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-The Editors-in-Chief

Thriving or Surviving? Examining the Effects of Self-Employment on Mental Health During the COVID-19 Pandemic*

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Abstract

The COVID-19 pandemic brought turbulent changes in both the labor market and individuals' mental well-being. This study investigates how self-employment affects workers' mental health by analyzing pandemic-period data, with a special focus on the ending of the Pandemic Unemployment Assistance (PUA). One major finding is self-employed individuals experienced slightly more mental distress during the COVID-19 pandemic in comparison to employees, controlling for various factors. Furthermore, married self-employed individuals exhibited lower psychological distress compared to their unmarried counterparts. By utilizing triple difference models, we find the ending of PUA had negative impacts on the mental health of both self-employed workers and employees, but the negative impact was unexpectedly more pronounced among employees.

I. Introduction

Mention of the COVID-19 pandemic may evoke memories of a time marked by lockdowns, business closures, and numerous uncertainties. Constant concerns about infection, lack of social activities, and financial instability collectively contribute to pervasive mental distress and anxiety. The COVID-19 pandemic has brought the critical issue of mental health to the forefront. The World Health Organization reported an increase of 25% in the global prevalence of anxiety and depression in the first year of the COVID-19 pandemic (World Health Organization 2022). The pervasive

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mental health challenges may be interconnected with significant employment crises induced by the COVID-19 pandemic (de Miquel et al. 2022, Smith and Edwards 2021). To reduce financial stress, a growing number of individuals sought alternative ways of earning a living and shifted to self-employment during the pandemic. In the US, the share of self-employed workers in the labor force had an increase of approximately 0.4 percentage points from February 2020 to August 2020 (Gregory et al. 2023).

In light of the COVID-19 pandemic, which has witnessed an upsurge in self-employment and concurrent mental health challenges, there exists a compelling need to explore the nature and extent of their correlation. Therefore, this paper contributes to the investigation of the impacts of self-employment on mental health during the COVID-19 pandemic. Our approach to this research question builds upon previous research that utilizes the difference-in-difference model to examine the impact of self-employment and pandemic unemployment insurance on individuals' mental health. Taking a step further, we analyze the issue by utilizing a simple OLS model, an OLS model with a moderating variable, an unweighted triple difference model, and a triple difference model with inverse propensity weighting (IPW). Especially, by introducing IPW to the triple difference model, our study balances observed characteristics between self-employed and employee groups and thus meets the parallel trend assumption, a facet that has been previously overlooked in the literature.

Existing literature on the mental health outcomes of self-employment has yielded diverse and inconsistent conclusions. For example, Zhou et al. (2023) suggest that self-employment significantly decreases the tendency of depression among the younger elderly aged 60–69, whereas Parslow et al. (2004) argue that self-employment has no positive impact on mental health for either females or males. Furthermore, most of the relevant past research was conducted before the COVID-19 pandemic. We believe the COVID-19 pandemic presents a distinctive context for this issue considering its impacts on self-employment and mental health. Therefore, given the inconsistency of previous studies, our study uses the more recent 2021 Household Pulse Survey dataset from the pandemic period in an attempt to get up-to-date insights and reconcile the existing conflicts.

By utilizing econometrics models and techniques, we find statistically significant evidence that self-employed workers tend to experience slightly more mental distress than employees during the pandemic. Additionally, our OLS model with marital status as a moderating variable offers deeper insights into group differences. We discover that the negative impact on the mental well-being of married individuals is smaller compared to their unmarried counterparts. In addition, we get unexpected results from analyzing the impact of ending Pandemic Unemployment Assistance (PUA) on workers' mental health. Both weighted and unweighted triple difference models show that mental distress increases among both self-employed workers and employees after the end of

PUA, but the increase is unexpectedly greater among employees, who were not the primary target of the PUA.

Our research paper is organized as follows. Section II reviews past literature on mental health outcomes of self-employment and provides background about the COVID-19 pandemic and the Pandemic Unemployment Assistance (PUA). Section III provides an overview of our dataset, key variables of interest, the termination of the PUA policy, and summary statistics. Section IV exhibits four empirical models and corresponding results: a simple OLS model, an OLS model with a moderating variable, and triple difference models with and without inverse propensity weighting. Section V presents the conclusion of the research and outlines possible insights for researchers and policymakers.

II. Literature Review and Background

2.1 Self-Employment and Mental Health

In the past decades, the rise of self-employment has shifted the structure of the economy from the traditional sectors to new industries (Audretsch and Thurik 2000). A self-employed person, unlike an employee who works for someone else, independently takes control of his/her own business and is fully responsible for all decisions made by the organizational unit (Bjuggren et al. 2012). Due to the differences in the underlying characteristics of job control and job demands between self-employment and traditional employment, these two forms of employment are expected to lead to different health outcomes. Past research suggests that compared to employees, the self-employed usually have better physical health outcomes, such as lower blood pressure, lower somatic morbidity, and lower prevalence rates of hypertension (Stephan and Roesler 2010). The differences in mental health outcomes, however, have received less attention in the literature compared with physical health, and the existing literature presents conflicting findings.

Research evidence from various countries and region reveal significant positive effects of self-employment on mental health. In China, Zhou et al. (2023) discover that self-employment significantly decreases depression tendencies among the younger elderly aged 60–69 through mechanisms of income growth effect and self-worth realization effect. In Germany, Nikolova (2019) finds the health effects of self-employment vary by the type of entrepreneurship. Relying on the Job Demand-Control model, Nikolova investigates the physical and mental health consequences of two types of self-employment: necessity entrepreneurship and opportunity entrepreneurship. He uses the difference-in-differences (DID) method after entropy balancing and finds that the necessity entrepreneurs experience improvements in their mental health but not in their physical health, while opportunity entrepreneurs experience gains in both physical and mental health. However, this study fails to take unobservable time-variant variables into account, and we adapt time-fixed effects in our model to deal with the problem.

Meanwhile, research by Stephan et al. (2020) in the United Kingdom finds that the impact on mental health changes over the course of self-employment. Using the Stressor-Strain Outcome model as their theoretical model, they apply pooled OLS regression, fixed effects regression, and the difference-in-difference models to investigate the physical and mental health effects of self-employment and test whether these health effects are due to enhanced stress and whether they differ between men and women. The results suggest that those with poorer mental health are more likely to self-select into self-employment. Compared to those who stay in paid employment, self-employed males but not self-employed women experience an initial boost in mental health at the early stage of self-employment due to reduced work-related strain, but the positive effects revert to pre-self-employment levels over the long term (four years). However, they find no relationship between self-employment and physical health.

Other research, however, displays little or no effects of self-employment on mental health. Tuttle and Garr (2009) in their analysis, point out that self-employment has no direct influence on the mental health of female workers. Parslow et al. (2004) even conclude that self-employment has no positive associations with mental health for men and women. Given the contradicted evidence and lingering debate in the literature, our study aims to reconcile the conflicting points of view and add evidence in the context of the United States during the pandemic.

2.2 COVID-19 and PUA

As a result of the COVID-19 pandemic, the working mode, mental health, and unemployment insurance have undergone significant changes, making the problem of self-employment and mental health even more complicated. During the pandemic, the US federal government implemented unprecedented unemployment benefits, including Pandemic Emergency Unemployment Compensation (PEUC), Pandemic Unemployment Assistance (PUA), FPUC (Federal Pandemic Unemployment Compensation), and Mixed Earner Unemployment Compensation (MEUC). The policy our research focuses on is the Pandemic Unemployment Assistance (PUA), enacted in March 2020 by President Trump signing into law the Coronavirus Aid, Relief, and Economic Security (CARES) Act. It targeted people who were unable to work as a direct result of COVID-19 and were not eligible for regular state unemployment benefits, such as independent contractors or self-employed workers. PUA provided up to 39 weeks of retroactive payments to qualifying individuals for weeks of unemployment, partial employment, or inability to work due to COVID-19 reasons starting on or after January 27, 2020, till December 31, 2020 (U.S. Department of Labor nd). In December

2020, President Trump signed the Consolidated Appropriations Act of 2021 to revive PUA through March 2021, and President Biden subsequently signed the American Rescue Plan in March 2021 to further extend PUA through September 6, 2021 (Holzer et al. 2021). However, during the validity period of PUA, many states opted out successively due to the strengthening labor markets and concern by businesses about "worker shortages." For instance, eight states opted out of PUA in June 2021 and two other states opted out of PUA in July 2021. Indiana and Maryland attempted to opt out but were forced by the court to continue paying PUA benefits. Twenty-four states and the District of Columbia did not terminate PUA until September 2021 (Congressional Research Service (2021)).

Recent research demonstrates the ambiguous effects of early termination of unemployment benefit programs like PUA and FDUC on employment and mental health. Coombs et al. (2022) suggest that the early termination of pandemic unemployment insurance leads to more job opportunities and increased earnings for beneficiaries. However, these additional job opportunities would have materialized a few months later even without the premature termination. Berkowitz and Basu (2021) find that the termination of FDUC leads to an increased risk for food insufficiency, depressive symptoms, and anxiety symptoms. Thus, given the contradicted evidence from the literature about self-employment and mental illness and the complications of the labor market and mental health resulting from the COVID-19 pandemic, it is worthwhile to use the up-to-date dataset and reliable methods to investigate what are the impacts of self-employment on mental health during the pandemic.

III. Data Description

3.1 Dataset Overview

The primary data source for this study is the Household Pulse Survey (HPS), which is a collaborative effort between the National Center for Health Statistics (NCHS) and the U.S. Census Bureau. This partnership of multiple federal agencies ensures the reliability of the data. The HPS contains data on participants' employment statuses, psychological distress levels, genders, ages, educational levels, races, information related to participants' households, etc. Data collection took place during the coronavirus pandemic, commencing on April 23, 2020. The purpose of the survey was to offer relevant information about the influence of COVID-19 in the U.S. and the impact of the government's COVID-19-related programs, hence appropriate for the purpose of our study. This survey recruited participants from different household units and diverse demographic groups, including different age groups, races, and educational levels, and thus national representative.

Our dataset has originally 781,861 observations. We constrain our sample to workers only, which includes self-employed workers and employees while excluding unemployed individuals. After applying the constraint, the number of observations in our dataset is reduced to 569,531. As a result, our dataset specifically focuses on workers with normal working age, spanning from age 18 to 64. Note that our dataset covers a one-year period from January to December 2021, with the exception of November for which data originally is missing.

It is essential to acknowledge a few limitations of our dataset. The dataset is based on self-reported questionnaires and the questionnaire was designed relatively quickly compared to other federal statistical surveys, which could lead to potential weaknesses in reliability and validity (Centers for Disease Control and Prevention 2023). Also, bias can arise due to the misunderstanding of the questions or the inaccurate responses by participants, and some individuals who did not provide identifiable contact information are not included in the dataset. Additionally, respondents who chose not to disclose their mental health status or failed to answer all questions were excluded.

3.2 Construction and Interpretation of Primary Variables

The treatment variable of this study is self-employment, which equals 1 if the individual is self-employed and equals 0 if the individual is an employee. This binary indicator is generated based on the original variable, the sector of employment, in our dataset. The sector of employment is categorized into 6 groups: government, private company, non-profit organization, self-employed, family business, and not employed. As mentioned, we first exclude the unemployed individuals since they are not subjects of this study. We label self-employment as 0 when the individual's employment sector is in government, private firms, nonprofit organizations, and family businesses, and as 1 when the employment sector is self-employment.

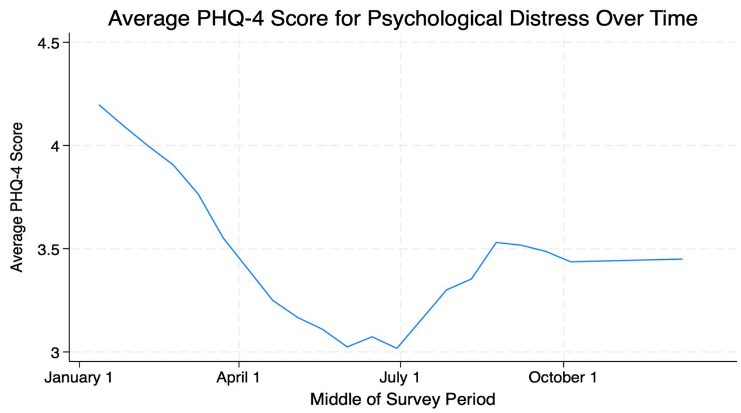
The continuous dependent variable is the PHQ-4 score for psychological distress, which is measured with the four-item patient health questionnaire for anxiety and depression. Each of the four items takes a score from 0 to 3, from least to most mental distress. By adding up the scores of the four items corresponding to participants' responses, we get a total PHQ-4 score, which has a maximum of 12 with a higher score representing more severe psychological distress. Getting a total score of 0-2 is viewed as normal, 3-5 as mildly depressed/anxious, 6-8 as moderately depressed/anxious, and 9-12 as severely depressed/anxious.

