Are Employers Biased Against Job-Seeking Parents?

W241 Final Paper, UC Berkeley MIDS

Claudia Durkin, Mark Herrera, Edward Kirton, Ash Moinzadeh

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Abstract

Employers seeking to attract top talent often boast of generous parental leave policies and cultures that prioritize work-life balance. However, many workers anecdotally report that parenthood has blocked them from new opportunities when searching for work, and academic research supports this assertion. We studied the impacts of a voluntary parenting leave on employment prospects for a data science candidate located in the San Francisco area. This experiment leverages a fictional job candidate, with top-tier education and experience, and in-demand skills. The most recent entry for the treatment resume was an eight-month career break to be a full-time parent, whereas the control resume showed an unexplained gap of the same duration (and is otherwise identical). The resumes were randomly assigned to job listings in the San Francisco Bay area sourced from Indeed, with 280 total applications submitted. The outcome, either positive outreaches (i.e. an invitation to interview) or a negative outreach (rejection or no response), was measured. Our analysis shows no significant statistical difference between the outcomes of these two groups. Given anecdotal evidence, and the literature cited in this paper, we expected to detect a treatment effect despite applying for jobs in a more liberal industry and geographic area. However, once data collection proved difficult, and our sample size shrunk to just over half its original size, our expectation in detecting a treatment effect changed due to low statistical power. We note that it was a job-seekers' market when our experiment began in October 2022, but by the time data collection ended in mid-November, several large tech firms had announced sizable layoffs, which may have impacted our experiment.

Introduction

We are interested in seeing how taking a voluntary leave from work for parenting affects one's employment prospects. Weisshaar (2018) conducted a study in which men and women who voluntarily opted out of work for family leave fared in job hunting responses compared to similar applicants who were either continuously employed or laid off. She found parents who opted out of work received significantly less responses to job applications, indicating a bias against such behavior, possibly due to the appearance of not being fully committed to work. Her analysis also indicated that the penalty was greatest against mothers in a more competitive job market (where employers have more applicants to choose from), and that the effect varied between job types. Other investigators (e.g. Ishizuka, 2021) also reported differential effects based upon job type.

The negative impact of motherhood on women's wages has been studied for decades (Waldfogel, 1997), though a recent meta-analysis (de Linde Leonard, 2020) has shown that the effect varies both considerably and globally, with estimated weights ranging from -0.098 in Germany to $+0.034$ in Belgium, and an effect < 0 indicates a negative effect on wages. The USA had a reported effect of -0.041, but there may be regional differences. Investigations in recent times have provided increased clarity on the contributions of sex, motherhood, as well as other factors such as race, education, industry, and the competitive employment environment. For example, England et al. (2016) describe an increased motherhood penalty upon privileged (e.g. by race or education) women.

Further research has indicated that, in the USA, parenthood is penalized for women but not for men (Correll, 2007), while other investigators have argued that the pay gap is related to caregiver vs breadwinner roles rather than sex (Bear, 2017). Generally, while considerable progress has been made towards reducing the gender pay gap in the USA over the decades, England et al. (2020) report improvements have slowed or stalled.

We are specifically interested in the potential reduction in job prospects for mothers who took career breaks to be full-time parents. Our hypothesis is that even in the liberal Bay Area, and even for highly-skilled data science candidates, we would receive fewer interview invitations for our treatment candidate compared to control.

Experimental Details

Comparison of Potential Outcomes

In this experiment, randomized participants, companies' hiring teams, received resumes in response to their job vacancies posted on a public site, Indeed. The treatment group received a resume where the most recent entry was a career break to be a full-time parent, and the control group received a resume with an unexplained gap of the same duration.

This is a post-test control group design, where the outcome occurs after the resumes are sent to job postings. There are two potential outcomes: a positive outcome (an invitation to interview) coded as a 1, or a negative outcome (an explicit rejection or no response) coded as a 0.

Figure 1: ROXO Grammar

Post-test Control Group Design	
Treatment group (resume with parental leave)	R X O
Control group (resume with unexplained break)	R - O
Note: X = treatment, - = no treatment, O = observation	

Data Collection and Randomization Process

To assess discrimination against job-seekers who took career breaks to be full-time parents, control and treatment resumes were submitted to a portfolio of job listings. Responses recorded from these applications were used to calculate an average treatment effect.

