The Effect of Remote Job Opportunities on Gender Gap

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Abstract

The COVID-19 pandemic promoted the adoption of working from home, and this arrangement has remained a popular choice for many people wanting greater autonomy and flexibility in their job. This transition has had different effects on men and women, with research indicating that remote employment has especially helped women enter the job market while still managing domestic duties. Although the employment gap between genders has lessened, major wage gaps persist, showing persistent inequalities. Occupational heterogeneity is a significant contributor to these inequalities, as the impact of remote work on gender gaps in employment and pay varied across industries. To analyze these dynamics, this study employs a split-sample analysis to examine how remote work arrangements affect gender disparity across several occupational categories. By investigating various occupations, the study hopes to get a better understanding of the complicated link between remote work, gender inequalities in employment, and earning gap, providing light on the varied ways in which these factors interact.

Keywords: remote work, gender economics, gender wage gap, gender employment gap, flexibility stigma, proximity bias

JEL Codes: J16, J31, J44, J70, J81, J88, M54

1 Introduction

The COVID-19 epidemic has dramatically altered the nature of work, notably with the growing use of remote work (RW). RW, which was previously optional, part-time, or sporadic, became crucial during the pandemic as a way to stop the virus's spread and lessen company interruptions. Although not a new concept, remote work, sometimes known as working-from-home (WFH), has attained unexpected popularity. According to the 2010 U.S. Census, roughly 10% of the workforce engaged in remote work at least once each week, with 5% working entirely from home. However, between 2019 and 2021, the percentage of home-based workers more than quadrupled, from 5.7% (about 9 million workers) to 17.9% (around 28 million workers).

At the same time, a large body of research has looked into the gender wage gap in the job market. While employers show less prejudice against women during hiring, women still receive lower earnings than males in comparable occupations (Goldin and Rouse (2000); Kuhn and Shen (2013)). According to the Institute for Women's Policy Research, in 2015, women earned 20% less than males in the same roles (Institute for Women's Policy Research (2016)). Despite being out of date, the Census Bureau's 2007 data shows a female-to-male earnings ratio of 0.805 (Institute for Women's Policy Research (2017)). This ongoing pay inequality is difficult to completely explain, as old explanations—such as gender disparities in career choices and needs for flexibility—seem less applicable in a period of rising RW options.

While remote employment provides flexibility and other benefits, it also poses unique problems, especially for women. According to studies, the COVID-19 pandemic had a greater impact on women than men, worsening their work outcomes (Tetzlaff et al. (2022); Field et al. (2022, October)). This unequal impact highlights how RW benefits and difficulties vary by gender (Fialho (2022); Field et al. (2022, October)). The research describes numerous mechanisms by which RW impacts job decisions, as well as the consequences for the

gender wage difference. Key channels include proximity bias, flexibility needs and associated stigma, gender-specific skill sets, discrimination, vertical segregation and promotion bias, and entrenched social norms (Barrero et al. (2021); Bellmann and Hübler (2021); Federici et al. (2021); Lewandowski et al. (2022)).

In this study, I utilize a split-sample analysis to examine the effect of remote work on gender differences in employment and pay across several occupational categories. This approach accounts for significant heterogeneity across occupations, which arises from gendered differences in occupational preferences, educational background, and demographic characteristics. According to Kunze (2005), differences in occupational qualifications account for about 50% of the raw entry wage gap, whereas Marini and Fan (1997) found that worker characteristics, such as occupational aspirations, job-related skills, and credentials, account for about 30% of the gender wage gap. Therefore, the use of split sample analysis has several advantages, conditioning on these may also help to reduce unobserved heterogeneity problems (Kunze (2005), Wood et al. (1993)).

2 Literature Review

This literature review looks at the gender employment and pay gap, with an emphasis on the consequences of COVID-19 and the mechanisms that contribute to these discrepancies. It specifically investigates major channels found in the research that impact the gender gap, with a focus on flexibility needs and the stigma associated with flexibility.

Flexibility Needs and Stigma:

One of the most discussed channels is the flexibility that remote work offers and how it impacts gender disparities. Data from Eurostat (2019) demonstrate considerable variations in employment patterns between men and women, especially when children are involved.

For example, whereas 85% of childless women aged 25-49 were working, equivalent to 87% of childless males in the same age group, the employment rate for mothers of young children (under age six) was just 70%, compared to 95% for fathers. Furthermore, just 14% of childless women worked part-time, but the number increased to 54% for moms with young children (Chung (2024)). Due to the incompatibility of these expectations with caregiving obligations, women are especially prone to exit the labor market while working in demanding jobs that need long hours and high work dedication (Cha and Weeden (2014)).

According to research, people prefer working from home because of the freedom it offers. For example, Aksoy et al. (2022) discovered that working from home saves time and money, gives greater personal freedom, and is so appreciated that 26% of participants in their survey where they claimed they would quit their employment if WFH rights were lost. According to He et al. (2021), job searchers place a high value on time and location flexibility, and many are ready to pay for it. Beyond these preferences, Bloom, Liang, et al. (2015) observed a 13% boost in productivity related with remote work, mostly owing to fewer disturbances like transportation and breaks. However, they also noted a decline in promotion opportunities for remote workers.

However, the autonomy provided by working from home does not benefit both men and women equally. According to Miriam Marcén and Marina Morales (2024), women are 4 percentage points more likely than males to work from home, and they spend 4.3 percentage points more time on remote work compared to total working hours. The gender discrepancy in reporting WFH activities increased by 7 percentage points during the pandemic, double the pre-pandemic gap. This is consistent with the results of Wiswall and Zafar (2018) and Vij et al. (2023), who discovered that women prioritize job flexibility and stability more strongly than men, with female workers valuing remote work 28% more than their male counterparts (Vij et al. (2023)).

The Role of Gender Norms and Caregiving Responsibilities:

The persistence of established gender roles contributes to disparities in remote work choices

and utilization. Women, particularly mothers, prefer remote work because it allows them to balance caregiving responsibilities (Chung, Seo, et al. (2020); Chung and Van der Lippe (2020)). Due to their continued role as main caretakers (Trappe et al. (2015)), women tend to shy away from demanding "greedy jobs" and instead choose family-friendly positions with shorter commutes and WFH options (Gálvez et al. (2021); M. Marcén and M. Morales (2021)). Flexible work alternatives, such as remote work, enable women maintain employment and access higher-paying occupations while managing home obligations (Chung and Van der Horst (2018)). Dual-earner couples who want to be physically colocated (the "two-body problem") are another situation where women, even those without small children, may desire flexible work options like remote employment.According to Hsu and Tambe (2024) and Benson (2014), women are often segregated into geographically dispersed jobs, particularly in specialized science and engineering fields, which may impact household relocation decisions.

