The Effect of Remote Work on Wage Dispersion: The Repercussions of the Pandemic on Job Industries

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Abstract

Since the pandemic, the United States has experienced a rise in the proportion of the labor force working from home, often called remote work or telework. Using the American Community Survey data from IPUMS, the aim is to examine the effect of a rise in remote work on wages among the American occupation industries. From 2018 to 2021, remote workers, on average, earned higher wages than onsite workers. However, from 2021 to 2022, changes in income for remote workers were ambiguous and industry-dependent. Yearly cross-sectional analyses and comparisons will be used to determine the initial impact of remote work on wages and will be both inclusive of and filtered by job industry. This allows for the control and examination of industrial characteristics that impact an individual's income.

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1 Introduction

Before the pandemic, working from home was a rare feat, as there was no reason for companies to offer that option for workers. However, following the COVID-19 pandemic, remote work, or telework, increased across all industries, but especially in technology-intensive sectors where jobs could be performed from the comfort of an individual's home. All job sectors experienced an increase in the percentage of workers participating in telework, with industries like information, finance, and professional and scientific services experiencing the greatest percent change. During the start of the post-pandemic period, individuals had less choice in choosing to telework as onsite work was strongly discouraged. From 2021 to 2022, the preference to work remotely becomes an option, exploiting the income premium that remote workers earn compared to onsite workers. I aim to show that first, individuals do indeed earn wage premia if they decide to work remotely, at least in technology-intensive industries, and second, that income premia varies across industries and is dependent on industrial characteristics.

2 Literature Review

In "The Evolution of Work from Home," Barrero, et al. first examine the transition of work-from-home (WFH) arrangements, particularly how variations in demographic and occupational factors affect both labor costs such as wages and productivity of workers. Depending on the industry of work, WFH arrangements allowed for flexibility of wages which in turn yielded a wage growth effect of about two percent since the pandemic. The ability to work remotely is limited by job design, company practices, employee requirements, and lifestyles. Online customer support, for example, can easily be done remotely, as tasks and online platforms can be completed and accessed in a non-office setting. These industry-specific trends exploit the divide between industry types in the decision and ability to work remotely. Barrero, et al. also found a positive correlation between population density and the percentage of workdays spent remotely, suggesting that the decision to telework not only varies by occupation but also systematically with local population density. Individuals working in cities like Brooklyn and Los Angeles worked more days remotely than individuals in cities like Enid, OK. Next, the demographic characteristics: age, education, and the number of household members all play key roles in an individual's decision to work onsite or remotely. They find that as educational attainment increases, remote work intensity increases. Individuals studied in the paper with only a high school diploma took 20% of paid workdays from home, while those with a four-year college degree took 34%. This aligns with the pattern that highly educated individuals work in technology-intensive sectors, which experience higher percentages of remote workers. They next find the level of remote workers peaks for individuals in their 30s, while lowest for those in their early 20s. This occurs due to the returns to networking, which is mainly participated in earlier in one's career. Lastly, those with children place enormous value on the ability to work remotely, demonstrating a greater willingness to pay for that option. Finally, productivity effects are discussed, with a focus on how allowing for remote work affects company output. It is observed that firms that strictly employ fully remote roles experience lower output levels than fully onsite firms. However, firms still opt for this decision since it reduces costs, which can offset the welfare losses of employing only remote roles.

In "Remote Work, Wages, and Hours Worked in the United States," Pabilonia and Vernon investigate how remote work affects wages and working hours. First, they discuss the wage premium for remote workers, where those who work from home earned 13.4% more than onsite workers in 2021. This average premium varied by industry, where technology-intensive occupations had much greater premia than labor-intensive sectors. The dispersion of wage premia suggests that occupations in which individuals have tasks that do not require onsite presence and rather could be completed in an autonomous environment benefited from the ability to telework. On the other hand, the labor-intensive industries, with the addition of the healthcare industry, where physical presence is required, received a wage penalty. Next, the authors compare the number of hours worked by both remote and onsite workers, before and after the pandemic. They found that before the pandemic, remote workers recorded longer work hours per workday than those working in person. However, by 2021, hours worked converged between those who worked remotely and those who worked onsite. According to Pabilonia and Vernon, this convergence was a result of the normalization of remote work after the pandemic. Following the pandemic, as work-life balance improved, adaptations by employers likely sparked the equalization of work hours for all employees. Finally, wage growth within and across occupations is analyzed, where within industries, remote workers received 13.2 percent higher wages than onsite workers in 2019, which grew to 17.4 in 2021. Across occupations, they find that changes in the proportion of remote workers within an industry do not completely explain the wage growth gap between remote and onsite workers. Specifically, a one percentage point increase in remote workers within a particular industry leads to a 0.02 percentage point increase in that occupation's wage growth. Furthermore, from 2019 to 2021, the percentage of remote workers increased by 15.4 points but only increased occupation-level wage growth by 0.4 points. In that same period, real wages grew by two percent across all industries.

In "The Shift to Remote Work Lessens Wage-Growth Pressures," Barrero, et al. discuss the impact of post-pandemic working conditions on wage-setting behaviors by firms, specifically that remote work is seen as an "amenity," therefore impacting wage growth and labor market dynamics. Higher-paying jobs in technology-intensive sectors experience larger shares of remote work benefits, which moderates wage growth, while in lower-wage industries, wage growth is correlated with the risks associated with the type of work. Barrero, et al. analyze 2022 data collected from the Survey of Business Uncertainty.[2] They analyze data from two questions: "Over the past 12 months, has your firm expanded the opportunities to work from home as a way to keep employees happy and to moderate wage-growth pressures?" and "Over the next 12 months, will your firm let employees work from home at least one day per week to restrain wage-growth pressures?" 38 percent of firms expanded remote work opportunities and 41 percent would in the following year. Of these firms that have or expect to offer telework, surveyors measure the level of firm restraint on wage-growth pressure, or how much firms moderate wage-growth. In total, the data displays a two percentage point increase in wage-growth moderation over two years. Furthermore, these "amenity-value shocks" are industry-type dependent, where jobs that involve face-to-face contact with consumers experience negative effects from the pandemic. Additionally, the authors find that these jobs that require physical proximity also offer relatively low pay compared to jobs that can be done remotely. Therefore, industry-dependent amenity value shocks disproportionately affect lower-wage jobs during and after the pandemic. These findings imply that the rise of remote work lessens the wage-growth pressure that firms face, highlighting the value of offering remote work to employees as a firm.