3.3 Trends in the Dependent Variable PHQ-4 Score

The following figure shows the average PHQ-4 score of workers over time in 2021. The average PHQ-4 score exhibits a notable decline from January to June, decreasing from approximately 4.2 to 3. Then, it shows a somewhat fluctuating pattern with a minor initial increase and a subsequent decrease until July. Thereafter, a distinct rise in the average PHQ-4 score is observed. The average

PHQ-4 score increases from 3 to 3.5 between July and late August, which aligns with the time some states ended PUA. Although a slight drop occurs afterward, the average PHQ-4 score stabilizes after October.

Figure 1: Average PHQ-4 Score for Psychological Distress Over Time



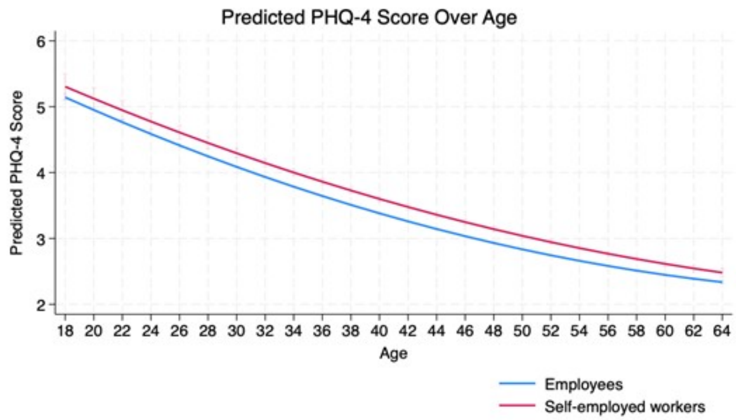
Notes: The figure illustrates the average PHQ-4 score among all workers over time in 2021. The horizontal axis represents the middle of the survey period, which are the dates in 2021. The calculation is made by getting the average PHQ-4 score at each midpoint of a survey period.

Figure 2 shows the downward trend of predicted PHQ-4 scores for both self-employed workers and employees over the working age range of 18 to 64, which suggests a decrease in depressive and anxiety symptoms as age increases. Both groups exhibit similar trends with a gradual flattening effect as age increases, which suggests the rates of change of predicted PHQ-4 scores decrease when age increases for self-employed individuals and employees. Notably, the curve for self-employed workers is always above the curve for employees, indicating self-employed individuals' higher mental distress than employees throughout the working age range. Also, as age progresses, the disparity in predicted PHQ-4 scores between groups widens slightly first but begins to narrow after around the age of 52.

3.4 Overview of PUA Termination

As mentioned in the literature review, the policy of interest in this study is the Pandemic Unemployment Assistance (PUA), which expanded the eligibility for unemployment benefits to self-employed workers. All states enacted the PUA in March 2020 according to the Coronavirus Aid, Relief, and Economic Security (CARES) Act, and it was extended by President Trump and President Biden to September 6, 2021. However, many states terminated the PUA prior to its expiration due to economic concerns. Iowa, Mississippi, and Missouri ended their PUA on June 12, 2021; Alabama, Idaho, and Indiana ended their PUA on June 19; Arkansas, Georgia, and Montana ended

Figure 2: Predicted PHQ-4 Score Over Age



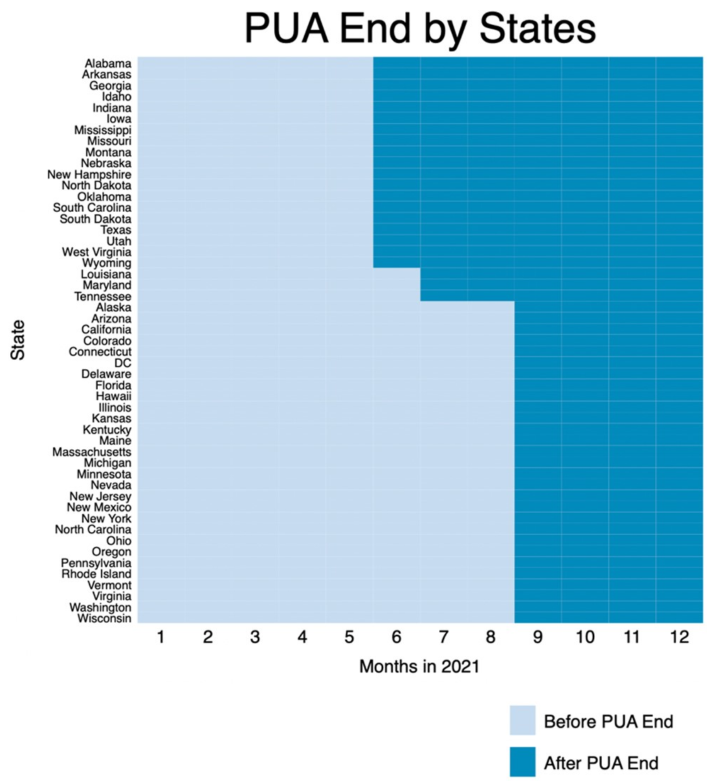
Notes: The figure illustrates the predicted PHQ-4 score over the working age range of 18 to 64 for employees and self-employed workers. The prediction is made by regressing the PHQ-4 score over age and age squared. The horizontal axis represents the age of the individual.

their PUA on June 26; Maryland and Tennessee ended their PUA on July 3; Louisiana ended its PUA on July 31. Other states such as Alaska and Arizona, continued the PUA until its expiration in September 2021.

Figure 3 shows the timeline of PUA programs across states. From the beginning of 2021 to May 2021, all states offered PUA. In June 2021, the first batch of nearly 20 states terminated PUA programs. Subsequently, in July, three more states opted out. The rest of the states continued PUA until its expiration in September 2021.

Figure 4 shows the distribution of PUA (Pandemic Unemployment Assistance) ending dates across states in the mainland U.S. There are six distinct PUA ending dates: June 12, 2021; June 19, 2021; June 26, 2021; July 3, 2021; July 31, 2021; and September 4, 2021. The shading on the map corresponds to the end dates of the PUA program, with darker shades indicating later end dates and paler shades representing earlier end dates. Overall, the map reveals that most states ended their PUA programs either in June or September, with only a few choosing to end their PUA programs in July. Although some exceptions exist, most states near the eastern and western coasts of the U.S. such as California and North Carolina tended to stick to PUA until its expiration in September. States in the central region like South Dakota, however, generally early terminated PUA in July or June. Another noteworthy observation is the tendency of neighboring or adjacent states to end their PUA programs on similar or closely aligned dates. For instance, both Iowa and Missouri ended their PUA programs on June 12, 2021, while both Idaho and Wyoming ended theirs on June 19.

Figure 3: Month of PUA End by States in 2021

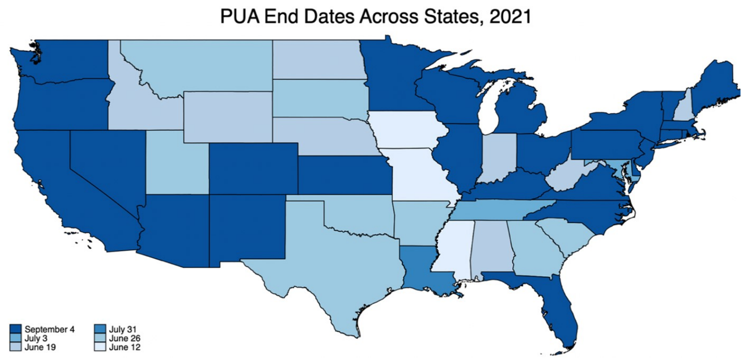


Notes: The figure illustrates the month of PUA end for each state in 2021. The horizontal axis represents months in 2021(i.e.:1 indicates the first month in 2021, which is January). The figure is created based on PUA end months, rather than exact dates. Therefore, if the program ended on any day in June, June and months after June are considered "After PUA Ends" while May and months before May are considered "Before PUA Ends."

3.5 Summary Statistics

Table 1 shows the summary statistics of all continuous variables used in our estimations. We observe that workers in our sample have an average age of 45.437 and an average distress score of 3.185, which reflects mild depression and anxiety. Also, the average new daily confirmed COVID cases per 100,000 is 185.057. Table 2 shows summary statistics of all categorical variables. Especially, we observe that 89.49% of our sample are self-employed and 10.51% of the sample are employees.

Figure 4: PUA End Dates Across States in 2021



Notes: The figure illustrates PUA end dates across different states in the U.S. mainland in 2021

Table 1: Summary Statistics of Continuous Variables

variables	**Mean**	**SD**
PHQ-4 score	3.185	3.463
Age	45.437	11.191
New Daily Confirmed COVID Cases	185.057	157.596

Notes: The table shows summary statistics for all continuous variables used in the estimation. Number of observations for each variable is 569,531. New daily confirmed COVID cases refers to new cases per 100,000 people over the past 7 days. Table 16 for variable description is attached in the Appendix.

Table 2: Summary Statistics of Categorical Variables

VARIABLES	**Categories**	**%**
Self-employment	Self-employed	89.49
	Employee	10.51
End of PUA	PUA not end	73.24
	PUA end	26.76
Married	No	39.78
	Yes	60.22
Gender	Male	41.24
	Female	58.76
Race	White	81.64

Continued on next page

Table 2 – Continued from previous page

VARIABLES	**Categories**	**%**
	Black	7.39
	Asian	6.16
	Other/mixed	4.8
Hispanic	Non-Hispanic	90.29
	Hispanic	9.71
Aggregated educational attainment	Less than high school	1.11
	High school degree	36.88
	Bachelor's degree	32.81
	Graduate degree	29.2
Total household income	Less than $25,000	5.14
	$25,000 - $34,999	5.79
	$35,000 - $49,999	8.2
	$50,000 - $74,999	14.87
	$75,000 - $99,999	13.69
	$100,000 - $149,999	19.76
	$150,000 - $199,999	10.39
	$200,000 and above	12.86
	Not reported	9.29

Notes: The table shows summary statistics for all categorical variables used in the estimation. Number of observations for each variable is 569,531. Total household income refers to the income in the previous year before tax deductions. Table 16 for variable description is attached in the Appendix.

Table 3 and Table 4 present the summary statistics of categorical and continuous variables categorized by employment groups before and after the end of PUA, respectively. Table 3 shows that self-employed workers are slightly elder than employees on average. According to the trend of the PHQ-4 score shown in Figure 2, elder people tend to experience less mental distress than younger people. However, the mean of the PHQ-4 scores for self-employed workers is higher than that for employees before the end of PUA, but the mean for self-employed workers becomes lower than that for employees after the end of PUA. This contradiction to our expectation that PUA alleviates the mental distress of the self-employed might be explained by the changes in other policies that happened at the same time, like the ending of the Federal Pandemic Unemployment Compensation (FPUC). Table 4 shows that our sample contains more married than unmarried, more female than male, and more white than other races among all self-employed workers and employees surveyed both before and after the end of PUA.

Table 3: Summary Statistics for Continuous Variables by Employment Groups, Before PUA Ended

	Self-employed			**Employee**		
	N	Mean	SD	N	Mean	SD
PHQ-4 score	43,139	3.211	3.512	372,998	3.187	3.463
Age	43,139	48.734	10.505	372,998	45.251	11.121
New Daily Cases	43,139	152.686	144.481	372,998	154.16	143.812

Summary Statistics for Continuous Variables by Employment Groups, After PUA Ended

	Self-employed			**Employee**		
	N	Mean	SD	N	Mean	SD
PHQ-4 score	16,705	3.125	3.487	136,689	3.179	3.445
Age	16,705	48.178	10.733	136,689	44.568	11.412
New Daily Cases	16,705	269.717	162.325	136,689	269.239	162.301

Notes: The tables shows summary statistics for all continuous variables used in the estimation for both self-employed workers and employees surveyed before and after the end of PUA. N refers to the number of observations in each category. SD refers to standard deviation. New daily confirmed COVID cases refers to new cases per 100,000 people over the past 7 days.

IV. Empirical Models

In this section, we investigate the relationship between self-employment and mental health through several empirical models. We first start with a simple OLS regression model, then an OLS model with a moderating variable, and finally present triple difference models without and with inverse propensity weighting (IPW).

