The Impact of Remote Work on Women's Labor Market Share

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Abstract

This paper examines whether remote work can improve women's representation in the U.S. labor market. Using data from the Quarterly Workforce Indicators (QWI) and job postings, I estimate the causal effects of changes in remote work share on the female share among new hires and in the workforce. To identify these effects, I employ two strategies: a difference-in-differences (DID) framework augmented with double machine learning (DML), and an instrumental variable (IV) approach. The results show that transitioning jobs from fully on-site to arrangements that include remote working days would raise the female share of new hires by about 10 percentage points and the overall female workforce share by about 6 percentage points. These gains are persistent over time and particularly pronounced in male-dominated industries. The findings highlight remote work as a promising mechanism for advancing gender equality in the labor market and increasing female labor force participation.

Keywords: Remote work, Women's labor market representation, Gender equality

JEL: J21, J63, J71

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1 Introduction

Women have historically been underrepresented in the labor market. In 1970, females accounted for less than 40% of the total employed workforce in the United States. Over the following decades, female labor force participation increased rapidly, and by 2000, women represented 46.5% of the workforce. Since then, however, progress has largely stalled: by 2019, the year before the widespread adoption of remote work, the female share had reached only 47.1%. This persistent under-representation is particularly striking given that women outnumber men in the overall population. As shown in Figure 1, the employment-to-population ratio gap between men and women has gradually narrowed but remains around 10 percentage points. Across the 19 industry sectors shown in Figure 2,[1] 12 have a female workforce share below 50%.

Why does this gap persist? Explanations based on human capital differences have become untenable over the course of the twenty-first century. First, technological progress has steadily reduced the prevalence of physically demanding jobs, meaning that biological differences in physical strength no longer constitute a major barrier to women's labor force participation. Second, women have surpassed men in educational attainment, eliminating the disadvantage of lower schooling that characterized much of the twentieth century.[2] These changes suggest that other barriers beyond human capital play a central role in sustaining gender inequality in labor market outcomes.

First, caregiving responsibilities remain a key constraint on women's labor market outcomes. Domestic responsibilities, particularly child care, continue to fall disproportionately on women, making rigid work arrangements in terms of hours and location a significant barrier. Second, women's career choices are constrained by household dynamics, most notably the "two-body problem." Evidence shows that in dual-earner households, family location de-

[1]Data from Quarterly Workforce Indicators (QWI), excluding public administration due to data availability.

[2]According to the 2020 American Community Survey (ACS), among individuals aged 25–54, 42% of women hold a college degree compared to 35% of men.

cisions often prioritize men's careers, limiting women's geographic mobility and professional advancement (Bielby and Bielby, 1992; Cooke, 2003; Nivalainen, 2005; Swain and Garasky, 2007; Sorenson and Dahl, 2016). These patterns reflect the persistence of traditional gender role ideologies, which continue to restrict women's labor supply.

On the one hand, these barriers constrain women's labor supply, and employers' perceptions of the risks associated with hiring female workers often lead to discrimination, which helps explain women's disadvantaged position in the labor market. On the other hand, they underscore the importance of flexibility as a potential mechanism for narrowing gender gaps. Even before 2020, when remote work was still rare, research had already documented women's stronger preference for job flexibility (Flabbi and Moro, 2012; Mas and Pallais, 2017; Wiswall and Zafar, 2017). Claudia Goldin, recipient of the 2023 Nobel Prize in Economics, emphasized the crucial role of job flexibility in advancing gender equality in the labor market (Goldin, 2014). Although the theoretical foundation for the impact of remote work on women's labor supply decisions is well established, the limited availability of remote jobs prior to 2020 made it difficult to establish direct causal evidence. Stimulated by the COVID-19 pandemic, remote work has become substantially more prevalent. By 2024, around 10 percent of job postings in the United States contained a remote component (Hansen et al., 2023). Moreover, the expansion of remote work has varied considerably across industries and locations.[3] The growth of remote work, and the variation in its adoption across regions and industries, provide a valuable research context for studying the role of job flexibility in women's labor market outcomes.

My study examines how remote work affects women's representation in the labor market. Specifically, I analyze whether shifting jobs from a traditional five-day, fully on-site schedule to arrangements that incorporate remote working days increases the share of women among new hires and in the overall workforce. I also investigate heterogeneous effects across industries and explore the underlying mechanisms through the composition of newly hired female

[3]Detailed trends and data are available at https://wfhmap.com/.

workers.

In this study, I use data from the Quarterly Workforce Indicators (QWI) to measure the female share of employment and data from Hansen et al. (2023) to capture the prevalence of remote work. First, I estimate a two-period difference-in-differences (DID) model at the county–by-industry level, using the female shares in new hires and in the workforce as the outcomes, and changes in remote work share as the treatment. To address concerns that county–industry–specific shocks during the pandemic may simultaneously be correlated with remote-work adoption and directly influence the outcomes, I include a rich set of covariates. Additionally I apply double machine learning (DML) to flexibly capture non-linear relationships between covariates and both the outcomes and the treatment. Second, as a complementary robustness analysis, I instrument changes in the county-level remote work share using counties' differential exposure to industry-level shifts in remote work adoption. This instrumental variable (IV) approach mitigates concerns about unobserved selection into remote work. Both identification strategies leverage variation in industry-level remote work adoption, which is primarily determined by task characteristics and can plausibly be treated as exogenous.

My study finds that increasing remote work raises female representation in the workplace. Specifically, shifting all jobs in a workplace from fully in-person to arrangements that include remote working days would increase the female share of new hires by about 10 percentage points and the overall female workforce share by about 6 percentage points. This effect is persistent and remains significant even in male-dominated industries. In addition, I examine the sources of this increase and find that it is driven by a combination of female job switchers and new entrants to the labor market.

This paper provides empirical evidence for the causal effect of remote work on women's share in the labor market, showing that traditional job structures with fixed hours and locations constitute significant barriers to female labor force participation. It contributes to the literature on remote work and gender inequality by offering novel evidence that remote work can advance women's representation and has the potential to reduce gender segregation in the labor market. In addition, the findings carry practical implications for policymakers and organizations seeking to promote workplace diversity and equality. Finally, in the context of population aging and declining fertility rates, remote work may help mitigate labor shortages by mobilizing greater female labor force participation.

The paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the data, measurement, and descriptive statistics. Sections 4 and 5 present the empirical strategy and the main results. Section 6 explores potential mechanisms. Sections 7 shows the robustness check results, and Section 8 discusses the implications and limitations. Finally, Section 9 concludes the paper.

2 Related Literature

The first branch of literature relevant to my study focuses on women's preference for job flexibility, providing a theoretical foundation for assessing how remote work may shape female labor market outcomes. These preferences were well established before the COVID-19 pandemic, at a time when remote work opportunities were still limited. Flabbi and Moro (2012), using CPS data, estimate that more than one-third of college-educated women positively value flexible jobs, with the value ranging from 1 to 10 cents per hour. Mas and Pallais (2017) use an experiment in the hiring process of a national call center to estimate the willingness-to-pay (WTP) distribution for alternative work arrangements. They find that women are willing to pay more than twice as much as men for the ability to work from home. Similarly, women are willing to pay nearly twice as much as men to avoid employer discretion in scheduling. Notably, women with young children exhibit an even higher WTP for working from home than other women. Consistent with these findings, Wiswall and Zafar (2017), using a survey of NYU undergraduates, find that women exhibit a much stronger preference for workplace hours flexibility, with an implied WTP of 7.3% of annual salary compared to 1.1% for men. These results align with evidence that women are more likely to be employed in jobs that offer greater flexibility (Goldin and Katz, 2011; Wasserman, 2022).

With the widespread adoption of remote work after the pandemic, recent studies have revisited flexibility preferences using broader samples and geographic contexts. Richards et al. (2024), analyzing surveys in Ireland, show that women express a stronger desire to work from home post-pandemic. Similarly, Artz et al. (2025), using data from the Survey of Working Arrangements and Attitudes in the United States, find that women consistently report a stronger preference for WFH than men. Together, these studies demonstrate both pre- and post-pandemic evidence that women value workplace flexibility more highly, suggesting that remote work may be particularly relevant for female labor supply decisions.