3 Data

My analysis is based on ACS data from IPUMS collected between 2018 and 2022. The American Community Survey (ACS) data is typically collected via household surveys where

[2] Survey data collected in 2022 from the Federal Bank Reserve of Atlanta, Stanford University, and the University of Chicago Booth School of Business

households have a 1-in-480 chance of being selected in a month. Out of 140 million eligible households, data is only collected from approximately 295,000 addresses.[3]

In the models and main analysis, 2020 is omitted for a couple of reasons. First, it highlights the pandemic's impact, separating pre- and post-pandemic to 2018-2019, and 2021-2022, respectively. Secondly, the pandemic disrupted the Bureau's data collection, forcing data from 2020 to be collected as estimates.[4] For my regressions, I place restrictions on age, place of work, hours worked in the previous year, and hours worked per week. Age was restricted to 25 to 45, encompassing the millennial generation, which includes those in the labor force a few years after the typical college graduation age and those who have been in the workforce for a couple of decades. Next, the individual's place of work was limited to the United States, as there are rare occasions of U.S. residents working in other countries. Finally, to ensure the analysis captures those actively participating full-time in the labor force, both hours worked in the previous year and hours worked per week are filtered such that individuals worked at least 48 hours in the last year and at least 40 hours per week.

To highlight the impact of telework between industry types, industries are selected for analysis based on the percent change in remote workers from pre- to post-pandemic, from 2019 to 2021.[5] In Figure 1, the pandemic seriously affected the percentage of remote workers in only four of the 14 major industries: professional, scientific, and technical services; information; finance, insurance, and real estate; and public administration. These four industries experienced at least a ten percentage point increase in remote workers from 2019 to 2021. Furthermore,

[3] Information collected from the American Community Survey Information Guide, provided by the United States Census Bureau: https://www.census.gov/content/dam/Census/programs-surveys/acs/about/ACS_Information_Guide.pdf

[4] Consistent with Pabelonia, et al (2023) and according to the Census Bureau, these estimates from 2020 produced an overrepresentation of the population that received both higher education and higher incomes, and also those who live in single-family households.

[5] See Figure 1 in Appendix 8.1

finance, insurance, and real estate; professional, scientific, and technical services; agriculture; and construction were selected for analysis, each experiencing a 22.6, 19, 2.3, and 3.1 percentage point increase from 2019 to 2021, respectively. The first two, which will be simply referred to throughout the paper as finance and professional services, experienced enormous increases in remote work post-pandemic compared to agriculture and construction, which are commonly considered labor-intensive industries. Finance and professional services were chosen simply due to their appeal as professions to economics students. Agriculture and construction were chosen as the two main industries that require manual labor.

The main explanatory variable is whether an individual worked from home in the previous workday or workweek. In the ACS data, this is accounted for in the variable TRANWORK.[6] Respondents to the survey have the option of selecting "worked at home" if they decided to telework for that workday or workweek, and will be classified as a remote worker in this analysis. Furthermore, if an individual responded "worked at home" for at least one day in the previous workweek, they are considered a remote worker. All other categories within TRANWORK are considered in-person or onsite workers. Other explanatory variables used include basic demographic characteristics, such as the individual's age, sex[7], educational attainment, number of children, and if the individual has a partner[8]. Furthermore, consistent with Pabilonia, et al. (2023), access to high-speed internet, HSINT[9], which measures whether the individual is subscribed to the internet using broadband (high speed) internet service such as

[6] Formally titled: "means of transportation to work"
[7] An individual's sex is coded for 1 being male and 0 being female
[8] Having a partner is a generated binary variable which indicates yes if the individual answered: "married, spouse present" and no for "married, spouse absent," "separated," "divoreced," "widowed," or "never married/single."
[9] HSINT was changed by the ACS in 2016 to better capture computer and internet usage, which enhances the strength of this variable as an instrument as internet access was and still is the most important resource in remote work.

cable, fiber optic, or DSL (digital subscriber line) service, is included as an instrument for the choice to work remotely in the Model (4). In Figure 5, the proportion of individuals who subscribe to high-speed internet is much greater in the technology-intensive sectors compared to the labor-intensive sectors. Finance and professional services both average above 90 percent of individuals subscribing to high-speed broadband services while 27 and 18 percent of those in agriculture and construction do not have access to high-speed internet.

The outcome variable examined in the models is the individual's total pre-tax annual income. In Figures 2 and 3, yearly trends in the average income are displayed for the four chosen industries for both remote and onsite workers. In the finance industry, only remote professional services experienced a steady increase in average income, while remote financial occupations experienced an increase from 2018 to 2021, but decreased in 2022. Both onsite average incomes increased from 2018 to 2019, significantly decreased in 2021, and rebounded in 2022. In the labor-intensive industries, both remote agriculture and remote construction experienced the same trend: a steady increase from 2018 to 2019 followed by a tremendous increase in 2021 only to decrease in the following year. Onsite average incomes for agriculture and construction workers followed a similar trend to onsite average incomes for finance and professional services, the difference being a milder increase and decrease in average incomes between 2019 and 2022. Income distribution is commonly right-skewed, as individuals making disproportionately large amounts of money make up only a small percentage of the population. So total income, INCTOT, is logged to normalize the distribution and make for better regression results.[10]

4 Models

When working with ACS data, there is a major caveat when analyzing through regressions. Having surveyed different households every year, data from different individuals

[10] See Figure 4 for histogram of logged income distribution

and a different number of individuals are collected, eliminating the use of panel data methods. In a perfect scenario, data from all individuals in the labor force is collected, allowing for the use of panel-level regressions. However, in this paper, only cross-section analysis methods are used. Additionally, for a more optimal sample size, only one subindustry is selected for each of the models, specifically: crop production, construction, financial investments, and scientific research and development.