4.1 Simple OLS Model

Our simple OLS model aims to predict the direct linear relationship between mental health score (PHQ-4 score) and self-employment. Compared with employees, self-employed workers enjoy more flexibility and autonomy over their work but also face financial and job insecurity and shoulder all responsibilities and risks. Given the challenging and unstable economic environment

Table 4: Summary Statistics for Categorical Variables by Employment Groups, Before and After the End of PUA

		Before PUA End				After PUA End			
		Self-employed		Employee		Self-employed		Employee	
Variables	Categories	N	%	N	%	N	%	N	%
Married		42,918		371,655		16,635		136,305	
	No		34.79		40.30		34.08		40.64
	Yes		65.21		59.70		65.92		59.36
Gender		43,139		371,998		16,705		136,689	
	Male		42.22		40.94		42.95		41.54
	Female		57.78		59.06		57.05		58.46
Race		43,139		372,998		16,705		136,689	
	White		84.37		81.12		84.93		81.81
	Black		5.22		7.43		6.11		8.14
	Asian		5.58		6.55		4.35		5.51
	Other/mixed		4.83		4.91		4.62		4.54
Hispanic		43,139		372,998		16,705		136,689	
	Non-Hispanic		89.54		90.03		90.44		91.23
	Hispanic		10.46		9.97		9.56		8.77
Aggregated educational attainment		43,139		372,998		16,705		136,689	
	Less than high school		2.10		1.01		2.02		0.96
	High school degree		38.68		36.08		41.19		37.97
	Bachelor's degree		30.90		33.17		29.93		32.78
	Graduate degree		28.32		29.74		26.86		28.30
Total household income		43,139		372,998		16,705		136,689	
	Less than $25,000		8.97		4.51		10.72		4.98
	$25,000 - $34,999		7.24		5.45		7.85		5.99
	$35,000 - $49,999		8.58		8.09		8.39		8.38
	$50,000 - $74,999		13.99		14.89		14.07		15.20
	$75,000 - $99,999		11.65		13.92		11.56		13.98
	$100,000 - $149,999		15.84		20.34		14.87		20.01
	$150,000 - $199,999		8.52		10.76		7.85		10.30
	$200,000 and above		15.22		12.96		14.03		11.72
	Not reported		9.99		9.08		10.67		9.46
HH has children under 18		43,139		372,998		16,705		136,689	
	No		56.61		57.13		57.36		57.93
	Yes		43.39		42.87		42.64		42.07

*Notes:*The table shows summary statistics for all categorical variables used in the estimation for both self-employed workers and employees surveyed before and after the end of PUA. N refers to the number of observations in each category. % refers to the percentage of workers in each category. Total household income refers to the income in the previous year before tax deductions.

during the COVID-19 pandemic, we hypothesize the negative impact of self-employment on mental health exceeds the positive impact, thus resulting in an overall negative impact. The following is the equation for our simple OLS model:

$$MHScore_{it} = \beta_0 + \gamma_1 SelfEmp_{it} + \beta_1 Z_{it} + u_s + \theta_t + \varepsilon_{it} \tag{1}$$

- The dependent variable $MHScore_{it}$ is the PHQ-4 score for psychological distress, with a higher score representing more severe distress.
- The treatment variable $SelfEmp_{it}$ is a binary variable for self-employment. It equals 1 if the worker is self-employed and 0 if the worker is an employee.
- The control variables Z_{it} include continuous variables age, age^2, and new daily confirmed COVID-19 cases, categorical variables education level, household income, and race, and binary variables for being female, having a Hispanic origin, having any children under age 18, and being married (marital status). These variables are employed to control for factors affecting the dependent variable PHQ-4 score.

- u_s represents the state-fixed effect.

- θ_t represents the time-fixed effect for the middle of the survey period.

- ε_{it} is the error term.

Our simple OLS model has a binary variable of self-employment as a treatment variable and a continuous variable of mental distress score, PHQ-4 score, as a dependent variable. The coefficient γ_1, which is the coefficient of the self-employment variable, represents the difference in predicted PHQ-4 scores for self-employed people and employees when holding other variables constant. A positive γ_1 means self-employed people have greater mental distress than employees, whereas a negative γ_1 means employees have more mental distress, all else equal. Thus, given our hypothesis, we expect a positive γ_1.

A series of control variables are introduced to manage the impacts of several factors on the dependent variable. Age is included as people of different ages face different kinds of pressure and anxiety. The variable age^2 can capture possible non-linear relationship between age and the PHQ-4 score. Variables for race, female, and Hispanic origin are included because of the potential discrimination they create in the workplace and life. Education level, household income, whether having any children under age 18, and whether being married are expected to create either emotional reassurance or stress for workers. More new cases of COVID-19 are expected to bring additional stress and anxiety about the infection. It is important to include state fixed effect u_s, because workers' mental health scores can differ across states due to factors like weather, state policies, and local culture. We also include a time-fixed effect θ_t, since workers' mental health might vary across time possibly caused by factors like policy change and seasonal shifts. ε_{it} represents all unobserved factors that are not captured by the model but influence the dependent variable, like time spent on social media, sports, with friends or families each week. We also make a heteroskedasticity assumption that ε_{it} is uncorrelated to the control variables and the dependent variable.

Table 5 above shows the results of our simple OLS model. The estimated coefficient for self-employment is 0.102, indicating the predicted PHQ-4 score of self-employed workers is 0.102 points higher than that of employees on average, ceteris paribus. This outcome aligns with our expectations and supports our hypothesis, underscoring the mental strain experienced by self-employed workers probably due to stressful workloads, financial uncertainty, and the lack of social benefits. It is important to note although this estimated coefficient is statistically significant, the magnitude is quite small considering the scale of the score from 0 to 12.

Table 5: Results of Simple OLS Model

Dependent Variable: PHQ-4 score	
VARIABLES	Simple OLS Model
Self-employment=1	0.102***
	(0.015)
Observations	567,513
R-squared	0.097
State fixed effect	YES
Time fixed effect	YES
Control variables	YES

Notes: The table shows the results of the simple OLS model. It is estimated based on Equation 1. The complete version is attached as Table 12 in the Appendix. The dependent variable is the PHQ-4 score, which is indicated in the first row of the table. Self-employment $= 1$ for self-employed, Self-employment $= 0$ for employees. Robust standard errors are in parentheses. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

4.2 OLS Model with Moderating Variable

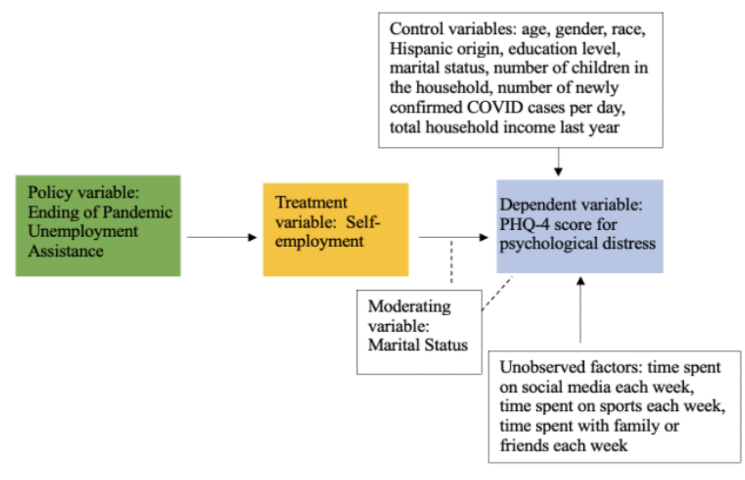
Based on the results of simple OLS regression and daily life experience, we hypothesize the impact of self-employment on mental health might vary across married workers and unmarried workers because marriage potentially provides more financial stability and emotional support. Therefore, we introduce the variable of being married as a moderating variable and add an interaction term of marital status and self-employment. The following is the equation for our OLS Model with a moderating variable:

$$MHScore_{it} = \beta_0 + \gamma_1 SelfEmp_{it} + \gamma_2 Married_{it} + \gamma_3 (Married_{it} \times SelfEmp_{it}) + \beta_1 Z_{it} + u_s + \theta_t + \varepsilon_{it} \quad (2)$$

- The moderating variable $Married_{it}$ is a binary variable for marital status. It equals 1 if the worker is married and equals 0 if unmarried.
- $Married_{it} \times SelfEmp_{it}$ is the interaction term of marital status and self-employment. It equals 1 only if the worker is self-employed and married.
- The control variables Z_{it} include age, age^2, new daily confirmed COVID-19 cases, education level, household income, race, being female, having a Hispanic origin, and having any children under age 18.

The following flow chart provides a visualization of the variables and their interrelationships in our OLS Model with a moderating variable.

Figure 5: Flow Chart of Variables



Notes: The figure is a flow chart of variables used in our OLS model with a moderating variable (Equation 2). Several possible unobserved factors are listed. Actual unobserved factors include but are not limited to those listed above.

Table 6: Coefficient Interpretation for OLS Model with a Moderating Variable

	Married	**Unmarried**	**Marriage Premium**
Self-employed workers	$\gamma_2 + \gamma_1 + \gamma_3$	γ_1	$\gamma_2 + \gamma_3$
Employee	γ_2	0	γ_2
Employment Group Difference	$\gamma_1 + \gamma_3$	γ_1	γ_3

Notes: The table presents the coefficient interpretation for our OLS model with a moderating variable (Equation 2). Employment Group Difference = coefficient for self-employed – coefficient for employee. Marriage premium = coefficient for married - coefficient for unmarried.

Table 6 above shows the coefficient interpretation for our OLS model with a moderating variable. This model allows us to get deeper insights into group differences. In Equation 2, γ_1 measures the impact of self-employment on predicted PHQ4-score among unmarried workers, and $\gamma_1 + \gamma_3$ measures the impact of self-employment on predicted PHQ4-score among married workers. Therefore, γ_3 indicates how the impact differs across married and unmarried groups.

Table 7: Results of OLS Model with Moderating Variable

VARIABLES	**OLS Model with Moderating Variable**
Self-employment=1	0.262***
	(0.027)
Married=1	-0.399***
	(0.011)
Self-employment × Married	-0.245***
	(0.031)
Observations	567,513
R-squared	0.097
State fixed effect	YES
Time fixed effect	YES
Control variables	YES

Notes: The table presents the results of our OLS model with a moderating variable. It is estimated based on Equation 2. The complete version is attached as Table 13 in the Appendix. The dependent variable is the PHQ-4 score, which is indicated in the first row of the table. Self-employment = 1 for self-employed, Self-employment = 0 for employees. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7 above presents the regression results of our OLS model with a moderating variable. The predicted PHQ-4 score for self-employed workers is a statistically significant 0.017 points higher than that for employees among married workers while it is statistically significant and 0.262 points higher among unmarried workers. Therefore, such difference in predicted PHQ-4 score for self-employed workers and employees is a statistically significant 0.245 points higher among married workers compared to unmarried workers. Overall, this result is consistent with the results of our simple OLS regression model as self-employed workers are predicted to have more stress and anxiety than employees among both married and unmarried groups. The smaller impacts of self-employment on mental health among married workers might be explained by the potential financial and emotional support offered by marriage.

4.3 Triple Difference Model

To further investigate the relationship between self-employment and mental health, it is important to consider socioeconomic factors. Therefore, we take a policy change, the end of Pandemic Unemployment Assistance, into account. The dates of ending PUA vary across states as mentioned previously, ranging from June 2021 to September 2021. The termination of PUA represents the cessation of providing unemployment benefits for the self-employed. Intuitively, PUA offers a form of emotional reassurance to self-employed workers as it assures them of financial support if they become unemployed, so ending PUA possibly removed such emotional security from self-employed workers. Therefore, we hypothesize ending PUA would have negative impacts on the mental health of self-employed workers while not influencing the mental health of employees as they are not the targets of PUA.

To further examine the differential impacts of ending PUA on mental health between employees and self-employed workers, we employed a triple difference model. It is important to note that all states are treated states and are switchers in our model since all of them implemented PUA in March 2020 and ended it by early September 2021. The following is the equation for our triple difference model:

$$MHScore_{it} = \beta_0 + \gamma_1 SelfEmp_{it} + \gamma_2 Post_{st} + \gamma_3 (Post_{st} \times SelfEmp_{it}) + \beta_1 Z_{it} + u_s + \theta_t + \varepsilon_{it} \tag{3}$$

- The post-policy variable $Post_{st}$ equals 1 if the observation is after the end of PUA and 0 if the observation is before the end of PUA for switchers (all states in our case).
- $Post_{st} \times SelfEmp_{it}$ is the interaction term of the post-policy indicator and the treatment indicator. It equals 1 only if the worker is self-employed, from switcher states, and surveyed after the end of PUA.

Table 8: Coefficient Interpretation for Triple Difference Model

	Before PUA End	**After PUA End**	**Pre and Post Difference**
Self-employed workers	γ_1	$\gamma_2 + \gamma_1 + \gamma_3$	$\gamma_2 + \gamma_3$
Employee	0	γ_2	γ_2
Group Difference	γ_1	$\gamma_1 + \gamma_3$	γ_3

Notes: The table presents the coefficient interpretation for our triple difference model (Equation 3). Pre and Post Difference = coefficient for After PUA End – coefficient for Before PUA End. Marriage premium = coefficient for self-employed workers - coefficient for employees.

Table 8 above shows the coefficient interpretation for our triple difference model (Equation 3). $\gamma_2 + \gamma_3$ measures the difference in the PHQ-4 score of self-employed workers before and after the ending PUA, which shows the effect of ending PUA on the PHQ-4 score of self-employed workers. γ_2 measures the effect of ending PUA on the PHQ-4 score of employees. γ_3, the coefficient of the interaction term, indicates the difference of such effects between self-employed workers and employees. We anticipate γ_3 to be positive as we expect a greater positive increase in the PHQ-4 score among self-employed workers than employees after the ending of PUA.

