

COMPENSATING FOR COVID:
A DIFFERENCE-IN-DIFFERENCES ANALYSIS OF VACCINE PREVALENCE ON
WAGES

by

James C. Orr

Submitted to the Distinguished Majors Program
Department of Economics
University of Virginia
April 15, 2022
Advisor: Lee Lockwood

Table of Contents

I.	Acknowledgements	3
II.	Abstract	4
III.	Introduction	5
IV.	Literature Review	6
V.	Method and Estimation Strategies	8
VI.	Data	9
VII.	Results and Interpretation	15
	1. Naïve Regression.....	15
	2. Phase 1B.....	16
	3. Vaccine Dominance.....	19
	4. Vaccine Prevalence.....	21
VIII.	Conclusion	23
IX.	References	25
X.	Appendix	26

Acknowledgements

I first want to thank Lee Lockwood for all of his support in the time I have been engaged on this project. Since the fall of 2021, Lee has been an amazing resource for ideas, advice, encouragement, and motivation. I am grateful for all our discussions and his guidance to always tackle the most daunting part first. I also want to thank Amalia Miller for her guidance through the program and commitment to my success.

I also want to thank my family for their support. Both of my parents, Jamie and Carrie Orr, have helped me become the person I am today in more ways than I can properly recognize. Without their support and without the support of my grandparents, Jim and Cathy Orr, in pursuit of my dreams and aspirations, I would not have had the opportunities I have had to grow and develop.

Additionally, I want to thank my friends who have kept me going along the way these past four years. I want to thank the other members of the DMP for their invaluable feedback. Ishaan, Erica, Dylan, Madison, Carly, Zach, Danny, Elizabeth, Lam, Yanwen, and Jay, each and every one of you have a place in this thesis for something you added in our many discussions. I especially want to thank my friend Kevin Baker, who not only inspired me to pursue the daunting task of two theses in the first place, but who never hesitated to reach out when he found something interesting for me to consider and never faltered to listen when I explained where my research was at.

Abstract

Applying a difference-in-differences approach, I estimate the response of log wage for medical essential workers to rising vaccine prevalence in 2021 on a national and regional scale dependent on the ability to work from home. Using CPS data coded by worker occupations and regional access to vaccines, I compare the changes in medical essential workers who can telework with those who cannot as a proxy for exposure to COVID-19 in the workplace. I apply a robust series of measurements of vaccine prevalence, considering state phase-in policy, mass vaccination, and vaccine rates. From this, I determine that increases in vaccine prevalence had no discernable impact on the wages of essential healthcare workers.

Keywords: labor economics, COVID-19 pandemic, health economics, essential workers, telework

I. Introduction

On December 11th, 2020, the Food and Drug Administration (FDA) in the United States announced that it would be granting Emergency Use Authorization (EUA) for Pfizer-BioNTech's vaccine for COVID-19 (Pfizer 2020). Subsequently, the Moderna and Johnson & Johnson vaccines obtained similar EUA grants from the FDA.

Studies at the time and throughout 2021 showed and continued to show a high effectiveness for all three vaccines at reducing risk of severe illness death from COVID-19, and in 2021 specifically, these studies demonstrated that the vaccine reduced risk of transmitting the virus to other people (Self, Tenforde, Rhoads et. al. 2021). For essential medical workers who had previously encountered an increased risk of COVID-19 exposure and thus an increased risk of severe illness and death, vaccine access and prevalence posed the possibility of changing circumstances drastically. The prospect of a safer workplace for those in the healthcare sector comes with the prospect of job conditions more attractive to workers.

However, prevalence of vaccination was not uniform by region. Data collected by Harvard University, Brown University, and the Bill & Melinda Gates Foundation as aggregated on "Track the Recovery"¹ demonstrates a wide gap between the Northeast and South. As of March 27th, 2022, across Alabama, Louisiana, and Mississippi, the average rate for adults of having one dose of a COVID-19 vaccine was 60.7%, while across Rhode Island, Massachusetts, and Connecticut, the average for the same was 96.3%.

This raises the question at the heart of this paper: to what extent did the wages of essential medical workers who cannot work from home change in response to the COVID-19

¹ This data is compiled by Opportunity Insights (2022), an organization operated at Harvard University in cooperation with Brown University as well as the Bill and Melinda Gates Foundation. For detailed graphs and data access, see: <https://www.tracktherecovery.org/>

vaccine availability nationally and regionally (specifically, in the American Northeast and South)?

Insight into this question not only informs policymakers who seek to promote future public health measures not only in terms of COVID-19, but also sheds light on the broader in relationship between public health measures and the compensation of healthcare workers. A finding that there are adverse effects on wages of healthcare workers may create a tradeoff for policymakers who would otherwise seeks to encourage public health measures, and a finding that there are no clear adverse effects may assuage those concerns.

II. Literature Review

My analysis here finds a unique place in the literature particularly through its novel contribution on the impact of COVID-19 vaccines on wages. Previous literature (among other things) considers non-wage measures of economic response to the pandemic and identifies relative risk of job loss based on occupational characteristics.

Regarding alternate economic responses to the pandemic, Anelli & Koenig (2021) examine the compensating differential created by risk from COVID-19 exposure primarily outside of wage impacts. They find a positive differential and a willingness to pay for increased workplace safety, which suggests that there is a valuation placed on decreased risk of death from COVID-19. Importantly, they identify that most of this compensation for increased risk comes in the form of nonwage benefits. However, for my analysis, this suggests that any reductions in wages from reduced risk of death identified in the data would if anything be an underestimate, suggesting that there is less reason to be concerned about benefits inflating results. In a different vein, Koebel & Pohler (2020) apply a similar kind of identification strategy to Anelli & Keonig, using a difference-in-differences approach to Canadian labor data from the Labour Force Survey

(LFS), but do so with an outcome variable of hours and instead treat “usual” hours as the control against which actual hours worked are compared. This analysis uses individual-level data, but unlike Gascon, Jackson, or Dingel & Neiman, they do not classify based on telework ability nor does it explicitly contemplate differences for medical workers. Ultimately, using their identification, they find that for the first few months of the pandemic in Canada, worker hours decreased substantially (especially at lower income quintiles), but eventually converged back to usual hours. This conclusion in particular informs my analysis here, as it would suggest that a positive wage growth in the first treatment phase would be an underestimate of the true effect (i.e. to say that lower hours worked would generally predict lower income, all else being equal).

