Gender Inequality in the Workplace: Hidden Channels of Discrimination

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Abstract

In the last couple of years, gender inequality has once again dominated the news space, this time, with calls for a "she-cession"* and other significant events in the female labor force. However, these sensationalist articles highlight a deeper source of inequality, underscoring systemic issues surrounding gender and motherhood. Our paper examines disparities between male and female incomes through the lens of experience and the number of children, in which we found that employers significantly discounted the value of education for women in the upper levels of income. Furthermore, we cross-examine panel data to utilize the exogenous shock of the GFC in order to gauge company disposition towards gender during times of crisis, where we found an unexpected significant difference between genders, with women being more likely to be employed than men.

https://www.nytimes.com/2020/05/09/us/unemployment-coronavirus-women.html

Contents

1 Introduction

The gender wage gap remains a permanent topic of discussion in the United States, with women still being paid on average less than men. Being so integral in social movements, the issue is often partisan and divisive, with truths deafened in the cacophony of modern media.[1] However, academia has long uncovered that despite characteristic differences in areas like industry, weekly hours worked, and other controlled metrics, a gender gap remains.[2]

As discussed previously in the literature, we delve into the effects of the pay gap on the highest margins of the income distribution. After accounting for lost labor time due to maternal leave, we find that for workers at the top of the wage distribution, firms value women's prior years of full-time job experience less than those of men. However, this discount does not exist for those lower on the distribution. Thus, we hypothesize that firms have a biased view of the ability of women in top leadership positions.

Additionally, using a difference-in-difference analysis, we utilize an exogenous shock to investigate if employers truly view male and female labor as perfect substitutes through which mechanism, employers could internally justify lower wages for women.

2 Literature Review

Since the 1950s push of "59 cents on the dollar," the pay gap has been decreasing in select occupations and industries, in part due to the closing of the gap in education and job selection (Goldin 2014). Progress in the wage gap rose substantially until the 1980s but slowed from the 1980s to the 2010s. Literature on decomposition analysis shows how despite matching characteristics between genders and employment, the gender wage gap is still significant (Korkeamäki 2019).

Papers in the past have isolated the "child penalty" as one of the contributing factors to this gender pay gap (Andresen 2022). We also expand on the causes of the wage gap utilizing the Mincer model used in the classic paper by Blau and Kahn (2017).

Our interest in the effects of more children on earnings coincides with the child penalty identified by Kleven (2019). However, instead of conducting an event study through first birth, we measure the effects of subsequent children on wages, observed through the intermediate channel of the employer's depreciation on experience for female workers. Our quantile analysis adds greater context to the effect of multiple children, clarifying its effects on the upper-income levels of women in the US workforce. Our focus on the US as opposed to the gender wage gap in other countries may prove relevant when compared with other fully developed nations.

1. https://www.pewresearch.org/social-trends/2017/10/18/wide-partisan-gaps-in-u-s-over-how-far-the-country-has-come-on-gender-equality/

Finally, our results relate to the unique disadvantages of higher-income women and contribute to the literature on not only the child penalty of working women but also, more loosely, psychological phenomena like women's recognition of work (Sarsons 2021) and the policy effect of adding more women to board positions (Bertrand 2019).

3 Data

We utilize the PSID dataset used in "The Gender Wage Gap: Extent, Trends, and Sources." (Blau and Kahn 2017) for our analysis. It is a repeated cross-sectional dataset. The authors have restricted the dataset to 25-64 year olds who are employed. The dataset contains variables on income, education, work experience (part-time and full-time), labor status, marital status, race, geography, and industry from 1981 to 2011. There are a total of 6 years and 33,398 observations. Each observation is a member of a household, sampled annually before 1999, and biennially after 1999.

