Pajamas & Paychecks:

How Work From Home Policies Are Reshaping Unemployment Across the U.S.

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Abstract

This paper explores the importance of work from home policies and investigates whether implementing remote work policies can decrease the unemployment rate in the United States. In particular, we use the Survey of Working Arrangements and Attitudes to estimate remote work share across states, the Bureau of Labor Statistics to examine unemployment rates across work industries, and the American Time Use Survey to capture telework potential scores for each industry. We find that fully remote work from home policies increase the unemployment rate, while hybrid work decreases the unemployment rate.

I. Introduction

A new normal, the COVID-19 pandemic, has reshaped the modern workplace environment. For the past decade, the improvement of internet and wireless technology have made physical location less important, and the pandemic has accelerated this process. Today, while many locations have returned to their pre-COVID operating models, many workers continue to work from home. Government incentives and company-specific policies have led to an increase in these remote working arrangements. This is not surprising since 58% of job holders in the US say they can work remotely at least part of the time (*Americans Are Embracing Flexible Work*, 2022). Work from home policies impact how businesses and corporations conduct their workforce. The process of working from home has changed the landscape of the working environment, but it has also generated significant controversy. The proponents of remote work policies argue that these policies can broaden the labor supply, reduce commute time, increase flexible working hours, and establish a healthy work-life balance (Gibbs et al., 2022). On the other hand, opponents of work from home policies argue that these policies reduce productivity. Opponents find that the lack of physical proximity reduces collaboration and hinders the company culture, which reduces productivity (Gibbs et al., 2022).

If this shift in working arrangements continues, there will be significant economic implications. Many papers have considered how remote work policies affect labor productivity, urban development, and labor force expansion. However, more information is needed about the relationship of working from home with unemployment, including the differences between the type of remote work (fully remote or hybrid) and the sectoral effects. This paper adds to the economic literature by considering how work from home policies affect unemployment rates across sectors. Understanding the relationship between these two factors can reveal the impact on specific sectoral demographics, identify potential job losses, and develop more effective business strategies and policy implications.

II. Literature Review

The rise of remote work since the pandemic has reshaped key aspects of the United States economy. Many scholars have researched remote work and have utilized many different econometrics models to study this area. The results and data from the following papers serve as a foundation for our research direction:

Sectoral Differences

Hansen et al. (2023) examine the sectoral differences between remote work adoption. Using a machine learning algorithm applied to over 250 million job vacancy openings across over twenty-four advanced countries, they found that remote work opportunities have grown more so in high-skill, computer-intensive sectors such as finance, insurance, and information technology.[1] Conversely, manufacturing and hospitality industries were shown to have a much lower proportion of remote work. This is also supported by the results of Bartik et al. (2020), who used firm-level surveys from small business leaders across the United States. They find the most significant changes in the professional, scientific, and technical services industries. The pandemic affected sectors where the transition to remote work is more difficult. Following this idea, Angelucci et al. (2020) found that due to COVID-19, 24 percent of non-remote workers lost their jobs, compared to only eight percent of remote workers. In terms of our research, instead of using the COVID-19 pandemic as a catalyst for a shift to remote work, we will examine how sectoral unemployment rates respond to remote work benefit policies. In doing so, we hope to

[1] Australia, Austria, Brazil, Canada, China, France, Germany, Greece, Hungary, India, Italy, Japan, Malaysia, Netherlands, Poland, Russia, Singapore, South Korea, Spain, Sweden, Taiwan, Turkey, UK, Ukraine, US

identify whether sectors with different capacities for remote work adoption, as determined by Hansen et al. (2023), Bartik et al. (2020), and Angelucci et al. (2020), experience different changes in their unemployment rate with targeted government benefits rather than an external crisis.

Demographics/Changes in Labor Force Participation

Lincicome (2024) concludes that the COVID-19 pandemic popularized working from home, boosting the labor force participation rate. Lincicome uses Work From Home Research's U.S. Survey of Working Arrangements and Attitudes (SWAA) to demonstrate that a ten percent rise in remote work is associated with an approximately 0.78 percentage point increase in employment among mothers compared to other women, with employment gaps specifically being narrowed in less family-friendly fields like finance and marketing. The findings from Lincicome (2024) reveal that remote work helps companies expand their talent pool because they can accommodate workers with specific needs. We hypothesize that this increase in labor force participation, as determined by Lincicome (2024), should decrease the natural rate of unemployment. Our research does not focus on underrepresented groups; rather, it investigates how changes in remote work share implicate unemployment rates across different sectors. Lincicome (2024) provides the intuition for why unemployment rates should fall in response to implementing remote work stimulus policies. Barrero, Bloom, and Davis (2023) examine how the COVID-19 pandemic significantly accelerated the shift to remote work, with remote workdays making up 28% of all paid workdays by the mid-point of 2023 (about four times the estimated share for 2019). The authors use their survey (SWAA) as data to investigate how remote work differs across demographics (education, age, and sex). We also use the SWAA data and will implement the same controls to ensure that the changes in remote work share and unemployment are not biased.

