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

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This paper examines the long-term effects of the accelerated adoption of work-from-home opportunities brought about by the pandemic on female labor force participation. It aims to explore whether the rise in remote work opportunities can explain the observed resilience and recent growth in female labor force participation and to investigate whether women were more adversely impacted or ultimately benefited more from work-from-home arrangements. Using a difference-in-differences and event study design, this paper exploits variation at the local labor market area (LMA) level pre- and post-pandemic, comparing individuals in LMAs with higher work-from-home potential to those in areas with lower work-from-home opportunities. My findings reveal that WFH opportunities have a significant and positive impact on female labor force participation, particularly for mothers and mothers with young children. At the LMA level, a one-standard-deviation increase in WFH opportunities is associated with a 0.32 percentage point increase in the probability of a female individual participating in the labor force. The effects are more pronounced for mothers (0.41 percentage point increase) and are largest for mothers with children under 5 (0.86 percentage point increase). Additionally, younger women achieve the greatest benefits from WFH, with effects decline with age; meanwhile, highly educated mothers of young children benefit the most, whereas women with lower educational attainment face structural barriers limiting their ability to fully leverage remote work opportunities. Furthermore, the results suggest that the positive effects of WFH opportunities may have a delayed impact, with the potential to grow as remote work arrangements become more stable 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, marked by a remarkable increase in female labor force participation (LFP) (Goldin, 1990; Goldin and Katz, 2002; Fernández, 2013). The most prominent rise 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 evidence showing it enhances job satisfaction and retains senior talent, countering arguments for mandatory in-office policies (Van Dijcke et al., 2024; Ding and Ma, 2024).

The rapid growth of work-from-home arrangements coincided with remarkable changes in female labor force participation over the course of the COVID-19 pandemic. Figure 1 illustrates the labor force participation rates for the working-age population (ages 15 to 64) in the United States from 2014 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 rebounding 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

[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

driven the labor market recovery and continue to play a crucial role in shaping its trajectory.

This smaller decline and steady rise in female LFP is surprising, given that researchers initially believed women were more impacted by the COVID-19 pandemic than men. This "she-cession" (Goldin, 2022) was driven by increased childcare burdens from school closures (Alon et al., 2020a), caregiving responsibilities for elderly relatives (Goldin, 2022), and disproportionate representation in disrupted frontline industries such as healthcare and retail (Alon et al., 2020b; Albanesi and Kim, 2021). Can the apparent conflict between the theoretical expectation that women were more adversely impacted by the pandemic and the empirical evidence showing smaller losses and a rise in female LFP be explained by the increasing opportunities for remote work?

Motivated by this observation, this paper examines the long-term effects of the accelerated adoption of work-from-home opportunities brought about by the pandemic on female labor force participation. It aims to explore whether the rise in remote work opportunities can explain the observed resilience and growth in female labor force participation and to investigate whether women were more adversely impacted or ultimately benefited more from work-from-home arrangements. In this paper, I utilize the work-from-home score developed by Dingel and Neiman (2020), which quantifies the ability of occupations to be performed remotely on a scale from 0 to 1. By linking these occupational-level scores to individual records from the American Community Survey (ACS) based on their reported occupation codes, I construct a measure of exposure to WFH opportunities at the local labor market area (LMA) level, capturing the fraction of jobs within each LMA that can potentially be performed remotely.

This approach builds on the methodology of Gupta et al. (2022), who measured work-from-home exposure at the ZIP code and metropolitan statistical area (MSA) levels, finding that areas with higher exposure to remote work experienced slower growth in house prices and rents. I extend this methodology by focusing on LMAs, which better capture the geographic scope of local economies. The central concept behind this WFH potential metric is to calculate the weighted average of teleworkability scores across occupations for each LMA and year. This method accounts for the distribution of jobs within each LMA, ensuring the metric accurately reflects the area's unique economic composition. Then, using a difference-in-differences and event study design (Sun and Abraham, 2021; Goodman-Bacon, 2021; Borusyak et al., 2024), this paper examines whether women in LMAs with higher work-from-home potential are more likely to participate in the labor force relative to men, compared to those in areas with lower remote work opportunities.

My findings reveal that WFH opportunities have a significant and positive impact on

role in driving the overall increase in labor force participation over the past five years, despite variations across demographic subgroups.

female labor force participation, particularly for mothers and mothers with young children. At the local labor market area level, a one-standard-deviation increase in WFH opportunities corresponds to a 0.32 percentage point increase in the probability of a female individual participating in the labor force. The effects are more pronounced for mothers (0.41 percentage point increase) and are largest for mothers with children under 5 (0.86 percentage point increase). Moreover, the impact of WFH opportunities diminishes with age, as younger women exhibit the largest gains while older women show smaller or insignificant effects. Differences by educational attainment also emerge: highly educated mothers, particularly those with young children, experience the most substantial benefits from WFH opportunities, whereas women with lower educational attainment face structural barriers that limit their ability to fully leverage these arrangements. Furthermore, my results show that this positive effect may have a delayed impact and the potential to continue growing in the long term as remote assignments become more stable and persistent.

These findings underscore that WFH opportunities do not disproportionately harm women nor exacerbate gender gaps in labor force participation. Instead, they provide much-needed flexibility, enabling women—especially those balancing caregiving responsibilities—to remain in or re-enter the workforce. The validity of these results is confirmed through a series of robustness checks, including the use of a shorter-period measure of WFH exposure, alternative WFH measures, weighted regressions that account for the ACS sampling design, adjustments for individuals' prior-year residence to account for potential mobility in response to WFH opportunities, and the use of six-digit occupation codes for greater occupational specificity. These analyses highlight the stability of the results and emphasize the transformative potential of WFH opportunities in fostering inclusivity and resilience in the labor market.

This paper contributes to several strands of literature. First, to the best of my knowledge, this is the first study to analyze the long-term effects of work-from-home exposure accelerated by the COVID-19 pandemic on female labor force participation at the commuting zone level. By focusing on this geographic scale and leveraging the robust design, large sample size, and comprehensive coverage of the American Community Survey, this paper provides a more precise understanding of how remote work opportunities have influenced gendered labor market outcomes across regions. Unlike existing studies that rely on specific survey data or focus on smaller population groups, this research offers a detailed exploration of the relationship between remote work opportunities and female labor force participation, contributing valuable insights into labor market transformations in the post-pandemic era.

Second, this paper adds to the extensive body of research on female labor force participation by providing new evidence on how modern labor market trends intersect with gender dynamics. Scholars attribute this growth to several key factors, including structural and economic transformations (Goldin, 1990; Costa, 2000), cultural changes and social learning (Fogli and Veldkamp, 2011; Fernández, 2013), and technological advancements that reduced the burden of household work (Greenwood et al., 2005; Vidart, 2024). Changes in fertility behavior, driven by broader economic growth (Galor and Weil, 1993), the introduction of the contraceptive pill (Goldin and Katz, 2002; Bailey, 2006), and reductions in childcare costs (Attanasio et al., 2008), along with medical advances (Albanesi and Olivetti, 2016), further contributed to reshaping societal norms and expanding economic opportunities for women. Building on this literature, this paper contributes by exploring how the rise of work-from-home opportunities—accelerated by the COVID-19 pandemic—has further influenced female labor force participation, providing a nuanced understanding of its implications for gendered labor market outcomes.

Third, this paper deepens our understanding of the role of remote work in shaping labor market outcomes, offering insights into its broader economic and social implications. The implications of remote work for the labor market have been widely debated. On one hand, evidence suggests that remote work saves commuting time, provides greater flexibility, and improves work-life balance, retention, and productivity (Harrington and Kahn, 2023; Bloom et al., 2015, 2024). Women and mothers, in particular, may benefit significantly from this flexibility, as research shows that flexible work arrangements, including remote options, play a critical role in increasing female labor force participation by enabling them to balance professional responsibilities with caregiving and domestic duties (Goldin, 2014; Bang, 2022; Harrington and Kahn, 2023). Moreover, women demonstrate a higher willingness to pay for WFH opportunities compared to men (Mas and Pallais, 2017; Drake et al., 2022; Maestas et al., 2023) and a stronger aversion to commuting (Black et al., 2014; Le Barbanchon et al., 2021; Meekes and Hassink, 2022).

On the other hand, concerns persist about potential reductions in productivity, opportunities for promotion, and collaboration, particularly in sectors where teamwork and in-person interactions are essential (Gibbs et al., 2021; Emanuel and Harrington, 2024). Furthermore, some researchers caution that the increased caregiving burdens during the pandemic, especially for women, may have offset the potential gains in workforce participation (Alon et al., 2020a,b). The findings of this paper provide empirical evidence that addresses these debates, highlighting the important role of work-from-home opportunities in supporting females, especially mothers and mothers with young children.

Fourth, this paper contributes to the growing body of research on the economic effects of the COVID-19 pandemic, illustrating how a global crisis can reshape entrenched patterns in labor force participation. This paper also engages with the ongoing debate on return-to-office policies, providing insights into their implications for gender equity in the labor market.

Finally, the findings hold important policy implications: policymakers aiming to support female labor force participation should adopt a holistic approach that extends beyond work-from-home opportunities, addressing persistent barriers such as caregiving responsibilities and access to affordable childcare. As hybrid and remote work arrangements become more integrated into the labor market, understanding their nuanced effects on diverse demographic groups will be essential for designing equitable and effective labor policies.

The rest of the paper is organized as follows: Section 2 discusses the data sources and the merging process. Section 3 details the construction of the work-from-home exposure measure and outlines the empirical strategies. Section 4 presents the results of the main analysis, heterogeneity analyses, and robustness checks. Section 5 discusses policy implications and concludes.

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 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 in individual level enables the construction of key labor market variables, including labor force participation, occupation, education, marital status, and age. This level of granularity is critical for exploring the gender-specific impacts of work-from-home (WFH) opportunities. Second, the ACS provides geographic identifiers that enable the analysis of variation in WFH exposure at the local labor market area (LMA) level. The ACS includes individual-level occupation data, which enables the calculation of occupation-level WFH potential within LMAs, facilitating a nuanced analysis of how differences in remote work opportunities across regions influence female labor force participation. Third, the ACS's large sample size and consistent annual coverage make it uniquely suited for examining labor market dynamics during the pandemic, which brought about a significant shift in WFH opportunities. Unlike smaller or more specialized surveys, the ACS minimizes biases and ensures that results are less affected by sampling variability, providing a robust foundation for studying the evolving patterns of labor force participation in the post-pandemic era.

One of the contribution of this paper is that, distinguished from the existing literature using the specific surveey data or looking at smaller group, The ACS's robust design, large sample size, and comprehensive coverage make it ideal for this research. By leveraging its unique features, this study provides a detailed exploration of the relationship between remote work opportunities and female labor force participation, contributing valuable insights into labor market transformations in the post-pandemic era.

Time Period. This study uses ACS data spanning from 2014 to 2023, capturing a critical period that includes both pre-pandemic and post-pandemic years. The sample begins in 2014, six years before the onset of the COVID-19 pandemic, to provide a robust pre-period for examining pre-trends and ensuring unbiased results. Including a six-year pre-period strengthens the pre-trend tests and solidifies the robustness of the findings. However, I also demonstrate that the results remain consistent and robust when using a shorter pre-period WFH measure (2017–2019). 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 examines long-term trends in labor force participation and the impacts of the accelerated adoption of remote work. The consistent methodology and annual nature of the ACS data ensure comparability across years, providing robust insights into how these dynamics evolved over time.

Key Variables. The primary outcome variable used in this study is each individual's employment status. This variable identifies whether the respondent was part of the labor force or unemployed during the week preceding the survey. The Standard Occupational Classification (SOC) code for each individual is used to link their occupation to the work-from-home (WFH) score at the occupational level, enabling an analysis of remote work potential. Additional key variables include demographic and socioeconomic characteristics such as sex, age, marital status, the presence of a child under age 5, race, and educational attainment. These variables are critical for examining heterogeneity in labor force participation and understanding the gender-specific impacts of WFH opportunities.

2.2 Labor Market Areas

Labor Market Areas (LMAs) and Commuting Zones (CZs) are geographic units designed to better represent local economies, overcoming the limitations of traditional county boundaries that often reflect political divisions rather than economic realities. Developed by the Economic

Research Service (ERS) of the U.S. Department of Agriculture, CZs and LMAs aim to capture the interrelationships between where people live and work, offering a more accurate delineation of local labor markets. CZs are clusters of U.S. counties characterized by strong commuting ties within clusters and weak ties between clusters, ensuring that they closely reflect the economic activity and labor force dynamics of specific regions.[2]

Using Labor Market Areas offers several advantages. Unlike counties or MSAs, LMAs better reflect the actual geographic scope of local labor markets by incorporating commuting ties between regions. This makes LMAs particularly well-suited for studying phenomena like remote work, which is influenced not only by local employment conditions but also by broader commuting patterns and regional interdependencies. Moreover, LMAs strike a balance between geographic granularity and economic relevance, avoiding the limitations of county-level data, which often reflect arbitrary political boundaries, and MSA-level data, which can be too broad and omit rural areas. An additional advantage is that LMAs in this study are constructed based on Public Use Microdata Areas (PUMAs), the smallest geographic units identified in the Census. This makes them more accurate for capturing individual-level labor market outcomes. Since the focus of this study is on female labor force participation—a labor market outcome—the use of LMAs ensures that the analysis is grounded in a framework that aligns closely with the realities of local labor markets. Therefore, by leveraging LMAs, this study captures a comprehensive measure of local labor markets that aligns closely with the realities of where people live and work. This approach ensures that the WFH measure provides a more accurate context for analyzing its impact on female labor force participation.

