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Work-From-Home Revolution: Enhancing Women's Participation in STEM

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Abstract

Women continue to be underrepresented in STEM occupations, despite sustained organizational efforts to improve retention and gender diversity. We ask whether increased work-from-home (WFH) opportunities raise young women's participation in STEM roles. Leveraging data from IPUMS-CPS, Survey of Working Arrangements and Attitudes (SWAA), and job postings offering WFH, and drawing on insights from human capital theory and organizational strategy, we implement two Difference-in-Differences designs that exploit exogenous occupation-level variation in WFH adoption induced by the COVID-19 pandemic. We find that high WFH adoption increases the probability of STEM employment among young women by 2.43 percentage points, a 13.6 percent rise relative to the pre-pandemic baseline. This result is robust to alternative specifications, clustering levels, treatment definitions, and matched sample checks. We also find that the impact varies across STEM sub-fields and increases with the intensity of WFH adoption. As such, the results suggests that the effect operates primarily through reduced skill loss enabled by stronger labor market attachment under WFH. These findings highlight WFH as a scalable organizational strategy to improve female retention and advance diversity in STEM occupations.

Keywords: Work from Home; women in STEM, human capital atrophy, Difference in Difference

JEL Codes: J24, J62, D31

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1 Introduction

The question of how to increase women's participation in Science, Technology, Engineering, and Mathematics (STEM) occupations is important but not new (Miller et al., 2015; Del Carpio and Guadalupe, 2022; Borges and Estevan, 2025). It holds strategic importance for both businesses and policymakers for at least four key reasons. First, greater participation improves the quality and productivity of the STEM workforce (Schiebinger, 2008; Xie et al., 2020). Second, it advances diversity, equity, and inclusion, objectives that many firms now treat as strategic priorities. Third, it helps reduce gender-based pay disparities. Evidence from Carter et al. (2017) shows that firms in the S&P 1500 with more female directors tend to have narrower pay gaps. Fourth, it strengthens the STEM talent pipeline, helping address skill shortages in critical sectors and supporting productivity growth. Still, despite decades of attention (Blickenstaff, 2005; Adams and Kirchmaier, 2016), women remain underrepresented in STEM, with global participation plateaued at roughly 35 percent since the mid and late 2000s (Jiang, 2021)[1]. This paper explores whether work-from-home (WFH) arrangements can shift that pattern, and identifies how much remote flexibility is needed to do so.

We place our work within the emerging literature that examines how remote work shapes women's labor market outcomes. Most existing studies focus on broad patterns, such as how WFH affects women's participation in the labor force (Jalota and Ho, 2024; Harrington and Kahn, 2025) or influences the diversity of applicants to remote roles (Hsu and Tambe, 2024). A wider literature looks at related issues, including the motherhood penalty and gendered labor supply decisions (Klerman and Leibowitz, 1994; Anderson et al., 2002). More recently, Del Carpio and Guadalupe (2022) have explored how social identity influences women's willingness to enter technology roles. But to our knowledge, no study directly connects WFH adoption to young women's representation in STEM. This paper aims to fill that gap.

We draw on human capital theory to make sense of this relationship and to measure its effect. Time out of the labor force disrupts the accumulation of skills and depreciates existing ones (Mincer and Polachek, 1974; Polachek, 1981). This is especially true in STEM, where skills atrophy more rapidly. That makes STEM jobs less appealing to those who expect career breaks, young women, for example, who anticipate time away for childbearing or caregiving. Even those with STEM degrees may avoid these jobs, not due to lack of interest or ability, but to avoid the higher cost of skill loss. What drives this sorting is the expectation of

[1]Source: UNESCO Global Education Monitoring Report - https://www.unesco.org/gem-report/en/publication/2024-gender-report (Last accessed on 25 August 2025)

interruption, not a difference in potential. While demand-side barriers often get the blame for low female representation in STEM, the evidence shows that many qualified women never enter STEM roles in the first place (Xie and Shauman, 2003; Glass et al., 2013).

This is where WFH starts to matter. It gives young women a way to handle caregiving, whether now or in the future, without quitting their jobs. Mothers of young children spend about 1.19 hours a day on daytime childcare on average [2]. Without flexibility, that time often comes at the cost of stepping out of work and losing earned skills. WFH lowers this cost of stepping out of work. It lets them care and work at the same time, cutting the risk of skill loss. The effect is strongest in fields like STEM, where skills losses are higher and happen more quickly (Polachek, 1981). In jobs where skills do not depreciate as fast, WFH does not make as much difference.

These theoretical insights lead directly to our empirical strategy. If WFH cuts the cost of staying in jobs where skills atrophy fast, then we should see more young women in those roles when remote work is an option. STEM jobs fall squarely in that category. The COVID-19 pandemic created a sharp, unexpected divide in WFH adoption across occupations. Some jobs, like software development, computer science, and psychological counseling, were structurally suited to remote work and shifted online quickly. Others, such as nursing, medical care, and food service, were not, and remained largely unchanged and required physical presence. We define high-WFH occupations using a threshold based on the share of job postings offering remote work. This natural variation allows us to form treatment and comparison groups. We then track these occupational groups over time using IPUMS-CPS data to estimate the causal impact of WFH adoption on young women's entry into STEM fields.

This structure lends itself naturally to a Difference-in-Differences (DID) framework. We use data from the IPUMS-CPS monthly supplement and job postings compiled by Hansen et al. (2023) to estimate the causal effect of high WFH adoption on young women's likelihood of participating in STEM occupations. Alongside this binary treatment definition, we incorporate a categorical measure of WFH intensity to examine how variation in the degree of remote work adoption influences this participation. To evaluate the validity of our empirical design, we perform pre-trend checks using event study plots and implement a range of sensitivity and placebo tests. We detect no violations of the identifying assumptions necessary for causal inference, reinforcing the interpretation that the estimated effects represent the causal impact of high WFH adoption.

The central result that emerges from this analysis is that occupations with high WFH adop-

[2] Source: Data from ATUS survey from 2020, 2022 and 2024

tion experienced a 2.43 percentage point, or 13.55 percent increase, in the likelihood of STEM participation among young women. The effect is statistically significant, robust to heteroskedasticity, and holds across different clustering levels and alternative thresholds used to define high WFH adoption. In contrast, and in line with theoretical predictions, we find no evidence of a corresponding increase in young women's employment in non-STEM occupations with high WFH adoption, nor any rise in STEM participation among young men. The zero effect in non-STEM suggests that flexibility and work-life balance, while valued, are not sufficient on their own to shift occupational choices. Rather, it is their interaction with the high rate of skill atrophy, a distinctive feature of STEM, that drives the observed pattern. The absence of an effect among men is also expected as men are less likely to have career breaks and therefore face lower risk of skill loss. To account for possible compositional changes between treatment and comparison groups due to WFH-related sorting, we replicate the analysis using a Difference-in-Differences design on a propensity score matched subsample. The results remain consistent. Overall, the evidence supports a human capital mechanism in which WFH allows young women to stay attached to the labor force during periods of childbearing and caregiving. By making it possible to manage these responsibilities without withdrawing from work, WFH helps prevent the loss of skills, losses that are especially pronounced in STEM occupations. This reduction in skill depreciation lowers the cost of continued participation and contributes to higher STEM entry. The size of the effect, however, varies across STEM sub-fields and industries.

In addition to estimating the average treatment effect, we explore how the effect of WFH adoption varies by intensity, using propensity score matched sub-samples. Increasing WFH adoption from 0–7 percent to 7–15 percent raises STEM participation among young women by 1.14 percentage points. A further shift from 7–15 percent to 15–23 percent yields a 2.34 percentage point increase. Finally, moving from 15–23 percent to above 23 percent results in a 4.27 percentage point gain. This monotonic pattern suggests that greater availability of remote work is associated with higher levels of STEM participation. That said, the relationship may plateau or even reverse at very high levels of WFH adoption, an empirical possibility we are unable to assess, as no occupation in our data exhibits a structure in which a very large share of its workforce works from home.

Despite the strategic advantage, the analysis has at least three limitations. First, while we argue that skill depreciation varies across occupations, skills are typically task-specific, and each occupation comprises a diverse set of tasks. As a result, our argument about occupational-level skill loss is made at an aggregate level and does not capture the task-level granularity that might be necessary for a more precise assessment. Second, our WFH measures rely on newly posted job advertisements. Although these postings offer a reasonable proxy for an organization's shift toward remote work, they may not reflect the full share of WFH jobs across all positions. This mismatch may introduce measurement error in the WFH variable. If this error remains stable over time, the estimates are likely to remain unbiased; if not, they may be affected. Third, while we define our binary WFH treatment cutoff based on average childcare demands reported in prior studies for children below six years of age, this threshold may not account for the wide variation in caregiving needs across different child age groups, for example, between mothers of infants and those of preschoolers. As a result, our treatment definition may incorporate some inaccuracy.

2 Broad Context and Related Literature

Broadly, this paper contributes to three strands of literature. First, we contribute to broadening the understanding of non-pecuniary benefits like remote work associated with job design and working arrangements. Second, our paper contributes to the literature on gender inclusivity and diversity in work places for STEM occupations arising out of these non-pecuniary benefits. Finally, we integrate the human capital literature with remote work literature to understand the broad implications for the labor market.

2.1 Remote work as a Non-Pecuniary Benefit

COVID-19 has made remote work more acceptable across organizations. It serves as a non-pecuniary benefit, especially for women in STEM and similar fields, where on-site presence is costly. In support of this, Lewandowski et al. (2022) find that individuals are willing to take a pay cut to be allowed to work from home. Similarly, Choudhury et al. (2024) through a field experiment in Bangladesh find that workers who spent around two days in the office each week on average report greater work-life balance and higher job satisfaction compared to workers who spent more days in the office.[3] In terms of preferences for remote work, Chen et al. (2023) through the Survey of Consumer Expectation (SCE) and longitudinal surveys conducted by NielsenIQ find that in February 2020 (pre-pandemic), the desired share of work to be done from home was 38 percent for women and 32 percent for men. By May 2020 (three months into the pandemic), this number increased by about 13 percentage points for both genders on average. Overall, studies like Bloom et al. (2022) document that hybrid mode of work was highly valued by employees on average, reducing attrition by 33 percent and improving job-satisfaction levels.

[3] The authors also find that too few days in office can be a cost in terms of higher isolation from colleagues.

As with employees, employers also find remote work beneficial. Contrary to the pre-pandemic belief, Barrero et al. (2021) find that the increase in the productivity in the post-pandemic period led firms to increase the planned levels of WFH they offer to employees. Not just WFH, but also Work-From-Anywhere (WFA) as per Choudhury et al. (2021), which is temporally and geographically more flexible, led to a 4.4 percent increase in output without affecting the incidence of rework. Similarly, Choudhury (2022) in a review integrates wide literature examining the value addition of geographic mobility for both organizations and individual workers.

Evidence also suggests that the ideal choice for remote work differs between men and women (particularly those with childcare responsibilities). Remote work often helps ease the constraint of childcare responsibilities for women, thereby leading them to value it higher than men (Mas and Pallais, 2017). Similarly, Arntz et al. (2022) use data from the German Socio-Economic Panel between 1997 and 2014 and find evidence that, even though employees without children worked an extra hour of unpaid work, they still reported higher job satisfaction after taking up WFH.

Although a substantial body of literature examines the evolving nature and benefits of remote work for both employees and employers, research on the minimum level of remote work required to support greater gender inclusivity and diversity remains limited. This paper contributes by identifying that threshold in the context of remote work as a non-pecuniary benefit.

2.2 Work From Home and Women's Work

Discussion related to workplace flexibility and its impact on careers of women can be found in Mincer (1993), where he finds that quit rates of women from labor force are strongly motivated by various family demands, including a need for flexible time schedule. Along similar lines, Polachek (1987) and Goldin (2014), find that the gender pay gap is higher in occupations that offer little temporal flexibility, have long working hours, and have a higher cost of intermittency. In her recent work Goldin (2022), also argues that remote work can be beneficial to college-educated mothers in the long run. Similarly, other studies related to remote work and employment outcomes for women include Heggeness and Suri (2021), which finds that custodial mothers of school-going children compared to non-mothers have a higher probability of reducing labor market participation when there is an increase in childcare responsibilities.

From perspective of literature in management, Sherman (2020) documents that relaxing the constraint of physical presence at work can enhance the well-being and productivity of working mothers. Another channel through which remote work impacts the employment of women is through reduced work commute. Given that women often take on a greater share of care responsibilities at home, the distance to work hinders job search and potential earnings (Petrongolo and Ronchi, 2020). Similarly, Olivetti and Petrongolo (2017) find that a greater work flexibility is both positively correlated with female employment and negatively correlated to employment gap.

While a lion's share of research indicates positive effects of remote work on gender equality, there is some evidence of a negative effect of remote work on careers of women as well. For example, Pabilonia and Vernon (2023) find that despite the increase in mothers and fathers time spent on caring for children and the time spent on household chores remaining the same, only mothers worked fewer paid hours during the pandemic. Furthermore, the authors also find that mothers working from home during the pandemic were more likely to spread their working hours throughout the day and take more breaks between the work hours. These potential disruptions could negatively affect their productivity in paid work.

Recent work by Hsu and Tambe (2024), using job applicant data from a leading startup job platform and through a matching approach, found that offering remote work attracts more experienced and gender diverse job applicants. Closer to our focus area, research by Harrington and Kahn (2025) documents that on average, a ten percent increase in the share of workers working primarily from home is associated with a 0.78 percentage point narrowing of the gap in employment between mothers and other women. The authors find that this is driven by college degrees where individuals tend to work in inflexible jobs which have high returns to long hours. In a related line, Zarate (2025) uses data from four Latin American countries and a pseudo-event study design to show that access to remote work raises employment near motherhood. Likewise, Jack et al. (2025) link administrative data on U.S. workers' fertility and labor market histories and finds that the parental earnings gap is partly due to mothers moving to lower-paying firms and that women are more likely to work remotely after their first child.

Many of the above studies related to WFH and women's work comment on improvements in career choices of women in the realm of motherhood penalties and associated costs of childcare. We contribute further to this strand of literature by combining two critical pieces of research agenda and viewing the outcomes related to women's work because of WFH closely through the lens of human capital literature (discussed in detail below). In fact, the Hsu and Tambe (2024) and Harrington and Kahn (2025) papers are the closest to our analysis.

However, we answer our question specifically using the human capital theory, something which has not been explored earlier.

2.3 Human Capital Accumulation and Depreciation, Remote Work and Occupational Choices

Seminal work of Polachek (1981) points to the existence of occupational segregation by gender. The central idea and logic being that wages on-the-job rise for an individual over the life-cycle as experience mounts. However, dropping out of the labor force or experiencing career interruptions disrupts on-the-job investments and causes the erosion of accumulated human capital, thereby reducing earning potential, also called skill atrophy. There are certain occupations where the atrophy is much higher compared to others, and thus it impacts women more than men, given the labor force intermittency they experience or expect to experience particularly around child-bearing age. Other such studies in the field of labor economics include Gronau (1988), which suggest that women often value job attributes that make their careers more friendly towards domestic responsibilities. The above literature along with the literature related to motherhood penalty for women explains to a great extent why women often do not choose occupations associated with high atrophy rates.

A consequence of this choice is often an under-representation of women in STEM disciplines across the pipeline, from STEM degrees to STEM occupations (Speer, 2023). The STEM pipeline involves pre-college, college attendance, choice of major, transition from college to early career occupation, and finally moving from early career job to mid career job. Across each of these stages, literature documents relevant under-representation for females in STEM disciplines. For example, in the pre-college stage, Bedard and Cho (2010) and Fryer and Levitt (2010) find differences in test scores between boys and girls, particularly for maths and science subjects. In case of college attendance, the works of Becker et al. (2010) and Goldin et al. (2006) explain the observed contradiction of women enrollment exceeding that of men in college through the channel of investments in human capital. The broad claim being that men suffer from a lack of discipline and perseverance, thereby leading to obstacles in their human capital accumulation. The third stage of the pipeline is related to the choice of major. Studies such as Astorne-Figari and Speer (2019) and Astorne-Figari and Speer (2018) find that women are more likely to move out of STEM majors, whereas men are more likely to drop out of college entirely. In addition, Hoisl and Mariani (2017) examine income differences between women and men in creative, highly skilled jobs tasked with achieving technological inventions. A key finding is that of low participation rates among women because they perceive lower expected returns from these jobs as compared to men, and having children may add to this penalty. As mentioned earlier, our focus in this paper is closely linked to the stage where an individual transitions from college to an early career occupation or is already in an early career job. Research in this space has focused on male dominance in STEM occupations and also the lack of STEM occupations offering flexibility and being less family friendly (Weisgram and Diekman, 2015; Kahn and Ginther, 2017; Delaney and Devereux, 2022). Other works like Del Carpio and Guadalupe (2022) have focused on how different measures like communicating information on tech careers to women can help counterbalance the male stereotypes associated with these careers.

3 Structural Basis of the Empirical Model

To derive an estimable framework, we embed the concept of skill loss from human capital theory into the occupational choice model proposed by Roy (1951). Human capital theory suggests that occupations differ in the rate at which skills depreciate, with STEM roles typically exhibiting higher depreciation due to their technical intensity. We exploit this heterogeneity between STEM and non-STEM occupations and introduce WFH adoption into the model as a mechanism that mitigates skill loss by enabling continued labor force attachment. This framework guides the development and empirical testing of our core hypothesis, that WFH adoption increases the likelihood of young women selecting into STEM occupations.

