The Impact of Post-Pandemic Hybrid Work Models on Employee Productivity in the United States

Karan Patel

Introduction

The Coronavirus (Covid-19) outbreak triggered one of the most significant shifts in business operations and practices in modern history. As businesses worldwide attempted to adapt to the new lockdown and social distancing measures, remote work became a staple for thousands of businesses and millions of employees across the United States. As businesses and employees adjusted, we began to notice the various benefits and pitfalls associated with remote work. As we entered the post-pandemic era, many organizations and employees sought to continue reaping the supposed benefits of hybrid work, adopting it as their primary work model. This transition sparked a nationwide debate that still goes on to this day, about the impact of hybrid work on employee productivity. Supporters argue that hybrid work minimizes business costs while enhancing employee well-being and efficiency, while others argue that it leads to employee complacency and lower productivity.

The adoption of hybrid work has many long lasting and future implications for businesses, employees, and the country. Understanding the productivity effects of hybrid work is crucial for making informed decisions about business operations strategy, workplace policies, associated risks, and cost efficiency. For employees, the long-lasting implications lie in employee well-being, job satisfaction, work-life balance, career development, and more. On a broader scale, understanding the effects of hybrid work can drive future employment policies, the labor market, and economic growth, all of these crucial for the United States and its future. Understanding the true impact of hybrid work models and its future implications on businesses and employees is crucial as people nationwide continue to navigate their careers and the future of work.

This paper explores how these post-pandemic hybrid work models have impacted employee productivity across various industries within the United States. Specifically, we compare industries that adopted hybrid work models (e.g technology and professional services) to those that rely on in-person work models (e.g retail and manufacturing) to understand the causal impact of hybrid work on productivity. Using labor productivity and output per worker as our key variables, we work toward answering the question: How did the adoption of post-pandemic hybrid work models affect employee productivity in the United States.

To address this question, we apply a Difference-in-Differences approach, utilizing panel data from the Bureau of Labor Statistics from 2018 to 2023. We compare two measures, labor productivity and output per worker, between industries that adopted hybrid work models (treatment) and industries that remained in-person (control). The Difference-in-Differences analysis will allow us to isolate the true causal relationship between hybrid work and productivity, controlling for trends and industry factors. With a focus on the United States, the methodology will provide a detailed analysis of how hybrid work has impacted productivity in the world's largest economy.

Data

The Bureau of Labor Statistics (BLS) is an agency of the United States Department of labor that focuses on collecting, calculating, and analyzing data about the United States labor market and economy. The agency utilizes surveys and census data to measure labor market activity, working conditions, price changes, and productivity within the United States and provides data essential to the public, employers, researchers, and government agencies. In this paper we will dive further into the productivity data provided by the Bureau of Labor Statistics, primarily focusing on the Labor Productivity and Costs program. The dataset provides detailed labor productivity and cost information on the various industries within the United States for all workers from 1988 to 2023, and can be found in the appendix. We size this dataset down to fit the needs of our proposed productivity analysis.

For the time frame, the data provides detailed information on labor productivity, output per worker, employment, hours worked, and more for select industries within the United States from 2018 to 2023. The years 2018-2019, the pre-pandemic period serves as the baseline for comparing productivity trends before the adoption of hybrid work. 2020-2021 highlights the pandemic or transition period in which many industries were forced to work in remote settings. 2022-2023 exemplifies the post-pandemic period, capturing the effects of hybrid work as businesses adapted to the new model. With a focus on the pre and post pandemic time frames, removal of the pandemic period, within the statistical software, prior to analysis is crucial to avoid bias in the analysis due to the effects of the pandemic.

