BLS WORKING PAPERS

U.S. Department of Labor
U.S. Bureau of Labor Statistics
Office of Productivity and Technology

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Working Paper 565
April 23, 2024

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April 23, 2024

Abstract

Remote work gradually increased in the United States during the four decades prior to the pandemic, then surged in 2020. Using the 2010–2021 American Community Survey, the authors examine trends in wage and hours differentials between remote and on-site workers as well as within-occupation differences in wage growth by remote work status for full-time workers. Throughout the period, remote workers earned higher wages than on-site workers, and the difference increased sharply during the pandemic. These findings are robust to correcting for selection. During the pandemic, real wages grew 3.5 percent faster for remote workers than on-site workers within occupation groups. In addition, increases in remote work within occupation groups were positively associated with occupation-level wage growth. Pre-pandemic, remote workers worked substantially longer hours per week than on-site workers, but by 2021, their hours were similar.

JEL codes: J20; J22; J31

Keywords: remote work; working from home; wages; hours; COVID-19

Acknowledgements: All views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics. We thank Adam Blandin, Steven Davis, Jay Stewart, Michael Zabek, and participants at the 2023 American Community Survey Data Users Conference, 2023 The Remote Work Conference at Stanford University, and 2024 ASSA meetings for useful suggestions.

1. Introduction

Wages are determined by a number of factors, including job tasks, productivity differences, compensating differentials for job amenities, search frictions, and monopsony power, among others. Working entirely remotely was a relatively rare phenomenon before the pandemic, and selection into telework was likely pervasive (Emanuel and Harrington 2023). Using data from the 2017–18 American Time Use Survey (ATUS), Pabilonia and Vernon (2022) find that some remote workers earned wage premia, while mothers, who often report their willingness to accept lower wages for flexible work arrangements in state-preference experiments and job posting experiments, paid a wage penalty (for examples of these experiments, see He et al. 2021; Maestas et al. 2023; Mas and Pallais 2017; Nagler et al. 2022).[1] During the pandemic, the number of workers who worked entirely remotely increased substantially because of safety measures put in place. Thus, at least at the start of the pandemic, both workers and employers did not choose to work from home based on their relative productivity differences. That mothers were more likely to work from home than fathers suggests selection based on other criteria, such as caregiving responsibilities (Pabilonia and Vernon 2023b). It is likely that employees who could work from home during the pandemic learned at this time about their preferences for this work location and their relative productivity when working from home versus at their employers' worksites, and this could have changed their demand for remote positions (Aksoy et al. 2022; Barrero et al. 2021; Nagler et al. 2022).[2]

[1] Using the German Socio-Economic Panel between 1997 and 2014, Arntz et al. (2022) find that wages increase for fathers when they start working from home on occasion but only for mothers when they change employers. They suggest that the difference could result from differences in bargaining within established relationships.

[2] Barrero et al. (2021) find that after the shift, 40 percent of workers perceived that they were more productive working from home, 45 percent were just as productive, and 15 percent were less productive. Using German data, Nagler et al. (2022) find that working from home is only one of many job amenities that workers value, and not the most valued one in 2022. Paid days off and reduced commutes were

Barrero et al. (2022) argue that the recent increase in remote work raises the amenity value of employment as it lowers the costs of commuting, and this should moderate upward wage pressures as workers may be willing to share some of this value with their employers. On the other hand, new technologies (for example, video conferencing, cloud computing, monitoring software) have increased worker productivity at home. Workers also may be more productive at home if, for example, they are less tired from eliminating a long and stressful commute or sleeping later in the morning, they can better manage their work and life responsibilities, they can work without interruptions in a quiet space, whereas they may be less productive if they need to work closely with teams, the nature of their work involves customer contact, they suffer from the social isolation of working from home, or they miss out on on-the-job training (Emanuel et al. 2023; Pabilonia and Vernon 2023a). Firms also should be able to reduce their office footprints (Abril et al. 2021; Bloom et al. 2021; Dalton et al. 2022; Gupta et al. 2022; White 2019). In addition, employers with more satisfied remote workers can reduce their employee turnover costs (Bloom et al. 2023b). Employers may share establishment-level productivity gains from either lower costs or increased worker productivity associated with remote work with their workers as pay raises or bonuses.[3] Workers may be more productive at home if, for example, they are less tired from eliminating a long and stressful commute or sleeping later in the

higher-valued amenities for German workers. Working from home was valued differently by different groups of workers, with higher valuations for female, young, higher-educated, and high-earning workers. In addition, workers currently working from home valued the option more than those not working from home.

[3] A couple of randomized-control trials in China, occurring both before and during the pandemic, (Bloom et al. 2015; Bloom et al. 2023b) show causal evidence of worker productivity gains from remote/hybrid work arrangements. Another randomized-control trial run in 2020 in Bangladesh by Choudhury et al. (2024) finds positive performance ratings on creativity and quality of work (a proxy for employee productivity) working an intermediate hybrid schedule compared with those working fewer or more days per week from home for managers, indicating that managers who work a hybrid schedule are not penalized in performance ratings. Lewandowski et al. (2022) find that 25–36 percent of employers who believe their workers are more productive value remote work similarly to workers' willingness to pay for a remote work option.

morning, they can better manage their work and life responsibilities, they can work without interruptions in a quiet space, whereas they may be less productive if they need to work closely with teams, the nature of their work involves customer contact, they suffer from the social isolation of working from home, or they miss out on on-the-job training (Emanuel et al. 2023; Pabilonia and Vernon 2023a). While remote work reduces the time and expense of commuting[4], some of the costs of working remotely might be passed along to the worker who needs a quiet workspace in their home and might have to invest in a larger, more expensive home or office equipment and may see an increase in their ongoing utility costs (Delventhal and Parkhomenko 2022). Also, for some, remote work may be viewed as an undesirable disamenity if they are left socially isolated from their peers or working from home while supervising their children (Bartel et al. 2012; Choudhury et al. 2024; Flood and Genadek 2023; Pabilonia and Vernon 2022, 2023b; Senik et al. 2024). Thus, in equilibrium, it is unclear what will happen to wage differentials for remote workers during the pandemic.[5] Around the world, it has been noted that it was the highest paid workers who could work remotely, and the pandemic has thus widened existing earnings inequalities (Aina et al. 2023; Bonacini et al. 2021; Flood and Genadek 2023).

In this paper, we extend earlier work by Oettinger (2011) and White (2019) on wage differentials for home-based workers using microdata from the 1980–2010 decennial Censuses and the American Community Survey (ACS) into the pandemic era. Between 1980 and 2000 for men and women in most occupation groups, home-based workers (today most often referred to

[4] Using pre-pandemic time diaries from the ATUS, Pabilonia and Vernon (2022) find that teleworkers gained about 75 minutes per day by eliminating their commute and reducing time spent grooming on their work-from-home days compared with their on-site days. Examining the 2020-21 ATUS time diaries (2020–21), we find that employees working from home spent 60 fewer minutes per day on commuting and grooming activities compared with those working on-site. The pre- and post-pandemic difference could be explained by differences in commuting patterns, with newly remote workers previously having slightly longer commutes (Barrero et al. 2021).
[5] See Lavetti (2023) for a discussion of the complexities of measuring compensating wage differentials.

as remote workers) paid a wage penalty, which shifted to a small wage premium by 2014. Using the ACS, we estimate trends in wage differentials between remote and on-site workers working full-time from 2010 to 2021, with a special focus on the change in the differentials during the pandemic. We also examine trends in hours differentials by remote status (where hours are usual hours worked per week). To account for potential selection into remote work, we use Oster's method relating selection on observables to selection on unobservables to assess the importance of omitted variables for our estimates (Oster 2019). For 2021, we also estimate a linear model with an endogenous binary treatment, instrumenting for remote work status alternatively with 1) the take-up rate of remote work in the respondent's four-digit occupation, 2) the feasibility of working from home in the respondent's four-digit occupation, and 3) the share of households using broadband internet in the respondent's county of residence. Given the sharp increase in remote work during the pandemic, we are also able to examine 2021 wage and hours differentials for heterogenous groups where varying degrees of selection may be present, including groupings by sex, college degree status, parental status, race/Hispanic ethnicity, disability status, occupation, and living in the principal city of a large metropolitan statistical area (MSA). We also examine whether workers across the wage distribution benefited from the rise in remote work. In addition, we perform two occupation-level analyses. We first test for differences in wage growth between 2019 and 2021 by remote worker status within detailed occupations. We then examine the relationship between overall occupation-level wage growth and the change in the percentage of remote workers in these occupations from 2019 to 2021. Higher wages for remote workers could be the result of higher worker productivity or firm productivity.

In a final analysis, we investigate two mechanisms that may lead to workers being more productive when working from home: 1) their job tasks are more amenable to being done from home and 2) they have more time to sleep.

We document a substantial jump in the average wage premium for remote workers during the pandemic from 7.8 percent in 2019 to 13.4 percent in 2021. Using an Oaxaca-style decomposition, we find that the increase in the overall wage premium is at least in part due to increases in the remote wage premia within occupations. In 2021, we find much larger than average wage premia in management and sales and related occupations but a wage penalty in healthcare support occupations. Focusing only on those working in white-collar occupations, in which over 10 percent of workers were working remotely in 2021, we find that fathers working remotely earned 14.5 percent, while mothers working remotely earned 14.0 percent. These premia are robust to adjusting for omitted variable bias using Oster's method. Our instrumental variable analyses also indicate large wage premia for remote work in 2021. Using quantile regression models, we find that white-collar workers across the wage distribution earned higher wages when working remotely, but with some heterogeneity in the differential. In occupation-level wage analyses, we find that real wages grew 3.5 percent faster for remote workers than for on-site workers within detailed occupation groups and a positive association between the change in remote work intensity and wage growth across occupations.

Turning to hours differentials, just prior to the pandemic in 2019, men working remotely worked 23 minutes longer per week than men working primarily in the office, and women working remotely worked 44 minutes longer per week than their on-site counterparts. In 2021, the differentials in usual hours fell, with men working remotely working 21 fewer minutes per week and women working remotely working 13 minutes more per week.

2. Background

2.1 Changes in the prevalence of remote work in the United States

In the decades prior to the pandemic, remote work had been gradually increasing in the United States as the technology infrastructure to support remote collaboration was expanding. When the pandemic hit, government stay-at-home orders led to a sudden increase in the share of jobs that were done entirely from home. According to the U.S. Census Bureau, the percentage of jobs that were done primarily from home increased from 2.3 percent of all jobs in 1980 to 5.7 percent of all jobs in 2019, including the self-employed (Burrows et al. 2023; Oettinger 2011). Then, in 2021, the percentage of primarily remote jobs jumped dramatically to 17.9 percent (Burrows et al. 2023).

The size of the immediate (2020) increase in entirely remote jobs during the pandemic, although assuredly large, has been difficult to pinpoint, given differences in survey questions, survey modes, samples (national representativeness), and the interruption of government surveys during the first few months of the pandemic. Using the Real-Time Population Survey, Bick et al. (2023) find that aggregate work from home increased from 14.4 percent of workdays in February 2020 to 39.6 percent in May 2020. Barrero et al. (2020–2024), using the Survey of Working Arrangements and Attitudes (SWAA), estimate that in May 2020 close to 61.5 percent of paid full workdays were worked from home. Then, the percentage of workdays worked from home fell from 51 percent in July 2020 to 28.1 percent in February 2024 (hovering below 30 percent since August 2022). The percentage of persons who worked either fully remotely or on a hybrid basis is also now plateauing at a much higher rate than pre-pandemic, with 22.7 percent of employed persons doing at least some of their paid work hours from home and 10.9 percent of employed persons doing all of their paid work hours from home as of February 2024, according to the Current Population Survey (CPS), the official U.S. household survey for employment and unemployment statistics (U.S. Bureau of Labor Statistics 2024b). Surveys of businesses indicate that work-from-home jobs are here to stay (Altig et al. 2021; Barrero et al. 2021; Bloom et al. 2023a). Barrero et al. (2021) highlight several interesting findings about work-from-home in the pandemic period that are relevant to this paper. First, 85 percent of workers perceived that their productivity working from home was as good as or better than their productivity working on-site. Second, employees' desires for work-from-home exceeded employers' plans for off-site work. Third, remote work intensity rose with earnings and education levels.

2.2 Prior evidence on COVID-19, remote work, and wages

We are interested in how this large, and potentially permanent, increase in remote work impacted wages and wage inequality. Early in the pandemic, Dingel and Neiman (2002) pointed out that jobs best suited for remote work, given their task requirements and production technologies, were well-paid white-collar occupations. Thus, the economic impact of the pandemic and take up of remote work would be unequal among workers and sectors.

There have been only a few prior studies that have addressed the impact of remote work on wages in the U.S. during the pandemic. Using data from the 2021 Business Response Survey to the Coronavirus Pandemic (establishments were surveyed July through September), Dalton and Groen (2022) find that within industry sectors, the establishments with the lowest average wages had less remote workers than those with the highest average wages. They also find that larger establishments offered more remote work, and prior research has found that larger establishments pay more (Bloom et al. 2018). Finally, they show that establishments that increased pay because of the pandemic had fewer jobs that were entirely remote than establishments that did not increase pay. Given their findings, Dalton and Groen (2022) suggest that establishments that do not allow a lot of remote work may compensate their employees with higher pay. However, their study does not quantify the magnitude of the pay changes, and the survey questions condition on changes in pay resulting from the pandemic rather than all changes in pay.

Barrero et al. (2023) suggest that higher earners have larger homes that allow them the possibility to work from home in a quiet, private office. This could allow them to be more productive working from home, producing more output per hour worked. If remote work is more productive, then this could result in increases in hourly wages. On the other hand, Barrero et al. (2023) outline several reasons that the rise in remote work could put downward pressure on wage. First, firms operating remotely may be able to recruit employees from areas offering lower wages. Second, if most people would prefer to work remotely some of the week and labor markets are competitive, then this newly available job amenity will increase labor supply at any given wage and thus lower the equilibrium wage.[6] Finally, labor supply will also increase as remote work creates job opportunities for parents who want to be near their children while working, those who live in rural areas, those with disabilities, etc. As evidence of the rise in remote work putting downward pressure on wages, Barrero et al. (2022) document that executives at U.S. firms in the spring 2022 Survey of Business Uncertainty reported that the expansion of remote work substantially moderated nominal wage-growth pressures over the prior 12 months during an inflationary period.

Outside of the U.S., a couple of papers have documented changes in wages due to the shift in remote work in Italy. Early in the pandemic, using Italian survey data on worker

[6] Lavetti (2023) outlines several reasons this reasoning might not be true. For example, there may be differences in worker productivity, search frictions, and differences in firm costs of providing remote work opportunities.

characteristics, Bonacini et al. (2021) conclude that the rise in remote work would increase average earnings, but the increased opportunity to work from home would favor older, male, highly-educated, and highly-paid employees, thus increasing earnings inequality.

Looking across the Italian wage distribution from 2019 Q1 to 2020 Q4, Aina et al. (2023) find that both before and during COVID-19, the wage distribution for those working from home more than twice a week was shifted to the right compared with those working from home less than that. Using quantile regression models that also account for sample selection bias using an inverse probability weighting estimator, they find that the pandemic resulted in increased wages for workers all along the wage distribution, but more so for those in the higher wage quantiles. The increase was driven by changes in the composition of occupations as the lowest paid exited the labor market. Having a work-from-home arrangement led to a wage premium for all workers; however, those at the 10th quantile had a higher remote wage premium than those at the median or 90th quantile.

We contribute to this scant literature on remote work and the wage distribution by focusing on wage changes associated with the rise in remote work during the pandemic in the United States using earnings data from the ACS. Given the size of the survey, we are able to examine wage changes within detailed occupations by remote status and also look at wage differences across heterogeneous groups that might be affected differently because of differences in skills, productivity, and firms' costs when working remotely.

3. Data and Descriptive Statistics

Our analyses are based on 2010–2021 ACS data extracted from IPUMS USA version 12.0 (Ruggles et al. 2022). The ACS is the largest U.S. household survey, with a 1% representative cross-sectional sample of the U.S. population surveyed annually by the U.S.

Census Bureau since 2001. For our main analyses, we restrict the sample to paid civilian, non-institutionalized, wage and salary employees aged 25–64 who worked full-time and at least 48 weeks over the prior 12 months, including paid absences, in the nonfarm sector. Thus, our main results include those who were, for the most part, continuously employed full-time through the pandemic. As a sensitivity analysis, we also perform some analyses including continuously employed part-time workers. In some of our analyses, we compare estimates from 2019 and 2021 in order to highlight the impact of COVID-19, skipping 2020 because the pandemic took its toll beginning mid-March of 2020, disrupting data collection for several months, hindering response rates, and leading the U.S. Census Bureau to release 1-year ACS estimates for 2020 as experimental.[7] Although we urge caution when interpreting results for 2020, the estimates are generally in line with those from 2021.[8]

We define remote worker status based on responses to the following ACS question: "How did this person usually get to work LAST WEEK?" If the household respondent answered "Worked from home," we classify the person as a remote worker. If instead they selected a mode of transportation (car, bus, subway, etc.), then we classify them as on-site worker. Remote workers may include hybrid workers working three days at home and two days in the office as

[7] The Census Bureau found that the 2020 data overrepresented the populations who were more educated, had higher incomes, and lived in single-family housing units (U.S. Department of Commerce 2021).
[8] We compare the composition of our 2020 and 2021 samples in Online Appendix Table A1. In 2021, respondents reported statistically significantly higher remote work shares, real hourly wages, annual earnings, and usual hours worked than in 2020. Respondents in 2021 were slightly older, more likely to have an advanced degree, less likely to have a cohabiting partner, had fewer household children, and had fewer other adults in the household. They were more likely to have a disability or live with a partner or parent with a disability. They were more likely be a government employee and to work in management, business operations, computer and mathematical, healthcare practitioners and technical, and transportation and material moving occupations, but less likely to work in legal, food preparation and serving, installation, maintenance, and repair, and sales. In terms of industries, workers in 2021 were more likely to work in retail trade, finance and insurance, administrative and support and waste management services, educational services, and public administration, but less likely to work in wholesale trade, arts, entertainment, and recreation, accommodation and food services, and other services than their 2020 counterparts.

worked from home would still be the primary work location. On-site workers could likewise include those who work from home one to two days per week. Thus, the percentage of remote workers in the ACS is a lower bound on the percentage of workers spending any of their full workdays at home and an upper bound on the percentage of full-time remote workers, although in 2020–2021, many employers allowed workers to work exclusively from home.[9]

In Figure 1, we compare our estimates of working from home for full-time full-year employees from our ACS sample to estimates from the American Time Use Survey (ATUS) (U.S Bureau of Labor Statistics 2023a). Our ATUS measure of working from home is the percentage of workdays worked from home for full-time employees and is based on working *exclusively* from home on weekdays with at least four hours of work.[10] After a long steady increase, we observe a surge in the percentage of remote workers starting in 2020. On average, in 2019, 4.1 percent of workers in the ACS were remote. By 2021, 19.9 percent were working remotely. The rise in remote work is similar in ATUS, with 27.3 percent of full workdays worked exclusively from home in 2021.[11] ATUS percentages are higher because they include those who work most of their days in the office but also those who work some days at home. Consistent with other surveys, the ACS data suggests that women were more likely to primarily work from home than men during the pandemic (22.1 percent versus 18.1 percent in 2021).[12]

[9] A big return to office push started in the fall of 2021 after the COVID-19 vaccines were readily available (Newport 2021).
[10] Brynjolfsson et al. (2023) provide a review of estimates of working from home from different U.S. surveys and discuss the difficulty of measuring the concept of "remote" work. In a review article, Kosteas et al. (2022) provide a global perspective on remote work intensity during at the start of the pandemic.
[11] Considering all workdays, Flood and Genadek (2023) find that in the latter half of 2020, 33.9 percent of workdays were primarily worked from home. Primarily here refers to at least half of the workday. In 2021, 28.4 percent of all workdays were primarily worked from home.
[12] Using the NLSY97 COVID-19 Supplement, Aughinbaugh et al. (2023) find that 29.3 percent of employed women and 21.3 percent of employed men worked exclusively from home in the spring of 2021. The samples are nationally representative of those born in 1980–84. In addition, a potential difference in the levels working remotely is that the NLSY97 includes self-employed workers, who had a greater relative propensity to work from home pre-pandemic (U.S. Bureau of Labor Statistics 2019).

Although remote work increased in all major occupation groups, the magnitude of the increases in remote work varied across occupations, because occupations differ in the composition of tasks that can be done at home (Dingel and Neiman 2020; Dey et al. 2020). The differences in tasks across occupations could also result in differences in remote work wage differentials. Comparing remote work across 22 major occupation groups, Figure 2 shows that the percentage of remote workers in 2021 was highest in computer and mathematical occupations at 55.1 percent, followed by business operations specialists at 45.5 percent. It was lowest in food preparation and serving, construction and extraction, and building and grounds cleaning and maintenance at about 4.0 percent. Over 10 percentage of workers in white-collar jobs worked remotely, whereas the percentage was lower for those working in blue-collar and healthcare jobs.

We examine two main outcome variables—hourly wage and usual hours worked each week. Respondents to the ACS are interviewed throughout the year (no interview date is available) and report on total pre-tax wage and salary income for the past 12 months. We calculate hourly wages by dividing income earned by the product of weeks worked over the past 12 months and usual hours worked each week, where the latter is capped at 84 hours per week and the reference period is the previous 12 months.[13] Note that hourly wages may be measured with error with respect to remote worker status because status refers to the previous week, whereas hours and earnings refer to the previous 12 months. While measurement error may attenuate ordinary least squares (OLS) estimates if the error does not vary systematically with remote status, it should not affect our conclusions. We convert nominal wages to real 2020–2021

[13] Prior to 2019, weeks worked were reported in wide intervals. In 2019, we examine the distribution of weeks within the intervals to assign an exact number of weeks worked in survey years prior to 2019. Specifically, we assign 52 weeks for those reporting 50–52 and 48.3 for those reporting 48–49 weeks.

dollars using a two-year moving average of the CPI-U (U.S. Bureau of Labor Statistics 2023b). We trim the sample by year to exclude the top and bottom 1% of real hourly wages.[14] As a robustness check, we estimate some specifications using annual earnings instead of the hourly wage.

