The Future of Work: Remote Opportunities and Female Labor Force Participation

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This paper examines the effects of the expansion of work-from-home (WFH) opportunities accelerated by the COVID-19 pandemic on female labor market outcomes. Using a difference-in-differences and event study design, this paper compares individuals in Metropolitan Statistical Areas (MSAs) with higher WFH potential to those in areas with lower WFH potential before and after the pandemic. The results indicate that relative to men, access to WFH opportunities significantly increases the likelihood of female labor force participation, employment, and full-time work. These effects are particularly strong among college-educated mothers and mothers with young children, with benefits diminishing with age. More broadly, the findings suggest that WFH opportunities can explain approximately 21 percent of the observed narrowing in the gender labor force participation gap between 2019 and 2023. Furthermore, the findings suggest that the positive effects of WFH opportunities remain stable over time, with the potential to grow as remote work arrangements become more established and persistent.

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[†]All code and public data are available at https://github.com/mengsong-econ?tab=repositories. Users are welcome to replicate the analysis and provide feedback or point out any errors I may have overlooked.

1 Introduction

The landscape of the labor force has undergone a significant transformation in recent decades, characterized by an overall upward trend in female labor force participation (LFP) (Goldin, 1990; Goldin and Katz, 2002; Fernández, 2013). This growth pattern in female LFP began in the early 20th century and has since been extensively studied (Costa, 2000; Goldin and Katz, 2002; Greenwood et al., 2005; Bailey, 2006; Attanasio et al., 2008; Albanesi and Olivetti, 2016; Vidart, 2024). More recently, the COVID-19 pandemic has brought about significant changes to societal and economic structures, with the labor market undergoing some of the most profound shifts. One notable transformation has been the rapid adoption of remote and hybrid work arrangements. Data from the U.S. Census Bureau's Household Pulse Survey (2022-2023) and the Survey of Working Arrangements and Attitudes reveal that full days worked from home made up 28 percent of paid workdays in June 2023, a fourfold increase compared to 2019 (Barrero et al., 2023). Importantly, this shift to new work arrangements has proven to be persistent and is likely to become permanent in the post-pandemic era, even as distancing mandates have ended and COVID-19 health risks have diminished (Barrero et al., 2021; Aksoy et al., 2022; Barrero et al., 2023; Bick et al., 2023). Even as Return-to-Office (RTO) mandates have gained traction, remote work continues to be highly valued by employees, with recent evidence showing that RTO policies reduce job satisfaction without improving firm performance and lead to an outflow of senior employees (Ding and Ma, 2023; Van Dijcke et al., 2024).

This paper examines the effects of the expansion of work-from-home (WFH) opportunities accelerated by the COVID-19 pandemic on female labor market outcomes. It explores whether the rise in remote work can explain the observed resilience and recent growth in female labor force participation, and whether women were more adversely impacted or ultimately benefited from these arrangements. I begin by constructing a measure of exposure to WFH opportunities at the Metropolitan Statistical Area (MSA) level, building on the methodology of Gupta et al. (2022) and the occupation-level WFH scores developed by Dingel and Neiman (2020). This measure reflects the share of jobs in each MSA that could be performed remotely, based on the weighted average of occupational teleworkability scores during the pre-pandemic period. Using a difference-in-differences and event study design, I then exploit variation across MSAs with higher versus lower pre-existing WFH potential to examine changes in female labor market outcomes before and after the pandemic. This design differs from recent work that conditions on spousal occupation to proxy for exposure to WFH shocks (Filippo et al., 2025), or that exploits degree-level differences in telework feasibility (Harrington and Kahn, 2025), both of which rely on stronger assumptions about assortative matching, educational sorting, and unobserved preferences. By exploiting MSA-level variation in WFH potential interacted with the pandemic shock, my design complements this work by extending causal evidence on broader shifts in women's labor market opportunities.

This research is motivated by the remarkable changes in female labor force participation that coincided with the rapid growth of work-from-home arrangements during the COVID-19 pandemic. Figure 1 illustrates the labor force participation rates for the working-age population (ages 25 to 64) in the United States from 2012 to 2023, based on data from the American Community Survey (ACS). The data reveal three key trends: (1) Male LFP experienced a sharper and larger decline in 2020, recovering quickly but took longer to rebound near-pre-pandemic levels. (2) Female LFP exhibited a smaller decline during the pandemic, followed by a slower recovery but steady growth in the post-pandemic period, ultimately reaching its highest recorded levels. (3) Across the entire span, male LFP remained relatively stable overall, whereas female LFP demonstrated a sustained upward trend. These findings are consistent with existing literature and various reports,[1] which highlight that prime-age women have driven the labor market recovery and continue to play a crucial role in shaping its trajectory.

However, this smaller decline and steady rise in female LFP is particularly notable given that early research predicted women would be disproportionately harmed by the COVID-19 pandemic. Termed the "she-cession" (Goldin, 2022), these concerns were grounded in women's heightened childcare responsibilities due to school closures (Alon et al., 2020a), increased caregiving for elderly relatives (Goldin, 2022), and overrepresentation in disrupted service-sector occupations such as healthcare and retail (Alon et al., 2020b; Albanesi and Kim, 2021). At the same time, prior research has also shown that women are more likely to be employed in occupations with higher remote-work potential and tend to place greater value on occupational flexibility(Bang, 2022; Tito, 2024; Garro-Marín et al., 2025). Figure 2 further validates that women not only matched but exceeded men in actual uptake of remote work arrangements during the pandemic. Importantly, the gender gap in work-from-home rates widened in the post-pandemic years, suggesting that women have continued to leverage these opportunities at higher rates than men. This trend calls for a deeper examination of gender disparities in the context of remote work and underscores the possibility that increased

[1] See, for example, U.S. Bureau of Labor Statistics (2023), which reported that the labor force participation rate for women aged 25 to 54 reached 77.6% in May 2023, the highest level since January 2007; NBC News (2023), which highlighted the role of prime-age women in driving the labor market recovery, noting that their participation rates returned to pre-pandemic levels by January 2023; and The Hamilton Project (2024), which emphasized that as of January 2024, 78% of women aged 25 to 54 were participating in the labor force, marking the highest rate on record. The report also noted that prime-age women have played a significant role in driving the overall increase in labor force participation over the past five years, despite variations across demographic subgroups.

access to flexible work arrangements may have supported and even strengthened female labor force attachment beyond the immediate crisis.

My findings reveal that WFH opportunities have a significant and positive impact on female labor force participation, employment rates, and the likelihood of full-time work. The effects are more pronounced for college-educated mothers and are largest for mothers with young children. At the MSA level, a one–standard deviation increase in WFH opportunities is associated with a 0.67 percentage point increase in labor force participation among mothers with young children, a 0.40 percentage point increase in employment, and a 0.78 percentage point increase in full-time work. To aid interpretation, I conduct a first stage analysis by regressing actual WFH behavior on the pre-pandemic WFH potential measure and use the resulting estimate to compute the Wald estimator. The estimates indicate that when local opportunities lead mothers with young children to take up WFH, they are about 18.01 percent more likely to participate in the labor force, 10.75 percent more likely to be employed, and 20.97 percent more likely to work full-time. These effects are economically meaningful. Between 2019 and 2023, the male–female labor force participation gap narrowed by about 1.4 percentage points, and my estimates imply that rising WFH opportunities account for roughly 0.3 percentage points of this change, representing about 21 percent of the observed convergence. [2] Moreover, the impact of WFH opportunities diminishes with age, as younger women exhibit the larger gains while older women show smaller or insignificant effects. Furthermore, I examine the post effects year by year and the results show that these positive effects remain stable over time, with the potential to grow as remote work arrangements become more established and persistent.

While the event study results exhibit clear parallel trends prior to the pandemic, a fundamental identification challenge arises from the fact that the COVID-19 pandemic was a universal shock that affected all metropolitan areas simultaneously. The concern is that the observed effects may not solely reflect the causal impact of WFH opportunities, but could instead be driven by differential pandemic-era effects across demographic groups that happen to correlate with WFH availability. To address this concern, I follow recent approaches used to study pandemic-period policy impacts (Jack et al., 2023; Ross et al., 2024) and demonstrate the stability of my estimates by allowing the relationship between labor force participation and all demographic controls to vary by year. In addition, the validity of my findings is supported by employing a triple-difference specification for identification and a series of robustness checks, including the use of a shorter-period measure of WFH exposure, alternative measures of WFH potential, weighted regressions that account for the ACS

[2] The main results section provides a more detailed discussion of the calculation and interpretation of these numbers.

sampling design, adjustments based on individuals' prior-year residence to address potential selective mobility, and excluding older cohorts for early retirement concerns. These analyses consistently confirm the stability of the results and underscore the transformative potential of WFH opportunities in promoting inclusivity and resilience in the labor market.

This paper contributes to several strands of literature. First, to the best of my knowledge, it is the first study exploiting geographic variation in WFH potential combined with the COVID-19 pandemic shock to provide population-level causal evidence on female labor market outcomes. The closest work by Filippo et al. (2025) focuses on intra-household spillovers by conditioning on husbands' occupations, while Harrington and Kahn (2025) examines the motherhood penalty using degree-level telework feasibility. These approaches are well-suited to their questions but necessarily rely on stronger assumptions about assortative matching or educational sorting. My study avoids these concerns by leveraging geographic variation in ACS data over a longer horizon and directly comparing men and women at the population level, providing a broader perspective on how WFH opportunities fundamentally shaped women's labor market outcomes. Additionally, while their studies either exclude the pandemic period or focus primarily on pre-COVID data, my study includes all periods—before, during, and after the pandemic—providing a more complete picture of how temporary responses evolved into lasting structural changes in work arrangements. At the same time, my findings are consistent with Harrington and Kahn (2025) in showing that college-educated mothers and mothers with young children experienced the largest gains from WFH, and the evidence on time reallocation within households documented by Filippo et al. (2025) helps to explain why mothers and women more generally benefited more than fathers and men.

Second, this paper contributes to the growing literature on COVID-19 and gender inequality by moving from early predictions and descriptive evidence to causal measurement. Alon et al. (2020a,b) emphasized women's disproportionate job losses during the pandemic and used descriptive evidence and macroeconomic modeling to predict both short-run harms and possible long-run benefits from telecommuting. Albanesi and Kim (2021) provided early descriptive evidence of gendered job losses, highlighting the roles of industry composition, family structure, and childcare constraints. While these studies focused on immediate or intermediate effects of the pandemic, my paper reexamines these questions with a longer time horizon and richer data, extending prior work by providing direct causal evidence. It confirms that women's labor force participation proved more resilient than initially predicted and goes beyond earlier studies by showing that the expansion of WFH opportunities was a measurable contributor to the narrowing gender gap in the post-pandemic labor market.

Third, this paper identifies work-from-home opportunities as a newly important driver of female LFP and a significant contributor to narrowing gender gaps. Historical growth in female LFP has been attributed to structural transformations (Goldin, 1990; Costa, 2000), cultural shifts (Fogli and Veldkamp, 2011; Fernández, 2013), technological advances reducing household burdens (Greenwood et al., 2005; Vidart, 2024), and changes in fertility behavior driven by the contraceptive pill (Goldin and Katz, 2002; Bailey, 2006) and reduced childcare costs (Attanasio et al., 2008). Prior studies remained uncertain whether recent female LFP gains would persist absent pandemic disruptions and whether remote work truly drives these improvements. This paper resolves both questions by providing causal evidence that flexible work arrangements significantly enhance women's labor supply and account for approximately 21% of the narrowing gender gap.

Fourth, this paper provides empirical evidence to inform the current debate surrounding remote work policies and return-to-office mandates. Evidence suggests remote work improves flexibility, work-life balance, and productivity (Harrington and Kahn, 2023; Bloom et al., 2015, 2024), particularly benefiting women who show higher willingness to pay for WFH opportunities (Mas and Pallais, 2017; Drake et al., 2022; Bang, 2022; Maestas et al., 2023). However, concerns remain about potential productivity and collaboration costs (Gibbs et al., 2021; Emanuel and Harrington, 2024), with some arguing that pandemic caregiving burdens offset women's potential gains (Alon et al., 2020a,b). The findings of this paper shed new light on WFH's role in supporting women, especially mothers, potentially mitigating the motherhood penalty. Importantly, this evidence suggests that WFH opportunities have lasting positive effects on the labor market, and these gains may strengthen as remote work transitions from a pandemic response to a structural feature of employment.

The rest of the paper is organized as follows: section 2 describes the data sources and the use of Metropolitan Statistical Areas as the geographic unit of analysis. Section 3 details the construction of the WFH measure, the empirical strategies, and the strategy for addressing identification concerns. Section 4 presents the results of the main analysis, heterogeneity analyses, and robustness checks. The final sections discuss the mechanisms, policy implications, and concluding remarks.

2 Data

2.1 Primary Data Source

American Community Survey. This study primarily relies on the American Community Survey (ACS), a nationally representative, repeated cross-sectional dataset conducted by the U.S. Census Bureau. The microdata are accessed through IPUMS USA, which harmonizes ACS variables and documentation to facilitate consistent analysis across survey years. The

ACS provides annual data on a 1% random sample of the U.S. population, making it an invaluable resource for analyzing labor market trends at both the individual and local levels. The ACS is particularly well-suited for this study for several reasons. First, its detailed demographic and economic information allows the analysis to be conducted at the individual level, which is essential for identifying gender-specific responses to WFH opportunities. Second, the ACS provides consistent geographic identifiers that enable the analysis of variation in WFH exposure at the MSA level. Combined with the ACS's individual-level occupation data, this provides the basis for the construction of an MSA-level WFH potential measure. Third, the ACS provides sampling weights that allow me to examine whether the results are specific to the ACS sample or can be extended to the broader U.S. population. While I use unweighted regressions as my primary specification for greater precision, I confirm that point estimates are similar when using ACS person weights. Fourth, the ACS includes information on each person's residence in the previous year, which helps me address concerns that WFH opportunities might encourage individuals to relocate and potentially confound the observed effects. Lastly, the ACS's national representativeness, large sample size, and consistent annual coverage make it uniquely suited for examining labor market dynamics before and after the pandemic. Distinct from prior work that focuses on immediate shocks using specialized survey data or narrower subpopulations, this paper provides a more comprehensive and detailed exploration of the relationship between remote work opportunities and female labor market outcomes.

Time Period. This study uses ACS data spanning from 2012 to 2023, capturing a critical period that includes both pre- and post-pandemic years. The sample begins in 2012 because the U.S. Census Bureau redraws Public Use Microdata Area (PUMA) boundaries every 10 years based on the most recent decennial census, and the 2010-based PUMAs were first implemented in the ACS for 2012 respondents. Seven years of data before the onset of the COVID-19 pandemic provide a robust pre-period for examining pre-trends, strengthening the validity of the parallel trends assumption and the overall robustness of the findings. I also demonstrate that the results remain consistent and robust when using a shorter pre-period WFH measure. The sample ends in 2023, as this represents the most recent ACS data available at the time of the study. By covering the years before, during, and after the pandemic, this study compares short- and long-term trends in labor force participation associated with the pandemic-induced acceleration of remote work adoption.

Key Variables. The primary outcome variables in this study are each individual's labor force participation, employment, and full-time work. Labor force participation indicates whether the respondent was employed or actively seeking work during the week preceding the survey. Employment status captures whether the individual was in the labor force and, if so, whether they were employed or unemployed. Full-time work is defined as working 35 or more usual hours per week. The Standard Occupational Classification (SOC) code reported by each respondent is used to link occupations to WFH scores, enabling the construction of the MSA-level WFH measure. Additional key variables include demographic and socioeconomic characteristics such as sex, age, marital status, the presence of children, race, and educational attainment. These variables are critical for examining heterogeneity in labor force participation and understanding the gender-specific impacts of WFH opportunities.

Sample Restriction. The analysis restricts the sample to the working-age population (ages 25–64) to ensure comparability across labor market outcomes and avoid distortions from retirement-related labor force transitions. This age range captures workers who have completed their education while avoiding the complexities of early retirement decisions that may confound the estimated effects of WFH opportunities. As a robustness check, I also present results restricting the sample to ages 25-54 to address concerns that workers aged 55-64 may make retirement decisions based on remote work availability rather than their underlying labor force attachment. This restriction yields even stronger effects, particularly among women who are more likely to retire at earlier ages. Additionally, individuals in military occupations are excluded from the sample, as Dingel and Neiman (2020) do not report WFH scores for those job categories. [3]

2.2 Occupational WFH Score

A key measure in this study is the assessment of remote work potential. I employ the Dingel and Neiman (2020) WFH measure, which assigns a binary score of 1 or 0 to each occupation, indicating whether the job can feasibly be performed entirely from home (1) or not (0). The construction of this measure relies on detailed occupational characteristics derived from the O*NET database, specifically leveraging information from the Work Context Questionnaire and the Generalized Work Activities Questionnaire. These surveys provide insights into job requirements, such as physical activities, equipment usage, and interpersonal interactions, enabling a robust classification of occupations' teleworkability.

To ensure that the WFH measure is robust and stable over time, I replicated their construction of the WFH score using different versions of the O*NET database spanning

[3] The excluded military-specific occupations are as follows: 551000 - Military Officer Special and Tactical Operations Leaders; 552000 - First-Line Enlisted Military Supervisors; 553000 - Military Enlisted Tactical Operations and Air/Weapons Specialists and Crew Members; and 559830 - Military, Rank Not Specified.

from 2016 to 2023. This replication reveals that the share of occupations classified as suitable for remote work consistently remains around 37% across all years, aligning with the results reported by Dingel and Neiman (2020). The stability of this score ensures that any observed effects in the analysis stem from the potential for remote work and not from temporal changes in occupational classifications. A brief overview of the measure and additional context are provided in the Appendix, with the replication results illustrated in Figure A5.

For this study, I link the WFH scores developed by Dingel and Neiman (2020) to individuals in the ACS based on their reported occupation codes. The ACS reports each person's primary occupation, classified according to the 2010 Standard Occupational Classification (SOC) system for data from 2010 to 2017, and the 2018 SOC system for data from 2018 onward. Since the WFH scores provided by Dingel and Neiman (2020) are based on the 2010 SOC system, I link individuals from 2012 to 2017 using a consistent classification system to ensure comparability with the WFH scores. In addition, because some occupations in the ACS are only reported at aggregated levels, I construct weighted averages of the original 6-digit WFH scores at broader occupational groupings. These aggregated scores are computed using employment weights obtained from the Bureau of Labor Statistics (BLS), ensuring that WFH classifications remain representative even when disaggregated occupation codes are not available. Since occupation-level employment counts may vary from year to year, I use the average employment shares across multiple years to construct stable weights and prevent fluctuations in a single year from distorting the aggregated WFH scores. Together, these steps minimize measurement error during the merging process and improve the accuracy of the pre-period WFH exposure measure.

2.3 Metropolitan Statistical Areas

Metropolitan Statistical Areas (MSAs) are geographic units defined by the U.S. Office of Management and Budget (OMB) that represent regions consisting of a large urban core together with surrounding communities that have a high degree of economic and social integration with the urban core.

Using MSAs offers several advantages for analyzing remote work and female labor force participation. First, these areas are designed to capture the economic and social interdependencies between central cities and their surrounding communities. This framework reflects the integrated nature of modern metropolitan economies and captures the geographic units where remote work opportunities are most concentrated. Second, ACS data identify MSAs using the 2013 definitions (MET2013), which provides a consistent definition of metropolitan areas across all years in the sample. This variable is particularly advantageous because it remains stable and, unlike other units, is not affected by changes in Public Use Microdata Areas (PUMAs) or county definitions across ACS releases. [4] Third, MSA-level analysis aligns with the standard approach in the remote work literature, including Dingel and Neiman (2020) and Gupta et al. (2022).

In the 2012-2023 sample period, the 2013 MSA definitions provide a consistent framework that encompasses a total of 282 MSAs. However, due to the underlying PUMA boundary changes, 18 MSAs that are identifiable in 2012-2021 do not appear in 2022-2023, while 22 MSAs that are identifiable in 2022-2023 do not appear in 2012-2021. To maintain consistency across the entire study period, I restrict the analysis to the 242 common MSAs that are identifiable in both time periods. Figure 3 presents the geographic distribution of pre-pandemic work-from-home exposure across these MSAs, revealing substantial variation in WFH opportunity intensity. The map demonstrates that MSAs with higher WFH exposure are predominantly located in technology and finance hubs along the coasts and in major metropolitan areas, while MSAs in manufacturing-heavy regions of the Midwest and resource-extraction areas show lower exposure levels. This geographic heterogeneity in pre-pandemic WFH capability provides the foundation for analyzing differential responses to remote work adoption during and after the pandemic across MSAs.