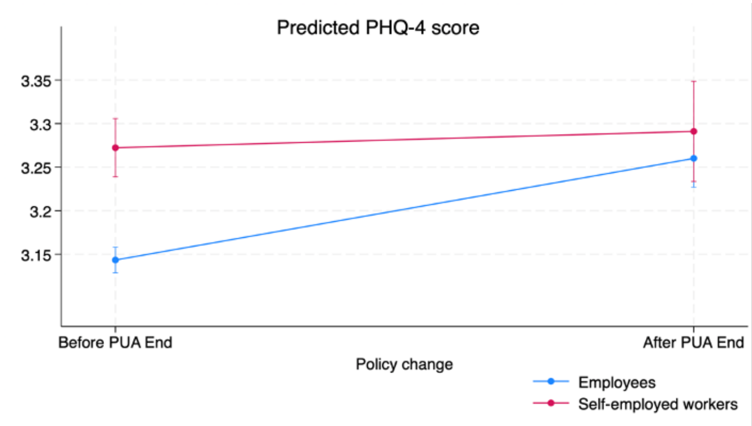
Table 9: Results of Triple Difference Model

VARIABLES	**Triple Difference Model**
Post-policy = 1, After PUA End	0.117***
	(0.022)
Self-employment = 1	0.129***
	(0.017)
Post-policy $\times$ Self-employment	-0.098***
	(0.032)
Observations	567,513
R-squared	0.097
State-fixed effect	YES
Time-fixed effect	YES
Control variables	YES

Notes: The table presents the results of our triple difference model. It is estimated based on Equation 3. The complete version is attached as Table 14 in the Appendix. The dependent variable is the PHQ-4 score, which is indicated in the first row of the table. Self-employment = 1 for self-employed, Self-employment = 0 for employees. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9 above presents the results of our triple difference model. For self-employed workers, their predicted PHQ-4 score is 0.019 points higher after ending PUA than before, which shows the predicted effect of ending PUA on self-employed workers. PHQ-4 scores for self-employed workers are predicted to be very similar before and after the end of PUA. Also, the PHQ-4 score of employees is predicted to have a 0.117 points increase after ending PUA. Therefore, ending PUA is predicted to have negative impacts on the mental health of both employees and self-employed workers as predicted PHQ-4 scores increase in both groups after PUA ends although the magnitudes of impacts are small for both. It is important to point out that the predicted increase in PHQ-4 score is 0.098 points lower for self-employed people than that for employees. Therefore, ending PUA has a more pronounced adverse effect on the mental health of employees compared to self-employed workers, which differs from our initial hypothesis. This difference can be clearly illustrated and supported by Figure 6. The red line representing self-employed workers is flatter while the blue line representing employees is steeper and the gap between predicted PHQ-4 scores of both employees and self-employed workers shrinks after the end of PUA.

Figure 6: Predicted PHQ-4 score of Employees and Self-employed Workers



Notes: The figure shows the predicted PHQ-4 score for employees and self-employed workers before and after the end of PUA. Calculations are based on Equation 3. The horizontal axis indicates before or after the PUA end.

This triple difference model has several assumptions. Firstly, we assume the absence of spillover effects between two groups that the response of one group to the ending of PUA does not have a ripple effect on another group. Second, we assume the exogeneity of control variables that control variables Z_{it} and error terms are uncorrelated ($\text{Cov}(Z_{it}, \varepsilon_{it}) = 0$). However, this assumption might be violated. For example, unobservable factors like time spent with families are likely to be affected by personal characteristics like gender and age. We also assume the exogeneity of the post-policy variable Post_{st} ($\text{Cov}(\text{Post}_{st}, \varepsilon_{it}) = 0$). However, this assumption is likely to be violated in our case. When states decide on PUA withdrawal dates, they might take labor factors into account. For example, states that worry more about labor shortages might withdraw from PUA early. Furthermore, we hold the conditional independence that the selection into the self-employed group is random conditional on control variables, the post-policy variable, and fixed effects. This assumption is likely to be violated because individuals' decision to be self-employed is largely determined by personal and social factors. Moreover, we assume a parallel trend that both self-employed workers and employees have the same PHQ-4 score before the end of PUA. This assumption is clearly violated. Other socioeconomic and policy changes that occurred simultaneously with the ending of PUA, like the ending of the Federal Pandemic Unemployment Compensation (FPUC), are likely to diverge the PHQ-4 score trend between self-employed workers and employees. To address the violation of assumptions, we introduce inverse propensity weight to the triple difference model to balance self-employed and employee groups.

4.4 Triple Difference Model with IPW

Before introducing inverse propensity weight, we conduct a t-test of observable characteristics of self-employed and employee groups. The result is shown in the second column of Table 10. Notice the two groups are significantly different in characteristics of female, age, age squared, race, Hispanic, education category, household income category, and married at the 1% significance level, and significantly different in having a kid younger than 18 years old at the 5% significance level. Thus, the control and treatment groups are significantly different in most observable characteristics.

To counterbalance the potential violations to the assumptions and remove the confounding, we create balancing groups based on observable characteristics and implement inverse propensity weighting. In the context of our research, the inverse propensity weight balances observed characteristics between two groups by placing more weight on workers who are predicted to have a higher likelihood of being employees while giving less weight to workers who are predicted to have more likelihood of being self-employed. The estimated propensity score is

$$\hat{p} = \text{Prob}(G_{i,t_0} = 1) = \alpha Z_{i,t_0} + \mu_{i,t_0}, \text{ where } G_{i,t_0} = \begin{cases} 1 & \text{if self-employed individual} \\ 0 & \text{if employee} \end{cases} \tag{4}$$

The estimated inverse propensity weight is

$$IPW = \begin{cases} 1/\hat{p}, & \text{if } G_{i,t_0} = 1 \\ 1/(1-\hat{p}), & \text{if } G_{i,t_0} = 0 \end{cases} \tag{5}$$

After applying IPW to adjust the group differences, we conduct a t-test again to check the differences in the observable characteristics between groups. The third column of Table 10 shows that after applying IPW, characteristics such as female, Hispanic, having kids younger than 18 years old, and household income categories are not significantly different between the control and treatment groups at any significance level; marital status is significantly different at 10% level between groups; age squared (age^2) is significantly different at 5% level; and age, race, and education category are still significantly different at 1% level. The t-test results after applying IPW indicate that we partially eliminate the differences in observable characteristics between groups, and we are more confident about the assumption of a parallel trend between the two groups.

Table 10: T-test for Observable Characteristics before and after IPW Adjustment

VARIABLES	**Before IPW**	**After IPW**
Married	0.055***	-0.005*
	(0.002)	(0.003)
Female	-0.013***	0.003
	(0.003)	(0.003)
Age of HH head	3.483***	-0.193***
	(0.056)	(0.071)
Age squared	314.028***	-14.003***
	(5.048)	(5.993)
Black	-0.022***	0.005***
	(0.001)	(0.002)
Asian	-0.010***	-0.001
	(0.001)	(0.001)
Other/mixed race	-0.001	0.003*
	(0.001)	(0.001)
Hispanic = 1	0.005***	0.001
	(0.002)	(0.002)
HH has children under 18 = 1	0.005***	0.004
	(0.003)	(0.003)
Aggregated educational attainment		
HS degree	0.026***	0.017***
	(0.002)	(0.003)
Bachelor's degree	-0.023***	-0.008***
	(0.002)	(0.003)
Graduate degree	-0.014***	-0.010***
	(0.002)	(0.003)
HH Income Category		
$25,000 - $34,999	0.018***	-0.001
	(0.001)	(0.001)
$35,000 - $49,999	0.005***	-0.001
	(0.001)	(0.001)
$50,000 - $74,999	-0.009***	-0.002
	(0.002)	(0.002)

VARIABLES	Before IPW	After IPW
$75,000 - $99,999	-0.023***	-0.001
	(0.002)	(0.002)
$100,000 - $149,999	-0.045***	0.002
	(0.002)	(0.002)
$150,000 - $199,999	-0.022***	0.000
	(0.002)	(0.002)
$200,000 and above	0.023***	-0.001
	(0.002)	(0.002)
Not reported	0.009***	0.004**
	(0.001)	(0.002)

*Notes:*The table presents the results of the t-test for observable characteristics before and after applying IPW.Two groups of the test are self-employed workers and employees.Total number of observations: N = 1,137,587 for applying IPW, and N = 414,537 after applying IPW.Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

After introducing IPW into our previously proposed triple difference model, estimate coefficients for the main group effect, main policy effect, and interaction term remain statistically significant, which implies ending PUA still has different effects across the two groups. The predicted PHQ-4 score is increased by 0.056 points for self-employed workers after the ending of PUA while it is increased by 0.178 points for employees following the end of PUA. The increase in predicted PHQ-4 score is 0.122 points lower among self-employed workers than among employees. It is important to note the increase in predicted PHQ-4 score for both groups and the difference in increase are all more pronounced in the weighted model than in the unweighted model. Overall, the triple difference model with IPW shows negative impacts of ending PUA on both groups in terms of mental health and the impact is more adverse for employees than for self-employed workers, which is consistent with the unweighted triple difference model but differs from our initial hypothesis. The unexpected result might be attributed to policy and socioeconomic changes that occurred simultaneously with the ending of PUA, like the ending of the Federal Pandemic Unemployment Compensation (FPUC) and gradual macroeconomic recovery from the impact of COVID-19.

V. Conclusion

This paper explores the impacts of self-employment on mental health during the COVID-19 pandemic. By utilizing econometrics models, this study approaches the question progressively and incorporates different factors to get a comprehensive understanding.

Table 11: Triple Difference Model with IPW vs Triple Difference Model Estimates

	Triple Difference Model with IPW	**Triple Difference Model**
Post policy = 1, After PUA End	0.178***	0.117***
	(0.039)	(0.022)
Self-employment=1	0.149***	0.129***
	(0.019)	(0.017)
Post-policy × Self-employment	-0.122***	-0.098***
	(0.037)	(0.032)
Observations	567,513	567,513
R-squared	0.098	0.097
State fixed effect	YES	YES
Time fixed effect	YES	YES
Control variables	YES	YES

Notes: The table presents the results of our triple difference model with IPW. It is estimated based on Equation 3. The results of our triple difference model without IPW are also attached for comparison. The complete version is attached as Table 15 in the Appendix. The dependent variable is the PHQ-4 score, which is indicated in the first row of the table. Self-employment = 1 for self-employed, Self-employment = 0 for employees. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Our simple OLS model and OLS model with marriage status as a moderating variable predict that self-employed workers face more mental distress than employees although the difference is small in magnitude. This result can be explained by the inherent financial uncertainties, the lack of social benefits, and the all-encompassing responsibility of managing their own business, which self-employed individuals typically face. Our unweighted and weighted triple difference models incorporate a policy change, the termination of PUA. Both models predict the negative effect of ending PUA on the mental health of self-employed workers and employees but the negative impact would be more pronounced among employees. This result deviates from our initial hypothesis that ending PUA is likely to induce anxiety and emotional insecurity among self-employed workers without significantly affecting employees. This unexpected result might be due to socioeconomic changes that coincided with the termination of the PUA, such as the end of the Federal Pandemic Unemployment Compensation and the gradual recovery of the macroeconomy.

This paper offers valuable insights for policymakers to consider the mental health factors of self-employed workers when planning for future crises. Possible approaches include enhancing the accessibility of mental health services, offering additional support for self-employed businesses, and tailoring financial relief programs specifically for self-employed individuals. Furthermore, the unanticipated findings in this study point to potential directions for future research. We encourage future researchers to explore and analyze alternative policy measures and socioeconomic shocks when investigating the issue of mental health and self-employment.