3.1 Broad Setup of the Model

Consider a setting with two mutually exclusive occupational choices: STEM and non-STEM. Each worker enters the labor market with initial endowments of STEM and non-STEM skills and builds on them through on-the-job training over her career. These skills may be correlated or uncorrelated. Each unit of skill carries a market value, with π_s denoting the price of STEM skills and π_n the price of non-STEM skills. Using these prices and the anticipated accumulation of skills, the worker selects the occupation that maximizes her expected lifetime earnings. The framework does not allow moonlighting.

If the worker chooses a STEM occupation and remains continuously employed, she accumulates S_i units of STEM skills over her career. Similarly, continuous employment in a non-STEM occupation allows her to accumulate N_i units of non-STEM skills. In contrast, if she participates intermittently, she accumulates fewer skills due to a shorter work span and the existing skills depreciate from infrequent use. Let δ_i^s and δ_i^n represent the rates at which STEM and non-STEM skills decline. Under intermittent employment, the worker therefore retains $(1 - \delta_i^s)S_i$ units of STEM skills and $(1 - \delta_i^n)N_i$ units of non-STEM skills over her career.

3.2 Earnings in STEM Occupations

Based on the structure outlined above and under the assumption of a competitive skill markets, the earnings of individual i when employed in a STEM occupation can be expressed as:

$$Y_{si} = \pi_s \times (1 - \delta_i^s) \times S_i \tag{1}$$

where, Y_{si} denotes the lifetime earnings in STEM occupation. Taking log on both sides of (1) yields

$$lnY_{si} = ln\pi_s + ln(1 - \delta_i^s) + lnS_i \tag{2}$$

The value of δ_i^s and δ_i^n lie between 0 and 1, and generally closer to zero than one. Given this small positive value, we apply a log approximation to the $ln(1 - \delta_i^s)$ term in the following equation:

$$lnY_{si} = ln\pi_s - \delta_i^s + lnS_i \tag{3}$$

3.2.1 Determinants of STEM Skills

Let the logarithm of skills S_i in equation (3) be determined by a number of observed and unobserved factors. Let X'_{si} be a vector of the observed determinants of STEM sector skills and ϵ_{si} be the unobserved determinants. X'_{si} can include factors that specifically enhance STEM sector skills (X'_{ssi}) and can include factors that generally influence skills in both the sectors (X'_{0i}). As an example, education and work experience might be factors that impact skills in both sectors, albeit differently. We further assume that the unobserved determinants of skills (ϵ_{si}) are known to the worker but unknown to the analyst. Assuming that these factors affect the log of skills linearly, we specify the skill equation in the STEM occupations as follows:

$$lnS_i = X'_{ssi}\gamma_{ss} + X'_{0i}\gamma_{0s} + \epsilon_{si} \tag{4}$$

where γ_{ss} and γ_{0s} are the vector of coefficients capturing the effects of the determinants on skill formation.

3.2.2 Rate of Decline of STEM Skills (δ_i^s)

As noted earlier, δ_i^s captures the rate at which STEM skills decline due to intermittent employment. A significant portion of this decline results from skill depreciation, or atrophy, associated with time away from STEM work. When a worker, particularly a female worker, gains access to WFH opportunities, her likelihood of intermittent participation decreases, thereby reducing the rate of skill decline. As a result, the effective loss of STEM skills over the career can be expressed as:

$$\delta_i^s = \theta_{0s} - \theta_{1s} \times WFH_i \tag{5}$$

The parameter $\theta_{0s} > 0$ denotes the baseline rate of decline of individual i's STEM-specific skills. Its magnitude is typically influenced by a combination of factors, including the worker's potential length of labor market intermittency, personal attributes (e.g., cognitive retention, health), the type of STEM skills acquired (e.g., mathematical vs. medical), and how frequently those skills are applied in the workplace. When WFH is introduced, workers are able to continue participating in the labor market while simultaneously managing domestic responsibilities such as child care. As a result, the expected duration of labor market absence declines, leading to a reduction in the skill atrophy rate. This reduction is captured by the parameter θ_{1s}, where $\theta_{1s} > 0$. The WFH variable is modeled as a binary indicator: $WFH = 1$ if individual i is exposed to high WFH arrangements, and $WFH = 0$ otherwise.

3.2.3 Earnings function in STEM occupations

Given the explicit component-wise specifications in equations (3), (4), and (5), the earnings function can now be expressed as follows:

$$lnY_{si} = ln\pi_s - \theta_{0s} + \theta_{1s} \times WFH_i + X'_{ssi}\gamma_{ss} + X'_{0i}\gamma_{0s} + \epsilon_{si} \tag{6}$$

3.3 Earnings in non-STEM Occupations

The derivation of the earnings function for non-STEM occupations follows similar steps and relies on a similar set of assumptions and structural components. Similar to the STEM sector, we assume that the skills market in the non-STEM sector is also perfectly competitive. Accordingly, the potential life-time earnings of a worker in the non-STEM sector can be expressed as:

$$Y_{ni} = \pi_n \times (1 - \delta_i^n) \times N_i \tag{7}$$

where, Y_{ni} denotes the lifetime earnings in non-STEM occupations. Taking log on both sides of (7) yields

$$lnY_{ni} = ln\pi_n + ln(1 - \delta_i^n) + lnN_i \tag{8}$$

Here as well, it is reasonable to assume that $0 \leq \delta_i^n \ll 1$, making the log approximation of $\ln(1 - \delta_i^n)$ both valid and practical. This allows the expression to appear in the following form:

$$lnY_{ni} = ln\pi_n - \delta_i^n + lnN_i \tag{9}$$

3.3.1 Determinants of non-STEM Skills

Similar to the STEM skill formulation, non-STEM skills are determined by X'_{nni}, X'_{0i}, and ϵ_{ni}. Accordingly, the skill accumulation function for the non-STEM sector can be specified as:

$$lnN_i = X'_{nni}\gamma_{nn} + X'_{0i}\gamma_{0n} + \epsilon_{ni} \tag{10}$$

where X'_{nni} denotes the vector of observed non-STEM-specific skill determinants, and X'_{0i} represents the vector of observed general skill determinants. In contrast, ϵ_{ni} captures unobserved factors influencing non-STEM skill accumulation. The vectors γ_{nn} and γ_{0n} are the corresponding parameter coefficients.

3.3.2 Rate of Decline of non-STEM Skills (δ_i^n)

Consistent with the STEM occupations, skill depreciation in non-STEM occupations is governed by the following functional form:

$$\delta_i^n = \theta_{0n} - \theta_{1n} \times WFH_i \tag{11}$$

Here, as in the STEM case, $\theta_{0n} > 0$ denotes the baseline decline rate of individual i's non-STEM skills. In contrast, $\theta_{1n} > 0$ captures the extent to which this decline rate is mitigated when the individual has access to WFH arrangements.

The usual assumption on the sign of θ_{0n} and θ_{1n}, similar to θ_{0s} and θ_{1s}, holds. In addition, as estimated by Polachek (1981), we take δ_i^s to be greater than δ_i^n. Therefore, we assume θ_{0s} to be greater than or equal to θ_{0n} and θ_{1s} to be strictly greater than θ_{1n}.

3.3.3 Earnings function in non-STEM occupations

Collecting the components from equations (9), (10), and (11), the potential earnings function in non-STEM occupations can be expressed as:

$$lnY_{ni} = ln\pi_n - \theta_{0n} + \theta_{1n} \times WFH_i + X'_{nni}\gamma_{nn} + X'_{0i}\gamma_{0n} + \epsilon_{ni} \tag{12}$$

3.4 Selecting STEM occupations

Occupational choice is driven by potential earnings, consistent with the Roy (1951) framework. A worker selects a STEM occupation if her expected earnings in STEM exceed those in non-STEM. Otherwise, she opts for a non-STEM occupation. Formally,

$$\text{Work in STEM Sector} = \begin{cases} 1 & \text{if } \ln(Y_{si}) \geq \ln(Y_{ni}) \\ 0 & \text{if } \ln(Y_{si}) < \ln(Y_{ni}) \end{cases}$$

where, Work in STEM Sector = 1 means that the individual works in STEM sector, and Work in STEM Sector = 0 means that the worker works in non-STEM sector. Given this choice rule, the probability of selecting into STEM sector is:

$$\begin{aligned} P(\text{STEM} = 1 \mid X = x) &= P\Big[\ln(Y_{si}) \geq \ln(Y_{ni})\Big] \\ &= P\Big[(\ln \pi_s - \ln \pi_n - \theta_{0s} + \theta_{0n}) + (\theta_{1s} - \theta_{1n}) \times WFH_i \\ &\quad + X'_{ssi}\gamma_{ss} - X'_{nni}\gamma_{nn} + (\gamma_{0s} - \gamma_{0n})X'_{0i} + \epsilon_{si} - \epsilon_{ni} \geq 0\Big] \end{aligned} \tag{13}$$

We model this discrete occupational choice using the standard Logit specification, commonly employed in empirical applications, as follows:

$$P(STEM = 1) = \frac{exp(\beta_0 + \beta_1 WFH_i + X_i'\gamma + u_i)}{1 + exp(\beta_0 + \beta_1 WFH_i + X_i'\gamma + u_i)} \tag{14}$$

where $\beta_0 = (\ln \pi_s - \ln \pi_n - \theta_{0s} + \theta_{0n})$; $\beta_1 = (\theta_{1s} - \theta_{1n})$; $X_i'\gamma = (X'_{ssi}\gamma_{ss} - X'_{nni}\gamma_{nn} + (\gamma_{0s} - \gamma_{0n})X'_{0i})$; and $u_i = (\epsilon_{si} - \epsilon_{ni})$

An attractive feature of the Logit specification is that the log(odds ratio) is a linear function, i.e.,

$$ln(\frac{p_i}{1 - p_i}) = \beta_0 + \beta_1 \times WFH_i + X_i'\gamma + \mu_i \tag{15}$$

where p_i is worker i's probability of selecting STEM occupations.

We provide further details on how we use the theoretical model in our empirical specification in the sections below.

4 Data

In this section, we provide details on the data sources we use, as well as details on the construction of various variables used in our empirical specification.

4.1 Description of Data Sources

Our empirical analysis combines three data sources. First, Survey of Working Arrangements and Attitudes (SWAA) (Barrero et al., 2021); Second, job postings data showing remote job openings across occupations (Hansen et al., 2023), and third, Current Population Survey (CPS) data from IPUMS.

We use the Survey of Working Arrangements and Attitudes (SWAA) to examine broad trends in remote work in the post COVID-19 period. The SWAA surveys roughly 10,000 US residents each month, aged between 20 and 64 years, who earned at least $10,000 in the previous year.[4] Each survey collects data on demographics, earnings, commuting, and especially on remote work experiences and expectations. Although the survey data is repeated cross-sectional since May 2020, we use aggregate responses from specific questions to analyze remote work patterns. Figure 1 shows one such pattern, where the share of full-time workdays at home on an average increased sharply after the pandemic began. This shift has remained stable since 2023 and suggests lasting changes in work habits. Another notable trend is that employers intend to offer nearly 1.5 days per week of remote work to workers on an average. Once again, this number is similar to actual WFH levels since mid 2022. Furthermore, workers aged 20 to 40 years more often work in hybrid or fully remote modes compared to other age groups. These trends may influence how individuals make occupational choices in response to steady remote work levels.

Our second data source is job postings data from Hansen et al. (2023). We use this data to create our treatment variable, explained further in the next subsection. Hansen et al. (2023) use large language models (LLMs) to measure the share of job vacancies offering at least one day per week of remote work. This data is monthly and classified according to the 2018 three-digit Standard Occupation Classification (SOC). We use data from January 2019 through September 2024. Although our analysis, shown in equation (16), is at the individual level with the possibility of mapping occupations at the four-digit SOC level, aggregating the treatment and comparison groups at the three-digit level may reduce accuracy. However, given the nature of occupations, we argue that estimates would not change significantly even

[4]The earnings requirement has eased over the past five years since the survey began. For further details, see Buckman et al. (2025).

with the availability of four-digit job postings data. One advantage of using job vacancy postings for treatment and comparison groups is that these postings reflect new job flows rather than current remote work arrangements. These flows can shape individuals' expectations, influencing their decisions about changing occupations. Figure 4 shows the change in the share of remote job postings from before to after the pandemic, summarized at the two-digit occupation level.

Finally, we use IPUMS-CPS data to test our empirical model from equation (16) (given later) at the individual level. The IPUMS-CPS data has information on our dependent variable and various control variables. The US Census Bureau conducts the CPS monthly for over 65,000 households. It provides detailed data on individuals and households, including demographics, employment status, education, and other factors. We use repeated cross-sectional CPS data from IPUMS, spanning January 2016 through February 2025, excluding 2020 and 2021. We remove these years to avoid effects of the pandemic and recession on occupational supply and demand. Additionally, we limit our sample to employed individuals, as occupational and industry information is unavailable for those unemployed or outside the labor force. Our analysis focuses on young individuals, defined as those between 18 and 41 years old. We choose this age group to align with our theoretical model, which emphasizes that young women frequently exhibit labor force intermittency, often due to childbearing and caregiving. Recent data indicates the average age at first birth for women was 27.5 years in 2021.[5] This age-group choice aligns with existing studies, such as Das and Polachek (2015), where the authors study the effect of California Paid Family Leave (CPFL) on young women's (less than 42 years of age) labor force participation and unemployment.

4.2 Variables for Empirical Estimation

We use IPUMS-CPS data and the Census Bureau's 2010 STEM definition to construct our outcome variable. The CPS data includes occupation codes for each person in our sample, across all years of study. These occupation codes follow a consistent coding scheme.[6] First, we match harmonized CPS occupation codes to the 2010 Census occupation codes. Then, we apply the Census Bureau's definition of STEM occupations to categorize jobs as either STEM or non-STEM. Thus, the outcome variable equals 1 for individuals in STEM jobs and 0

[5]Source: `https://www.cdc.gov/nchs/fastats/births.htm`

[6]IPUMS-CPS provides harmonized occupation codes in the variable occ2010 for all periods in our analysis. It also includes the variable occ, which reflects the most recent census occupation codes. We create a mapping between Census 2010 codes and the occ2010 codes by using data from 2011 to 2019, where both variables are available. We then use this mapping to apply various classifications based on the Census 2010 occupation scheme

otherwise. Since our analysis tests a theory related to skill atrophy by occupation, we exclude non-STEM jobs with high atrophy rates from our main outcome measure. These high-atrophy occupations include management, business and financial, and legal roles, classified as non-STEM but identified with high atrophy in Polachek (1981). Figures 2, A2, and A3 show broad trends in STEM occupation choices among young women and men. Figure 2 shows the proportion of young men and women in STEM occupations. Figure A2 shows the proportions of young men and women choosing STEM jobs out of their respective totals across years. Similarly, Figure A3 provides these proportions at an year monthly level.

In addition to our main outcome variable, we use two other outcome measures for robustness checks, discussed later in the results section. The first is low-atrophy, high-WFH occupations. We code this outcome as 1 for individuals in occupations with high WFH and low atrophy. These occupations are non-STEM, not managerial, business, financial, or legal, but still have high WFH levels. Individuals in non-STEM occupations with low WFH and low atrophy receive a value of 0. The second additional outcome is high-atrophy occupations, excluding STEM fields apart from health occupations. Here, we assign a value of 1 to individuals in managerial, business, financial, or legal occupations, all of which are non-STEM and have high atrophy rates (Polachek, 1981). Additionally, health occupations are also coded as 1. Individuals in other non-STEM occupations are coded as 0. We discuss these definitions and variables further in the robustness subsection.

The primary independent variables in this study are binary indicators for treatment and comparison groups, pre- and post-treatment periods, and their interaction. In our empirical section, we focus primarily on the interaction term's coefficient. This coefficient provides the causal effect estimate of interest. We code the treatment variable as 1 for individuals in the treatment occupations and 0 otherwise. We use three steps to define treatment and comparison groups. First, we map three-digit 2018 SOC codes to 2010 Census occupation codes using crosswalks provided by the US Census Bureau. This mapping is necessary because the treatment intensity from Hansen et al. (2023), the share of remote job vacancies, is reported at the 2018 SOC level. However, CPS individual-level data uses harmonized codes, requiring conversion to Census 2010 codes and then to the 2018 SOC classification. Next, we calculate the minimum remote job postings share needed for women to handle childcare at home at least one day weekly. This threshold is 6.9764 percent; Appendix C explains its calculation. The intuitive idea being that working remotely saves commute time and provides flexible time which women can then use for providing child care without reducing their work hours. Finally, we classify occupations as treatment (i.e., high WFH) if the remote postings share exceeds this threshold for all months from January 2023 to September 2024.

Occupations below this threshold belong to the comparison group. We select these 21 months because remote work stabilized during this period.

Our classification into treatment and comparison groups closely aligns with definitions in Dingel and Neiman (2020). We argue that some occupations naturally allow work from home, while others do not. Job postings data capture these differences, guiding our treatment and comparison assignments. Detailed listings of treatment and comparison group occupations appear in Appendix D.