In Figures 3A-D, we show average nominal and real wages by sex and by remote worker status. Remote workers of both sexes earned higher wages than on-site workers throughout the period, and there is a striking widening of the raw wage gap during the pandemic. On average, real wages rose for remote workers but fell slightly for on-site workers during the pandemic. Figures 3E-H show a similar story for average nominal and real annual earnings.

In Figure 4, we show trends in usual weekly hours worked by sex and by remote worker status. Initially, in 2010, on average, hours were substantially higher for remote workers than on-site workers (4.9 percent higher for men and 5.5 percent higher for women). Over the period, however, hours of remote and on-site workers slowly converged. During the pandemic, hours were about the same for men while women working remotely worked about 1.4 percent more hours than their on-site counterparts.

Figure 5 shows kernel density distributions of real wages and usual weekly hours worked in 2019 and 2021 by sex and by remote worker status. In both years, wages were positively skewed, more so for remote workers than on-site workers and for men working remotely than women working remotely. In addition, the wage distribution for remote workers shifted farther to the right in 2021, while the distribution for on-site workers became more concentrated at the lower end. The hours distribution shows that most men working on-site reported 40 hours of work in 2019 while the hours distribution for men working remotely was more spread out around

[14] Appendix Table A2 shows the wage distribution for each sample year.

40 hours. On the other hand, the hours distribution for women in 2019 was similar by remote worker status. For both sexes, there were also smaller peaks in hours at 45, 50, and 60 hours. In 2021, however, both male and female remote workers had a greater likelihood of working exactly 40 hours than did their on-site counterparts. Using Kolmogorov-Smirnov tests, we can reject the hypothesis that the distributions of remote and on-site workers are identical (Appendix Table A3).

4. Econometric Models

Remote workers and on-site workers have different observable characteristics (Table 1). For example, remote workers are more likely to be female, married, and have at least a bachelor's degree. They also may have different unobservable characteristics, which if correlated with both our outcome variables and remote status would bias results based on OLS estimation. To identify the effects of working from home on wages (and hours) at the individual level, we use several empirical strategies: (1) estimate a linear model by OLS with control variables to address selection on a rich set of observables, (2) estimate bounds on the size of the effects based on Oster's method that relates selection on observables to selection on unobservables, and (3) estimate a linear model with an endogenous binary treatment by full maximum likelihood (FML) using the 2021 data only. We also estimate residualized quantile regression models to estimate remote wage differentials along the wage distribution. Finally, we perform two analyses to examine the relationship between wage growth and remote work at the occupation level.

4.1 Linear model estimated by OLS

We begin our econometric analysis by estimating conditional wage and weekly hours worked differentials for remote workers for each year separately from 2010 to 2021 by sex as follows:

$$\ln(Y_{it}) = \alpha + \beta Remote_{it} + \gamma X_{it} + \varepsilon_{it} \tag{1}$$

where our outcome variable, $\ln(Y_{it})$, is either the natural log of hourly wage (or annual earnings) or the natural log of hours worked by individual i in year t, $Remote_{it}$ is a binary indicator for remote worker, X_{it} is a vector of controls for the demographic and job characteristics of individual i, α is a constant, β is our coefficient interest measuring the average treatment effect (ATE), γ is a vector of coefficients on our control variables, and ε_{it} represents the error term. The vector X_{it} includes a quadratic in age, the number of household children under age 5, the number of household children age 5 to 17, and the number of adult household members excluding the respondent and any partner, and binary indicators for educational attainment (less than high school, associate degree, bachelor's degree, and advanced degree), non-Hispanic Black, Hispanic, married, cohabiting, own disability, living with a partner or parent with a disability, government employee, 21 occupation groups, 18 industry groups, lives in a MSA, and Census divisions.[15] These regressions are estimated by OLS using ACS person-level weights. We calculate robust standard errors clustered at the household level. We note that although these analyses are motivated by Oettinger (2011) and White (2019), our specification includes more control variables and we exclude the farm sector, which has always had a high share of remote workers. In addition, Oettinger (2011) included part-time and part-year workers in all of his analyses, while White (2019) included only full-time, full-year workers as we do for our main analysis.[16]

[15] OLS estimates are similar if we control for state rather than Census division, but some of our endogenous binary treatment models would not converge using states; therefore, for consistency, we estimate all specifications with controls for Census division.

[16] As a sensitivity analysis, for 2019–2021, we estimate specifications including part-time workers and find similar results. However, we do not include part-year workers, who increased in number during the pandemic, because they may be different on multiple dimensions, making it difficult to accurately compute their wages. Many of these workers likely experienced a significant furlough and potentially had different jobs with different hours and earnings that were difficult to measure, leading to substantial

4.2 Estimate bounds on β using Oster's method

Positive OLS coefficients on remote status would imply that remote workers receive a wage premium, which may be a consequence of higher productivity while working from home, a compensation for a lack of other benefits (e.g., employees working remotely take on additional expenses for their home office and utilities), efficiency wages, or a sign of selection of higher ability or more tenured and more trusted workers by employers into remote status.[17] However, high-wage (and high ability) workers may be more willing to accept a lower wage for the option to work from-home, i.e., a compensating wage differential, which would reduce the premium all else equal (Lavetti 2023). It is also possible that OLS coefficients underestimate the true effects of remote work if, for example, workers with a lower work ethic choose remote jobs and are likely to earn lower wages. For example, Emmanuel and Harrington (2023) found that prior to the pandemic, less productive workers selected into remote work jobs at a U.S. Fortune 500 firm's call centers. They also found that remote workers were less likely to be promoted. If productive workers believe that being visible on-site increases their chance of promotion (and consequently higher wages), they may be less likely to select remote jobs. However, during the pandemic, the stigma of working from home has diminished and thus the promotion potential of remote workers may have changed (Barrero et al. 2021). In addition, during the pandemic, risk averse workers were more likely to work remotely to lower their chances of contracting the virus (Barrero et al. 2023), while there is some evidence that risk averse workers earn lower wages (Lavetti 2020). If so, OLS estimates would be biased downward during the pandemic. Remote

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measurement error in computing wages. We calculated their mean wages in 2021, but they seemed unrealistically high. Thus their omission from the comparisons.

[17] Although we mention tenure and trustworthiness here because they have been mentioned in prior literature on work from home, we show later that wage premia exist even for those in management occupations, which would seem to negate positive selection into remote work on these workers' characteristics.

work also eliminates significant fixed time and monetary costs of commuting (Edwards and Field-Hendrey 2002; Vernon and Pabilonia 2022). Thus, the availability of remote work could alter the reservation wage and induce low-wage workers to participate in the labor market, resulting in a negative correlation between the unobservables in the wage regression and remote work status. On the other hand, higher wage earners tend to have longer commutes and a higher opportunity cost of their time, so they may be more likely to choose to work remotely (Barrero et al. 2021).[18] Thus, the sign of any bias in the OLS estimates is unclear.

In one attempt to assess whether the signs of our estimates are robust to adjusting for selection on unobservables, we estimate bounds on β using a method popularized in Oster (2019). Oster betas, β*, are calculated as:

$$\beta^* = \beta - \delta\left[\dot{\beta} - \beta\right]\left(\frac{R_{max} - R}{R - \dot{R}}\right) \tag{2}$$

where β and R are the coefficient on $Remote_{it}$ and the R-squared from estimating equation 1, respectively, and $\dot{\beta}$ and $\dot{R}$ are the coefficient on $Remote_{it}$ and the R-squared from a regression with no controls, respectively. Because there may be positive or negative selection as described above, we calculate Oster betas assuming both that $\delta = 1$, which means that selection on observables is equal to selection on unobservables and has the same sign, and $\delta = -1$, which means that selection on observables is equal to selection on unobservables but has the opposite sign. We also assume that R_{max} = 1.3*R as suggested in Oster (2019) based on comparing plausibly biased observational estimates to causal effects from randomized control trials.[19] If an

[18] Using our sample of full-time workers in the ACS, we find that one-way commute times in 2019 (before the pandemic) rose as income rose across income quintiles: 25 min in quintile 1, 27 min in quintile 2, 28 min in quintile 3, 30 min in quintile 4, and 32 min in quintile 5 (top quintile).
[19] R_{max} is the R-squared from a hypothetical regression that includes controls for unobservable characteristics.

estimated range bounded by β and β* when $\delta = 1$ includes zero, then the sign of our OLS estimate is not robust to correcting for omitted variable bias.

4.3 Linear model with an endogenous binary treatment

For the full sample of men and women in 2021, we also estimate the causal effect of remote work by estimating the following linear model with an endogenous binary treatment by FML:[20]

$$\ln(Y_i) = \alpha_0 + \alpha_1 Remote_i + \alpha_2 X_i + \epsilon_{it} \tag{3}$$

$$Remote_i^* = \pi_0 + \pi_1 X_i + \pi_2 IV_i + \varphi_{it} \tag{4}$$

$$Remote_i = \begin{cases} 1 \; if \; Remote_i^* > 0 \\ 0 \; if \; Remote_i^* \leq 0 \end{cases} \tag{5}$$

Equation 3 is a linear model with an endogenous binary treatment variable, $Remote_i$. Equation 4 is a selection equation where the outcome variable, $Remote_i^*$, is a continuous latent variable for the worker's propensity to work from home behind the observed binary variable $Remote_i$. X_i is a vector of exogenous controls as defined in equation 1. α_2 and π_1 are vectors of coefficients on the exogenous explanatory variables in X_i to be estimated. α_0 and π_0 are constant terms to be estimated.

To identify the effect of remote work, the model includes an additional exogenous explanatory variable, an instrumental variable (IV_i), in the selection equation. The instrumental variable needs to be highly predictive of remote worker status but uncorrelated with the error term of the wage and hours regressions; in other words, COV$(IV_i, \epsilon_i) = 0$. IV_i should be related to the outcome only through its relationship with the remote worker status. We use three instrumental variables in alternative specifications. Our first IV_i is the percent of workers in the

[20] We use the treatreg command in STATA.

same detailed occupation as the respondent who work remotely. When there are sufficient observations (N ≥30), we estimate the percent of remote workers using those in the same four-digit occupation. In a few cases, when the number of workers in this group is less than 30, we instead use the percent remote in the respondent's two-digit occupation and major industry.[21] This instrument measures the actual take up of remote work. The second instrument is an index of the feasibility of working from home in the respondent's detailed occupation based on Dingel and Neiman (2020). This instrument measures the potential for an occupation to be done fully remotely. A final instrument is the share of households in the respondent's county of residence with a broadband internet subscription. In our results discussed in the next section, the coefficients on our instruments, π_2, are always highly statistically significant and the p-values from Wald tests of excluding the instrument are less than 0.001, which suggests that the instruments are strong.[22]

The IV estimate, α_1, our coefficient of interest in this model, is not directly comparable to the OLS estimate, β, because it measure the local average treatment effect (LATE) (Imbens and Angrist 1994). It represents the effect of remote status on those whose remote status can be changed by the instrument, the compliers. It does not identify the effects for those who would always choose to work from home. In the pandemic, we can think of it as measuring effects for the group who were told to work from home to slow the spread of the virus. In addition, the IV estimate could be larger than the OLS estimate if remote work status is measured with error. If the error is classical measurement error, the OLS estimate is attenuated.

[21] Only 181 out of 795,029 observations were not assigned the percent at the detailed occupation level.
[22] Because the first stage is estimated as a probit model, an instrumental variable is technically not necessary for identification like it is in a 2SLS model. Thus, when including one instrument, we can still test whether the model is just identified versus over identified. Because we cluster the standard errors and use weights, the likelihood function does not reflect the non-sphericity of the errors, so we use Wald tests for our overidentifying restrictions tests.

The error terms in this model, ϵ_{it} and φ_{it}, are assumed to follow a bivariate normal distribution with mean zero and variance-covariance matrix $\begin{bmatrix} \sigma_\epsilon^2 & \rho\sigma_\epsilon\sigma_\varphi \\ \rho\sigma_\epsilon\sigma_\varphi & 1 \end{bmatrix}$. The sign of the correlation coefficient, ρ, tells us the direction of the correlation between the error terms of the wage (or hours) equation and the remote work selection equation. When estimating the model, we cluster the standard errors at the level of the instrument (occupation or county). Using Wald tests, we test and can reject in all the wage regression specifications the null hypothesis that the correlation between the error terms is zero. When we reject the null hypothesis, this suggests that using the treatment effect model is appropriate. However, in the hours regression specifications, we cannot always reject the null hypotheses, in which case the OLS estimates are preferred.

4.4 Residualized quantile regression models

To estimate remote wage premia along the wage distribution, we estimate a two-step quantile treatment effects models for 2019 and 2021 using the "rqr" command in STATA developed by Borgen et al. (2022) to identify unconditional quantile treatment effects. In the first stage, we regress $Remote_{it}$ on the controls X_i by OLS and obtain the residuals, $\widetilde{Remote}_{it}$.

$$Remote_{it} = \omega_0 + \omega_1 X_{it} + \varepsilon_i \tag{6}$$

$$\widetilde{Remote}_{it} = Remote_{it} - \widehat{Remote}_{it} \tag{7}$$

In the second stage, the log wage denoted by $\ln(Y_{it})$ is regressed on $\widetilde{Remote}_{it}$ using the CQR algorithm:

$$\sum_{i:\ln(Y_{it}) \geq \beta_0^{(\tau)} - \beta_1^{(\tau)}\widetilde{Remote}_{it}}^{N} \tau \left|\ln(Y_{it}) - \beta_0^{(\tau)} - \beta_1^{(\tau)}\widetilde{Remote}_{it}\right| + \sum_{i:\ln(Y_{it}) < \beta_0^{(\tau)} - \beta_1^{(\tau)}\widetilde{Remote}_{it}}^{N} (1-\tau)\left|\ln(Y_{it}) - \beta_0^{(\tau)} - \beta_1^{(\tau)}\widetilde{Remote}_{it}\right| \tag{8}$$

4.5 Occupation-level analyses

For our occupation-level analyses, we first use aggregated data at the occupation-remote worker status cell level to estimate the difference in average wage growth between 2019 and 2021 using the following model:

$$\ln(\overline{w}_{ort}) = \delta_0 + \delta_1 Remote_{ot} + \delta_2 Year2021_t + \delta_3 Remote_{ot} \times Year2021_t + \delta_4 P_{ort} + occ_o + \nu_{ort} \quad (9)$$

where $\ln(\overline{w}_{ort})$ is the natural log of the average wage in detailed occupation *o* by remote status group *r* at time *t* (*t* equals either 2019 or 2021), $Remote_{ot}$ is a binary indicator for remote worker group for occupation o, $Year2021_t$ is a binary indicator for year equals 2021, P_{ort} is a vector of cell-level average demographic and industry controls, occ_o is a vector of occupation fixed effects, δ_0 is a constant term, δ_1 and δ_2 are coefficients to be estimated (δ_1 is the difference in average wages between remote workers and on-site workers in 2019, δ_2 is the growth in wages over the period for on-site workers), δ_3 tells us whether wages grew faster or slower during the pandemic for remote workers relative to on-site workers, δ_4 is a vector of coefficients on average demographic and industry controls, and ν_{ort} represents the error term. We use four observations for 294 four-digit occupation groups where we have at least 10 observations for each of the four occupation-group-year cells within an occupation group. Regressions are weighted using the sum of the person weights for each cell, and we cluster the standard errors at the occupation level.

In a final model, to test whether the rise of remote work moderated wage pressures across occupations, we estimate the relationship between the absolute change in the percentage of remote workers and the cumulative growth in average wages from 2019 to 2021 across four-digit occupations while controlling for compositional changes in the workforce as follows:

$$\Delta \ln(\overline{w}_o) = \sigma + \rho \Delta \overline{Remote}_o + \nu \Delta \bar{A}_o + \omega_o \quad (10)$$

where $\overline{w}_o$ is the average wage in occupation o, $\overline{Remote}_o$ is the percentage of workers in occupation o who are remote, $\bar{A}_o$ is a vector of demographic and industry group means for workers in occupation o (the controls are similar to those used in equation 1 but we include 10-year age brackets instead of a quadratic in age), σ is a constant term, Δ represents the difference in the variable between 2021 and 2019, ρ is the coefficient of interest describing the association between the change in the occupation-level remote worker intensity and the growth in occupation-level wages, ν is a vector of coefficients on the control variables, and ω_o represents the error term. We restrict the analysis to those occupations with at least 30 observations in both 2019 and 2021 (516 occupations in total). Regressions are weighted using the sum of the 2021 person weights for each occupation group, and robust standard errors are reported.

5. Results

5.1 Hourly wage and annual earning differentials

Figure 6 shows trends in adjusted hourly wage differentials (and annual earnings differentials) with 95% confidence intervals by sex, along with Oster betas, from equations 1 and 2. Tables 2 and 3 also report full sets of coefficient estimates for the wage and hours regressions, respectively, for 2010, 2019, and 2021. As we saw in the raw mean differences, we find that among full-time wage and salary employees, remote workers earned wage premia throughout the period and that the premium jumped sharply in 2020 and 2021.[23] Table 4 reports the coefficients on the interaction of $Remote_{it}$ and $female_{it}$ when we fully interact all the independent

[23] As a sensitivity analysis, we estimate specifications including part-time workers for the 2019–2021 period. Trends in the wage premia are similar; however, the coefficient estimates are slightly lower in magnitude than those obtained using full-time workers only (Appendix Table A4). In another sensitivity analysis, we estimate specifications after trimming the top and bottom 5% of the wage distribution (Appendix Table A5). Again, trends are similar.

variables in equation 1 with the female indicator. In some years, the interaction term is positive, suggesting the differentials vary by sex. However, the general trends in the wage differentials hold similarly for men and women (see Panel A of Table 4). In 2010, remote workers earned 6.8 percent more per hour than on-site workers, and by 2019, the wage premium was still only about 7.8 percent.[24] In 2021, however, remote workers earned 13.3 percent more than on-site workers (almost double the 2010 wage differential). We also find similar trends in returns to remote work when using annual earnings instead of hourly wages as the outcome (Table 4 Panel B). However, there is a sex difference in the 2021 earnings differential, with men earning 12.4 percent more when working remotely and women earning 14.1 percent more when working remotely.

The Oster betas assuming $\delta = 1$ are below zero for men in most years, indicating the premia may not be robust to adjusting for selection on unobservables if selection on observables works in the same direction as the selection on observables. However, for women, the Oster betas assuming $\delta = 1$ exceed zero in all years, so the wage premia for remote work are robust to selection on unobservables. If we were to assume $\delta = -1$, then we would conclude wage differentials are positive. The first two columns of Table 5 show the results from the endogenous binary treatment models for the effects of remote work on wages in 2021, when those who could feasibly work from home were much more likely to do so because of the pandemic. In each wage specification, ρ is negative and statistically significant, indicating that unobservable factors that increase wages are negatively correlated with unobservables that determine remote work. Therefore, the assumption of $\delta = -1$ for calculating the ranges of the wage differentials using Oster's method seems more reasonable. The IV estimates are 2–3 times larger than the OLS estimates depending on the instrument variable used, but they measure the LATE and are still

[24] Percents are calculated as $(\exp(\beta) - 1) \times 100$.

less than the unconditional mean differences. Thus, on the whole, these estimates suggest substantial wage premia for remote workers and are supportive of the hypothesis that remote work is productivity enhancing.

5.2 Hours worked differentials

While hourly wage premia for remote workers are similar for men and women, hours differentials between remote and on-site workers differ by sex (Table 4 Panel C). Prior to the pandemic, remote workers of both sexes worked longer hours than their on-site counterparts, with women having a larger gap in hours than men. In 2019, men working remotely worked 23 minutes per week longer than men working on-site, while women working remotely worked 44 minutes longer than women working on-site (assuming a 43.5-hour workweek). In 2020 and 2021, the hours differentials are quite a bit lower. In 2021, men working remotely worked 21 fewer minutes per week than men working on-site, while women working remotely worked 13 minutes longer than women working on-site. Thus, the reason we see a sex difference in the annual earnings differentials (women higher than men) but not the hourly wage differentials in 2021 is the sex difference in the weekly hours worked differentials.

In the pre-pandemic years, the Oster betas all exceed zero, suggesting that the positive hours differentials are robust to unobservable factors (Figures 7a and 7b). It is not surprising that the hours differential was negative for men and closer to zero for women during the pandemic, because previously on-site workers who historically worked less joined the remote worker group. As a comparison, ATUS time diaries suggest that among workers with at least four hours of work on their diary day in 2021, men worked 12 fewer minutes and women worked 2 fewer minutes on weekdays when working from home compared with on-site, but the unadjusted mean sex difference is not statistically significant at conventional levels (authors' own calculations).[25]

In the third and fourth columns of Table 5, we present the results from the endogenous binary treatment models for the effects of remote work on hours in 2021. The results are more mixed than they were in the wage models. For men, we find evidence of negative hours differentials using two of the three instruments, which are almost quadruple the size of the OLS estimate (and also larger than the Oster beta). When instrumenting with either the share of remote workers in a respondent's detailed occupation or the share of households with broadband internet in a respondent's county, ρ is positive and statistically significant, suggesting that unobservable factors that increase hours are positively correlated with unobservables that determine remote work. However, when instrumenting using the remote work feasibility index, we cannot reject the hypothesis that $\rho = 0$. A possible explanation for a positive ρ is if men who prefer working from home will work longer hours when given the opportunity to work remotely. Remote workers have additional time in the day when their commutes are eliminated, and prior research (Aksoy et al. 2023) shows that some workers stated that they used some of their eliminated commute time from the shift to work from home during the pandemic to work longer hours. For women, we cannot reject the hypothesis that $\rho = 0$ using any of the instruments; thus, the OLS estimates indicating slightly positive effects of remote work on hours are preferred.