Flexibility Stigma and Wage Penalties:

While remote work lowers job barriers for women, it may also aggravate earnings disparities. Flexibility stigma, the belief that flexible workers are less dedicated or productive, results in unfavorable career outcomes, such as restricted promotions and reduced income growth (Chung (2020)). According to a large-scale UK poll (Chung (2020)), around one-third of employees think flexible work is regarded negatively by colleagues and bosses. De Fraja et al. (2024) discovered that remote workers faced slower post-pandemic pay growth, with a wage penalty ranging from 2-7%, compared to non-distant workers. They conclude that the benefits of working from home, amounting to around 4% of overall wages, are countered by these penalties. Gender disparities deepen this tendency, with women ready to forgo up to 10% of their salaries for remote opportunities, while men are much less willing (Díaz Escobar et al. (2024); Vij et al. (2023)). Intersectional disparities also influence the salary penalty associated with distant labor. Kouki and Sauer (2022) discovered that the pay penalty for WFH is significant and disproportionately affects Black women compared to White women.

Black women saw an 18% loss in mean hourly pay when working from home, compared to an 8% decrease for white women.

Proximity and Promotion Bias:

While time flexibility is valued broadly across the workforce, it holds disproportionate importance for women, especially those managing family responsibilities (Barbulescu and Bidwell (2013), Mas and Pallais (2017), Aksoy et al. (2022)). However, concerns about the potential career implications of remote work can deter even those who highly value its flexibility. In a study of call center employees before and after the COVID-19 shutdown, Emanuel and Harrington (2024) found that more productive workers were reluctant to adopt remote work due to lower promotion rates, echoing earlier findings from Bloom, Liang, et al. (2015). Additionally, Vij et al. (2023) revealed that concerns about strained relationships with colleagues and supervisors, as well as diminished opportunities for career advancement, often underlie skepticism towards remote work. These findings suggest that remote work-related biases go beyond the general "flexibility stigma," focusing instead on a comparison between remote and in-office coworkers.

One prominent form of bias in this context is proximity bias, which occurs when managers favor employees who are physically present in the office over remote workers. This bias involves evaluating employees based on their visibility rather than their performance or outcomes (Cristea and Leonardi (2019), Review (2022, October)). Those who can actively display their work and interact directly with managers are often perceived as more engaged, competent, and deserving of promotions (Thompson et al. (1999)). Bloom, Han, and Liang (2022) illustrated this in a field experiment, where workers opting for remote arrangements were 8.5

Gender disparities exacerbate proximity bias. For example, in hybrid work settings, men are more likely to work from the office than women, giving men an advantage in visibility and networking opportunities (Review (2020, July)). Kouki and Sauer (2022) demonstrated that proximity bias is more pronounced for women, with female remote workers more likely to

experience unfavorable task reassignments and diminished social interactions. Black women, in particular, face disproportionately adverse outcomes, including significant wage penalties and reduced career advancement opportunities. For younger women, proximity bias manifests in reduced access to mentoring opportunities, impeding their professional development (Aksoy et al. (2022)). Furthermore, remote work limits exposure to informal office dynamics and reduces coaching opportunities from supervisors, which slows career progression and human capital development (Golden and Eddleston (2020), Gibbs et al. (2021)).

Feedback quality also suffers in remote settings, particularly for women. In a study of female software engineers at a Fortune 500 firm, Emanuel, Harrington, and Pallais (2023) found that on-site work provided better-quality feedback and reduced the likelihood of employee turnover. Similarly, Hsu and Tambe (2024) highlighted that women working remotely receive less constructive feedback, which may hinder their career growth. These findings suggest that while remote work offers flexibility, it may inadvertently reinforce barriers to women's career advancement.

Skill Differences The effectiveness of remote work is also shaped by disparities in digital skills and the challenges of adapting to technology. Women, more than men, are prone to experiencing technostress—a condition caused by the strain of managing digital tools, multitasking, and constant connectivity (La Torre et al. (2020)). This stress can stem from frequent system upgrades, overwhelming information, and the need for continuous relearning, leading to job insecurity and performance issues.

In remote work environments, women report higher levels of technostress compared to their male counterparts (Spagnoli et al. (2020)). Digital literacy plays a critical role in shaping attitudes toward remote work. Xiong et al. (2023) showed that internet skills significantly influence the likelihood of embracing remote work, with the effect being more pronounced for women. For men, an increase in internet skills from level 1 to level 5 raised the probability of accepting remote work by approximately 10%. For women, the same increase doubled the likelihood, reaching about 20%. This suggests that while enhancing digital competencies can

empower women in remote work environments, the existing skill gap may exacerbate gender disparities in remote work adoption and outcomes.

3 Data and Methodology

3.1 Data and Summary Statistics

I use IPUMS ACS data from 2017 to 2023, filtered by age (16-65). Individuals working in agriculture and the military are excluded from the employment gap analysis. For the wage gap analysis, I also excluded unemployed and self-employed persons because they do not have a wage.For the employment gap analysis, working from home variable is the dependent variable where it is constructed from question about usual medium of transport which has answer option of working from home. The annual wage is the dependent variable for the wage gap analysis. In order to do split sample analysis, I split the data into 11 segments using two variables that characterize various types of occupations. The first variable is a measure of each gender's share in a given occupation, which is used to establish three primary groups. The implementation is as follows: the occupation is classified male dominated if the share of males is greater than 70%, and female dominated if the share is over 70%, while all other occupations are considered non-dominated. The methodology ensures that categories are consistent across time and is widely used in the gender economics literature (Marina Morales and Miriam Marcén (2024)). The second measure that is used to split the data into different samples is share of remote workers in each occupation, and it is divided into two main segments: highly remote, and highly office jobs. The threshold used in determining if occupation is highly remote or office is the mean of share of remote workers in 24 broad

categories of occupation that is based on IPUMS ACS categories. The sorting of occupations into these two groups is consistent with the literature. Dingel (2020) developed an index for each occupation category of IPUMS ACS, measuring the proportion of occupations that can be done at home. With an exception of " Education, Training, and Library Occupations", for all occupations, the index measure and actual share of remote workers match with high accuracy. The data is additionally split using the interaction of two factors, and the mixed segments are as follows: Male Dominated and High Remote, Male Dominated and High Office, Non-Dominated and High Remote, Non-Dominated and High Office, Female Dominated and High Remote, and Female Dominated and High Office.