2.4 Summary Statistics

Table 1 presents the summary statistics for the key variables used in the analysis, which is conducted at the individual level. The dataset comprises 12,174,093 observations, with 6,045,693 female individuals and 6,128,400 male individuals from 2012 to 2023. The data reveal gender differences across several key labor market outcomes. Women exhibit lower labor force participation rates, employment rates, and full-time work rates compared to men. However, women show greater standard deviations for these variables, indicating more heterogeneity in labor market attachment among women than men.

Marriage rates are somewhat lower among women, while they are more likely to be parents. The presence of children under 5 years old remains nearly identical across genders. A notable pattern emerges in educational attainment, where women demonstrate substantially higher college education rates and correspondingly lower non-college education rates compared to

[4] PUMAs represent the lowest level of geography identified in the ACS, and the Census Bureau redraws PUMA boundaries every 10 years based on population information from the most recent decennial census. In my sample, data from 2012-2021 are based on the 2010-based PUMAs, while 2022 and 2023 data are based on 2020 PUMA definitions. Using alternative geographic units such as labor market areas, commuting zones, or counties would require complex crosswalks between 2010 and 2020 PUMA definitions and across different geographic definitions over time. These crosswalk procedures would introduce measurement error and significantly complicate the analysis without providing clear advantages over the stable MSA definitions.

men. The age distribution remains relatively consistent across genders, with roughly equal representation in each age bracket.

Please note that in the regressions, the largest groups within categorical variables serve as the omitted categories to address potential collinearity issues in the model. These include White individuals, those with college education, and individuals aged 55–64.

3 Empirical Strategy

To explore the causal impact of WFH opportunities on female labor market outcomes, I employ difference-in-differences and event study designs that leverage variation in WFH potential across MSA and over time. This section outlines the construction of the WFH exposure measure, provides an overview of the empirical models used to estimate the effects of WFH opportunities, and describes the strategies implemented to ensure robust and unbiased results.

3.1 Measuring Exposure to Work-From-Home Opportunity

$$\text{WFH Measure}_{m,pre} = \frac{1}{T_{pre}} \sum_{t \in T_{pre}} \sum_{o} \left(\frac{\text{Number of jobs}_{m,o,t}}{\sum_o \text{Number of jobs}_{m,o,t}} \times \text{Teleworkability score}_o \right) \tag{1}$$

Equation (1) provides the formula for constructing the WFH measure based on the methodology of Gupta et al. (2022). The idea is to calculate the weighted average teleworkability score for each MSA m over the pre-period T_{pre}. This is a two-step process. In the first step, the measure is constructed by calculating the occupation weight for each occupation by dividing the number of jobs in each occupation o by the total number of jobs in the MSA for that year. This weight is then multiplied by the corresponding teleworkability score for that occupation, as developed by Dingel and Neiman (2020). Notably, to count the number of jobs in each MSA, I apply ACS person weights, which indicate how many persons in the U.S. population are represented by a given person in the sample. This step outputs a WFH score for each MSA for each year in the pre-period.

In the second step, the final measure is the average of these yearly values across all years in the pre-period. In this context, I designate the years 2012 to 2019 as the pre-period T_{pre}. To ensure robustness, I also calculate the mean WFH measure over a shorter pre-period (2015 to 2017) and confirm that the results remain consistent. This provides a stable, time-invariant measure of work-from-home potential for each MSA during the pre-pandemic period.

This approach ensures that the WFH measure reflects the distribution of teleworkable jobs across occupations within an MSA while accounting for temporal stability. The use of ACS person weights means the WFH score represents broader population-level WFH potential across MSAs rather than just the survey sample. Averaging over these periods reduces noise from year-to-year fluctuations in occupational composition and local labor market conditions, ensuring that the measure reflects long-term structural WFH potential rather than short-term variability. Additionally, using a pre-period invariant measure minimizes potential endogeneity concerns, as it ensures that the WFH measure is not influenced by changes in labor market conditions during the post-pandemic period. This approach also facilitates meaningful comparisons across MSAs, as all areas are evaluated based on their pre-pandemic WFH potential, providing a robust foundation for analyzing how the pandemic shock affected remote work opportunities differently across regions.

The main WFH measure used in the regressions is constructed based on the employed female population across all occupations, following Equation (1). This measure serves as the primary WFH index because employed females are a key demographic in examining the relationship between teleworkability and female labor force participation. By focusing on this group, the measure effectively reflects how remote work opportunities align with the unique employment patterns and challenges faced by women in the workforce.

In addition to the main WFH measure, I construct several alternative measures using different definitions and sampling criteria to ensure robustness. Table 2 presents the summary statistics for these alternative WFH measures. All measures share a common conceptual foundation, following the methodology outlined in Equation (1). The measures differ in their population focus: *wfh_main* focuses on employed females and serves as the primary indicator used in the regression analysis; *wfh* considers all individuals regardless of employment status or gender; *wfh_lfp* includes individuals in the labor force; *wfh_emp* restricts to employed individuals; *wfh_female* focuses on all females; and *wfh_lfp_female* considers females in the labor force.

Key observations from the summary statistics reveal that measures focusing on employed populations (*wfh_main*, *wfh_emp*) exhibit higher mean teleworkability scores compared to broader population measures. The *wfh* measure, which includes all individuals, shows the lowest mean, reflecting the inclusion of non-working populations with potentially lower teleworkability. All measures demonstrate similar cross-MSA variation, indicating consistent geographic patterns in teleworkability across different population definitions, and my findings remain robust across these alternative measures.

3.2 Empirical Specifications

The empirical strategy uses the geographic and temporal variation in the exposure to WFH opportunities to identify its effects on the labor market outcomes of female individuals. Specifically, I estimate the following difference-in-differences specification:

$$Y_{imt} = \delta \cdot (\text{WFH}_{m,\text{pre}} \times \text{Post}_t) + \mathbf{X}'_{it}\beta + \alpha_m + \lambda_t + \varepsilon_{imt} \tag{2}$$

Here, Y_{imt} represents the labor market outcome of individual i in MSA m at time t including labor force participation (LFP), employment, and full-time work status. $\text{WFH}_{m,\text{pre}}$ measures the pre-pandemic, time-invariant potential for remote work in MSA m, calculated using Equation (1). This variable is standardized to have a mean of 0 and a standard deviation of 1. $Post_t$ is an indicator for the post-pandemic period, covering the years 2021 to 2023. The coefficient of interest, δ, captures the average effect of pre-pandemic WFH potential on labor market outcomes during the post-pandemic period. A positive and statistically significant δ would indicate that individuals residing in MSAs with higher exposure to WFH opportunities experienced greater improvements in labor market outcomes relative to those in areas with lower WFH potential, following the onset of the pandemic.

The specification includes MSA and year fixed effects, α_m and λ_t, which control for time-invariant differences across MSAs and common shocks affecting all individuals in a given year, respectively. Additionally, the vector of individual-level controls $\mathbf{X}_{it}$ includes variables such as age, race, marital status, educational attainment, and the presence of children under age five, to adjust for observable differences across individuals. Standard errors are clustered at the MSA level to account for within-region correlation in the error terms.

A key assumption for this analysis is the parallel trends assumption. This assumption posits that, in the absence of the treatment (i.e., the COVID-19 pandemic and the associated increase in WFH opportunities), the labor force participation trends for individuals in MSAs with different levels of pre-pandemic WFH potential would have followed similar trajectories over time. This assumption implies that any observed divergence in trends post-2020 can be attributed to the differential exposure to WFH opportunities rather than pre-existing differences. To assess the validity of this identification strategy and to examine the dynamics of the effect, I estimate the following event study specification:

$$Y_{imt} = \sum_{s \neq 2019} \delta_s \cdot (\text{WFH}_{m,\text{pre}} \times \mathbf{1}\{t = s\}) + \mathbf{X}'_{it}\beta + \alpha_m + \lambda_t + \varepsilon_{imt} \tag{3}$$

The COVID-19 pandemic, which began in 2020, is considered the "treatment" year in this analysis. Accordingly, 2019 serves as the reference year, and the coefficient for this year is normalized to zero. All the other variables are defined as in Equation (2). Standard errors are clustered at the MSA level to account for potential correlation in the error terms within metropolitan areas.

Lastly, to better understand how the effects of WFH opportunities evolved in specific post-pandemic years, I estimate a difference-in-differences specification that allows the treatment effect to vary by year. This model captures the heterogeneity in the association between pre-pandemic WFH potential and labor market outcomes across the years 2021 to 2023. The specification is as follows:

$$\begin{aligned} Y_{imt} = \ & \delta_{2021} \cdot (\mathrm{WFH}_{m,\mathrm{pre}} \times \mathbf{1}\{t = 2021\}) \\ & + \delta_{2022} \cdot (\mathrm{WFH}_{m,\mathrm{pre}} \times \mathbf{1}\{t = 2022\}) \\ & + \delta_{2023} \cdot (\mathrm{WFH}_{m,\mathrm{pre}} \times \mathbf{1}\{t = 2023\}) \\ & + \mathbf{X}'_{it}\beta + \alpha_m + \lambda_t + \varepsilon_{imt} \end{aligned} \tag{4}$$

Here, $\mathbf{1}\{t = 2021\}$, $\mathbf{1}\{t = 2022\}$, and $\mathbf{1}\{t = 2023\}$ are year-specific indicator variables for the post-pandemic period. The coefficients of interest, δ_{2021} through δ_{2023}, estimate the association between pre-pandemic WFH potential at the MSA level and labor market outcomes in each post-pandemic year individually. All other variables are defined as in the baseline specification. This model provides a more granular view of how the effects of WFH opportunities evolved over time, enabling an assessment of whether the relationship between WFH potential and labor market outcomes changed across the years following the onset of the pandemic.

3.3 Threats to Identification

3.3.1 Validity of WFH Measure and COVID-19 Effects

To validate the WFH measure and establish that COVID was the primary driver of remote work expansion, I examine whether areas with higher pre-pandemic remote work potential experienced greater increases in actual work-from-home behavior after the pandemic began.

$$WFH\_Behavior_{imt} = \delta \cdot (\mathrm{WFH}_{m,\mathrm{pre}} \times \mathrm{Post}_t) + \mathbf{X}'_{it}\beta + \alpha_m + \lambda_t + \varepsilon_{imt} \tag{5}$$

As shown in equation (5), I regress the actual WFH behavior on the constructed WFH measure following the same difference-in-differences design with year and MSA fixed effects. The methodology leverages the ACS transportation-to-work variable, which surveys each employed individual about their primary method of commuting, including an option for working from home. By interacting the WFH measure with the post-pandemic indicator, I can isolate the effect of COVID-19 in activating latent remote work potential, demonstrating that the pandemic served as the key driver converting pre-existing telework capacity into actual remote work behavior.

Table 3 presents the first-stage results across different demographic groups. The coefficients are positive and statistically significant across all subgroups, indicating that the WFH measure captures actual WFH behavior well. MSAs with higher pre-pandemic teleworkability scores experienced larger increases in actual WFH behavior post-2019. The effects are particularly pronounced for college-educated mothers compared to non-college mothers, reflecting differential capacity to transition to remote work. The high F-statistics across all specifications demonstrate strong predictive power of the WFH measure.

$$WFH\_Behavior_{imt} = \sum_{s \neq 2019} \delta_s \cdot (\text{WFH}_{m,\text{pre}} \times \mathbf{1}\{t = s\}) + \mathbf{X}'_{it}\beta + \alpha_m + \lambda_t + \varepsilon_{imt} \qquad (6)$$

To better understand the temporal dynamics, I estimate an event study specification as shown in equation (6). Figure 4 presents the corresponding output and reveals two key observations: it verifies that there were no differential pre-trends between high and low WFH potential areas before the pandemic, and it traces the evolution of remote work adoption over time, demonstrating that COVID-19 activated latent telework capacity. This finding is consistent with Barrero et al. (2021), who document that WFH adoption was induced by COVID-19 and much of it has persisted long after the pandemic.

Both the cross-sectional and temporal evidence demonstrate the strong predictive power of the WFH measure in capturing actual remote work patterns. This validation exercise serves as a "pseudo first-stage" analysis that aids interpretation of subsequent estimates and confirms the measure's empirical relevance. While actual WFH behavior represents a more endogenous response to pandemic conditions, the pre-determined teleworkability measure provides a more exogenous source of variation for identifying causal effects on labor market outcomes. Note that this is not a strictly instrumental variables approach, so there is no need to examine exclusion restrictions or other traditional IV assumptions.

3.3.2 Additional Identification Concerns

Beyond the parallel trends assumption and the validity of the WFH measure that are fundamental to the methodology, a core identification assumption in this paper is that there are no other COVID-related changes that correlate with both the WFH measure and female labor force participation. In other words, the COVID-19 pandemic represents a universal shock that affected all metropolitan areas, making it difficult to distinguish whether the estimated effects reflect the causal impact of WFH opportunities or differential pandemic effects across demographic groups that happen to correlate with WFH availability. While the event study analysis will demonstrate no evidence of differential pre-trends, parallel pre-trends alone are insufficient when analyzing shocks that affect all units simultaneously. The concern is that the pandemic may have changed the relationship between individual demographic characteristics and labor market outcomes in ways that bias the estimates.

Following the approach developed in recent work analyzing pandemic-period policy effects (Jack et al., 2023; Ross et al., 2024), I address this identification challenge by allowing all demographic control variables to vary by year, effectively permitting the relationship between observable characteristics and labor market outcomes to vary freely across the pandemic period. The idea is that by allowing demographic characteristics to have different effects in each year, I can control for any pandemic-induced changes in how these characteristics relate to labor market outcomes, thereby isolating the true effect of WFH opportunities from general demographic shifts during the crisis.

Another critical concern in WFH research is that WFH opportunities might encourage individuals to relocate, potentially confounding the observed effects in several ways. Individuals may relocate to areas with greater WFH potential, introducing selection bias and skewing results to reflect the characteristics of movers rather than the broader population. Additionally, reverse causality may arise if labor force participation decisions drive mobility, complicating the interpretation of causal relationships. Furthermore, mobility could create endogeneity by linking labor market outcomes to residential changes rather than directly to WFH opportunities.

In this study, the construction of the WFH measure at the MSA level already accounts for this concern. MSAs represent regions consisting of a large urban core together with surrounding communities that have a high degree of economic and social integration with the urban core. This aggregation ensures that the WFH measure captures regional labor market conditions rather than individual residential changes. However, to address the mobility concern, I use WFH measures constructed based on individuals' previous year residence. This approach ensures that if individuals moved to take advantage of WFH opportunities, using their previous year's location means that the WFH measure reflects the labor market conditions they faced before making any relocation decisions, thereby eliminating the endogeneity concern.

The results from these approaches and additional robustness checks will be discussed in the robustness analysis section.

4 Results

4.1 Effects on All Females

Figure 5 presents the event study estimates of the effects of WFH opportunities on labor force participation, separately for males (panel a) and females (panel b). The figure displays coefficients and 95% confidence intervals estimated from Equation (3), capturing the differential association between pre-pandemic WFH potential and labor force participation over time.

Several key findings emerge from the analysis. First, in both panels, the coefficients for the pre-pandemic years are small in magnitude and statistically insignificant, hovering close to zero. This pattern supports the parallel trends assumption required for valid difference-in-differences identification. Second, the results reveal striking gender differences in the post-pandemic period. For males, the estimates remain close to zero and statistically insignificant throughout most of the post-2019 periods, with only slight effects emerging around 2022, suggesting at most a negligible impact of WFH opportunities on male labor force participation. In contrast, for females, the coefficients show a modest but consistent positive trend in the post-pandemic years. While the effects remain relatively small in magnitude, there appears to be a slight upward trajectory in 2022 and 2023, suggesting that females may have experienced small gains in labor force participation in areas with higher WFH potential.

Table 4, columns (1) and (2), report the estimated effects of WFH opportunities on labor force participation for all male and female individuals, respectively. Panel A presents the average effect for the post-pandemic period, estimated using Equation (2), while Panel B provides year-specific estimates based on Equation (4).

The results further confirm the pronounced gender divergence. For males, there is no statistically significant association between WFH exposure and labor force participation, either on average or in any individual post-pandemic year. The lack of corresponding effects among males serves as an important placebo test. This will alleviate concerns that effects aren't driven primarily by movement down for men but is truly an increase in LFP for women. In contrast, the results for females indicate a positive and statistically significant relationship. On average, a one-standard deviation increase in WFH opportunities at the MSA level is associated with a 0.10 percentage point increase in female labor force participation. Looking at individual years in Panel B, the positive effects for women are statistically significant in 2022 and 2023, while the 2021 estimate, though positive, is not statistically significant, possibly due to persistent pandemic-related disruptions in that year.

To better understand the magnitude of these estimates, Panel C presents the pseudo first-stage results and Panel D provides the Wald estimator results using the reduced-form estimate divided by first stage estimates. For females, a one-standard deviation increase in WFH potential is associated with a 3.43% relative increase in labor force participation. This effect is small in magnitude, but demonstrates positive trends of remote work opportunities on women's labor market engagement.

Looking at other labor market outcomes, Table 5 presents the results for employment and Table 6 for full-time work. For all females, the average effects are not statistically significant, indicating no clear evidence that WFH opportunities affect general female employment or full-time work participation. This pattern suggests that while WFH opportunities encourage women to enter the labor force, the effects are concentrated at the extensive margin of participation rather than translating into immediate employment or changes in work intensity, as such transitions may require additional time to materialize.

4.2 Effects on Mothers

Examining the effects of WFH opportunities on parental labor force participation is particularly important in light of the well-documented "motherhood penalty." While both fathers and mothers balance work and family responsibilities, mothers often face disproportionate caregiving burdens that can lead to reduced labor force participation, lower earnings, and constrained career advancement opportunities (Goldin, 2014; Bang, 2022; Harrington and Kahn, 2023; Tito, 2024). In contrast, fathers' labor supply tends to be less sensitive to such caregiving demands, often due to persistent gender norms around household roles. In this section, I compare the effects of WFH opportunities on labor force participation for fathers and mothers, using the same empirical specification as before, but restricting the sample to these two subgroups. This analysis provides insight into whether the flexibility associated with remote work can alleviate structural constraints faced disproportionately by mothers, and whether WFH availability has contributed to a widening gap in labor market responses between fathers and mothers in the post-pandemic period.

Figure 6 presents the event study results for fathers (panel a) and mothers (panel b), derived from Equation (3) with the sample restricted to these groups. The pre-treatment estimates from 2012 to 2019 are small and statistically insignificant for both groups, providing further support for the parallel trends assumption in the parent subsample. Starting in 2020, a clear divergence emerges. The coefficients for fathers remain close to zero and statistically insignificant throughout the post-pandemic years, indicating little to no response of male parental labor supply to variation in local WFH exposure. In contrast, the coefficients for mothers begin to rise steadily after 2020, with the effect becoming statistically significant by 2022 and remaining so in 2023. This dynamic pattern suggests that WFH opportunities had a more meaningful and sustained impact on maternal labor force participation.

Table 4, columns (3) and (4), provides complementary evidence. Panel A shows that from 2021 to 2023, a one-standard deviation increase in pre-pandemic WFH potential is associated with a 0.08 percentage point increase in labor force participation for fathers, and a 0.23 percentage point increase for mothers. The effect size for mothers is nearly three times as large as that for fathers. Panel B presents year-specific effects. While fathers show a marginally significant effect only in 2021, mothers exhibit larger and statistically significant coefficients in both 2022 and 2023, with both estimates significant at the 1% level. According to Panel D, the average effect for mothers represents an 8.47% relative increase in labor force participation.

I did not observe clear effects on mothers' employment, similar to the general female population. Surprisingly, mothers show positive and significant effects on full-time work participation, as shown in Table 6. A one-standard deviation increase in WFH potential is associated with a 0.40 percentage point increase in full-time work for mothers, representing a 17.54% relative increase according to Panel D. This indicates that while WFH opportunities may not immediately translate into employment gains for mothers, they enable those who are already working to transition into more intensive work arrangements. The ability to work remotely appears to reduce the constraints that previously made full-time employment challenging for mothers, allowing them to increase their work hours and commitment without sacrificing family responsibilities.

4.3 Effects on College Mothers

Prior research has shown that college-educated women, including mothers, are more likely to be employed in occupations that are amenable to remote work. In contrast, noncollege mothers are often overrepresented in service-oriented or manual jobs that require physical presence and are less adaptable to remote arrangements (Flabbi and Moro, 2012; Harrington and Kahn, 2023; Hu et al., 2024). These differences suggest that the labor market benefits of remote work may be disproportionately concentrated among more educated women. To explore this possibility, I estimate the effects of WFH opportunities separately for college and noncollege mothers using the same Difference-in-Differences and event study specifications.

Figure 7 presents the event study estimates of the effects of WFH opportunities on labor force participation for college mothers (panel a) and noncollege mothers (panel b). The pre-treatment estimates for both groups are small and statistically insignificant, supporting the parallel trends assumption. However, a notable divergence emerges following the onset of the pandemic. For college-educated mothers, the coefficients become increasingly positive starting in 2020, showing a steady upward trend through 2023. In contrast, noncollege mothers show coefficients that remain centered around zero with wider confidence intervals and no statistically significant post-treatment effects.