Key variables for the analysis include labor productivity, output per worker, sectoral output price deflator, unit labor costs, real sectoral output, employment, and hourly compensation. Labor productivity and output per worker serve as the dependent variables for the two regression models, helping highlight the differences in productivity at an industry level as well as employee level. Real sectoral output, serving as a control variable, reflects the total output of an industry, adjusted for inflation and is unlikely to be directly influenced by hybrid work models. Unit labor costs, serving as a control variable, measures the cost of labor per unit of output, helping control for cost pressure that could affect productivity. Similarly, hourly compensation, serving as another control variable, helps control for differences in labor costs across industries. Sectoral output price deflator as another control variable accounts for inflation and deflation within an industry, helping control for the changes in the value of output that are not related to productivity. Finally, employment serves as a control variable that controls for and measures the size of a workforce within an industry.

Industry wise, we select nine industries for the control group and nine industries for the treatment group represented by their NAICS identification code. The control industries include those that didn't adopt or have lower hybrid model adoption rates and were not affected by the mild industrial materials manufacturing recession. The treatment group consists of industries that fully adopted or had higher adoption rates of hybrid work models, majority of which are within the information and professional services sectors. Both the treatment and control groups are detailed in Table 1 with their corresponding NAICS codes. Cumulatively, these modifications create a data set, included in the appendix, well suited for the Difference-in-Difference analysis detailing industry productivity over the necessary time frames.

Table 1: Control and Treatment Groups

Control		**Treatment**	
Industry	**NAICS Code**	**Industry**	**NAICS Code**
Mining	21	Software Publishers	5112
Oil and Gas Extraction	211	Wired and Wireless Telecommunications Carriers	5173
Food Manufacturing	311	Accounting, Tax Preparation, Bookkeeping, and Payroll Services	5412
Apparel Manufacturing	315	Travel Arrangement and Reservation Services	5615
Food and Beverage Stores	445	Commercial Banking	52211
Warehousing and Storage	493	Architectural Services	54131
Food Services and Drinking Places	722	Engineering Services	54133
Agriculture, Construction, and Mining Machinery	3331	Advertising Agencies	54181
Janitorial Services	56172	Employment Placement Agencies and Executive Search Services	56131

Methodology

To estimate the causal impact of hybrid work on productivity in the United States, we implement a Difference-in-Differences (DiD) approach. This model compares the change in productivity in industries that adopted hybrid work (treatment group) to the change in productivity in industries that remained in person (control group), before and after the adoption of hybrid work. As mentioned previously, the treatment period begins in 2022, when hybrid work models became widely utilized and adopted in many industries. The pre-treatment period includes years 2018 and 2019, excluding those industries that were affected by the manufacturing recession in 2019. Additionally, we look to exclude 2020 and 2021 to avoid the disruptions in the United States economy caused by the COVID-19 pandemic.

The analysis uses panel data from the Labor Productivity Dataset detailed above and found in the appendix which includes annual observations for the key control variables detailed in the data section of the paper. Additionally, we introduce three new variables for the Difference-in-Differences analysis including:

Hybrid Work Adoption (hybrid): A dummy binary variable indicating whether an industry adopted hybrid work models. Industries that adopted hybrid work (treatment) are coded as 1 and those that remained in-person (control) are coded as 0.

Post-COVID (post_covid): A dummy binary variable indicating whether the observation is from the treatment period (2022-2023). Observations within the treatment period are coded as 1, while those from the pre-treatment period (2018-2019) are coded as 0.

Hybrid × Post-COVID (hybrid_post): The interaction term between the treatment and post-treatment indicators, capturing the effect of hybrid work adoption on productivity in the post-treatment period

The dummy variables help represent both the treatment and control groups as well as both the pre and post-treatment time periods, enabling the use of a single regression equation to compare the groups at the aforementioned time periods. The interaction term assists with determining the effect of the treatment across time periods, in this case, helping determine the effect of hybrid work on productivity post-pandemic within the United States.

In addition, a well specified Difference-in-Differences model relies on the Parallel Trends Assumption which requires that the trend of the outcome variable for both the treatment and the control group be similar prior to the application of the treatment. This is tested empirically through a balance test as well as visualized graphically for assurance.

