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

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Abstract

Remote wage employment gradually increased in the United States during the four decades prior to the pandemic, then surged in 2020 due to social distancing policies implemented to stem the spread of COVID-19. Using the 2010–2021 American Community Survey, the authors examine trends in wage and hours differentials for full-time remote workers and office-based workers as well as within occupation differences in wage growth by work location. Throughout the period, remote workers earned higher wages than those working on-site, and the difference increased sharply during the pandemic. Real wages grew 3.4 percent faster for remote workers within detailed occupation groups and remote work intensity was positively associated with wage growth across occupations. Before the 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

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1. Introduction

Wages are determined by a number of factors, including job tasks, productivity differences, compensating differentials, 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) found that some U.S. 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 the latter, 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 in the office, and this could have changed their demand for remote positions (Aksoy et al. 2022; Barrero et al. 2021; Nagler et al. 2022).[2] Barrero et al.

[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 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.

(2022) argue that the recent increase in remote work raises the amenity value of employment, 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 and firms 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. 2023). 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] 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 a disamenity if they are left socially isolated from their peers or working from home while supervising their children (Bartel et al. 2012; Flood and Genadek 2023; Pabilonia and Vernon 2022; 2023b). Thus, in equilibrium, it is unclear what will happen to

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In addition, workers currently working from home valued the option more than those not working from home.

[3] A couple of randomized-control trials show casual evidence of worker productivity gains from remote/hybrid work arrangements (Bloom et al. 2015; Bloom et al. 2023; Choudhury et al. 2022). 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 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). 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.

[4] Using pre-pandemic time diaries from the ATUS, Pabilonia and Vernon (2022) find that workers gained about 75 minutes per day by eliminating their commuting and reducing time spent grooming on their work-from-home days.

wage differentials for remote workers. 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 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 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 as remote workers) paid a wage penalty, which shifted to a small wage premium by 2014. We estimate trends in wage differentials between remote and on-site workers from 2010 to 2021, with a special focus on the change in the differentials during the pandemic. We also examine trends in hours differentials (where hours are usual hours worked per week). To account for potential selection, 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 respondents' detailed occupation, 2) the teleworkability of respondents' detailed occupation, and 3) the share of households using broadband internet in respondents' county of residence. Given the sharp increase in remote work during the pandemic, we are also able to examine wage and hours differentials for 2021 across 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). In addition, we perform occupation-level analyses where we first test for differences in wage growth between 2019 and 2021 by remote worker status within detailed occupations and 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.

We find a substantial jump in the wage premium for remote workers during the pandemic. In 2021, on average, full-time remote workers earned 13.4 percent more than office-based workers, with larger premia in management, computer science and math, legal, and sales 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 14.3 percent, while mothers working remotely earned 13.9 percent. These premia are robust to adjusting for omitted variable bias. We find that the increase is due to increases in remote work shares within occupations, and not due to changes in the occupational composition. Our instrumental variable analyses also indicate large wage premia for remote work in 2021. In occupation-level analyses, we find that real wages grew 3.4 percent faster for remote workers than office-based workers within detailed occupation groups, but only a small, positive association between the change in remote work intensity and wage growth across occupations. Just prior to the pandemic, men working remotely worked 21 minutes longer per week than men working primarily in the office, and women working remotely worked 47 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 10 minutes more per week.

2. Data and Descriptive Statistics

Our analyses are based on 2010–2021 ACS data from IPUMS USA version 22.0 (Ruggles et al. 2022). The ACS is a 1% sample of the U.S. population collected 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. As a sensitivity analysis, we also include part-time workers. In some of our analyses, we compare estimates from 2019 and 2021, skipping 2020 in order to highlight the impact of COVID-19, 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.[6] Although we urge caution when interpreting results for 2020, the estimates are generally in line with those from 2021.[7]

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 an office-based worker or on-site worker (we use these terms interchangeably throughout the paper). Remote workers may include hybrid workers working three days at home and two days in the office while office-based workers could include those who work from home 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

[6] 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).
[7] The characteristics of our main analysis sample in 2020 and 2021 are in Appendix Table A1. In 2021, respondents reported statistically significantly higher real hourly wages, annual earnings, and usual hours worked than in 2020. Respondents in 2021 were slightly older, more educated, less likely to have a cohabiting partner, and had fewer children. They were more likely to work in management, computer and mathematical, healthcare, and material moving occupations, but less likely to work in food preparation and sales. In terms of industries, 2021 workers were more likely to work in retail trade, finance and insurance, and public administration, but less likely to work in wholesale trade, arts and entertainment, accommodation and food services, or other services than their 2020 counterparts.

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.

In Figure 1, we compare our estimates of remote work based on the ACS to estimates obtained from the American Time Use Survey (ATUS) (U.S Bureau of Labor Statistics 2023a). The ACS measure of working from home is the percentage of full-time employees who report work from home as their usual mode of transportation to work. 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 days with at least four hours of work, including weekend days.[9] 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, 19.7 percent were working remotely. The rise in remote work is similar in ATUS, with 26.3 percent of all full workdays were exclusively worked from home in 2021.[10] ATUS percentages are higher because they include those who work most of their days in the office but also 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 (21.8 percent versus 17.9 percent in 2021).[11]

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[9] Brynjolfsson et al. (2023) provide a review of estimates of working from home from different surveys and discuss the difficulty of measuring the concept of "remote" work.

[10] 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.

[11] 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 but of different cohorts of workers. 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 was quite uneven across occupations, because occupations differ in the composition of tasks that can easily be done from home (Dingel and Neiman 2020; Dey et al. 2020). 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 and financial operations at 44.0 percent. It was lowest in food preparation and serving, material moving, construction and extraction, and building and grounds cleaning and maintenance at about 4.0 percent. Over 10 percent of workers in white-collar jobs worked remotely, whereas the number was lower 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 (though we do not know the interview date) 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. 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 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 dollars using a two-year moving average of the CPI-U (U.S. Bureau of Labor Statistics 2023b). We trim the sample to exclude the top and bottom 1% of real hourly wages. As a robustness check, we estimate some specifications using annual earnings instead of the hourly wage.

In Figures 3a and 3b, we show average nominal and real wages by remote worker status, respectively. Remote workers consistently earned higher wages than office-based 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. Looking across the 22 major occupation groups in Figure 4, we find that unadjusted real wage differentials for remote workers rose substantially in 18 occupations between 2019 and 2021, with the largest increase in legal occupations (a 1 percent wage premium turned into a 26 percent wage premium). The wage premia stayed about the same in sales as well as office and administrative support occupations.

In Figure 5, we show trends in usual hours worked per week by remote work status. Initially, in 2010, on average, unadjusted hours were substantially higher for remote workers than office-based workers. Over the period, however, hours slowly converged and during the pandemic were about the same for the two groups.

Figure 6 shows kernel density distributions of real wages and weekly hours worked in 2019 and 2021 by remote worker status. In both years, wages are positively skewed, more so for remote workers than on-site workers. In addition, the wage distribution for remote workers shifted farther to the right in 2021 relative while the distribution for on-side workers became more concentrated at the lower end. The distribution of work hours shows that most men who were full-time on-site employees reported 40 hours of work in 2019, whereas the distribution of hours for male remote workers was more spread out around 40 hours. The distribution of hours for women 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, remote workers in both sexes had a greater likelihood of working exactly 40 hours than did on-site workers. Using Kolmogorov-Smirnov tests, we can reject the hypothesis that the distributions are identical (Appendix Table A4).

3. Econometric Models

Remote workers and office-based workers have different observable characteristics (see Table 1). For example, remote workers are more likely to be married and have children. They also are likely to have different unobservable characteristics, which if correlated with both our outcome variables and working from home would bias results based on ordinary least squares estimation (OLS). 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 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. We then perform two analyses to assess the relationship between wages and remote work at the occupation level.

3.1 Ordinary least square estimation

We begin our econometric analysis by estimating conditional wage and usual hours worked differentials for remote workers for each year separately 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, number of own children under age 5, number of own children aged 5 to 17, and number of adult family members excluding respondent/partner, and binary indicators for educational attainment (less than high school, some college, bachelor's degree, and master's degree or higher), 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 8 Census divisions.[12] These regressions are estimated by OLS using ACS person-level weights. We calculate robust standard errors clustered at the household level. We note that our specification includes more control variables than Oettinger (2011) and White (2019), and that we exclude the farm sector, which has a high share of remote workers.

3.2 Estimate bounds on β using Oster's method

Positive OLS coefficients on remote status 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, or a sign of selection of higher ability or more tenured and more trusted workers by employers into remote status. On the other hand, it is also possible that OLS coefficients underestimate the true effects if, for example, workers with a lower work ethic choose remote jobs and are likely to earn lower wages. Emmanuel and Harrington (2023) found that less productive workers choose 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

[12] OLS estimates are similar if we use state rather than Census divisions but some of the endogenous binary treatment models would not converge using states; therefore, for consistency, we estimate all specifications with Census division fixed effects.

higher wages), they also may be less likely to select remote jobs. Although during the pandemic, the stigma of working from home may have diminished and thus the promotion potential may have changed because of the large experiment in working from home and common shock to employers (Barrero et al. 2021). However, during the pandemic, risk averse workers might have been more likely to work remotely to lower their chances of contracting the virus, and there is some evidence that risk averse workers earn lower wages (Barrero 2023; Lavetti 2020). If this was the case, OLS estimates would be biased downward during the pandemic. 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:

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

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 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).[14] If an 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.

[14] R_{max} is the R-squared from a hypothetical regression that includes controls for unobservable characteristics.

In addition, we estimate separate models across various subsamples where the degree of selection on unobservables may vary. For example, workers are not likely to move into management positions if they are unmotivated or untrustworthy.

3.3 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:[15]

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

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

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

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 $\pi_1$are coefficients on the exogenous explanatory variables in X_i to be estimates. 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, $\text{COV}(\epsilon_i, \varphi_i) = 0$). It should be related to the outcome only through its relationship with the remote worker status. We use three

[15] We use the treatreg command in STATA.

instrument variables in alternative specifications. Our first IV_i is the percent of workers in the same occupation as the respondent who work remotely. When there are sufficient observations, we estimate the percent of remote workers using those in the same three-digit occupation. When the number of workers in this group is less than 30, we instead use the percent remote in the intermediate occupation and major industry. This instrument measures the actual take up of remote work. A second instrument is an index of teleworkability for the respondents' 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 coefficient on our instrument, π_2, is always highly statistically significant and the *p*-values from Wald tests of excluding the instrument are less than 0.001 suggesting the instruments are strong.[16]

The IV estimate, α_1, our coefficient of interest in this model, is unbiased and consistent. However, it is not directly comparable to the OLS estimate, β, because the IV estimate is a 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.

[16] Because the first stage is estimated as a probit model, an instrumental variable is technically not necessary for identification as 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.

The error terms 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/hours equation and the remote work selection equation. When estimating the model, we cluster the standard errors at the level of the instrument. Using Wald tests, we test and can reject in all the wage regression specifications that 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.

3.4 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:

$$\ln(\overline{w}_{ort}) = \delta_0 + \delta_1 Remote_{ot} + \delta_2 Year2021_t + \delta_3 Remote_{ot} \times Year2021_t + \delta_4 P_{ort} + occ_o + \nu_{ort} \quad (6)$$

where $\ln(\overline{w}_{ort})$ is the natural logarithm 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 office-based workers in 2019, δ_2 is the growth in wages over the period for office-based workers), δ_3 is our coefficient interest that tells us whether wages grew faster or slower during the pandemic for remote workers relative to office-based workers, δ_4 is a vector of coefficients on average demographic controls, and ν_{ort} represents the error term. We use four observations on 294 three-digit occupation groups when 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, at the three-digit occupation level, to test whether the rise of remote work moderated wage pressures across occupations, we estimate the relationship between the absolute change, Δ, in the percentage of remote workers and the cumulative growth in average wages during the pandemic from 2019 to 2021 while controlling for compositional changes in the workforce as follows:

$$\Delta \ln(\bar{w}_o) = \sigma + \rho\Delta\overline{Remote}_o + \nu\Delta\bar{A}_o + \omega_o \tag{7}$$

where $\bar{w}_o$ is the average wage in detailed occupation o, $\overline{Remote}_o$ is the percentage of workers in occupation o who are remote, $\bar{A}_o$ is a vector of occupation-level percentage of workers in demographic and industry controls (the controls are similar to those used in equation 1 but we use age bins 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 the 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 2019 and 2021 (516 occupations).[17] Regressions are weighted using the sum of the 2021 person weights for each occupation group, and robust standard errors are reported.

[17] The results are the same if we restrict the analysis to occupations with at least 100 observations.

4. Results

Wage differentials

Figure 7 shows trends in the adjusted hourly wage differentials with 95% confidence intervals by sex, along with Oster betas, which represent a lower bound for the estimated wage differentials here, 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.[18] Table 4 reports the coefficients on the interaction of $Remote_{it}$ and $female_{it}$ when we fully interact all the independent variables in equation 1 with the female indicator. We find that these trends in the wage differentials hold similarly for men and women overall (see Panel A of Table 4). In 2010, remote workers earned 6.1 percent more than on-site workers, and by 2019, the premium was only 7.7 percent (Figure 7).[19] In 2021, remote workers earned 13.2 percent more than on-site workers (almost double the 2019 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). The Oster betas assuming $\delta = 1$ are below zero for men in all 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. For women, the Oster betas assuming $\delta = 1$ exceed zero in 2012 through 2021. Assuming $\delta = -1$, then we conclude wage differentials are positive and may exceed the OLS estimates. The first two columns of Table 6 show the results from the endogenous binary treatment models for the effects

[18] Results are similar but the wage premia are slightly smaller when we include part-time workers, which suggests that part-time workers who work remotely earn smaller wage premia (see Appendix Table A3).
[19] Percents are calculated as $(\exp(\beta) - 1) \times 100$.

of remote work on wages in 2021 when those who could work from home were much more likely to do it. 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 less than the unconditional mean differences. Thus, on whole, these estimates suggest substantial wage premia for remote workers and are supportive of the hypothesis that remote work is productivity enhancing.