Since the ACS data only identify PUMAs, I construct CZs by mapping PUMAs to CZs using the 1990 CZ definitions and the crosswalks provided by Dorn (2009) and Autor et al. (2019). PUMAs represent the smallest geographic units identified in the Census and are population-defined areas, each containing approximately 100,000 residents, with no fewer than 100,000 in any PUMA. As population distribution and density evolve over time, the Census Bureau redraws PUMA boundaries every 10 years, based on data from the most recent decennial census, to maintain the population threshold while avoiding significant deviations.[3]

In my analysis, data from 2014 to 2021 are based on the 2010 PUMA definitions, whereas data from 2022 and 2023 are based on the 2020 PUMA definitions. Since the crosswalks provided by Autor and Dorn are constructed using the 2010 PUMA definitions, I first use

[2]For additional details on Labor Market Areas and Commuting Zones, refer to the Economic Research Service (ERS) webpage and Dr. David Dorn's website. More recent CZs have been developed and are accessible through the Penn State website under Labor-sheds for Regional Analysis.

[3]For more details on PUMA background and updates to their definitions, visit: Census Bureau's PUMA Guidance.

the Census Bureau's 2010–2020 PUMA crosswalk to align the 2022 and 2023 PUMAs with the 2010 definitions. Once aligned, I apply the Autor and Dorn crosswalk to map PUMAs to CZs. This methodology ensures a high degree of consistency across all years in my sample while minimizing potential bias.

2.3 Work-From-Home Data

A key measure in this study is the assessment of remote work potential. I employ the Dingel and Neiman (2020) work-from-home (WFH) measure, which assigns scores ranging from 0 to 1 for each occupation, reflecting its feasibility to be performed entirely from home. 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. A brief overview of the methodology used to construct the WFH measure is provided in the Appendix.

To ensure that the WFH measure is robust and stable over time, I replicated the construction of the WFH measure using different versions of the O*NET database spanning 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 measure ensures that any observed effects in the analysis stem from the potential for remote work and not from temporal changes in occupational classifications. Further details on the construction and stability of the WFH measure, as well as the replication results, can be found in ith the results illustrated in Figure A5.

For this study, I link the WFH scores developed by Dingel and Neiman (2020) to individuals in the American Community Survey (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 2018 SOC system, I use the Census Bureau's SOC 2010-to-2018 crosswalk to map these teleworkability scores to occupations coded under the 2010 SOC system. This process ensures compatibility across all years of analysis and allows me to assign a WFH score to each individual in the dataset. After linking the ACS data to the WFH scores and commuting zone data, each person in the dataset is assigned their occupation's WFH score and corresponding commuting zone. Using this information, I construct my WFH measure by calculating the fraction of jobs within each local labor market area (LMA) that can potentially be performed remotely.

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 21,328,755 observations, representing individuals from 2014 to 2023. The average work-from-home (WFH) measure is 0.472 in the pre-COVID period, with a relatively low standard deviation of 0.030, indicating limited variation in WFH opportunities across observations before the pandemic. The mean labor force participation (LFP) rate is 0.752, suggesting that approximately 75.2% of the working-age population is engaged in the labor market. The sample is roughly gender-balanced, with 51.6% of individuals identified as female and 48.4% as male.

In terms of demographic composition, 75.9% of the sample identifies as White, 7.7% as Black, 11.8% as Hispanic, and 4.6% as Asian. The data also show that 65.9% of individuals are married, while 12.5% have children under the age of 5. Low education is defined as an educational attainment level of high school or below, while high education refers to college-level attainment and above, with 43.8% and 56.2% of the sample falling into these respective categories. Regarding age distribution, the sample skews slightly older, with 30.6% of individuals aged 55–64 and smaller proportions in the younger age brackets: 21.7% aged 25–34, 22.5% aged 35–44, and 25.2% aged 45–54. These descriptive statistics provide a comprehensive overview of the demographic and socioeconomic characteristics of the sample, serving as a foundation for the subsequent analysis.

Please note that individuals with military-specific occupations are excluded from the sample for two primary reasons: (1) these occupations are not relevant to WFH research, and (2) Dingle and Neiman's classification of teleworkable occupations also excludes this category.[4] Furthermore, in the regressions, the largest groups within categorical variables—namely, White individuals, those with high education, and individuals aged 55–64—are excluded as controls to address potential collinearity issues in the model.

3 Empirical Strategy

To explore the causal impact of work-from-home (WFH) opportunities on female labor force participation (LFP), I employ difference-in-differences and event study designs that

[4]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.

leverage variation in WFH potential across commuting zones (CZs) and over time. This section outlines the construction of the WFH potential measure, provides an overview of the empirical models used to estimate the effects of WFH opportunities, and describes the strategies employed to ensure robust and unbiased results.

3.1 Measuring Exposure to Work-From-Home Opportunity

3.1.1 Main Measure

To construct the WFH measure for commuting zones, I build on the methodology of Gupta et al. (2022), who measured work-from-home exposure at the ZIP code and metropolitan statistical area (MSA) levels. Instead of measuring exposure at these levels, I calculate the measure at the commuting zone level to better capture local labor market dynamics.

$$\text{WFH Measure}_{c,t} = \sum_{o} \left(\frac{\text{Number of jobs}_{c,o,t}}{\sum_{o} \text{Number of jobs}_{c,o,t}} \times \text{Teleworkability score}_{o} \right) \tag{1}$$

Equation (1) provides the formula for constructing the WFH measure. The idea is to calculate the weighted average teleworkability score for each commuting zone c in year t. Specifically, the measure is constructed by summing the products of the number of jobs in each occupation o and the teleworkability score for that occupation, divided by the total number of jobs in the commuting zone for that year. This approach ensures that the WFH measure reflects the distribution of teleworkable jobs across occupations within a commuting zone. By aggregating individual teleworkability scores at the commuting zone level, this measure captures regional variations in remote work potential and provides a comprehensive indicator of work-from-home exposure across local labor markets.

Specifically, the main WFH measure used in the regressions is constructed by counting the employed female population across all occupations, following Equation (1). This measure serves as the primary WFH indicator because employed females are a key demographic in examining the relationship between teleworkability and female labor force participation. By concentrating 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, offering valuable insights into the role of WFH potential in shaping their labor market outcomes.

After constructing the WFH measure for each commuting zone for each year, I calculate a pre-period invariant WFH measure by taking the mean of the WFH scores for each CZ over the years 2014 to 2019, designated as the pre-period. This provides a stable, time-invariant measure of work-from-home potential for each commuting zone during the pre-period. To ensure robustness, I also calculate the mean WFH measure over a shorter pre-period (2017 to 2019) and confirm that the results remain consistent. 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 commuting zones, as all zones are evaluated based on their pre-pandemic WFH potential, providing a robust foundation for analyzing the relationship between remote work opportunities and labor market outcomes.

3.1.2 Alternative Measures

In addition to the main WFH measure, which accounts for the entire employed female population across all occupations in each local labor market during the pre-period, I construct several alternative measures using slightly different definitions and sampling criteria. Specifically, the choice of population group (such as all individuals, employed individuals, or females only) and whether population weights are applied may lead to variations in the measured teleworkability of a local labor market.

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), which computes the weighted average teleworkability score at the commuting zone level. The unweighted measures (*wfh*, *wfh_emp*, and *wfh_fem*) refine this approach by focusing on specific subpopulations: *wfh* considers all individuals regardless of sex, *wfh_emp* includes only those currently in the labor force, and *wfh_fem* restricts the sample to females.

Meanwhile, *wfh_fem_wt* and *wfh_emp_fem_wt* use the same conceptual structure but replace "number of jobs" with "weighted jobs" based on person weights (*perwt*) and an adjustment factor (*afactor*). This results in the following weighted version of Equation (1):

$$\text{WFH Measure}_{c,t}^{(\text{weighted})} = \sum_o \left(\frac{\text{Weighted jobs}_{c,o,t}}{\sum_o \text{Weighted jobs}_{c,o,t}} \times \text{Teleworkability score}_o \right) \tag{2}$$

where

$$\text{Weighted jobs}_{c,o,t} = \text{Number of jobs}_{c,o,t} \times \text{perwt} \times \text{afactor}.$$

The variable *afactor* is from the crosswalk that indicates the fraction of a Public Use Microdata Area (PUMA)'s population that maps to a given Commuting Zone (CZ). By incorporating this adjustment factor, the weighted measures (*wfh_fem_wt* and *wfh_emp_fem_wt*) account for the differences in population distribution between PUMAs and CZs. This adjustment ensures that the teleworkability measure better reflects the true population totals within each CZ, rather than relying solely on unadjusted sample weights.

3.2 Empirical Specifications

The empirical strategy uses the geographic and temporal variation in the exposure to work-from-home (WFH) opportunities to identify its effects on the labor force participation of female individuals. Specifically, I estimate the following event study specification:

$$\begin{aligned}
\mathrm{Y}_{ict} = {} & \beta_0 + \beta_1 \cdot \mathit{Female}_i + \beta_2 \cdot (\mathit{Female}_i \times \mathrm{WFH}_{c,\mathrm{pre}}) \\
& + \sum_{j=2014, j\neq 2019}^{2023} \gamma_t \cdot (\mathit{Female}_i \times \mathrm{Year}_t) \\
& + \sum_{j=2014, j\neq 2019}^{2023} \delta_t \cdot (\mathit{Female}_i \times \mathrm{WFH}_{c,\mathrm{pre}} \times \mathrm{Year}_t) \\
& + \mathbf{X}'_{it}\beta + \phi_{ct} + \epsilon_{ict}
\end{aligned} \tag{3}$$

Here, Y_{ict} represents the labor force participation status of individual i in commuting zone c at time t. *Female* is a dummy variable indicating whether the individual i is female. WFHc, pre measures the pre-pandemic, time-invariant WFH potential of commuting zone c, calculated across the years 2014–2019. This variable is standardized to have a mean of 0 and a standard deviation of 1. 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.

The commuting zone-by-year fixed effects ϕ_{ct} account for baseline differences across commuting zones and any time-varying factors common to all individuals within a given commuting zone. These fixed effects absorb the direct effect of WFH potential $WFH_{c,pre}$, direct post-pandemic effects, and their two-way interaction $WFH_{c,pre} \times Post_t$. In the above equation, the "post" period is implicitly captured through the year indicators $Year_t$, which allow for time-specific effects relative to the 2019 baseline. 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 $Female_i \times WFH_{c,pre}$ 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 $Female_i \times WFH_{c,pre} \times Year_t$ 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.

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 commuting zones 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 summarize the average effect of WFH opportunities in the post-period, I estimate the following difference-in-differences specification:

$$\begin{aligned}
\mathrm{Y}_{ict} = &\alpha_0 + \alpha_1 \cdot \mathit{Female}_i + \alpha_2 \cdot (\mathit{Female}_i \times \mathrm{WFH}_{c,\mathrm{pre}}) \\
&+ \kappa \cdot (\mathit{Female}_i \times \mathit{Post}_t) \\
&+ \lambda \cdot (\mathit{Female}_i \times \mathrm{WFH}_{c,\mathrm{pre}} \times \mathit{Post}_t) \\
&+ \mathbf{X}'_{it}\beta + \tau_{ct} + \mu_{ict} \qquad (4)
\end{aligned}$$

Here, *Post* is an indicator denoting the post-pandemic period covering years of 2021 to 2023. The coefficients of interest, λ, captures the average effect of WFH potential on female labor force participation during the post-pandemic period. A positive and statistically significant λ would indicate that female individuals from commuting zones with higher exposure to WFH potential experienced relatively greater increases in labor force participation compared to their counterparts in commuting zones with lower WFH potential, after the onset of the pandemic. All the other variables are defined as in Equation (3). Standard errors are clustered similarly at the commuting zone-by-year level to account for potential correlation in the error term within commuting zones over time. This specification allows us to evaluate how the increase in WFH opportunities post-pandemic affected female labor force participation on average, conditional on commuting zone-level WFH potential and other individual-level controls.