This pattern is reflected in the regression results reported in Table 4, columns (5) and (6). Panel A shows that a one-standard deviation increase in pre-pandemic WFH potential is associated with a 0.31 percentage point increase in labor force participation for college mothers. For noncollege mothers, the estimated effect is negative and statistically insignificant. Panel B further highlights the divergence in year-specific effects. College mothers exhibit consistently positive and statistically significant effects in 2021, 2022, and 2023. In contrast, noncollege mothers show no statistically significant effects in any post-pandemic year except for 2021, where the estimate is negative and significant, suggesting a potential short-term constraint for this group as WFH opportunities expanded but remained inaccessible to them. As shown in Panel D, the average effect for college mothers represents a 10.18% relative increase in labor force participation.

To assess the economic significance of my estimated effects, I can compare them to the broader trends in labor force participation shown in Figure 1. Between 2019 and 2023, the male-female labor force participation gap narrowed by approximately 1.4 percentage points, from 8.4 to 7.1 percentage points. My analysis finds that a two standard deviation increase in metropolitan WFH potential increases mothers' labor force participation by 0.6 percentage points. Given that mothers comprise approximately half of my female sample, this translates to a 0.3 percentage point increase in overall female labor force participation rates. This suggests that the expansion of WFH opportunities can explain roughly 21% (0.3/1.4) of the observed convergence in male-female labor force participation rates during this period. This back-of-the-envelope calculation demonstrates that my estimated effects are not only statistically significant but also economically meaningful, accounting for a substantial portion of the recent narrowing of the gender participation gap in the U.S. labor market.

As for employment outcomes in Table 5, unlike the general female population or all mothers, college mothers show positive and statistically significant effects. A one-standard deviation increase in WFH potential is associated with a 0.23 percentage point increase in employment for college mothers, representing a 7.80% relative increase. Figure 8 presents the corresponding event study results. We observe a slightly noisy pre-trend for college mothers, likely due to contamination from the male group.

To address this concern and further test the differences between mothers and fathers as well as between college and noncollege mothers, I employ a difference-in-differences-in-differences (DDD) specification with event study detailed in the appendix. Figure A1 shows the event study results for employment using the triple difference model. The pre-pandemic coefficients hover around zero with no discernible trend for both mothers and college mothers, confirming that the parallel trends assumption holds when controlling for male employment patterns. Beginning in 2020, both panels show a modest but persistent increase, with college mothers exhibiting a slightly more pronounced and sustained effect compared to all mothers, indicating that WFH opportunities differentially benefited mothers' employment, particularly among those with college education.

The largest effects arise for full-time work participation among college mothers. Table 6 shows that college mothers experience a 0.65 percentage point increase in full-time work for a one-standard deviation increase in WFH potential, representing a substantial 25.21% relative increase. This effect is consistently significant across all post-pandemic years and represents the strong labor market response observed in the analysis. Figure 9 presents the event study results for mothers (panel a) and college mothers (panel b). Both panels demonstrate clean pre-trends near zero, with college mothers showing a slight early uptick, but remaining very flat from 2014 onward. The post-pandemic period reveals a clear upward trajectory for both groups, with college mothers showing particularly strong and sustained increases in full-time work participation. This pattern suggests that WFH opportunities enable mothers, especially those with higher education, to transition from part-time or irregular work arrangements to more intensive employment commitments, likely by reducing the work-family conflict that previously constrained their labor supply decisions.

Table A1 presents the triple difference estimates comparing the effects of WFH opportunities on mothers relative to fathers. The results confirm significantly stronger positive effects on mother labor market outcomes, with college mothers showing particularly robust responses across all outcomes. Importantly, these triple difference findings closely align with the main two-way DID results, confirming that the observed improvements in female labor outcomes reflect genuine gender-specific benefits rather than economy-wide trends affecting both sexes.

4.4 Effects on Mothers with Young Children

Understanding how WFH opportunities affect mothers with young children is particularly important, as this group faces the most severe work-family constraints. Research has consistently shown that mothers of young children experience the steepest penalties in labor market participation and career advancement, with sharp and immediate earnings losses that emerge following childbirth and persist over time (Kleven et al., 2019,?, 2021; Goldin, 2014; Harrington and Kahn, 2023). The presence of young children creates substantial barriers to traditional work arrangements, making remote work opportunities potentially transformative for this population. If WFH can meaningfully reduce these constraints, we would expect to see the strongest positive effects among mothers with young children.

My findings confirm this hypothesis. Table 7 presents the WFH effects for parents with children under age 5, representing a more restrictive definition than the previous analysis that included parents with children of any age. Consistent with earlier results, fathers with young children exhibit only minimal effects on labor force participation. In contrast, mothers with children under age 5 demonstrate consistently positive effects across all three outcomes. Most notably, the magnitude of effects for this group is substantially larger—approximately 2 to 3 times greater than the effects observed for mothers with children of any age. At the MSA level, a one–standard deviation increase in WFH opportunities is associated with a 0.67 percentage point increase in labor force participation among mothers with young children, a 0.40 percentage point increase in employment, and a 0.78 percentage point increase in full-time work. In relative terms, these estimates imply a 22.52 percent increase in labor force participation, a 14.18 percent increase in employment, and a 29.60 percent increase in full-time work among mothers with young children.

Moreover, the temporal pattern reveals particularly striking results: while employment effects remain stable, both labor force participation and full-time work effects increase progressively from 2021 to 2023, with 2023 showing the largest effects. This pattern suggests that WFH opportunities play two roles: WFH sets the floor by preventing employment from dropping, making it easier for mothers with young children to stay attached to work; WFH also raises the ceiling by lowering barriers to participation and hours, enabling more mothers to join the labor force and move into full-time positions. Given that remote work assignments were less prevalent in 2023 than during the height of the pandemic, this surprising pattern suggests that WFH effects may have lasting benefits and potential for growth as remote work arrangements become more established and permanent.

The corresponding event study is presented in Figure A2. The results are slightly noisier than previous analyses, likely reflecting the endogenous nature of fertility decisions, as mothers' choices regarding childbearing may correlate with pre-pandemic remote work opportunities in their local labor markets. Nevertheless, the analysis reveals no evidence of pre-existing trends.

These pronounced effects can be explained by how remote work addresses the specific challenges of early motherhood. Remote work fundamentally transforms childcare arrangements by eliminating commute time, providing schedule flexibility, and enabling both parents to share caregiving responsibilities more equitably. This allows mothers to maintain stronger labor force attachment during the critical early child-rearing years when career interruptions typically impose the significant long-term penalties.

4.5 Heterogeneity Analysis

While the overall findings provide important insights, the impact of WFH opportunities may vary significantly across subgroups due to differing labor market dynamics, structural barriers, and socio-economic contexts. To better understand the nuanced effects of WFH opportunities on female labor outcomes, this section examines heterogeneity across key demographic groups, including marital status, age, and race. These analyses shed light on the distributional effects of WFH opportunities, offering a more comprehensive understanding of how remote work shapes labor market outcomes across diverse populations.

4.5.1 Heterogeneity by Marital Status

The heterogeneous effects by marital status reflect fundamental differences in household structure, financial constraints, and work-family dynamics. Married women often face more complex household optimization decisions, where remote work opportunities can reduce the traditional trade-offs between career advancement and family responsibilities. In contrast, unmarried women may have greater labor market flexibility but also face different economic pressures, including the need for financial independence without spousal income support. These structural differences suggest that the benefits of WFH opportunities may be distributed unevenly across marital groups.

Table 10 presents the heterogeneous effects of WFH opportunities by marital status. For males, the effects remain minimal with no meaningful differences between married and unmarried men. In contrast, married women experience significant positive effects on labor force participation and full-time work, while unmarried women show negative effects across all labor market outcomes.

The contrasting patterns suggest that WFH opportunities primarily benefit women in traditional household structures where work-family balance considerations are most binding. For married women, remote work appears to alleviate constraints that previously limited their labor market engagement, enabling both increased participation and work intensity. For unmarried women, who may face different employment barriers unrelated to childcare or household responsibilities, remote work opportunities provide less obvious advantages.

4.5.2 Heterogeneity by Age

WFH opportunities may have varying impacts across different age groups, as the adoption and effectiveness of remote work can depend on technological proficiency, adaptability, and life-stage priorities. To better understand how WFH opportunities affect women across life stages, I analyze the effects of WFH arrangements for four primary working-age cohorts: 25–34, 35–44, 45–54, and 55–64.

Tables 11 and 12 present the heterogeneous effects by age for all females and mothers, as well as college and noncollege mothers respectively. The results reveal a clear age gradient in the benefits of WFH opportunities. For labor force participation among all females, the strongest effects are concentrated among younger women aged 25-34 and those aged 35-44, with both groups showing significant positive responses of approximately 0.2 percentage points. The pattern becomes even more pronounced when examining mothers specifically, where women aged 25-34 show the largest response with a 0.53 percentage point increase representing a 23.33% relative effect. For full-time work, mothers aged 35-44 experience a notable 0.74 percentage point increase.

The age heterogeneity is most dramatic when comparing college and noncollege mothers across all outcomes. College mothers show positive effects across labor force participation, employment, and full-time work, with particularly strong responses among younger cohorts aged 25-44. The effects are especially pronounced for full-time work, where college mothers aged 35-44 experience a remarkable 34.49% relative increase. In stark contrast, noncollege mothers face negative effects across all outcomes, with those aged 35-44 experiencing substantial declines in labor force participation and employment.

These findings highlight a clear age gradient in the benefits of WFH opportunities, with younger workers demonstrating greater responsiveness to remote work arrangements. This pattern likely reflects younger individuals' greater familiarity with digital technologies and higher adaptability to new work arrangements, particularly during early career stages when establishing work-life balance is crucial. Conversely, older workers may face higher adjustment costs when transitioning to remote work setups and may have more established workplace routines that are difficult to modify. These age-related differences are further amplified by educational attainment, as younger college-educated women benefit from both their adaptability to digital work environments and their employment in occupations that are more amenable to remote arrangements.

4.5.3 Heterogeneity by Race

Understanding the impact of WFH opportunities requires examining how labor market dynamics differ across racial and ethnic groups. These differences are shaped by historical inequities, occupational clustering, and cultural factors that contribute to the varying experiences of WFH across racial groups, influencing both the adoption and effectiveness of remote work for women. To explore these dynamics, I analyze the effects of WFH opportunities on female labor market outcomes across four racial groups: White, Black, Hispanic, and Asian women. Subgroup analyses are also conducted for all mothers and for college and noncollege mothers within each racial category.

The racial heterogeneity results are presented in Tables 13 and 14. A clear pattern emerges showing that White women derive the primary benefits from WFH opportunities, while other racial groups experience limited or adverse effects. This disparity intensifies when focusing on mothers, where White mothers experience a substantial 0.34 percentage point increase in labor force participation, while mothers from other racial groups show little to no significant improvement.

The intersection of race and education reveals even more pronounced disparities in WFH benefits. College-educated White and Asian mothers consistently benefit across all labor market outcomes, with White college mothers showing exceptionally strong improvements in full-time work participation. However, noncollege mothers from minority backgrounds experience severely negative effects, with Black noncollege mothers facing dramatic declines in full-time work participation and Hispanic noncollege mothers experiencing substantial employment losses.

These disparities reflect fundamental differences in occupational positioning and structural barriers across racial groups. White and Asian women are disproportionately concentrated in professional and managerial occupations that are highly compatible with remote work arrangements, while Black and Hispanic women are more likely to work in service-oriented, healthcare support, and manual occupations that require physical presence. Additionally, the digital divide in technology access, differences in educational attainment, and varying housing conditions suitable for remote work create compounding disadvantages for women of color. The severe negative effects for noncollege mothers from minority backgrounds likely stem from their concentration in essential worker roles that became more demanding during the pandemic while simultaneously being excluded from the flexibility and job security benefits that remote work provided to professional workers.

4.6 Robustness Analysis

To validate the reliability of my findings, I implement a series of robustness checks that systematically address potential concerns regarding measurement validity, methodological approach, and data construction procedures. Specifically, I examine the robustness of the results by using year-varying controls, shorter-period measures of WFH exposure, alternative measures of WFH potential, weighted regressions that account for the ACS sampling design, adjustments based on individuals' prior-year residence to address potential selective mobility, and excluding older cohorts for early retirement concerns. These checks collectively strengthen confidence in the conclusions by demonstrating their stability under varying conditions and assumptions.

4.6.1 Robustness Analysis Using Year-Varying Controls

As discussed in the identification threats section, a key concern is that the pandemic may have altered how demographic characteristics relate to labor market outcomes, potentially biasing my estimates. To address this concern, I implement year-varying controls following Jack et al. (2023); Ross et al. (2024). This approach allows all control variables to have different effects in each year, thereby controlling for any shifts in how observable characteristics relate to labor market outcomes during the pandemic period. Specifically, I compare estimates from models that include standard controls, no controls, and year-varying controls.

Table A2 presents the results comparing specifications without controls (odd columns) against specifications including year-varying controls (even columns) across three outcomes. Compared to my main model that includes the standard controls, the table shows that the estimates remain consistent when the model excludes the controls or includes the year-varying controls. For labor force participation, the average effect decreases modestly from 0.31 percentage points to 0.26 percentage points when including year-varying controls, while remaining highly significant. Employment effects decline from 0.24 to 0.19 percentage points, and full-time work effects show minimal change from 0.64 to 0.61 percentage points. Panel B reveals that year-specific effects follow similar patterns across specifications, with 2022 showing the most robust effects. The modest attenuation in effect sizes when including year-varying controls suggests that some portion of our estimated effects may indeed reflect heterogeneous pandemic impacts, but the core relationship between WFH opportunities and mothers' labor market participation remains substantial and statistically significant.

The robustness of the results to no controls or year-varying controls provides compelling evidence that my findings reflect genuine WFH effects rather than spurious correlations arising from heterogeneous pandemic impacts across demographic groups. By allowing demographic characteristics to have different relationships with labor market outcomes in each year, I effectively rule out the alternative explanation that my results simply capture differential pandemic recovery patterns that happen to correlate with WFH availability.

4.6.2 Robustness Analysis Using Weighted Regressions

The American Community Survey provides person weights that indicate the number of individuals in the U.S. population represented by each sample observation. The decision to incorporate these weights in regression analysis depends fundamentally on the research objective: whether the goal is to estimate effects for the specific ACS sample or to produce nationally representative estimates of population-level effects.

In the main analysis, person weights were not applied in the regressions for several reasons. First, I compare the results from weighted and unweighted regressions, finding that estimates from unweighted regressions are more precise, which is important in this analytical context. Second, the analysis spans both the COVID-19 and post-COVID periods, during which ACS sampling methods and response rates may have changed significantly. Incorporating weights in this context could introduce inconsistencies and affect the balance of the estimates. Third, both the treatment variable (exposure to WFH opportunities) and the outcomes are designed to be independent of the ACS sampling design.

Nonetheless, it is crucial to test the robustness of the results by incorporating weights. Figure A3 presents an example of the event study results examining the effects of work-from-home opportunities on three outcomes for college mothers. The parallel trends assumption holds consistently across all outcomes as in the main analysis. The post-pandemic effects are particularly strong, especially for full-time work, where the coefficients show a clear upward trajectory beginning in 2021 and strengthening through 2023.

Table A3 presents the regression results from the robustness analysis using weighted regressions. The results closely align with those reported in the main analysis, which uses unweighted regressions with controls. A negligible decrease in magnitude is observed, which may be attributed to the broader population representation achieved by incorporating weights. The positive and statistically significant effects of WFH opportunities for college mothers remain evident across all outcomes.

These findings underscore the robustness of the main results and confirm that the observed relationship between WFH opportunities and female labor market outcomes is not sensitive to the inclusion of weights. The weighted analysis enhances representativeness while maintaining consistency with the unweighted estimates across labor force participation, employment, and full-time work outcomes. This robustness analysis reinforces the reliability of the causal estimates and strengthens confidence in the generalizability of the conclusions regarding

WFH's positive impact on women's labor outcomes.

4.6.3 Robustness Analysis Using Previous Residence

The identification threats section discussed how individual mobility could introduce bias if people relocate to areas with better WFH opportunities. Although MSA-level aggregation mitigates this concern by reflecting regional rather than individual residential patterns, I further address potential mobility bias by using WFH measures constructed from individuals' prior-year locations rather than current residence. By using prior-year residence, any observed effects reflect the influence of historical WFH opportunities on current labor market outcomes, rather than individuals' strategic relocation decisions based on remote work availability.

Table A4 presents the results using WFH measures constructed based on individuals' previous year residence. The estimates demonstrate remarkable consistency and stability compared to the main results, providing strong evidence that mobility concerns do not bias the findings. For college mothers, the average effects on labor force participation, employment, and full-time work are virtually identical to those reported in the main analysis. The year-specific effects in Panel B follow nearly identical patterns, with 2022 continuing to show the strongest effects across all outcomes. The pseudo first-stage results remain robust, and the overall magnitudes of the Wald estimator coefficients show minimal variation from the baseline specifications. The consistency of estimates across different residence-based measures provides compelling evidence that the observed effects reflect genuine WFH responses rather than selective migration artifacts.

4.6.4 Robustness Analysis Excluding Older Cohorts

I focus my analysis on individuals aged 25-64, which represents the standard working age population used in labor economics research and by the Bureau of Labor Statistics. This age range captures workers who have likely completed their education and entered the labor force while avoiding the complexities of retirement transitions that typically occur after age 65.

As a robustness check, I also present results restricting the sample to ages 25-54 to address potential concerns about early retirement confounding the estimated effects of work-from-home opportunities. Workers aged 55-64 may have accumulated sufficient wealth or pension benefits to consider early retirement, and the availability of remote work might influence their retirement timing rather than their underlying labor force attachment. This concern is particularly relevant for women, who are more likely to retire at earlier ages and may be more sensitive to work-life balance considerations in their retirement decisions.

As shown in Table A5, the results remain stable, with even larger magnitudes for all outcome variables. The larger effect sizes in the younger cohort support the hypothesis that early retirement considerations may have attenuated the estimated effects in the full sample, as workers aged 55-64 may have been less responsive to WFH opportunities due to proximity to retirement. These findings confirm that the core relationship between WFH opportunities and female labor force participation is robust and, if anything, stronger when focusing on the population most actively engaged in career and family decisions.

4.6.5 Robustness Analysis Using a Shorter-Period Measure

In the main analysis, I average teleworkability scores for each MSA over a broader pre-period (2012–2019) to capture a stable, pre-pandemic measure of WFH potential. However, this seven-year window may encompass broader economic or occupational shifts that are less relevant to the immediate pre-pandemic period. To address this concern, I construct an alternative WFH measure using only the years 2015–2019, applying the same approach described in Equation (1). By focusing on a shorter period, I reduce the influence of longer-run trends that could confound the analysis in a difference-in-differences framework. Moreover, comparing the results from this shorter window to those obtained using the 2012–2019 average allows me to verify that any observed effects are not driven by the choice of baseline period.

Table A6 confirms that the findings are highly consistent with those reported for the longer pre-period. The results using the 2015-2019 baseline period demonstrate remarkable stability across all outcomes and subgroups. For college mothers, the average effects on labor force participation, employment, and full-time work remain virtually unchanged compared to the main analysis using the 2012-2019 period. The year-specific patterns in Panel B continue to show the strongest effects in 2022 and 2023, with consistent magnitudes and statistical significance levels. The first-stage results remain robust with strong F-statistics, indicating that the instrument performs equally well regardless of the baseline period chosen. This consistency demonstrates that the observed effects are not sensitive to the choice of baseline years, providing additional evidence of robustness and reinforcing confidence in the primary conclusions.

4.6.6 Robustness Analysis Using Alternative WFH Measures

In addition to the primary WFH measure used in the main analysis, I construct several alternative measures to test whether the results are robust to different definitions and sampling criteria. As discussed in Section 3.1, the choice of population (e.g., all individuals, only employed individuals, or only females) may affect the measured teleworkability of an MSA. By examining these variations, I can determine whether the observed findings are sensitive to the way WFH potential is calculated, thereby enhancing confidence in the robustness of the results.

Figure A4 presents the event study results using alternative WFH measures, with each row representing a different measure and each column corresponding to one of two subgroups: mothers and college mothers. Across all 10 panels, the results show trends consistent with the main analysis. First, there is no statistically significant evidence of pre-existing trends before 2020, supporting the parallel trends assumption critical for the validity of the identification strategy. Second, beginning in 2020, labor force participation starts to rise, particularly in 2023, where a statistically significant and robust increase is observed across both subgroups. This post-pandemic trend reflects the growing impact of WFH opportunities on enabling labor market engagement. These results reinforce the robustness of the main findings by demonstrating that the positive impact of WFH opportunities on female labor force participation persists regardless of how regional teleworkability is measured or which population is used as the basis for constructing the WFH index.