To investigate changes in the likelihood of employment, we also chose to pull data from IPUMS CPS. The dataset is in panel format, containing 2 observations for the same person from 2008 and 2009. This dataset contains household covariates such as number of children and household income, demographic variables, and other variables pertaining to labor status such as employment and wages. We keep those who are still in the labor force in both years (working or looking for work) and drop observations from the army. Then, we distinguish government jobs by the worker class variable and recode the industries by sectors IT, Finance, Real Estate, Tech, and Admin/Management.

4 Empirical Methods

4.1 Quantile Regression Model

We initially begin by hypothesizing that if a wage gap exists between women and men, firms must discount female wages by some factor, i.e:

$$W^m = W$$
$$W^f = \gamma * W,\ 0 < \gamma < 1$$

Where W^m and W^f are the wages set for women and men respectively, W is the standard wage, and γ is the factor by which firms discount the value of women's labor, after accounting for which, men's and women's labor become perfect substitutes. Please note that this model takes inspiration from the one presented in (Bharadwaj et al, 2013). If the pay gap does not exist, γ should be equal to one. If it does, γ will be less than 1. γ might depend on factors such as how experience and amount of kids are valued across genders.

To estimate whether γ is 1 or not, we use the Mincer Earnings Function Mincer, J. (1958) as the basis of our prediction model for wages. The basic model is:

$$ln(wages) = \rho * YrsSchool + \beta_0 * YrsExp + \beta_1 * YrsExp^2$$

We recognize that due to motherhood and time constraints, some women may opt to take part-time jobs during their career, which may be weighed differently by employers, to account for this, we separate years of full-time work and part-time work. To find whether differences between how experience is considered differently for men and women exist, we introduce a dummy and interaction term for years of full-time work. To isolate and observe if the impacts of having children on wages are different across genders, introduce an interaction term for gender and the number of kids. We control for geographic, family, and labor-related covariates. We also include time-fixed effects through dummy variables for years to reduce the impact of macroeconomic and social trends.

$$\begin{gathered} ln(HrlyWages) = \rho * YrsSchool + \beta_0 * YrsFullTime \\ + \beta_1 * YrsPartTime + \beta_2 * YrsFullTime^2 \\ + \gamma_0(Female * YrsFullTime) + \gamma_1(Female * YrsFullTime^2) \\ + \theta(Female * Children) + X_{i,t} + \mu_t \end{gathered}$$

As the literature suggests that progress on closing the pay gap has slowed in the past decades, we limit our sample to years after 2000, thus we include 2007, 2009, and 2011, yielding a sample size of 17,727 observations, with each year having a similar amount of observations. The literature also suggests that the pay gap only exists in higher income distributions. Thus, we run this model for each 5th percentile of the log(realhourlywage) to see changes in our coefficients of interest. We use the PSID dataset from (Blau and Kahn, 2017) to estimate this, as it contains our desired experience variables.

4.2 Difference-in-Differences Model

In order to identify corporations' different attitudes towards the employment of women, we utilize the exogenous shock of the GFC recession to examine whether firms value male labor more. The reasoning being that if firms do not consider male and female labor as perfect substitutes, and have discriminatory views favoring men, female workers will experience an employment shock higher than men.

To act as the control group, we selected government workers, who experienced fewer layoffs than private workers. Our treatment group is private workers, and the treatment period is the year 2009. The surveys we obtain are collected in March of each year, thus the difference in the two periods align with the worst of the layoffs experienced in the GFC. We propose the model:

$$P(employed) = \alpha + \beta_0 * Private_i + \beta_1 * Female_i + \beta_2 * PostGFC_t$$
$$+ \beta_2(Private_i * Female_i) + \beta_4(Private_i * PostGFC_t) + \beta_5(Female_i * PostGFC_t)$$
$$+ \gamma(Private_i * Female_i * PostGFC_t) + X_{i,t}$$

Where γ is our parameter of interest that measures the impact on private female employees, $X_{i,t}$ are demographic, household, and labor-related controls. The estimates are obtained using a linear probability model.