Our other independent variable is a dummy indicating the post-treatment period. We code it as 0 for months before March 2020 and 1 thereafter. March 2020 marks the start of the post-pandemic period because the US declared a federal emergency on March 13, 2020, shortly after the World Health Organization declared the pandemic on March 11, 2020. As mentioned earlier, we do not use data for years 2020 and 2021 in our estimation strategy.

Finally, we include several control variables to limit the risk of omitted variable bias. These controls include years of education, work experience, number of children, number of children under age five, family income, marital status, race, work status, and state and metropolitan fixed effects. Table I1 provides details and units of measurement for these variables. We also weight all estimates using the *compwt* variable from IPUMS-CPS. These weights makes the sample representative of the population, thus improving the generalizability of our results.

4.3 Descriptive Statistics

In general, the share of young women in STEM jobs was rising even before the pandemic. However, this share grew faster after the pandemic began; the same period when WFH became a common and accepted practice (see Figure 1). In Figure 2, we show that women made up 34.13 percent of all young workers in STEM in 2015. By 2019, this rose to 35.26 percent, an increase of about 1 percentage point over four years. By 2025, the share reached 37.97 percent, a rise of 2.7 percentage points since the pandemic began. Similarly, in context of our dependent variable, i.e. proportion of young women choosing to be in STEM occupations, we observe from Figure 3 that the proportion increased more strongly in the treatment group compared to the comparison group at the year-month level. Overall, we report the descriptive statistics for individuals in our treatment and comparison group in the pre- and post-treatment period across multiple characteristics like age, education level, family income among others in Table A1 and Table A3.

We provide the average proportions of young women in STEM occupations in the treatment and comparison group across the pre and post periods in Table A2. Using these averages, we find that the increase in young women choosing to be in STEM occupations was greater in the treatment group in the post-period. A basic DID calculation shows an effect of 2.99 percentage points. This corresponds to a 16.7 percent increase (a 2.99 percentage point rise relative to 17.96 percent of young women in STEM jobs in the pre-period treatment group).

We next contrast the descriptive trends observed in the preceding paragraph to those for young men. In this regard, Figure A1 shows that while the share of young men in STEM jobs in the treatment group rose slightly at first, it later fell. This drop did not occur in the comparison group. Figure A3 also shows that the post-pandemic rise in STEM participation was faster for young women than for young men.

In sum, the descriptive statistics and comparisons suggest that the share of young women grew faster for the treatment group after the pandemic. However, these patterns are only suggestive and correlational, not causal. They do not control for other confounding factors that may influence outcomes. To address this, we carry out a formal empirical analysis based on our identification strategy. This allows us to estimate the causal effect of increased WFH on young women's participation in STEM occupations. We present this analysis in the sections below.

5 Empirical Strategy

Equation (15) expresses the odds ratio of worker i's occupational choice, which is influenced, among other factors, by the worker's access to WFH arrangements. Since the worker actively selects into occupations with varying levels of WFH access, this access becomes an endogenous choice variable. This endogeneity can potentially undermine identification of the causal effect.

Another potential challenge arises from the structural differences between occupations that adopted high levels of WFH and those that did not. These occupations may differ in both observed and unobserved ways. If such differences did not exist, most occupations would have adopted WFH when COVID-related restrictions made remote work necessary. Given these structural distinctions, a simple OLS regression or comparison of average outcomes across the two groups may yield biased and inconsistent estimates of the treatment effect.

To address the inherent selection differences across occupations and individuals, we apply a canonical DID framework. We define the treatment group as occupations that offered high levels of WFH, and the comparison group as those with low WFH availability. The post-treatment period, denoted by $Post$, begins after the onset of COVID-19. Based on this setup, the estimable specification takes the following form:

$$log(\frac{p}{1-p}) = \kappa_0 + \kappa_1 Post_i + \kappa_2 WFH_i + \kappa_3 Post_i \times WFH_i + X'\gamma + \sigma_i \tag{16}$$

5.1 Identification

The DID framework effectively accounts for time-invariant unobserved differences across occupations and workers, thereby addressing selectivity bias. However, other sources of bias may persist, and the validity of the DID estimator relies on an additional set of identifying assumptions.

The first key assumption is the no anticipation assumption, which requires that individuals and firms do not adjust their choices in advance based on the expectation of WFH arrangements. In this setting, the assumption is likely to hold, as the onset of COVID-19 was largely unexpected and gave individuals and firms minimal time to revise their behavior before the shift to remote work took place.

The second requirement is the Stable Unit Treatment Value Assumption (SUTVA), which holds that the average outcome for the comparison group should remain unaffected by the treatment assignment in the treatment group. This assumption may be violated if workers shift from low-WFH to high-WFH occupations to gain flexibility, or if changes in the employment structure of high-WFH occupations influence occupational choices in the low-WFH group. However, this risk appears limited, as high-WFH occupations typically demand skill sets that differ substantially from those required in low-WFH roles. If the skills were similar, most occupations would have already adopted WFH arrangements. This structural mismatch reduces the likelihood of worker movement across groups. In addition, the labor market for high-WFH occupations likely operates separately from that of low-WFH occupations, further minimizing spillover effects. Therefore, SUTVA is likely to hold in this context.

The third concern involves the common trend requirement between the treatment and comparison groups, which is central to the validity of the DID approach. We address this by demonstrating that the conditional parallel trends assumption holds, as evidenced in the event study graph presented later (Figure 5).

5.2 Estimation

Two key issues arise in the estimation. First, equation (16) cannot be estimated directly because the probabilities used as dependent variables are not observed. Second, even if estimation were possible, the coefficient κ_3, under all identifying assumptions, captures the causal effect of high WFH on the log odds ratio, not on the probability of STEM participation. Estimating the model using a standard logit regression would yield inaccurate treatment effect estimates due to the nonlinearity of the logit function. We address both issues using the approach outlined below.

Because the logit model directly maps to the log odds ratio, we estimate a logit specification as the first step to obtain a consistent estimate of κ_3. This approach leads to the following standard logit model, which yields $\hat{\kappa}_3$.

$$P[STEM = 1] = \frac{exp[\kappa_0 + \kappa_1 Post_i + \kappa_2 WFH_i + \kappa_3 Post_i \times WFH_i + X'\gamma + \sigma_i]}{1 + exp[\kappa_0 + \kappa_1 Post_i + \kappa_2 WFH_i + \kappa_3 Post_i \times WFH_i + X'\gamma + \sigma_i]} \quad (17)$$

Once we obtain $\hat{\kappa}_3$ from the estimated logit model, we compute the corresponding treatment effect of interest. Accordingly, we express $\hat{\kappa}_3$ as follows:

$$\hat{\kappa}_3 = log(\frac{p_{post}}{1 - p_{post}}) - log(\frac{p_{pre}}{1 - p_{pre}}) \quad (18)$$

Here, p_{post} and p_{pre} represent the probabilities of STEM participation in the post- and pre-COVID periods, respectively. Since we can compute p_{pre} directly from the pre-COVID data, we use the estimated value of $\hat{\kappa}_3$ along with p_{pre} to compute p_{post} using the following formula:

$$\hat{p}_{post} = \frac{exp^{(log(\frac{\hat{p}_{pre}}{1-\hat{p}_{pre}}) + \hat{\kappa}_3)}}{1 + exp^{(log(\frac{\hat{p}_{pre}}{1-\hat{p}_{pre}}) + \hat{\kappa}_3)}} \quad (19)$$

Thus, we estimate the treatment effect, or the average treatment effect on the treated (ATT), using the following expression (see Appendix B for the derivation):

$$ATT = (\hat{p}_{post} - \hat{p}_{pre}) \quad (20)$$

5.2.1 Estimation of ATT with Categorical WFH Adoption

A more practical question that organizations are likely to consider is the impact on STEM participation when they shift their level of WFH adoption from one level to another. For instance, if organizations contemplate the effect of rise in the proportion of roles under WFH from m percent to n percent, then the estimates of ATT above will not provide an appropriate answer. Neither will comparing the difference in ATT for the groups of individuals that selected the m level of WFH and those that selected n level of WFH. As such, in this context, the groups could be different for two reasons. The individuals that currently choose m percent WFH occupations can have inherently different likelihood of STEM participation than the groups that choose n percent. Moreover, it is quite conceivable that the gain from moving from m to n percent is higher for the individuals that chose n percent than those who choose to be in occupations offering m percent. The former difference is the selectivity at the level and the later difference is selectivity of gain. As per Callaway et al. (2024), the effect of this shift can be expressed as

$$Effect = E[Y_t(n)|WFH = m] - E[Y_t(m)|WFH = m] \tag{21}$$

where $E[Y_t(m)|WFH = m]$ is the observed outcome of individuals choosing m, when they actually are in occupations offering m level of WFH, and $E[Y_t(n)|WFH = m]$ is the average outcome for individuals who are in occupations offering m percent WFH but could instead adopt n percent WFH. Unfortunately, the latter term, $E[Y_t(n)|WFH = m]$ is not observed. Rather what is observed is $E[Y_t(m)|WFH = m]$. The following expression makes this link clear:

$$\begin{aligned} \text{Effect} \quad &= \left(\underbrace{E[Y_t(n) \mid WFH = n] - E[Y_t(0) \mid WFH = n]}_{1} \right) \\ &- \left(\underbrace{E[Y_t(m) \mid WFH = m] - E[Y_t(0) \mid WFH = m]}_{2} \right) \\ &+ \left(\underbrace{ATT(n|WFH = m) - ATT(n|WFH = n)}_{3} \right) \end{aligned} \tag{22}$$

Where, part 1 refers to ATT for individuals who are in occupations offering n percent WFH, actually receiving n percent WFH. Part 2 refers to ATT for individuals who are in occupations offering m percent WFH, actually receiving m percent WFH and part 3 refers to Selectivity bias at gains, which we referred to in the previous paragraph.

As Callaway et al. (2024) point out in case of multi-valued treatment, the movement from no

WFH to 7 percent WFH is not the same as going from 7 percent WFH to 15 percent WFH. With multi-valued treatment, both the selectivity at the level and selectivity at the gains are in operation. To see the effect one would like to know what would be the change in average outcome of individuals in the 0 to 7 percent WFH group, if they moved to occupations offering 7 to 15 percent WFH, which is unobserved. To estimate the size of the effect pointed out in equation (22), we use propensity score methods along with certain assumptions, both of which are discussed in detail in appendices. As an example, we comment on the increase in probability of young women in choosing STEM occupations, when the average level of job postings offering work from home increases from the group 0-7 percent to 7-15 percent and 7-15 percent to 15-23 percent, and so on. Further details are provided in Appendix H.

6 Results

The empirical analysis shows that occupations with high levels of WFH adoption experienced a substantial increase in the share of young women working in STEM roles. Our benchmark regression (Table 1, Model 2) indicates that the proportion of women in STEM among all female workers in these high WFH occupations rose by 2.43 percentage points, or by 13.6 percent, from 17.96 percent before the pandemic to 20.26 percent after. These results are robust to heteroskedasticity (Model 2) and to clustering standard errors at the state, occupation, and state-occupation levels (Table 1, Models 3, 4 and 5). A 2.43 percentage point gain driven by a single managerial decision represents a substantial shift by any standard. For context, the National Center for Science and Engineering Statistics reports that it took a full decade for this share to rise by just 3 percentage points—from 15 percent to 18 percent.[7]

6.1 Causal Impact or Confounders: Robustness Checks and Falsification Tests

While the results above are compelling, they rely on the validity of underlying assumptions. The following analysis addresses potential concerns about assumption violations and tests the robustness of our findings.

6.1.1 Event study plots to check Parallel Trends

Because this is a difference-in-differences (DID) analysis, it is essential to verify the parallel trends assumption in the empirical setting. We begin with a visual diagnostic by plotting

[7] https://ncses.nsf.gov/pubs/nsb20245/representation-of-demographic-groups-in-stem

group-level averages of the outcome variable in the pre-pandemic period to assess whether treatment and comparison groups followed similar trends. As shown in Figure 3, the trends appear visually non-parallel, raising potential concerns about the validity of the assumption.

However, for DID estimation, it is sufficient to satisfy the conditional parallel trends assumption given observed co-variates, which is a weaker assumption. To assess this, we implement an event study–style regression that compares annual outcomes between treated and untreated groups, using the 2019 and the first two months of 2020 difference as the baseline. As emphasized in Wooldridge (2023) and Roth and Sant'Anna (2023), the linear parallel trends assumption does not remain invariant under nonlinear transformations of the outcome variable. Accordingly, we estimate the logit specification and examine the interaction term coefficients to evaluate parallel trends in the odds ratio. Appendix E outlines the details of this estimation strategy.

Figure 5 presents event study estimates comparing the difference in logit coefficients (log odds of choosing a STEM occupation) between the treatment and comparison groups, using 2019 as the reference year. In all years prior to 2019, none of the interaction terms are statistically significant. This indicates that, after controlling for co-variates, young women in high-WFH and low-WFH occupations exhibited similar trends in STEM participation before the pandemic. The absence of significant pre-treatment differences supports the validity of the conditional parallel trends assumption necessary for the DID framework. However, for the years 2022 through 2025, a period marked by widespread adoption of high WFH practices, the estimates show significant positive differences in the STEM proportions variable between the treatment and comparison groups.

6.1.2 Sensitivity of high WFH Definition

We define a high-WFH occupation as one in which more than 6.97 percent of jobs can be performed remotely. This threshold is grounded in the childcare literature, as detailed in Appendix C. However, any measurement error in this threshold could affect the classification of occupations and, consequently, the estimated effects. To test the robustness of our results, we consider an alternative cutoff value.

We redefine high-WFH occupations as those with more than 9.52 percent of jobs suitable for remote work. As shown in Appendix Table G2, this more stringent threshold yields an even larger estimated effect: a 2.9 percentage point increase in young women's STEM participation. In contrast, the corresponding estimate for young men is statistically insignificant, at just 0.39 percentage points. These findings suggest that our benchmark results are robust to alternative definitions of high-WFH occupations.

6.1.3 DID with Propensity Score Matched Groups

We initially assumed limited cross-occupational mobility, given the specificity of occupational skills and the difficulty workers face in moving across occupations. This implicit cost of mobility supports the plausibility of the Stable Unit Treatment Value Assumption (SUTVA). To assess whether compositional changes drive our results, we apply a DID approach to a propensity score–matched subsample. We match treatment and comparison groups in the pre-COVID period using observable characteristics, such as family income, number of children, and number of children under age five, and then identify comparable individuals in the post-COVID period. Since the matched samples are now comparable, concerns regarding SUTVA violations no longer apply.

The estimates from this analysis show a 2.32 percentage point increase in the share of women in STEM occupations. The near-identical magnitude compared to the benchmark regression suggests that compositional shifts do not drive the results and supports the validity of the SUTVA assumption. Detailed results are presented in Table 6.

In addition to examining compositional changes through movements between the treatment and comparison groups, we also account for potential shifts caused by new young women entering the workforce in the post-treatment period. These new entrants may differ from those already in our sample. We address this concern in two ways. First, overall workforce levels remain largely similar during our analysis period, as shown in Appendix F. Second, we conduct our DID analysis on a matched sample, which ensures that we compare similar individuals across treatment and comparison groups, even if new entrants differ from existing workers.

6.1.4 WFH Adoption or Trend

Although the overall rise in young women's STEM participation between 2011 and 2021 is moderate, a disproportionately large increase during the latter half of this period could raise concerns about the validity of our estimated treatment effect. If women began entering STEM fields at an accelerating rate after 2016, particularly in high-WFH occupations, then the observed post-pandemic change might simply reflect pre-existing differential trends. To assess this possibility, we conduct a falsification test to examine whether pre-pandemic trends, especially after 2016, could account for the estimated effect. For the same we consider the years 2017 and 2018 as pre-period and years 2019 and first two months of 2020 as post period. Rest of our empirical specification remains same as the benchmark DID.

Results from the falsification test are insignificant and thus suggest absence of any trend in participation in STEM occupations for young women in the high-WFH group. Table 2 provide the detailed results for the same.

6.2 Human Capital or Other Work-Life Balance Aspects

Although not focused specifically on STEM participation, prior studies have shown that WFH benefits women in various labor market outcomes. A recurring theme across these studies is the improvement in work-life balance enabled by remote work. Our findings align with this theme. However, in the context of STEM participation, we go a step further and argue that work-life balance improves women's outcomes specifically through mechanisms related to human capital investment and depreciation.

To test this hypothesis empirically, we address several identification concerns. If human capital dynamics are the primary channel, rather than other aspect of work-life balance, then we should not observe similar effects for groups who benefit from WFH-induced work-life balance but are either unaffected or less affected by career interruptions or non-linear human capital accumulation. Young men serve as a useful examination group in this regard: they likely benefit from improved work-life balance but do not typically experience the same non-monotonic investment in human capital or intermittent labor force participation. Hence, if human capital investment and depreciation are the sole drivers of the change in STEM participation due to adoption of WFH, we should observe no effect for young men.

Consistent with this hypothesis, Table 3 reports no statistically significant change in STEM participation among young men in high-WFH occupations following the pandemic. A triple-difference specification comparing young women to young men produces estimates for young women that closely align with those from our main analysis, reinforcing the null effect for young men (Table 1, Column 6). Assuming that other dimensions of work-life balance affect young women and men similarly, these results imply that the observed increase in women's STEM participation is driven by mechanisms related to human capital investment and depreciation, factors that differ between the two groups, rather than by broader improvements in work-life balance driven by other factors.