Research on gender segregation in the labor market is also relevant to my study, as this literature documents both the patterns and dynamics of segregation across industries and occupations and highlights the role of women's choices in shaping these outcomes. Women and men remain unevenly distributed across industries and occupations (Blau et al., 2012; Blau and Kahn, 2017; Hegewisch and Williams-Baron, 2017; Cortés and Pan, 2023). A supply-side explanation emphasizes that women disproportionately sort into lower-paying but more flexible jobs in order to balance work and family responsibilities. Barbulescu and Bidwell (2013), examining the job search behavior of MBA students, find that women are less likely than men to apply for finance and consulting jobs and more likely to apply for general management positions, partly because of their preferences for work–life balance. Hegewisch and Williams-Baron (2017) further highlight the role of women's choices in shaping labor market outcomes by showing that states with the most extensive work–family supports have the lowest gender wage gaps, while those with the least supports have the highest. This evidence reinforces the view that women's preferences contribute to sustaining occupational segregation.

Finally, a small but growing body of recent work examines how remote work may directly alter female labor supply, which motivates my research. Tito (2024) provides evidence that remote work enhances women's labor force attachment by reducing the probability of labor force exit. Hsu and Tambe (2025) show that switching a job posting from on-site to remote increases the share of female applicants by about 15%. These studies highlight the potential of remote work to change female labor supply, raising the critical question that my study addresses: whether these shifts ultimately translate into greater female representation in the labor market.

3 Data, Measurement, and Descriptive Statistics

3.1 Data Sources

The data of study mainly come from two sources: the Quarterly Workforce Indicators (QWI) and job posting data from Hansen et al. (2023).

Female employment data used in this study are mainly drawn from the Quarterly Workforce Indicators (QWI), a set of economic indicators that include employment, job creation and destruction, wages, hires, and other measures of employment flows. These indicators are reported by detailed firm characteristics and worker demographics. I extract employment, hiring, and separation data by gender for each county and 2-digit NAICS industry from the QWI. From these data, I calculate the female share of total employees and new hires, as well as separation rates for both genders. In addition, I use the QWI to construct county–industry characteristics that serve as covariates in the double machine learning model, including the distributions of firm size, firm age, worker age, gender, education, race, and ethnicity. However, the QWI data do not allow identification of the source of female new hires, such as whether they transition from unemployment or switch from other jobs. Accordingly, I rely on Job-to-Job Flows (J2J) data for the analysis of hiring sources. The J2J data distinguish between hires from nonemployment and hires from other employers.

Commonly used survey-based data sources for measuring remote work include the American Community Survey (ACS), the Current Population Survey (CPS), and the American

Time Use Survey (ATUS). While these datasets provide individual-level information on remote work status, they classify remote work based on respondents' places of residence rather than the locations of their employers. As a result, remote work measures constructed from these surveys cannot be directly matched to workplace-based outcomes such as female employment shares.

To address this mismatch, I measure the share of remote jobs across industries and counties using job posting data from Hansen et al. (2023), *Remote Work across Jobs, Companies, and Space*. The authors employ a large language model (LLM) to analyze job postings and classify whether a position offers remote work for at least one day per week. The monthly data used in my study span from 2019 to 2024 and are provided by the research team at the industry-occupation-county level. Importantly, these data identify remote positions based on employers' business locations rather than workers' residences. This feature allows remote job shares and female employment shares to be aligned at the same workplace location, overcoming a key data limitation in studying this question.

3.2 Measurement and Descriptive Statistics

In my study, consistent with Hansen et al. (2023), a job is defined as remote if it offers remote work at least one day per week. The remote share for group g in period t is calculated as the proportion of job postings classified as remote within the group. Specifically, the measure is computed as follows:

$$\text{Remote Share}_{g,t} = \frac{\#\text{Remote job postings in group } g \text{ during period } t}{\#\text{Total job postings in group } g \text{ during period } t}, \tag{1}$$

where g denotes either a county or an industry-county group. This measure captures the share of jobs within a workplace—defined as either a county or an industry within a county—that are not traditional fully on-site positions but instead allow some degree of flexibility, including both hybrid and fully remote arrangements.

Figure 3 presents the evolution of remote job rates across industries over time. The share of remote jobs in the U.S. began to rise sharply in the second quarter of 2020, following the onset of the COVID-19 pandemic. Both the level and the change in remote job shares exhibit substantial variation across industries. While pre-pandemic remote work adoption was limited across all industries, those with relatively higher pre-pandemic remote work levels—such as Information, Public Administration, Finance, and Professional Services—experienced increases of 10 to 20 percentage points. In contrast, industries with relatively lower pre-pandemic remote work levels, including Retail, Hospitality, and Health Care, saw changes of less than 3 percentage points.

Compared to industry-level variation, county-level differences in remote work shares are smaller but still notable. Figure 4 presents maps that illustrate the spatial distribution of remote job shares and their changes. The average remote job share across counties increased from 2.8% in 2019 to 5.8% in 2021. During the same period, the variation across counties also widened, with the standard deviation rising from 3.7 percentage points to 5.3 percentage points. While some counties saw minimal changes in remote job share, others experienced substantial shifts, with the maximum increase reaching 48 percentage points.

I measure the change in remote work share for each county-industry group by comparing the value in 2019 to the early post-pandemic period, April 2020 to December 2021. Specifically, I compute the difference in remote share—defined in Equation (1)—between these two periods using Equation (2):

$$\Delta Remote\, Share_{ci} = Remote\, Share_{ci,04/2020-12/2021} - Remote\, Share_{ci,2019}. \tag{2}$$

This change in remote share can arise from two sources: existing jobs shifting from on-site to remote arrangements, or the creation of new remote jobs. Since I calculate the change using periods immediately before and after the pandemic, the difference primarily reflects adjustments in existing jobs rather than the emergence of entirely new positions.

Figure 5 shows the distribution of these changes. On average, the remote share increased by 4.1 percentage points. About 33% of county-industry groups experienced a change of less than 1 percentage point, while 10.6% of groups saw an increase greater than 10 percentage points. The median change is 2 percentage points. In Table 1, I divide all county–industry groups into two categories based on whether their change in remote-work share is above or below the median. The table shows that the two groups differ across several other characteristics. Groups with below-median changes in remote-work share tend to be smaller in size, as measured by the number of hires and total employment, have fewer large and older firms, and have lower shares of prime-working-age and college-educated workers. However, they exhibit higher shares of female workers in both new hires and total employment prior to the pandemic.

I present the female share and the remote job share for each 2-digit NAICS industry in Figure 6. The female share is based on data from Q4 2019, while the remote share reflects the average remote job share in the post-pandemic period, from April 2020 to September 2024. The figure provides a descriptive overview of industries' remote work intensity and gender composition. Among the 19 industries, 12 are male-dominated (with more than 50% male workers). Of the 6 high-remote industries—defined as those with an average post-pandemic remote share above 10%—only one has a female majority (more than 50% of workers are women. This pattern reflects the broader gender imbalance in the labor market, particularly within high-remote industries.

4 Identification Strategy

This section outlines the identification strategies used in the paper to estimate the causal effects of remote work on female representation in the labor market, focusing on the female share of new hires and the overall female workforce share.

First, I estimate a two-period difference-in-differences (DID) model augmented with double machine learning (DML) to flexibly control for covariates. Second, as a complementary robustness analysis, I implement an instrumental-variable (IV) strategy to mitigate concerns about unobserved selection into remote work. In my analysis, the pre-period is defined as 2019, the year prior to the COVID-19 pandemic when remote jobs were not yet prevalent. The post-period is defined as April 2020 to December 2021, capturing the initial rise of remote work. While most of the analysis focuses on this period, when studying the effects on female workforce share, I extend the post-period to 2022 Q4, 2023 Q4, or 2024 Q3 to examine longer-term effects.

4.1 Difference-in-Differences (DID) with Double Machine Learning (DML)

I begin the analysis by estimating a two-period difference-in-differences (DID) model with a continuous treatment:

$$Y_{g,t} = \alpha + \beta^{DD} Post_t \times \Delta Remote\, Share_g + \gamma_g + \sigma_t + \epsilon_{g,t}, \tag{3}$$

where g denotes the group of the observation. In the DID analysis, I define each county-by-industry combination as a group.[4] $Y_{g,t}$ denotes the outcome observed for group g in the last quarter of the pre- and post-periods, specifically Q4 2019 and 2021 Q4. In analyses where the post-period is extended, I instead use outcomes from 2022 Q4, 2023 Q4, or 2024 Q3. The treatment variable is defined as the change in the remote job share for group g, calculated as the difference in remote share between the pre- and post-periods (Equation (2)). The regression model includes group fixed effects (γ_g) and time fixed effects (σ_t).