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Appendix

Table 12: Results of Simple OLS Model

Dependent Variable: PHQ-4 score	
Self-employment=1	0.102***
	(0.015)
Married = 1	-0.423***
	(0.011)
Female = 1	0.599***
	(0.009)
Age of HH head	-0.021***
	(0.003)
Race categories = 2, [2] Black	-0.318***
	(0.018)
Race categories = 3, [3] Asian	-0.437***
	(0.018)
Race categories = 4, [4] Other/mixed	0.305***
	(0.023)
Hispanic = 1	-0.072***
	(0.016)
HH has children under 18 = 1	-0.040***
	(0.010)
Aggregated educational attainment = 2, [2] HS degree	0.042
	(0.048)
Aggregated educational attainment = 3, [3] Bachelor's degree	-0.185***
	(0.048)
Aggregated educational attainment = 4, [4] Graduate degree	-0.162***
	(0.049)
Categories for total HH income = 2, [2] 25, 000−34,999	-0.334***
	(0.031)
Categories for total HH income = 3, [3] 35, 000−49,999	-0.611***
	(0.029)
Categories for total HH income = 4, [4] 50, 000−74,999	-0.957***
	(0.026)
Categories for total HH income = 5, [5] 75, 000−99,999	-1.264***
	(0.027)
Categories for total HH income = 6, [6] 100, 000−149,999	-1.573***
	(0.026)
Categories for total HH income = 7, [7] 150, 000−199,999	-1.788***
	(0.028)
Categories for total HH income = 8, [8] $200,000 and above	-2.032***
	(0.027)
Categories for total HH income = 13, [13] Not reported	-1.494***
	(0.028)
Constant	6.442***
	(0.101)
Observations	567,513
R-squared	0.097
State fixed effect	YES
Time fixed effect	YES
Control variables	YES

Notes: The table shows the complete results of the simple OLS regression model. It is estimated based on Equation 1. Dependent variable is the PHQ-4 score, which is indicated in the first row of the table. Self-employment $= 1$ for self-employed, Self-employment $= 0$ for employees. Total household income refers to the income in the previous year before tax deductions. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables age^2 and new daily confirmed cases are omitted because their estimate coefficients are 0.

Table 13: Results of OLS Model with Moderating Variable

	Dependent Variable: PHQ-4 score
Self-employment = 1	0.262***
	(0.027)
Married = 1	-0.399***
	(0.011)
Self-employment x Married	-0.245***
	(0.031)
Female = 1	0.601***
	(0.009)
Age of HH head	-0.021***
	(0.003)
Race categories = 2, [2] Black	-0.316***
	(0.018)
Race categories = 3, [3] Asian	-0.437***
	(0.018)
Race categories = 4, [4] Other/mixed	0.304***
	(0.023)
Hispanic = 1	-0.071***
	(0.016)
HH has children under 18 = 1	-0.041***
	(0.010)
Aggregated educational attainment = 2, [2] HS degree	0.043
	(0.048)
Aggregated educational attainment = 3, [3] Bachelor's degree	-0.184***
	(0.048)
Aggregated educational attainment = 4, [4] Graduate degree	-0.162***
	(0.049)
Categories for total HH income = 2, [2] $25,000 - $34,999	-0.324***
	(0.031)
Categories for total HH income = 3, [3] $35,000 - $49,999	-0.598***
	(0.029)
Categories for total HH income = 4, [4] $50,000 - $74,999	-0.944***
	(0.026)
Categories for total HH income = 5, [5] $75,000 - $99,999	-1.252***
	(0.027)
Categories for total HH income = 6, [6] $100,000 - $149,999	-1.562***
	(0.026)
Categories for total HH income = 7, [7] $150,000 - $199,999	-1.777***
	(0.028)
Categories for total HH income = 8, [8] $200,000 and above	-2.020***
	(0.028)
Categories for total HH income = 13, [13] Not reported	-1.483***
	(0.028)
Constant	6.433***
	(0.101)
Observations	567,513
R-squared	0.097
State fixed effect	YES
Time fixed effect	YES
Control variables	YES

Notes: The table shows the complete results of the OLS model with a moderating variable. It is estimated based on Equation 2. Dependent variable is the PHQ-4 score, which is indicated in the first row of the table. Self-employment = 1 for self-employed, Self-employment = 0 for employees. Total household income refers to the income in the previous year before tax deductions. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14: Results of Triple Difference Model

	Dependent Variable: PHQ-4 score
Post policy = 1, After PUA End	0.117***
	(0.022)
Self-employment = 1	0.129***
	(0.017)
Post-policy x Self-employment	-0.098***
	(0.032)
Female = 1	0.599***
	(0.009)
Age of HH head	-0.020***
	(0.003)
Race categories = 2, [2] Black	-0.318***
	(0.018)
Race categories = 3, [3] Asian	-0.437***
	(0.018)
Race categories = 4, [4] Other/mixed	0.305***
	(0.023)
Hispanic = 1	-0.072***
	(0.016)
HH has children under 18 = 1	-0.040***
	(0.010)
Aggregated educational attainment = 2, [2] HS degree	0.043
	(0.048)
Aggregated educational attainment = 3, [3] Bachelor's degree	-0.184***
	(0.048)
Aggregated educational attainment = 4, [4] Graduate degree	-0.162***
	(0.049)
Categories for total HH income = 2, [2] $25,000 - $34,999	-0.334***
	(0.031)
Categories for total HH income = 3, [3] $35,000 - $49,999	-0.611***
	(0.029)
Categories for total HH income = 4, [4] $50,000 - $74,999	-0.957***
	(0.026)
Categories for total HH income = 5, [5] $75,000 - $99,999	-1.265***
	(0.027)
Categories for total HH income = 6, [6] $100,000 - $149,999	-1.574***
	(0.026)
Categories for total HH income = 7, [7] $150,000 - $199,999	-1.789***
	(0.028)
Categories for total HH income = 8, [8] $200,000 and above	-2.033***
	(0.027)
Categories for total HH income = 13, [13] Not reported	-1.494***
	(0.028)
Married = 1	-0.423***
	(0.011)
Observations	567,513
R-squared	0.097
State fixed effect	YES
Time fixed effect	YES
Control variables	YES

Notes: The table presents the complete results of our triple difference model. It is estimated based on Equation 3. Dependent variable is the PHQ-4 score, which is indicated in the first row of the table. Self-employment = 1 for self-employed, Self-employment = 0 for employees. Total household income refers to the income in the previous year before tax deductions. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Variables age^2 and new daily confirmed cases are omitted because their estimate coefficients are 0.

Table 15: Triple Difference Model with IPW vs. Triple Difference Model Estimates

	Triple Difference Model with IPW	Triple Difference Model
Post-policy = 1, After PUA End	0.178***	0.117***
	(0.039)	(0.022)
Self-employment = 1	0.149***	0.129***
	(0.019)	(0.017)
Post-policy x Self-employment	-0.122***	-0.098***
	(0.037)	(0.032)
Female = 1	0.596***	0.599***
	(0.017)	(0.009)
Age of HH head	-0.022***	-0.020***
	(0.003)	(0.003)
Race categories = 2, [2] Black	-0.289***	-0.318***
	(0.042)	(0.018)
Race categories = 3, [3] Asian	-0.411***	-0.437***
	(0.037)	(0.018)
Race categories = 4, [4] Other/mixed	0.386***	0.305***
	(0.045)	(0.023)
Hispanic = 1	-0.127***	-0.072***
	(0.032)	(0.016)
HH has children under 18 = 1	-0.075***	-0.040***
	(0.020)	(0.010)
Aggregated educational attainment = 2, [2] HS degree	0.037	0.043
	(0.071)	(0.048)
Aggregated educational attainment = 3, [3] Bachelor's degree	-0.150***	-0.184***
	(0.072)	(0.048)
Aggregated educational attainment = 4, [4] Graduate degree	-0.155***	-0.162***
	(0.072)	(0.049)
Categories for total HH income = 2, [2] $25,000 - $34,999	-0.363***	-0.334***
	(0.046)	(0.031)
Categories for total HH income = 3, [3] $35,000 - $49,999	-0.618***	-0.611***
	(0.045)	(0.029)
Categories for total HH income = 4, [4] $50,000 - $74,999	-1.056***	-0.957***
	(0.043)	(0.026)
Categories for total HH income = 5, [5] $75,000 - $99,999	-1.331***	-1.265***
	(0.043)	(0.027)
Categories for total HH income = 6, [6] $100,000 - $149,999	-1.583***	-1.574***
	(0.042)	(0.026)
Categories for total HH income = 7, [7] $150,000 - $199,999	-1.834***	-1.789***
	(0.046)	(0.028)
Categories for total HH income = 8, [8] $200,000 and above	-2.082***	-2.033***
	(0.043)	(0.027)
Categories for total HH income = 13, [13] Not reported	-1.494***	-1.494***
	(0.044)	(0.028)
Married = 1	-0.517***	-0.423***
	(0.020)	(0.011)
Observations	567,513	567,513
R-squared	0.098	0.097
State Fixed Effect	YES	YES
Time Fixed Effect	YES	YES

Notes: The table presents the results of our triple difference model with IPW. It is estimated based on Equation 3. The results of our triple difference model without IPW are also attached for comparison. The dependent variable is the PHQ-4 score, which is indicated in the first row of the table. Self-employment $= 1$ for self-employed, Self-employment $= 0$ for employees. Total household income refers to the income in the previous year before tax deductions. Robust standard errors are in parentheses. $***p < 0.01$, $**\, p < 0.05$, $*p < 0.1$. Variables age^2 and new daily confirmed cases are omitted because their estimate coefficients are 0.

Table 16: Variable Description

Variable Name	Vector	Variable Label	Type	Notes about Variable Construction
PHQ-4 Score	Yit	phq4score	continuous	Higher score means more severe psychological distress
Self-employment	Xit*	self_emp	binary	=1 if the individual is self-employed, =0 if the individual is an employee
PUA end date	Pst	pua_end	date	End date of the Pandemic Unemployment Assistance for each state
Marital status	Mit	married	binary	=1 if married, =0 if not married
Age	Zit	age	continuous	Age of the individual
Age squared (age^2)	Zit	age2	continuous	Age of the individual squared
Female	Zit	female	binary	=1 if female, =0 if male
Race	Zit	race	categorical	=1 if White, =2 if Black, =3 if Asian, =4 if Other/mixed
Hispanic	Zit	hispanic	binary	=1 if Hispanic, =0 if not Hispanic
Education categories	Zit	educag	categorical	=1 if less than High School, =2 if High School degree, =3 if Bachelor's degree, =4 if Graduate degree
Household has kid under 18	Zit	hhhaskid18	binary	=1 if household has children under 18, =0 otherwise
Total household income categories	Zit	hhcinccat	categorical	Income categories, =13 if not reported
New COVID-19 cases	Zit	sw_cases_new	continuous	New daily confirmed COVID cases per 100,000 people over the past 7 days

Notes: Xit is created using the categorical variable emp_sector in the dataset. Self_emp = 1 when emp_sector = 4 (self-employed) and self_emp = 0 when emp_sector = 1, 2, 3, and 5 (government, private company, non-profit organization, and family business). Total household income refers to the income in the previous year before tax deductions.

Food Stamp Recipiency on Household Food Expenditures & Food Sufficiency: An Analysis of the Effects of Food Price Inflation

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Abstract

What are the impacts on food expenditures and food sufficiency amidst the high post-COVID inflation? The post-pandemic recovery period has introduced new challenges across various food sectors in the United States, encompassing issues like labor shortages and supply chain disruptions that have contributed to increased consumer prices. Our study investigates the responses of two distinct groups: non-SNAP recipients and SNAP recipients. We examine how different degrees of food inflation shocks influence both groups' food expenditures and self-reported food sufficiency. Results show that after accounting for group characteristics and potential biases, we find an observable difference in food expenditure and sufficiency during times of high food inflation among food stamp recipients. The findings are of great importance to policymakers, nutrition experts, and other scholars examining different periods of food inflation.

I. Introduction

No consumer welcomes the idea of paying more for the same set of goods they typically purchase. The post-pandemic period has witnessed a significant surge in food prices, surpassing the already-rising pre-COVID trend. Notably, several food price indices, such as the FAO Food Price Index, reached their highest levels in a decade by May 2021 (Richardson 2021). These price

*We express our gratitude to Klara Peter for her invaluable assistance in preparing and cleaning the dataset used for our paper's analyses

fluctuations are apparent to every consumer as they navigate their household food purchases, raising concerns about the impact of inflation on the portion of household income allocated to food expenses and the choices made regarding food sufficiency. Economist Shelby Myers, affiliated with the American Farm Bureau Federation, characterizes this shift as the "accordion effect." This effect, stemming from the pandemic's cycle of closures, reopenings, and shifts in consumer buying patterns, has led to a surge in domestic prices, impacting consumers nationwide (Reiley and Fowers 2021). In this research paper, our primary aim is to evaluate the influence of household participation in the Supplemental Nutritional Assistance Program (SNAP) on both food expenditure and food security within households. Our central objective is to examine the variations in food spending and food security between economically vulnerable low-income households that receive SNAP benefits and those that do not, particularly in the high inflation environment experienced from 2021 to 2022.

We contribute to the existing research landscape by employing a difference-in-difference model to assess the projected food expenditures of both SNAP recipients and non-SNAP recipients in response to the escalating food price inflation. We categorize different levels of food price inflation in an ordinal manner, based on varying inflation percentages, and designate these as our policy shocks. To distinctly represent SNAP recipients and non-SNAP recipients, we rely on self-reported survey data. Through our analysis, we aim to demonstrate that as food price inflation fluctuates, both expected food expenditures and self-reported food sufficiency adapt to the increased price level. Our dataset encompasses the period from 2021 to 2022, providing a contemporary context for household food expenditures and food sufficiency. Traditionally, food prices have exhibited an annual increase of roughly 2%. However, in our period of interest spanning from 2021 to 2022, Americans experienced a large surge, with food prices surging by 11%. This marks the most substantial annual increase in food prices since the 1980s (GAO 2023). Furthermore, our research delves into inflation data from the same time frame, an element unexplored in prior studies, shedding light on the role of recent high inflation shocks for these two groups of interest.