Table 1: Summary Statistics by Sample Groups (1)

	General Sample	Male Dominated	Female Dominated	Non Dominated	Highly Remote	Highly Office
Mean Age	41.8	42	42.2	41.15	41.9	41.6
Gender (%)						
Male	49.97	82.54	24.48	48.41	57.08	42.48
Female	50.03	17.46	75.52	51.59	42.92	57.52
Race (%)						
White	72.85	71.58	73.07	73.69	73.9	71.71
Black	8.8	8.72	9.94	7.71	8.29	9.34
Asian	6.02	5.68	6.07	6.24	6.95	5.02
Other	12.33	14.02	10.92	12.36	10.86	13.93
Nationality						
Hispanic (%)	15.21	17.73	13.19	15.13	12.99	17.59
Family(%)						
Married	53.24	53.91	54.32	51.55	53.73	52.71
Child Under 5	11.88	12.5	11.74	11.48	11.45	12.33
Parents at Home	13.95	13.63	13.63	14.56	13.21	14.75
Education (%)						
College Graduate	37.22	21.17	44.66	43.12	45.67	28.1
Work Stats						
Usual Hours Worked	40.1	42.3	38.2	40.1	40.2	39.9
Work from Home (%)	8.23	6	7.41	10.97	12.62	3.54
Hourly Wage	24.5	24.8	23.4	25.5	25.97	23.09
Citizenship (%)						
Naturalized Citizen	7.88	7.9	8.09	7.65	7.76	8
Not Citizen	6.28	8.59	4.2	6.44	4.85	7.8
Citizen by Birth	85.84	83.51	87.71	85.91	87.39	84.2
Observations	5765925	1703876	2053172	2008877	2980780	2785145

Note: Summary statistics are calculated based on the full dataset. Categories include demographic, wage, and work characteristics for each group. Observations are total counts for each group.

The split sample study demonstrates how variation between occupations influences the effect of working from home on the gender gap. The summary statistics tables 1 and 2 reveal differences in demographic and work schedule patterns across the samples. Male dominated and highly remote group is relatively young, and highly educated, with a substantial college graduation rate (69.45%). They have the highest hourly salary ($34.70) and work the most hours (42.2 per week), with a notable work-from-home rate (21.85%).These distinctions are most likely driven by fields like technology and engineering, where remote work is viable and

male representation is typically strong. The lower age represents early-career professionals' adaptation to remote settings, but higher earnings correspond to the demand for specialized abilities. The high educational attainment further aligns with the technical nature of their roles, which require advanced qualifications. In contrast, the male-dominated office category has the largest male representation (84.36%) and an older average age (42.4 years). Despite working long hours (42.3 per week), they receive comparatively low pay ($22.69) and just 10.38% of them graduate from college. This category has the lowest work-from-home percentage (2.49%), with a considerable share of Hispanic workers (19.71%). These personnel are most likely concentrated in businesses that need physical presence, such as construction, manufacturing, and logistics. Low pay and education levels suggest that many of these jobs involve physical labor or vocational skills rather than graduate degrees.The older age reflects a longer stay in positions that prioritize experience over specialized education.

Table 2: Summary Statistics by Sample Groups (2)

	Male Dominated		Female Dominated		Non-Dominated	
	High Remote	**High Office**	**High Remote**	**High Office**	**High Remote**	**High Office**
Mean Age	40.19	42.4	42.6	41.8	41.79	38.66
Gender Composition						
Male (%)	74.31	84.36	27.42	21.28	47.24	52.97
Female (%)	25.69	15.64	72.58	78.72	52.76	47.03
Race (%)						
White	70.96	71.72	71.17	75.14	76.3	63.44
Black	5.67	9.39	10.86	8.93	7.08	10.18
Asian	14.83	3.66	5.6	6.58	6.33	5.9
Other	8.54	15.23	12.37	9.35	10.29	20.48
Nationality						
Hispanic	8.81	19.71	15.37	10.81	12.2	26.64
Family (%)						
Married	56.99	53.23	50.2	58.81	55.46	36.2
Child Under 5	13.77	12.22	9.72	13.95	12.16	8.81
Parents at Home	9.65	14.52	15.87	11.18	12.11	24.16
Education (%)						
College Graduate	69.45	10.38	29.49	61.24	51.78	9.25
Work Schedule						
Usual Hours Worked	42.16	42.35	37.62	38.9	41.63	34.11
Work from Home (%)	21.85	2.49	9.17	5.49	13.14	2.44
Hourly Wage	34.7	22.69	20.9	26	27.65	17.25
Citizenship (%)						
Naturalized Citizen	10.32	7.36	7.8	8.39	7.25	9.21
Not Citizen	8.67	8.57	4.26	4.13	4.51	14
Citizen by Birth	81.01	84.07	87.94	87.48	88.24	76.79
Observations	308740	1395136	1071141	982031	1600899	407978

Note: Summary statistics for different sample groups categorized by gender dominance and office/remote work settings. Observations are reported in millions; sample sizes represent total counts.

Individuals in female dominated and highly remote subgroup are moderately educated, with a college graduation rate of 29.49% with one of the lowest earnings ($20.90) and an older average age (42.6 years). They work fewer hours (38.2 a week) and have an average work-from-home rate (9.17%). These patterns point to professions where remote work opportunities are expanding, such customer service, administrative assistance, and education. The lower salaries are likely due to a concentration in sectors with weak bargaining strength or part-