5 Mechanism and Policy Implications

5.1 Intra-Household Time Reallocation

A natural concern with the MSA-level design is that the estimated effect of local WFH potential on women's outcomes could partly reflect within-household adjustments driven by spousal work arrangements. Filippo et al. (2025) show that increases in husbands' WFH opportunities can relax time constraints at home and reallocate caregiving responsibilities, potentially raising wives' labor supply. To isolate the own-opportunity channel emphasized in my baseline from this spousal mechanism, I augment the design to explicitly control for the husband's WFH treatment and examine how the baseline effect changes.

First, I re-estimate the baseline difference-in-differences model from equation (2) on a restricted wife-husband sample. Specifically, I link each married woman to her co-resident husband and restrict to opposite-sex couples, keeping the same controls, fixed effects, and inference as before.

Second, following Filippo et al. (2025), I add the husband channel:

$$\begin{aligned} Y_{imt} = {} & \delta \cdot (\text{WFH}_{m,\text{pre}} \times \text{Post}_t) \\ & + \theta \cdot (\mathbf{1}\{o(H) \in \text{High}\Delta\text{WFH}\} \times \text{Post}_t) \\ & + \mathbf{X}'_{it}\beta + \alpha_m + \lambda_t + \phi_{o(H)} + \varepsilon_{imt} \end{aligned} \tag{7}$$

Here, $\mathbf{1}\{o(H) \in \text{High}\Delta\text{WFH}\} = 1$ if the husband's occupation $o(H)$ belongs to the set of "high-WFH" occupations, defined using Dingel and Neiman (2020) teleworkability. Concretely, I closely follow Filippo et al. (2025) and aggregate 6-digit SOC teleworkability to 3-digit SOC using pre-period employment weights to obtain a high-WFH occupation set for each 3-digit SOC group, and classify occupations as treated when they are at or above the median across 3-digit SOC occupations. I interact this indicator with the post-period dummy. The vector $\mathbf{X}_{it}$ is the same as in the baseline; α_m and λ_t are MSA and year fixed effects; and $\phi_{o(H)}$ are husband-occupation fixed effects at 3-digit SOC as in Filippo et al. (2025), which absorb time-invariant differences across husband occupations. Standard errors are clustered at the MSA level.

5.2 Access and Responsiveness to WFH Opportunities

This study shows that work-from-home opportunities substantially increase women's labor force participation, employment, and full-time work, with especially strong effects for college-educated mothers and those with young children. These benefits are largely concentrated among younger, married, and highly educated women, while older, less-educated, and minority noncollege mothers experience limited or even adverse effects. Notably, men and fathers show minimal responsiveness to WFH opportunities, highlighting the gendered nature of these benefits. The differential effects of work-from-home opportunities across demographic groups can be explained through two primary channels: differential access to WFH opportunities and varying responsiveness to flexible work arrangements.

Differential Access to WFH Opportunities. The first mechanism relates to unequal exposure to teleworkable occupations across education levels. College-educated women are disproportionately employed in professional, managerial, and technical occupations that are highly amenable to remote work, such as finance, consulting, information technology, and administrative roles (Flabbi and Moro, 2012; Harrington and Kahn, 2023; Hu et al., 2024). These positions typically involve knowledge work that can be performed effectively using digital tools and communication technologies. In contrast, women with lower educational attainment are more likely to work in service-oriented, manufacturing, or care-related occupations that require physical presence and interpersonal interaction, making remote work infeasible. This occupational sorting creates fundamental disparities in who can access WFH opportunities, explaining why the benefits are concentrated among more educated women while others face structural barriers that limit their ability to capitalize on remote work arrangements.

Differential Responsiveness to WFH Opportunities. The second mechanism concerns varying degrees of responsiveness to flexible work arrangements, particularly driven by gender differences in labor supply elasticity and work-family constraints. Extensive literature demonstrates that women, especially mothers, exhibit higher labor supply elasticity and place greater value on workplace flexibility compared to men (Goldin, 2014; Mas and Pallais, 2017; Drake et al., 2022). Mothers face disproportionate caregiving responsibilities and work-family conflicts that traditional employment arrangements often fail to accommodate (Alon et al., 2020a). Remote work alleviates these constraints by eliminating commuting time, providing schedule flexibility, and enabling better integration of work and family responsibilities. This explains why mothers, particularly those with young children, show the strongest positive responses to WFH opportunities, while men generally exhibit minimal effects regardless of parental status.

5.3 Policy Implications

This study demonstrates that post-pandemic work-from-home opportunities have significant implications for female labor force participation on both the extensive and intensive margins. The results align with and provide additional empirical support for policy recommendations in the broader literature on work flexibility and gender equity. Goldin (2014) advocates for workplace restructuring that eliminates employer incentives to reward inflexible work schedules, and this study's positive effects on maternal employment provide compelling evidence for such temporal flexibility reforms. Mas and Pallais (2017) document strong worker demand for remote work options, and my findings reinforce their assessment by demonstrating substantial labor market benefits, particularly for mothers who face the greatest work-family trade-offs. Emanuel and Harrington (2024) emphasize the need to address promotion penalties that discourage remote work adoption, and this study's evidence of persistent WFH benefits suggests the pandemic may indeed have corrected employer misperceptions about remote work productivity as they hypothesized. However, the findings also highlight important limitations to remote work as a uniform policy solution. The pronounced disparities across educational, racial, and age groups suggest that remote work expansion alone may not address and could potentially exacerbate existing labor market inequalities.

6 Conclusion

The paper aims at measuring and examining the effects of access to WFH opportunities that were accelerated by the COVID-19 pandemic on female labor market outcomes in the United States. Using American Community Survey data spanning 2012-2023 that detail individual residence and occupation, I constructed a measure of WFH exposure at the Metropolitan Statistical Area (MSA) level based on occupational teleworkability scores. Employing a difference-in-differences and event study design that exploits geographic variation in pre-existing WFH potential across MSAs, the analysis provides causal evidence that WFH opportunities significantly increase the likelihood of female labor force participation, employment, and full-time work. This finding is robust across various specifications intended to address biases caused by differential pandemic effects across demographic groups, potential endogeneity from selective mobility and residential sorting, and data handling and measurement concerns.

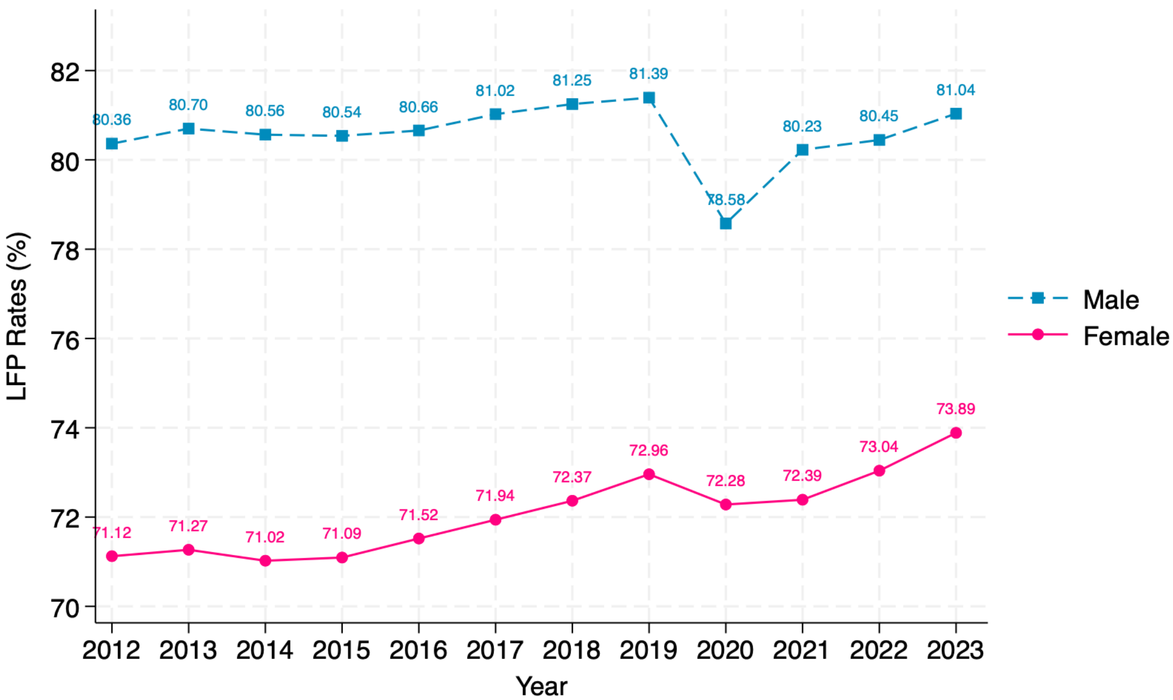
The analysis reveals that WFH opportunities have the most pronounced effects among college-educated mothers and those with young children. In terms of economic magnitude, a one standard deviation increase in WFH opportunities is associated with an 18.01 percent increase in labor force participation, a 10.75 percent increase in employment, and an 20.97 percent increase in full-time work among mothers with young children. These effects are economically meaningful, with WFH opportunities explaining approximately 21 percent of the observed narrowing in the gender labor force participation gap between 2019 and 2023. Moreover, WFH effects vary significantly by age, marital status, and race. Younger women consistently exhibit the largest gains, while the benefits are heavily concentrated among married women and White college-educated mothers. In contrast, men, including fathers, exhibit little to no change in labor market behavior in response to WFH exposure, while non-college, Black, or Hispanic women experience smaller or even negative effects.

The differential effects across demographic groups reflect both varying access to WFH opportunities and differing responsiveness to flexible work arrangements. From a policy perspective, while WFH expansion can effectively support female and maternal labor force participation, complementary policies may be needed to ensure broader workforce benefits and prevent the exacerbation of existing inequalities.

More generally, this paper provides new empirical evidence on the transformative potential of flexible work arrangements in promoting gender equity in the labor market. The heterogeneous effects of WFH opportunities suggest that while WFH arrangements can serve as a powerful tool for reducing the motherhood penalty among advantaged women, they may inadvertently exacerbate existing inequalities if access remains concentrated among higher-skilled occupations. Nevertheless, the research design and findings presented in this paper may be useful for examining similar questions in other contexts. For example, this approach could be extended to study the effects of other flexible work policies such as flexible scheduling, hybrid assignments, compressed workweeks, or job-sharing arrangements on various demographic groups. Additionally, the methodology could be applied to examine how WFH opportunities affect other outcomes such as fertility decisions, childcare arrangements, wage growth, the gender wage gap, or career advancement, provided researchers can construct appropriate measures of policy exposure at the geographic level. The persistent nature of the effects observed in this study also suggests that as remote work becomes a permanent feature of the post-pandemic labor market, its role in shaping gender dynamics in employment will likely continue to evolve, warranting continued investigation of both its benefits and potential unintended consequences across different segments of the workforce.

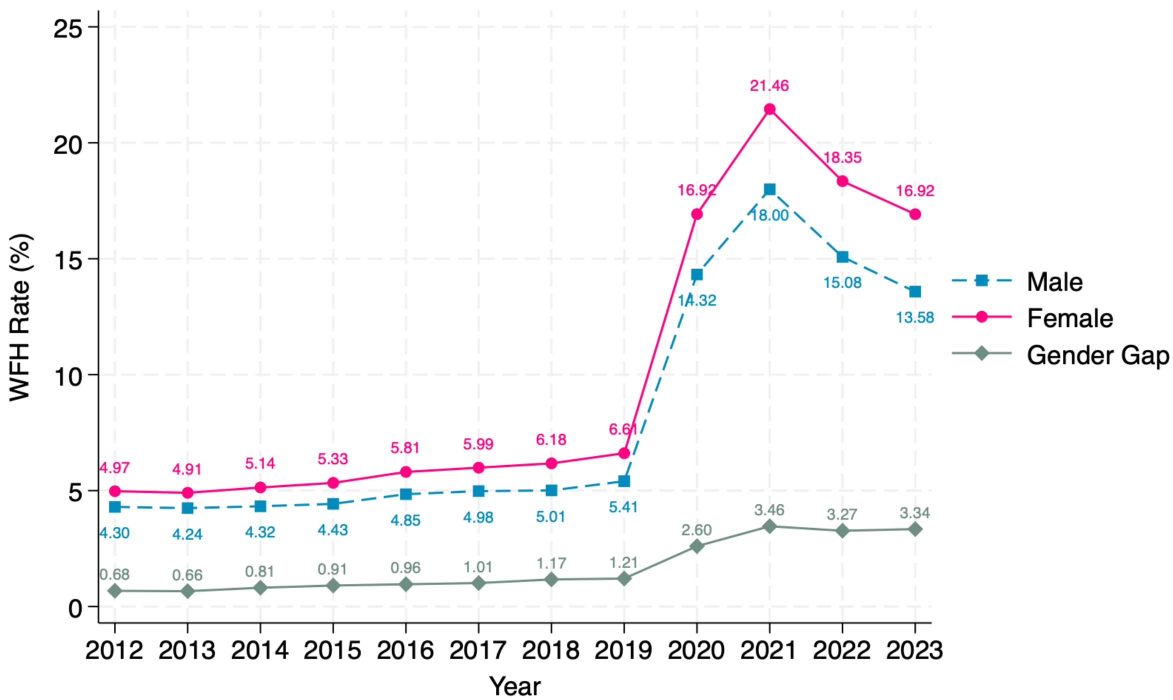
7 Figures and Tables

Figure 1: Labor Force Participation Rates by Sex



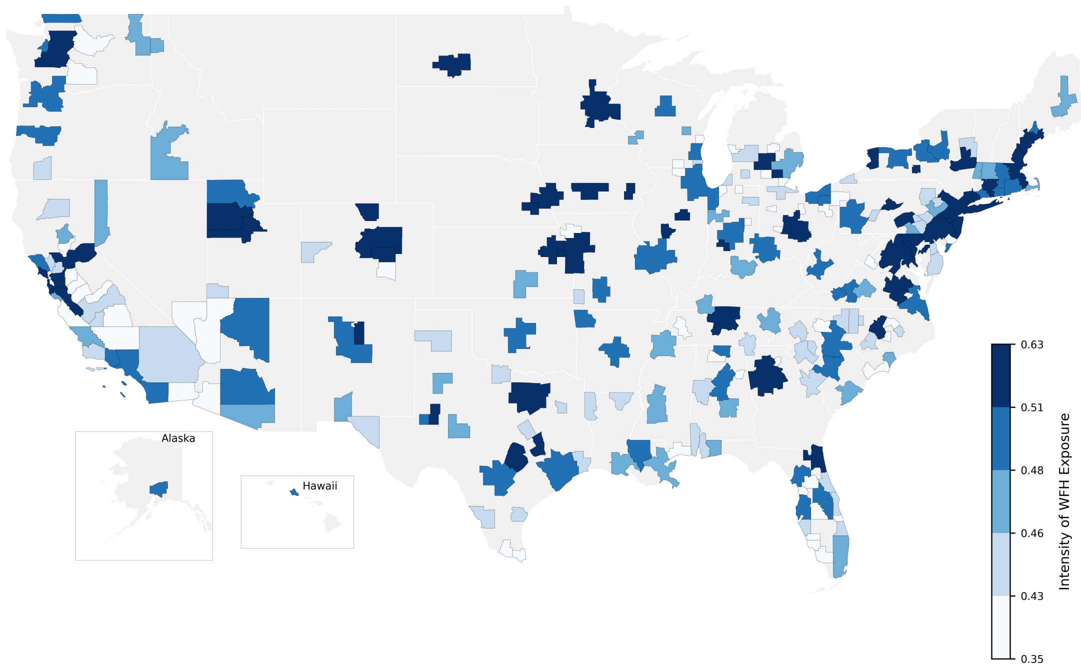
Notes: This figure presents the labor force participation rates from 2012 to 2023, separately for males and females. The data source is the American Community Survey (ACS) and reflects the working-age population (ages 25 to 64) in the United States. The values are expressed as percentages and are not seasonally adjusted.

Figure 2: Actual Work-From-Home Rates by Sex



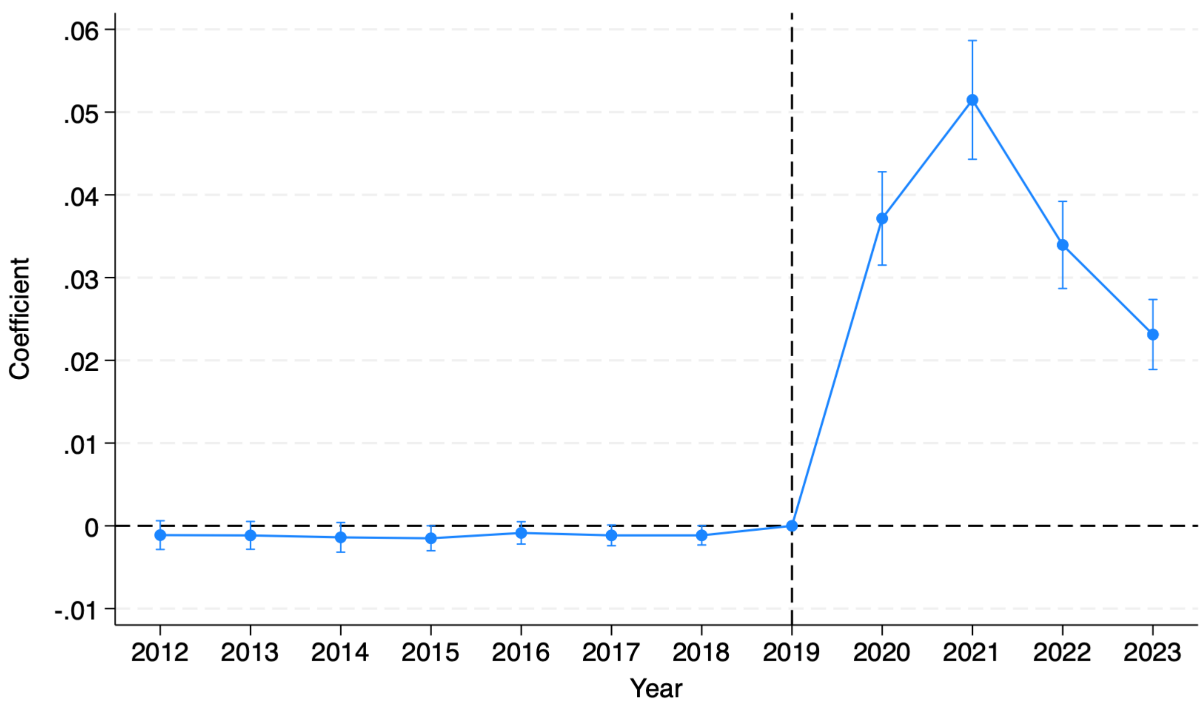
Notes: This figure presents the actual work-from-home rates from 2012 to 2023, separately for males and females. The data source is the American Community Survey (ACS) and reflects the working-age population (ages 25 to 64) in the United States, only for the people in the labor force.

Figure 3: Geographic Variation in Pre-Pandemic Exposure to Work-from-Home Opportunity



Notes: This figure shows pre-pandemic work-from-home exposure across 242 MSAs from 2012-2019, based on Dingel and Neiman (2020) teleworkability scores weighted by local occupational distributions. Darker shades indicate higher WFH exposure intensity.