Methodology Frameworks

The methodology of the following papers serves as a framework for developing our approach to answering our research question:

Cowan and Garcia (2024) investigate how political factors, specifically state-level voting patterns in the 2020 United States presidential election, affected the persistence of remote work across states. The authors use a two-way fixed effects regression model and incorporate continuous treatment variables (representative of political partisanship) and year and state fixed effects. They also develop a teleworkability score based on the specific tasks associated with each occupation. Occupations that require minimal physical interaction, equipment handling, or on-site presence, such as software development or data analysis, receive high scores (closer to one), indicating greater remote work feasibility. On the other end of the spectrum, occupations that demand physical presence, like healthcare or construction, receive lower scores (closer to 0). Our project will also implement a teleworkability score and time and state fixed effects controls. However, our teleworkability score will be derived from the Bureau of Labor Statistics (BLS) scoring guidelines. We will use the BLS data because the values are created at the sector level instead of the occupational level. Implementing time and state-fixed effects will allow us to remove the effects of inherent variation between states and sector-level occupational flexibility from our results over time. Finally, instead of Cowan and Garcia’s (2024) two-way fixed effect model, we use a difference-in-differences (DiD) model because we examine discrete policy interventions.

Mondragon and Wieland (2022) analyze how the variation in remote work share across United States metropolitan areas influenced housing price growth during the pandemic. Their approach uses pre-pandemic remote work adaptability as an instrument in identifying a causal relationship between remote work share and housing markets in 2020. The authors apply this methodology to avoid reverse causality bias (unobserved shocks to housing demand and prices during the pandemic likely affect remote work share in 2020). In our study, since our variables, remote work share and unemployment rate, do not present a reverse causality issue, we will implement a simple regression model (similar to the second stage of the instrumental variable regression), directly correlating the share of remote workers within each sector with subsequent changes to unemployment rates. This adaptation will enable us to isolate the effect of remote work share without being concerned about overfitting.

III. Remote Work Benefit Policies

We look at several state policies that promote remote work job creation. We consider the following policies below:

Oklahoma launched the Oklahoma Remote Quality Jobs Incentive Act in July 2021 to attract industries with high concentrations of remote workers to the state. If companies hired remote employees, they received quarterly cash payments of up to five percent of new payrolls for ten years. To be eligible, businesses must meet an average wage threshold and create $2.5 million in new annual payrolls within the next three years (Oklahoma Department of Commerce 2021).

Maryland initiated the Maryland Telework Assistance Grant Program in August 2021, offering grants of up to $25,000 to help businesses and nonprofits establish telework capabilities.

To be eligible, companies needed to have a physical location in Maryland, and companies with less than 50 employees received priority. The funding is for purchasing telework infrastructure (e.g., telework equipment, software, and technical services) that enables smaller businesses to adopt and maintain a remote work model (Maryland Department of Commerce 2021).

Vermont started its New Remote Worker Relocation Program in February 2022. This program offers grants of up to $7,500 to remote workers who decide to move to the state. It helps with relocation costs and provides financial assistance, encouraging remote employees to move (State of Vermont 2021). Eligibility depends on the worker working full-time remotely in Vermont.

In March 2024, Wisconsin extended its Business Development Tax Credit to include hybrid and remote work arrangements. The program provides tax credits for creating new full-time jobs, with additional credit for positions that offer higher wages or better employee benefits. Businesses had to invest at least $250,000 to receive credits of up to ten percent on annual wages for qualifying employees (Wisconsin Economic Development Corporation 2024).

These state-level remote work policies present issues as the definitions and criteria used to identify them are not standardized. For instance, Vermont defines remote work as full remote work, while Wisconsin also encompasses hybrid work arrangements, complicating businesses operating across state lines. Moreover, these programs, including Oklahoma's Remote Quality Jobs Incentive Act and Maryland's Telework Assistance Grant Program, are relatively new and not very popular. Thus, it is difficult to discern the results and the effectiveness of these programs. Also, disparities exist in the targeted sectors of these policies. Oklahoma targets big enterprises, while Maryland targets small ones, highlighting the differences between how the policies intend to boost remote work.