5.3 Remote work and the gender wage gap

Although we do not find that the remote wage premia differ by gender during the pandemic, we also explored whether the large gender difference in the percentage of remote

[25] Flood and Genadek (2023) find that during the pandemic, the workday span as measured by the start and stop of work for the day was shorter for those working from home on average, but slightly longer for those working at home at least four hours on their diary day because these workers worked later in the evening.

workers (17.9 percent for men versus 21.8 percent women in 2021) can explain any of the gender wage gap. We perform a Blinder-Oaxaca decomposition of the gender wage gap using a pooling model (Blinder 1973; Oaxaca 1973; Jann 2008). Before the pandemic in 2019, we do not find that gender differences in the share of remote workers explain much of the gender wage gap (Table 6). However, in 2021, we find that the 16 percent gender wage gap would have been 0.54 percent larger without remote work. Remote work has a positive effect on wages, and women are more likely to do remote work. Therefore, remote work played a small, but statistically significant, role in reducing gender wage inequality.

5.4 Heterogeneity by occupation

Although remote workers earned wage premia on average, there was also considerable heterogeneity in both the increase in remote work and wage differentials across occupations (Figures 2 and 8). Following Oettinger (2011), we use an Oaxaca-style decomposition to decompose changes in both the remote worker share and the raw mean log wage between 2010 and 2019 and between 2019 and 2021 (Table 7). Over the nine years between 2010 and 2019, the remote worker share rose by 1.9 percentage points, while during the pandemic, in a two-year span (2019–2021), the remote worker share rose by 15.7 percentage points (Table 7 Panel A). Over both periods, the increase in remote work was almost entirely because of increases in remote worker shares **within** occupations rather than changes in the composition of employment across occupations.

Turning to changes in wages (Table 7 Panel B), we see a rapid acceleration in the relative wage gains of remote workers (5.7 percentage points between 2010 and 2019 and 11.9 percentage points between 2019 and 2021). The increase in the wage gap between remote and on-site workers over the 2019–2021 period can be explained primarily by the same components that explained the increase over the 2010–2019 period. Between 2019 and 2021, changes in mean demographic and industry characteristics between remote and on-site workers accounted for 67 percent of the relative wage gain of remote workers, while changes in remote wage premia **within** occupations accounted for 48 percent of the relative wage gain.

Figure 8 shows the adjusted wage differentials for remote workers (and Oster betas) in 22 occupations for 2021. Computing the percentages from their corresponding coefficients, we find wage premia that exceed the average in sales and related (20.8 percent), management (16.8 percent), production (14.7 percent), arts, design, entertainment, sports and media (14.6 percent), business operations specialists (14.0 percent), life, physical, and social science (13.9 percent), and legal (13.4 percent) occupations. In healthcare support, however, remote workers paid a wage penalty of 5.5 percent. In most occupations, the wage premia are robust to correcting for omitted variable bias. Exceptions include healthcare practitioners and technical occupations and building and grounds cleaning and maintenance occupations. This suggests that workers in most occupations were more productive working from home than on-site during the pandemic, which could be because a considerable amount of business shifted online. It is not surprising that those in sales positions working remotely did extremely well, because a randomized-control trial in which call center workers were randomly selected to work from home found that those working remotely experienced a productivity boost (e.g., Bloom et al. 2015). Even more remarkable is the fact that we find a substantial premium among managers, a group of individuals who likely have greater tenure, trustworthiness, and motivation than others, and we would not expect them to negatively select into working from home.

Figure 9 shows the hours differentials in the same 22 occupations in 2021. Remote workers in six of the occupations (arts, design, entertainment, sports, and media; community and social service; management; architecture and engineering; legal; and protective service) usually worked statistically significantly fewer hours per week than did on-site workers. However, the hours differential in sales and related occupations may not be robust if there is negative selection into remote status in this industry. In only four of the 22 occupations did remote workers work statistically significantly more hours per week than on-site workers (healthcare support; personal care and service; building and grounds cleaning and maintenance; and financial specialists). Given the increased demand for healthcare and telehealth during the pandemic, it is perhaps not surprising that there was a large positive hours differentials for remote workers in healthcare support occupations, which could also explain why we see a wage penalty for this occupation alone. We also cannot reject the hypothesis that hours are equal for remote and on-site healthcare support workers. It is also perhaps not surprising that those working remotely in personal care and services worked more hours, because during the peak of the pandemic, for example, many hairdressers offered personal services from home and were in more demand by those practicing social distancing. The other 12 occupations had little to no difference in usual hours by remote work status.

In Figure 10, we present trends in the wage differentials for white-collar and blue-collar occupations. Not surprisingly, given the relative feasibility of working from home for workers within these groups, we see a large difference in the wage differentials across these broad occupation groups. Remote white-collar workers earned substantial wage premia throughout the period, which are robust to adjusting for selection on unobservables as evidenced by the Oster betas. During the pandemic in 2021, the lower bound on the wage premium exceeded 5 percent. In contrast, remote blue-collar workers paid wage penalties until 2020, and in 2021, they earned a small 3.6 percent wage premium (not robust if there is positive selection into remote work).

Figure 11 reports hours differentials for these groups. Prior to the pandemic, those working remotely in both groups worked longer hours. However, during the pandemic, remote white-collar employees worked slightly fewer hours than those working on-site, although the difference was not economically meaningful. Blue-collar workers' hours differentials converged toward zero but were still about 10 minutes more per week for remote workers than on-site workers in 2021. Henceforth, we focus on subsamples of workers within white-collar occupations where remote work is more prevalent and thus selection is likely less an issue.

5.5 Heterogeneity by sex and parental status

Figures 12 and 13 show trends in wages and hours differentials by sex and by parental status for those working in white-collar occupations.[26] Looking first at wage differentials, we see similar trends among the four groups, with wage premia for those working remotely. However, we find large differences in the Oster betas for women by parental status, suggesting a higher degree of selection on observables for mothers. In addition, in 2021, the wage premium for remote work was statistically significantly higher for women with no children than it was for any of the other three groups (15.8 percent versus 14–14.5 percent).

Turning to the hours differentials, we see similar downward trends for both fathers and men without own household children; and that during the pandemic, those working remotely worked fewer hours than their counterparts working on-site, as we previously found looking at all men. For women, we find slightly different trends in the hours differentials by parental status, although the differentials are for the most part trending toward zero. During the pandemic, the hours differentials are small, and for mothers, the differential is not robust to adjusting for omitted variable bias.

[26] Parental status is defined based upon living with own minor children.

5.6 Heterogeneity across various subsamples of white-collar workers in 2021

In Figure 14, for 2021, we present OLS estimates and Oster betas from equations 1 and 2, respectively, for subsamples by sex and by age of youngest own household child, by college degree status, by race and Hispanic ethnicity, by disability status, by sector of employment, and by whether they live in a principal city or suburbs of the 15 largest MSAs or outside of the 15 largest MSAs. Even though parents were often at home working alongside their children, who may have interrupted their work activities (Lyletton et al. 2023; Pabilonia and Vernon 2023b), we still find that remote workers earned higher wages regardless of the age of their youngest own household child. However, mothers working at home with a child aged 0–4 had a slightly lower wage premium than other parents (12.9 percent versus over 14.1 percent), although we cannot reject the hypothesis that the coefficients across the regressions are equal at conventional levels. The difference, however, would be consistent with the hypotheses that mothers of young children 1) have slightly lower productivity than others due to more frequent interruptions from their children and/or 2) are more likely to accept or stay in lower paying jobs or are less likely to advocate for a raise in jobs allowing them to work remotely. The fact that the wage premium was still high for mothers of young children may also be because mothers whose paid work productivity was lower exited the labor force during the pandemic. The wage premia for remote workers differ by college degree status, with those with a college degree earning 15.3 percent more and those without a college degree earning 13.7 percent more. The wage premia for remote work differed by race and Hispanic ethnicity, with non-Black, non-Hispanic (NBNH) workers and Hispanic workers earning substantially higher returns for remote work than Black, non-Hispanic workers (15.0, 14.3, and 11.6 percent, respectively).

There has been considerable interest in whether people with disabilities will supply more labor given the new remote work climate (Ameri et al. 2022; Ne'eman and Maestas 2023). Those who may have previously found commuting to be too difficult/costly due to mobility impairments or who needed to remain close to medical equipment and doctors can now work from the comfort of their home in many occupations. Remote work has the potential to decrease pay differentials between those with and without disabilities if those with disabilities can increase their job tenure and raises are determined by performance rather than discriminatory practices that have been disadvantageous to those with disabilities (Schur et al. 2013). Our estimates show that people with disabilities working remotely earned more than people with disabilities working on-site during the pandemic, although the wage differential was smaller than the one for people without disabilities (12.5 percent versus 15.1 percent). However, it is also possible that during the pandemic, the ranks of workers with disabilities rose with more persons experiencing long-COVID, and some of these workers had previously high-paying jobs that could be done at home and which they could continue to do from home.[27]

We see a large difference in wage premia by sector of employment. During the pandemic, many government employees were considered non-essential workers and were encouraged to work from home. Those working in the private sector earned 15.7 percent more when working remotely, while those working for the government earned only 10.5 percent more. These differences in wage premia should not be surprising given the relative nominal wage rigidity in government pay schedules resulting in workers being more likely to be compensated based on job tenure rather than achievement. And during the recovery phase of the pandemic, private

[27] Between 2019 and 2021, the number of employed persons with disabilities rose from 5,858,000 to 5,950,000 (U.S. Bureau of Labor Statistics 2020; 2022). Nineteen percent of adults in the United States reported that they had symptoms of long-COVID in early June 2022 (National Center for Health Statistics. U.S. Census Bureau, Household Pulse Survey 2022–2023).

sector workers experienced greater growth in wages in general between the fourth quarter of 2020 and the fourth quarter of 2021 than did state and local government employees; therefore, talented remote workers may have been more likely to have been rewarded in the private sector (Maciag 2022).

Finally, we compare wage premia for remote work for those living in and outside of the principal city in the 15 largest MSAs as well as for those living outside the 15 largest MSAs. The wage premium was smaller in the principal city of the 15 largest MSAs and statistically significantly different from the wage premium for those living outside the 15 largest MSAs (12.6 percent versus 14.5 percent). This finding is consistent with the donut effect story (Biljanovska & Dell'Ariccia 2023; Gupta et al. 2022; Ramani & Bloom 2022), where home prices rose less in city centers as more highly paid remote workers seeking larger living/working spaces moved out of the principal city to suburbs and exurbs, bidding up home prices there in the process.

In all of the subsamples, the signs of the estimates are robust to correcting for omitted variable bias. In Appendix Table A6, we show that the IV estimates are 3–5 times larger than the OLS estimates, using the share who worked remotely in the respondent's occupation as an instrument. The estimates measure the LATE and confirm large returns to working from home across the various subsamples when controlling for negative selection.

Figure 15 shows coefficient estimates from the hours worked regression and the corresponding Oster betas for the same subsamples of white-collar workers as presented in Figure 14. For the most part, the hours differentials between remote and on-site workers are small. The largest differential is for remote working fathers with a child aged 0–4 who worked about 32 fewer minutes per week (assuming a 43.5-hour workweek), followed by remote fathers of school-age children only and remote government employees who worked about 26 and 24 fewer minutes per week respectively than their on-site counterparts. In contrast, remote mothers with school-age children reported only a small increase in work hours compared to their on-site counterparts (13 more minutes). NBNH workers, college-educated workers, workers without disabilities, and those workers living outside the largest MSAs show small decreases in hours when working remotely that are robust to correcting for omitted variable bias. Black workers, Hispanic workers, and workers with disabilities work the same hours regardless of their work location. Workers without a college degree worked more when they were remote, but the estimate is not robust to negative selection bias.

5.7 Remote wage premia across the wage distribution

Up until this point, we have estimated wage premia for remote work for the average wage earner, albeit we have examined heterogeneity across demographic, geographic, and job characteristics. However, remote work differentials also may differ across the wage distribution, and thus the rise in remote work could potentially change wage inequality. To look at differences across the wage distribution, we estimate quantile wage regressions for white-collar workers by sex.[28] For both men and women, wage premia for remote work varied across the distribution in 2019 (Figure 16). For women, those in the lower end of the wage distribution had lower wage premia. For men, those in both the lower and upper ends of the distribution had lower wage premia than those in the middle of the wage distribution. In 2021, wage premia for remote work rose substantially across the entire wage distribution, exceeding 10 percent across the entire range of wages. Those at the lower end of the wage distribution saw the largest wage gains for remote work. For women, those in the top half of the distribution had wage premia exceeding 15

[28] Due to convergence issues, we were unable to estimate instrumental variable quantile wage regressions.

percent. For men, those at the 90th percentile of wage earners had a slightly lower premium than those in the rest of the wage distribution.

5.8 Wage growth within detailed occupations by remote status

Turning to the results from our occupation-level regression analyses, we first show results from equation 9 in Table 8 to compare wage growth within detailed occupations by remote status. We find that in 2019, those working remotely earned only slightly more than those working on-site within detailed occupations (2 percent more), but the estimate was not statistically significant at conventional levels. In addition, over the 2019–21 period, there was no real wage growth for on-site workers within occupations. However, in 2021, remote workers earned 3.5 percent more than on-site workers within the same detailed occupation; therefore, wage growth was also 3.5 percent faster. Wage growth results are similar but slightly lower in magnitude, if we include part-time workers in the analysis sample.

5.9 Wage growth between occupations by changes in remote worker shares

Figure 17 shows the relationship between occupation-level average cumulative real wage growth and the change in the percentage of remote workers in the occupation over the 2019–2021 period using four-digit occupation groups. The size of the bubbles represents the occupation's relative employment. The trendline represents the slope of a linear regression, weighted by employment in each occupation. Controlling for compositional changes over the period, we find that a one percentage-point increase in the percentage of remote workers in an occupation is associated with a 0.031 percentage point increase in the occupation-level real wage growth, and the relationship is statistically significant.[29] From 2019 to 2021, the average

[29] As a robustness check, we restricted the analysis to occupations with at least 100 observations and find almost identical results (see Appendix Table A7). As a sensitivity analysis, we include part-time workers

percentage of remote workers increased by 15.5 percentage points across occupations. This suggests that the rise in remote work is associated with a 0.5 percentage-point increase in occupation-level real wage growth, whereas occupation-level real wages grew about 2.1 percent on average.

6. Mechanisms for wage premia

We investigate two possible mechanisms through which remote wage premia are a result of increased productivity while working from home. First, workers may be more or less productive working from home based on their job tasks, and it may be more or less costly for employers to have their employees working from home based on tasks. For example, if jobs require frequent face-to-face communication, it can be more costly to try to do the job at home. Following Oettinger (2011) and Dingel and Neiman (2020), we investigate the bivariate relationship between the two-digit occupation-level remote wage premia/penalties in 2021 and the share of workers in the occupation that could feasibly work entirely from home given the task content of jobs, where the latter is calculated using Dingel and Neiman's occupation-level feasibility of working from home indexes and the 2021 ACS detailed occupation employment shares. Table 9 reports results using our OLS and IV estimates of remote wage premia/penalties. We find that the larger the share of workers in an occupation that can feasibly work entirely from home, the larger is the remote wage premium.

Second, using data from the 2020–2021 ATUS, we estimate an endogenous binary treatment effects model (similar to the one specified in equations 3–5) to examine the effects of working from home on the time people wake up in the morning. There is a wide body of research

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and find that a one percentage-point increase in the percentage of remote workers in an occupation is associated with a 0.021 percentage point increase in the occupation-level wage growth.

suggesting that sleep increases cognition, and cognition increases individual worker productivity (Cost-Font et al. 2024; Pabilonia and Groen 2019). In addition, Gibson and Shrader (2018) find that sleep increases wages, presumably by increasing productivity. The ATUS 24-hour diary day starts at 4 a.m., and thus we cannot estimate the full-night sleep occurring before the workday. However, time-use research (Cowan et al. 2023; Pabilonia and Groen 2019; Stewart 2012) suggests that people more often adjust their wake-up times than their bedtimes to deal with early work and school schedules. Thus, a later wake-up time implies a longer night of sleep. Workers who forgo their commute by working from home, or spend less time grooming, could use some of their time savings to sleep later in the morning (Pabilonia and Vernon 2022). In these models, we instrument for working from home using our IV1, the share in the respondent's occupation who worked remotely. We find that on work-from-home days compared with on-site days, full-time workers sleep 1.9 hours later in the morning on average (Table 10).[30] The effects of remote work on wake-up time were much stronger for men than women. They were also stronger for mothers than for women without minor children in the household. (We cannot reject the hypothesis that $\rho = 0$ in the case of women without minor children in the household, so OLS estimates are preferred.) Thus, we find that workers could potentially be earning wage premia by working remotely due to sleep-enhancing productivity effects.

7. Conclusion

Using the ACS, we examine trends in wage and hours differentials for workers who are primarily remote relative to workers who are primarily on-site from 2010 through 2021, with a special focus on changes during the pandemic period from 2019 to 2021. There are three main

[30] The raw difference in mean wake-up time between workers on remote and on-site workdays is 35 minutes.

takeaways from these analyses. First, on average, remote workers earn more than on-site workers, even when controlling for selection into remote work. Comparing various subsamples of workers among those in white-collar jobs, we found that most groups of remote workers earned wage premia in 2021, even those in management occupations. Blue-collar workers, however, paid a remote wage penalty until 2020 when they earned a small wage premium. White-collar workers along the wage distribution also earned premiums, although not equally. Thus, those with access to white-collar jobs benefited from this work-from-home revolution. Among them, Black workers and those with disabilities earned lower premium than other workers. Second, during the pandemic, wages grew faster for remote workers than on-site workers within occupations. Third, at the beginning of the period, remote workers had higher usual weekly hours worked than on-site workers; but this gap fell steadily over the period, and in 2021, hours of remote workers had converged with the hours of on-site workers.

Overall, our findings are consistent with remote work being productivity enhancing for many workers, which has been a highly debated topic. During the pandemic, when remote work was highly prevalent, wages were substantially higher for remote workers than on-site workers while hours were similar. We found that the larger is the share of workers in a two-digit occupation that could feasibly do all their work from home, the larger is the occupation’s remote wage premium. Finally, using pandemic-era time diaries from the ATUS, we found that remote workers had later wake-up times than on-site workers, which could mean that workers were more refreshed after their night’s sleep on work-from-home days. We do not find evidence to support claims that workers in 2021 were willing to pay substantially for the option to work from home, although equilibrium wage determination is complex and we find that mothers earned slightly lower wage premia when working from home versus on-site compared with women with no minor children at home. This motherhood difference in returns to remote work is consistent with either mothers' being more likely to be interrupted during work hours as they worked at home alongside their children, which could be detrimental for their productivity, or mothers' being willing to forego some of their earnings for the opportunity to work from home.

There were other possible explanations for remote wage premia that would also be interesting to investigate in future research. For example, firms may have offered higher wages to workers with technical skills to prevent turnover, or the pandemic created a lot of churning and workers switching jobs were able to negotiate higher pay and remote work.

Our findings have implications for policymakers concerned about wage inequality, the gender wage gap, and long-run growth as we move into a post-pandemic world. We found that the rise in remote work, especially among women, led to a small decline in the gender wage gap. If more women can maintain higher-paying jobs because of these new flexible job opportunities, they will be more productive throughout their careers, which should further decrease the gender wage gap. The same would hold true for workers with disabilities.

In the pandemic period that we studied (2020–2021), many individuals worked from home because of the health threat. In the future, workers and firms will decide on the optimal mix of work-from-home days given the job tasks to be performed, production processes, firm culture, and family/life circumstances. Workers who are less productive working from home will find jobs at a worksite. This could potentially shrink remote wage premia in the future while allowing aggregate wages and productivity to continue to rise.