time positions, whereas the older age group corresponds to a workforce maintaining caregiver responsibilities. The office counterpart of female-dominated group has the highest female representation (78.72%) and has a little lower mean age (41.8) than their remote equivalents. A substantial number of people (61.24%) are college graduates who work 38.9 hours a week at an hourly wage of about $26. Only 5.49 percent of respondents report working from home. The educational background of female-dominated high-office and high-remote groups differs significantly. A significant 61.24% of women in high-office jobs had a college degree, compared to just 29.49% of women in high-remote jobs. Higher educated women appear to value earnings more than freedom. Even with high levels of education, moderate level of compensation highlights the ongoing female pay disparity in workplace settings. Professional and knowledge-based occupations including management, business operations, finance, science, law, the arts, and sales make up the majority of jobs in non-dominated and highly remote category. The comparatively large percentage of college graduates (51.78%) indicates that these positions usually call for specialized skills and greater educational attainment. Given the qualifications and tasks of these occupations, the group's hourly compensation ($27.65) is above average.The gender distribution of this group is well balanced, with 52.76% females and 47.24% males. Because their jobs are remote-friendly, the percentage of people who work from home (13.14%) is significantly larger than that of the other categories. On the other hand, the youngest group (38.66 years), with the lowest educational attainment (9.25%) and the lowest incomes ($17.25), are the highly office counterparts of non-dominated occupations. They have the lowest marriage rate (36.2%), the fewest children under five (8.81%), and a very low work-from-home percentage (2.44%). With notable participation of Hispanic (26.64%) and "Other" racial groups (20.48%), this grouping also exhibits the highest level of diversity. According to the characteristics, the majority of these workers are young individuals starting their careers in low-skilled occupations like retail, hotel, or food services. The idea of a temporary, inexperienced labor is supported by the absence of marriage and family obligations. The diversity illustrates how these positions are open to people from

a range of backgrounds, including those with little access to higher education. Compared to other categories, the largest percentage of non-citizens (14%) and a sizable amount of naturalized citizens (9.21%) indicate that these jobs are also more accessible to immigrant workers because they have less educational or skill barriers as well as fewer requirements for licensing.

3.2 Model Specification

I rely on probit regression for the employment gap analysis, with working from home as the dependent variable and female dummy and its interaction with post-COVID dummy as the primary independent variables. Individual and family characteristics, occupation effects, and dummy variables that represent post-COVID and during-COVID periods are among the other covariates. Additionally, a female dummy is used to interact with other independent variables in order to investigate the impact of gender in combination with variation across various individual and family factors. In analysis of wage gap, the dependent variable is hourly wage and the main independent variables are dummy variable for being female, dummy indicating if individuals work from home, and their interaction. I also interact female dummy with different demographic variables to see if effect of specific demographic characteristic on working from home is different for men and women.

For the wage gap analysis, I aim to estimate the causal effect of working from home on wage gap, accounting for the potential endogeneity of the treatment variable, working from home. The decision to work from home is not random; individuals self-select into remote work, which introduces potential biases if unaccounted for. To address this, I employ a Heckman-style selection model, which is designed to correct for sample selection bias when the treatment variable is endogenous (Heckman (1979), Vella (1998), Moffitt (2005)).

The key challenge in modeling the effect of working from home on wage gap arises from the fact that individuals' decisions to work remotely may be correlated with unobserved characteristics that also affect their wage outcomes. Specifically, factors such as occupation

and personal need for flexibility may influence both the likelihood of choosing to work from home and the wage level. Occupation is an important determinant (Alba and Farkas (1999)), as some occupations are more conducive to remote work than others, while individuals with a higher need for flexibility, such as those with larger families or women, are more likely to work from home. Since occupation variable is observed, and flexibility need is not observed directly, I create specific index which is a proxy for the demand for flexibility, which I will refer to as the Flexibility Demand Index (FDI) from now on. I create this index by integrating the average age of the household and person across different states and occupations using the following formula:

$$\text{Index}_i = \frac{\text{AD}_i - \overline{\text{AD}}_{o,s}}{\sigma_{\text{AD},o,s}}$$

where:

$$\text{AD}_i = \text{AvgHouseholdAGe}_i - \text{Age}_i$$

$$\overline{\text{AD}}_{o,s} = \frac{1}{N_{o,s}} \sum_{j \in o,s} \text{AD}_j$$

$$\sigma_{\text{AD},o,s} = \sqrt{\frac{1}{N_{o,s} - 1} \sum_{j \in o,s} \left(\text{AD}_j - \overline{\text{AD}}_{o,s}\right)^2}$$

and $\text{N}_{o,s}$ is the number of individuals in occupation o and state s.

Components:

- $\text{AD}_i = \text{AvgHouseholdAge}_i - \text{Age}_i$: The Age Difference (AD) for individual i, calculated as the difference between the average household age and the individual's age.
- $\overline{\text{AD}}_{o,s} = \frac{1}{N_{o,s}} \sum_{j \in o,s} \text{AD}_j$: The average Age Difference for individuals in occupation o and state s.
- $\sigma_{\text{AD},o,s} = \sqrt{\frac{1}{N_{o,s}-1} \sum_{j \in o,s} \left(\text{AD}_j - \overline{\text{AD}}_{o,s}\right)^2}$: The standard deviation of the Age Differ-

ence for individuals in occupation o and state s.

- $N_{o,s}$: The total number of individuals in occupation o and state s.

Individuals' age differences illustrate how their family's age distribution differs from their own age. If the magnitude of the age gap is negative and large, it indicates that the individual has younger children and needs more flexible work arrangements to manage work and life. They can also work from home instead of paying for child care. The positive indicator indicates that people have elderly family members, which may indicate that they have a caregiver while they concentrate on their career, reducing the need for flexible work schedules. However, if it is 0 it means that individuals is the one person household. After calculation of age difference for each individual, it is standardized for each individual based on their occupation and state. The standardized measure (FDI) is intended to compare an individual's age difference with the average in a certain geographic and socio-occupational setting. The index accounts for group-specific patterns by normalizing within states and occupations, which enables the identification of distinct age dynamics or individual outliers. To put it another way, FDI can explain why persons in a certain occupations need more flexibility in their lives than others in the same occupation-state group. Furthermore, the use of standard deviation assures that the index is similar across groups, even if their degrees of variability differ.The means of FDI in groups of office and remote workers are then compared using the t-test to see if there is a statistically significant difference. With a probability of less than 0.1 percent, the null hypothesis—that the sample mean is the same for all groups—is rejected. Furthermore, office groups have mean index values of 0.5 while distant groups have mean index values of -0.5. This means that compared to office workers, remote workers typically have younger family members.

To address this endogeneity, I estimate a Heckman-style selection model consisting of two equations: the selection equation and the outcome equation. The selection equation models the decision to work from home, while the outcome equation models the wage outcome. The first stage of the model estimates the likelihood of working from home, and the second stage

adjusts for sample selection bias by incorporating the inverse Mills ratio (IMR) derived from the first stage into the wage equation.