The regressions are weighted by the total size of each group in 2019, giving more weight to larger groups. For the female share in new hires, group size is measured by the total number of new hires, and for the female workforce share, it is measured by total employment. This

[4]In the later specification of the IV model, I alternatively define groups at the county level.

reflects the idea that smaller groups are more sensitive to changes in worker counts. For example, an increase of 10 female workers could substantially alter the female share in a small group, while the same numerical change would have a much smaller impact in a larger group. By weighting more heavily toward larger groups, the analysis places greater emphasis on changes that are less likely to be driven by small-sample fluctuations.

Since the model includes only two time points, it can be rewritten as:

$$\Delta Y_g = \alpha + \beta^{DD}\,\Delta \text{Remote Share}_g + \epsilon_g. \tag{4}$$

Equation (4) presents the difference-in-differences (DID) specification in a concise form. It captures the relationship between changes in the share of remote work and changes in the outcome variable across groups. The coefficient β^{DD} can be interpreted as a causal effect under the parallel trends assumption, which posits that, in the absence of differential changes in remote work share, outcomes across groups would have evolved along similar trends. Equivalently, this implies that $\Delta\text{Remote Share}_g$ in Equation (4) is assumed to be exogenous with respect to other factors affecting ΔY_g.

The variation in the treatment variable, $\Delta\text{Remote Share}_g$, can be decomposed into three components: (i) county-wide variation, (ii) industry-wide variation, and (iii) idiosyncratic variation at the county-industry level. To credibly identify a causal effect, it is essential that the variation used in estimation be exogenous. Among the three sources of variation, industry-level variation can reasonably be treated as exogenous. This variation primarily reflects inherent job characteristics—such as task composition, requirements for physical presence, and the degree of digitalization—that differ systematically across industries and were predetermined prior to the COVID-19 pandemic.

The other two sources raise additional concerns. First, county-level variation is closely related to heterogeneous exposure to COVID-19 and differences in local policies, both of which may influence remote-work adoption as well as labor market outcomes. For example, counties that experienced more severe outbreaks or stricter lockdown policies adopted remote work more rapidly, while also seeing larger disruptions in hiring and employment. Second, beyond county-level shocks, it is possible that certain county–industry–specific characteristics affect both remote-work adoption and employment decisions during the pandemic. This could potentially introduce endogeneity into the idiosyncratic component of variation. However, such concerns are likely to be limited: although local and group specific factors may influence employment dynamics, there is no clear reason to expect these factors to differentially affect men and women, and thus they are less likely to bias estimates of changes in the female share.

I address these endogeneity concerns by controlling for county fixed effects and group characteristics in the DID specification. One approach is to include these covariates linearly using

$$\Delta Y_g = \alpha + \beta^{\text{linear}}\, \Delta \text{Remote Share}_g + \theta X_g + \epsilon_g, \tag{5}$$

where X_g is a high-dimensional vector of county fixed effects and county-industry characteristics. For the estimator β^{linear} to be unbiased, the linearity assumption must hold—specifically, the relationship between ΔRemote Share$_g$ and X_g must be linear. However, this linearity assumption is strong and untestable in practice, especially in settings with complex or high-dimensional covariates.

To allow for nonlinear relationships between covariates and both the outcome and treatment variables, and to accommodate high-dimensional covariates, I implement the double machine learning (DML) estimator (Chernozhukov et al., 2018; Shi et al., 2023) by applying the following partially linear model:

$$\begin{aligned} \Delta Y_g &= \beta^{DML} \Delta \text{Remote Share}_g + g_0(X_g) + \varepsilon_g, \quad & E[\varepsilon_g | \Delta \text{Remote Share}_g, X_g] = 0, \\ \Delta \text{Remote Share}_g &= m_0(X_g) + \zeta_g, & E[\zeta_g | X_g] = 0, \end{aligned} \tag{6}$$

where X_g is a high-dimensional vector of potential confounders, including county fixed effects, the proportions of workers by firm size, firm age, education, race, and ethnicity groups, as well as the proportions of female workers by age group.[5]

Naïve inference, which plugs the machine-learning prediction $\hat{g}_0(X_g)$ directly into Equation (4) to estimate the causal parameter, is generally invalid because machine-learning methods introduce regularization bias that distorts the estimation of β. To overcome regularization bias, DML employs an orthogonalization step, which proceeds as follows:

1. **Estimate the conditional expectation functions (CEFs).** Using a machine learning method (in my case, random forests), estimate

$$m_0(X_g) = E[\Delta \text{Remote Share}_g \mid X_g], \qquad l_0(X_g) = E[\Delta Y_g \mid X_g].$$

2. **Compute residuals.** Construct the residualized treatment and outcome:

$$\hat{u}_g = \Delta \text{Remote Share}_g - \hat{m}_0(X_g), \qquad \hat{v}_g = \Delta Y_g - \hat{l}_0(X_g).$$

3. **Regress residualized outcome ($\hat{v}_g$) on residualized treatment ($\hat{u}_g$).**

To mitigate bias from overfitting, I implement 5-fold cross-fitting when estimating $\hat{\beta}^{DML}$. Specifically, the sample is randomly partitioned into five equally sized folds. In each iteration, four folds are used as the training sample and the remaining fold serves as the hold-out sample. I train the random forest learners m_0 and l_0 on the training sample and then generate out-of-sample predictions for the hold-out sample to obtain residuals. This procedure is repeated across all five folds so that each observation is used exactly once for out-of-sample prediction.

The identification of the causal estimator relies on the Conditional Independence Assumption (CIA), which requires that, conditional on county-by-industry group characteristics and

[5] Table 10 in Appendix C compares the estimates obtained from the linear specification in Equation (5) with those from the DML method in Equation (6).

county fixed effects, the change in remote share is unrelated to other factors that affect the outcomes. Under the DID framework, this implies that groups with the same characteristics within the same county would have followed parallel trends in the absence of variation in the change in remote share.

Compared to Equation (3), the double machine learning approach addresses potential endogeneity concerns by comparing industry groups within the same county while accounting for group-specific observed characteristics. However, this approach cannot fully address potential selection on unobserved characteristics, if such selection exists. To further strengthen causal identification, I implement an instrumental variable approach as a robustness check.

4.2 Instrumental Variable (IV) Method

I implement an instrumental variable method using a Bartik-style instrument (Bartik, 1991). The IV analysis is conducted at the county level. This approach leverages national trends in remote-work adoption across industries, combined with pre-pandemic variation in industry composition across counties, to isolate exogenous variation in remote-work exposure.

Specifically, I instrument the county-level change in remote-work share, $\Delta\text{Remote Share}_c$, using the following Bartik-style instrument:

$$Z_c = \sum_{i \in I} l_{i,c}^{2019} \cdot \Delta\text{Remote Share}_i, \tag{7}$$

where $l_{i,c}^{2019}$ is the employment share of industry i in county c in the pre-pandemic year 2019, and $\Delta\text{Remote Share}_i$ is the national-level change in remote work share in industry i (Goldsmith-Pinkham et al., 2020). The instrument captures a county's exposure to the change in remote work.

I follow the two-stage least squares (2SLS) approach. In the first stage, I regress the county-level change in remote-work share on the instrument using Equation (8) to isolate the component of $\Delta\text{Remote Share}_c$ that is uncorrelated with ε_c. I then compute the predicted values of $\Delta\text{Remote Share}_c$, denoted by $\Delta\widehat{\text{Remote Share}}_c$.

$$\Delta\text{Remote Share}_c = \alpha_1 + \beta_1 Z_c + \varepsilon_c. \tag{8}$$

In the second stage, I regress the change in the outcome variable on the predicted change in remote share:

$$\Delta Y_c = \alpha + \beta^{IV} \cdot \Delta\widehat{\text{Remote Share}}_c + \epsilon_c. \tag{9}$$

Conditional on a non-zero first stage ($\hat{\beta}_1$ is significantly different from 0), the validity of the instrumental variables (IV) strategy rests on three key assumptions. First, the **monotonicity** assumption requires that the instrument affects the endogenous variable, the change in remote work share, in the same direction across all counties. Second, the **exclusion restriction** stipulates that the instrument influences the outcome solely through its effect on remote work. Third, the **independence** assumption requires that there are no confounders of the association between the instrument and the outcome. This independence assumption can be satisfied through the exogeneity of the pre-determined industry shares $l_{i,c}^{2019}$, which requires that these shares not be systematically related to county characteristics that also influence changes in the outcome over the study period. To strengthen the case for exogeneity, I use employment shares measured in 2019, which were determined prior to the onset of the COVID-19 pandemic and are therefore plausibly uncorrelated with post-pandemic shocks or trends.