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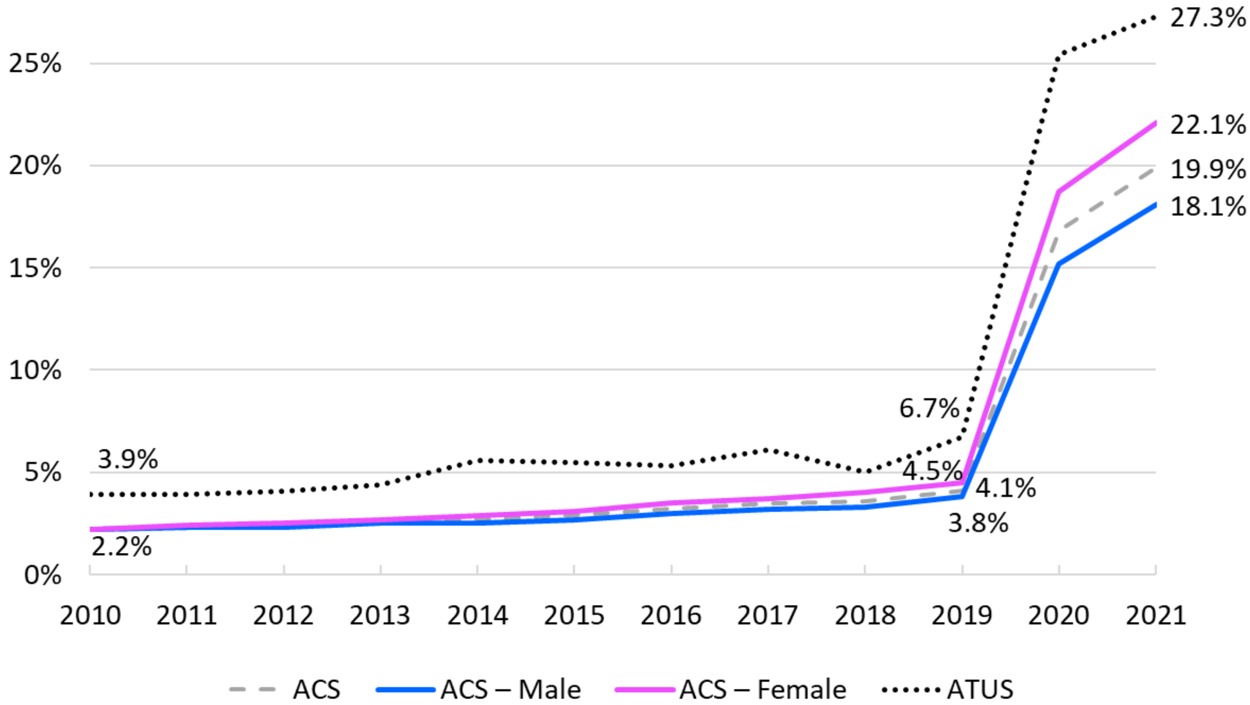
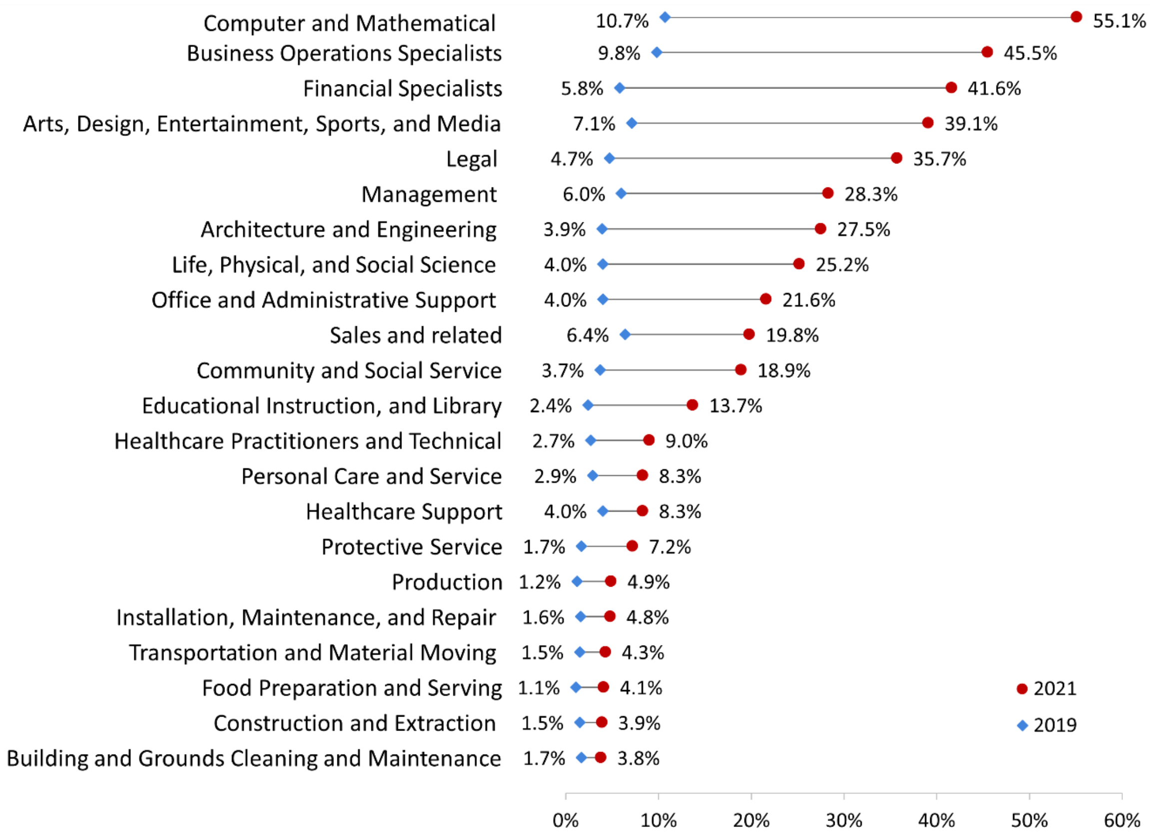
Fig. 1 Percentage of people working primarily from home and percentage of workdays exclusively worked from home among full-time employees in the nonfarm sector



Notes: The ACS measure of working from home is the percentage of full-time full-year employees who report worked from home as their usual mode of transportation to work. The ATUS measure is the percent of workdays worked from home for full-time employees and is based on working *exclusively* from home on days with at least four hours of work, including weekend days. ATUS estimates are higher because they include those who work most of their days in the office but some days at home. Estimates are weighted using survey weights.

Source: American Community Survey (ACS); American Time Use Survey (ATUS)

Fig. 2 Percentage of remote workers by occupation

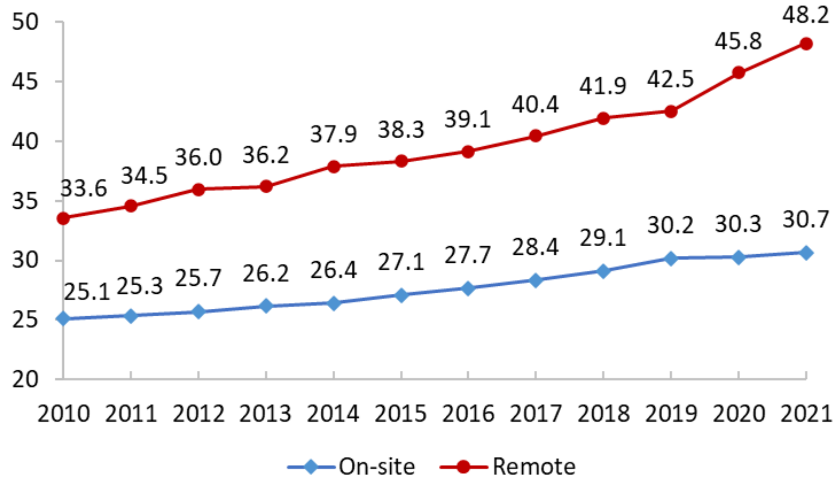


Notes: ACS weights are used here and in all other calculations.

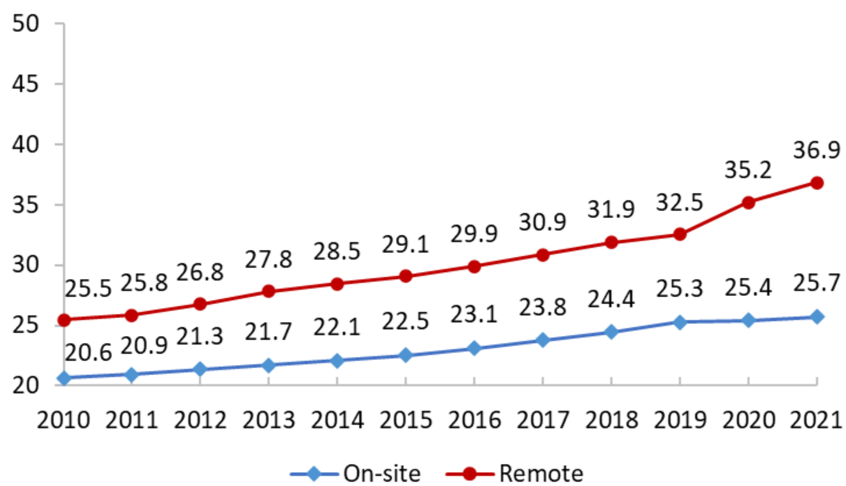
Source: American Community Survey

Fig. 3 Average wages and earnings by remote worker status

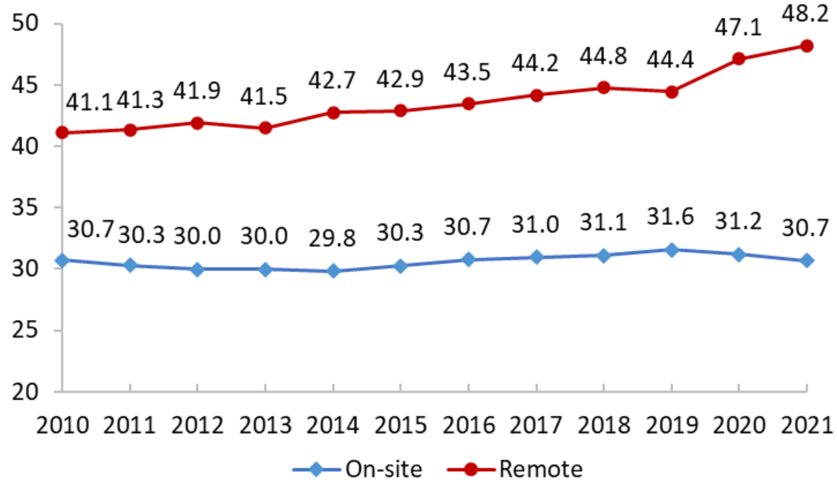
A. Nominal wages in current dollars (Men)



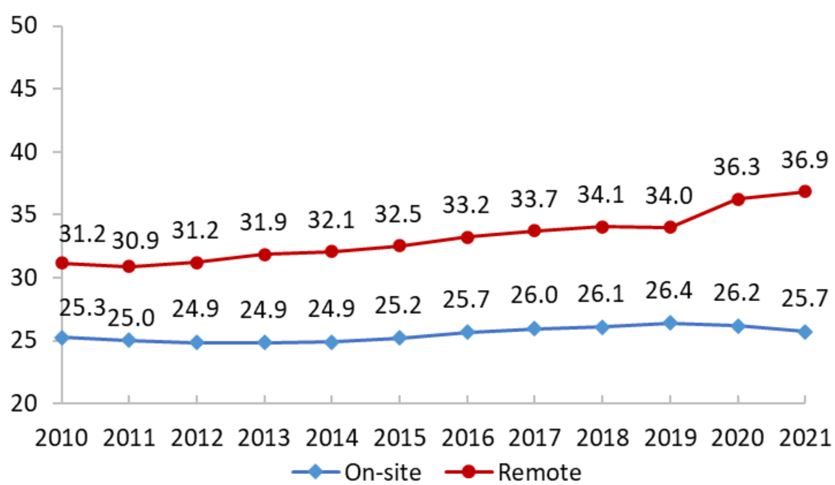
B. Nominal wages in current dollars (Women)



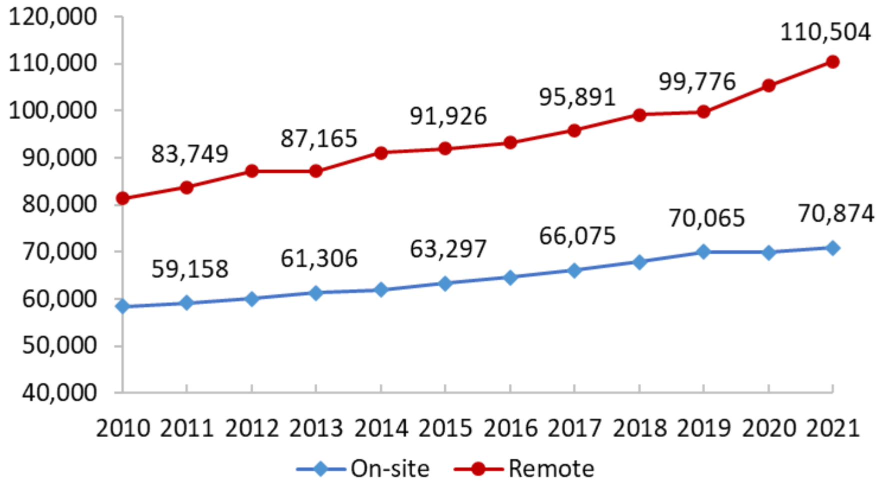
C. Real wages in 2021 dollars (Men)



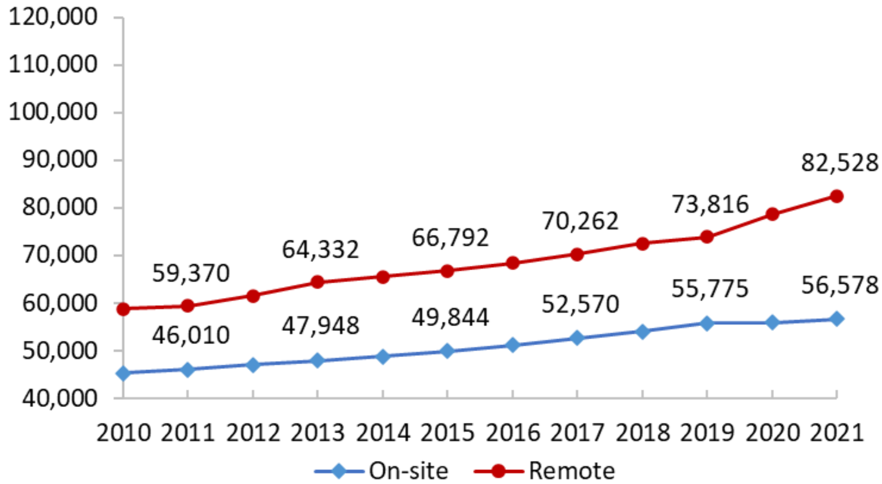
D. Real wages in 2021 dollars (Women)



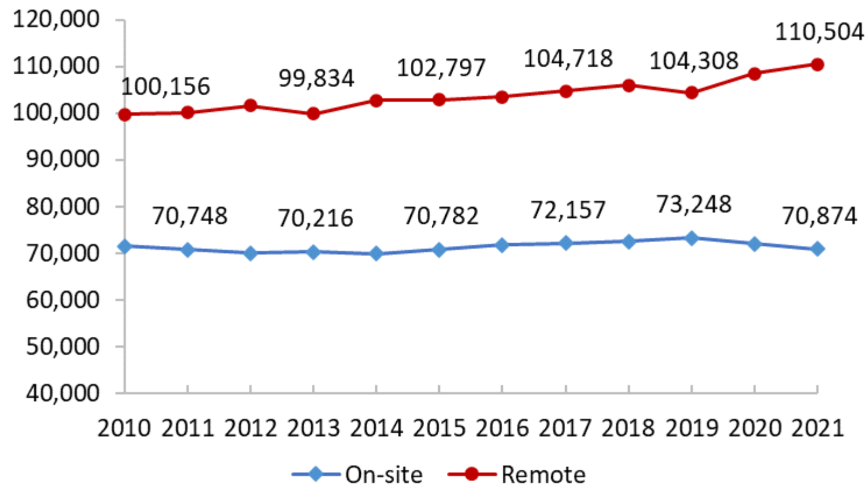
E. Nominal annual earnings in current dollars (Men)



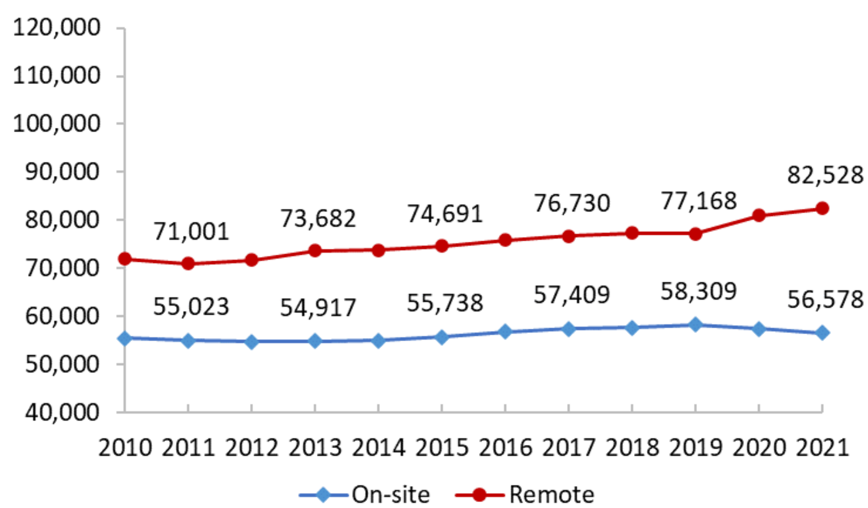
F. Nominal annual earnings in current dollars (Women)



G. Real annual earnings in 2021 dollars (Men)



H. Real annual earnings in 2021 dollars (Women)

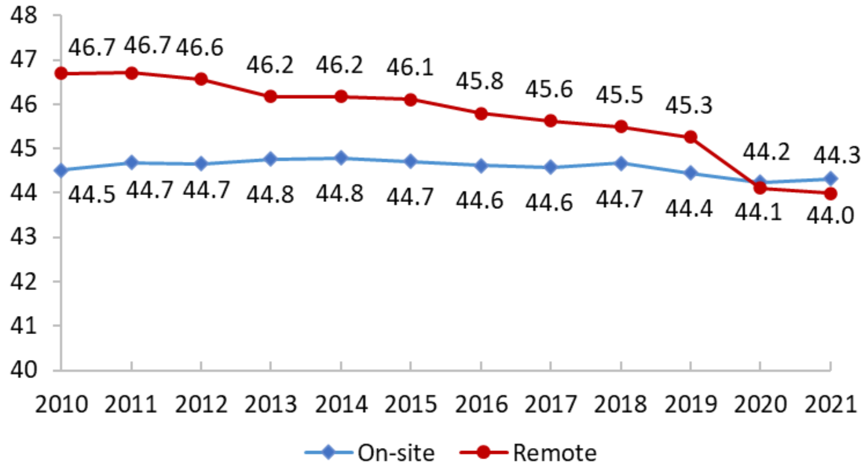


Notes: Here and elsewhere in the paper, we used the average of current and prior year CPI to adjust for inflation because income is reported for 12 months prior to the survey. Hence, 2021 dollars are actually 2020-21 dollars.