As illustrated in Section 3, human capital investment and depreciation are particularly relevant in STEM occupations, where skill atrophy is more pronounced than in other fields. If the human capital depreciation hypothesis holds, then WFH adoption should have little to no impact on occupations characterized by low skill atrophy. To test this, we compare outcomes for young men and women working in low-atrophy occupations and examine whether young women experience any significant changes. As expected, the estimates reported in Table 4 and Figure 6 show virtually no effect for young women in these occupations (-0.007). This insignificant result suggests that, in low-atrophy occupations, young men and women respond similarly to WFH adoption, thereby underscoring the distinct role of human capital investment and depreciation in driving women's increased participation in STEM, a high atrophy occupation.

The results thus far suggest that human capital investment and depreciation are key drivers of the observed changes in STEM participation. We further test this hypothesis by examining whether similar effects emerge in other high-atrophy occupations, such as legal and managerial roles, which were excluded from the benchmark regression due to the study's focus on STEM. Table 5 shows that young women in these high-WFH, high-atrophy occupations also experience a statistically significant increase in participation, with an estimated rise of 0.6 percentage points, or 1.5 percent. Although the magnitude is smaller than that observed in STEM, this finding offers additional support for our hypothesis.

There are several plausible explanations for the smaller effect. These occupations may differ in ways that generate heterogeneous responses to WFH, or the number of available positions may be more limited due to demand-side constraints, which would suppress employment growth in equilibrium. Nevertheless, the observed increase reinforces the empirical relevance of human capital dynamics in explaining gender shifts in high-atrophy fields.

6.3 Heterogeneous Treatment Effects

Overall, the rise in WFH has a positive and significant effect on young women's participation in STEM jobs. But this effect may not be the same across all STEM jobs or across the industries where these jobs exist. The size of the effect may vary with the current share of young women and men in each job or industry. This leads to the key question: How does the rise in WFH change the chances that young women choose certain jobs within STEM occupations or industries over others? We discuss these two aspects of heterogeneity below.

6.3.1 Effect of WFH within STEM occupations

We divide STEM jobs into three subgroups: math and technology jobs, science jobs, and engineering jobs. To test for differences in effects across these subgroups, we use the same empirical model as in equation (16). The only change is in the dependent variable. When we study math and technology jobs, for example, the dependent variable equals 1 for those jobs and health jobs, and 0 for non-STEM jobs. We exclude other STEM subgroups from the dependent variable and focus only on the subgroup we use to test for heterogeneity.

Table 7 shows that math and technology jobs have the largest treatment effect (ATT of 1.84 percentage points), followed by science (1.14 pp) and engineering (0.58 pp). Women have long been underrepresented in engineering and computing jobs. The larger rise in technology jobs may help close that gap. However, the smaller effect in engineering suggests that male-dominated fields may need greater access to WFH to draw more women than the current threshold of 6.97 percent.

6.3.2 Effect of WFH across industry

We next study how treatment effects vary across 12 major industries. To do this, we change the dependent variable to equal 1 for STEM jobs within the industry of interest and for healthcare jobs, and 0 for non-STEM jobs. For example, in the business and professional services industry, we code all STEM jobs, such as management analysts, accountants, auditors, and software developers as 1. We code all non-STEM jobs as 0.

According to data from the U.S. Bureau of Labor Statistics, the six industries with the highest share of female workers are: education and health services, financial activities, other services, leisure and hospitality, public administration, and wholesale and retail trade. Table 8 shows that the largest effects of increased WFH occur in financial activities (ATT of 2.07 percentage points), wholesale and retail trade (1.35 pp), and education and health services (0.89 pp). In contrast, male-dominated industries show no significant positive change. One possible reason is that these industries may not support sustained remote work, which could limit their ability to attract more women.

6.4 Non Binary WFH Adoption

The aggregate finding that WFH adoption above 6.97 percent (high WFH) significantly increases the share of women in STEM roles is informative. However, organizations typically do not shift from offering no WFH to a uniformly high level. A more actionable metric is the impact of scaling up WFH adoption incrementally. Treating WFH intensity as a multi-valued measure, comparable to a continuous variable, as detailed in Section 5.2.1, we assess the effects of moving from 0–7 percent to 7–15 percent, 7–15 percent to 15–23 percent, and 15–23 percent to above 23 percent.

Figure 7 presents the results. Moving from 0–7 percent to 7–15 percent WFH adoption increases the share of women in STEM by 1.14 percentage points. The next shift, from 7–15 percent to 15–23 percent, raises the share by 2.34 percentage points. A further increase from 15–23 percent to above 23 percent yields a 4.27 percentage point gain. These findings reveal a clear upward trend: as WFH adoption intensifies, women's participation in STEM occupations rises at an increasing rate. One plausible explanation for this monotonic pattern is that the overall level of current WFH adoption remains modest as most organizations still offer WFH in fewer than 40 percent of roles. Beyond a certain threshold, however, growth in WFH share may slow, and its effect on STEM participation may taper or even reverse, potentially producing a non-monotonic relationship. We additionally implement a robustness test using alternate groupings of our WFH treatment variable, namely: (i) 0 to 9.5 percent job postings offering remote work; (ii) 9.5 percent to 18 percent job postings offering remote work; (iii) 18 percent to 27 percent job postings offering remote work and (iv) greater than 27 percent job postings offering remote work. Our results remain similar in case of these alternate groupings as well. Detailed results for the same are presented in Table H1.

7 Conclusion and Discussion

This paper explores whether greater workplace adoption of remote work (WFH) increases young women's participation in STEM occupations. Our findings suggest it does. We estimate that higher WFH availability raises the likelihood of STEM participation among young women by 2.43 percentage points, a 13 percent increase from the pre-pandemic baseline. This is a substantial shift, especially when compared to the 3-percentage point gain observed over the entire decade from 2011 to 2021, despite several ongoing policy and organizational efforts to improve gender diversity in STEM. Encouragingly, the effect becomes stronger as WFH adoption intensifies across occupations.

These results offer a perspective on why many well-intentioned initiatives have achieved only modest success. A large share of existing interventions (e.g., mandatory hiring targets) focus on increasing demand for women workers. Yet such measures can only be effective if there is a sufficient supply of women willing and able to take up STEM roles. Our results point to a complementary channel: remote work lowers the cost of labor market continuity by reducing the risk of skill loss, which has historically deterred many women from entering or staying in high-atrophy occupations like STEM. In this way, WFH helps unlock an underutilized talent pool.

Importantly, remote work also addresses another key limitation of current strategies: scalability. Programs like returnships, reskilling courses, or workplace daycare offer valuable support, but they often come with high administrative costs and limited reach. Moreover, such programs attempt to repair skill gaps after they have already formed. In contrast, WFH operates preventively. It enables women to remain continuously employed, thereby preserving human capital that might otherwise erode. Given its relatively low cost of implementation and broad applicability, WFH emerges as a scalable and sustainable solution.

The wider institutional benefits are equally compelling. WFH may help reduce exposure to everyday discrimination, particularly in male-dominated fields (Doering and Tilcsik, 2025). STEM occupations, where women have long been underrepresented, stand to benefit most. Additionally, unlike targeted interventions that may prompt resistance or perceived unfairness, remote work is widely applicable and neutral in design. It avoids backlash while still delivering tangible gains. It also avoids the unintended substitution effects associated with policies like paid leave (Das and Polachek, 2015), where employers may sideline younger women in favor of other demographics.

The implications go further. If remote work lowers the long-run cost of pursuing a STEM career, more young women may begin to view these fields as viable and attractive. Over time, this could shift not only labor market outcomes but also educational choices, increasing the pipeline of female STEM talent. Seen in this light, WFH is not merely an operational adjustment, it is a strategic tool. Firms striving to enhance both productivity and inclusion and policymakers working to widen opportunity, may gain by embracing the potential of remote work.

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Tables and Figures

This section presents the various tables and figures from our analysis.

Tables

Table 1: Estimates of High WFH adoption on STEM Participation for Young Women

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Post	0.190***	0.045*	0.045	0.045	0.045	0.011
	(0.008)	(0.022)	(0.050)	(0.039)	(0.042)	(0.021)
Gender						1.464***
						(0.011)
WFH	0.011	-0.386***	-0.386***	-0.386	-0.386	2.593***
	(0.009)	(0.010)	(0.050)	(1.028)	(0.210)	(0.011)
Post × Gender						0.012
						(0.017)
Post × WFH	0.171***	0.157***	0.157***	0.157*	0.157***	-0.001
	(0.014)	(0.015)	(0.026)	(0.070)	(0.033)	(0.018)
Gender × WFH						-2.994***
						(0.015)
Post × Gender × WFH						0.153***
						(0.024)
ATT Point Estimate (pp)	2.66	2.43	2.43	2.43	2.43	2.37
Controls	N	Y	Y	Y	Y	Y
R-squared	0.003	0.1776	0.1776	0.1776	0.1776	0.3114
Observations	808,651	800,591	800,591	800,591	800,591	1,687,247

Standard errors in parentheses

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Notes: The above table presents results from our benchmark specification presented in equation 16. As referred in the main text, model (2) presents the benchmark analysis results. The dependent variable across the model is whether the individual works in STEM occupation or non-STEM occupation. Model (1) and Model (2) present robust standard errors, while Model (3), Model (4) and Model (5) present standard errors clustered at the state level, the 3-digit SOC-2018 occupation level and the state and 3-digit SOC-2018 occupation level respectively. Model (6) presents results from triple DID for young women with respect to young men. Model (6) reports robust standard errors. The ATT point estimates remain similar across the specifications. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race and state and metropolitan fixed effects. All regressions are weighted using the *compwt* variable available in IPUMS-CPS and commonly used to generate labor market statistics.

Table 2: Falsification Tests for Checking Pre-Trends

Variables	STEM Occupation
Post	0.012
	(0.023)
WFH	-0.366***
	(0.014)
Post × WFH	-0.002
	(0.023)
Controls	Y
R-squared	0.1707
Observations	389,655

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: The table above presents results for the falsification test that is used to understand whether there were any differential trends between the treatment and comparison group in the period prior to the pandemic. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race and state and metropolitan fixed effects. All regressions are weighted using the *compwt* variable available in IPUMS-CPS and commonly used to generate labor market statistics.

Table 3: Impact of High WFH adoption on Young Men's STEM Participation

Variables	STEM Occupation
Post	-0.022
	(0.028)
WFH	2.598***
	(0.012)
Post × WFH	-0.003
	(0.018)
ATT Estimate (pp)	-0.08
Controls	Y
R-squared	0.44
Observations	886,533

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This table presents results from the benchmark regression for young men, used as a falsification test to evaluate whether the reduction in atrophy is specific to females. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race and state and metropolitan fixed effects. All regressions are weighted using the *compwt* variable available in IPUMS-CPS and commonly used to generate labor market statistics.

Table 4: Impact in Low Atrophy, High WFH Occupations - Robustness Test

Variables	Low Atrophy
Post	0.037**
	(0.016)
Gender	0.947***
	(0.007)
Post × Gender	-0.007
	(0.010)
Controls	Y
R-squared	0.0929
Observations	1,379,470

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This table presents results from a robustness check to test whether there is any positive effect for young women in low-atrophy, high-WFH occupations. For the detailed definition of the outcome variable check the data section. The variable *Gender* equals 1 for women and 0 for men. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race and state and metropolitan fixed effects. All regressions are weighted using the *compwt* variable available in IPUMS-CPS and commonly used to generate labor market statistics.

Table 5: Impact on Other High Atrophy Occupations - Robustness Test

	Model (1)	Model (2)
Post	0.081***	-0.008
	(0.018)	(0.026)
WFH	0.924***	3.083***
	(0.008)	(0.011)
Post $\times$ WFH	0.024*	0.003
	(0.012)	(0.017)
ATT Estimate (pp)	0.57	0.080
Controls	Y	Y
R-squared	0.1797	0.4294
Observations	909,007	933,057

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This table presents robustness checks using high-atrophy occupations as the dependent variable, not considered in the benchmark regression. These include legal, business and financial, and management occupations. Model (1) presents results for young women, while Model (2) presents results for young men. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race and state and metropolitan fixed effects. All regressions are weighted using the compwt variable available in IPUMS-CPS and commonly used to generate labor market statistics.

Table 6: Impact Estimation with Propensity Score Matched Sub-samples

Variables	STEM Occupation
Post	-0.014
	(0.041)
WFH	-0.113***
	(0.019)
Post $\times$ WFH	0.1506***
	(0.0302)
ATT Estimate (pp)	2.32
Controls	Y
R-squared	0.1874
Observations	312,235

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: The table presents results from our benchmark DID specification after matching based on propensity scores. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race, and state and metropolitan fixed effects. All regressions are weighted using the *compwt* variable available in IPUMS-CPS and commonly used to generate labor market statistics.

Table 7: Heterogeneous Effects across STEM Occupations

	Model (1)	Model (2)	Model (3)
	Math and Tech Occupations	Science Occupations	Engineering Occupations
Post × WFH	0.197***	0.198***	0.135***
	(0.019)	(0.023)	(0.027)
ATT (in pp)	1.84	1.14	0.58

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: This table presents the heterogeneity in results across different STEM sub-fields. The specification remains consistent with the benchmark regression, with only the dependent variable changed for each column. Model (1) presents results for the empirical specification with the dependent variable being Maths and Tech occupations. Model (2) presents results for the empirical specification with the dependent variable being science occupations and Model (3) presents results for the empirical specification with the dependent variable being Engineering occupations. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race and state and metropolitan fixed effects. All regressions are weighted using the *compwt* variable available in IPUMS-CPS and commonly used to generate labor market statistics.

Table 8: Heterogeneous Effects across Various Industries

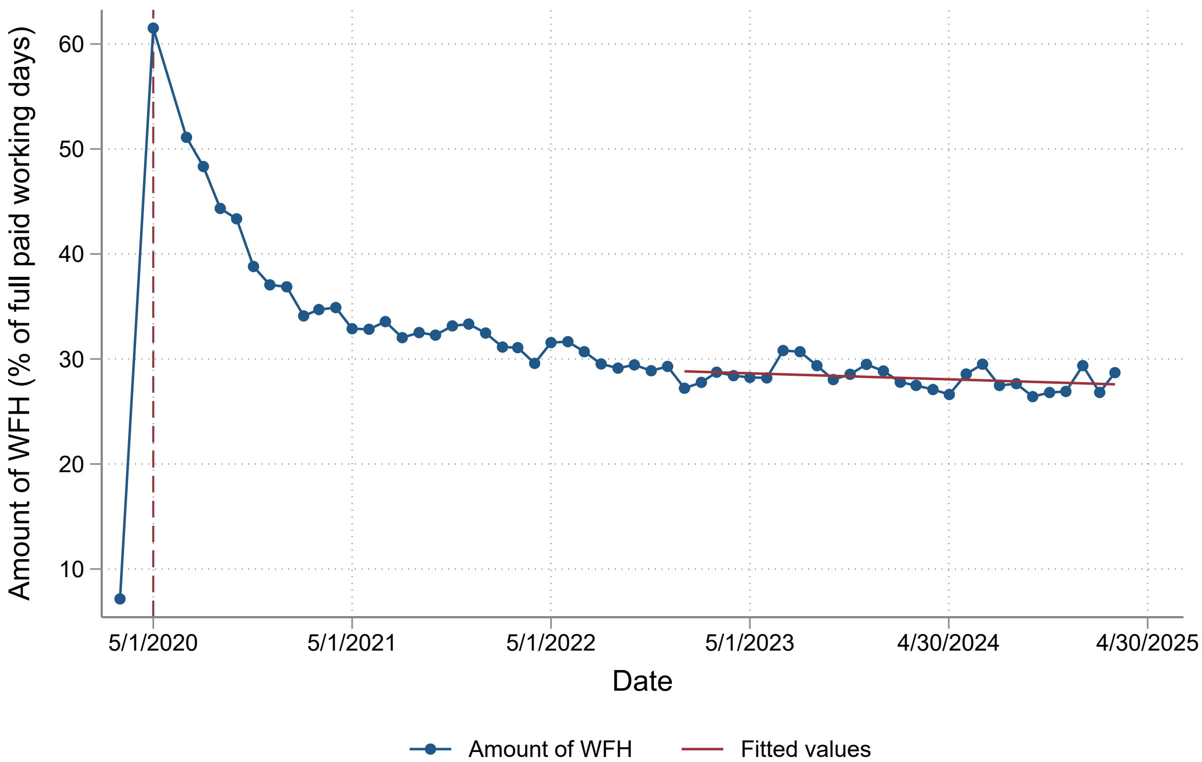
Industry	Post × WFH	ATT (in pp)
Agriculture, Forestry, Fishing, and Hunting	0.44	0.56
	(0.45)	
Construction	0.20	0.39
	(0.56)	
Manufacturing	-0.07	-0.45
	(0.13)	
Wholesale and Retail Trade	0.26***	1.35
	(0.04)	
Transportation and Utilities	-0.38	-0.60
	(0.30)	
Information	-0.50*	-0.93
	(0.28)	
Financial Activities	0.17**	2.07
	(0.087)	
Professional and Business Services	0.011	0.18
	(0.037)	
Education and Health	0.073***	0.89
	(0.017)	
Leisure and Hospitality	0.16	1.15
	(0.17)	
Other Services	0.21*	0.58
	(0.11)	
Public Administration	-0.184***	-0.87
	(0.06)	

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: The table presents heterogeneity in results across different industries for young women. Results for the mining industry are excluded due to a small number of observations. The empirical specification is consistent with the benchmark regression, with only the dependent variable changed. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race and state and metropolitan fixed effects. All regressions are weighted using the *compwt* variable available in IPUMS-CPS and commonly used to generate labor market statistics.