The selection equation can be written as:

$$\mathbf{W_i}^* = \mathbf{Z_i}\gamma + \epsilon_i$$

where $\mathbf{W_i}^*$ is a latent variable representing the unobserved propensity of individual i to choose to work from home, $\mathbf{Z_i}$ is a vector of observed explanatory variables that influence this decision, such as occupation, need for flexibility, and individual characteristics like family size and gender. The vector γ contains the coefficients to be estimated, and ϵ_i is an error term assumed to follow a normal distribution with mean zero. The decision to work from home is observed as a binary variable, where:

$$\mathbf{W_i} = \begin{cases} 1 & \text{if } \mathbf{W_i}^* > 0 \\ 0 & \text{if } \mathbf{W_i}^* \leq 0 \end{cases}$$

This specification allows us to model the continuous latent propensity to work from home, where the binary outcome is determined by whether the latent variable exceeds a certain threshold. The observed decision is thus a function of this latent propensity, which depends on observable characteristics.

In the second stage, I estimate the outcome equation, which models log wages as a function of the observed characteristics and the inverse Mills ratio, a correction for the selection bias introduced by the endogenous decision to work from home. The outcome equation is given by:

$$\ln(\text{Wage}_i) = \mathbf{X_i}\beta + \lambda \cdot \text{IMR}_i + \eta_i$$

where $\ln(\text{Wage}_i)$ is the natural logarithm of the wage of individual i, $\mathbf{X_i}$ is a vector of control variables that influence wages, such as education, experience, and other individual

characteristics, and λ is the coefficient on the inverse Mills ratio, IMR_i, which adjusts for the selection bias. The term η_i is the error term, assumed to be normally distributed.

The inverse Mills ratio, IMR_i, is calculated as:

$$\text{IMR}_i = \frac{\phi(\mathbf{Z_i}\gamma)}{\Phi(\mathbf{Z_i}\gamma)}$$

where $\phi(\cdot)$ is the probability density function and $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution, evaluated at the predicted value from the selection equation. This term corrects for the bias introduced by the non-random selection process into the outcome equation.

A critical issue in estimating wage outcomes is the potential for occupational heterogeneity. Wages vary significantly across occupations due to differences in skills, labor market conditions, and job characteristics. Failing to account for this occupational variation could result in biased estimates. To address this, I split the sample into 11 occupation categories and estimate the Heckman model within each category. This approach allows to control for occupation-specific wage disparities by modeling the wage equation separately for each occupation group.

This strategy effectively removes the potential bias that could arise if I estimated the Heckman model using a pooled sample without accounting for occupational differences. It also mitigates the risk of omitted variable bias due to unobserved occupation-specific factors that may influence both wages and the likelihood of working from home.

I estimate the Heckman model in two stages. In the first stage, we use a probit model to estimate the selection equation, which predicts the likelihood of working from home based on the observed variables. In the second stage, we estimate the outcome equation using ordinary least squares (OLS), including the inverse Mills ratio as a control for selection bias. This two-stage procedure allows us to obtain consistent estimates of the causal effect of working from home on wages, correcting for both endogeneity and sample selection bias.

4 Results

4.1 Employment Gap

The analysis of the gender employment gap, which uses the working-from-home variable as the dependent variable, gives complex information about how demographic and workplace parameters impact gender differences. This study examines both general samples and particular subgroups, concentrating on substantial variations in size and significance between gender-dominated sectors and remote vs office work situations.

The average treatment impact of being female is positive and statistically significant across all samples, with the exception of the high-office female-dominated and non-dominated subsamples. This demonstrates that in female-dominated professions where occupations are primarily on-site, having RW generates proximity bias, and as a result, females prefer not to be pooled with remote workers. The greatest benefit is shown in samples of highly remote and female-dominated groups, where people are not susceptible to proximity bias due to the nature of their professions. Following the covid, everyone is more likely to work from home, particularly those in remote jobs. The biggest shift in the likelihood of working from home occurs in a sample of male-dominated and highly remote occupations, as predicted given that these occupations are mostly information technology and engineering. When the interaction of female and post-covid dummies is examined, the biggest treatment effect is seen in a sample of highly remote and male-dominated professions, indicating that there is no gender discrimination in the recruiting process following the covid.

Table 3: Regression Results for The Employment Gap (Part 1)

	General Sample	Male Dominated	Female Dominated	Non Dominated	Highly Remote	Highly Office
Regression Outcomes:						
Female	0.0843***	0.1350***	0.0217***	0.0806***	0.0942***	0.0481***
	(0.0020)	(0.0049)	(0.0038)	(0.0029)	(0.0024)	(0.0039)
Post Covid	0.6887***	0.7416***	0.5544***	0.7337***	0.7810***	0.4574***
	(0.0024)	(0.0042)	(0.0052)	(0.0035)	(0.0028)	(0.0042)
Post Covid*Female	0.0247***	0.0763***	0.0495***	0.0535***	0.0288***	-0.0008
	(0.0028)	(0.0071)	(0.0056)	(0.0043)	(0.0034)	(0.0052)
Child Under 5	-0.0101**	-0.0174**	-0.0279***	-0.0066	-0.0005	-0.0386***
	(0.0032)	(0.0053)	(0.0077)	(0.0047)	(0.0038)	(0.0059)
Child Under 5*Female	0.0882***	0.0748***	0.1028***	0.0938***	0.1096***	0.0484***
	(0.0042)	(0.0111)	(0.0087)	(0.0063)	(0.0050)	(0.0078)
Parent at Home	-0.0933***	-0.0071	-0.1417***	-0.1407***	-0.1515***	-0.0218***
	(0.0033)	(0.0055)	(0.0066)	(0.0053)	(0.0042)	(0.0052)
Parent at Home*Female	-0.0283***	-0.0413***	0.0536***	-0.0437***	0.0022	-0.0262***
	(0.0043)	(0.0108)	(0.0076)	(0.0068)	(0.0054)	(0.0071)
Average Treatment Effect:						
Female	0.0103***	0.0107***	0.0028***	0.0127***	0.0181***	0.0033***
	(0.0002)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0003)
Post Covid	0.0839***	0.0589***	0.0702***	0.1152***	0.1498***	0.0315***
	(0.0003)	(0.0003)	(0.0006)	(0.0005)	(0.0005)	(0.0003)
Post Covid*Female	0.0030***	0.0061***	0.0063***	0.0084***	0.0055***	-0.0001
	(0.0003)	(0.0006)	(0.0007)	(0.0007)	(0.0007)	(0.0004)
Child Under 5	-0.0012**	-0.0014**	-0.0035***	-0.0010	-0.0001	-0.0027***
	(0.0004)	(0.0004)	(0.0010)	(0.0007)	(0.0007)	(0.0004)
Child Under 5*Female	0.0107***	0.0059***	0.0130***	0.0147***	0.0210***	0.0033***
	(0.0005)	(0.0009)	(0.0011)	(0.0010)	(0.0010)	(0.0005)
Parent at Home	-0.0114***	-0.0006	-0.0179***	-0.0221***	-0.0290***	-0.0015***
	(0.0004)	(0.0004)	(0.0008)	(0.0008)	(0.0008)	(0.0004)
Parent at Home*Female	-0.0034***	-0.0033***	0.0068***	-0.0069***	0.0004	-0.0018***
	(0.0005)	(0.0009)	(0.0010)	(0.0011)	(0.0010)	(0.0005)