Hours 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 21 minutes per week longer than men working on-site, while women working remotely worked 47 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 10 minutes longer than women working on-site. Except for in the pandemic years, the Oster betas are all greater than zero, suggesting that the positive hours differentials are robust to unobservable factors (Figures 8a and 8b). It is not surprising that average usual hours worked by remote workers was lower 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 in 2021, men worked 12 fewer minutes and women worked 2 fewer minutes on weekdays with at least four hours of work when working from home compared to on-site, but the unadjusted mean differences are not statistically significant at conventional levels (authors' own calculations).[20] In the third and fourth columns of Table 6, 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 evidence of negative hours differentials using two of the three instruments, which are again are double the size of the OLS estimates. When instrumenting with either the share of remote workers in respondents' detailed occupation or the share with broadband in respondents' county, ρ is positive and statistically significant, suggesting unobservable factors that increase hours are positively correlated with unobservables that determine remote work. However, when instrumenting using the teleworkability index, we cannot reject the hypothesis that $\rho = 0$. A positive ρ could occur if men who prefer remote work will work longer hours when given the opportunity to work remotely. 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.

Heterogeneity by occupation

Although remote workers earned a wage premium on average, there was also considerable heterogeneity in the increase in both remote work and wage differentials across occupations (Figures 2 and 9). Following Oettinger (2011), we calculate an Oaxaca-style decomposition of the change in both the remote worker share and the raw mean log wage between 2010 and 2019 and between 2019 and 2021 (Table 5). Over the nine years between

[20] 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.

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. 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, we see the rapid acceleration in relative gains for remote workers (5.7 percentage points between 2010 and 2019 and 12.9 percentage points between 2019 and 2021). The increase in the wage gap over the 2019–2021 period can be explained primarily by the same components that explained the increase over the 2010–2019 period, as well as earlier periods considered in Oettinger (2011). Between 2019 and 2021, Table 5 Panel B shows that changes in the mean demographic characteristics between remote and on-site workers accounted for 67 percent of the relative wage gains for remote workers, while changes in remote wage premia within occupations accounted for 48 percent of the relative wage gains.

Figure 9 shows the adjusted wage differentials for remote workers (and Oster betas) in 22 occupations in 2021. Computing the percentages from their corresponding coefficients, we find wage premia that exceed the average in sales (20.7 percent), management (16.5 percent), arts, design, entertainment, sports and media (14.6 percent) , production (14.5 percent), life, physical, and social science (13.9 percent), and legal (13.7 percent) occupations. In healthcare support, however, remote workers paid a wage penalty (5.2 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 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).

Figure 10 shows the hours differentials in the same 22 occupations in 2021. Remote workers in a number of occupations (sales; arts, design, entertainment, sports, and media; management; architecture and engineering; community and social service; transportation; legal; and protective service) worked fewer usual hours per week than did on-site workers. In only four of the 22 occupations did remote workers work substantially more than on-site workers: healthcare support, personal care and service, building and grounds cleaning and maintenance, and material moving. This may seem counterintuitive given the small percentage of workers in these occupations working from home; however, during the peak of the pandemic, for example, many hairdressers offered personal services from home and been in more demand by those practicing social distancing. The other occupations saw little difference in usual hours by remote work status.

In Figure 11, we present trends in the wage differentials for white-collar and blue-collar occupations. Not surprisingly, given the relative teleworkability of occupations within these groups (see Dingel and Neiman 2020), we see a large difference in the wage differentials across these broad occupation groups. Overall, 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 reached about 5 percent. In contrast, remote blue-collar workers paid wage penalties until 2020, and in 2021, they earned a 3.5 percent wage premium (again supported by the Oster betas). Figure 12 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 workers worked slightly fewer hours than those working on-site, although the difference was not economically meaningful. Blue-collar workers' hours differentials converged toward zero. Henceforth, we focus on subsamples of workers within white-collar occupations where remote work is more prevalent and selection is likely less an issue.

Heterogeneity by sex and parental status

Figures 13 and 14 show trends in wages and hours differentials by sex and parental status for those working in white-collar occupations.[21] Looking first at wage differentials, we see similar trends among the four groups, with higher wages for those working remotely. The largest differences are in the Oster betas for women by parental status, suggesting a higher degree of selection on observables for mothers. Turning to the hours differentials, these figures confirm that during the pandemic, all men working remotely worked fewer hours than men working on-site. 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 not robust to adjusting for omitted variable bias (as we saw for all women in Figure 8b).

Heterogeneity across various subsamples of white-collar workers in 2021

In Figure 15, for 2021, we present OLS estimates and Oster betas from equations 1 and 2, respectively, for subsamples by age of youngest child, college degree status, non-Hispanic Black, Hispanic ethnicity, disability status, sector of employment for workers in white-collar occupations, and living in a principal city of the 15 largest MSAs. Even though parents were

[21] Parental status is defined as living with minor children in the household.

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 child. However, mothers working at home with a child aged 0–4 had a slightly lower wage premium than other parents (12.6 percent versus over 14.0 percent). This finding is consistent with the hypotheses that mothers 1) had slightly lower productivity than others due to interruptions from their children and/or 2) were more likely to accept or stay in lower paying jobs or were 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. College-educated workers made up most remote workers (80 percent); however, we find similar wage premia for remote white-collar workers by college degree status. The wage premia for remote work differed by race and Hispanic ethnicity, with non-Hispanic white and Hispanic workers earning substantially higher returns for remote work than Non-Hispanic Black workers (15.0, 14.1, and 11.5 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 (12.2 percent versus 15.0 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.[22]

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 15.6 percent more when working remotely, while those working for the government earned only 10.5 percent more. These differences in wage premiums 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 sector workers also 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). Also, perhaps industries that have been growing the most since the pandemic—those with heavy use of information technology—bid up workers with IT skills from other industries by offering higher wages, and the same industries are either amenable to remote work or offer it to attract more skilled workers.

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

[22] Between 2019 and 2021, the number of employed persons with disabilities rose from 5,858 to 5,950 (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).

wage premium was smaller in the principal city of the 15 largest MSAs (10.5 percent versus 13.9 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 A4, we show that the IV estimates are 3–4 times larger than the OLS estimates using the share of who worked remotely in the respondent's occupation. Again, the estimates measure the LATE and again confirm large returns to working from home across the various subsamples when controlling for negative selection.

Figure 16 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 15. The differentials in paid work hours are small for the most part. The largest differential is for remote working fathers with a youngest child aged 0–4 (working about 34 fewer minutes assuming a 43.5-hour workweek), followed by fathers of school-age children only and government employees who worked about 23 fewer minutes per week than their on-site counterparts. In contrast, mothers with school-age children only report a small increase in paid work compared to their on-site counterparts (13 more minutes). Whites, the college-educated, workers without disabilities, those living in a principal city within the top 15 largest MSAs, and those living outside the largest MSAs show small decreases in hours when working remotely that are robust to correcting for omitted variable bias. Non-Hispanic Blacks, Hispanics, those without a college degree, and workers with disabilities work the same hours regardless of their work location.

Wage growth within detailed occupations by remote status

Turning to the results from our occupation-level regression analyses, we first show results from equation 6 without demographic and industry controls (column 1 of Table 7). These results indicate that within occupations, remote workers earned 13.2 percent more on average than on-site workers in 2019, on-site workers earned 1.1 percent less in 2021 than in 2019, and remote workers earned 17.4 percent more than on-site workers in 2021. However, when we control for average demographics and the industry distribution that varied considerably within groups across time (see Table 1), we find that in 2019, those working remotely earned on average the same as those working on-site within detailed occupations. In addition, over the 2019–21 period, there was no real wage growth for on-site workers within occupations. However, in 2021, remote workersearned 3.4 percent more than on-site workers within the same detailed occupation; therefore, wage growth was also 3.4 percent faster.

Wage growth across occupations by 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 across three-digit occupation groups over the 2019–2021 period. The size of the bubbles represents the occupation's relative employment. The trendline represents the slope of a linear regression, weighted by the employment of each occupation. Controlling for compositional changes, we find that a one percentage-point increase in the percentage of remote workers in an occupation is associated with a 0.023 percentage point increase in the occupation-level wage growth. Between 2019 and 2021, the average percentage of remote workers across occupations increased by 15.4 percentage points. This suggests that the rise in remote work is associated with only a 0.4 percentage-point increase in the occupation-level wage growth, whereas real wages grew by about 2 percent across occupations. This is consistent with the decomposition in Table 5 Panel B that suggests that changes in the composition of remote employment across occupations explains only a small part of the mean log wage gap between remote and on-site workers.

5. Conclusion

Using the ACS, we examine trends in wage and hours differentials for primarily remote workers relative to primarily on-site workers from 2010 through 2021, with a special focus on changes during the pandemic period from 2019 to 2021. There are three main takeaways from these analyses. First, on average, remote workers earn more than on-site workers even when controlling for selection into remote work. Second, wages grew faster for remote workers than on-site workers during the pandemic. Third, usual hours for remote workers fell steadily between 2010 and 2021, and in 2021, their hours had converged with the hours of on-site workers.

Comparing various subsamples of workers among those in white-collar jobs, we found that most groups of remote workers earned wage premia in 2021. However, marginalized groups of workers often earned slightly lower returns to working from home, and thus the growth in remote work during the pandemic magnified preexisting wage inequalities. Overall, our results suggest that remote work may be productivity enhancing for many workers. 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 mothers with young children earned slightly lower wage premia when working from home versus the office, which is consistent with their being more likely to be interrupted during work hours than were fathers and nonparents.

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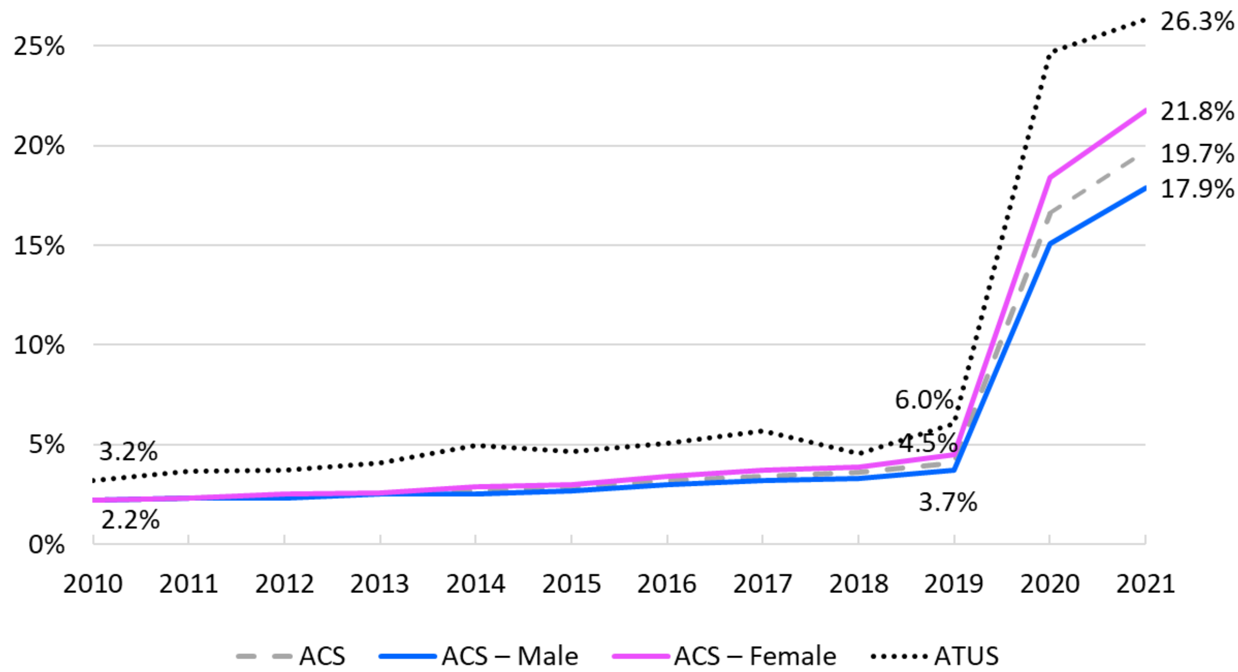
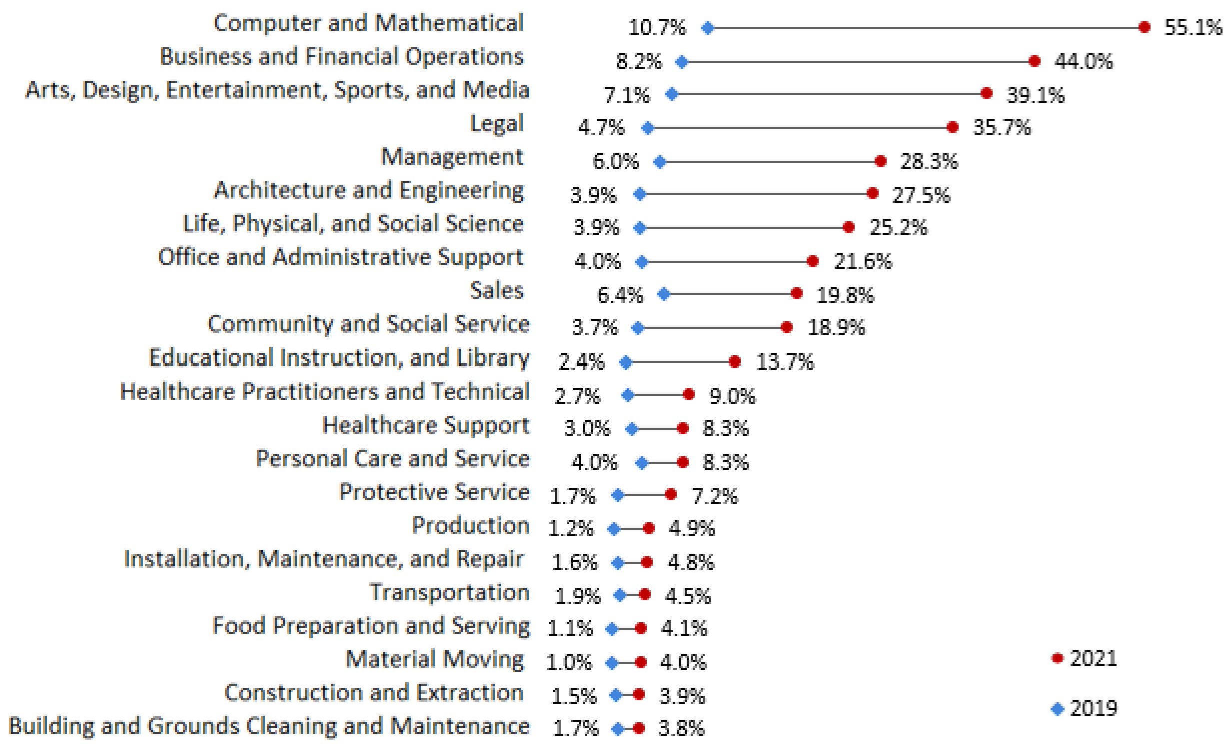
Fig. 1 Percentage of people working primarily from home and percentage of workdays exclusively worked from home among full-time employees in the nonfarm sector



