Gender Preferences in Job Vacancies and Workplace Gender Diversity

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Abstract

In spring 2005, the *Ombud for Equal Treatment* in Austria launched a campaign notifying employers and newspapers that gender preferences in job ads were illegal. At the time over 40% of vacancies on the nation's largest job board stated a gender preference; within a year the rate fell below 5%. We merge job board vacancies and employer records to study how the campaign affected hiring choices and the gender diversity of occupations and workplaces. Using pre-campaign data, we predict the use of gender preferences, then conduct a difference-in-differences analysis of hiring outcomes for vacancies with predicted male or female preferences, relative to those with no predicted preferences. The elimination of explicit gender preferences boosted the share of women hired for jobs that were likely to be targeted to men (and vice versa). At the firm level, we find that the campaign led to a rise in the share of women at firms that were more likely to use male SGP's, and a symmetric increase in the share of men at firms that were likely to use female SGP's, with no effects on firm survival, employment, or average wages.

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1 INTRODUCTION

Rules and customs governing gender roles in the workplace have gradually eased over the last century (Goldin, 2014). Nevertheless, women and men still tend to work in different jobs and at different firms.[1] One of the traditional mechanisms reinforcing this segregation was the use of stated gender preferences (SGP's) in recruiting (see Darity and Mason, 1998). While such statements were outlawed in the U.S. in the 1970s, they were still in use in many countries, including Austria, at the turn of the 21st century. In 2005, however, an Austrian government agency – the *Ombud for Equal Treatment* (OET) – launched a campaign to notify employers and newspapers that the use of gender preferences was illegal (as it had been for two decades) and subject to financial penalties (newly introduced in 2004). Within a year the fraction of job ads specifying a gender preference on the country's largest job board fell from 40% to under 5%, providing a novel natural experiment to evaluate the impacts of SGP's on hiring outcomes and gender segregation.

We study this episode by linking information from vacancies from the job board to administrative records on the firms posting the vacancies and the workers who filled them. The resulting data set allows us to document how the use of SGP's in the pre-campaign period varied across employers and occupations, and how their elimination affected hiring outcomes for vacancies that were likely to include gender preferences. We also study impacts on firm-wide outcomes, comparing post-2005 shifts in the share of female employees at firms that were more or less likely to use SGP's prior to the campaign, as well as firm survival and growth.

Prior to 2005, most stated gender preferences matched the modal gender in the targeted occupation and at the hiring firm's workplace. Vacancies with a gender preference were very likely (>90%) to be filled by a candidate of the preferred gender, even when that preference differed from the modal gender in the occupation or the workplace, suggesting that stated preferences were strong signals of firms' hiring intentions. But would the elimination of these signals change actual hiring outcomes?

[1] On the issue of occupational segregation, see Cortes and Pan, 2017. On the issue of workplace segregation see Hellerstein *et al.* (2008) for the U.S., Mumford and Smith (2009) for the U.K., Card *et al.* (2016) for Portugal, and Gerard *et al.* (2018) for Brazil.

Or would firms reach the same decisions even without the use of SGP's?

To answer this question we use pre-campaign vacancies to predict the use of SGP's within firm-occupation cells. We then conduct a difference-in-differences analysis of hiring outcomes for vacancies posted between 2000 and 2010 with ***predicted*** male or female preferences, relative to vacancies with no predicted preference. Our approach is similar to the designs used to study the effect of the minimum wage on workers most likely to be affected by a rise in the minimum (e.g., Cengiz *et al.*, 2022) and sidesteps the problem that SGP's largely disappeared after the OET campaign.

We find that the 2005 campaign led to a highly significant 2.3 percentage point (ppt) increase in the fraction of women hired to fill vacancies with a predicted male preference, and an even larger 3.7 ppt. rise in the fraction of men hired to fill vacancies with a predicted female preference. Given the misclassification rates in our prediction model, the implied causal effects for vacancies that would have used gender preferences in the absence of the campaign are roughly double that size, implying important changes in hiring outcomes. The OET campaign appears to have caused some firms to "change their minds" – hiring workers who would have been screened out by their stated gender preferences prior to the campaign.

To explore further, we examine hetereogeneity in the effects of the OET campaign based on the match between the predicted gender preference and the modal gender in the targeted occupation. For the majority of vacancies where the predicted preference matches the modal gender (*stereotypical preferences)* the campaign worked as intended, increasing the hiring rate of the non-preferred gender and increasing gender diversity in the targeted occupation and at the recruiting workplace. For vacancies where the predicted preference is the opposite of the modal gender (*non-stereotypical preferences*) the campaign also led to a rise in hiring of the non-preferred gender. This shift, however, contributed to a reduction in the gender diversity of the targeted occupation, and a nuanced pattern of effects on workplace diversity.

Our main results are based on vacancies at frequent-posting firms, allowing us to construct firm-specific predictions for the use of SGP's. To test whether similar impacts were present at smaller firms, we develop an alternative predictor of gender preferences that relies on the interaction between the occupation and industry of the advertised job and the (lagged) share of female workers at the firm. Using predicted preferences from this approach, we confirm the results for our frequent-poster sample, including the pattern of results for stereotypical and non-stereotypical preferences.

Finally, we return to our subsample of frequent-posting firms and examine the longer-term effects of the campaign. We find that it led to significant increases in the share of female employees at firms that were likely to use male SGP's in the pre-campaign period, and a symmetric rise in the share of males at firms that were likely to use female SGP's. These shifts led to an overall rise in gender diversity at both sets of firms. Perhaps surprisingly, however, we find no evidence that the elimination of gender preferences harmed firm survival, employment growth, or average wages at firms that were using these signals prior to the campaign.

Our findings contribute to the large literature on gender segregation in occupations and workplaces, including Cortes and Pan (2017), Blau (1977), Groshen (1991), Petersen and Morgan (1995), and Bayard *et al.* (2003). Specifically, we show the importance of direct preference signals – now outlawed in most European countries but still in use around the world – in reinforcing gender segregation.[2]

We also contribute to a growing literature concerned with policies that restrict the collection of information at early stages of the job matching process, including criminal records (Agan and Starr, 2018; Doleac and Hansen, 2020), credit histories (Bos *et al.*, 2018; Ballance *et al.*, 2020), applicant names (Behaghel *et al.*, 2015), and drug use (Wozniak, 2015). As in this literature, the key question in our paper is whether the prohibition of early-stage information affects ultimate hiring outcomes. Consistent with at least some of these studies, we find that it does. We also show that disallowing early-stage preference signals does not seem to adversely affect firms that were most likely to use them.

Our work is closely related to a series of recent studies of gender preferences in Chinese job matching markets by Peter Kuhn, Kailing Shen, and co-authors, including Kuhn and Shen (2013),

[2] Bamieh and Ziegler (2022) study whether another direct employer signal – the wage – affects the gender gap in wages, in the context of a 2011 reform on pay transparency in Austria using a firm-by-occupation cells classification approach.

Helleseter *et al.* (2016), and Kuhn *et al.* (2020). Kuhn and Shen (2013) develop a signaling model of the decision by employers to state a gender preference that compares the cost of screening extra job applications to the expected benefits of being able to evaluate applicants of both genders. Implicit in this model is the assumption – verified by Kuhn *et al.* (2020) – that gender preferences strongly deter applications from the non-preferred gender.

Most directly, our paper is related to Kuhn and Shen (2023), who study the effects of a decision by a job board in one Chinese city to eliminate SGP's from all posted vacancies. This instantaneous change allows Kuhn and Shen to compare applications to the same vacancy before and after the removal of SGP's, providing a credible design for measuring the reactions of applicants to SGP's. They find that the removal of SGP's led to an increase in the share of applications from the non-preferred gender group. They also show that the share of call-backs to applicants of the non-preferred gender rose after SGP's were removed – consistent with our findings on hiring.We view our results as complementary to those of Kuhn and Shen (2023): they have information on applications and employer call-backs, whereas we have information on hiring and firm-wide outcomes. The consistency of the findings across the two settings and between call-backs and hiring outcomes is reassuring.[3] We add to the literature by observing actual *hiring decisions*, by examining effects on workplace diversity, by distinguishing between stereotypical and non-stereotypical SGP's, and by studying longer-term outcomes at firms that were most likely to use gender preferences prior to the information campaign.

2 Background and Conceptual Framework

2.1 Background

A long-standing policy concern is that employers exert discriminatory preferences in hiring, harming opportunities for certain groups, including women.[4] Our focus – and the focus of the OET cam-

[3]Potential differences between callback and hiring decisions are emphasized by Cahuc *et al.* (2019) and Jarosch and Pilossoph (2019).

[4]For example, Black (1995) presents an equilibrium search model and shows that the presence of some discriminating employers can harm the target group. See Lang and Lehmann (2012) for additional references

paign – is at the earliest stage of the hiring process, when firms post information about job openings that is used by job seekers to direct their search efforts. Employers can signal their gender preferences in a newly posted vacancy in several ways. Most directly, they can state a preferred gender for applicants. Historically, such statements were widespread (e.g., Darity and Mason, 1998). The text in a vacancy can also provide clues about employer preferences, particularly in the German language, where gendered occupational titles may suggest a preferred gender (e.g. the use of *Bauarbeiter* for a male construction worker versus *Bauarbeiterin* for a female construction worker).

Gender preferences in help-wanted ads were outlawed in the U.S. by a 1973 Supreme Court decision, nearly a decade after the Civil Rights Act banned discrimination in hiring.[5] Similar changes came somewhat later in other countries. Austria adopted its first Equal Treatment Act (ETA) in 1979 and outlawed gender discrimination in job advertisements in a 1985 amendment, albeit without explicit sanctions. Fines for the use of SGP's by temporary help agencies were introduced in 1992, and extended to the entire private sector in 2004. Title 1 of the 2004 amendment to the ETA states that recruiters *"may not advertise a position publicly or within an enterprise (company) exclusively for men or women"*, and rules out the use of any language suggesting a preferred gender.[6] Exceptions to this policy can only be made in special cases (e.g., in the search for a care worker at a shelter for women).

In the second quarter of 2005, the *Ombud for Equal Treatment* (OET), an agency that acts as an advocate and adviser on equity issues, conducted a study of job advertisements in Austria's major newspapers, looking for compliance with the 2004 law. The OET found that only 68% of nearly 36,000 ads were fully or partially gender neutral (Lujanski-Lammer, 2006). In response the agency

[5]The case, Pittsburgh Press Co. v. Pittsburgh Commission on Human Relations, 413 U.S. 376 (1973), specifically focused on the practice of listing help wanted advertisements by gender in a newspaper. We are unaware of studies of the effect of this ruling, though Beller (1983) presents an analysis of the effect of the 1964 Civil Rights Act in the U.S. on gender segregation across occupations.

[6]This meant that advertisements had to be made gender neutral by specifying both male and female forms of any occupation, e.g. *Bauarbeiter/Bauarbeiterin*. Title I of ETA also prohibits discrimination in promotion and pay, while Title II prohibits discrimination on the basis of ethnicity, age, religion, or sexual orientation. Some provisions required changes to state laws, which had to be in effect by December 2004. Recruiters who post an SGP face a fine of 360 Euros after one warning for private sector recruiters and with no warning for public sector recruiters. Job seekers can seek damages of one month's salary if they would have received the job but for gender, and 500 Euros in case a recruiter ignored an application because of gender.

launched a major information campaign, alerting newspapers, firms, and temporary help agencies to the law and offering suggestions on how to write gender-neutral advertisements. Six months later the OET collected a new round of data and found that compliance with the law had increased to about 79%, a substantial gain. We show in the next section that by mid-2006 the vast majority of vacancies in the Austrian Employment Service's online job board had eliminated gender preferences.

2.2 Conceptual Framework

Next, we outline a simple conceptual framework, based on the model developed by Kuhn and Shen (2013) (hereafter, KS) that informs our analysis of the OET campaign. We assume that gender preferences are signals to job searchers about a firm's preferences. On the supply side of the market, we assume that worker i applies to vacancy j if the subjective probability of being hired λ_{ij} exceeds some threshold τ_i. In the absence of a SGP, we assume that λ_{ij} is based on the gender composition of the relevant occupation, as well as characteristics of the industry and perhaps the specific workplace, reflecting prior information available to searchers. When a gender preference is stated, we assume that searchers update their estimate of λ_{ij}. In a Bayesian framework we would expect such updating to be particularly important for *non-stereotypical* gender preferences (where the gender preference differs from the modal gender in the occupation). Although we do not see job applications in our setting, we can observe the gender of hired workers, which nearly always match the employer's stated preferences, even in the non-stereotypical case (see below). Assuming this pattern is known to job seekers, a stated gender preference is likely to deter some people of the opposite gender from applying.

On the demand side, a key question is why a firm would want to limit applications by specifying a gender preference. KS assume that ***all*** applicants for a job are screened (i.e., firms cannot costlessly triage their non-preferred gender), and that screening reveals a candidate's match value for a job. Match values are assumed to have gender-specific means and an idiosyncratic component. If the distributions of match values for male and female candidates are far apart, then it is optimal for the firm to announce a gender preference and restrict the application pool.[7] Such a divergence is more likely if the firm has strong tastes for one gender over the other, or if there are true gender differences in productivity – conditions that would also lead to a larger gender imbalance in the existing workforce of the firm (especially at smaller firms where most of the employees perform the same job). Thus we would expect SGP's to mainly reinforce existing patterns of gender segregation.

When SGP's are eliminated, the impact on hiring will depend on how applicants respond to the absence of SGP's, and on how firms select from the resulting applicant pool. The removal of an SGP will presumably draw more applications from the non-preferred gender, and may also discourage applicants from the preferred gender, shifting the gender composition of the pool and potentially affecting the average match quality of applicants.[8] If the firm has strong tastes for the preferred gender, or there are large productivity differences between men and women in the job (i.e., the same conditions under which SGP's are most likely to be used in the KS model), then the change in the application pool will not necessarily lead to any change in the gender of the hired candidate, though screening costs per hire could rise. On the other hand, if the firm was using out-dated priors in deciding whether to specify a SGP, managers may be surprised by the quality of applicants of the non-preferred gender, and ultimately may hire a candidate who would not have applied when SGP's were allowed, or would have been screened out of the applicant pool for being the wrong gender. As we show below, this seems to be the case in our setting.

Assuming that the removal of SGP's leads to some increase in hiring of the non-preferred gender, the impacts on gender diversity of the occupation and workplace depend on whether the firm was using stereotypical or non-stereotypical SGP's, and on the alignment between the modal gen-

[7]Specifically KS assume that the match value of candidate i for a given opening j is a random variable $v_{ij} = v^{G(i)} + \beta\epsilon_{ij}$ where v^G is the mean for gender group G, $G(i)$ is an index function given $i's$ gender, β is a scaling factor, and ϵ_{ij} is an extreme value type 1 variate. Assuming that firms evaluate all applications they receive, and that people of a given gender only apply if their gender group is invited, they show that a firm's decision depends on $(v^M - v^F)/\beta$. When this term exceeds some threshold $c_U > 0$ it is efficient to only invite applications from men, when it falls below another threshold $c_L < 0$ it is efficient to only invite applications from women, and in the intermediate range it is efficient to invite both groups.

[8]Indeed, Kuhn and Shen (2023) find that the composition of the applicant pool changes dramatically, and the total application flows to previously gendered job ads increase by around 10%, when SGP's are eliminated. The quality of applications also increases somewhat when gender statements are abolished.

der in the occupation and at the workplace. In the case of a stereotypical SGP (e.g., a preference for male applicants for an auto mechanic job) the removal of SGP's will increase the chances of hiring a non-stereotypical candidate, which will tend to diversify the gender composition of the occupation. The impact on workplace diversity will depend on whether the stereotypical gender for the targeted occupation matches the majority gender at the workplace. If it does, then hiring a non-stereotypical worker for the occupation will also increase gender diversity at the workplace. If not (e.g., a preference for a female office assistant at a predominantly-male construction firm) then hiring a non-stereotypical candidate would reduce the gender diversity of the workplace.

In the case of non-stereotypical preferences, the removal of SGP's will tend to increase the chances of hiring a gender-stereotypical worker, and will therefore reduce the gender diversity of the targeted occupation. The impact on workplace diversity will again depend on whether the stereotypical gender for the targeted occupation matches the majority gender at the workplace. For example, consider a mainly-male engineering firm that values diversity and specifies a preference for female candidates when SGP's are allowed. In this case, the OET campaign could actually lower the probability of hiring a female candidate, leading to reductions in the gender diversity of the occupation and the firm. On the other hand, consider a construction firm that would specify a preference for a male office assistant if SGP's were allowed. In this case, the OET campaign could increase the probability of hiring a female candidate, leading to a reduction in the gender diversity of the occupation but an increase in the gender diversity of the workplace.

3 Job Vacancies and the Use of Gender Preferences

3.1 Data Sources

We use data from the job matching platform of the Austrian Employment Service, *Arbeitsmarktservice* (AMS), which has published information on job vacancies since 1987.[9] The platform includes

[9]The AMS administers Austria's unemployment benefit system through its local offices in each of the country's 104 labor market districts. Unemployment insurance claimants have to register in person at these offices and meet with staff in order to maintain their benefit eligibility.

almost 60% of all vacancies posted by Austrian firms, with higher coverage rates in manufacturing and construction and lower rates in banking and finance (Kettemann *et al.*, 2018; Mueller *et al.*, 2019; Ziegler, 2021). Employers use preconfigured fields to enter information about their open job and the characteristics of applicants they are looking for, including their preferred gender (which can be left blank). The preferred gender field has remained in the system despite legal prohibitions on gender preferences to accommodate searches for exempted jobs. Information from this field allows us to examine the use of gender preferences before and after the 2005 OET campaign.

AMS staff use information from the vacancy system for their *Vorauswahl* (or "pre-selection") service, which routes lists of their clients – registered job seekers, most of whom are unemployed – to firms with openings. Firms can select interviewees from among those suggested by AMS staff; they can also consider direct applications from individual workers. Vacancy information is also used by AMS clients and other job searchers. If an AMS client is hired to fill a job opening, the identity of the client is recorded in the system - a feature we use below.

The AMS job board differs from some other job information systems (such as the one studied by Kuhn and Shen, 2013) in the direct role played by AMS staff, even though most applications are from job seekers directly rather than mediated by AMS caseworkers.[10] Nevertheless, as we show below, the agreement rate between stated gender preferences and the gender of the hired workers in the pre-campaign years of our sample is very similar to the agreement rate between SGP's and job applicant genders in the job board studied by Kuhn *et al.* (2020). This suggests that intermediation by AMS staff does not necessarily amplify or dampen the role of SGP's in the matching process relative to one driven by worker-level choices.

3.2 AMS Vacancies

We use AMS vacancies from 2000 to 2010, providing data for 5 years before and 5 years after the OET campaign. We observe the preconfigured fields submitted by employers, including their target

[10]A recent study by Schmidpeter and Winter-Ebmer (2020) finds that AMS case-workers tend to push their clients to accept jobs quickly, with little consideration of wages in the new job.

occupation, education requirements for the job, whether the job is full- or part-time, and whether the contract is fixed-term or open-ended. We also observe the initial posting date and the date the vacancy was filled or closed (if it was withdrawn without being filled). Finally, and crucially for our purposes, we observe the gender preference selected by the employer.[11] We do observe the text of the vacancy postings, so we cannot directly verify that the gender preference field aligns with other information in the vacancy, such as the use of a gendered noun used to describe the occupation. We note, however, that after 2006 newspaper ads in Austria almost always included both female and male forms of the occupation title.