Our proposed model is different from a traditional DiD, as it contains an interaction term of 3 variables. Our reasoning for differentiation between government and private workers is that government workers were more insulated from layoffs during the crisis. If a female private worker is less likely than her male counterpart to be employed in the post-treatment period, this will suggest that firms have an implicit preference for men over women, as seen from their behavior during a period when money has become unexpectedly tight.

To partially check our parallel trends assumption, we see that government and private workers closely tracked each other before 2008 (Figure 3). From this figure, we also see government employment remaining stable while private employment falls, backing our reasoning.

We acknowledge that there may be some spillover effect between the two sample years as a result of the heightened job security when working for the government, which may underestimate the difference between private and public workers.

5 Results and Conclusion

5.1 Discussion of Findings

From our quantile regression analysis (Table 1), we found that firms discount the previous full-time work experience of women more than they do that of men, only at the highest percentiles of the income distribution (Figure 1). We also obtain a significant coefficient around the 40th percentile. This difference exists but is very small, becoming at most a 1% discount at its higher magnitude. This finding expands on previous research by detailing the mechanism through which firms discount female wages. It appears that female experience, one at high-level positions, by a significant margin (-1.2%) holds less importance than male experience for firms. In this paper, we don't analyze why firms make this differentiation. It could be that firms are simply discriminating at higher levels (glass ceiling effect), or another unobserved wage mechanism exists. Analyzing the effects of recent DEI policies pushing for increased representation in board-level positions would likely shine some light on this topic. However, given our limited time, we cannot delve into this policy.

We also find that firms discount female wages by around 4-7% more than men on the median for each additional child below the 50th percentile (Figure 2). This follows from previous research that suggested female workers suffer wage penalties for bearing children. What is more interesting is that the magnitude of this discount declines for females on higher income quantiles to around 1.2%, although remaining significant. It is possible that higher-earning women are able to bargain better to offset the motherhood penalty. We did not analyze why higher-earning women are less affected by their childbearing status. However, there is likely great potential for future researchers to delve further into this topic.

Our difference in differences analysis of the GFC on the likelihood of female employment did yield significant results (Table 2). However, to the contrary of our initial hypothesis. Females were more likely to be employed after the GFC than men. We ran this regression with limited samples of higher-earning workers and found a similar significant result for the top 15% of workers. Ostensibly, it appears that firms did, in fact, view female labor as a perfect substitute (after accounting for the wage discount discussed before) for male labor, and did not have a propensity to lay off women more than men. However, an alternative explanation may be that companies desired cheaper labor, and as a result, cut loose their more sizable male wages. Combined with our previous analysis, this shows that as long as firms pay some women employees less, they have no problem employing them. Again, this points to the possible effect of discrimination still implicit in firm hiring behavior. A more complex economic model that takes into account discrimination could shine more light on this issue.

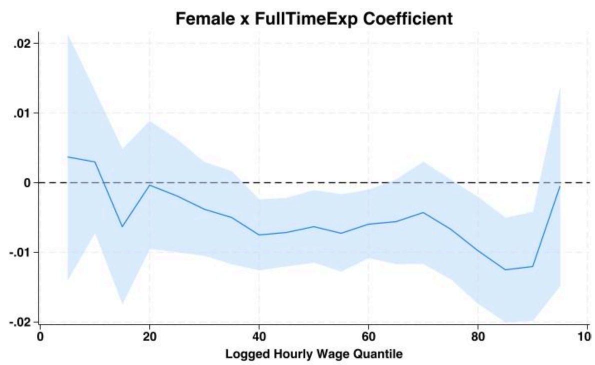
5.2 Possible Robustness Checks

If we had more time to implement our model, we would have included sector and occupation fixed effects in our quantile analysis to account for heterogeneity by these factors. This could also be done by running separate regressions by sector, however, due to computational limitations of quantile regression and accounting for our time, we could not properly implement these.