To deduce the drivers of income dispersions among industries, I use several regression models: (1) linear OLS regressions for each year controlling for remote work and demographic characteristics, (2) OLS regressions for each year controlling for remote work and demographic characteristics, with the inclusion of interaction terms, and (3) an instrumental variable model where remote work is instrumented for by the individual's access to high-speed broadband internet. It is to be noted that the variables in all models will have subscripts i and t which denote the observation for individual i in year t, though the data is not panel. Person weights are accounted for in Models (1) and (3), and robust standard errors are used across all models.

4.1 Controlling for Remote Work and Demographics by Year

I start my analysis with a basic linear OLS regression of $remote_{i,t}$, a binary variable that indicates whether the individual teleworked, and a vector of demographic variables, on the log of total income. This model is calculated for each of the four years as follows:

$$linctot_{i,t} = \alpha + \beta remote_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \tag{1}$$

where α is a constant, β is the coefficient of interest that measures the average difference in income a remote worker earns over an onsite worker, $\epsilon_{i,t}$ the error term, and γ a vector of coefficients on $X_{i,t}$, the vector of demographic characteristics. The vector of demographics includes age, sex, educational attainment, number of children, and if the individual has a partner.

A positive coefficient on $remote_{i,t}$ indicates that on average, remote workers earn more than onsite workers, while a negative coefficient is the opposite.

4.2 Controlling for Remote Work and Demographics with Interaction Terms

Now, I include an interaction term between remote work and years as follows:

$$log(avginc)_t = \alpha + \beta_1 remote_t + \beta_2 year_t + \beta_3 (remote \times year)_t + \gamma X_t + \delta_t + \epsilon_t \quad (2)$$

In Model (2), $linctot_t$ is the log of average income in year t. The average income variable was calculated by collapsing the existing total income data by industry, remote status, and year. α is a constant, $remote_t$ is a binary variable that indicates a remote worker, X_t a vector that includes control variables age, sex, education, number of children, and whether the individual has a partner, δ_t accounts for industry fixed effects, and ϵ_t the error term. Since I am comparing effects on income on a year-to-year basis, the variable $year_t$ is a dummy indicator for the year that is being analyzed. For example, in a model for the year 2022, $year_t = 1$ if $year == 2022$. $remote \times year$ is the interaction term that captures the differential effect of remote work in the given year.

4.3 Instrumenting for Remote Work

Finally, I estimate the causal effect of the decision to telework by estimating a similar linear model to Model (1), now using $hsint$ as an instrument for $remote$ as follows:

$$linctot_{i,t} = \alpha + \beta remote_{i,t} + \gamma X_{i,t} + \epsilon_{i,t} \quad (3)$$

$$remote^*_{i,t} = \pi_0 + \pi_1 hsint_{i,t} + \pi_2 X_{i,t} + \nu_{i,t} \quad (4)$$

In the first stage regression, Model (4), the endogenous binary variable $remote^{*}_{i,t}$ is dependent on the instrument $hsint_{i,t}$ and the same vector of exogenous demographic controls, $X_{i,t}$. In the second stage regression, the identical regression as Model (1) is run. In this model, the choice of instrumental variable $hsint$ depends on its strength as an instrument, specifically that it must explain the choice to work remotely and not be correlated with the error $\epsilon_{i,t}$. Additionally, access to high-speed internet should only explain the individual's income through its relationship with the decision to work remotely.

5 Results

5.1 Remote Work and Demographics on Income

Agriculture Demographics Model

When accounting for demographic characteristics of individuals, the coefficient on remote is insignificant except for in 2018 at the 10 percent level, where remote workers earned 14.6 percent less income than onsite workers. This is consistent with agriculture being a labor- and physical-presence-dependent industry. Table 1 depicts results where coefficients from 2019 to 2022 are all positive and indicate less than 10 percent increases in incomes of those teleworking, while working remotely correlates to a 14.6 percent decrease in 2018. All demographic variables across all years are positive and are statistically significant at the one percent level with the exception of number of children. All constants are positive and statistically significant at the one percent level.

Construction Demographics Model

In the construction industry, controlling for demographic variables, remote work is statistically significant at the one percent level post-pandemic and insignificant prior to the pandemic and is positive in all years except 2019. That is, in 2019, remote workers actually earned 5.5 percent less income than onsite workers, which even though insignificant, aligns with the reliance on in-person work in labor-intensive industries like construction. In 2021 and 2022, remote workers earned 12.1 and 8.9 percent greater incomes than onsite workers. All demographic variables are positive and significant at the one percent level with the exception of number of children in 2019, 2021, and 2022. All constants are positive and statistically significant at the one percent level.

Finance Demographics Model

The model for the financial industry was by far the most economically significant so far. In this model, remote work was statistically significant at the five, one, and ten percent levels in 2019, 2021, and 2022, respectively. The coefficients on remote work were negative pre-pandemic and positive post-pandemic, highlighting the premium that remote workers earned following the pandemic and onsite workers earned before the pandemic. Constants and demographic variables continue to be positive and statistically significant at the one percent level except for the number of children in 2019, 2021, and 2022, which was significant at the ten and five percent levels in 2019 and 2022 and insignificant in 2021.

Professional Services Demographics Model

The professional services model displayed extremely high significance levels across all variables except the number of children. Coefficients on remote work were all positive and significant at the one percent level except in 2018 which was significant at the five percent level. The similarities in magnitude align with Model (1) where wage premia was already prevalent in research and development. Like the other models, the constants and demographic variables were all positive, and as mentioned, statistically significant at the one percent level except number of children, which is significant at the five percent level post-pandemic and insignificant in 2018 and 2019.

Comparison of Model (1) Results Across Industries

The results mostly align with economic theory and literature, that individuals earn an income premium in technology-intensive sectors when they decide to work remotely, whereas individuals in labor-intensive industries either earn less when they work remotely or do not experience significant changes.