Regarding job loss and occupational characteristics, Gascon (2020) created classifications for the 808 Occupation Employment Survey (OES) occupation codes on whether they are deemed essential, whether they can telework, and whether they are salaried or likely to be salaried. Dingel & Neiman (2020) apply a similar approach to Gascon did for an expanded set from OES that includes subsets of OES occupation codes and classifies for telework ability on that more granular axis. Dingel & Neiman’s classification allowed me up to update Gascon’s classifications to reflect occupations who were initially coded by Gascon as not being able to telework but were shown to be able to do so during the pandemic (e.g. recreational therapists). Regarding their findings, Gascon focuses on the macroeconomic implications and estimates the costs of expanding unemployment insurance based on possible actualizations of unemployment rates. Dingel & Neiman set out with a descriptive question of how many jobs can be done from home, finding that 37 percent of US jobs can be done from home and that on average, these jobs are paid more than jobs that cannot be done from home. Looking at the job characteristic of telework ability from a different angle, Jackson (2020) considers the impacts of occupation

characteristics on labor demand from a regional policy perspective. Jackson used publicly available BLS-OES data collected about categories and frequencies of jobs, and from there, applied occupations into 4 types: essential workers who cannot work from home, essential workers who can work from home, nonessential workers who can work from home, and nonessential workers who cannot work from home. This research demonstrated that in the American Northeast, the most vulnerable type of worker with respect to unemployment risk was a nonessential worker who could not work from home. Despite developing a model through which to analyze the compensation of four categories of worker in the pandemic, he only applied it to one, leaving open the research of the effect of the pandemic on essential workers who can and cannot work from home.

For this research, I answer a novel form of the question that Anelli & Koenig asked using data from Gascon but reverse it to consider the effects of reduced risk of death from vaccine prevalence instead of increased risk of death from the pandemic. In addition, I estimate the effects across the most (and least) vaccinated regions² of the United States, the Northeast and the South. I also draw on the same kind of BLS-OES occupation classifications that Jackson did, expanding the analysis to include log wages, contemplating the economic effects beyond the descriptive estimations of current state that Dingel & Neiman did. In sum, I contribute to the literature by considering the impact of vaccine access on wages, by applying difference-in-difference estimates to occupation types over a longer range, and refining existing classifications to focus on medical workers.

² Opportunity Insights (2022). <https://www.tracktherecovery.org/>

III. Data

I use data from the CPS and the "Track the Recovery" project. Drawing on CPS data prepared by IPUMS CPS, I gathered person-state-time level data on $n = 56439$ for wage-earning medical workers from 2016 to 2021, which I narrowed down to $n = 15388$ observations of data for wage-earning medical essential workers at the national level for the considered time range of 2020-2021. This includes $n = 2910$ observations at the regional level for the Northeast. Narrowed down to 2021, from February to October, there are $n = 6683$ observations at the national level, $n = 1160$ observations in the Northeast, and $n = 1450$ observations in the South. These observations include important data for controls, such as demographic data (age, race, sex, etc.) and relevant nonwage economic indicators (including hours worked per week, education, experience, etc.). To account for outliers and increase interpretability, I adjust the hourly wage data first to winsorize values above and below 99th and 1st percentiles, and then take the natural log of the adjusted wages. Turning to the "Track the Recovery" data, this project provides information on total vaccination rates for adults (both for at least one dose and full vaccination series completion), new vaccinations, as well as COVID-19 infection and death rates. These data can be analyzed at lower geographic levels (including state and county) as well as at an aggregated national level. In tandem with the CPS data, there is sufficient information to measure wages and vaccine indicators over time at both the national and regional geographic levels of analysis.

IV. Method and Estimation Strategies

The method of analysis for this project is difference-in-difference. In order to uncover the effect of prevalent vaccine use on the workers most exposed to risk from COVID-19, I compare

wage-earning essential medical workers in occupations that cannot work from home with those who can work from home in relation to three different measurements of vaccine prevalence:

1. *Phase 1B*: A dummy variable for whether the state the observation is in has at that time entered a vaccination phase past the inclusion of all essential medical workers (often referred to as “Phase 1B”). (Applied only at the regional level).
2. *Vaccine Dominance*: A dummy variable for whether 50% of the adult population at the geographic level of analysis has taken at least one dose of the COVID-19 vaccine.
3. *Vaccine Rate*: A continuous variable representing the percent of the adult population at the geographic level of analysis that has received at least one dose of the COVID-19 vaccine.

This analysis treats the changes in wages for wage-earning essential medical workers who can work from home as a counterfactual to the changes that workers who cannot work from home otherwise would have experienced. Those who cannot work from home are compared with those who can because not working from home is a proxy for increased risk of exposure to COVID-19 in the workplace. For this to be a valid counterfactual, as is standard in difference-in-difference analyses, the parallel trends assumption for all groups of comparison must be satisfied. Here, that means there must be sufficient data to suggest that the wage changes for wage-earning essential medical workers who cannot work from home have a similar slope in the “before” time frame to those can work from home. For both levels of analysis to be valid (national and regional), the assumption must hold. Initial findings suggest strong feasibility for a difference-in-differences analysis during the pandemic, both at the regional and national levels and regardless of whether wage or log wage is used as the outcome (see Figures 1 and 2). Here, I chose to analyze a winsorized log wage, which reduces the skewness of the wage distribution (see Appendix 1 and

2). In the Northeast, specifically in what I have termed for this analysis the “vaccine belt,”³ data suggests that for the majority of 2020 as well as during the first few months of 2021, there are comparable trends for those who can and cannot work from home. The same trend is observed in the American South.⁴ At the national level, similar trends are demonstrated, but there is slightly more variation in the data on those who cannot work from home.