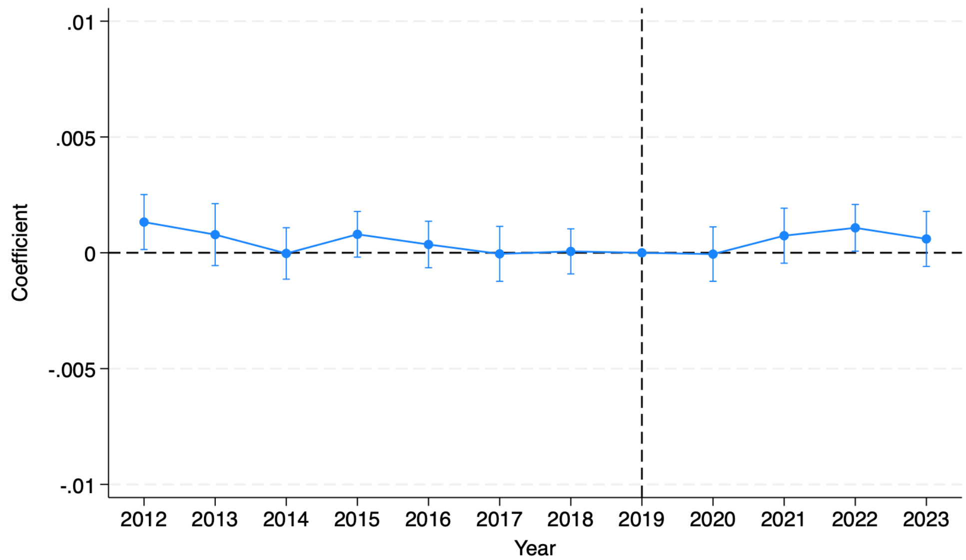
Figure 4: First Stage: WFH Measure Response to COVID-19 Shock



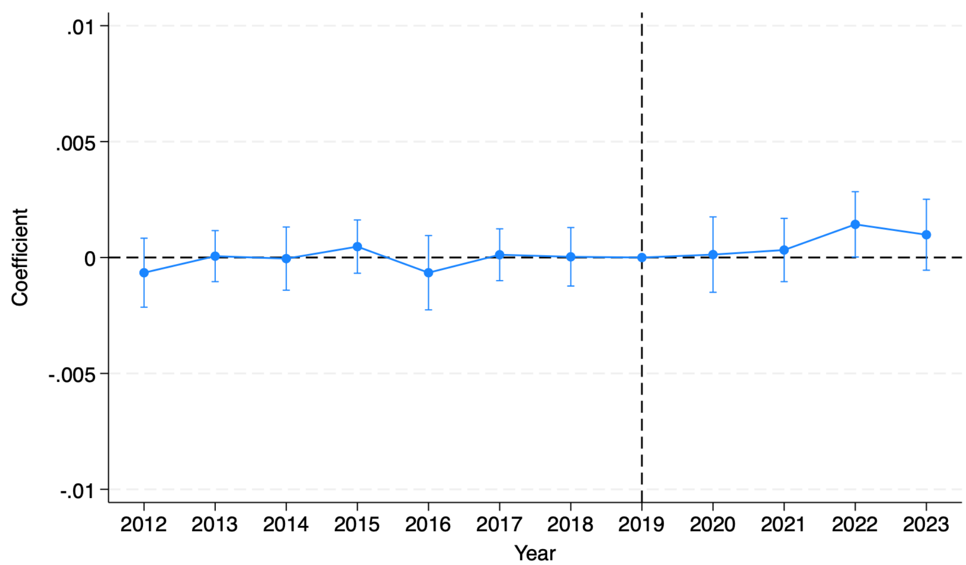
Notes: This figure presents an event study analysis examining the relationship between WFH measures and actual work-from-home behavior for females before, during, and after the COVID-19 pandemic. The actual WFH behavior leverages the transportation-to-work variable of the ACS, which surveys each employed individual about their primary mode of commuting, including an option for working from home.

Figure 5: Effects of WFH Opportunities on LFP

(a) Male



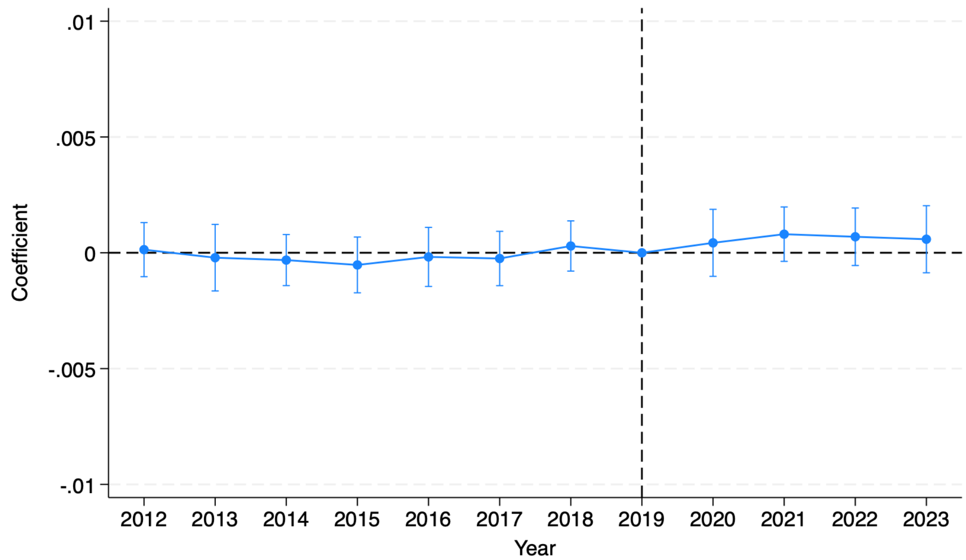
(b) Female



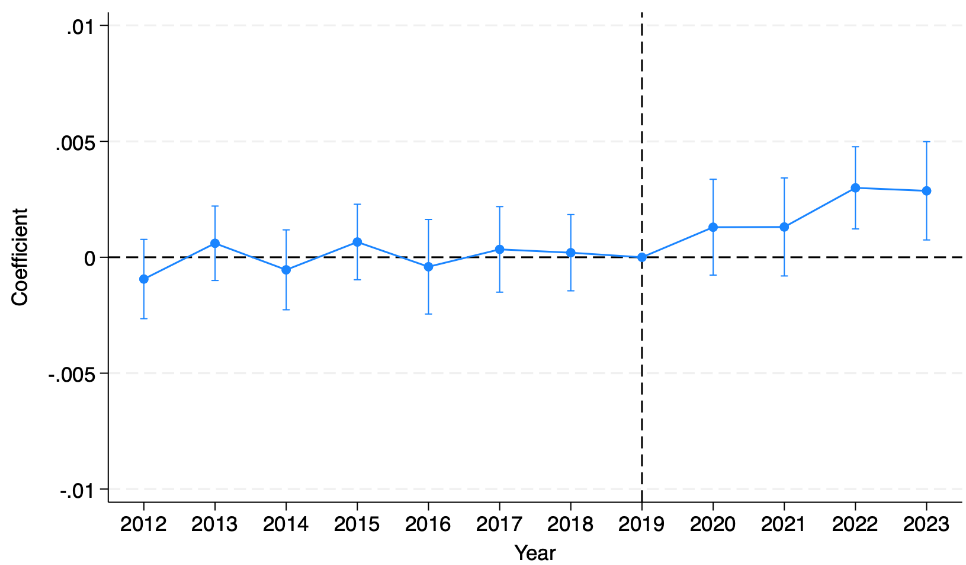
Notes: This figure compares the effects of individual-level exposure to WFH opportunities on labor force participation for (a) male and (b) female. It displays the coefficients and corresponding 95% confidence intervals for the Equation (3). The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure 6: Effects of WFH Opportunities on LFP

(a) Fathers



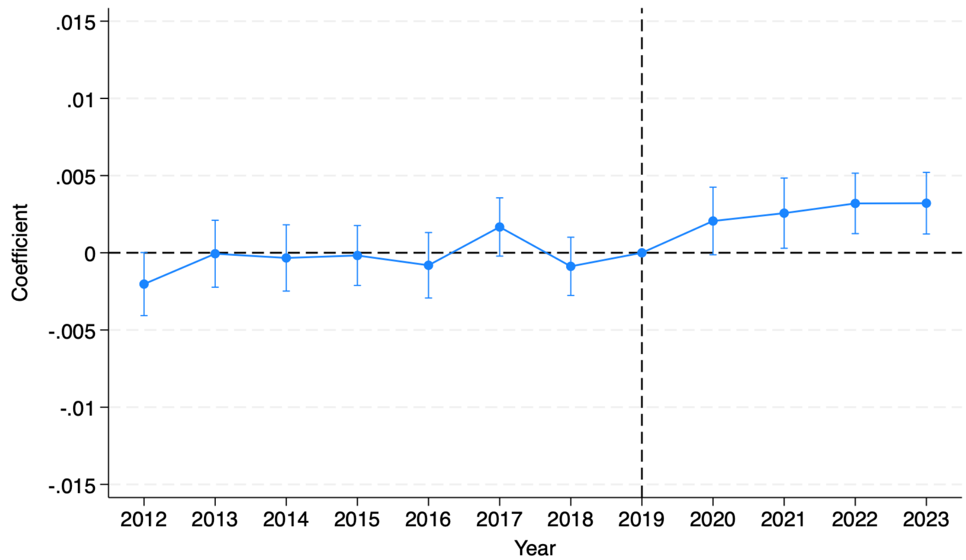
(b) Mothers



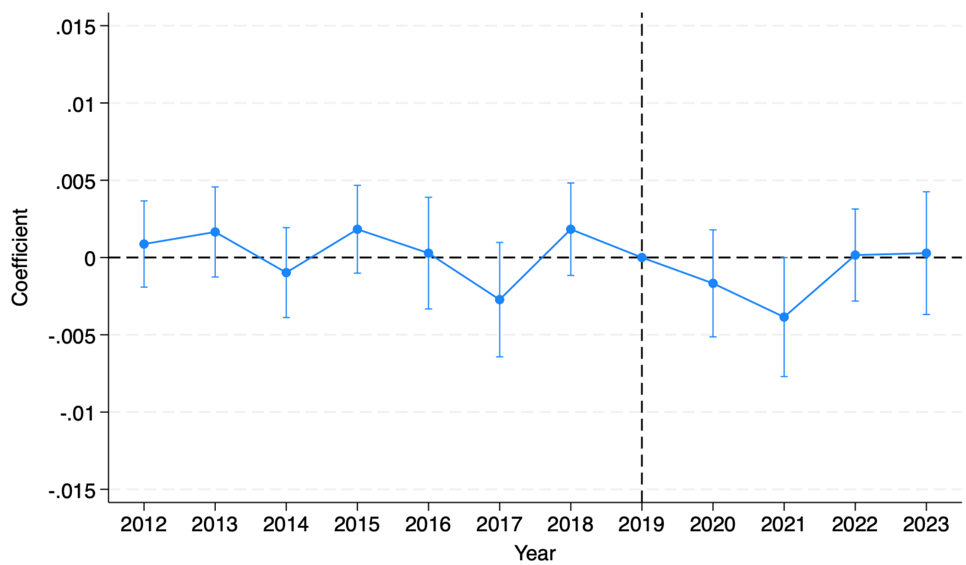
Notes: This figure compares the effects of individual-level exposure to WFH opportunities on labor force participation for (a) fathers and (b) mothers. It displays the coefficients and corresponding 95% confidence intervals for the Equation (3). The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure 7: Effects of WFH Opportunities on LFP

(a) College Mothers



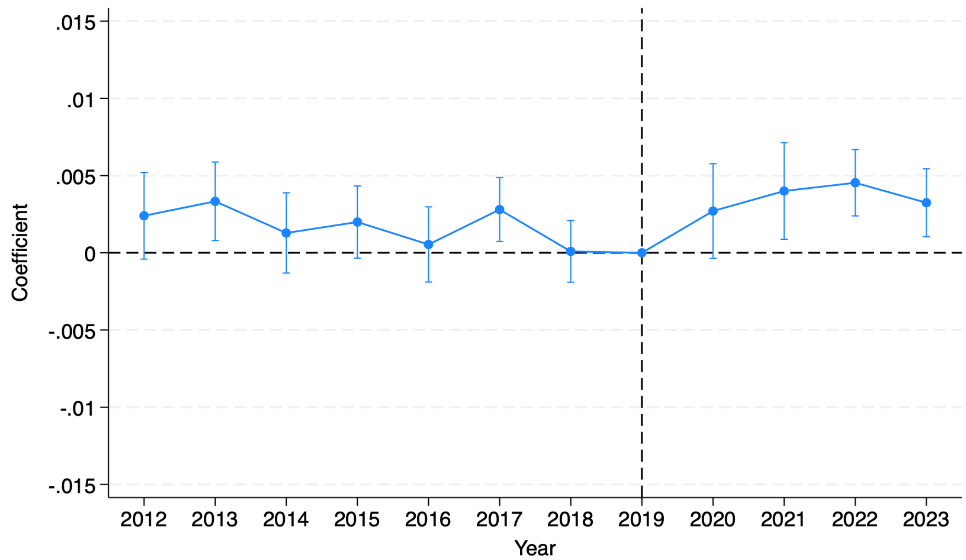
(b) Noncollege Mothers



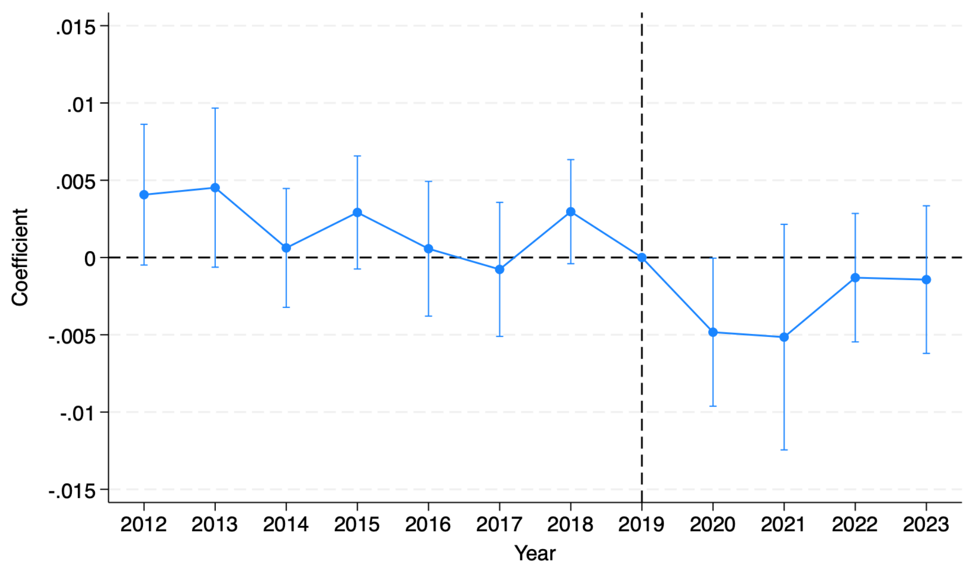
Notes: This figure compares the effects of individual-level exposure to WFH opportunities on labor force participation for (a) college mothers and (b) noncollege mothers. It displays the coefficients and corresponding 95% confidence intervals for the Equation (3). The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure 8: Effects of WFH Opportunities on Employment

(a) College Mothers



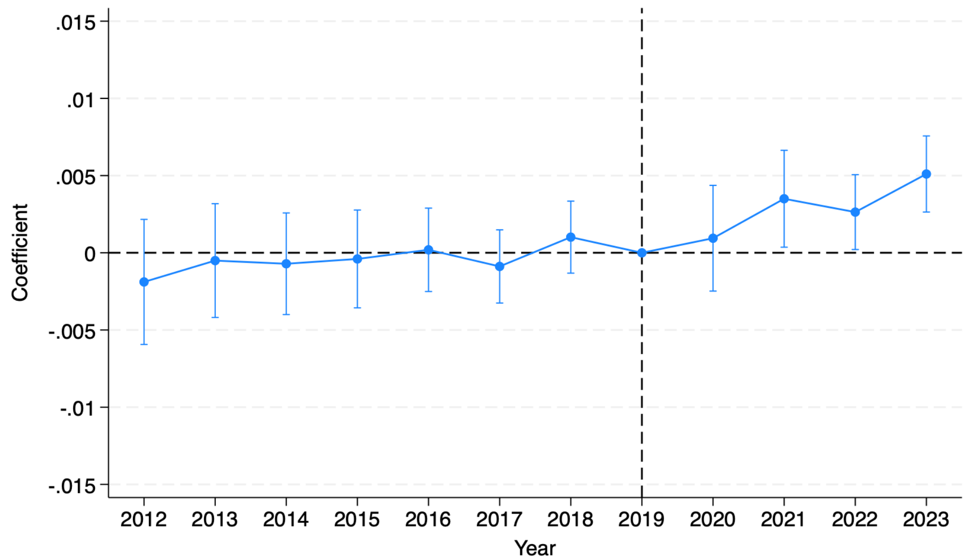
(b) Noncollege Mothers



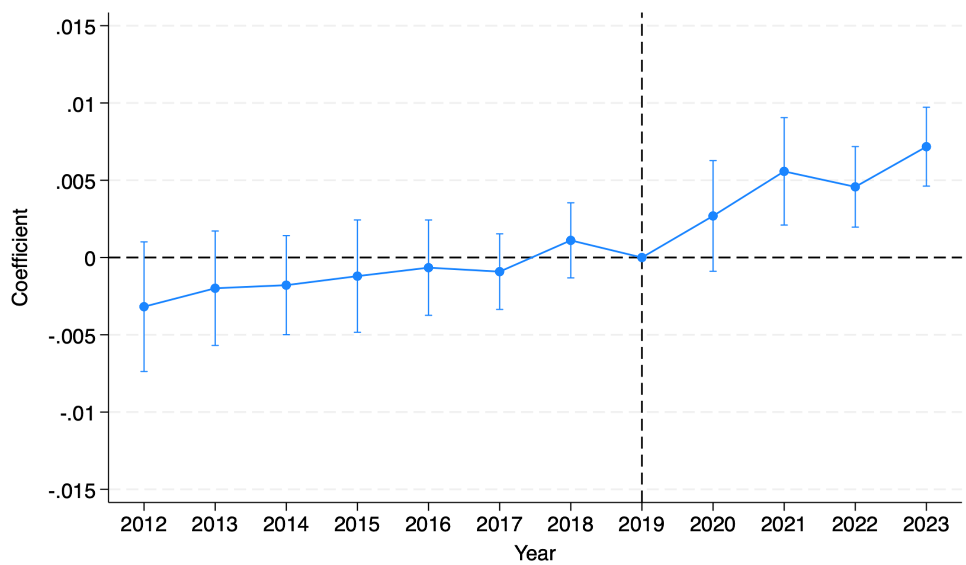
Notes: This figure compares the effects of individual-level exposure to WFH opportunities on employment status for (a) college mothers and (b) noncollege mothers. It displays the coefficients and corresponding 95% confidence intervals for the Equation (3). The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure 9: Effects of WFH Opportunities on Full-Time Work

(a) Mothers



(b) College Mothers



Notes: This figure compares the effects of individual-level exposure to WHF opportunities on full-time work for (a) college mothers and (b) noncollege mothers. It displays the coefficients and corresponding 95% confidence intervals for the Equation (3). The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Table 1: Summary Statistics

	Female		Male	
Variable	Mean	SD	Mean	SD
Labor Force Participation	0.8733	0.3326	0.9280	0.2585
Employment	0.8376	0.3688	0.8891	0.3140
Full-Time Work	0.7639	0.4247	0.8956	0.3058
White	0.6171	0.4861	0.6342	0.4817
Black	0.1081	0.3106	0.0849	0.2787
Hispanic	0.1614	0.3679	0.1724	0.3778
Asian	0.0814	0.2735	0.0780	0.2682
Married	0.6158	0.4864	0.6459	0.4782
Children	0.5111	0.4999	0.4614	0.4985
Children Under 5	0.1290	0.3352	0.1303	0.3367
College Education	0.6837	0.4651	0.6168	0.4862
Noncollege Education	0.3163	0.4651	0.3832	0.4862
Age 25-34	0.2499	0.4329	0.2467	0.4311
Age 35-44	0.2398	0.4269	0.2441	0.4296
Age 45-54	0.2569	0.4369	0.2579	0.4375
Age 55-64	0.2535	0.4350	0.2512	0.4337
Observations	6,045,693		6,128,400	

Notes: This table presents summary statistics for key variables used in the analysis, conducted at the individual level from 2012 to 2023. The sample is restricted to working-age individuals aged 25-64, and individuals with military-specific occupations are excluded. College education refers to college-level attainment and above, while noncollege education includes high school or below.

Table 2: WFH Measures Summary Statistics

Variable	Mean	SD	25th Percentile	75th Percentile	Unique N	Total N
wfh_main	0.4991	0.0406	0.4777	0.5228	242	12,174,093
wfh	0.4196	0.0514	0.3905	0.4488	242	12,174,093
wfh_lfp	0.4226	0.0519	0.3967	0.4505	242	12,174,093
wfh_emp	0.4283	0.0513	0.4041	0.4545	242	12,174,093
wfh_female	0.4890	0.0420	0.4650	0.5151	242	12,174,093
wfh_lfp_female	0.4941	0.0415	0.4686	0.5186	242	12,174,093

Notes: This table presents summary statistics for WFH measures constructed at the MSA level for the pre-period (2012–2019) using Equation (1). All measures apply ACS person weights and vary by population focus: *wfh_main* focuses on employed females (primary measure); *wfh* includes all individuals; *wfh_lfp* covers individuals in the labor force; *wfh_emp* restricts to employed individuals; *wfh_female* includes all females; and *wfh_lfp_female* covers females in the labor force. Each measure computes the weighted average teleworkability at the MSA level using occupation-level scores from Dingel and Neiman (2020).