Difference-in-Differences Model:

(1) $LaborProductivity_i = \beta_0 + \beta_1 Hybrid + \beta_2 PostCOVID + \beta_3(Hybrid * PostCOVID) + X_i + \epsilon_i$

(2) $OutputPerWorker_i = \gamma_0 + \gamma_1 Hybrid + \gamma_2 PostCOVID + \gamma_3(Hybrid * PostCOVID) + Z_i + \delta_i$

(3) $Y_i = \lambda_0 + \lambda_1 Hybrid + \alpha_i$

Equation 1 represents the estimation model for the first and primary measure of productivity where $LaborProductivity_i$ is the measure of labor productivity, $Hybrid$ is a dummy variable that indicates whether hybrid work has been adopted or not, $PostCOVID$ is a dummy variable that indicates post or pre-treatment, $(Hybrid * PostCOVID)$ is the interaction term and its coefficient (β_3) is our estimator of interest, X_i is a vector of control variables, ϵ_i is the error term. Equation 2 represents the estimation mode for output per worker which is the second measure of productivity at the employee level where $Output\ per\ Worker_i$ is the new measure of labor productivity, γ_3 is the new coefficient of interaction term and the estimator, Z_i is a vector of control variables, δ_i is the error term, and all other variable definitions remain the same

Equation 3 represents the balance test to assist in proving the parallel trends assumption where Y_i represents each covariate in the model (e.g. labor productivity, employment, etc). Since we check for the balance test and parallel trends assumption pre-treatment the second dummy variable and interaction term will result in 0 so they are excluded from the analysis.

Analysis of the Difference-in-Differences model will consist of robust standard errors for both regression equations 1 and 2. This is derived from the potential of heteroskedasticity or a varying distribution by year due to natural fluctuations in labor productivity and output per worker. Analysis of Equation 3 also contains robust standard errors for better accuracy.

Results

Balance Check with Robust Standard Errors

The initial analysis examines the balance between the treatment and control groups within the pre-treatment time frame in order to understand whether the data satisfies the parallel trends assumption. This balance check was conducted using regression models for various model outcomes: labor productivity, real sectoral output, unit labor cost, output per worker, employment, hourly compensation, and sectoral output price deflator, with a focus on labor productivity and output per worker as they represent the dependent variables of later analysis. The results of these regressions are presented in Table 2.

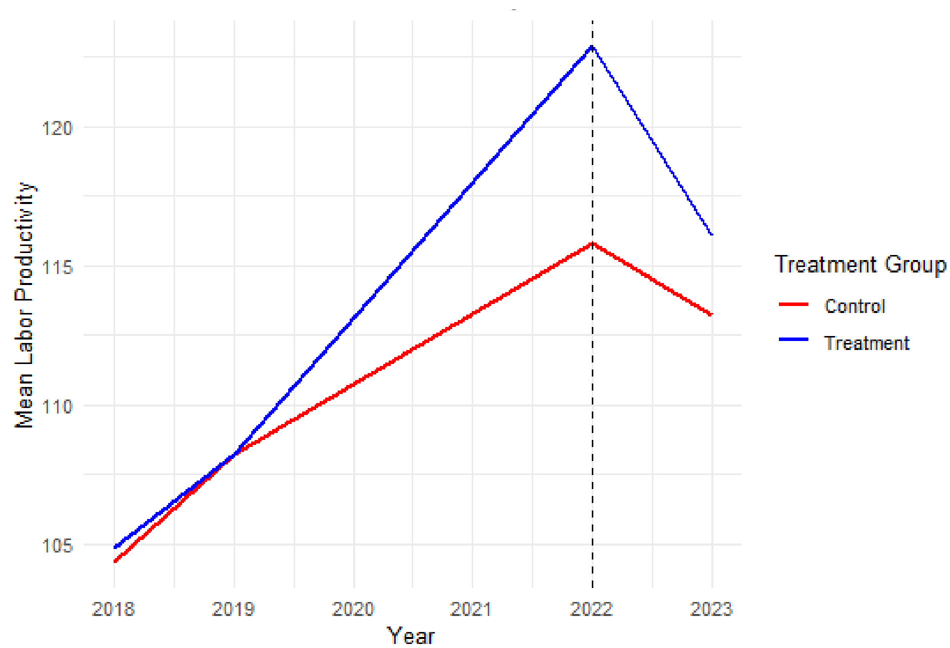
Table 2: Balance Check with Robust Standard Errors