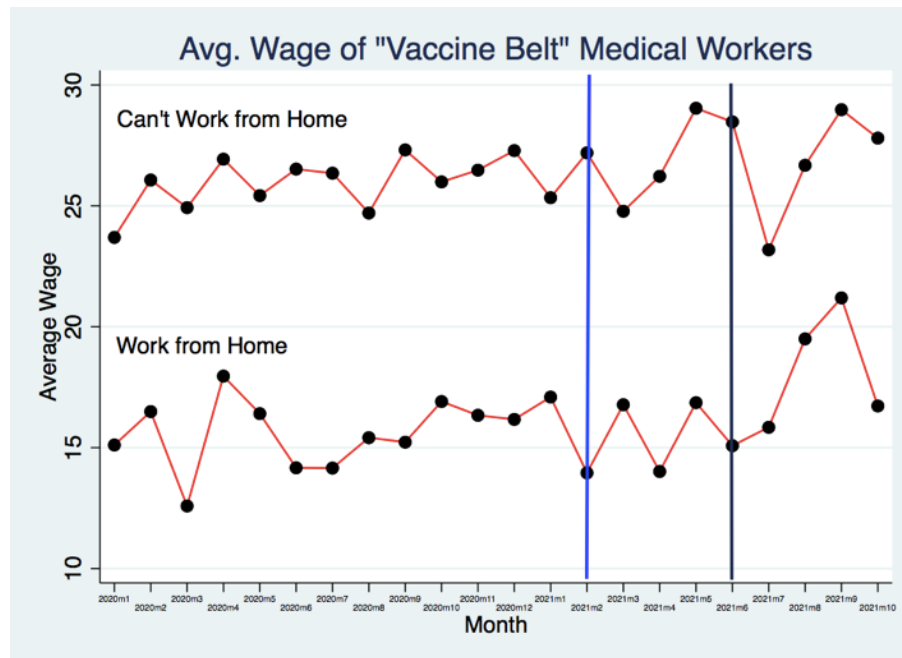


Figure 1: Average Wages Over Time in the Northeast for Essential Medical Workers Who Can and Cannot Work from Home (Jan 2020 – Oct 2021). The light blue line indicates the start of COVID vaccine data availability, and the dark blue line indicates the month where 50% of adults have taken at least one dose.

³ This term refers to a group of states in the Northeastern United States which at an early stage had at least 50% of their state’s adult population take at least one dose of the COVID-19 vaccine, and subsequently remained one of the most vaccinated regions in the US. This includes Connecticut, Delaware, Massachusetts, Maine, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont.

⁴ For this analysis, the American South includes Alabama, Louisiana, Mississippi, Florida, Georgia, Arkansas, Tennessee, Texas, Oklahoma, and Kentucky.

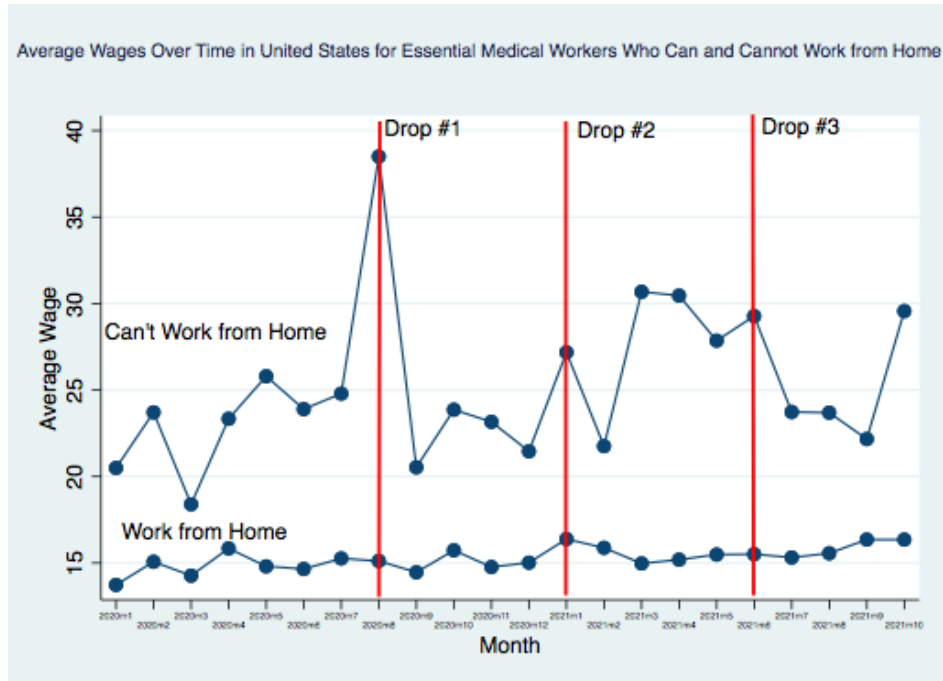


Figure 2: Average Wages Over Time in the US for Essential Medical Workers Who Can and Cannot Work from Home (Jan 2020 – Oct 2021). Each red line indicates a drop of interest in wages for those who cannot work from home.