The initial segment of our paper provides essential background information regarding the Supplemental Nutritional Assistance Program, which is central to our study's treatment effect. Subsequently, we delve into the existing body of literature to explore how previous episodes of high food inflation have influenced food spending and food sufficiency. Following this, we present summary statistics and visually represent our dataset, encompassing responses from the Household Pulse Survey (HPS) spanning from 2021 to 2022, alongside Consumer Price Index (CPI) inflation data from the same period. We then explain our empirical model, which forms the backbone of our difference-in-difference (DID) analysis. Within our DID model, featuring fixed effects for division and interview period, we estimate the impact of varying inflation shock levels on food expenditures for both our non-SNAP recipient and SNAP recipient groups. To mitigate potential sources of bias, we use propensity scores and inverse propensity weighting (IPW) to achieve a balance between these two groups. Subsequently, we reevaluate our DID model with fixed effects to examine the influence of food stamp recipiency from 2021 to 2022. Finally, we employ a multinomial logit model to gain insights into how food stamp recipiency affects self-reported food sufficiency given differing levels of monthly food inflation.

II. Background on the Supplemental Nutritional Assistance Program (SNAP)

A specific subgroup within the U.S. population that is of significant consideration during periods of escalating food inflation consists of households that receive assistance through the Supplemental Nutritional Assistance Program. SNAP, a federal initiative, is designed to provide financial support to low-income households and individuals, enabling them to access essential food resources to enhance their overall well-being. According to initial estimates from the USDA in December 2022, SNAP extends its assistance to over 42.5 million Americans. SNAP recipients can utilize their benefits to acquire a variety of food items, including fruits, vegetables, meat, poultry, fish, dairy products, and more, with nonfood items and alcoholic or tobacco products being excluded. It is estimated that SNAP can reduce the ”overall prevalence of food insecurity by as much as 30%.” This reduction occurs as SNAP empowers households to supplement their food purchases and allocate a larger portion of their budgets to other fundamental needs (Keith-Jennings et al. 2019).

Over the years, SNAP has undergone various revisions, yet its core structure has remained consistent since 1979, characterized by standardized eligibility criteria and uniform benefit amounts across the nation (Gunderson 2018). As of 2021, SNAP benefits average approximately $127 per person per month. However, during the circumstances of the COVID-19 pandemic, this monthly benefit amount saw a significant increase, reaching nearly $220 per month (CBPP 2022). It is important to note that contemporary SNAP aims not only to augment food consumption for disadvantaged households and individuals but also to improve the nutritional quality of the diets of eligible participants. This dual focus reflects SNAPS’s commitment to addressing not just food access but also the nutritional well-being of those it serves.

III. Literature Review

Past research has explored the connection between food expenditure and food sufficiency within the context of SNAP participation status over various time frames. An investigation conducted for the period spanning 2009 to 2011 on behalf of the USDA by Nord (2011) uncovered that the reduction in real added SNAP benefits by about half, driven by increased inflation, resulted in a 4.4% decline in food expenditures for SNAP recipients. Nord's research approach aligns with our paper, as it involves a comparative analysis of food spending between households that receive SNAP benefits and those that do not during the respective study periods. Literature that examines the effects of inflationary policy shocks typically incorporates Consumer Price Index (CPI) data into their modeling techniques. An illustrative study conducted by Schnepf and Richardson in 2009 observed that the share of food expenditures in total household expenditures diminishes as household income levels rise. The implications of such inflationary effects suggest that SNAP recipient households, characterized by their lower household income, exhibit greater sensitivity to retail food price increases resulting from higher inflation levels.

Employing the difference-in-differences estimation method, Katare and Kim (2017) directed their research toward quantifying the impacts of the 2013 SNAP benefit reduction on food security. Their analysis was based on data from the Current Population Survey Food Security Supplement spanning from 2012 to 2014. Utilizing a DID model to gauge the disparity between changes in the outcome for the group receiving SNAP benefits before and after the benefit reduction, and the changes in the outcome for the non-SNAP group during the same period, they discover that reduced SNAP benefits significantly threaten food security for SNAP participating households. Recent literature by Restrepo (2023) challenges the assumption that the observed effects of SNAP on food insecurity from prior studies apply to the pandemic era. Restrepo employed a longitudinal panel of sample adults initially interviewed in 2019 and re-interviewed between August and December 2020, drawing from the National Health Interview Survey. Like the dataset used for our analysis, Restrepo (2023) incorporated Consumer Price Index (CPI) data for food at home (FAH) and food away from home (FAFH) at the regional quarter level to account for inflation. Their analysis also included data on unemployment rates, FAH CPI, and FAFH CPI, sourced from the Bureau of Labor Statistics, to control variations in region-level economic conditions and food prices over time. In contrast to income-eligible SNAP non-participants, their findings indicated that SNAP participants during the pandemic had a 37% lower risk of food insecurity.

IV. Data Methods & Summary Statistics

The dataset used in our research was collected from the Household Pulse Survey conducted by the U.S. Census Bureau, in coordination with several other federal agencies. This survey was designed to gauge the socioeconomic impacts of the COVID-19 pandemic on American households. It encompasses fundamental demographic questions along with a range of questions about COVID-19 vaccinations, housing security, food sufficiency, employment, and other relevant areas.

The Household Pulse Survey is an ongoing biweekly survey as of September 2023. The data collected is longitudinal, focusing on survey responses gathered between 2021 and 2022. This dataset comprises 1,307,487 observations, all from individuals aged 18 to 64. There is a vast amount of basic demographic information collected from each participant, which allows for more informed calculations and conclusions from the data analysis. A limitation stemming from this advantage is the limited level of detail that can be gathered because of the structured format of the survey questions. The survey questions often provide participants with pre-defined answer options, which may not always capture the full nuance and necessary details of their responses. Another constraint arises from the self-reported nature of the data, as individuals fill out the survey themselves. Self-reporting can introduce potential data reliability issues that lead to skewed results, as people may not consistently provide accurate responses to every question in the survey.

In our dataset, the treatment variable is food stamp recipiency, represented as a binary variable. In the Household Pulse Survey, SNAP benefit recipiency is determined based on responses to the question: ”Do you or does anyone in your household receive benefits from the Supplemental Nutrition Assistance Program (SNAP) or the Food Stamp Program?” A value of 0 denotes individuals or households not receiving food stamps, corresponding to respondents who answered ”no” in the questionnaire. Similarly, a value of 1 signifies individuals or households that do receive food stamps, in alignment with respondents who answered ”yes.”

The continuous outcome variable we are using is household food spending. Data from the Household Pulse Survey includes responses from participants regarding their expenditures on both groceries and prepared meals over the previous week. These spending measures are adjusted using an adult equivalence scale, which assigns a value of 1 for the first adult, an additional 0.75 for each subsequent adult, and an extra 0.5 for each child under the age of 18 residing in the household. This adjustment takes into consideration the concept of economies of scale, where the cost of meal preparation per person tends to decrease as more individuals take part in a shared meal. Furthermore, food expenditure is adjusted to account for price inflation using the Food CPI in urban areas, with June 2019 serving as the reference month in this dataset.

Table 1 provides the summary statistics and the mean differences for food stamp recipients and food stamp non-recipients before applying the shock of food inflation. Notably, food stamp recipients reveal lower mean levels of food spending compared to non-recipients. When adjusted for different variables, more differences emerge between the two groups. It is important to note that all the unadjusted mean differences are statistically significant, but not all adjusted differences are statistically significant. Significance can be interpreted by using the key below the table.

The coefficient of the marital status variable shows that widowed individuals have negligible differences in food spending between food stamp recipients and non-recipients. However, divorced and never-married individuals in the food stamp recipients group spend less than those in the non-

Table 1: Summary Statistics with Mean Differences

	(1)	(2)	(3)	(4)
Variable	**Food Stamp Recipients**	**Food Stamp Non-Recipients**	**Un-Adjusted Mean Difference**	**Adjusted Mean Difference**
	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)
Food Spending	129.688	138.454		
	(102.743)	(98.622)		
Marital Status				
Married	0.299	0.608		
	(0.458)	(0.488)		
Widowed	0.039	0.019	0.019***	-0.000
	(0.193)	(0.136)	(0.001)	(0.002)
Divorced	0.254	0.133	0.113***	-0.007
	(0.435)	(0.339)	(0.003)	(0.005)
Separated	0.057	0.017	0.040***	0.001
	(0.232)	(0.128)	(0.001)	(0.002)
Never married	0.352	0.223	0.135***	-0.018**
	(0.478)	-0.417	(0.003)	(0.007)
Education Attainment				
Less than High School	0.023	0.004		
	(0.151)	(0.066)		
Some High School	0.055	0.009	0.045***	-0.001
	(0.227)	(0.096)	(0.001)	(0.001)
High school graduate or equivalent	0.244	0.093	0.145***	-0.012***
	(0.429)	(0.290)	(0.002)	(0.003)
Some college	0.326	0.193	0.136***	-0.015**
	(0.469)	(0.395)	(0.003)	(0.006)
Associate's Degree	0.136	0.103	0.034***	-0.009**
	(0.343)	(0.304)	(0.002)	(0.004)
Bachelor's degree	0.145	0.323	-0.172***	-0.004
	(0.352)	(0.468)	(0.003)	(0.012)
Graduate degree	0.071	0.274	-0.206***	0.041***
	(0.257)	(0.446)	(0.003)	(0.015)
Age Of Household Head	45.211	46.087	-1.031***	0.235
	(11.389)	(11.574)	(0.084)	(0.256)
=1 if Female	0.744	0.594	0.147***	-0.066***
	(0.436)	(0.491)	(0.004)	(0.013)

Table 1: Summary Statistics with Mean Differences

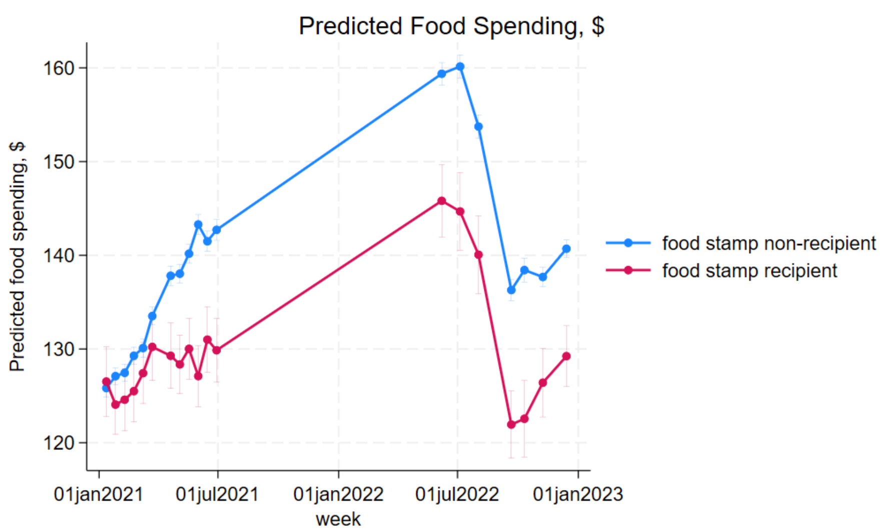
	(1)	(2)	(3)	(4)
Variable	**Food Stamp Recipients**	**Food Stamp Non-Recipients**	**Un-Adjusted Mean Difference**	**Adjusted Mean Difference**
	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)	Mean (Std. Dev)
Number of people in Household	3.464	2.891	0.576***	0.281***
	(1.888)	(1.444)	(0.011)	(0.027)
# of Children under 18 in HH	1.206	0.735	0.451***	-0.031
	(1.360)	(1.068)	(0.008)	(0.020)
Income Categories				
Less than $25,000	0.434	0.059		
	(0.496)	(0.236)		
$25,000 - $34,999	0.156	0.061	0.100***	-0.002
	(0.363)	(0.240)	(0.002)	(0.002)
$35,000 - $49,999	0.112	0.086	0.033***	-0.002
	(0.315)	(0.281)	(0.002)	(0.003)
$50,000 - $74,999	0.094	0.152	-0.051***	-0.005
	(0.292)	(0.359)	(0.003)	(0.006)
$75,000 - $99,999	0.042	0.136	-0.092***	-0.005
	(0.202)	(0.343)	(0.002)	(0.006)
$100,000 - $149,999	0.032	0.191	-0.159***	0.003
	(0.175)	(0.393)	(0.003)	(0.010)
$150,000 - $199,999	0.011	0.100	-0.091***	0.019
	(0.103)	(0.300)	(0.002)	(0.012)
$200,000 and above	0.007	0.127	-0.126***	-0.004
	(0.082)	(0.333)	(0.002)	(0.015)
Race				
White	0.668	0.822		
	(0.471)	(0.383)		
Black	0.199	0.069	0.142***	0.001
	(0.399)	(0.253)	(0.002)	(0.004)
Asian	0.035	0.059	-0.024***	0.041***
	(0.183)	(0.236)	(0.002)	(0.012)
Other/mixed	0.099	0.050	0.044***	-0.007***
	(0.298)	(0.219)	(0.002)	(0.002)
Observations	62,076	657,466	244,573	244,573

Notes: For Marital Status, “Married” is the base. For Educational Attainment “Less than High School” is the base. For Income Categories, “Less than $25,000” is the base. For Race, “White” is the base. Data: HPS. Robust standard errors in parentheses *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$

recipient group. Analysis of educational attainment shows that individuals with a high school degree, some college education, and an associate degree who receive food stamps spend less than their non-recipient counterparts. On the other hand, individuals with a graduate degree who receive food stamps spend more than non-recipients. Looking at the impacts of income categories, those earning between \$25,000 - \$34,999 and \$35,000 - \$49,999 among food stamp recipients spend less than their non-recipient counterparts. When looking at race, Asian individuals who receive food stamps spend more than their non-recipient counterparts.