IV. Data

We analyze data from a pooled cross-sectional dataset from Barrero, Bloom, and Davis's (2023) SWAA. The SWAA has collected information in monthly waves since May 2020 about individuals' demographic characteristics and working arrangements. It includes state-level and sector-specific information, allowing us to track trends in remote work behavior over time. This online survey dataset targets 2,500 to 10,000 U.S. residents aged 20-64. While the dataset is updated monthly, our research uses their data from May 2020 to September 2024. The study has gathered over 200,000 respondents. However, it disregards observations that fail attention checks (~12% of the sample) and "speeders" (~16% of the sample).[2] The median response time is seven to 12 minutes after removing the "speeders." The survey imposes a prior-year earnings requirement. Specifically, the requirement was $20,000 in 2019 for the March 2021 and earlier waves and $10,000 in 2019 for the April 2021 to December 2021 waves. The survey transitioned gradually to the lower earnings requirement from April to September 2021. In early 2022, they transitioned to a requirement of $10,000 in the prior year, which applies to subsequent waves.

The most significant limitation of this data set is that the SWAA is a pooled cross-sectional dataset that cannot track specific individuals over time. Because of this, we can only capture snapshots of working arrangements monthly and, unfortunately, overlook changes in individual behaviors across different stages of COVID-19. To combat this, we convert our dataset into a panel at the industry level. In doing so, our observations are now at the industry level but may not fully represent the sector as a whole.

In addition, to supplement our analysis of the SWAA data, we draw on the BLS data. The BLS contains data on employment, wage and earnings, occupational outlook, and many other

[2] "Speeders" are respondents who complete the survey significantly faster than expected. Therefore, they may not have fully engaged with the survey questions.

relevant factors that will allow us to analyze the relationship between remote work and unemployment trends. For our research, we pulled the unemployment rate by industry. The BLS data uses different industry labeling characteristics. Therefore, before using this data, we standardized their industry labels to match the SWAA labels. More specifically, we binned the BLS industries to the SWAA industry variables. The following variables are in the SWAA data but not in the BLS: "Education," "Healthcare," "Hospitality & Food," "Real Estate," "Retail Trade," "Utilities," and "Arts & Entertainment." To standardize these variables, we categorized "Hospitality & Food" and "Arts & Entertainment" with the "other" unemployment from the BLS. The "Education" and "Healthcare" variables were already combined by the BLS, and therefore, we also combined the unemployment rate for these variables. We placed "Real Estate" into the "Finance & Insurance" bin from the BLS as they are in the same supersector (financial activity). We placed "Retail Trade" with "Wholesale" and "Utilities" with trade as they were in the same supersector.

The BLS also stores data collected from the American Time Use Survey (ATUS). Inspired by Cowan and Garcia's (2024) use of the telework potential score, we found data for telework potential among industries. Unlike the unemployment rate data, we did not have to bin these variables because they were all included in the SWAA dataset. Finally, we cleaned our data by converting it from monthly to quarterly and excluded industries with fewer than 30 observations per quarter.[3]

Before we created our empirical model and strategy, we created the following figures to motivate our study. Table 1 below reports our summary statistics.

[3] We decided 30 observations to be our minimum due to the central limit theorem, which states that the sample size is sufficiently large if the sample size is $n \geq 30$.

Table 1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min.	Max
Earnings, $'000s	272327	101.7702	149.4722	15	1000
Age	275879	41.128	10.90396	25	57
Education	275879	15.09137	2.437314	10	21
Female	142643	51.44828	.5	0	100
100*1(Ever WFH during Covid)	62558	68.3	46.5	0	100
100*1(Currently WFH post Covid)	208222	32.2	46.7	0	100

We use observations from 275,879 respondents across all 50 U.S. states from the SWAA dataset. Our income variable measures earnings in nominal thousands of dollars from 2019.[4] The average respondent made $101,770 in 2019. However, there remains a high standard deviation of 149.472, highlighting high-income variability among the respondents. Our lowest respondent earned around $15,000 in 2019, while the highest earned $1,000,000. The average respondent is 41.13 years old, and our data consists of a moderate spread, indicated by a 10.90 standard deviation. The oldest respondents are 57, and the youngest is 25, which makes sense as the survey targets individuals in the workforce.

Education records a respondent's highest year of education. The most schooling our respondents had was 21 years, meaning they would have likely completed an advanced graduate degree, while the minimum was 10 years, suggesting education ended around middle school. However, on average, our respondents obtained 15 years of education, placing them in their third year of college. The low standard deviation of 2.44 suggests less variability in educational attainment. Regarding gender, 51% of respondents are female, and 49% are male, implying a balanced gender distribution. This binary indicator equals 100 if a respondent identifies as a female.

[4] Note that while the survey collects data from May 2020, the survey contains questions that refer to earlier time periods.

We define "During COVID" as January 2020 - December 2021 and "Post-COVID" as January 2022 - Present. The last two variables capture remote work behavior. The Ever WFH during COVID variable shows if a respondent worked from home at least once during the pandemic. 68.3% of the respondents worked remotely at some point during the pandemic (indicated by a mean of 68.3). The Currently WFH post Covid shows if a respondent still currently works from home. 32.2% of respondents continue to work from home (mean of 32.2), showing the remote work shift, with about 1⁄3 of the workforce continuing to work from home post-pandemic.