Gender Preferences in AMS versus Other Job Postings

A potential concern is AMS data cover only a subset of vacancies in Austria. Fortunately, an OET report (Lujanski-Lammer, 2006) summarizes the use of gender preferences in vacancy listings in the main newspapers in Austria before and after their information campaign that can be compared to the stated preferences in AMS. Column (1) of Table 1 shows the fractions of posted vacancies in the OET's database with a stated or implied gender preference in March/April of 2005 and December 2005. Column 2 shows the fractions of vacancies in the AMS system with a stated male or female gender preference in the same time periods.

For March/April of 2005, the OET data show that 23% of newspaper job ads had a male SGP, while 8% had a female SGP. In the AMS system in these months the corresponding fractions were 20% and 14%, respectively. By December 2005, both data sources show that the share of ads with a male gender preference fell by about 9-11 percentage points, while the share with a female preference fell by 1-2 percentage points. Although the shares of job ads with gender preferences are not identical in the OET sample and the AMS, we conclude that the two data sources show broadly similar patterns of use of SGP's prior to the OET campaign, and very similar declines in the use of SGP's in 2005.

[11] We use the terms 'firm', 'employer', and 'workplace' interchangeably in the text, but note that our data provides information on workplaces.

Table 1: Use of Stated Gender Preferences and Other Characteristics of Vacancies

	Vacancies Surveyed by OET	Vacancies Posted in AMS System				
		All	**AMS Client Matched**	**With PGP Ext Sample**	**More than 5 vacancies**	**With PGP Firm-Occup.**
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: SGP - Comparison AMS vs Other Job Postings (2005)						
Preference for Men						
March/April 2005	0.23	0.20	0.21	0.21	0.21	0.21
December 2005	0.14	0.09	0.10	0.11	0.1	0.1
Change	-0.10	-0.11	-0.11	-0.10	-0.11	-0.11
Percentage Change	-42%	-53%	-51%	-48%	-52%	-52%
Preference for Women						
March/April 2005	0.08	0.14	0.16	0.17	0.16	0.17
December 2005	0.07	0.12	0.13	0.14	0.13	0.15
Change	-0.01	-0.03	-0.03	-0.03	-0.03	-0.02
Percentage Change	-16%	-20%	-19%	-18%	-19%	-12%
Panel B: SGP - pre-campaign period (2000-2004)						
Preference for Men		0.22	0.25	0.26	0.27	0.23
Preference for Women		0.19	0.21	0.22	0.21	0.23
Panel C: Vacancy Characteristics (2000-2010)						
Vacancy Duration (days)		53.23	41.03	40.89	41.03	41.74
Full Time Position		0.78	0.78	0.77	0.77	0.74
Unlimited Contract		0.78	0.82	0.80	0.80	0.75
Posted by small firm (≤ 5 employees)		0.46	0.43	0.42	0.36	0.28
Requesting at least upper secondary education		0.51	0.46	0.46	0.45	0.39
Observations		3,259,322	698,372	500,579	436,557	197,130
Observations - pre-campaign period		1,212,282	292,353	217,565	170,857	89,960

Notes: Panel A of this table compares the share of job advertisements with a gender preference in Austrian newspapers and in four subsamples of the AMS Data for two periods: just before the campaign (March-April 2005) and after the campaign (December 2005). Panel B shows the share of job advertisements with a gender preference in four subsamples of the AMS Data for the pre-campaign period in our data (2000-2004). Panel C reports means and shares of selected characteristics of vacancies in four subsamples of the AMS Data for the period 2000-2010. The sub-sample *All* refers to all vacancies posted in the AMS System, *AMS Client Matched* is the subset of vacancies filled through AMS that we matched with a firm in the Austrian Social Security Database (ASSD), *With PGP Ext Sample* is the subsample containing vacancies posted in industry, occupation, lagged firm gender share cells with at least 2 vacancies in the pre-campaign period and 2 vacancies in the post-campaign period, *More than 5 vacancies* refers to all vacancies posted by frequent postings firms (firms posting more than 5 job ads in the pre-campaign period), *With PGP Firm-Occup* is the subsample of all vacancies posted by frequent postings firms that posted at least 2 vacancies in the corresponding occupation in the pre-campaign period and in the post-campaign period. Vacancy Duration is measured as the difference between the last day of the vacancy closing month and the vacancy posting date.

LINKING AMS VACANCIES TO SOCIAL SECURITY DATA

The employer identifiers used in the AMS vacancy system cannot be directly linked to other administrative data sets. Our approach is to focus on vacancies filled by an AMS client, for which we observe a person identifier that can be linked to the Austrian Social Security Database (ASSD) – the main source for employer-employee data for the private sector in Austria (see Zweimüller *et al.*, 2009). Specifically, for each vacancy filled by an AMS client, we find the job spell for the hired worker in the ASSD with a starting date closest to the closing date of the vacancy, dropping cases where the gap in dates is too large, or where the worker had multiple job starts in the same window. We provide a full description of the matching procedure in Appendix A.[12]

Column 3 of Table 1 shows the characteristics of filled vacancies that we can successfully match to the ASSD (about 21% of all vacancies).[13] Column 4 shows a subset of these vacancies for which we can predict gender preferences – we use these in our extended difference-in-differences models in Section 4.3, below.[14] For most of the analysis in this paper we focus on "frequent posting" firms with 5 or more vacancies in the pre-campaign period that can be matched to the ASSD: we can use these vacancies to identify consistent users of male or female SGP's in the pre-campaign period. Characteristics of the vacancies from frequent posting firms are shown in column 5 of Table 1. Finally, for our main analysis of vacancy-specific outcomes, we further narrow attention to vacancies in a 3-digit occupation for which a firm posted at least 2 vacancies prior to 2005 and at least 2 vacancies after 2005. Using this subset of vacancies we can form a "leave-out" predicted probability of using female or male SGP's in the pre-campaign period that is specific to the firm and occupation. This sample is described in column 6 of Table 1.

Reassuringly, we see in Panel A of Table 1 that the fractions of vacancies with male and female

[12]We investigated the possibility of using AMS-filled vacancies to create a broader cross-walk between the employer id's used by AMS and those used in the ASSD. Unfortunately, we found that the AMS reuses the same id for different firms in different years. We are nevertheless grateful to a referee for suggesting this idea.

[13]About 89% of all AMS vacancies were filled, 28% of filled vacancies were filled by an AMS client, and we can match about 85% of those clients to the ASSD data set. In Appendix Tables B.1 we show 1-digit industry and occupation shares for all vacancies and for the subsets at different steps on the way to the matched ASSD sample.

[14]We predict gender preferences for the broad set of vacancies using leave-out means for cells formed by interacting the occupation of the vacancy, the industry of the firm, and the lagged fraction of female workers at the firm. Vacancies that are unique to their cell are excluded.

SGP's in different time periods is relatively stable as go from column 2 to column 6, though the share with a male SGP is a little lower in our main vacancy analysis sample in column 6. Likewise, in Panel C we show that the average duration of vacancies, the shares of vacancies offering full time positions and unlimited contracts, and the share targeted to workers with at least upper secondary education are all fairly similar across the columns. One characteristic that varies more is the share of vacancies posted by small firms (≤ 5 employees), which is 46% in column 2 and 42% in column 4 (our extended sample), but falls to 36% in column 5, and to 28% in column 6. Not surprisingly, small firms are less like to be frequent posters, and even less likely to post multiple vacancies in the same occupation.

We interpret the similarity across columns 1-6 of Table 1, particularly in the use of gender preferences in the pre-campaign period, as suggesting that an analysis based on subsamples vacancies created by frequent posters are likely to be informative about the overall effects of the campaign.[15]

Did the OES Campaign Affect the Use of AMS?

A possible concern for our analysis is that the OET campaign caused some employer to reduce their use of the AMS system – perhaps switching to informal recruiting networks to avoid scrutiny. In the appendix, we provide statistics on the use of the platform, and on the number of vacancies filled by AMS clients between 2000 and 2010 (see Figure B.1 and Table B.2). These data show that the number of vacancies posted on the AMS system grew by about 40% from 2000 and 2010, as did the number of filled vacancies, with no trend break after 2005.[16] The number of vacancies filled by AMS clients also rises, but somewhat more slowly. Our interpretation of the downward trend in the fraction of vacancies filled by AMS clients is that it was driven by a fall in the ratio of unemployed job seekers (who make up the bulk of AMS clients) to the number of vacancies – i.e., a tightening of the labor market – particularly up to 2008.[17]

[15]As a check, in a previous version of this paper we re-estimated models for our extended vacancy analysis sample using inverse probability weighting to reflect the probability that a given vacancy is included in that sample. The results, available upon request, are very similar to the unweighted estimates.

[16]Total outflows from the vacancy pool and the number of filled vacancies have almost identical trends suggesting that recruiting difficulty was not affected by the campaign, as we document in our empirical analysis section.

[17]There was a relative rise in the number of job seekers in 2008 and 2009 reflecting the onset of the financial crisis, but during this period the number of jobs filled by AMS clients also falls.

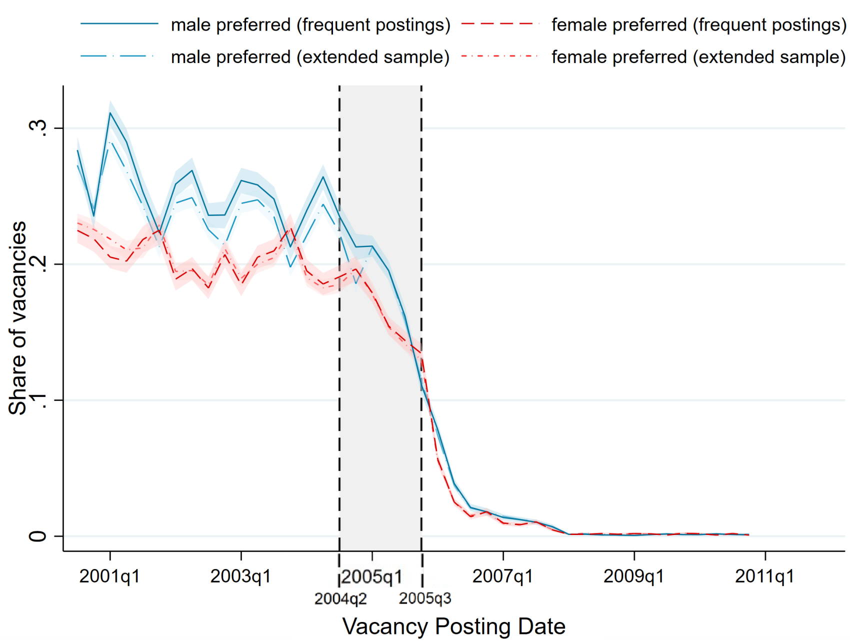
Overall, we believe the evidence gives no indication of a shift away from use of the AMS system following the 2005 campaign.[18]

3.3 Use of Stated Gender Preferences

Trends in the Use of Gender Preferences

We begin our analysis with Figure 1, which shows the quarterly fraction of vacancies with a stated gender preference between 2000 and 2010. We show use of SGP's in both our extended sample of all AMS-filled vacancies (the sample described in column 3 of Table 1) and in the subsample of vacancies from frequent posters (described in column 5).

Figure 1: Use of Stated Gender Preferences in Posted Vacancies



Notes: This figure shows that share of posted vacancies in the AMS job board system that specify a preference for females (dashed line and dot-dashed line), or males (solid and dot-long-dashed line). The vertical dashed lines depict the date of a law change introducing sanctions for posting gender preferences (Spring 2004), and the time just after an information campaign to alert employers and newspapers about the law (Summer 2005). The *extended sample* includes all 698,372 vacancies posted in the 2000-2010 period, filled through AMS, and matched with a firm in the Austrian Social Security Database (ASSD) (column 3 of Table 1). The *frequent postings sample* includes all 436,557 vacancies posted by frequent postings firms (column 5 of Table 1).

[18] As a further check, in Appendix B we report detailed descriptive statistics on other vacancy characteristics and find that the characteristics of vacancies filled by AMS clients in our matched sample do not differ much from the overall population of AMS vacancies. We also examine the gender composition of newly filled jobs in our matched sample and find that it closely tracks the gender composition of all new employment spells in Austria over the sample period. We are therefore reasonably confident that the use of the platform was not significantly affected by the campaign.

Prior to 2005 the fractions of vacancies with male or female preferences were relatively stable, apart from some seasonality in the share of male SGP's. Use rates of SGP's were also very similar in our full sample of AMS-matched vacancies and in vacancies posted by frequent-posting firms. At the July 1 2004 date, when fines for using gender preferences were added to the Equal Treatment Act, there is no break in the use of stated preferences, suggesting that the law had little or no impact. In the second quarter 2005, however, the share of vacancies with expressed preferences begin to decline sharply, and by mid-2006 it had fallen to under 5%. The trend break in 2005 coincides exactly with the OET information campaign, which began in the second quarter of 2005, giving us confidence that the OET campaign was the main factor behind the near-elimination of SGP's in Austria.

Stated Preferences Before the OET Campaign

How did vacancies with a stated gender preference in the pre-2005 period differ from those with no SGP? We investigate these differences in Table 2, using vacancies of frequent posters. Parallel results for our extended sample of AMS-matched vacancies are presented in the Appendix Table C.1. As shown in the table, about 21% of vacancies stated a gender preference for females (column 2), 27% for males (column 4), and 52% stated no preference (column 3). During these years females made up about 45% of all people hired to fill vacancies on the AMS system (see column 1). The share of women hired for jobs with no SGP was quite similar to this overall share, but for vacancies with a female SGP, 96% were filled by a female, while for vacancies with a male SGP, only 3% were filled by a female. Thus, compliance with SGP's was extremely high.

We also report the mean and median duration of filled vacancies, the mean log daily wage associated with the newly created jobs, and the duration of these jobs (mean and median). We see a couple of interesting patterns here. First, job openings with an SGP *for either gender* tend to be filled a little faster.[19] Second, jobs created by filling a vacancy with a female SGP – which are nearly

[19]The vacancy filling times reported in Table 2 are based on the number of days between the posting date of the vacancy and the day the new employee started work. The latter is only available for vacancies filled by AMS clients that can be matched to the ASSD. In Table 1, discussed earlier, we use an alternative definition based on the elapsed time

all held by women – pay relatively low wages but have longer durations than those created by filling vacancies with no SGP (some of this pay gap could be due to differences in hours of work). Symmetrically, jobs created from a vacancy with a male SGP – which are nearly all held by men – pay relatively high wages and have shorter durations.

Table 2: Characteristics of Filled Vacancies by Use of Gender Preferences, Pre-campaign

	Total	**Stated Gender Preference**		
		Female SGP	**No SGP**	**Male SGP**
	(1)	(2)	(3)	(4)
Share of vacancies	1.000	0.206	0.524	0.270
Panel A: Outcomes				
Share of women hired (share)	0.448	0.964	0.460	0.031
Vacancy filling time (mean)	32.34	29.67	34.46	30.22
Vacancy filling time (median)	21	19	23	19
Log wage of the hire (mean)	3.82	3.58	3.83	3.99
Job duration (mean)	375	406	387	330
Job duration (median)	162	183	169	137
Panel B: Context				
Share of women in the firm (share)	0.459	0.672	0.480	0.255
Share of women in occupation (share)	0.467	0.648	0.497	0.271
Panel C: Vacancy Characteristics				
Posted by small firm, ≤ 5 employees (share)	0.326	0.370	0.320	0.303
Requesting at least upper secondary education (share)	0.381	0.264	0.435	0.364

Notes: This table reports means, medians, and shares of selected characteristics of vacancies by Stated Gender Preference (SGP) for 170,857 vacancies posted by frequent postings firms (firms posting more than 5 job ads in the pre-campaign period). Vacancy filling time refers to the difference in days between the starting date of the new job associated with the vacancy and the posting date of the vacancy.

Panel B shows the shares of female workers in firms and occupations using different kinds of gender preferences. On average, female SGP's are posted by firms with nearly 67% female workers, while male SGP's originate from firms with only 25% female workers. Similarly, the targeted occupations for vacancies with female SGP's are about 65% female, while the occupations for vacancies with a male SGP are about 27% female.

from the day the vacancy was posted to the last day of the month in which it was removed from the AMS job board, which is available for all vacancies.

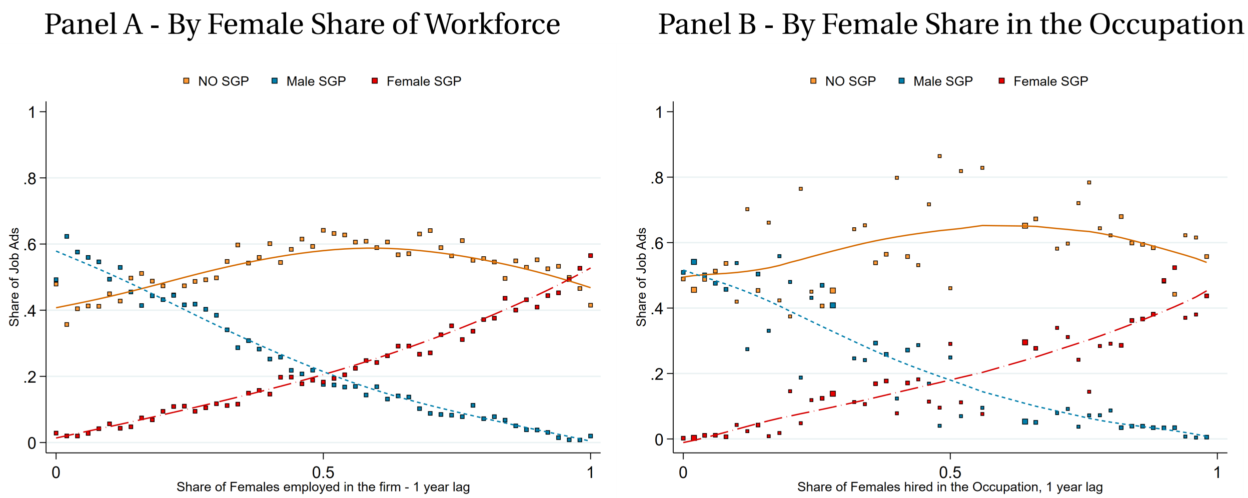
Panel C provides evidence on firm size and the education requirements for jobs advertised with different gender preferences. Female SGP's are more likely to be used by small firms, and are less likely to be used in posts that specify a minimum upper secondary education requirement, whereas male SGP's are more likely used by larger firms looking for workers with higher levels of education. Vacancies with no SGP are in the middle in terms of the share of small firms, but have higher education requirements than those with either type of gender preference.

To give a richer picture of the relationships between SGP's and the characteristics of the occupations and firms posting the associated vacancies, we matched filled vacancies from frequent posters in the pre-campaign period to the fraction of female employees at the posting firm in the year prior to the post, and to the share of female workers hired to fill vacancies in the target occupation in the previous year.[20] Panel A of Figure 2 shows the shares of vacancies with a female, male, or no SGP, plotted against the share of female workers in the firm; Panel B shows the same shares plotted against the share of females hired in the target occupation. The figures show that the probability of a male SGP falls monotonically with the share of females in the workplace or target occupation, while the probability of a female SGP rises monotonically. Vacancies with no SGP tend to be posted by firms with a more equal share of males and females, and in occupations with a similar gender balance.

Next we look at the relationship of SGP's to the probability of hiring a female or male worker, focusing on differences by female share at the workplace or occupation. Panle A of Figure 3 shows the average share of women hired by firms with different (lagged) female employment shares, conditional on the type of SGP (male, female, or none). The figure reveals stark differences in outcomes for these three types of vacancies, even controlling for workplace composition. In the absence of any SGP (the yellow line in the figure), the fraction of females hired is approximately linear in the lagged female share, with an intercept that is close to 0 and a slope that is close to 1. For vacan-

[20]As fraction of female employees in the firm we use a discrete measure with 51 bins of equal size. For the classification of targeted occupation, we have 44 distinct categories. We note that the ASSD has no information on occupations, so we cannot classify the share of females in a given occupation at a given workplace. Our results align well with similar results in Kuhn and Shen 2023.