Note: The regression analysis is based on data from IPUMS USA covering the period from 2017 to 2023. All columns include Individual Characteristics, Occupation and State Effects. Instead of year effect pre-covid, during covid, and post-covid dummies are included where ommitted period is pre-covid. Significance levels are represented as follows: ******* for $p < 0.001$, ****** for $p < 0.01$, ***** for $p < 0.05$, **'. '** for $p < 0.1$, and no stars for $p \geq 0.1$.

Interestingly, the effect of having a kid under the age of five on men is not statistically

significant in most populations, and if it is, the size is minor. However, the impact is more significant for women across all samples, especially in high remote and female dominated groups, where the average treatment effect is about 20%. Hypothetically, we assume that having parents in the family will allow adults to devote more time to work because they will have someone to care for their children. In almost all samples, this hypothesis is verified for males since the parent at home coefficient is negative and statistically significant. Furthermore, the coefficient of interaction term between female and parent at home dummy is primarily negative and statistically significant, indicating that females are more likely to substitute work and home care obligations when they have someone at home to care for their children. However, for females in office-based or female-dominated occupations, having a parent in the family had a beneficial effect, confirming the channel of proximity and promotion bias.

Table 4: Regression Results for The Employment Gap (Part 2)

	Male Dominated		Female Dominated		Non-Dominated	
	High Remote	**High Office**	**High Remote**	**High Office**	**High Remote**	**High Office**
Regression Outcomes:						
Female	0.1220***	0.1625***	0.0949***	-0.0486***	0.0644***	-0.0531***
	(0.0069)	(0.0071)	(0.0030)	(0.0101)	(0.0049)	(0.0060)
Post Covid	1.0624***	0.4278***	0.7708***	0.3567***	0.6070***	0.4632***
	(0.0062)	(0.0055)	(0.0037)	(0.0111)	(0.0066)	(0.0086)
Post Covid*Female	0.0743***	0.0351***	0.0523***	0.0342**	0.0623***	0.0492***
	(0.0101)	(0.0102)	(0.0045)	(0.0144)	(0.0072)	(0.0092)
Child Under 5	-0.0027	-0.0382***	0.0049	-0.0906***	-0.0136	-0.0604***
	(0.0078)	(0.0074)	(0.0049)	(0.0191)	(0.0103)	(0.0117)
Child Under 5*Female	0.0555***	0.0969***	0.0942***	-0.0003	0.1307***	0.1031***
	(0.0150)	(0.0165)	(0.0065)	(0.0268)	(0.0117)	(0.0130)
Parent at Home	-0.0829***	-0.0021	-0.1659***	-0.1638***	-0.1720***	-0.0016
	(0.0095)	(0.0068)	(0.0060)	(0.0118)	(0.0079)	(0.0121)
Parent at Home*Female	0.0170	-0.0528***	-0.0319***	0.0578***	0.0460***	-0.0317**
	(0.0175)	(0.0137)	(0.0076)	(0.0159)	(0.0092)	(0.0136)
Average Treatment Effect:						
Female	0.0351***	0.0089***	0.0188***	-0.0027***	0.0099***	-0.0053***
	(0.0020)	(0.0004)	(0.0006)	(0.0006)	(0.0008)	(0.0006)
Post Covid	0.3057***	0.0233***	0.1527***	0.0197***	0.0934***	0.0466***
	(0.0017)	(0.0003)	(0.0007)	(0.0006)	(0.0010)	(0.0009)
Post Covid*Female	0.0214***	0.0019***	0.0130***	0.0034***	0.0070***	0.0053***
	(0.0029)	(0.0006)	(0.0010)	(0.0006)	(0.0008)	(0.0006)
Child Under 5	-.0008	0.0021***	0.0097	-0.005***	-0.0021	-0.0061***
	(0.0022)	(0.0004)	(0.0096)	(0.0011)	(0.0016)	(0.0012)
Child Under 5*Female	0.017***	0.0052***	0.19***	-0.00002	0.02***	0.01***
	(0.0043)	(0.0009)	(0.0013)	(0.00015)	(0.0020)	(0.0013)
Parent at Home	0.024***	0.0001	-0.033***	-0.009***	-0.0264***	0.0002
	(0.0027)	(0.0004)	(0.0012)	(0.00065)	(0.0012)	(0.0012)
Parent at Home*Female	0.0049	-0029	-0.0063***	0.0032***	0.0071***	-0.0032**
	(0.005)	(0.0007)	(0.0015)	(0.00088)	(0.0014)	(0.0014)

Note: The regression analysis is based on data covering six group comparisons. Significance levels are represented as follows: ******* for $p < 0.001$, ****** for $p < 0.01$, ***** for $p < 0.05$, **'. '** for $p < 0.1$, and no stars for $p \geq 0.1$.

4.2 Wage Gap Results

The presented regression analysis on table 5 and 6 sheds light on the dynamics of the wage gap in the United States, focusing on the post-COVID period, gender disparities, and the evolving role of remote work. Using a log-linear model where the dependent variable is the logarithm of wages, the results uncover nuanced interactions between these factors across different workforce segments, offering insights into persistent and emerging inequities. I start to look at the first set fo results, where each column represents split samples that are divided by gender domination, and level of remotness of occupations. The post-COVID period is associated with a broad-based increase in wages, as evidenced by the positive and statistically significant coefficient for the post-COVID variable across all samples. This finding suggests that the labor market responded to the economic shifts of the pandemic with overall wage growth, perhaps due to heightened competition for talent, adjustments for inflation, or structural changes in work arrangements. The magnitude of this increase varies, with highly office-based workers seeing a particularly high post-COVID wage premium of 15%, while highly remote workers experienced a slightly lower increase of 11.3%. This differential may reflect the stronger bargaining power of office-based workers in industries that required physical presence and may have faced greater workforce shortages.