After the basic demographics of our respondents, we turn to the following figures for a more nuanced understanding of the respondents.

Table 2:
Full-Time Working Arrangements in the US Sept 2023 to Sept 2024, % Distributions

	Fully Onsite	Hybrid	Fully Remote	% of All Workers.
All workers	47.3	47.7	5.1	100
Self-employed, excluding contractors & gig workers	24.1	53.1	22.8	7
Contractors and gig workers	27.1	53	19.9	2.6
All employees	49.6	47.1	3.3	90.3
- In firms with 1 to 9 employees	54.5	37.2	8.2	5.8
- In firms with 10 to 49 employees	57	39.4	3.6	12.5
- In firms with 50 to 99 employees	47.4	49.4	3.2	12.9
- In firms with 100 to 499 employees	48.2	49.1	2.7	20.9
- In firms with 500+ employees	48	49.2	2.7	38.2
Government employees, excluding the armed forces	54.2	43	2.8	4.1

We define workers as employees who work at least five days per week. We consider employees fully onsite if they can exclusively perform their jobs at a physical location, hybrid workers if they perform their jobs at a physical or a remote location (their home), and fully remote workers if they can perform all their job responsibilities remotely. Table 2 highlights the distribution of these working arrangements based on these definitions. The split for all workers is almost equal between fully onsite at 47.3% and hybrid at 47.7%, with only a small percentage of 5.1% working fully remotely. This demonstrates that hybrid work has become the new normal in the workplace. Self-employed employees have the highest proportion of fully remote workers at 22.8% and hybrid at 53.1%. This chart also highlights the importance of firm size. Smaller firms have more fully onsite workers (54.5%), whereas bigger firms show greater adoption of hybrid work. This indicates that a physical presence is still important, even post-COVID. This chart emphasizes the importance of flexibility in the workplace, and the hybrid work model seems to balance onsite demand and remote flexibility.

Figure 1: Working Arrangements by Industry from Sept 2023 to Sept 2024

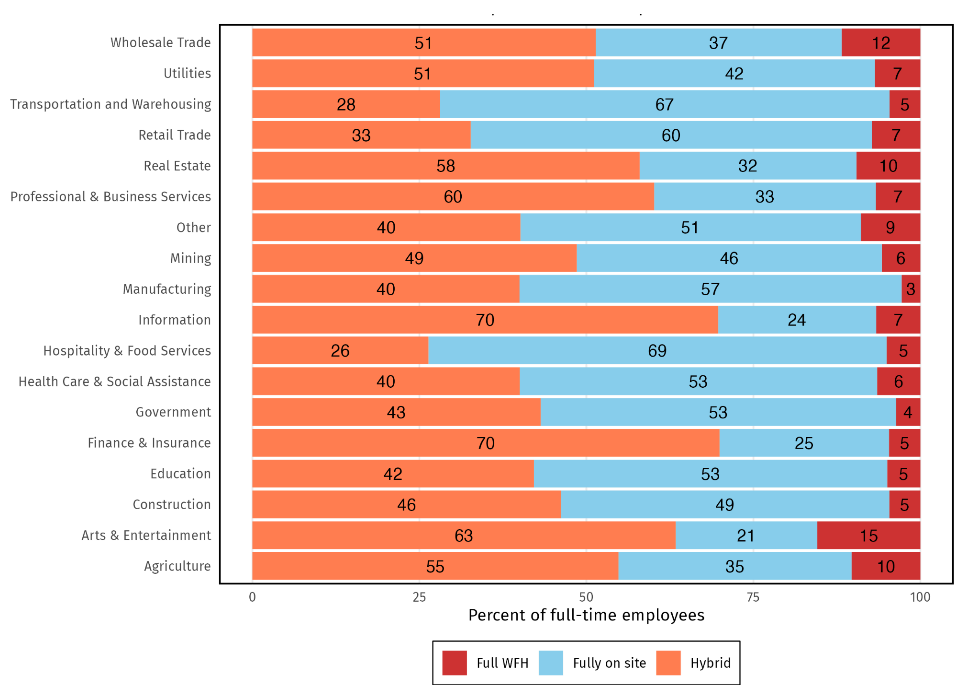

Figure 1 breaks down the distribution of working arrangements across industries. We omitted both Mining and Agriculture industries due to a small sample size. From this figure, we see that industries that are more fully on-site are typically labor-intensive. Notable industries include agriculture (55% fully onsite), construction (46% fully onsite), manufacturing (40% fully onsite), and mining (49% onsite). On the other hand, industries that are more digital have a greater percentage of remote or hybrid work adoption. These findings align with the findings of Hansen et al. (2023) and Bartik et al. (2020).