5.2 Remote Work, Demographics, Interaction, and Industry-Level Effects on Income

2018 Interaction Model

In 2018, accounting for the current year and industry fixed effects, remote workers actually saw a decrease in incomes by 2.7 percent, though insignificant. The coefficient on the dummy indicator for year was significant at the one percent level and showed that in 2018, compared to other years, remote workers earned 11.9 percent less income, which is feasible considering 2018 was before the pandemic. Next, the interaction term $remote \times year_{2018}$ was insignificant and positive, indicating a differential income effect of 3.6% for remote workers in 2018. The three industry fixed effects displayed mixed results, where construction and financial industry fixed effects were both statistically significant at the one percent level and positive, indicating 28.5 and 40.2 percent greater incomes with reference to the agricultural sector as the reference industry. Strangely, scientific research and development experienced a 21 percent decrease in income relative to crop production, though this coefficient is insignificant.

2019 Interaction Model

In 2019, the coefficient on remote was again insignificant and negative, which again aligns with theory. The year dummy for 2019 was insignificant and signaled a 1.4 percent difference between remote and onsite workers where onsite workers earned a greater wage premium. The interaction term is statistically significant at the five percent level and shows a 10.9 percent increased income effect in remote workers in 2019 relative to other years. For industry fixed effects, the coefficient on construction was significant at the one percent level and indicates a 25.8 percent increase in income relative to agriculture. Additionally, the financial sector was insignificant while scientific research and development was significant at the ten percent level and displayed a negative gap of 43.7 percentage points compared to those in agriculture.

2021 Interaction Model

The first post-pandemic model exhibits lackluster results, where coefficients on remote work, year, and interaction term are insignificant. However, the coefficients on construction and financial fixed effects are significant at the one and five percent level, while the coefficient on scientific research and development is again insignificant.

2022 Interaction Model

The fourth and final model from Model (2) also has an insignificant coefficient on remote work and the interaction term, though the year dummy is significant at the one percent level and shows a positive 14.2 percent difference in incomes relative to other years. Additionally, income increases due to construction and financial fixed effects are statistically significant at the one percent level and are 35.1 and 47.5 percent, respectively, whereas the coefficient on scientific research and development fixed effects are negative and insignificant.

A Discussion of Results

Even though the coefficient on remote is statistically insignificant for all years, there is a steady increase in the magnitude, indicating the presence of wage premia for remote workers across all four subindustries. With the addition of industrial fixed effects, the construction sector has significant effects on an individual's wage with agriculture as the reference sector. The coefficients are large in magnitude and statistically significant at the one percent level every year, displaying the differences in remote income premia between labor-intensive industries. The financial sector shows similar effects in magnitude, though insignificant in 2019 and only significant at the five percent level in 2021. Professional services industry effects were negative, contradicting theory and literature, though were all insignificant aside from 2019, which was a pre-pandemic year anyways. Finally, post-pandemic coefficients on the year dummy and interaction term are disappointing from a statistics standpoint, as they fail to be significant except for the dummy for 2022. The sign on the year dummies is consistent with theory, however, where post-pandemic years have a positive impact on incomes while pre-pandemic years are the opposite. Furthermore, the interaction terms boast opposite signs for pre- and post-pandemic years, which aligns with the intuition that compared to their counterparts, remote workers in post-pandemic years earn higher incomes than in pre-pandemic years.

5.3 Access to High-Speed Internet as an Instrument for Remote Work on Income

Discussion of Instrumenting for Remote Work

For each year and industry, I analyze and compare the statistics and tests from the first stage regressions, specifically the F test of excluded instruments and its statistic and p-value. In Table 10, F statistics across all years are less than 10, indicating that in the agriculture sector, instrumenting for remote work with access to high-speed internet is not suitable. In Table 11, the F statistic in 2021 is greater than 10 and significant at the one percent level, indicating that for the construction industry in 2021, access to broadband internet is a strong instrument for choosing to work remotely. In all other years for construction, however, F statistics are far less than 10. In Table 12, the financial sector, both post-pandemic years support that broadband internet is a strong instrument for teleworking, boasting F statistics greater than 10 and significance at the one percent level. In the pre-pandemic years, F statistics are less than 10. Finally, in Table 13, only 2021 has an F statistic over 10 at the one percent level, with the other years indicating access to high-speed internet being a weak instrument. We observe these results for multiple reasons. First, pre-pandemic years shouldn't display any reason for internet access being a strong instrument for remote work as telework was yet to be popularized, which is consistent with Tables 17 to 20. Next, immediately following the pandemic in 2021, all but the agriculture industry experienced significance in access to broadband internet as a strong instrument for remote work. This was expected in the finance and professional services sector, and surprising in the construction industry. Lastly, in 2022, only the financial sector had a strong F statistic, contradicting expectations of technology-intensive industries maintaining a strong correlation between internet access and remote work. With these first-stage regression results, results from Model (4) in the agriculture, construction, and professional services sectors should be studied with caution.

Further Discussion of IV Model Results

In Tables 17 to 20, I observed that using access to high-speed internet was only a strong instrument for the construction, financial, and professional services industries in the year 2021. This has strong implications for understanding the regression results in Tables 13 to 16, and aligns with the statistical significance of the coefficient on remote work of one, ten, and one percent levels in the three respective industries. Additionally, remote work in the professional services industry is significant at the ten percent level in 2019 and 2022. With these results and the pursuit of instrumenting for remote work, the effect of remote work on incomes can only truly be studied in 2021 for three of the four analyzed industries.

6 Robustness Checks & Limitations

The main difficulty of this paper arose in the selection of industrial sectors and their respective subindustries. Only choosing four industries and subsequently four subindustries (occupations), produces a non-representative sample, among other errors. First, in the data collection process, ACS data as a whole is not completely representative of the American population. The selection of subindustry further worsens the problem as the focus might exclude outlier subindustries (such as investment banking and small financial cooperatives in the financial sector) which causes skewness of results. Thus, the sample chosen only reflects a subset of the wage dispersion, biasing the relationship between the choice to telework and income. The selection of variables also causes omitted variable bias, as there are many other variables not included in this analysis that impact an individual's income. Endogeneity is another source of omitted variable bias; for example, a high-skilled worker self-selects into a remote role, where remote work being endogenous means there is a correlated omitted variable that also influences both remote work and income. Furthermore, in the instrumental variable model, internet access is not the only determinant of the decision to work remotely. Secondly, there may be measurement error present in the data, as survey data often exhibits error due to misclassification of categorical variables or under- or over-reporting of continuous variables. Next, there is collinearity present in the models, such as between remote work and education, where higher levels of education may cause the option into remote work. Collinearity does not affect the bias of estimators but reduces the precision.