Notes: The ACS measure of working from home is the percentage of full-time 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

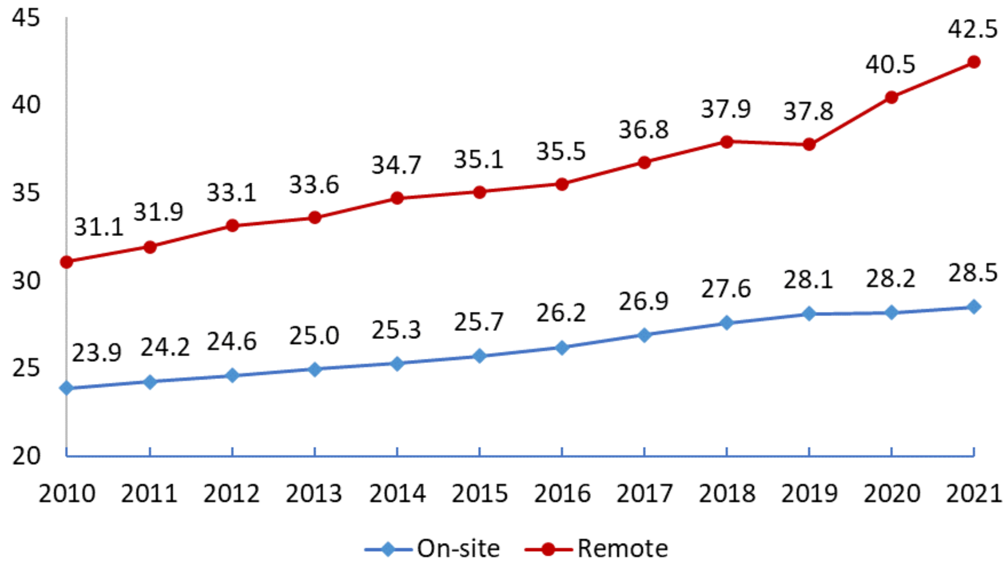


Notes: ACS weights are used here and in all other calculations.

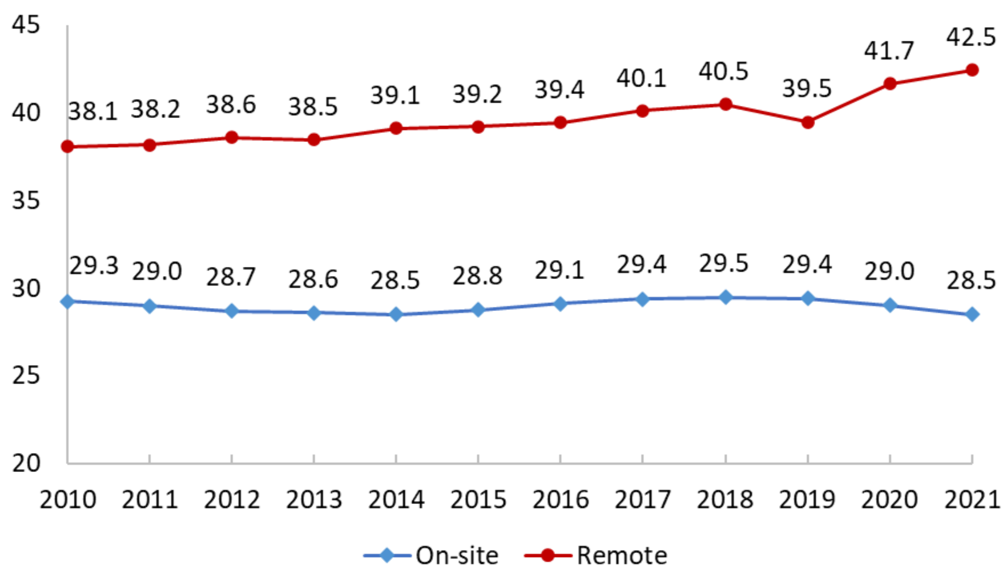
Source: American Community Survey

Fig. 3 Wages by remote worker status

a. Nominal wages

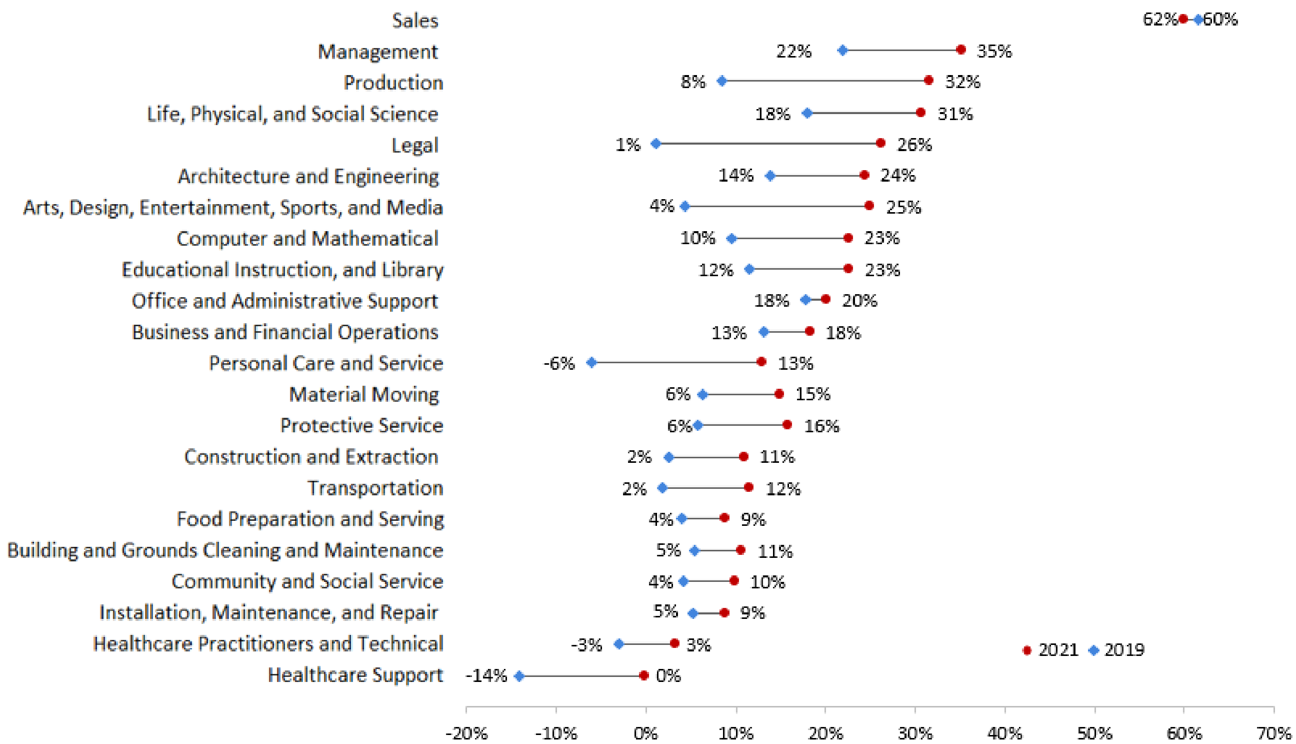


b. Real wages in 2021 dollars



Source: American Community Survey

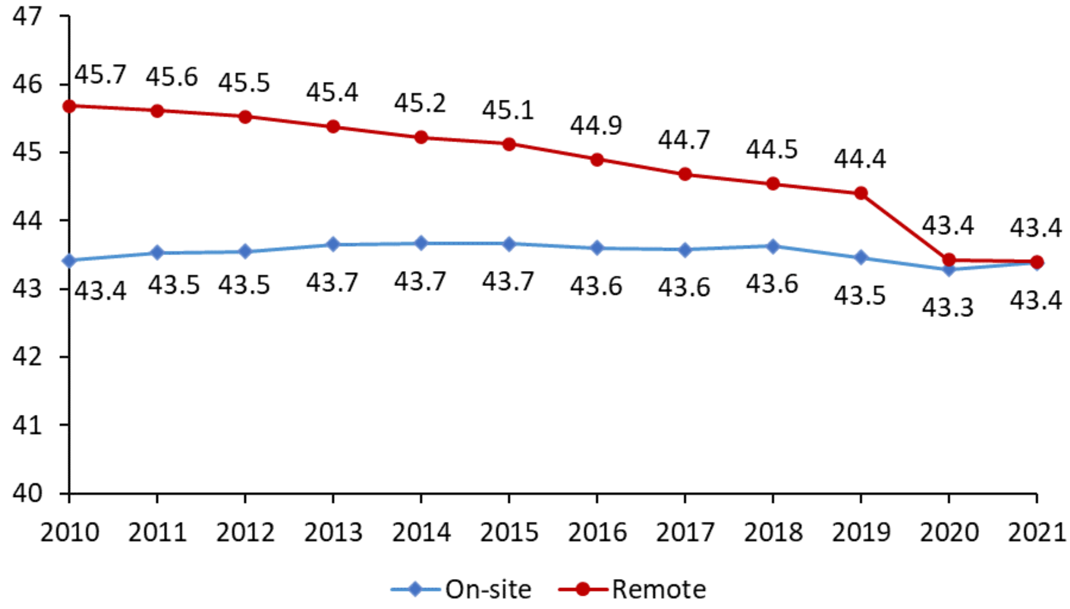
Fig. 4 Unadjusted wage differentials for remote workers in 2019 and 2021



Notes: The numbers represent percentage differences between average remote and on-site wages relative to on-site wages.

Source: American Community Survey

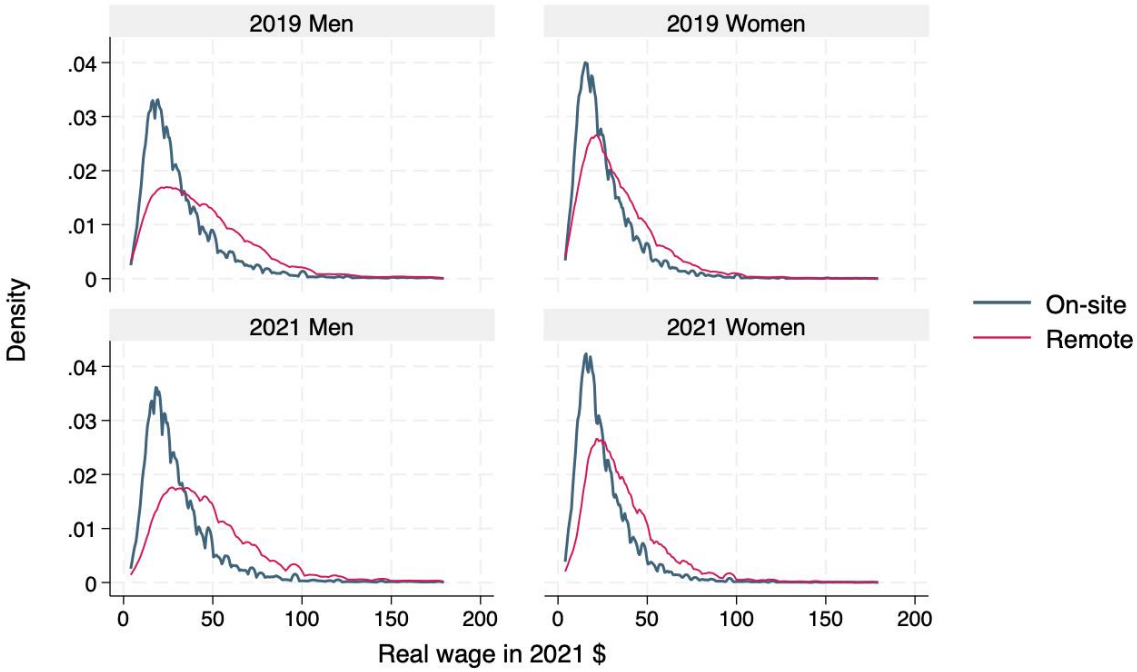
Fig. 5 Usual weekly hours worked by remote worker status