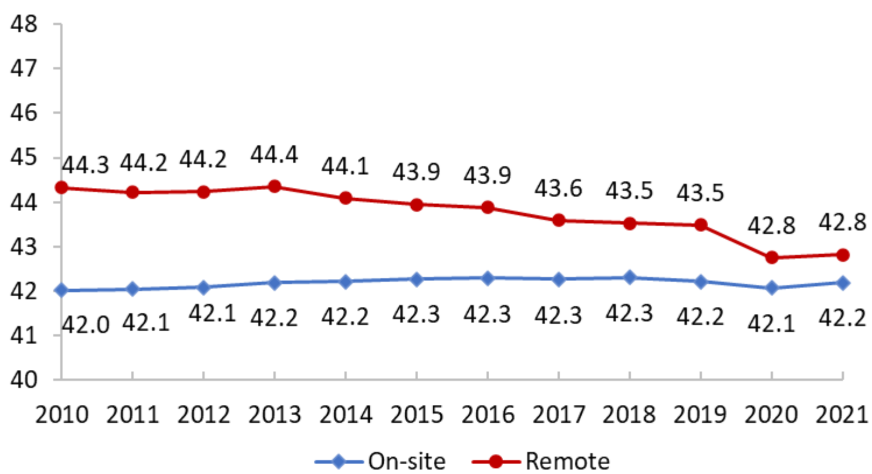
Source: American Community Survey

Fig. 4 Usual weekly hours worked by remote worker status

A. Men



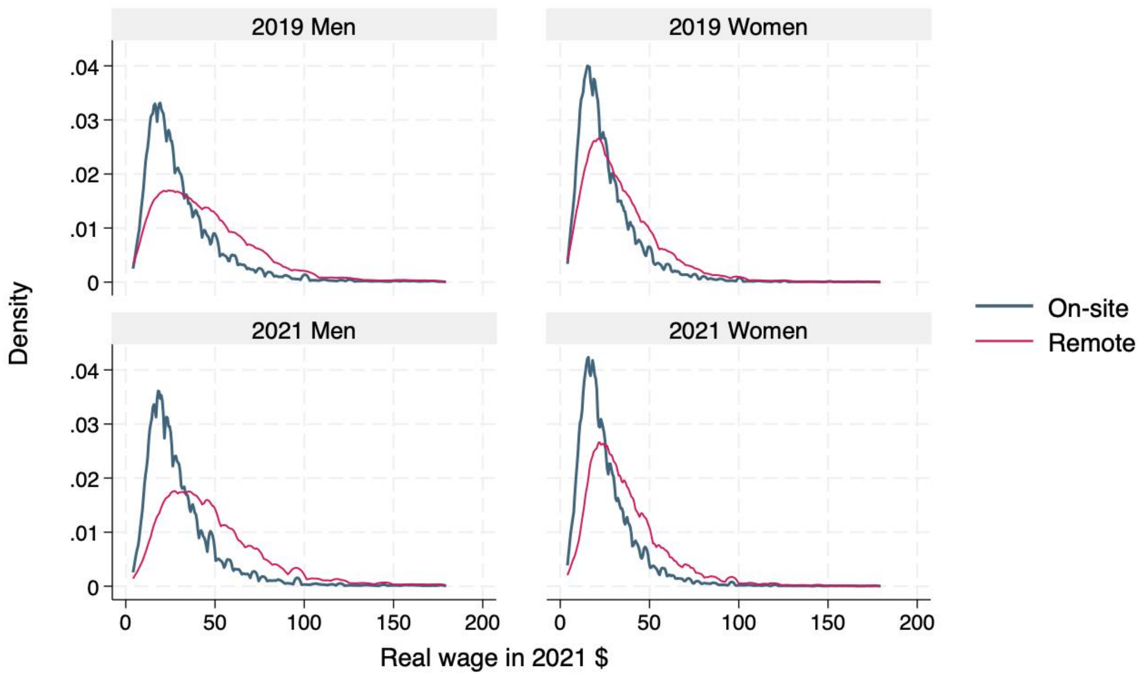
B. Women



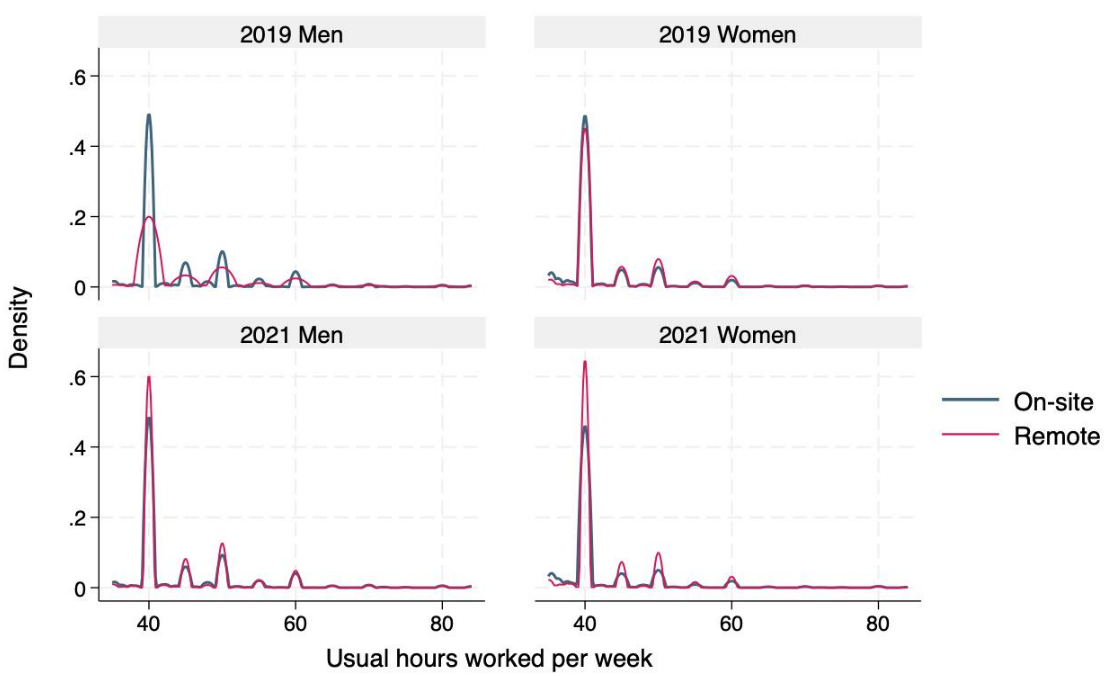
Source: American Community Survey

Fig. 5 Kernel density estimates, 2019 and 2021

A. Real wage



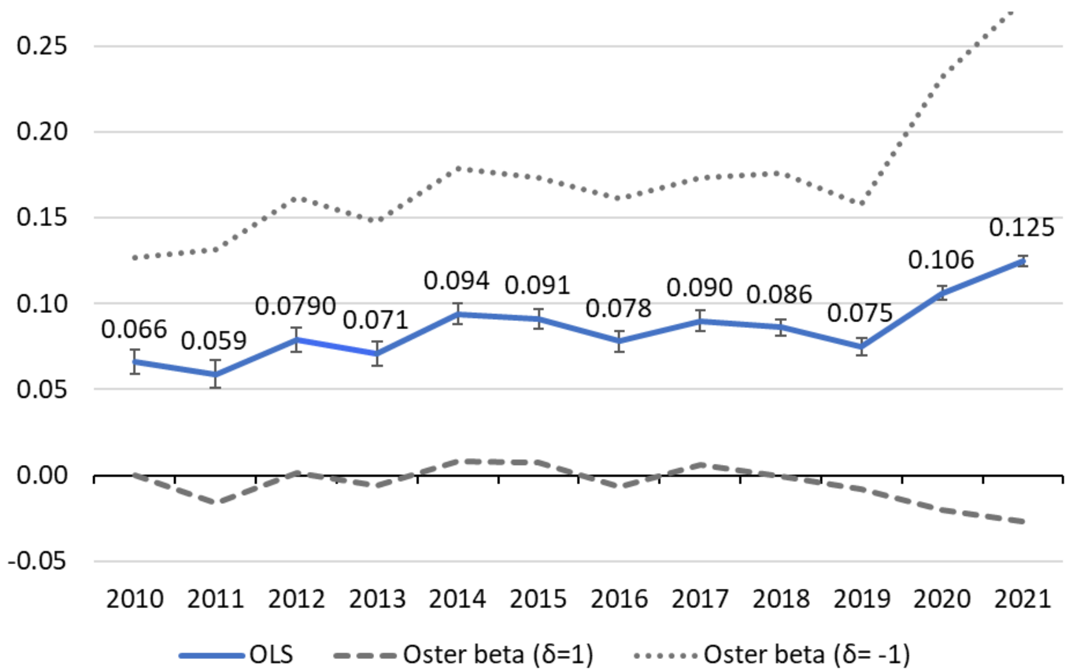
B. Usual weekly hours worked



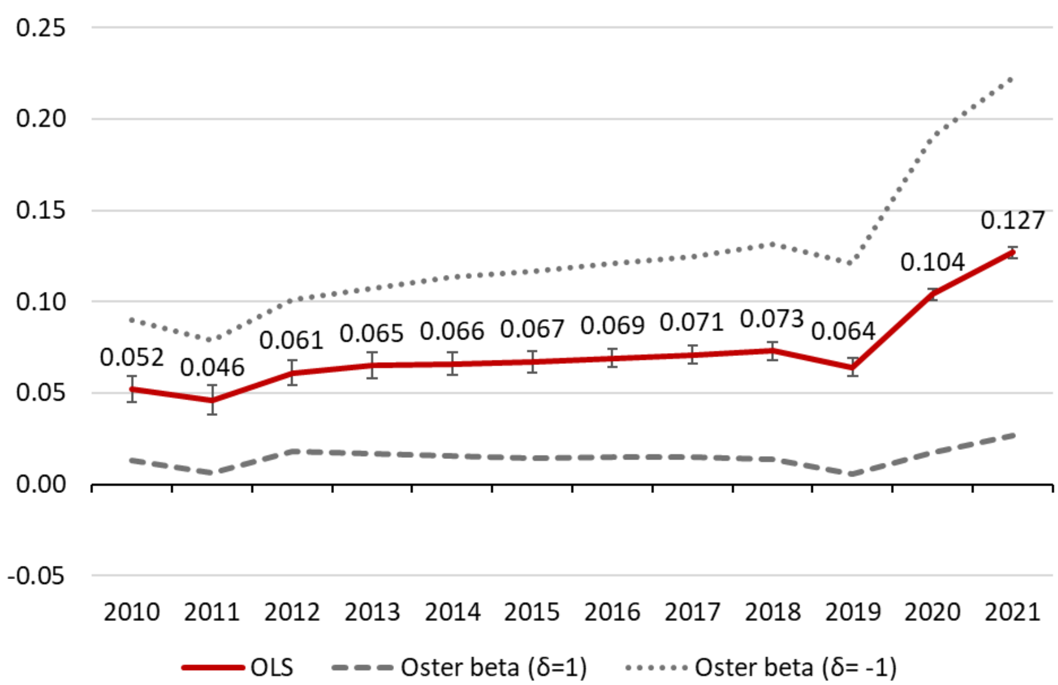
Source: American Community Survey

Fig. 6 Hourly wage and annual earnings regression coefficients on remote worker and Oster betas

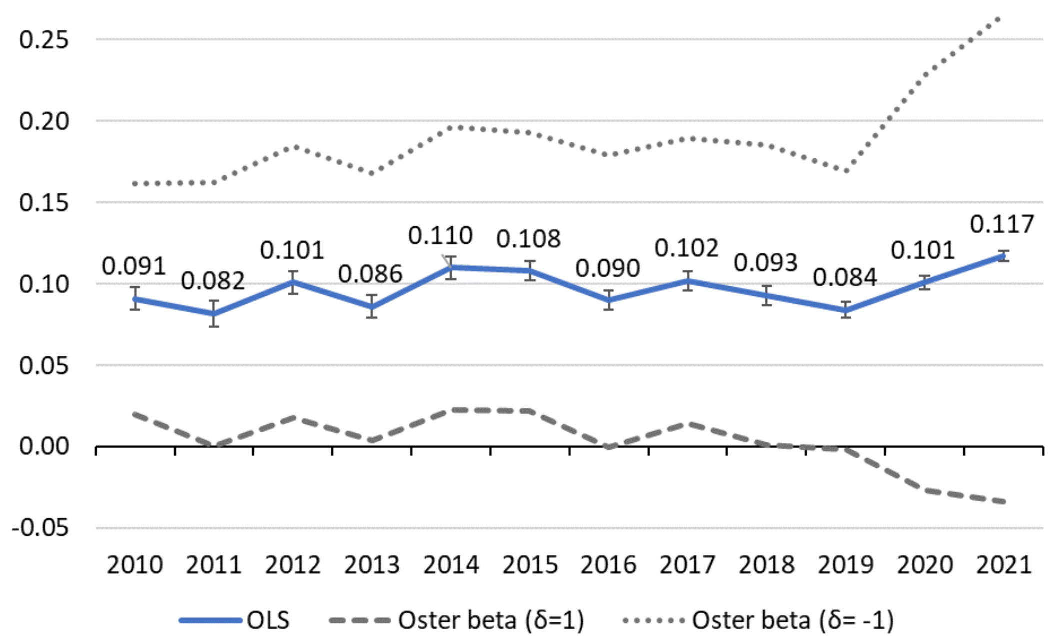
A. Hourly wage (Men)



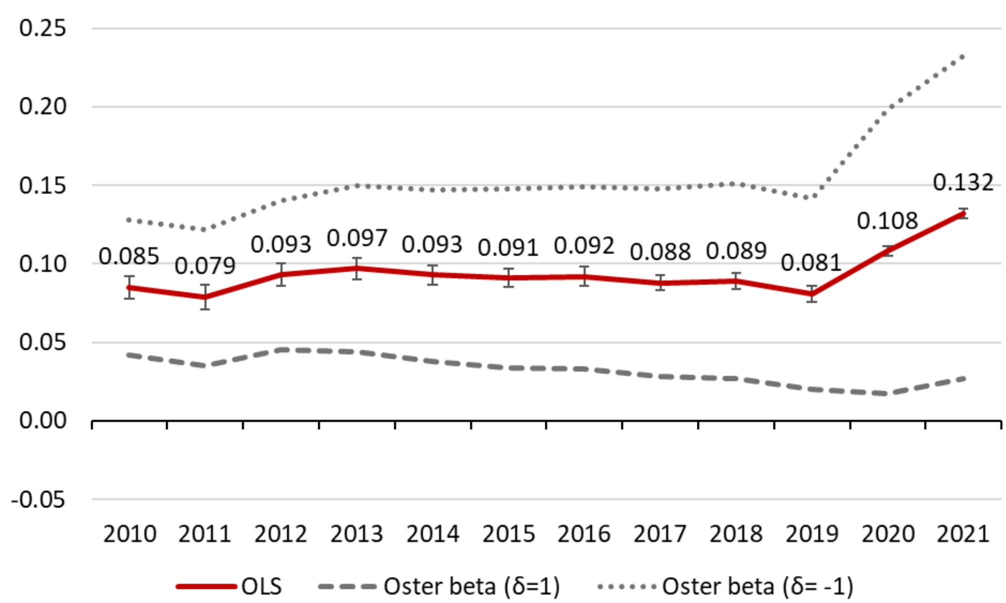
B. Hourly wage (Women)



C. Annual earnings (Men)



D. Annual earnings (Women)

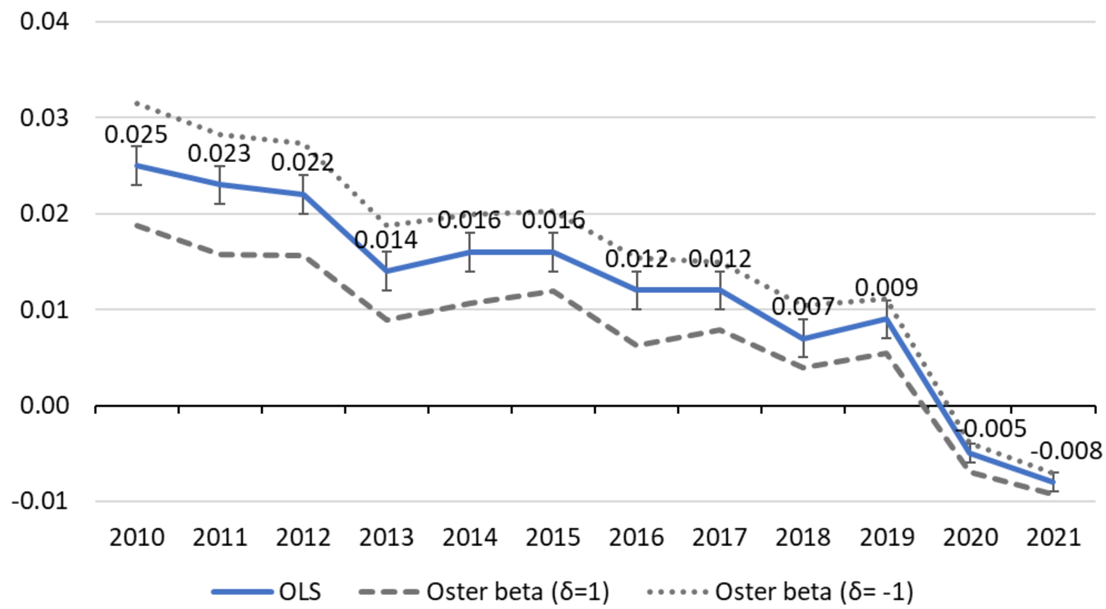


Notes: Estimates from equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

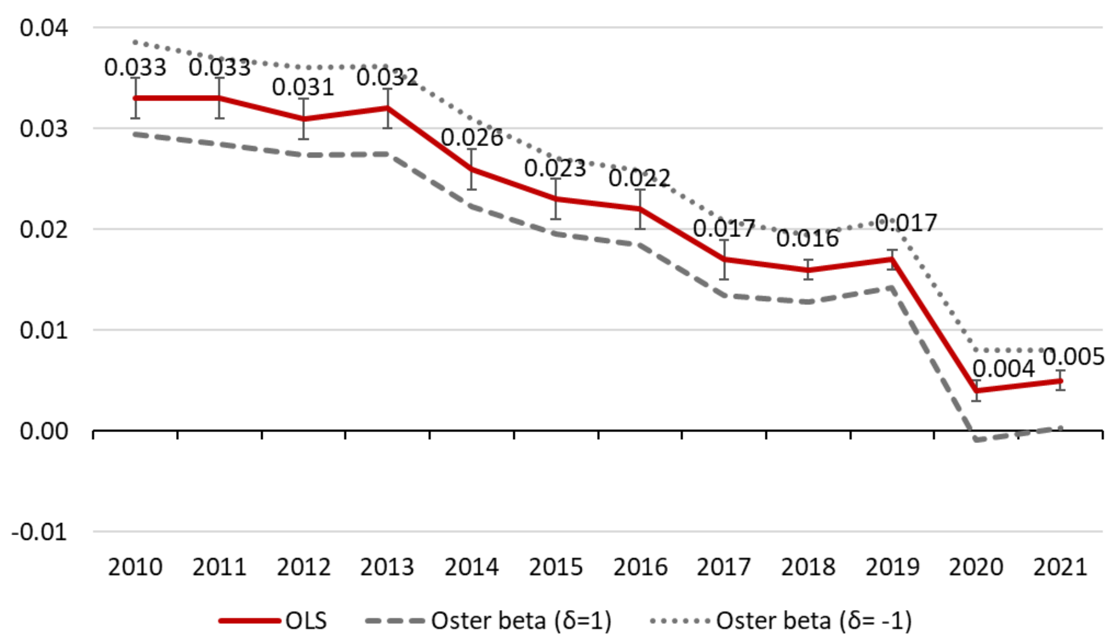
Source: American Community Survey

Fig. 7 Weekly hours worked regression coefficients on remote worker and Oster betas

A. Men



B. Women



Notes: Estimates from equations 1 and 2. See Table 3 for the full list of controls. Error bars represent 95% confidence intervals.

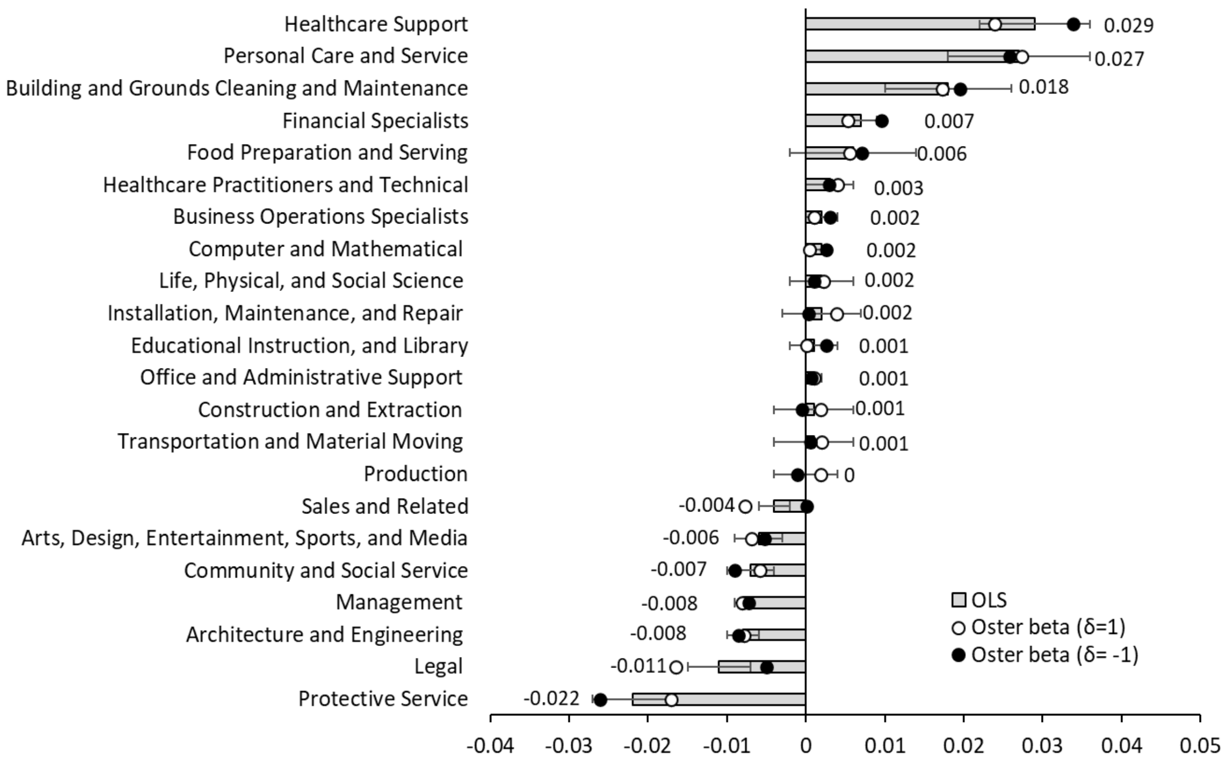
Source: American Community Survey

Fig. 8 Coefficients on remote worker from wage regressions by occupation and Oster betas, 2021

Notes: Estimates from equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

Source: American Community Survey

Fig. 9 Coefficients on remote worker from hours worked regressions by occupation and Oster betas, 2021

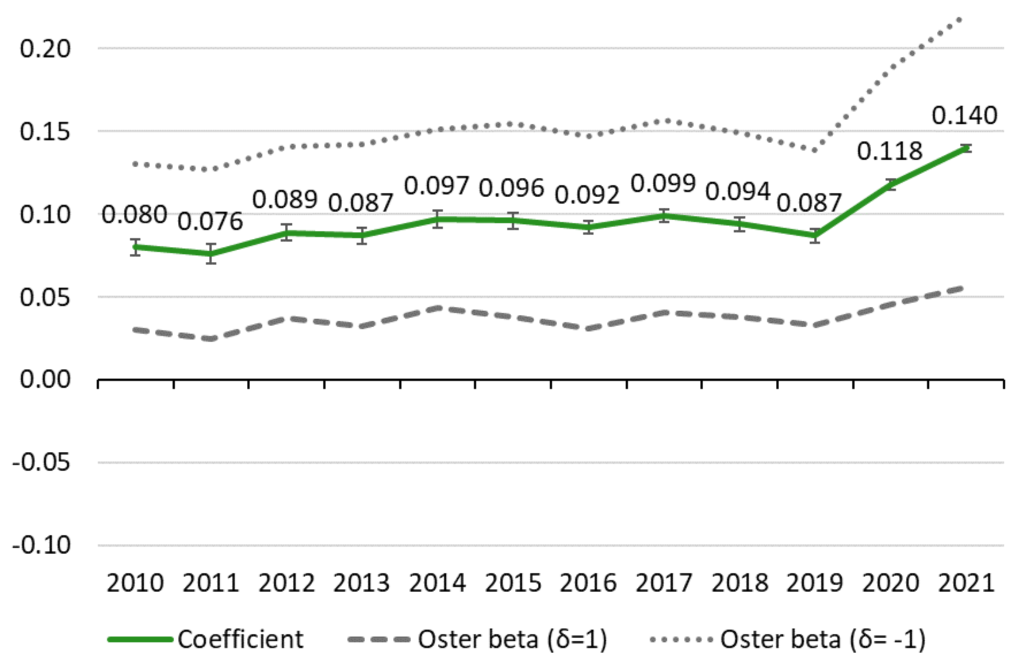


Notes: Estimates from equations 1 and 2. See Table 3 for the full list of controls. Error bars represent 95% confidence intervals.

