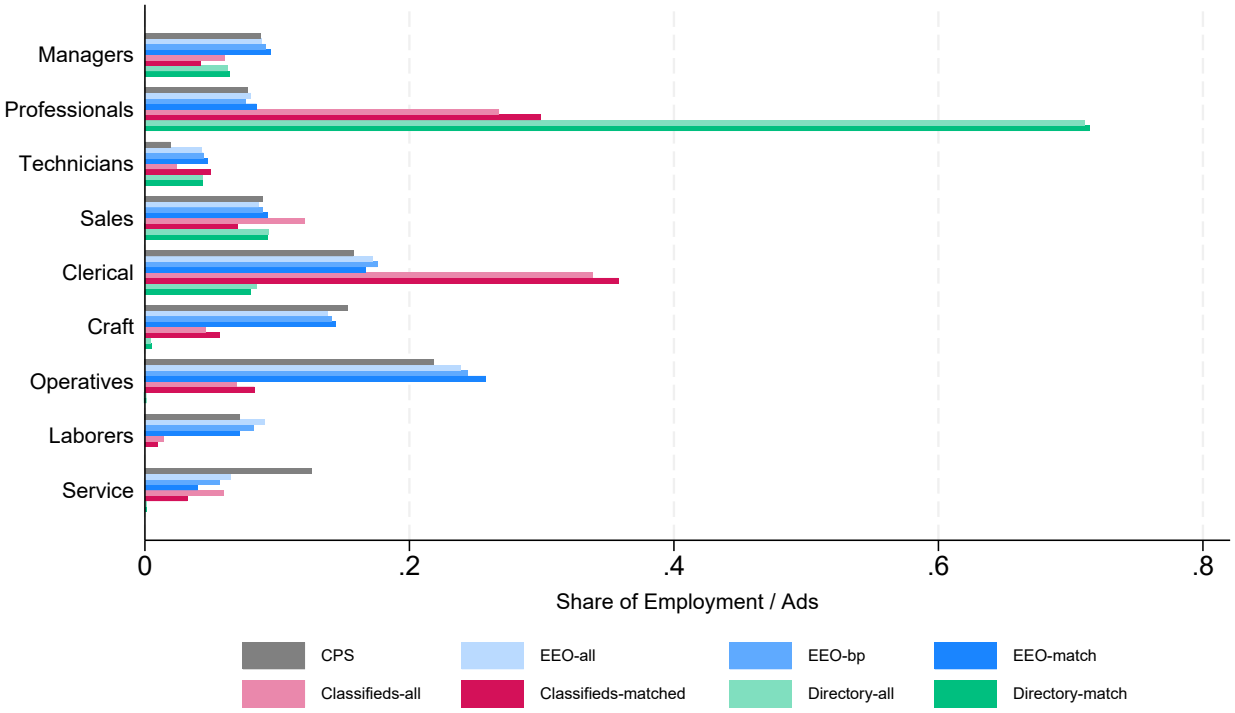
3.6 Data Representativeness

We confront several issues regarding representativeness across the different datasets. The EEO-1 filings contain information for large U.S. companies and federal contractors. Thus the data are selected both in terms of a company's presence and persistence over time. The classifieds and directory listings each reflect a non-random sample of firms' gender preferences. The directory includes firms that were recruiting at the college level and were responsive to the authors' survey. The newspaper dataset is broader in terms of the mix of job types represented, but still selects on the types of firms and jobs that both list in these three major newspapers and include enough information to make the listing useful. The newspaper data concentrate in the Boston and New York labor markets, but because these are major news publications, they still contain a substantial number of ads for employment across the country.

To better understand these selection issues, we conduct several analyses. Figure 1 compares the occupational distribution of employment in the 1960s across the March Current Population Survey (CPS) and the EEO for various subsamples. We focus on the broad EEO occupation categories

and show ad distributions for the classifieds and directory as well.[19] Employment in the EEO and its subsamples are fairly representative of CPS employment. We do see an overrepresentation of operatives and laborers in the EEO and an underrepresentation in services, reflecting differences in the underlying industrial mix (see figure B.2). These differences are more pronounced across two subsamples of the EEO filings: "EEO-bp" restricts to a balanced panel of firms (EINs) that can be observed in each of the first three decades (1960s, 1970s, and 1980s), while "EEO-match" further restricts to firms that match one of the ad sources.

Figure 1: Occupational Distributions Across Datasets



Notes: We summarize employment shares across the broad EEO occupation categories in the 1968-69 Current Population Survey March Supplement and the EEO-1 filings for the same years. The lightest blue includes all filers; the next shade restricts to a balanced panel of firms that are observed in the 1960s, 1970s, and 1980s (EEO-bp); the darkest blue further restricts the balanced panel to firms that match either the directory or the classifieds. We also plot ad shares in the classifieds (red) and directory (green). The darker red and green panels restrict to ads that can be matched to a firm in the EEO.

The distribution of job ads across broad EEO occupations shows some differences across the two vacancy sources and when compared to employment shares. (Job ads need not match the distributions of employment stocks, but the comparison provides a useful benchmark.) The classifieds (red bars) substantially overrepresent professionals and clerical workers, and underrepresent production

[19] We restrict employment to 1968 and 1969 since the CPS had only very aggregated industry and occupation categories prior to then. CPS employment is restricted to private sector workers who are not self employed. For the classifieds, we limit to 1946-1970, our preferred sample years for measuring gender targeting.

workers.[20] The recruiting directory is even more skewed: the vast majority of its listings are in professional occupations, though there are still nontrivial fractions in other white-collar jobs.

The darker red and green bars restrict to ads that can be matched to firms in the EEO. These ads look fairly representative to the samples as a whole.

In appendix B, we offer a more in-depth analysis of EEO employment, compared to the CPS, over time, across space, and by gender and occupation. We find that the EEO-1 filings capture 50% of private sector employment in the first half of the sample, and fall to 40% in the 1990s. The dropoff is more pronounced in our balanced panel and matched sample: the sample restricted to firms in operation in the 1960s grows increasingly out of date. We also find that female workers are underrepresented in the EEO, compared to the CPS. Still, employment distributions across gender and occupations track each other fairly well over time.

We offer internally consistent analyses of these datasets, acknowledging the representation issues. It is beneficial that we can leverage two different sources of gender preferences. On the one hand, the directory offers more precision: the ads (and scraping) are much cleaner, fields are regularized and complete. However, they only cover college recruiting behavior for the employers that the authors could reach. The classifieds, on the other hand, cover a much broader set of listings, but do overrepresent the northeast and are much noisier. The fact that we will find consistent results across the two datasets with different advantages and disadvantages is helpful for drawing broader conclusions.

4 Gender targeting before Civil Rights

4.1 Gender targeting rates

Table 1 lists the job titles with the highest gender targeting rates for both the classifieds and the directory.[21] The lists of titles align fairly well with stereotypical male and female roles. In the classifieds, male jobs include various sales positions, while female jobs are mainly secretarial-related and nursing. Explicit openness to both men and women is quite uncommon in the classifieds in this time period and the most prominent titles here are a broad mix. In the directory, the titles skew professional. Most jobs are male dominated and the top 10 list includes lawyers and architects as well as a range of others (engineers and economists are also extremely male dominated but fall just outside the top 10). Only a small handful are female dominated: home economists, nurses,

[20] Atalay et al. [2020] discuss the representativeness of the newspaper job ad data. They reach similar conclusions regarding the occupational composition, finding an overrepresentation of white- and pink-collar jobs—Sales, Business and Finance, Architecture and Engineering, and Office and Administrative Support—and fewer ads in blue-collar occupations than in the workforce. They argue that these differences largely reflect how job seekers find employment: in the latter set of occupations, workers are more likely to contact the employer directly or find work through friends and relatives.

[21] We have cleaned these job titles to regularize the text, but there is still quite a bit of noise in the classifieds stemming from typos or especially detailed job titles. To cut out some of that noise we restrict our attention to classifieds titles with at least 200 ads and directory titles with at least 25 ads (the lower threshold in the directory is because the directory is a much smaller and cleaner dataset).

secretaries, librarians, and medical technicians. There is a larger mode of male-female jobs, which include life sciences positions, fine arts, and banking personnel.

Table 1: **Top 10 most gender-targeted job titles**

Panel A: Newspaper Classifieds 1946-1970

Rank	Explicit Male Targeting		Explicit Female Targeting		Male-Female Targeting	
	Title	Share	Title	Share	Title	Share
1	Collector salesperson	0.30	Clerical s trainee	0.43	Insurance sales career	0.40
2	Technical assistant	0.30	Gal guy fri personnel	0.32	Testy sales	0.19
3	Paper salesperson	0.25	Secretary advertising agency	0.32	Optician	0.15
4	Auto parts manager	0.25	Phone clerk	0.31	Sales position	0.13
5	Auto sales manager	0.25	General office worker	0.28	Mail clerk messenger	0.12
6	Truck salesperson	0.24	Bookkeeper stenographer	0.25	Art assistant	0.11
7	Crew manager	0.24	Long distance telephone operator	0.24	Hair dresser	0.11
8	Assistant to sales manager	0.23	Typist gal guy fri	0.23	Gal guy fri personnel	0.10
9	Hardware salesperson	0.23	Receipt trainee	0.23	Hair stylist	0.10
10	Salesperson trainee	0.23	Tutors private instruction	0.21	Temporary personnel	0.08

Panel B: 1958 College Recruiting Directory

	Male targeting		Female targeting		Male-Female targeting	
Rank	Title	Share	Title	Share	Title	Share
1	Forester	1.00	Home economist	0.95	Biologist	0.67
2	Plant management	0.99	Nurse	0.95	Illustrator	0.67
3	Safety	0.97	Secretaries stenographer	0.88	Bacteriologist	0.60
4	Agriculturist	0.95	Librarian	0.71	Pharmacologist	0.59
5	Agronomist	0.95	Medical technician	0.51	Spectroscopist	0.59
6	Lawyer	0.95	Bookkeeper	0.12	Biochemist	0.52
7	Foreign trade	0.94	Banking	0.07	Artist	0.49
8	Architect	0.94	Editor	0.05	Underwriter	0.44
9	Industrial administration	0.93	Food technologist	0.05	Banking	0.43
10	Traffic transportation	0.93	Journalist	0.03	Mathematician	0.41

Notes: This table lists the job titles where explicit gender targeting was most common. After regularizing job titles for consistency, we further restrict to those with at least 200 postings in the classifieds to clean out some additional noise in the text. For the directory, we restrict to titles with at least 25 listings. The regularizing of job ads combines close variations, so for instance "gal guy fri" groups together the titles "gal fri" and "guy fri", with the former being much more common. In the directory, many titles included "personnel" at the end, which we also removed in order to regularize, e.g., "safety" refers to the job title "safety personnel".

The higher rates of gender targeting in traditionally-male or traditionally-female jobs holds more systematically. Table 2 gives average rates of gender targeting in each dataset, by EEO occupation category. The classifieds show more pronounced male targeting in managerial, sales, and blue collar positions. The directory has a more limited set of occupations but also shows the strongest male targeting for salespeople, along with managers. Both datasets have much higher female targeting in clerical positions, though the directory also has considerable female targeting among technicians (likely explained by the fact that technicians include nurses, based on the EEO descriptions). Professional jobs in the directories are not likely to ask for women only (there are

very few teaching positions for instance) but this is the most likely group to ask for both men and women.

Table 2: Occupation-level summary statistics

Panel A: Newspaper Classifieds 1946-1970

Occupation	Male-Only	Female-Only	Male-Female
Managers	0.066	0.023	0.015
Professionals	0.046	0.017	0.017
Sales	0.093	0.022	0.016
Clerical	0.028	0.071	0.012
Technicians	0.042	0.019	0.024
Craft	0.075	0.012	0.014
Operatives	0.064	0.022	0.015
Laborers	0.072	0.026	0.015
Service	0.040	0.052	0.021
Total	0.049	0.039	0.015

Panel B: 1958 College Recruiting Directory

Occupation	Male-Only	Female-Only	Male-Female
Managers	0.882	0.001	0.117
Professionals	0.775	0.020	0.205
Sales	0.835	0.010	0.155
Clerical	0.191	0.635	0.174
Technicians	0.465	0.377	0.158
Total	0.723	0.086	0.190

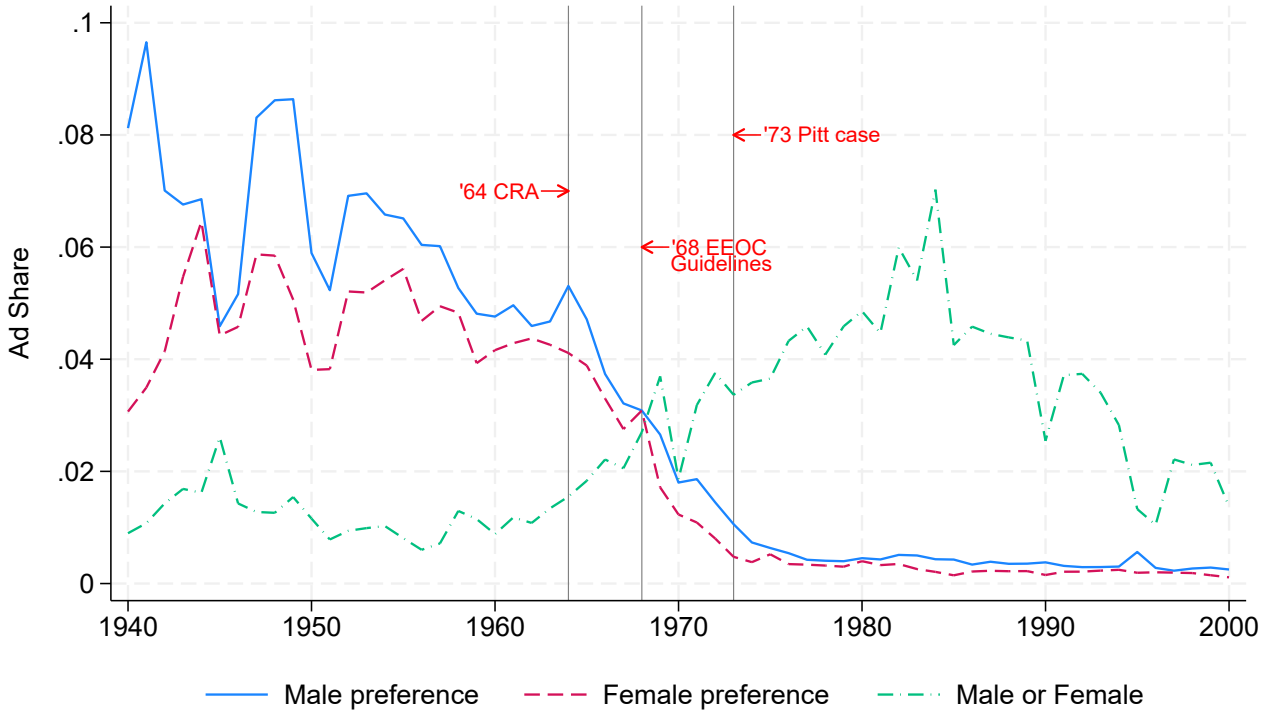
Notes: We summarize rates of gender targeting in the job ads datasets by broad EEO occupation category. The top panel focuses on the classifieds – restricting to 1946-1970; the bottom panel focuses on the 1958 college recruiting directory.

Goldin [1986] explores a 1940 Bureau of Labor Statistics (BLS) survey of firms employing office workers in 5 U.S. cities (Houston, Kansas City, Los Angeles, Philadelphia, and Richmond) asking about personnel practices. She finds that the majority (63%) of large firms in her sample have explicit occupation-segregation policies for both genders (and 72% have explicit policies regarding at least one gender). Women's jobs were mid-level clerical positions such as stenographers, typists, switchboard operators, etc. Many of the same jobs have a high preference for female workers in table 1. Men's jobs were both high level positions such as accountants and managers, but also many menial positions such as messengers. Our analysis, which also includes non-office positions, shows also that manual jobs are more likely to require men.

4.2 Gender targeting over time

Figure 2 shows the full time series of gender targeting in the classifieds dataset. Explicit male and female targeting are most pronounced at the beginning of the sample period. In the 1940s, 7.4 percent of ads mentioned a preference for male applicants; 5.1 percent of ads include a mentioned

Figure 2: Trends in explicit gender targeting



Notes: We plot ad shares for each type of gender targeting, by year. Common keywords indicating gender preferences are listed in appendix table D.1. The passage of the 1964 Civil Rights Act (CRA), 1968 EEOC guideline revision on segregated pages, and the Pittsburgh Press Supreme Court ruling are indicated with vertical lines. See appendix figure D.3 for separate trends by newspaper and type of ad. See appendix figure D.4 for a time series that restricts to firms that can be matched to the balanced panel EEO.

preference for female applicants. In the 1950s, these rates were 6.0 percent and 4.7 percent, respectively. Similar to studies focused on gender targeting in modern-day China, Mexico, and Austria, we also find that, conditional on having a gender preference, it is roughly equally likely that the preference will be for a woman as for a man [Kuhn and Shen, 2013; Helleseter et al., 2020; Card et al., 2024].

The figure also indicates with vertical lines the passage of the 1964 Civil Rights Act (CRA), the EEOC 1968 guideline revision for segregated pages, and the Pittsburgh Press Supreme Court case, mentioned above. Gender targeting declines beginning in the 1950s, long before major employment discrimination legislation, and the declines are rather gradual. Still, even by 1970, five years after the foundation of the EEOC, a sizable fraction of ads mentioned an explicit gender preference. By 1980, however, essentially zero ads include an explicit gender preference.[22] Perhaps surprising when compared to this newspaper sample, the fourth edition of the college placement directory, published in 1965, had removed explicit gender preferences entirely [Zimmerman and Lavine, 1965].

[22]The level is not precisely zero due to measurement error but by the 1990s, male and female targeting rates range from 0.1% to 0.2%.

By contrast, the share of ads explicitly mentioning an openness to hiring either gender gradually increases in the first decades of our sample, averaging around 1 percent in the 1950s and peaking in the 1980s at 7 percent.

Appendix figure D.3 reports these trends separately by newspaper and ad type (classifieds versus display ads). Explicit gender targeting was present across all sources and shows a similar decline over this period. Male preferences were much larger in the *Wall Street Journal* and also more pronounced among *New York Times* display ads, both likely due to occupational mix. Appendix figure D.4 gives the time series when restricting to firms that can be matched to the EEO. Trends are very similar, though because the sample is much smaller there are some anomalies, such as a large spike in targeting in 1945.[23]

The decline in gender targeting exhibited in figure 2 might in part be due to trends in demand for skill or other changes in the occupation structure over this time period. Appendix figure D.5 decomposes the change in explicit targeting from the baseline time period into within and between occupation components. We allow changes in ad shares across 4-digit SOC occupation codes to drive changes in gender targeting, separately from within occupation changes in explicit targeting behavior. Interestingly, we find that the entire decline is due to within occupation changes in explicit targeting.

We focus especially on the 1946-1970 period, which avoids World War II and the anomalous year (1945) in the EEO-matched dataset. Another reasonable choice would be to limit to ads posted before the EEOC was established in 1965 even though targeting was largely unregulated in practice until the early 1970s; results are quite consistent with this alternative restriction.