To do this, a web scraping algorithm written in Python was used to collect job information from Indeed. A query was sent through Indeed's job search feature on October 13th, 2022 to identify Data Science job opportunities that were within a 25 miles radius from Hayward, CA. A total of 434 jobs were returned by the query, and the results were distributed between 31 result tabs. Each result tab was converted into an HTML file and was sequentially opened and parsed using Python's *path* and *beautifulsoup* modules. *Beautifulsoup* was used to identify the div components of each HTML file, and the job titles, Indeed application URLs, employer names, employer URLs, and work addresses for each position were extracted and transferred to a tab-delimited text file.

The tab-delimited file was loaded into R, and each application was assigned a unique application ID. Applications with repeat URLs were dropped. A group assignment function was created to homogeneously, and randomly, assign job applications with treatment and control statuses (see **CONSORT Discussion**). Finally, additional covariates indicating a given employer's company size and public/private status were appended by researching each employer's name through *Crunchbase* and *Bloomberg.* The resulting table was exported to a CSV file and uploaded to Google Sheets for the application delivery phase.

Given the sheer number of applications submitted, great caution was taken during the application phase to prevent contamination and data entry errors. This meant that treatment and control resumes were created and uploaded to Google Drive in advance (see **Treatment**), alongside go-to application responses. Unique Gmail accounts and Indeed credentials were likewise assigned for each experimental resume. Two volunteers were hired, trained, and closely supervised to aid with timely and compliant delivery of applications.

All applications were submitted between 10-17-2022 and 10-19-2022. Employer responses were collected for a full month (31 days) following initial application dates, after which null responses were coded as negative. Outcomes of interest included a clear indication to proceed with a first interview, a clear indication that a given resume was rejected for interview, or a non-response.

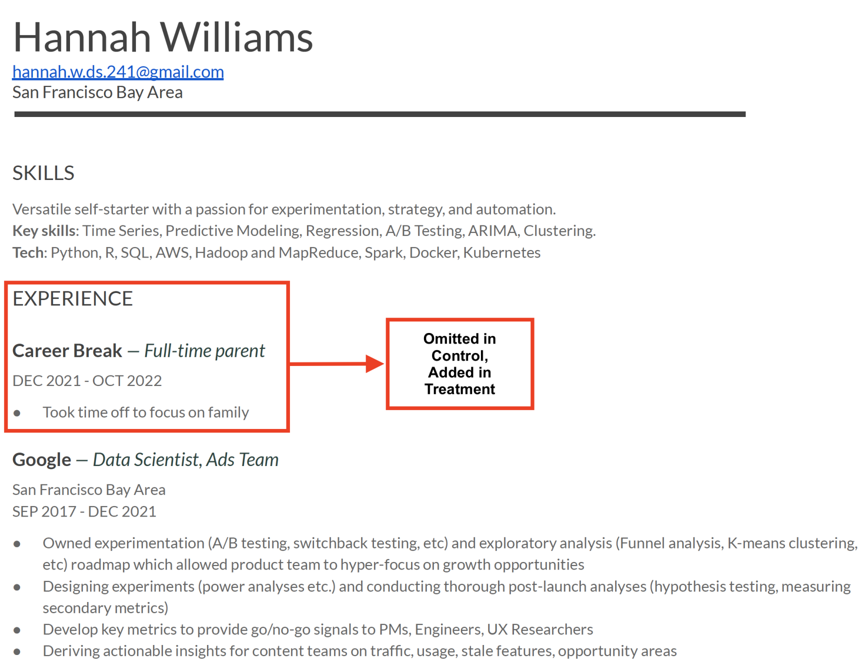
Treatment

We created a baseline resume for a mid-career data science candidate with a competitive skillset drawing on industry knowledge of technical recruiting standards in the Bay area. Our fictional candidate was a woman, with top-tier education, experience in Fortune 500 firms and in-demand skills. It could be inferred from the resume that the candidate was around 30-35 years old (see *Appendix 1*).

We aimed to avoid introducing any unintended biases, including racial biases from names. First and last names were chosen from popular names lists. The first name, Hannah, was a top-baby name in the 1990s; the surname, Williams, is the third most common in the US. We used a Google Document resume template and Gmail accounts, as some email services, such as Hotmail, could signal a candidate being older.

The treatment and control resumes were identical except for descriptions of a 10-month employment gap leading up to the present. In the treatment resume, this gap was explicitly labeled in the work experience section of the resume. In the control resume, there was no such description, but rather an unexplained gap.