Balance Check with Robust Standard Errors

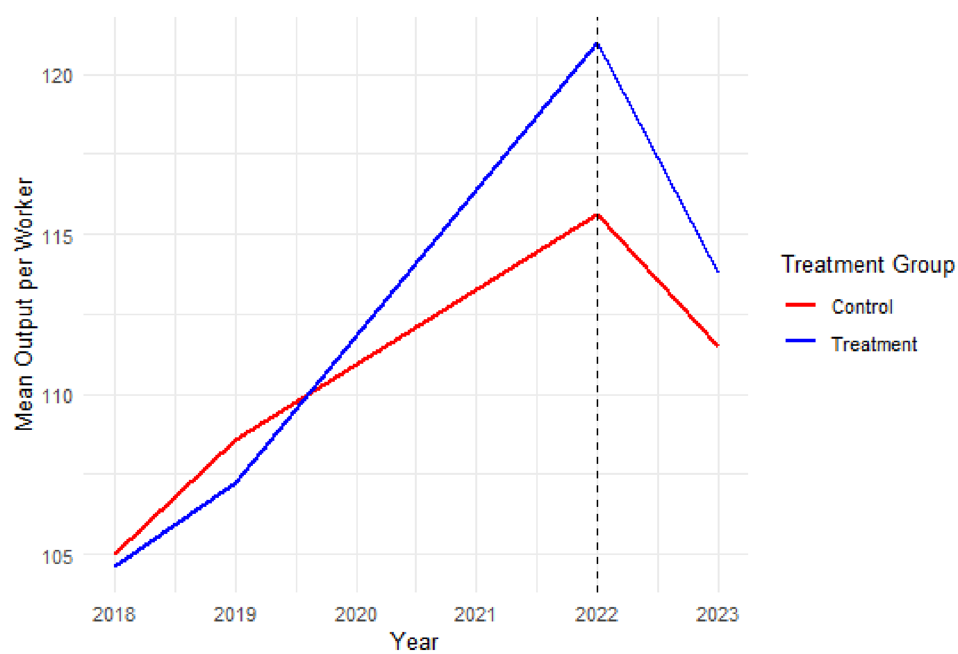
	Dependent variable:						
	Labor Productivity	Real Sectoral Output	Unit Labor Cost	Output per Worker	Employment	Hourly Compensation	Sectoral Output Price Deflator
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hybrid	0.273	-0.525	0.605	-0.864	0.221	1.255	-2.250
	(3.048)	(2.633)	(2.653)	(3.150)	(2.256)	(0.959)	(1.457)
Constant	106.283***	108.617***	97.646***	106.790***	102.092***	102.972***	104.387***
	(2.353)	(2.173)	(2.129)	(2.592)	(1.651)	(0.564)	(1.268)
Note:							*p<0.1; **p<0.05; ***p<0.01

As seen in Table 2, the coefficients for the Hybrid treatment variable across all seven outcomes were found to be statistically insignificant. The specific coefficients are as follows: labor productivity (0.273), real sectoral output (-0.525), unit labor cost (0.605), output per worker (-0.864), employment (0.221), hourly compensation (1.255), and sectoral output price deflator (-2.250). All seven variables are non-significant at levels $p < 0.10$, $p < 0.05$, and $p < 0.01$. This likely suggests that prior to the treatment period, there were no significant differences between the treatment and control groups across the seven key variables. Even better is that there was no difference between the treatment and control prior to the treatment period for our dependent labor productivity and output per worker variables which likely means that the pre-treatment values and trends were likely similar for the treatment and control groups.We can visually see this in Graphs 1 and 2 below that illustrate the similarities in values and trend between the treatment and control groups prior to the treatment period of 2022-2023. When analyzing these graphs, it's important to note that years 2020 and 2021 were omitted from the data set, meaning we should focus on the trend between 2018 and 2019. We can clearly see that for both dependent variables, the control and treatment groups both had positive trends from 2018 to 2019 and are likely heading into the pandemic time frame. We also see that the yearly values, which are the mean taken over each group for each year, are nearly similar. This culminates into satisfying the parallel trend assumption allowing us to continue to the Difference-in-Differences analysis.