Focusing in on each of the particular measurements for the difference-in-differences, there are strong indicators for feasibility regarding all three. First, in terms of the Phase 1B analysis, all vaccine belt states have publicly available information on when Phase 1B was initially rolled out. While the federal government’s delegation to the states in terms of how they may design their roll-out procedures creates slightly different standards and terminology in each state, every state has a stage at which it moves onto a new phase after all essential medical workers have been included in the pool of eligible vaccine recipients. Additionally, this measurement has the clear advantage over the other two in terms of its ability to target the vaccination of essential medical workers, as it contemplates a date at which their access to vaccines would be abundant, while the other two are primarily guided by general adult population indicators. Second, regarding the vaccine dominance measurement, the “Track the

Recovery” data provides a clear indicator for the precise date that the 50% rate is reached. While this date often does not line up with the 19th of the month date that the CPS is conducted, this mild imprecision is expected in monthly data. One benefit of this measurement over the other two is that it contemplates the possibility that wage responses only exist when there is a sufficient *en masse* vaccination rate in an area, which neither the policy-focused Phase 1B measurement nor the continuous nature of the vaccine rate measurement would clearly recognize. Finally, the measurement that has the most precision for connecting the CPS with the “Track the Recovery” data is the vaccine rate measurement. The continuous nature of this variable relative to the dummy variables in the other two measurements allows for more variation over time, and the daily collection of this data allows a rate to be directly attributed to the assumed 19th of the month date for CPS data collection.⁵

These three different measurements, Phase 1B, vaccine dominance, and vaccine rate, come with the following regressions⁶:

$$1) Y_{ijt} = \alpha + \beta_1 WFH_{ij} + \beta_2 Phase1B_{jt} + \beta_3 (WFH \times Phase1B_{ijt}) + \gamma X_{ijt} + \varepsilon_{ijt}$$

$$2) Y_{ijt} = \alpha + \beta_1 WFH_{ij} + \beta_2 VaccineDom_{jt} + \beta_3 (WFH \times VaccineDom_{ijt}) + \gamma X_{ijt} + \varepsilon_{ijt}$$

$$3) Y_{ijt} = \alpha + \beta_1 WFH_{ij} + \beta_2 VaccineRate_{jt} + \beta_3 (WFH \times VaccineRate_{ijt}) + \gamma X_{ijt} + \varepsilon_{ijt}$$

Collectively, these three measures of vaccine prevalence cast a wide net for identifying the effects of vaccine prevalence on wages. The first regression explicitly seeks to capture effects after essential medical workers have had sufficient access to vaccines, the second contemplates

⁵ For more information on the methodology used to collect CPS data, see the Census Bureau’s documentation: <https://www.census.gov/programs-surveys/cps/technical-documentation/methodology.html>

⁶ For the sake of clarity, Y is an outcome variable measuring the natural log of reported hourly wage, WFH is a dummy variable indicating whether the reported occupation is a job that can be done from home, $Phase1B$ and $VaccineDom$ are dummy variables indicating the measurement conditions described above, X is a vector of controls with vector γ as coefficients, and β_3 on the interaction term is the difference-in-difference estimation for the given regression. “ i ” indexes for individuals, “ j ” for states, and “ t ” for time.

the possibility of a sudden shift in response to mass vaccination in a geographic area, and the third allows for subtler responses over time.

Naturally, this research design comes with its own limitations that are worth acknowledging. While a difference-in-difference approach often has clear benefits over a before-and-after and a cross-sectional analysis (insofar as it helps account for persistent differences across groups and secular time effects), it does not permit the same randomization as that which occurs in randomized control trials. Thus, the ability to parse out causation is limited by the credibility of the parallel trends assumption and by the confidence in a lack of endogeneity or omitted variable bias. While there are no clear indicators of either endogeneity or omitted variable bias with this design, without randomization in controlled settings, it would be improper to discount them as possible sources of noise. Additionally, regarding the time range of analysis, the difficulty of disentangling wage responses to vaccine prevalence to responses to rising risk from COVID-19 variants (in this time period, largely the Delta variant) is an issue that may create noise in the analysis of the data over time, as rise in vaccinations over time corresponds to a rise in the dominance of variants. Even if it cannot be addressed by a control variable for the percent of COVID-19 cases in a state that are from the Delta variant, we should expect biases any results towards zero and thus means that significant results are an underestimate. This is because if fear of illness or death from variants increases the compensating differential for workers who cannot work from home, it would run contrary to the reduced risk of illness or death as a result of vaccination. Regardless, I include by-month case rates and death rates as controls to account for the variance that variants introduce.

Further, a common limitation of CPS data is its sample size. As discussed above, the research design involves narrowing down the scope of analysis to essential medical workers in

2021, meaning that there are fewer observations than would otherwise be preferred. Of course, this fact does not rule out drawing conclusions from the data that does exist, but it is nonetheless an important context in which to place the results.

V. Results and Interpretation

1. “Naïve” Regression

To begin to understand the mechanics of this issue, a useful place to start is with two deceptively simple questions: what is the relationship between an ability to work from home and wages of essential medical workers, and what is the relationship between a state’s rate of vaccination and wages of essential medical workers? Conducting a “naïve” regression is one way to obtain a broad (but biased) indication of what is going on with these variables. Here, these regressions suggest a strong negative relationship between an ability to work from home and the wages of this group (see Table 1). This contradicts the notion that jobs that can be done from home are higher paying on average at the very least for this particular subset of workers. Intuitively, this makes sense, as the kinds of jobs in the medical sector that can be done from home are ones that do not involve intensive surgery and command a higher pay. This result appears at both the national and regional levels.

Turning then to the simple relationship between the vaccine rate and wages, the relationship is significantly positive at the national level but not in the vaccine belt or the South. This provides contrary evidence to the hypothesis that higher rates of vaccination lead to lower wages for essential medical workers. The fact that there are differences in what is observed nationally from what is observed regionally supports the methodological decision to consider the vaccine belt and the South as regions separate from the rest of the United States.