Figure 2: Snapshot of treatment resume


Hannah Williams
hannah.w.ds.241@gmail.com
San Francisco Bay Area

SKILLS

Versatile self-starter with a passion for experimentation, strategy, and automation.
Key skills: Time Series, Predictive Modeling, Regression, A/B Testing, ARIMA, Clustering.
Tech: Python, R, SQL, AWS, Hadoop and MapReduce, Spark, Docker, Kubernetes

EXPERIENCE

Career Break — *Full-time parent*
DEC 2021 - OCT 2022
- Took time off to focus on family

Google — *Data Scientist, Ads Team*
San Francisco Bay Area
SEP 2017 - DEC 2021
- Owned experimentation (A/B testing, switchback testing, etc) and exploratory analysis (Funnel analysis, K-means clustering, etc) roadmap which allowed product team to hyper-focus on growth opportunities
- Designing experiments (power analyses etc.) and conducting thorough post-launch analyses (hypothesis testing, measuring secondary metrics)
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We took great care to avoid inconsistencies between treatment and control applications by creating a document of answers to application questions (see *Appendix 2*). We did not apply to postings that required in-depth written content such as cover letters. All data entry personnel were trained to use this document and monitored via Zoom to ensure compliance.

Consolidated Standards of Reporting Trials (CONSORT) Discussion

We programmatically randomized job listings sourced from Indeed to either treatment or control. The subjects in our experiments were companies and their hiring teams, with whom we made contact by submitting applications.

To facilitate coding outcomes to the appropriate applications, we recorded the company name, recruiter name, email address, and date of response. This enabled us to tie a response to a specific application. Additionally, we collected publicly available data on company size and whether they were public or privately held. Data were stored on a private Google Drive.

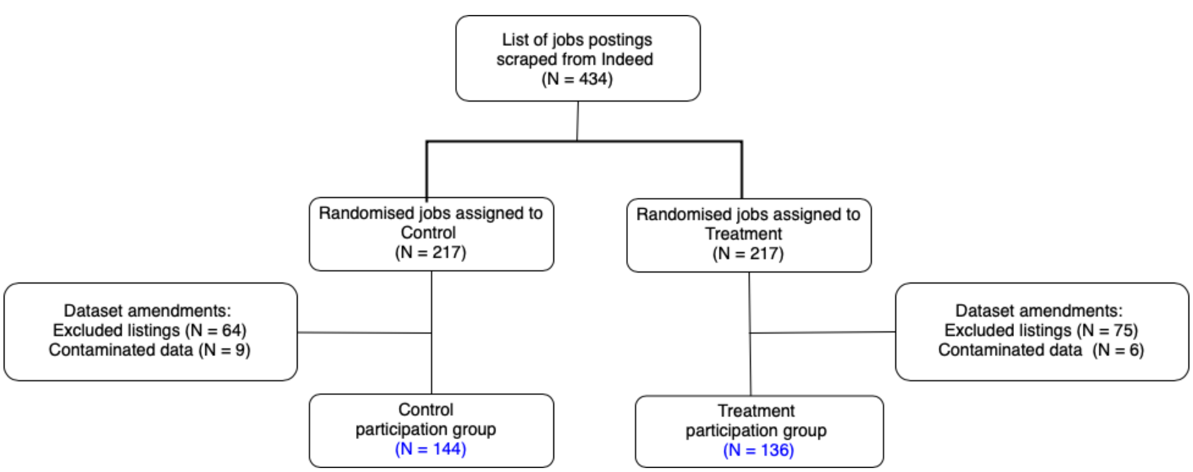
The interaction with companies and their representatives was a direct result of applying to Indeed-sourced jobs. From an ethical viewpoint, we understood that we were using our subjects' time needed to review our fictitious resume and send an outreach. We kept interactions to a minimum; we never responded to hiring teams when asked for an interview. The exception was when they did not identify which listing they represented, in which case we wrote short emails requesting clarification.

We have taken care with the data collected and we will be archiving our fictitious candidates' email accounts and data sheets containing recruiter's information. Further, no identifying features of the hiring teams were used in our modeling (rather, it was only for our own internal tracking of outreaches) and data with identifying features, such as recruiters' names, has not been uploaded to our repo. Subjects information has not been shared outside our team. We will only maintain the raw files used in modeling, without personal information.

Observation Tracking

The figure below shows the observation tracking from start to finish of our experiment. We started with 434 job listings. These were randomly assigned to treatment and control ($N = 217$ each). We excluded 140 listings which required personal essays or government ID, or where the link to submit expired. We removed an additional 14 observations that we deemed contaminated when we realized they received both treatment and control resumes for similar but separate listings. These amendments resulted in 144 control and 136 treatment observations, for a total of 280.