In Model (3), where I instrument for remote work using access to high-speed internet, there is a tradeoff between using OLS methods and an instrumental variable. The advantages of using OLS estimators include better efficiency, assuming OLS assumptions hold, and ease of interpretation of coefficients. Disadvantages include biasedness and inconsistency of estimators if endogeneity exists and omitted variable bias, both prevalent in my models. Assuming a strong instrument, using an instrumental variable model corrects for endogeneity, which provides a consistent estimator, and accounts for unobserved variables. However, the downside to an instrumental variable model is finding an instrument that actually accounts for unobserved phenomena, which if not a strong instrument, causes biased and inconsistent estimates. Furthermore, estimators in an instrumental variable model are less precise with higher standard errors due to less variation in the variable being instrumented.

As robustness checks and in line with Pabilonia, et al. (2023), robust standard errors are used across all regression models. Both the Breusch-Pagan and White's Test are used to measure heteroskedasticity in the models. Mixed results and repeated presence of heteroskedasticity impact the efficiency of estimators and hypothesis testing. Specifically, it is understood that remote work does not necessarily correlate to higher wages in labor-intensive industries, even post-pandemic. However, to uncover the same correlation in technology-intensive sectors, the ability to state positive correlation becomes challenging with the presence of heteroskedasticity.

7 Conclusions

Using data collected by the ACS through IPUMS, I examine the effects remote work had on individual incomes across labor-intensive and technology-intensive industries, specifically deducing the differences in incomes of remote and onsite workers across occupational sectors. On average, remote workers in the professional services industry experienced a constant increase in income while onsite workers in the professional services industry and all workers in the financial sector experienced ambiguous changes in income. In the labor-intensive industries, all remote workers experienced an increase in wages from 2018 to 2021, though declining in 2022, depicting the adjustment back to onsite work, with fully onsite workers experiencing a decline in incomes from 2019 to 2021. The decline from 2021 to 2022 can be attributed to the relaxation of limiting onsite work, where companies start to offer the option to work remotely, and where subsequently some individuals return back to in-person work.

When turning to the regression analyses, I decide to select subindustries to reduce sample size, which at times negatively affected results. In technology-intensive industries, remote workers earned income premia primarily in 2021, and ambiguous in 2022. As for those in labor-intensive sectors, wage premia was dependent on external factors not included in the model as results were not statistically significant. When accounting for industry-level fixed effects, I was able to highlight differences in incomes across industries, where there was high significance across and between industry types. Finally, to account for unobserved factors and consistent with Pabilonia, et. al (2023), access to high-speed internet was used as an instrument for remote work. However, due to its lack of strength in my model in years except 2021, this model yielded insignificant results. On a positive note, the choice of access to high-speed internet was fitting in 2021, which was optimal as it was the first post-pandemic year, and displayed a strong positive correlation between remote work and incomes across all sectors.

8 Appendix

8.1 Figures

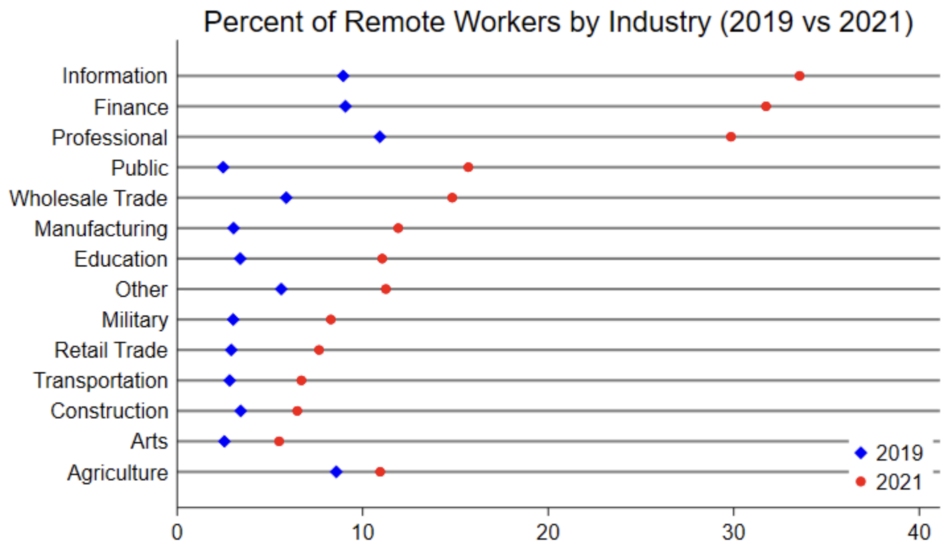

Figure 1: percent of remote workers by industry (2019 vs 2021)