Table 3: Predictive Power of WFH Measure

	(1) All Males	(2) All Females	(3) Fathers	(4) Mothers	(5) College Mothers	(6) Noncollege Mothers
Coefficient	0.0407***	0.0334***	0.0427***	0.0312***	0.0345***	0.0115***
	(0.0020)	(0.0024)	(0.0019)	(0.0022)	(0.0025)	(0.0017)
F-statistic	242.30	161.06	167.23	148.65	180.34	132.54
Control Mean	0.0475	0.0570	0.0475	0.0599	0.0686	0.0419
N	5448818	5063881	2616003	2579363	1764971	814392

Notes: This table presents pseudo first-stage results validating the WFH measure against actual work-from-home behavior across different demographic groups. The analysis uses a difference-in-differences design with year and MSA fixed effects. Actual WFH behavior is measured using the ACS transportation-to-work variable, which surveys each employed individual about their primary mode of commuting, including an option for working from home. Standard errors are clustered at the MSA level. The F-statistics demonstrate strong predictive power of the WFH measure across all specifications.

Table 4: Effects of WFH Opportunities on Labor Force Participation

	(1) All Males	(2) All Females	(3) Fathers	(4) Mothers	(5) College Mothers	(6) Noncollege Mothers
Panel A: Average Effect						
2021 - 2023	0.0004	0.0010**	0.0008**	0.0023***	0.0031***	-0.0013
	(0.0003)	(0.0005)	(0.0003)	(0.0006)	(0.0006)	(0.0012)
Panel B: Year-Specific Effects						
2021	0.0004	0.0004	0.0009*	0.0012	0.0027***	-0.0040**
	(0.0005)	(0.0006)	(0.0005)	(0.0008)	(0.0009)	(0.0018)
2022	0.0007	0.0015**	0.0008	0.0029***	0.0033***	-0.0000
	(0.0005)	(0.0006)	(0.0005)	(0.0007)	(0.0007)	(0.0013)
2023	0.0002	0.0010*	0.0007	0.0028***	0.0033***	0.0001
	(0.0004)	(0.0006)	(0.0005)	(0.0009)	(0.0008)	(0.0017)
Panel C: Pseudo First Stage						
2021 - 2023	0.0407***	0.0334***	0.0427***	0.0312***	0.0345***	0.0115***
	(0.0020)	(0.0024)	(0.0019)	(0.0022)	(0.0025)	(0.0017)
F-statistic	242.30	161.06	167.23	148.65	180.34	132.54
Panel D: Wald Estimator						
2021 - 2023	0.0098	0.0299	0.0187	0.0737	0.0899	-0.1130
Relative effect (%)	1.06	3.43	1.96	8.47	10.18	-13.36
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.9286	0.8722	0.9550	0.8704	0.8833	0.8459
N	6128400	6045693	2827514	3089872	2058570	1031302

Notes: Panel A reports results from estimating equation (2), and Panel B presents results from equation (4). The dependent variable across all models is labor force participation. Standard errors are clustered MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects of WFH Opportunities on Employment

	(1) All Males	(2) All Females	(3) Fathers	(4) Mothers	(5) College Mothers	(6) Noncollege Mothers
Panel A: Average Effect						
2021 - 2023	-0.0013**	-0.0004	-0.0005	0.0007	0.0023***	-0.0040**
	(0.0006)	(0.0008)	(0.0006)	(0.0009)	(0.0006)	(0.0019)
Panel B: Year-Specific Effects						
2021	-0.0010	-0.0004	-0.0002	0.0004	0.0024**	-0.0065**
	(0.0012)	(0.0013)	(0.0011)	(0.0015)	(0.0012)	(0.0032)
2022	-0.0007	0.0004	-0.0002	0.0014	0.0029***	-0.0027
	(0.0007)	(0.0008)	(0.0006)	(0.0009)	(0.0008)	(0.0017)
2023	-0.0022***	-0.0012	-0.0012*	0.0002	0.0016*	-0.0028
	(0.0006)	(0.0009)	(0.0007)	(0.0011)	(0.0009)	(0.0020)
Panel C: Pseudo First Stage						
2021 - 2023	0.0407***	0.0334***	0.0427***	0.0312***	0.0345***	0.0115***
	(0.0020)	(0.0024)	(0.0019)	(0.0022)	(0.0025)	(0.0017)
F-statistic	242.30	161.06	167.23	148.65	180.34	132.54
Panel D: Wald Estimator						
2021 - 2023	-0.0319	-0.0120	-0.0117	0.0224	0.0667	-0.3478
Relative effect (%)	-3.60	-1.43	-1.27	2.69	7.80	-43.96
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.8881	0.8352	0.9250	0.8326	0.8543	0.7912
N	6128400	6045693	2827514	3089872	2058570	1031302

Notes: Panel A reports results from estimating equation (2), and Panel B presents results from equation (4). The dependent variable across all models is employment status. Standard errors are clustered MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of WFH Opportunities on Full-Time Work

	(1) All Males	(2) All Females	(3) Fathers	(4) Mothers	(5) College Mothers	(6) Noncollege Mothers
Panel A: Average Effect						
2021 - 2023	-0.0008	0.0010	-0.0010	0.0040***	0.0065***	-0.0039*
	(0.0007)	(0.0009)	(0.0007)	(0.0011)	(0.0013)	(0.0021)
Panel B: Year-Specific Effects						
2021	-0.0019*	0.0005	-0.0020**	0.0038**	0.0063***	-0.0046
	(0.0010)	(0.0012)	(0.0009)	(0.0016)	(0.0018)	(0.0030)
2022	-0.0009	0.0006	-0.0012	0.0029**	0.0053***	-0.0047**
	(0.0008)	(0.0010)	(0.0008)	(0.0011)	(0.0014)	(0.0023)
2023	0.0003	0.0018	0.0000	0.0054***	0.0079***	-0.0025
	(0.0007)	(0.0011)	(0.0006)	(0.0014)	(0.0015)	(0.0025)
Panel C: Pseudo First Stage						
2021 - 2023	0.0407***	0.0334***	0.0427***	0.0312***	0.0345***	0.0115***
	(0.0020)	(0.0024)	(0.0019)	(0.0022)	(0.0025)	(0.0017)
F-statistic	242.30	161.06	167.23	148.65	180.34	132.54
Panel D: Wald Estimator						
2021 - 2023	-0.0197	0.0299	-0.0234	0.1282	0.1884	-0.3391
Relative effect (%)	-2.20	3.95	-2.53	17.54	25.21	-48.59
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.8947	0.7573	0.9269	0.7308	0.7472	0.6980
N	5741376	5423338	2713552	2766878	1875167	891711

Notes: Panel A reports results from estimating equation (2), and Panel B presents results from equation (4). The dependent variable across all models is full-time work. Standard errors are clustered MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effects of WFH on Parents with Young Children

	Labor Force		Employment		Full-Time	
	(1) Mothers children 5	(2) Fathers children 5	(3) Mothers children 5	(4) Fathers children 5	(5) Mothers children 5	(6) Fathers children 5
Panel A: Average Effect						
2021 - 2023	0.0067***	0.0014***	0.0040***	-0.0009	0.0078***	-0.0007
	(0.0014)	(0.0005)	(0.0013)	(0.0008)	(0.0014)	(0.0009)
Panel B: Year-Specific Effects						
2021	0.0047**	0.0004	0.0025	-0.0005	0.0068***	-0.0012
	(0.0019)	(0.0008)	(0.0022)	(0.0014)	(0.0022)	(0.0012)
2022	0.0070***	0.0012*	0.0049***	-0.0014*	0.0071***	-0.0024
	(0.0018)	(0.0007)	(0.0016)	(0.0008)	(0.0022)	(0.0016)
2023	0.0084***	0.0025***	0.0045***	-0.0007	0.0093***	0.0017*
	(0.0018)	(0.0008)	(0.0017)	(0.0010)	(0.0018)	(0.0010)
Panel C: Pseudo First Stage						
2021 - 2023	0.0372***	0.0500***	0.0372***	0.0500***	0.0372***	0.0500***
	(0.0031)	(0.0023)	(0.0031)	(0.0023)	(0.0031)	(0.0023)
F-statistic	200.44	156.11	200.44	156.11	200.44	156.11
Panel D: Wald Estimator						
2021 - 2023	0.1801	0.0280	0.1075	-0.0180	0.2097	-0.0140
Relative effect (%)	22.52	2.89	14.18	-1.91	29.60	-1.50
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.7996	0.9694	0.7583	0.9409	0.7084	0.9314
N	779976	798829	779976	798829	652529	777263

Notes: The table presents estimation results for parents with young children. The identification strategy remains identical to the baseline specification, with the sample restricted to those who have children under age 5. Standard errors are clustered MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Household WFH Effects on Labor Force Participation: Separating Own and Spousal Channels

Panel A: All Education Levels

	No Children		Children		Young Children	
	Baseline	Decomposed	Baseline	Decomposed	Baseline	Decomposed
Wife	0.0024***	0.0020***	0.0032***	0.0024***	0.0069***	0.0050***
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0015)	(0.0015)
Husband		0.0090***		0.0128***		0.0272***
		(0.0012)		(0.0013)		(0.0027)
Control Mean	0.8624	0.8624	0.8603	0.8603	0.7825	0.7825
N	3000854	3000854	1965635	1965635	567297	567297

Panel B: College-Educated

	No Children		Children		Young Children	
	Baseline	Decomposed	Baseline	Decomposed	Baseline	Decomposed
Wife	0.0031***	0.0027***	0.0035***	0.0030***	0.0071***	0.0056***
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0015)	(0.0015)
Husband		0.0061***		0.0090***		0.0211***
		(0.0011)		(0.0014)		(0.0027)
Control Mean	0.8750	0.8750	0.8718	0.8718	0.8035	0.8035
N	2174423	2174423	1432100	1432100	462521	462521
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
MSA F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Husband Occ. F.E.	No	Yes	No	Yes	No	Yes

Notes: This table presents within-household WFH effects on labor force participation for married women across education levels and family compositions. The sample is restricted to married women with co-resident husbands in opposite-sex couples. Baseline models include only wife WFH exposure; decomposed models add husband WFH treatment and husband occupation fixed effects to isolate the spousal channel from own-opportunity effects. Columns show subsamples by presence of children and children under age five (young children), and by college attainment. Standard errors clustered at the MSA level are reported in parentheses. All models include year and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Household WFH Effects on Labor Force Participation: Separating Own and Spousal Channels

Panel A: All Education Levels

	No Children		Children		Young Children	
	Baseline	Decomposed	Baseline	Decomposed	Baseline	Decomposed
Wife	0.0024***	0.0027***	0.0032***	0.0033***	0.0069***	0.0063***
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0015)	(0.0015)
Husband		-0.0046***		-0.0020*		0.0077***
		(0.0011)		(0.0012)		(0.0024)
Control Mean	0.8624	0.8624	0.8603	0.8603	0.7825	0.7825
N	3000854	3000854	1965635	1965635	567297	567297

Panel B: College-Educated

	No Children		Children		Young Children	
	Baseline	Decomposed	Baseline	Decomposed	Baseline	Decomposed
Wife	0.0031***	0.0036***	0.0035***	0.0040***	0.0071***	0.0070***
	(0.0006)	(0.0006)	(0.0007)	(0.0007)	(0.0015)	(0.0015)
Husband		-0.0093***		-0.0078***		0.0013
		(0.0011)		(0.0012)		(0.0025)
Control Mean	0.8750	0.8750	0.8718	0.8718	0.8035	0.8035
N	2174423	2174423	1432100	1432100	462521	462521
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
MSA F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Husband Occ. F.E.	No	No	No	No	No	No

Notes: This table presents within-household WFH effects on labor force participation for married women across education levels and family compositions. The sample is restricted to married women with co-resident husbands in opposite-sex couples. Baseline models include only wife WFH exposure; decomposed models add husband WFH treatment to isolate the spousal channel from own-opportunity effects. Columns show subsamples by presence of children and children under age five (young children), and by college attainment. Standard errors clustered at the MSA level are reported in parentheses. All models include year and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Heterogeneous Effects of WFH Opportunities by Marital Status

	Males		Females	
	Married	Unmarried	Married	Unmarried
Panel A: Labor Force Participation				
Average Effect	0.0005	0.0001	0.0018***	-0.0003
	(0.0004)	(0.0006)	(0.0005)	(0.0006)
Control Mean	0.9366	0.9134	0.8541	0.9015
Wald Estimator	0.0115	0.0028	0.0536	-0.0090
Relative effect (%)	1.23	0.31	6.27	-1.00
Panel B: Employment				
Average Effect	-0.0006	-0.0030***	0.0005	-0.0020*
	(0.0005)	(0.0010)	(0.0007)	(0.0011)
Control Mean	0.9089	0.8489	0.8245	0.8526
Wald Estimator	-0.0139	-0.0836	0.0149	-0.0602
Relative effect (%)	-1.53	-9.84	1.81	-7.06
Panel C: Full-Time Work				
Average Effect	-0.0002	-0.0021*	0.0030***	-0.0027***
	(0.0006)	(0.0011)	(0.0010)	(0.0011)
Control Mean	0.9203	0.8448	0.7358	0.7912
Wald Estimator	-0.0046	-0.0585	0.0893	-0.0813
Relative effect (%)	-0.50	-6.93	12.13	-10.28
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
Pseudo First Stage	0.0433***	0.0359***	0.0336***	0.0332***
	(0.0020)	(0.0023)	(0.0024)	(0.0024)
F-statistic	204.29	262.59	159.20	224.92
N	3958338	2170062	3722994	2322699

Notes: The table presents estimation results by marital status for both males and females. The dependent variables are labor force participation (Panel A), employment (Panel B), and full-time work (Panel C). Standard errors are clustered at the MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Heterogeneous Effects of WFH Opportunities by Age: All Females and Mothers

	All Females				All Mothers			
	25-34	35-44	45-54	55-64	25-34	35-44	45-54	55-64
Panel A: Labor Force Participation								
Average Effect	0.0021**	0.0022***	-0.0001	-0.0005	0.0053***	0.0026***	0.0007	0.0006
	(0.0008)	(0.0007)	(0.0005)	(0.0011)	(0.0015)	(0.0008)	(0.0006)	(0.0012)
Control Mean	0.8767	0.8964	0.9082	0.8071	0.8145	0.8844	0.9101	0.8398
Wald Estimator	0.0543	0.0615	-0.0031	-0.0192	0.1900	0.0741	0.0222	0.0236
Relative effect (%)	6.19	6.86	-0.35	-2.38	23.33	8.38	2.44	2.81
Panel B: Employment								
Average Effect	-0.0004	0.0006	-0.0010	-0.0014	0.0029*	0.0010	0.0000	-0.0007
	(0.0010)	(0.0010)	(0.0009)	(0.0014)	(0.0016)	(0.0010)	(0.0009)	(0.0017)
Control Mean	0.8310	0.8581	0.8728	0.7783	0.7619	0.8481	0.8777	0.8096
Wald Estimator	-0.0103	0.0168	-0.0314	-0.0538	0.1040	0.0285	0.0000	-0.0276
Relative effect (%)	-1.24	1.95	-3.60	-6.91	13.65	3.36	0.00	-3.41
Panel C: Full-Time Work								
Average Effect	-0.0014	0.0046***	0.0010	-0.0015	0.0037**	0.0074***	0.0029**	0.0004
	(0.0013)	(0.0013)	(0.0011)	(0.0012)	(0.0016)	(0.0013)	(0.0013)	(0.0020)
Control Mean	0.7641	0.7624	0.7689	0.7316	0.7063	0.7353	0.7415	0.7320
Wald Estimator	-0.0362	0.1285	0.0314	-0.0577	0.1326	0.2108	0.0921	0.0157
Relative effect (%)	-4.74	16.86	4.09	-7.89	18.78	28.68	12.42	2.15
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo First Stage	0.0387***	0.0358***	0.0318***	0.0260***	0.0279***	0.0351***	0.0315***	0.0254***
	(0.0027)	(0.0027)	(0.0022)	(0.0026)	(0.0021)	(0.0026)	(0.0022)	(0.0027)
F-statistic	193.03	199.14	164.51	181.91	122.01	213.39	142.37	91.88
N	1510553	1449580	1553162	1532398	647801	1051070	924771	466230

Notes: The table presents estimation results by age groups for all females and mothers. The dependent variables are labor force participation (Panel A), employment (Panel B), and full-time work (Panel C). Standard errors are clustered at the MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Heterogeneous Effects of WFH Opportunities by Age: College and Noncollege Mothers

	College Mothers				Noncollege Mothers			
	25-34	35-44	45-54	55-64	25-34	35-44	45-54	55-64
Panel A: Labor Force Participation								
2021-2023	0.0056***	0.0044***	0.0010	0.0011	0.0012	-0.0049***	-0.0015	0.0005
	(0.0014)	(0.0009)	(0.0009)	(0.0013)	(0.0026)	(0.0018)	(0.0016)	(0.0021)
Control Mean	0.8278	0.8938	0.9211	0.8583	0.7905	0.8627	0.8895	0.8139
Wald Estimator	0.1672	0.1173	0.0295	0.0386	0.1481	-0.3889	-0.1271	0.0376
Relative effect (%)	20.20	13.13	3.20	4.50	18.74	-45.08	-14.29	4.62
Panel B: Employment								
2021-2023	0.0041***	0.0034***	0.0012	0.0007	-0.0019	-0.0072***	-0.0039**	-0.0021
	(0.0014)	(0.0010)	(0.0010)	(0.0017)	(0.0033)	(0.0025)	(0.0020)	(0.0028)
Control Mean	0.7912	0.8665	0.8946	0.8316	0.7090	0.8055	0.8458	0.7789
Wald Estimator	0.1224	0.0907	0.0354	0.0246	-0.2346	-0.5714	-0.3305	-0.1579
Relative effect (%)	15.47	10.46	3.96	2.96	-33.08	-70.93	-39.07	-20.26
Panel C: Full-Time Work								
2021-2023	0.0072***	0.0097***	0.0046***	0.0035	-0.0043*	-0.0031	-0.0044*	-0.0048
	(0.0018)	(0.0016)	(0.0016)	(0.0022)	(0.0026)	(0.0030)	(0.0025)	(0.0032)
Control Mean	0.7340	0.7501	0.7519	0.7482	0.6535	0.6994	0.7212	0.7081
Wald Estimator	0.2149	0.2587	0.1357	0.1228	-0.5309	-0.2460	-0.3729	-0.3609
Relative effect (%)	29.27	34.49	18.05	16.41	-81.25	-35.17	-51.71	-50.96
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo First Stage	0.0335***	0.0375***	0.0339***	0.0285***	0.0081***	0.0126***	0.0118***	0.0133***
	(0.0026)	(0.0030)	(0.0024)	(0.0032)	(0.0022)	(0.0017)	(0.0020)	(0.0022)
F-statistic	116.03	217.71	131.71	66.59	87.57	119.33	69.75	29.33
N	418503	746512	617560	275995	229298	304558	307211	190235

Notes: The table presents estimation results by age groups for college and noncollege mothers. The dependent variables are labor force participation (Panel A), employment (Panel B), and full-time work (Panel C). Standard errors are clustered at the MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Heterogeneous Effects of WFH Opportunities by Race: All Females and Mothers

	All Females				All Mothers			
	White	Black	Hispanic	Asian	White	Black	Hispanic	Asian
Panel A: Labor Force Participation								
2021-2023	0.0016***	0.0001	-0.0002	0.0002	0.0034***	0.0014	-0.0012	0.0018
	(0.0005)	(0.0011)	(0.0014)	(0.0013)	(0.0006)	(0.0011)	(0.0016)	(0.0019)
Control Mean	0.8683	0.8914	0.8728	0.8774	0.8672	0.9011	0.8634	0.8711
Wald Estimator	0.0489	0.0031	-0.0097	0.0045	0.1090	0.0519	-0.0764	0.0399
Relative effect (%)	5.64	0.35	-1.11	0.51	12.57	5.76	-8.85	4.58
Panel B: Employment								
2021-2023	0.0002	0.0000	-0.0030	0.0007	0.0018**	0.0015	-0.0040*	0.0028
	(0.0007)	(0.0017)	(0.0020)	(0.0016)	(0.0007)	(0.0019)	(0.0022)	(0.0023)
Control Mean	0.8383	0.8282	0.8251	0.8469	0.8384	0.8329	0.8143	0.8424
Wald Estimator	0.0061	0.0000	-0.1456	0.0156	0.0577	0.0556	-0.2548	0.0621
Relative effect (%)	0.73	0.00	-17.65	1.84	6.88	6.67	-31.29	7.37
Panel C: Full-Time Work								
2021-2023	0.0022***	-0.0076***	0.0011	0.0063***	0.0064***	-0.0088***	0.0029	0.0086***
	(0.0008)	(0.0012)	(0.0022)	(0.0023)	(0.0013)	(0.0015)	(0.0025)	(0.0027)
Control Mean	0.7496	0.7988	0.7468	0.7805	0.7118	0.7969	0.7331	0.7633
Wald Estimator	0.0673	-0.2353	0.0534	0.1403	0.2051	-0.3259	0.1847	0.1907
Relative effect (%)	8.98	-29.45	7.15	17.98	28.81	-40.90	25.20	24.98
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo First Stage	0.0327***	0.0323***	0.0206***	0.0449***	0.0312***	0.0270***	0.0157***	0.0451***
	(0.0029)	(0.0042)	(0.0024)	(0.0036)	(0.0028)	(0.0044)	(0.0024)	(0.0033)
F-statistic	238.21	31.81	87.74	95.52	202.76	28.54	63.93	113.57
N	3731058	653771	975899	492128	1765684	344219	610265	272667