Given that the IV approach addresses both observed and unobserved selection, it is the preferred model in this study. However, in analyses where the IV approach is not appropriate—for example, owing to insufficient variation across industries—I present the DML results as the main findings.

In this study, both approaches exploit industry-level variation in changes in remote-work share and treat this variation as exogenous. A potential concern is that industry-specific shocks during the pandemic may be correlated with both the change in remote-work share and labor market outcomes. Although the existence of such shocks cannot be completely ruled out, they are unlikely to threaten the validity of the analysis for two reasons. First, the probability that industry-specific shocks systematically affected men and women differently is small. Most industry-level disruptions during the pandemic—such as operational constraints or fluctuations in labor demand—primarily influenced overall employment levels rather than altering gender-specific hiring or employment incentives. In other words, these shocks were largely orthogonal to gender, absent direct mechanisms that would cause firms to adjust male and female employment differentially. Thus, even if these shocks are correlated with changes in remote-work adoption, they are unlikely to generate changes in the female share. Second, I conduct a long-run analysis extending through the end of 2024. With a longer time horizon, the influence of pandemic-specific shocks should diminish; if the estimates were driven primarily by such shocks, the effects would be expected to weaken or disappear over time. Instead, if the effects persist, it would suggest that the results are not attributable to temporary, pandemic-specific shocks.

5 Results

This section presents the empirical findings on the impact of remote work on women's labor market share. The analysis focuses on the female share among new hires and within the overall workforce. I also examine the dynamics of these effects over time and explore heterogeneity across industries. In analyzing the heterogeneous effects, I pay particular attention to industries with low female representation. The goal is to assess whether remote work can serve as a tool to reduce gender segregation across industries.

5.1 The Effects of Remote Work on Female Labor Market Share

Previous research has shown that women place a higher value on job flexibility when making employment choices (Barbulescu and Bidwell, 2013; Mas and Pallais, 2017; mee, 2022; Atkin et al., 2023). More recently, Hsu and Tambe (2025) finds that shifting a job posting from on-site to remote increases the share of female applicants by 15%. However, whether this greater willingness to apply ultimately translates into higher female representation in the workforce depends not only on supply-side preferences but also on demand-side hiring decisions. A substantial body of research has documented the existence of gender-based discrimination in hiring (Rivera and Tilcsik, 2016; Yavorsky, 2019; Birkelund et al., 2021; Barron et al., 2025). Thus, the ultimate effects of remote work on female employment outcomes remain an open question. Building on these insights, I examine whether the rise of remote work is associated with an increase in the share of women among new hires and in the overall workforce.

Table 2 reports estimates of the effects of changes in the remote work share on female labor market outcomes in 2021 Q4, measured by the female share of new hires and the overall workforce. Columns (1) and (2) present results from the difference-in-differences (DID) specification in Equation (3) and the double machine learning (DML) model in Equation (6), respectively. Column (3) reports results from my preferred specification—the instrumental variable (IV) approach.

Table 2, Panel A presents the estimated effects of remote work on the female share of new hires across county–industry groups. Across all three specifications, the coefficients on remote work are positive and highly significant, ranging from 0.097 to 0.121. These estimates are similar in magnitude, providing consistent evidence that greater remote work adoption raises women's share among new hires. Controlling for county fixed effects and group characteristics in the DID model reduces the coefficient from 0.121 to 0.101 (column (1) to Column (2)), suggesting that part of the initial association was driven by confounders at the county and county–industry levels. Nonetheless, the relatively small change in magnitude indicates that the main effect remains robust. My preferred specification, the IV model in Column (3), yields a coefficient of 0.097. This implies that shifting all job postings in a county–industry group from in-person to remote would increase the female share of new hires by about 10 percentage points. To put this magnitude in perspective, women constituted 49.8% of all new hires nationally in Q4 2019, indicating that the estimated effect is substantial.

Given the positive impact on women's share in hiring, I next examine the causal effect of remote work on women's overall workforce representation. Table 2, Panel B presents the results. Across all three specifications, the coefficients are positive and statistically significant, ranging from 0.036 to 0.058. According to the IV specification in Column (3), a complete shift from on-site to remote work in a county–industry group would cause a 5.8 percentage point increase in the female workforce share. Relative to the national level of 48.5% in Q4 2019, this magnitude may appear modest. However, placed in historical context, the effect is substantial. As shown in Figure 7, women's workforce share increased by only about 0.5 percentage points over the past two decades, rising from 46.5% in December 2000 to 47.0% in December 2024. Against this backdrop of slow, long-run change, the increase associated with remote work represents a dramatic acceleration in women's representation in the labor market.

The results above indicate positive effects of remote work on women's representation among new hires and in the overall workforce during the initial post-pandemic period, as observed in Q4 2021. To assess the persistence of this impact, I extend the observation window to Q4 2022, Q4 2023, and Q3 2024. While the outcome variable varies across years, the treatment is fixed and defined as the change in remote job share between 2019 (pre-pandemic) and the period spanning 2020 Q4 to 2021 Q4. This design allows the estimates to capture the long-run consequences of the initial adoption of remote work.

The results in Table 3 indicate that the effect of remote work is persistent and increases modestly over time, reaching over 7 percentage points in later years (Column (3)). The IV estimates in Column (3) are consistently larger than those in Columns (1) and (2), even after accounting for the larger standard errors. This pattern also suggests that, even after controlling for county fixed effects and group-specific characteristics, the DID estimates may still be downward biased due to unobserved confounding factors.

The persistence and gradual amplification of the effect have two important implications.

First, they highlight remote work's potential as a lasting mechanism for improving women's representation in the labor market. Second, they suggest that the estimates are less likely to be driven by pandemic-induced temporary shocks correlated with changes in remote work, but instead more plausibly reflect the causal impact of remote work itself.

In Appendix A, I also show the impact of remote work on the separation rates of males and females. Although remote work lowers the separation rate for females, it affects males to a similar extent. Therefore, I conclude that the main reason for the increase in the female workforce share is attributable to the rise in female hires.

Taken together, the evidence from both new hires and the overall workforce paints a consistent picture: remote work not only attracts more female applicants (Hsu and Tambe, 2025) but also translates into a measurable increase in women's share in the labor market. Importantly, the workforce-level effects are smaller in magnitude than those for new hires, reflecting the gradual adjustment of workforce composition as hiring flows accumulate. Moreover, the fact that the workforce effect remains positive and strengthens over time suggests that the initial hiring gain persists and contributes to long-run improvements in women's representation in the labor market.

5.2 Heterogeneity by industry

The findings above indicate that remote work is a potential tool for improving women's representation in the workplace. In this section, I examine whether this impact is concentrated in particular industries or is more broadly distributed across the economy. To do so, I analyze heterogeneous treatment effects across industries. Using the female employment share in Q4 2019 and the post-pandemic remote-work share, I classify industries into four groups: (1) high-remote, female-dominated; (2) low-remote, female-dominated; (3) low-remote, male-dominated; and (4) high-remote, male-dominated.

This classification allows me to assess whether the magnitude of the effect varies with an industry's initial gender composition and its exposure to remote work. More importantly, it helps evaluate whether the expansion of remote work has the potential to reduce gender-based industrial segregation.

Based on the findings above, I next examine heterogeneous treatment effects across industries. Using the female employment share in Q4 2019 and the post-pandemic remote-work share, I classify industries into four categories: (1) high-remote, female-dominated; (2) low-remote, female-dominated; (3) low-remote, male-dominated; and (4) high-remote, male-dominated. The objective is to assess whether the magnitude of the effect varies with the industry's initial female employment share and its level of remote work, and, in turn, whether the expansion of remote work can help reduce gender-based industrial segregation.