Table 1: Naïve Regression Results of WFH Occupations and Vaccine Rates on Log Wages

	(1)	(2)	(3)	(4)	(5)	(6)
	WFH, National	WFH, Northeast	WFH, South	Vaccine Rate, National	Vaccine Rate, Northeast	Vaccine Rate, South
Coefficient	-.44120***	-.35969***	-.4513***	.00031***	.00131	.00011
	(.01964)	(.04956)	(.04077)	(.00001)	(.00094)	(.00017)
Constant	3.1162***	3.1146***	3.0510***	2.992932***	3.0041***	2.9877***
	(.00789)	(.01938)	(.01345)	(.01777)	(.04368)	(.02554)
Observations	4766	884	1450	4766	884	1450

Source: Data from Community Population Survey supplemented by Gascon (2020) occupation classifications; Track the Recovery.

*Note: Standard errors are in parentheses. Northeast includes CT, DE, MA, ME, NH, NJ, NY, PA, RI, and VT. The time frame pulls from March to September 2021. * - $p < .10$, ** - $p < .05$, *** - $p < .01$*

2. Phase 1B

There is substantial variation in the date at which different vaccine belt and Southern states started expanding vaccine access beyond essential medical workers (see Appendix 1). This variation is expected due to the federal delegation of this process to states, it may explain some inconsistency in the log of wage from Figure 1.

Difference-in-difference estimations do not suggest that essential healthcare workers who could not work from home experienced a unique change in their wages relative to those who could work from home once their state entered Phase 1B (Table 2). Rather, a state entering Phase

1B does not appear to impact the wages of its essential healthcare workers. This holds true at the national and regional levels of analysis.

Had there been massive decreases in wages for these workers once they all had the opportunity to vaccine against COVID-19, we would have expected this analysis to detect that. Instead, these results provide confidence that a state’s decision to proceed to Phase 1B in its vaccination program did not disparately impact the wages of in-person workers.

Table 2: Difference-in-Difference Analysis of “Phase 1B” on Log of Hourly Wage

	(1)	(2)	(3)
	National	Northeast	South
Work from Home	-0.562*** (0.123)	-0.506* (0.203)	-0.584*** (0.155)
Phase 1B	0.0135 (0.0346)	0.0879 (0.0732)	-0.0182 (0.0391)
WFH x Phase 1B	0.160 (0.126)	0.136 (0.207)	0.136 (0.160)
Years of College	0.00141*** (0.000195)	0.00122*** (0.000309)	0.00146*** (0.000252)
Age	0.00513*** (0.000638)	0.00339*** (0.000965)	0.00638*** (0.000849)
Female	-0.126*** (0.0249)	-0.0761* (0.0378)	-0.163*** (0.0330)
Black	-0.266*** (0.0221)	-0.262*** (0.0366)	-0.260*** (0.0276)

AAPI ⁷	0.0140 (0.0425)	-0.0125 (0.0586)	0.0408 (0.0619)
American Indian	0.0241 (0.146)	-0.0959 (0.272)	0.0181 (0.172)
New COVID Case Rate	-0.000497 (0.000507)	-0.000159 (0.00138)	-0.000556 (0.000537)
New COVID Death Rate	0.0783* (0.0323)	0.0424 (0.0833)	0.125*** (0.0360)
Constant	2.915*** (0.0497)	2.924*** (0.0925)	2.872*** (0.0613)
Observations	6203	1160	1449

Source: Data from Community Population Survey supplemented by Gascon (2020) occupation

*classifications; Track the Recovery. Note: Standard errors are in parentheses. Time frame pulls from January to October 2021. * - $p < .10$, ** - $p < .05$, *** - $p < .01$*

Additionally, a state's decision to proceed to this phase was not associated with a universal change in wages for essential medical workers at any geographic level of analysis. Most states made this decision during February to April of 2021 a period of time in which wages for essential medical workers were already declining (see Appendix 4). The subsequent rise in wages during the summer of 2021 may initially be assumed to relate to rising case and death rates associated with new COVID-19 variants, but outside of the South (a less vaccinated region), the death rate was hardly a significant predictor of wages.

⁷ In this context, "AAPI" stands for Asian American and Pacific Islander.

3. Vaccine Dominance

Conducting a similar difference-in-difference analysis using the vaccine dominance measurement produces similar results to Phase 1B (Table 3). On the one hand, these results re-affirm the above hypothesis that achieving vaccine prevalence does not significantly, disparately, and immediately reduce the wages of in-person essential healthcare workers. However, unlike the above results, they introduce the first negative coefficients on the difference-in-difference estimators.

The results at the national level and in the South are statistically the same as 0, and do not present any significant evidence that a population having more than 50% of its members vaccinated against COVID-19 reduces its in-person workers wages. These results do detect a generally significant, positive coefficient for the new COVID death rate, which may encourage future research into the possibility that a rise in deadlier COVID-19 variants are increasing wages of healthcare workers.

Table 3: Difference-in-Difference Analysis of “Vaccine Dominance” on Log of Hourly Wage

	(1)	(2)	(3)
	National	Northeast	South
Work from Home	-0.448*** (0.0210)	-0.437*** (0.0510)	-0.447*** (0.0516)
Post-Vaccine Dominance	0.0232 (0.0143)	-0.0303 (0.0320)	-0.0262 (0.0310)
WFH x PVD	-0.0197 (0.0319)	0.146 (0.0782)	-0.0216 (0.0769)
Years of College	0.00151***	0.00119***	0.00147***