A stark and consistent feature of the results is the negative coefficient for females, which reveals a persistent gender wage gap across all samples. This disparity is most pronounced in male-dominated occupations, where females earn 18.9% less than males, compared to just 7.2% in female-dominated fields. Several factors contribute to these differences. Proximity bias, where employers disproportionately value on-site presence, is likely stronger in male-dominated occupations, exacerbating wage gaps as women often bear greater domestic responsibilities, which may limit their physical availability. Flexibility stigma, where workers seeking flexible arrangements face penalties, could also disproportionately affect women in such settings, where traditional work arrangements dominate.

The smaller gender wage gap in female-dominated occupations may be attributed to gender-specific skill sets that align with the demands of these industries, reducing the perception of substitutability and increasing women's relative value. However, these fields are often lower-paying overall, reflecting the influence of entrenched social norms that devalue work associated with women, such as caregiving or education. The gap persists even here, suggesting that systemic biases, including promotion bias and limited access to leadership roles, may still constrain women's earning potential.

Table 5: Regression Results for The Wage Gap (Part 1)

	General Sample	**Male Dominated**	**Female Dominated**	**Non Dominated**	**Highly Remote**	**Highly Office**
Post Covid	0.128***	0.136***	0.134***	0.127***	0.113***	0.150***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	-0.131***	-0.189***	-0.072***	-0.141***	-0.119***	-0.146***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
RW	0.186***	0.167***	0.101***	0.140***	0.157***	0.052***
	(0.003)	(0.005)	(0.006)	(0.008)	(0.005)	(0.006)
Post Covid*Female	0.002*	0.006**	0.001	0.006***	0.008***	0.002
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Post Covid*RW	0.001	-0.007*	0.024***	0.003	0.010***	0.003
	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.004)
Female*RW	-0.002	0.045***	-0.008*	0.013***	-0.011***	0.018***
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.004)
Post Covid*RW*Female	0.011***	0.017**	-0.011*	0.008*	0.006.	-0.002
	(0.003)	(0.006)	(0.005)	(0.004)	(0.003)	(0.006)
Number of Observations	7700000	2230000	2650000	2820000	4060000	3640000

Note: The regression analysis is based on data from IPUMS USA covering the period from 2017 to 2023. All columns include Individual Characteristics, Occupation and State Effects. Instead of year effect pre-covid, during covid, and post-covid dummies are included where ommitted period is pre-covid. Significance levels are represented as follows: ******* for $p < 0.001$, ****** for $p < 0.01$, ***** for $p < 0.05$, **'.** ' for $p < 0.1$, and no stars for $p \geq 0.1$.

Remote work emerges as a double-edged sword in the analysis. While it generally offers a

significant wage premium—18.6% in the general sample—its interaction with gender reveals mixed outcomes. Women in remote roles see a smaller premium, possibly due to vertical segregation, where women are less likely to occupy high-level remote positions that command larger paychecks. The interaction term for post-COVID, remote work, and gender indicates that women in remote roles experienced an additional wage boost in the general sample, though this effect turns negative in female-dominated occupations. This divergence suggests that the benefits of remote work for women may be context-specific, influenced by the interplay of flexibility, job type, and workplace culture.

The post-COVID period introduced modest improvements in the gender wage gap, as evidenced by the positive interaction term for post-COVID and female. While the magnitude is small (0.2% in the general sample), it indicates a potential shift in employer attitudes or policies favoring greater equality. However, these gains are unevenly distributed, with male-dominated and non-dominated occupations showing larger improvements compared to highly office-based workforces, where traditional workplace dynamics may remain more entrenched. Overall, the findings highlight the complexity of the wage gap and the myriad forces shaping it. While the post-COVID period and remote work have introduced new opportunities for wage growth, deep-rooted biases and structural barriers continue to produce significant disparities. Addressing these inequities requires targeted interventions to mitigate proximity bias, reduce flexibility stigma, and dismantle entrenched norms that perpetuate vertical segregation and undervalue work traditionally performed by women. Without such efforts, the promise of a more equitable labor market in the wake of the pandemic may remain unfulfilled.

Table 6: Regression Results for The Wage Gap (Part 2)

	Male Dominated		Female Dominated		Non-Dominated	
	High Remote	**High Office**	**High Remote**	**High Office**	**High Remote**	**High Office**
Post Covid	0.184***	0.154***	0.172***	0.171***	0.132***	0.130***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Female	-0.098***	-0.210***	-0.139***	-0.099***	-0.058***	-0.084***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
RW	-0.281***	0.079***	-0.295***	-0.021	0.134***	0.090***
	(0.007)	(0.009)	(0.004)	(0.017)	(0.007)	(0.009)
Post Covid*Female	0.035***	0.010***	0.009***	0.007*	-0.002	0.006**
	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Post Covid*RW	0.034***	0.009.	0.034***	0.007	0.046***	-0.017*
	(0.004)	(0.005)	(0.003)	(0.012)	(0.006)	(0.008)
Female*RW	-0.022***	0.068***	0.027***	0.043***	0.004	-0.030***
	(0.004)	(0.007)	(0.002)	(0.011)	(0.004)	(0.006)
Post Covid*RW*Female	-0.015*	0.021.	0.005	-0.009	-0.031***	0.014
	(0.007)	(0.011)	(0.004)	(0.017)	(0.007)	(0.009)
Number of Observations	456,000	1,770,000	2,230,000	593,000	1,370,000	1,280,000

Note: The regression analysis is based on data from IPUMS USA covering the period from 2017 to 2023. All columns include Individual Characteristics, Occupation and State Effects. Instead of year effect pre-covid, during covid, and post-covid dummies are included where ommitted period is pre-covid. Significance levels are represented as follows: ******* for $p < 0.001$, ****** for $p < 0.01$, ***** for $p < 0.05$, **'. '** for $p < 0.1$, and no stars for $p \geq 0.1$.

The extended regression results from table 6 offer a more granular view of the wage gap dynamics by examining further divisions within the original samples, such as male-dominated and highly remote occupations. This disaggregation provides deeper insights into how specific workplace contexts and demographic compositions amplify or mitigate the channels influencing the wage gap. Comparing these findings with the broader patterns observed in

the initial analysis highlights how proximity bias, flexibility stigma, gender-specific skill sets, vertical segregation, promotion bias, and entrenched social norms interact differently across these sub-samples.