The results in Table 4 show substantial effects in male-dominated industries. In both new hires (Panel A) and the overall workforce (Panel B), the estimated effects are large and statistically significant in industries where women were initially underrepresented. This pattern holds regardless of whether the industry adopted remote work at a high or low level after the pandemic, although industries with lower remote-work adoption exhibit larger effects. This suggests that even modest adoption of remote work can substantially reduce barriers for women entering male-dominated industries. In contrast, effects are smaller and imprecisely estimated in female-dominated industries, partly because the number of high-remote female-dominated industries is limited.

These findings indicate that remote work is especially effective in attracting women to industries that have historically exhibited low female representation. The evidence highlights remote work's potential to facilitate female entry into traditionally male-dominated sectors and, in doing so, to promote a more inclusive labor market by reducing industry-level gender segregation.

6 Sources of the Female Workforce Increase

The preceding analysis shows that remote work increases women's share among new hires and contributes to gradual improvements in overall workforce representation. The finding that separation rates decline by similar magnitudes for men and women further suggests that these gains are driven primarily by higher female hiring rather than lower female exits. This raises a natural next question: from where do these additional female hires originate? One possibility is that women already in the workforce switch into remote jobs through job-to-job transitions; another is that women who were previously unemployed or out of the labor force enter as new participants.

Table 5 sheds light on this mechanism by examining two potential channels of female hiring: job-to-job transitions and hires from persistent nonemployment. Due to data limitations, information on the composition of new hires is not available at the county level; therefore, the analysis is conducted at the metropolitan level. Panel A reports the estimated effect of remote work on the female share of job-to-job hires, while Panel B focuses on hires from nonemployment.

The results reveal a clear pattern. Remote work significantly increases female representation through both channels, but the magnitudes are notably larger for hires from nonemployment. According to the IV estimates, a full shift of jobs from on-site to remote would raise the female share of job-to-job hires by about 8.8 percentage points, compared with a 25.5 percentage point increase among hires from nonemployment. Because this analysis is conducted at the metropolitan level, the relatively small sample size results in wide confidence intervals, making the point estimates less precise. Nonetheless, the consistently positive and statistically significant coefficients underscore that remote work meaningfully expands women's participation through both job switching and new entry.

These findings suggest that remote work not only reshuffles women across existing jobs but also brings new entrants into the labor market. By lowering barriers to labor force participation—particularly for women facing constraints such as caregiving responsibilities—

remote work expands the pool of female workers and sustains long-run gains in women's workforce representation.

7 Robustness Check

The validity of the difference-in-differences (DID) framework relies on the parallel trends assumption, which requires that, absent differential treatment, county-industry groups would have followed similar trends. In the context of this study, this means that without variation in remote work adoption, the female share of new hires and the overall workforce would have evolved similarly across groups.

For DID specifications, I test this assumption by examining pre-trends. Specifically, I re-estimate Equation (3) and Equation (6) using the change in female shares from 2017 to 2019—a period prior to the sharp increase in remote work—as the outcome variable. If groups that later experienced larger increases in remote work share had already exhibited stronger gains in female representation, this would raise concerns about endogeneity. The results, reported in Table 6, show no evidence of systematic pre-trends. A small negative pre-trend of –0.008 is observed in the DID estimates for female workforce share, but the magnitude is modest. This suggests that the true effect may be even larger than the DID estimate of a 4 percentage point increase.

The identification of the IV approach depends on the exogeneity of the industries shares. The underlying assumption is that counties with different initial industry compositions would have counterfactually evolved in a similar way, thus the predicted remote work change in Equation (9) is an exogenous shock. To assess this, I examine the relationship between counties' pre-2020 industry shares and pre-trends in the female share. Specifically, I run a series of regressions in which the change in county-level female shares between 2017 and 2019 is regressed on each industry share. Table 7 reports results for the top five high-remote industries, as well as the aggregated instrument. Consistent with the DID checks, I find no evidence of systematic pre-trends. Counties with higher initial concentrations in high-remote industries did not experience differential trends in female hiring or workforce share prior to the pandemic.

These results provide reassurance that the main findings are not driven by pretrends and support the interpretation of the estimated effects as causal.

8 Discussion

The findings of my study have practical implications for both public policy and organizational strategy. First, as remote work increases the female share in both new hires and the overall workforce, it can serve as a policy tool to improve female representation in the labor market and promote gender equality. Importantly, this impact is not confined to traditionally female-dominated industries; rather, the effects in male-dominated industries are significant and even larger, suggesting that remote work may be a powerful tool to reduce gender segregation in the labor market. Second, my findings show that part of the increase in the female share of new hires associated with remote work comes from women who were previously persistently unemployed. This indicates that remote work encourages female labor force participation. Such an effect is particularly meaningful in the context of population aging and declining fertility rates, where policies that raise participation are critical for addressing labor shortages. Finally, the research provides a valuable perspective for firms to weigh the costs and benefits of remote work arrangements in terms of workforce stability and diversity.

This study has several limitations that also suggest directions for future research. First, the analysis focuses on the ultimate labor market outcomes of remote work and does not disentangle whether the observed increase in female representation is driven primarily by labor supply or by labor demand. While increases in female hires and employment are directly related to women's labor supply decisions, remote work may also reduce employer discrimination—for instance, by lowering employers' perceived risk that women of childbearing age will exit the labor market. Future research could distinguish between these mechanisms to better identify the channels through which remote work affects the outcomes. Second, due to data restrictions, a job is defined as "remote" as long as it includes at least one remote day. The effects of fully remote jobs may therefore be larger than the estimates presented here, and future studies with richer data could shed light on the heterogeneity between hybrid and fully remote work. Finally, the estimated effect on the female share in the overall workforce should be interpreted as a local effect. The observed changes reflect a combination of job switchers and new entrants. A comprehensive estimate at the aggregate level would require isolating the contribution of new entrants alone, which would likely yield smaller effects.

9 Conclusion

The study provides empirical evidence on the impact of remote work on female labor market representation. First, the findings show that remote work significantly increases the female share among new hires and in the overall workforce. Transitioning jobs from a fully on-site schedule to one that includes remote working days results in a 10-percentage-point increase in the female share of new hires. These gains in hiring translate into broader workforce changes, raising the overall female workforce share by about 6 percentage points. Moreover, the effect on women's workforce share is persistent over time. Second, the effects on the female share in both new hires and the workforce are particularly pronounced in male-dominated industries, suggesting that remote work has the potential to reduce gender segregation in the labor market. Third, by exploring the sources of the increase, I find that it is driven by both job switchers and new entrants.

The findings highlight that rigid job structures with fixed hours and locations continue to be major barriers to women's participation. By relaxing these constraints, remote work emerges as a powerful mechanism for advancing women's representation and reducing gender segregation in the labor market. The results carry important implications for organizations and policymakers: remote work can serve as a tool to promote diversity and equality in the workplace. Moreover, in the context of population aging and declining fertility rates, expanding flexible work arrangements may help mitigate labor shortages by mobilizing greater female labor force participation.

Future research should investigate the mechanisms behind these effects, particularly the relative roles of supply-side responses versus demand-side changes in employer behavior, and compare the impacts of hybrid versus fully remote work. Despite these open questions, the evidence presented here underscores that remote work is not only a workplace innovation but also a potential lever for promoting gender equality and sustaining labor market growth.