Figure 2: US WFH Rates by Industry Sector Between Sept 2023 to Sept 2024, Employees Who Work Five or More Days per Week

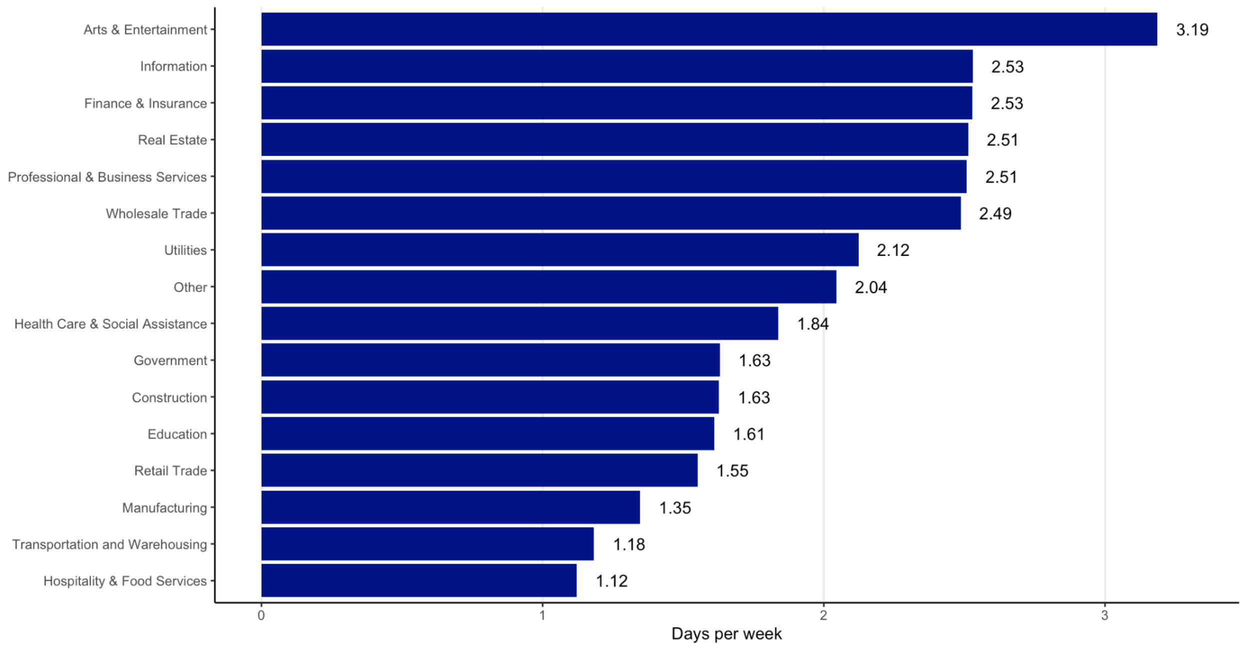

Figure 2 demonstrates the significant variability across industry sectors among employees who work at least five days per week. The Arts & Entertainment sector averages 3.19 work from home days per week, the highest rate of all industries. The Hospitality & Food Service industry has the lowest remote work rate (1.12 days per week). The "high skill" information sectors, such as Finance & Insurance and Professional Business Services, have high remote work rates. We observe higher adoption rates for remote work in areas with less physical demands. The distribution from Figure 2 highlights the potential for remote work that is heavily dependent on industrial characteristics, again aligning with the findings of Hansen et al. (2023) and Bartik et al. (2020).