	(0.000124)	(0.000308)	(0.000252)
Age	0.00518***	0.00345***	0.00640***
	(0.000408)	(0.000964)	(0.000849)
Female	-0.104***	-0.0793*	-0.163***
	(0.0156)	(0.0378)	(0.0330)
Black	-0.247***	-0.254***	-0.260***
	(0.0162)	(0.0365)	(0.0276)
AAPI	0.0703**	-0.00640	0.0404
	(0.0231)	(0.0585)	(0.0619)
American Indian	0.0737	-0.0763	0.0168
	(0.0575)	(0.272)	(0.172)
New COVID Case Rate	-0.000498	0.000217	-0.000313
	(0.000385)	(0.00139)	(0.000603)
New COVID Death Rate	0.0487*	-0.00211	0.132***
	(0.0217)	(0.0849)	(0.0354)
Constant	2.924***	3.025***	2.856***
	(0.0242)	(0.0643)	(0.0505)
Observations	6180	1160	1449

Source: Data from Community Population Survey supplemented by Gascon (2020) occupation

classifications; Track the Recovery. Note: Standard errors are in parentheses. Time frame pulls from

*January to October 2021. * - $p < .10$, ** - $p < .05$, *** - $p < .01$*

For the sake of checking robustness, the same regression was conducted for alternate time ranges within 2021 (see Appendix 5). No significant results were produced either.

4. Vaccine Rate

Finally, a difference-in-difference estimation which uses the vaccine rate as its measurement of vaccine prevalence does not detect any significant relationship (see Table 5). This result should be particularly telling because it includes greater variance in the extent to which the population has been vaccinated. In all levels of analysis, there was a positive (but not significant) relationship between the difference-in-difference estimator and wages. Additionally, this result is robust to the use of either first-dose or full vaccination as the measurement of vaccine rate.

The fact that this result is consistent across national and regional levels is surprising given regional diversity in the United States. In the context of the COVID-19 vaccine, this is especially noteworthy, as there has been a documented difference in vaccination rate by party affiliation (Kates, Tolbert, & Rouw 2022). These results suggest that on the pure metric of vaccination rate, focusing on a particular region does not create a significant relationship between vaccine rate and the relative wages of in-person essential medical workers and virtual workers.

Table 4: Difference-in-Difference Analysis of Vaccine Rate on Log of Hourly Wage

	(1)	(2)	(3)
	National	Northeast	South
Work from Home	-.4611*** (.0325)	-0.426*** (0.0851)	-0.505*** (0.0785)
Vaccine Rate	.00025*** (.00007)	0.000294 (0.000175)	-0.000191 (0.000175)

WFH x Vaccine Rate	.00002	0.000263	0.000371
	(.0002)	(0.000371)	(0.000528)
Years of College	.0015***	0.00119***	0.00147***
	(.0004)	(0.000308)	(0.000252)
Age	.00512***	0.00343***	0.00640***
	(.00041)	(0.000962)	(0.000849)
Female	-.10344***	-0.0759*	-0.162***
	(.0156)	(0.0378)	(0.0330)
Black	-.24659***	-0.259***	-0.261***
	(.01620)	(0.0365)	(0.0277)
AAPI	.06512***	-0.00707	0.0418
	(.02311)	(0.0585)	(0.0619)
American Indian	-.07666	-0.0912	0.0222
	(.05745)	(0.272)	(0.172)
New COVID Case Rate	-.00063*	0.00009	-0.00043
	(.00036)	(0.00136)	(0.00055)
New COVID Death Rate	.068***	0.110	0.131***
	(.00036)	(0.0947)	(0.0354)
Constant	2.8937***	2.925***	2.873***
	(.02611)	(0.0781)	(0.0527)
Observations	6180	1160	1449

Source: Data from Community Population Survey supplemented by Gascon (2020) occupation

classifications; Track the Recovery.

*Note: Standard errors are in parentheses. Time frame pulls from January to October 2021. * - $p < .10$, ***

*- $p < .05$, *** - $p < .01$*

It is also important to note that while the significant and positive relationship between vaccine rate and wages on the national level appears here, this should not be interpreted as evidence that having a higher vaccine rate *causes* higher wages. It is just as plausible that the reverse is true, that being paid more corresponds with being in an area more likely to be vaccinated.

VI. Conclusions

Ultimately, the analysis did not reveal a persistent significant relationship between vaccine prevalence and the wages of essential medical workers who cannot work from home (see Table 5). While vaccine rate itself had a significant positive relationship with wages on a national scale, this did not bear out when interacting that variable with Work From Home status. Thus, the appropriate conclusion to reach is that the data does not currently allow us to rule out the null hypothesis. Put succinctly, we cannot conclude that vaccine prevalence negatively or positively impacted the wages of essential medical workers.

Table 5: Summary of Relationships Found

	Phase 1B	Vaccine Dominance	Vaccine Rate
National	Positive, not significant	Positive, not significant	Positive, not significant
Northeast	Positive, not significant	Negative, not significant	Positive, not significant
South	Positive, not significant	Negative, not significant	Positive, not significant

The quality and variety of the difference-in-difference estimators should provide confidence in these results. However, there would be greater limitations associated with a single-difference estimation strategy. If there were decreased confidence in the applicability of the

difference-in-difference estimators, the results contained herein could be biased away from a negative relationship between the log of wages and vaccine prevalence because of a number of factors the data cannot currently account for. First, it is likely that a relaxation of pandemic-related rules that goes in tandem with vaccination status increased public desire for elective medical procedures. To the extent that these procedures are more lucrative for medical workers, that could have increased demand for their services and counterbalanced wage decreases that would result from increased vaccination. However, not only would we expect this desire to rise and fall with fear of COVID (making case rates an effective control), the difference-in-difference estimation strategy provides reasonable confidence that this trend would affect both the work from home and the non-work from home groups equally.