Lastly, to better understand the effect of WFH opportunities on labor force participation in specific post-pandemic years, I estimate a difference-in-differences specification that allows for year-specific effects. This specification takes the following form:

$$\begin{aligned}
\mathrm{Y}_{ict} = {} & \alpha_0 + \alpha_1 \cdot \mathit{Female}_i + \alpha_2 \cdot (\mathit{Female}_i \times \mathrm{WFH}_{c,\mathrm{pre}}) \\
& + \kappa_1 \cdot (\mathit{Female}_i \times \mathit{2021}_t) \\
& + \kappa_2 \cdot (\mathit{Female}_i \times \mathit{2022}_t) \\
& + \kappa_3 \cdot (\mathit{Female}_i \times \mathit{2023}_t) \\
& + \lambda_1 \cdot (\mathit{Female}_i \times \mathrm{WFH}_{c,\mathrm{pre}} \times \mathit{2021}_t) \\
& + \lambda_2 \cdot (\mathit{Female}_i \times \mathrm{WFH}_{c,\mathrm{pre}} \times \mathit{2022}_t) \\
& + \lambda_3 \cdot (\mathit{Female}_i \times \mathrm{WFH}_{c,\mathrm{pre}} \times \mathit{2023}_t) \\
& + \mathbf{X}'_{it}\beta + \tau_{ct} + \mu_{ict}
\end{aligned} \tag{5}$$

Here, $\mathit{2021}_t$, $\mathit{2022}_t$, and $\mathit{2023}_t$ are indicators for the years 2021, 2022, and 2023, respectively. The coefficients of interest, λ_1, λ_2, and λ_3, estimate the effect of WFH potential in commuting zones on female labor force participation for each post-pandemic year individually. All other variables remain the same as previously defined. This specification provides a more granular view of how WFH potential influenced female labor force participation over time, allowing us to assess whether the effects vary across specific post-pandemic years.

4 Results

4.1 Effects on All Females

In Figure 2, I present the event study results of work-from-home (WFH) opportunities on female labor force participation. Specifically, the figure shows the coefficients and associated 95% confidence intervals estimated from Equation (3). These results provide insights into the dynamics of WFH opportunities on female labor force participation before and after the onset of the COVID-19 pandemic.

The figure highlights several important observations. First, there is no statistically significant evidence of pre-existing trends prior to the onset of the pandemic in 2020. This supports the parallel trends assumption, which is a critical requirement for the validity of the Differences-in-Differences (DiD) estimation. The coefficients for the pre-pandemic years (2014–2019) are small in magnitude and not statistically significant, indicating that female labor force participation was relatively stable before the widespread adoption of WFH.

Second, starting in 2020, the year COVID-19 disrupted labor markets and accelerated the adoption of remote work, female labor force participation began to rise. This upward trend continued through 2021, although the effect in that year was not statistically significant, showing only a gradual increase. Notably, there was a small drop in the effect size in 2022, which may be attributed to a temporary decrease in WFH opportunities as schools reopened and workplaces transitioned back to in-person operations. However, the overall post-pandemic trend remains positive. Importantly, in 2023, I observe a statistically significant and robust increase in female labor force participation, suggesting that the impact of WFH opportunities may have a delayed effect and has the potential to continue growing in the long term.

Table 3, columns (1) and (2), report the estimated effects of work-from-home opportunities on labor force participation for all female individuals. Specifically, Panel A presents the average effect of WFH opportunities, estimated using equation (4), while Panel B provides year-specific effects for the post-pandemic period, estimated using equation (5). Column (1) shows results without controls, whereas column (2) includes controls for additional covariates. The results are very similar, with the size slightly smaller when controls are included. The results indicate a significant and positive association between WFH opportunities and female labor force participation on average and in 2023. Since the WFH variable is standardized with a mean of 0 and a standard deviation of 1, a one-standard-deviation increase in work-from-home opportunities at the local labor market area (LMA) level is, on average, associated with a 0.32 percentage point increase in the likelihood of a female individual participating in the labor force. This positive effect of WFH opportunities is particularly pronounced in 2023, underscoring their sustained role in enhancing female labor force participation during the post-treatment period.

Although the effect in 2021 and 2022 is not statistically significant, it may have been mitigated by the pandemic's profound shocks to the labor market and women's disproportionate burden during this period. First, women were disproportionately affected by pandemic-related closures, as they are overrepresented in service industries that were severely disrupted. Second, school closures likely increased the burden of childcare responsibilities on women, further limiting their ability to participate in the labor force. Both factors may have mitigated the effect size observed in 2021 and 2022. By 2023, however, when WFH opportunities became more widespread and persistent, industries and service sectors reopened, and schools returned to in-person operations, the negative effects on women began to diminish. This allowed the benefits of WFH opportunities to become more prominent, leading to a significant and robust increase in female labor force participation.

This finding supports the hypothesis that WFH opportunities offer greater flexibility, enabling women to engage more actively in the labor force. It also sheds light on the resilience and steady growth in female labor force participation during and after the pandemic, suggesting that women may have adapted more swiftly to the evolving work environment compared to men. This underscores the pivotal role of WFH opportunities in shaping labor market dynamics.

4.2 Effects on Mothers

Examining the effects of WFH opportunities on mothers' labor force participation is particularly important due to the well-documented "motherhood penalty." Mothers often face unique challenges in balancing work and family responsibilities, which can lead to reduced labor force participation, lower earnings, and limited career advancement opportunities compared to their childless counterparts. These challenges are especially pronounced for mothers with young children, as children under the age of five typically require more intensive caregiving, making flexibility in work arrangements even more critical. In this section, I specifically analyze the effects on mothers, with a focus on two subgroups: (a) all mothers and (b) mothers with children under five years old. The model specification is identical to equation (3), with the only difference being that the sample is restricted to these two subgroups. By doing so, this analysis aims to shed light on how WFH opportunities may alleviate some of the barriers faced by mothers, particularly those with young children.

Figure 3 (a) presents the event study results for all mothers. The analysis shows no statistically significant evidence of pre-trend differences before the onset of the COVID-19 pandemic in 2020, which supports the parallel trends assumption. During the pandemic year of 2020, a positive shift in labor force participation is observed, although it is not statistically significant. The effect gradually grows stronger in the post-pandemic years, particularly in 2023, where a statistically significant and robust increase in labor force participation is evident. This suggests that WFH opportunities may have provided much-needed flexibility for mothers to re-enter or remain in the workforce as childcare burdens eased and workplaces adapted to more flexible arrangements.

For mothers with children under five years old, the event study results shown in Figure 3 (b) similarly demonstrate no significant pre-pandemic trends, further validating the model's assumptions. However, this subgroup appears to experience slightly larger fluctuations during the pandemic and recovery period. In 2020, the effect begins to increase, but it remains statistically insignificant. By 2022, a notable rise in labor force participation is observed, with a statistically significant and pronounced effect emerging in 2023. This pattern indicates that mothers with young children, who face higher caregiving demands, may have benefited disproportionately from the flexibility offered by WFH opportunities. The larger effect size in 2023 suggests a delayed yet meaningful impact as these mothers adapted to the evolving labor market conditions.

Table 3, columns (3) and (4), present the estimated effects of work-from-home (WFH) opportunities on labor force participation for mothers. Panel A reports the average effect of WFH opportunities, estimated using equation (4), while Panel B provides year-specific effects for the post-pandemic period, estimated using equation (5). Column (3) shows results without controls, whereas column (4) includes controls for additional covariates. The results indicate a significant and positive association between WFH opportunities and labor force participation among mothers on average and in 2023. A one-standard-deviation increase in WFH opportunities at the local labor market area level is associated with a 0.41 percentage point increase in the probability that a mother participates in the labor force. This suggests that the flexibility offered by WFH opportunities may be particularly beneficial for mothers balancing work and caregiving responsibilities, especially in the post-pandemic period when WFH opportunities became more persistent.

Table 3, columns (5) and (6), focus on the estimated effects of work-from-home (WFH) opportunities on labor force participation for mothers with children under five years old. As with previous columns, Panel A reports the average effect estimated using equation (4), and Panel B presents year-specific effects for the post-pandemic period based on equation (5). Column (5) shows results without controls, while column (6) includes additional covariates. The findings reveal a significant and robust association between WFH opportunities and labor force participation for this group, particularly in 2023. A one-standard-deviation increase in WFH opportunities at the LMA level corresponds to a 0.86 percentage point increase in the probability that mothers with young children participate in the labor force.

Notably, the average effect of WFH opportunities on mothers with children under five years old is nearly three times larger than the effect observed for all females and twice as large as the effect for all mothers. In 2023, this effect becomes even more pronounced, with the impact on mothers with young children being almost four times greater than for all females and three times greater than for all mothers. These findings highlight the crucial role of WFH opportunities in facilitating labor force participation among mothers, particularly those with young children who often face the greatest caregiving responsibilities. The significant increases observed in 2023 suggest that the widespread adoption of flexible work arrangements may continue to reduce structural barriers for mothers in the labor market, enabling them to balance work and family responsibilities more effectively and fostering greater inclusivity in workforce participation.

4.3 Heterogeneity Analysis

To better understand the nuanced effects of WFH opportunities on female labor force participation, this subsection examines heterogeneity across key demographic groups, including age, education, and race. 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. Analyzing these variations is critical to identifying which groups benefit the most—or the least—from the increased availability of remote work options. Specifically, I assess the differential impacts of WFH opportunities on labor force participation across age cohorts, educational attainment levels and racial or ethnic groups. 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.

4.3.1 Heterogeneity by Age Groups

Existing literature highlights that work-from-home 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. Younger individuals, particularly those in the early stages of their careers, may benefit more from WFH due to greater familiarity with digital tools and a higher capacity to adapt to remote work setups. In contrast, older individuals may face higher costs associated with setting up remote work arrangements and adjusting established work habits, which could make WFH less appealing or effective for them. These differences may be particularly pronounced for women, who often balance professional responsibilities with caregiving roles at different life stages. Understanding how these dynamics play out is crucial for identifying disparities in WFH benefits and tailoring policies to address them. Therefore, to better understand how WFH opportunities affect women across life stages, I analyze the effects on labor force participation for four primary working-age cohorts: 25–34, 35–44, 45–54, and 55–64.

Table 4.1 presents estimation results for all females across four various age groups. Panel A reports the average effect of WFH opportunities, estimated using equation (4), while Panel B provides year-specific effects for the post-pandemic period, estimated using equation (5). The results in Panel A reveal significant heterogeneity in the impact of WFH opportunities across age groups. For younger women aged 25–34, WFH opportunities are associated with a statistically significant average increase in labor force participation of 0.0052 ($p < 0.01$). This effect diminishes slightly as age increases, with a 0.0037 ($p < 0.05$) average increase observed for women aged 35–44 and a 0.0030 ($p < 0.05$) increase for those aged 45–54. For older women aged 55–64, however, WFH opportunities have no significant average effect, with an estimated coefficient of -0.0007. These findings suggest that younger women, who may be more technologically adept and adaptable to remote work, benefit more from WFH opportunities compared to their older counterparts, who might face higher adjustment costs or reduced incentives to participate in the labor force due to proximity to retirement.

Panel B provides year-specific effects, offering further insight into how the impact of WFH opportunities evolved over the post-pandemic period. In 2021, only the youngest age group (25–34) exhibits a statistically significant increase in labor force participation, with an effect size of 0.0049 ($p < 0.10$). For the other age groups, the estimates are small and statistically insignificant, reflecting the initial disruptions caused by the pandemic. In 2022, the effects for all age groups remain modest and insignificant, as conditions began returning to normal with the reopening of schools, the easing of pandemic-related restrictions, and the resurgence of return-to-office mandates. Consequently, WFH opportunities were not as widespread in 2022 compared to the peak levels observed in 2021. By 2023, however, the benefits of WFH opportunities become more pronounced. The effect size increases significantly for women aged 25–34 (0.0063, $p < 0.05$), aged 35–44 (0.0091, $p < 0.01$), and aged 45–54 (0.0044, $p < 0.05$), indicating a stronger and more sustained impact of WFH opportunities as they became more widespread and normalized in the labor market. For women aged 55–64, the effects remain statistically insignificant across all years, with a slightly negative effect (-0.0015) in 2023.

To further investigate the heterogeneous effects of WFH opportunities on female labor force participation, Table 4.2 presents results for mothers, while Table 4.3 focuses on mothers with children under 5 across four age groups. The findings reveal age-related differences in how mothers benefit from WFH opportunities. For mothers overall, the effects are most pronounced for younger age groups, particularly those aged 25–34 (0.0081, $p < 0.01$) and 35–44 (0.0045, $p < 0.05$), indicating that younger mothers are better positioned to leverage the flexibility of remote work to balance caregiving and labor market participation. The effect diminishes for mothers aged 45–54 (0.0030, $p < 0.10$) and becomes insignificant for those aged 55–64, who are less likely to have young children and may face fewer caregiving responsibilities. For mothers with children under 5, the effects are stronger and statistically significant for younger age groups, with notable gains for those aged 25–34 (0.0078, $p < 0.01$) and 35–44 (0.0089, $p < 0.01$). Even mothers aged 45–54 exhibit significant increases (0.0170, $p < 0.01$), highlighting the critical role of WFH in supporting this subgroup's ability to balance intense caregiving demands. Notably, for mothers aged 55–64, the effects are not meaningful as they are less likely to have young children.