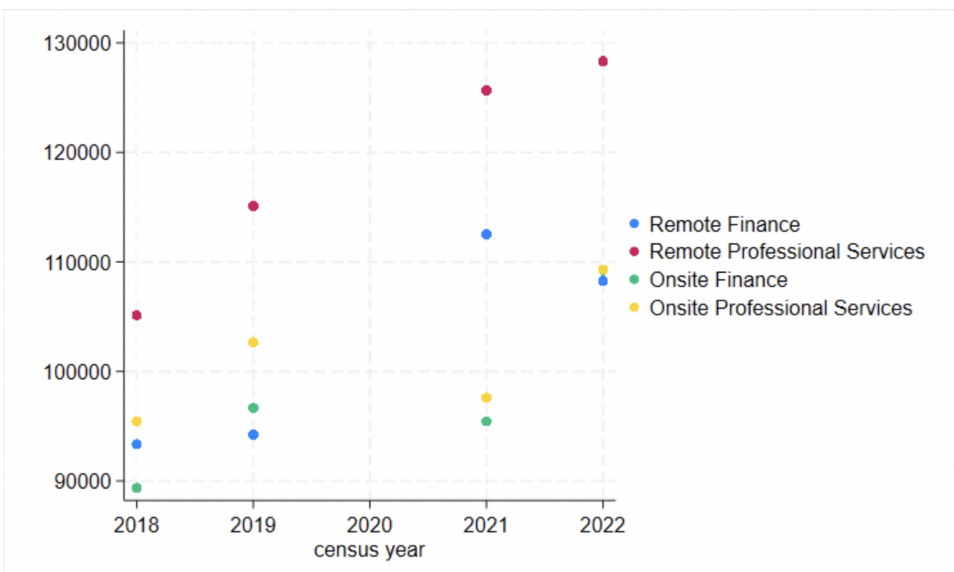

Figure 2: average income of remote and onsite workers in finance and professional services industries from 2018 to 2022, excluding 2020

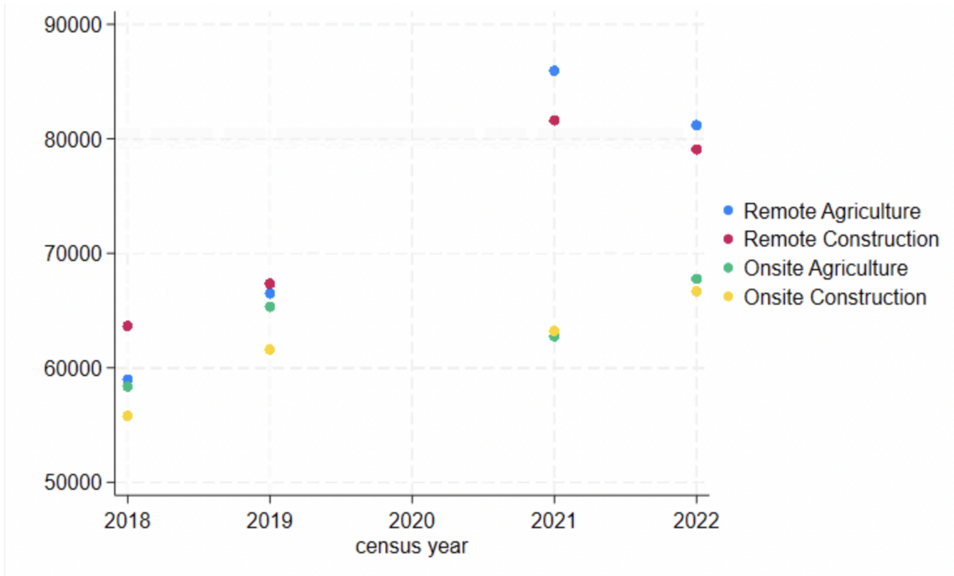

Figure 3: average income of remote and onsite workers in agriculture and construction industries from 2018 to 2022, excluding 2020

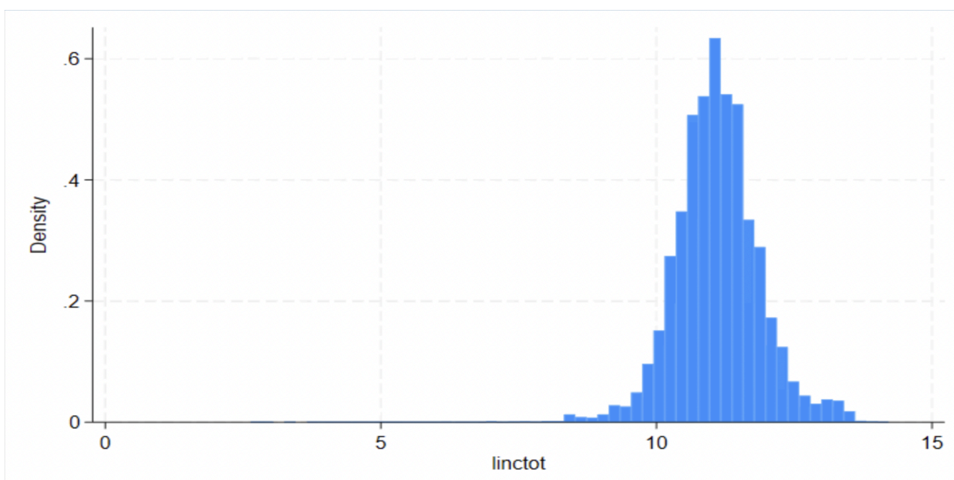

Figure 4: logged income distribution

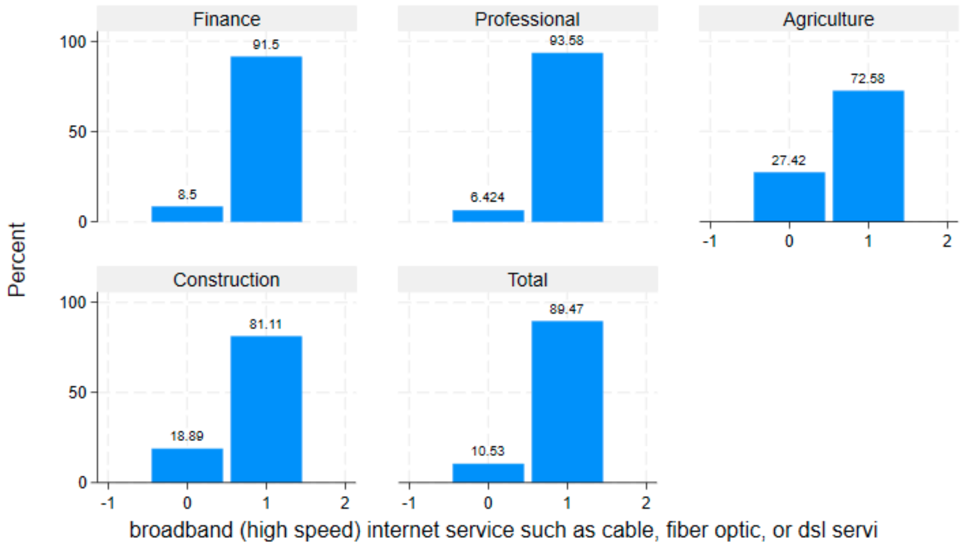

Figure 5: percentage of individuals that have access to high-speed internet, by industry group