Future research (if data becomes available) should attempt to control for additional factors that might increase or decrease the demand for or supply of medical labor. This includes, but is not limited to, average reported fear of COVID-19, disease rates, crime rates, and the price of inputs to medical labor. If researchers contemplate other labor sectors (particularly groups of non-medical essential workers), the relevant factors that impact demand for those services ought to also be accounted for. Additionally, with the introduction of boosters, researchers should consider whether access to boosters for essential medical workers plays a role in any wage changes. While COVID-19 may not affect all of our lives the same way it did from March 2020 to March 2022, future researchers will be presented the opportunity and challenge of assessing the relationship between COVID-19 vaccines and the compensation of the workers responsible for combatting the virus.

References

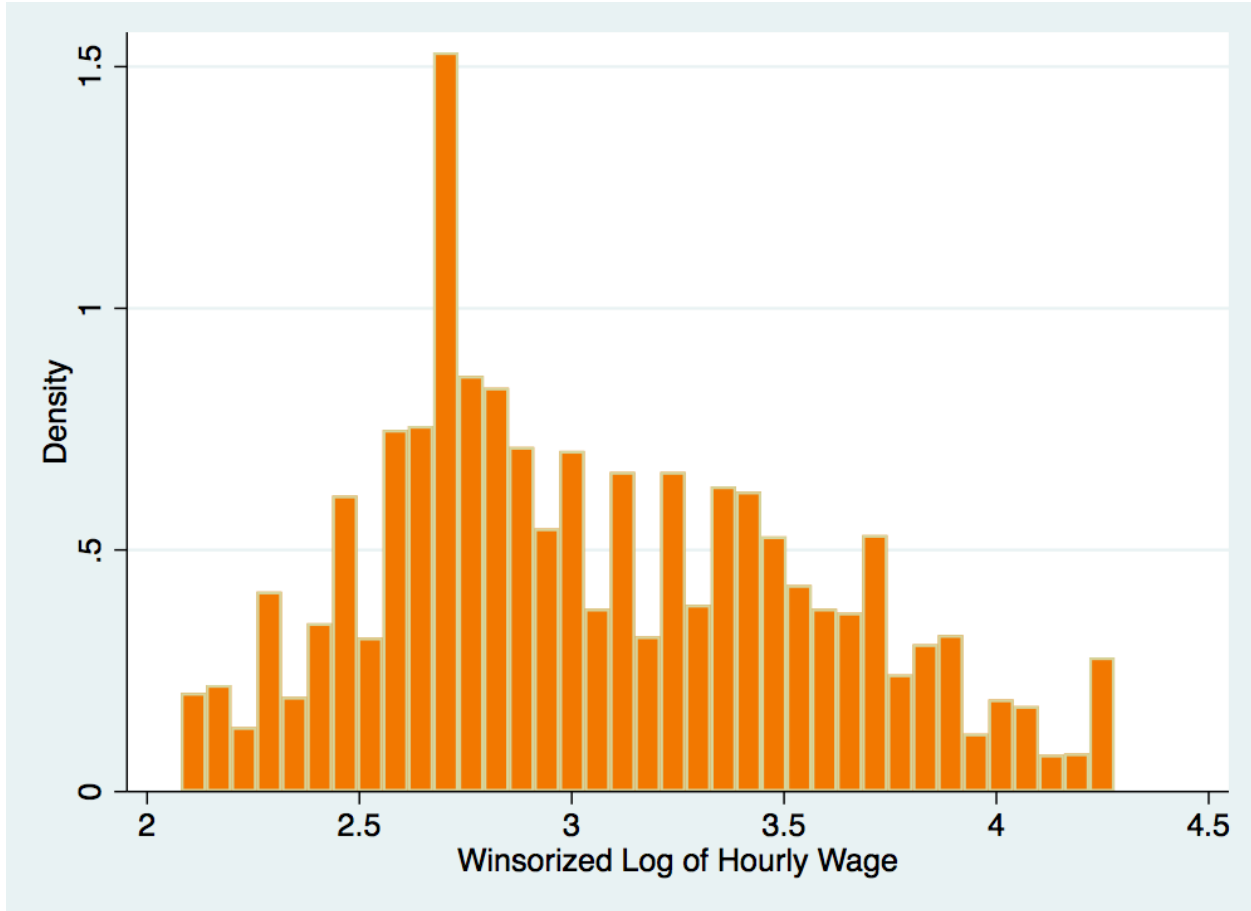
- Anelli, M. & Koenig, F. (2021). Willingness to Pay for Workplace Safety. *National Bureau of Economic Research*.
- Dingel, J. & Neiman, B. (2020). How Many Jobs Can be Done at Home? *Becker Friedman Institute*.
- Gascon, C. (2020). COVID-19: Which Workers Face the Highest Unemployment Risk? *Federal Reserve Bank of St. Louis*.
- Jackson, O. (2020). An Approach to Predicting Regional Labor Market Effects of Economic Shocks: The COVID-19 Pandemic in New England. *Federal Reserve Bank of Boston Current Policy Series*.
- Kates, J., Tolbert, J., & Rouw, A. (2022, Jan. 19). The Red/Blue Divide in COVID-19 Vaccination Rates Continues: An Update. *Kaiser Family Foundation Policy Watch*.
- Koebel, K., & Pohler, D. (2020, Oct. 1). Labor Markets in Crisis: The Double Liability of Low-Wage Work During COVID-19. *Industrial Relations*, 59(4), 503 - 531.
- Pfizer (2020, Dec. 11). Pfizer and BioNTech Celebrate Historic First Authorization in the U.S. of Vaccine to Prevent COVID-19. *Pfizer*.
- Self, W., Tenforde, M., Rhoads, J., et al (2021, Sep. 1). Comparative Effectiveness of Moderna, Pfizer-BioNTech, and Janssen (Johnson & Johnson) Vaccines in Preventing COVID-19 Hospitalizations Among Adults Without Immunocompromising Conditions — United States, March–August 2021. *MMWR Morb Mortal Wkly Rep* 2021.