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Figures

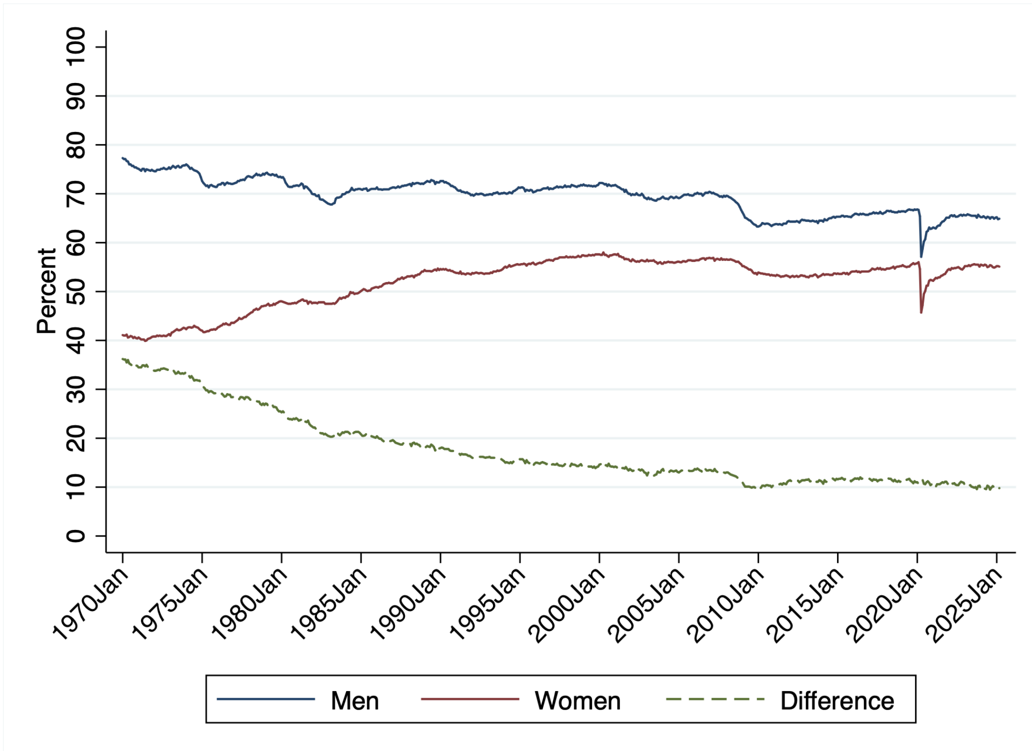

Figure 1: Employment-to-population ratio by gender, U.S. Jan 1970–Feb 2025

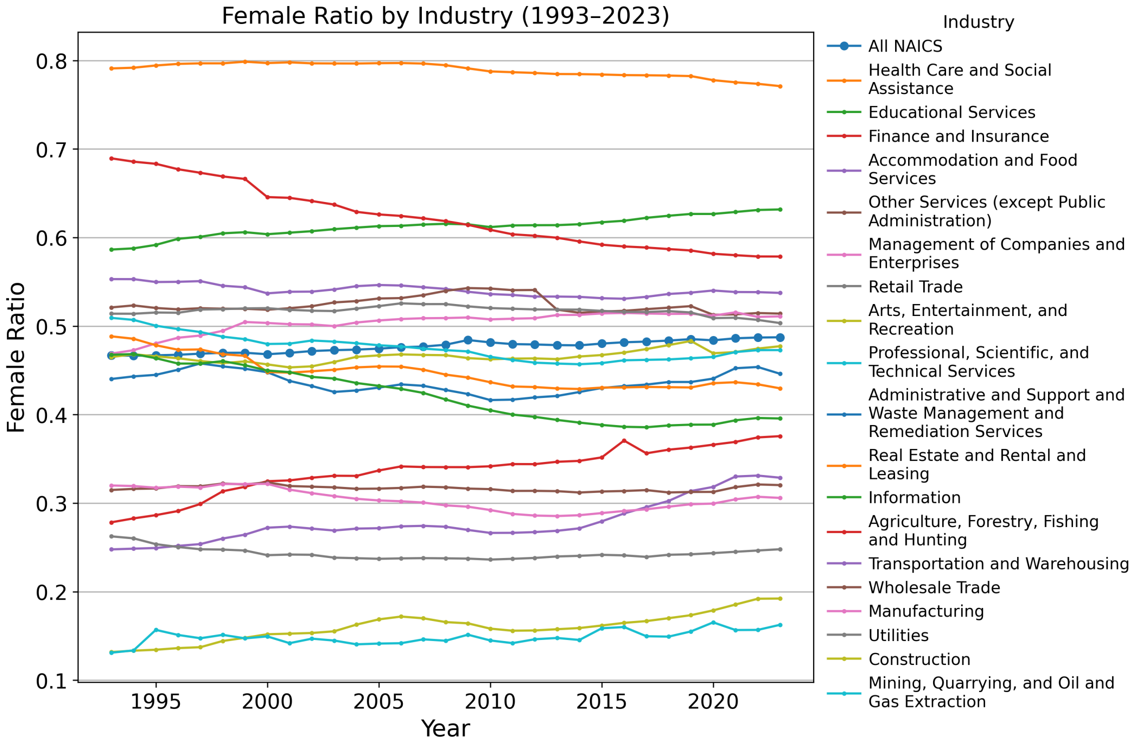

Figure 2: Female share by industry, U.S. 1993-2023

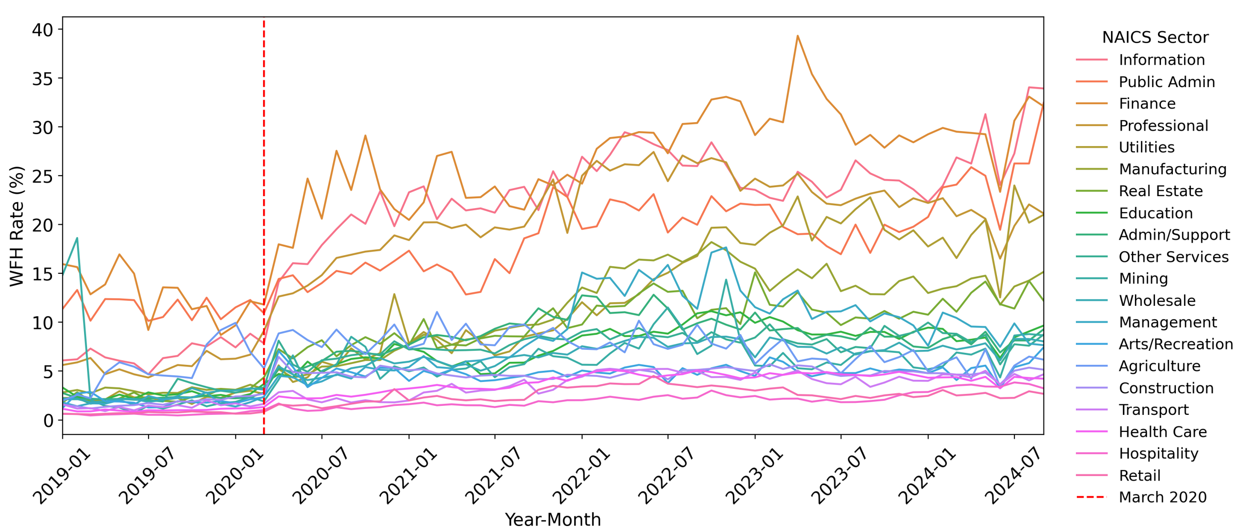

Figure 3: Remote job rate by industry, U.S. Jan 2019–Sep 2024

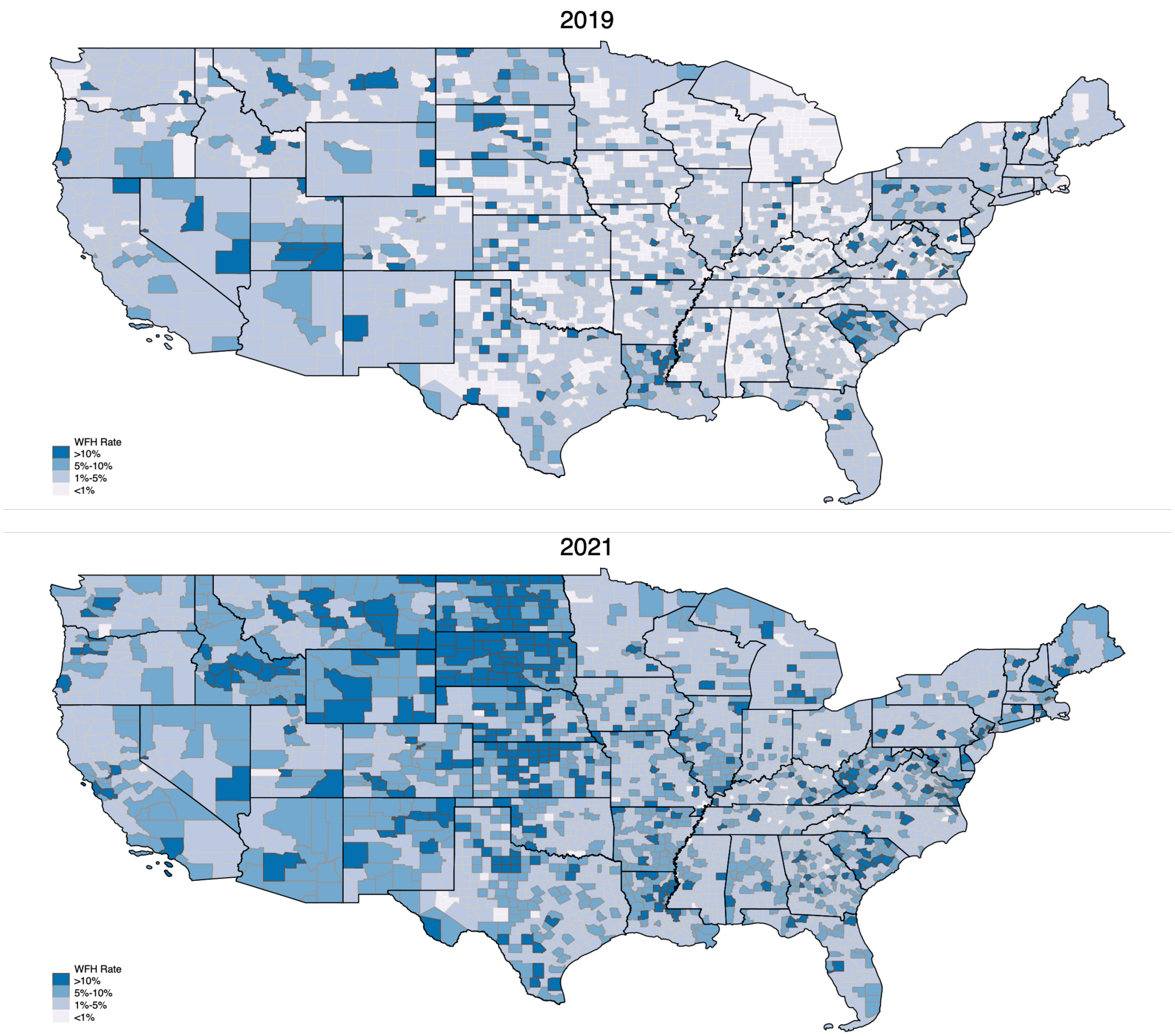

Figure 4: Remote job rate by county, U.S. 2019 v.s. 2021

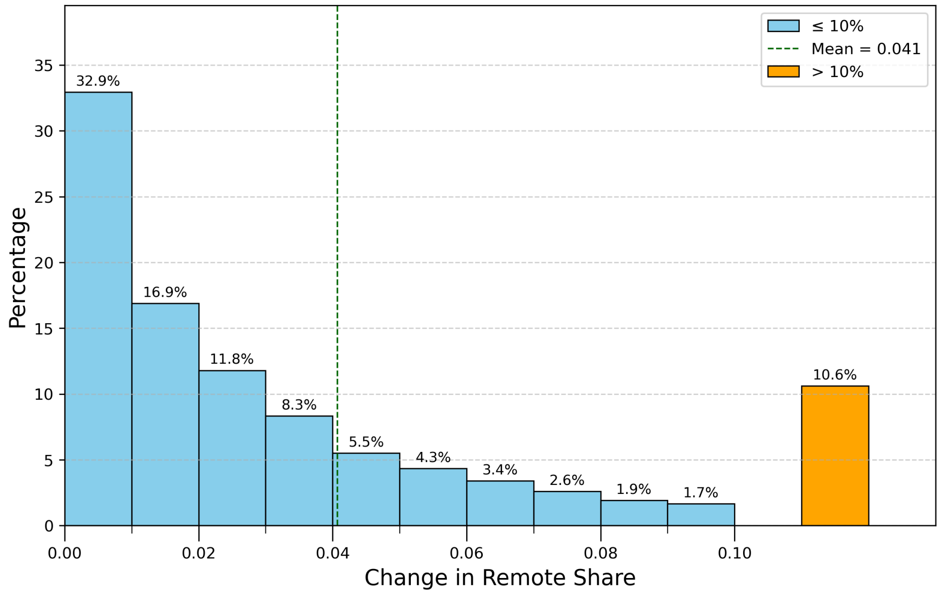

Figure 5: Change in remote job share by county-industry group, U.S. from year 2019 to Apr 2020-Dec 2021

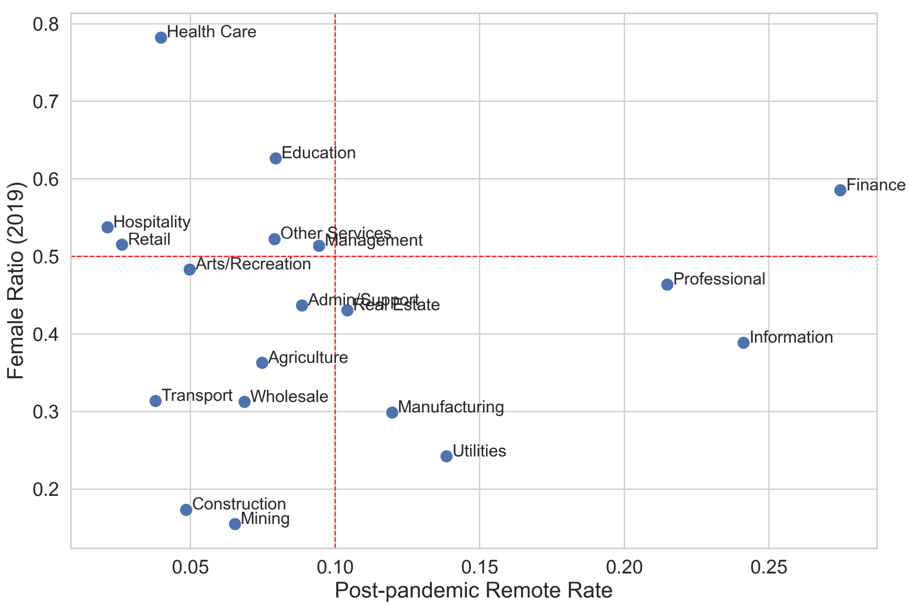

Figure 6: Industry female share in Q4 2019 and post-period remote job share

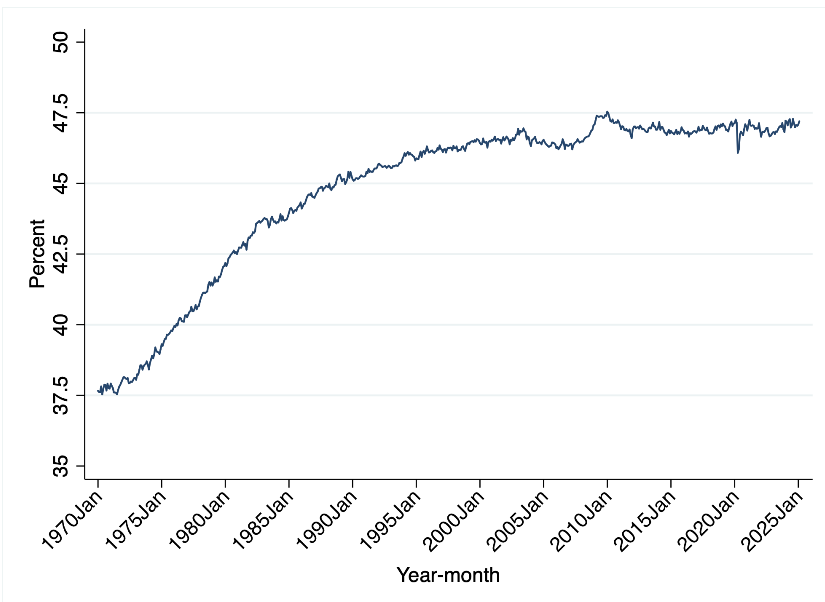

Figure 7: Share of Female Employees in Total Employment, U.S. Jan 1970–Feb 2025

Tables

Table 1: Summary Statistics

	(1) Below median	(2) Above median	(3) Diff.	(4) SE (Diff.)	(5) N
Δ Remote share change	0.007	0.069	-0.063***	0.001	16,676
Hires	967.451	1341.413	-373.961***	55.248	16,676
Employment	6256.497	11584.538	-5328.041***	375.104	16,676
Female share in new hires	0.519	0.475	0.044***	0.003	16,676
Female share in workforce	0.508	0.463	0.045***	0.003	16,676
job postings (2019)	780.611	2345.788	-1565.177***	85.064	16,676
Firm size $\geq$ 500 (share)	0.442	0.449	-0.007*	0.004	14,828
Firm age $\geq$ 11 (share)	0.788	0.797	-0.009***	0.002	15,770
Age 25–54 (share)	0.593	0.638	-0.046***	0.001	16,668
College (share)	0.176	0.248	-0.073***	0.001	16,671
White (share)	0.817	0.815	0.002	0.002	16,671
Hispanic (share)	0.102	0.114	-0.012***	0.002	16,519