Notes: The table presents estimation results by race for all females and mothers. The dependent variables are labor force participation (Panel A), employment (Panel B), and full-time work (Panel C). Standard errors are clustered at the MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Heterogeneous Effects of WFH Opportunities by Race: College and Noncollege Mothers

	College Mothers				Noncollege Mothers			
	White	Black	Hispanic	Asian	White	Black	Hispanic	Asian
Panel A: Labor Force Participation								
2021-2023	0.0035***	0.0021	0.0008	0.0036**	0.0014	-0.0008	-0.0032	-0.0054
	(0.0007)	(0.0013)	(0.0013)	(0.0017)	(0.0014)	(0.0023)	(0.0023)	(0.0041)
Control Mean	0.8783	0.9193	0.8856	0.8769	0.8375	0.8730	0.8465	0.8559
Wald Estimator	0.1101	0.0686	0.0327	0.0702	0.0800	-0.0537	-0.5926	-1.2273
Relative effect (%)	12.53	7.47	3.69	8.00	9.55	-6.15	-70.01	-143.39
Panel B: Employment								
2021-2023	0.0021***	0.0026	0.0000	0.0052***	-0.0003	-0.0016	-0.0074**	-0.0067
	(0.0008)	(0.0017)	(0.0018)	(0.0019)	(0.0016)	(0.0033)	(0.0030)	(0.0050)
Control Mean	0.8552	0.8657	0.8479	0.8503	0.7932	0.7819	0.7886	0.8216
Wald Estimator	0.0660	0.0850	0.0000	0.1014	-0.0171	-0.1074	-1.3704	-1.5227
Relative effect (%)	7.72	9.81	0.00	11.92	-2.16	-13.73	-173.77	-185.34
Panel C: Full-Time Work								
2021-2023	0.0080***	-0.0056***	0.0056**	0.0114***	-0.0018	-0.0142***	0.0000	-0.0048
	(0.0013)	(0.0018)	(0.0024)	(0.0033)	(0.0018)	(0.0035)	(0.0033)	(0.0055)
Control Mean	0.7222	0.8327	0.7725	0.7848	0.6823	0.7381	0.7018	0.7056
Wald Estimator	0.2516	-0.1830	0.2286	0.2222	-0.1029	-0.9530	0.0000	-1.0909
Relative effect (%)	34.83	-21.98	29.59	28.32	-15.08	-129.12	0.00	-154.61
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo First Stage	0.0318***	0.0306***	0.0245***	0.0513***	0.0175***	0.0149***	0.0054***	0.0044*
	(0.0030)	(0.0045)	(0.0032)	(0.0038)	(0.0018)	(0.0036)	(0.0018)	(0.0025)
F-statistic	190.47	27.19	54.11	116.91	146.18	3.87	11.45	7.71
N	1,308,916	210,823	271,928	199,816	456,768	133,391	338,337	72,851

Notes: The table presents estimation results by race for college and noncollege mothers. The dependent variables are labor force participation (Panel A), employment (Panel B), and full-time work (Panel C). Standard errors are clustered at the MSA level and are shown in parentheses. All models include year fixed effects and MSA fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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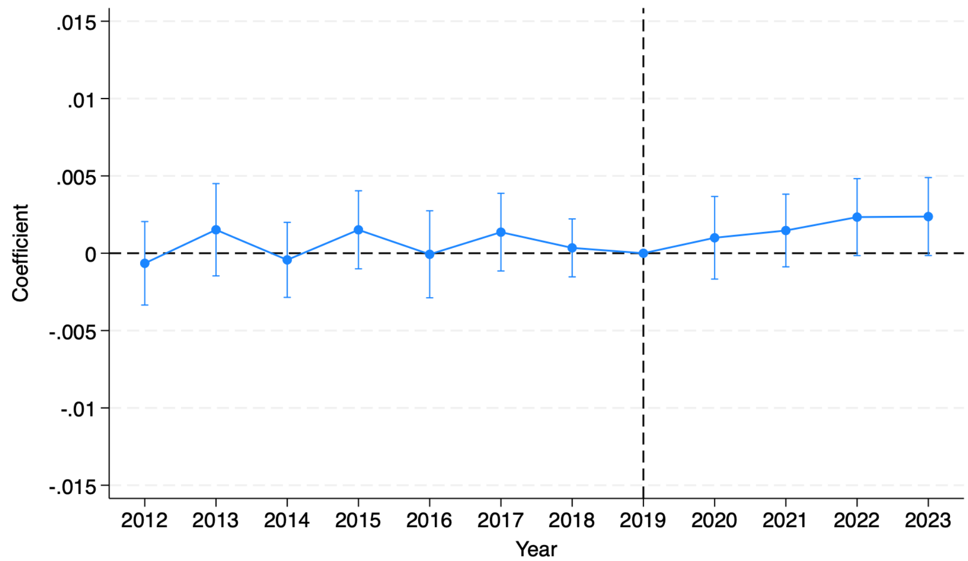
Supplemental Appendix

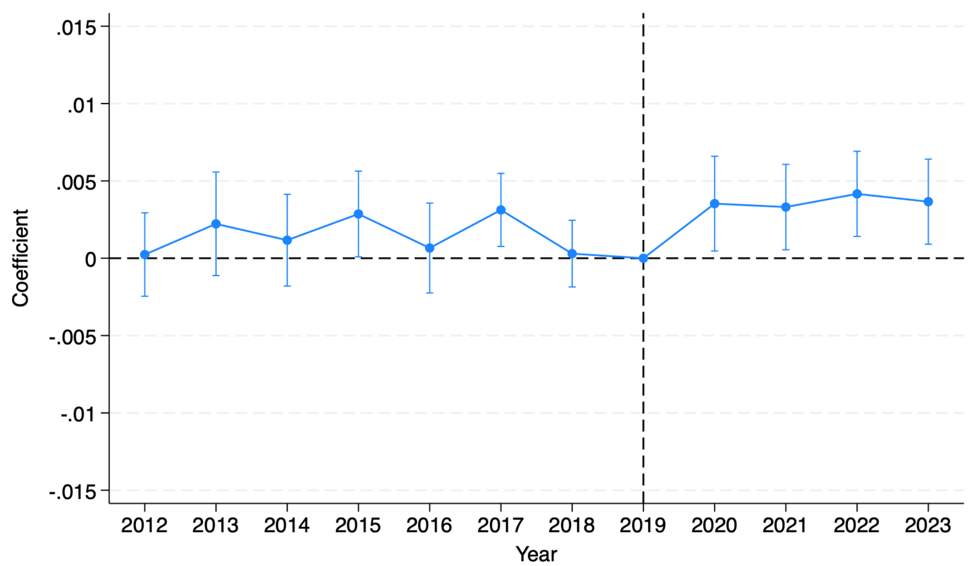
"The Future of Work: Remote Opportunities and Female Labor Force Participation"

Figure A1: Effects of WFH Opportunities on Employment: Analysis Using DDD Specification

(a) Mothers



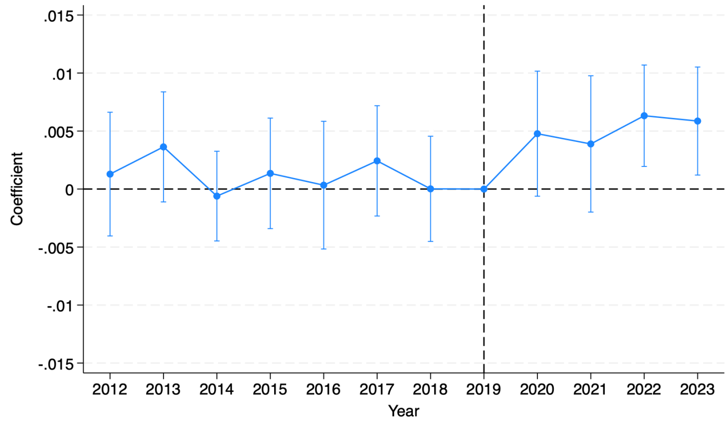
(b) College Mothers



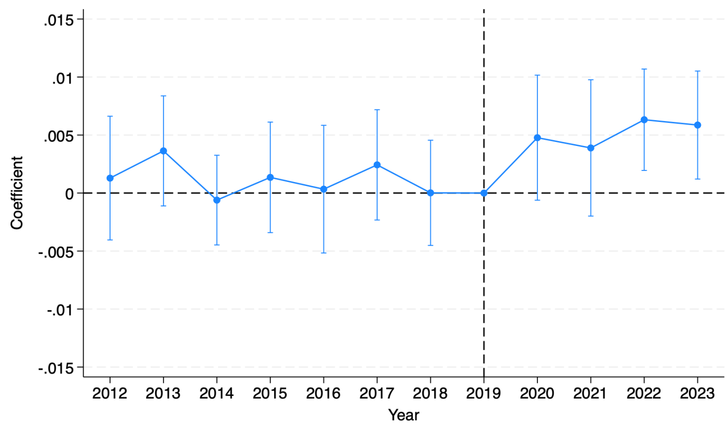
Notes: This figure compares the effects of individual-level exposure to WFH opportunities on employment for (a) mothers and (b) college mothers. The model specification follows the DDD approach in Equation (8). It displays the coefficients and corresponding 95% confidence intervals for the triple interaction terms from Equation (8). The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA-by-year level, and the WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure A2: Effects of WFH on Mothers with Young Children

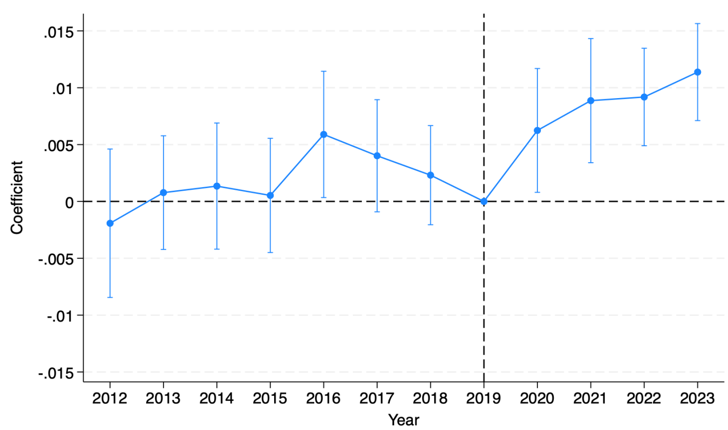
(a) Labor Force



(b) Employment



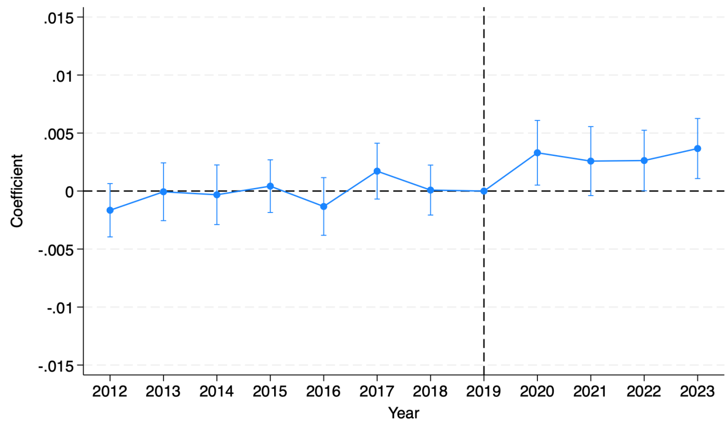
(c) Full-Time Work



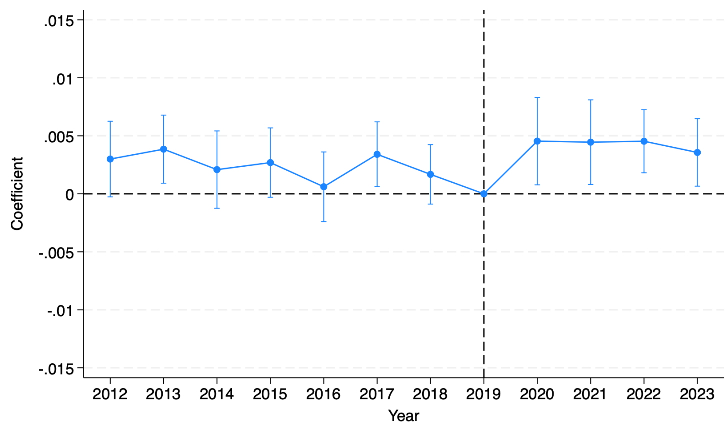
Notes: This figure compares the effects of individual-level exposure to work-from-home (WFH) opportunities on college mothers across three outcomes: (a) labor force participation, (b) employment, and (c) full-time work. The model specification is identical to Equation (3), with the regressions weighted by ACS person weights to achieve broader population representation. The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA level, and the WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure A3: Effects of WFH Opportunities on College Mothers: Robustness Using Weighted Regressions

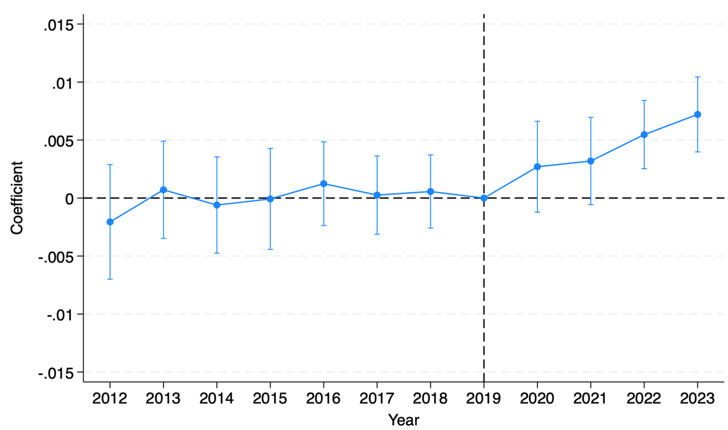
(a) Labor Force



(b) Employment



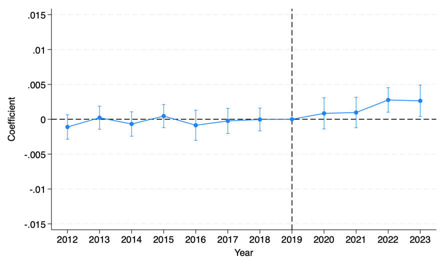
(c) Full-Time Work



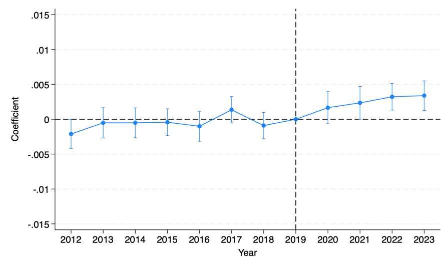
Notes: This figure compares the effects of individual-level exposure to WFH opportunities on college mothers across three outcomes: (a) labor force participation, (b) employment, and (c) full-time work. The model specification is identical to Equation (3), with the regressions weighted by ACS person weights to achieve broader population representation. The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA level, and the WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure A4: Effects of WFH Opportunities on Female LFP: Robustness Using Alternative WFH Measures

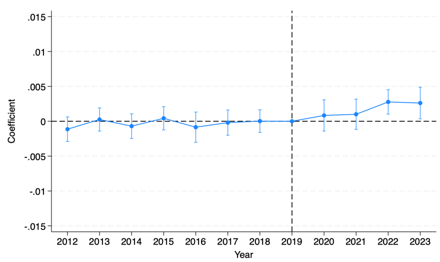
(a) Mothers - *wfh*



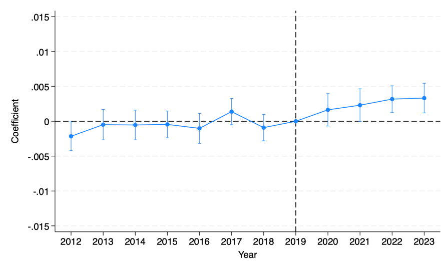
(b) College Mothers - *wfh*



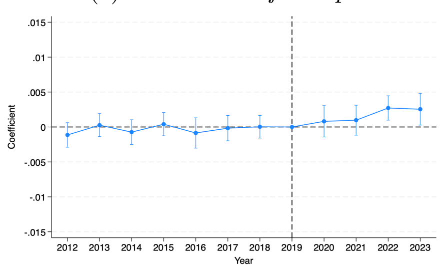
(c) Mothers - *wfh_lfp*



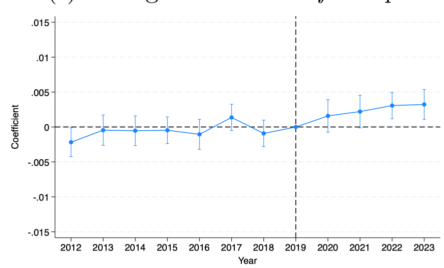
(d) College Mothers - *wfh_lfp*



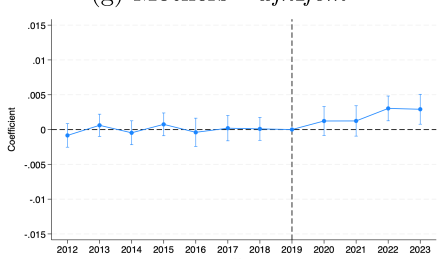
(e) Mothers - *wfh_emp*



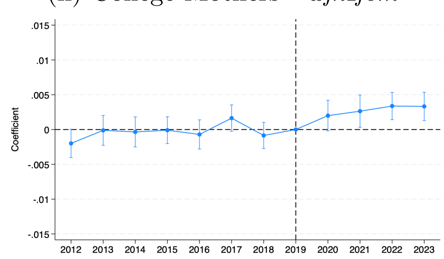
(f) College Mothers - *wfh_emp*



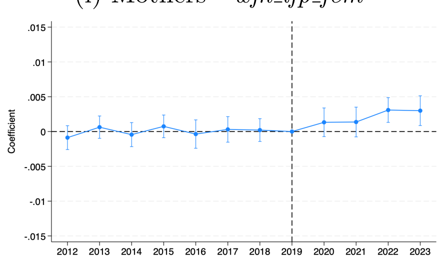
(g) Mothers - *wfh_fem*



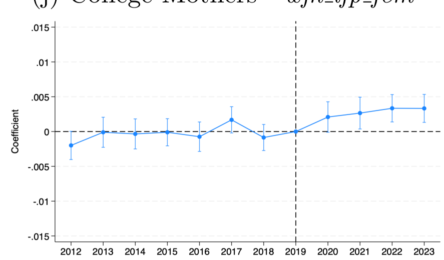
(h) College Mothers - *wfh_fem*



(i) Mothers - *wfh_lfp_fem*

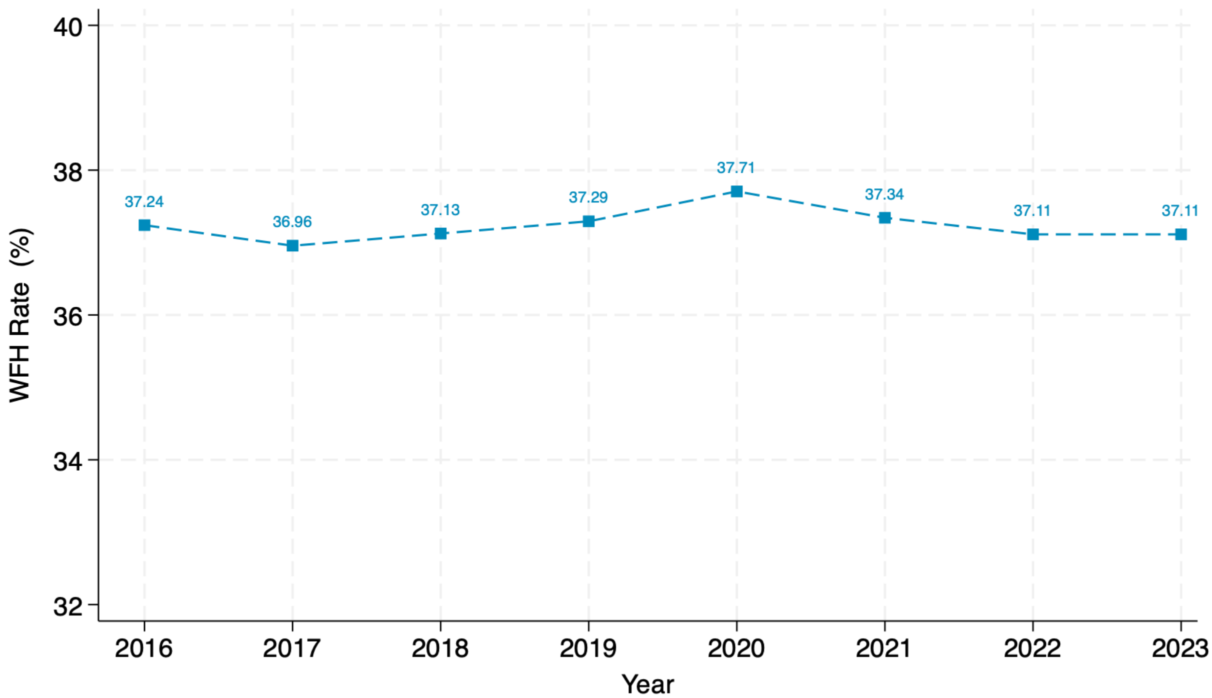


(j) College Mothers - *wfh_lfp_fem*



Notes: This figure compares the effects of individual-level exposure to different WFH measures on female labor force participation for mothers (left column) and college mothers (right column). Each row corresponds to a different WFH measure. It displays the coefficients and corresponding 95% confidence intervals for the triple interaction terms from Equation (3). The year 2019, one year prior to the onset of the COVID-19 pandemic, is used as the reference point and normalized to zero. Standard errors are clustered at the MSA level, and each WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure A5: Stability of Dingel & Neiman WFH Measure



Notes: This figure replicates Dingel and Neiman's WFH measure using O*NET data from 2016 to 2023, showing the percentage of occupations classified as suitable for remote work across different years. The results indicate that the WFH rate remains consistently around 37%, aligning with the original analysis by Dingel and Neiman (2020). This stability underscores the robustness of the measure, ensuring that any observed effects are attributable to WFH potential rather than temporal changes in occupational classifications.