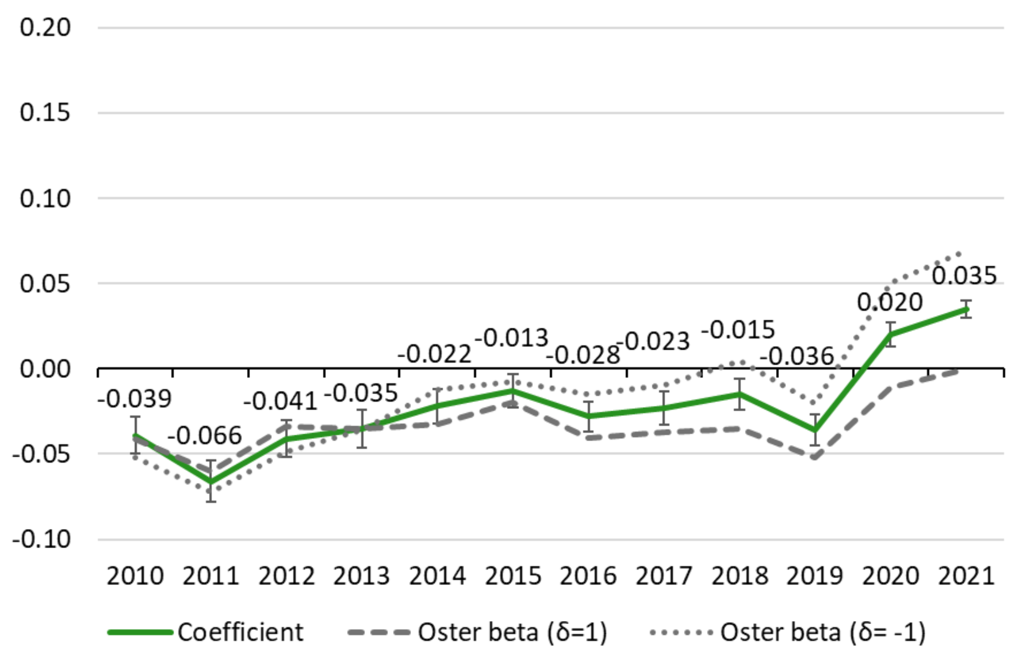
Source: American Community Survey

Fig. 10 White-collar and blue-collar wage regression coefficients on remote worker and Oster betas

A. White-collar Occupations



B. Blue-collar Occupations

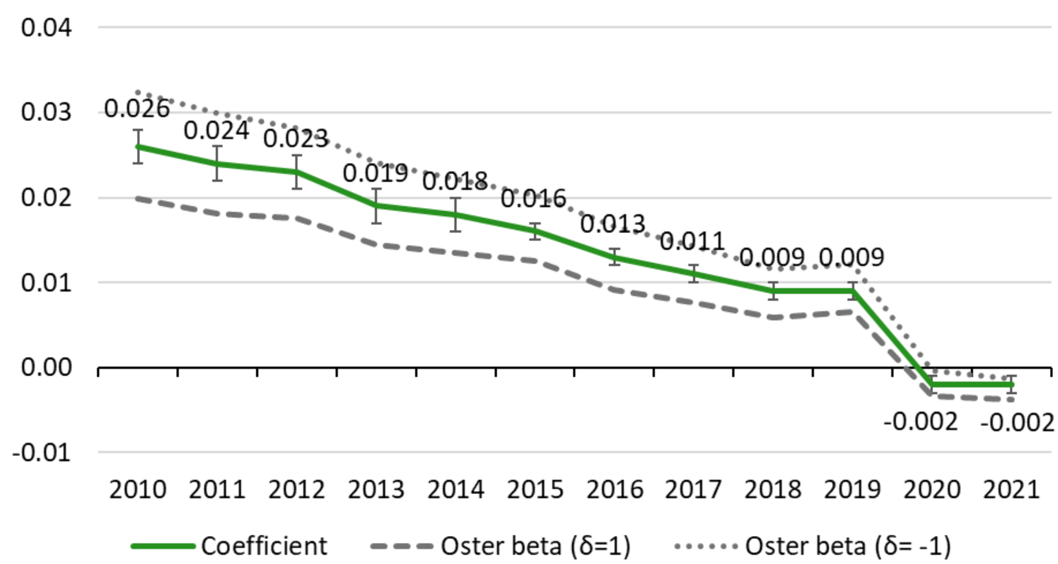


Notes: Estimates from equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

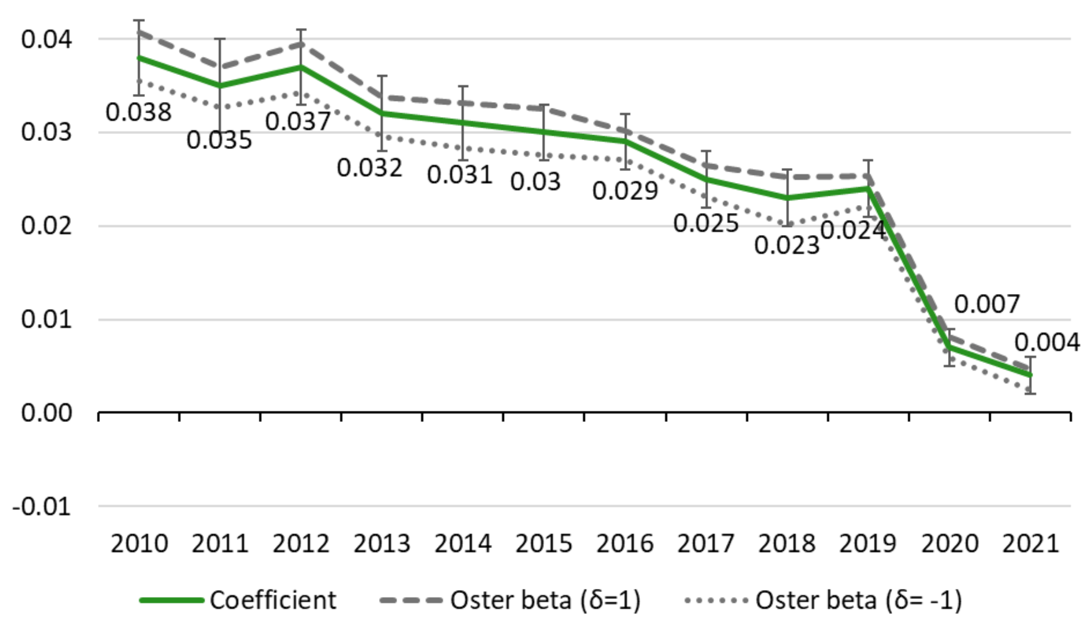
Source: American Community Survey

Fig. 11 White-collar and blue-collar hours worked regression coefficients on remote worker and Oster betas

A. White-collar occupations



B. Blue-collar occupations

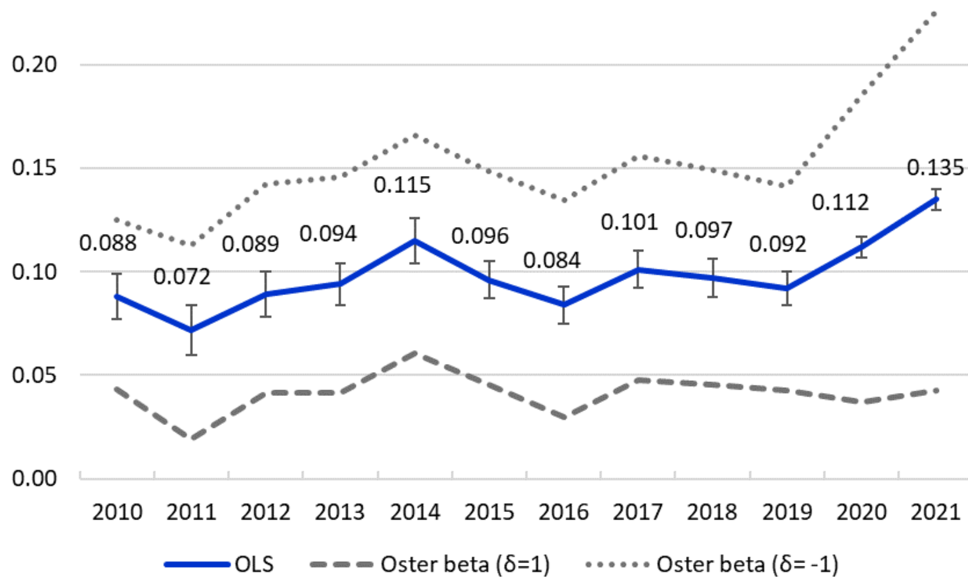


Notes: Estimates from equations 1 and 2. See Table 3 for the full list of controls. Error bars represent 95% confidence intervals.

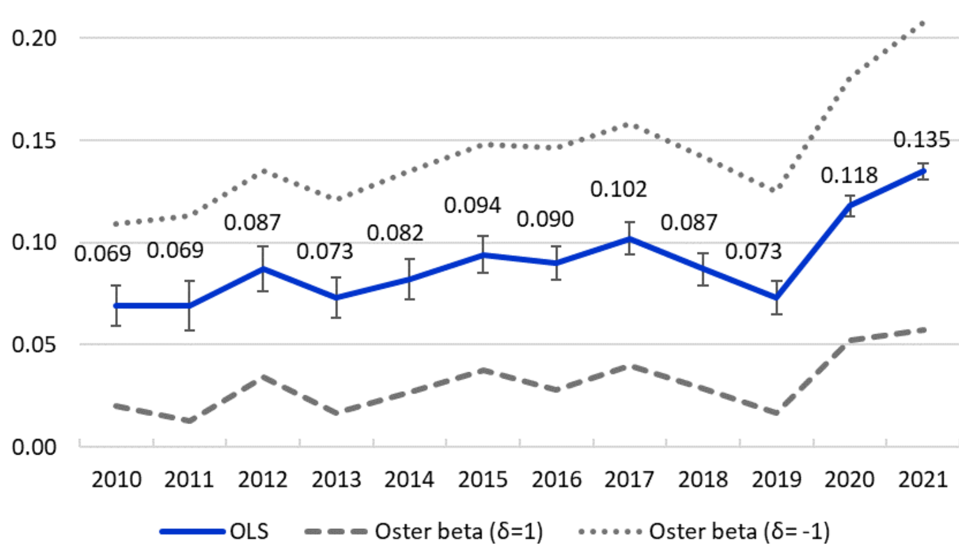
Source: American Community Survey

Fig. 12 White-collar workers by parental status: Wage regressions coefficients on remote worker and Oster betas

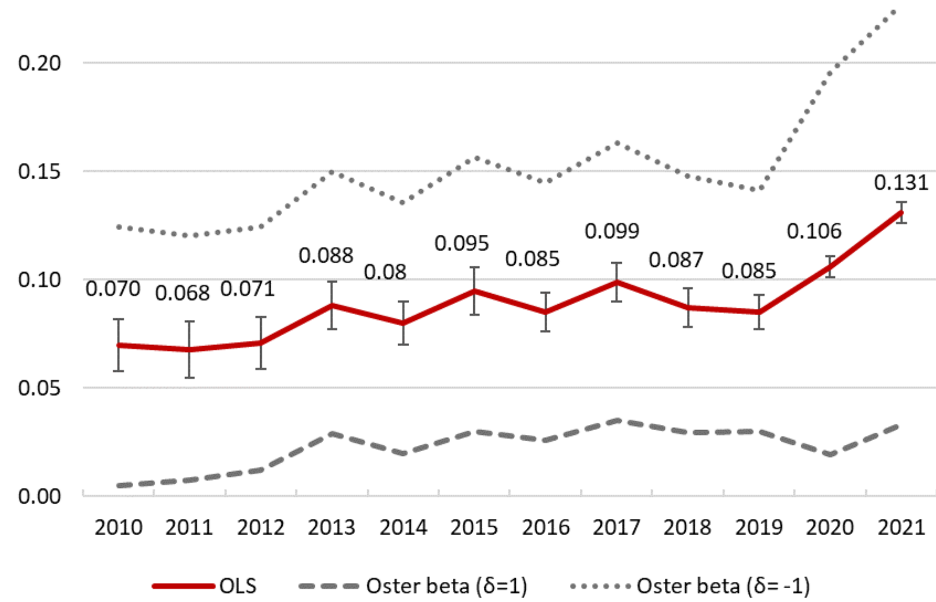
A. Fathers



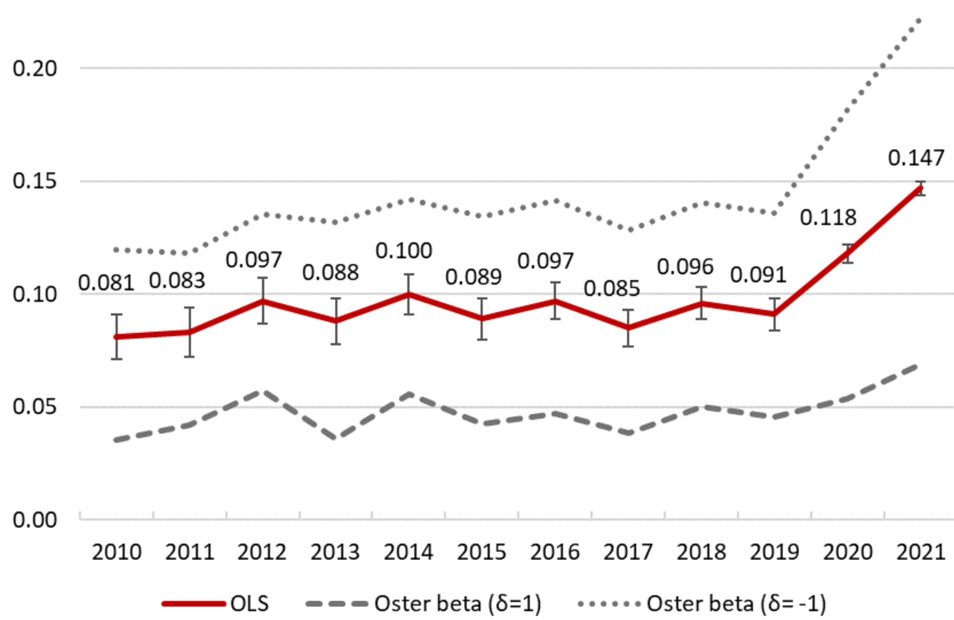
B. Men with no household children



C. Mothers



D. Women with no household children

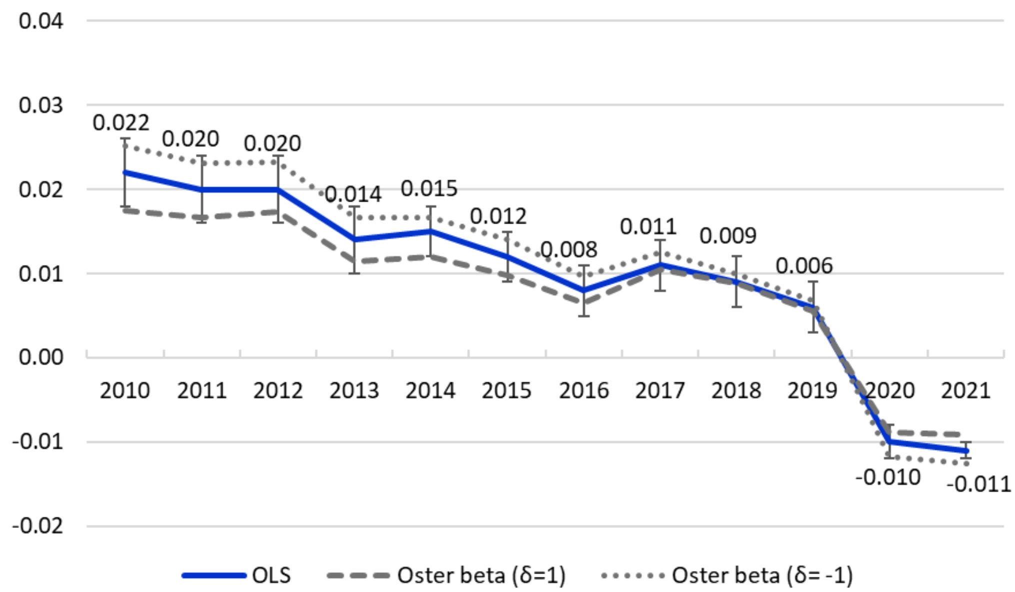


Notes: Estimates from equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

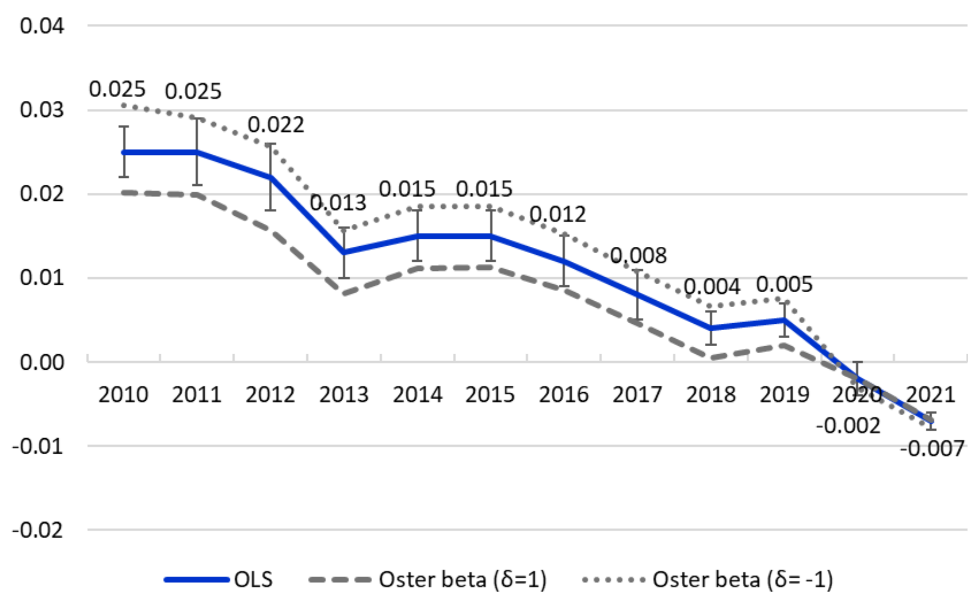
Source: American Community Survey

Fig. 13 White collar workers by parental status: Hours worked coefficients on remote worker and Oster betas

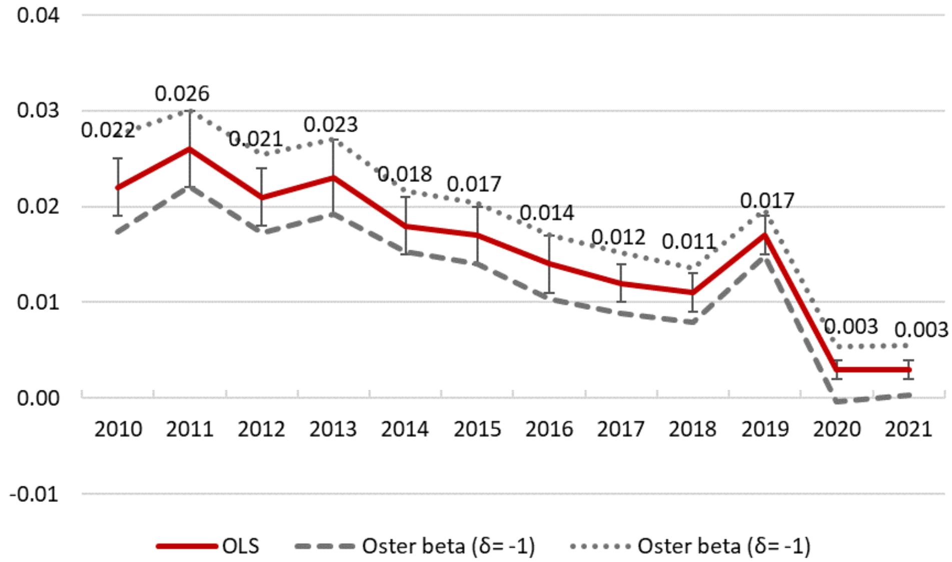
A. Fathers



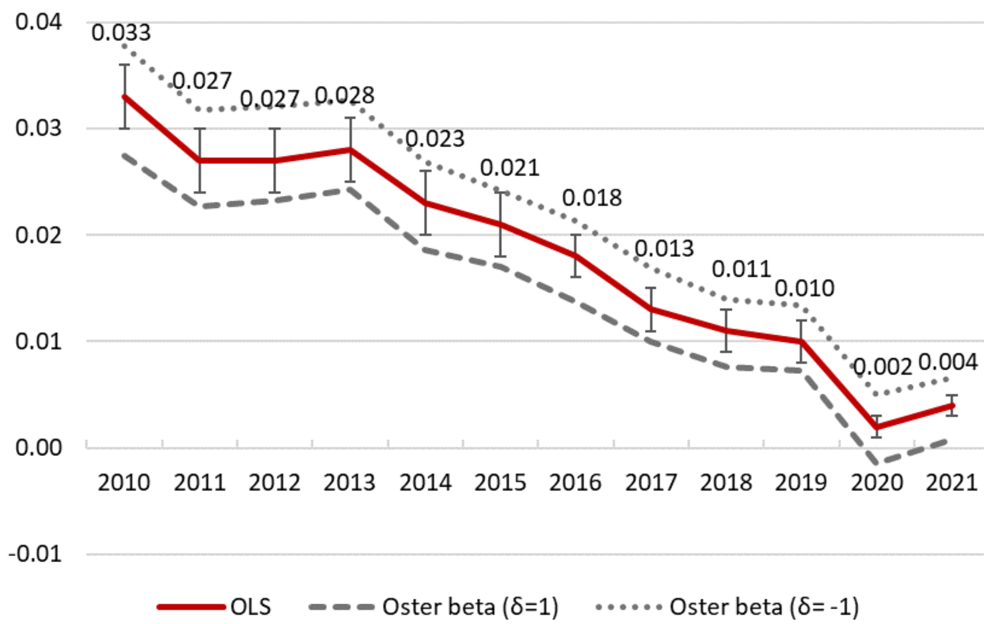
B. Men with no household children



C. Mothers



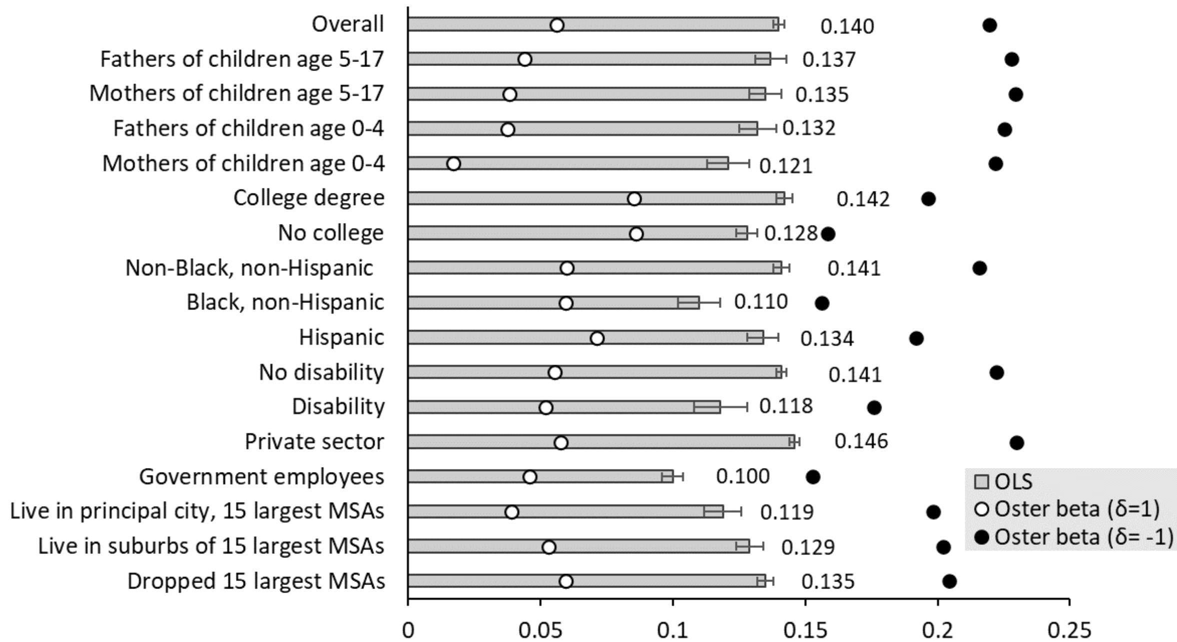
D. Women with no household children



Notes: Estimates from equations 1 and 2. See Table 3 for the full list of controls. Error bars represent 95% confidence intervals.