Overall, the findings highlight a clear age gradient in the benefits of WFH opportunities for female labor force participation. Younger women consistently exhibit the largest and most significant increases, demonstrating that they are better positioned to leverage the flexibility and productivity gains associated with remote work. This trend is particularly pronounced for mothers, especially those with young children, who benefit significantly from the ability to balance caregiving responsibilities with labor market participation. In contrast, older women appear less responsive to these opportunities, likely due to higher adjustment costs, reduced incentives to remain in the labor force as they approach retirement, or the absence of young children requiring intensive caregiving. These results underscore the importance of tailoring policies and workplace initiatives to address the unique needs of different demographic groups, particularly by supporting younger women and mothers in maximizing the benefits of WFH arrangements while considering strategies to engage older women who may face distinct challenges in adopting remote work.

4.3.2 Heterogeneity by Educational Groups

Educational attainment is a key factor influencing labor market outcomes, particularly in determining how individuals adapt to and benefit from work-from-home (WFH) opportunities. Highly educated individuals often possess greater access to digital tools, technological proficiency, and job roles that are more conducive to remote work. Conversely, individuals with lower levels of education may face structural barriers, such as a higher prevalence of manual or location-dependent jobs and limited access to the necessary infrastructure for remote work. For women, these differences are often compounded by caregiving responsibilities and their significant representation in female-dominant occupations and service industries, both of which further shape how WFH opportunities are utilized across educational groups. To explore this, I examine the effects of WFH opportunities on female labor force participation across two educational groups: those with lower educational attainment (defined as high school or less) and those with higher educational attainment (defined as college degree or higher). Additionally, I analyze heterogeneity within these groups for mothers and mothers with children under 5.

Table 5 presents the estimation results for both low and high educational groups. Panel A reports the average effect of WFH opportunities, while Panel B provides year-specific effects for the post-pandemic period. The findings reveal important disparities in how WFH impacts female labor force participation across educational groups. Among women with lower educational attainment, WFH opportunities are associated with a modest but significant average increase in labor force participation (0.0040, $p < 0.05$), with similar effects for mothers (0.0039, $p < 0.05$). However, for mothers with children under 5, the effect is not significant, suggesting that the caregiving challenges for this subgroup may limit the benefits of WFH opportunities despite the flexibility it offers.

In contrast, for women with higher educational attainment, the effects vary more widely by subgroup. For all women in this group, the average effect is smaller and not statistically significant (0.0021), but the effects are significant and larger for mothers (0.0034, $p < 0.10$) and particularly for mothers with children under 5 (0.0081, $p < 0.01$). These findings highlight the value of WFH arrangements in enabling highly educated mothers, especially those with young children, to balance their dual responsibilities.

Panel B reveals how these effects evolved over time. For women with lower education, the year-specific effects are minimal until 2022, when mothers experience a modest but statistically significant increase in labor force participation (0.0052, $p < 0.10$). By 2023, the impact becomes more pronounced, with a notable rise for all low-education women (0.0056, $p < 0.05$) and mothers with children under 5 (0.0103, $p < 0.05$), suggesting a delayed yet growing influence of WFH opportunities as remote work became more normalized. For women with higher education, the year-specific effects in 2023 are similarly significant, with the largest increases observed for mothers (0.0065, $p < 0.05$) and mothers with children under 5 (0.0168, $p < 0.01$). This pattern highlights the continued integration of remote work into roles typically held by highly educated women, especially those balancing intensive caregiving responsibilities.

Overall, the findings demonstrate that educational attainment plays a critical role in shaping how women benefit from WFH opportunities. While WFH offers advantages to women across all educational levels, the benefits are most pronounced for highly educated mothers, particularly those with young children. In contrast, women with lower educational attainment experience relatively stable—or slightly diminished—gains when transitioning from all females to mothers and then to mothers with children under 5, highlighting additional constraints in fully leveraging remote work. Conversely, the effects for highly educated women increase markedly from the broader sample to mothers and reach their peak for mothers with young children. This divergence underscores the amplifying role of education in enhancing the advantages of remote work, particularly for mothers balancing intensive caregiving demands, while also highlighting the structural barriers faced by women with lower educational attainment.

4.3.3 Heterogeneity by Race Groups

Understanding the impact of work-from-home (WFH) opportunities requires examining how labor market dynamics differ across racial and ethnic groups. These differences are shaped by historical inequities, occupational clustering, and varying levels of access to flexible work arrangements. Intersecting factors such as caregiving responsibilities, systemic barriers, workplace policies, and cultural factors further 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 force participation across four racial groups: White, Black, Hispanic, and Asian women. Subgroup analyses are also conducted for mothers and mothers with children under 5 within each racial category.

Table 6 presents the estimation results for the racial groups. The findings reveal notable disparities in how WFH opportunities affect female labor force participation across these groups. Among White women, the average effects are significant and grow substantially from the broader sample to mothers, with the largest benefits observed for mothers with children under 5. This suggests that WFH opportunities provide meaningful flexibility for White women, particularly those balancing work with intensive caregiving responsibilities. For Black and Hispanic women, however, the effects are less consistent. While there are some gains for mothers with young children, the overall average effects are smaller and often insignificant, highlighting potential barriers to accessing remote work in these populations. Asian women also exhibit limited benefits, with only minor increases in labor force participation across all subgroups.

These patterns underscore how structural inequalities and occupational disparities intersect with WFH opportunities. For White women, who are more likely to hold remote-work-compatible jobs, WFH provides a clear pathway to balancing caregiving demands with labor market participation. In contrast, Black and Hispanic women face greater barriers, likely due to overrepresentation in roles with limited remote work potential and additional challenges such as access to technology or flexible work policies. Asian women, while often employed in high-skill roles, may encounter cultural or systemic factors that moderate the uptake or effectiveness of WFH opportunities.

Overall, the results emphasize the importance of considering racial and ethnic heterogeneity in the design of remote work policies. While WFH has the potential to reduce caregiving barriers and enhance labor force participation, its benefits are not equally distributed across racial groups. Policies that address structural barriers, improve access to remote work infrastructure, and support women in occupations less conducive to WFH are critical for ensuring that all women, regardless of race, can fully benefit from the flexibility and opportunities afforded by remote work arrangements.

4.4 Robustness Analysis

To ensure the validity and reliability of the findings, I conduct a series of robustness checks to address potential concerns about measurement, methodology, and data construction. These analyses aim to verify whether the observed effects of work-from-home (WFH) opportunities on female labor force participation are consistent across alternative specifications and data handling approaches. Specifically, I examine the robustness of the results by using a shorter period to define WFH measures, employing several alternative WFH measures, incorporating person weights into the regression models, using the last year's residence to account for potential mobility in the presence of work-from-home opportunities, and the use of six-digit occupation codes for greater occupational specificity. These checks collectively strengthen the confidence in the conclusions by demonstrating their stability under varying conditions and assumptions.

4.4.1 Robustness Analysis Using a Shorter-Period Measure

In the main analysis, I average teleworkability scores for each commuting zone over a broader pre-period (2014–2019) to capture a stable, pre-pandemic measure of work-from-home (WFH) potential. However, this six-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 2017–2019, 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 (DiD) framework. Moreover, comparing the results from this shorter window to those obtained using the 2014–2019 average allows me to verify that any observed effects are not driven by the choice of baseline period.

Figure A1 replicates the event study analysis for all females using the shorter pre-period (2017–2019) to construct the WFH measure, following the same method as in the main analysis. The pre-pandemic coefficients continue to show no discernible pattern or statistically significant differences, affirming the parallel trends assumption. Moreover, the post-pandemic trends closely mirror those observed in Figure 2, suggesting that relying on a narrower baseline period does not fundamentally alter the trajectory of the estimated effects.

Figure A2 applies the shorter pre-period measure to the subgroup of mothers while maintaining the same empirical framework, again validating the parallel trends assumption. The estimated post-period coefficients follow a pattern similar to that of Figure 3, indicating that changes in the baseline pre-period do not substantially affect the overall trends or magnitudes of the effects.

Table A1 replicates the analysis using the shorter pre-period (2017–2019) WFH measure and confirms that the findings are highly consistent with those reported for the longer pre-period (2014–2019). As in Table 3, all three models in Table A1 include controls, ensuring a direct comparison with the main specification. Across the three columns—All Females, Mothers, and Mothers with Children Under 5—the average effect (Panel A) remains positive and statistically significant, closely mirroring the overall pattern observed in Table 3. Moreover, the year-specific results (Panel B) again indicate a stronger effect in 2023, suggesting that WFH opportunities become increasingly beneficial for female labor force participation over time.

The robustness analysis using the shorter pre-period (2017–2019) measure confirms that the main findings are consistent and reliable. The results align closely with those obtained using the broader pre-period (2014–2019), with no significant differences in pre-pandemic trends and similar post-pandemic patterns. This consistency underscores that the observed effects of WFH opportunities on female labor force participation are not driven by the choice of baseline years. By validating the findings under an alternative specification, the analysis provides additional evidence of their robustness, reinforcing confidence in the primary conclusions.

4.4.2 Robustness Analysis Using Alternative WFH Measures

In addition to the primary work-from-home (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. Specifically, the choice of population (e.g., all individuals, only employed individuals, or only females) and the use of population weights may affect the measured teleworkability of a local labor market. 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 A3 presents the event study results using alternative WFH measures, with each row representing a different measure and each column corresponding to one of three subgroups: all females, mothers, and mothers with children under 5. Across all 15 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 DiD framework. The coefficients for the pre-pandemic years (2014–2019) are small and statistically insignificant, indicating stable female labor force participation prior to widespread WFH adoption. Second, beginning in 2020, labor force participation starts to rise, particularly in 2023, where a statistically significant and robust increase is observed across all subgroups. This post-pandemic trend reflects the growing impact of WFH opportunities on enabling labor market engagement.

Importantly, the patterns are consistent across the three subgroups— all females, mothers, and mothers with children under 5. While the magnitude of effects varies slightly, the overall trends remain similar: stable pre-pandemic participation, an initial rise during 2020, and a more pronounced effect in 2023. These findings suggest that WFH opportunities provided comparable benefits across demographic groups, with mothers and mothers with young children showing slightly larger gains, likely due to the increased flexibility WFH offers in balancing work and caregiving responsibilities.

These results reinforce the robustness of the main findings by showing that the trends remain stable across various definitions and adjustments. The inclusion of weighted measures, which account for survey design and accurately reflect population distributions, further validates the results by ensuring they are not influenced by inconsistencies in population mapping. This robustness analysis provides additional confidence in the reliability of the conclusions, demonstrating that the positive impact of WFH opportunities on female labor force participation is a generalizable and meaningful phenomenon, regardless of how WFH measure is defined or calculated.

4.4.3 Robustness Analysis Using Weighted Regressions

In the main analysis, person weights (*perwt*) were not applied in the regressions for several reasons. First, the treatment variable (e.g., exposure to WFH opportunities) and the outcome (e.g., labor force participation) are designed to be independent of the ACS sampling design. Since this study focuses on estimating causal effects rather than making population-level inferences, unweighted regressions are sufficient for capturing the DiD effects within the sample. 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, the large sample size of the ACS ensures that unweighted estimates remain unbiased and consistent while providing precise coefficients. Fourth, the Census updates PUMA definitions every 10 years, and the data for 2022 and 2023 rely on a new PUMA definition, which could complicate the consistent application of weights across the entire study period.

Nonetheless, it is crucial to test the robustness of the results by incorporating weights. The *perwt* variable in the ACS accounts for the sampling design and indicates how many individuals in the U.S. population are represented by a given person in the sample. Using weights is a good approach to maintaining representativeness, especially when generalizing the impact of WFH opportunities on female labor force participation to the broader population.

Figure A4 presents the event study results examining the effects of work-from-home opportunities on labor force participation across three subgroups: (a) all females, (b) mothers, and (c) mothers with children under 5, using weighted regressions to account for the ACS sampling design. The findings demonstrate that the parallel trends assumption holds consistently across all subgroups, with no statistically significant pre-existing trends observed before 2020, further validating the robustness of the DiD framework. For all females (panel a), a slight decline in labor force participation is observed in 2021 compared to the unweighted results, which may be attributed to the inclusion of weights that adjust for the representation of underrepresented groups in the sample. This adjustment likely accounts for more granular variation across demographic and geographic distributions. For mothers (panel b) and mothers with children under 5 (panel c), the trends align closely with the unweighted analysis, showing no significant deviations and maintaining similar post-pandemic trajectories. In particular, the positive effects of WFH opportunities on labor force participation remain strong in the post-pandemic years, with significant increases observed in 2023.