8.2 Tables

	(1) m2_ag2018	(2) m2_ag2019	(3) m2_ag2021	(4) m2_ag2022
remote	-0.146^{*}	0.054	0.095	0.054
	(0.077)	(0.090)	(0.079)	(0.080)
age	0.013^{***}	0.017^{***}	0.013^{***}	0.009^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
sex	0.314^{***}	0.265^{***}	0.281^{***}	0.168^{***}
	(0.045)	(0.047)	(0.043)	(0.037)
educ	0.089^{***}	0.086^{***}	0.082^{***}	0.080^{***}
	(0.006)	(0.006)	(0.006)	(0.008)
nchild	0.011	0.002	0.008	0.011
	(0.013)	(0.016)	(0.012)	(0.011)
partner	0.276^{***}	0.125^{***}	0.155^{***}	0.154^{***}
	(0.038)	(0.043)	(0.034)	(0.035)
_cons	8.965^{***}	9.107^{***}	9.285^{***}	9.619^{***}
	(0.124)	(0.118)	(0.121)	(0.144)
r2	0.176	0.169	0.159	0.129
N	3127.000	2619.000	2859.000	3236.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1: Model (1) results for agriculture industry

	(1) m2_cn2018	(2) m2_cn2019	(3) m2_cn2021	(4) m2_cn2022
remote	0.060	-0.055	0.121***	0.089***
	(0.039)	(0.037)	(0.027)	(0.027)
age	0.016***	0.014***	0.015***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
sex	0.177***	0.172***	0.185***	0.188***
	(0.022)	(0.021)	(0.023)	(0.021)
educ	0.095***	0.093***	0.087***	0.086***
	(0.003)	(0.003)	(0.003)	(0.003)
nchild	0.019***	0.002	0.007	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)
partner	0.216***	0.187***	0.166***	0.182***
	(0.014)	(0.014)	(0.015)	(0.014)
_cons	9.204***	9.432***	9.462***	9.574***
	(0.050)	(0.051)	(0.050)	(0.047)
r2	0.147	0.148	0.139	0.139
N	1.7e+04	1.6e+04	1.5e+04	1.7e+04

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2: Model (1) results for construction industry

	(1) m2_fn2018	(2) m2_fn2019	(3) m2_fn2021	(4) m2_fn2022
remote	-0.068	-0.124**	0.051*	-0.105***
	(0.067)	(0.055)	(0.026)	(0.025)
age	0.025***	0.032***	0.028***	0.028***
	(0.003)	(0.003)	(0.003)	(0.003)
sex	0.386***	0.336***	0.288***	0.300***
	(0.032)	(0.027)	(0.027)	(0.025)
educ	0.177***	0.194***	0.163***	0.182***
	(0.010)	(0.011)	(0.011)	(0.010)
nchild	0.070***	0.028*	0.012	0.036**
	(0.015)	(0.017)	(0.013)	(0.015)
partner	0.209***	0.175***	0.213***	0.163***
	(0.035)	(0.029)	(0.031)	(0.030)
_cons	8.424***	8.193***	8.684***	8.599***
	(0.128)	(0.137)	(0.144)	(0.129)
r2	0.250	0.264	0.216	0.238
N	4948.000	5127.000	5286.000	5720.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3: Model (1) results for finance industry

	(1) m2_ps2018	(2) m2_ps2019	(3) m2_ps2021	(4) m2_ps2022
remote	0.113^{**}	0.132^{***}	0.190^{***}	0.169^{***}
	(0.045)	(0.033)	(0.022)	(0.022)
age	0.038^{***}	0.036^{***}	0.031^{***}	0.027^{***}
	(0.003)	(0.002)	(0.002)	(0.002)
sex	0.113^{***}	0.164^{***}	0.175^{***}	0.119^{***}
	(0.025)	(0.022)	(0.021)	(0.022)
educ	0.115^{***}	0.124^{***}	0.100^{***}	0.121^{***}
	(0.010)	(0.009)	(0.009)	(0.012)
nchild	0.018	-0.006	0.025^{**}	0.030^{**}
	(0.014)	(0.012)	(0.012)	(0.012)
partner	0.183^{***}	0.149^{***}	0.093^{***}	0.104^{***}
	(0.030)	(0.026)	(0.024)	(0.024)
_cons	8.515^{***}	8.618^{***}	9.030^{***}	9.025^{***}
	(0.123)	(0.114)	(0.105)	(0.157)
r2	0.262	0.278	0.248	0.221
N	3103.000	3208.000	3686.000	3999.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 4: Model (1) results for professional industry

	(1) int_2018
remote	-0.027
	(0.053)
year_2018	-0.119^{***}
	(0.026)
remote_year_2018	0.036
	(0.038)
age	-0.052
	(0.042)
sex	-0.860^{**}
	(0.315)
educ	0.228^{***}
	(0.040)
nchild	0.300^{*}
	(0.164)
partner	-0.046
	(0.463)
170.ind	0.000
	(.)
770.ind	0.285^{***}
	(0.049)
6970.ind	0.402^{***}
	(0.105)
7460.ind	-0.210
	(0.141)
_cons	11.506^{***}
	(1.265)
r2	0.989
N	32.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

	(1) int_2019
remote	-0.026
	(0.068)
year_2019	-0.014
	(0.035)
remote_year_2019	0.109^{**}
	(0.049)
age	-0.063
	(0.053)
sex	-1.010^{**}
	(0.465)
educ	0.249^{***}
	(0.059)
nchild	0.149
	(0.247)
partner	-0.336
	(0.567)
170.ind	0.000
	(.)
770.ind	0.258^{***}
	(0.060)
6970.ind	0.253
	(0.170)
7460.ind	-0.437^{*}
	(0.215)
_cons	12.268^{***}
	(1.893)
r2	0.980
N	32.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