Notes: Industry-county groups are divided into two subsets at the median of the change in remote share (Equation (2)). Number of job postings comes from Hansen et al. (2023) 2019 data; all other variables use QWI Q4 2019 data. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 2: The Effects of Remote Work on Female Share in Hiring and the Workforce, 2021

	(1) β^{DD}	(2) β^{DML}	(3) β^{IV}
Panel A. Female Share in New Hires			
Δ Remote Share	0.121***	0.101***	0.097***
	(0.014)	(0.014)	(0.028)
No. of Cty-Ind Groups	16,572	15,736	
No. of Counties			2,545
Panel B. Female Share in Workforce			
Δ Remote Share	0.040***	0.036***	0.058***
	(0.005)	(0.004)	(0.010)
No. of Cty-Ind Groups	16,957	15,736	
No. of Counties			2,546

Notes: Regressions are weighted by the size of each group in Q4 2019, measured by total hires in Panel A and total employment in Panel B. Standard errors are clustered at the county level. The first-stage and reduced-form regression results for the IV specification are reported in Appendix B. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: The Effect of Remote Work on Female Workforce Share, 2021 to 2024

	(1) β^{DD}	(2) β^{DML}	(3) β^{IV}
2021	0.040***	0.036***	0.058***
	(0.005)	(0.004)	(0.010)
2022	0.054***	0.049***	0.070***
	(0.006)	(0.005)	(0.012)
2023	0.055***	0.049***	0.080***
	(0.006)	(0.005)	(0.016)
2024	0.056***	0.046***	0.073***
	(0.006)	(0.006)	(0.015)

Notes: Regressions are weighted by the size of each group based on the total employment in Q4 2019. Standard errors are clustered by county. The first-stage and reduced-form regression results for the IV specification are reported in Appendix B. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Heterogeneous Effects across Industries

	Female-dominated		Male-dominated	
	(1) High-remote Female-dominated	(2) Low-remote Female-dominated	(3) Low-remote Male-dominated	(4) High-remote Male-dominated
Panel A. Female share in new hires:				
DD	0.094	0.043*	0.149***	0.052***
	(0.100)	(0.023)	(0.021)	(0.018)
DML	0.078	0.029*	0.136***	0.035*
	(0.059)	(0.017)	(0.024)	(0.018)
Panel B. Female share in workplace:				
DD	-0.004	0.016*	0.062***	0.021***
	(0.014)	(0.009)	(0.014)	(0.006)
DML	0.008	0.020***	0.061***	0.014***
	(0.011)	(0.007)	(0.012)	(0.007)
No. of industries	1	6	7	5

Notes: Regressions are weighted by the size of each group in Q4 2019, measured by total hires in Panel A and total employment in Panel B. Standard errors are clustered by county. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The Effects of Remote Work on Female Share in Job-to-Job Hires and Hires from Persistent Nonemployment, 2021

	(1) β^{DD}	(2) β^{DML}	(3) β^{IV}
Panel A. Female Share in Job-to-Job Hires			
Δ Remote Share	0.081***	0.064***	0.088*
	(0.016)	(0.016)	(0.053)
No. of Metro-Ind Groups	8,686	4,343	
No. of Metros			279
Panel B. Female Share in Hires from Persistent Nonemployment			
Δ Remote Share	0.141***	0.061***	0.255***
	(0.015)	(0.019)	(0.066)
No. of Metro-Ind Groups	8,664	4,332	
No. of Metros			279

Notes: Regressions are weighted by the size of each group in Q4 2019, measured by total hires in Panel A and total employment in Panel B. Standard errors are clustered by metropolitan. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Relationship between change in remote shares and pre-trends in outcomes

	β^{DD}	β^{DML}
Female Share of New Hires	-0.013	-0.028
	(0.014)	(0.024)
Female Workforce Share	-0.008***	0.002
	(0.003)	(0.004)

Notes: Regressions are weighted by the size of each county-industry group in Q4 2019, measured by the number of new hires and total employment. Standard errors are clustered by county. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Relationship between county industry shares and pre-trends in outcomes

	(1) Z_c	(2) Information	(3) Professional	(4) Finance	(5) Administrative	(6) Real Estate
Female share in new hires	-0.086	0.003	-0.020	0.026	-0.030*	0.072
	(0.074)	(0.027)	(0.013)	(0.023)	(0.016)	(0.060)
Female workforce share	0.007	0.009	-0.002	0.001	0.011	0.063**
	(0.033)	(0.010)	(0.005)	(0.008)	(0.007)	(0.031)

Notes: Regressions are weighted by the size of each county in Q4 2019, measured by the number of new hires and total employment. Column (1) reports the regression of the county-level pre-trend in the female share on the instrument. The remaining columns report separate regressions of the county-level pre-trend on each initial industry share. Standard errors are clustered by county. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix

A The Effect of Remote Work on Separation

Table 8 shows the impact on separation rates separately for female and male workers. In this context, remote share of job postings is used as an proxy of remote work change of all jobs. For females, all jobs changing from in-person to at least one-day remote reduces separation rates by 12 percentage points (column (3)). This suggests that remote work helps retain female employees. The effects for males are similarly negative and significant, although slightly smaller in magnitude in the IV estimates. This parallel decline indicates that remote work benefits both genders in terms of job retention.

Table 8: The Effect of Remote Work on Separation

	(1) β^{DD}	(2) β^{DML}	(3) β^{IV}
Panel A. Female			
Δ Remote Share	-0.103***	-0.0834***	-0.117***
	(0.012)	(0.010)	(0.031)
Const.	0.159***	0.000	0.024***
	(0.000)	(0.000)	(0.001)
No. of Cty-Ind Groups	16,091	15,281	
No. of Counties			2,465
Panel B. Male			
Δ Remote Share	-0.101***	-0.101***	-0.080***
	(0.018)	(0.017)	(0.023)
Const.	0.166***	0.000	0.016***
	(0.000)	(0.000)	(0.001)
No. of Cty-Ind Groups	16,202	15,392	
No. of Counties			2,465

Notes: Regressions are weighted by the size of each group measued by the total employment. Standard errors are clustered by county. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Instrumental Variables Regression Results

Table 9: Instrumental Variables Regression Results

	(1) β^{IV}	(2) First Stage	(3) Reduced Form
New Hires	0.097***	3.046***	0.294***
	(0.028)	(0.205)	(0.078)
Workforce 2021	0.058***	3.012***	0.175***
	(0.010)	(0.220)	(0.025)
Workforce 2022	0.070***	3.030***	0.213***
	(0.012)	(0.221)	(0.031)
Workforce 2023	0.080***	2.998***	0.241***
	(0.016)	(0.229)	(0.041)
Workforce 2024	0.073***	2.935***	0.213***
	(0.015)	(0.210)	(0.045)

Notes: Regressions are weighted by the size of each county in Q4 2019, measured by the number of new hires and total employment. Standard errors are clustered by county. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C Comparison of Estimates Using Linear Covariate Controls and Double Machine Learning

Compared to the linear DID model in Equation (5), the Double Machine Learning (DML) approach relaxes this linearity assumption by allowing for flexible, potentially nonlinear relationships between covariates and both the treatment and outcome variables. Table 10 compares the estimates obtained from the linear specification in Equation (5) with those from the DML method in Equation (6). The differences in the results indicate that the functional form of the covariates plays an important role in the estimation.

Table 10: Comparison of Estimates Using Linear Covariate Controls and Double Machine Learning

	(1) Linear DID	(2) DML
New Hires	0.089***	0.101***
	(0.016)	(0.014)
Workforce 2021	0.013**	0.036***
	(0.006)	(0.004)
Workforce 2022	0.007	0.049***
	(0.007)	(0.005)
Workforce 2023	-0.010	0.049***
	(0.007)	(0.005)
Workforce 2024	-0.030***	0.046***
	(0.008)	(0.006)

Notes: Regressions are weighted by the size of each county-industry group in Q4 2019, measured by the number of new hires and total employment. Standard errors are clustered by county. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.