Figure 3: Percent of days worked from home by education level

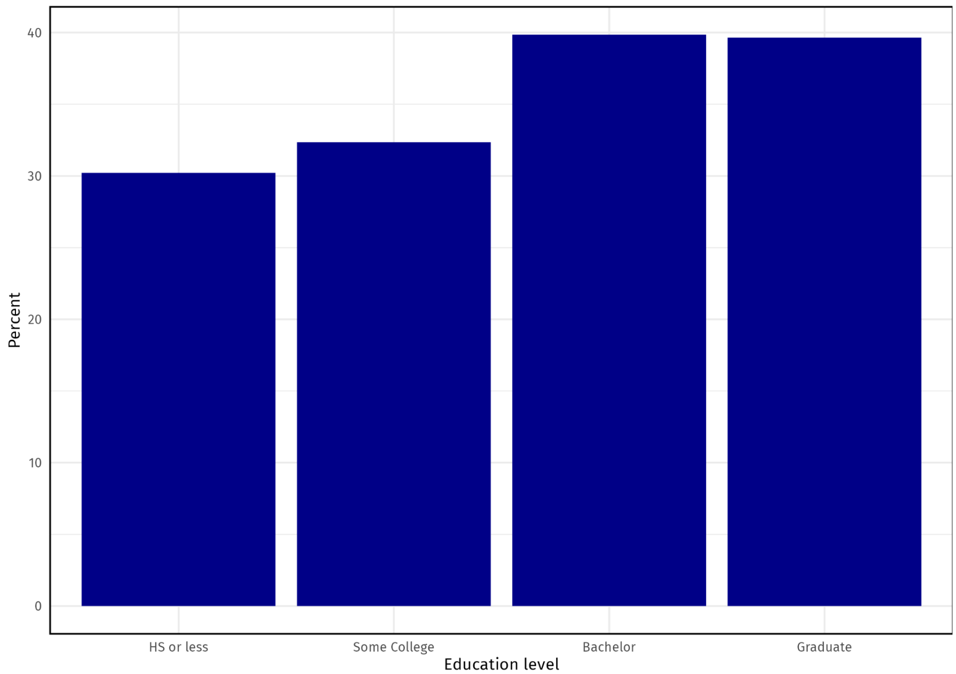

Figure 3 demonstrates the relationship between education level and days worked from home. We see employees with higher education levels (bachelor's or graduate degree) report higher levels of work from home percentage. On the other hand, employees with reported education have lower reported levels of working from home. This highlights education as a determinant of remote work policies and how work from home opportunities may increase inequality between education groups as less educated workers are still confined in physical work places. These findings remain consistent with the findings of Hansen et al. (2023) and Bartik et al. (2020). These figures provided the context for our dataset and aided us in the development of our empirical strategy.

V. Empirical Strategy and Methodology

Our study takes a two-stage approach, with the first stage investigating the impact of remote work benefit policies on remote work share in each industry, followed by a second stage targeting the effect of changing remote work share on unemployment rates between sectors. This two-stage method is utilized because it removes the possibility of simultaneity bias within the model. We believe that while remote work benefit policy influences unemployment rates, changes to unemployment rates may change the implementation of remote work benefit policies. For example, policymakers might boost remote work benefit programs to stimulate employment if unemployment rises. If this regression were to be run with a single-stage approach, it would not be possible to clearly define the causal direction from work from home policy to unemployment rates.

The first stage of our empirical model is specified as follows:

$$y_{ist} = \alpha + \beta_1(Treatment_{st} \times Post_t) + \gamma_s + \delta_t + \lambda_1 Teleworkability_i + \lambda_2 Age_i$$

$$+ \lambda_3 Race/Ethnicity_i + \lambda_4 Education_i + \lambda_5 Gender_i + \epsilon_{ist}$$

This regression y_{ist} represents the remote work share for industry(i) in state(s) at time(t). This remote work share will initially be defined by the number of remote workers working completely remotely. The key variable, $(Treatment_{st} \times Post_t)$, is binary and takes the value of one if the state has passed a remote work benefit policy in time (t), with $Post_t$ being an indicator variable for the period after the policy was introduced. The coefficient β_1, which is the interaction term, gives the DiD estimator, representing the impact of the policy on remote work share by comparing the changes in treated states versus control states. We believe the main assumptions of the DiD model hold, including the beliefs that policy interventions in the treatment states are not related to the state baselines and that the parallel trends assumption holds. The model also contains state and year-fixed effects, which exist to remove the influence of state-specific characteristics and broader time trends that affect all states equally. $Teleworkability_i$ is another included control that accounts for the varying potential of different jobs to be performed remotely, ultimately helping to isolate the policies' effect on remote work adoption regardless of occupational flexibility. Other control variables include Age_i, $Race/Ethnicity_i$, $Education_i$, and $Gender_i$. These controls capture demographic differences across industries that may affect the adoption of remote work.

The second stage of our model is specified as follows:

$$Unemployment_{ist} = \alpha + \beta_1 RemoteWork_{ist} + \gamma_s + \delta_t + \lambda_1 Age_i$$
$$+ \lambda_2 Race/Ethnicity_i + \lambda_3 Education_i + \lambda_4 Gender_i + \epsilon_{ist}$$

This model $Unemployment_{ist}$ represents the unemployment rate for industry(i) in state(s) at time(t). We run this second regression to examine the relationship between remote work share, found in the previous model, as a predictor of unemployment. $RemoteWork_{ist}$ represents the share of remote work in state(s) at a time(t). The coefficient β_1 measures the influence of remote work on unemployment. $\beta_1 > 0$ implies that increased remote work is associated with increased unemployment rates. On the other hand, $\beta_1 < 0$ means that an increase in remote work is associated with lower unemployment rates. Like previously, we use the same control variables (Age, Race/Ethnicity, Education, Gender) to capture demographic differences.