Figure 2: Use of Gender Preferences, Pre-campaign



Notes: This Figure shows the share of vacancies that specify preferences for females (red line), males (blue line), or no gender preference (yellow line), gender composition of the firm in the year prior to the hire (Panel A) and share of females hired in the occupation in which the vacancy is advertised in the year prior to the hire (Panel B). The sample includes only filled vacancies matched with a firm in the ASSD and consists of 170,875 vacancies posted in the 2000-2004 by firms that posted at least 5 vacancies in the AMS in that period (column 5 of Table 1).

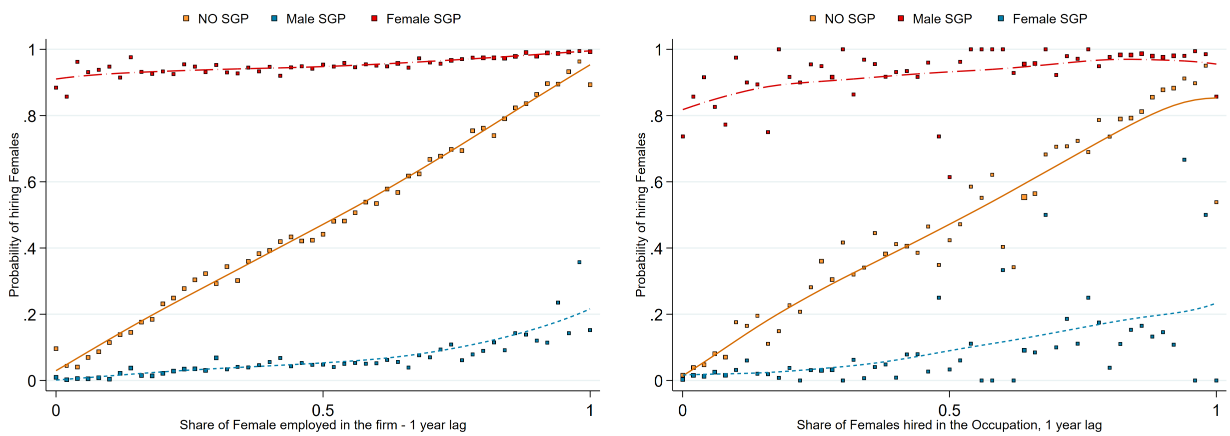
cies with a male SGP (blue line), however, the fraction of females hired rises only slightly with the workplace share of females, reaching about 20% at firms that had all female workers in the previous year. In contrast, for vacancies with a female SGP (red line), the fraction of females hired starts at around 90% at workplaces with no women in the previous year, and rises slightly to essentially 100% at all-female workplaces.

A similar pattern emerges when we classify vacancies by the share of females hired in the target occupation in the previous year. As shown in Panel B, there is a very clear Z pattern between the probability of hiring a female candidate and the share of females typically hired in a given occupation, depending on the type of SGP. Even in mainly male occupations (to the left of the graph), a vacancy with a female SGP is likely to be filled by a female. Likewise, even in mainly female occupations (to the right of the graph), a vacancy with a male SGP is likely to be filled by a male.

To summarize this descriptive evidence: prior to the 2005 campaign, over 40% of vacancies were posted with a stated gender preference. Most SGP's were aligned with the modal gender in the target occupation and in the employer's existing workforce, though a minority were trying to recruit the opposite gender. Firms that stated a gender preference were very likely to recruit a worker of the

Figure 3: Probability of Hiring a Female by Use of Gender Preferences, Pre-campaign

Panel A - By Female Share of Workforce | Panel B - By Female Share in the Occupation



Note: This Figure shows the share of females hired by whether the vacancy stated a preference for females (red line), males (blue line), or neither, and by the gender composition of the firm in the year prior to the hire (Panel A) and share of females hired in the occupation in which the vacancy is advertised in the year prior to the hire (Panel B). The sample includes only filled vacancies matched with a firm in the ASSD and consists of 170,875 vacancies posted in the 2000-2004 by firms that posted at least 5 vacancies in the AMS in that period (column 5 of Table 1).

preferred gender, even in cases where the SGP differed from the majority gender of the specified occupation or at the recruiting firm.[21] What we cannot tell from the pre-2005 data is whether firms that would have advertised for a particular gender when SGP's were allowed would change their hiring decisions once SGP's disappeared, and whether the prohibition of gender preferences would lead to longer-term problems for these firms. These are the questions to which we now turn.

4 Effects of the Campaign on Hiring to Fill Vacancies

Since the OET campaign successfully eliminated the use of stated gender preferences in most vacancies, we cannot observe the gender preferences that employers would have used in the absence of the campaign. Instead, we develop a prediction model that identifies vacancies that would have been likely to specify a male or female SGP, or no SGP, in the pre-campaign period. We refer to these

[21]Figure C.1 show very similar patterns using our extended sample. Table D.1 in the Appendix presents a series of results from regression models that examine the impact of SGP's in the pre-campaign period on vacancy filling times, and on the probability of a female hire, controlling for occupation, industry, and the lagged female share of employees, in our extended analysis sample. Consistent with the simple statistics in Table 2, these models show that the use of stated gender preferences was associated with faster filling times; and that stating a female or male gender preference led to a large boost in the probability of hiring a new worker of that gender.

as “predicted gender preferences” (PGP’s). Then we use this model to classify vacancies *before and after the campaign* into the three groups, and examine the relative changes in hiring patterns for the three sets of vacancies after the campaign. This approach is similar to research designs that examine the effects of a minimum wage increase on workers with a high probability of earning less than the new minimum wage in the absence of the increase, used for example by Card and Krueger (1995) and Cengiz *et al.* (2022).[22]

4.1 CLASSIFYING VACANCIES BY PREDICTED GENDER PREFERENCE

We use data on filled vacancies in the 2000-2004 period to assign predicted gender preferences. Specifically, we begin by defining a set of firm×3-digit occupation cells and assigning each vacancy to one of the cells. (Recall that our main vacancy analysis sample is selected so each vacancy is in a cell with at least 2 vacancies in the 2000-2004 period and 2 vacancies in the 2005-2010 period). For each pre-campaign vacancy j we define a variable S_j equal to 1 if it has a female SGP, equal to -1 if it has a male SGP, and equal to 0 otherwise. (Note that $S_j = S_j^f - S_j^m$, where S_j^f is a dummy for a stated female preference and S_j^m is a dummy for a stated male preference). We then calculate the leave-out mean (LOM) value $\overline{S}_{\sim j}$ for vacancies in each firm×occupation cell, and assign this back to vacancies in the pre-campaign *and* post-campaign periods.[23] Finally, we classify a vacancy as predicted to have a female SGP (indicated by a dummy D_j^f) if $\overline{S}_{\sim j}$ is above some threshold:

$$D_j^f = 1[\overline{S}_{\sim j} > c_1]$$

and as predicted to have a male SGP (identified by D_j^m) if $\overline{S}_{\sim j}$ is below some other threshold:

$$D_j^m = 1[\overline{S}_{\sim j} < c_2].$$

[22] Botosaru and Gutierrez (2018) discuss identification and estimation in related studies using repeated cross sectional data in which treatment status is only observed after treatment.

[23] Since post-campaign vacancies are never used in calculating $\overline{S}_{\sim j}$, the LOM for those vacancies is just the mean across all other pre-campaign vacancies in the same cell.

We select the thresholds $c_1$and c_2 so that the mean fractions of predicted female and male preferences match the actual rates in the pre-campaign period.[24]

We illustrate the predictive performance of our model by year from 2000 to 2007 in Appendix Figure F.1. Specifically, we show the share of vacancies with a given SGP in a year that were predicted to have that preference by our model (i.e., $E[D_j^f|S_j^f = 1]$ and $E[D_j^m|S_j^m = 1]$). Over the entire 8-year sample period – including the 3 out-of-sample years from 2005 to 2007 – the fraction of correctly predicted male SGP's lies in the range of 70-75%, while the faction of correctly predicted female SGP's is in the range of 60-65%, suggesting that our procedure performs relatively well.[25]

4.2 Measuring Effects on Hiring Outcomes

4.2.1 Basic Model

We evaluate the effects of the OET campaign on the use of stated gender preferences using a simple difference in differences approach that compares pre- and post-campaign outcomes for vacancies with a predicted female preference ($D_j^f = 1$) or predicted male preference ($D_j^m = 1$) relative to those with no predicted preference ($D_j^f = D_j^m = 0$). Let y_j represent an outcome associated with the vacancy (e.g., the gender of the hired candidate). Then we fit models of the form:

$$y_j = \beta_0 + \beta_1 D_j^f + \beta_2 D_j^m + \lambda_1 D_j^f Post_j + \lambda_2 D_j^m Post_j + X_j\delta + \varepsilon_j \tag{1}$$

where $Post_j$ is an indicator for vacancy j being listed in 2006 or later, and X_j is a set of control variables, including time effects (which absorb the main effect of $Post_j$), firm effects, and dummies for occupation.[26]

[24]This procedure is equivalent to calculating the leave-out mean fractions of vacancies in each firm×occupation cell with female and male SGP's, $\overline{S}_{\sim j}^f$ and $\overline{S}_{\sim j}^m$, respectively, then classifying a vacancy based on whether $\overline{S}_{\sim j}^f - \overline{S}_{\sim j}^m$ is above some threshold (for a female SGP) or below some other threshold (for a male SGP).

[25]Not surprisingly, the correct prediction rate for vacancies with no gender preference falls in 2005 and later years, reflecting the massive shift toward this category evident in Figure 1.

[26]We estimate heteroskedasticity-robust standard errors for this model. We have also used a bootstrap procedure to estimate confidence intervals for the estimated coefficients in our extended vacancy sample and found they are very similar to the intervals based on the robust standard errors, results are in appendix figures H.5 and H.6.

The coefficients λ_1 and λ_2 in equation (1) measure the changes in the outcome y between the pre-campaign and post-campaign period for vacancies that were predicted to have a female or male SGP, respectively, controlling for any permanent differences across firms or between occupations. Since the law did not directly affect vacancies with no gender preference, their outcomes are a natural comparison group. We note, however, that general equilibrium effects could potentially affect the applicant pools for these vacancies.[27]

Interpretation of the Model

Since we are using predicted rather than actual gender preferences, equation (1) can be interpreted as the reduced-form from a two-stage-least-squares procedure in which predicted gender preferences are used as instruments for actual gender preferences. To formalize this reasoning, assume that the structural model of interest is:

$$y_j = \alpha_0 + \alpha_1 S_j^f + \alpha_2 S_j^m + \theta_1 S_j^f Post_j + \theta_2 S_j^m Post_j + X_j \gamma + \varepsilon_j \tag{2}$$

where S_j^f and S_j^m indicate *notional* SGP's (i.e., the preferences that employers actually express up to 2005, and would have expressed after 2005 if there was no campaign). In this model, θ_1 and θ_2 measure the changes in outcome y between vacancies in the pre-campaign period that were posted with given SGP and vacancies in the post-campaign period that would have been posted with that gender preference if such preferences were allowed. These treatment effects are conceptually the same as those measured in the design of Kuhn and Shen (2023), which compares applications for the same vacancy after SGP's are eliminated.

We assume that notional SGP's are related to predicted gender preferences (our instrumental variables) by a pair of first stage equations with constant coefficients between the pre- and post-

[27] Kuhn and Shen (2021, Figure 5) show the numbers of applications received per week for vacancies with different gender preferences around the time gender preferences were removed from the job board they study. There is no obvious shift in arrivals for previously gender-neutral vacancies, nor is there a change in the share of females in the applicant pool in their Figure 2a.

campaign periods:

$$S^f_j = \pi_0 + \pi_1 D^f_j + \pi_2 D^m_j + X_j \pi_x + \xi^f_j \tag{3}$$

$$S^m_j = \psi_0 + \psi_1 D^f_j + \psi_2 D^m_j + X_j \psi_x + \xi^m_j \tag{4}$$

where ξ^f_j, ξ^m_j are prediction errors. Here π_1 and π_2 represent the changes in the probability of an actual female SGP if the vacancy has a predicted female or male preference, respectively. We expect π_1 to be positive and reasonably large if our prediction model has signal content. (A prefect predictor means $\pi_1 = 1$). We expect π_2 to be negative though smaller in magnitude than π_1, because a predicted male preference makes the probability of a female SGP less likely than if there was no gender preference. Similar reasoning suggests that corresponding coefficients ψ_2 and ψ_1 in equation (4) will be large and positive, and small and negative, respectively.

Substituting the first stage equations into the structural model leads to the following expressions for the coefficients in the reduced form model (1):

$$\lambda_1 = \theta_1 \pi_1 + \theta_2 \psi_1 \tag{5}$$

$$\lambda_2 = \theta_1 \pi_2 + \theta_2 \psi_2. \tag{6}$$

Notice that if π_2 and ψ_1 are close to zero, then $\lambda_1 \approx \theta_1 \pi_1$ is just an attenuated version of θ_1 and $\lambda_2 \approx \theta_2 \psi_2$ is just an attenuated version of θ_2, where the attenuation factors reflect the "reliability rates" of the the corresponding predicted gender preference indicators (conditional on the $X's$).[28] We can estimate (3) and (4) on pre-campaign vacancies, and actually do so in the next subsection, and find that π_2 and ψ_1 are relatively small in magnitude, so this intuition is roughly correct.

Before proceeding, however, it is worth discussing two specification issues for our model. A first issue is whether the OET campaign may have had a direct effect on firm hiring decisions, on top of any indirect effect through the prohibition of SGP's. As noted by Imbens and Rubin (2015), the

[28]For example, if $\pi_2 = 0$ then $\pi_1 = cov[S^f_j, D^f_j | X_j] / var[D^f_j | X_j]$,which is the standard expression for the reliability of a noisy measure D of some variable of interest S.

presence of such alternative treatment channels violates the stable unit treatment value assumption (SUTVA) condition needed for interpreting a 2SLS system. A concern could arise, for example, if the OET campaign coincided with other efforts to promote the hiring of women. Our reading is that this did not happen: the OET focused exclusively on SGP's in their 2005 campaign. Moreover, as we show in the next section, we find that the campaign led to fairly similar gains in hiring of men and women, while we suspect that other efforts of the OET would largely focus on the hiring of women.

A second concern is that our econometric model uses vacancies with no predicted gender preference as a control group for two treatment groups: vacancies with a predicted female preference, and vacancies with a predicted male preference. Recently, Goldsmith-Pinkham *et al.* (2022) have noted that in such settings, when the baseline model includes control variables, there may be a "contamination bias" in the estimated effects of the two treatments.[29] In the Appendix, we present two checks for the presence of such bias. First, we estimate models with no control variables (Figure H.3), and show that these lead to roughly similar estimates of the effect of the OET campaign on rates of hiring female candidates for vacancies with predicted male and female gender preferences. Second, in Figure H.4 we estimate two additional sets of models that combine the control group of vacancies with no predicted preference with either male PGP vacancies (one of the treatment groups) or female PGP vacancies (the other treatment group). Here, we find estimates that are very close to our baseline estimates that pool the two treatment groups with the control group.

4.2.2 First-Stage Model: How Informative are Predicted Gender Preferences?

Columns 1 and 3 of Table 3 present estimates of the first stage equations (3) and (4) using observed SGP's in the 1999-2004 period. (Columns 2 and 4 show models that interact predicted gender preferences with indicators for whether the PGP matches the modal gender of the occupation or not. We return to these models in Section 4.2.4.) In column 1 we see that $\widehat{\pi}_1 = 0.411$ and $\widehat{\pi}_2 = -0.041$, while in column 3 we see that $\widehat{\psi}_1 = -0.021$ and $\widehat{\psi}_2 = 0.530$. Thus, as expected, a predicted preference

[29] More formally, contamination bias arises because regression adjustment for the control variables in the model may lead to a situation where the other treatment are no longer ignorable when estimating a given treatment's effect.

for one gender is associated with a relatively large boost (40-50 percentage points) in the probability that preference was actually expressed, relative to vacancies with neither male or female PGP's, while a predicted preference of the opposite gender is associated with a small reduction in that relative probability. The highly significant values for $\widehat{\pi}_1$ and $\widehat{\psi}_2$ suggest that our *firm*×*occupation*-based predictions have substantial power, even controlling for permanent differences in the probability of hiring a female candidate across firms and in different occupations. Their magnitudes suggest that the coefficients λ_1 and λ_2 are attenuated by a factor of roughly one-half relative to the effects we would estimate if we could see the desired preferences of job recruiters in the post-campaign period. In other words, the true effects of eliminating stated gender preferences may be about 2 times larger than the estimates we obtain from the reduced form model.

Table 3: Relationship between Predicted and Actual Gender Preferences, Pre-campaign

Dependent Variable:	***Male SGP***		***Female SGP***	
	(1)	(2)	(3)	(4)
No PGP	omitted	omitted	omitted	omitted
Male PGP	0.530***		-0.041***	
	(0.004)		(0.002)	
Female PGP	-0.021***		0.411***	
	(0.002)		(0.004)	
Stereotyping based on gender composition of occupation				
M PGP in F occupation		0.476***		-0.038***
[Non-stereotypical Male PGP]		(0.011)		(0.006)
M PGP in M occupation		0.539***		-0.033***
[Stereotypical Male PGP]		(0.005)		(0.002)
F PGP in F occupation		-0.017***		0.392***
[Stereotypical Female PGP]		(0.002)		(0.005)
F PGP in M occupation		-0.055***		0.543***
[Non-stereotypical Female PGP]		(0.009)		(0.012)

Notes: This table reports estimated coefficients and robust standard errors (in parentheses) from OLS regressions of the event of having a male (columns 1-2) or female (columns 3-4) stated gender preference (SGP) in a given vacancy on predicted gender preferences for that vacancy. All models include firm, occupation and year fixed effects. The sample includes 89,960 vacancies posted by frequent postings firms in the AMS, filled and matched with a firm in the ASSD data and classified by predicted gender preference (PGP): vacancies posted by frequent postings firms that posted at least 2 vacancies in the corresponding occupation in the pre-campaign period and in the post-campaign period (column 6 of Table 1).

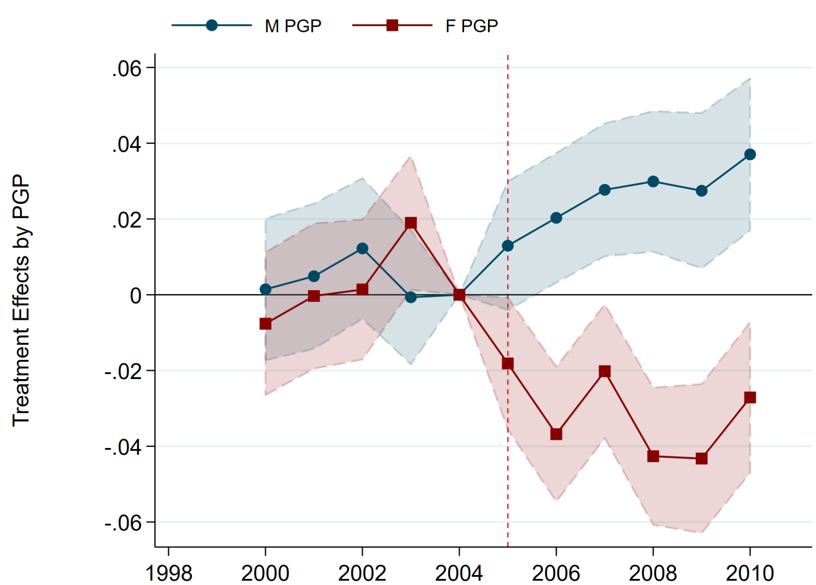
4.2.3 Estimation Results for Basic Differences-in-Differences Model

With this background we turn the estimation results from our main difference-in-differences model. We being with an event study analysis in Figure 4. This is based on a slight generalization of equation (1):

$$y_j = \beta_0 + \sum_{k=2000, k\neq 2004}^{k=2010} (\beta_{1k} D_j^f + \beta_{2k} D_j^m) \times 1[year(j) = k)] + X_j \delta + \varepsilon_j, \tag{7}$$

where y_j indicates that vacancy j was filled by a female candidate, $year(j)$ is an index function giving the year that vacancy j was posted, and $\{\beta_{1k}, \beta_{2k}\}$ are year-specific coefficients giving the difference in the probability of hiring a female for vacancies with predicted preferences for females ($D_j^f = 1$) or males ($D_j^m = 1$) in year, relative to vacancies with no predicted preference. As is standard, we normalize the coefficients from each year by deviating them from their estimated values in 2004, the year before the start of the OET campaign.