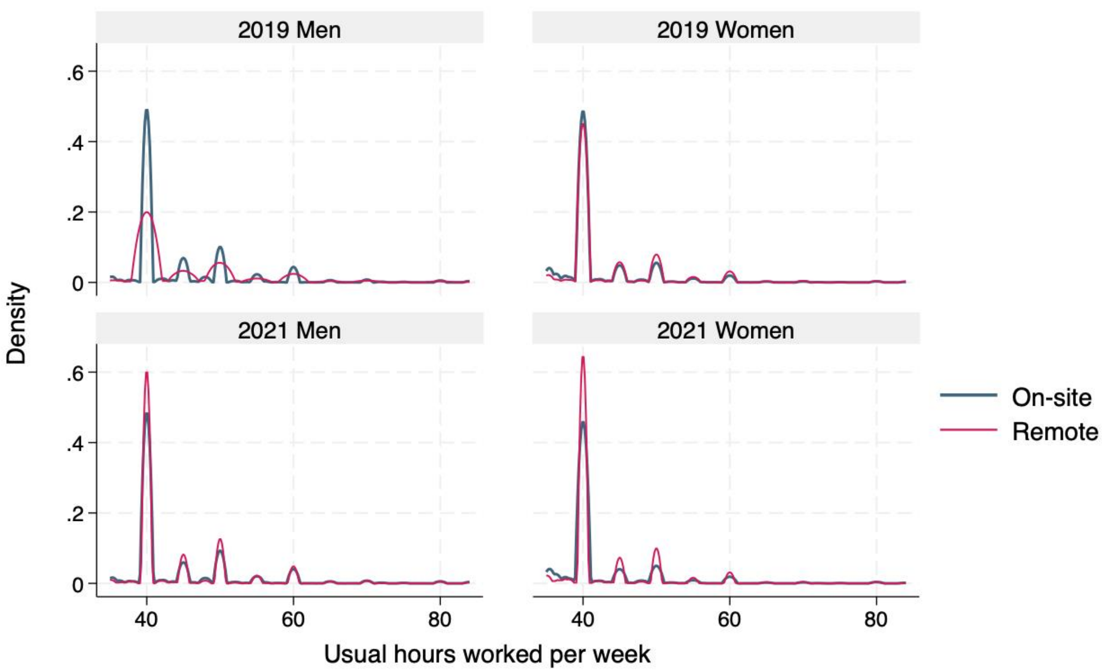
Source: American Community Survey

Fig. 6 Kernel density estimates, 2019 and 2021

a. Real wage



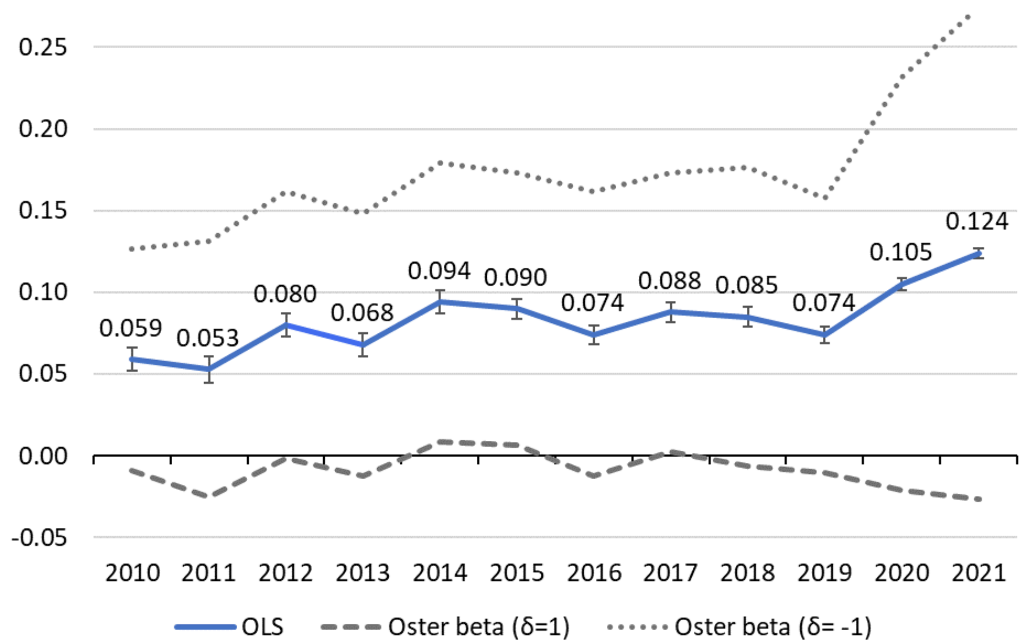
b. Usual weekly hours of work



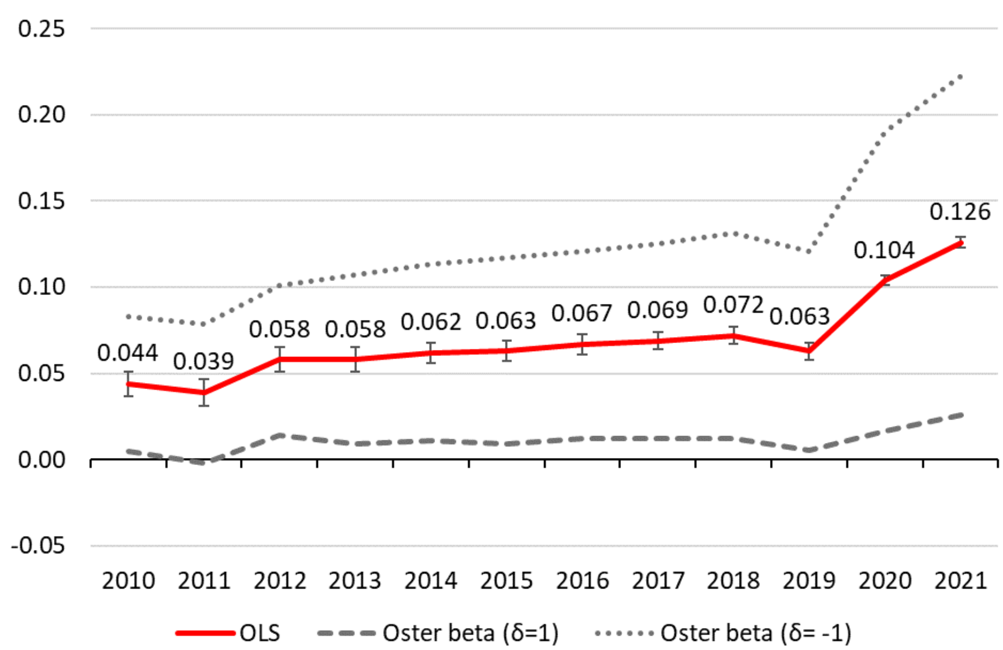
Source: American Community Survey

Fig. 7 Wage regression coefficients on remote worker and Oster betas

a. Men



b. Women

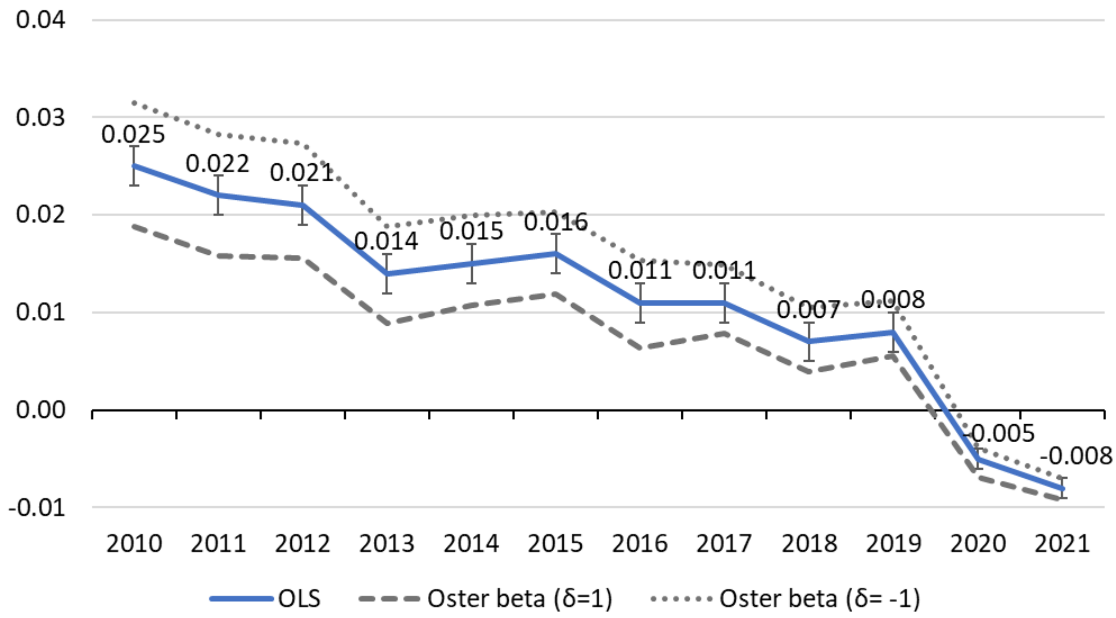


Notes: Estimates of equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

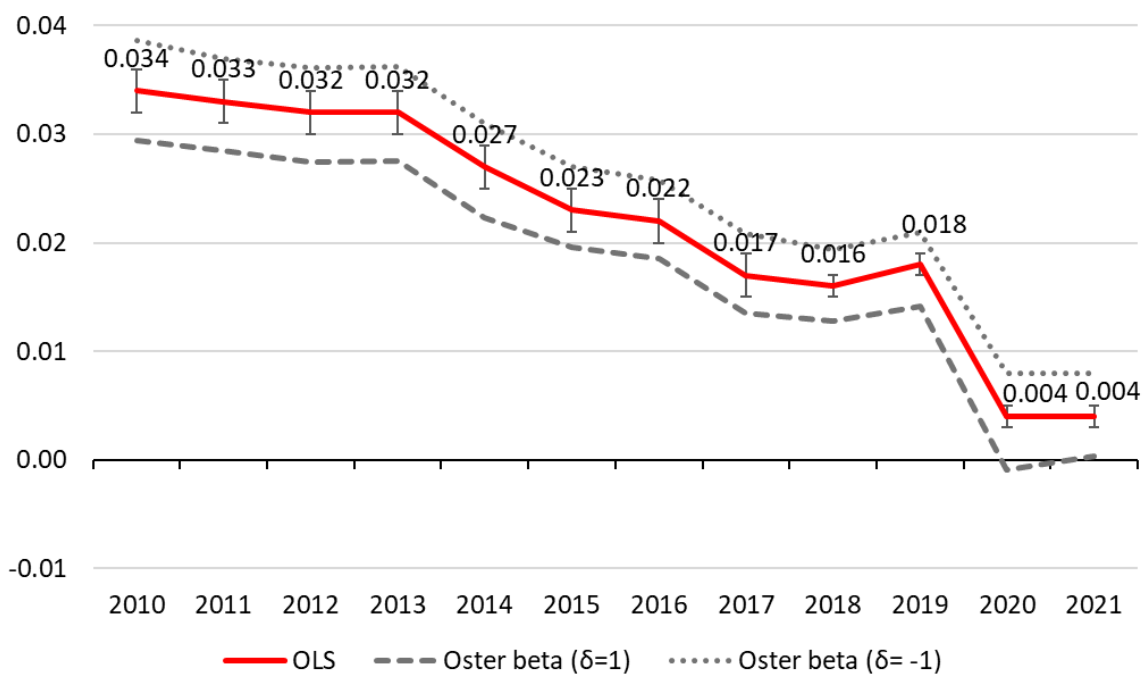
Source: American Community Survey

Fig. 8 Weekly hours worked regression coefficients on remote worker and Oster betas