VI. Results

Table 3 reports the regression results from the first stage of our empirical model when remote work share includes only those who work fully from home. These results explore the relationship between remote work share based on the state policies described above, controlling for state, time, and demographic characteristics:

Table 3: Remote Work Policy's Effect on Remote Work Share (Remote Workers Defined as Fully Work from Home)

Regression Results for Remote Work Share

Dependent Variable: Remote Work Share

Variable	**Coefficient**	**Standard Error**
State Has Policy	0.006***	(0.001)
Ability to Telework Rate	-0.0001***	(0.00000)
Year	0.009***	(0.0001)
Age (Quant.)	-0.00004***	(0.00001)
Education	-0.0003***	(0.0001)
Gender (Female = 1)	-0.002***	(0.0002)
White	-0.0001	(0.001)
Black	-0.001	(0.001)
Hispanic	-0.002***	(0.001)
Asian	-0.003***	(0.001)
Native American	-0.001	(0.001)
Native Hawaiian	0.003**	(0.001)
Constant	-17.800***	(0.137)
Observations	168,208	
R2	0.119	
Adjusted R2	0.119	
Residual Std. Error	0.030 (df = 168166)	
F Statistic	495.000*** (df = 46; 168161)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Our results display that if the state has a remote work policy (State Has Policy Variable), we observe a coefficient of 0.006. This means that having a policy that targets remote work is associated with an increase in the share of remote work within an industry by 0.6 percentage points. This is a statistically significant result at the 1% level ($p < 0.01$). This implies that policies such as incentives for relation, grants, or tax credits have a very slight positive effect on remote work adoption. In addition, we see a temporal trend as the coefficient for year highlights an increase in remote work share by 0.9 percentage points. This result is logical, as there is a continued shift towards working from home arrangements post-COVID-19. Our R^2 and Adjusted R^2 values are both 0.119, implying that 11.9% of the variation within remote work is explained by our model. In addition, our F-statistic is 495 ($p< 0.01$), indicating that the model is robust.

Our second stage regression is reported in Table 4, continuing with the definition of remote workers as only those who work fully from home. These results focus on how the share of remote workers influences unemployment rates within different industries:

Table 4: Remote Work Share (Remote Workers Defined as Fully Work from Home) Effect on Unemployment Rate

Regression Results for Industry Unemployment Rate

Dependent Variable: Industry Unemployment Rate

Variable	Coefficient	Standard Error
Remote Work Share	0.078***	(0.002)
Age (Quant.)	-0.00003***	(0.00001)
Education	-0.002***	(0.0001)
Gender	0.004***	(0.0001)
White	-0.0003	(0.001)
Black	-0.001*	(0.001)
Hispanic	-0.0003	(0.001)
Asian	-0.002***	(0.001)
Native American	0.0002	(0.001)
Native Hawaiian	0.001	(0.001)
Constant	0.044***	(0.001)
Observations	162,895	
R2	0.019	
Adjusted R2	0.019	
Residual Std. Error	0.027 (df = 162884)	
F Statistic	308.000*** (df = 10; 162884)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Looking at this model, we find that remote work share has a coefficient of 0.078, meaning a one percentage point increase in remote work share is associated with a 7.8 percentage point increase in an industry's unemployment rate. This is statistically significant at the 1% level ($p < 0.01$). However, these results do not align with our hypothesis that industries with higher remote work adoption are less likely to experience a decrease in jobs (because of increased employee flexibility) and, therefore unemployment rate. Our intuition is that in this scenario, we had not considered that there might be potential displacement effects for fully remote workers or structural adjustments in industries transitioning to a fully remote work environment. Reviewing our control variables, we arrive at the same conclusion as the previous model, as there are very small differences when controlling for age, education, gender, and race/ethnicity. Our R^2 and Adjusted R^2 values are both 0.019, meaning our model explains 1.9% of the variation in the unemployment rate between industries. Although this R^2 is quite low, the value is in alignment with Mondragon and Weiland (2022), whose regressions also had low R^2 values in the range of 0.05 and 0.15. Finally, our F-statistic is 366 and is significant ($p < 0.01$), representing the overall robustness of the model.