Table A1: Effects of WFH Opportunities on Mothers: Analysis Using DDD Specification

	Labor Force		Employment		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mothers	College Mothers	Mothers	College Mothers	Mothers	College Mothers
Panel A: Average Effect						
2021 - 2023	0.0016**	0.0024***	0.0015*	0.0021***	0.0049***	0.0064***
	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0010)	(0.0013)
Panel B: Year-Specific Effects						
2021	0.0006	0.0019*	0.0009	0.0017	0.0055***	0.0064***
	(0.0010)	(0.0011)	(0.0009)	(0.0011)	(0.0014)	(0.0017)
2022	0.0020**	0.0026***	0.0018*	0.0026***	0.0038***	0.0053***
	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0012)	(0.0016)
2023	0.0023**	0.0027**	0.0018*	0.0021*	0.0054***	0.0074***
	(0.0010)	(0.0011)	(0.0011)	(0.0012)	(0.0014)	(0.0016)
Panel C: Pseudo First Stage						
2021 - 2023	0.0312***	0.0345***	0.0312***	0.0345***	0.0312***	0.0345***
	(0.0022)	(0.0025)	(0.0022)	(0.0025)	(0.0022)	(0.0025)
F-statistic	148.65	180.34	148.65	180.34	148.65	180.34
Panel D: Wald Estimator						
2021 - 2023	0.0513	0.0696	0.0481	0.0609	0.1571	0.1855
Relative effect (%)	5.89	7.88	5.78	7.13	21.50	24.83
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.8704	0.8833	0.8326	0.8543	0.7308	0.7472
N	5917386	3803329	5917386	3803329	5195366	3408518

Notes: This table reports results from estimating the triple-difference specification in Equation (8), which compares the effects of WFH opportunities on mothers relative to fathers to isolate gender-specific responses. Standard errors are clustered at the MSA-by-year level and are shown in parentheses. All models include MSA-by-year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Effects of WFH Opportunities on College Mothers: Robustness Using Alternative Control Specifications

	(1) Labor Force	(2) Labor Force	(3) Employment	(4) Employment	(5) Full-Time	(6) Full-Time
Panel A: Average Effect						
2021 - 2023	0.0031***	0.0026***	0.0024***	0.0019***	0.0064***	0.0061***
	(0.0006)	(0.0005)	(0.0007)	(0.0006)	(0.0013)	(0.0012)
Panel B: Year-Specific Effects						
2021	0.0025***	0.0022***	0.0024**	0.0018	0.0060***	0.0058***
	(0.0009)	(0.0008)	(0.0012)	(0.0012)	(0.0017)	(0.0016)
2022	0.0033***	0.0029***	0.0030***	0.0028***	0.0052***	0.0055***
	(0.0008)	(0.0007)	(0.0009)	(0.0008)	(0.0015)	(0.0014)
2023	0.0034***	0.0027***	0.0018*	0.0013	0.0079***	0.0072***
	(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0015)	(0.0014)
Panel C: Pseudo First Stage						
2021 - 2023	0.0345***	0.0345***	0.0345***	0.0345***	0.0345***	0.0345***
	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)	(0.0025)
F-statistic	180.34	180.34	180.34	180.34	180.34	180.34
Panel D: Wald Estimator						
2021 - 2023	0.0899	0.0754	0.0696	0.0551	0.1855	0.1768
Relative effect (%)	10.18	8.53	8.15	6.45	24.83	23.65
Controls	No	No	No	No	No	No
Year Controls	No	Yes	No	Yes	No	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.8833	0.8833	0.8543	0.8543	0.7472	0.7472
N	2058570	2058570	2058570	2058570	1875167	1875167

Notes: This table reports results from estimating Equations (2) and (4) with different control variable choices. The identification strategy remains identical to the baseline specification, with odd columns presenting results without any controls and even columns including year-varying controls. Standard errors are clustered at the MSA level and are shown in parentheses. All models include MSA fixed effects and year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Effects of WFH Opportunities on Mothers: Robustness Using ACS Person Weight

	Labor Force		Employment		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mothers	College Mothers	Mothers	College Mothers	Mothers	College Mothers
Panel A: Average Effect						
2021 - 2023	0.0014*	0.0027***	-0.0002	0.0018**	0.0024*	0.0050***
	(0.0008)	(0.0008)	(0.0012)	(0.0008)	(0.0012)	(0.0012)
Panel B: Year-Specific Effects						
2021	0.0001	0.0023*	-0.0007	0.0020	0.0008	0.0029
	(0.0011)	(0.0012)	(0.0019)	(0.0014)	(0.0018)	(0.0019)
2022	0.0013	0.0024**	0.0000	0.0021**	0.0025*	0.0051***
	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0014)	(0.0015)
2023	0.0029**	0.0034***	0.0002	0.0011	0.0039**	0.0069***
	(0.0012)	(0.0011)	(0.0015)	(0.0012)	(0.0017)	(0.0017)
Panel C: Pseudo First Stage						
2021 - 2023	0.0268***	0.0311***	0.0268***	0.0311***	0.0268***	0.0311***
	(0.0020)	(0.0023)	(0.0020)	(0.0023)	(0.0020)	(0.0023)
F-statistic	163.04	187.40	163.04	187.40	163.04	187.40
Panel D: Wald Estimator						
2021 - 2023	0.0522	0.0868	-0.0075	0.0579	0.0896	0.1608
Relative effect (%)	6.00	9.83	-0.90	6.77	12.27	21.52
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.8704	0.8833	0.8326	0.8543	0.7308	0.7472
N	3089872	2058570	3089872	2058570	2766878	1875167

Notes: This table reports results from estimating Equations (2) and (4) with regressions weighted by ACS person weights to achieve broader population representation. Standard errors are clustered at the MSA level and are shown in parentheses. All models include MSA fixed effects and year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effects of WFH Opportunities on Mothers: Robustness Using Previous Residence

	Labor Force		Employment		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mothers	College Mothers	Mothers	College Mothers	Mothers	College Mothers
Panel A: Average Effect						
2021 - 2023	0.0022***	0.0030***	0.0007	0.0023***	0.0041***	0.0065***
	(0.0006)	(0.0005)	(0.0009)	(0.0006)	(0.0012)	(0.0014)
Panel B: Year-Specific Effects						
2021	0.0011	0.0026***	0.0003	0.0023**	0.0039**	0.0065***
	(0.0008)	(0.0008)	(0.0015)	(0.0011)	(0.0017)	(0.0018)
2022	0.0029***	0.0033***	0.0015	0.0030***	0.0030**	0.0053***
	(0.0007)	(0.0007)	(0.0009)	(0.0008)	(0.0012)	(0.0015)
2023	0.0026***	0.0031***	0.0002	0.0015	0.0052***	0.0076***
	(0.0009)	(0.0009)	(0.0011)	(0.0010)	(0.0014)	(0.0015)
Panel C: Pseudo First Stage						
2021 - 2023	0.0315***	0.0348***	0.0315***	0.0348***	0.0315***	0.0348***
	(0.0021)	(0.0024)	(0.0021)	(0.0024)	(0.0021)	(0.0024)
F-statistic	134.70	165.17	134.70	165.17	134.70	165.17
Panel D: Wald Estimator						
2021 - 2023	0.0698	0.0862	0.0222	0.0661	0.1302	0.1868
Relative effect (%)	8.02	9.76	2.67	7.74	17.82	25.00
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.8705	0.8833	0.8326	0.8543	0.7308	0.7472
N	3089238	2058117	3089238	2058117	2766364	1874798

Notes: This table reports results from estimating Equations (2) and (4) with WFH measures constructed based on individuals' previous year residence to address potential mobility concerns. Standard errors are clustered at the MSA level and are shown in parentheses. All models include MSA fixed effects and year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Effects of WFH Opportunities on Mothers: Robustness Excluding Older Cohorts

	Labor Force		Employment		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mothers	College Mothers	Mothers	College Mothers	Mothers	College Mothers
Panel A: Average Effect						
2021 - 2023	0.0026***	0.0034***	0.0010	0.0025***	0.0047***	0.0070***
	(0.0007)	(0.0006)	(0.0008)	(0.0006)	(0.0011)	(0.0013)
Panel B: Year-Specific Effects						
2021	0.0013	0.0027***	0.0006	0.0024**	0.0045***	0.0067***
	(0.0009)	(0.0009)	(0.0015)	(0.0011)	(0.0014)	(0.0017)
2022	0.0032***	0.0037***	0.0017**	0.0034***	0.0037***	0.0057***
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0012)	(0.0015)
2023	0.0032***	0.0036***	0.0005	0.0019**	0.0060***	0.0086***
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0014)	(0.0015)
Panel C: Pseudo First Stage						
2021 - 2023	0.0324***	0.0356***	0.0324***	0.0356***	0.0324***	0.0356***
	(0.0022)	(0.0025)	(0.0022)	(0.0025)	(0.0022)	(0.0025)
F-statistic	162.20	195.89	162.20	195.89	162.20	195.89
Panel D: Wald Estimator						
2021 - 2023	0.0802	0.0955	0.0309	0.0702	0.1451	0.1966
Relative effect (%)	9.16	10.77	3.69	8.19	19.87	26.32
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.8756	0.8869	0.8365	0.8576	0.7306	0.7470
N	2623642	1782575	2623642	1782575	2361182	1629801

Notes: This table reports results from estimating Equations (2) and (4) with the sample restricted to ages 25-54 to address potential concerns about early retirement confounding the estimated effects. Standard errors are clustered at the MSA level and are shown in parentheses. All models include MSA fixed effects and year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effects of WFH Opportunities on Mothers: Robustness Using Shorter-Period Measure

	Labor Force		Employment		Full-Time	
	(1)	(2)	(3)	(4)	(5)	(6)
	Mothers	College Mothers	Mothers	College Mothers	Mothers	College Mothers
Panel A: Average Effect						
2021 - 2023	0.0022***	0.0030***	0.0007	0.0022***	0.0041***	0.0067***
	(0.0006)	(0.0006)	(0.0009)	(0.0006)	(0.0011)	(0.0013)
Panel B: Year-Specific Effects						
2021	0.0009	0.0024***	0.0002	0.0021*	0.0038**	0.0065***
	(0.0008)	(0.0009)	(0.0014)	(0.0012)	(0.0015)	(0.0018)
2022	0.0028***	0.0032***	0.0014	0.0028***	0.0031***	0.0056***
	(0.0007)	(0.0007)	(0.0009)	(0.0008)	(0.0012)	(0.0015)
2023	0.0029***	0.0035***	0.0004	0.0018*	0.0055***	0.0080***
	(0.0009)	(0.0008)	(0.0010)	(0.0009)	(0.0014)	(0.0015)
Panel C: Pseudo First Stage						
2021 - 2023	0.0312***	0.0347***	0.0312***	0.0347***	0.0312***	0.0347***
	(0.0022)	(0.0026)	(0.0022)	(0.0026)	(0.0022)	(0.0026)
F-statistic	153.17	182.01	153.17	182.01	153.17	182.01
Panel D: Wald Estimator						
2021 - 2023	0.0705	0.0865	0.0224	0.0634	0.1314	0.1931
Relative effect (%)	8.10	9.80	2.69	7.42	17.99	25.84
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Control Mean	0.8704	0.8833	0.8326	0.8543	0.7308	0.7472
N	3089872	2058570	3089872	2058570	2766878	1875167

Notes: This table reports results from estimating Equations (2) and (4) using WFH measures constructed from a shorter pre-period (2015-2019) to address potential concerns about longer-run trends confounding the analysis. Standard errors are clustered at the MSA level and are shown in parentheses. All models include MSA fixed effects and year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix: Analysis Using DDD Specification

While the standard two-way fixed effects difference-in-differences model provides a transparent framework for my estimations, incorporating a Difference-in-Differences-in-Differences (DDD) specification offers additional analytical advantages and addresses potential confounding factors. The key insight is that if males do not exhibit corresponding effects from WFH opportunities, they serve as an excellent control group for identifying female-specific responses. The lack of significant effects among males would constitute an important placebo test, alleviating concerns that the observed effects are driven by broader economic trends, regional shocks, or methodological artifacts rather than representing genuine increases in female labor force participation. However, if males also experience labor market effects from WFH opportunities, perhaps through different mechanisms or with different magnitudes, the triple-difference approach provides crucial advantages by allowing us to isolate the differential impact on women relative to men.

Specifically, I estimate the following triple-difference specification:

$$\begin{aligned} \mathrm{Y}_{imt} = {} & \alpha_1 \cdot \mathit{Female}_i + \alpha_2 \cdot (\mathit{Female}_i \times \mathrm{WFH}_{m,\mathrm{pre}}) \\ & + \kappa \cdot (\mathit{Female}_i \times \mathit{Post}_t) \\ & + \lambda \cdot (\mathit{Female}_i \times \mathrm{WFH}_{m,\mathrm{pre}} \times \mathit{Post}_t) \\ & + \mathbf{X}'_{it}\beta + \tau_{mt} + \mu_{imt} \end{aligned} \tag{8}$$

Here, *Female* is a dummy variable indicating whether the individual i is female. *Post* is an indicator denoting the post-pandemic period covering years of 2021 to 2023. The MSA-by-year fixed effects ϕ_{mt} account for baseline differences across MSA and any time-varying factors common to all individuals within a given MSA. These fixed effects absorb the direct effect of WFH potential, direct post-pandemic effects, and their two-way interaction $WFH_{m,pre} \times Post_t$. The remaining terms in the specification capture additional variation as follows. First, the $Female_i$ term reflects the baseline difference in labor force participation between women and men. Second, the interaction term $Female_i \times WFH_{m,pre}$ isolates how pre-pandemic WFH potential influences female labor force participation, independent of time. Third, $Female_i \times Year_t$ captures time-varying differences in labor force participation trends for women relative to men.

Lastly, the triple interaction term $Female_i \times WFH_{m,pre} \times Year_t$ estimates the differential impact of WFH potential on female labor force participation over time relative to men, which is the primary coefficient of interest in this analysis. Additionally, the vector of individual-level controls X_{it} includes variables such as age, race, marital status, educational attainment, and the presence of children under age 5 to adjust for other potential confounding factors. Standard errors are clustered at the MSA-by-year level.

Figure A1 shows the event study results for employment using the triple difference model. When using the two-way DID in the main analysis for mothers and college mothers, we observe small trends that might be contaminated by broader labor market effects affecting males as well. The triple difference event study presents clear parallel trends that validate the identification strategy and demonstrate that the effects are genuinely gender-specific rather than reflecting economy-wide changes that also impact male employment patterns. The pre-pandemic coefficients hover around zero with no discernible trend, confirming that the parallel trends assumption holds when controlling for male employment patterns. Beginning in 2020, the coefficients show a modest but persistent increase, indicating that WFH opportunities differentially benefited female employment relative to male employment.

Table A1 presents the triple difference estimates comparing the effects of WFH opportunities on mothers relative to fathers. The results confirm significantly stronger positive effects on mother labor market outcomes, with college mothers showing particularly robust responses across all outcomes. Importantly, these triple difference findings closely mirror the main two-way DID results, confirming that the observed female labor force participation gains represent gender-specific benefits for women rather than general labor market improvements affecting both men and women.

Appendix: Dingel and Neiman WFH Measure

Overview and Construction of the WFH Measure

Dingel and Neiman (2020) developed a measure to classify occupations based on their feasibility to be performed entirely from home. The foundation of their classification system relies on two comprehensive surveys from O*NET, a database sponsored by the US Department of Labor that provides detailed information about nearly 1,000 occupations. The first survey, called the Work Context Questionnaire, examines physical and social factors that shape the nature of work, such as interpersonal relationships, physical conditions, and structural job characteristics. The second survey, the Generalized Work Activities Questionnaire, focuses on general job behaviors that occur across multiple jobs, including how workers process information, interact with others, engage in mental tasks, and produce work outputs. These surveys are quite robust, with the median occupation receiving responses from 26 and 25 workers respectively for the Work Context and Generalized Work Activities questionnaires.

The authors developed a systematic approach to classify jobs as unable to be performed at home based on specific criteria from these surveys. From the Work Context survey, they identified seven key conditions that would make remote work impossible. These include using email less than monthly, dealing with violent people weekly, working outdoors daily, having weekly exposure to diseases or infections, experiencing minor injuries weekly, spending the majority of time walking or running, or requiring protective equipment for most of the workday. Similarly, from the Generalized Work Activities survey, they identified eight critical activities that, if rated as "very important," would preclude working from home. These activities include performing physical tasks, handling objects, controlling machines, operating vehicles, working directly with the public, and various types of equipment maintenance and inspection.

To validate their classification, Dingel and Neiman manually reviewed and scored occupations, achieving strong alignment between their algorithmic and manual assessments. They further integrated these classifications with employment data from the Bureau of Labor Statistics (BLS), enabling them to calculate weighted measures of work-from-home feasibility. These weights reflected both the prevalence and wages of each occupation, ensuring the measure accurately captured the economic significance of remote work potential.

The final WFH measure assigned a binary classification to each occupation, indicating whether it could be performed entirely from home. These binary scores were then aggregated across industries, metropolitan areas, and national employment data to estimate the share of jobs suitable for remote work. Their analysis revealed that approximately 37% of U.S. jobs could be done entirely from home, with substantial variation across cities, industries, and income levels. By mapping U.S. occupational codes to international standards, they extended their methodology to other countries, highlighting disparities in remote work feasibility between high- and low-income economies.

Stability of the Measure

I employ Dingel and Neiman's WFH measure at the occupational level by linking the scores to individuals in the dataset based on their reported occupation codes. However, the O*NET database, which forms the basis of Dingel and Neiman's measure, undergoes regular updates to reflect the evolving nature of work and maintain its relevance in a dynamic labor market. These updates, conducted multiple times annually, incorporate new data on job requirements, worker attributes, and workplace conditions derived from comprehensive surveys such as the Work Context Questionnaire and the Generalized Work Activities Questionnaire. Additionally, frequent revisions ensure alignment with updated national occupational standards, such as the Standard Occupational Classification (SOC) system, enhancing consistency and accuracy in occupational data.

It is crucial to assess whether the WFH measure remains stable over time, as this ensures that any observed effects arise from the potential for remote work rather than changes in the underlying occupational classifications. While the O*NET database is updated multiple times each year, I focus on the major updates typically released each August to evaluate the temporal stability of the WFH measure.

Figure A5 presents a replication of Dingel and Neiman's WFH construction using O*NET data from 2016 to 2023. The results indicate that the share of occupations classified as suitable for remote work consistently remains around 37% across all years, with negligible fluctuations, which aligns with the results reported in Dingel and Neiman's original analysis. This consistency demonstrates the robustness of the measure and ensures that the analysis effectively isolates the effects of work-from-home potential without being confounded by temporal variations in occupational classifications. Such stability is critical for evaluating the long-term implications of remote work opportunities on labor market outcomes.