Figure 3: Observation Tracking



Power Calculation

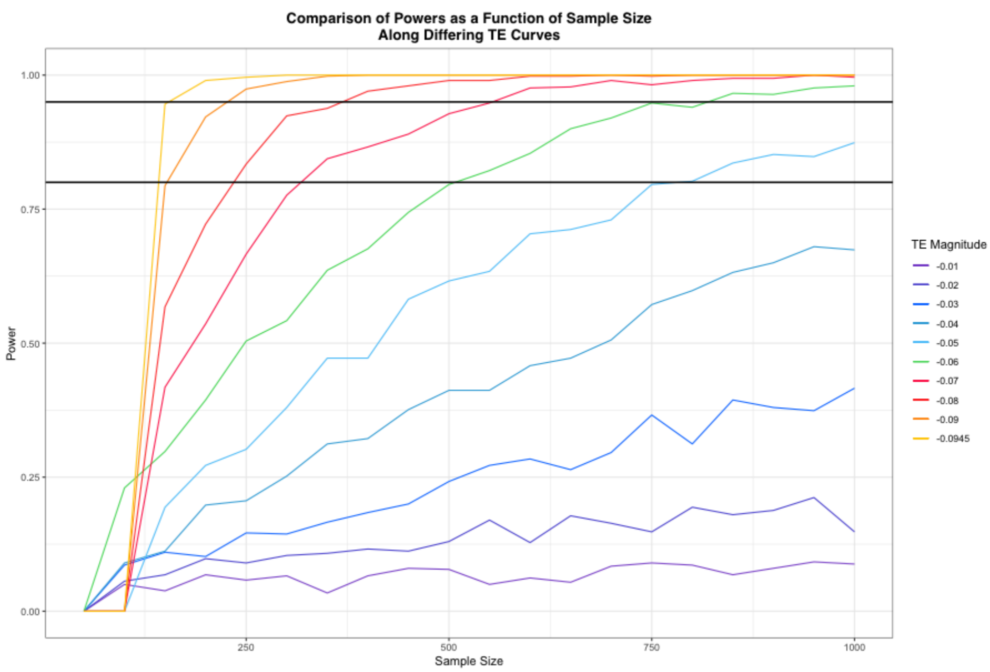
A power analysis was conducted to predict the number of participants required to detect a treatment effect. The α value designated for this power analysis is 0.05, the baseline positive response rate to job applications is 0.0945 (Weisshaar, 2018), and the desired power was 0.8.

Power curves were generated by simulating various treatment effect sizes, and observing what proportion of p-values satisfy the specified alpha at varying sample sizes. The curves were generated by selecting a treatment effect size and plotting the power as a function of sample size. The curves were then used to determine the appropriate sample size for the experiment to be appropriately powered.

To effectively satisfy timeframe and labor constraints, a conventional power of 0.8, and a sample size of approximately 500 job listings, were selected based on the graph outlined in *Figure 3*. This meant that a magnitude of treatment effect bias equaling 0.07 was intended for this experiment. Effectively translating this metric of treatment effect bias to practical experimental doses was a highly qualitative process, and may have impacted results recorded by downstream statistical analysis. Similarly, the desired sample size was not achieved due to reasons detailed in *Observational Tracking*. Therefore, we only expected to be able to detect a potential treatment effect of magnitude 0.08 or greater.

For an in-depth view of our power analysis code, see *https://github.com/eskirton/241_final_project/blob/main/power_analysis_algorithm.Rmd*.

Figure 4: Power Curve



Analysis

Data

Each row of our final data represents a unique job listing, with columns for treatment assignment, job name, company name, company size, public/private status, and outcome. The *outcome* variable was coded 1 for a positive response inviting us to proceed in the application process, and 0 otherwise (both rejections and non-responses were coded 0).

During data collection, we received several messages from recruiters inviting us to interview for opportunities that could not be tied to specific applications in our original dataset. We believe this was the product of recruiters posting jobs on Indeed using the names of companies they represent, but routing applications directly to their inboxes. We recorded four such positive responses for the control resume. To properly assign these outcomes to our dataset, we changed the outcome value from 0 to 1 for four randomly selected control observations.

The *treatment* column indicates whether the application received the resume highlighting a career break to be a full-time parent (treatment == 1) or the resume with an unexplained employment gap of the same duration (`treatment == 0`). Job name, company name, and related date columns were primarily used for organization during data collection and were not used in models.