Source: American Community Survey

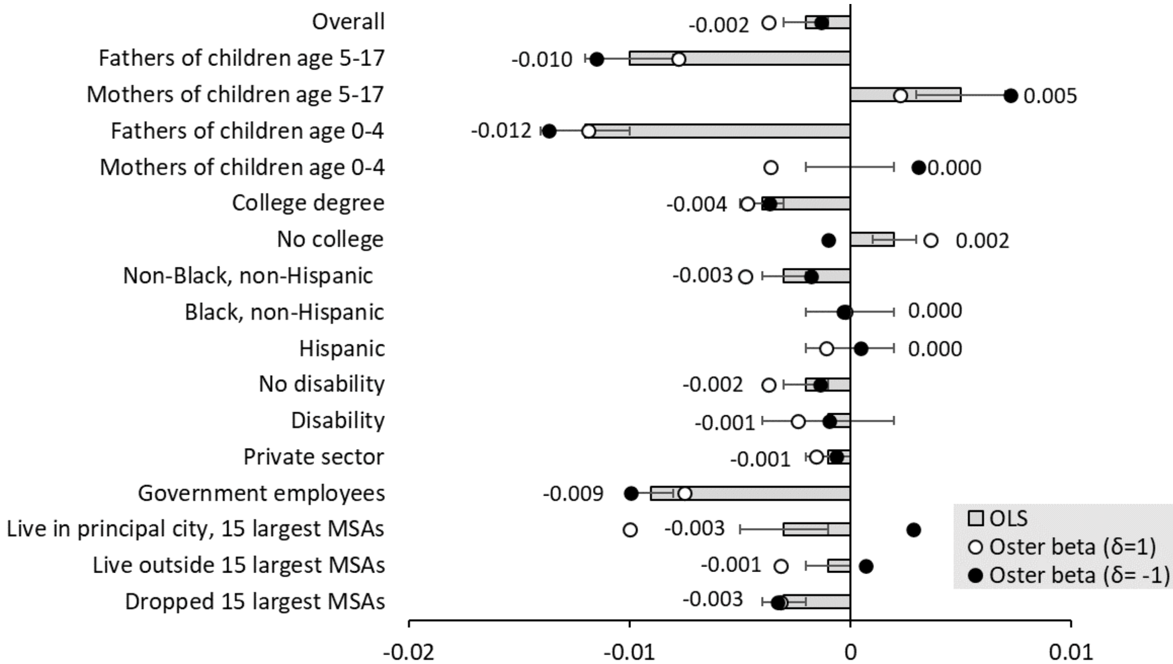
Fig. 14 Wage regression coefficient estimates on remote worker and Oster betas for subsamples of white-collar workers, 2021



Notes: Estimates from equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals. Mothers and fathers are divided into subsamples by the age of their youngest household child.

Source: American Community Survey

Fig. 15 Weekly hours worked regression coefficient estimates on remote worker and Oster betas for subsamples of white-collar workers, 2021

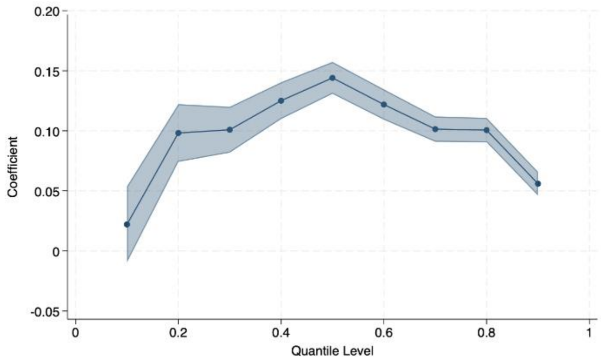


Notes: Estimates from equations 1 and 2. See Table 3 for the full list of controls. Error bars represent 95% confidence intervals. Mothers and fathers are divided into subsamples by the age of their youngest own household child.

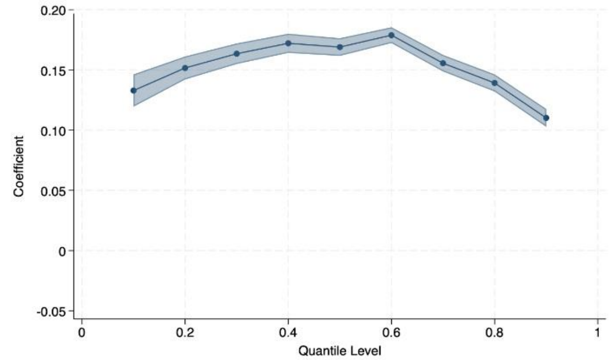
Source: American Community Survey

Fig. 16 Quantile wage regression coefficients for white-collar workers

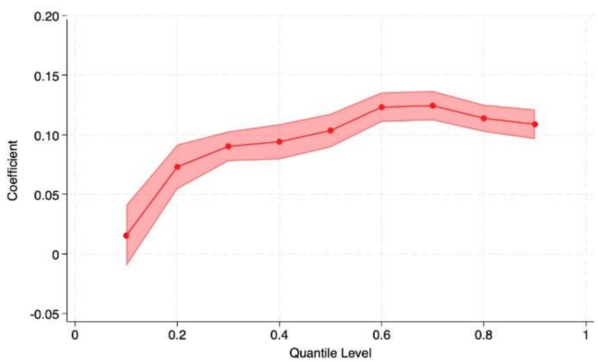
A. 2019 Men



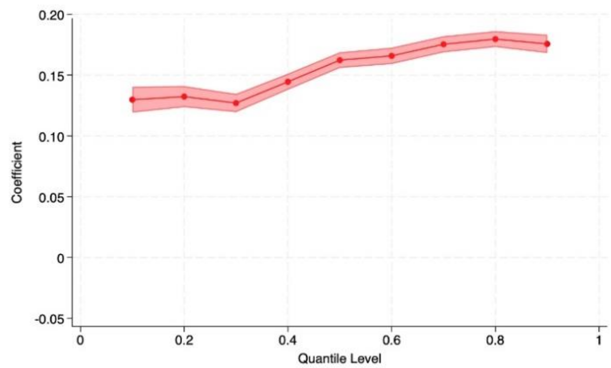
C. 2021 Men



B. 2019 Women



D. 2021 Women



Notes: See Table 2 for the full list of controls. The shaded errors represent 95% confidence intervals.

Source: American Community Survey

Fig. 17 The relationship between occupation-level cumulative real wage growth and the change in the percentage of remote workers among full-time workers, 2019 to 2021

Notes: The size of the bubbles represents the occupation's relative employment. The fit of the line comes from Equation 6. Regression is weighted by occupation employment in 2021. Occupations with fewer than 30 workers in 2019 or 2021 are excluded. Controls include changes in the average shares of workers who are female, Non-Hispanic Black, Hispanic, have no high school diploma, associate degrees, bachelor's degrees, advanced degrees, age 25–34, age 35–44, age 45–54, married, cohabiting, have a disability, live with a parent or spouse who has a disability, government employees, live in a metropolitan statistical area, in industry groups, Census divisions, as well as the mean number of household children under age 5, number of household children age 5–17, number of other adults, as well as changes in the shares of workers by major industry.

Source: American Community Survey

Table 1 Summary statistics for selected years

	2010 On-site	2010 Remote	2019 On-site	2019 Remote	2021 On-site	2021 Remote
Real hourly wage in 2021 $	28.23	36.54	29.26	39.24	28.50	42.46
	(18.11)	(23.1)	(20.37)	(25.21)	(19.84)	(26.42)
Usual weekly hours of work	43.381	45.606	43.449	44.375	43.386	43.401
	(7.34)	(8.81)	(7.431)	(7.953)	(7.521)	(6.94)
Real annual earnings in 2021 $	64206.21	86969.55	66545.93	90762.02	64600.05	96353.14
	(45686.8)	(59913.8)	(50970.7)	(62979.1)	(49844.1)	(65662.2)
Female	0.456	0.460	0.449	0.499	0.439	0.506
Age	43.162	44.880	42.923	44.587	43.330	42.723
	(10.648)	(9.992)	(11.161)	(10.594)	(11.174)	(10.775)
No high school degree	0.104	0.058	0.101	0.048	0.107	0.027
High school degree	0.443	0.328	0.401	0.278	0.409	0.208
Associate degree	0.096	0.086	0.099	0.091	0.103	0.072
Bachelor's degree	0.227	0.359	0.248	0.382	0.233	0.416
Advanced degree	0.130	0.169	0.150	0.201	0.148	0.276
Non-Hispanic Black	0.114	0.069	0.123	0.089	0.117	0.097
Hispanic	0.142	0.092	0.177	0.105	0.186	0.111
Non-Hispanic non-Black	0.744	0.839	0.699	0.807	0.697	0.792
Single	0.338	0.275	0.363	0.290	0.348	0.299
Married	0.591	0.659	0.550	0.635	0.557	0.608
Cohabiter	0.072	0.065	0.087	0.074	0.095	0.093
Number of HH children age<5	0.211	0.205	0.197	0.197	0.190	0.193
	(0.519)	(0.515)	(0.500)	(0.502)	(0.495)	(0.491)
Number of HH children age 5-17	0.608	0.629	0.592	0.618	0.602	0.546
	(0.952)	(0.977)	(0.951)	(0.954)	(0.963)	(0.900)
Number of other HH adults	0.658	0.500	0.761	0.562	0.751	0.512
	(1.223)	(1.037)	(1.294)	(1.126)	(1.293)	(1.046)
Disability	0.041	0.043	0.045	0.041	0.053	0.045
Partner/parent has a disability	0.067	0.058	0.074	0.065	0.082	0.060
Government employee	0.192	0.088	0.173	0.085	0.197	0.148
Lives in metropolitan area	0.794	0.846	0.826	0.880	0.803	0.924
Occupation						
Management	0.115	0.183	0.124	0.187	0.121	0.194
Business Operations Specialists	0.029	0.068	0.039	0.099	0.032	0.109
Financial Specialists	0.029	0.031	0.025	0.037	0.021	0.060
Computer and Mathematical	0.034	0.097	0.042	0.119	0.029	0.146
Architecture and Engineering	0.026	0.023	0.028	0.026	0.028	0.043
Life, Physical, and Social Science	0.011	0.008	0.012	0.012	0.013	0.018
Community and Social Service	0.021	0.023	0.021	0.018	0.021	0.020
Legal	0.012	0.010	0.012	0.014	0.011	0.024
Educational Instruction, and Library	0.059	0.032	0.059	0.034	0.068	0.044
Arts, Design, Entertainment, Sports, and Media	0.014	0.023	0.015	0.027	0.012	0.030
Healthcare Practitioners and Technical	0.061	0.026	0.068	0.045	0.079	0.032
Healthcare Support	0.022	0.023	0.028	0.027	0.030	0.011
Protective Service	0.029	0.012	0.027	0.011	0.031	0.010

	2010 On-site	2010 Remote	2019 On-site	2019 Remote	2021 On-site	2021 Remote
Food Preparation and Serving	0.031	0.010	0.033	0.009	0.027	0.005
Building and Grounds Cleaning and Maintenance	0.031	0.020	0.029	0.012	0.030	0.005
Personal Care and Service	0.017	0.038	0.013	0.009	0.010	0.004
Sales and Related	0.090	0.182	0.078	0.125	0.074	0.074
Office and Administrative Support	0.151	0.111	0.113	0.110	0.111	0.124
Construction and Extraction	0.045	0.015	0.053	0.019	0.055	0.009
Installation, Maintenance, and Repair	0.041	0.022	0.038	0.015	0.043	0.009
Production	0.072	0.022	0.070	0.019	0.073	0.015
Transportation and Material Moving	0.060	0.021	0.073	0.026	0.081	0.015
Industry						
Forestry, fishing, hunting, and mining	0.008	0.004	0.008	0.004	0.007	0.003
Utilities	0.014	0.007	0.012	0.006	0.012	0.013
Construction	0.052	0.026	0.068	0.035	0.074	0.023
Nondurable manufacturing	0.050	0.040	0.047	0.031	0.049	0.032
Durable manufacturing	0.089	0.093	0.086	0.062	0.088	0.068
Wholesale trade	0.034	0.061	0.031	0.040	0.028	0.025
Retail trade	0.097	0.075	0.090	0.058	0.097	0.054
Transportation and warehousing	0.046	0.028	0.052	0.032	0.056	0.023
Information	0.025	0.056	0.020	0.043	0.015	0.050
Finance and insurance	0.061	0.102	0.056	0.142	0.043	0.158
Real estate, rental and leasing	0.016	0.031	0.016	0.026	0.016	0.014
Professional, scientific, and management, and administrative and waste management services	0.066	0.164	0.076	0.221	0.061	0.220
Administrative and support and waste management services	0.033	0.046	0.036	0.045	0.035	0.032
Educational services	0.095	0.046	0.094	0.051	0.106	0.076
Health care and social assistance	0.144	0.101	0.146	0.100	0.159	0.090
Arts, entertainment, and recreation	0.014	0.010	0.015	0.011	0.012	0.009
Accommodation and food services	0.043	0.021	0.047	0.020	0.037	0.010
Other services, except public administration	0.036	0.049	0.034	0.033	0.034	0.026
Public administration	0.076	0.039	0.065	0.039	0.070	0.072
N	731,805	16,520	808,450	35,630	632,995	162,034

Notes: ACS weights are used. Standard deviation in parentheses. Source: American Community Survey

Table 2 Wage regression results (OLS estimates)

	2010		2019		2021	
	Male	Female	Male	Female	Male	Female
Remote	0.066***	0.052***	0.075***	0.064***	0.125***	0.127***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.003)	(0.003)
Age	0.048***	0.038***	0.040***	0.039***	0.041***	0.039***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age squared	-0.045***	-0.035***	-0.036***	-0.035***	-0.037***	-0.035***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No high school degree	-0.157***	-0.142***	-0.131***	-0.102***	-0.118***	-0.078***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)
Associate degree	0.067***	0.091***	0.055***	0.070***	0.053***	0.053***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Bachelor's degree	0.222***	0.281***	0.230***	0.283***	0.220***	0.271***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Advanced degree	0.378***	0.466***	0.407***	0.487***	0.380***	0.460***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Non-Hispanic Black	-0.103***	-0.048***	-0.126***	-0.062***	-0.118***	-0.057***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Hispanic	-0.139***	-0.083***	-0.115***	-0.095***	-0.108***	-0.078***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married	0.101***	0.030***	0.121***	0.041***	0.120***	0.047***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Cohabiter	0.000	0.004	0.020***	0.001	0.013***	0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of HH children age<5	0.006***	0.025***	0.014***	0.027***	0.013***	0.025***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of HH children age 5-17	0.016***	-0.003***	0.015***	0.001	0.017***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of other HH adults	-0.027***	-0.023***	-0.028***	-0.023***	-0.025***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Disability	-0.083***	-0.083***	-0.076***	-0.075***	-0.069***	-0.083***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)
Partner/parent has a disability	-0.075***	-0.044***	-0.081***	-0.054***	-0.075***	-0.043***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Government employee	0.051***	0.078***	0.011***	0.047***	0.007*	0.046***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Lives in metropolitan area	0.104***	0.143***	0.093***	0.133***	0.084***	0.113***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
N	402996	345329	458959	385121	429669	365360
R-squared	0.422	0.437	0.429	0.445	0.426	0.432

Notes: ACS weights are used. Regressions also include occupation, industry, and Census division fixed effects. Robust standard errors clustered at the household level are in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey

Table 3 Hours worked regression results (OLS estimates)

	2010		2019		2021	
	Male	Female	Male	Female	Male	Female
Remote	0.025***	0.033***	0.009***	0.017***	-0.008***	0.005***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Age	0.004***	0.004***	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	-0.005***	-0.004***	-0.003***	-0.004***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No high school degree	-0.010***	-0.006***	-0.005***	-0.004***	-0.003**	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Associate degree	0.001	0.002**	0.003***	0.000	0.000	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bachelor's degree	0.016***	0.024***	0.007***	0.015***	0.005***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Advanced degree	0.049***	0.060***	0.027***	0.043***	0.023***	0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-Hispanic Black	-0.025***	-0.011***	-0.025***	-0.011***	-0.023***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	-0.021***	-0.009***	-0.018***	-0.011***	-0.015***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	0.011***	-0.008***	0.012***	-0.007***	0.010***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cohabiter	0.005***	-0.002	0.007***	-0.002*	0.004***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of HH children age<5	0.001**	-0.006***	0.002***	-0.006***	-0.000	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of HH children age 5-17	0.002***	-0.004***	0.001***	-0.003***	0.001**	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of other HH adults	-0.005***	-0.001***	-0.005***	-0.002***	-0.005***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disability	0.001	0.003**	0.007***	0.005***	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Partner/parent has a disability	-0.002	0.003***	-0.003***	0.001	-0.001	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Government employee	-0.042***	-0.010***	-0.029***	-0.004***	-0.029***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lives in metropolitan area	-0.003***	0.005***	-0.004***	0.003***	-0.005***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	402996	345329	458959	385121	429669	365360
R-squared	0.089	0.074	0.063	0.054	0.054	0.044

Notes: ACS weights are used. Regressions also include occupation, industry, and Census division fixed effects. Robust standard errors clustered at the household level are in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey

Table 4 Regressions with full interactions with a female indicator (OLS estimates)

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Panel A. Log real wages												
Remote	0.066***	0.059***	0.079***	0.071***	0.094***	0.091***	0.078***	0.090***	0.086***	0.075***	0.106***	0.125***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)
Female	0.071**	-0.028	-0.010	-0.055	-0.011	-0.025	-0.083**	-0.007	-0.065**	-0.106***	-0.151***	-0.145***
	(0.030)	(0.035)	(0.033)	(0.034)	(0.031)	(0.030)	(0.032)	(0.031)	(0.032)	(0.033)	(0.041)	(0.034)
Remote × Female	-0.014	-0.013	-0.018*	-0.006	-0.027***	-0.024***	-0.009	-0.019**	-0.012*	-0.012	-0.002	0.002
	(0.010)	(0.011)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.005)	(0.004)
Observations	748325	731859	746832	767579	773076	789030	798737	819877	832829	844080	643850	795029
R-squared	0.442	0.441	0.442	0.441	0.444	0.446	0.448	0.446	0.445	0.446	0.444	0.438
Panel B. Log real annual earnings												
Remote	0.091***	0.082***	0.101***	0.086***	0.110***	0.108***	0.090***	0.102***	0.093***	0.084***	0.101***	0.117***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.004)	(0.003)
Female	-0.075**	-0.171***	-0.173***	-0.223***	-0.193***	-0.179***	-0.218***	-0.170***	-0.214***	-0.260***	-0.319***	-0.277***
	(0.031)	(0.036)	(0.033)	(0.034)	(0.032)	(0.031)	(0.033)	(0.031)	(0.033)	(0.034)	(0.041)	(0.035)
Remote × Female	-0.006	-0.003	-0.009	0.011	-0.017*	-0.016*	0.002	-0.014*	-0.004	-0.003	0.007	0.015***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.005)	(0.004)
Observations	748325	731859	746832	767579	773076	789030	798737	819877	832829	844080	643850	795029
R-squared	0.468	0.466	0.465	0.464	0.465	0.466	0.467	0.463	0.461	0.460	0.456	0.450
Panel C. Log hours worked												
Remote	0.025***	0.023***	0.022***	0.014***	0.016***	0.016***	0.012***	0.012***	0.007***	0.009***	-0.005***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Female	-0.145***	-0.143***	-0.162***	-0.168***	-0.181***	-0.154***	-0.135***	-0.163***	-0.148***	-0.153***	-0.167***	-0.133***
	(0.010)	(0.012)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.011)	(0.010)	(0.012)	(0.011)
Remote × Female	0.008***	0.010***	0.009***	0.017***	0.010***	0.007***	0.010***	0.006**	0.008***	0.009***	0.009***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	748325	731859	746832	767579	773076	789030	798737	819877	832829	844080	643850	795029
R-squared	0.112	0.113	0.110	0.110	0.107	0.102	0.094	0.091	0.088	0.083	0.076	0.068

Notes: ACS weights are used. Robust standard errors clustered at the household level are in parentheses. See Table 2 for controls. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey

Table 5 Instrumental variable results for 2021

	Log wages		Log hours worked	
	Men	Women	Men	Women
Unconditional mean difference	0.465***	0.366***	-0.005***	0.015***
	(0.003)	(0.003)	(0.001)	(0.001)
OLS	0.125***	0.127***	-0.008***	0.005***
	(0.003)	(0.003)	(0.001)	(0.001)
IV1: Share of remote workers by detailed occupation				
First stage coefficient on IV	2.401***	2.632***	2.180***	2.550***
	(0.105)	(0.122)	(0.089)	(0.131)
Demographic, industry, occupation, Census division controls	X	X	X	X
Second stage				
Remote	0.377***	0.333***	-0.031***	0.004
	(0.034)	(0.041)	(0.010)	(0.014)
Demographic, industry, occupation, Census division controls	X	X	X	X
ρ	-0.305***	-0.269**	0.091***	0.003
	(0.039)	(0.045)	(0.034)	(0.060)
P-value for Wald test that ρ=0	<0.001	<0.001	0.009	0.959
P-value for Wald test of overidentifying restrictions	<0.001	<0.001	<0.001	<0.001
IV2: Dingel and Neiman index of feasibility of working from home by detailed occupation				
First stage coefficient on IV	0.354***	0.295***	0.320***	0.266***
	(0.054)	(0.078)	(0.052)	(0.080)
Demographic, industry, occupation, Census division controls	X	X	X	X
Second stage				
Remote	0.289***	0.292***	-0.023	0
	(0.022)	(0.033)	(0.014)	(0.010)
Demographic, industry, occupation, Census division controls	X	X	X	X
ρ	-0.197***	-0.211***	0.057	0.023
	(0.024)	(0.037)	(0.050)	(0.040)
P-value for Wald test that ρ=0	<0.001	<0.001	0.263	0.56
P-value for Wald test of overidentifying restrictions	<0.001	<0.001	<0.001	0.001
IV3: Share of households using broadband internet by county				
First stage coefficient on IV	1.952***	2.082***	1.947***	2.048***
	(0.195)	(0.213)	(0.168)	(0.180)
Demographic, industry, occupation controls	X	X	X	X
Second stage				
Remote	0.306***	0.332***	-0.029***	0.003
	(0.017)	(0.017)	(0.005)	(0.007)
Demographic, industry, occupation, Census division controls	X	X	X	X
ρ	-0.217***	-0.263***	0.076***	0.007
	(0.019)	(0.020)	(0.017)	(0.030)
P-value for Wald test that ρ=0	<0.001	<0.001	<0.001	0.814
P-value for Wald test of overidentifying restrictions	<0.001	<0.001	<0.001	<0.001

Notes: ACS weights are used. IV1 and IV2: Robust standard errors are clustered at the level of the occupation. IV3: Robust standard errors are clustered at the county level. For IV3, region was removed from controls in hours regressions for convergence reasons. The first stage in this test is just identified by functional form.