Below are two figures that visually demonstrate the treatment variable with predicted household food spending. To visually convey the relationship between the treatment variable and predicted household food spending, we present two figures. Figure 1 illustrates the predicted food spending over time, denominated in dollars, while Figure 2 depicts the predicted food spending with the age of the head of the household.

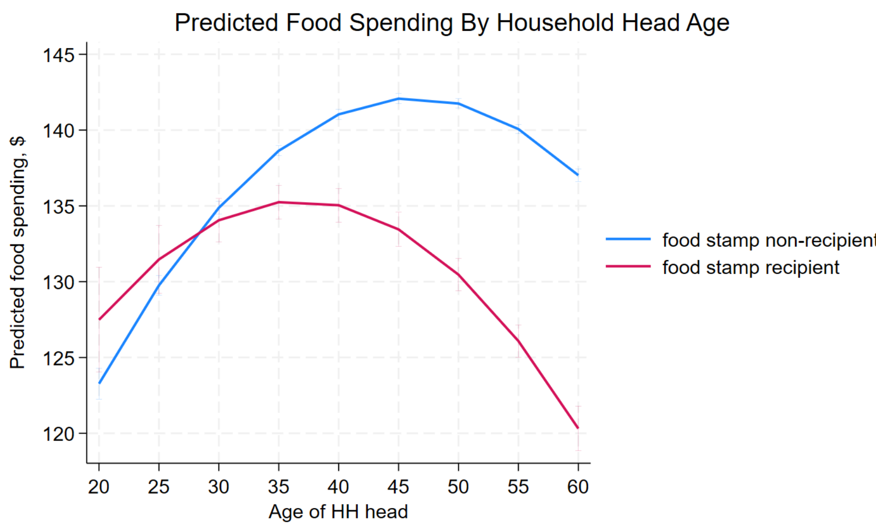
Figure 1: Graph of Predicted Food Spending Over Time



Notes: This figure shows the progression of food spending from 2021-2022, x-axis is the week in which the respondents completed the survey, y-axis is predicted food spending on prepared meals and groceries. Data: HPS

Figure 1 illustrates the evolution of predicted food spending from January 2021 to January 2023. It features two distinct trend lines that delineate the divergent spending patterns of individuals who receive SNAP benefits and those who do not. This graph was created by regressing food spending on the interaction of food stamp recipiency and time. The results of this regression enabled us to create lines that predict food spending based on food stamp recipiency status throughout each survey. Subsequently, we plotted these lines, positioning predicted food spending on the y-axis and time on the x-axis. Initially, both groups followed comparable levels of spending. However, individuals not receiving food stamps experience a substantial increase in food spending, creating a noticeable gap between the two groups. The actual month-to-month increase in food spending becomes more similar around July 2021, with a consistent rise until July 2022. At this juncture, there is a sharp decline in food spending for both groups over the subsequent months. Only around October to November 2022 does food spending begin to rebound for both groups, with a slightly swifter increase for those receiving food stamps.

Figure 2: Graph of Predicted Food Spending over Household Head life cycle



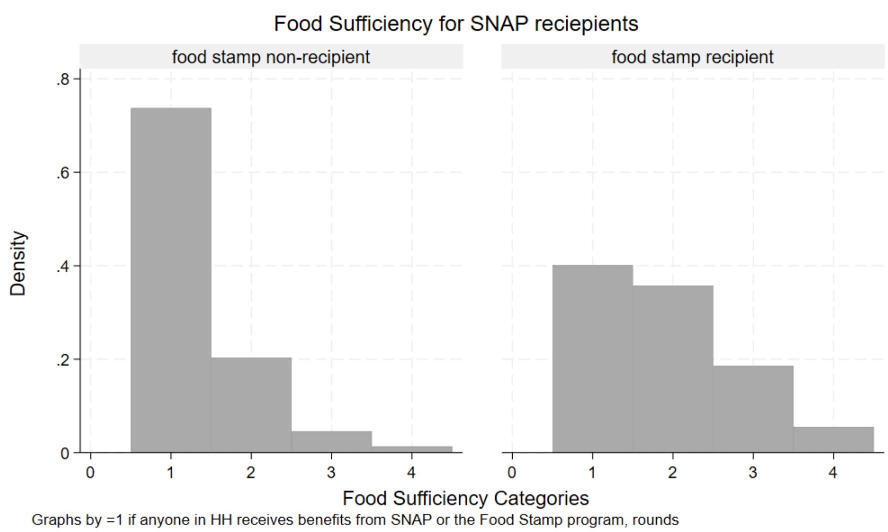
Notes: This figure shows the progression of food spending over the life cycle of the household head, the x-axis is the age of the household head (does not take into account other family members' age), the y-axis is predicted food spending on prepared meals and groceries. Data: HPS

Figure 2 presents the evolution of predicted food spending across different age groups of household heads, focusing on individuals aged 20 to 60. This graph was generated by regressing food spending on the interaction between food stamp recipiency and the "age of the head of household" variable squared. We then used this regression to predict food spending based on food stamp recipiency status throughout the head of the household's life cycle, spanning from age 20 to age 60 in five-year intervals. Finally, we plotted the predicted food spending on the y-axis and age on the x-axis. Two distinct trend lines depict the contrasting patterns between recipients of SNAP benefits and non-recipients. Within the younger age bracket, those who receive food stamps are projected to spend approximately $3-4 more than those who do not. Both groups exhibit a concave relationship with food spending concerning age. However, it becomes evident that household heads who receive food stamps tend to progressively reduce their food expenditures after reaching age 35, with predicted spending reaching $120 by age 60. In contrast, for those not receiving SNAP benefits, Figure 2 illustrates a decline in food spending that initiates around age 45, with projected spending ending at approximately $137 for individuals aged 60. It is worth noting that the peak point of food spending is approximately $7 higher for those who are not beneficiaries of food stamps.

In our model, we utilize a categorical outcome variable that measures food sufficiency. Within the Household Pulse Survey, food sufficiency is assessed through responses to the question: ”Getting enough food can also be a problem for some people. In the last 7 days, which of these statements best describes the food eaten in your household?” Respondents are presented with four statement choices to select from, which are as follows:

1. Enough of the kinds of food (I/we) wanted to eat.
2. Enough, but not always the kinds of food (I/we) wanted to eat.
3. Sometimes not enough to eat.
4. Often not enough to eat.

Figure 3: Food Sufficiency Breakdown by SNAP Recipiency

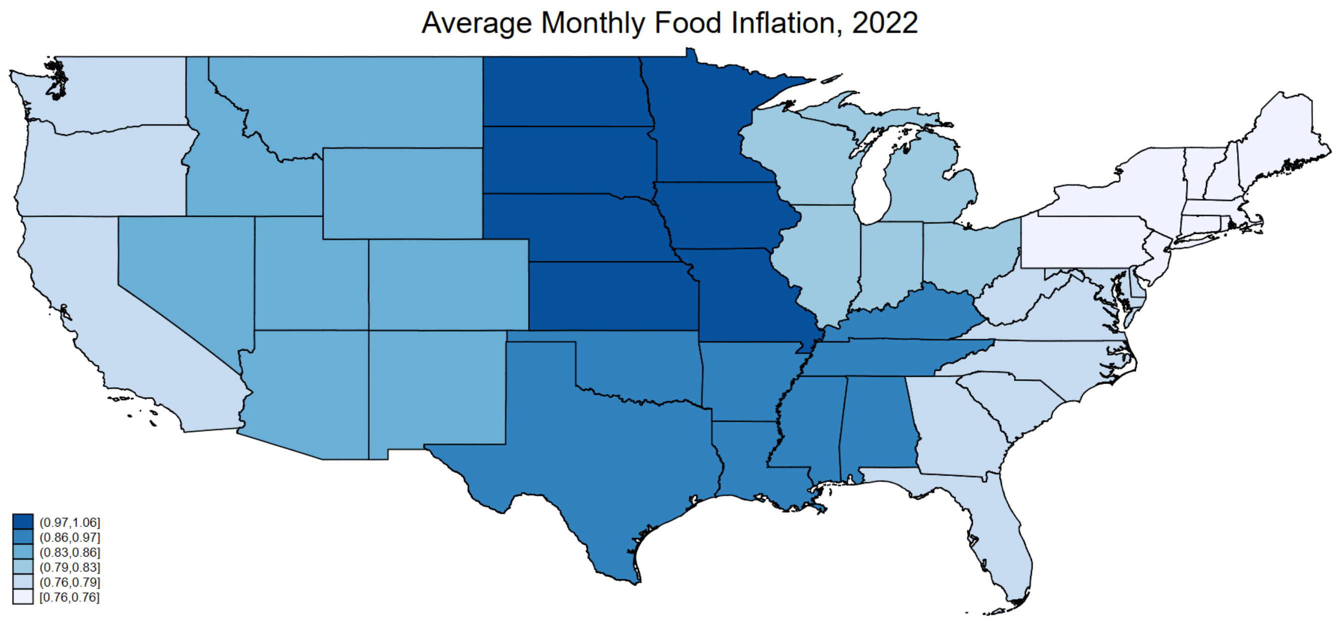


Notes: Illustrates the breakdown of self-reported food sufficiency categories among SNAP recipients and non-recipients. Categories include respondents with enough to eat and preferred foods (Category 1), enough to eat but not always preferred foods (Category 2), insufficient food with hunger (Category 3), and insufficient food without hunger (Category 4). Data: HPS

The histogram depicted on the left side of Figure 3 illustrates the distribution of responses to the question regarding self-reported food sufficiency, with a focus on individuals who do not receive SNAP benefits. This histogram highlights that most survey participants who do not receive food stamps reported having enough to eat, and their food aligns with their preferences. A smaller number of respondents mentioned having enough to eat but not always their preferred choice and even fewer indicated that they sometimes do not have enough to eat. Almost no respondents stated that they often do not have enough to eat. Overall, the histogram is right-skewed, with most responses favoring the first choice, but there are very few outliers to the right of that category.

The histogram on the right side of Figure 3 displays the distribution of responses to the same question regarding food sufficiency, specifically for individuals who receive SNAP benefits. In this

Figure 4: Map of Food Inflation by Region in 2022



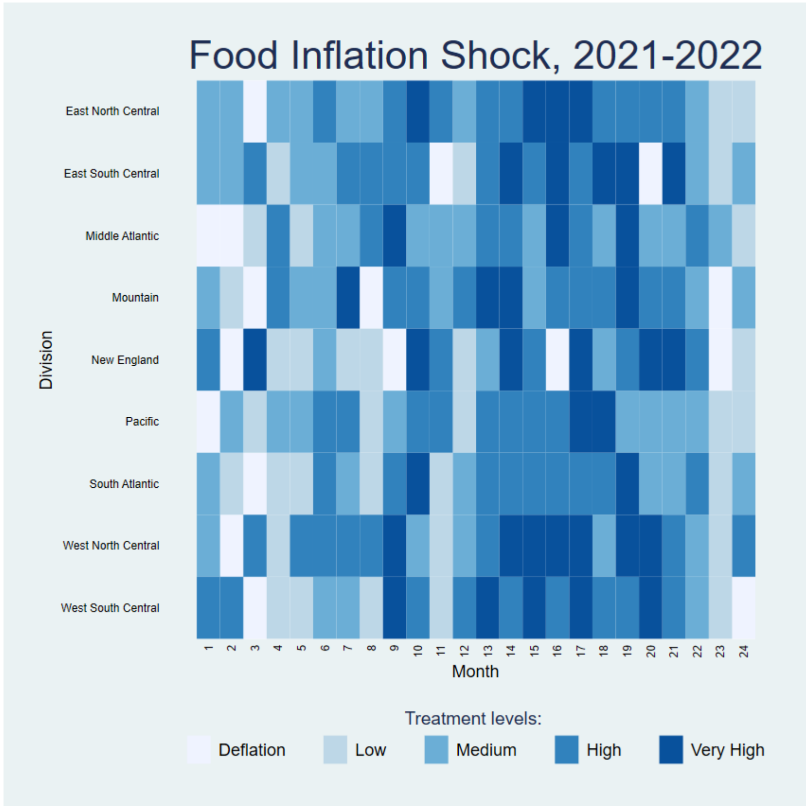
Notes: The map only depicts average monthly food inflation for regions of the mainland United States and no other US territories. The different shading represents the intensity of average monthly food inflation with darker shades representing higher average monthly food inflation across a region. Data: CPI

histogram, it is evident that most survey participants who receive food stamps reported that they have enough to eat, and the food they have aligns with their preferences. A smaller, albeit similar, number of respondents indicated that they have enough to eat but not always their preferred choice. The histogram displays a right skew, indicating that many responses lean toward the first choice, although there are some outliers – individuals who responded that they often do not have enough to eat.