Table A2 presents the regression results from the robustness analysis using weighted regressions. Panel A reports the average treatment effect of WFH opportunities on female labor force participation, estimated using equation (4), while Panel B provides year-specific effects based on equation (5). The results closely align with those reported in Table 3 , which uses unweighted regressions with controls. The estimates remain largely consistent, indicating that the observed effects are robust to the inclusion of weights. A negligible decrease in one or two estimates is observed, which may be attributed to the broader population representation achieved by incorporating weights. The positive and statistically significant effects of WFH opportunities on female labor force participation, particularly in 2023, remain evident across all subgroups— all females, mothers, and mothers with children under 5.

These findings underscore the robustness of the main results and confirm that the observed relationship between WFH opportunities and female labor force participation is not sensitive to the inclusion of weights. By incorporating the *perwt* variable, the analysis enhances the representativeness of the results, ensuring that the estimates reflect the broader population while maintaining consistency with the unweighted findings. This robustness analysis reinforces the reliability of the causal estimates and bolsters the generalizability of the conclusions, demonstrating that the positive impact of WFH opportunities on female labor force participation persists across different methodological approaches.

4.4.4 Robustness Analysis Using Previous Residence

One 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 commuting zone (CZ) level already accounts for this concern. CZs are clusters of U.S. counties defined based on residence-to-work commuting data, characterized by strong within-cluster and weak between-cluster commuting ties. This aggregation ensures that the WFH measure captures regional labor market conditions rather than individual residential changes.

To further validate the results, this section conducts a robustness analysis using individuals' previous year residence to disentangle the true impact of WFH opportunities from potential mobility-driven confounders. The ACS data includes each person's previous year residence at both the PUMA and state levels. As in the main analysis, I will construct the WFH measure at the commuting zone level; however, in this case, the measure will reflect individuals' exposure to WFH opportunities in the commuting zones where they resided in the previous year. By incorporating the residence from one year prior, this analysis ensures that the observed effects are not driven by recent relocations but instead reflect the true impact of WFH on labor force participation.

Table A3 presents the regression results from the robustness analysis using individuals' previous year residence. The findings are consistent with those from the main analysis, confirming the robustness of the observed effects of WFH opportunities on female labor force participation. The results show positive and statistically significant effects across all subgroups, with the impact being particularly notable for mothers with young children. Year-specific effects further highlight that the influence of WFH opportunities strengthens over time, particularly in the post-pandemic period. These results validate that the observed effects are not confounded by recent relocations and provide additional support for the causal interpretation of WFH opportunities in enabling female labor force participation.

However, there are some limitations. The significance level for one or two estimates is slightly lower, and the sample size is reduced compared to the main analysis. These differences likely stem from data limitations related to how previous residence is reported. Although the ACS reports last year's residence using the *migpuma1* variable, this system differs fundamentally from the *puma* variable used for current residence. *migpuma1* represents broader geographic areas based on *puma* boundaries. The *puma*-to-*migpuma1* crosswalk defines *migpuma1* boundaries using *puma* boundaries, but the relationship is one-directional: each *migpuma1* corresponds exactly to one or more *pumas* and to one or more counties or county equivalents. Therefore, since a single *migpuma1* can encompass multiple residence *pumas*, it is often impossible to map a *migpuma1* to a single residence *puma* with precision.[5]

[5] For example, Alabama *migpuma1* = 00490 corresponds to Alabama *pumas* 00401, 00402, 00403, and

Additionally, individuals who did not reside in the United States or Puerto Rico one year ago, or who resided in Puerto Rico one year ago and now reside in the U.S., are excluded from the sample. These data limitations and the merging process inevitably lead to some data loss, slightly reducing the precision of the estimates. Nevertheless, the analysis provides valuable evidence supporting the robustness of the results and highlights the sustained impact of WFH opportunities on female labor force participation.

4.4.5 Robustness Analysis Using 6-Digit Occupation Codes

In this study, I follow the methodology of Gupta et al. (2022) to construct work-from-home exposure measures at the local labor market level. Similar to their analysis, I aggregate the WFH scores to the 2-digit occupation level and assign each individual the corresponding score based on their 2-digit occupation code. However, the original WFH scores developed by Dingel and Neiman (2020) are more granular, utilizing 8-digit occupation codes. To ensure the robustness of my results, it is crucial to examine whether the findings hold when WFH scores are assigned at a more detailed occupational level.

Since ACS occupational classifications are available at the 6-digit level, this robustness analysis aggregates the 8-digit WFH scores to the 6-digit level and directly links them to each individual's reported occupation. This approach allows for a more precise assignment of WFH exposure and serves as a rigorous check on the validity of the main findings.

Table A4 displays the findings from the robustness check that uses 6-digit occupation codes to assign work-from-home (WFH) scores. Panel A summarizes the average impacts of WFH opportunities on female labor force participation (LFP), while Panel B breaks down the year-specific effects for 2021, 2022, and 2023. These results largely mirror those presented in Table 3, which relied on 2-digit occupation codes and included controls. The similarity in estimates reinforces the robustness of the original analysis to this more detailed occupational classification.

A noteworthy distinction arises for Mothers with children under 5 in 2021, where the effect becomes both positive and statistically significant when using 6-digit codes, compared to an insignificant result in the main analysis. This suggests that utilizing finer occupational detail may provide additional sensitivity to capture early impacts of WFH opportunities on specific subgroups. Importantly, the overall positive and statistically significant effects,

00501, indicating that the area of *migpuma1* = 00490 is defined as the combination of the areas of these four *pumas*. Someone in the 2023 ACS who resided in any of these four *pumas* in 2022 will have *migpuma1* = 00490. This does not mean that everyone currently residing in one of these four *pumas* all lived in the same migration *puma* in the previous year. For example, someone residing in the city of Huntsville, Alabama (*puma* 00403) in 2023 may have resided in Tuscaloosa, Alabama in 2022 and will be assigned the corresponding *migpuma1* value for this city (01200) in the 2023 ACS.

particularly for 2023, remain consistent across all subgroups—All Females, Mothers, and Mothers with children under 5. This consistency underscores the validity of the findings while highlighting an important nuance for mothers of young children.

5 Conclusion and Policy Implications

This paper examines the long-term effects of the accelerated adoption of WFH opportunities brought about by the COVID-19 pandemic on female labor force participation. By leveraging a Differences-in-Differences and event study design, the analysis exploits variation at the local labor market area (LMA) level, comparing individuals in LMAs with higher WFH potential to those in areas with lower WFH opportunities.

The results reveal that WFH opportunities have a significant and positive impact on female labor force participation. A one-standard-deviation increase in WFH opportunities at the LMA level is associated with a 0.32 percentage point increase in the probability of a female individual participating in the labor force. The effects are even more pronounced for mothers and mothers with young children, who often face greater caregiving demands. For mothers, a one-standard-deviation increase in WFH opportunities corresponds to a 0.41 percentage point increase in the probability of labor force participation. The impact is largest for mothers with children under 5, with a one-standard-deviation increase in WFH opportunities resulting in a 0.86 percentage point increase in the probability of labor force participation. These findings highlight the crucial role of WFH in enabling women, particularly those balancing work and caregiving responsibilities, to remain in or re-enter the workforce. Robustness checks using alternative WFH measures, weighted regressions, and adjustments for data consistency confirm the stability of these results, reinforcing their reliability.

From a policy perspective, these findings highlight the transformative potential of WFH to promote inclusivity in the labor market. Policies should prioritize flexible work arrangements, subsidized childcare, and targeted training programs to support younger women and mothers with young children, who benefit most from WFH opportunities. For older women, initiatives such as subsidized technology training, mentorship programs, or part-time remote roles can address higher adjustment costs and encourage participation. Enhancing access to remote work for women with lower educational attainment requires addressing structural barriers like occupational segregation and limited digital infrastructure, alongside investments in upskilling programs and equitable workplace policies. Moreover, significant racial and ethnic disparities in WFH benefits call for targeted measures to reduce occupational clustering, improve technology access, and foster workplace flexibility for underrepresented groups. These efforts are essential to ensure WFH opportunities promote diversity, inclusivity, and equitable labor market participation across all demographics.

However, this study acknowledges certain limitations. The latest ACS data available ends in 2023, and it remains to be seen how WFH evolves in 2024 and beyond, particularly as workplaces continue to adapt to a post-pandemic norm. Additionally, the Census updates PUMA definitions every 10 years, and the transition to new PUMA boundaries in 2022 and 2023 may introduce inconsistencies with earlier data. Future research should prioritize constructing coherent commuting zone definitions to address these challenges and monitor how WFH continues to shape labor market outcomes. Despite these limitations, this study highlights the potential of WFH to foster resilience and growth in female labor force participation, offering a pathway to greater flexibility and inclusivity in the evolving labor market.

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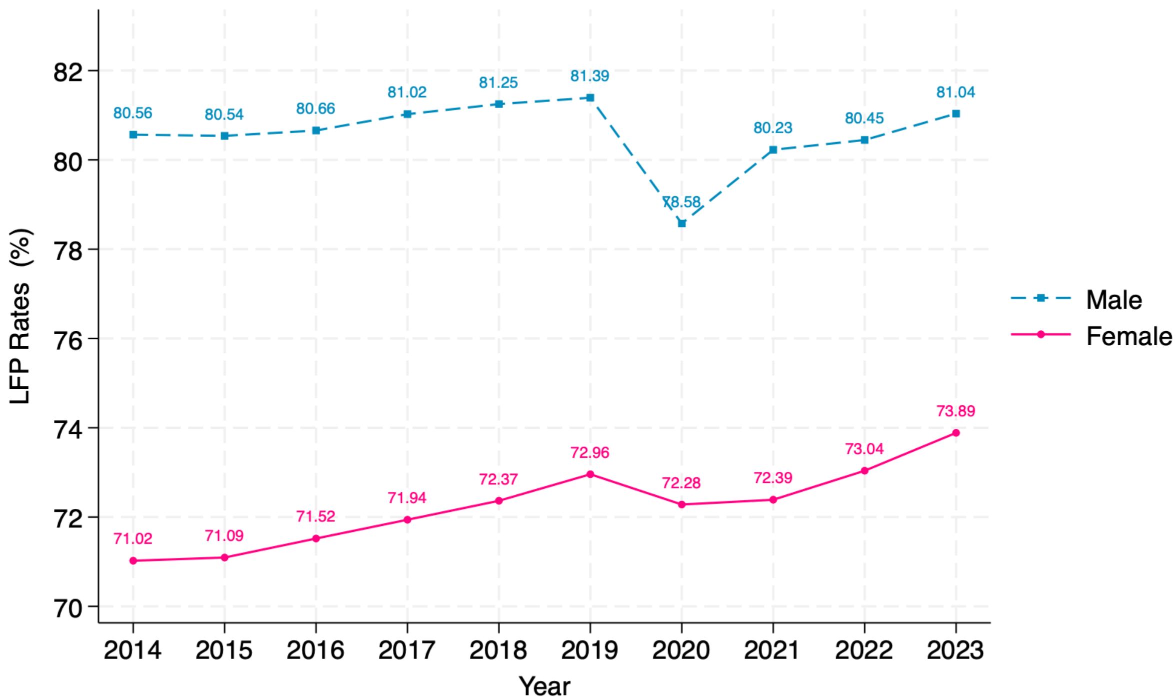
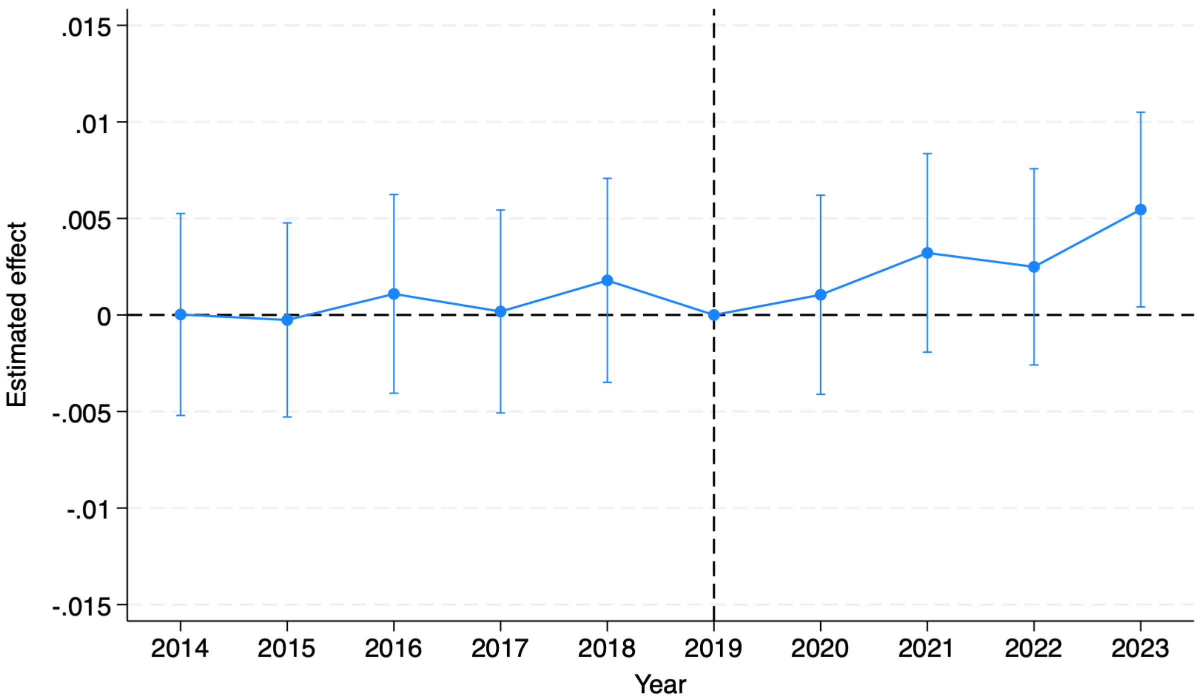
6 Figures and Tables

Figure 1: Labor Force Participation Rates by Sex



Notes: This figure presents the labor force participation rates from 2014 to 2023, separately for males and females. The data source is the American Community Survey (ACS) and reflects the working-age population (ages 15 to 64) in the United States. The values are expressed as percentages and are not seasonally adjusted.

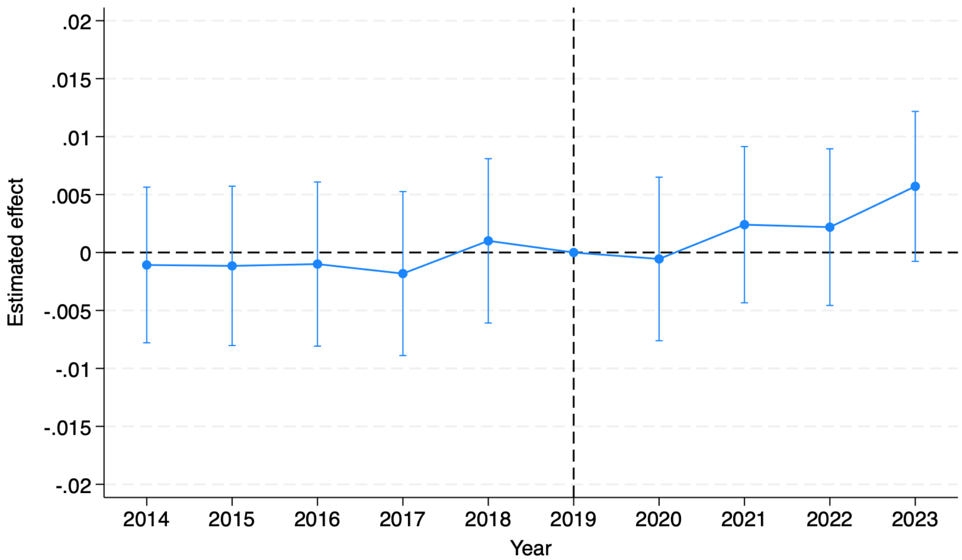
Figure 2: Effects of WFH Opportunities on Female LFP



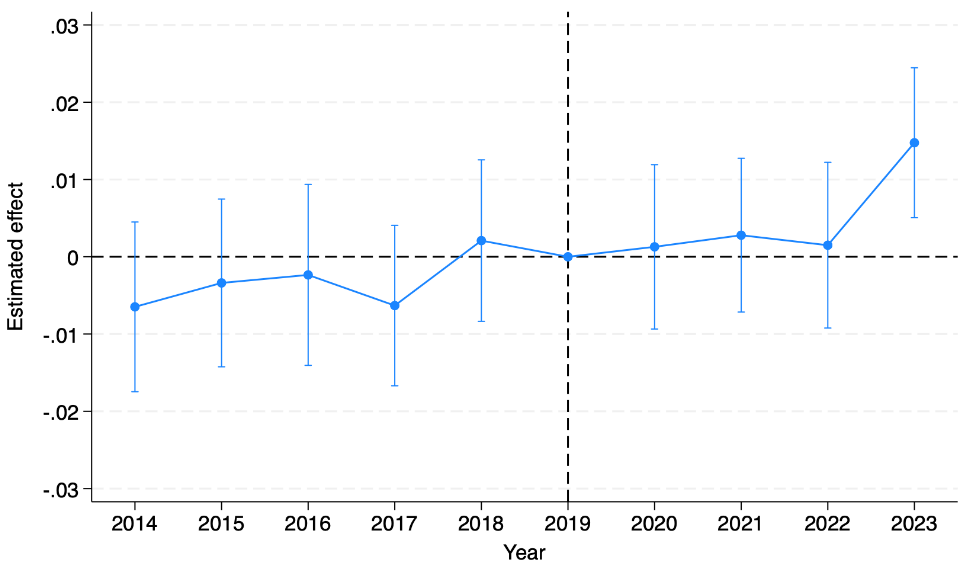
Notes: This figure illustrates the effect of individual-level exposure to work-from-home (WFH) opportunities on the labor force participation of female individuals. It displays the coefficients and corresponding 95% confidence intervals for the triple interaction terms from equation (3). The year 2019, 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 commuting zone-by-year level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure 3: Effects of WFH Opportunities on Mothers

(a) Mothers



(b) Mothers with children under 5



Notes: This figure compares the effects of individual-level exposure to work-from-home (WFH) opportunities on labor force participation for (a) mothers and (b) mothers with children under 5 years old. The model specification is identical to Equation (3), with the only difference being that the sample is restricted to mothers in (a) and mothers with children under 5 in (b). 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 commuting zone-by-year level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Table 1: Summary Statistics

Variable	Mean	SD	Observations
WFH Measure	0.472	0.030	21,328,755
Labor Force Participation	0.752	0.432	21,328,755
Female	0.516	0.500	21,328,755
Male	0.484	0.500	21,328,755
White	0.759	0.427	21,328,755
Black	0.077	0.266	21,328,755
Hispanic	0.118	0.323	21,328,755
Asian	0.046	0.209	21,328,755
Married	0.659	0.474	21,328,755
Children Under 5	0.125	0.330	21,328,755
Low Education	0.438	0.496	21,328,755
High Education	0.562	0.496	21,328,755
Age 25-34	0.217	0.413	21,328,755
Age 35-44	0.225	0.417	21,328,755
Age 45-54	0.252	0.434	21,328,755
Age 55-64	0.306	0.461	21,328,755

Notes: The table above presents the summary statistics for the outcome and control variables used in the analysis from 2014 to 2023. The Work-From-Home (WFH) measure reported here is not standardized and represents the average for the pre-COVID period, spanning 2014 to 2019, at the commuting zone level. Low education is defined as an educational attainment level of high school or below, while high education refers to college-level attainment and above. Individuals with military-specific occupations are excluded from the sample.

Table 2: WFH Measures Summary Statistics

Variable	Mean	SD	25th Percentile	75th Percentile	Unique N	Total N
wfh_main	0.472	0.030	0.450	0.492	528	21,328,755
wfh	0.398	0.046	0.362	0.428	528	21,328,755
wfh_emp	0.402	0.046	0.365	0.431	528	21,328,755
wfh_fem	0.466	0.032	0.444	0.487	528	21,328,755
wfh_fem_wt	0.454	0.031	0.432	0.474	528	21,328,755
wfh_emp_fem_wt	0.460	0.030	0.438	0.478	528	21,328,755

Notes: The table above presents the summary statistics for the WFH measures used in the analysis. These measures, constructed at the commuting zone level for the pre-COVID period (2014–2019), vary by population scope and weighting methodology. The primary measure, *wfh_main*, captures teleworkability for employed females, reflecting their key role in this study's focus on female labor force participation. The unweighted measures include *wfh*, considering all individuals; *wfh_emp*, including only those in the labor force; and *wfh_fem*, restricting to females. All unweighted measures are constructed based on Equation (1), which computes the weighted average teleworkability score for commuting zones. Weighted measures (*wfh_fem_wt* and *wfh_emp_fem_wt*) follow the same structure but use the adjusted equation shown in Equation (2), incorporating person weights (*perwt*) and the adjustment factor *afactor* to ensure that PUMA-to-CZ population distributions are accurately reflected.

Table 3: Effects of WFH Opportunities on Female LFP

	(1) All Females	(2) All Females	(3) Mothers	(4) Mothers	(5) Mothers children 5	(6) Mothers children 5
Panel A: Average Effect						
2021 - 2023	0.0034***	0.0032**	0.0045**	0.0041**	0.0090***	0.0086***
	(0.0013)	(0.0013)	(0.0018)	(0.0017)	(0.0026)	(0.0025)
Panel B: Year-Specific Effects						
2021	0.0030	0.0027	0.0035	0.0031	0.0053	0.0051
	(0.0020)	(0.0020)	(0.0027)	(0.0026)	(0.0037)	(0.0036)
2022	0.0021	0.0020	0.0032	0.0029	0.0039	0.0038
	(0.0020)	(0.0019)	(0.0027)	(0.0026)	(0.0043)	(0.0041)
2023	0.0051**	0.0049***	0.0068***	0.0064***	0.0181***	0.0171***
	(0.0020)	(0.0019)	(0.0025)	(0.0024)	(0.0035)	(0.0034)
Controls	No	Yes	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	21328755	21328755	9993925	9993925	2660791	2660791

Notes: Panel A reports results from estimating equation (4), and Panel B presents results from equation (5). The dependent variable across all models is labor force participation. Standard errors are clustered at the commuting zone-by-year level and are shown in parentheses. All models include commuting zone-by-year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.1: Effects of WFH Opportunities on Female LFP: Heterogeneity by Age Groups for All Females

	(1) Age 25-34	(2) Age 35-44	(3) Age 45-54	(4) Age 55-64
Panel A: Average Effect				
2021 - 2023	0.0052***	0.0037**	0.0030**	-0.0007
	(0.0018)	(0.0017)	(0.0013)	(0.0013)
Panel B: Year-Specific Effects				
2021	0.0049*	-0.0005	0.0028	0.0017
	(0.0028)	(0.0026)	(0.0023)	(0.0021)
2022	0.0043	0.0024	0.0019	-0.0024
	(0.0026)	(0.0028)	(0.0019)	(0.0019)
2023	0.0063**	0.0091***	0.0044**	-0.0015
	(0.0027)	(0.0023)	(0.0021)	(0.0022)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
N	4638128	4793062	5368907	6528658

Notes: The table presents estimation results for all females across various age groups. Panel A reports results from estimating equation (4), and Panel B presents results from equation (5). The dependent variable across all models is labor force participation. Standard errors are clustered at the commuting zone-by-year level and are shown in parentheses. All models include commuting zone-by-year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.2: Effects of WFH Opportunities on Female LFP: Heterogeneity by Age Groups for Mothers

	(1) Age 25-34	(2) Age 35-44	(3) Age 45-54	(4) Age 55-64
Panel A: Average Effect				
2021 - 2023	0.0081***	0.0045**	0.0030*	-0.0007
	(0.0023)	(0.0020)	(0.0018)	(0.0020)
Panel B: Year-Specific Effects				
2021	0.0075**	-0.0010	0.0021	0.0043
	(0.0031)	(0.0032)	(0.0031)	(0.0029)
2022	0.0034	0.0039	0.0034	-0.0011
	(0.0039)	(0.0031)	(0.0024)	(0.0029)
2023	0.0138***	0.0105***	0.0035	-0.0056
	(0.0032)	(0.0027)	(0.0027)	(0.0035)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
N	2123951	3380675	2892992	1596307

Notes: The table presents estimation results for all **mothers** across various age groups. Panel A reports results from estimating equation (4), and Panel B presents results from equation (5). The dependent variable across all models is labor force participation. Standard errors are clustered at the commuting zone-by-year level and are shown in parentheses. All models include commuting zone-by-year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.3: Effects of WFH Opportunities on Female LFP: Heterogeneity by Age Groups for Mothers with Children under 5

	(1) Age 25-34	(2) Age 35-44	(3) Age 45-54	(4) Age 55-64
Panel A: Average Effect				
2021 - 2023	0.0078***	0.0089***	0.0170***	0.0561*
	(0.0028)	(0.0028)	(0.0060)	(0.0311)
Panel B: Year-Specific Effects				
2021	0.0047	0.0034	0.0328***	0.0613
	(0.0038)	(0.0042)	(0.0094)	(0.0495)
2022	0.0045	0.0038	-0.0130	0.0534
	(0.0047)	(0.0041)	(0.0090)	(0.0423)
2023	0.0146***	0.0195***	0.0312***	0.0537
	(0.0041)	(0.0036)	(0.0100)	(0.0437)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes
N	1504242	1021445	122080	10984

Notes: The table presents estimation results for all **mothers with children under 5** across various age groups. Panel A reports results from estimating equation (4), and Panel B presents results from equation (5). The dependent variable across all models is labor force participation. Standard errors are clustered at the commuting zone-by-year level and are shown in parentheses. All models include commuting zone-by-year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effects of WFH Opportunities on Female LFP: Heterogeneity by Educational Groups

	(1) Low Edu all females	(2) Low Edu mothers	(3) Low Edu children 5	(4) High Edu all females	(5) High Edu mothers	(6) High Edu children 5
Panel A: Average Effect						
2021 - 2023	0.0040**	0.0039**	0.0038	0.0021	0.0034*	0.0081***
	(0.0016)	(0.0019)	(0.0027)	(0.0013)	(0.0019)	(0.0030)
Panel B: Year-Specific Effects						
2021	0.0032	0.0023	0.0001	0.0019	0.0033	0.0053
	(0.0023)	(0.0027)	(0.0037)	(0.0021)	(0.0030)	(0.0045)
2022	0.0032	0.0052*	0.0014	0.0006	0.0006	0.0023
	(0.0024)	(0.0030)	(0.0044)	(0.0019)	(0.0029)	(0.0046)
2023	0.0056**	0.0042	0.0103**	0.0038**	0.0065**	0.0168***
	(0.0024)	(0.0028)	(0.0043)	(0.0019)	(0.0027)	(0.0041)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	9341938	4164419	952316	11986817	5829506	1708475

Notes: The table presents estimation results for all females, mothers and mothers with children under 5 across various educational groups. Low education is defined as an educational attainment level of high school or below, while high education refers to college-level attainment and above. Panel A reports results from estimating equation (4), and Panel B presents results from equation (5). The dependent variable across all models is labor force participation. Standard errors are clustered at the commuting zone-by-year level and are shown in parentheses. All models include commuting zone-by-year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effects of WFH Opportunities on Female LFP: Heterogeneity by Race Groups

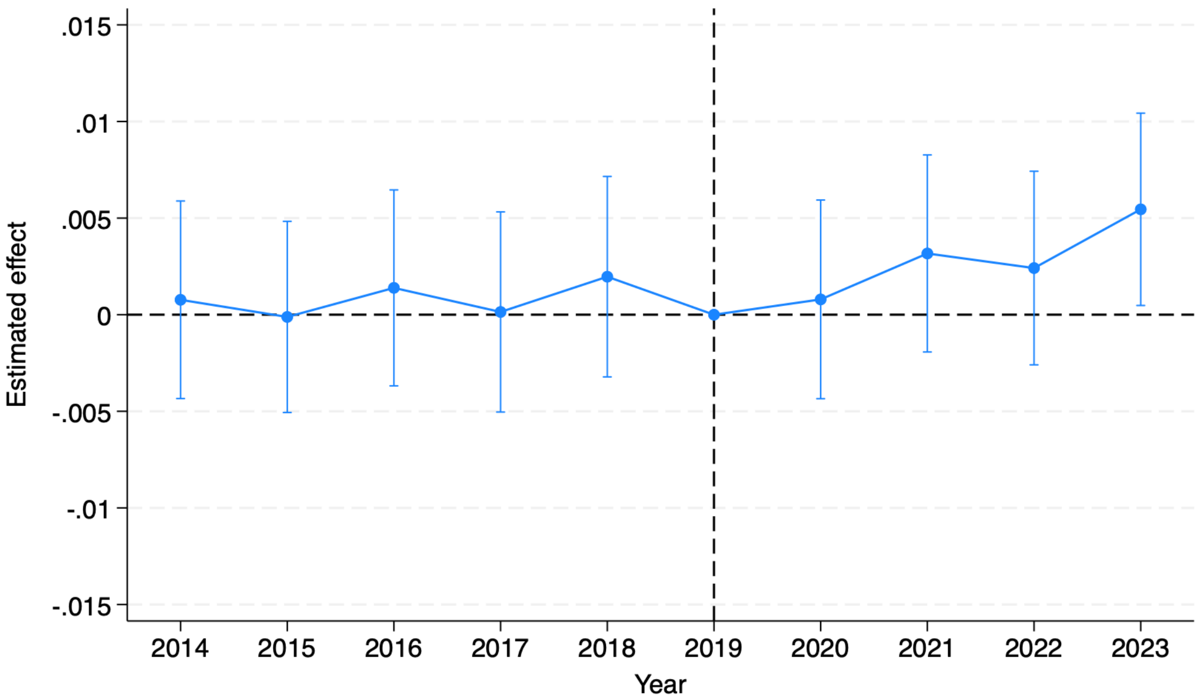
	(1) White all females	(2) White mothers	(3) White children 5	(4) Black all females	(5) Black mothers	(6) Black children 5
Average Effect	0.0034***	0.0044***	0.0085***	0.0019	-0.0002	0.0032
	(0.0012)	(0.0015)	(0.0028)	(0.0016)	(0.0022)	(0.0045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	16195532	7259518	1952239	1635776	723920	158596

	(7) Hispanic all females	(8) Hispanic mothers	(9) Hispanic children 5	(10) Asian all females	(11) Asian mothers	(12) Asian children 5
Average Effect	-0.0024	0.0001	0.0087*	0.0001	0.0048	0.0007
	(0.0031)	(0.0033)	(0.0046)	(0.0045)	(0.0043)	(0.0080)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	2524586	1478478	405149	972578	531059	142866

Notes: The table presents estimation results for all females, mothers and mothers with children under 5 across various race groups. Table reports results from estimating equation (4). The dependent variable across all models is labor force participation. Standard errors are clustered at the commuting zone-by-year level and are shown in parentheses. All models include commuting zone-by-year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

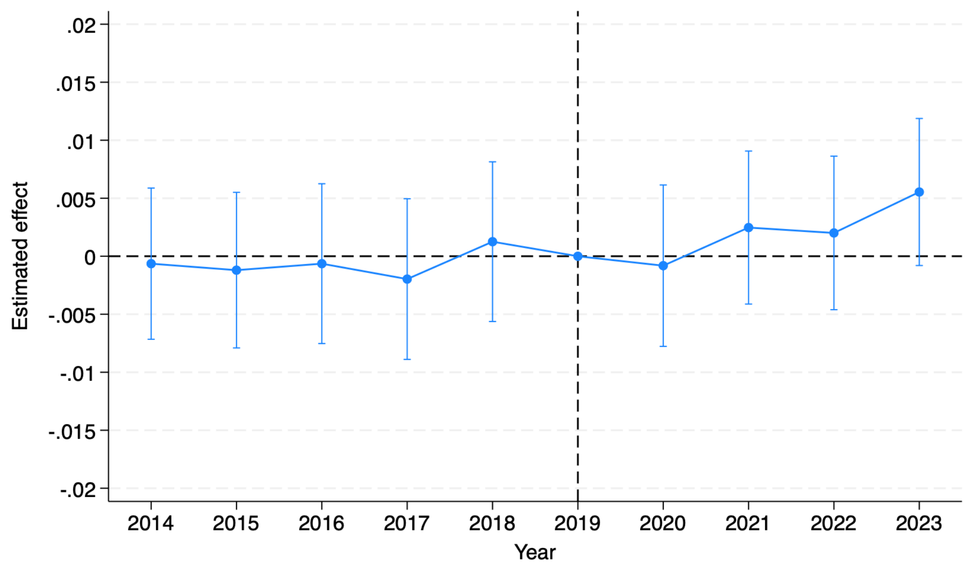
Figure A1: Effects of WFH Opportunities on Female FLP: Robustness Using Shorter-Period Measure



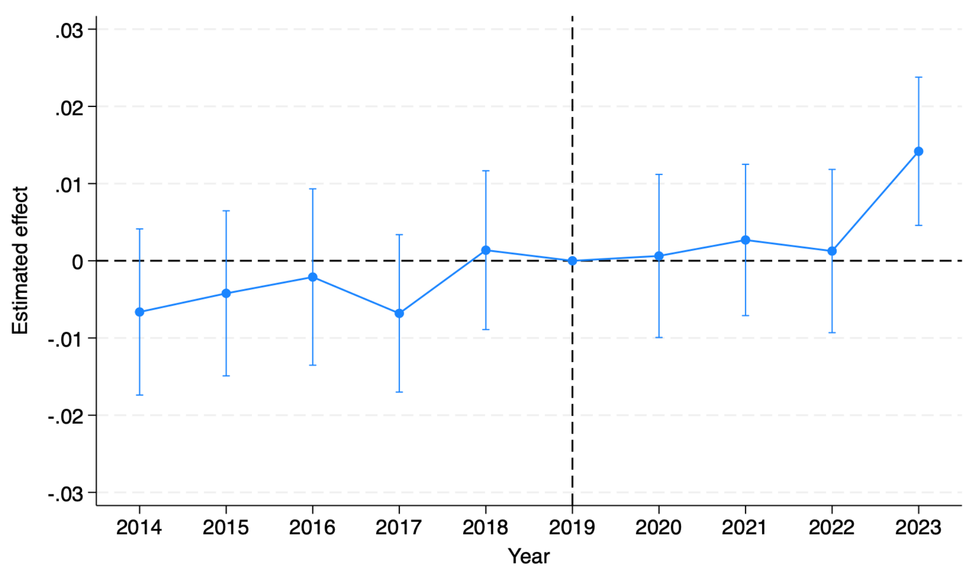
Notes: This figure illustrates the effect of individual-level exposure to work-from-home (WFH) opportunities on the labor force participation of female individuals. It displays the coefficients and corresponding 95% confidence intervals for the triple interaction terms from equation (3). The year 2019, 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 commuting zone-by-year level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure A2: Effects of WFH Opportunities on Mothers: Robustness Using Shorter-Period Measure

(a) Mothers

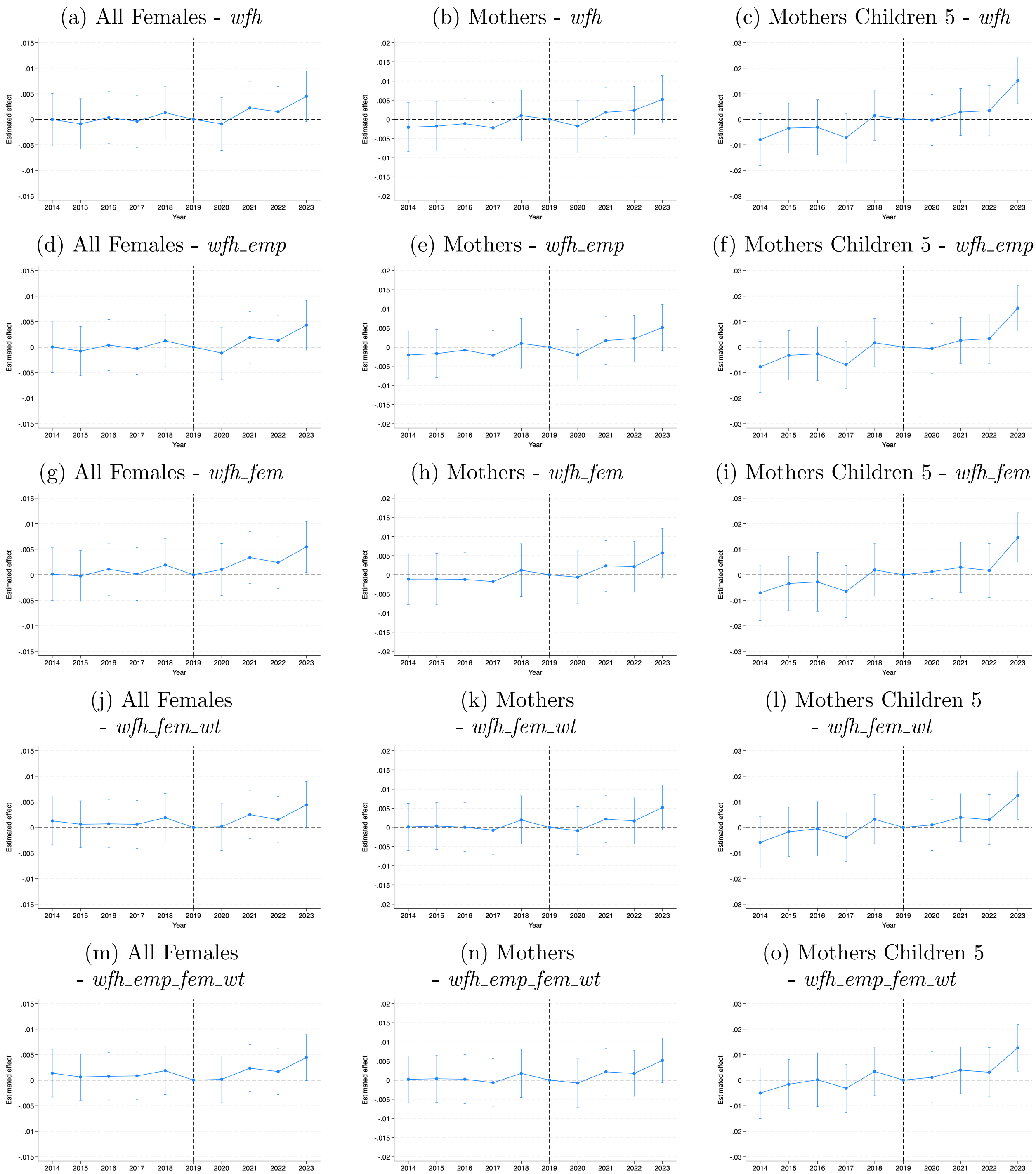


(b) Mothers with children under 5



Notes: This figure compares the effects of individual-level exposure to work-from-home (WFH) opportunities on labor force participation for (a) mothers and (b) mothers with children under 5 years old. The model specification is identical to Equation (3), with the only difference being that the sample is restricted to mothers in (a) and mothers with children under 5 in (b). 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 commuting zone-by-year level. The WFH measure is standardized to have a mean of 0 and a standard deviation of 1.

Figure A3: Effects of WFH Opportunities on Female LFP: Robustness Using Alternative WFH Measures



(a) All Females - *wfh* (b) Mothers - *wfh* (c) Mothers Children 5 - *wfh*

(d) All Females - *wfh_emp* (e) Mothers - *wfh_emp* (f) Mothers Children 5 - *wfh_emp*

(g) All Females - *wfh_fem* (h) Mothers - *wfh_fem* (i) Mothers Children 5 - *wfh_fem*

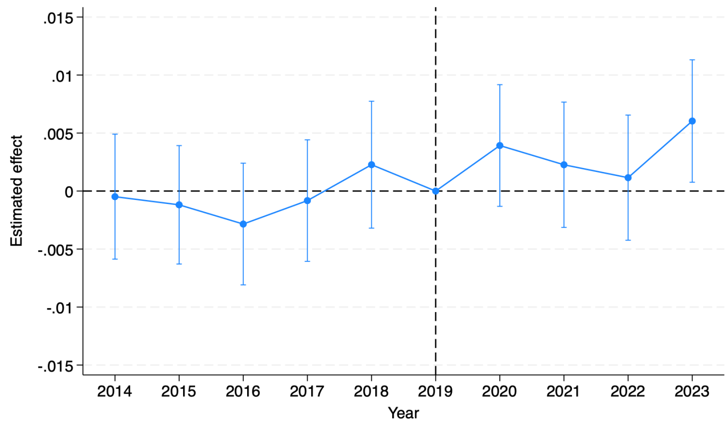
(j) All Females - *wfh_fem_wt* (k) Mothers - *wfh_fem_wt* (l) Mothers Children 5 - *wfh_fem_wt*

(m) All Females - *wfh_emp_fem_wt* (n) Mothers - *wfh_emp_fem_wt* (o) Mothers Children 5 - *wfh_emp_fem_wt*

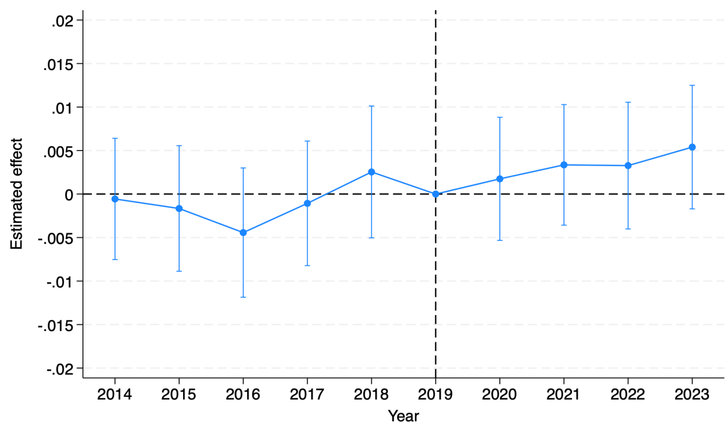
Notes: Each row corresponds to a different WFH measure, and each column represents one of three subgroups: all females, mothers, and mothers children 5. Figures display coefficients and 95% confidence intervals for the triple interaction terms from equation (3). The year 2019 serves as the reference point normalized to zero. Standard errors are clustered at the commuting zone-by-year 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 Weighted Regressions

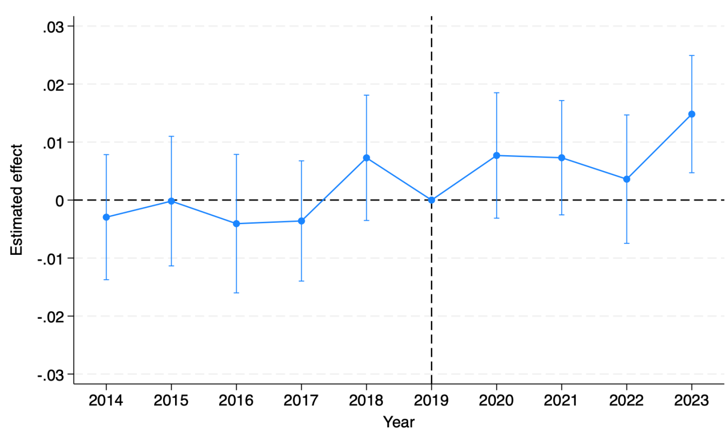
(a) All Females



(b) Mothers

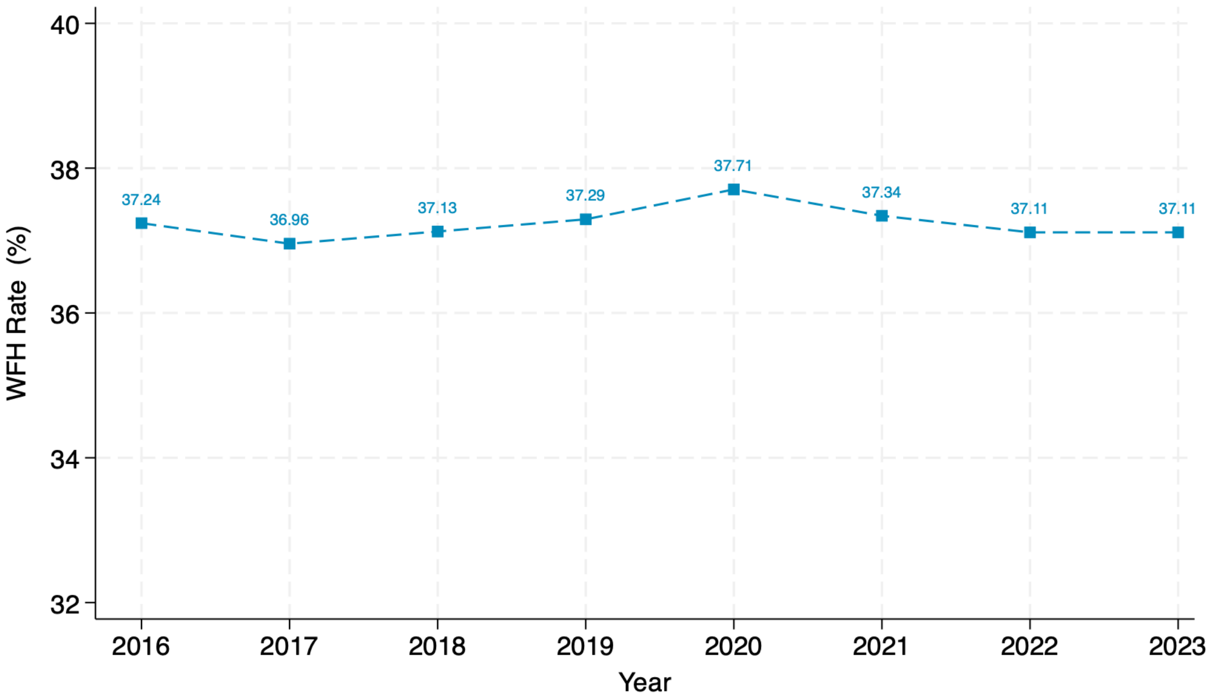


(c) Mothers Children 5



Notes: This figure compares the effects of individual-level exposure to work-from-home (WFH) opportunities on labor force participation across three subgroups: (a) all females, (b) mothers, and (c) mothers with children under 5. The model specification is identical to Equation (3), with the inclusion of person weights (*perwt*) to adjust for sampling design. It displays the coefficients and corresponding 95% confidence intervals for the triple interaction terms from Equation (3). The year 2019 is normalized to zero as the reference point. Standard errors are clustered at the commuting zone-by-year level, and the 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. 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 Female FLP: Robustness Using Shorter-Period Measure

	(1) All Females	(2) Mothers	(3) Mothers children 5
Panel A: Average Effect			
2021 - 2023	0.0030**	0.0039**	0.0087***
	(0.0012)	(0.0016)	(0.0025)
Panel B: Year-Specific Effects			
2021	0.0025	0.0030	0.0054
	(0.0019)	(0.0025)	(0.0036)
2022	0.0017	0.0026	0.0040
	(0.0019)	(0.0025)	(0.0041)
2023	0.0048**	0.0061***	0.0169***
	(0.0019)	(0.0023)	(0.0034)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
N	21328755	9993925	2660791

Notes: Panel A reports results from estimating equation (4), and Panel B presents results from equation (5). The dependent variable across all models is labor force participation. Standard errors are clustered at the commuting zone-by-year level and are shown in parentheses. All models include commuting zone-by-year fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Effects of WFH Opportunities on Female LFP: Robustness Using Weighted Regressions

	(1) All Females	(2) Mothers	(3) Mothers Children 5
Panel A: Average Effect			
2021 - 2023	0.0030**	0.0044***	0.0079***
	(0.0013)	(0.0017)	(0.0025)
Panel B: Year-Specific Effects			
2021	0.0021	0.0038	0.0067**
	(0.0021)	(0.0024)	(0.0033)
2022	0.0010	0.0037	0.0030
	(0.0021)	(0.0027)	(0.0042)
2023	0.0059***	0.0059**	0.0142***
	(0.0020)	(0.0026)	(0.0035)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
N	21328755	9993925	2660791

Notes: Panel A presents the average treatment effects of WFH opportunities on female labor force participation (LFP), estimated using equation (4). Panel B reports year-specific effects based on equation (5). The dependent variable in all models is labor force participation. Standard errors, clustered at the commuting zone-by-year level, are shown in parentheses. All models include commuting zone-by-year fixed effects. This analysis serves as a robustness check by weighting all regressions using the ACS *perwt* variable to account for sampling design, ensuring that the estimates are representative of the broader population. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Effects of WFH Opportunities on Female LFP: Robustness Using Previous Residence

	(1)	(2)	(3)
	All Females	Mothers	Mothers Children 5
Panel A: Average Effect			
2021 - 2023	0.0030**	0.0034**	0.0083***
	(0.0013)	(0.0017)	(0.0026)
Panel B: Year-Specific Effects			
2021	0.0029	0.0026	0.0062*
	(0.0020)	(0.0027)	(0.0038)
2022	0.0016	0.0021	0.0027
	(0.0020)	(0.0026)	(0.0042)
2023	0.0045**	0.0056**	0.0162***
	(0.0019)	(0.0025)	(0.0036)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
N	20135899	9520119	2463404

Notes: Panel A reports results from estimating equation (4), showing the average treatment effect of WFH opportunities on labor force participation. Panel B presents year-specific effects estimated using equation (5). The dependent variable across all models is labor force participation. Standard errors, clustered at the commuting zone-by-year level, are shown in parentheses. All models include commuting zone-by-year fixed effects. Robustness is tested by using the last year's residence to account for potential mobility. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Effects of WFH Opportunities on Female LFP: Robustness Using 6-Digit Occupation Codes

	(1) All Females	(2) Mothers	(3) Mothers Children 5
Panel A: Average Effect			
2021 - 2023	0.0034***	0.0040**	0.0088***
	(0.0013)	(0.0016)	(0.0023)
Panel B: Year-Specific Effects			
2021	0.0031	0.0036	0.0063**
	(0.0020)	(0.0024)	(0.0032)
2022	0.0022	0.0029	0.0042
	(0.0019)	(0.0025)	(0.0038)
2023	0.0049**	0.0055**	0.0160***
	(0.0019)	(0.0023)	(0.0032)
Controls	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes
N	21328755	9993925	2660791

Notes: Panel A presents the average treatment effects of WFH opportunities on female labor force participation, estimated using equation (4). Panel B reports year-specific effects based on equation (5). The dependent variable in all models is labor force participation. Standard errors, clustered at the commuting zone-by-year level, are shown in parentheses. All models include commuting zone-by-year fixed effects. Robustness is tested by assigning WFH scores at the 6-digit occupation code level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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.