Graph 1: Labor Productivity Trends Pre-Treatment



Graph 2: Output per Worker Trends Pre-Treatment



Difference-in-Differences Analysis with Robust Standard Errors

The main focus of this analysis was to estimate the impact of the hybrid treatment variable during the post-covid period, using a Difference-in-Difference approach. The model included an interaction term between the hybrid and post-covid variables and several control variables mentioned earlier included as covariates. The results of the regression are presented in Table 3.

Table 3: Difference-in-Differences Analysis of Labor Productivity and Output Per Worker with Robust Standard Errors

DiD Models with Robust Standard Errors

	Dependent variable:	
	Labor Productivity	Output per Worker
	(1)	(2)
Hybrid	0.395	0.048
	(0.718)	(0.551)
PostCOVID	-0.690	0.524
	(3.510)	(3.669)
Hybrid X Post	-2.181	-2.041
	(2.567)	(2.634)
Real Sectoral Output	0.567^{***}	1.060^{***}
	(0.212)	(0.227)
Unit Labor Cost	-0.283	0.195
	(0.260)	(0.248)
Employment	-0.516^{**}	-1.020^{***}
	(0.236)	(0.245)
Hourly Compensation	0.508^{*}	-0.057
	(0.254)	(0.253)
Sectoral Output Price Deflator	0.079	0.079
	(0.049)	(0.049)
Constant	64.465^{***}	74.438^{***}
	(15.977)	(15.645)
Note:		*p<0.1; **p<0.05; ***p<0.01

Focusing on our variable of interest, Hybrid X Post, the interaction term between the hybrid work treatment and post-pandemic timeframe, labor productivity analysis resulted in a coefficient of -2.181 with a robust standard error of 2.567 and the output per worker coefficient resulted in -2.041 with a robust standard error of 2.634 On a surface level, this indicates that there is a negative relationship between hybrid work and productivity overall, however, we find that neither of these results are statistically significant at any significance level as shown by the table. This suggests that the hybrid treatment variables did not have a statistically significant effect on labor productivity or output per worker.

The coefficient for the PostCOVID variable of -0.690 indicates a negative relationship with productivity. On the other hand, a coefficient of 0.524 indicates a positive relationship with output per worker. However, neither of these values were statistically significant at any significance level highlighting PostCOVID's minimal effect on these two variables.

In terms of control variables, the results show that real sectoral output had a significant positive effect on both labor productivity and output per worker, with coefficients of 0.567 and 1.060 respectively, highlighting higher labor productivity and output per worker with increases in real sectoral output. Additionally, the employment variable revealed a statistically significant negative relationship with both labor productivity (-0.516 at $p<0.05$) and output per worker (-1.020 at $p<0.01$), highlighting decreases in productivity with increases in employment. Finally, hourly compensation produced a statistically significant positive effect on labor productivity (0.508 at $p < 0.10$), but had no statistically significant effect on output per worker. The rest of the control variables (Sectoral Output Price Deflator, Unit Labor Cost, etc) produced statistically insignificant relationships in the data.

Discussion

The results of this analysis provide insights into the impact of hybrid work models on labor productivity and output per worker during the post-pandemic period. Findings show that the interaction between the hybrid treatment and the post-pandemic period did not have a statistically significant effect on either labor productivity or output per worker. While the coefficients of interest were negative, the lack of statistical significance shows us that if there was a potential effect due to hybrid work then it wasn’t strong enough to be found in this sample. Essentially, as far as this sample goes, there is no statistical evidence that shows hybrid work models have an effect on productivity and more research may have to be done.