The two covariate features used in our models were company size and public/private status. The *public* column indicates whether the company is publicly traded (`public == 1`) or privately held (`public == 0`). The *company_size* column is a categorical variable with the groups: *250 or less*, *251 - 1,000*, *1,001 - 10,000*, and *over 10,000*. In order to use our company size variable effectively in models, we coded it as a factor variable and set the smallest group (*250 or less*) as the reference group. *Figure 4* visually depicts how these covariates balance along treatment and control group assignments.

Company Size	Public	Private	Total
250 or less	2	91	93
251 - 1,000	13	31	44
1,001 - 10,000	35	28	63
over 10,000	61	19	80
Total	111	169	280

Models

We created three models.

1. a basic model regressing outcome on treatment
2. one that incorporates company public/private status
3. one that incorporates company size (but not the public/private variable)

We decided against fully nesting these models after exploratory analysis showed public/private status and company size to be highly correlated (i.e. 91 of 93 companies of size 250 or less were private, and 61 of 80 of over 10,000 size were public). *Figure 5* visually depicts this positive correlation.

Results

Table 1: OLS estimates of resume treatment effects

	(Resume treatment)	(+Company status)	(+Company size)
Resume treatment	-0.025	-0.027	-0.030
	(0.046)	(0.046)	(0.046)
Company is publically traded		0.043	
		(0.048)	
Company size: 251-1,000			0.191^{**}
			(0.080)
Company size: 1,001-10,000			0.048
			(0.060)
Company size: over 10,000			0.049
			(0.055)
Constant	0.194^{***}	0.178^{***}	0.142^{***}
	(0.033)	(0.038)	(0.042)
Observations	280	280	280
R^2	0.001	0.004	0.028
Adjusted R^2	-0.003	-0.003	0.013
Residual Std. Error	0.387 (df = 278)	0.387 (df = 277)	0.384 (df = 275)
F Statistic	0.299 (df = 1; 278)	0.558 (df = 2; 277)	1.945 (df = 4; 275)
Note:			*p<0.1; **p<0.05; ***p<0.01

Ultimately, while the treatment coefficients in all models indicate small negative effects, the standard errors are too large to claim statistical significance. We did not see any increase in explanatory power of the models when adding the public or company size variables. The lone statistically significant coefficient in the table seems to indicate that companies of size 251-1,000 may be slightly more likely to respond to applications compared to companies sized 250 or less, however even this is only at the $p < 0.1$ level.

Figure 5: Covariate Count Comparisons Between Treatment and Control

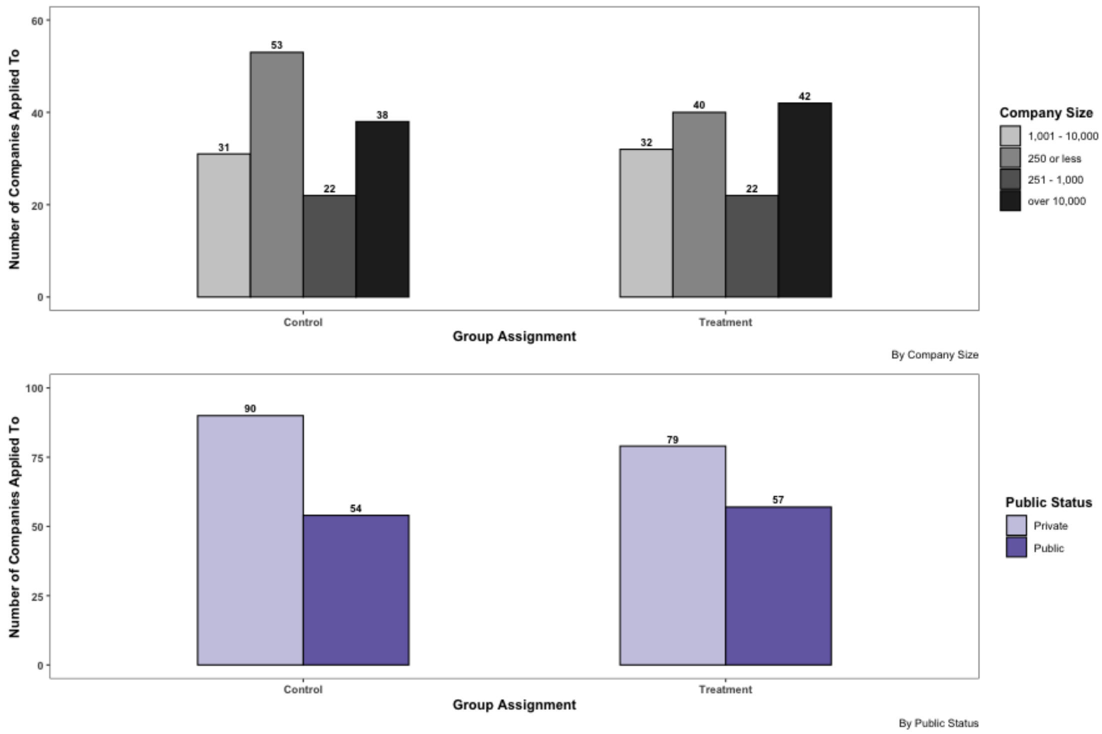
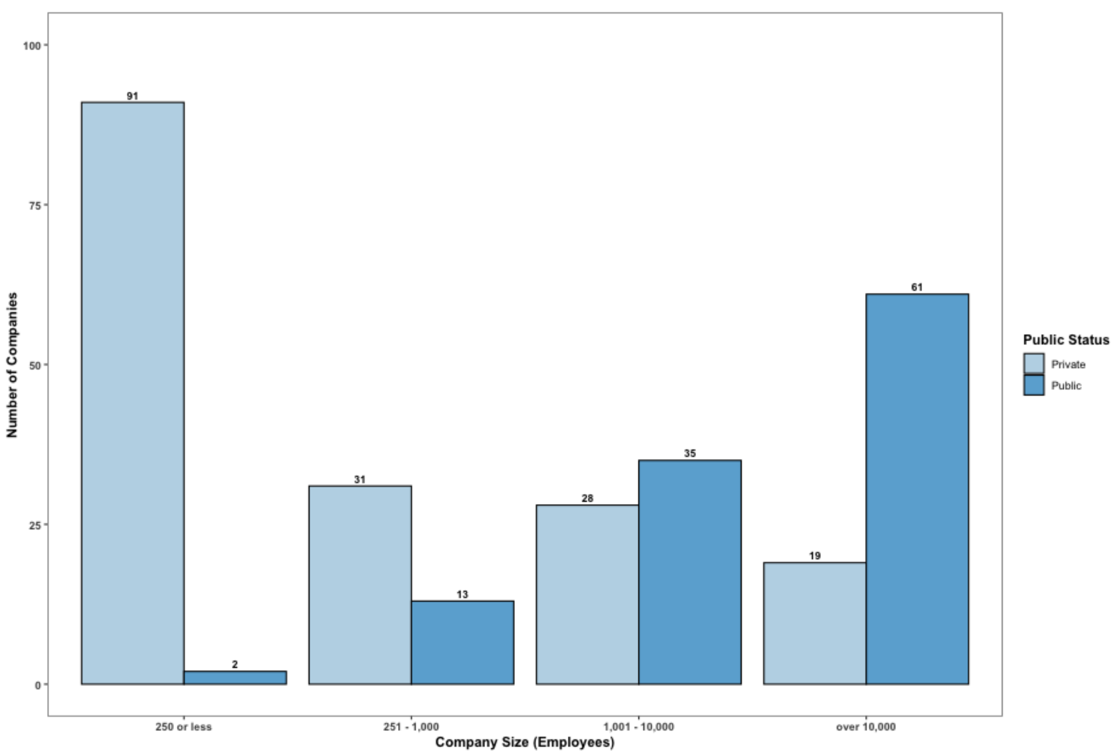


Figure 6: Public Status Counts Per Company Group Size



Conclusion

There was no significant difference (at $\alpha = 0.05$) in interview requests between our test and control conditions. That is, reporting opting-out from employment for child-rearing was not penalized compared to an unexplained employment gap. In particular, our study sought to measure the treatment effect for job-seekers with a Master's degree in Data Science in the San Francisco Bay area as the literature has reported industry and locale-specific differences. Thus our results may differ from another field or city. Our narrow focus limited the number of job applications in our study but our power analysis supports the conclusion that if a motherhood penalty does exists, it's effect is small. Lastly, repeating the study at various points in time would be required to identify whether an larger effect exists in this market under different competitive conditions.