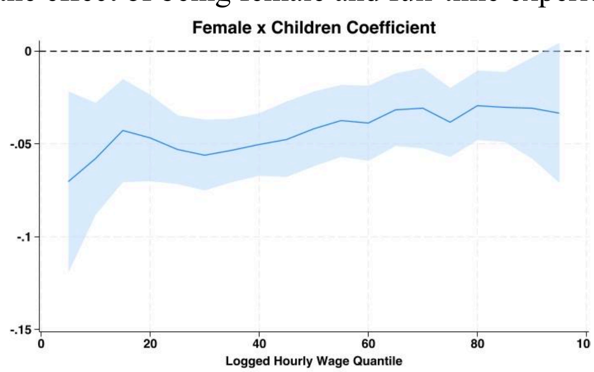
For our DiD analysis, we could have conducted a placebo test, using a period before or after our treatment time (the GFC) to check our parallel trend assumptions (Figure 3). We could also have utilized an Event Study approach, including leads and lags to the GFC, however, due to the nature of IPUMS CPS longitudinal data, which only tracks people over a one-year period (2 observations), this was unfeasible to implement. We could have also utilized logit or probit regressions instead of an LPM to verify our result further, however, due to the nature of the data we were unable to run these computations in Stata.

6 Appendix

6.1 Quantile Regression Graphs by Coefficient



(Figure 1: Measuring the effect of being female and full-time experience across quantiles)



(Figure 2: Measuring the effect of being female and the amount of children across quantiles)

6.2 Quantile Regression Coefficients

	Q05	Q10	Q25	Q50	Q75	Q90
Female × Children	-0.070**	-0.058***	-0.053***	-0.042***	-0.038***	-0.031**
	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Female × Experience	0.003	0.003	-0.002	-0.006**	-0.007*	-0.012***
	(0.686)	(0.569)	(0.648)	(0.018)	(0.066)	(0.003)
R-squared	0.12	0.14	0.18	0.22	0.25	0.29

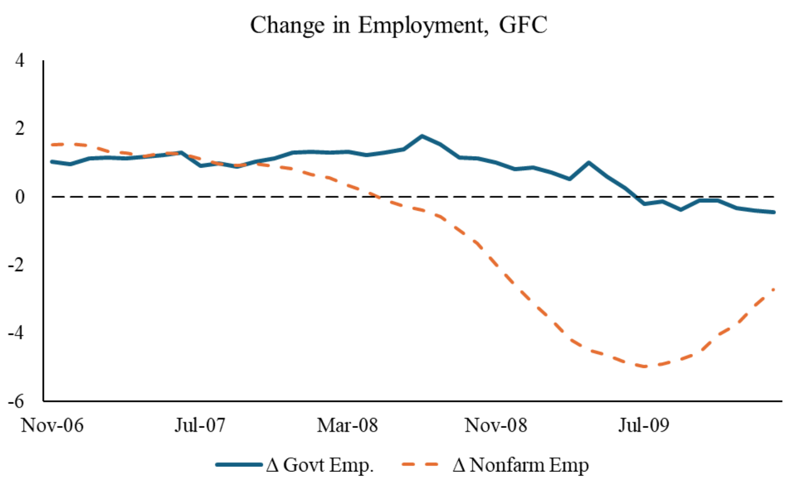
(Table 1: Interaction terms for the log(realhrwage) regression across different quantiles)

6.3 DiD Regression Coefficients

	All Obs	Top 45% Earners	Top 15% Earners
Posttreat × Privwkr × Female	0.0171**	0.0153	0.0368**
	(0.028)	(0.094)	(0.016)
R-squared	0.5631	0.0489	0.0536
Observations	59,128	26,112	8,617

(Table 2: Interaction terms for the likelihood of employment regression across different samples)

6.4 DiD Parallel Trends Assumption



(Figure 3: Parallel Trends Assumption Check for DiD Model, from FRED)

A Note on Time

Due to logistical constraints not discussed in this paper, we began our work after the SuperBowl showing on Sunday. In total, we spent 8 hours on this task.

7 References

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