a. Men



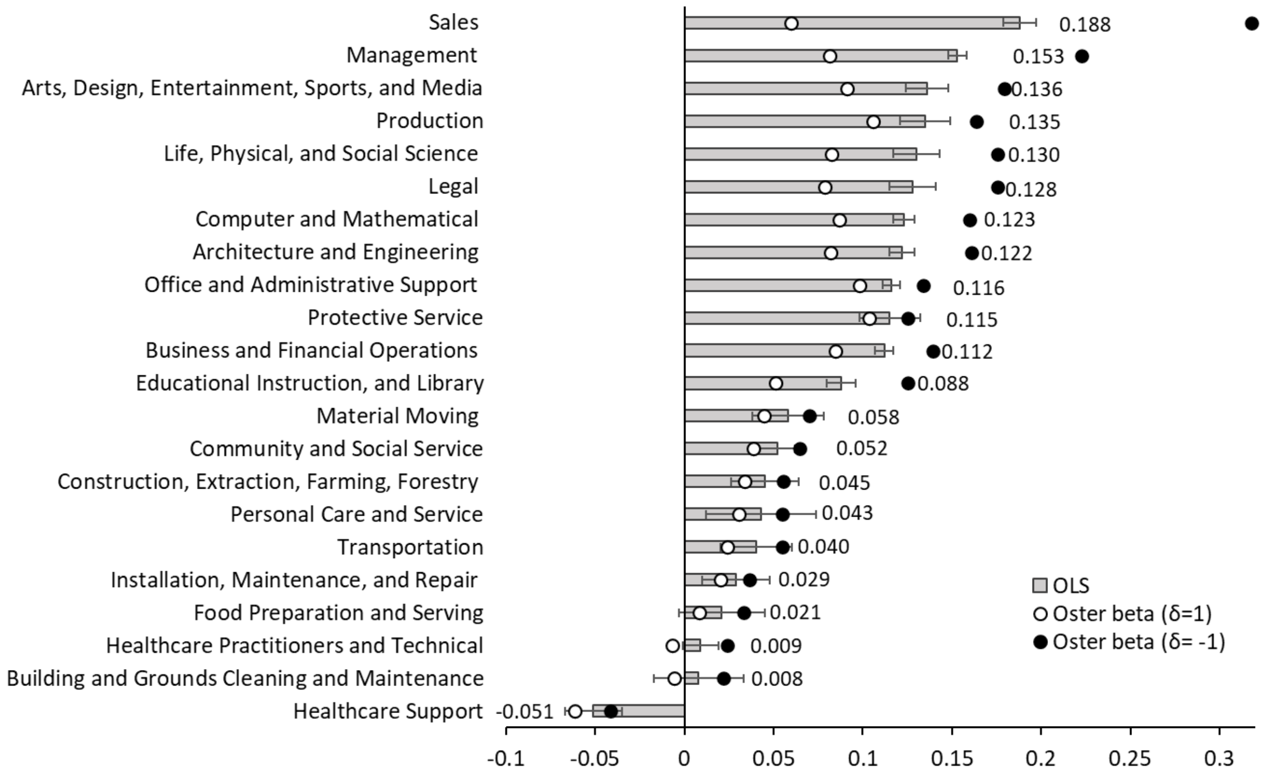
b. Women



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

Source: American Community Survey

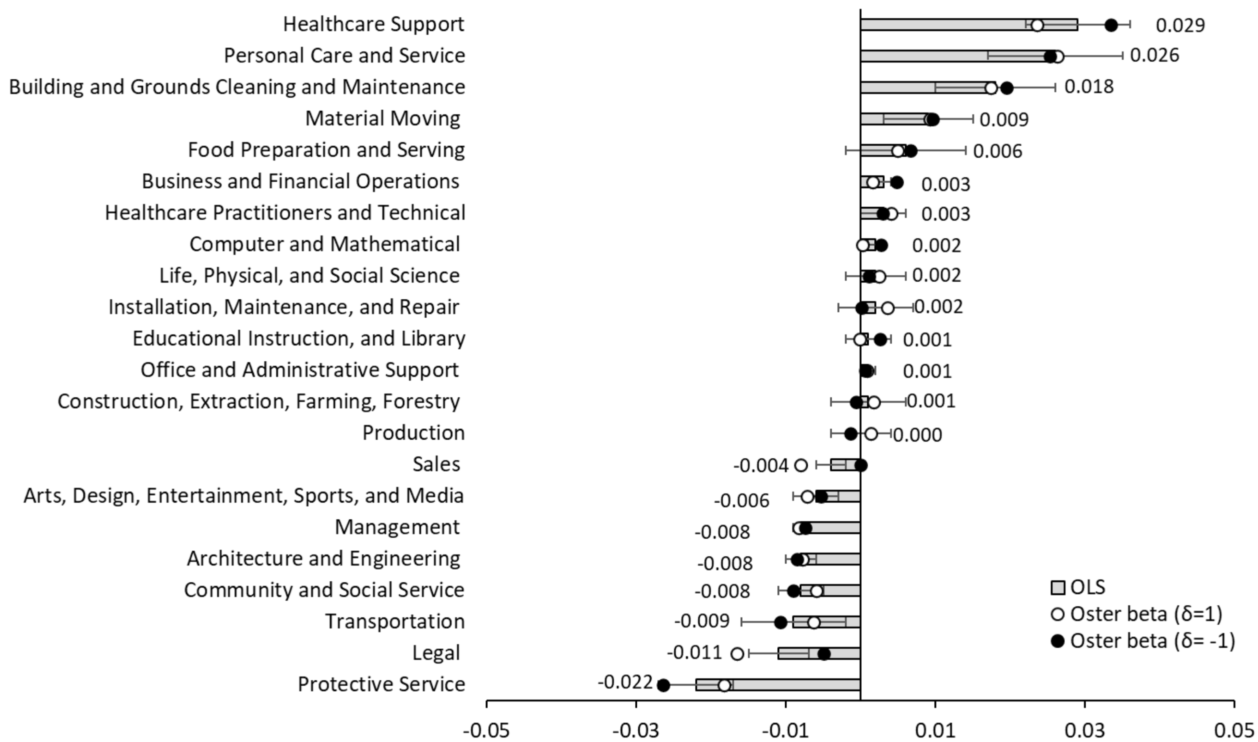
Fig. 9 Coefficients on remote worker from wage regressions by occupation and Oster betas, 2021



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

Source: American Community Survey

Fig. 10 Coefficients on remote worker from hours worked regressions by occupation and Oster betas, 2021

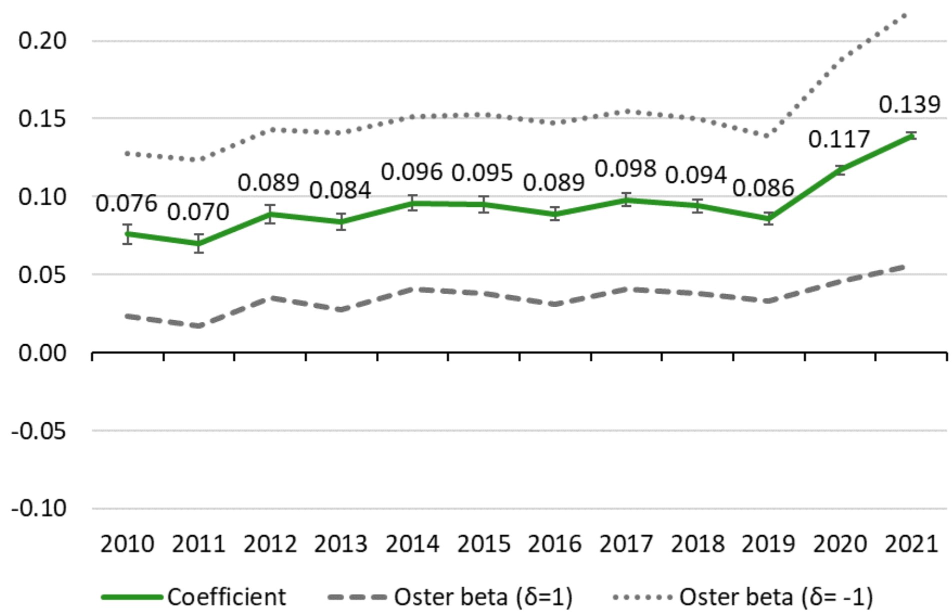


Notes: Estimates of equations 1 and 2. See Table 3 for the full list of controls. Diamonds represent Oster betas. Error bars represent 95% confidence intervals.

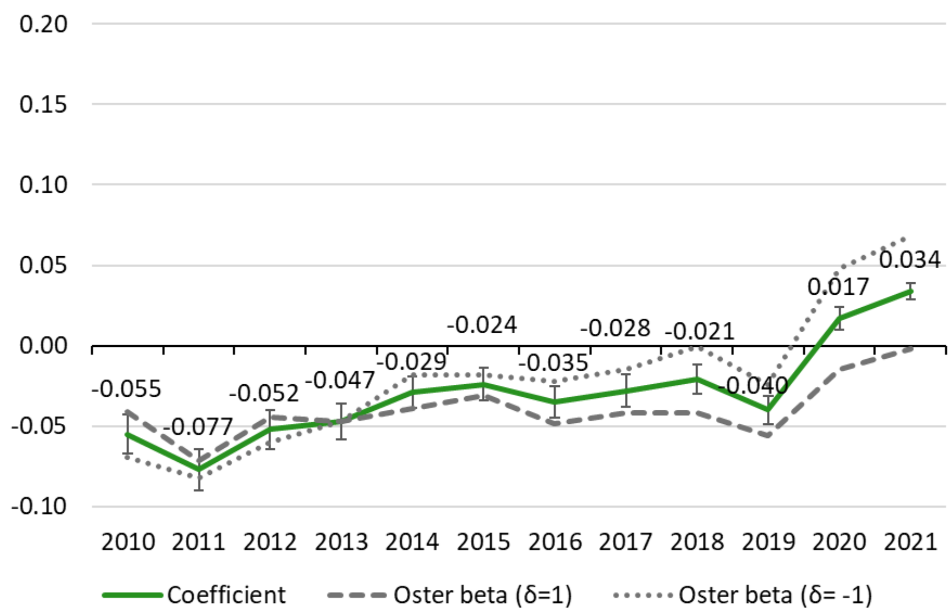
Source: American Community Survey

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

a. White-collar Occupations



b. Blue-collar Occupations

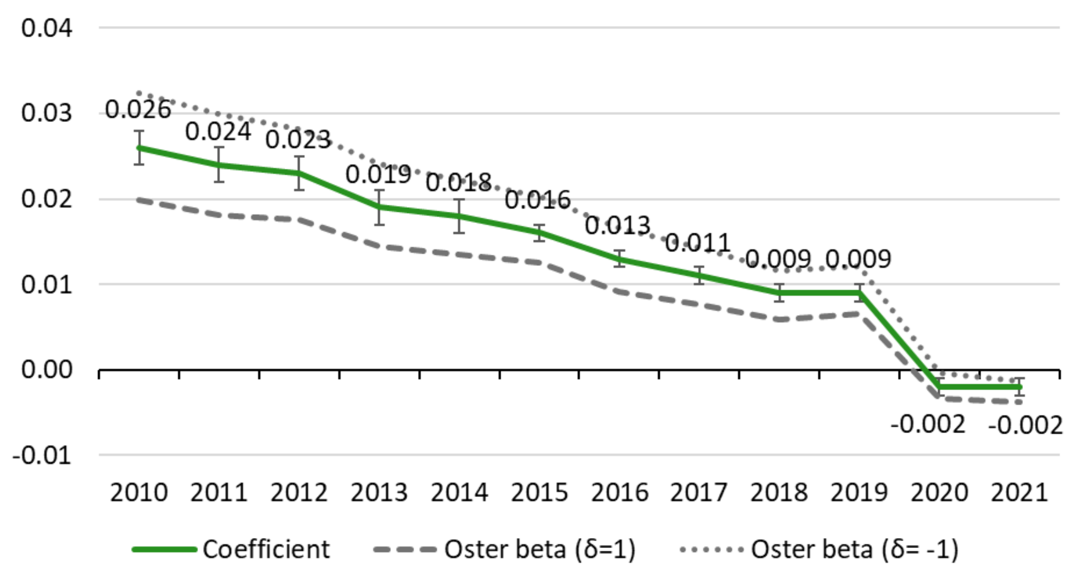


Notes: Estimates of equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

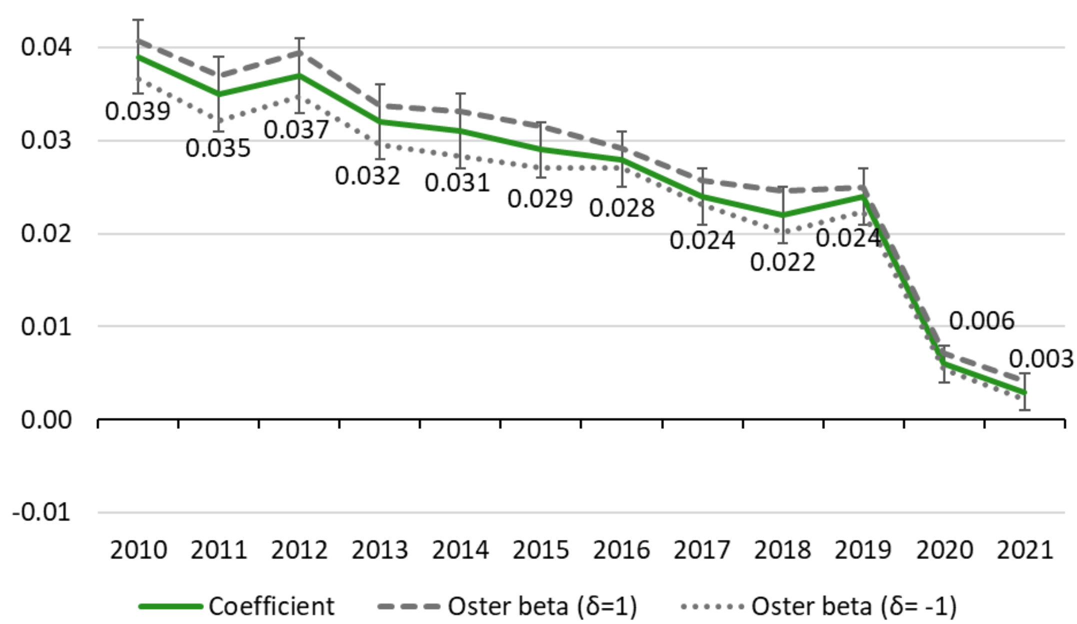
Source: American Community Survey

Fig. 12 White-collar and blue-collar hours worked regression coefficients on remote worker and Oster betas

a. White-collar Occupations



b. Blue-collar Occupations

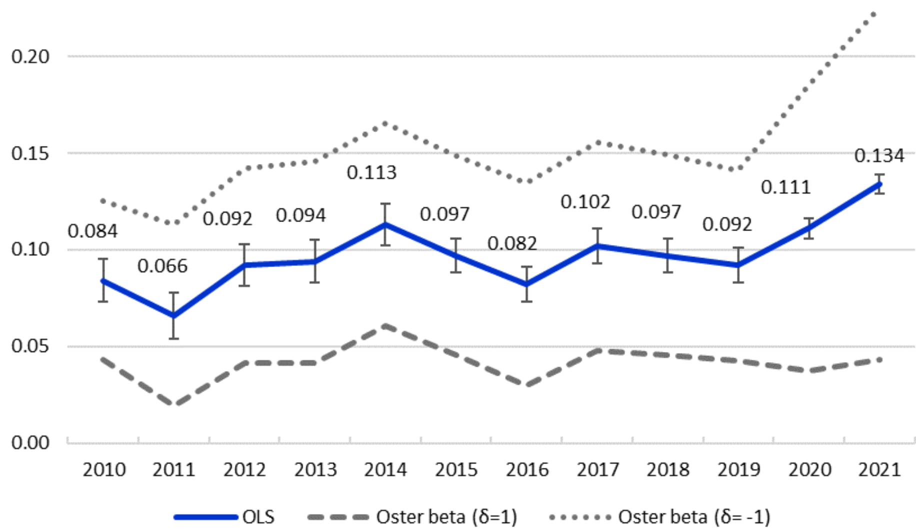


Notes: Estimates of equations 1 and 2. See Table 3 for the full list of controls. Error bars represent 95% confidence intervals.

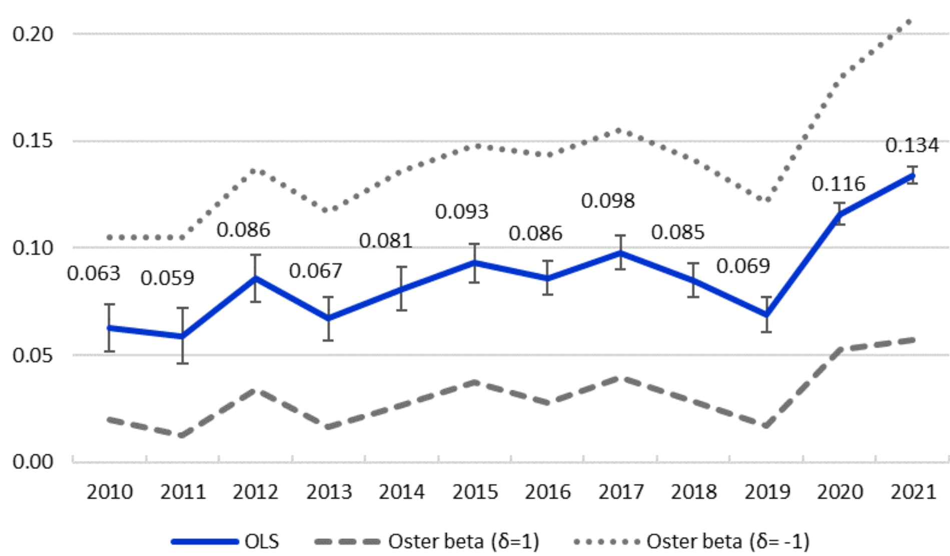
Source: American Community Survey

Fig. 13 White-collar workers by parental status: Wage regressions coefficients on remote worker and Oster betas

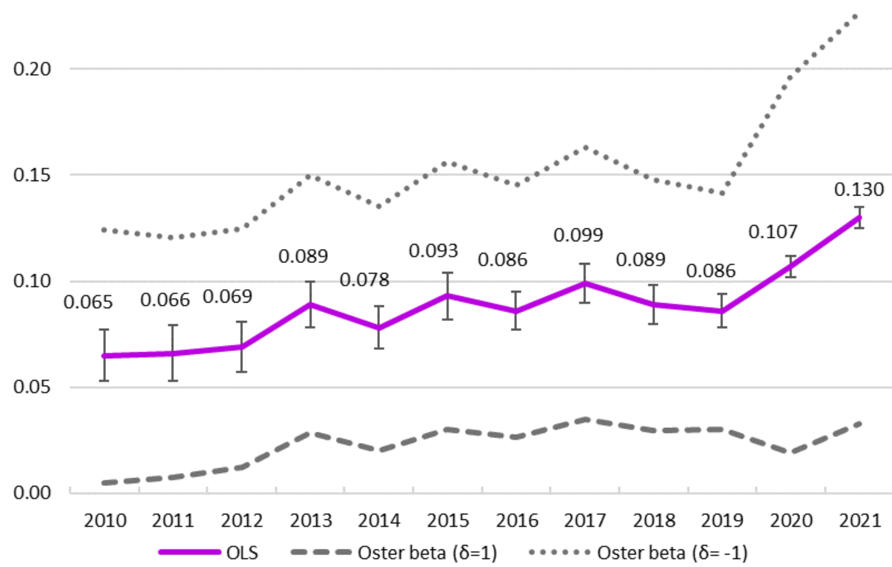
a. Fathers



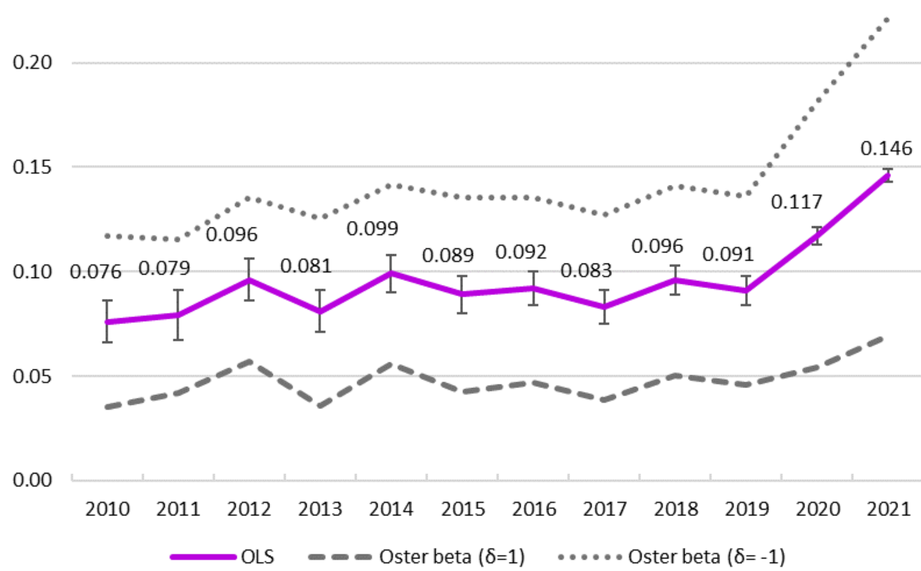
b. Men with no children



c. Mothers



d. Women with no children

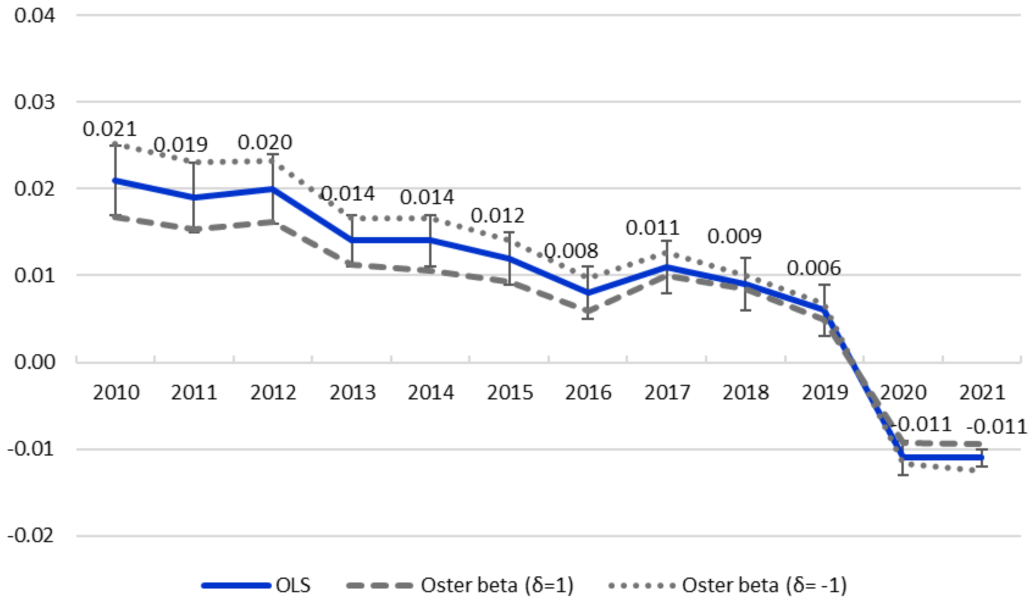


Notes: Estimates of equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

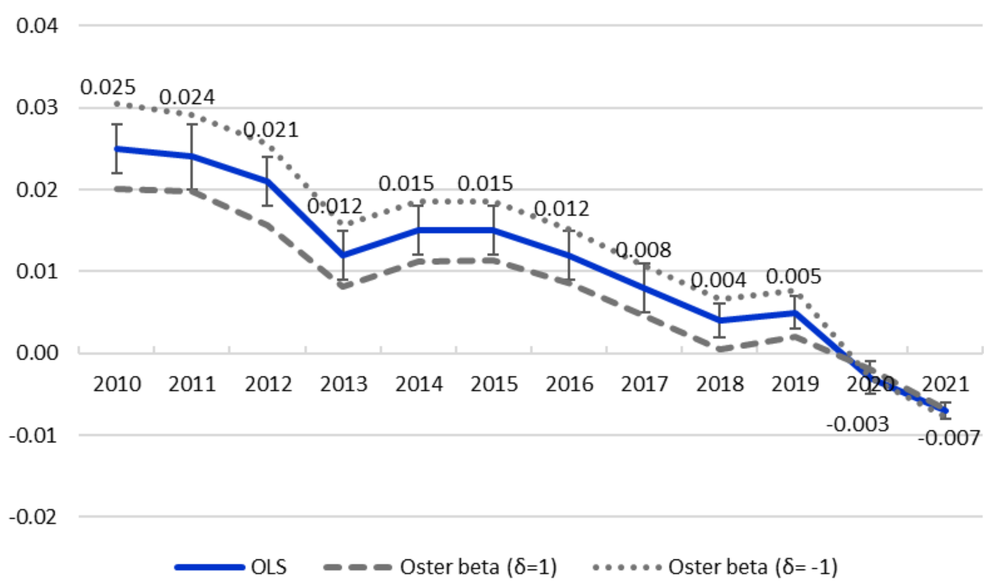
Source: American Community Survey

Fig. 14 White collar workers by parental status: Hours worked coefficients on remote worker and Oster betas

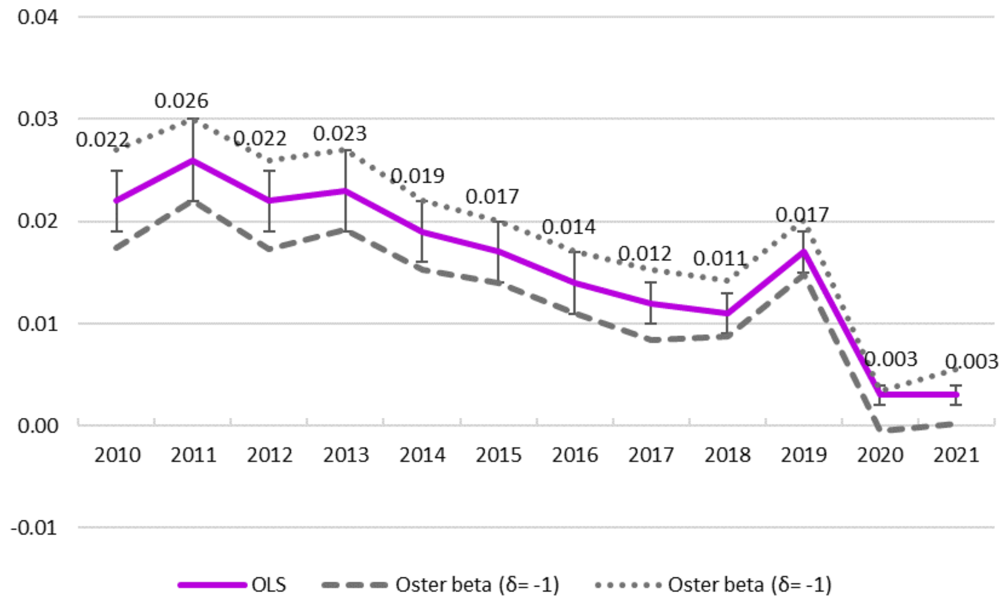
a. Fathers



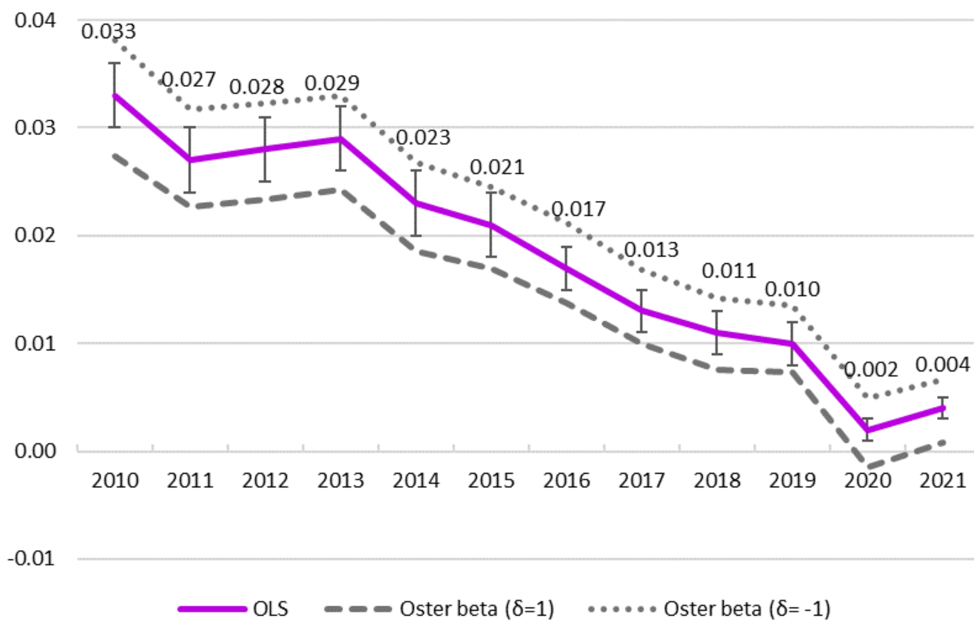
b. Men with no children



c. Mothers



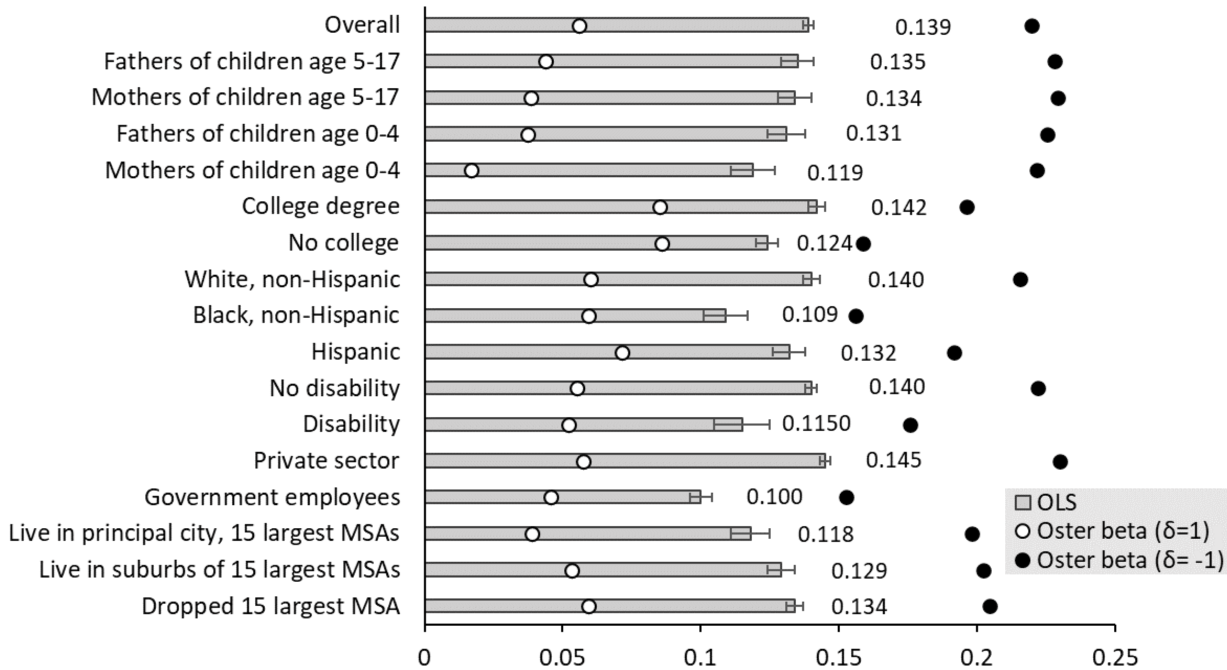
d. Women with no children



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

Source: American Community Survey

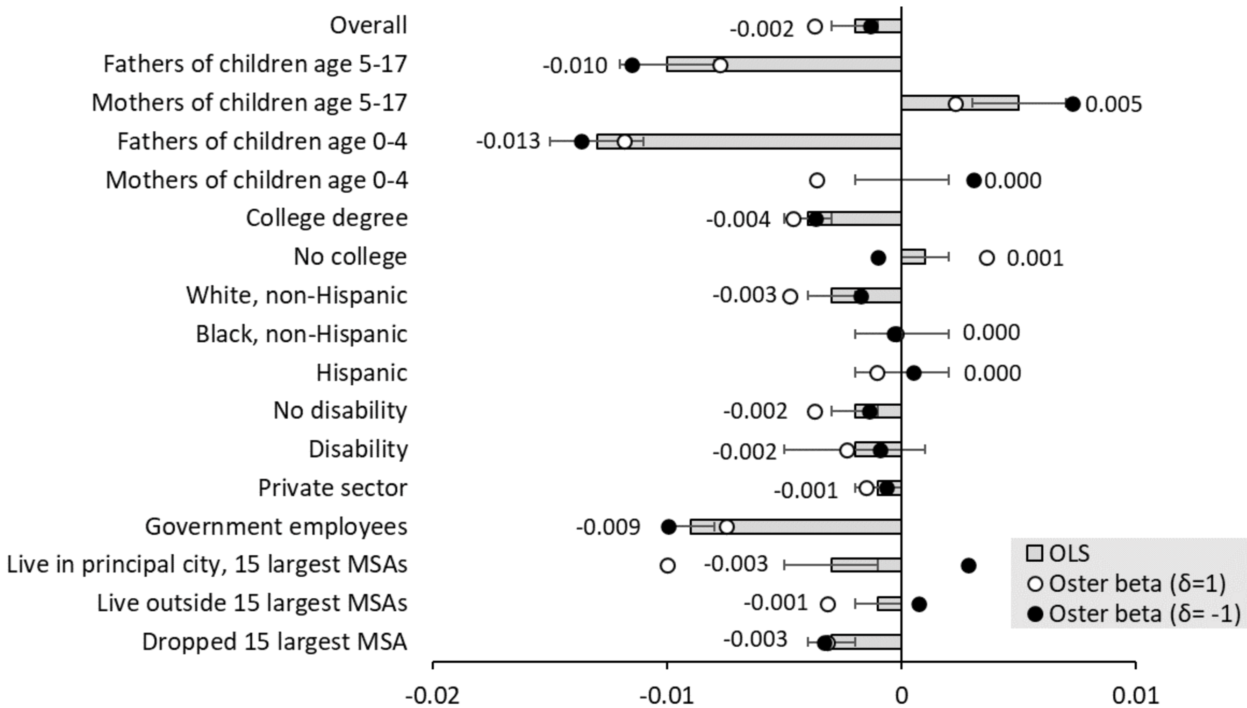
Fig. 15 Wage regression coefficient estimates on remote worker and Oster betas for subsamples of white-collar workers, 2021



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

Source: American Community Survey

Fig. 16 Hours worked regression coefficient estimates on remote worker and Oster betas for subsamples of white-collar workers, 2021



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

Source: American Community Survey

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

Notes: The size of the bubbles represents the occupation's relative employment. Regression is weighted by the number of workers in occupation 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, some college, high school graduates, graduate 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 as well as the mean number of children under age 5, number of 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 $	29.26	38.07	29.40	39.49	28.50	42.46
	(20.43)	(26.16)	(20.95)	(25.96)	(19.84)	(26.42)
Usual weekly hours of work	43.419	45.687	43.463	44.406	43.386	43.401
	(7.375)	(8.897)	(7.443)	(7.981)	(7.521)	(6.94)
Real annual earnings in 2021 $	65486.44	89154.67	66935.20	91487.26	64600.05	96353.14
	(51119.7)	(66740.8)	(52749.3)	(65374.1)	(49844.1)	(65662.2)
Female	0.455	0.458	0.448	0.499	0.439	0.506
Age	43.177	44.927	42.929	44.601	43.330	42.723
	(10.647)	(9.98)	(11.161)	(10.593)	(11.174)	(10.78)
No high school degree	0.076	0.042	0.070	0.031	0.072	0.015
Some college	0.317	0.280	0.297	0.260	0.299	0.207
College degree	0.227	0.358	0.248	0.382	0.233	0.416
Graduate degree	0.131	0.170	0.151	0.202	0.148	0.281
Non-Hispanic black	0.114	0.069	0.123	0.089	0.117	0.097
Hispanic	0.142	0.093	0.177	0.104	0.186	0.111
Married	0.591	0.660	0.550	0.636	0.557	0.608
Cohabiter	0.072	0.066	0.087	0.074	0.095	0.093
Number of own children age<5	0.172	0.183	0.164	0.176	0.160	0.179
	(.469)	(.488)	(.458)	(.476)	(.454)	(.473)
Number of own children age 5-17	0.616	0.652	0.591	0.634	0.609	0.566
	(1.021)	(1.047)	(1.018)	(1.02)	(1.038)	(0.97)
Number of other adults	0.483	0.346	0.560	0.386	0.563	0.368
	(1.085)	(0.893)	(1.159)	(0.95)	(1.161)	(0.914)
Disability	0.041	0.043	0.045	0.041	0.053	0.045
Partner/parent has a disability	0.067	0.059	0.074	0.065	0.082	0.060
Government employee	0.191	0.088	0.173	0.085	0.197	0.148
Lives in metropolitan area	0.795	0.845	0.826	0.880	0.803	0.924
Occupation						
Management	0.116	0.184	0.124	0.187	0.121	0.194
Business and Financial Operations	0.058	0.098	0.064	0.135	0.053	0.170
Computer and Mathematical	0.034	0.096	0.042	0.119	0.029	0.146
Architecture and Engineering	0.025	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	0.019	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, 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
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	0.039	0.013	0.009	0.010	0.004
Sales	0.090	0.182	0.078	0.126	0.074	0.074

	2010 On-site	2010 Remote	2019 On-site	2019 Remote	2021 On-site	2021 Remote
Office and Administrative Support	0.150	0.110	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	0.021	0.038	0.015	0.043	0.009
Production	0.072	0.022	0.070	0.019	0.073	0.015
Transportation	0.036	0.015	0.039	0.017	0.041	0.008
Material Moving	0.023	0.006	0.034	0.008	0.040	0.007
Industry						
Forestry, fishing, hunting, and mining	0.009	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	0.101	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	0.165	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	0.044	0.021	0.048	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
Observations	738,575	16,815	810,534	35,757	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	
	Men	Women	Men	Women	Men	Women
Remote	0.059***	0.044***	0.074***	0.063***	0.124***	0.126***
	(0.007)	(0.007)	(0.005)	(0.005)	(0.003)	(0.003)
Age	0.050***	0.040***	0.041***	0.040***	0.041***	0.040***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age squared	-0.047***	-0.038***	-0.037***	-0.037***	-0.037***	-0.037***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No high school degree	-0.155***	-0.138***	-0.140***	-0.097***	-0.120***	-0.076***
	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)
Some college	0.094***	0.106***	0.073***	0.088***	0.073***	0.074***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
College degree	0.290***	0.337***	0.272***	0.324***	0.259***	0.304***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Graduate degree	0.465***	0.524***	0.456***	0.523***	0.420***	0.489***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Non-Hispanic black	-0.127***	-0.062***	-0.142***	-0.071***	-0.131***	-0.066***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Hispanic	-0.167***	-0.105***	-0.126***	-0.109***	-0.121***	-0.090***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married	0.116***	0.040***	0.135***	0.051***	0.128***	0.052***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Cohabiter	0.012**	0.012***	0.034***	0.011**	0.021***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of own children age<5	0.009***	0.033***	0.014***	0.031***	0.014***	0.032***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Number of own children age 5-17	0.016***	-0.008***	0.011***	-0.004***	0.014***	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of other adults	-0.017***	-0.018***	-0.023***	-0.020***	-0.020***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Disability	-0.084***	-0.081***	-0.079***	-0.074***	-0.068***	-0.081***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Partner/parent has a disability	-0.076***	-0.046***	-0.080***	-0.050***	-0.073***	-0.041***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Government employee	0.047***	0.085***	0.011**	0.053***	0.008*	0.053***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Lives in metropolitan area	0.093***	0.123***	0.081***	0.118***	0.072***	0.097***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	407584	347806	460387	385904	429669	365360
R-squared	0.423	0.436	0.429	0.444	0.427	0.433

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	
	Men	Women	Men	Women	Men	Women
Remote	0.025***	0.034***	0.008***	0.018***	-0.008***	0.004***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Age	0.005***	0.004***	0.003***	0.004***	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	-0.004***	-0.000	0.000	-0.002	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Some college	0.010***	0.008***	0.010***	0.006***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College degree	0.024***	0.029***	0.013***	0.020***	0.009***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Graduate degree	0.059***	0.065***	0.037***	0.048***	0.031***	0.042***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-Hispanic black	-0.027***	-0.010***	-0.028***	-0.011***	-0.025***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Hispanic	-0.024***	-0.009***	-0.021***	-0.011***	-0.018***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Married	0.012***	-0.007***	0.013***	-0.006***	0.011***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cohabiter	0.006***	-0.002	0.009***	-0.002	0.005***	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of own children age<5	0.001	-0.009***	0.001	-0.008***	-0.001	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of own children age 5-17	0.001***	-0.004***	0.001	-0.004***	0.000	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of other adults	-0.005***	-0.003***	-0.005***	-0.003***	-0.005***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Disability	0.001	0.003*	0.006***	0.005**	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Partner/parent has a disability	-0.001	0.004***	-0.002	0.002*	0.000	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Government employee	-0.041***	-0.009***	-0.029***	-0.004***	-0.029***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lives in metropolitan area	-0.002	0.005***	-0.003**	0.003***	-0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	407584	347806	460387	385904	429669	365360
R-squared	0.095	0.075	0.070	0.056	0.059	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	0.059***	0.053***	0.080***	0.068***	0.094***	0.090***	0.074***	0.088***	0.085***	0.074***	0.105***	0.124***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)
Female	0.045	-0.014	-0.004	-0.066*	-0.028	-0.053*	-0.084**	-0.021	-0.089***	-0.115***	-0.168***	-0.159***
	(0.031)	(0.036)	(0.034)	(0.034)	(0.032)	(0.031)	(0.033)	(0.031)	(0.032)	(0.033)	(0.041)	(0.034)
Remote × Female	-0.015	-0.015	-0.022**	-0.009	-0.031***	-0.027***	-0.008	-0.019**	-0.013*	-0.010	-0.001	0.002
	(0.010)	(0.011)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.005)	(0.004)
Observations	755390	738348	752846	772886	778219	793424	802215	823878	836481	846291	644286	795029
R-squared	0.442	0.442	0.443	0.442	0.443	0.445	0.446	0.446	0.444	0.445	0.444	0.439
Panel B: Log real annual earnings												
Remote	0.084***	0.075***	0.102***	0.082***	0.109***	0.106***	0.085***	0.100***	0.093***	0.082***	0.099***	0.116***
	(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	-0.098***	-0.156***	-0.165***	-0.236***	-0.209***	-0.205***	-0.220***	-0.187***	-0.238***	-0.269***	-0.336***	-0.295***
	(0.032)	(0.037)	(0.034)	(0.035)	(0.033)	(0.032)	(0.034)	(0.032)	(0.033)	(0.034)	(0.042)	(0.035)
Remote × Female	-0.006	-0.004	-0.012	0.009	-0.020**	-0.020**	0.004	-0.013*	-0.004	-0.001	0.008	0.014***
	(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	755390	738348	752846	772886	778219	793424	802215	823878	836481	846291	644286	795029
R-squared	0.469	0.468	0.467	0.466	0.465	0.466	0.467	0.463	0.460	0.461	0.457	0.452
Panel C: Log hours worked												
Remote	0.025***	0.022***	0.021***	0.014***	0.015***	0.016***	0.011***	0.011***	0.007***	0.008***	-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	-0.143***	-0.141***	-0.161***	-0.170***	-0.180***	-0.153***	-0.136***	-0.165***	-0.149***	-0.154***	-0.168***	-0.136***
	(0.010)	(0.012)	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.010)	(0.012)	(0.011)
Remote × Female	0.009***	0.011***	0.010***	0.018***	0.011***	0.007***	0.011***	0.006**	0.009***	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	755390	738348	752846	772886	778219	793424	802215	823878	836481	846291	644286	795029
R-squared	0.117	0.118	0.116	0.114	0.112	0.106	0.097	0.095	0.093	0.087	0.080	0.072

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

	2010–19	2019–21
Panel A.		
Total change in remote employment share	0.0185	0.1569
Part due to changes in the composition of wage and salary employment across occupations	0.0004	0.0058
Part due to changes in remote employment shares within occupations	0.0189	0.1511
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 skill gap between remote workers and on-site workers	0.0294	0.0793
Part due to changes in the returns to observed skills, given the mean gap in observed skills	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 6. Instrumental variable results

	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	0.124***	0.126***	-0.008***	0.004***
	(0.003)	(0.003)	(0.001)	(0.001)
IV1: Share of remote workers by detailed occupation				
First stage				
IV	2.403***	2.646***	2.193***	2.565***
	(0.101)	(0.109)	(0.079)	(0.130)
Demographic, industry, occupation, Census division controls	X	X	X	X
Second stage				
Remote	0.377***	0.330***	-0.031***	0.004
	(0.034)	(0.032)	(0.010)	(0.014)
Demographic, industry, occupation, Census division controls	X	X	X	X
ρ	-0.307***	-0.267***	0.088***	0.001
	(0.039)	(0.044)	(0.034)	(0.059)
P value for Wald test that ρ=0	<0.001	<0.001	0.009	0.980
IV2: Dingel and Neiman index of teleworkability by detailed occupation				
First stage				
IV	0.354***	0.288***	0.320***	0.260***
	(0.054)	(0.078)	(0.052)	(0.081)
Demographic, industry, occupation, Census division controls	X	X	X	X
Second stage				
Remote	0.295***	0.289***	-0.019	0
	(0.022)	(0.032)	(0.017)	(0.011)
Demographic, industry, occupation, Census division controls	X	X	X	X
ρ	-0.204***	-0.209***	0.042***	0.019
	(0.023)	(0.035)	(0.061)	(0.043)
P value for Wald test that ρ=0	p<0.001	<0.001	0.494	0.658
IV3: Broadband share of households by county				
First stage				
IV	1.968***	2.071***	1.932***	2.037***
	(0.199)	(0.211)	(0.168)	(0.179)
Demographic, industry, occupation controls	X	X	X	X
Second stage				
Remote	0.310***	0.329***	-0.027***	0.004
	(0.017)	(0.017)	(0.005)	(0 .008)
Demographic, industry, occupation, Census division controls	X	X	X	X
ρ	-0.235***	-0.261***	0.067***	0.001
	(0.022)	(0.020)	(0.018)	(0.034)
P value for Wald test that ρ=0	<0.001	<0.001	<0.001	0.965

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. Wald test of exclusion restriction is always significant with p<0.001. The first stage in this test is just identified by functional form. Source: American Community Survey, Dingel and Neiman (2020)

Table 7 Occupation-level real wage growth between 2019 and 2021 for remote versus on-site workers (OLS estimates)

	Log Mean Wage (1)	Log Mean Wage (2)
Remote	0.124***	0.013
	(0.019)	(0.012)
Year 2021	-0.011***	0.001
	(0.004)	(0.003)
Remote × Year 2021	0.037**	0.020*
	(0.014)	(0.011)
Controls	No	Yes
Observations	1176	1176
R-squared	0.991	0.997
Joint hypothesis test:		
Remote + Remote × Year 2021	0.160***	0.033***
	(0.013)	(0.008)

Note: 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, some college, high school graduates, graduate 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 as well as the mean number of children under age 5, number of children age 5–17, number of other adults. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey

Table A1 Comparison of summary statistics for 2020 and 2021

	2020	2021	*P* value for difference (2021 – 2020)
Remote	0.167	0.197	
Real hourly wage in 2021 $	31.12	31.26	0.003
	(21.92)	(22.02)	
Usual weekly hours worked	43.310	43.389	0.000
	(7.292)	(7.41)	
Real annual earnings in 2021 $	70533.22	70868.37	0.005
	(54681.4)	(54816.6)	
Female	0.452	0.452	0.637
Age	42.995	43.210	0.000
	(11.12)	(11.1)	
No high school degree	0.061	0.061	0.840
Some college	0.287	0.281	0.000
College degree	0.268	0.269	0.190
Graduate degree	0.171	0.173	0.008
Non-Hispanic black	0.114	0.113	0.286
Hispanic	0.171	0.171	0.735
Married	0.569	0.567	0.224
Cohabiter	0.096	0.095	0.013
Number of own children age<5	0.168	0.164	0.000
	(0.463)	(0.458)	
Number of own children age 5-17	0.604	0.601	0.202
	(1.03)	(1.024)	
Number of other adults	0.546	0.524	0.000
	(1.164)	(1.119)	
Disability	0.048	0.051	0.000
Partner/parent has a disability	0.076	0.077	0.065
Government employee	0.185	0.187	0.080
Lives in metropolitan area	0.827	0.827	0.606
Occupation			
Management	0.133	0.135	0.001
Business and Financial Operations	0.075	0.076	0.029
Computer and Mathematical	0.051	0.052	0.012
Architecture and Engineering	0.030	0.031	0.788
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	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	0.035	0.035	0.519
Material Moving	0.031	0.033	0.000
Industry			
Forestry, fishing, hunting, and mining	0.007	0.007	0.110
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	0.003
N	644,286	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 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	0.2664	0	On-site	0.19	0
Remote	-0.0002	0.998	Remote	-0.0002	0.999
Combined K-S	0.2664	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 of work					
Men 2019			Women 2019		
On-site	0.048	0	On-site	0.0795	0
Remote	-0.0004	0.994	Remote	0	1
Combined K-S	0.048	0	Combined K-S	0.0795	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 A3 Regressions with part time workers included (OLS estimates)

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
MEN												
Panel A: Log real wages												
Remote	0.055***	0.055***	0.081***	0.067***	0.090***	0.088***	0.074***	0.089***	0.084***	0.071***	0.101***	0.122***
	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)	(0.003)
Part-time	-0.137***	-0.158***	-0.169***	-0.167***	-0.174***	-0.175***	-0.158***	-0.173***	-0.167***	-0.115***	-0.087***	-0.066***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.008)	(0.006)
N	433124	424992	435845	448386	451903	459390	464319	474716	481483	488269	370099	454754
R-sq	0.425	0.430	0.433	0.434	0.433	0.437	0.437	0.437	0.436	0.424	0.423	0.417
Panel B: Log hours worked												
Remote	0.013***	0.013***	0.011***	0.009***	0.009***	0.011***	0.007***	0.007***	0.006***	0.004*	-0.005***	-0.010***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Female	-0.620***	-0.625***	-0.632***	-0.625***	-0.631***	-0.625***	-0.625***	-0.631***	-0.632***	-0.673***	-0.684***	-0.705***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
N	433124	424992	435845	448386	451903	459390	464319	474716	481483	488269	370099	454754
R-squared	0.431	0.429	0.425	0.423	0.424	0.415	0.414	0.410	0.409	0.430	0.439	0.428
WOMEN												
Panel C: Log real wages												
Remote	0.033***	0.033***	0.045***	0.041***	0.052***	0.061***	0.058***	0.060***	0.062***	0.056***	0.097***	0.118***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)
Part-time	-0.109***	-0.116***	-0.122***	-0.129***	-0.123***	-0.123***	-0.120***	-0.127***	-0.124***	-0.098***	-0.102***	-0.079***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
N	419580	409288	413107	420394	421236	426485	430502	441346	445701	458108	346142	424952
R-squared	0.436	0.434	0.436	0.436	0.440	0.440	0.441	0.441	0.438	0.427	0.425	0.419
Panel D: Log hours worked												
Remote	-0.009***	-0.013***	-0.011***	-0.004	-0.009***	-0.012***	-0.006**	-0.010***	-0.010***	-0.012***	-0.004***	-0.002*
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Female	-0.589***	-0.590***	-0.589***	-0.589***	-0.588***	-0.587***	-0.587***	-0.588***	-0.585***	-0.616***	-0.624***	-0.629***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
N	419580	409288	413107	420394	421236	426485	430502	441346	445701	458108	346142	424952
R-squared	0.543	0.540	0.540	0.541	0.540	0.540	0.537	0.538	0.534	0.540	0.536	0.527

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 A4 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)	OLS R-squared	IV		ρ		N
Overall	0.341***	(0.002)	0.139***	(0.002)	0.056	0.220	0.413	0.460***	(0.049)	-0.403	(0.053)	496238
Fathers of children age 5-17	0.353***	(0.006)	0.135***	(0.006)	0.044	0.228	0.360	0.470***	(0.048)	-0.412	(0.055)	59485
Mothers of children age 5-17	0.363***	(0.007)	0.134***	(0.006)	0.038	0.229	0.417	0.359***	(0.057)	-0.305	(0.065)	65092
Fathers of children age 0-4	0.351***	(0.008)	0.131***	(0.007)	0.037	0.225	0.380	0.493***	(0.048)	-0.455	(0.053)	34456
Mothers of children age 0-4	0.364***	(0.010)	0.119***	(0.008)	0.017	0.222	0.465	0.364***	(0.057)	-0.339	(0.069)	27804
College degree	0.280***	(0.003)	0.142***	(0.003)	0.085	0.196	0.355	0.467***	(0.069)	-0.411	(0.074)	300556
No college	0.221***	(0.004)	0.124***	(0.004)	0.086	0.159	0.299	0.446***	(0.056)	-0.397	(0.057)	195682
White, non-Hispanic	0.331***	(0.003)	0.140***	(0.003)	0.060	0.216	0.414	0.421***	(0.050)	-0.362	(0.057)	339991
Black, non-Hispanic	0.237***	(0.009)	0.109***	(0.008)	0.059	0.156	0.340	0.401***	(0.057)	-0.363	(0.062)	34711
Hispanic	0.290***	(0.007)	0.132***	(0.006)	0.071	0.192	0.352	0.471***	(0.046)	-0.412	(0.045)	56701
No disability	0.343***	(0.002)	0.140***	(0.002)	0.055	0.222	0.415	0.462***	(0.049)	-0.405	(0.053)	472503
Disability	0.276***	(0.011)	0.115***	(0.010)	0.052	0.176	0.352	0.401***	(0.055)	-0.347	(0.061)	23735
Private sector	0.356***	(0.003)	0.145***	(0.002)	0.058	0.230	0.421	0.524***	(0.043)	-0.457	(0.046)	385476
Government employees	0.250***	(0.005)	0.100***	(0.004)	0.046	0.153	0.391	0.266***	(0.053)	-0.240	(0.065)	110762
Live in principal city,15 largest MSAs	0.316***	(0.008)	0.118***	(0.007)	0.039	0.198	0.375	0.573***	(0.043)	-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	0.454***	(0.049)	-0.406	(0.053)	88558
Dropped 15 largest MSA	0.317***	(0.003)	0.134***	(0.003)	0.059	0.204	0.408	0.436***	(0.050)	-0.389	(0.055)	316742

Notes: Each number comes from a separate regression or test. OLS coefficients and Oster betas are shown in Figure 14. 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