Appendix 1

Control Resume

Hannah Williams

hwill.2241@gmail.com
San Francisco Bay Area

SKILLS

Versatile self-starter with a passion for experimentation, strategy, and automation.
Key skills: Time Series, Predictive Modeling, Regression, A/B Testing, ARIMA, Clustering.
Tech: Python, R, SQL, AWS, Hadoop and MapReduce, Spark, Docker, Kubernetes

EXPERIENCE

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Ernst & Young LLP — *Business Intelligence Analyst*

New York, NY
AUG 2015 - SEP 2017

- Supply chain optimization developing novel mathematical models to achieve maximum performance and $25MM savings for a Fortune 500 client
- Led A/B testing, exploratory data analysis, and dashboarding through R-Shiny for CRM, Landing Page Optimization, and Paid Media acquisition channels for multiple Fortune 500 clients

Goldman Sachs — *Quantitative Analyst*

New York, NY
JUL 2012 - AUG 2015

- Built statistical models, research analytics for devising trading strategies in multi-billion dollar asset management business
- Created and improved risk management and performance monitoring tools for portfolio managers and traders

EDUCATION

UC Berkeley School of Information — *Master of Information & Data Science* | AUG 2013 - MAY 2015 | GPA: 4.0

Key Courses: Machine Learning at Scale, Experiments & Causal Inference

Carnegie Mellon University — *BS Chemical Engineering* | *AUG 2007 - MAY 2012 | GPA: 3.96*

Appendix 1 (continued)

Treatment Resume

Hannah Williams

hannah.w.ds.241@gmail.com
San Francisco Bay Area

SKILLS

Versatile self-starter with a passion for experimentation, strategy, and automation.
Key skills: Time Series, Predictive Modeling, Regression, A/B Testing, ARIMA, Clustering.
Tech: Python, R, SQL, AWS, Hadoop and MapReduce, Spark, Docker, Kubernetes

EXPERIENCE

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Appendix 2

Responses Used in Applications

Demographics:

Gender: Female

Race: Two-or-more races

Veteran: No

LGBTQ+: No

Tell me about yourself? My name is Hannah Williams, and I have worked as a Data Scientist in Google's Advertising Team for four years. My work has primarily centered around developing machine learning algorithms and convolutional neural networks to maximize the effectiveness of advertisements on the platform. To improve the effectiveness of ads, I clustered users into groups based on demographic covariates and search tendencies, and determined how, using techniques like A/B testing, click rates for advertisements differed between treatment and control groups. As a result, Google's advertising department has been able to deploy these machine learning and statistical pipelines at scale, which has allowed Google to more accurately, and precisely, target candidates along various advertising campaigns. As a potential employee of ECCE, I hope to further contribute to ECCE's machine learning endeavors at an equivalent scale, and to likewise integrate with ECCE's community of skilled data professionals.

Tell me about your strengths: Having worked as a Data Scientist for four years on Google's Advertising Team, I have developed a deep understanding of machine learning and research design methodologies. Due to the extensive nature of the machine learning field, I have collaborated with a wide variety of cross-functional teams in order to deliver machine learning products at scale, and have carried data science projects from conception to completion. I excel at working with a wide range of professionals, and in determining how my colleagues can best apply their skills and abilities in completing team objectives.

Where do you see yourself in five years? In five years, my goal is to become a Chief Data Scientist or Chief Intelligence Officer, whose role would be to simultaneously direct institutions towards embracing cutting edge technologies, while also overseeing the creation of stable and effective data pipelines that maximize company revenue and efficiency.

Tell me about a time where you encountered a business challenge? While I was employed at Google, my department was tasked with delivering a report on adaptable-and-targeted advertising algorithms. While many of the C-Suite executives at Google believed that an adaptable-and-targeted advertising pipeline could be deployed within a year's time, the team leads in my department realized that generating a machine learning product that yielded reproducible results required extensive rounds of experimentation with varying degrees of treatment effects and sample sizes. In spite of these limitations, I proposed to my team that we should utilize an agile framework with a clearly defined number of project iterations, and to likewise state our development goals within each phase of delivery. My colleagues and I developed unsupervised learning algorithms that effectively clustered participants along each advertising campaign and performed block randomized experiments that observed treatment effect heterogeneities amongst Google users. The results of these experiments inspired the Advertising Team to move this pipeline out of alpha-phase and into optimization and field application.

What are the most important things you are looking for in your next role Given that my previous experience centered around building scalable machine learning algorithms, my goal is to work in an environment that allows me to both design and implement large scale and autonomous machine learning architectures.

Why are you leaving your current job? Having worked as a Data Scientist for four years, and in IT for ten years, I decided to take a brief hiatus so that I could redefine my career goals, and prioritize more personal endeavors in the meantime.

What are your salary expectations? $150K.

How did you hear about this job? Indeed.