Source: 2021 American Community Survey, Dingel and Neiman (2020)

Table 6 Blinder-Oaxaca decomposition of the gender wage gap

	2010	2019	2021
Male log wage	3.2554	3.2699	3.3204
Female log wage	3.0767	3.1070	3.1580
Male-Female Gap	0.1787	0.1629	0.1624
Explained	0.0173***	0.0016	-0.0023*
	(0.0013)	(0.0013)	(0.0014)
Unexplained	0.1614***	0.1613***	0.1647***
	(0.0015)	(0.0015)	(0.0016)
Explained			
Remote	-0.00002	-0.0005***	-0.0054***
	(0.00002)	(0.00004)	(0.0002)
Other controls	0.0173***	0.0021	0.0031**
	(0.0013)	(0.0013)	(0.0013)
Unexplained			
Remote	0.0003	0.0005	-0.0004
	(0.0002)	(0.0003)	(0.0008)
Other controls	0.2317***	0.0549*	0.0205
	(0.0298)	(0.0325)	(0.0334)
Constant	-0.0705**	0.1060***	0.1446***
	(0.0298)	(0.0326)	(0.0334)
Sample size	748,325	844,080	795,029

Notes: This decomposition is based on a pooling model and the STATA "oaxaca" ado file (Jann 2008). Robust standard errors clustered at the household level are reported in parentheses. See Table 2 for the full list of controls. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey

Table 7 Decompositions of changes over time in the remote employment share and the mean log wage gap between remote and on-site workers, by time period

	2010–19	2019–21
Panel A. Total change in remote employment share	0.0191	0.1567
Part due to changes in the composition of wage and salary employment across occupations	0.0006	0.0059
Part due to changes in remote employment shares within occupations	0.0185	0.1508
Panel B. Total change in mean log wage gap between remote and on-site workers	0.0567	0.1185
Part due to changes in the mean observed demographic and industry characteristics gap between remote workers and on-site workers	0.0294	0.0793
Part due to changes in the returns to observed demographic and industry characteristics, given the mean gap in observed characteristics	0.0107	-0.0213
Part due to changes in the composition of remote employment across occupations	-0.0028	0.0032
Part due to changes in remote wage premia within occupations	0.0195	0.0573

Notes: This table is similar to Table 5 in Oettinger (2011).

Source: American Community Survey

Table 8 Occupation-level real wage growth between 2019 and 2021 for remote versus on-site workers (Fixed Effect estimates)

	Full-time workers	With part-time workers
Remote	0.020	0.022
	(0.013)	(0.014)
Year 2021	0.005	0.005
	(0.003)	(0.003)
Remote × Year 2021	0.014	0.007
	(0.012)	(0.013)
R-squared	0.997	0.997
Joint hypothesis test:		
Remote + Remote × Year 2021	0.034***	0.030***
	(0.007)	(0.008)

Note: N = 1176. The dependent variable is the natural logarithm of the mean wage at the occupation level. Regressions are weighted using the sum of the person weights for each cell. Robust standard errors in parentheses are clustered at the occupation level. Occupations with fewer than 10 observations in any of the four occupation-group-year cells are excluded (N = 294). Controls include the average share of workers who are female, Non-Hispanic Black, Hispanic, have no high school diploma, associate degrees, bachelor's degrees, advanced degrees, age 25–34, age 35–44, age 45–54, married, cohabiting, have a disability, live with a parent or spouse who has a disability, government employees, live in a metropolitan statistical area, in industry groups, in Census divisions, as well as the mean number of household children under age 5, number of household children age 5–17, number of other adults. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey

Table 9 The relationship between the remote wage premia and the share of workers in the occupation that can feasibly do their work from home across major occupations in 2021

	OLS Wage premium	IV Wage premium
Share of workers in occupation that can work from home	0.087***	0.401***
	(0.028)	(0.118)
R-squared	0.341	0.390

Notes: N = 22. The share of workers in each major occupation that can work from home is the sum of the products of each detailed occupation employment share and Dingel and Neiman's detailed occupation-level index of feasibility of working from home. The IV wage premium is from the endogenous treatment effects model using IV1, which is the share of remote workers by detailed occupation. Observations are weighted by occupation employment. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey; Dingel and Neiman (2020)

Table 10 The effect of remote work on wake-up time in 2020–2021

	All	Men	Women	Fathers	Men with no household children	Mothers	Women with no household children
Unconditional mean difference	0.589***	0.572***	0.610***	0.538***	0.597***	0.589***	0.639***
	(0.057)	(0.079)	(0.081)	(0.104)	(0.114)	(0.112)	(0.111)
OLS	0.492***	0.420***	0.527***	0.553***	0.463***	0.586***	0.431***
	(0.061)	(0.087)	(0.086)	(0.111)	(0.115)	(0.116)	(0.117)
IV1: Share of remote workers by detailed occupation							
First stage coefficient on IV	2.314***	1.982***	3.376***	2.118***	2.619***	4.619***	4.250***
	(0.309)	(0.345)	(1.133)	(0.676)	(0.413)	(0.556)	(0.466)
Second stage							
Remote	1.914***	2.068***	1.221	1.935**	2.146***	1.190***	0.550**
	(0.218)	(0.293)	(1.263)	(0.943)	(0.327)	(0.211)	(0.249)
ρ	-0.733***	-0.800***	-0.472	-0.838***	-0.833***	-0.460***	-0.104
	(0.072)	(0.080)	(0.457)	(0.145)	(0.081)	(0.135)	(0.170)
P-value for Wald test that ρ=0	<0.001	<0.001	0.593	0.049	<0.001	0.002	0.577
P-value for Wald test of overidentifying restrictions	<0.001	<0.001	<0.001	0.015	<0.001	<0.001	<0.001
Observations	2283	1220	1063	586	635	470	593

Notes: The dependent variable is wake-up time in hours since midnight. Wake-up time is from the last recorded episode of sleep (including spells of sleeplessness) occurring before noon. Results are not sensitive to including sleeplessness episodes. The sample includes full-time wage and salary workers age 25–64 observed on a non-holiday, weekday workday defined as a day with at least four hours of work. A remote worker is a worker who worked at least four hours from home on their diary day and no time at a workplace. All regressions (first and second stages) include the following controls: a quadratic in age and indicators for education, Black, Hispanic, spouse present, partner present, child age 0–4 present, child age 5–17 present, disability, government job, union member, metropolitan residence, Census division, year, month and 19 industry groups. Regressions in columns 4–7 by parental status exclude industry indicators for convergence reasons. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Time Use Survey, May 10, 2020–December 31, 2021

Remote Work, Wages, and Hours Worked in the United States

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April 23, 2024

Online Appendix

Table A1 Comparison of summary statistics for 2020 and 2021

	2020	2021	*P*-value for difference (2021 – 2020)
Remote	0.167	0.197	0.000
Real hourly wage in 2021 $	31.09	31.26	0.000
	(21.92)	(22.02)	
Usual weekly hours worked	43.307	43.389	0.000
	(7.292)	(7.41)	
Real annual earnings in 2021 $	70445.50	70868.37	0.000
	(54681.4)	(54816.6)	
Female	0.452	0.452	0.631
Age	42.995	43.210	0.000
	(11.12)	(11.1)	
No high school degree	0.091	0.091	0.929
High school degree	0.372	0.369	0.005
Associate degree	0.097	0.097	0.581
Bachelor's degree	0.268	0.269	0.210
Advanced degree	0.171	0.173	0.006
Non-Hispanic Black	0.114	0.113	0.286
Hispanic	0.171	0.171	0.735
Non-black, non-Hispanic	0.715	0.715	0.584
Single	0.335	0.338	0.005
Married	0.569	0.567	0.224
Cohabiter	0.096	0.095	0.011
Number of children age<5	0.197	0.190	0.000
	(.463)	(.458)	
Number of children age 5-17	0.597	0.591	0.002
	(1.03)	(1.024)	
Number of other adults	0.740	0.704	0.000
	(1.164)	(1.119)	
Disability	0.048	0.051	0.000
Partner/parent has a disability	0.076	0.077	0.061
Government employee	0.185	0.187	0.095
Lives in metropolitan area	0.827	0.827	0.622
Occupation			
Management	0.133	0.135	0.001
Business Operations Specialists	0.047	0.047	0.063
Financial Specialists	0.028	0.029	0.302
Computer and Mathematical	0.051	0.052	0.013
Architecture and Engineering	0.030	0.031	0.816
Life, Physical, and Social Science	0.015	0.014	0.332
Community and Social Service	0.021	0.021	0.122
Legal	0.014	0.013	0.089
Educational Instruction, and Library	0.063	0.064	0.284
Arts, Design, Entertainment, Sports, and Media	0.016	0.015	0.061
Healthcare Practitioners and Technical	0.067	0.070	0.000
Healthcare Support	0.026	0.026	0.612
Protective Service	0.027	0.027	0.744
Food Preparation and Serving	0.024	0.022	0.000
Building and Grounds Cleaning and Maintenance	0.024	0.025	0.071
Personal Care and Service	0.009	0.009	0.966
Sales and Related	0.076	0.074	0.001

Office and Administrative Support	0.116	0.113	0.000
Construction and Extraction	0.047	0.046	0.337
Installation, Maintenance, and Repair	0.037	0.036	0.051
Production	0.062	0.062	0.513
Transportation and Material Moving	0.066	0.068	0.003
Industry			
Forestry, fishing, hunting, and mining	0.007	0.007	0.000
Utilities	0.012	0.013	0.581
Construction	0.064	0.064	0.256
Nondurable manufacturing	0.045	0.045	0.622
Durable manufacturing	0.083	0.084	0.125
Wholesale trade	0.030	0.028	0.000
Retail trade	0.086	0.089	0.000
Transportation and warehousing	0.049	0.049	0.536
Information	0.022	0.022	0.437
Finance and insurance	0.063	0.066	0.000
Real estate, rental and leasing	0.016	0.016	0.016
Professional, scientific, and management, and administrative and waste management services	0.092	0.092	0.312
Administrative and support and waste management services	0.034	0.035	0.061
Educational services	0.099	0.100	0.087
Health care and social assistance	0.146	0.146	0.842
Arts, entertainment, and recreation	0.013	0.012	0.000
Accommodation and food services	0.035	0.032	0.000
Other services, except public administration	0.033	0.032	0.029
Public administration	0.069	0.071	0.004
N	643,850	795,029	

Notes: The last column shows *p* values from adjusted Wald test of equality of means in 2020 and 2021.

Source: American Community Survey

Table A2 Wage distribution

year	p1	p5	p25	p50	p75	p95	p99
2010	5.02	8.75	15.90	23.55	35.33	67.12	141.78
2011	4.83	8.61	15.52	23.00	35.07	67.84	143.97
2012	4.78	8.41	15.41	22.41	34.87	67.24	145.25
2013	4.71	8.26	15.42	22.58	35.24	66.63	153.08
2014	4.82	8.13	15.18	22.70	35.25	67.78	151.48
2015	4.84	8.13	15.36	22.94	35.48	69.43	161.29
2016	4.81	8.54	15.75	23.49	36.31	71.01	163.03
2017	4.80	8.56	15.75	23.63	36.75	71.40	165.07
2018	4.74	8.64	15.40	23.46	36.50	72.54	167.53
2019	4.51	8.62	15.80	24.13	37.53	74.89	167.80
2020	4.21	8.91	16.83	24.75	39.61	76.74	176.79
2021	4.04	9.13	16.83	25.00	38.46	76.92	179.49

Note: ACS weights are used. The sample includes paid civilian, non-institutionalized, wage and salary employees aged 25–64 who worked full-time and at least 48 weeks over the prior 12 months, including paid absences, in the nonfarm sector. Wages are calculated as annual earnings divided by the product of usual hours and weeks worked and are reported in 2021 dollars.

Source: American Community Survey

Table A3 Kolmogorov–Smirnov tests for comparison between distributions of on-site and remote workers in 2019 and 2021

	D	*P* value		D	*P* value
Panel A. Wages					
Men 2019			Women 2019		
On-site	0.2667	0	On-site	0.19	0
Remote	-0.0001	1	Remote	-0.0003	0.998
Combined K-S	0.2667	0	Combined K-S	0.19	0
Men 2021			Women 2021		
On-site	0.3496	0	On-site	0.2783	0
Remote	0	1	Remote	0	1
Combined K-S	0.3496	0	Combined K-S	0.2783	0
Panel B. Usual hours worked					
Men 2019			Women 2019		
On-site	0.047	0	On-site	0.0791	0
Remote	-0.0005	0.992	Remote	0	1
Combined K-S	0.047	0	Combined K-S	0.0791	0
Men 2021			Women 2021		
On-site	0.0172	0	On-site	0.0619	0
Remote	-0.0208	0	Remote	-0.0026	0.412
Combined K-S	0.0208	0	Combined K-S	0.0619	0

Notes: ACS weights are used.

Source: American Community Survey

Table A4 Regression results with part-time workers included (OLS estimates)

	Men			Women		
	2019	2020	2021	2019	2020	2021
Panel A: Log real wages						
Remote	0.062***	0.104***	0.129***	0.041***	0.095***	0.121***
	(0.006)	(0.004)	(0.003)	(0.006)	(0.004)	(0.003)
Part-time	-0.056***	-0.026***	-0.005	-0.098***	-0.108***	-0.085***
	(0.007)	(0.009)	(0.008)	(0.004)	(0.005)	(0.004)
Observations	499432	378770	465978	465391	351799	432479
R-squared	0.393	0.390	0.382	0.382	0.378	0.368
Panel B: Log hours worked						
Remote	0.006***	-0.004***	-0.008***	-0.013***	-0.003**	-0.001
	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Part-time	-0.722***	-0.736***	-0.762***	-0.638***	-0.644***	-0.651***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.003)	(0.003)
Observations	499432	378770	465978	465391	351799	432479
R-squared	0.434	0.444	0.437	0.527	0.527	0.521

Notes: ACS weights are used. Robust standard errors clustered at the household level are in parentheses. See Table 2 for additional controls. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey

Table A5 Regressions with top and bottom 5% of wage distribution trimmed (OLS estimates)

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Panel A. Male												
Log real wages												
Remote	0.055***	0.049***	0.072***	0.058***	0.073***	0.077***	0.068***	0.077***	0.069***	0.067***	0.092***	0.107***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.002)
Observations	366906	360618	372061	382975	387858	393958	397891	408321	414989	418304	319439	392225
R-squared	0.376	0.378	0.385	0.385	0.388	0.387	0.390	0.392	0.392	0.390	0.400	0.400
Log hours worked												
Remote	0.028***	0.025***	0.024***	0.016***	0.019***	0.020***	0.014***	0.016***	0.010***	0.011***	-0.004***	-0.007***
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	366906	360618	372061	382975	387858	393958	397891	408321	414989	418304	319439	392225
R-squared	0.090	0.089	0.087	0.086	0.082	0.080	0.070	0.068	0.068	0.066	0.060	0.056
Panel B. Female												
Log real wages												
Remote	0.060***	0.051***	0.067***	0.067***	0.066***	0.063***	0.074***	0.072***	0.073***	0.068***	0.093***	0.115***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.002)
Observations	416427	406412	410464	418040	419020	424769	428825	439915	443783	457336	346002	424952
R-squared	0.430	0.426	0.429	0.428	0.432	0.431	0.433	0.432	0.429	0.418	0.415	0.408
Log hours worked												
Remote	0.033***	0.033***	0.028***	0.031***	0.024***	0.024***	0.022***	0.018***	0.016***	0.017***	0.004***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	321102	312368	317836	325090	327407	331872	336350	345527	350745	357189	273964	338446
R-squared	0.078	0.076	0.076	0.080	0.076	0.073	0.071	0.066	0.063	0.058	0.053	0.047

Notes: ACS weights are used. Robust standard errors clustered at the household level are in parentheses. See Table 2 for controls. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey

Table A6 Wage regression coefficient estimates on remote worker: OLS, IV and Oster betas for subsamples of white-collar workers, 2021

	Unconditional mean difference		OLS		Oster beta (δ=1)	Oster beta (δ= -1)	*R*-squared	IV		ρ		N
Overall	0.341***	(0.002)	0.140***	(0.002)	0.056	0.220	0.413	0.464***	(0.049)	-0.403	(0.053)	496238
Fathers of children age 5-17	0.353***	(0.006)	0.137***	(0.006)	0.044	0.228	0.359	0.474***	(0.048)	-0.412	(0.055)	59485
Mothers of children age 5-17	0.363***	(0.007)	0.135***	(0.006)	0.038	0.229	0.417	0.361***	(0.058)	-0.305	(0.065)	65092
Fathers of children age 0-4	0.351***	(0.008)	0.132***	(0.007)	0.037	0.225	0.379	0.496***	(0.048)	-0.455	(0.053)	34456
Mothers of children age 0-4	0.364***	(0.010)	0.121***	(0.008)	0.017	0.222	0.465	0.369***	(0.058)	-0.339	(0.069)	27804
College degree	0.280***	(0.003)	0.142***	(0.003)	0.085	0.196	0.355	0.470***	(0.069)	-0.411	(0.074)	300556
No college	0.221***	(0.004)	0.128***	(0.004)	0.086	0.159	0.296	0.455***	(0.056)	-0.397	(0.057)	195682
Non-Black, non-Hispanic	0.331***	(0.003)	0.141***	(0.003)	0.060	0.216	0.413	0.425***	(0.050)	-0.362	(0.057)	339991
Black, non-Hispanic	0.237***	(0.009)	0.110***	(0.008)	0.059	0.156	0.340	0.400***	(0.058)	-0.363	(0.062)	34711
Hispanic	0.290***	(0.007)	0.134***	(0.006)	0.071	0.192	0.350	0.479***	(0.045)	-0.412	(0.045)	56701
No disability	0.343***	(0.002)	0.141***	(0.002)	0.055	0.222	0.414	0.466***	(0.049)	-0.405	(0.053)	472503
Disability	0.276***	(0.011)	0.118***	(0.010)	0.052	0.176	0.351	0.415***	(0.053)	-0.347	(0.061)	23735
Private sector	0.356***	(0.003)	0.146***	(0.002)	0.058	0.230	0.421	0.530***	(0.043)	-0.457	(0.046)	385476
Government employees	0.250***	(0.005)	0.100***	(0.004)	0.046	0.153	0.391	0.264***	(0.053)	-0.240	(0.065)	110762
Live in principal city,15 largest MSAs	0.316***	(0.008)	0.119***	(0.007)	0.039	0.198	0.375	0.575***	(0.042)	-0.526	(0.038)	41628
Live in suburbs of 15 largest MSAs	0.317***	(0.005)	0.129***	(0.005)	0.053	0.202	0.406	0.456***	(0.049)	-0.406	(0.053)	88558
Dropped 15 largest MSAs	0.317***	(0.003)	0.135***	(0.003)	0.059	0.204	0.407	0.441***	(0.049)	-0.389	(0.055)	316742

Notes: Each number comes from a separate regression or test. OLS coefficients and Oster betas are shown in Figure 15. Standard errors clustered at the occupation level are in parentheses. IV uses IV1: Share of remote workers by detailed occupation. Not shown in the table: Wald tests that ρ=0 and Wald tests of overidentifying restrictions, which are significant in all samples with $p<0.0001$.

Source: American Community Survey

Table A7 Wage growth and the change in the percentage of remote workers regression coefficients in various samples

	Full-time workers	With part-time workers
A. At least 30 observations in occupation		
Change in remote share	0.031***	0.021*
	(0.012)	(0.013)
Change in share of part-time workers		-0.214*
		(0.123)
Constant	0.011***	0.015***
	(0.003)	(0.003)
Observations	516	516
R-squared	0.303	0.276
Mean wage growth(log ratio)	0.020	0.026
Mean change in remote share	0.155	0.147
B. At least 100 observations in occupation		
Change in remote share	0.032***	0.022*
	(0.012)	(0.013)
Change in share of part-time workers		-0.309**
		(0.130)
Constant	0.012***	0.015***
	(0.003)	(0.003)
Observations	459	459
R-squared	0.327	0.315
Mean wage growth(log ratio)	0.020	0.026
Mean change in remote share	0.155	0.148

Note: The dependent variable is log wage ratio of mean wage in detailed occupation in 2021 to 2019. Regressions are weighted by the number of workers in occupation in 2021. Panel A: occupations with fewer than 30 workers in 2019 or 2021 are excluded. Panel B: occupations with fewer than 100 workers in 2019 or 2021 are excluded. Controls include changes in the average shares of workers who are female, Non-Hispanic Black, Hispanic, have no high school diploma, associate degrees, bachelor's degrees, advanced degrees, age 25–34, age 35–44, age 45–54, married, cohabiting, have a disability, live with a parent or spouse who has a disability, government employees, live in a metropolitan statistical area, in Census divisions, as well as the mean number of household children under age 5, number of household children age 5–17, number of other adults as well as changes in the shares of workers by major industry. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey