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DISCUSSION PAPER SERIES

IZA DP No. 16420

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ABSTRACT

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

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 4.4 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, hours were similar.

JEL Classification: J20, J22, J31

Keywords: remote work, working from home, wages, usual hours worked, COVID-19

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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

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). Given the sharp increase in remote work, we are also able to examine wage and hours differentials 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, and occupation. In addition, we test for differences in wage growth between 2019 and 2021 by remote worker status within detailed occupations. Finally, we examine the relationship between overall occupation-level wage growth from 2019 to 2021 and the percentage of remote workers in these occupations in 2021.

We find a substantial jump in the wage premium for remote workers during the pandemic. In 2021, on average, remote workers earned 14.2 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 white-collar occupations in which over 10 percent of workers were working remotely in 2021, we find that fathers working remotely earned 14.8 percent, while mothers working remotely earned 14.2 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. In occupation-level analyses, we find that real wages grew 4.4 percent faster for remote workers than office-based workers within detailed occupation groups, and remote work intensity in occupations was positively associated with wage growth across occupations. Just prior to the pandemic, men working remotely worked 15 minutes longer per week than men working primarily in the office, and women working remotely worked 46 minutes longer per week than their on-site counterparts. In 2021, the differentials in usual hours fell, with men working remotely working 13 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). 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.[5] 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 in March of 2020, disrupting data collection and leading the U.S. Census Bureau to release 1-year ACS estimates for 2020 as experimental.

[5] Given our restriction to 48 weeks, those selected in each year will vary due to job losses in the pandemic. Because workers in leisure and hospitality were most affected and earn lower wages, the true wage premia for remote work could be even higher than we estimate.

We define remote worker status based on responses to the following 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 full workdays at home and an upper bound on the percentage of full-time remote workers, although during the pandemic 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.[6] 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

[6] 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.

26.3 percent of all full workdays were exclusively worked from home in 2021.[7] 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).[8]

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 43.8 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

[7] 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.

[8] 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).

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 drop observations with real hourly wages below $3. We also note that even within our group of full-time workers, we see considerable variation in usual weekly hours (see Table 1 for means and standard deviations for wages and hours in selected years). As a robustness check, we also estimate some specifications using annual earnings instead of 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 4 percent wage penalty turned into a 31 percent wage premium). The wage premia stayed about the same in office and administrative support occupations as well as in installation, maintenance, and repair occupations. Wage penalties for remote workers in health care occupations decreased.

In Figure 5, we show trends in usual hours worked by remote work status. Initially, in 2010, 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.

3. Econometric Models

Remote workers and office-based workers have different observable characteristics. For example, remote workers are more likely to be married and have children. They are also likely to have different unobservable characteristics (see Table 1). We begin our econometric analysis by estimating adjusted wage and usual hours worked differentials for remote workers for each year separately by sex as follows:

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

where our outcome variable, $\ln(Y_{it})$, is either the natural log of hourly wage (or annual income) 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, 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), race (non-Hispanic Black, non-Hispanic Asian, and non-Hispanic other race), Hispanic, married, cohabiting, own disability, living with a partner or parent with a disability, government employee, 21 occupation groups, 17 industry groups, and state fixed effects. All regressions are estimated by ordinary least squares (OLS) using person-level weights. We calculate robust standard errors. We note that our specification here 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.

Positive 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, more trusted workers into remote status. Ideally, we would want to control for unobservable characteristics of workers and jobs such as motivation, other potentially valued job amenities such as flexibility in scheduling hours, job tenure or workers' firm size, but these are not available in the ACS. These unobservable characteristics may be correlated with both wages/hours and remote worker status, which could lead to biased estimated wage/hours differentials. In order 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).[9] Oster betas, β*, are calculated as:

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

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. We assume that $\delta = 1$, which means that selection on observables is equal to selection on unobservables and has the same sign. We also assume that R_{max} = 1.3*R as suggested in Oster (2019).[10] For most of our estimates, Oster betas represent lower bounds on the coefficients. If an estimated range bounded by β and β* includes zero, then the sign of our OLS estimate is not robust to correcting for omitted variable bias.

[9] Pabilonia and Vernon (2022) find that 90 percent of teleworkers have some flexibility in scheduling their hours. Mas and Pallais (2017), however, find that while workers are willing to pay more for work from home, most do not value flexible scheduling.

[10] R_{max} is the *R*-squared from a hypothetical regression of 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. We also believe that our wage differentials for the pandemic period are likely to be less subject to the above-mentioned types of selection on unobservables given the common shock to employers.

We also use aggregated data at occupation-remote worker status cell level to estimate the difference in average wage growth between 2019 and 2021 using the following model:

$$\ln(\overline{w}_{ort}) = \delta_0 + \delta_1 Remote_{ot} + \delta_2 Year2021_t + \delta_3 Remote_{ot} \times Year2021_t + \delta_4 P_{ort} + occ_o + \nu_{ort} \quad (3)$$

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 295 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 occupation level, to test whether the take-up of remote work moderated wage pressures across occupations, we estimate the relationship between the percentage of remote workers in 2021 and the growth in average wages during the pandemic as follows:

$$\ln(\overline{w}_{o2021}) - \ln(\overline{w}_{o2019}) = \sigma + \rho\%Remote_{o2021} + \omega_o \quad (4)$$

where $\overline{w}_{ot}$ is the average wage in detailed occupation o at time t, $\%Remote_{o2021}$ is the percent of workers in occupation o who are remote in 2021, σ is a constant term, ρ is the coefficient of interest describing the association between occupation-level remote worker intensity and the growth in occupation-level wages, and ω_o represents the error term. We restrict the analysis to those occupations with at least 30 observations (498 occupations).[11] Regressions are weighted using the sum of the 2021 person weights for each occupation group, and robust standard errors are reported.

4. Results

Wage differentials

Figure 6 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. Table 4 reports the coefficients on the interaction of $Remote_{it}$ and $female_{it}$ when we

[11] Our findings are similar when using occupations with at least 100 observations.

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 5.4 percent more than on-site workers, and by 2019, the premium was only 7.7 percent.[12] In 2021, remote workers earned 14.2 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 income instead of hourly wages as the outcome (Table 4 Panel B). The Oster betas are below zero for men in all years, indicating the premia are not robust to adjusting for selection on unobservables (Figure 6). For women, the Oster betas exceed zero in 2012 through 2021.

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 16 minutes per week longer than men working on-site, while women working remotely worked 46 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 13 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 differentials are robust to unobservable factors (Figures 7a and 7b). It is not surprising that average usual hours worked by remote workers were lower during the pandemic, because previously on-site workers who historically worked less

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

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).[13]

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 8). 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 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 15.6 percentage points. Over both periods, the increase in remote work was almost entirely due to 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 (6.4 percentage points between 2010 and 2019 and 13.2 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 A shows that changes in the mean demographic characteristics between remote and on-site workers accounted for 67 percent of the relative gains for remote workers, while Table 5

[13] 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.

Panel B shows that changes in remote wage premia within occupations accounted for 48 percent of the relative gains.

Figure 8 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 (22.5 percent), management (16.5 percent), production (15.3 percent), and arts, design, entertainment, sports and media (14.5 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 9 shows the hours differentials in the same 22 occupations in 2021. Remote workers in a number of occupations (sales; management; arts, design, entertainment, sports, and media; community and social service; transportation; architecture and engineering; legal; 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: personal care and service, healthcare support, 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 10, 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 significant 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 5 percent. In contrast, remote blue-collar workers paid wage penalties until 2021, when they earned a 4.1 percent wage premium (again supported by the Oster betas). Figure 11 reports hours differentials for these groups. Prior to the pandemic, those working remotely in both groups worked longer hours. However, during the pandemic, remote white-collar 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 12 and 13 show trends in wages and hours differentials by sex and parental status for those working in white-collar occupations.[14] 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 by parental status, suggesting a higher degree of selection on

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

observables within the parent groups. Turning to the hours differentials, we find no large differences by parental status for men. 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 7b).

Heterogeneity across various subsamples of white-collar workers in 2021

In Figure 14, we present OLS estimates and Oster betas from equations 1 and 2, respectively, for subsamples by age of youngest child, college degree status, race/Hispanic ethnicity, disability status, and sector of employment for workers in white-collar occupations in 2021. Even though parents were often at home working alongside their children, who may have interrupted their work activities (Lyletton et al. 2023; Pabilonia and Vernon 2023b), we still find that remote workers earned higher wages regardless of the age of their youngest child. However, mothers working at home with a child aged 0–4 had a slightly lower wage premium than other parents (13.0 percent versus 14.8 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 wage premia were still relatively high for mothers of young children may also be a result of exit from the labor force of mothers whose paid work productivity was lower. 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 Asian, non-Hispanic white, and Hispanic workers earning substantially higher

returns for remote work than Non-Hispanic Black workers (17.8, 15.2, 14.7, and 10.6 percent, respectively).

There has been considerable interest in whether people with disabilities will supply more labor given the new remote work climate (Ameri et al. 2022; Ne'eman and Maestas 2023). Those who may have previously found commuting to be too difficult/costly due to mobility impairments or who needed to remain close to medical equipment and doctors can now work from the comfort of their home in many occupations. Remote work has the potential to decrease pay differentials between those with and without disabilities if those with disabilities can increase their job tenure and raises are determined by performance rather than discriminatory practices that have been disadvantageous to those with disabilities (Schur et al. 2013). Our estimates show that people with disabilities working remotely earned more than people with disabilities working on-site during the pandemic, although the wage differential was smaller than the one for people without disabilities (11.9 percent versus 15.4 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.[15]

Finally, 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 16 percent more when working remotely, while those working for the government earned only 9.2 percent more. These differences in wage premiums should not be surprising given the relative nominal wage

[15] 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).

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. In all of the subsamples, the signs of the estimates are robust to correcting for omitted variable bias.

Figure 15 shows coefficient estimates from the hours worked regression and the corresponding Oster betas for the same subsamples of white-collar workers as presented in Figure 14. 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 31 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. Whites, Asians, the college-educated and workers without disabilities show a small decrease in hours when working remotely. 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 3 without demographic and industry controls (column 1 of Table 6). 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 1.3 percent less in 2021 than in 2019, and remote workers earned 19.4 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. Remote workers, on the other hand, earned 4.4 percent more than on-site workers in 2021.

Wage growth across occupations by remote worker shares

Figure 16 shows the bivariate relationship between occupation-level average cumulative real wage growth over the 2019–2021 period and the percentage of remote workers in the occupation in 2021 across three-digit occupation groups. The size of the bubbles represents the occupation's relative employment. The dotted line represents a linear regression, weighted by the relative employment of each occupation. We find that a one percentage-point increase in the percentage of remote workers in an occupation is associated with a 0.026 percentage-point increase in occupation-level cumulative wage growth. During the pandemic, 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 a 0.4 percentage-point increase in occupation-level wage growth for the average occupation during the pandemic, which is large, given that real wages increased by 2 percent on average across occupations.

5. Conclusion

Using the ACS, we examine trends in wage and hours differentials for primarily remote workers relative to primarily on-site workers, with a special focus on changes during the pandemic period. There are three main takeaways from these analyses. First, on average, remote workers earn more than on-site workers. 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, even after evaluating the robustness of our results for omitted variable bias using a method proposed by Oster (2019). 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.

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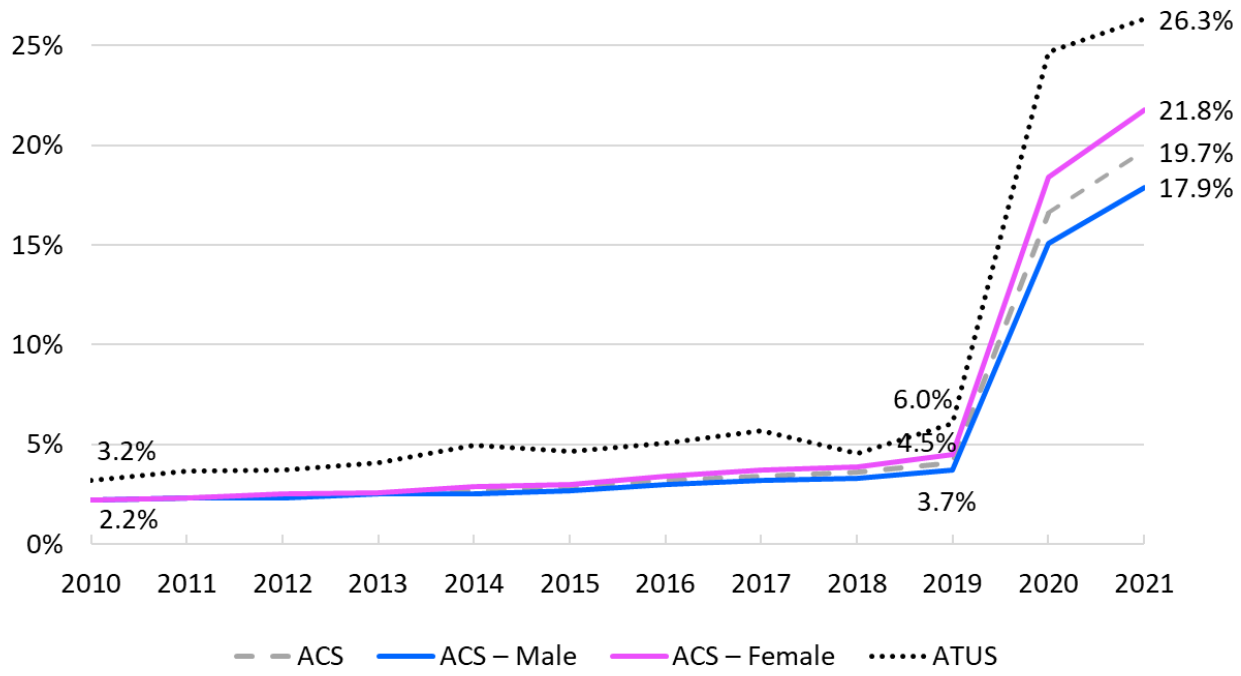
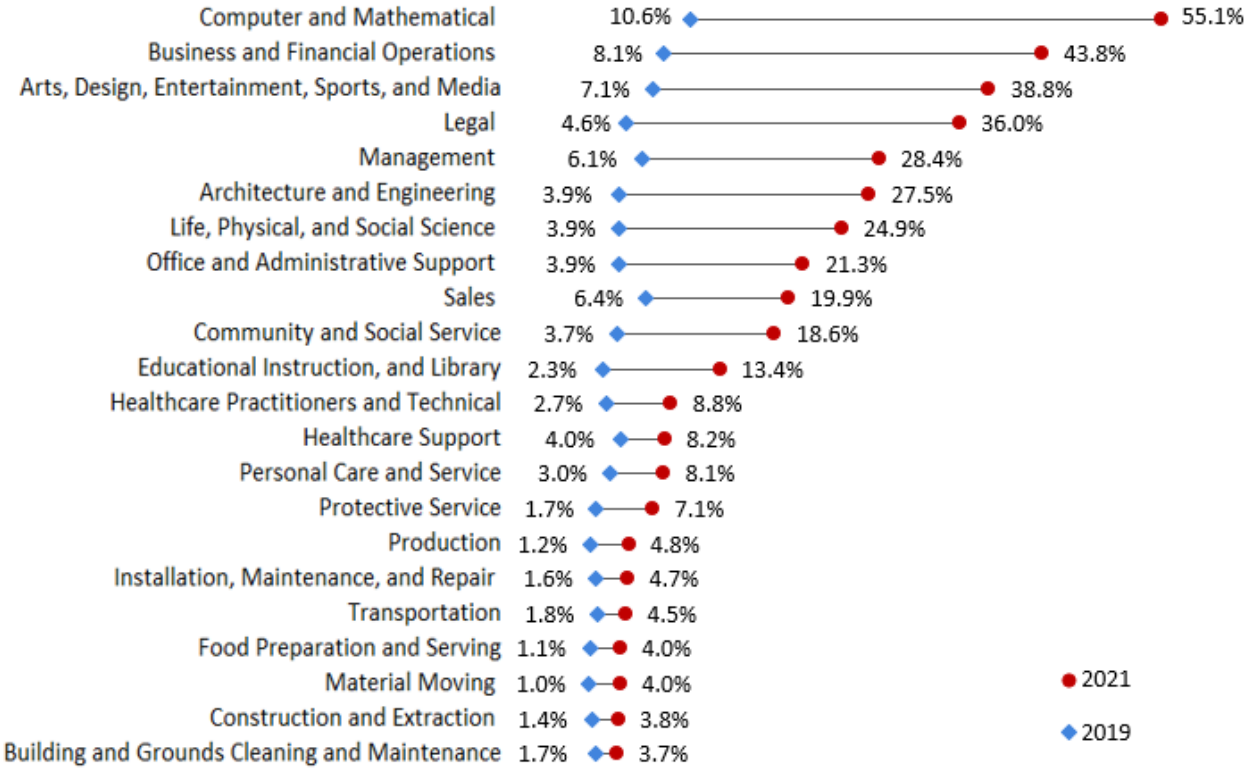
Fig. 1 Percentage of people working primarily from home and percentage of workdays exclusively worked from home among full-time employees in the nonfarm sector



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

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.

Fig. 2 Percentage of remote workers by occupation

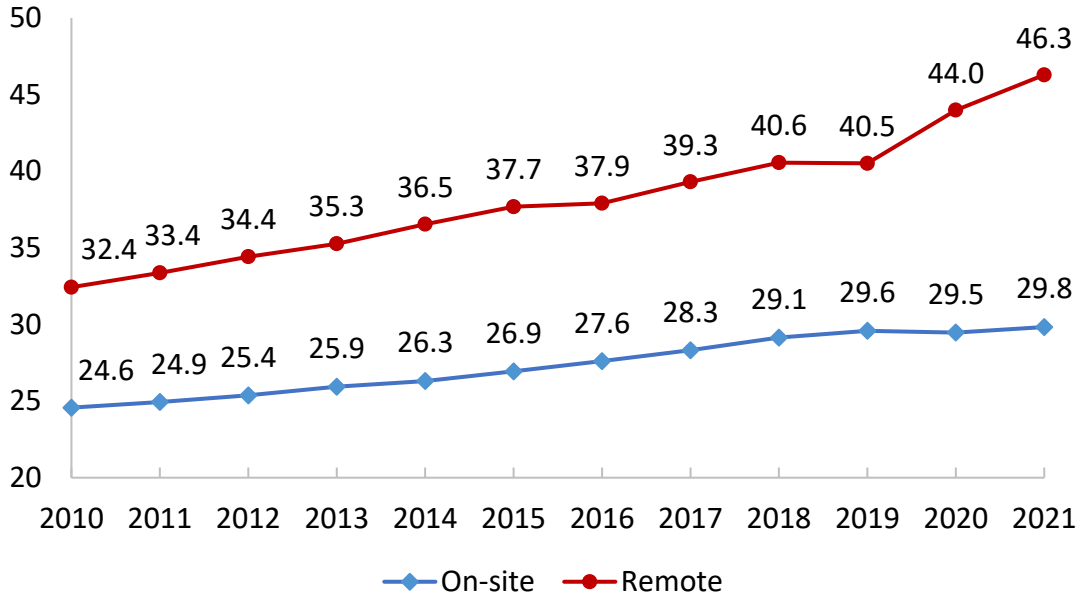


Source: American Community Survey

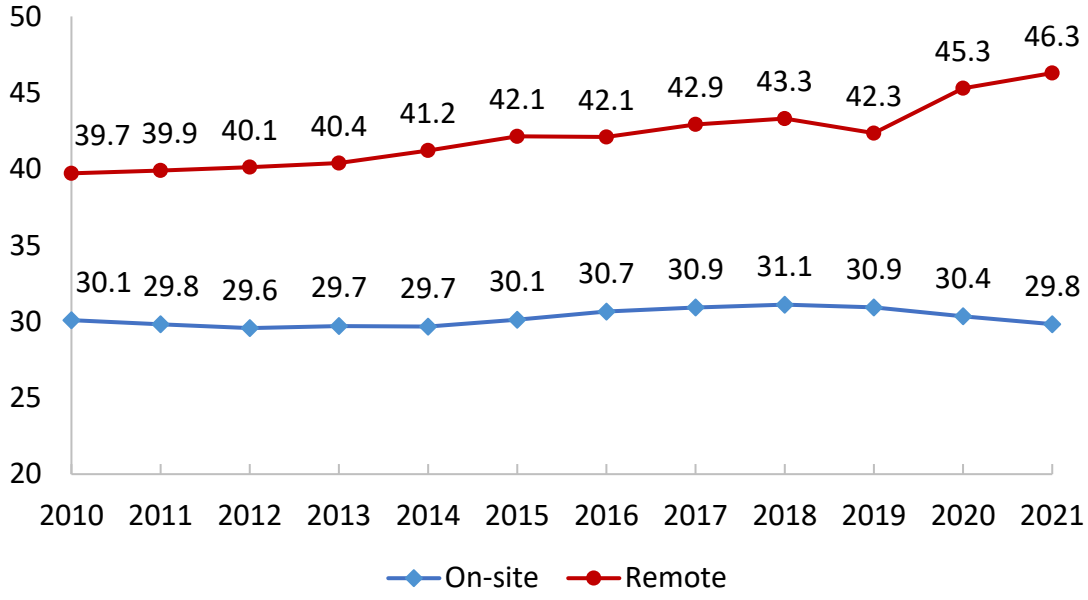
Notes: ACS survey weights are used here and in all other calculations.

Fig. 3 Wages by remote worker status

a. Nominal wages

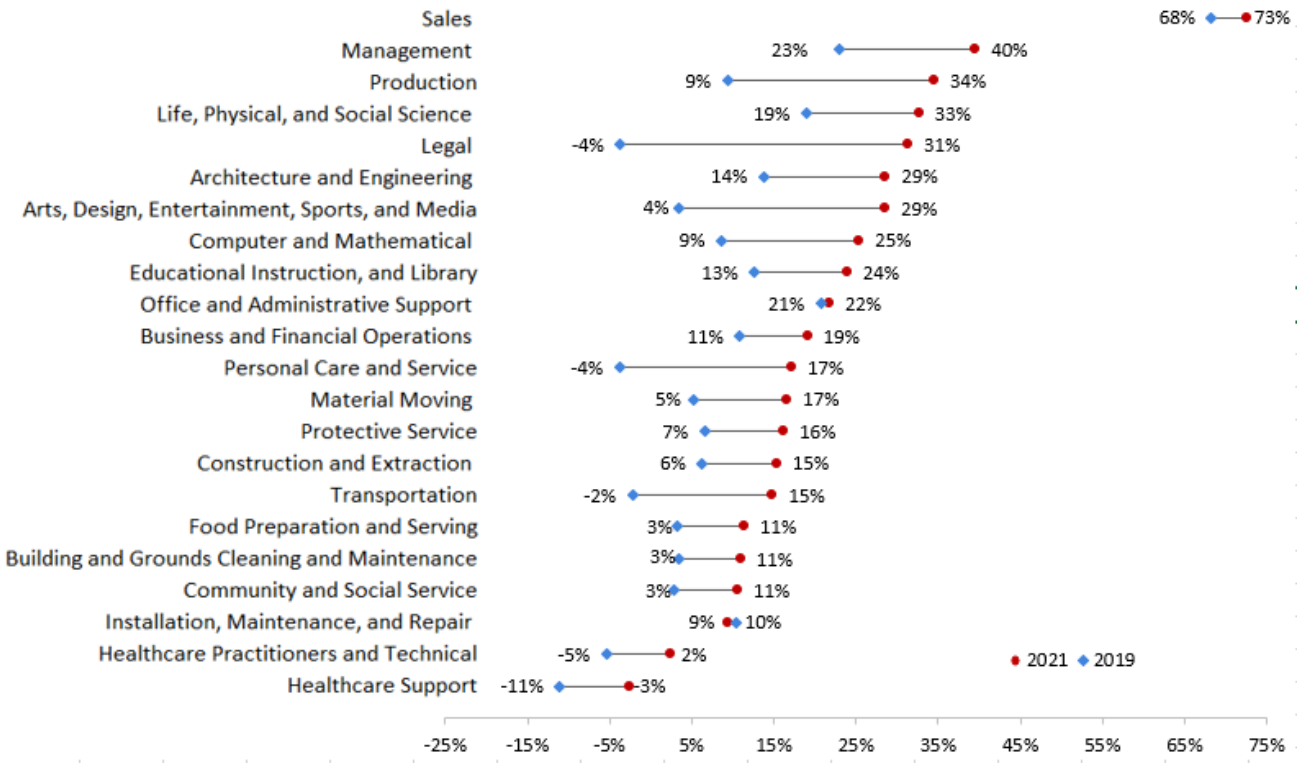


b. Real wages in 2021 dollars



Source: American Community Survey

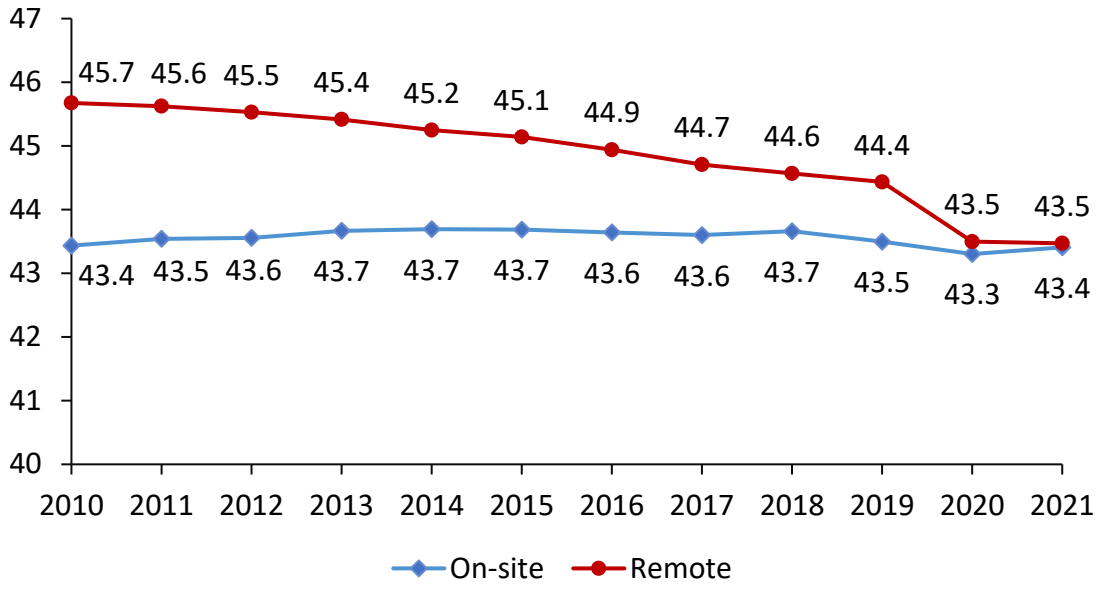
Fig. 4 Unadjusted wage differentials for remote workers in 2019 and 2021



Source: American Community Survey

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

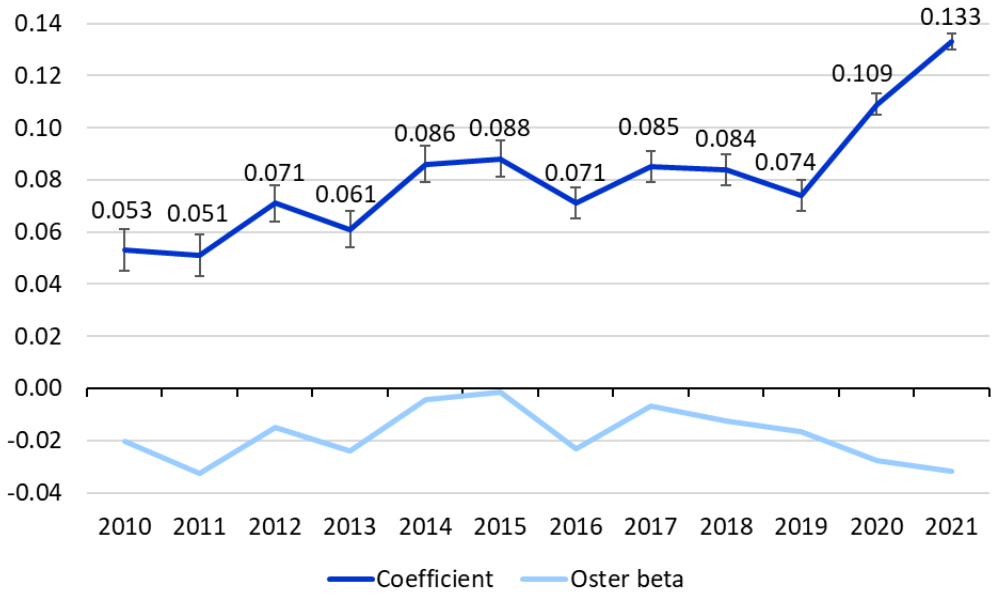
Fig. 5 Usual weekly hours worked by remote worker status



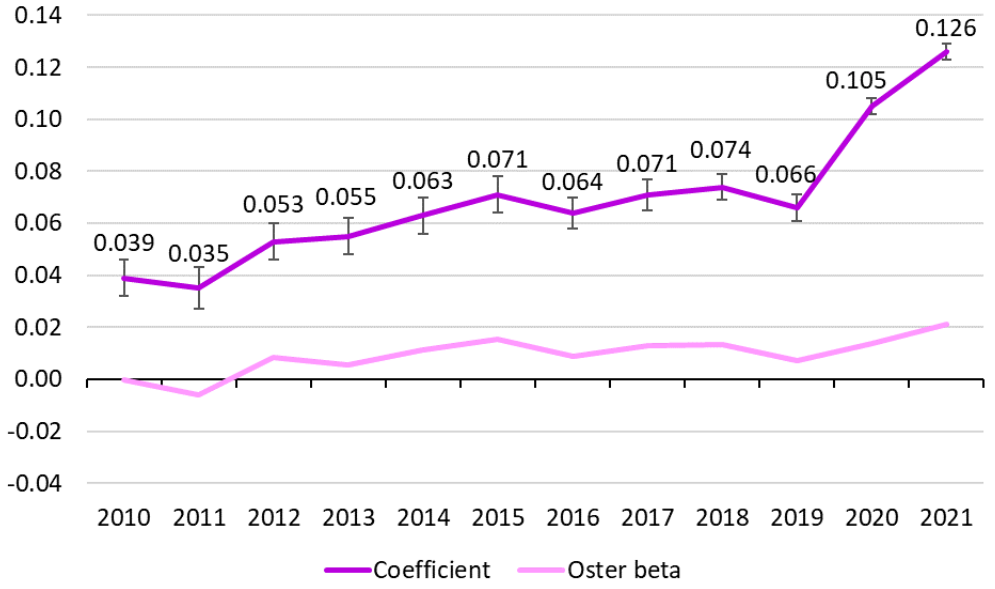
Source: American Community Survey

Fig. 6 Wage regression coefficients on remote worker and Oster betas

a. Men



b. Women

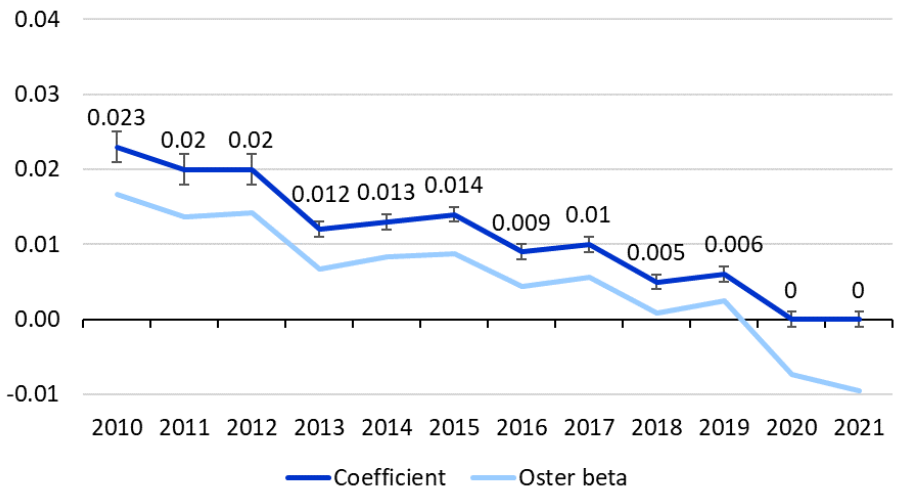


Source: American Community Survey

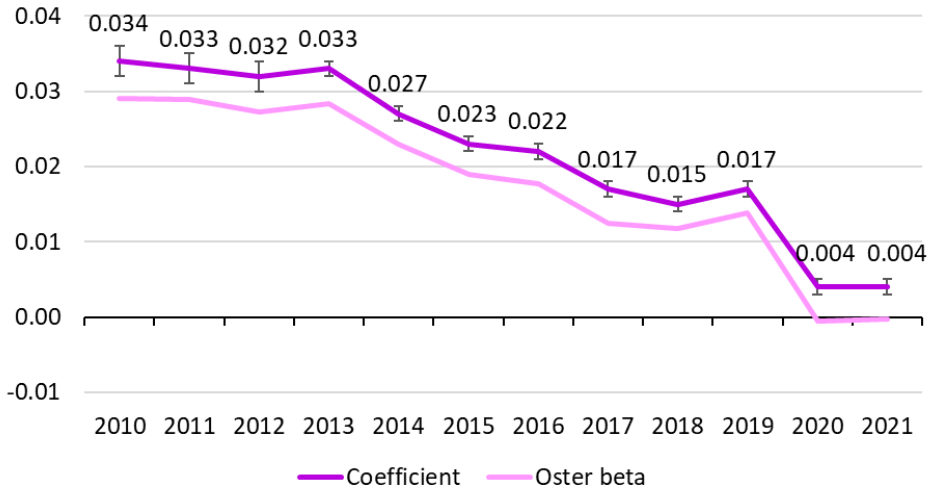
Notes: Estimates of equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

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

a. Men



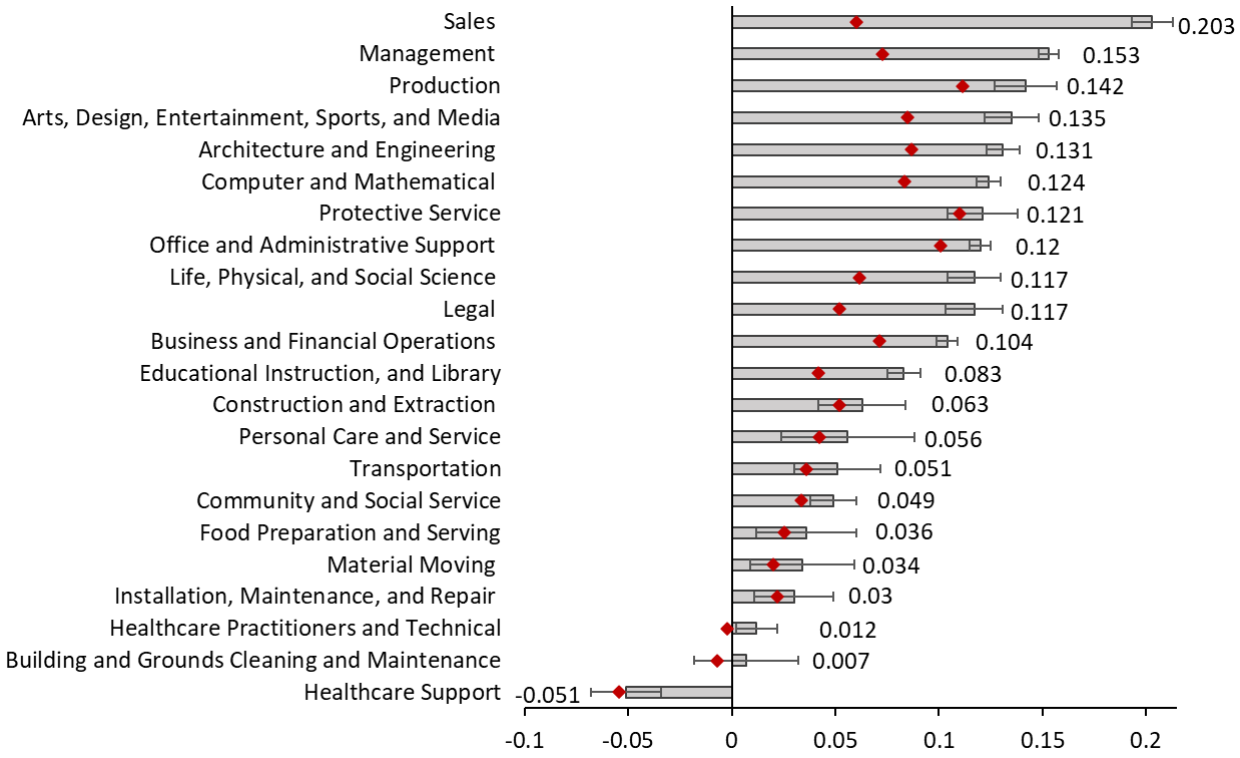
b. Women



Source: American Community Survey

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

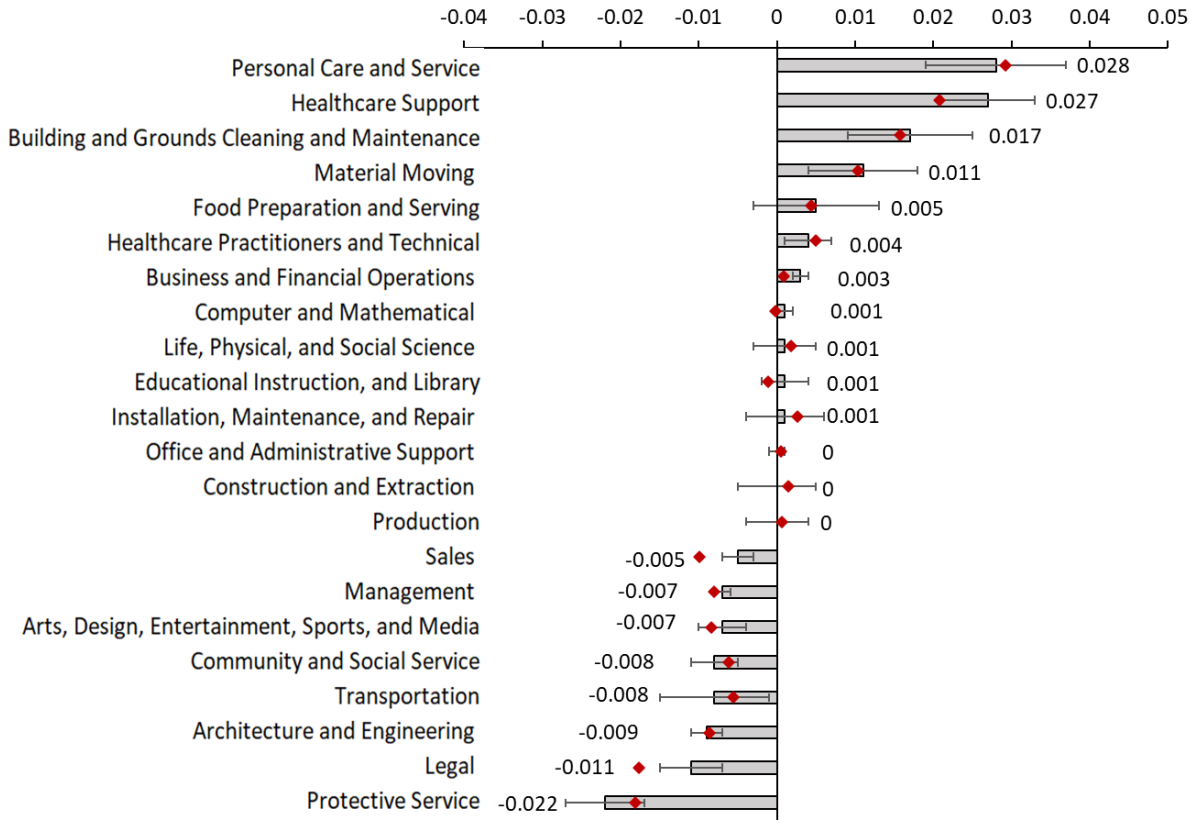
Fig. 8 Coefficients on remote worker from wage regressions by occupation and Oster betas, 2021



Source: American Community Survey

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.

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

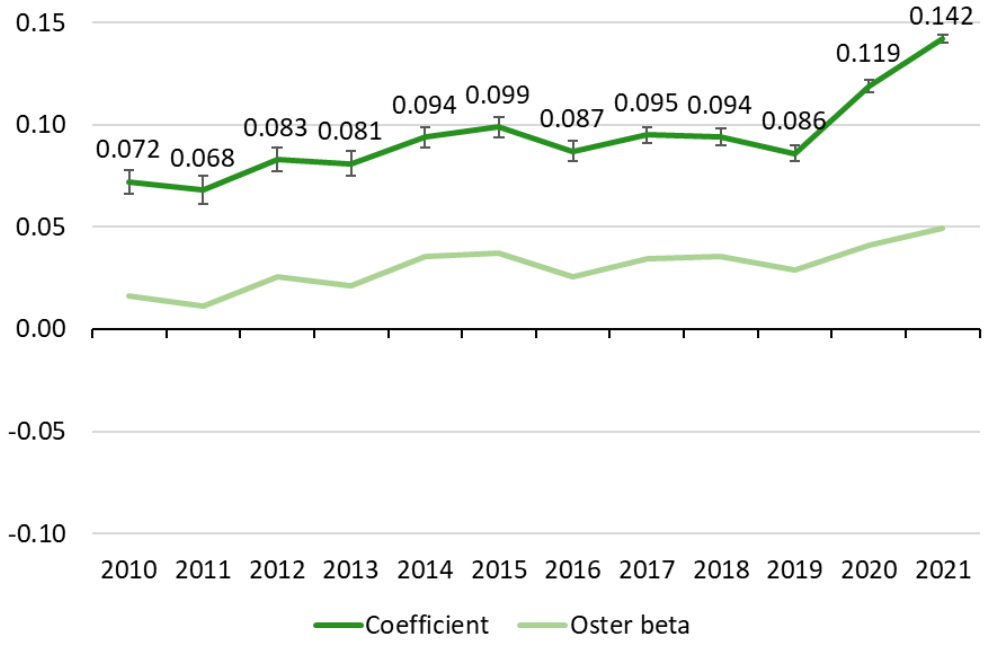


Source: American Community Survey

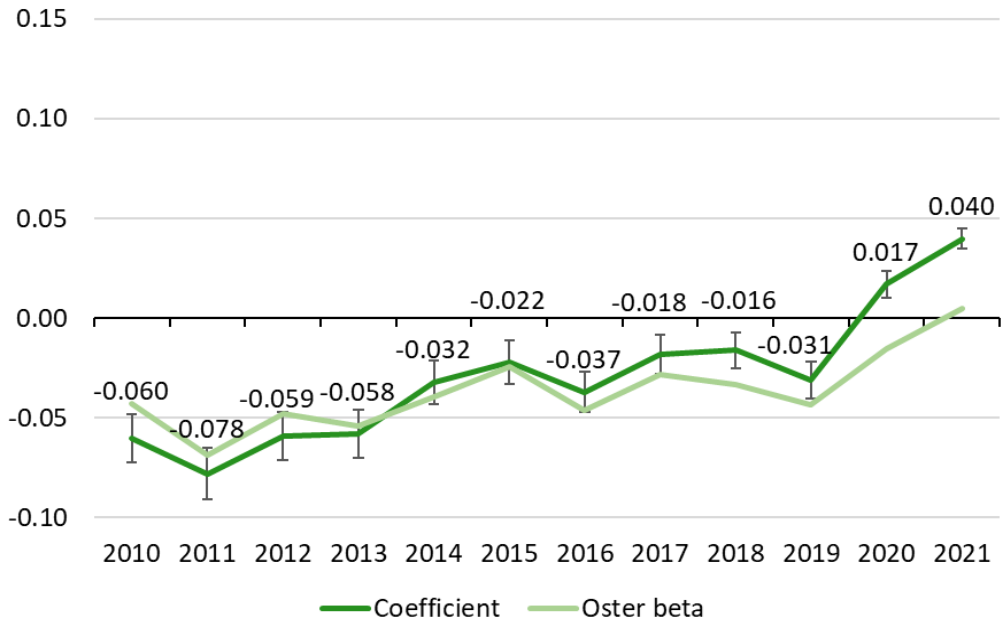
Notes: Estimates of equations 1 and 2. See Table 3 for the full list of controls. Diamonds represent Oster betas. Error bars represent 95% confidence intervals.

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

a. White-collar Occupations



b. Blue-collar Occupations

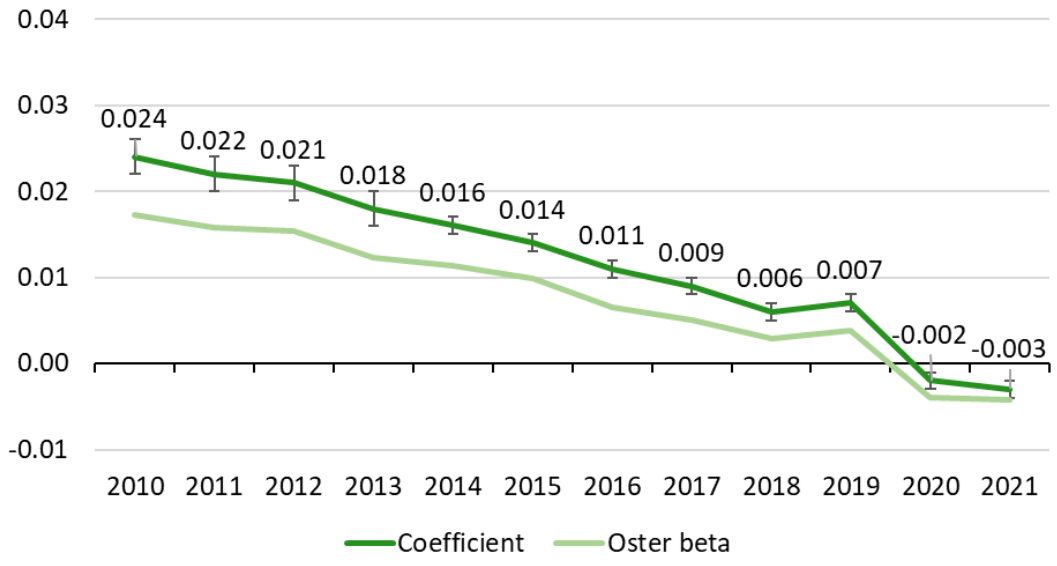


Source: American Community Survey

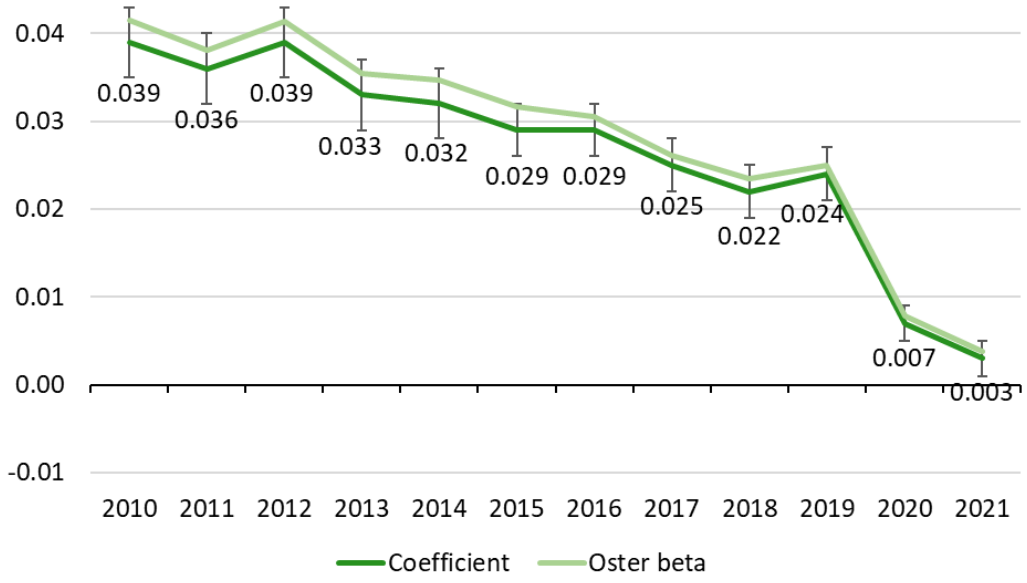
Notes: Estimates of equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

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

a. White-collar Occupations



b. Blue-collar Occupations

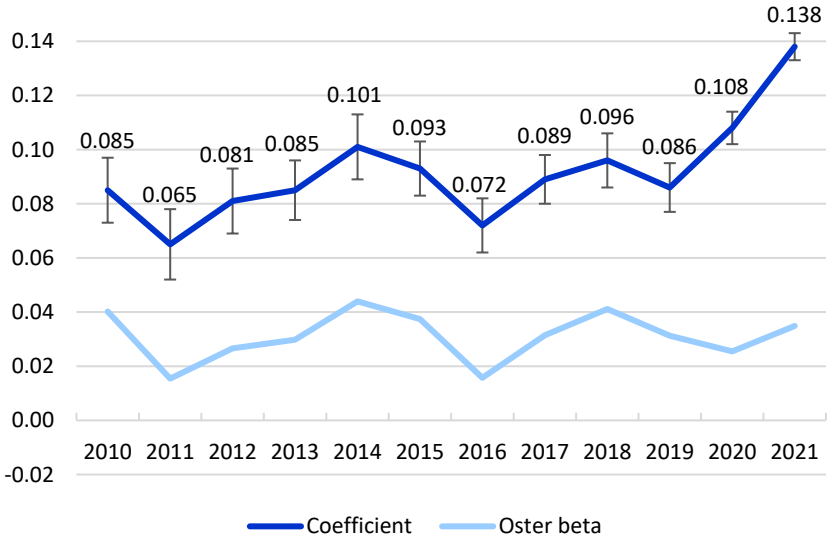


Source: American Community Survey

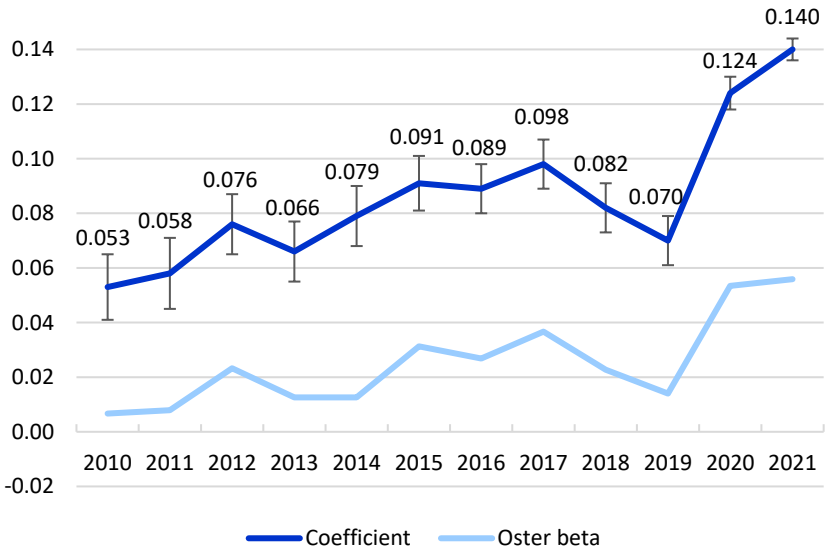
Notes: Estimates of equations 1 and 2. See Table 3 for the full list of controls. Error bars represent 95% confidence intervals.

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

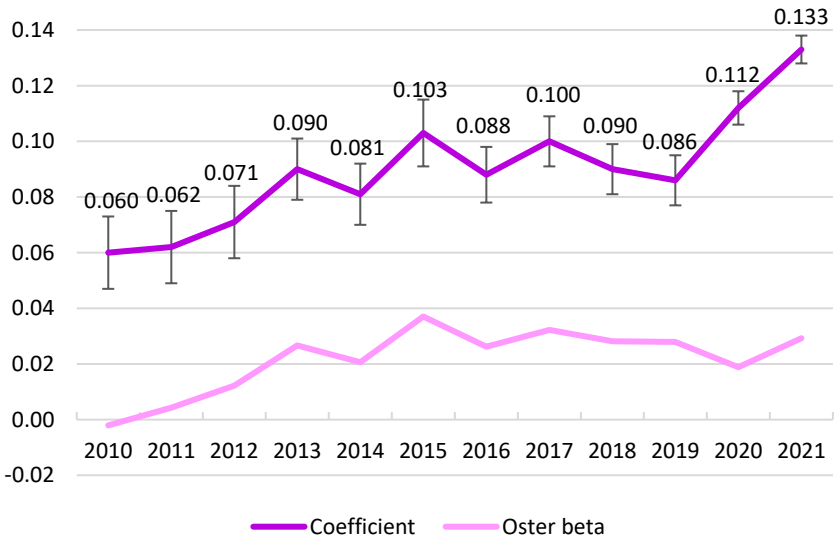
a. Fathers



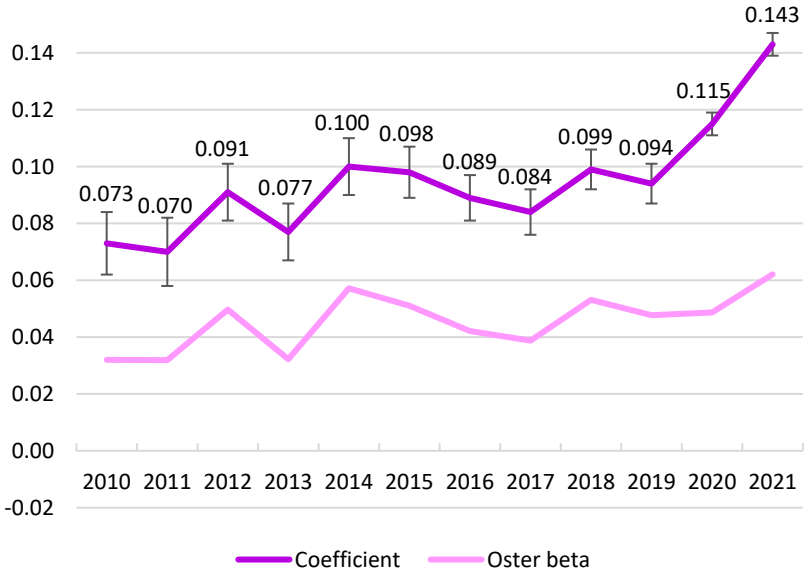
b. Men with no children



c. Mothers



d. Women with no children

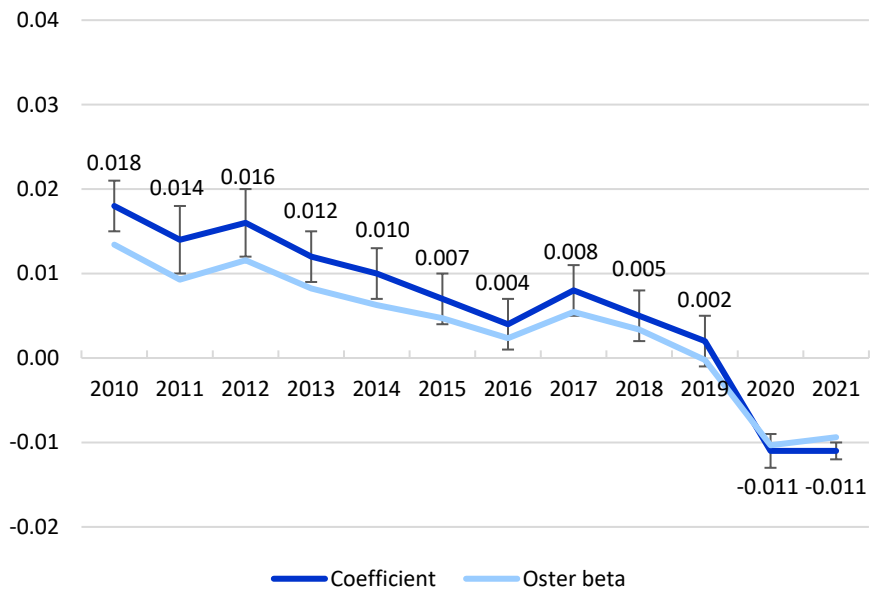


Source: American Community Survey

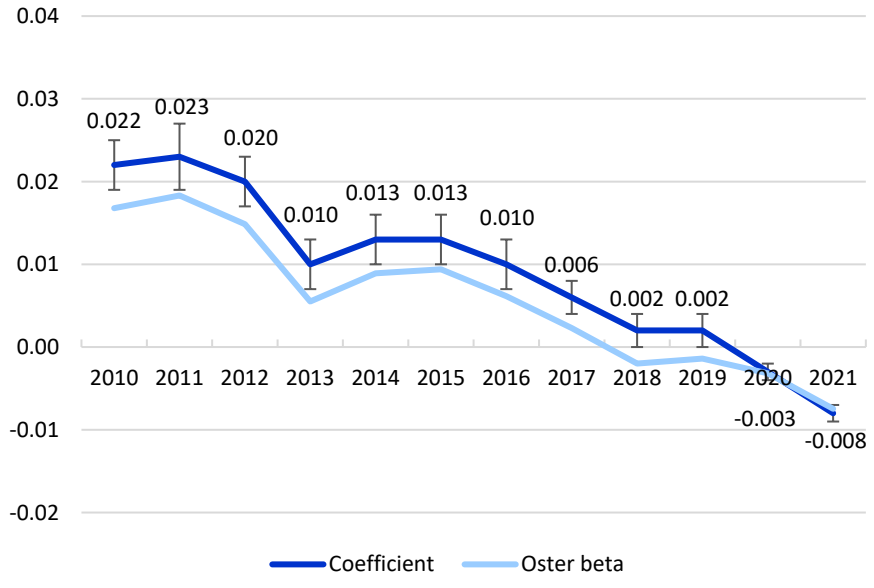
Notes: Estimates of equations 1 and 2. See Table 2 for the full list of controls. Error bars represent 95% confidence intervals.

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

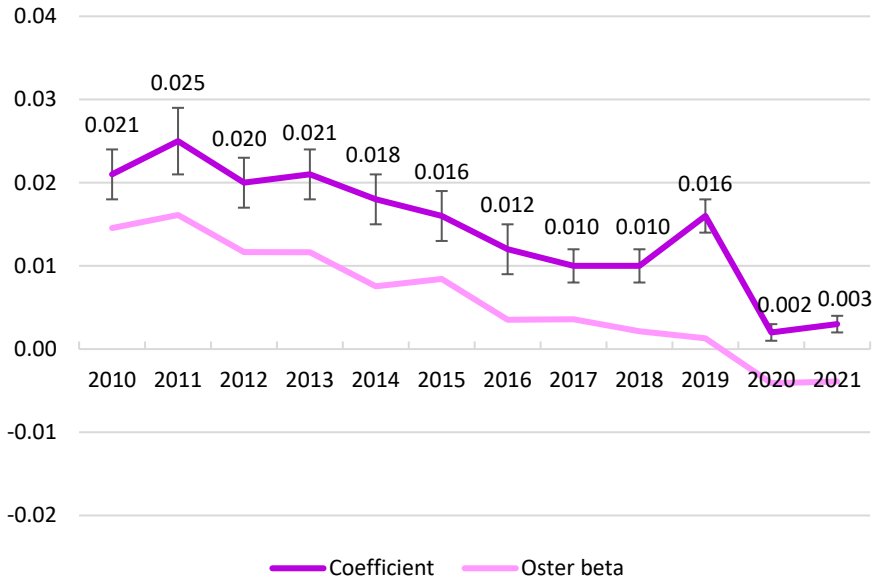
a. Fathers



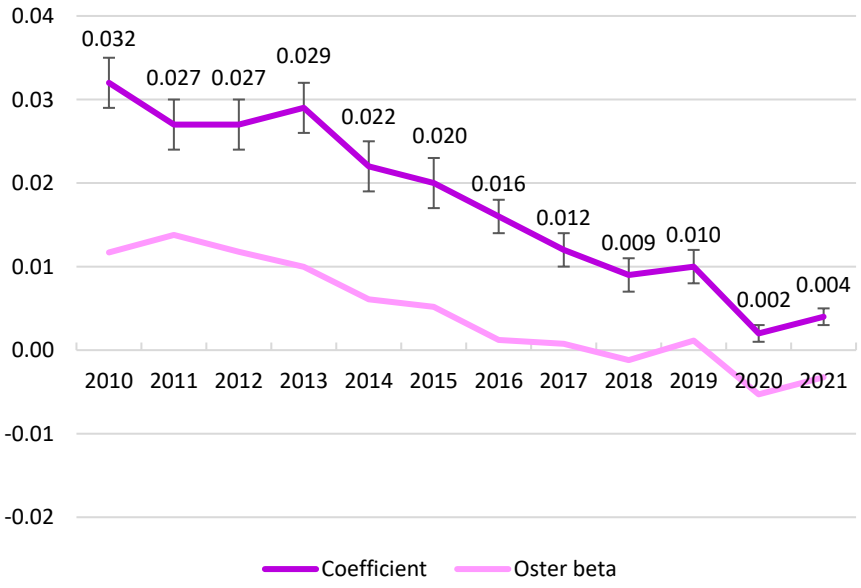
b. Men with no children



c. Mothers



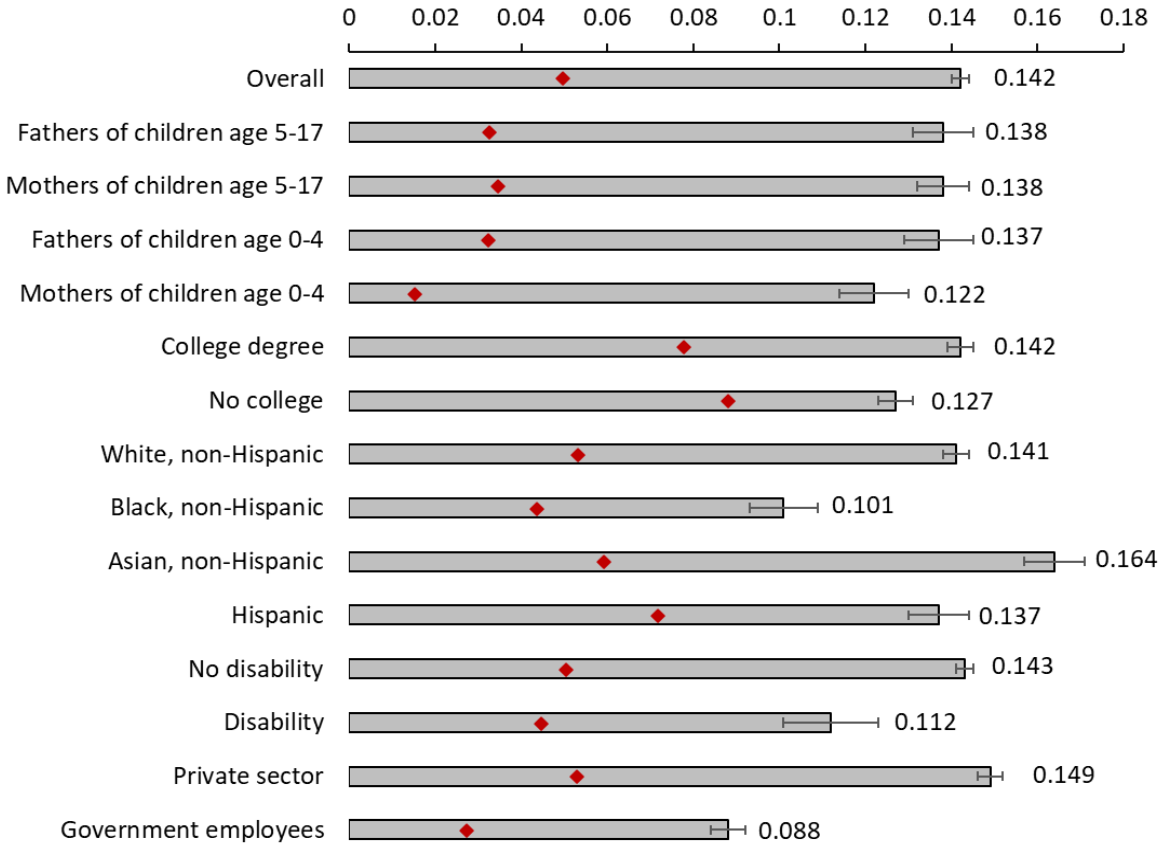
d. Women with no children



Source: American Community Survey

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

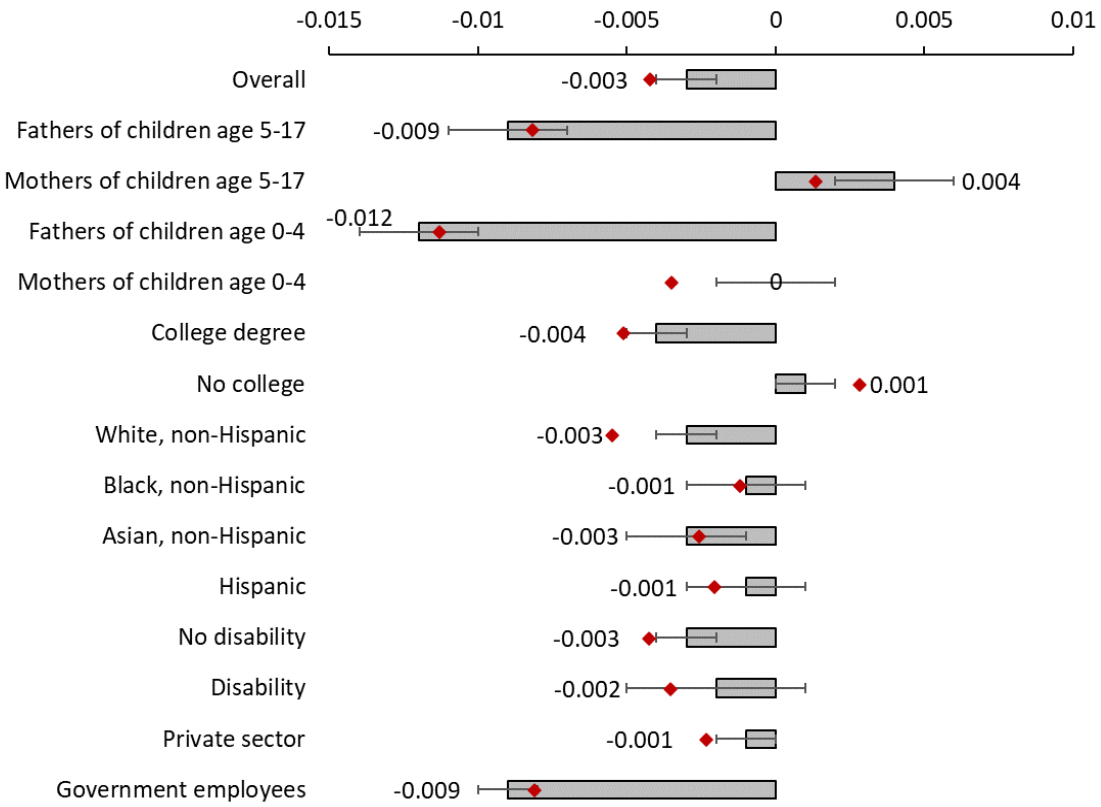
Fig. 14 Wage regression coefficient estimates on remote worker and Oster betas for subsamples of white-collar workers, 2021



Source: American Community Survey

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.

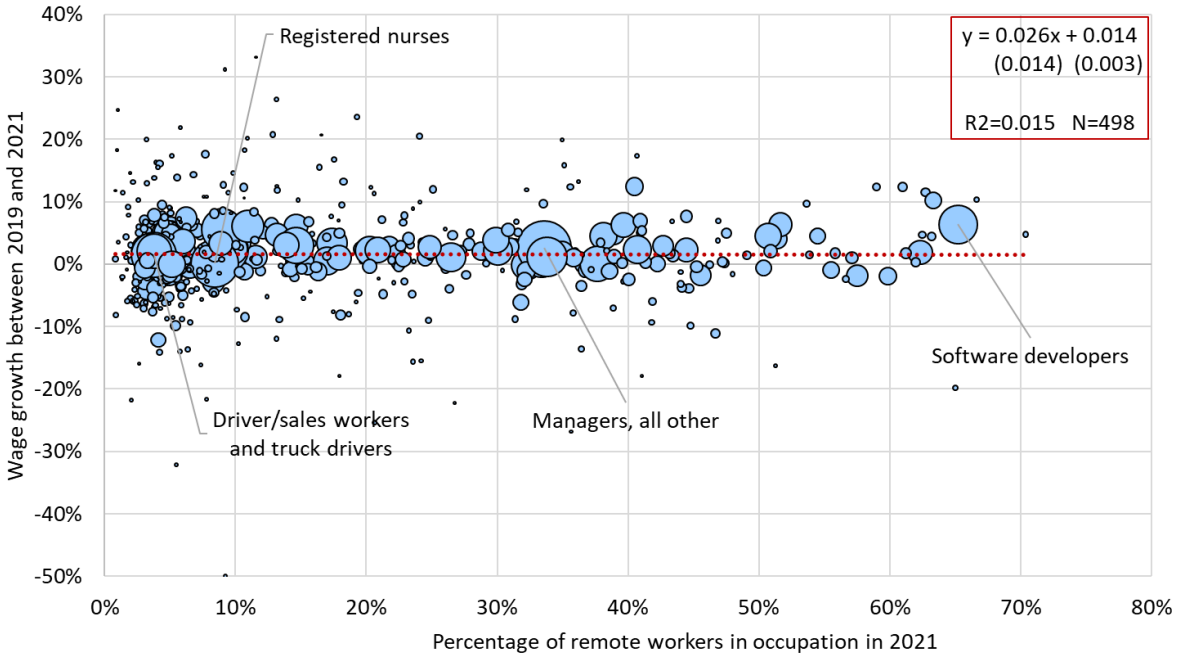
Fig. 15 Hours worked regression coefficient estimates on remote worker and Oster betas for subsamples of white-collar workers, 2021



Source: American Community Survey

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.

Fig. 16 The relationship between occupation-level real cumulative wage growth from 2019 to 2021 and remote work intensity in 2021



Source: American Community Survey

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.

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 $	30.091	39.716	30.932	42.349	29.831	46.287
	(24.416)	(31.657)	(27.981)	(35.29)	(26.458)	(38.318)
Usual weekly hours of work	43.435	45.675	43.497	44.434	43.408	43.471
	(7.398)	(8.905)	(7.476)	(7.988)	(7.543)	(6.97)
Real annual earnings in 2021 $	67429.73	92722.82	70665.93	98118.85	67718.21	105583.30
	(59932.6)	(77290.5)	(69199.4)	(85519.0)	(64473.1)	(93363.1)
Female	0.456	0.456	0.448	0.495	0.439	0.500
Age	43.204	44.980	42.967	44.671	43.350	42.815
	(10.648)	(9.98)	(11.16)	(10.586)	(11.171)	(10.758)
No high school degree	0.076	0.042	0.070	0.031	0.072	0.015
Some college	0.316	0.278	0.295	0.258	0.297	0.204
College degree	0.227	0.358	0.248	0.383	0.233	0.415
Graduate degree	0.133	0.171	0.153	0.205	0.150	0.281
Non-Hispanic black	0.114	0.068	0.123	0.088	0.118	0.095
Non-Hispanic Asian	0.056	0.055	0.068	0.065	0.059	0.108
Non-Hispanic other race	0.019	0.020	0.026	0.027	0.044	0.046
Hispanic	0.141	0.093	0.177	0.104	0.186	0.110
Married	0.592	0.661	0.551	0.638	0.558	0.612
Cohabiter	0.071	0.065	0.087	0.074	0.095	0.092
Number of own children age<5	0.174	0.184	0.166	0.176	0.162	0.179
	(0.471)	(0.491)	(0.461)	(0.476)	(0.458)	(0.474)
Number of own children age 5-17	0.617	0.655	0.593	0.636	0.611	0.573
	(1.022)	(1.051)	(1.02)	(1.02)	(1.039)	(0.970)
Number of other adults	0.483	0.350	0.560	0.384	0.563	0.366
	(1.084)	(0.901)	(1.159)	(0.948)	(1.163)	(0.911)
Disability	0.042	0.043	0.046	0.041	0.054	0.045
Partner/parent has a disability	0.067	0.060	0.074	0.065	0.082	0.060
Government employee	0.191	0.088	0.172	0.084	0.196	0.145
Lives in metropolitan area	0.795	0.846	0.827	0.881	0.805	0.925
Occupation						
Management	0.116	0.187	0.125	0.191	0.121	0.198
Business and Financial Operations	0.058	0.098	0.064	0.134	0.053	0.169
Computer and Mathematical	0.034	0.095	0.042	0.118	0.029	0.145
Architecture and Engineering	0.025	0.023	0.028	0.026	0.027	0.042
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	0.020	0.018	0.021	0.020
Legal	0.013	0.011	0.012	0.014	0.011	0.025
Educational Instruction and Library	0.060	0.032	0.060	0.033	0.069	0.043
Arts, Design, Entertainment, Sports, Media	0.014	0.023	0.015	0.027	0.012	0.030
Healthcare Practitioners and Technical	0.062	0.026	0.069	0.045	0.080	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	0.032	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

	2010 On-site	2010 Remote	2019 On-site	2019 Remote	2021 On-site	2021 Remote
Personal Care and Service	0.017	0.040	0.013	0.009	0.010	0.004
Sales	0.090	0.183	0.079	0.128	0.074	0.075
Office and Administrative Support	0.149	0.109	0.112	0.108	0.110	0.121
Construction and Extraction	0.045	0.015	0.053	0.019	0.055	0.009
Installation, Maintenance, and Repair	0.040	0.021	0.037	0.015	0.043	0.009
Production	0.072	0.022	0.069	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	0.008	0.004	0.008	0.004	0.007	0.003
Construction	0.052	0.026	0.068	0.035	0.073	0.023
Food and beverage manufacturing	0.016	0.011	0.016	0.008	0.017	0.007
Wholesale trade	0.034	0.061	0.030	0.041	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
Utilities	0.014	0.007	0.012	0.006	0.012	0.013
Information	0.025	0.056	0.020	0.043	0.015	0.051
Finance and insurance, and real estate and rental and leasing	0.078	0.133	0.073	0.168	0.060	0.173
Professional, scientific, and management, and administrative and waste management services	0.066	0.165	0.076	0.223	0.061	0.222
Educational services	0.096	0.045	0.095	0.050	0.106	0.075
Arts, entertainment, and recreation, and accommodation and food services	0.058	0.031	0.062	0.031	0.050	0.019
Other services, except public administration	0.036	0.049	0.034	0.033	0.034	0.026
Public administration	0.075	0.039	0.064	0.038	0.069	0.070
Health care	0.125	0.077	0.128	0.081	0.141	0.074
Manufacturing, other	0.123	0.123	0.117	0.086	0.119	0.093
Social assistance	0.019	0.025	0.018	0.018	0.019	0.015
Administrative and support and waste management services	0.033	0.046	0.036	0.045	0.035	0.032
Observations	756,207	17,097	831,633	36,618	651,203	166,316

Source: American Community Survey

Notes: Standard deviation in parentheses.

Table 2 Wage regression results (OLS estimates)

	2010		2019		2021	
	Men	Women	Men	Women	Men	Women
Remote	0.053***	0.039***	0.074***	0.066***	0.133***	0.126***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.003)	(0.003)
Age	0.051***	0.042***	0.043***	0.042***	0.042***	0.041***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age squared	-0.048***	-0.039***	-0.038***	-0.038***	-0.038***	-0.038***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No high school degree	-0.157***	-0.143***	-0.143***	-0.104***	-0.124***	-0.075***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.004)	(0.006)
Some college	0.095***	0.107***	0.072***	0.087***	0.071***	0.073***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
College degree	0.304***	0.342***	0.292***	0.330***	0.278***	0.310***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Graduate degree	0.497***	0.540***	0.505***	0.542***	0.466***	0.507***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Non-Hispanic black	-0.136***	-0.064***	-0.157***	-0.079***	-0.148***	-0.070***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)
Non-Hispanic Asian	-0.146***	-0.070***	-0.076***	-0.039***	-0.055***	-0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Non-Hispanic other race	-0.094***	-0.050***	-0.075***	-0.043***	-0.054***	-0.041***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)	(0.005)
Hispanic	-0.175***	-0.106***	-0.137***	-0.115***	-0.133***	-0.094***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married	0.119***	0.040***	0.140***	0.054***	0.137***	0.056***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Cohabiter	0.012**	0.013***	0.034***	0.013***	0.021***	0.022***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Number of own children age<5	0.012***	0.033***	0.017***	0.034***	0.016***	0.033***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)
Number of own children age 5-17	0.018***	-0.008***	0.014***	-0.003**	0.016***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of other adults	-0.017***	-0.019***	-0.023***	-0.020***	-0.020***	-0.016***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Disability	-0.088***	-0.081***	-0.092***	-0.079***	-0.076***	-0.088***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Partner/parent has a disability	-0.079***	-0.047***	-0.087***	-0.054***	-0.077***	-0.045***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Government employee	0.038***	0.084***	0.002	0.051***	-0.004	0.053***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Lives in metropolitan area	0.096***	0.123***	0.085***	0.123***	0.078***	0.099***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	416,981	356,323	473,285	394,966	442,736	374,783
R-squared	0.426	0.436	0.429	0.441	0.426	0.428

Source: American Community Survey

Notes: ACS survey weights used. Regressions also include occupation, industry, and state fixed effects. Robust standard error in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Table 3 Hours worked regression results (OLS estimates)

	2010		2019		2021	
	Men	Women	Men	Women	Men	Women
Remote	0.023***	0.034***	0.006***	0.017***	-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**	0.001	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***	0.007***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
College degree	0.024***	0.029***	0.014***	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***	0.049***	0.031***	0.043***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-Hispanic black	-0.027***	-0.010***	-0.028***	-0.011***	-0.024***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-Hispanic Asian	-0.030***	-0.003*	-0.032***	-0.008***	-0.030***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Non-Hispanic other race	-0.005	0.010***	-0.007**	0.007**	0.003	0.005***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Hispanic	-0.023***	-0.010***	-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	0.005***	-0.002	0.009***	-0.002*	0.005***	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of own children age<5	0.000	-0.009***	0.001	-0.009***	-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	-0.003***	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*	0.007***	0.005**	0.006***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Partner/parent has a disability	-0.001	0.004***	-0.002	0.002*	-0.000	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Government employee	-0.041***	-0.009***	-0.029***	-0.005***	-0.029***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lives in metropolitan area	-0.002*	0.005***	-0.003**	0.003***	-0.004***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	416,981	356,323	473,285	394,966	442,736	374,783
R-squared	0.097	0.075	0.072	0.057	0.062	0.046

Source: American Community Survey

Notes: ACS Survey weights used. Regressions also include occupation, industry, and state fixed effects. Robust standard error in parentheses. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

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	0.053***	0.051***	0.071***	0.061***	0.086***	0.088***	0.071***	0.085***	0.084***	0.074***	0.109***	0.133***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.003)
Female	-0.008	-0.091*	-0.070*	-0.118**	-0.098**	-0.101**	-0.134***	-0.065	-0.166***	-0.152***	-0.214***	-0.236***
	(0.033)	(0.038)	(0.035)	(0.036)	(0.035)	(0.034)	(0.035)	(0.034)	(0.035)	(0.037)	(0.044)	(0.037)
Remote × Female	-0.014	-0.017	-0.017	-0.006	-0.023*	-0.017	-0.007	-0.015	-0.009	-0.008	-0.004	-0.007
	(0.011)	(0.012)	(0.011)	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.005)	(0.004)
Observations	773,304	755,973	770,758	791,766	796,917	813,257	823,307	844,977	857,772	868,251	661,958	817,519
R-squared	0.444	0.445	0.447	0.444	0.446	0.448	0.448	0.447	0.445	0.445	0.443	0.438
Panel B: Log real annual income												
Remote	0.076***	0.071***	0.091***	0.073***	0.100***	0.102***	0.081***	0.095***	0.089***	0.080***	0.104***	0.125***
	(0.008)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.003)
Female	-0.157***	-0.229***	-0.229***	-0.282***	-0.270***	-0.255***	-0.270***	-0.220***	-0.310***	-0.297***	-0.393***	-0.376***
	(0.034)	(0.039)	(0.036)	(0.037)	(0.035)	(0.034)	(0.036)	(0.035)	(0.035)	(0.038)	(0.045)	(0.037)
Remote × Female	-0.004	-0.004	-0.005	0.015	-0.009	-0.008	0.006	-0.007	0.001	0.003	0.005	0.005
	(0.011)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.005)	(0.004)
Observations	773,304	755,973	770,758	791,766	796,917	813,257	823,307	844,977	857,772	868,251	661,958	817,519
R-squared	0.472	0.472	0.472	0.468	0.469	0.470	0.469	0.466	0.463	0.462	0.457	0.451
Panel C: Log hours worked												
Remote	0.023***	0.020***	0.020***	0.012***	0.013***	0.014***	0.009***	0.009***	0.005**	0.006***	-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	-0.149***	-0.137***	-0.159***	-0.165***	-0.171***	-0.154***	-0.136***	-0.154***	-0.143***	-0.145***	-0.178***	-0.140***
	(0.010)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.011)
Remote × Female	0.010***	0.013***	0.012***	0.021***	0.014***	0.010***	0.013***	0.007**	0.010***	0.012***	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	773,304	755,973	770,758	791,766	796,917	813,257	823,307	844,977	857,772	868,251	661,958	817,519
R-squared	0.118	0.120	0.117	0.116	0.113	0.109	0.100	0.097	0.096	0.090	0.083	0.074

Notes: ACS Survey weights used. Robust standard errors 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	0.0188	0.1560
Part due to changes in the composition of wage and salary employment across occupations	0.0004	0.0057
Part due to changes in remote employment shares within occupations	0.0184	0.1503
Panel B.		
Total change in mean log wage gap between remote and onsite workers	0.0643	0.1320
Part due to changes in the mean observed skill gap between remote workers and onsite workers	0.0274	0.0884
Part due to changes in the returns to observed skills, given the mean gap in observed skills	0.0141	-0.0208
Part due to changes in the composition of remote employment across occupations	-0.0028	0.0014
Part due to changes in remote wage premia within occupations	0.0255	0.0630

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

Source: American Community Survey

Table 6 Occupation-level real wage growth between 2019 and 2021 for remote versus on-site workers (OLS estimates)

	Log Mean Wage	Log Mean Wage
	(1)	(2)
Remote	0.127***	0.008
	(0.023)	(0.015)
Year 2021	-0.013***	-0.001
	(0.004)	(0.005)
Remote × Year 2021	0.050***	0.035**
	(0.017)	(0.015)
Controls	No	Yes
Observations	1180	1180
R-squared	0.990	0.996
Joint hypothesis test:		
Remote + Remote × Year 2021	0.177***	0.043***
	(0.014)	(0.011)

Note: The dependent variable is the natural logarithm of the mean wage at the occupation level. Controls include average share of workers who are female, black, Asian, other race, Hispanic, have no high school diploma, high school graduates, graduate degree, married, cohabiting, have a disability, live with a parent or spouse who has a disability, government employees, live in a metropolitan location, in industry groups as well as mean age, number of children under age 5, number of children age 5–17, number of other adults. Regressions are weighted by occupation size. Occupations with fewer than 10 observations in each year-occupation-remote cell are excluded. Robust standard errors in parentheses are clustered at the occupation level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Source: American Community Survey