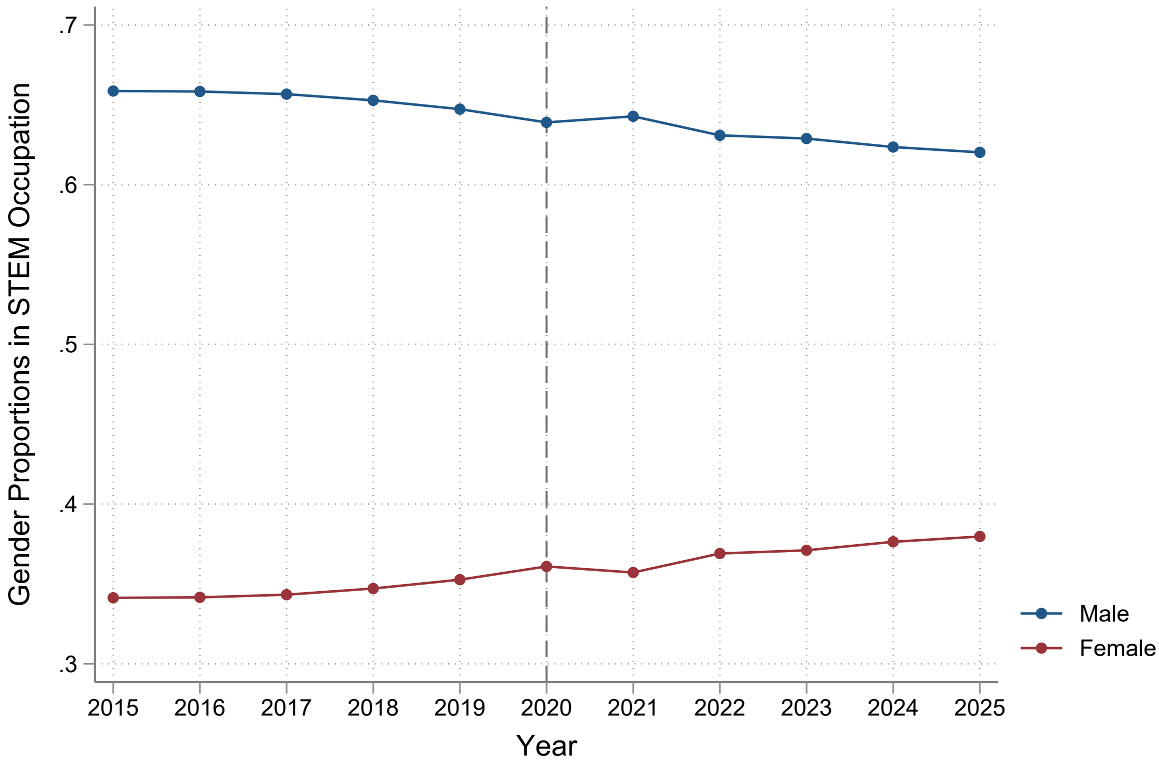
Figures

Figure 1: Amount of WFH pre COVID-19 and post COVID-19



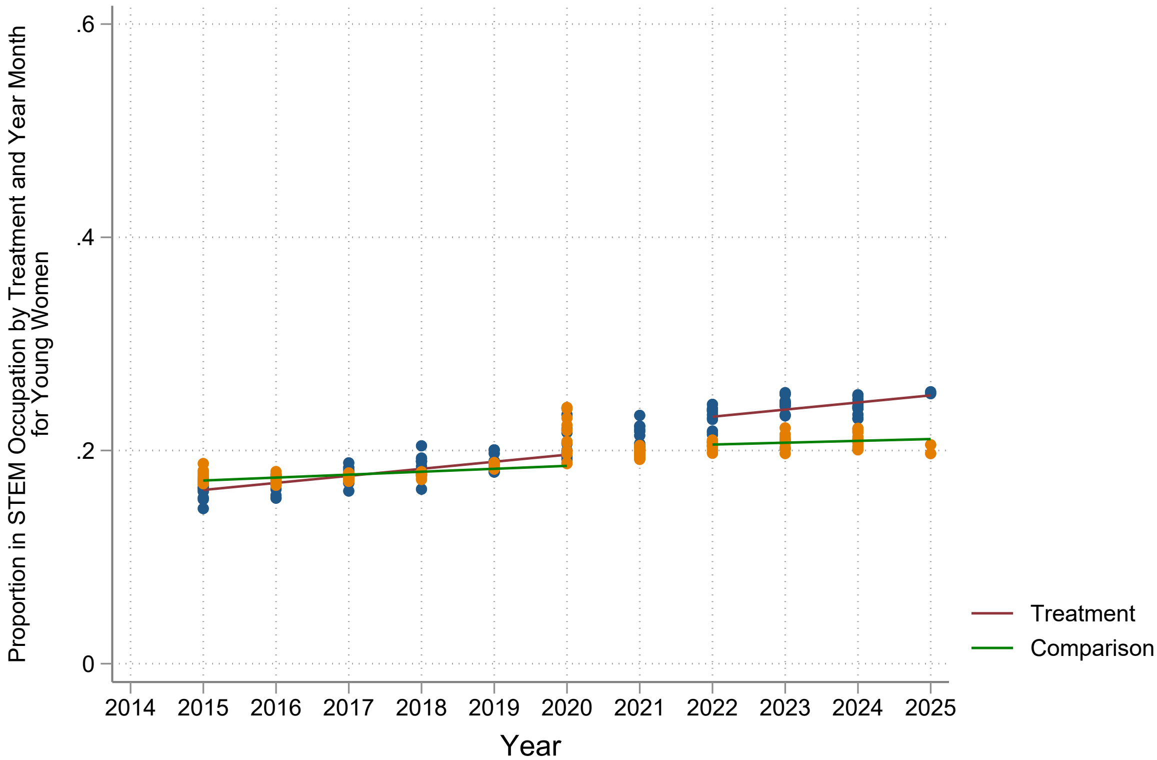
Source: Adopted from Survey of Working Arrangements and Attitudes from Barrero et al. (2021) (Data until March 2025). This figure presents the increase in WFH levels post COVID-19 period. The amount of WFH in terms of percent of full paid working days worked remotely has stayed steady from 2023 onward.

Figure 2: Gender wise proportion in STEM Occupations



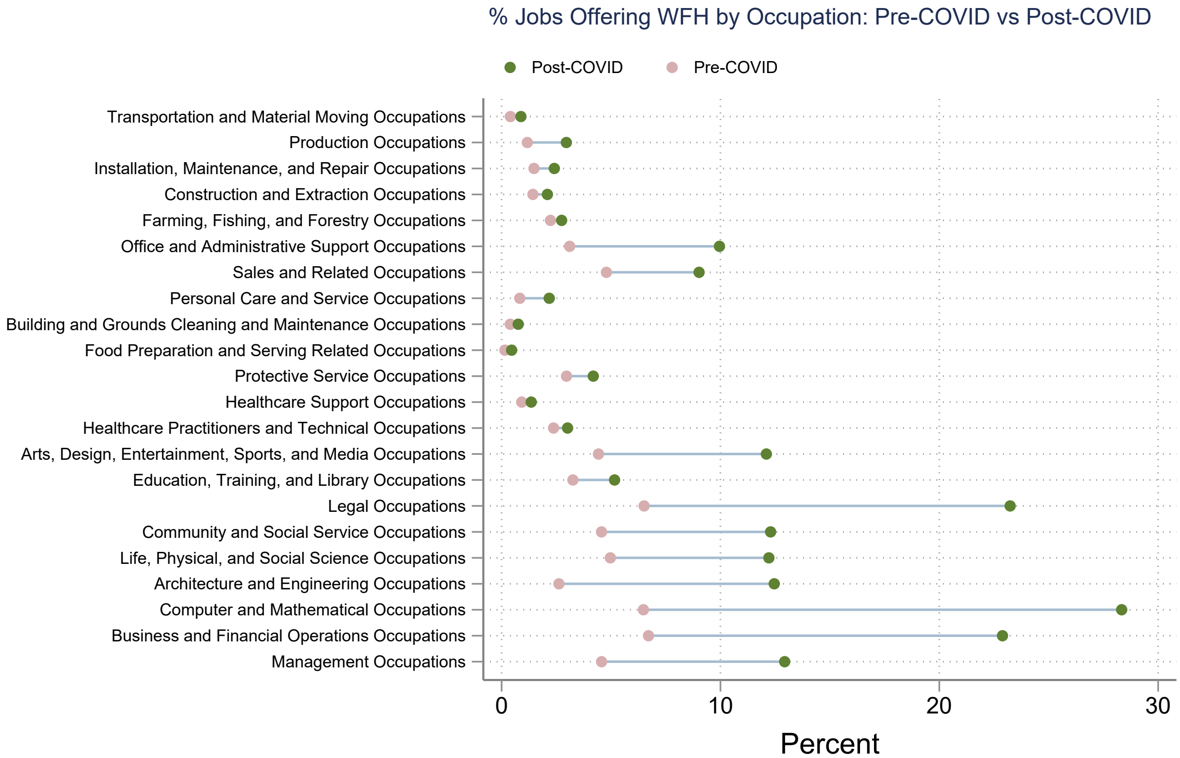
Source: Current Population Survey. The figure shows that women's share of STEM jobs has increased over time, with faster growth after the pandemic. Unlike the other tables and figures, which use the U.S. 2010 Census definition and exclude middle-skill occupations from STEM definition, this figure includes middle-skill STEM jobs to align more closely with public data on gender shares in STEM. Participation patterns differ across job types: in 2021, the ratio of men to women in science and engineering jobs was 2.75 to 1, while in middle-skill STEM jobs it was 8.5 to 1; in contrast, women outnumbered men in science- and engineering-related jobs, with a ratio of 1 to 2. Additional details are available at: `https://ncses.nsf.gov/pubs/nsb20245/representation-of-demographic-groups-in-stem`

Figure 3: Proportion in STEM Occupations for young women in treatment and comparison group



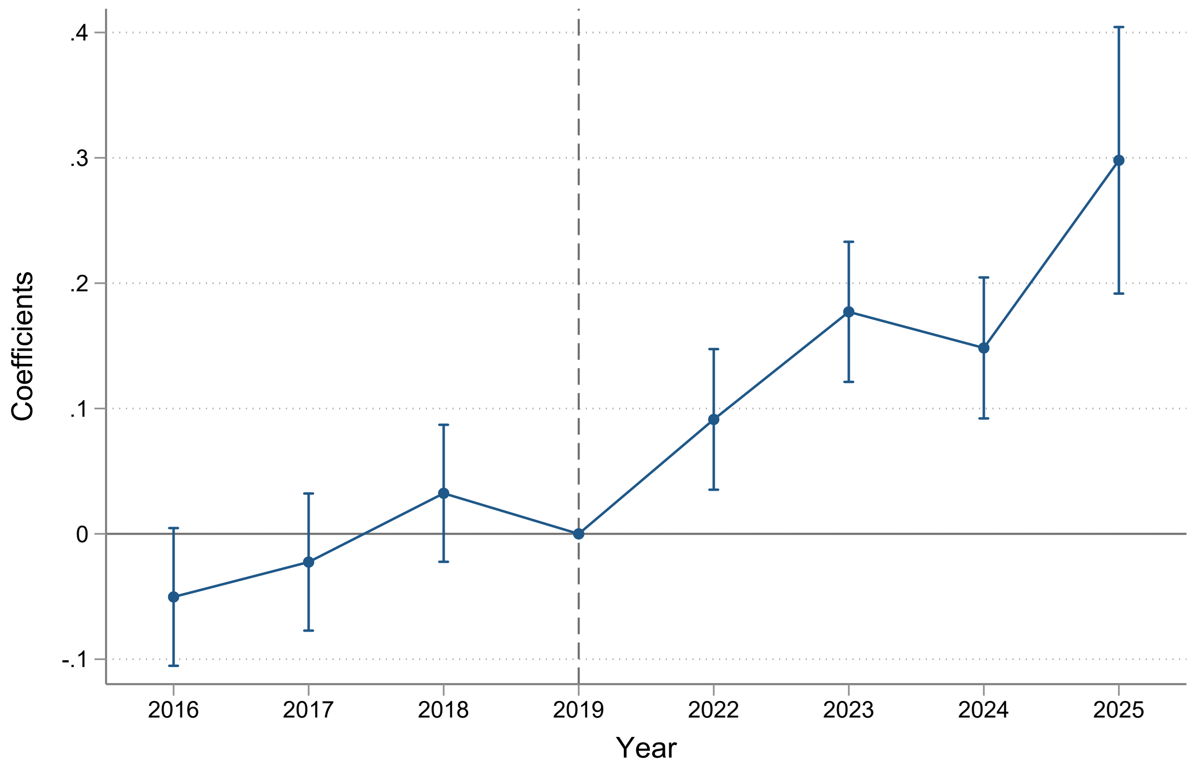
Source: Current Population Survey. This figure shows the proportion of young women—out of all working young women—in the treatment and comparison groups who chose to be in STEM occupations. Following the onset of the pandemic, the figure reveals a noticeable increase in STEM participation rates among the treatment group, indicating a potential shift in occupational sorting dynamics.

Figure 4: Heterogeneous increase in WFH across occupations



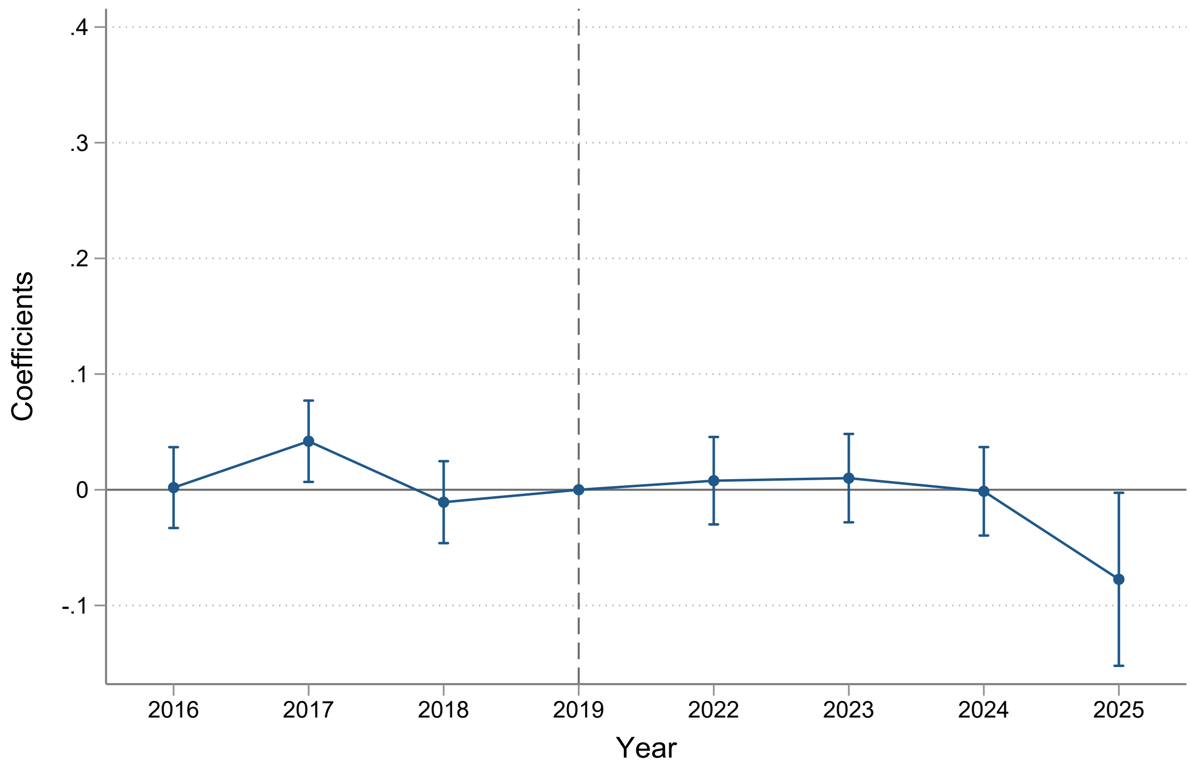
Source: Remote Work across Jobs, Companies, and Space (Hansen et al. (2023)) (Data until September 2024). This figure shows the change in the share of job postings that offer remote work for at least one day per week, grouped by broad 2018 two-digit SOC codes. Management, business and financial, computer and mathematical, and legal jobs show the largest rise from the pre-COVID to post-COVID period

Figure 5: Pre-trends in STEM Participation in Treatment & Comparison groups: The Event Study Plots



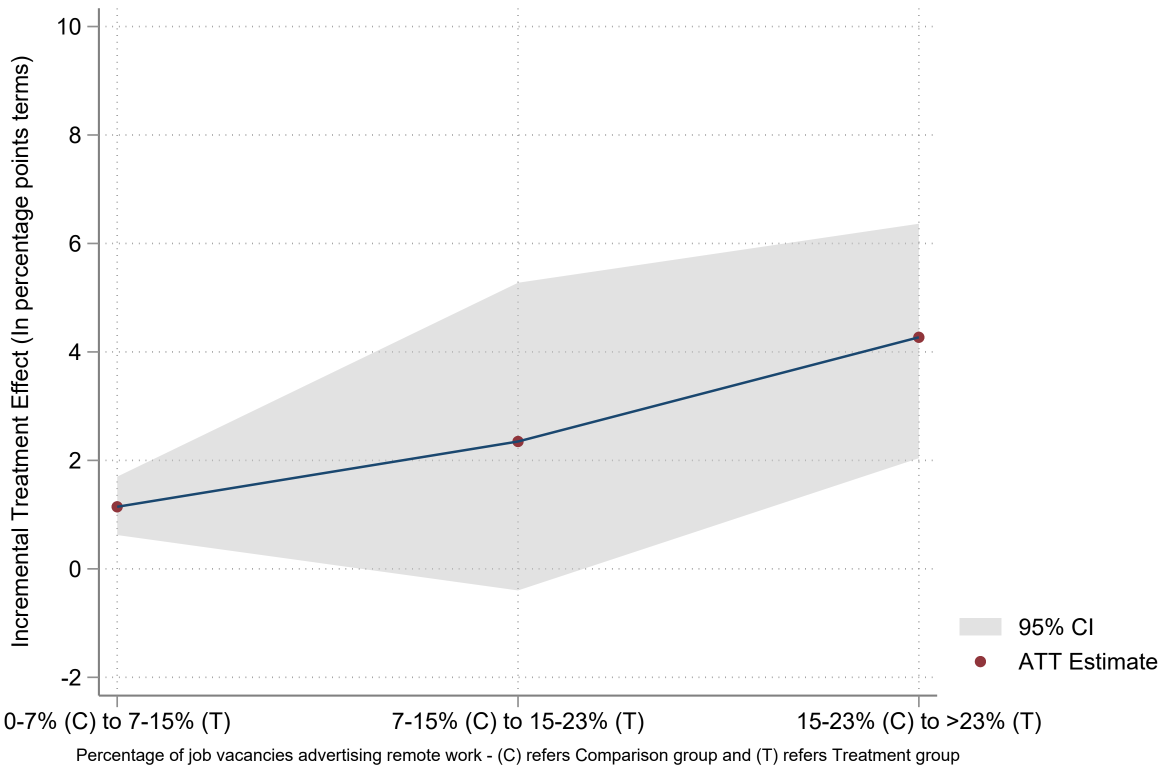
This figure is based on author's estimation. The event study plot provides evidence that there were no differential pre-trends between the treatment and comparison groups prior to the onset of the pandemic. The coefficients are based on the estimation Equation (E1). We present 95% confidence intervals from our estimation.

Figure 6: Impact among Young Women for High WFH Low Atrophy Occupations: Event Study Plots



This figure is based on author's estimation. The event study plot provides no suggestive evidence that young women choose high WFH and low atrophy occupations differently compared to young men post pandemic. The estimation framework for the event study plot remains the same as the previous event study plot in line with Equation (E1). We present 95% confidence intervals from our estimation.

Figure 7: WFH Adoption intensity & Impact on STEM Participation



The figure is based on author's estimation. It provides the incremental treatment effect in percentage point terms along the intensive margin of WFH intensity. The increase in treatment effect is 1.14 percentage points when one moves from 0-7% group to 7-15% group. It is 2.34 percentage points moving from 7-15% group to 15-23% group and it is 4.27 percentage points when moving from 15-23% group to greater than 23%

Appendix A Descriptive Statistics and Additional Tables and Figures

We present the descriptive statistics and additional tables and figures from our analysis in this section.

Appendix A.1 Additional Tables

Table A1: Proportions in treatment and comparison group across periods

Period	Comparison Group	Treatment Group
Pre	58.55%	41.45%
Post	55.64%	44.36%

Table A2: Proportion of young women in STEM occupations by group and time period

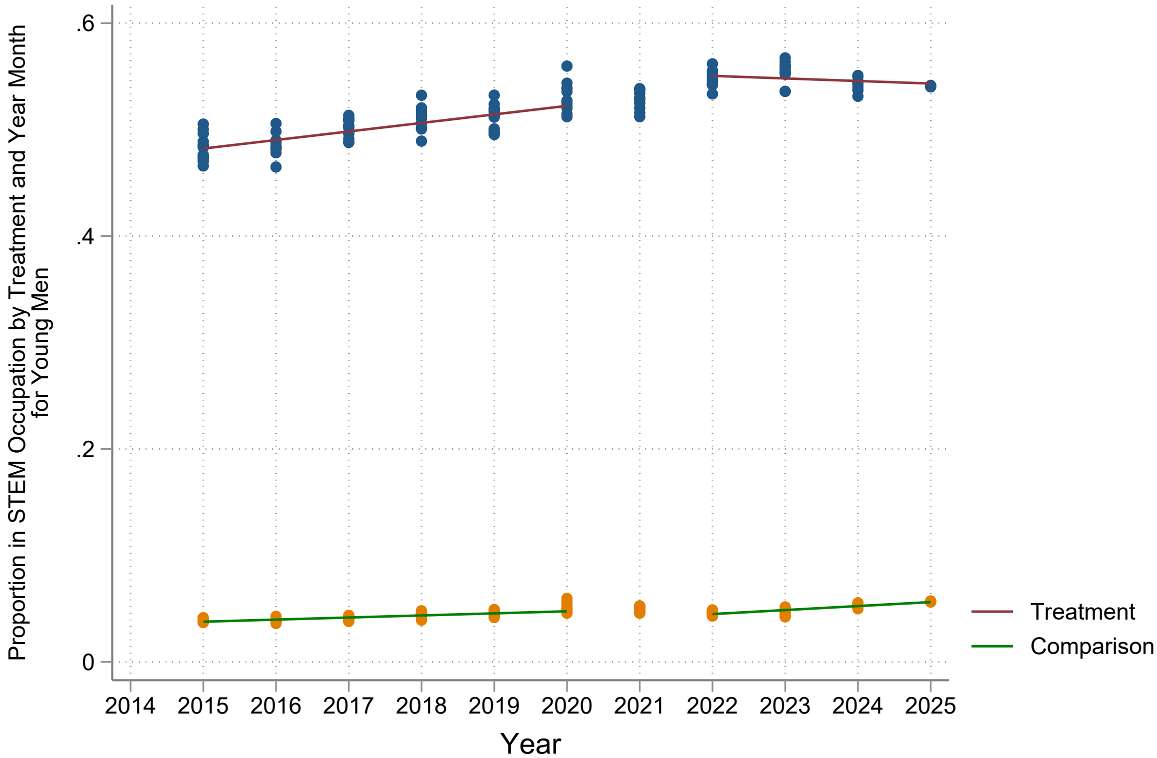
Group	Pre-period	Post-period
Comparison Group	0.178	0.208
Treatment Group	0.180	0.239

Table A3: Descriptive statistics by group and time period

Variable	Pre-Period		Post-Period	
	Comparison Group	Treatment Group	Comparison Group	Treatment Group
Age (mean)	29.37	31.15	29.54	31.43
Education (In %)				
Bachelor's degree and above	31.49	53.85	34.24	58.32
Below Bachelor's degree	68.51	46.15	65.76	41.68
Marital Status				
Naver Married (In %)	54.09	45.22	56.73	47.62
Married	45.91	54.78	43.27	52.38
Number of Children (mean)	0.276	0.272	0.25	0.259
Atleast one child below 5 years (in %)	22.13	22.06	20.01	20.96
Family Income (in %)				
>$50,000	58.01	72.88	69.36	82.5

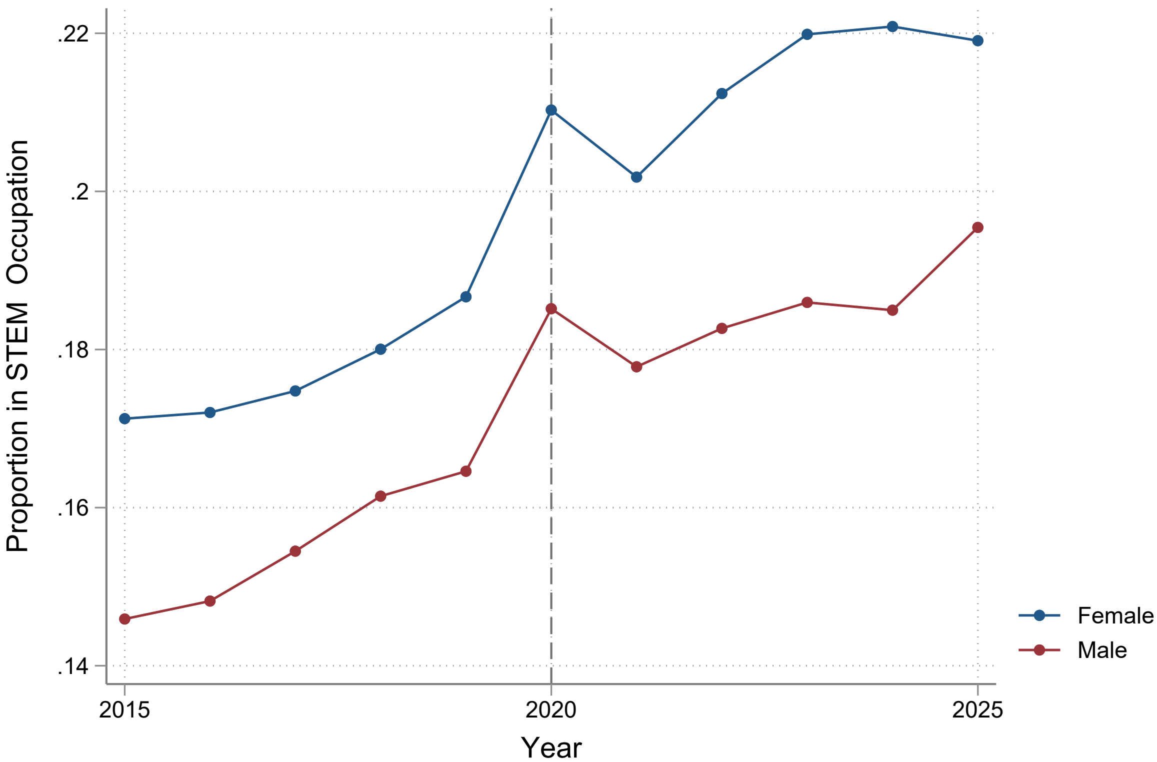
Appendix A.2 Additional Figures

Figure A1: Proportion in STEM Occupations for young men in treatment and comparison group



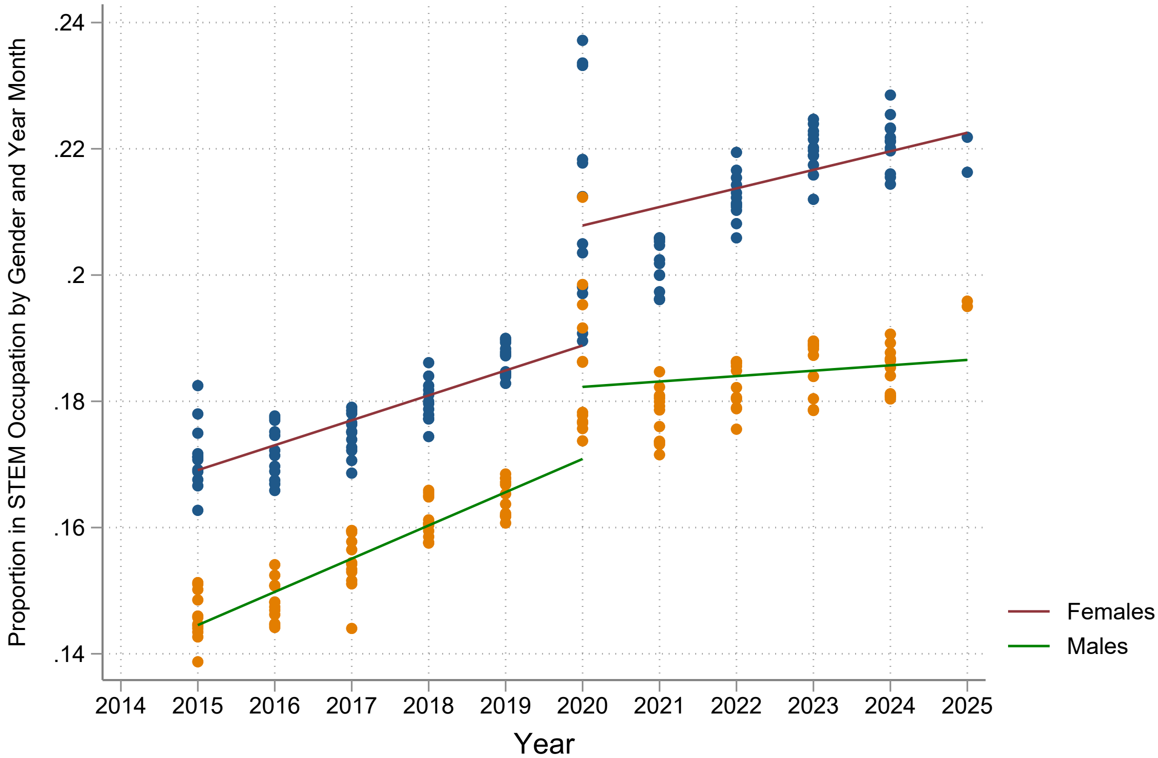
Source: Current Population Survey

Figure A2: Proportion in STEM Occupations for young men vs young men



Source: Current Population Survey

Figure A3: Proportion in STEM Occupations for young men vs young women at year month level



Source: Current Population Survey

Appendix B Comment on the choice of Logit analysis and derivation of point estimate

We use a logit model for our benchmark regression instead of a linear probability model. The primary reason for the same is that in a linear probability model the probability is not bounded between 0 and 1. For accuracy of predictions, we therefore use a logit model.

To estimate the ATT in percentage point terms from the logit model, we use the following steps: First, we use the interpretations of the coefficients in terms of increase in log odds ratio. I.e. the coefficient κ_3 (interaction between post and WFH_i) is interpreted as the change in log odds ratio for one unit increase in the interactions. This can be written in the following form below:

$$log(\frac{p_{post}}{1-p_{post}}) - log(\frac{p_{pre}}{1-p_{pre}}) = \kappa_3 \tag{B1}$$

Next, since we know the proportion of individuals in STEM occupations in the pre-period, we replace that in the above equation in p_{pre}. Solving further for p_{post} gives us the following then:

$$\frac{p_{post}}{1-p_{post}} = exp^{(log(\frac{p_{pre}}{1-p_{pre}})+\kappa_3)} \tag{B2}$$

which can further be simplified to get p_{post} as:

$$p_{post} = \frac{exp^{(log(\frac{p_{pre}}{1-p_{pre}})+\kappa_3)}}{1+exp^{(log(\frac{p_{pre}}{1-p_{pre}})+\kappa_3)}} \tag{B3}$$

And finally, the estimate of ATT in percentage point terms can be found to be $p_{post} - p_{pre}$

Appendix C Estimation for threshold job postings to classify occupations into high and low WFH group

Suppose child care requires x minutes. Let H represent the standard workday in minutes, and let C denote the daily commute time. In a work-from-office setting, time is inflexible, preventing the worker from attending to child care during work hours. As a result, the effective time available for child care is zero.

In contrast, a work-from-home (WFH) arrangement introduces flexibility and eliminates commuting, providing the worker with $H + C$ minutes to allocate between work and child care. To meet both obligations without sacrificing work productivity, the total available time must be at least equal to the combined demand for work and child care: $H + C \geq H + x$. This condition simplifies to $C \geq x$, indicating that the saved commute time must exceed the child care requirement.

Under WFH, the flexible block of time $H + C - x$ enables the worker to perform both paid work and child care without reducing total work hours. This is because if we assume that most child care needs arise during standard office hours (excluding commute time), the individual can use saved commute time to make up for any work time lost to child care during the day. However, the portion of time used to compensate for lost work is no longer available as flexible time. Within the remaining block $H + C - x$, the worker can allocate up to x minutes to child care while still fulfilling the full 8-hour work requirement.

Let q denote the probability of receiving a WFH assignment. The expected time available for child care is then:

$$q \times (H + C - x) \tag{C1}$$

To ensure that the worker can provide at least x minutes of child care on average, this expected value must be greater or equal to x. Solving the equation:

$$q \times (H + C - x) \geq x \tag{C2}$$

yields the minimum WFH probability required:

$$q \geq \frac{x}{H + C - x} \tag{C3}$$

This threshold q represents the minimum share of job postings offering remote work needed to accommodate child care responsibilities without reducing work output.

In context of our paper we define the treatment group as occupations that offer enough WFH flexibility to allow women to meet the daytime primary care needs of young children (under 6 years old) at least one day per week. This care need accounts for roughly 20 percent of total weekly child care. We focus on children under age six because care for this group is the most rigid and least avoidable. If WFH provides the flexibility to care for younger children, it is likely sufficient for caring for older children as well.

To find the value of x required for equation (C3), we use data from the American Time Use Survey (ATUS). In 2019, women spent about 70 minutes per day on primary child care, with similar figures in 2021 (71 minutes) and 2023 (74 minutes).[8] [9] [10] As primary child care is non-substitutable and unavoidable [11], many women exit the labor force to meet this need (Goldin, 2022). The stability of this time use, even as WFH increased, suggests that 72 minutes is a reasonable daily benchmark for required child care.

Assuming a 24-hour day divides into three broad segments—8 hours for sleep, 8 hours for work, and 8 discretionary hours—we estimate that half of the 72 minutes of child care (i.e., 36 minutes) fall within the daytime work period. Thus, a woman would need at least 36 minutes (x in equation C3) of flexible time during the workday to meet minimum primary care needs for a young child.

Next, we estimate whether a WFH day can support this need. A typical WFH day saves 72 minutes of commuting time (Aksoy et al., 2023). This refers to C in equation (C3). The average workday is made up of 480 minutes, referred to as H in equation (C3). Together, this provides a total of 552 minutes ($H + C$). A woman can allocate 36 of those minutes to child care without reducing total working hours or increasing the length of her workday when she works remotely.

This setup implies that she borrows 36 minutes from her total work day for child care, and then compensates for the 36 minutes of lost work time from the commute time she saves while working remotely. Thus, she has 516 minutes ($H + C - x$) of flexible time in this setting for undertaking child care.

[8] 2019 data source: https://www.bls.gov/news.release/archives/atus_06252020.pdf

[9] 2021 data source: https://www.bls.gov/news.release/archives/atus_06232022.pdf

[10] 2023 data source: https://www.bls.gov/news.release/archives/atus_06272024.pdf

[11] As per ATUS, primary child care includes activities like breast-feeding, bathing the baby, changing diapers among others. All these activities are non-substitutable in nature

WFH offers three distinct advantages for meeting child care needs in this context. First, the 36 minutes required for primary care are rarely continuous. These interruptions occur in short, unpredictable intervals, making it hard to plan for them in advance. Second, WFH allows a parent to keep the child in their presence throughout the workday. This proximity enables responsive care as needs arise, without major disruption. Third, while only 36 minutes of flexible time are needed to offset care-related interruptions, a typical WFH day—with saved commute time—provides 516 minutes of flexible time. This makes it easier to absorb the caregiving without reducing work output. By contrast, even if a policy allowed a woman to bring her child to the workplace, the 36 minutes required for child care would likely extend her workday rather than fit within it. Moreover, the structure of in-office work does not offer the same flexibility to absorb these interruptions. Unlike remote work, which allows women to shift tasks and rearrange their schedules around care needs, office-based jobs typically lack such adaptability. As a result, the rigidity of workplace hours makes it difficult to integrate child care without reducing work hours or increasing total time spent on the job.

This can be illustrated with a simple example. Consider a woman whose typical workday runs from 9:30 a.m. to 6:00 p.m., with a 30-minute lunch break. She works in two uninterrupted blocks: from 9:30 a.m. to 1:30 p.m., and then from 2:00 p.m. to 6:00 p.m., with lunch between 1:30 p.m. and 2:00 p.m. Assuming her one-way commute takes 36 minutes (half of the total 72-minute round-trip), her effective workday, including commute time, spans from 8:54 a.m. to 6:36 p.m.

Now consider the case where she cannot work from home. If a child care need arises during the day, she must either reduce her working hours or extend her workday to meet both work and care demands. In this case, providing care without sacrificing work hours requires lengthening the workday beyond the 6:36 p.m. end time, which adds further strain and reduces overall flexibility.

In contrast, if she can work remotely, she does not need to extend her workday to provide child care. She can incorporate the 36 minutes of care into her day by rearranging work tasks across the work day without reducing total work time. For example, if her child needs care from 9:30 a.m. to 9:45 a.m. and then again from 1:15 pm to 1:36 pm, she can begin working at 9:45 a.m. and continue until 1:15 p.m., completing three hours and 30 minutes of work. She can then resume work from 2:06 p.m. to 6:36 p.m., completing the remaining four and a half hours. Alternatively, if the child requires continuous care between 9:30 a.m. to 10:06 a.m.; she could work from 10:06 a.m. to 2:30 p.m. (4 hours and 24 minutes) and again from 3:00 p.m. to 6:36 p.m. (3 hours and 36 minutes). In both cases, her total workday stays within the original 8:54 a.m. to 6:36 p.m. window. She meets her child care needs without reducing her 8 hours of work, using the saved commute time to make up for time spent on child care during work hours.

Thus, to find the required share of job postings offering WFH that enable a woman to undertake child care, we replace the values of H, C and x in equation (C3) to estimate q. This yields the value of q to be 6.97 percent. This represents the minimum threshold of job postings offering remote work to provide sufficient time for one day of child care without affecting the number of hours required for work.

Based on this estimated threshold we then classify occupations as high-WFH and designate them as the treatment group if they offer atleast this level of WFH continuously for 21 months from January 2023 to September 2024. The list for the high and low WFH occupations and the treatment and comparison groups is provided in next section.

Appendix D List of occupations in treatment and comparison group

The list of occupations defined in the treatment and comparison group is provided below:

Table D1: Treatment and Comparison Group Occupations by Work-from-Home Intensity

Treatment Group Occupations (High WFH)	**Comparison Group Occupations (Low WFH)**
Advertising, Marketing, Promotions, Public Relations, and Sales Managers	Agricultural Workers
Architects, Surveyors, and Cartographers	Air Transportation Workers
Business Operations Specialists	Assemblers and Fabricators
Computer Occupations	Baggage Porters, Bellhops, and Concierges
Counselors, Social Workers, and Other Community and Social Service Specialists	Building Cleaning and Pest Control Workers
Drafters, Engineering Technicians, and Mapping Technicians	Construction Trades Workers
Engineers	Cooks and Food Preparation Workers
Financial Clerks	Electrical and Electronic Equipment Mechanics, Installers, and Repairers
Financial Specialists	Entertainers and Performers, Sports and Related Workers
Information and Record Clerks	Entertainment Attendants and Related Workers
Law Enforcement Workers	Extraction Workers
Lawyers, Judges, and Related Workers	Food Processing Workers
Legal Support Workers	Food and Beverage Serving Workers
Librarians, Curators, and Archivists	Funeral Service Workers
Life Scientists	Grounds Maintenance Workers
Life, Physical, and Social Science Technicians	Health Technologists and Technicians
Mathematical Science Occupations	Healthcare Diagnosing or Treating Practitioners
Media and Communication Workers	Helpers, Construction Trades
Operations Specialties Managers	Home Health and Personal Care Aides; and Nursing Assistants, Orderlies, and Psychiatric Aides
Other Management Occupations	Material Moving Workers
Other Office and Administrative Support Workers	Metal Workers and Plastic Workers
Other Sales and Related Workers	Motor Vehicle Operators
Physical Scientists	Occupational Therapy and Physical Therapist Assistants and Aides
Sales Representatives, Services	Other Food Preparation and Serving Related Workers
Sales Representatives, Wholesale and Manufacturing	Other Healthcare Support Occupations
Secretaries and Administrative Assistants	Other Installation, Maintenance, and Repair Occupations
Social Scientists and Related Workers	Other Personal Care and Service Workers
Supervisors of Office and Administrative Support Workers	Other Production Occupations
Supervisors of Production Workers	Other Protective Service Workers
Top Executives	Other Transportation Workers
	Personal Appearance Workers
	Postsecondary Teachers
	Preschool, Elementary, Middle, Secondary, and Special Education Teachers
	Printing Workers
	Rail Transportation Workers
	Religious Workers
	Retail Sales Workers
	Supervisors of Building and Grounds Cleaning and Maintenance Workers
	Supervisors of Construction and Extraction Workers
	Supervisors of Food Preparation and Serving Workers
	Supervisors of Installation, Maintenance, and Repair Workers
	Supervisors of Personal Care and Service Workers
	Supervisors of Sales Workers
	Supervisors of Transportation and Material Moving Workers
	Textile, Apparel, and Furnishings Workers
	Vehicle and Mobile Equipment Mechanics, Installers, and Repairers
	Water Transportation Workers
	Woodworkers

Appendix E Empirical Estimation Strategy for Conditional Parallel Trends

As presented in the main analysis and results section, we first check if parallel trends hold for our DID design using visual diagnostics by plotting group level averages of the outcome variable across the treatment and comparison group for pre- and post-pandemic periods. This is shown in Figure 3. As is seen, the simple group level averages suggest parallel trends do not exist.

However, in a DID setting, if parallel trends do not exist, the other strategy is to check the existence of conditional parallel trends. We therefore plot the conditional parallel trends of the transformed outcome variable itself, in line with Wooldridge (2023) and Roth and Sant'Anna (2023). We use the following empirical specification to test the same:

$$\begin{aligned} log(\frac{P_{its}}{1-P_{its}}) = \gamma_s + \lambda_t \\ + \sum_{\tau=-4}^{-1} \beta_t \times D_{st} + \sum_{\tau=0}^{3} \delta_t \times D_{st} + x_{ist} + \epsilon_{ist} \end{aligned} \tag{E1}$$

where, γ_s and λ_t are group and time fixed effects respectively. Treatment occurs at time (τ) = 0 (year 2022) and we include q leads/ anticipatory effects, which in this case is 4 (years 2016, 2017, 2018 and 2019) and m lags or post-treatment effects, which for our empirical specification is 3 (years 2023, 2024 and first two months of 2025). x_{ist} include all control variables used in the benchmark empirical specification.

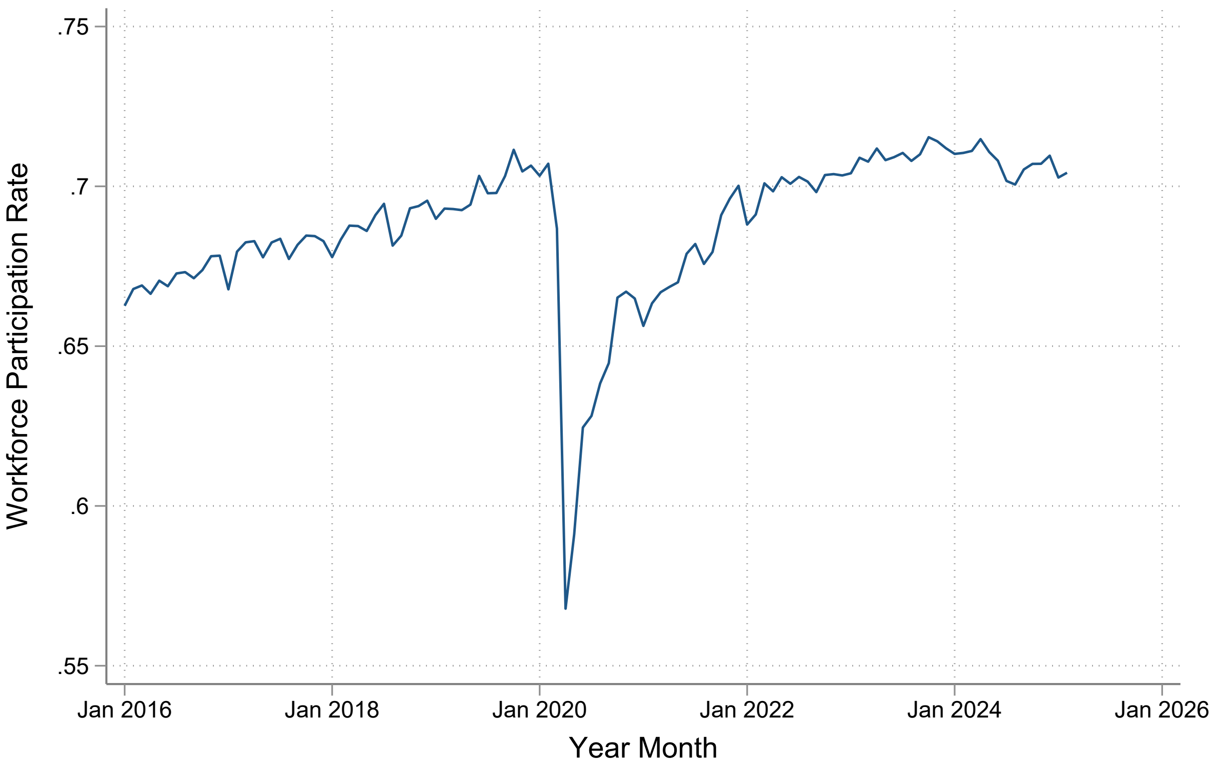
The results presented in Figure 5 suggest existence of conditional parallel trends for young women between the treatment and comparison groups in the pre-period.

Appendix F Brief on Compositional Changes impacting our estimates

We recognize that compositional changes in the treatment and comparison groups, whether through new entrants into the workforce or mobility across occupations, could undermine the Stable Unit Treatment Value Assumption (SUTVA), and in turn, the validity of our estimates. To address this, we first compare workforce participation rates among young women in the pre-treatment period (2019 to early 2020) with those observed from 2022 onward, when the immediate effects of the pandemic had receded. As shown in Figure F1, these rates remain virtually unchanged, suggesting broad stability in the underlying population.

However, unchanged participation rates do not preclude reallocation between high- and low-WFH occupations or selective entry over time. To account for these possibilities, we construct a propensity score matched sample based on pre-treatment characteristics and restrict the analysis to this cohort throughout the study period. While this matched sample represents a subset of the full working sample, it provides a cleaner comparison by holding initial composition fixed. We then re-estimate the DID model on this matched subample, as described in section 6.1.3. If SUTVA were violated, one would expect to see divergence between these estimates and those from the full sample benchmark results. Instead, we find that the estimated treatment effect remains close to our benchmark results, reinforcing the credibility of our identification strategy.

Figure F1: Changes in Workforce Participation for young women



Source: Current Population Survey

Appendix G Robustness Related to percentage of job postings offering remote work

We also check for robustness using alternative definition of threshold job postings. In the estimations provided in Appendix C, instead of half of the childcare done during daytime, if we assume two-thirds childcare is done during the same, our new threshold job postings become approximately 9.52 percent. The results in this case are as follows:

Table G1: Proportion of young women in STEM occupations by group and time period

	Pre-period	Post-period
Comparison Group	0.171	0.197
Treatment Group	0.256	0.325

Table G2: Results from Benchmark Regressions Using Alternative Threshold for WFH

	Model (1)	Model (2)
	STEM Occupation	STEM Occupation
Post	0.050**	-0.094***
	(0.022)	(0.031)
WFH	-0.042***	3.097***
	(0.011)	(0.013)
Post × WFH	0.146***	0.021
	(0.017)	(0.021)
ATT Estimate (pp)	2.87	0.39
Controls	Y	Y
R-squared	0.178	0.5141
Observations	716,418	830,089

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Notes: Model (1) presents results from the benchmark regression using a logit specification for young women. Model (2) presents results for young men. The control variables include education years, work experience, number of children, number of children below five years, family income, work status, race and state and metropolitan fixed effects. All regressions are weighted using the *compwt* variable available in IPUMS-CPS and commonly used to generate labor market statistics.

Appendix H Details and Robustness for Non Binary Treatment Estimates

Appendix H.1 Detailed Estimation Strategy for Non Binary Treatment in Context of the Paper

The objective is to assess how young women's STEM participation responds to rising levels of WFH adoption. While the binary treatment captures the average change in STEM participation when WFH adoption crosses a fixed threshold (6.97 percent), this exercise traces the marginal effects of moving from one intensity level of WFH to the next. This refinement is particularly valuable for firms that already operate at a given level of WFH and wish to know the potential impact of increasing adoption to the next level. Beyond providing a broad view of the WFH-STEM participation relationship, this approach yields finer-grained insights that speak directly to the marginal effects of incremental shifts in WFH intensity, offering practical guidance for organizations contemplating adjustments from one adoption tier to the next.

To examine how incremental shifts in WFH intensity affect young women's STEM participation, we partition the continuous WFH measure into four tiers: (i) 0–7 percent, (ii) 7–15 percent, (iii) 15–23 percent, and (iv) above 23 percent. While this discretization helps firms to devise actionable strategies, it raises two estimation challenges.

The first challenge stems from temporal variation in occupational WFH intensities. Since our data span multiple months and years, a given occupation may move between WFH tiers over time, though relatively uncommon empirically. For example, occupations reporting 15–23 percent WFH in some months may report 7–15 percent in others. The reverse may also happen. Assigning such an occupation to treatment or comparison groups based on the WFH intensity across time risks violating the SUTVA. This instability complicates causal interpretation, particularly in a DID framework that assumes fixed group membership.

The second challenge involves selection on gains. As emphasized by Heckman et al. (2006) and Callaway et al. (2024), workers may sort into WFH tiers not just by exposure level, but by their expected returns from being there. Thus, occupations adopting 15–23 percent WFH may differ systematically from those at 7–15 percent, not only in unobserved characteristics, but also in how they respond to changes in WFH exposure. In this case, simply differencing two DID estimates that each use a common base category (e.g., 0–7 percent) does not recover the marginal effect of moving from one adjacent tier to the next. Instead, it conflates level effects with heterogeneous treatment gains.

To navigate these complications, we adopt a two-part strategy. First, we enforce strict group assignment so that the group memberships are mutually exclusive to avoid compositional overlap. For example, when comparing occupations in the 15–23 percent WFH tier (treatment group) to those in the 7–15 percent tier (comparison group), we classify an occupation into the treatment group only if it remains in the 15–23 percent range for at least 11 out of the 21 post-pandemic months (during the period January 2023 to September 2024). For the other 10 months when it is not offering 15-23 percent, we drop them. Similarly, occupations that stay in the 7–15 percent range for at least 11 months are placed in the comparison group. If that occupation reports a different WFH intensity during the remaining 10 months or fewer, those observations are excluded from the analysis. This rule ensures mutually exclusive group membership and preserves compositional consistency, a necessary condition for credible DID estimation.

While this classification scheme ensures that treatment and comparison groups are mutually exclusive, it does not, on its own, prevent compositional shifts over time within each group. For example, an occupation that offers 15–23 percent WFH for 11 months would enter the treatment group. However, if the same occupation shifts to a different WFH intensity in subsequent months, it would no longer qualify as treated. Such movements generate time-varying group membership, thereby undermining the core DID requirement of temporal stability in group composition. To safeguard against this, we implement propensity score matching to construct subsamples that are not only comparable across groups but also stable across time. This matching approach ensures that treated and comparison units retain consistent characteristics throughout the observation window. Given our maintained assumption that tasks are stable within occupations and do not overlap across treatment arms, the application of this strategy supports the credibility of the SUTVA condition and the internal validity of the estimated effects.

We then implement a DID analysis on the matched subsamples to estimate the causal impact of rising WFH intensity. We assume unidirectionality in selection into treatment based on both levels and gains. This assumption prevents confounding, where different gains and levels could yield the same propensity score. Under it, matched individuals align in both levels and gains. The use of DID, rather than simple mean comparisons across matched treatment and comparison groups, serves an important purpose. Even after propensity score matching, there may remain unobserved, time-invariant differences between treatment and comparison groups if the propensity score model is misspecified. DID controls for such remaining differences by differencing out unobserved group-specific fixed effects, thereby providing more credible estimates of the treatment effect. As such:

$$\begin{aligned}
\text{Effect} \quad &= E[Y_t(n)|WFH = m] - E[Y_t(m)|WFH = m] \\
&= E[Y_t(n) - Y_{t-1}(m)|WFH = m] - E[Y_t(m) - Y_{t-1}(m)|WFH = m] \\
&= \underbrace{E[Y_t(n) - Y_{t-1}(m)|WFH = n]}_{\text{Matched sample hence replace m with n}} - E[Y_t(m) - Y_{t-1}(m)|WFH = m] \\
&= E[\Delta Y_t|WFH = n] - E[\Delta Y_t|WFH = m]
\end{aligned} \tag{H1}$$

This estimation strategy is applied across each adjacent pair of WFH adoption tiers: from 0–7 percent to 7–15 percent, from 7–15 percent to 15–23 percent, and from 15–23 percent to above 23 percent. We do not examine higher ranges, as very few occupations in our sample have adopted WFH at more intense levels. Accordingly, each estimate is based on clearly defined treatment and comparison groups, before and after the pandemic, ensuring consistency in comparison and interpretability of effects.

To test the sensitivity of our findings to the WFH classification scheme, we replicate the analysis using an alternative tier structure: 0–9.5 percent, 9.5–18 percent, 18–27 percent, and above 27 percent. The results remain consistent across both schemes.

Figure H1: Matching quality between 0 to 7% category and 7 to 15% category in pre-period

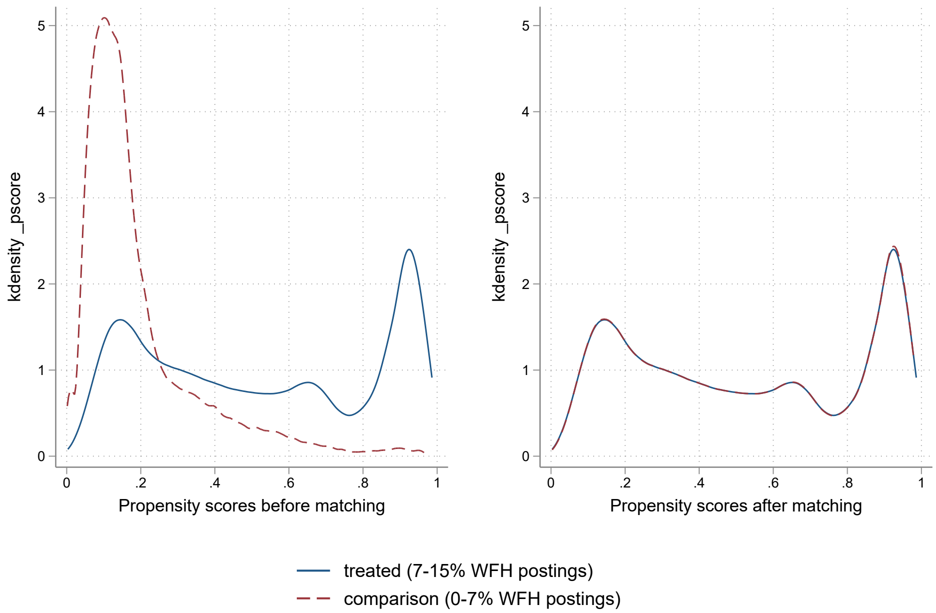


Figure H2: Matching quality between 0 to 7% category and 7 to 15% category in post-period

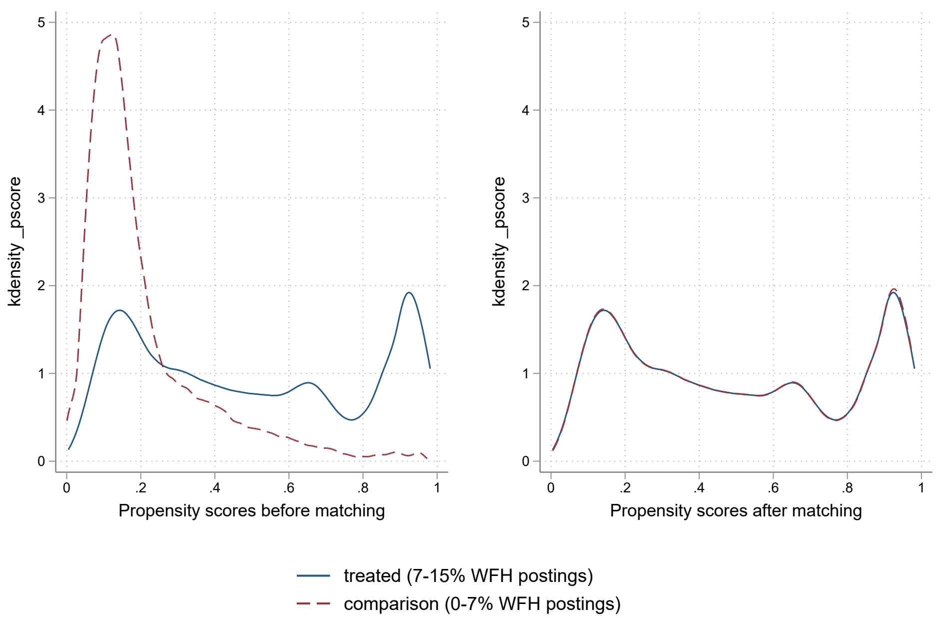


Figure H3: Matching quality between 7 to 15% category and 15 to 23% category in pre-period

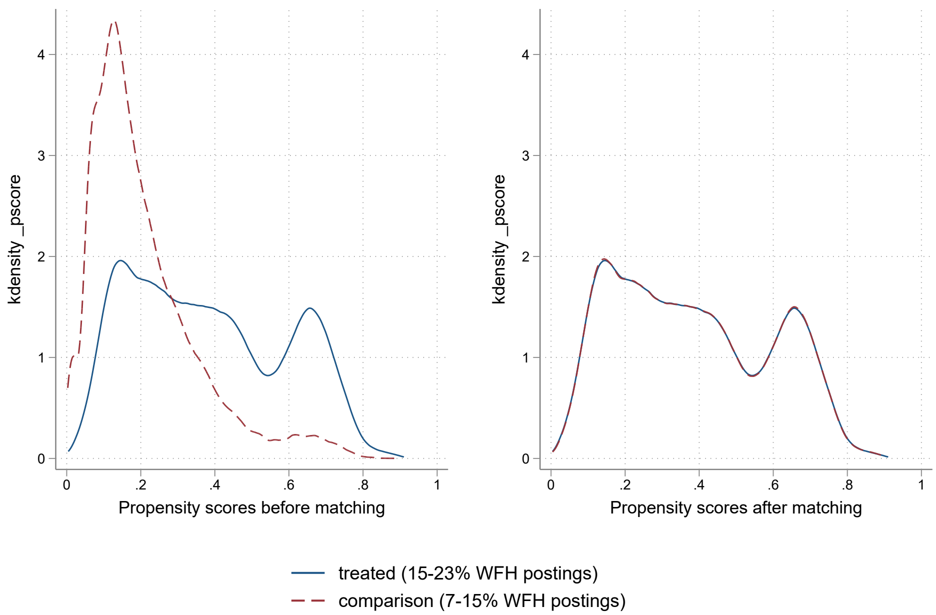


Figure H4: Matching quality between 7 to 15% category and 15 to 23% category in post-period

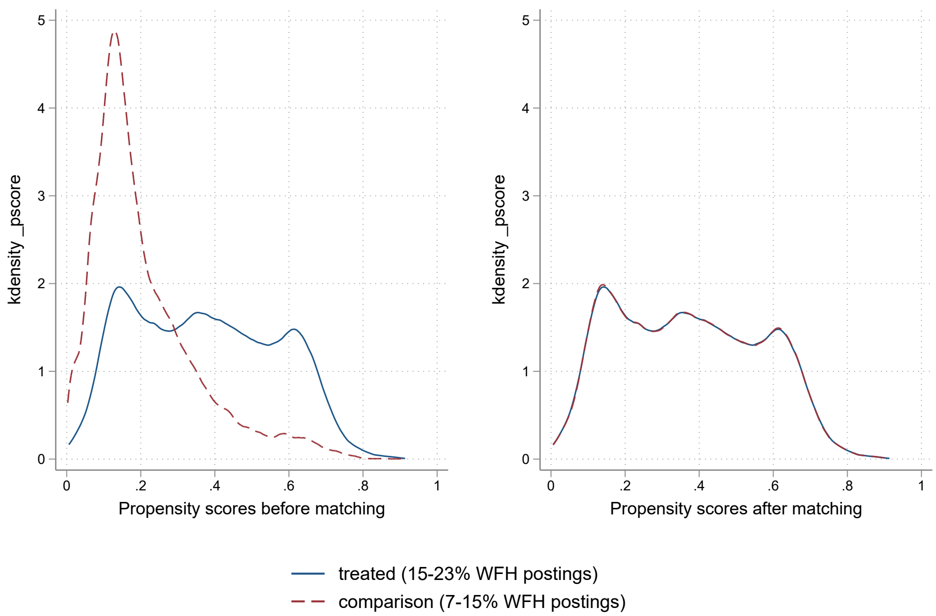


Figure H5: Matching quality between 15 to 23% category and > 23% category in pre-period

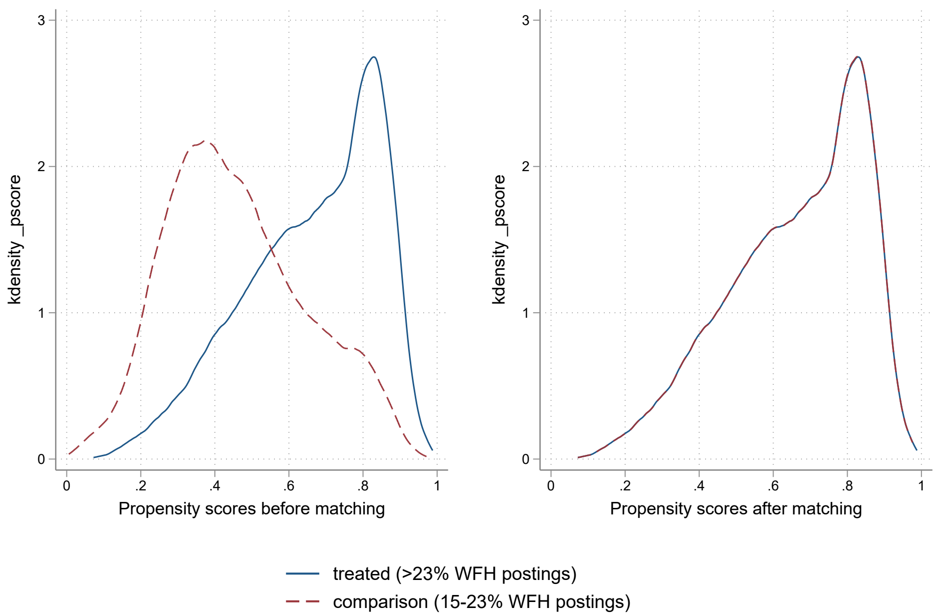
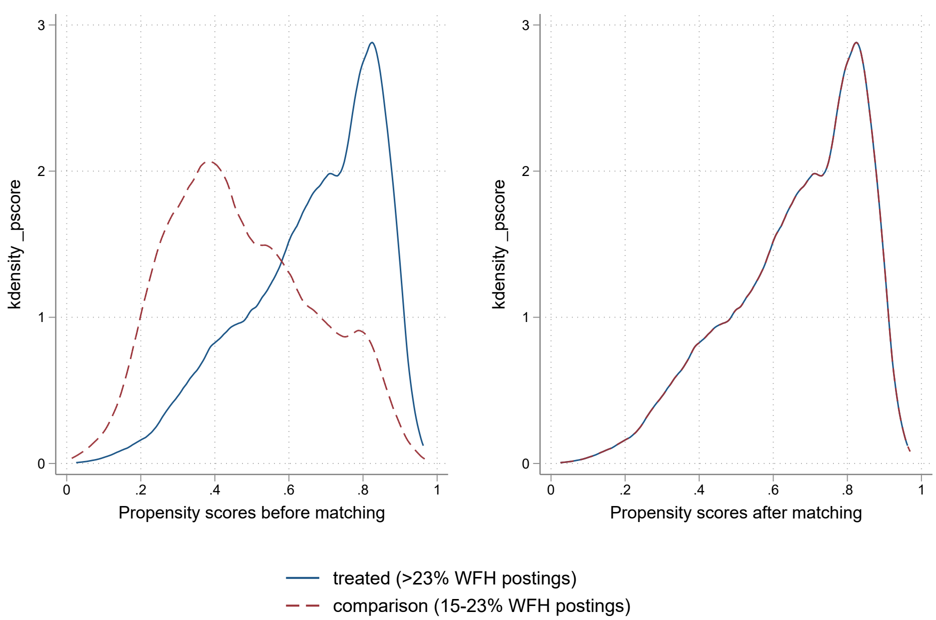


Figure H6: Matching quality between 15 to 23% category and > 23% category in post-period



Appendix H.2 Robustness for non binary treatment using alternate threshold level of job postings

Our alternate definition of threshold job postings is approximately 9.52 percent. Using this definition, we create different treatment intensity groups: (i) 0 to 9.5 percent; (ii) 9.5 percent to 18 percent; (iii) 18 percent to 27 percent, and (iv) greater than 27 percent. Next, we check whether similar results hold compared to our original treatment intensity groups, using this alternative definition. Table H1 below provides detailed results:

Table H1: Robustness results for non binary treatment using alternate definition of treatment intensity

Treatment Intensity Category	Incremental Treatment Effect (In pp)
0-9.5% to 9.5-18%	0.56***
9.5-18% to 18-27%	4.24**
18-27% to >27%	6.97***
Standard errors in parentheses	
* p<0.1; ** p<0.05; *** p<0.01	

Appendix I Definition for Variables in Empirical Strategy

The definitions for the dependent variables, the independent variables and the control variables are provided below

Table I1: Variable definitions and units

Variable	Definition	Unit
Outcome Variables:		
STEM Occupation	Takes value 1 for individuals in STEM occupations and value 0 for those in non-STEM occupations. Excludes management, business, financial, and legal occupations.	Binary
Low Atrophy high WFH	Takes value 1 for individuals in high WFH non-STEM occupations (excluding management, business, financial, and legal). Value is 0 for non-STEM low WFH occupations.	Binary
Other high atrophy occupations	Takes value 1 for management, business, financial, legal and health occupations; value is 0 for non-STEM occupations.	Binary
Independent Variables:		
Treat	Dummy variable that takes value 1 if an individual is in a treatment group occupation; 0 otherwise.	Binary
Post	Dummy variable that takes value 1 for periods from March 2020 onward; 0 for earlier periods.	Binary
Control Variables:		
Education years	Total years of education based on the highest qualification. Grades 1–4 coded as 2.5 years; grades 5–6 as 5.5 years; grades 7–8 as 7.5 years; bachelor's as 15.5 years; master's as 17.5 years; doctorate as 20 years.	Years
Work Experience	Estimated as: age - education years - 6 (since IPUMS-CPS lacks direct measure).	Years
Number of children	Number of own children in the household.	Count
Family income	Income of the householder's family; grouped into categories.	USD
Work Status	Full-time/part-time employment status; includes working part-time for economic reasons, not at work, etc.	Factor
Race	Race of the respondent.	Factor
Marital Status	Marital status; includes married (spouse present or absent), separated, divorced, widowed, never married.	Factor
Number of children below 5 years	Number of own children in the household under age 5.	Count
State fixed effects	Name of the U.S. state.	Factor
Metropolitan fixed effects	Status of metropolitan or central/principal city.	Factor