4.3 Correlates of gender targeting

We next explore covariates associated with gender targeting. We bring in census data from 1960 to compare ad characteristics to the employed population at the occupation level.[24] Figure 3 summarizes the relationship between gender targeting and the hours-weighted male employment share at the 4-digit SOC occupation level using bin scatters.

Across both vacancy datasets, we find that occupations with higher male employment shares are more likely to target men (blue) and less likely to target women (red). These results are reassuring that stated requirements in job ads are linked to employment outcomes. There is little relationship between an openness to both genders and this occupational outcome.

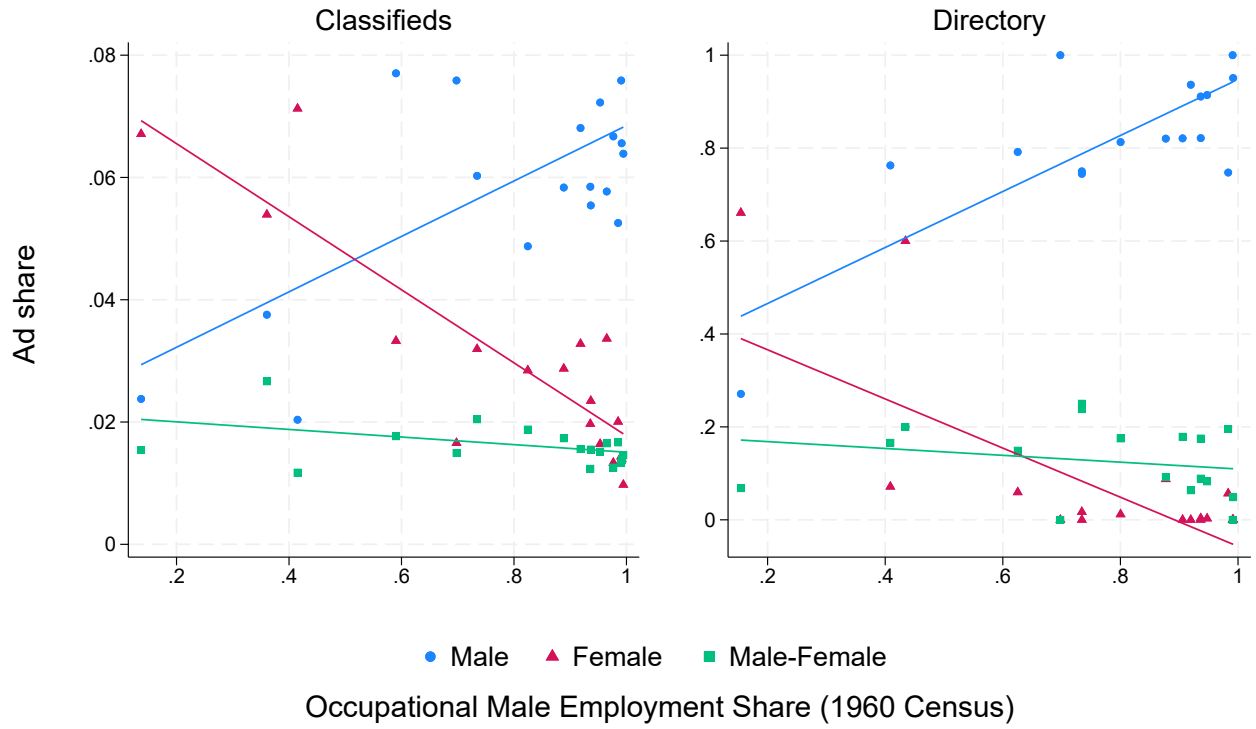
Also, as discussed above, we see mean differences in ad characteristics across ads with different gender targets, such as differences in education requirements. To better understand the drivers of these relationships we perform simple regression analyses.

Table 3 summarizes analysis using the classifieds. Ads can have no gender target, or target men, women, or express an openness to both. We use two different outcomes to summarize these

[23]There is also a much larger 1980s peak in the rate at which firms indicated an openness to either gender. The rise of the term "eeo-mf" drives the peak and is naturally more pronounced among firms regulated by the EEOC.

[24]We prefer using the 1960 Census, rather than in combination with the 1940 and 1950 Censuses because employment variables for the latter are only available for the sample-line subset of respondents.

Figure 3: Explicit Gender Targeting and Occupational Employment Share



Notes: We relate gender targeting to male hours-weighted employment shares measured in the 1960 census. Underlying data points are at the 4-digit SOC occupation level, which we use to create bin scatters weighting by total hours worked in the 1960 census. The y-axis plots the share of ads with gender preferences (aggregated from 1946-1970 in the classifieds).

possibilities. The left 3 columns explore the propensity to include any gender target, while the right panel explores the rate of male targeting in a sample that conditions on any targeting. We control for a cubic in ad length and fixed effects for year and ad source (newspaper-by-ad type). Standard errors are clustered at the 4-digit occupation level.

The first column in each panel includes a range of possibly relevant ad and occupation characteristics. Ads with higher male employment shares in the 1960 census are less likely to gender target (column 1) but conditional on targeting, they are more likely to target men (column 4) – confirming that the relationship in figure 3 holds within ad-level controls. We found that some of the other occupation characteristics were important in isolation. For instance, occupational hours worked and average wages are positively correlated with male targeting. However, in the horserace, most of the effect loads on male employment share.

Turning to ad characteristics, we find that ads with gender targeting are less likely to have education and experience requirements, and less likely to post a salary. They are also more likely to be posted on segregated pages. They do often contain other job characteristics such as indicating a regular or irregular schedule and indicating a preference for a married applicant or a preference

for an attractive applicant. Subsequent columns include 4-digit occupation and then job title fixed effects and show these relationships hold even with these controls, suggesting they are not driven by production processes within the job itself.

Perhaps more interesting are columns 4-6, which show predictors of male targeting in a sample of more complete ads that have any gender target. We find ads with higher posted salaries are more likely to target men, rather than women or being open to both.[25] Only a small subset of ads post a salary – roughly 4% – and male targeted ads are more likely to have salary information.[26]

Male ads are also more likely to have education and experience requirements, compared to the other targets. They are less likely to advertise a regular schedule and more likely to advertise an irregular one. They are more likely to be posted on a male segregated page. They are also more likely to demand a married applicant and less likely to specify an attractive applicant. Finally, they are much more likely to be posted on a male page and much less likely to be posted on a female page. The share of ads posted on a male page is roughly 30% so explicitly targeted ads are twice as likely to show up on a targeted page. Again, the fact that these relationships hold even within job title fixed effects suggests that features of the job itself or the production process do not drive the correlations across these ad features, but rather a collection of firm's idiosyncratic preferences.

One final point of note, the (adjusted) R-squares at the bottom of the table show that it is difficult to predict whether an ad has any gender target and we gain little explanatory power by adding occupation fixed effects. Job title fixed effects explain more, increasing the R-squared by about two-thirds. Once we condition on having a gender preference, ad and occupation characteristics can explain about 20% of the variation in the likelihood of targeting men (the mean male targeting rate is 0.47) and adding occupation fixed effects improves the predictive power to 28%. Job title fixed effects double the predictive power, compared to the baseline model.

Table 4 shows analogous regressions for targeting in the directory. We again find that occupational male employment share in the 1960 census is strongly predictive of male targeting, and other occupation variables are not. In addition, male targeted ads are less likely to ask for advanced degrees. Because there are very few ads that target only women, this result – which holds within occupation and job title fixed effects – comes from the much higher education requirements among ads targeting both men and women (appendix table D.3). One possible interpretation is that employers have more difficulty finding workers for more specialized jobs (i.e., jobs requiring advanced degrees) and so they become more open to hiring women.

We have fewer covariates in the Directory but we do have a clean measure of firm size. We find larger firms are more likely to target men, even holding constant the types of jobs they are hiring for.

Overall, we find that explicit targeting is prevalent across the two datasets in the pre civil

[25]This result is consistent with the classic finding that male-dominated occupations tend to pay more than female-dominated ones [England, 1992]. Our result holds even within 4-digit occupation fixed effects.

[26]The pay rate typically is also posted with a pay frequency – hourly, weekly, monthly or yearly. Before including posted log salary in this regression, we residualize it on pay rate frequencies so that levels are meaningful across the different listings. In order to compare other covariates in the table using the full sample, we include ads with missing salary information by adding a value of zero to posted salary when missing and also including the indicator variable.

rights period. The propensity is much lower in the classifieds, possibly obscured by the presence of page targeting, which may have been sufficient for employers who wanted to explicitly target. We find gender targeting is correlated with education requirements and other ad features. Still, we do not know whether gender targeting has consequences for employment segregation. While we do find that male targeting is correlated with male employment share at the detailed occupation level, that result could be driven by occupational norms. Naturally many push and pull factors might be at play in the sorting of men to traditionally-male jobs and the sorting of women to traditionally-female jobs. Next, we take advantage of the EEO merge to examine relationships between idiosyncratic gender targeting at the firm level and employment segregation.

Table 3: **Gender Targeting and Job Skill: Classifieds**

Dep var:	Any Targeting			Male targeting		
Sample:	All			Ads with targeting		
	(1)	(2)	(3)	(4)	(5)	(6)
Posted log salary	-0.013***	-0.013***	-0.007**	0.027***	0.020**	0.017
	(0.002)	(0.002)	(0.003)	(0.009)	(0.008)	(0.014)
Missing salary	0.009***	0.009***	0.008***	-0.042***	-0.035***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.007)
Education Requirement	-0.023***	-0.021***	-0.018***	0.014	0.015***	0.010
	(0.002)	(0.002)	(0.001)	(0.011)	(0.006)	(0.007)
Experience Requirement	-0.020***	-0.018***	-0.016***	0.025***	0.026***	0.018***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.005)	(0.005)
Regular schedule indicated	0.023***	0.023***	0.016***	-0.160***	-0.133***	-0.102***
	(0.004)	(0.004)	(0.005)	(0.011)	(0.008)	(0.008)
Irregular schedule indicated	0.026***	0.025***	0.018***	0.097***	0.089***	0.067***
	(0.003)	(0.004)	(0.004)	(0.009)	(0.009)	(0.010)
Male page	0.010***	0.010***	0.006***	0.248***	0.222***	0.154***
	(0.003)	(0.002)	(0.002)	(0.029)	(0.028)	(0.034)
Female page	0.015***	0.015***	0.009***	-0.299***	-0.269***	-0.187***
	(0.002)	(0.002)	(0.002)	(0.034)	(0.030)	(0.024)
Male-female page	0.006***	0.006***	0.002	0.016	0.009	-0.005
	(0.002)	(0.002)	(0.002)	(0.014)	(0.015)	(0.017)
Preference for married	0.100***	0.096***	0.080***	0.231***	0.221***	0.189***
	(0.009)	(0.009)	(0.011)	(0.020)	(0.022)	(0.029)
Preference for attractive	0.075***	0.071***	0.058***	-0.177***	-0.160***	-0.113***
	(0.011)	(0.011)	(0.010)	(0.029)	(0.027)	(0.038)
Occ. Male Employment Share	-0.030***			0.341***		
	(0.006)			(0.046)		
Occ. Average Log Wage	-0.015			0.104		
	(0.010)			(0.067)		
Occ. Gender Pay Gap	0.012			0.074		
	(0.018)			(0.108)		
Occ. College share	-0.027**			-0.165***		
	(0.013)			(0.061)		
Occ. Annual Hours per Worker (100s)	0.001			0.002		
	(0.001)			(0.006)		
Occ. Average Age	0.000			0.006		
	(0.001)			(0.006)		
Observations	4,418,617	4,418,617	4,418,617	456,342	456,342	456,342
Adjusted R2	0.057	0.060	0.095	0.338	0.373	0.481
Outcome mean	0.104	0.104	0.104	0.474	0.474	0.474
Basic controls	X	X	X	X	X	X
Occ FEs		X			X	
Job title FEs			X			X

Notes: Standard errors in parentheses clustered on 4-digit occupation. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The sample is restricted to classified ads posted between 1946 and 1970. We summarize ad-level regressions where the outcome is whether the ad has any target (columns 1-3) or having a male target in a sample that conditions on any targeting (columns 4-6). Basic controls are included in all specifications and consist of a cubic in ad length (# of words) and controls for year, source (newspaper)-by-ad type (display or classified) fixed effects. Occupational variables are obtained from the U.S. Census and matched at the 4-digit SOC occupation level. Log(salary) has been residualized on pay frequency (hourly, weekly, monthly, or annually); we dummy out missing observations with a zero and include an indicator for missing salary. Education (experience) requirement equals 1 if the ad indicates any education (experience) is required for the position. The second column includes 4-digit occupation fixed effects, while the third includes job title fixed effects.

Table 4: **Gender Targeting and Job Skill: Directory**

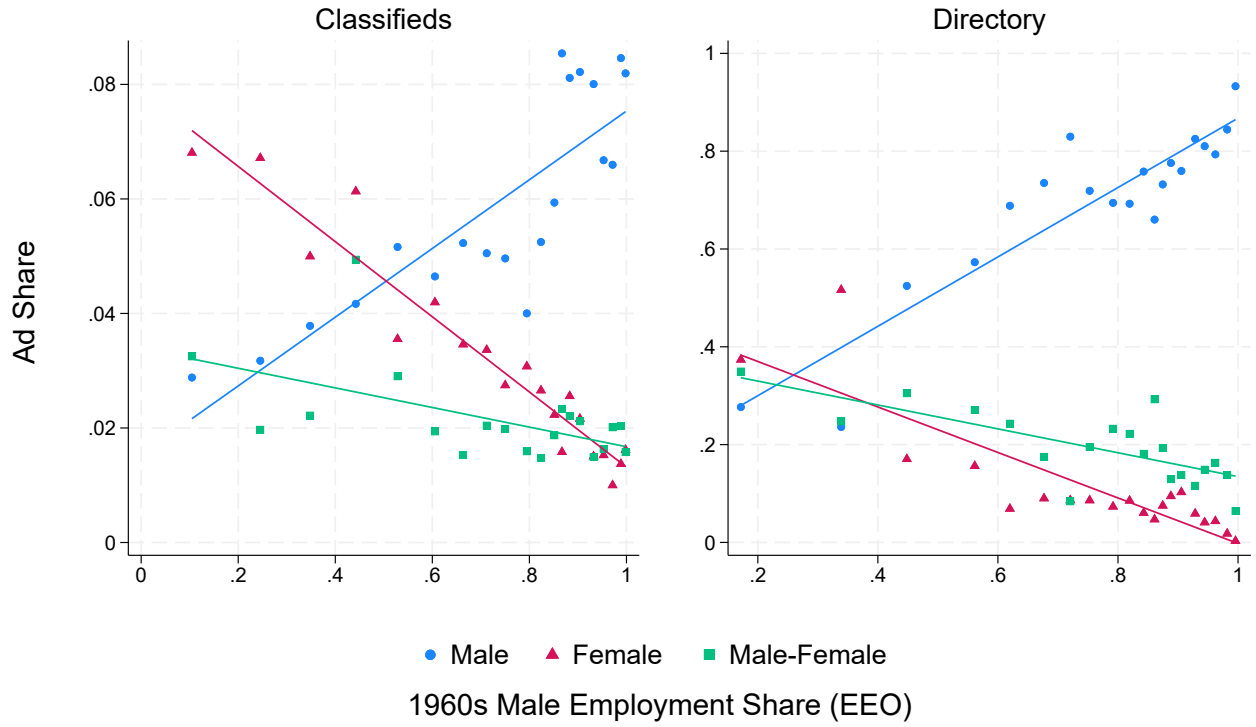
Dep var:	Male targeting		
	(1)	(2)	(3)
Master's requirement	-0.051***	-0.057***	-0.056***
	(0.016)	(0.015)	(0.013)
Doctorate requirement	-0.156***	-0.141***	-0.151***
	(0.032)	(0.024)	(0.017)
# employees (10,000s)	0.010***	0.008***	0.008***
	(0.002)	(0.001)	(0.001)
# ads (100s)	-0.529***	-0.390***	-0.401***
	(0.086)	(0.072)	(0.066)
Occ. Male Employment Share	0.982***		
	(0.213)		
Occ. Average Log Wage	-0.110		
	(0.103)		
Occ. Gender Pay Gap	0.174		
	(0.113)		
Occ. College share	-0.138		
	(0.156)		
Occ. Annual Hours per Worker (100s)	-0.027		
	(0.028)		
Occ. Average Age	0.014		
	(0.012)		
Observations	11,226	11,226	11,226
Adjusted R2	0.233	0.309	0.355
Outcome mean	0.724	0.724	0.724
Occ FEs		X	
Job title FEs			X

Notes: Standard errors in parentheses clustered on 4-digit occupation. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We summarize ad-level regressions in the 1958 directory where the outcome is whether the ad targeted only men. Column 1 includes a constant and no other controls. Column 2 ads 4-digit occupation fixed effects; column 3 adds job title fixed effects.

5 Gender Targeting and Employment

Descriptives

Figure 4: Gender Targeting and 1960's Male Employment Shares



Notes: We plot binscatters of gender targeting and male employment shares measured in the EEO. Underlying data are firm-by-broad occupation group cells. We bin observations based on their male employment share averaged over the 1966-1969 EEO-1 filings. We plot means of male employment shares and gender targeting measures in the directory (left) and the classifieds (right).

Figure 4 summarizes the relationship between a firm's gender targeting in the pre–civil rights period and the firm's male employment share in the earliest EEO filings – averaging over 1966-1969 for precision. These 1960s reports fall in fairly close proximity to our targeting measures: 1946-1970 for the classifieds and 1958 for the directory. We plot bin scatters based on firm-by-broad occupation cells. In both datasets, we find strong positive relationships with male targeting: firm-occupation cells with higher male employment shares in the 1960s also had a higher share of male-targeted ads pre–civil rights. Female and male-female targeting both exhibit negative relationships with male employment shares at the firm, with a weaker effect for male-female targeting.

In this section, we wish to understand whether gender targeting and the barriers to gender integration that it represents drive gender segregation. However, the correlations in figure 4 could be driven by occupational norms. For instance a firm hiring in an especially male category (e.g., management) or an especially female category (e.g., clerical) could have gender-targeted vacancies

reflecting these norms and gender-segregated employment. In this case, the targeting reflects the norms of gender segregation in the occupation rather than the targeting causing segregation at the firm. Occupational norms may themselves arise from discrimination, worker sorting, or other factors, and it would be difficult to separate which factor drives a correlation between targeting and employment. Next, we describe how we leverage idiosyncratic gender targeting to better distinguish firm preferences from other factors driving occupational sorting.

Methods

Do firm preferences over gender drive representation in employment? Does anti-discrimination policy curtail this behavior? We explore these questions using equations 1 and 2, respectively.

In equation 1, we regress male employment share (emp^m) in broad occupation group o, firm f, and year t on male targeting (G_{of}) in the firm-occupation cell. Because female targeting is rare in the directories while male-female targeting is rare in the classifieds, and because the two types of targeting exhibit broadly similar patterns with respect to the male employment share, we group them together to comprise the omitted category. By estimating this regression separately by decade (d, which is implicitly a function of t), we allow the relationship between pre-civil rights gender targeting and employment to vary over time. Regressions are weighted by employment in the firm-occupation-year, and standard errors are clustered by firm. We include fixed effects for the nine broad EEO occupation categories (γ_o) and explore a range of additional controls which vary at the firm and/or occupation level (X_{of}), which we discuss next.

$$emp^m_{oft} = \alpha^d G_{of} + \gamma^d_o + \theta^d X_{of} + \varepsilon_{oft} \tag{1}$$

A positive correlation between the firm's male targeting and male employment share does not in and of itself imply that firm preferences drive gender sorting. Occupation fixed effects are a coarse control for whether firms with stronger male targeting have different employment structures that favor men for other reasons. However, heterogeneity within broad occupations could be a driving factor. A firm with strong male targeting in professional occupations might be searching for engineers – a male-dominated profession –, while a firm with strong female targeting in professional occupations might be searching for librarians – a female-dominated occupation. If these firms also have greater male or female employment shares, respectively, we would not know whether the correlation was driven by their taste or worker preferences, education backgrounds, etc. Likewise, firms with greater male targeting may have production processes that favor men compared to firms with less male targeting – even if they both recruit in the same broad occupation category.

In order to isolate idiosyncratic firm preferences from occupational norms, we calculate the mean male targeting rate at the detailed occupation level (4-digit SOC), and make this a firm-specific measure by leaving out the firm's own targeting. We average these leave-out means across all ads a firm posts within a broad EEO occupation category. Our preferred male-targeting measure

is the deviation of the firm's actual targeting rate within an EEO occupation category from this leave-out occupational targeting rate. We also experiment with using the raw male targeting ad share and controlling directly for the leave-out mean. While gender sorting at the broad occupation level could be driven by a range of push and pull factors, these are unlikely to be drivers of the relationships isolated with α^d.

Our method allows us to take into account the mix of detailed occupations at the firm – inferring based on the firm's distribution of ads – even while the EEO outcomes are measured at the broad occupation level. In addition to the leave-out means in gender targeting, we also explore controls for other occupation characteristics. These are measured at the 4-digit occupation level, which we again aggregate using the distribution of ads to weight within a broad EEO group. These controls, along with fixed effects for industry and state, help adjust for differences in production processes or availability of labor that are correlated with male targeting and employment share, but are not captured by average gender targeting across detailed occupations. We include controls for the following occupational characteristics, constructed using the 1960 census: male employment share, average college share, and average log wage. These could be especially important as we consider how the relationship in equation (1) evolves over time. For example, firms with more traditionally-male occupations or more skilled employment in the 1960s may evolve differently over the remainder of the 20th century due to technological change or increased educational attainment of women, and these differences could be correlated with changes in gender integration.

We also include six occupational indices explored in Cortes and Pan [2018]. They use O*NET to calculate attributes of jobs in recent years that might be salient to women including: cognitive skill, competitiveness, flexibility, physicality, the social contribution of the job, and interactive skills. They show these attributes correlate with occupational gender segregation today, so they may also be predictive of how firms' employment shares evolved as women entered the workforce.

We argue that after including these detailed occupational controls, any remaining correlation between idiosyncratic male targeting and male employment shares is driven by a firm's taste over gender. The key identifying assumption is that conditional on these controls, no other factor correlated with idiosyncratic male targeting drives male representation in employment. We cannot necessarily pinpoint that male targeting in advertisements per se drives the relationship, as gender preferences may permeate personnel decisions in many ways. Rather, male targeting captures a workplace environment with barriers to female integration, at least in certain jobs.

Equation 2 examines whether firm-occupations with stronger and weaker gender targeting show any convergence in male employment shares over time.

$$emp^m_{oft} = \sum_{\delta \neq 1960} \left(\beta^\delta [G_{of} \mathbf{1}\{d = \delta\}] + \gamma^\delta_o + \theta^\delta X_{of} \right) + \lambda_{of} + \varepsilon_{oft} \tag{2}$$

Here, we stack all years in the sample, absorb the main effect of gender targeting with firm-occupation fixed effects (λ_{of}), and estimate whether the within firm-occupation relationship be-

tween gender targeting pre-1970 and male employment share varies by decade (the coefficients β^{δ}).[27] We also explore a specification that allows the effect to vary by year, but pooling by decade offers more precision.

These regressions allow us to ask whether the male employment share for firm-occupations with more male targeting converges to the share at firm-occupations with less male targeting. If the removal of targeting per se impacts representation, we should see convergence. We would also expect convergence if other anti-discrimination measures differentially impact firms with greater gender targeting. Recall the EEOC had little enforcement power in the 1960s so we would expect impacts only later. Effects may also be more evident later as the EEO employment data measure stocks not flows, and targeting in job ads should affect new hires.

For this regression to be viewed as a test of the impacts of anti-discrimination policy on more discriminatory firms, the identifying assumption is that firms with greater male targeting would not have differentially changed their male employment shares for reasons other than these policies. Our measure of idiosyncratic targeting, as well as the occupational controls described above (interacted with decade), adjust for the fact that firms with greater male targeting may have production processes that would naturally evolve to favor women. For instance, manufacturing firms may heavily rely on production workers in the 1960s – jobs which favor men – but later adopt technologies that increasingly favor women. Firms that employ an educated workforce may have increased female employment shares over time as female educational attainment rose.

However, during the sample period, many changes impacted women at work. The 1980s and 1990s in particular were a period of significant convergence of women and men in the labor market due to a variety of factors besides federal discrimination policy, including delayed marriage, increased educational attainment, increased labor force participation, and changing societal norms. If these changes impact all firms equally, then our identifying assumption holds. However, we would also see convergence if these other societal changes differentially affected the firms who previously were more heavily engaged in targeting. On the other hand, if less discriminatory firms were more responsive to these societal changes, this force would push towards divergence and potentially cancel out any differential impacts of anti-discrimination policy on targeting firms. We discuss this channel in more detail below.

For all of these analyses, we estimate regressions separately for gender targeting measures in the directory and classifieds. For the classifieds regression, we also control separately for the rate of no targeting (also expressed as a deviation from the leave-out mean in the no targeting rate). This approach allows for better comparability across the two datasets. Also, due to measurement error, ads where we were unable to pick up any targeting measures may not serve as a good counterfactual since we might have missed instances of actual targeting, and this is another reason we control for them separately instead.[28] Finally, we standardize gender targeting measures so that magnitudes

[27] We can also understand convergence by comparing the coefficients α^{d} from equation 1 across decades. Results are similar but equation 2 is preferred because it holds constant firm-occupation composition, yielding more precision in the comparisons over time.

[28] These specification choices mean that we cannot tell whether correlations between male targeting rates and

of coefficients are comparable across datasets.

Results

Table 5 summarizes results from estimating equation 1 for the 1960s. Our baseline specification in column 1 includes occupation fixed effects. As above, we find that idiosyncratic male targeting positively predicts male employment in the 1960s, and the relationship holds within broad occupation groups. In the classifieds (panel A) we find a one-standard deviation increase in male targeting increases male employment shares in the 1960s by 7.4 percentage points (roughly 10% of the mean male employment share). We find a very similar magnitude (6.5 ppts) in the directory and both effects are significant at the 1% level.

The table explores several sets of controls that might drive the correlation between male targeting and male employment. Column 2 adds state and industry (one-digit SIC) fixed effects to the baseline specification, while column 3 adds the additional occupation controls. Columns 4 and 5 test whether functional form matters by using the raw preference measures and controlling directly for the leave-out means instead, and by estimating a fractional logit, respectively. The significant correlation between a firm's idiosyncratic male targeting rate and its male employment share is robust across the specifications.

We next examine these relationships in subsequent decades. We plot coefficients from our baseline (column 1 of Table 5) specification for each decade in the top panel of figure 5. We find magnitudes fall in subsequent decades though point estimates are still positive and statistically significant. Appendix table D.4 shows effects hold across decades and specification. Gender preferences of firms in the 1960s predict gender segregation throughout the 20th century. Relationships between pre-civil rights male targeting and male employment shares are significant at the 1% level or better in all decades and specifications, except in the 1990s for targeting measured in the directories significance levels in some specifications are at the 5 or 10% level.

The bottom panel of figure 5 summarizes equation 2, which helps us isolate convergence over time by controlling for firm-occupation fixed effects. The specification in this panel also includes occupation-by-decade fixed effects to control flexibly for broad trends in gender integration across occupations. We find negative interaction terms that increase in magnitude with time. Firms with stronger and weaker male preferences converge towards each other in the male employment share. By 1990, a firm with a one standard deviation higher male preference in the classifieds has undone nearly 2 percentage points of their relatively higher male employment share, roughly one-quarter of the 1960s difference. In the directory the effect is also negative and about 20% of the 1960s gap.

Table 6 shows that this convergence holds conditional on several sets of controls. Column 1

convergence over time are driven by firms with strong male preferences, strong female preferences, or both. Still, for comparability across datasets, these choices make the most sense. In addition, measurement in the classifieds is quite noisy so we limit to firms that post at least 10 ads in the occupation group (three-quarters of weighted observations). This restriction is not necessary in the directories which 1) have cleaner classification of titles across firms, 2) often include many titles in each firm's listing, and 3) have some kind of targeting for every type of ad. However, it makes little difference whether we impose this restriction or not.

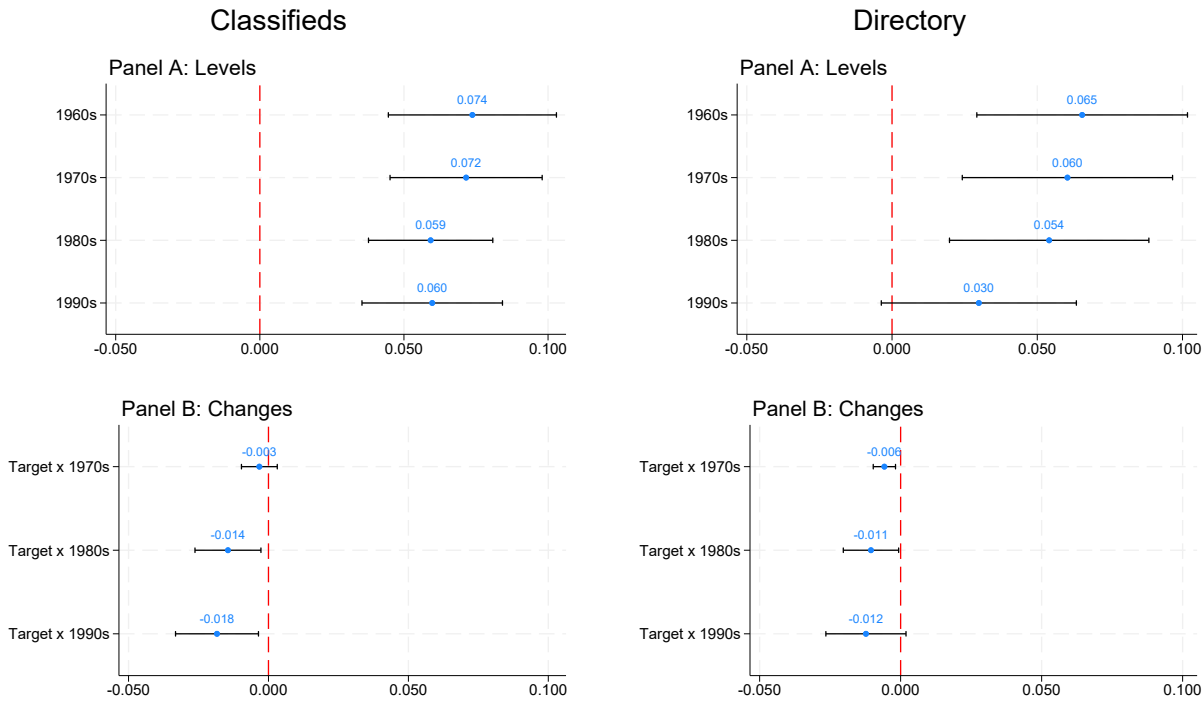
Table 5: **1960's Male Employment Shares and Gender Targeting: Regression Analysis**

Dependent variable:	Male Employment Share				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	FL
Panel A:	Classifieds				
Male Target	0.074***	0.060***	0.052***	0.062***	0.105***
	(0.015)	(0.013)	(0.013)	(0.016)	(0.023)
Observations	12,592	12,592	12,592	12,592	12,592
R2	0.595	0.657	0.682	0.619	
Panel B:	Directory				
Male Target	0.065***	0.065***	0.063***	0.090***	0.082***
	(0.019)	(0.017)	(0.016)	(0.025)	(0.020)
Observations	10,147	10,146	10,145	10,147	10,147
R2	0.769	0.790	0.803	0.770	
Occupation FEs	X	X	X	X	X
Industry and State FEs		X	X		
Census Occ Controls			X		
Leave-out mean as control				X	
Fractional Logit					X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are in parentheses, clustered on firm. The table summarizes regressions as in equation 1. Observations are firm-occupation-year cells and weighted by EEO employment. The dependent variable is the male employment share measured in the EEO-1 filings and is restricted to the 1960s. The main regressor, male targeting is defined (in columns 1-3 and 5) as the deviations from the firm's leave-out mean at the detailed occupation level measured in the classifieds between 1946 and 1970 (panel A) and the 1958 recruiting directory (panel B). In the classifieds analysis, we also control for the rate of no targeting. Occupations fixed effects are for the 9 broad EEO groupings; industries are 1-digit SIC codes. Census occ controls are 4-digit SOC occupation-level variables (average log wage, college share, male share, and six indices from Cortes and Pan [2018]). Column 4 uses raw male targeting as the regressor of interest and controls separately for the leave-out mean. Column 5 reports marginal effects from a fractional logit. Regressors are scaled so coefficients can be interpreted as the impact of a one standard deviation increase in male targeting.

reports the baseline specification. Column 2 adds controls for industry-by-decade and state-by-decade, while column 3 interacts each of the occupation controls with decade fixed effects. To the extent that the occupational desegregation of women was more pronounced in jobs with different attributes or different worker characteristics at baseline, these controls are helpful, in case they correlate with gender targeting as well. We do find that these attributes predict male employment shares increasingly over time: for instance, firms recruiting in more male occupations become increasingly female over time, as do firms recruiting in occupations with greater social contribution; firms recruiting in occupations with less flexibility become increasingly male. However, these controls do not impact the key coefficients of interest. We also address the functional form concern in

Figure 5: Male Employment Shares over Time and Male Targeting



Notes: The top panel plots coefficients on male targeting from equation 5 estimated separately by decade and controlling for occupation fixed effects. The bottom panel plots coefficients on male targeting interacted with decade dummies using equation 2, controlling for firm-by-occupation and occupation-by-decade fixed effects. 95% confidence bars are also shown. Male targeting is measured as the deviation from the leave-out mean at the detailed occupation level. Regressors are scaled so coefficients can be interpreted as the impact of a one standard deviation increase in male targeting. These coefficients are also summarized in the column 1 specification in tables 5, 6, and D.4.

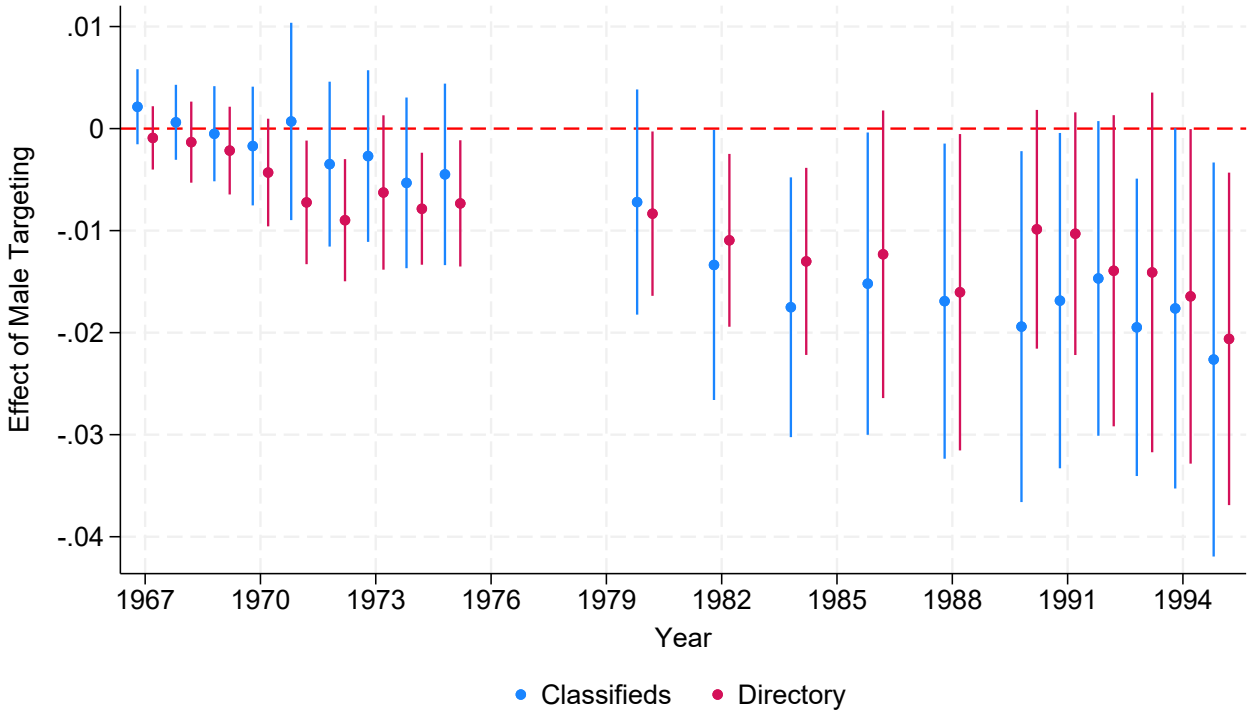
columns 4 and 5.

The convergence between more and less discriminatory firms holds across specification. Magnitudes are largest in the 1990s, though effects in earlier decades are more precise.

Figure 6 explores convergence in more detail by plotting year-by-year effects of male targeting, compared to a 1966 benchmark. These estimates are noisier but still instructive. We see point estimates that are precisely zero in the 1960s. Effects become negative as we move into the 1970s though estimates in the classifieds are noisy. The relationship between male targeting in the pre-period and male employment share becomes more negative, and statistically different from the effect in 1966 for both vacancy sources starting in the 1980s. It is difficult to pinpoint the timing of various policy changes more precisely. The EEO-1 filings are missing for the second half of the 1970s. In addition, employment stocks will be slow moving, compared to changes in hiring behavior.

An alternative explanation for the convergence is that preferences regarding gender simply become outdated. The ads are measured prior to the 1970s but we track employment for the next

Figure 6: Male Employment Shares over Time and Male (relative to female) Targeting



Notes: We plot coefficients on male targeting-by-year interactions based on an alternate version of equation 2. 95% confidence bars are also shown. We interact the targeting variables with year fixed effects and also control for occupation-by-year and firm-by-occupation fixed effects. Male targeting is measured as the deviation from the leave-out mean at the detailed occupation level. Regressors are scaled so coefficients can be interpreted as the impact of a one standard deviation increase in male targeting.

several decades. First, this explanation seems unlikely since we still find statistically significant relationships between targeting and 1990s employment. Preference measures do not become completely irrelevant. Still, to probe this explanation further, we measure whether relationships with other ad characteristics also become attenuated. Figure D.6 plots the relationship between ad shares across broad occupation groups and employment shares in each occupation group by decade, using the same set-up. We find strong positive relationships that persist across the decades. Rather than attenuating, effects remain constant when using ad shares in the classifieds and even diverge over time when using ad shares in the directory. In the latter case, baseline ad shares across occupations increasingly predict differences across firms in their occupational employment distributions. Thus it is certainly not the case that all ad characteristics become obsolete, even decades later.

Discussion

The results in this section point to a set of firms that made heavier use of male targeting before the civil rights era and had persistently higher male employment shares throughout the second half

of the 20th century, albeit with a weakened relationship over time. Our controls and our measure of firm-level idiosyncratic targeting are aimed at ruling out that different production processes or supply side factors drive these results. Given controls for industry, state, and detailed occupation characteristics, it should not be the case that firms with more idiosyncratic male targeting are more likely to hire more men for reasons other than their preferences. Controlling for these factors also implies they cannot explain differences in the trajectory of male employment share over time. Instead, it is likely that the firm-level idiosyncratic targeting captures meaningful differences across firms in gender preferences.

Targeting per se can drive sorting if qualified female applicants are deterred from applying due to the language of the ad, but targeting may also reflect intangible barriers at the firm level which then drive higher male employment shares. Because we find the correlation persists long after gender targeting, effects must at least in part be driven by workplace environments that are not caused by ads per se. Managers with strong gender preferences may continue to tip the scales via more subtle personnel practices. Or, in a less overt manner, networks built up over years when gender discrimination was less regulated could drive persistence [Miller, 2017].

Our sample period is one of several important anti-discrimination policies, as well as many societal changes related to women in the labor market, including increased education, attachment, and changing norms. This landscape makes especially noteworthy the persistent correlation, albeit with modest weakening, between male targeting in the pre–civil rights era and male employment share through the 1990s. Anti-discrimination policy might have had much larger effects on gender-targeting firms. If job ads per se drove the sorting then it is sensible that outlawing gender targeting would have a bigger effect on these firms. Other closely related anti-discrimination policies might have made it more difficult for these firms to express their preferences as well. We find the heavily-targeting firms converge only modestly towards the firms that targeted less. However, a potential force pushing in the opposite direction is differential employer responses to other societal changes in this period. Firms that did not openly express male preferences may have been more receptive to an expanding pool of qualified women precisely because they held weaker discriminatory preferences.

6 Conclusion

This paper provides the first extensive, large scale characterization of gendered language in job advertisements in the United States during the period when gender targeting was legal and prominent. We find that gender targeting aligns with stereotypes at the occupation level. In addition, when focusing on firm-level preferences that deviate from norms, we find gender targeting significantly predicts gender employment segregation. Firms with discriminatory preferences saw persistently lower gender integration through the end of the 20th century. Even so, we see evidence of some convergence following the major policy reforms of the late 1960s and early 1970s that solidified protections for women in the workplace.

Over the second half of the 20th century, women joined the labor force en masse and began

to enter traditionally male jobs. So there is scope for non-discriminatory firms to pull ahead. At the same time, discriminatory behaviors were increasingly outlawed, making it difficult for discriminatory firms to continue to meet their preferences. We argue that these changes drove modest convergence between more and less discriminatory firms.

Our results point to a set of "hold out" firms that made heavy use of male targeting before the civil rights era and had persistently higher male employment shares throughout the second half of the 20th century. While there has been some convergence, more work was necessary as late as 1995 to increase this convergence between firms that were more and less hostile towards gender integration decades earlier.

Table 6: **Convergence in Male Employment Shares and Gender Targeting**

Dependent variable:	Male Employment Share				
	(1)	(2)	(3)	(4)	(5)
	OLS	OLS	OLS	OLS	FL
Pane A:	Classifieds				
Male Target × 1970s	-0.003	-0.004	-0.005	-0.004	-0.008
	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)
Male Target × 1980s	-0.014**	-0.012*	-0.012**	-0.014**	-0.037***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.013)
Male Target × 1990s	-0.018**	-0.015*	-0.013	-0.016*	-0.043***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.016)
Observations	58,516	58,514	58,514	58,516	58,549
R2	0.969	0.970	0.971	0.969	
Pane B:	Directory				
Male Target × 1970s	-0.006***	-0.006***	-0.005***	-0.007**	-0.014***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)
Male Target × 1980s	-0.011**	-0.011**	-0.010*	-0.013*	-0.036***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.010)
Male Target × 1990s	-0.012*	-0.011	-0.009	-0.015	-0.056***
	(0.007)	(0.007)	(0.006)	(0.011)	(0.013)
Observations	45,462	45,462	45,454	45,462	45,480
R2	0.971	0.972	0.973	0.971	
Occupation-by-decade FEs	X	X	X	X	X
Firm-by-occupation FEs	X	X	X	X	
Industry/State-by-decade FEs		X	X		
Census Occ-by-decade Controls			X		
Leave-out mean-by-decade as control				X	
Fractional Logit					X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are in parentheses, clustered on firm. The table summarizes regressions as in equation 2. Observations are firm-occupation-year cells and weighted by EEO employment. The dependent variable is the male employment share measured in the EEO-1 filings between 1966 and 1995. The main regressor, male targeting interacted with decade dummies, is defined (in columns 1-3 and 5) as the deviations from the firm's leave-out mean at the detailed occupation level measured in the classifieds between 1946 and 1970 (panel A) and the 1958 recruiting directory (panel B). In the classifieds analysis, we also control for the rate of no targeting interacted with decade. Occupations fixed effects are for the 9 broad EEO groupings; industries are 1-digit SIC codes. Census occ controls are 4-digit SOC occupation-level variables (average log wage, college share, male share, and six indices from Cortes and Pan [2018]) and are interacted with decade dummies. Column 4 uses raw male targeting as the regressor of interest and controls separately for the leave-out mean interacted with decade. Column 5 reports marginal effects from a fractional logit and omits firm-by-occupation fixed effects because an incidental parameters problem. Regressors are scaled so coefficients can be interpreted as the impact of a one standard deviation increase in male targeting.

References

Ashenfelter, Orley and James Heckman, "Measuring the Effect of an Anti-Discrimination Program," in Orley Ashenfelter and James Blum, eds., *Evaluating the Labor-Market Effects of Social Programs*, Princeton, NJ: Princeton University Press, 1976, pp. 46–89.

Atalay, Enghin and Sarada Sarada, "Firm Technology Upgrading through Emerging Work," *Unpublished manuscript*, 2020.

_ , Phai Phongthiengtham, Sebastian Sotelo, and Daniel Tannenbaum, "New Technologies and the Labor Market," *Journal of Monetary Economics*, 2018, *97*, 48–67.

_ , _ , _ , and _ , "The Evolving U.S. Occupational Structure," *American Economic Journal: Applied Economics*, 2020, *12* (2), 1–36.

Bailey, Martha J., "More Power to the Pill: The Impact of Contraceptive Freedom on Women's Life Cycle Labor Supply," *Quarterly Journal of Economics*, 2006, *121* (1), 289–320.

_ , Thomas Helgerman, and Bryan A. Stuart, "How the 1963 Equal Pay Act and 1964 Civil Rights Act Shaped the Gender Gap in Pay," *Quarterly Journal of Economics*, 2024, *139* (3), 1827–1878.

Bayard, Kimberly, Judith K. Hellerstein, David Neumark, and Kenneth R. Troske, "New Evidence on Sex Segregation and Sex Differences in Wages from Matched Employee-Employer Data," *Journal of Labor Economics*, 2003, *21* (4), 887–922.

Beller, Andrea H., "The Effects of Title VII of the Civil Rights Act of 1964 on Women's Entry into Nontraditional Occupations: An Economic Analysis," *Law and Inequality*, 1983, *1* (1), 73–90.

Bem, Sandra L. and Daryl J. Bem, "Does Sex-Biased Job Advertising "Aid and Abet" Sex Discrimination?," *Journal of Applied Social Psychology*, 1973, *3* (1), 6–18.

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz, "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors," *American Economic Journal: Applied Economics*, July 2010, *2* (3), 228–55.

Blau, Francine D., *Equal Pay in the Office*, Lexington, MA: Lexington Books, 1977.

_ and Lawrence M. Kahn, "Changes in the Labor Supply Behavior of Married Women: 1980–2000," *Journal of Labor Economics*, 2007, *25* (3), 393–438.

_ and _ , "The Gender Wage Gap: Extent, Trends, and Explanations," *Journal of Economic Literature*, 2017, *55* (3), 789–865.

_ , Peter Brummund, and Albert Yung-Hsu Liu, "Trends in Occupational Segregation by Gender 1970–2009: Adjusting for the Impact of Changes in the Occupational Coding System," *Demography*, 10 2012, *50* (2), 471–492.

Card, David, Ana Rute Cardoso, and Patrick Kline, "Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women," *Quarterly Journal of Economics*, 2016, *131* (2), 633–686.

_ , **Fabrizio Colella, and Rafael Lalive**, "Gender Preferences in Job Vacancies and Workplace Gender Diversity," *The Review of Economic Studies*, 08 2024, *92* (4), 2437–2471.

Carrington, William J., Kristin McCue, and Brooks Pierce, "Using Establishment Size to Measure the Impact of Title VII and Affirmative Action," *The Journal of Human Resources*, 2000, *35* (3), 503–523.

Chay, Kenneth Y., "The Impact of Federal Civil Rights Policy on Black Economic Progress: Evidence from the Equal Employment Opportunity Act of 1972," *ILR Review*, 1998, *51* (4), 608–632.

Cortes, Patricia and Jessica Pan, "Occupation and Gender," in Susan L. Averett, Laura M. Argys, and Saul D. Hoffman, eds., *The Oxford Handbook of Women and the Economy*, Oxford University Press, 07 2018.

Darity, William A. and Patrick L. Mason, "Evidence on Discrimination in Employment: Codes of Color, Codes of Gender," *Journal of Economic Perspectives*, 1998, *12* (2), 63–90.

Donohue III, John J., "Employment Discrimination Law in Perspective: Three Concepts of Equality," *Michigan Law Review*, 1994, *92* (8), 2583–2612.

Donohue, John J. and James Heckman, "Continuous Versus Episodic Change: The Impact of Civil Rights Policy on the Economic Status of Blacks," *Journal of Economic Literature*, 1991, *29* (4), 1603–1643.

Endres, Kathleen L., ""Help-Wanted Female": Editor & Publisher Frames a Civil Rights Issue," *Journalism & Mass Communication Quarterly*, 2004, *81* (1), 7–21.

England, Paula, *Comparable Worth: Theories and Evidence* Social Institutions and Social Change, New York: Aldine de Gruyter, 1992.

Equal Employment Opportunity Commission, "Job Opportunities Advertising," *Federal Register*, August 1968, *33*, 11539.

Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, Daniel Backman, Etienne Breton, Grace Cooper, Julia A. Rivera Drew, Stephanie Richards, David Van Riper, and Kari C. W. Williams, "IPUMS CPS: Version 13.0 [dataset]," 2025.

Freeman, Jo, "How Sex Got into Title VII: Persistent Opportunism as a Maker of Public Policy," *Minnesota Journal of Law & Inequality*, 1991, *9* (2), 163–184.

Goldin, Claudia, "Monitoring Costs and Occupational Segregation by Sex: A Historical Analysis," *Journal of Labor Economics*, 1986, *4* (1), 1–27.

_ , "Marriage Bars: Discrimination Against Married Women Workers, 1920's to 1950's," in Patrice Higonnet and David S. Landes Henry Rosovsky, eds., *Favorites of Fortune Technology, Growth, and Economic Development since the Industrial Revolution*, Harvard University Press, 1991, pp. 511–538.

_ , "The Quiet Revolution That Transformed Women's Employment, Education, And Family," *American Economic Review*, 2006, *96* (2), 1–21.

_ , "A Grand Gender Convergence: Its Last Chapter," *American Economic Review*, 2014, *104* (4), 1091–1119.

_ **and Lawrenace Katz**, "The Power of the Pill: Oral Contraceptives and Women's Career and Marriage Decisions.," *Journal of Political Economy*, 2002, *110* (4), 730–770.

Groshen, Erica L., "The Structure of the Female/Male Wage Differential: Is It Who You Are, What You Do, or Where You Work?," *Journal of Human Resources*, 1991, *26* (3), 457–472.

Hellerstein, Judith K. and David Neumark, "Workplace Segregation in the United States: Race, Ethnicity, and Skill," *Review of Economics and Statistics*, 2008, *90* (3), 459–477.

_ **,** _ **, and Melissa McInerney**, "Changes in Workplace Segregation in the United States Between 1990 and 2000: Evidence from Matched Employer-Employee Data," in Stefan Bender, Julia Lane, Kathryn Shaw, Fredrik Andersson, and Till von Wachter, eds., *The Analysis of Firms and Employees: Quantitative and Qualitative Approaches*, Chicago: University of Chicago Press, 2008, pp. 163–195.

Helleseter, Miguel Delgado, Peter Kuhn, and Kailing Shen, "The Age Twist in Employers' Gender Requests," *Journal of Human Resources*, 2020, *55* (2), 428–469.

Kerman, Peter W., "Sex Discrimination in Help Wanted Advertising," *Santa Clara Law Review*, 1974, *15* (1), 183–209.

Kuhn, Peter and Kailing Shen, "What Happens When Employers Can No Longer Discriminate in Job Ads?," *American Economic Review*, April 2023, *113* (4), 1013–48.

Kuhn, Peter J. and Kailing Shen, "Gender Discrimination in Job Ads: Evidence from China," *Quarterly Journal of Economics*, 2013, *128* (1), 287–336.

_ **and** _ , "Gender-Targeted Job Ads in the Recruitment Process: Evidence from China," *Journal of Development Economics*, 2020, *147*, 102531.

Kurtulus, Fidan Ana, "The Impact of Affirmative Action on the Employment of Minorities and Women: A Longitudinal Analysis Using Three Decades of EEO-1 Filings," *Journal of Policy Analysis and Management*, 2016, *35* (1), 34–66.

Leonard, Jonathan S., "The Impact of Affirmative Action on Employment," *Journal of Labor Economics*, 1984, *2* (4), 439–463.

_ , "Women and Affirmative Action," *Journal of Economic Perspectives*, March 1989, *3* (1), 61–75.

Lichtash, Terry, "Ives-Quinn Act–The Law Against Discrimination," *St. John's Law Review*, 1945, *19* (2), 170–176.

Miller, Conrad, "The Persistent Effect of Temporary Affirmative Action," *American Economic Journal: Applied Economics*, July 2017, *9* (3), 152–90.

Occhialino, Anne Noel and Daniel Vail, "Why the EEOC (Still Matters)," *Hofstra Labor & Employment Law Journal*, 2005, *22* (2), 671–708.

Office of the President of the United States, "Executive Order No. 11246: Equal Employment

Opportunity," 30 Fed. Reg. 12319 (September 28, 1965) 1965.

OpenAI, "GPT-5 Technical Overview," `https://openai.com/index/introducing-gpt-5/` 2025. GPT-5 language model accessed through ChatGPT in October 2025.

Pan, Jessica, "Gender Segregation in Occupations: The Role of Tipping and Social Interactions," *Journal of Labor Economics*, 2015, *33* (2), 365–408.

Pedriana, Nicholas and Amanda Abraham, "Now You See Them, Now You Don't: The Legal Field and Newspaper Desegregation of Sex-Segregated Help Wanted Ads 1965–75," *Law & Social Inquiry*, 2006, *31* (4), 905–938.

Pittsburgh Press Co. v. Pittsburgh Commission on Human Relations, 413 U.S. 376, 1973.

Ruggles, Steven, Sarah Flood, Matthew Sobek, Daniel Backman, Grace Cooper, Julia A. Rivera Drew, Stephanie Richards, Renae Rodgers, Jonathan Schroeder, and Kari C.W. Williams, "IPUMS USA: Version 16.0," 2025.

Smith, James P. and Finis R. Welch, "Black Economic Progress After Myrdal," *Journal of Economic Literature*, 1989, *27* (2), 519–564.

United States Congress, "Civil Rights Act of 1964," Pub. L. No. 88–352, 78 Stat. 241 1964. Section 709(c), codified at 42 U.S.C. § 2000e–8(c).

United States Equal Employment Opportunity Commission, "Equal Employment Opportunity Report No. 1: Job Patterns for Minorities and Women in Private Industry 1966," Technical Report Report No. 1, U.S. Equal Employment Opportunity Commission, Washington, DC 1966. Part 1. HathiTrust Digital Library.

U.S. Equal Employment Opportunity Commission, "Job Classification Guide: To Be Used with Employer Information Report EEO-1 (Standard Form 100)," Job Classification Guide, U.S. Equal Employment Opportunity Commission, Washington, DC 1994. Office of Program Operations, ORPP–Program Research and Surveys Division.

_ , "EEO-1 Job Classification Guide: A Guide Which Maps 2000 Census Job Codes and Titles into the Ten (10) EEO-1 Survey Job Categories," Technical Report, U.S. Equal Employment Opportunity Commission, Washington, DC May 2006. Office of Research, Information and Planning, Program Research and Surveys Division. Effective beginning with the 2007 EEO-1 survey.

Zimmerman, O. T. and Irvin Lavine, *College Placement Directory*, 4 ed., Dover, NH: Industrial Research Service, 1965.

Zimmerman, Oswald Theodore and Irvin Lavine, *College Placement Directory*, 3rd ed., Dover, NH: Industrial Research Service, 1958. Digitized version available via HathiTrust Digital Library.

Appendix

A Data Appendix

A.1 EEO-1 Filings

We construct measures of EIN-year level employment in the EEO. Multi-establishment companies were instructed to file an EEO report for each establishment, as well as a consolidated report for the entire company. The public EEO data contains both establishment-level and consolidated reports from 1970 through 1974 and again starting in 1978. In the years before 1970, and in 1975, the public EEO data contain only the establishment-level reports. For each entry in the public EEO data, there is a variable denoting the type of report that was filed.

We focus on the non-consolidated reports as the consolidated reports are often incomplete. We sum employment levels by occupation and gender across establishment-level reports within an EIN. We use these sums to calculate the male share within a firm occupation. We checked that occupation totals sum almost exactly to aggregates in most cases, and male and female totals sum to overall totals.

There are a small number of outliers. Most notably 1978 female totals drastically undercount female employees. Male and female employment sums do not add up to the totals and female employment shares are off compared to the CPS. As such, we drop the 1978 reports.

A.2 Newspaper Data

Additional Details on Processing the Job Ad Text

We rely heavily on the earlier work using this dataset of ProQuest Newspaper text. See appendices in Atalay et al. [2018, 2020] and Atalay and Sarada [2020] for details. They detail their steps to identifier markers that separate ads and clean and code information within the ad. As in the original papers, we limit our attention to the 33.8% of ads with 15 or more words where greater than 65% of the words within the ad are spelled correctly. They use a series of markers to identify the boundary of an ad and often many of these markers appear in a row resulting in a large number of distinct ads that are very short. The restriction on ad length and accuracy helps remove these lines spuriously identified as new ads.

Identifying Firm Names

Atalay and Sarada [2020] provides a first attempt at identifying who posted the job ad. They search job ad text for strings which indicate a firm name (e.g., "corp", "associates"). They also search for phone numbers and addresses. If a phone number or address is ever linked to a firm name, that same firm name is associated with all instances.

Given our goal of matching to firm names in EEO-1 filings, we explicitly search for the 2,000 most common company names within the EEO-1 database, excluding a few which we suspect are

likely to lead to false positive matches. These would include many firm names that comprise short abbreviated strings: "gm", "ibm", and "ge" are prime examples.

With these added firm names from the manual search, we pursue one final pass of combining firm names identified via the earlier paper.

Measuring Gender Targeting

In order to identify gender targeting at the ad level, we search the body of the ad for any of the terms listed in the dictionaries, below. We also provide frequencies of the most common strings in table D.1. We classify an ad as explicitly targeting a male candidate if it includes one of the strings within the "male-targeted" dictionary from below and does not include any of the strings from the "joint male/female" dictionary. Because of errors in processing ProQuest ads, we sometimes have difficulty identifying the start of a new ad and thus some observations may append together several ads. This measurement issue drives a small number of observations to trigger strings from both the "male-targeted" and "female-targeted" dictionaries. For this reason, to define an ad as explicitly male targeting we further require that the ad does not have any strings from the "female-targeted" dictionary. We define an ad as explicitly targeting a female candidate analogously: It has a string from the "female–targeted" dictionary and no strings within either the "joint male/female" dictionary or the "male-targeting" dictionary.

Male-targeted dictionary strings. The male-targeted dictionary searches for the following strings:

- Other: "male applicant", "for man", "for men", "for a man", "for boy", "for a boy", "for a guy", "seeks man", "seeks men", "seeks a man", "needs a man", "needs man", "needs men", "right man", "qualified man", "man office", "office man", "career minded man", "career minded men", "career minded guy", "career-minded man", "career-minded men", "career-minded guy", "career man", "career men", "career guy", "prefer man", "prefer boy", "prefer guy", "prefer a man", "prefer a guy", "prefer a boy", "prefer men", "college man", "college men", "for male", "for a male", "seeks male", "seeks a male", "needs male", "needs a male", "prefer male", "prefer a male", "right male", and "qualified male".

- Personal characteristics: "bright man", "bright men", "alert boy", "alert man", "alert men", "hard-working man", "hard-working men", "intelligent man", "intelligent boy", "efficient man", "efficient men", "efficient boy", "conscientious boy", "conscientious man", "conscientious men", "capable man", "capable men", "reliable man", "reliable men", "cultured man", "cultured men", "cultured boy", "responsible man", "responsible men", "responsible boy", "competent man", "competent men", and 'competent boy".

- Age-related terms: "young men", "young man", "young boy", "young guy", "mature men", "mature man", "mature boy", "elderly men", "elderly man", "older men", "older man", "mature guy", "elderly guy", and 'older guy".

- Experience-related terms: “experienced men”, “experienced man”, “ex pd man”, “exp’d man”, “ex pd men”, “ex pd boy”, “experienced boy”, and ‘experienced guy”.
- Friday-type terms: “guy fri” and ‘man fri”.
- Position-category terms: “male position”, “boys boy”, “boy men”, “boys men”, “boys-men”, “boys–men”, and “boys – men”.
- Marital-status terms: “married man”, “married men”, “married guy”, “single man”, “single men”, and ‘single guy”.

Female-targeted dictionary strings. The female-targeted dictionary searches for the following strings:

- Other: “female applicant”, “for a woman”, “for a girl”, “for a gal”, “for woman”, “for women”, “for a lady”, “for girl”, “for gal”, “seeks gal”, “seeks woman”, “seeks women”, “seeks a woman”, “needs a gal”, “needs a woman”, “needs woman”, “needs women”, “needs gal”, “right gal”, “right woman”, “qualified woman”, “seeks girl”, “seeks a girl”, “needs a girl”, “seeks a gal”, “needs girl”, “right girl”, “qualified girl”, “girl office”, “office girl”, “office gal”, “career minded woman”, “career minded gal”, “career minded girl”, “career minded women”, “career-minded gal”, “career-minded woman”, “career-minded women”, “career-minded girl”, “career woman”, “career women”, “career gal”, “hard-working women”, “prefer woman”, “prefer girl”, “prefer gal”, “prefer a woman”, “prefer a gal”, “prefer a girl”, “prefer lady”, “prefer a lady”, “prefer ladies”, “college woman”, “college women”, “for female”, “for a female”, “seeks female”, “seeks a female”, “needs female”, “needs a female”, “prefer female”, “prefer a female”, “right female”, “qualified female”, “for lady”, “for ladies”, “seeks lady”, “seeks ladies”, “seeks a lady”, “needs lady”, “needs ladies”, “needs a lady”, “right lady”, “right ladies”, “qualified lady”, “qualified ladies”, “career minded lady”, “career minded ladies”, “career-minded lady”, “career-minded ladies”, “career lady”, “career ladies”, “college lady”, “college ladies”, “office lady”, and ‘office ladies”.
- Personal characteristics: “bright gal”, “bright woman”, “bright women”, “bright girl”, “alert gal”, “alert girl”, “alert woman”, “alert women”, “capable girl”, “capable woman”, “capable women”, “capable gal”, “hard-working woman”, “hard-working girl”, “hard-working gal”, “intelligent women”, “intelligent girl”, “intelligent woman”, “intelligent gal”, “efficient woman”, “efficient women”, “efficient girl”, “efficient gal”, “conscientious girl”, “conscientious woman”, “conscientious women”, “conscientious gal”, “reliable woman”, “reliable girl”, “reliable women”, “reliable gal”, “cultured woman”, “cultured women”, “cultured girl”, “cultured gal”, “responsible woman”, “responsible women”, “responsible girl”, “responsible gal”, “competent woman”, “competent women”, “competent girl”, “competent gal”, “bright lady”, “bright ladies”, “alert lady”, “alert ladies”, “capable lady”, “capable ladies”, “hard-working lady”, “hard-working ladies”, “intelligent lady”, “intelligent ladies”, “efficient lady”, “efficient

ladies", "conscientious lady", "conscientious ladies", "reliable lady", "reliable ladies", "cultured lady", "cultured ladies", "responsible lady", "responsible ladies", "competent lady", and "competent ladies".

- Age-related terms: "young gal", "young women", "young woman", "young lady", "young girl", "young ladies", "mature gal", "mature women", "mature woman", "mature girl", "mature ladies", "mature lady", "elderly women", "elderly woman", "elderly lady", "elderly ladies", "older gal", "older woman", and "older women".

- Experience-related terms: "experienced gal", "experienced women", "experienced woman", "ex pd woman", "exp'd woman", "ex pd women", "ex pd girl", and 'experienced girl".

- Friday-type terms: "gal fri", "girl fri", and '-gal fri".

- Position-category terms: "female position", "girls girl", "girls women", "girl women", "business gal", "girls-women", "girls–women", and 'girls – women".

- Marital-status terms: "married gal", "married woman", "married women", "married lady", "married ladies", "married girl", "housewife", "housewive", "single gal", "single woman", "single women", "single lady", "single ladies", and 'single girl".

Joint male/female dictionary strings. The joint male/female dictionary searches for the following strings (where ? is a one-character wild card):

- Dictionary-list strings: "boy girl", "boys girls", "female male", "gal guy", "girl boy", "girls boys", "guy gal", "housewives or men", "m f", "male female", "male or female", "man and woman", "man gal", "man or woman", "man woman", "men and women", "men or women", "men women", "or man", "or woman", "woman man", and "women men".

- Additional wildcard strings: "boy ? girl", "boy girl", "boys ? girls", "boys ?? girls", "boys ??? girls", "boys girls", "female ? male", "female ?? male", "female ??? male", "female male", "girl ? boy", "girl boy", "girls ? boys", "girls ?? boys", "girls ??? boys", "girls boys", "male ? female", "male ?? female", "male ??? female", "male female", "man ? woman", "man ?? woman", "man woman", "men ? women", "men ?? women", "men ??? women", "men women", "woman ? man", "woman ?? man", "woman man", "women ? men", "women ?? men", "women ??? men", and "women men".

In order to identify gender targeted pages, we search as follows. We look for the specific string "help wanted male" occurring either (i) in the first ad of the page or (ii) at least twice in the body of at least two ads.[29] Since the digitization process is imperfect, we apply a list of string

[29]We include the second criterion to allow for the possibility that the digitization technology leads us to miss the first instance of "help wanted male."

substitutions before searching for this particular string.[30] We similarly search for "help wanted female" in assigning pages of ads as those with a female header and "help wanted male female" in assigning pages of ads as those explicitly open to both male and female candidates.[31] The latter was common in the early 1970s. After that, the job pages in our dataset instead included "help wanted" as a header; we do not separately record these.

Additional Vacancy-Related Information Finally, we record additional information on job scheduling: (i) no weekends, (ii) no Saturdays, (iii) no Sundays, (iv) no evenings, (v) 40-hour work weeks, (vi) 37-hour work weeks, (vii) 35-hour work weeks, (viii) 30-hour work weeks, (ix) 5-day work weeks, (x) 4-day work weeks, (xi) 2–4-day work weeks, (xii) 3–4-day work weeks, (xiii) an 8:30 to 4:30 schedule, (xiv) an 8:45 to 4:30 schedule, (xv) a 9:30 to 4:30 schedule, (xvi) a 9:30 to 5:30 schedule, (xvii) an 8 to 3 schedule, (xviii) an 8 to 4 schedule, (xix) a 9 to 3 schedule, (xx) a 9 to 4 schedule, (xxi) a 9 to 5 schedule, (xxii) a 10 to 6 schedule, (xxiii) a 7 to 3 schedule, (xxiv) a 7 to 4 schedule, (xxv) a 9 to 5:30 schedule, (xxvi) flexible hours,[32] **(xxvii)** overtime, **(xxviii)** a requirement to work weekends, **(xxix)** a requirement to travel, **(xxx)** a requirement to work nights, **(xxxi)** the phrase full time", and (xxxii) the phrase "part time". The most frequently occurring are mentions of a 5-day work week, that the job is part time, that the job is full time, and a 9 to 5 work schedule.

We code regular schedule to equal 1 if the ad mentions any of the following: no weekend work, weekly hours falling between 30 and 40, days per week being less than 6, or specific time of day ranges. Specifically, we search for the phrases "no weekend", "no Saturday," "no Sunday", "no evening", "X hours per week" for values of X in 30, 35, 37, 40, "X days per week" for X in 4, 5, 2-4, 3-4, "8:30-4:30", "8:45-4:30", "9:30-4:30", "9:30-5:30", "8:00-3:00", "8:00-4:00", "9:00-3:00", "9:00-4:00", "9:00-5:00", "10:00-6:00", "7:00-3:00", "7:00-4:00", "9:00-5:30". To indicate that a schedule is irregular or lacking in flexibility, we use whether the ad indicates weekend work, overtime work, travel or night work (without the word "no" in front).

Representativeness of the Sample

We examine the extent to which "male" versus "female" occupations are differently represented in the newspaper ads.[33]

[30] For example, we substitute "help wantedmale", "help wanted ! male", "help warded male" (all of these appearing in the initial digitized test) to "help wanted male".

[31] When assigning a page to be male-specific, we require that the string "help wanted male female" is absent.

[32] Specifically, we search for the following strings: *flexible ho*", flexible hr", **choose your ho**".

[33] Earlier work [Atalay et al., 2020] explored two other dimensions along which our dataset may not be representative of the U.S. labor market. The focus, there, was on differences in the task content of ads in our sample relative to types of jobs in which individuals worked. First, our sample is informative about job matches formed via newspaper ads. But workers and firms meet one another through other channels: through referrals, through unsolicited job site visits by the applicant, etc... Appendix C.2 of Atalay et al. [2020] uses the 1968-1993 CPS-ASEC. In these years, unemployed individuals were asked about their job search methods. The extent to which employers rely on newspaper ads to fill vacancies increased over this 25 year period, is higher in occupations rich in cognitive tasks, and is lower in occupations rich in manual tasks. However, there are no differential trends in the extent to which cognitive (or manual) occupations filled vacancies through newspaper ads. Second, our sample draws on ads

Table A.1: Representativeness in the Occupational Mix: Correlation Coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Male Page	0.169	0.054	-0.113	0.071	0.332***	0.099	-0.171	0.169***
Female Page	-0.219*	-0.076	-0.108	-0.112*	-0.304***	-0.079	-0.080	-0.069
Male Explicit	-0.073	-0.140	-0.198*	-0.054	0.236**	0.008	-0.387***	0.115*
Female Explicit	-0.266**	-0.038	-0.071	-0.122*	-0.329***	-0.019	-0.080	-0.059
Male Implicit	0.193*	0.170	0.333***	0.220***	0.323***	0.159	0.234**	0.225***
Female Implicit	-0.212*	-0.077	0.072	-0.096	-0.340***	-0.114	0.054	-0.102
Decade	1950	1960	1970	1950-70	1950	1960	1970	1950-70
Weight by # of Ads?	No	No	No	No	Yes	Yes	Yes	Yes

Notes: This table presents the correlations between $\log \nabla_{od}$ and occupation-decade average measures placement on male- or female-segregated pages; male or female explicit targeting; or male or female implict targeting. For our newspaper data, our decade average for "1950" draws on ads posted between 1945 and 1954; "1960" draws on ads posted between 1955 and 1964; and "1970" draws on ads posted between 1965 and 1974. *** refers to a p-value between 0 and 0.01; ** refers to a p-value between 0.01 and 0.05; and * refers to a p-value between 0.05 and 0.10.

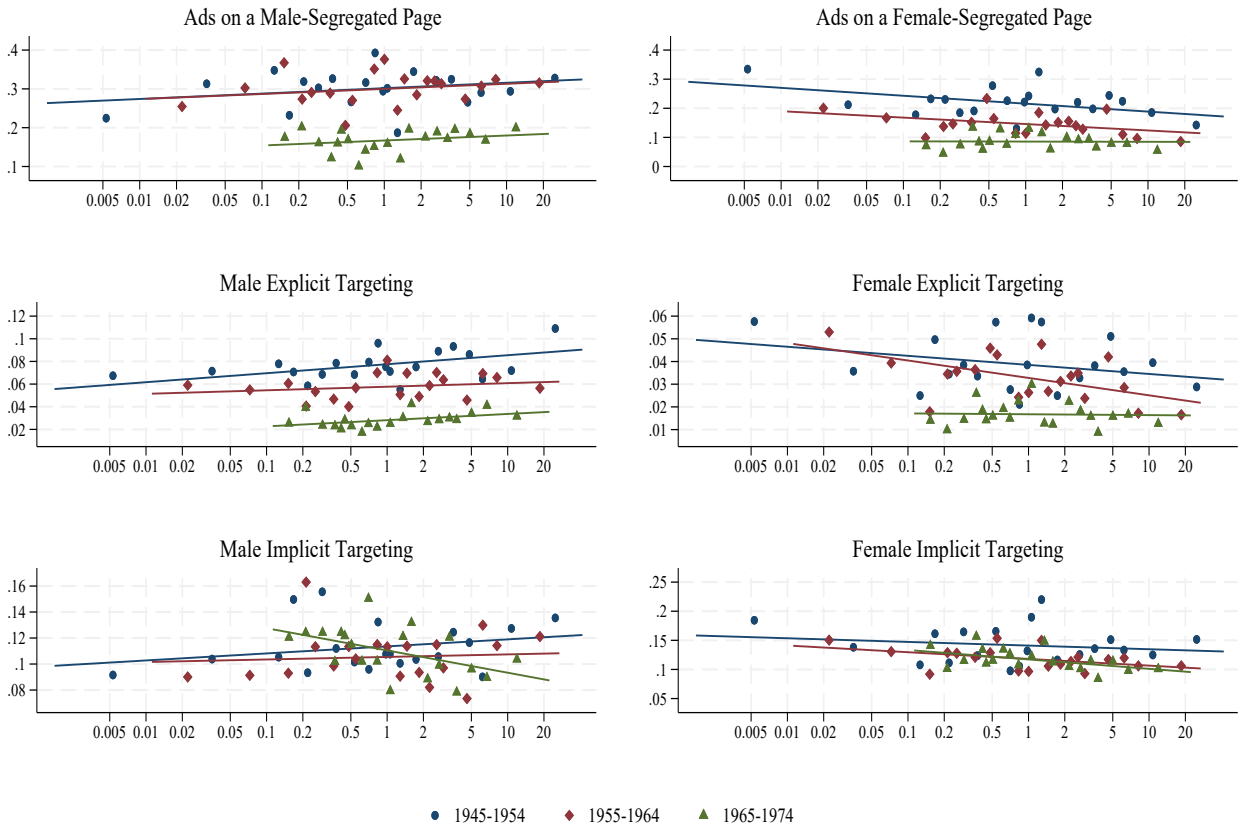
For our first assessment of the representativeness of our sample, we compute ∇_{od} as the ratio of the share of newspaper ads in decade d corresponding to 4-digit occupation o to the share of employment in occupation o as recorded in the decennial census. As an example, among ads placed between 1945 and 1954, 0.61% were for Supervisors of Production Workers (SOC=5110) and 7.03% were for Secretaries and Administrative Assistants (SOC=4360). The share of employment in the 1950 Census was 1.86% and 4.08% respectively. So, in our dataset, Production Workers are under-represented ($\nabla_{od} = \frac{0.61}{1.86} = 0.33$) while Secretaries and Administrative Assistants are over-represented ($\nabla_{od} = \frac{7.03}{4.08} = 1.73$). More generally, ∇_{od} is greater than 1 for finance occupations, architecture/engineering occupations, and office administrative occupations, and less than 1 in transportation, production, and installation/maintenance occupations.

In Figure A.1, we compare ∇_{od} to measures of the genderedness of the occupation. In the top panels, we present binscatter plots of the relationships between ∇_{od} and the share of ads on a male-segregated page (top left panel) or the share of ads on a female-segregated page (top right panel.) Early in the sample, there is a (marginally significant) relationship whereby occupations over-represented in the newspaper text tend to appear more on male-segregated pages and less on female-segregated pages. In the middle columns, we consider a second measure of occupations' genderedness: the frequency of explicit male (middle left) or explicit female (middle right) targeting. Here, too, there is a negative relationship between explicit female targeting and ∇_{od}, but only when comparing ads placed between 1945 and 1954 and employment in 1950. Finally, the bottom panels compare the frequency of gender-specific codewords (mentions per ad) and ∇_{od}.

In Table A.1, we collect the correlations corresponding to each panel of Figure A.1, indicating

published in newspapers circulating in Boston and New York; the help wanted ads are overwhelmingly for jobs in these metropolitan areas. While it is impossible for us to compare newspaper ads for these metro areas to those in the rest of the U.S., we are able to compare Boston and New York job ads to those in the remainder of the country for a later period, in which firms posted ads online. Appendix C.3 of Atalay et al. [2020] documents that jobs posted in the Boston and New York MSAs are relatively rich in non-routine analytic and interactive tasks, but that these differences primarily reflect differences in the occupational mix across geographies. Controlling for occupation fixed effects reduces the differences in job content across metro areas.

Figure A.1: Representativeness in the Occupational Mix



Notes: This figure presents binscatter plots, comparing $\log \nabla_{od}$ (the ratio of the occupations ad share to its census employment share) to the occupation-decade average measures of genderedness. For occupations' job ad shares, we compute averages across three ten-year periods: between 1945 and 1954, between 1955 and 1964, and 1965 and 1974. These averages are plotted on the y-axis of each panel. For each of these ten-year periods, the x-axis axis gives the corresponding occupations' ratio of ad share-to employment share in the decadal census (e.g., we compare ad shares in 1945-1954 to employment shares in 1950.)

which of these panels' relationships are statistically significant. Many relationships are significant in the 1950s but less so for later years.

A.3 Recruiting Directory

Data Cleaning and Construction

We extract the recruiting directory data from the already-available OCR version of the directory pdf, using a program written for Claude. This results in a JSON file which we convert to Stata using a Python code.

After evaluating the text extraction, we identified several issues in which the extracted text did not match the pdf. These appeared around alphabet changes in the middle of a page in the directory. In these cases, the extracted text would often mistakenly continue from the bottom of a column to the top of a page rather than staying below the new letter. For at least some of these, the mistake was in the OCR that had already been done rather than in the Claude extraction. We went through each alphabet change in the directory to determine if there were mistakes in the extraction. When there were mistakes we manually input the data from the directory (typing it into a csv file) for the pages surrounding and including the alphabet change. We then merged on directory company name the original directory data to the directory data we constructed by hand when there were mistakes. We drop the observations that match on recruiting directory name (where there might have been a mistake), and then append the dataset with the observations we wrote by hand. This procedure removes the mistakes that existed in the original data.

Matching Recruiting Directory Names and EEO Names

We begin by identifying matches in the EEO to the names in the 1958 Recruiting Directory. Our matching process takes the Jaro-Winkler distance between each company name in the recruiting directory and company name in the EEO. We limit attention to companies in the EEO whose EIN falls in the balanced panel. We collect the top two matches in terms of the Jaro-Winkler distance and manually evaluate accuracy. Our first pass conducts minimal cleaning on company names before matching. For example, we take out periods and commas, and "inc" and "co". We conduct two more passes with broader cleanings and fixing issues we became aware of in earlier rounds. We manually check new matches each time and append all matches together.

Company names in the EEO may be associated with multiple EINs, and in the first two passes we randomly picked one company name-EIN pair in the EEO for each company name. This may have restricted the matches between recruiting directory company names and EINs. To amend this, in the third pass we implement Jaro-Winkler matching between recruiting directory and EEO company names, keeping one company name in the EEO per EIN, and then keep the top two matches to the recruiting directory. We evaluate these top matches by hand, for those that we had not identified in the previous two rounds.

We then have a dataset with matches between company names in the Recruiting Directory and

company names in the EEO, across these three rounds of matches. Within any round of matching, companies in the Recruiting Directory may match to two EEO companies (and potentially two different EINs), and so across all three rounds of matches companies in the Recruiting Directory may match to several different company names and EINs in the EEO.

A.4 Census and Current Population Survey Data

We obtain decennial census data for the years 1940-2000 and Current Population Survey Data for the 1966-1995 March Supplements from IPUMS [Ruggles et al., 2025; Flood et al., 2025].

In the Censuses, most years are 5% samples; for 1970 we use both 1% state form samples. 1940 and 1950 are 1% samples which we further limit to the sample-line respondents. In these waves, detailed employment and education information is only asked to one member of the household, the sample-line respondent. As such, these waves have much smaller samples and require the use of sample line weights. All other samples use person weights.

In both the censuses and the CPS, we restrict to those currently employed for wage and salary income (non self-employed), age 14-64. The censuses exclude those living in institutionalized group quarters and those with allocated occupation and income measures.

We harmonize weeks and hours worked across censuses as follows. We use the available numeric measures for 1940, 1950, and 1980-2000.[34] For other years, only interval-coded measures are available. We convert these to numeric values by assigning the mean within each interval, calculated from the 1980 Census when both variables are available.

Wages are annual wage and salary income divided by annual weeks worked times hours worked per week. We replace topcoded values with 1.5 times the top code and CPI adjust to 2000 dollars.[35]

We calculate the male employment share as the sum of person weights times annual hours worked (weeks times hours) among males divided by the sum amount all workers. Occupation-level weights are the annual hours-weighted person weights in each occupation in the employed sample (with our additional restrictions).

These variables are defined at the Census 1990 occupation level or the 1950 Census occupation codes for 1940, which we crosswalk to SOC occupation codes using the 2000 Census. We keep all 1990 or 1950 codes associated with a given 2000 SOC code and use the 2000 Census of employed person to generate weights within each SOC code. We then merge these into the vacancy datasets at the 4-digit SOC level where possible and if not we use the 3-digit.

[34] The weeks measure is annual weeks worked in the previous year. Hours refer to hours worked last week in all years except 2000, when we use usual hours worked.

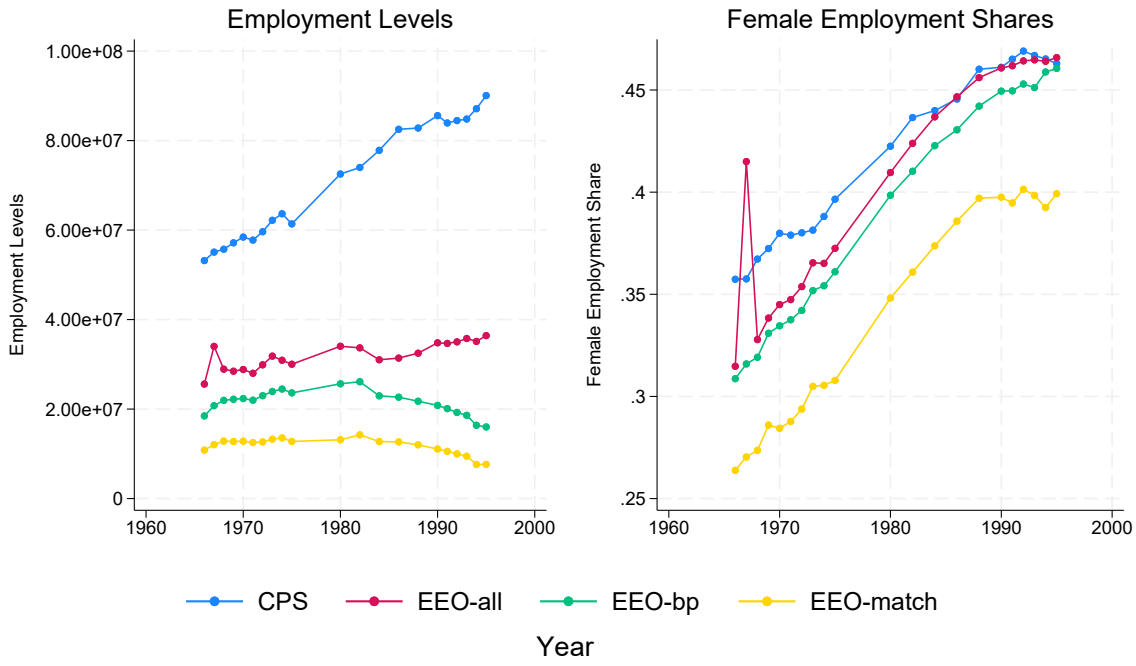
[35] Income corresponds to the previous calendar year so we CPI adjust to that year as well. Topcoded income values for 1990 and 2000 are already replaced by the median or mean of topcoded values in the state, so we make no further adjustments.

B Representativeness of EEO-1 Filings

This section compares employment trends, occupational shares, and gender distributions between the EEO-1 filings nationally representative Current Population Survey and Census data.

Figure B.1 plots employment trends in the various EEO samples and the CPS. In employment levels, the full EEO sample (red line) captures about 50% of CPS private employment (blue) in the first half of the sample and falls to about 40% by the end of the sample. Series track each other reasonably well in the first half of the sample. There is a slight relative employment decline in the EEO in the 1980s, that is much more pronounced in the balanced panel and matched samples. These samples that restrict to being in operation in the 1960's become increasingly out of date.

Figure B.1: Employment: CPS vs. EEO Restrictions

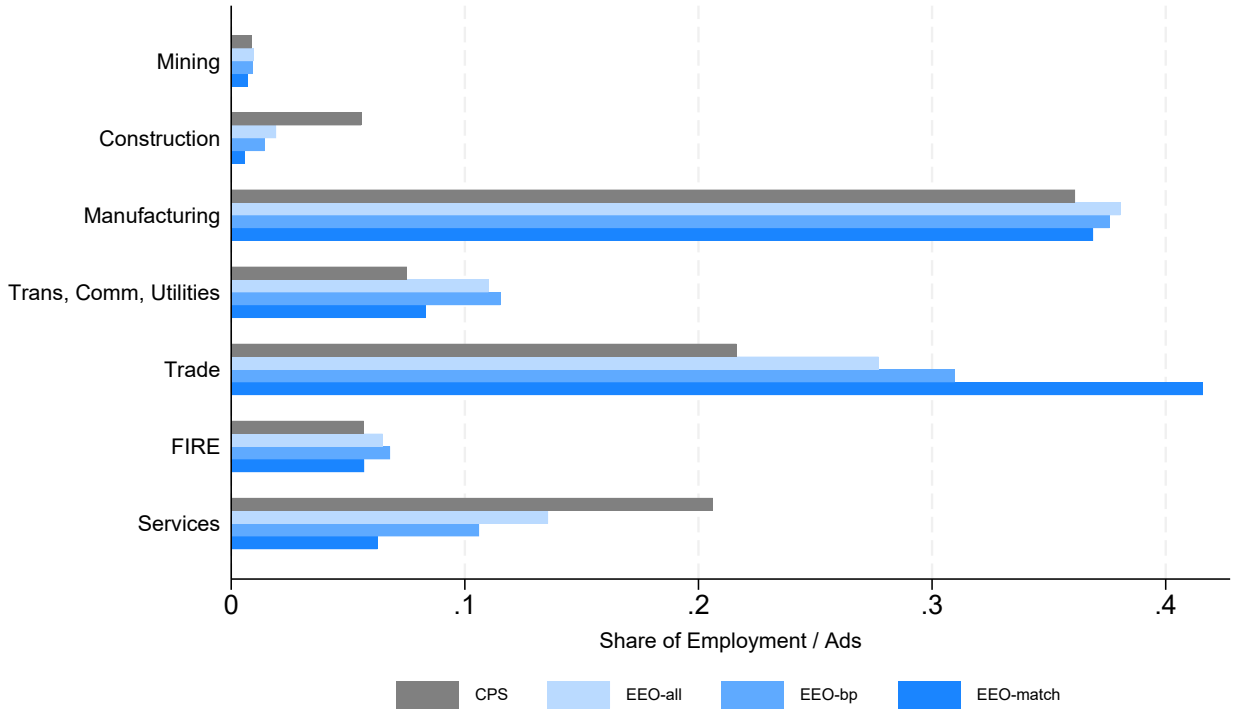


Notes: We plot aggregate employment trends (left) and female employment shares (right) for the CPS, the full EEO data and EEO data with various restrictions. Balanced panel (bp) is defined as firms (EINs) observed in the 1960s, 1970s, and 1980s. EEO-match restricts to firms that have at least 1 ad in the classifieds or directory datasets.

Even while employment levels diverge later in the sample period, employment distributions match more closely. The right panel plots female employment shares across the samples. The EEO samples under represent women, but all samples experience similar increases in female representation such that the patterns match each other well.

Figure B.2 compares the industrial composition of employment in the 1960s across the Current Population Survey and the EEO for various subsamples. The EEO overrepresents manufacturing and logistics, and underrepresents construction and services, differences which were also reflected in the occupational mix.

Figure B.2: Industry Distributions Across Datasets



Notes: We summarize employment shares across broad industry categories in the 1968-69 Current Population Survey March Supplement and the EEO-1 filings for the same years. The lightest blue includes all filers; the next shade restricts to a balanced panel of firms that are observed in the 1960s, 1970s, and 1980s (EEO-bp); the darkest blue further restricts the balanced panel to firms that match either the directory or the classifieds.

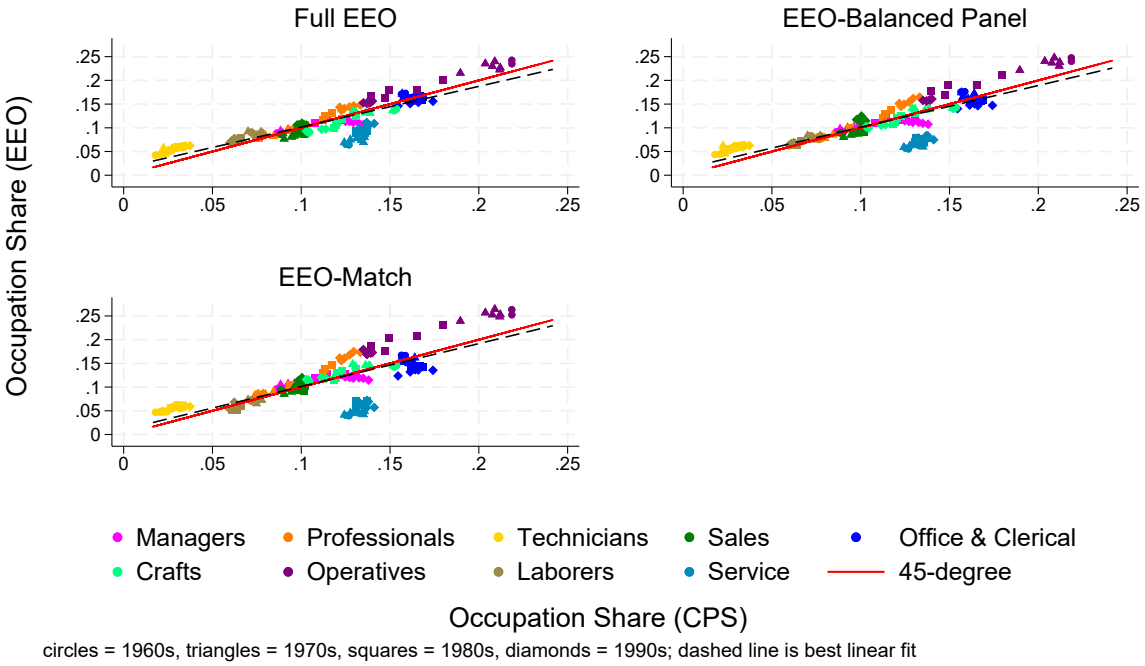
For understanding the internal validity of the results, we need to know whether the representativeness of the sample was changing over time. Figure B.3 presents scatters of CPS occupational employment shares on the x-axis and EEO employment shares on the y-axis in each year; the three panels show the different EEO samples.[36] All series match quite well the occupation distributions and changes over time, with points clustering along the 45 degree line (red), and the same for the best linear fit (black dashed). For instance, operatives have the highest employment shares in the 1960s (purple circles) and decline substantially over subsequent decades. This decline is seen and at similar magnitudes across the CPS and all the EEO samples.

Across samples, the EEO data do underrepresent service jobs and overrepresent production jobs, an artifact of the industrial mix. These deviations are more pronounced in the matched samples but fairly stable over time.

Figure B.4 compares female employment shares within occupation across samples. Female employment shares within occupations track each other well for the most part. The EEO data overrepresent women in laborer positions (tan) and underrepresent women in most other positions.

[36] We exclude 1966 and 1967 since those CPS's included a much more coarse occupation coding that is difficult to accurately map to EEO categories.

Figure B.3: Occupational Employment Shares: EEO vs. CPS



Notes: We compare the share of employment in each broad occupation group in the CPS (x-axis) and EEO sample (y-axis) by year. Each dot is an occupation-year pair. We highlight decades with different symbols. The four panels correspond to the different EEO restrictions.

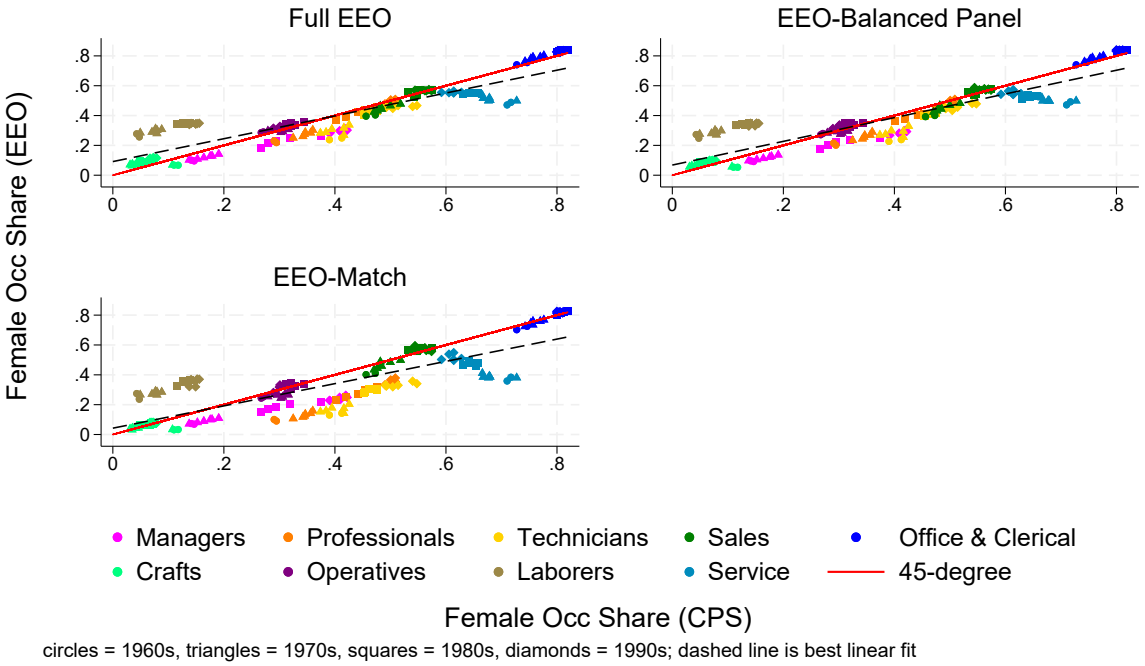
The underrepresentation of women in professional and technical occupations is more pronounced in the matched samples. Still, changes over time track each other well, with the exception of service positions where women become better represented over time in the EEO compared to the CPS.

Finally, we examine the geography of employment in the EEO to non-self employment in the 1960 Census. The larger samples in the Census allow us to make these comparisons while the CPS would not. As our focal unit is the EIN, we assign the state with the most employment across all establishment-level filings for a given EIN.

In the left panel, we plot the ratio of EEO employment to Census employment in the state for two different EEO samples: the full EEO sample to the EEO-matched sample. (The balanced panel looks very similar to the full EEO.) On the x-axis, the full EEO sample is substantially smaller than the Census, of course, with all states except Connecticut and Delaware having a ratio less than 1. (These ratios being higher than one is because we assign employment across all establishments to the modal state so there is some measurement error here.) Michigan, New York, and Illinois also capture high fractions of Census employment in the EEO.

These ratios can be compared to those calculated from the EEO-matched sample on the y-axis. All data points are lower than their state's value on the x-axis because the sample is restricted. However, the relative representation is similar, indicated by the upward sloping line. The restricted sample does over-represent the northeast (CT, DE, NY, and NJ are all above the best fit regression

Figure B.4: Occupational Female Employment Shares: EEO vs. CPS

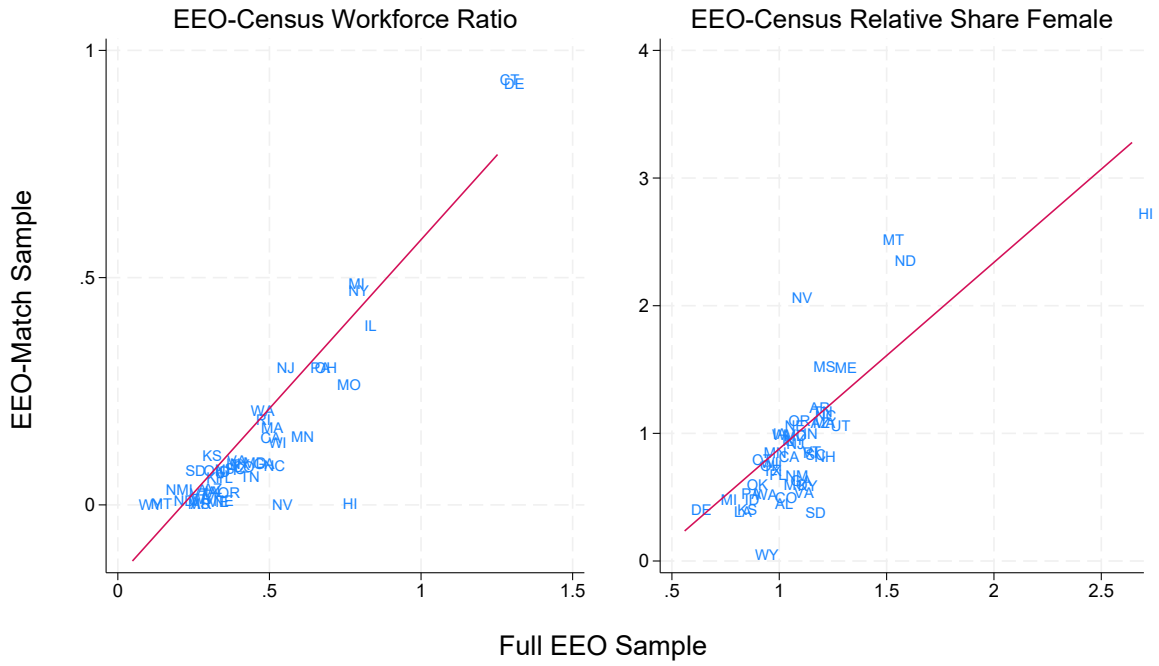


Notes: We compare the share of employment that is female within in each broad occupation group in the CPS (x-axis) and EEO sample (y-axis) by year. Each dot is an occupation-year pair. We highlight decades with different symbols. The three panels correspond to the different EEO restrictions.

line in red) but most states are still represented in proportion to the overall EEO sample.

The right panel compares the state's female employment share in the EEO to that in the census. While some states in the EEO overrepresent women and other states underrepresent them, the relationship is very similar across the two EEO samples. This can be seen in that the best fit regression line (red) is very close to the 45 degree line.

Figure B.5: Employment Comparisons by State: EEO vs. 1960 Census



Notes: In the left panel, we compare the EEO-Census employment ratio in the state when using the full EEO sample (x-axis) to the EEO-matched sample (y-axis). In the right panel, we plot the EEO's female employment share in the state relative to the state's female employment share in the census. EEO state-level employment is calculated by taking an unweighted average across all years. Best fit regression lines across states are plotted in red.

C Segregated Pages

In this section, we conduct companion analyses in the classifieds for ads placed on segregated pages. As shown in the text, explicitly targeted ads are much more likely to be posted on segregated pages; the two measures are highly correlated. We view page targeting as an alternative symbol of employer preferences, but possibly a weaker one. Although there is variation in whether an ad is posted on a segregated page, it is unclear to us to what extent that page was the employer's choice versus a norm the newspaper followed.

Table C.1 presents analogous results to those summarized in table 3. Here the outcomes are whether the ad was posted on a segregated page (columns 1-3) or a male page in a sample that conditions on some kind of page targeting (columns 4-6). About half of the ads in our sample are posted on a segregated page and, conditional on being in a segregated page about half of ads or on a male page.

Most patterns are similar for these outcomes. Ads on segregated pages are less likely to have education requirements and more likely to have scheduling requirements. They are in occupations with lower male employment shares in the 1960 census as well as a workforce that is less likely to have college and is younger. Ads on segregated pages are also much more likely to have explicit gender targeting as well. Adding occupation fixed effects and then job title fixed effects does not help explain these correlations. Also, these controls do not have additional explanatory power – the adjusted R-square is roughly 10% in all three columns. Thus page targeting is not purely a default for certain job titles, say.

Conditional on page targeting (columns 4-6), ads posted on male (compared to female or male-female) pages follow similar patterns to ads with explicit male targeting. For instance, they are more skilled, more likely to have irregular schedules, etc. They are also much more likely to have explicit male targeting and much less likely to have explicit female targeting.

Next we examine the relationship between page targeting and employment outcomes. We estimate analogous regressions to equations 1 and 2 but use as the gender targeting measure the share of ads in the firm-by-broad occupation that are posted on male targeted pages. This share is expressed as a deviation from the firm's leave-out mean in the detailed (4-digit) occupation and is standardized. Regressions also control for the rate of posting on non-targeted pages. The omitted category is thus posting in female or male-female pages. Due to measurement error in page targeting, we do not think ads coded as non-targeted make the best comparison group.

We find that male, compared to (mostly) female page targeting is associated with higher male employment shares in the EEO filings and effects are significant. These results mirror those for explicit targeting. A one-standard deviation higher male targeting rate is associated with a 7 to 8 ppt higher male employment share in the firm-by-broad occupation cell.

We also see convergence in this relationship over time. Panel B shows that by the 1990's the relationship between male page targeting and male employment shares has narrowed by a point – or roughly 15% of the 1960s relationship. It is somewhat counterintuitive that the coefficients in panel A do not show the same convergence across time. Panel B examines within firm-occupation changes

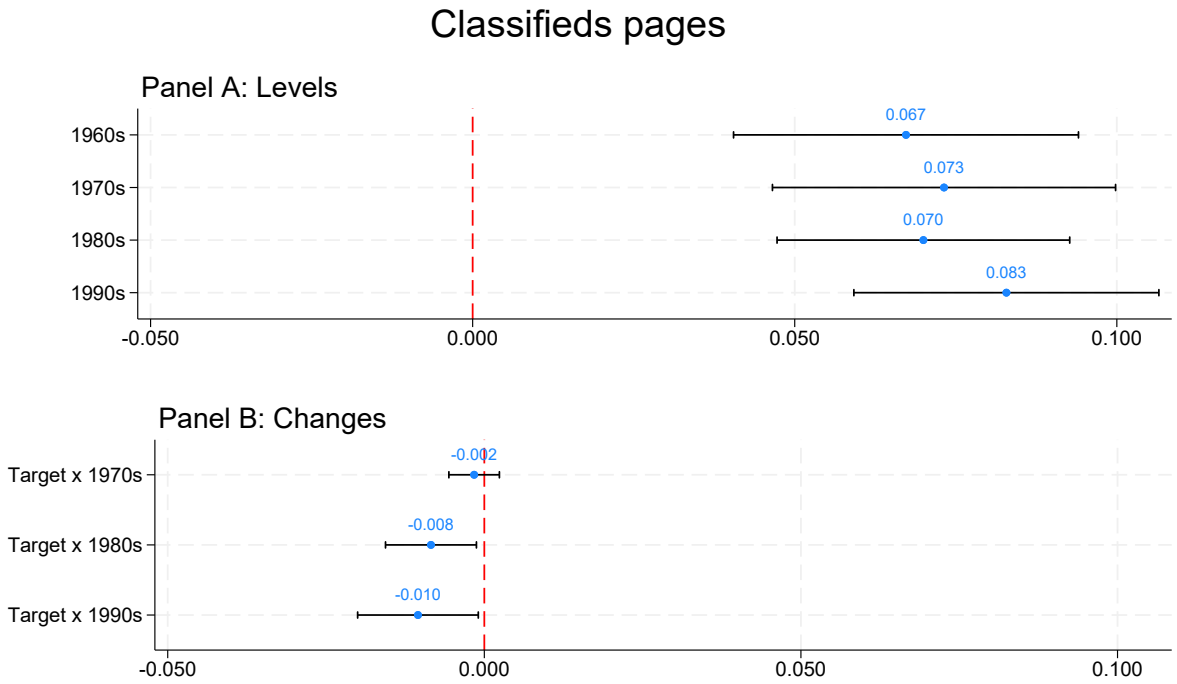
Table C.1: **Page Targeting in the Classifieds and Job Skill**

Dep var:	On a Segregated Page			On a Male Page		
Sample:	All			Ads on segregated pages		
	(1)	(2)	(3)	(4)	(5)	(6)
Posted log salary	-0.049***	-0.045***	-0.025***	0.029***	0.020***	0.020***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Missing salary	-0.037***	-0.037***	-0.036***	-0.071***	-0.059***	-0.044***
	(0.004)	(0.003)	(0.004)	(0.008)	(0.007)	(0.007)
Education Requirement	-0.021***	-0.022***	-0.023***	0.039***	0.039***	0.034***
	(0.002)	(0.003)	(0.003)	(0.009)	(0.007)	(0.008)
Experience Requirement	0.002	0.003	-0.008**	0.062***	0.050***	0.034***
	(0.003)	(0.003)	(0.003)	(0.008)	(0.006)	(0.005)
Regular schedule indicated	0.043***	0.041***	0.026***	-0.247***	-0.199***	-0.134***
	(0.006)	(0.006)	(0.006)	(0.015)	(0.011)	(0.010)
Irregular schedule indicated	0.028***	0.027***	0.015***	0.083***	0.070***	0.049***
	(0.004)	(0.004)	(0.004)	(0.011)	(0.010)	(0.012)
Explicit male	0.034***	0.032***	0.020***	0.237***	0.210***	0.147***
	(0.003)	(0.003)	(0.002)	(0.027)	(0.024)	(0.028)
Explicit female	0.025***	0.025***	0.014***	-0.339***	-0.305***	-0.212***
	(0.004)	(0.004)	(0.004)	(0.039)	(0.033)	(0.029)
Explicit male-female	0.032***	0.031***	0.029***	0.032***	0.034***	0.048***
	(0.004)	(0.004)	(0.004)	(0.010)	(0.011)	(0.012)
Preference for married	-0.124***	-0.124***	-0.132***	0.154***	0.142***	0.103***
	(0.008)	(0.008)	(0.009)	(0.026)	(0.025)	(0.030)
Preference for attractive	0.025*	0.022*	0.003	-0.207***	-0.172***	-0.072**
	(0.013)	(0.012)	(0.016)	(0.045)	(0.033)	(0.029)
Occ. Male Employment Share	-0.022**			0.477***		
	(0.010)			(0.066)		
Occ. Average Log Wage	0.036**			0.082		
	(0.015)			(0.071)		
Occ. Gender Pay Gap	0.023			0.019		
	(0.019)			(0.127)		
Occ. College share	-0.077***			-0.053		
	(0.020)			(0.074)		
Occ. Annual Hours per Worker (100s)	-0.001			-0.003		
	(0.001)			(0.007)		
Occ. Average Age	-0.004***			0.011		
	(0.001)			(0.007)		
Observations	4,418,617	4,418,617	4,418,617	2,116,644	2,116,644	2,116,644
Adjusted R2	0.091	0.092	0.102	0.345	0.393	0.501
Outcome mean	0.482	0.482	0.482	0.497	0.497	0.497
Basic controls	X	X	X	X	X	X
Occ FEs		X			X	
Job title FEs			X			X

Notes: Standard errors in parentheses clustered on 4-digit occupation. $^{*}p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We present analogous regressions to those reported in table 3 in the text. The sample is restricted to classified ads posted between 1946 and 1970. We summarize ad-level regressions where the outcome is whether the ad was posted on a segregated page (columns 1-3) or on a male page in a sample that conditions on being on a segregated page (columns 4-6).

by including additional fixed effects. Apparently the sample composition changes somewhat in the 1990s towards firm-occupation cells with stronger relationships. Adjusting for this compositional

Figure C.1: Male Page Targeting and Male Employment Shares over Time

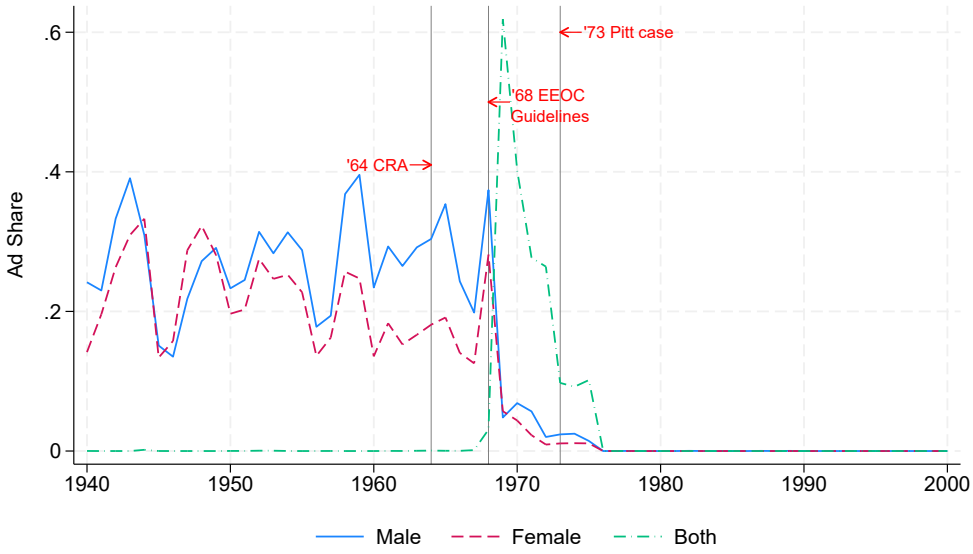


Notes: See figure 5 in the text. This figure plots an analogous version where the explanatory variable is the rate of male page targeting, expressed as a deviation from the firm's leave-out mean in the 4-digit occupation. 95% confidence bars are also shown. Regressors are scaled so coefficients can be interpreted as the impact of a one standard deviation increase in male targeting.

change, we actually see convergence as in the explicit targeting case.

D Additional Tables and Figures

Figure D.1: Trends in targeted pages



Notes: This figure presents the share of ads which appear in pages with "Help Wanted-Male," " Help-Wanted-Female," and "Help Wanted-Male Female" as a header, by year. The stoppage in gendered page targeting was the direct result of a lawsuit filed by the National Organization of Women (NOW) against the *New York Times*, ruled in favor of NOW in 1968. For a brief period following the lawsuit, a substantial fraction of ads appeared on pages with "Help Wanted—Male Female" as the header, though this practice dropped quickly from use.

Figure D.2: A listing from the 1958 Directory

Eastman Kodak Co.

343 State St., Rochester 4, N. Y.

Nature of business: Manufacture of photographic supplies and apparatus, synthetic fibers, and plastic compounds, industrial and fine chemicals, specialized optical and electronic apparatus.

Location of principal plants: Rochester, N. Y.; Kingsport, Tenn.; Longview, Tex.

Total employees (approx.): 50,900

EASTMAN KODAK 111

Graduates hired per year (approx.): 250

Training program: On-the-job.

College recruiting program: Yes.

Personal interview required: Yes.

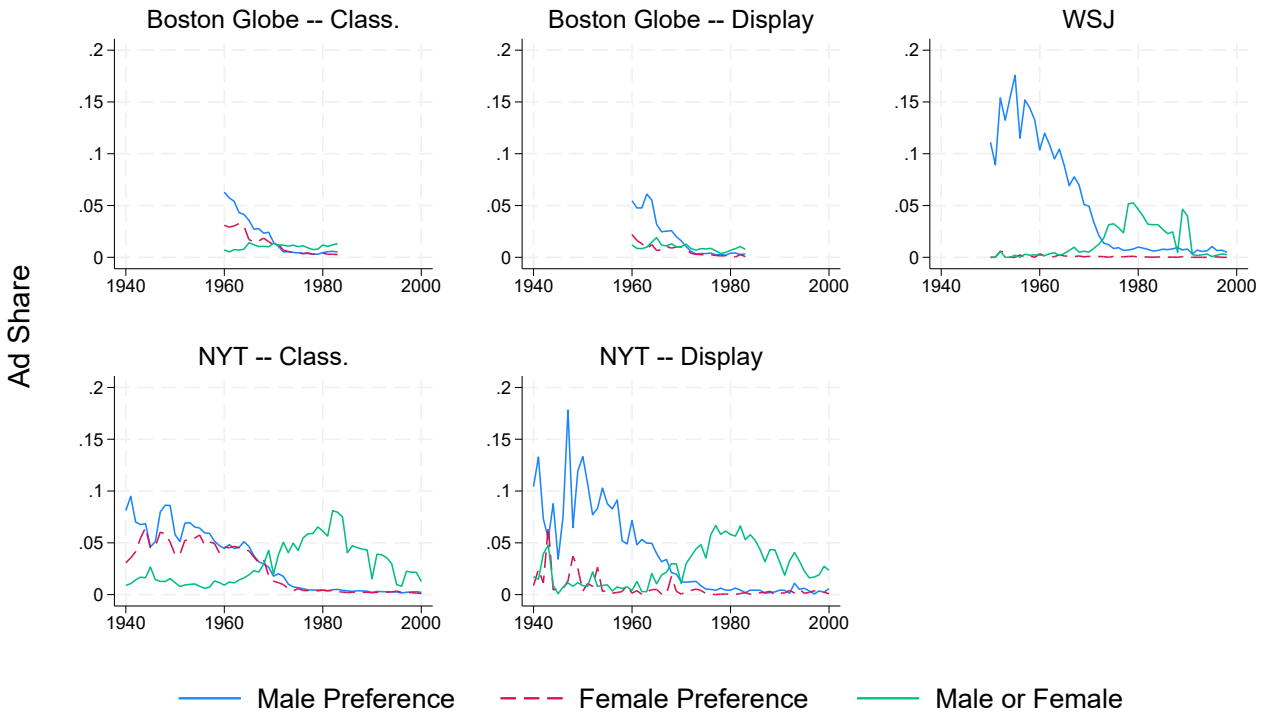
Whom to contact: J. H. Howard, Director, Business and Technical Personnel Department.

Graduates normally interested in:

Accountants: men (B, M).
Advertising personnel: men (B).
Advertising writers: men (B).
Auditors: men (B).
Business administration majors: men (B, M).
Chemists—analytical, organic, physical, textile: men (B, M, D); women (B).
Credit personnel: men (B).
Editors: men (B).
Industrial administration personnel: men (B, M).
Engineers, chemical: men (B, M, D).
Engineers—civil, electrical, electronic, industrial, mechanical, metallurgical, textile; men (B, M).
Industrial designers: men (B).
Journalists: men (B).
Lawyers, patent: men (B, M, D).
Librarians: women (B).
Market research personnel: men (B, M).
Mathematicians: men (B, D); women (B).
Medical technicians: women (B).
Metallurgists: men (B).
Nurses: women (B).
Photographers: men (B).
Physicists: men (B, M, D); women (B).
Purchasing personnel: men (B).
Sales personnel: men (B).
Secretaries & stenographers: women (B).
Statisticians: men (B, M).
Technical writers: men & women (B).
Traffic & transportation personnel: men (B, M).

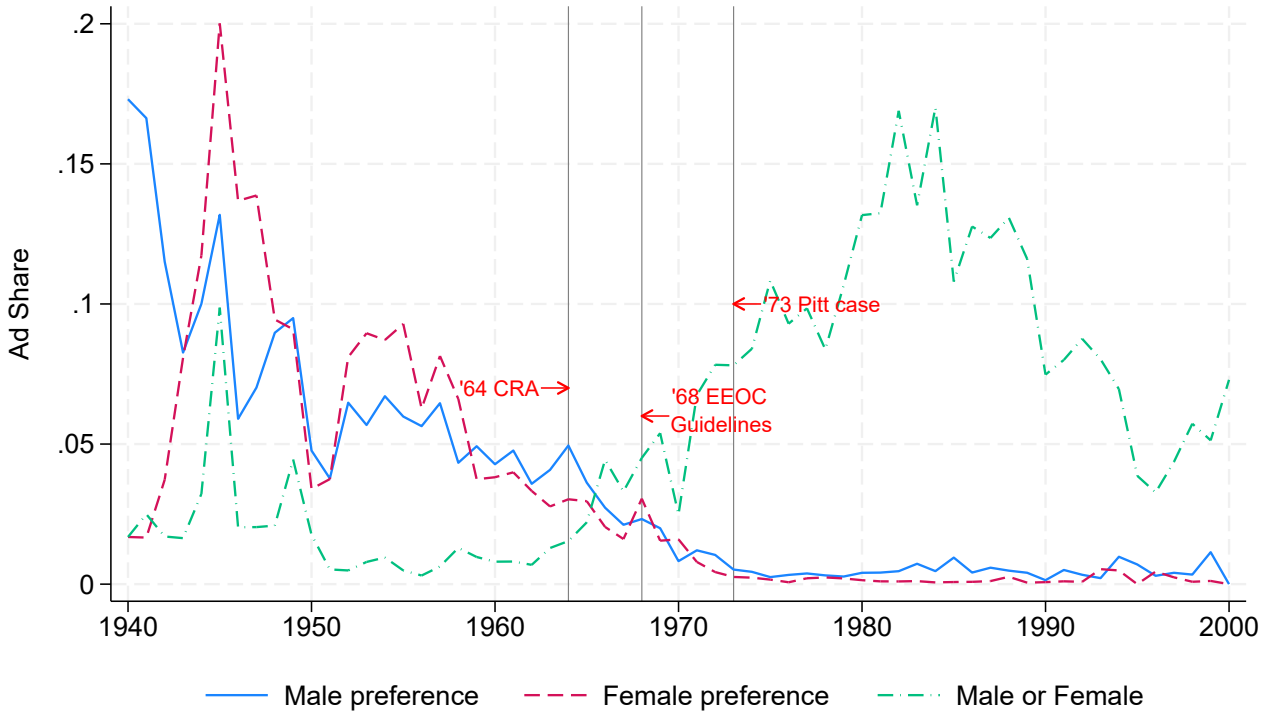
Notes: This listing for Eastman Kodak appears on pages 110-11 in the 1958 College Placement Directory [Zimmerman and Lavine, 1958]. B stands for bachelors, M for masters, and D for doctorate education requirements.

Figure D.3: Trends in Explicit Targeting by Source and Ad Type



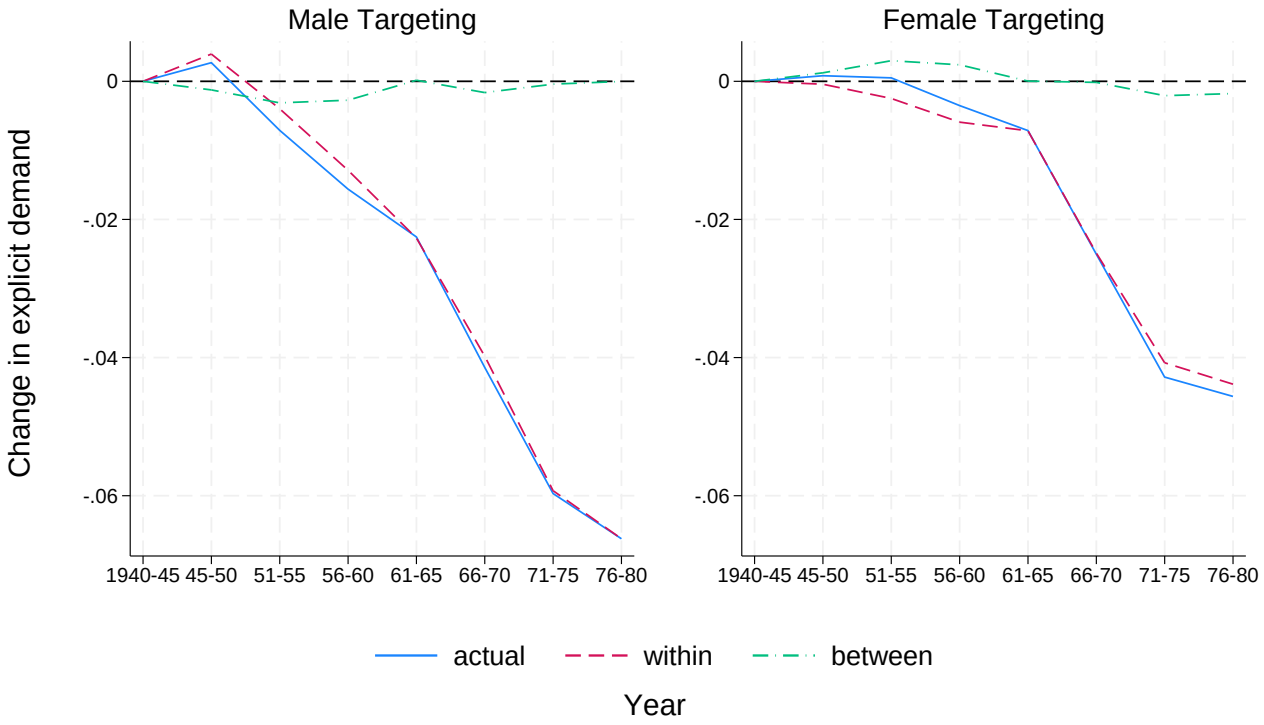
Notes: See figure 2. This figure plots trends separately for each newspaper source and type of ad. Newspapers are the Boston Globe, the Wall Street Journal, and the New York Times. Ads can either be in the classifieds or on display.

Figure D.4: Trends in explicit gender targeting: Restricting to EEO Matched Sample



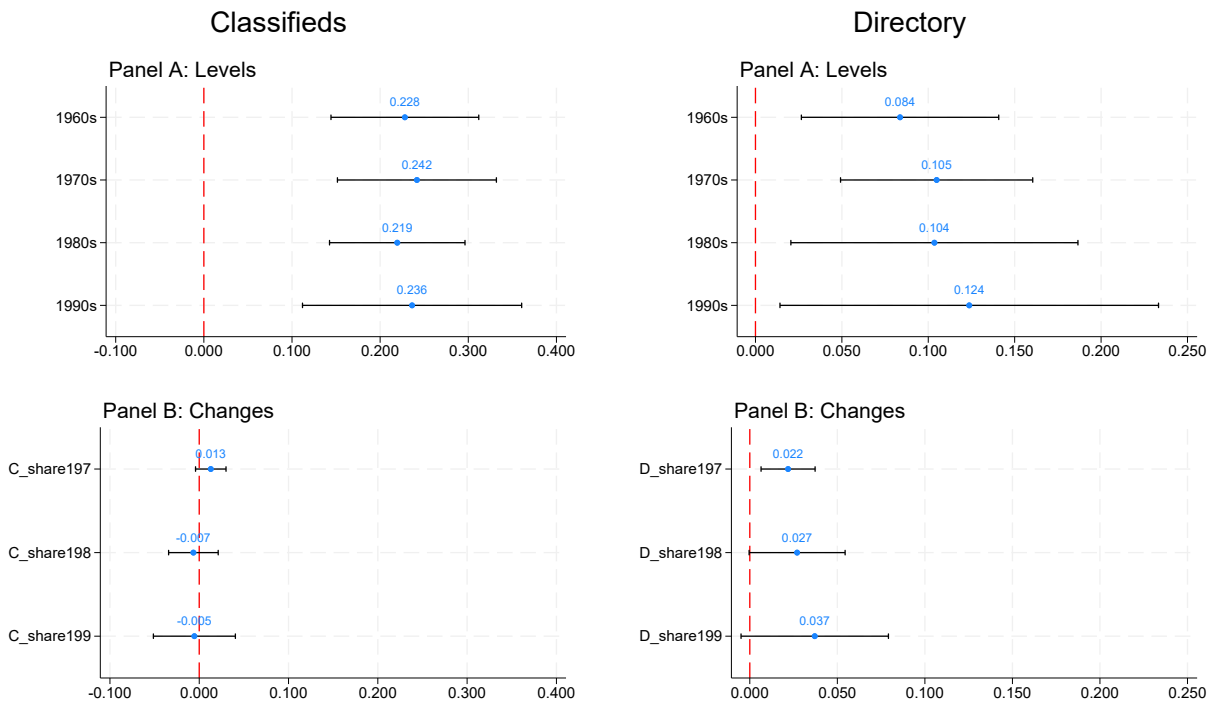
Notes: See figure 2. This figure restricts the sample to firms that can be matched to the balanced-panel EEO sample (i.e., firms present in the 1960's, 70's, and 80's).

Figure D.5: Changes in explicit gender targeting: within and between occupation



Notes: This figure plots the change in the share of ads with an explicit gender target from the baseline 1940-45 period to the indicated 5-year grouping. We also decompose this change into the amount attributed to changes in ad shares across 4-digit SOC occupation codes ("between") and within occupation changes in targeting ("within"). We find the decline in gender targeting is entirely driven by within occupation targeting behavior, with almost no role for changes in ad shares between occupations. The change in male targeting can be expressed as a within and between occupation component as follows: $\Delta m_t = \sum_o m_{ot}(w_{ot} - w_{o,1940}) + \sum_o (m_{ot} - m_{o,1940})w_{o,1940})$; o are occupations and t are 5 year bins, w_{ot} is the share of ads in occupation o at time t, and m_{ot} are the share of ads with an explicit male preference in occupation o and year t. The former gives the change in targeting that would be implied if only occupation (o) level weights are allowed to change and within occupation targeting is held fixed at its t value. The latter gives the change in targeting that would be implied if only within occupation targeting is allowed to change and occupation weights are held fixed at their 1940 level. In practice, there are two possible orders to perform the decomposition and, since they produce similar results, we simply average the two. The within component equals: $\frac{1}{2}\sum_o (m_{ot} - m_{o,1940})(w_{o,t} + w_{o,1940})$ and the between component equals: $\frac{1}{2}\sum_o (m_{ot} + m_{o,1940})(w_{ot} - w_{o,1940})$.

Figure D.6: Occupation employment shares on ad shares



Notes: We estimate versions of equations 1 (top panel) and 2 (bottom panel) where the outcome is the employment share of the occupation group and the key regressor is the ad share for that occupation group. Observations are at the firm-occupation-year level. Ad shares are measured in 1946-1970 in the classifieds (left) and in the 1958 directory (right). We use the baseline specification in each panel.

Table D.1: Most Common Types of Explicit Gender Targeting

Male term	Share of ads (%)	Female term	Share of ads (%)
young man	1.13	gal fri	0.74
right man	0.75	girl office	0.47
for man	0.59	young lady	0.42
for men	0.49	housewive	0.33
young men	0.34	young woman	0.27
experienced man	0.28	girl fri	0.24
man fri	0.27	girls women	0.21
for a man	0.15	elderly lady	0.11
experienced men	0.14	young women	0.11
seeks man	0.11	mature woman	0.11
ex pd man	0.10	for girl	0.09
qualified man	0.10	young girl	0.09
capable man	0.09	for women	0.09
married man	0.07	for gal	0.08
needs man	0.07	bright girl	0.08
college men	0.06	office girl	0.06
prefer man	0.06	young ladies	0.05
mature man	0.06	bright gal	0.05
office man	0.05	alert girl	0.05
man office	0.05	for woman	0.05
guy fri	0.05	mature women	0.05
ex pd men	0.05	for ladies	0.04
seeks men	0.04	right girl	0.04
needs men	0.04	capable girl	0.04
married men	0.04	for lady	0.04
Any explicit male targeting	4.92	Any explicit female targeting	3.92

Notes: We list the most common types of gender targeting in the classifieds dataset for ads listed between 1946 and 1970 along with their frequencies.

Table D.2: **Summary Statistics by Gender Preference: Classifieds 1946-1970**

	Explicit Gender Targeting			
	Male	Female	Either	None
Ad requirements:				
Number of words in the ad	89.84	84.47	99.01	50.42
Any education requirement	0.11	0.08	0.11	0.08
Any experience requirement	0.11	0.07	0.11	0.08
Any skill requirement	0.55	0.47	0.51	0.39
Preference for married	0.06	0.01	0.01	0.01
Preference for attractive	0.0006	0.0066	0.0017	0.0011
Regular schedule indicated	0.124	0.383	0.152	0.143
Irregular schedule indicated	0.015	0.006	0.007	0.006
Male page	0.41	0.04	0.25	0.24
Female page	0.04	0.45	0.13	0.17
Male-female page	0.032	0.026	0.148	0.070
Ad source:				
Boston Globe	0.021	0.014	0.027	0.040
New York Times	0.957	0.986	0.969	0.947
Wall Street Journal	0.02	0.00	0.00	0.01
Display Ad	0.036	0.006	0.029	0.040
Occupation-Level (1960 Census):				
Male Employment Share	0.743	0.484	0.664	0.665
Average Log Wage	2.36	2.26	2.34	2.35
Gender Pay Gap	0.28	0.20	0.22	0.23
College share	0.14	0.10	0.16	0.14
Annual Hours per Worker	1880.07	1745.87	1836.94	1847.15
Average Age	36.45	35.40	36.05	35.89
Share of ads	0.049	0.039	0.015	0.896
Total ads	232708	185324	72587	4240243

Notes: Means of main variables from the classifieds dataset for the 1946-1970 period. Occupation variables are created in the 1960 Census. Male employment share is the fraction of total hours worked in the occupation attributed to men. Average wage is total wage and salary income divided by annual hours worked; top-coded values are multiplied by 1.5 and wages are CPI adjusted to 2000 dollars. See appendix A.2 for details on measuring ad requirements.

Table D.3: **Summary Statistics by Gender Preference: Directory**

	Gender Targeting		
	Male	Female	Both
Male Education Requirements:			
Bachelor's share	0.96	.	0.96
Master's share	0.32	.	0.49
Doctorate's share	0.13	.	0.32
Female Education Requirements:			
Bachelor's share	.	0.99	0.96
Master's share	.	0.09	0.48
Doctorate's share	.	0.003	0.305
Company-Level:			
# employees	10508	8081	8917
# ads	12.53	12.91	15.66
Occupation-Level (1960 Census):			
Male Employment Share	0.85	0.20	0.81
Average Log Wage	2.56	2.34	2.53
Gender Pay Gap	0.18	0.01	0.10
College share	0.35	0.15	0.37
Annual Hours per Worker	1986.37	1682.08	1966.96
Average Age	35.78	35.44	35.16
Share of ads	0.723	0.086	0.190
Total ads	8245	983	2170

Notes: Means of main variables from the 1958 College Placement Directory. An observation is a job title listing within a company entry. Ads can list multiple education requirements; this table summarizes the presence of the indicated requirement. Entries also list the number of employees which we average across all entries for a given company name, weighing by the number of titles in each listing. The number of ads sums all the titles across a company's entries. Occupation variables are created in the 1960 Census. Male employment share is the fraction of total hours worked in the occupation attributed to men. Average wage is total wage and salary income divided by annual hours worked; top-coded values are multiplied by 1.5 and wages are CPI adjusted to 2000 dollars.

Table D.4: **Male Employment Shares by Decade and Gender Targeting**

Dependent variable:	Male Employment Share									
Targeting Source:	Classifieds					Directory				
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FL	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) FL
Pane A:	1970's									
Male Target	0.072***	0.058***	0.047***	0.053***	0.102***	0.060***	0.059***	0.057***	0.083***	0.083***
	(0.013)	(0.011)	(0.011)	(0.015)	(0.022)	(0.018)	(0.017)	(0.017)	(0.025)	(0.021)
Observations	20,477	20,477	20,477	20,477	20,477	16,084	16,084	16,083	16,084	16,084
R2	0.614	0.685	0.720	0.659		0.769	0.790	0.799	0.769	
Pane B:	1980's									
Male Target	0.059***	0.054***	0.043***	0.040***	0.093***	0.054***	0.053***	0.054***	0.075***	0.080***
	(0.011)	(0.011)	(0.010)	(0.012)	(0.020)	(0.018)	(0.016)	(0.014)	(0.024)	(0.023)
Observations	13,518	13,517	13,517	13,518	13,518	10,103	10,103	10,102	10,103	10,103
R2	0.628	0.703	0.744	0.687		0.772	0.797	0.808	0.773	
Pane C:	1990's									
Male Target	0.060***	0.054***	0.037***	0.035***	0.103***	0.030*	0.030**	0.036***	0.042*	0.056**
	(0.012)	(0.011)	(0.009)	(0.013)	(0.023)	(0.017)	(0.015)	(0.013)	(0.023)	(0.024)
Observations	11,962	11,962	11,962	11,962	11,962	9,146	9,146	9,141	9,146	9,146
R2	0.583	0.684	0.755	0.690		0.740	0.790	0.804	0.742	
Occupation FEs	X	X	X	X	X	X	X	X	X	X
Industry and State FEs		X	X				X	X		
1960 Census Occ Controls			X					X		
Leave-out mean as control				X					X	
Fractional Logit					X					X

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors are in parentheses, clustered on firm. See table 5. This table reports results for EEO filings in the 1970's, 1980's, and 1990's across panels A, B, and C, respectively.