Appendices

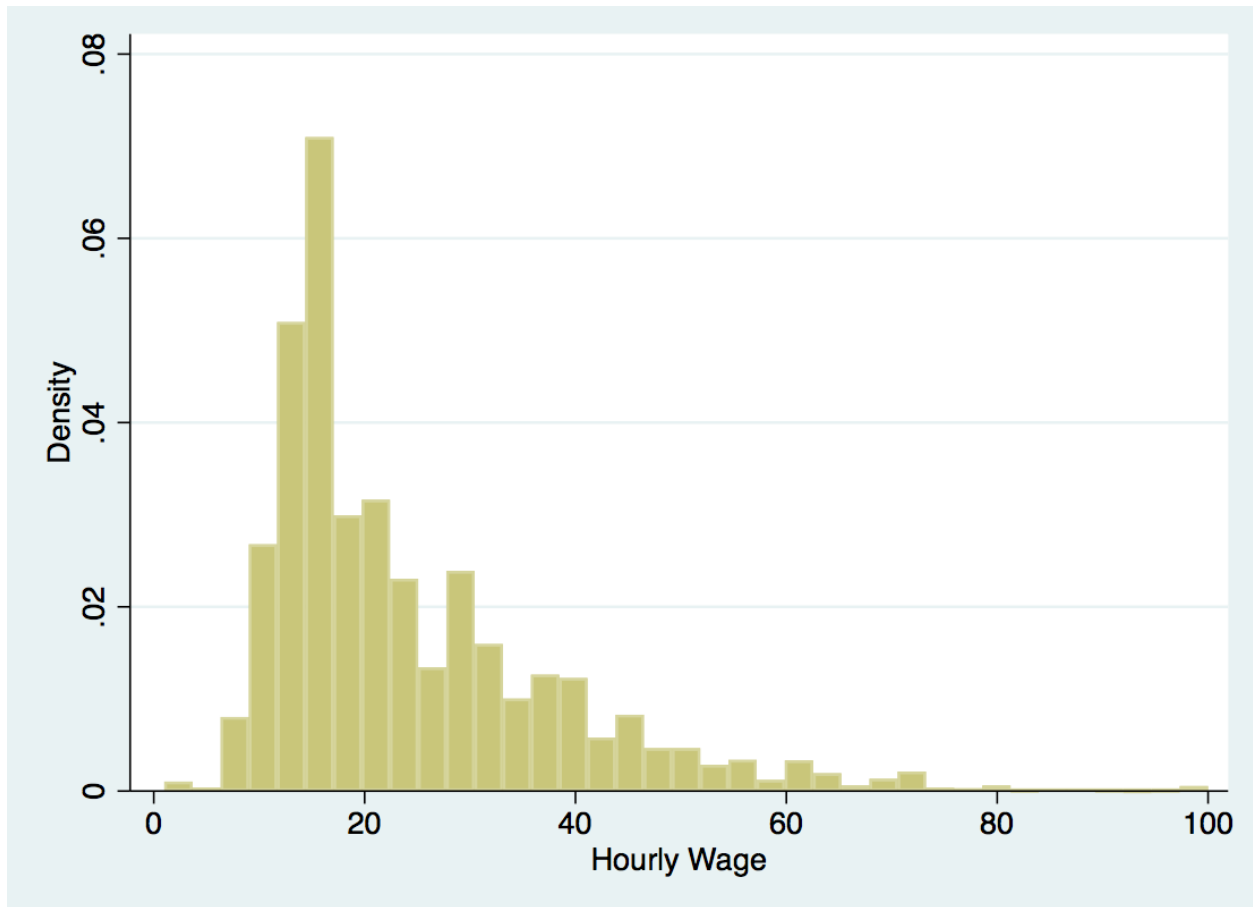
Appendix 1: “Phase 1B” Timeline Across Vaccine Belt and South

	<i>Date of Phase</i>	<i>Source</i>
<i>Connecticut</i>	Jan. 18, 2021	Multistate.us
<i>Delaware</i>	Jan. 19, 2021	Multistate.us
<i>Massachusetts</i>	Feb. 1, 2021	Mass.gov
<i>Maine</i>	Jan. 19, 2021	Maine.gov
<i>New Hampshire</i>	Feb. 5, 2021	DHHS.NH.gov
<i>New Jersey</i>	Jan. 14, 2021	State.NJ.US
<i>New York</i>	Jan. 18, 2021	Governor.NY.gov
<i>Pennsylvania</i>	Apr. 4, 2021	Health.PA.gov
<i>Rhode Island</i>	Feb. 18, 2021	Multistate.us
<i>Vermont</i>	Mar. 8, 2021	Governor.Vermont.gov
<i>Alabama</i>	Mar. 22, 2021	governor.alabama.gov
<i>Arkansas</i>	Feb. 23, 2021	Multistate.us
<i>Florida</i>	Mar. 22, 2021	FloridaHealthCovid19.gov
<i>Georgia</i>	Mar. 15, 2021	DPH.Georgia.gov
<i>Kentucky</i>	Feb. 1, 2021	Kentucky.gov
<i>Louisiana</i>	Mar. 22, 2021	Multistate.us
<i>Mississippi</i>	Jan, 2021	Multistate.us
<i>Oklahoma</i>	Feb. 22, 2021	Multistate.us
<i>Tennessee</i>	Feb. 22, 2021	Newschannel5.com
<i>Texas</i>	Dec. 28, 2020	Multistate.us

Appendix 2: Histogram of Winsorized Log of Hourly Wage



Appendix 3: Histogram of Hourly Wage



Appendix 4: Average Log of Winsorized Wage Over Time



Appendix 5: Robustness Check for National Vaccine Dominance

Time Range	Results
January to October 2021 (original)	Negative, not significant
March to August 2021	Positive, not significant
April to July 2021	Negative, not significant
January to August 2021	Negative, not significant