Findings

One possible explanation for the insignificant results is that the hybrid work model may not have been disruptive enough to generate measurable changes in productivity within sectors. Many firms adopt new work models, operations models, technologies, and strategies at different stages and rates. The period of 2022 to 2023 may have been slightly on the earlier end resulting in lower adoption rates than anticipated. These lower rates can be due to transition periods, learning curves, adaptation challenges, and more. Additionally, firms level strategies may have larger influence on productivity than anticipated resulting in accuracies due to firm level differences.

A few things we can conclude at this stage are that sectoral output plays a huge role in sector labor productivity and output per worker as per the model, which logically makes sense. Additionally, we can conclude that employment seems to have a statistically significant negative effect on both labor productivity and output per worker which suggests that these values worsen as companies and industries hire more and more workers. This makes sense in the context of output per worker because as the number of workers increases it can certainly lead to diminishing marginal returns on output per worker. In terms of labor productivity, while statistically significant, the true effect is quite small and can likely be attributed to the effect on output per worker. Finally, due to the lack of strong significance with the hourly compensation variable it is likely that hourly wages have a little to no effect on productivity.

Limitations and Future Research

Despite the robustness and preparation of the Difference-in-Difference methodology used in this study, there are several limitations that need to be acknowledged. First, is the limited access to firm level data. Due to the aggregation of many firms within an industry, it becomes difficult to accurately understand the true hybrid adoption rates or percentages. By utilizing firm level data researchers can expand on this model by utilizing company policies and accounting for firm to firm variations, leading to improved heterogeneous effects that are not appropriately represented in the sectoral and industry data.

Secondly, the timeframe of the study could play a large role in the lack of significant results. Measuring within the 2020-2023 time frame might be too close to the end of the pandemic which likely means it marks the beginning of hybrid adoption which may be a transition or adaptation period for a lot of companies. A better way to approach this if given access to the data would be to explore data from 2023-2024. This, while still relatively early, would provide far better hybrid adoption rates and would account for the transition and adaptation period in 2022.

Thirdly, the model can be improved to account for more variables within business and firms. The results suggest that any productivity effects of hybrid work are either too small to detect at this aggregated industry level or are offset by other factors. As mentioned above, a great way to combat this is to explore the same question with firm level data, however, at the same time determining factors that may offset productivity effects and controlling for them will help produce more significant and accurate results.

Conclusion

With the amount of debate going on throughout the country on the benefits of hybrid word and its effect on employees and productivity, it's not surprising to come out of this study nearly answerless. Big firms such as Amazon and JPMorgan are shifting away from hybrid work due to inefficiencies and employee complacency whereas companies like Adobe, Microsoft, Google and more continue to embrace their hybrid environments. With such a mix of work environments in every industry as well as changes due to firm level shifts and remote adoption it's certainly difficult to tell whether hybrid environments have any effect on productivity, even technology giants aren’t sure. Future research should explore firm-level data and variations to better understand the true effects of hybrid work and its long-term effects on the workforce.

Works Cited

Wooldridge, Jeffrey M. Econometric Analysis of Cross Section and Panel Data. 2nd ed., MIT Press, 2010.

RStudio Team. RStudio: Integrated Development for R. Posit Software, PBC, 2023, www.posit.co.

Bureau of Labor Statistics. U.S. Department of Labor. www.bls.gov. Accessed 21 Mar. 2025.

"Difference-in-Difference Estimation." Columbia University Mailman School of Public Health, www.publichealth.columbia.edu/research/population-health-methods/difference-difference-estimation. Accessed 21 Mar. 2025.

Tsipursky, Gleb. "The Surprising Rise of Hybrid Work." Forbes, 10 May 2023, www.forbes.com/sites/glebtsipursky/2023/05/10/the-surprising-rise-of-hybrid-work/.

R Core Team. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, 2023, www.r-project.org.