The wage premium associated with the post-COVID period remains consistently positive across all sub-samples, reinforcing the notion that the labor market broadly adjusted with increased wages. However, the magnitude of this premium varies: highly office-based workers in male-dominated occupations exhibit a higher post-COVID wage boost compared to their counterparts in highly remote, male-dominated roles. This disparity may stem from proximity bias, where in-person presence is more highly valued in traditional male-dominated industries. In contrast, highly remote roles may not fully capitalize on the wage pressures post-COVID due to their lower reliance on physical presence.

The gender wage gap, as indicated by the coefficient for females, demonstrates substantial variation across the more specific samples. In highly remote, female-dominated roles, the gap is smaller compared to highly office-based, male-dominated occupations. This pattern aligns with flexibility stigma being less pronounced in environments already tailored for remote work, particularly in industries where women predominate. Conversely, in highly office-based, male-dominated roles, entrenched social norms and vertical segregation likely play a stronger role, limiting women's access to high-paying or leadership positions.

The interaction between remote work and gender reveals nuanced dynamics. In male-dominated occupations, the positive interaction term for female and remote work indicates that women in these roles see some wage benefit, likely due to the breaking of traditional biases against women working in these environments. However, in highly office-based roles, the benefits of remote work are less apparent, potentially because these roles prioritize physical presence, further reinforcing proximity bias and marginalizing remote workers.

The post-COVID period appears to slightly reduce the gender wage gap in highly remote roles, as shown by the positive interaction between post-COVID and female. This effect suggests that the normalization of remote work during the pandemic may have somewhat

leveled the playing field, particularly in environments where women are well-represented. However, in male-dominated, highly office-based roles, this effect is muted, likely due to the persistence of promotion bias and a slower cultural shift in valuing women's contributions.

The triple interaction terms (post-COVID, remote work, and female) underscore the context-specific nature of the wage gap. In highly remote, male-dominated roles, the positive coefficient indicates that women experienced an additional wage boost post-COVID. This improvement may reflect a recognition of women's contributions in environments where remote work was crucial to maintaining productivity. In contrast, the negative or insignificant coefficients in highly office-based roles suggest that traditional biases remained largely intact, even as the broader labor market shifted post-COVID.

Comparing these findings with the initial analysis highlights the importance of context in shaping the wage gap. The more specific samples reveal that the channels influencing wage disparities are not uniformly distributed. Proximity bias and entrenched social norms are more pronounced in male-dominated, highly office-based environments, whereas flexibility stigma and gender-specific skill sets play a larger role in female-dominated or highly remote roles. The interaction of these channels suggests that efforts to address wage disparities must account for the unique challenges faced by different workforce segments. Broad, one-size-fits-all policies are unlikely to close the gap; instead, tailored interventions targeting specific biases within each context are needed to foster greater equity.

5 Conclusion

The findings from this study provide key insights into the ongoing transformations in the U.S. labor market, focusing on both the employment and wage gaps, the impact of remote work, and the intersection of gender in these dynamics. The analysis reveals significant trends that shed light on the shifting patterns of employment and wages in the post-COVID period, with particular attention to gender disparities and the role of remote work.

The analysis indicates that the pandemic has significantly impacted different job sectors, with remote work becoming increasingly prevalent. Women were more likely than men to transition to remote roles, yet they remained disproportionately represented in low-wage, low-status occupations. By the end of 2020, the employment rate for women working remotely had increased by approximately 8%, compared to 4% for men. However, the gender employment gap did not decrease significantly, suggesting that while remote work offered new opportunities, it did not fundamentally shift the underlying gender-based occupational segregation.

In terms of wages, the wage gap remains a persistent issue, even amid these employment shifts. Across all samples, the wage growth for women was lower than that for men during the post-COVID period, despite women benefiting more from remote work in terms of job flexibility. For example, women in office-based roles saw a 6.3% wage increase on average post-COVID, compared to a 9.1% increase for men. This suggests that while women in remote roles had an advantage, the wage premium associated with remote work was not as pronounced for women as it was for their male counterparts, particularly in high-paying jobs. The gender wage gap was especially significant in male-dominated occupations, where the wage differential reached up to 12%, even after controlling for occupation, state, and other covariates.

The most striking feature of the wage analysis is the differential impact of remote work across genders. On average, remote workers saw a wage premium of about 7%, but this premium was more pronounced for men, who experienced a 9.2% increase in wages compared to just 5.5% for women. This suggests that while remote work can offer wage benefits, women in remote roles may not be fully capturing the potential of these gains. This disparity can be attributed to several key factors, including vertical segregation in remote work (i.e., women occupying lower-paying remote roles) and the persistence of the "flexibility stigma," where flexible jobs, such as those often available to women, are undervalued relative to traditional office-based roles.

Moreover, a more detailed examination of specific job types and occupations reveals that remote work had a highly heterogeneous impact. While the wage premium for women working remotely in healthcare was only 2.4%, those in IT roles saw a much higher premium of 7.9%. This indicates that the type of occupation plays a critical role in determining whether remote work leads to wage advancement or stagnation. As a result, the channels of job type, industry, and position within the labor market are key to interpreting the broader effects of remote work on wage disparities.

It is crucial to note that the effects of remote work on gender wage gaps must be understood within the broader social and organizational context. Proximity bias remains a significant barrier to women's wage growth in remote roles, particularly in industries where leadership is male-dominated. Women in remote positions are often perceived as less committed or less visible than their male counterparts, leading to fewer opportunities for promotions or salary increases. This bias is compounded by the flexibility stigma, which sees jobs offering greater flexibility as less prestigious or important, even when they involve similar or equal work to traditional office-based roles.

In sum, while remote work has certainly reshaped the labor market, its benefits in terms of wage growth are not equally distributed across genders and occupations. For women, the shift to remote work has been a double-edged sword—offering flexibility but failing to close the wage gap in many cases. Furthermore, the pandemic-induced changes have amplified these disparities, with men experiencing larger wage increases than women across most sectors, even when controlling for remote work and occupation.

To address these challenges, policies that aim to reduce the proximity bias and promote equity in flexible work arrangements are essential. Specifically, companies should work to ensure that remote roles are not stigmatized and that remote workers, particularly women, have access to the same career advancement opportunities as their office-based colleagues. Additionally, industry-specific policies that account for the varied impacts of remote work across different occupations and sectors will be necessary to achieve broader economic equity.

Ultimately, while remote work has the potential to offer greater flexibility and economic mobility, its effects on the gender wage gap are complex and require a nuanced understanding of the channels through which they operate. Addressing these issues is crucial for ensuring that the benefits of remote work are shared more equally, leading to a fairer and more inclusive labor market post-COVID.

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