Figure 4: Probability that Hired Worker is Female: Event Study Results



Note: This figure reports the estimation results for models of the event that a newly hired worker is female. Coefficients of the interaction term between year and indicators for vacancies classified as Male or Female PGP are reported. Solid lines represent point estimates, shadow areas show the 95% confidence intervals. Controls include firm, occupation and year fixed effects. The sample includes vacancies posted by frequent posting firms that posted at least 2 vacancies in the corresponding occupation in the pre-campaign period and in the post-campaign period. (See column 6 of Table 1).

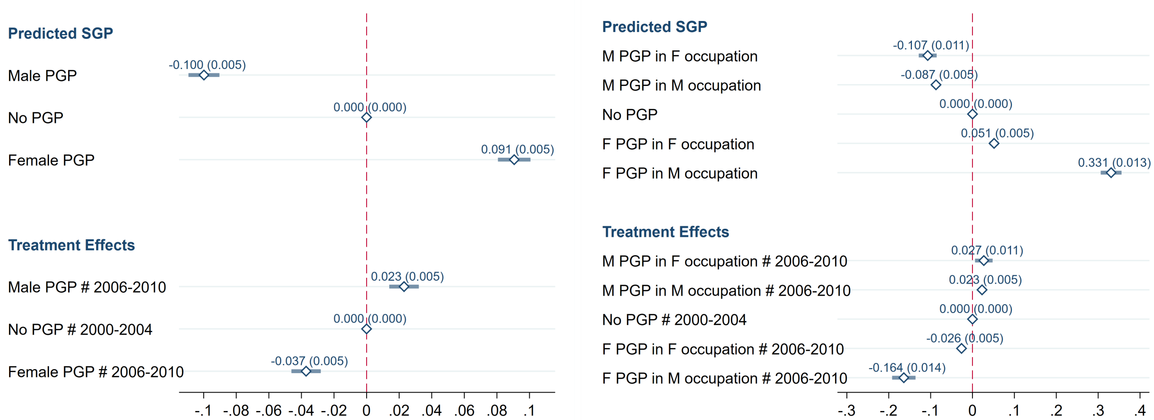
Reassuringly, the graph shows no evidence of pre-trends in the hiring rates of women for jobs with predicted female or male gender preferences. Starting in 2005, however, there is a clear divergence in hiring outcomes at the two sets of vacancies, with a ***rise*** in the fraction of women hired for job openings with a male PGP, stabilizing at about +3 or +4 percentage points after 2007, and a fall in the fraction hired to fill job openings with a female PGP, stabilizing at about -3 or -4 percentage points after 2007.

Panel A of Figure 5 summarizes the estimated coefficients from our reduced form model (equation 1), estimated over the period 2000-2010 but excluding the transitional year, 2005. We report the estimated main effects of the PGP variables ($\widehat{\beta}_1$and $\widehat{\beta}_2$) in the upper part of the figure. For reference we also show a 0 coefficient representing the comparison group of vacancies with neither PGP. We report the estimated interactions between the PGP dummies and the post-period dummy ($\widehat{\lambda}_1$and $\widehat{\lambda}_2$) in the lower part of the figure, again showing a 0 coefficient for the comparison group of vacancies with neither PGP.

Figure 5: Probability that Hired Worker is Female: Difference in Differences Results

Panel A. Baseline Model

Panel B. Stereotypical Vacancies



Notes: This figure reports the estimation results for models of the event that a newly hired worker is female. Panel A uses the specification of equation 1, distinguishing between Male and Female PGP. Panel B use the specification of equation 8, distinguishing between Stereotypical and Non-Stereotypical vacancies based on the match between the predicted gender preference and the gender composition of the occupation. Diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to vacancies posted in 2000-2004, treatment effects refer to vacancies posted in 2006-2010. Vacancies posted in 2005 are dropped from the regression. Controls include firm, occupation and year fixed effects. The sample includes vacancies posted by frequent postings firms that posted at least 2 vacancies in the corresponding occupation in the pre-campaign period and in the post-campaign period. (column 6 of Table 1)

The estimated β coefficients in the upper part of the figure show that in the pre-campaign period, vacancies with a male PGP had a 10.0 percentage point (ppt) lower probability of hiring a female candidate relative to vacancies with neither PGP, while vacancies with a female PGP have an 9.1 ppt higher probability of hiring a female. If we assume a 50% attenuation in the effects of PGP status relative to true SGP status, these estimates imply that stating a male SGP leads to 20 ppt lower probability of hiring a female relative to no SGP, while stating a female SGP leads to a 20 ppt increase in this rate, controlling for occupation and firm fixed effects. The implied gap in the probability that the hired worker is female between job openings with female and male SGP's is therefore around 40 ppt.

Looking next at the treatment effects in the lower part of the figure, the estimates show that after the OET campaign the probability of hiring a female candidate increased by 2.3 percentage points for vacancies with a male PGP (standard error = 0.005), which is about one-quarter of the pre-campaign gap in the female hiring rate relative to vacancies with neither PGP. The corresponding effect on the probability of hiring a female for vacancies with a predicted female PGP is -3.7 ppt (s.e. = 0.005), which is about one-third of the pre-campaign gap for these vacancies relative to the comparison group. Accounting for the attenuation arising from the slippage in our prediction models, these implied treatment effects are relatively large. They suggest that the elimination of gender preferences in job ads led to a roughly 5 ppt increase in the probability of hiring women to fill jobs that would have been advertised with a male gender preference in the absence of the new law, and a 7 ppt increase in the hiring of men to fill jobs that would have been advertised with a male gender preference. The combination of the two effects, therefore, closed a little over a quarter of the pre-campaign gap in the rate of hiring women between jobs that specified a gender preference for men versus women.

The point estimates of λ_1 and λ_2 in Panel A of Figure 5 suggest that the OET campaign led to a somewhat larger increase in the hiring of men to fill positions with a predicted female preference than in the hiring of women to fill positions with a predicted male preference. A similar, though more pronounced, pattern is reported by (Kuhn and Shen, 2023), who find that the elimination of

SGP's in their setting led to a 4× larger effect on applications of men for jobs with female preferences than on applications of women for jobs with male preferences. We caution, however, that the gap in the magnitude of the treatment effects in our setting is not statistically significant (consistent with the patterns in Figure 4).

4.2.4 Stereotypical vs Non-stereotypical Vacancies

Our baseline model (equation 2) makes no distinction between SGP's that align with the modal gender in the occupation and those that do not. Consideration of the Z pattern in Figure 3-B, however, suggests that in the pre-campaign era, female SGP's had larger effects on the probability of hiring a female (relative to the counterfactual of no gender preference) in mainly male occupations, while male SGP's had larger effects on the probability of hiring a male in mainly female occupations. In other words, consistent with the simple conceptual model described above, SGP's mattered more when they differed from the modal gender in the underlying occupation. Would the removal of SGP's therefore lead to larger effects on the hiring outcomes for vacancies with such non-aligned preferences?

To proceed we label a vacancy as pertaining to a female occupation (indicated by the variable O_j^f) if >50% of all EU workers outside Austria in that occupation are women; we label the remaining vacancies as pertaining to male occupations (indicated by the variable O_j^m).[30] We classify vacancies as having a ***stereotypical*** PGP if the predicted gender preference is concordant with gender composition of the occupation (i.e., $D_j^f O_j^f = 1$ or $D_j^m O_j^m = 1$), and as having a ***non-stereotypical*** PGP otherwise.

Table 4 presents some descriptive information on stereotypical and non-stereotypical PGP's in the pre-campaign period (where we can see actual gender preferences as well as our predicted preferences). Columns 1 and 2 show characteristics of vacancies with a male PGP, classified as non-stereotypical (column 1) or stereotypical (column 2). Note that only about 15.5% (= 100 ×

[30] We use occupational data from the 2004 wave of the EU SILC database. We measure occupations at the 2-digit level, which is not as granular as the level used in Figure 3-B. We use gender shares outside Austria to avoid potential reflection problems in the measured effects of stereotypical and non-stereotypical vacancies.

$0.031/(0.031+0.200)$) of male PGP's are non-stereotypical. Similarly, columns 4 and 5 show characteristics of vacancies with a female PGP, classified as either stereotypical (column 4) or non-stereotypical (column 5). Again, only about 12.3% ($= 100 \times 0.025/(0.025+0.203)$)of female PGP vacancies are non-stereotypical. For reference column 3 presents data for vacancies with no predicted gender preference.

Table 4: Characteristics of Vacancies by use Stereotypical and Non-Stereotypical PGP's

	Predicted Gender Preference				
	M PGP in F Occ [Non-stereo Male PGP]	**M PGP in M Occ** [Stereo Male PGP]	**Neutral**	**F PGP in F Occ** [Stereo Female PGP]	**F PGP in M Occ** [Non-stereo Female PGP]
	(1)	(2)	(3)	(4)	(5)
Panel A: SGP					
Male SGP	0.664	0.747	0.098	0.024	0.110
Neutral	0.290	0.234	0.764	0.337	0.197
Female SGP	0.046	0.019	0.139	0.639	0.693
Panel B: Context					
Share of women in occupation	0.622	0.163	0.542	0.716	0.343
Share of women in the firm	0.334	0.201	0.525	0.766	0.564
Shares	0.031	0.200	0.542	0.203	0.025

Notes: This table reports summary statistics for vacancies posted in 2000-2004, classified by predicted gender preference (PGP) and stereotype status. Stereotyping is based on the match between the predicted gender preference and the modal gender of the occupation. The sample includes 89,960 vacancies posted by frequent postings firms in the AMS, filled and matched with a firm in the ASSD data and classified by predicted gender preference (PGP): vacancies posted by frequent postings firms that posted at least 2 vacancies in the corresponding occupation in the pre-campaign period and in the post-campaign period (column 6 of Table 1).

For each type of PGP we show the shares with various actual gender preferences, as well as two pieces of contextual information: the share of women in the desired occupation; and the share of women in the firm that posted the vacancy. There are a number of interesting patterns in the table. First, looking at the agreement between predicted and actual SGP's, we see that, as might be expected, the concordance is a little higher for stereotypical than non-stereotypical PGP's. For example, 74.7% of stereotypical male PGP's have an actual male SGP, versus 66.4% of non-stereotypical male PGP's. A second observation is that there is a relatively large gap in the share of the preferred gender in the target occupation between vacancies with stereotypical and non-stereotypical PGP's.

For example, stereotypical female PGP's are used in occupations that are on average 71.6% female, whereas non-stereotypical female PGPS are used in occupations that are only 34.3% female. Similarly, stereotypical male PGP's are used in occupations that are on average 83.7% male, whereas non-stereotypical male PGPS are used in occupations that are only 37.8% male.

There is also a gap of the same sign, but of smaller magnitude, in the lagged share of the preferred gender at firms posting the two types of vacancies. Male gender preferences tend to be used by firms with more men than women, but stereotypical male SGP's are concentrated at "very male" workplaces (~80% male) while non-stereotypical male preferences are used by firms with a somewhat lower share of men (67%). Likewise, female preferences tend to be used at mainly female firms, but stereotypical female preferences are concentrated at "very female" workplaces (77% female) while non-stereotypical female PGP's are used by firms that have 56% female workers – only a little above the share of women at firms with no predicted gender preference.

Impacts of the Campaign on Hiring Outcomes by Stereotypical PGP Status

We use an extended version of equation (1) to measure the effects of the 2004 campaign for 4 distinct types of vacancies, based on PGP and the modal gender in the target occupation:

$$
\begin{aligned}
y_j &= \beta_0 + \beta_1 D_j^f O_j^f + \beta_2 D_j^f O_j^m + \beta_3 D_j^m O_j^m + \beta_4 D_j^m O_j^f \\
&+ \lambda_1 D_j^f O_j^f Post_j + \lambda_2 D_j^f O_j^m Post_j + \lambda_3 D_j^m O_j^m Post_j + \lambda_4 D_j^m O_j^f Post_j + X_j \delta + \varepsilon_j \qquad (8)
\end{aligned}
$$

As before, the β_k coefficients measure differences across vacancies in the outcome y before the campaign is implemented, while the λ_k coefficients measure changes in the outcome after the introduction of the campaign (λ_1 and λ_3 for stereotypical vacancies, and λ_2 and λ_4 for non-stereotypical vacancies).

As in the simpler model (1), the estimates of the λ_k coefficients in equation (8) will be attenuated relative to the coefficients in a model that had the firm's actual gender preferences on the right hand side. In Appendix E we present an analysis similar to that in equations (3)-(6) discussing the attenuation effects using a two-stage least squares framework. The associated first stage models for this framework are presented columns 2 and 4 in Table 3. These models relate actual SGP's (observed in the pre-campaign period) to predicted gender preferences, allowing different effects for stereotypical and non-stereotypical PGP's. The estimates suggest that stereotypical PGP's are slightly stronger predictors of actual gender preferences than non-stereotypical PGP's. For example, in column 2 of Table 3, we see that a stereotypical predicted male preference raises the probability of a true male gender preference by about 54 ppt, while a non-stereotypical predicted male preference raises the probability by 48 ppt. Likewise, in column 4, we see that a predicted stereotypical female preference raises the probability of a true female gender preference by about 54 ppt percentage points, versus a 39 ppt effect for a predicted non-stereotypical female preference. By comparison, predicted preferences of one gender (whether stereotypical or non-stereotypical) have small negative effects on the likelihood of an actual preference for the opposite gender. Given the magnitudes of these coefficients, the analysis in the Appendix suggests that the expected attenuation factors for the reduced form model (8) are likely to be in the range of 50% – not too different from the attenuation in our basic model (2)

Estimation results for equation (8) are summarized in Panel B of Figure 5.[31] The estimates show that in the pre-campaign period a non-stereotypical male PGP had a somewhat bigger negative effect on the probability of hiring a female candidate than a stereotypical male PGP (-10.5 ppt vs -8.7 ppts). For female PGP's the divergence is larger, with a +5.1 ppt effect for a stereotypical PGP and a +33.3 ppt effect for a non-stereotypical female PGP. Across all 4 types of predicted gender preferences the campaign significantly moderated the effects of gender preferences on the probability of hiring a female candidate, offsetting about one-quarter of the pre-campaign effects of predicted male PGP's, and closer to one-half of the pre-campaign effects of predicted female PGP's.

The relatively large +33.1% estimate of the effect of non-stereotypical female PGP's in the pre-campaign period, coupled with the -16.4% estimate of the impact of the campaign on female hiring

[31] As in our basic model we include fixed effects for time, occupation, and firm.

for vacancies with these PGP's, suggest that stated preferences for female candidates in mainly male occupations were particularly informative to job searchers prior to the OET campaign, and that the loss of these signals led to more stereotypical (i.e., male) hiring after 2005. This shift, in turn, contributed to the larger net reduction in female hiring for vacancies with female PGP's after 2005 than in male hiring for vacancies with male PGP's, noted in our discussion of the results in Panel A of Figure 5.

4.3 Gender Diversity in Occupations and Workplaces

Next we turn to the question of how the OET campaign affected the gender diversity of occupations and workplaces in Austria.

To answer this question we define a simple indicator of the diversifying effect of a new hire, $d_j \equiv |H_j - F_j|$ where $H_j = 1$ if the person hired to fill vacancy j is female (and 0 otherwise), and F_j represents the share of female workers in the targeted occupation or at the workplace posting the vacancy in the previous year. d_j measures the deviation of the gender of the new hire from the existing gender composition of the occupation or workforce,[32] and ranges from 0 (when a worker is hired for a job in an occupation or workplace that is 100% the same gender) to 1 (when the new worker is the opposite gender of everyone else in the same occupation or at the workplace). In the pre-2005 period, the mean value of the occupational diversity indicator was 0.35, while the mean value of the workplace diversity index was 0.22, suggesting that newly hired workers tended to match the modal gender of the targeted occupation and the workplace, with a somewhat stronger match at the workplace level.

Panel A of Figure 6 reports estimates of our simple reduced form model (equation 2) and the variant that distinguishes between stereotypical and non-stereotypical vacancies (equation 8), where the dependent variable is the occupational diversity indicator. Panel B presents a parallel set of

[32]For the share of female workers in the occupation we use information from the EU SILC database at 2-digits occupation cells. Rearranging the indicator shows that $d_j = H_j(1 - F_j) + (1 - H_j)F_j$, so d_j is higher if a new hire enters a firm or occupation with more co-workers of opposite gender. We have also analyzed an alternative measure $e_j \equiv H_j(1 - C^f_j) + (1 - H_j)C^f_j$ where $C^f_j = 1[F_j > 0.5]$ identifies occupations or firms with more than 50% women employed. This gives similar patterns of estimates.

results for models where the dependent variable is the workplace diversity indicator.

Looking first at the results from our simpler specification (in the left two panels), we see that, as expected, the use of gender preferences in the pre-2005 period was associated with lower values of both the occupational and workplace diversity indicators. The impact of the OET campaign was to increase the gender-diversifying effect of new hires in both the targeted occupation and at the hiring workplace, with the largest effect (+0.021) on diversification of workplaces that were predicted to use male gender preferences, and smaller but still significant effects on occupational diversity and on diversification of workplaces that were predicted to use female gender preferences (in the range of +0.005 to +0.008).

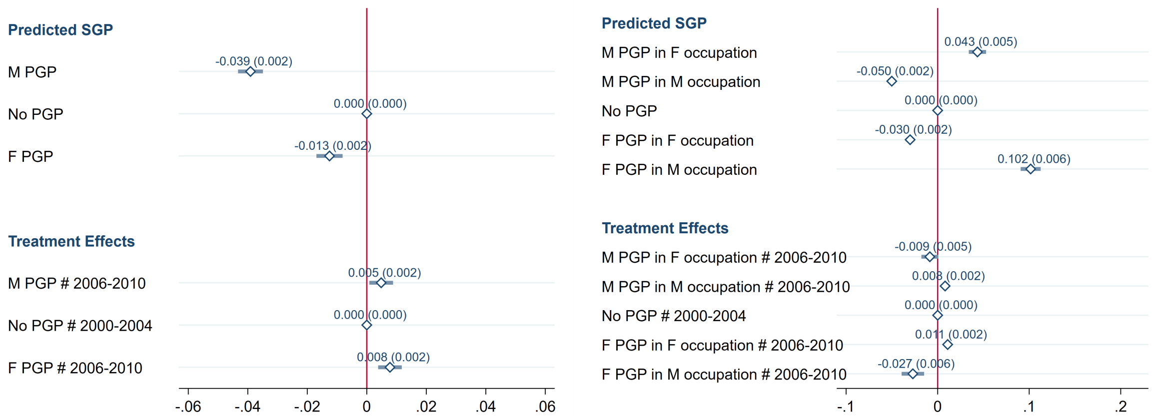
Looking next at the results from our models that distinguish between stereotypical and non-stereotypical gender preferences, we see that in the case of occupational diversity (Panel A.2), the pre-campaign effects of different gender preferences follow the expected pattern. Specifically, stereotypical PGP's were associated with *reductions* in the occupational-diversifying effects of new hires, relative to the comparison group of vacancies with no PGP, while non-stereotypical PGP's were associated with *increases* in the occupational-diversifying effects of new hires. After the campaign, vacancies with stereotypical PGP's were more likely to be filled by people with a non-stereotypical gender for the target occupation, leading to an increase in the diversifying effect of new hires for vacancies with a male PGP in a mainly male occupation (+0.008), and of new hires for vacancies with a female PGP in a mainly female occupation (+0.011). Similarly, vacancies with predicted non-stereotypical preferences were more likely to be filled by people of the *stereotypical* gender for the target occupation, leading to a reduction in the diversifying effect of new hires for vacancies with a male PGP in a mainly female occupations (-0.009), and of new hires for vacancies with a female PGP in a mainly male occupations (-0.027). Consistent with the results in Panel B of Figure 5, where we saw a relatively large effect of the OET campaign on the probability of hiring a female candidate for vacancies with a non-stereotypical female PGP, the largest change in the diversifying effect of new hires is also for these vacancies.