Appendix 2 (continued)

Responses Used in Applications

Why did you apply for this position? ~ Why do you want to work here? o Having researched ECCE's company philosophy and developmental goals, I am enthusiastic about how I can contribute my Data Science expertise towards ECCE's pursuits. My experience in building machine learning algorithms in a research context directly benefits ECCE by improving ECCE's ability to automate data collection, analysis, and feature prediction. With this in mind, I believe that my skills and experience match the requirements listed by this position, and that my approach to Data Science complements ECCE's needs.

What are your weaknesses? I view my work in a very structured and organized way. If I am working on a project, I design a roadmap that works with clear deadlines. While I do understand the periodic need to deviate from project roadmaps, I find it difficult to adapt when those deviations don't consider the bigger picture.

Job Experience Go-Tos: 10 Years: A/B Testing ARIMA ("Autoregressive Integrated Moving Average" Analysis) AWS Clustering Dashboarding Data Pipelines Data Warehousing Data Science Projects Experience Docker ETL / Extract Transform Load Exploratory Data Analysis Funnel Analysis Hadoop HC (High Capacity) Domain Knowledge Hypothesis Testing Kubernetes MapReduce Power Analysis Predictive Modeling Python R Regression SAS Spark/PySpark SQL Statistical Modeling Time Series 4 Years: Business Intelligence (BI) Platforms: R-Shiny Built Architectures: "I have built a CRM, a Landing Page, a Dashboard and Paid Media Acquisition Channels." C, C# "Productionizing (Deploying) Models (At Scale)"

Tell your professional story in a tweet. I have collaborated with a wide variety of cross-functional teams in order to deliver machine learning products at scale, and have carried data science projects from conception to completion.

What is the best or worst piece of professional advice you have received? Best advice: "Never assume your data is without errors – garbage in, garbage out!"

What is your experience with ETL tools or coding? Please explain.

I have significant experience in both architecting ETL/ELT pipelines to support data science platforms (when working in a full-stack capacity) as well as partnering with data engineering teams to help define requirements and test features in the platforms they build to support my work. Almost all of my work has involved coding and I am most comfortable in Python and R, and make heavy use of advanced SQL for scripting and database management.

Appendix 3

Test for Covariate Inbalance

An F-test is used to confirm our randomization was adequate by checking if the covariates unexpectedly predict the treatment assignment.

```
null_mod <- d[ , lm(treatment ~ 1)]
full_mod <- d[ , lm(treatment ~ 1 + public + company_size_factor)]
cov_bal_anova <- anova(full_mod, null_mod, test='F')
cov_bal_anova
```

```
## Analysis of Variance Table
##
## Model 1: treatment ~ 1 + public + company_size_factor
## Model 2: treatment ~ 1
##   Res.Df    RSS Df Sum of Sq     F Pr(>F)
## 1    275 69.491
## 2    279 69.943 -4  -0.45177 0.447 0.7746
```

A probability of 0.7745866 » 0.05, indicating our randomization procedure was successful.

References

1. Waldfogel, Jane. “The effect of children on women’s wages.” American sociological review (1997): 209-217.
2. de Linde Leonard, Megan, and T. D. Stanley. “The wages of mothers’ labor: A meta-regression analysis.” Journal of Marriage and Family 82.5 (2020): 1534-1552.
3. England, Paula, et al. “Do highly paid, highly skilled women experience the largest motherhood penalty?.” American sociological review 81.6 (2016): 1161-1189.
4. Correll, Shelley J., Stephen Benard, and In Paik. “Getting a job: Is there a motherhood penalty?.” American journal of sociology 112.5 (2007): 1297-1338.
5. England, Paula, Andrew Levine, and Emma Mishel. “Progress toward gender equality in the United States has slowed or stalled.” Proceedings of the National Academy of Sciences 117.13 (2020): 6990-6997.
6. Bear, Julia B., and Peter Glick. “Breadwinner bonus and caregiver penalty in workplace rewards for men and women.” Social Psychological and Personality Science 8.7 (2017): 780-788.
7. Weisshaar, Katherine. “From opt out to blocked out: The challenges for labor market re-entry after family-related employment lapses.” American Sociological Review 83.1 (2018): 34-60.
8. Ishizuka, Patrick. “The motherhood penalty in context: Assessing discrimination in a polarized labor market.” Demography 58.4 (2021): 1275-1300.
9. U.S. Bureau of Labor Statistics. https://www.bls.gov/opub/ted/2022/californias-jobless-rate-decreased-2-1-percentage-points-over-the-year-ended-october-2022.htm