We next run the two-stage model with the definition of remote workers including hybrid workers. Table 5 reports the regression results from the first stage of the model:

Table 5: Remote Work Policy's Effect on Remote Work Share (Remote Workers Defined Including Hybrid Workers)

Regression Results for Remote Work Share

Dependent Variable: Hybrid Work Share

Variable	**Coefficient**	**Standard Error**
State Has Policy	0.057***	(0.004)
Ability to Telework Rate	0.002***	(0.00001)
Year	-0.021***	(0.0003)
Age (Quant.)	-0.0003***	(0.00002)
Education	0.005***	(0.0002)
Gender (Female = 1)	0.012***	(0.0005)
White	0.0004	(0.002)

Black	-0.006***	(0.002)
Hispanic	-0.003	(0.002)
Asian	0.0003	(0.002)
Native American	0.009***	(0.003)
Native Hawaiian	0.029***	(0.004)
Constant	43.500***	(0.515)
Observations	143,622	
R2	0.410	
Adjusted R2	0.410	
Residual Std. Error	0.081 (df = 143575)	
F Statistic	2,168.000*** (df = 46; 143575)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Our results illustrate that if the state has a remote work policy (State Has Policy Variable), we observe a coefficient of 0.057. This means that having a policy that targets remote work is associated with an increase in the share of remote work within an industry by 5.7 percentage points. This result is statistically significant at the 1% level ($p < 0.01$). This implies that policies such as incentives for relation, grants, or tax credits have a substantial positive effect on remote work adoption with hybrid workers included (versus a minimal positive effect for fully remote workers alone). Surprisingly, we find a negative year coefficient of -0.021, which, with this definition of remote worker, might reflect a shift toward either fully remote or traditional office setups rather than hybrid setups. Our R^2 and Adjusted R^2 values are both 0.410, implying that 41.0% of the variation within remote work is explained by our model. In addition, our F-statistic is 2,168 ($p< 0.01$), indicating that the model is robust.

Our second empirical regression is reported in Table 6, continuing with the amended definition of remote workers to include hybrid workers. These results focus on how the share of remote workers influences unemployment rates within different industries:

Table 6: Remote Work Share (Remote Workers Defined Including Hybrid Workers) Effect on Unemployment Rate

Regression Results for Industry Unemployment Rate

Dependent Variable: Industry Unemployment Rate

Variable	Coefficient	Standard Error
Hybrid Work Share	-0.016***	(0.001)
Age (Quant.)	-0.00004***	(0.00001)
Education	-0.002***	(0.0001)
Gender	0.004***	(0.0002)
White	-0.001*	(0.001)
Black	-0.002***	(0.001)
Hispanic	-0.001	(0.001)
Asian	-0.002***	(0.001)
Native American	0.00003	(0.001)
Native Hawaiian	0.002**	(0.001)
Constant	0.053***	(0.001)
Observations	138,309	
R2	0.013	
Adjusted R2	0.013	
Residual Std. Error	0.028 (df = 138298)	
F Statistic	187.000*** (df = 10; 138298)	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Reviewing this regression, we find that remote work share has a coefficient of -0.016, meaning a one percentage point increase in remote work share is associated with a 1.6 percentage point decrease in an industry's unemployment rate. This is statistically significant at the 1% level ($p < 0.01$). These results follow our hypothesis and suggest that including hybrid work arrangements may help stabilize or sustain employment. Reviewing our control variables, we found very small differences when controlling for age, education, gender, and race/ethnicity. Our R2 and Adjusted R2 values are both 0.019, meaning our model explains 1.9% of the variation in the unemployment rate between industries. However, this again aligns with Mondragon and Weiland (2022). Finally, our F-statistic is 187 and is significant ($p < 0.01$), representing the overall robustness of this version of the model.

While our study found statistically significant results, some limitations may have made our research suboptimal. First, differences in industry titles between the SWAA and BLS datasets meant we needed to standardize these labels ourselves. Furthermore, because remote work policy has only been implemented within the last four years, we cannot assess the impact of remote work policies over the long term. Policies like relocation grants or telework incentives may take years to show their full effects, which we cannot capture with our current data. Continuing with this idea, the relative novelty of remote work targeted policy meant that at the time of this study, only four states had fully implemented comprehensive remote work development legislation. Had this type of policy been more common and utilized for a longer period, more states would likely have installed these policies, possibly even allowing us to dissect the policies themselves at a more granular level. Despite these limitations, policymakers can use our study as a foundation for future research, and focus more specifically on hybrid policies. Future studies should be completed to differentiate between policy measures and further look into the isolated effects of hybrid and fully work from home employment opportunities.

VII. Conclusion

In this paper, we examined the relationship between work from home policies and unemployment rates. By investigating this relationship, we contribute to the ongoing discussions of remote work policy. Using a variety of data from SWAA, the BLS, and ATUS, we took a two-stage approach to measure one, the effect of remote work policy on remote work share, and two, the effect of remote work share on the unemployment rate. We find that with an increase in fully remote work, there is an increase in the unemployment rate. However, when considering hybrid work, we find that with an increase in hybrid working arrangements, there is a decrease in the unemployment rate. We interpret these results as indicating the need for a mediator. Our findings suggest that hybrid work strikes a balance between workplace flexibility and productivity. We interpret our findings as evidence for hybrid-specific remote work policies rather than fully remote ones. Future studies should elaborate on the impact of industry, education, and the demographic characteristics of the workforce on such effects.

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