	(1) int_2021
remote	-0.008
	(0.089)
year_2021	0.025
	(0.035)
remote_year_2021	-0.022
	(0.064)
age	-0.061
	(0.077)
sex	-0.937
	(0.578)
educ	0.259^{***}
	(0.064)
nchild	0.387
	(0.251)
partner	-0.408
	(0.553)
170.ind	0.000
	(.)
770.ind	0.304^{***}
	(0.077)
6970.ind	0.348^{**}
	(0.157)
7460.ind	-0.290
	(0.189)
_cons	11.729^{***}
	(2.305)
r2	0.978
N	32.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

	(1) int_2022
remote	0.044
	(0.051)
year_2022	0.142^{***}
	(0.029)
remote_year_2022	-0.079
	(0.049)
age	-0.138^{***}
	(0.047)
sex	-0.533
	(0.441)
educ	0.267^{***}
	(0.045)
nchild	0.528^{***}
	(0.178)
partner	0.604
	(0.383)
170.ind	0.000
	(.)
770.ind	0.351^{***}
	(0.063)
6970.ind	0.475^{***}
	(0.132)
7460.ind	-0.084
	(0.147)
_cons	13.199^{***}
	(1.698)
r2	0.987
N	32.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 5: Model (2) results

	(1) iv_ag2018	(2) iv_ag2019	(3) iv_ag2021	(4) iv_ag2022
remote	-10.785	-64.474	44.712	-6.234
	(14.407)	(507.451)	(178.460)	(4.987)
age	0.053	0.174	-0.054	0.038*
	(0.058)	(1.246)	(0.282)	(0.023)
sex	0.352*	-0.732	2.566	-0.006
	(0.180)	(7.880)	(9.325)	(0.169)
educ	0.242	0.868	-0.762	0.173**
	(0.209)	(6.160)	(3.386)	(0.073)
nchild	-0.010	0.106	0.157	-0.029
	(0.071)	(0.824)	(0.631)	(0.044)
partner	0.373**	1.166	-0.324	0.136
	(0.189)	(8.163)	(2.152)	(0.096)
_cons	7.412***	3.758	10.475*	8.738***
	(2.229)	(42.296)	(5.769)	(0.708)
N	3127.000	2619.000	2859.000	3236.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 6: Model (3) results for agriculture

	(1) iv_cn2018	(2) iv_cn2019	(3) iv_cn2021	(4) iv_cn2022
remote	32.528	-30.248	3.541***	7.951
	(39.596)	(53.221)	(1.274)	(5.914)
age	-0.020	0.070	0.011***	0.010*
	(0.044)	(0.098)	(0.002)	(0.005)
sex	1.438	-0.408	0.505***	0.846*
	(1.551)	(1.063)	(0.131)	(0.504)
educ	0.037	0.163	0.043**	0.021
	(0.076)	(0.125)	(0.017)	(0.049)
nchild	0.043	0.040	0.028**	-0.020
	(0.059)	(0.093)	(0.012)	(0.024)
partner	-0.003	0.362	0.100***	0.148***
	(0.305)	(0.350)	(0.036)	(0.057)
_cons	8.750***	8.522***	9.330***	9.028***
	(0.731)	(1.652)	(0.111)	(0.464)
N	1.7e+04	1.6e+04	1.5e+04	1.7e+04

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 7: Model (3) results for construction

	(1) iv_fn2018	(2) iv_fn2019	(3) iv_fn2021	(4) iv_fn2022
remote	8.236	-10.770	0.675*	1.328
	(7.491)	(12.980)	(0.399)	(0.849)
age	0.011	0.061*	0.025***	0.024***
	(0.015)	(0.036)	(0.003)	(0.005)
sex	0.431***	0.307***	0.325***	0.345***
	(0.083)	(0.108)	(0.039)	(0.045)
educ	0.270***	0.170***	0.143***	0.173***
	(0.087)	(0.046)	(0.017)	(0.014)
nchild	0.125*	0.084	0.024	0.057***
	(0.071)	(0.093)	(0.017)	(0.022)
partner	0.002	0.158	0.219***	0.150***
	(0.226)	(0.117)	(0.033)	(0.043)
_cons	7.519***	8.042***	8.621***	8.288***
	(0.882)	(0.479)	(0.154)	(0.253)
N	4948.000	5127.000	5286.000	5720.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 8: Model (3) results for finance

	(1) iv_ps2018	(2) iv_ps2019	(3) iv_ps2021	(4) iv_ps2022
remote	-3.984	3.043*	1.146***	1.708*
	(3.585)	(1.701)	(0.395)	(1.035)
age	0.053***	0.026***	0.026***	0.019***
	(0.014)	(0.007)	(0.004)	(0.006)
sex	-0.064	0.300***	0.267***	0.262**
	(0.170)	(0.087)	(0.049)	(0.104)
educ	0.153***	0.093***	0.054**	0.073**
	(0.035)	(0.020)	(0.023)	(0.035)
nchild	0.041	-0.014	0.047**	0.029
	(0.040)	(0.023)	(0.019)	(0.021)
partner	0.213***	0.061	0.059*	0.034
	(0.063)	(0.071)	(0.035)	(0.058)
_cons	7.976***	8.996***	9.239***	9.220***
	(0.511)	(0.278)	(0.168)	(0.237)
N	3103.000	3208.000	3686.000	3999.000

Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 9: Model (3) results for professional services

	stats ag2018	ag2019	ag2021	ag2022
F Statistic	.596	.016	.063	1.85
P value	.44	.899	.802	.174

Table 10: agriculture first stage regression statistics for Model (3)

	stats cn2018	cn2019	cn2021	cn2022
F Statistic	.68	.327	12.186	1.983
P value	.41	.568	0	.159

Table 11: construction first stage regression statistics for Model (3)

	stats fn2018	fn2019	fn2021	fn2022
F Statistic	1.497	.815	14.563	7.976
P value	.221	.367	0	.005

Table 12: finance first-stage regression statistics for Model (3)

	stats ps2018	ps2019	ps2021	ps2022
F Statistic	1.61	6.464	12.083	3.779
P value	.205	.011	.001	.052

Table 13: professional services first stage regression statistics for Model (3)

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