In the case of workplace diversity, the results in Panel B.2 are more nuanced. As noted in the Sec-

Figure 6: Effects on Newly Hired Workers on Gender Diversity

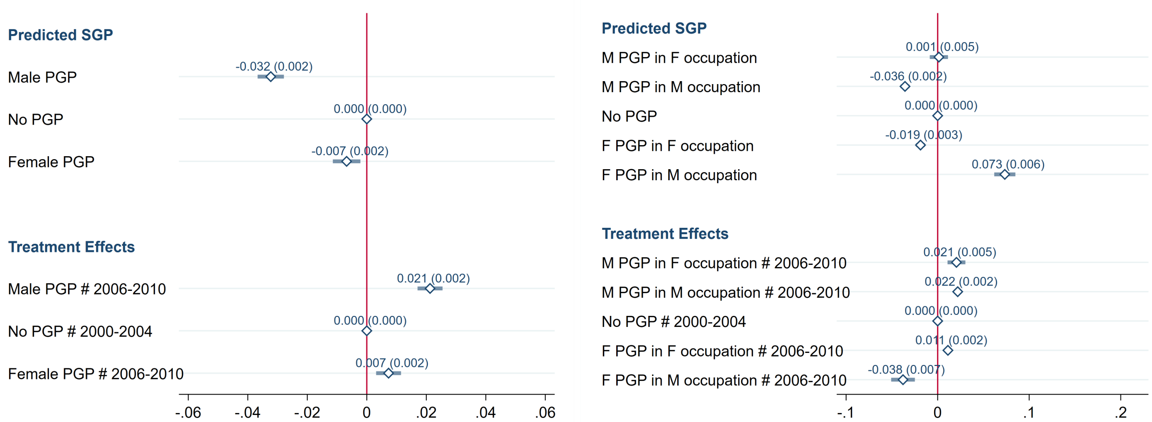
Panel A - Occupation Diversity

A.1 Baseline Model A.2 Stereotypical Vacancies



Panel B - Workplace Diversity

B.1 Baseline Model B.2 Stereotypical Vacancies



Notes: This figure reports estimation results for models where the dependent variable is an index measuring the effect of the newly hired worker on the gender diversity of the target occupation (Panel A) or the employer's workplace (Panel B). Panels A.1 and B.1 use the specification of equation 1, distinguishing between Male and Female PGP's. Panels A.2 and B.2 use the specification of equation 8, distinguishing between Stereotypical and Non-Stereotypical vacancies based on the match between the predicted gender preference and the modal gender in the occupation. Diamonds represent the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to vacancies posted in 2000-2004, treatment effects refer to vacancies posted in 2006-2010. Vacancies posted in 2005 are dropped from the regression. Controls include firm, occupation and year fixed effects. The sample includes vacancies posted by frequent postings firms that posted at least 2 vacancies in the corresponding occupation in the pre-campaign period and in the post-campaign period. (column 6 of Table 1) tion 2.2, the workplace effect of a change in the hiring of workers whose gender matches the stereotype for their **occupation** depends on whether the modal gender of the workplace is the same as that of the targeted occupation. This is typically but not always the case. With that in mind, we note that in the pre-2005 period, stereotypical PGP's were associated with significantly less workplace gender diversification (-0.036 in the case of a male PGP for a mainly male occupation, and -0.019 in the case of female PGP for a mainly female occupation). Non-stereotypical male PGP's (i.e., those for mainly female occupations) were associated with a small, insignificant effects on workplace diversity in the pre-2005 period, but non-stereotypical female PGP's (i.e., those for mainly male occupations) were associated with a large positive effect on workplace diversity.

After the OET campaign the workplace-diversifing effects of stereotypical PGP's became less negative (treatment effect = +0.022 for stereotypical male PGP's and +0.011 for stereotypical female PGP's), while the workplace-diversifying effect of non-stereotypical female PGP's became less positive (treatment effect = -0.038). But somewhat unexpectedly, the workplace diversifying effect of non-stereotypical male PGP's increased by +0.021, rather than fell.

To gain further insight into this result we estimated an extended model in which we classified male and female PGP's by both the modal gender of the targeted occupation and the modal gender of the workplace. These models (reported in Appendix Figure H.1) allow for heterogeneous effects of 8 different types of PGP's in the pre-2005 period (e.g., female PGP × mainly female occupation × mainly female workplace, and 8 corresponding post-2005 treatment effects. The OET campaign increased hiring of women on vacancies with a male PGP for a mainly female occupation *at mainly female workplaces* and therefore reduced the workplace-diversifying effect of a new hire. The campaign also increased hiring of women on vacancies with male PGP's in mainly female occupations *at mainly male workplaces*, but in this case, hiring more female candidates <u>increased</u> the workplace-diversifying effect of the gender preference. Interestingly, the latter treatment effect was 3× larger in magnitude than the former, and since the use of non-stereotypical male preferences was more frequent at mainly-male than at mainly-female workplaces, the overall treatment effect of the OET campaign on the workplace diversifying effect of non-stereotypical male PGP's is positive, despite a negative effect on workplace diversity in mainly female workplaces.[33]

In summary: the overall effect of the OET campaign was to increase the gender-diversifying effects of hiring associated with vacancies with predicted gender preferences at both the occupational and workplace level. Nevertheless, there was some heterogeneity in the treatment effect for different types of vacancies. At the occupational level, the elimination of stereotypical gender preferences helped increase the gender diversity of occupation-specific hiring, while the elimination of non-stereotypical gender preferences worked in the opposite direction. But since non-stereotypical preferences represented only about 1/5 of all stated gender preferences, the net impact was diversifying. At the workplace level, the elimination of stereotypical gender preferences of both genders helped increase the gender diversity of workplaces, as did the elimination of non-stereotypical male preferences, but the elimination of non-stereotypical female preferences led to reduction in the workplace-diversifying effect of new hires. Again, however, the overall impact was driven by the effects on the much larger share of stereotypical gender preferences.

4.4 Results for the Extended Vacancy Sample

4.4.1 Predicting Gender Preferences in the Extended Sample

So far we have focused on measuring the effects of the OET campaign using filled vacancies for frequently posting firms in occupations where the firm posted multiple vacancies. As noted in Table 1, however, this sample contains only about 1/3 of all AMS-filled vacancies in our data set. In this section, we use an expanded sample of vacancies to probe the robustness of our findings. Since many firms post only one or two vacancies over our entire sample period, we have to modify our model for predicting gender preferences. As in our main analysis, we use a leave-out mean procedure, based

[33] Appendix Table H.1 reports the number of non-stereotypical and stereotypical vacancies posted in mainly female vs mainly male workplaces. A similar pattern of opposing results for the effect of the campaign on the workplace diversifying effect of non-stereotypical female PGP's at mainly male and mainly female workplaces is also present (see Appendix Figure H.1). However, the treatment effect of the OET campaign on the diversifying effect of female PGP's in mainly male occupations at mainly male workplaces is much larger in magnitude than the effect of similar vacancies at mainly female workplaces. Consequently, the OET campaign reduced the average workplace-diversifying effect of non-stereotypical female PGP's.

on filled vacancies in the 2000-2004 period. But to account for infrequent posters, we combine information on the occupation (in 97 categories) and industry (in 86 categories) of the j^{th} vacancy, together with data on the lagged female share at the posting establishment (in 51 intervals). We assign vacancies to occupation×industry×female-share cells, and estimate the leave-out mean of the same variable S_j defined above (equal to 1 if a vacancy has a female SGP, -1 if it has a male SGP, and 0 otherwise). We then classify a vacancy as having a female PGP if this mean is above one threshold, and having a male SGP if it is below a second threshold, where (as before) the thresholds are set so the predicted shares of gender preferences match the actual shares. We use these predicted gender preferences in models based on equations (1) and (8), including unrestricted fixed effects for occupation, industry, and the lagged female share of employees.

The predicted gender preferences from this procedure are less informative than those based on previous vacancies posted by the same firm. Specifically, the fraction of correctly predicted male SGP's in the 2000-2006 period falls from around 75% to 60%, while the fraction of correctly predicted female SGP's falls from about 65% to around 55% (see Appendix Figure F.1). Moreover, as shown in Appendix Table F.1, when we re-estimate the first stage models from Table 3 using PGP's based on occupation×industry×female share cells, we see that the effect of a predicted male or female gender preference on the actual occurrence of such a preference falls from 40-50% to (in columns 1 and 3 of Table 3) to 17-19% (in columns 1 and 3 of Appendix Table F.1). Similar effects are also evident in the predictive power of stereotypical and non-stereotypical PGP's. The coefficients in Appendix Table F.1 imply that the estimated coefficients in our difference-in-difference models are likely to be attenuated by a factor of 80% relative to the true effects in a model with desired gender preferences on the right hand side, compared to an attenuation factor of around 50% using our main prediction models.[34]

[34] A small share of this reduction in predictive power is attributable to the expansion of the sample. When we use predictions based on occupation, industry and lagged gender share but limit the sample to vacancies at the frequent poster, the relationship between actual and predicted gender preferences is somewhat stronger – see Appendix Table F.2.

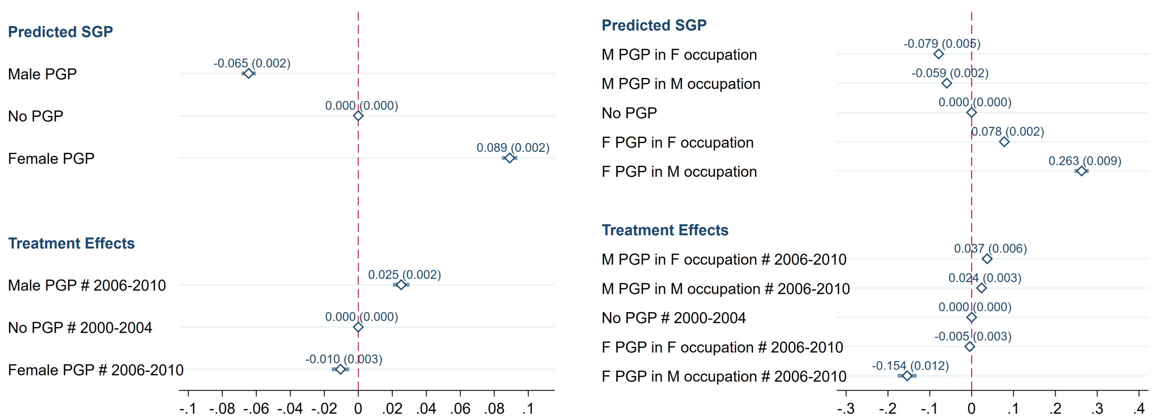
4.4.2 Effects on Female Hiring Rate and Workplace Gender Diversity

Figure 7 presents estimates from equations (1) and (8) using our extended sample of vacancies. Comparing the results in Panel A to those in Panel A of Figure 5 , we see that the estimated coefficients from equation (1) are roughly the same size. Taking account of the greater degree of expected attenuation for the models in Figure 7, however, this suggests that the OET campaign may have had significantly larger impacts on the gender of new hires at at smaller/infrequently posting firms.

Figure 7: Probability that Hired Worker is Female: Extended Sample

Panel A. Baseline Model

Panel B. Stereotypical Vacancies



Notes: This figure reports the estimation results for models of the event that a newly hired worker is female. Panel A uses the specification of equation 1, distinguishing between Male and Female PGP. Panel B use the specification of equation 8, distinguishing between Stereotypical and Non-Stereotypical vacancies based on the match between the predicted gender preference and the gender composition of the occupation. Classification is based on industry, occupation, lagged firm gender share cells. Diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to vacancies posted in 2000-2004, treatment effects refer to vacancies posted in 2006-2010. Vacancies posted in 2005 are dropped from the regression. Controls include industry, occupation, lagged firm gender share, and year fixed effects. The sample includes vacancies posted in industry, occupation, lagged firm gender share cells with at least 2 vacancies in the pre-campaign period and 2 vacancies in the post-campaign period (column 4 of Table 1).

Panel B of Figure 7 summarize estimates of the coefficients from equation (8), which can be compared to those in Panel B or Figure 5 . As is the case for the estimates for our simpler specification, the coefficient estimates from the extended vacancy sample have the same signs and are, on average, only slightly smaller in magnitude than those from the frequent poster sample. Again, this similarity implies that the OET campaign had larger effects on the hiring outcomes at smaller/infrequently posting firms.

We also estimated models showing the impact of the OET campaign on the diversifying effects of new hires in the extended vacancy sample. These estimates are reported in Appendix Figure H.2, and can be compared to parallel results for our main sample in Figure 6. The estimated coefficients from equations (1) and (8) are qualitatively and quantitatively similar in the extended sample and the baseline sample. Both samples show that on average the OET campaign increased the diversity of occupations and workplaces in Austria, despite the anti-diversity effects of eliminating the relatively small set of non-stereotypical female gender preferences.

4.5 Results for Firm Outcomes

To this point, our models have focused on outcomes associated with specific vacancies. We have asked whether a particular vacancy was more or less likely to be filled by a female candidate, and whether the addition of the newly hired worker increased or reduced the gender diversity of the occupation or the firm's workforce. In this section we turn to a broader analysis of firm-wide outcomes. We ask: what happened to firms that were particularly likely to use SGP's in the pre-campaign period? Did they ultimately hire more or less female workers in the years after the campaign? Were they less likely to survive after losing the ability to search for workers of their preferred gender? Did they cut their hiring, or lower their overall level of wages, relative to firms that were less likely to use SGP's?

To answer these questions we return to our sample of firms that posted at least five job ads in the 2000-2004 period. Unlike in our analysis of vacancy outcomes, however, we do not impose any further restrictions on the posting of vacancies for specific occupations, nor do we require a firm to post any vacancies in the post-campaign period, or even to be active after 2005.[35] We take the average value of the 3-way SGP indicator across all the pre-campaign vacancies posted by a given firm and classify the firm as a likely user of *female* SGP's if the average is above a first cutoff, a likely

[35] Of all the frequently-posting firms, 7,468 are alive throughout the entire period, 2000-2010; 3,863 firms die during the period, 766 firms are born during the period, and 278 firms are born and die during the period.

user of *male* SGP's if the average is below a second cutoff, and a likely *non-user* of SGP's otherwise.[36] We choose the cutoffs so the share of vacancies from the predicted female SGP users matches the share of female SGP's in the overall sample, and the share of vacancies from the predicted male SGP users matches the share of male SGP's.

Effects on the Female Share of Employees and Gender Diversity

Using this 3-way classification of firms we being by conducting event-study and difference-in-differences analyses of two related outcomes: the share of female workers at the firm in year t (F_{jt}), and an index of gender diversity in the firm's workforce in year t, $1-2|F_{jt}-1/2|$.[37] This index is 0 if the firm has only one gender and 1 if it has 50% female workers, and rises linearly between the extremes of either 0 or 100% female. The models include firm effects and a set of 2-digit industry×year effects to capture any economy-wide trends in the relative employment of women that may differ by industry.

The event study coefficients for the share of female workers are presented in Figure 8.A.1; the associated difference in difference coefficients (which measure the average change from the pre-campaign period to the post-campaign period for SGP users relative to non-users) are shown in Figure 8.A.2. The estimates in Figure 8.A.1 show that in the years before the campaign, the female shares at SGP users were moving in parallel with the female share at non-users. Starting in 2005, however, we see a positive trend in the female share at likely users of male SGP's, and a negative trend at likely users of female SGP's – exactly as would be expected if the new vacancies at these firms were more likely to be filled by workers of the (previously) non-preferred gender. The difference-in-difference coefficients suggest that on average over the 2006-2010 period the OET campaign led to a 1.6 percentage point rise in the share of women at firms that were likely to use male SGP's, and a

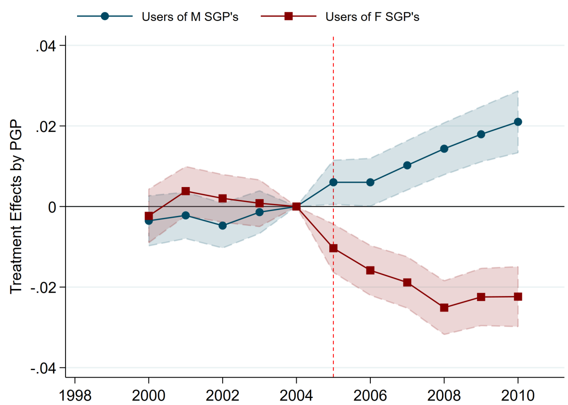
[36]There are a few firms that use male and female SGP's at roughly equal rates. Our procedure classifies these as non-users. We have also conducted an analysis that identifies firms that are likely to use both male and female SGP's, separately from those that use neither preference. Since the "use both types of gender preferences" group is relatively small, it makes little difference, so, in the interest of simplicity, we focus on a simpler specification. Also, some firms post non-stereotypical vacancies (mainly male firm posts female PGP's, or vice versa). Non-stereotypical firms are rare, and the effects of the campaign are in line with results for non-stereotypical vacancies. Again, in the interest of simplicity, we focus on resuls that classify firms into likely (male or female) gender preference vs not using gender preference.

[37]Section G in the Appendix shows that this firm level outcome is the (negative of the) firm's contribution to a weighted version of Duncan and Duncan (1955)'s dissimilarity index in a balanced labor market.

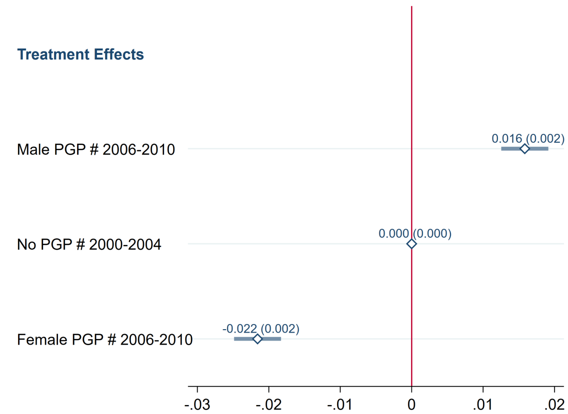
Figure 8: Impact of PGP on Workplace Composition and Diversity

Panel A - Share of females at firm

A.1 Event Study

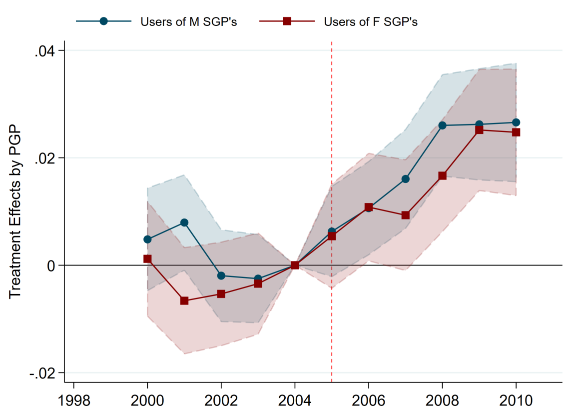


A.2 Difference in Differences

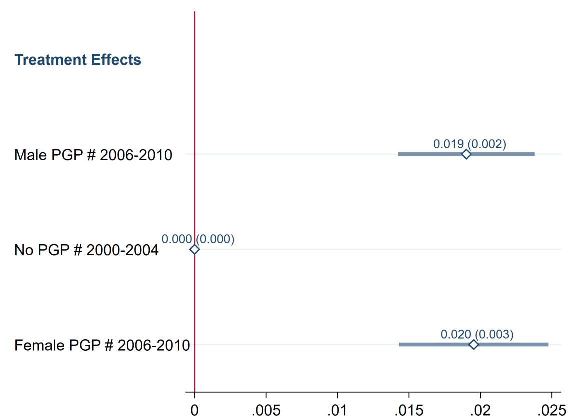


Panel B - Workplace Diversity

B.1 Event Study



B.2 Difference in Differences



Notes: This figure reports the estimation result for difference-in-differences models of the effect of the 2005 campaign on the share of female employees at the firm ((Panel A) or an index of gender diversity at the firm (Panel B). In Panel A the dependent variable is the share of female workers among the workforce of the firm in each year, in Panel B the dependent variable ranges from 0 to 1: 1 indicates that half of the employees in the firms are male and half are female and 0 indicates all males or all females. For plots on the left hand side, solid lines represent estimates and shadow areas show the 95% confidence intervals. For plots on the right hand side, diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to 2000-2004, treatment effects refer to 2006-2010. Vacancies posted in 2005 are dropped from the regression. Controls include year effects, firm effects, and industry x year effects. The sample includes all firms in the frequent postings firms sample.

2.1 percentage point fall at firms that were likely to use female SGP's.

Panel B of Figure 8 shows corresponding event study coefficients and difference-in-differences estimates for our gender segregation index. Again, the pre-2005 event study coefficients show no significant trends for SGP users relative to non-users. But after 2005 there is a steady upward trend in gender diversity at both sets of SGP-users. The difference in differences coefficients suggest that the OET campaign led to a 0.020 rise in gender diversity over the 2006-2010 period for firms that were likely to use either female or male SGP's in the pre-2005 period. Compared to the mean value of the index of 0.46 in the pre-2005 period, this represents a roughly 4.3% percentage effect.

Effects on Firm Survival, Firm Size, and Average Wages

The OET campaign led to significant shifts in the gender composition of firms that were most intensive users of SGP's. Did the campaign have other effects on these firms? Standard optimizing models suggest that limiting a firm's recruiting tools could have a cost. For example, in Kuhn and Shen's (2013) model, firms that were previously using SGP's will incur additional screening costs that are not fully offset by gains in match quality associated with the extra applications from the non-preferred gender. Those costs could lead previous users of SGP's to exit the market or contract.

Figure 9 presents a series of event study coefficient graphs and difference-in-differences estimates that summarize the relative impacts of the OET campaign on former SGP users in three domains: going out of business (Panel A); firm size (Panel B); and average daily wages (Panel C). For the analysis of firm exit, we use simple linear probability survival models with industry×year effects (but no firm effects).[38] For the analysis of firm size and wages we use models with firm fixed effects and industry×year effects. In addition, the model for wages includes a measure of the share female of employees at the firm, to control for differences in the rate of part time work between men and women.

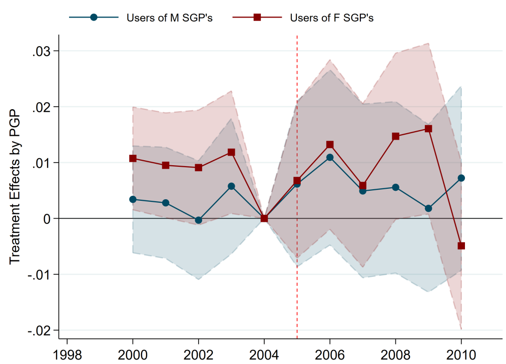
The results in Panel A suggest that the OET campaign had no effect on the probability of firm

[38]For these models, the sample in each year is the set of firms that are still active as of the end of the previous year, and the dependent variable is an indicator for exiting the market in that year (which is 0 until a firm exits).

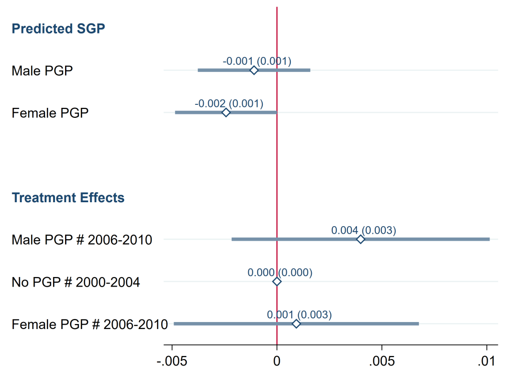
Figure 9: Impact of PGP on the Firm Outcomes

Panel A - Firm Death

A.1 Event Study

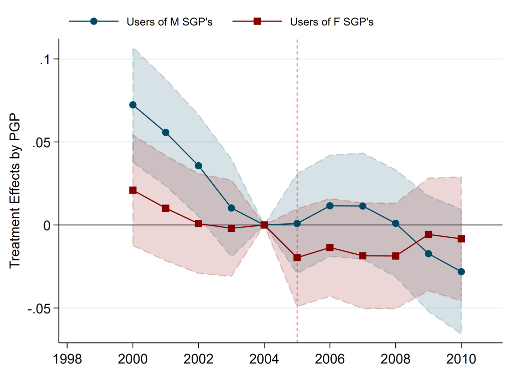


A.2 Difference in Differences

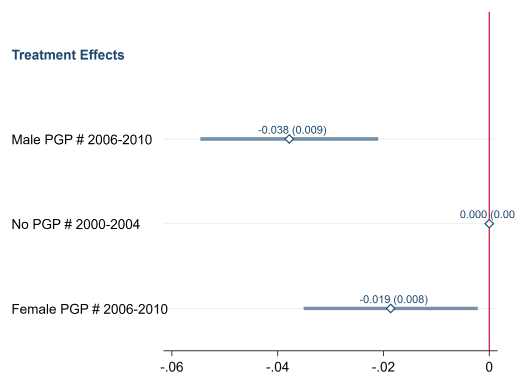


Panel B - Firm Size

B.1 Event Study

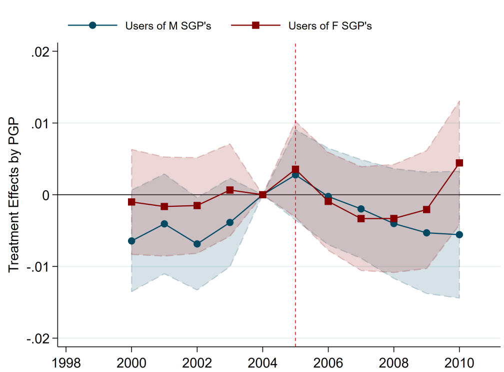


B.2 Difference in Differences

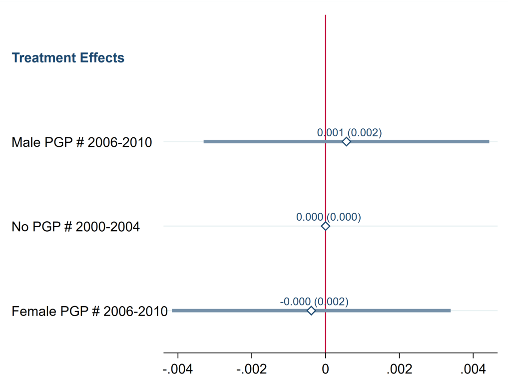


Panel C - Average Wage

C.1 Event Study



C.2 Difference in Differences



Notes: This figure reports estimates for models of the effect of the OET campaign on various firm level outcomes. In Panel A the dependent variable takes value 1 for the year in which a firm exits from the ASSD, and 0 for all the years in which the firm is present in the ASSD (i.e., has at least one paid worker). In Panel B, the dependent variable is the log of the number of workers employed by the firm each year. In Panel C, the dependent variable is the average daily wage paid to workers employed by the firm in a given year. For plots on the left hand side, solid lines represent estimates and dotted lines show the 95% confidence intervals. For plots on the right hand side, diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals, pre-campaign period refers to 2000-2004, treatment effects refer to 2006-2010. Vacancies posted in 2005 are dropped from the regression. Controls include year effects, firm effects, and industry x year effects. The sample includes all firms in the frequent postings firms sample.

death. The exit rates of firms that were likely to use male and female gender preferences are slightly but insignificantly higher than those of non-using firms before 2004; this gap stays constant after 2005. We note that the confidence intervals around our difference in differences estimates are relatively narrow, allowing us to rule out impacts of the campaign of 1 percentage point per year or more on previous SGP users, which is small considering the annual death rate of around 5.2 percent in the post-campaign period.

Firms that were previously users of SGP's might be no more likely to go out of business in the post-campaign period, but might be less likely to grow because of the extra costs imposed by being unable to express their gender preferences. As shown in Panel B of Figure 9, likely users of both male and female SGP's had similar rates of employment growth relative to non-SGP users in the 2000-2004 period, and this pattern persisted after 2005. Again, the confidence intervals around our difference-in-differences estimates are relatively narrow, allowing us to rule out impacts of the campaign of anything over 1 percentage point - a relatively small effect.

Finally, the results in Panels C of Figure 9 show that average wages were trending similarly for male and female SGP users relative to non-users prior to the OET campaign, and that this continued after 2005. We can also rule out relatively small impacts of the campaign, given the rather narrow confidence intervals for our difference in differences estimates.

We conclude that 2005 OET campaign did not have measurable adverse effects on the survival, firm size, or average wages of firms that were most likely to use SGP's in 2000-2004. The impacts of the campaign on the firms that were most likely to use them in the pre-period are precisely estimated with minimum detectable effect sizes being small compared to the means of the variables. While these results do not rule out possible impacts on other firm outcomes, they do suggest that the first-order effects of the campaign were to increase gender diversity within occupations and workplaces, without any large effects on firm performance.

5 Conclusion

In Spring 2005 the Austrian *Ombud for Equal Treatment* (OET) launched a campaign to alert employers and newspapers that gender preferences in job advertments were illegal. Over the next year, the use of stated gender preferences on the job board of the Austrian Employment Service fell from 40% of all vacancies to less than 5%. We use data on filled vacancies from this board to study how the elimination of stated gender preferences affected vacancy-related hiring and a variety of firm-wide outcomes. To study hiring, we focus on a set of frequent-posting firms that listed multiple vacancies in the same occupation in the pre-campaign period. We use a leave-out-mean procedure to predict the use of gender preferences. Then we estimate simple difference in differences models, comparing pre- and post-campaign hiring outcomes for vacancies with predicted male or female preferences, relative to vacancies with no predicted preference. These models can be interpreted as reduced form estimates from a model of hiring outcomes for vacancies with different latent gender preferences that are only observed in the pre-2005 period.

Our results show that the elimination of stated gender preferences led to a significant 2.2 percentage point increase in the fraction of women hired to fill vacancies with a predicted male preference, and a slightly larger 3.7 point increase in the fraction of men hired to fill vacancies with a predicted female preference. Scaling these effects to reflect the attenuation between predicted and actual gender preferences, we infer that the OET campaign had relatively large effects on job opportunities for the previously non-preferred groups. We also show that after the campaign, new hires for job openings that would have been expected to state male or female preferences were less likely to match the dominant gender in the target occupation or at the workplace of the posting firm, mitigating some of the anti-diversity impacts of explicit gender preferences.

Looking further into stereotypical versus non-stereotypical preferences, we find that the post-campaign increases in hiring of the the non-preferred gender were larger for vacancies with non-stereotypical gender preferences. This was particularly true for vacancies with a predicted preference for females in majority-male occupations. As a result, some of the diversifying effect of these vacancies was diluted after 2005.

While the OET's campaign led to more diverse hiring on a vacancy-by-vacancy basis, one might still be concerned that there was little impact at highly segregated workplaces. Moreover, eliminating the ability to advertise gender preferences could have negatively effected firms that previously relied on these signals. Looking at firm-wide outcomes for firms that filled at least five job ads prior to the campaign, we find that the most intensive users of male SGP's in the pre-campaign period experienced systematic gains (of roughly 2 percentage points) in the share of female employees after 2005, compared to neutral firms, while the heaviest users of female preferences experienced symmetric growth in the share of males. We find no negative effects on firm survival rates, total employment, or average wages at the most intensive users of gender preferences.

This pattern of evidence suggests that job seekers and firms adapted to the elimination of gender preference statements after the OET campaign. On the worker side, our findings on hiring outcomes, and related findings from Kuhn and Shen (2023) on job application flows, suggest that applicant pools became more gender-diverse after the campaign. In our setting this change may have been driven in part by changes in the referral practices of case workers at the Austrian Employment Service. On the firm side, our most surprising finding (again, consistent with results in Kuhn and Shen, 2023) is that some firms that would have specified a gender preference prior to the campaign responded to the newly diverse applicant pool by actually hiring workers of the opposite gender, rather than ignoring their applications. In most cases the net effect of these responses was to increase the gender diversity of hiring at both the occupation and workplace level, though in situations where an employer would have used a non-stereotypical gender preference the effect was mostly in the opposite direction.

Overall, our findings suggest that any negative effects of eliminating early job market signals of gender preference were mainly confined to the set of firms with non-stereotypical hiring goals. For the larger set of firms with stereotypical preferences, eliminating the ability to advertise these preferences led to an increase in the hiring of the opposite gender group. Taken together with the finding of no negative effects on the affected firms, we conclude that many of the stereotypical preferences observed before the campaign were likely based on outdated priors, rather than on true productivity gaps or on rigidly held discriminatory beliefs that would be immune to policy.

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APPENDIX

A Database Construction

The AMS vacancy database contains the stock of all the open vacancies at a monthly frequency. The database records inflow dates (posting dates) and outflow dates (closing dates), as well as the outcome of each closed vacancy – whether an AMS client was hired to fill the vacancy; or it was filled by some other worker; or whether it was closed without a hire (or with no information on the hiring outcome).[39]

The full database contains about 13.9 millions observations for the period 1997-2013, among which 5.2 millions are recorded as outflows. We consider only vacancy outflows, and first step toward the construction of our database is providing an opening date for each vacancy in the outflow subsample. The AMS system has a vacancy identifier, however, these are sometimes re-utilized for new openings. We match vacancy inflows to outflows using the vacancy identifier (*vdgnr*) and 10 other time-invariant vacancy characteristics. In this process the sample size reduces by 118,136 units (2%).

Our empirical analysis focuses only on vacancies filled by AMS clients, since they contain a person identifier (*penr*) that allows us to get information on the hired person including their gender. This subsample contains 1.2 millions vacancies, corresponding to about one quarter of all the hires[40].

The second step of our database construction is matching the AMS vacancy outflows with the employment spells in the ASSD database (*qualifikation*). This is the most challenging part of the process since the firm identifiers in the AMS (*btrnr*) and in the ASSD (*benr*) database differ.[41] We

[39] This usually happens when the firm withdraws the job ad because it is no longer interested in finding a new worker, or when the firm loses contact with the AMS.

[40] The portion of lapsed vacancies is about 13% of the total number of outflows.

[41] We have explored constructing our own cross-walk between AMS firm identifiers and ASSD firm identifiers based on the existing links through workers filling AMS vacancies. This cross-walk would be feasible if both AMS firm identifiers are stable in time, and if the worker filling a vacancy is unique. We find that both conditions are violated: 46% of all firms which posted two or more vacancies had more than one firm identifiers in AMS, and 83% of the firms that filled a vacancy in AMS at a point in time had two or more workers starting a job during the same time period in ASSD.

proceed as follows:

- We first clean the employment spells database. We merge all spells between the same firm and worker pair with a break of less than 70 days, and drop all the spells related to social security, sick leave, unemployment, retirement status, self employment, and employment in the civil service.

- We then match each individual hired in the vacancy database with the spell database through the worker id (*penr*). At this point for each vacancy we have a list of all the employment spells of the hired worker and we need to identify the spell that the vacancy refers to. To do that we consider only the spells starting around the closing date of the vacancy (-40, +90 days) and we drop all spells ending before the closing date of the vacancy.

- At this point we have a unique vacancy-spell match for most of the vacancies. For the remaining ones, we compare the pair AMS firm identifier (*btrnr*) and ASSD firm identifier (*benr*) with the "*cross-walk*" document provided by the *Bundesministerium fuer Arbeit, Soziales und Konsumentenschutz*[42]. For vacancies with at least a match with the cross-walk document we get the first one in chronological order among the matched ones, for the others we get the first in chronological order among all the identified spells.

At the end of this procedure we are able to have a pair vacancy-employment spell for 88% of the sub-sample of vacancies for which we observe a worker identifier.

The last step is getting the firm information, the worker information and the earnings. We do this by matching our database with employers database and workers database through the firm id (*benr*) and the worker id (*penr*) contained in the employment spell data. The final *vacancy-employer-employee* sample contains 987,271 observations for the period 1997-2013[43].

Table A.1 shows how the number of observations decreases at each of the steps above.

[42]This document matches the two identifiers, even though we tested the validity of the crossing with poor results, we believe that it contains some information that we can exploit to refine our matching algorithm.

[43]In the paper we focus on the period 2000-2010 for a total of 698,372 observations

Table A.1: Sample Size by Step of Data Construction

Steps	Observations
1) All vacancies, after restrictions (from September 1997 to December 2013)	13,906,275
2) Outflows of Vacancies	5,214,539
3) Outflows of Vacancies with Inflow date - With non missing key variables: 4,998,146 - From January 2000 to December 2010: 3,259,322	5,096,403
4) With AMS client hire and matched	1,169,203
5) Drop 414 duplicates	1,168,789
6) Merge with Employment Spells Database	1,042,794
7) Merge with Firms Database	1,041,094
8) Generate key variables, including occupations codes	1,016,843
9) Get worker personal information (gender, birthdate)	1,014,701
10) Get wages - From January 2000 to December 2010: 698,372	987,271

Notes: This table shows the number of observations in the database at each stage of the sample construction for the period 1997-2013.

B DATABASE DESCRIPTIVE STATISTICS

Table B.1: Subsample Descriptions

	Vacancies Posted in AMS System			
	All	**With Hire**	**With AMS Client Hire**	**AMS Client Matched**
	(1)	(2)	(3)	(4)
Panel A: SGP - pre-campaign period (2000-2004)				
Preference for Men	22%	22%	25%	25%
Preference for Women	19%	20%	21%	21%
Panel B: Vacancy Characteristics (2000-2010)				
Vacancy Duration (days)	53.23	52.47	41.17	41.03
Full Time Position	78%	78%	78%	78%
Unlimited Contract	78%	77%	81%	82%
Posted by small firm (≤ 5 employees)	46%	46%	43%	43%
Requesting at least upper secondary education	51%	51%	45%	46%
Panel C: Job Ads by Industry				
Agriculture, hunting and forestry	0.24%	0.25%	0.17%	0.17%
Mining and quarrying	0.10%	0.10%	0.14%	0.15%
Manufacturing	10.47%	10.81%	14.16%	14.62%
Electricity, gas and water supply	0.09%	0.10%	0.09%	0.09%
Construction	7.23%	7.05%	8.73%	8.81%
Wholesale and retail trade	15.22%	15.82%	16.90%	17.37%
Hotels and restaurants	24.20%	25.39%	19.77%	19.26%
Transport, storage and communication	3.74%	3.87%	4.18%	4.26%
Financial intermediation	0.95%	0.83%	0.64%	0.65%
Real estate, renting and business activities	27.07%	25.44%	22.68%	21.92%
Public administration and defence; compulsory social security	1.99%	1.85%	2.38%	2.44%
Education	0.95%	0.86%	0.76%	0.77%
Health and social work	3.47%	3.47%	4.78%	4.88%
Other community, social and personal service activities	4.27%	4.14%	4.59%	4.60%
Panel D: Job Ads by Occupation				
Legislators, senior officials and managers	1.00%	0.99%	0.63%	0.65%
Professionals	1.96%	1.73%	0.87%	0.83%
Technicians and associate professionals	9.95%	9.31%	6.64%	6.82%
Clerks	6.79%	7.01%	8.20%	8.50%
Service workers and shop and market sales workers	33.89%	35.25%	30.52%	30.45%
Skilled agricultural and fishery workers	0.42%	0.42%	0.41%	0.41%
Craft and related trades workers	21.01%	19.88%	19.80%	20.06%
Plant and machine operators and assemblers	5.97%	6.06%	7.54%	7.67%
Elementary occupations	19.02%	19.34%	25.40%	24.61%
Observations	3,259,322	2,890,924	818,289	698,372

Notes: This table shows the share of job postings by stated gender preferences, vacancy characteristics, and broad categories of industries for four different subsamples in four subsamples of the AMS Data for the period 2000-2010. The sub-sample *All* refers to all vacancies posted in the AMS System *With Hire* is for vacancies that are filled, *With AMS Client Hire* is the sub-set of vacancies filled through AMS, and *AMS Client Matched* is the sub-set of the AMS hires that we matched with a firm in the Austrian Social Security Database (ASSD). Vacancy Duration is the difference between the last day of the vacancy closing month and the vacancy posting date.

Table B.2: Trends by outcome, matching and PGP

Posting Year	All Outflows N. of obs.	Hired N. of obs.	Hired AMS N. of obs.	Matched N. of obs.	Non - class N. of obs.	M-PGP N. of obs.	N-PGP N. of obs.	F-PGP N. of obs.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2000	262,708	231,139	73,404	63,486	16,070	12,818	24,468	10,130
2001	225,091	197,457	61,832	52,840	13,204	10,134	20,514	8,988
2002	231,876	214,785	65,861	55,920	13,421	10,755	22,286	9,458
2003	240,098	220,506	68,938	58,751	14,936	11,048	23,192	9,575
2004	252,509	233,192	72,302	61,356	17,154	10,762	23,813	9,627
2005	272,944	247,747	80,887	68,832	20,285	12,107	26,085	10,355
2006	315,259	277,681	86,080	73,831	23,305	14,118	26,273	10,135
2007	360,054	313,993	85,598	72,245	22,836	12,199	26,577	10,633
2008	377,905	330,243	80,938	68,466	19,705	11,411	26,972	10,378
2009	335,569	294,998	69,254	59,238	17,219	9,908	22,735	9,376
2010	385,309	329,183	73,195	63,407	19,658	10,788	23,696	9,265
	4,998,146	**4,333,444**	**1,151,996**	**987,271**	**486,692**	**126,048**	**266,611**	**107,920**

Figure B.1: Comparison of Samples

Notes: This figure shows the unemployment rate, and various vacancy rates between 2000 and 2010. The 'all vacancies rate' is the ratio of all vacancies posted to the platform in a year relative to employment in that year. The 'hired vacancies rate' is the ratio of vacancies posted in a year that were filled to employment in that year. The 'hired AMS rate' is the ratio of vacancies filled by a worker known to the AMS, to total employment. The 'matched AMS rate' is the ratio of vacancies filled by a worker known to AMS and in our matched sample, to total employment. Source: The raw numbers on vacancies in Table B.2, employment numbers from OECD Labor Force Statistics.

C SGP before the OET Campaign - Extended Sample

Table C.1: Characteristics of Filled Vacancies by use of SGP, Pre-campaign - Extended Sample

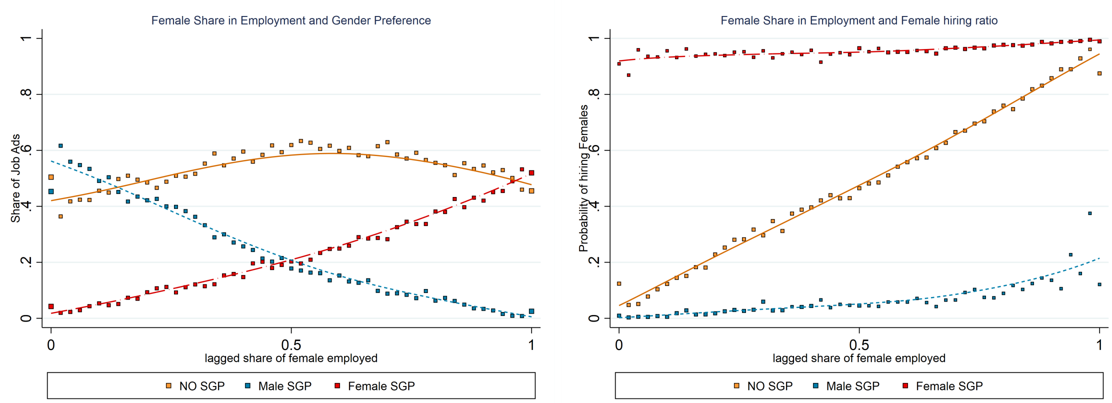
	Total	Stated Gender Preference		
		Female SGP	No SGP	Male SGP
	(1)	(2)	(3)	(4)
Share of vacancies	1.000	0.213	0.529	0.259
Panel A: Outcomes				
Share of women hired (share)	0.457	0.967	0.462	0.028
Vacancy filling time (mean)	32.71	30.70	34.53	30.65
Vacancy filling time (median)	21	20	23	19
Log wage of the hire (mean)	3.81	3.58	3.83	3.98
Job duration (mean)	388	425	397	338
Job duration (median)	171	195	177	144
Panel B: Context				
Share of women in the firm (share)	0.464	0.691	0.480	0.247
Share of women in occupation (share)	0.473	0.659	0.496	0.271
Panel C: Vacancy Characteristics				
Posted by small firm, ≤ 5 employees (share)	0.431	0.495	0.428	0.386
Requesting at least upper secondary education (share)	0.421	0.324	0.389	0.476

Notes: This table reports means, medians, and shares of selected characteristics of vacancies by Stated Gender Preference (SGP) for vacancies posted in the extended sample. Vacancy filling time refers to the difference in days between the starting date of the new job associated with the vacancy and the posting date of the vacancy.

Figure C.1: Use of SGP by Female Share of Workforce, Extended Sample

Panel A. Use of SGP

Panel B. Probability of Hiring a Female



Note: This Figure shows the share of vacancies that specify preferences for females (red line), males (blue line), or no gender preference (yellow line) in Panel A and the share of females hired by whether the vacancy stated a preference for females (red line), males (blue line), or neither, and by the gender composition of the firm in the year prior to the hire. The sample includes vacancies in the extended sample with a PGP.

D Vacancy Filling Times and Female Hires (pre-campaign)

Stated gender preferences appear to influence hiring outcomes, but is there any evidence that they affect hiring efficiency (as is assumed in the KS model)? To assess this we look at vacancy filling times. Columns 1-4 of Table D.1 present a series of simple models that relate the days required to fill a vacancy to the use of SGP's. To help provide a context for these models we also present a parallel set of models for the event that a female was hired to fill the vacancy (columns 5-8). We look at all vacancies (columns 1 and 5), and separately at vacancies for mainly male occupations (columns 2 and 6), for occupations with a mix of male and female workers (columns 3 and 7), and for mainly female occupations (columns 4 and 8).

We classify workplaces as "female" (more than 50% females in the previous year, with label "F workplace") or "male" (more than 50% males in the previous year, , with label "M workplace") and include as the main variables of interest indicators for a male or female SGP, interacted with dummies for mainly male or mainly female workplaces. All the models include fixed effects for occupation and industry, time effects, and dummies for 51 different intervals of the lagged share of females at the workplace.

Looking at the vacancy filling time results we see two broad patterns. First, the use of SGP's tends to (if anything) reduce vacancy filling times. Second, SGP's for the gender that is the opposite of the workplace majority tend to have the largest negative effects. The large negative effects of a female SGP in filling an opening for mainly male occupation at a mainly male workplace (-4.440 days, in the 4th row of column 2) and of a male SGP in recruiting for a mainly female occupation at a mainly female workplace (-5.684 days, in the first row of column 4) are particularly interesting. In both cases, the employer is stating a preference for a non-stereotypical gender (different than the majority of the occupation and of the existing workforce), and yet the time to fill the vacancy is reduced. As shown in the corresponding models for the gender of the newly hired worker (columns 6 and 8), such preferences have large effects on the probability of hiring the preferred gender, consistent with the patterns in Figure 3. Thus, it appears that employers with non-stereotypical preferences could easily find workers to match those preferences. Taken together, the results on filling times and gender outcomes suggest that in the pre-campaign period there were more females looking for jobs in mainly male occupations, and more males looking for jobs in mainly female occupations, than were demanded by the relatively small share of employers who were seeking to recruit them.

Table D.1: Vacancy Filling Time and Hiring a Female Worker - Extended Sample

	OLS Estimation							
Dependent Variable:	*Vacancy Filling Time - in days*				*Female hire*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M SGP in F workplace	-2.140***	-2.960***	2.038	-5.684***	-0.378***	-0.306***	-0.348***	-0.443***
[Non-stereotypical Male SGP]	(0.446)	(0.836)	(1.504)	(0.752)	(0.005)	(0.010)	(0.017)	(0.009)
M SGP in M workplace	-1.212***	-0.394	-0.739	-4.637***	-0.139***	-0.081***	-0.231***	-0.277***
[Stereotypical Male SGP]	(0.289)	(0.375)	(0.831)	(1.019)	(0.002)	(0.003)	(0.009)	(0.011)
F SGP in F workplace	-3.042***	-2.662***	-2.099**	-3.148***	0.240***	0.447***	0.182***	0.227***
[Stereotypical Female SGP]	(0.296)	(1.022)	(1.053)	(0.356)	(0.003)	(0.012)	(0.011)	(0.004)
F SGP in M workplace	-3.274***	-4.440***	-4.572***	-2.196***	0.469***	0.673***	0.335***	0.423***
[Non-stereotypical Female SGP]	(0.405)	(0.807)	(0.931)	(0.770)	(0.004)	(0.009)	(0.011)	(0.008)
All Vacancies	✓				✓			
Male Occupations		✓				✓		
Neutral Occupations			✓				✓	
Female Occupations				✓				✓
Observations	255,969	102,630	48,046	105,293	255,969	102,630	48,046	105,293

Notes: OLS estimation of the effect of the SGP on vacancy filling time and hiring gender. Period 2000-2004 (pre-campaign). Controls include occupation, industry and firm gender composition fixed effects as well as year FE. Beta coefficients reported and robust standard errors in parentheses. Columns (1) and (5) concerns all observations. In column (2) and (6) only job openings in female occupations are used, in column (3) and (7) in neutral occupations and in column (4) and (8) in male occupations only. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. The sample includes vacancies in the extended sample.

E Attenuation with (Non-)stereotypical Vacancies

We are using predicted SGP's rather than actual gender preferences, so equation (2) can be interpreted as the reduced-form from a two-stage-least-squares procedure in which we estimate the first stage models using only data from the pre-campaign period, and allow the effects of the endogenous variables to vary between the pre-campaign and post-campaign periods. To formalize this, let S_j^f and S_j^m represent dummies for actual SGP's in the pre-campaign period or *desired* SGP's in the post-campaign period (i.e., the preferences that employers would have stated if there was no effort to eliminate SGP's). Let C_j^f represent workplaces with a majority of women (F workplace), and C_j^f represents workplaces with a majority of men (M workplace). Assume that the true model generating outcome y is:

$$
\begin{aligned}
y_j = \alpha_0 + \alpha_1 S_j^f C_j^f + \alpha_2 S_j^f C_j^m + \alpha_3 S_j^m C_j^m + \alpha_4 S_j^m C_j^f \\
+ \theta_1 S_j^f C_j^f Post_j + \theta_2 S_j^f C_j^m Post_j + \theta_3 S_j^m C_j^m Post_j + \theta_4 S_j^m C_j^f Post_j + X_j \gamma + \varepsilon_j
\end{aligned}
\tag{E.0.1}
$$

This has the same form as equation (2) but relates the outcome to true (or desired) SGP's. Assume that the actual/desired SGP's are related to predicted preferences by a pair of simple models with constant coefficients between the pre- and post-campaign periods:

$$
S_j^f = \pi_0 + \pi_1 D_j^f C_j^f + \pi_2 D_j^f C_j^m + \pi_3 D_j^m C_j^m + \pi_4 D_j^m D_j^f + X_j \pi_x + \xi_j^f \tag{E.0.2}
$$

$$
S_j^m = \psi_0 + \psi_1 D_j^f C_j^f + \psi_2 D_j^f C_j^m + \psi_3 D_j^m C_j^m + \psi_4 D_j^m C_j^f + X_j \psi_x + \xi_j^m \tag{E.0.3}
$$

where ξ_j^f, ξ_j^m are prediction errors. Here π_1 and $\pi_2$represent the increment in the probability of an actual female SGP if the vacancy (π_1 for the stereotypical, and π_2 for the non-stereotypical vacancies) relative to the omitted category of a prediction of no SGP. π_3 and π_4 represent the increment in the probability of an actual female SGP if the vacancy has a predicted male stereotypical SGP (π_3 for the stereotypical, and π_4 for the non-stereotypical vacancy), again relative to the case where it is predicted to have no SGP. Thus we expect π_1 and π_2 to be positive, whereas $\pi_3$and π_4 will be negative. Similar reasoning suggests that ψ_3 and ψ_4 will be positive and $\psi_1$and ψ_2 will be negative.

Combining equation (E.0.1) with (E.0.2) and (E.0.3) shows that the difference-of-differences coefficients in (8) are:

$$\lambda_1 = \theta_1\pi_1 + \theta_4\psi_1 \tag{E.0.4}$$

$$\lambda_2 = \theta_2\pi_2 + \theta_3\psi_2 \tag{E.0.5}$$

$$\lambda_3 = \theta_3\psi_3 + \theta_2\pi_3 \tag{E.0.6}$$

$$\lambda_4 = \theta_4\psi_4 + \theta_1\pi_4 \tag{E.0.7}$$

Notice that if we ignore ψ_1 and ψ_2,then λ_1 is an attenuated version of θ_1 and λ_2 is an attenuated version of ψ_2, where the attenuation factors reflect the fractions of predicted vacancies with female stereotypical (π_1) or non-stereotypical (π_2) preferences (conditional on the $X's$). Also, if we ignore π_3 and π_4,then λ_3 is an attenuated version of θ_3 and λ_4 is an attenuated version of θ_4, where the attenuation factors reflect the fractions of predicted vacancies with male stereotypical (ψ_3) or non-stereotypical (ψ_3) preferences that actually have these preferences (conditional on the $X's$). More generally we would expect ψ_1, ψ_2 π_3, and π_4 to be small in magnitude (though in each case negative), so the intuition of the benchmark case remains true.

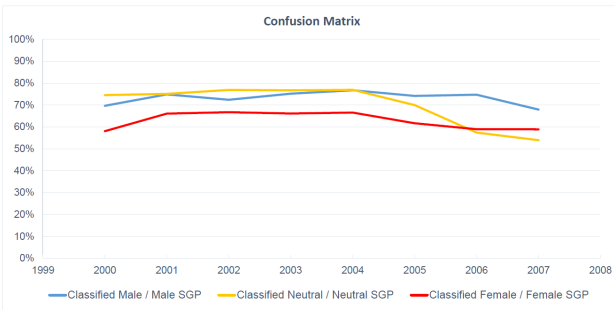
Columns 2 and 4 of Table 3 present estimates of equations (E.0.3) and (E.0.3) using the observed SGP's in the 1999-2003 period and predictions from our first (leave-out-mean based) classification model. We see that $\pi_1 = 0.171$, $\pi_2 = 0.230$ and, while $\psi_1 = -0.012$ and $\psi_2 = -0.082$. Thus, controlling for industry, occupation, and the firm's lagged gender composition, having a stereotypical female predicted SGP raises the probability of an SGP of that gender by 17 percentage points relative to a vacancy that is predicted to have no SGP, while having a male non-stereotypical SGP of the opposite gender lowers the probability by 1 percentage point relative to the no-SGP base.

F PREDICTED GENDER PREFERENCE

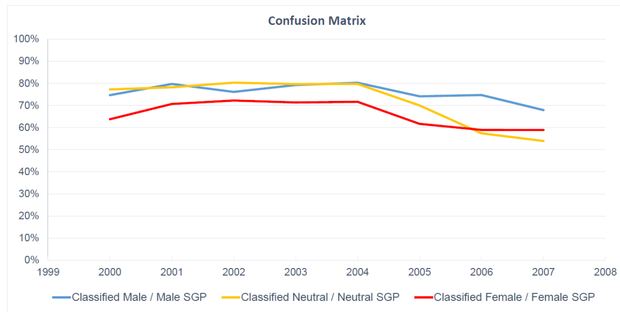
Figure F.1: Prediction Quality

Panel A - Frequent Postings Sample

A.1 Leave-one-out

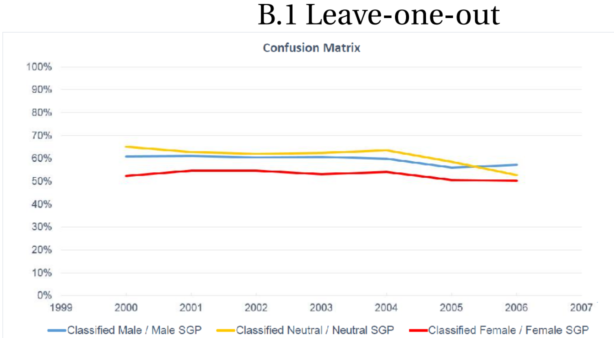


A.2 No Leave-one-out

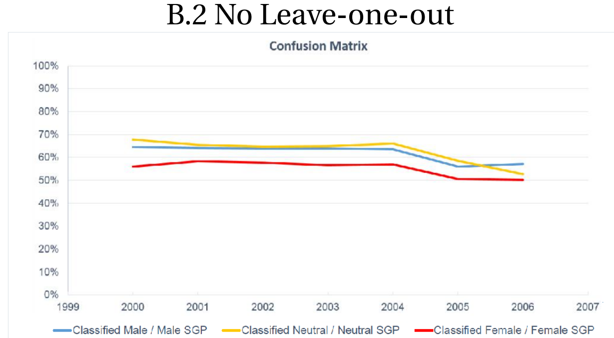


Panel B - Extended Sample

B.1 Leave-one-out



B.2 No Leave-one-out



Notes: This figure shows the share of Stated Gender Preferences (SGP) that are correctly predicted by our Predicted Gender Preference (PGP), by year. The classification period is 2000-2004. Classification is performed through a fully saturated regression model. In panels A.1 and B.1 we correct estimates through the leave one-out mean method. The sample in Panel A includes vacancies posted by frequent postings firms, with a PGP. The sample in Panel B includes vacancies in extended sample with a PGP. The sample in figures (c) and (d) includes vacancies in the extended sample, with a PGP.

Table F.1: Predicted and Actual Gender Preferences - extended sample

Dependent Variable:	***Male SGP***		***Female SGP***	
	(1)	(2)	(3)	(5)
Male PGP	0.192***		-0.035***	
	(0.004)		(0.001)	
Female PGP	-0.027***		0.173***	
	(0.002)		(0.004)	
Stereotyping based on the gender composition of occupation				
M PGP in F occupation		0.156***		-0.026***
[Non-stereotypical Male PGP]		(0.009)		(0.004)
M PGP in M occupation		0.196***		-0.032***
[Stereotypical Male PGP]		(0.004)		(0.002)
F PGP in F occupation		-0.017***		0.158***
[Stereotypical Female PGP]		(0.002)		(0.004)
F PGP in M occupation		-0.148***		0.360***
[Non-stereotypical Female PGP]		(0.010)		(0.013)

Notes: This table reports estimated coefficients and robust standard errors (in parentheses) from OLS regressions of the event of having a male (columns 1-2) or female (columns 3-4) stated gender preference (SGP) in a given vacancy on predicted gender preferences (PGP) for that vacancy. Predictions are based on occupation, industry and lagged gender share. Controls include occupation, industry and firm gender composition and year FE. All models include fixed effects for industry, occupation, and the gender composition of the firm's workforce as well as year effects. The sample includes vacancies in the extended sample with a PGP.

Table F.2: Predicted and Actual Gender Preferences - alternative classification

Dependent Variable:	***Male SGP***		***Female SGP***	
	(1)	(2)	(3)	(4)
Male PGP	0.248***		-0.037***	
	(0.004)		(0.002)	
Female PGP	-0.034***		0.217***	
	(0.002)		(0.005)	
Stereotyping based on gender composition of occupation				
M PGP in F occupation		0.232***		-0.032***
[Non-stereotypicalMale PGP]		(0.011)		(0.005)
M PGP in M occupation		0.246***		-0.032***
[StereotypicalMale PGP]		(0.005)		(0.002)
F PGP in F occupation		-0.018***		0.197***
[Stereotypical Female PGP]		(0.002)		(0.005)
F PGP in M occupation		-0.182***		0.406***
[Non-stereotypical Female PGP]		(0.010)		(0.014)

Notes: This table reports estimated coefficients and robust standard errors (in parentheses) from OLS regressions of the event of having a male (columns 1-2) or female (columns 3-4) stated gender preference (SGP) in a given vacancy on predicted gender preferences (PGP) for that vacancy. Predictions are based on occupation, industry and lagged gender share. Controls include occupation, industry and firm gender composition and year FE. All models include fixed effects for industry, occupation, and the gender composition of the firm's workforce as well as year effects. The sample includes vacancies in the frequent postings firm sample with a PGP.

G DIVERSITY RESULTS

Recall that the Duncan and Duncan (1955) Index of dissimilarity is defined as

$$D = \frac{1}{2}\sum_{j=1}^{J}\left|\frac{m_j}{M} - \frac{f_j}{F}\right|$$

where j indexes firms, f_j is number of women in firm j, m_j is number of men, and $n_j = m_j + f_j$ is total employment in firm. $F = \sum_{j=1}^{J} f_j$ is total number of women, and M is total number of men, and $N = M + F$ is total employment. Let G be the one-half of the size of the population, so $G = \frac{1}{2}N$. Note that $G = M = F$ in case the labor market is balanced in terms of gender. Similarly, let $g_j \equiv= \frac{1}{2}n_j$ be one half of the firm's employment.

Let's introduce a weighted version of the Duncan Index, which uses the inverse of each firm's employment share as its weight:

$$D_w = \frac{1}{2}\sum_{j=1}^{J}\frac{N}{n_j}\left|\frac{m_j}{M} - \frac{f_j}{F}\right|$$

D_w is like D but it treats excess employment share of one gender in a large firm as being less of a contribution to dissimilarity than in a small firm (since contributions are weighted with the inverse of the employment share).

We now rearrange D_w so as to get the outcome variable we use in the paper.

$$\begin{aligned} D_w &= \frac{1}{2}\sum_{j=1}^{J}\frac{N}{n_j}\left|\frac{m_j}{G}\frac{G}{M} - \frac{f_j}{G}\frac{G}{F}\right| && \text{(G.2.1)} \\ &= \frac{1}{2}\sum_{j=1}^{J}\frac{N}{G}\left|\frac{m_j}{n_j}\frac{G}{M} - \frac{f_j}{n_j}\frac{G}{F}\right| && \text{(G.2.2)} \end{aligned}$$

Suppose now that women and men are equally present in the labor force, so $G = F = M$, then things become simpler. Note that $|m_j - \bar{g}_j| = |\bar{g}_j - f_j|$ so $|m_j - f_j| = 2|\bar{g}_j - f_j|$.

$$D_w = \frac{1}{2}\sum_{j=1}^{J}\frac{2N}{G}\left|\frac{\bar{g}_j}{n_j}-\frac{f_j}{n_j}\right| \tag{G.2.3}$$

$$= \sum_{j=1}^{J} 2\left|\frac{1}{2}-\frac{f_j}{n_j}\right| \tag{G.2.4}$$

Recall that the firm level diversity outcome variable we study is

$$1-2\left|\frac{1}{2}-\frac{f_j}{n_j}\right|$$

Define an index of diversity (or similarity) as

$$1-D_w \equiv 1-\sum_{j=1}^{J} 2\left|\frac{1}{2}-\frac{f_j}{n_j}\right|$$

The outcome variable we analyze is then each firm's contribution to diversity, measured as absence of weighted dissimilarity, in a labor market with a balanced share of women and men.

H ADDITIONAL RESULTS

H.1 STEREOTYPICAL PGP, HETEROGENEOUS EFFECTS BY WORKPLACE

Table H.1: Distribution of vacancies by PGP and Workforce composition

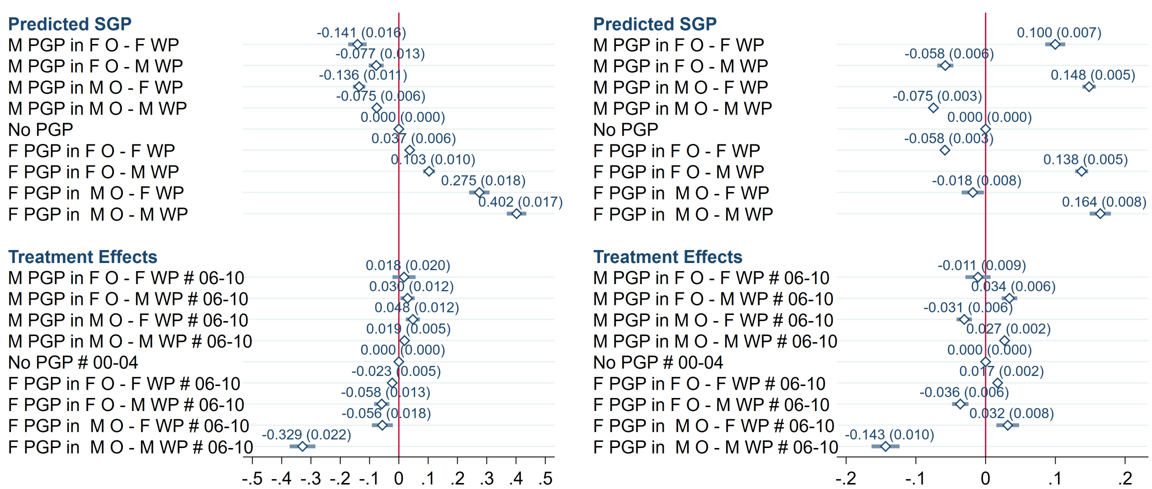
Stereotypical/Non-Stereotypical PGP by Occupations	Workforce Composition					
	Female WP	Male WP	No PGP	Female WP	Male WP	Total
M PGP in F occupation	1,595	4,563	0	0	0	6,158
M PGP in M occupation	4,570	34,046	0	0	0	38,616
No PGP	0	0	108,190	0	0	108,190
F PGP in F occupation	0	0	0	36,538	3,783	40,321
F PGP in M occupation	0	0	0	2,267	1,576	3,843
Total	6,165	38,609	108,190	38,805	5,359	195,128

Notes: This table reports the number of job advertisements by PGP and gender composition of the firm's workforce. The sample includes vacancies in the frequent postings firm sample with a PGP.

Figure H.1: Heterogeneous Effects Stereotypical and Non-Stereotypical Vacancies

Panel A. Female Hiring

Panel B. Workplace Diversity



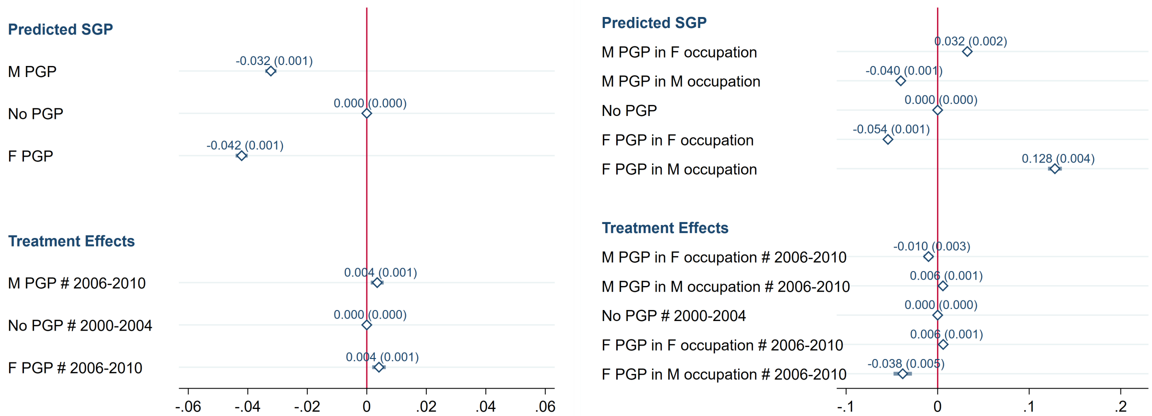
Notes: This figure reports the estimation result capturing the effect of eliminating stated gender preferences on female hiring (Panel A) and workplace composition (Panel B). We distinguish between Stereotypical and Non-Stereotypical vacancies based on the match between the predicted gender preference and the gender composition of the occupation and compute heterogeneous effects based on the gender composition of the firm. Diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to vacancies posted in 2000-2004, treatment effects refer to vacancies posted in 2006-2010. Vacancies posted in 2005 are dropped from the regression. Controls include firm, occupation and year fixed effects. The sample includes vacancies posted by frequent postings firms that posted at least 2 vacancies in the corresponding occupation in the pre-campaign period and in the post-campaign period. (column 6 of Table 1)

H.2 Extended Sample - Diversifying Hires

Figure H.2: Effects on Diversifying Hires - Extended Sample

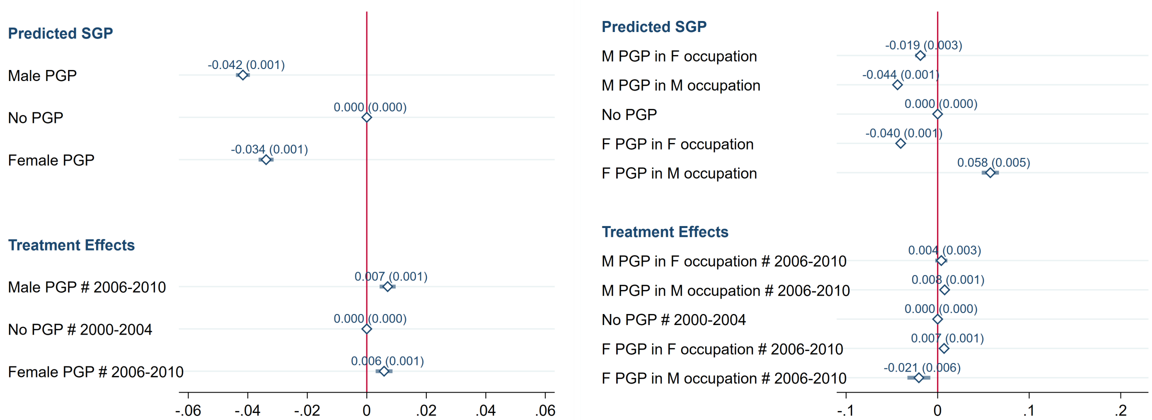
Panel A - Occupation Diversity

A.1 Baseline Model | A.2 Stereotypical Vacancies



Panel B - Workplace Diversity

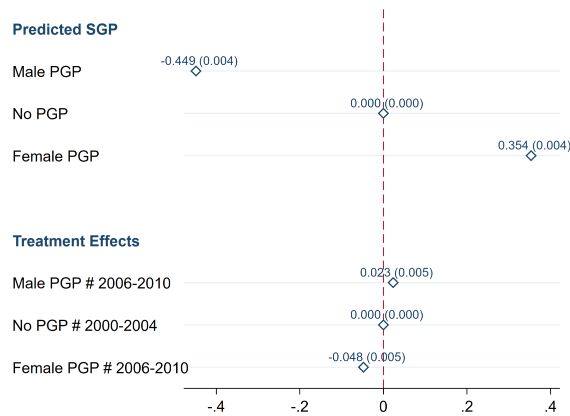
B.1 Baseline Model | B.2 Stereotypical Vacancies



Notes: This figure reports the estimation result capturing the effect of eliminating stated gender preferences on workplace composition. Panel A uses the specification of equation 1, distinguishing between Male and Female PGP. Panel B use the specification of equation 8, distinguishing between Stereotypical and Non-Stereotypical vacancies based on the match between the PGP and the gender composition of the occupation. Diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to vacancies posted in 2000-2004, treatment effects refer to vacancies posted in 2006-2010. Vacancies posted in 2005 are dropped from the regression. Controls include industry, occupation, workforce gender composition and year fixed effects. The sample includes vacancies in the extended sample with a PGP.

H.3 Contamination Bias

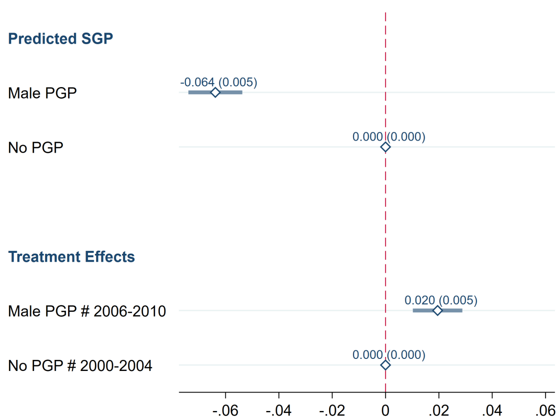
Figure H.3: Probability of Female : Model with no controls



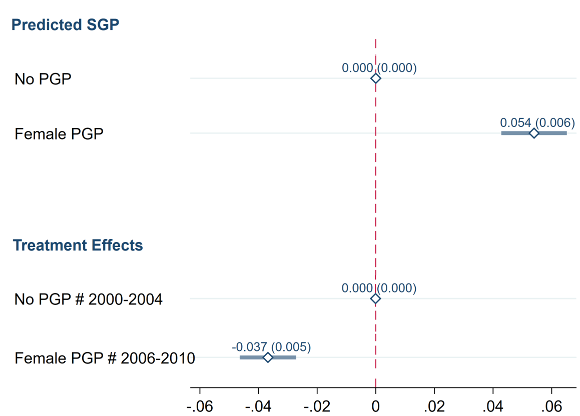
Notes: This figure reports the estimation results capturing the effect of eliminating stated gender preferences on the hiring of females. Diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to vacancies posted in 2000-2004, treatment effects refer to vacancies posted in 2006-2010. Vacancies posted in 2005 are dropped from the regression. The sample includes vacancies in the frequent postings sample with a PGP. Controls include dummy for post 2006.

Figure H.4: Probability of Female Hire: Estimating Effects for Male and Female PGP's Separately

Panel A. Male PGP



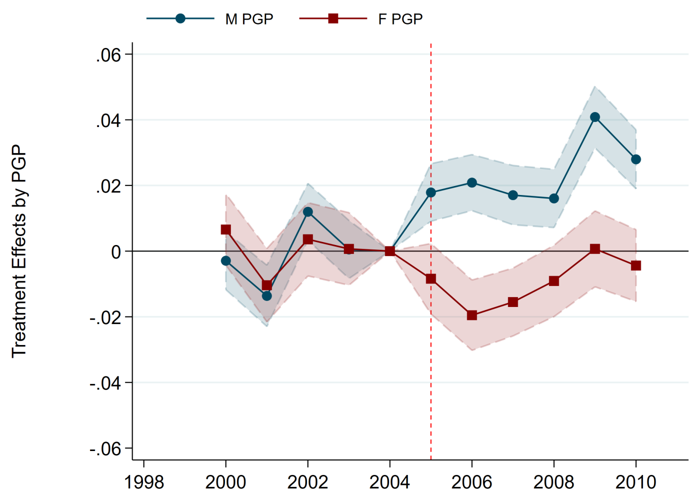
Panel B. Female PGP



Notes: This figure reports the estimation results capturing the effect of eliminating stated gender preferences on the hiring of females. Diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to vacancies posted in 2000-2004, treatment effects refer to vacancies posted in 2006-2010. Vacancies posted in 2005 are dropped from the regression. The sample includes vacancies in the frequent postings sample with a PGP. In Panel A, all vacancies classified as Female PGP are dropped from the sample; in Panel B, all vacancies classified as Male PGP are dropped from the sample. Controls include firm, occupation and year fixed effects.

H.4 BOOTSTRAP

Figure H.5: Female Hire: Event History Results - Bootstrap (Extended Sample)

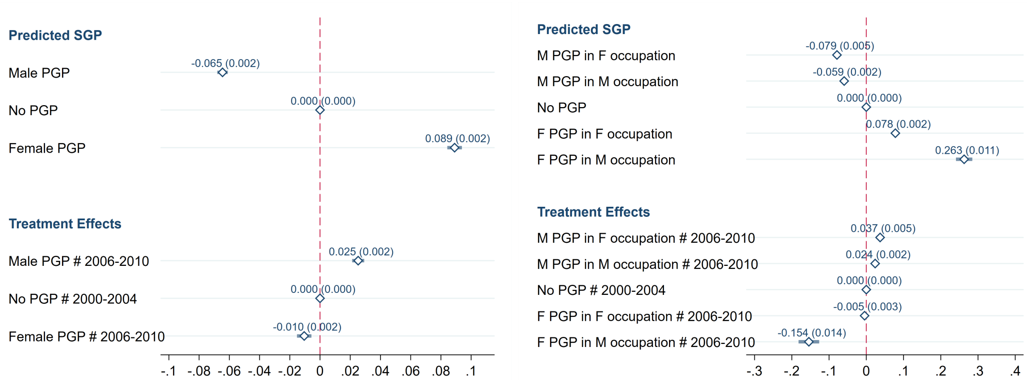


Note: This figure reports the estimation results capturing the effect of eliminating stated gender preferences on the hiring of females. Coefficients of the interaction term between year and indicators for vacancies classified as Male or Female PGP are reported. Solid lines represent point estimates, shadow areas show the 95% confidence intervals. Controls include firm, occupation and year fixed effects and standard errors are bootstrapped with 1000 replications. The sample includes vacancies in the extended sample with a PGP

Figure H.6: Female Hire: Difference in Differences Results - Bootstrap (Extended Sample)

Panel A. Baseline Model

Panel B. Stereotypical Vacancies



Notes: This figure reports the estimation results capturing the effect of eliminating stated gender preferences on the hiring of females. Panel A uses the specification of equation 1, distinguishing between Male and Female PGP. Panel B use the specification of equation 8, distinguishing between Stereotypical and Non-Stereotypical vacancies based on the match between the PGP and the gender composition of the occupation. Diamonds represent to the point estimates, horizontal lines show the 95% confidence intervals. Pre-campaign period refers to vacancies posted in 2000-2004, treatment effects refer to vacancies posted in 2006-2010. Vacancies posted in 2005 are dropped from the regression. Controls include firm, occupation and year fixed effects and standard errors are bootstrapped with 1000 replications. The sample includes vacancies in the extended sample with a PGP