Something to be noted with these histograms is the larger discrepancy between the group sizes in each histogram of Figure 3. This can be interpreted as the following: people who receive food stamps could be less food sufficient, as they responded more frequently to the questions that are associated with low food sufficiency. By choosing these variables as our treatment and outcome variables respectively, we can see if there is a significant relationship between receiving SNAP benefits and how much each household spends on food every week.

Figure 4, presented above, provides an overview of the average monthly food inflation across various geographic regions of the mainland United States for the year 2022. Notably, the map visualization excludes the regions of Hawaii and Alaska. The variation in blue shading on the map signifies different levels of food inflation within the various Consumer Price Index (CPI) divisions. The Northeast region of the United States exhibits the lowest monthly food inflation, denoted by the lightest blue shading. Conversely, the Midwest region experiences the highest levels of food price inflation, marked by the darkest blue shading. The range in average monthly food inflation

Figure 5: Panel view of Food Price Inflation by Region for Years 2021-2022



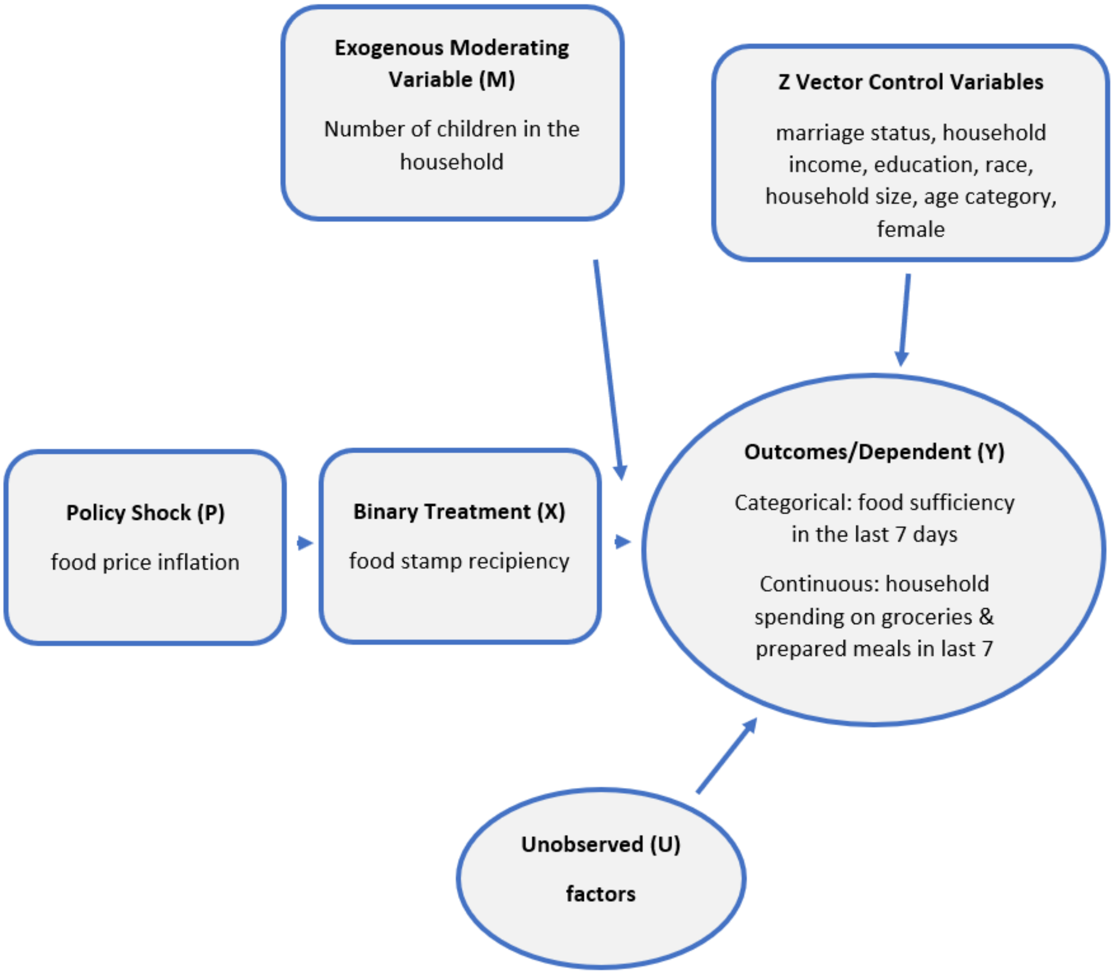
Notes: Illustrates the dynamics of food price inflation across different regions in the United States for the years 2021-2022. Each panel represents a specific region, showcasing the fluctuations in monthly food inflation. The variations in color intensity highlight the different levels of inflation experienced by different geographical divisions. Data: CPI

for 2022 highlights the diversity of food inflation experiences for SNAP recipients across different areas of the United States. This variation inevitably influences their capacity to afford groceries and food purchases, irrespective of their SNAP benefit status.

In Figure 5, we present a panel view of our shock variable, which is categorized into five distinct groups representing different levels of food price inflation. The majority of U.S. divisions experience inflation ranging from medium to very high levels between the 12 to 22-month period. This visualization illustrates the variability in food price inflation across months, highlighting that not all regions undergo very high food inflation simultaneously. What is also noteworthy is the presence of deflation in several divisions during the initial months of 2021 and at various points throughout the observation period. This challenges the conventional notion that inflation was the sole trend during our period of interest, underscoring instances where food prices decreased.

V. Empirical Framework

Figure 6: Empirical Framework Diagram



The binary treatment variable we have chosen, denoted as X, focuses on household food stamp recipiency. Our initial outcome of interest pertains to household food spending, which refers to expenses on groceries and prepared meals over the past 7 days. This spending is adjusted for adult equivalency and the Consumer Price Index and treated as a continuous variable. Our hypothesis centers on the belief that an individual's recipiency of food stamps will have a discernible impact on their weekly food expenditure. The logic behind this is that recipients of food stamps are provided with additional purchasing capacity for eligible food items compared to those who do not receive SNAP benefits. Our second outcome of interest relates to a categorical variable that has 4 different self-reported evaluations of food sufficiency. We anticipate that food stamp recipiency will have a substantial impact on an individual's ability to modify their self-rated food sufficiency. Those who can use food stamps for their grocery expenses are likely to experience an increase in their self-rated food sufficiency category. Additionally, food stamp recipiency is expected to influence the allocation of food spending between groceries and expenditures related to eating outside the home (e.g., fast food, restaurants, etc.). This allocation is an important aspect of food sufficiency that deserves consideration when assessing the impact of food stamp benefits.

Our primary hypothesis regarding the treatment variable and the continuous outcome variable for food spending is that individuals receiving food stamps will exhibit increased food spending. In this hypothesis, income is controlled for such that differing income levels are considered in our exploration of food spending. We recognize that individuals receiving lower levels of income are those who will be receiving food stamps and thus are controlling for differing income levels in our analysis. However, it is worth noting that the effect of the treatment variable on food spending may not be straightforward. Ambiguity arises because food stamp recipients may not necessarily choose to increase their food consumption; they may maintain their dietary preferences and not spend more on household groceries, despite their recipiency for food stamps. We also hypothesize that food stamp recipiency is likely to exert a positive influence on food sufficiency in the last 7 days, primarily because it enhances a household's ability to afford a more ample food supply. However, there is a counterbalancing hypothesis to consider: food stamp recipiency might also negatively impact on food sufficiency. This negative effect could stem from individuals using food stamps to purchase more of these less nutrient-dense foods, thus failing to significantly improve their food sufficiency. It is also plausible that other variables, such as rising food prices or individual dietary preferences, could outweigh the influence of SNAP benefits, resulting in little to no observable effect on food sufficiency. In our study of food sufficiency and food stamp recipiency, we are still controlling for differing income levels.

Our selection of control variables includes marital status, education, age, gender, household size, income, and race. We have chosen these control variables because we believe they influence our two outcome variables. Marital status and household size, for instance, have a notable impact on the quantity of food consumed, which consequently affects both food spending and food sufficiency. Income plays a pivotal role in determining both the quantity and quality of food that can be procured, thus influencing both food spending and food sufficiency. Additionally, factors such as education, gender, age, and race can also significantly impact food choices. Men and women, for instance, may exhibit varying food preferences, as can individuals from different racial backgrounds, educational levels, and age groups.

As for our moderating variable, we consider the number of children within a household. This variable accounts for the greater food spending necessitated by the presence of more mouths to feed in a household compared to one without children. The impact of food stamp recipiency on food spending and food sufficiency is expected to vary based on whether the household has children, with the effects becoming more pronounced in households with numerous children. Our shock variable is monthly food inflation, expressed as a percentage. This variable is continuous in nature, but we have also devised a categorical version with five distinct categories. The baseline category signifies a period of deflation. Category 2 corresponds to low inflation when food inflation falls between 0 and 34%. Category 3 is designated for medium inflation, occurring when food inflation ranges from 35 to 67%. Category 4 represents high inflation, spanning food inflation rates between 68 and 111%. Category 5 pertains to very high inflation, occurring when monthly food inflation exceeds 111%.

Below is the simple OLS model that was used to examine how food stamp recipiency impacts food expenditure:

$$\ln(Y_i) = \beta_0 + \gamma_1 X_{it} + \beta_1 Z_{it} + \theta_t + \mu_s + \varepsilon_i \tag{1}$$

- Y_i – food spending (continuous outcome variable)
- X_{it} – food stamp recipiency, variable = 1 if individual receives food stamps
- θ_t – time fixed effects
- μ_s – division fixed effects
- ϵ_i – i.i.d error term

In the OLS model, we adhere to fundamental assumptions of the error term. Exogeneity asserts that the error term in our regression model is uncorrelated with the values of our explanatory variables, such as SNAP benefit recipiency and other socio-demographic factors. Potential unobserved factors such as outside funding sources, the industry of employment, and the frequency of food assistance might influence food spending and potentially violate the exogeneity assumption. This might introduce bias into the coefficient estimates above.

A model with the moderating variable, the number of children in the household, is shown below.

$$\ln(Y_i) = \beta_0 + \gamma_1 X_{it} + \gamma_2 M_i + \gamma_3 (X_{it} \cdot M_{it}) + \beta_1 Z_{it} + \theta_t + \mu_s + \varepsilon_i \tag{2}$$

The results from both simple OLS models show that all covariates look significant in predicting food spending. Concerning the income categories, we find that all income categories are statistically significant in predicting food expenditures. Income is an important factor to consider when looking at food expenditures. Our OLS model findings align with our initial assumption that households in lower income brackets tend to spend less on food. The covariates of age and gender seem to have a small and negative, but statistically significant effect on food expenditures.

One noticeable difference in the results for the simple OLS model that includes the moderating variable in Table 2 is that the coefficient for food stamp recipiency is negative, compared to the

Table 2: Coefficients from the Simple OLS Models		
	(1)	(2)
Variable	**Simple OLS Model**	**Simple OLS Model with Moderating Variable**
=1 if Food Stamp Recipient	0.113***	-0.0147**
	-0.00434	-0.00664
1 Child Under 18		0.122***
		-0.00276
Receives Food Stamps & 1 Child Under 18		0.127***
		-0.00996
Marital Status		
Divorced	-0.00747**	-0.0241***
	-0.0031	-0.00309
Never Married	-0.0696***	-0.0468***
	-0.00279	-0.00281
Education		
High school graduate or equivalent	-0.172***	-0.170***
	-0.0158	-0.0157
Bachelor's degree	-0.189***	-0.195***
	-0.0156	-0.0155
Female	-0.0517***	-0.0545***
	-0.00189	-0.00188
Total number of people in HH	-0.114***	-0.178***
	-0.00073	-0.00109
Income Categories		
\$25,000 - \$34,999	0.123***	0.113***
	-0.00581	-0.00578
\$50,000 - \$74,999	0.257***	0.251***
	-0.00509	-0.00507
\$100,000 - \$149,999	0.393***	0.391***
	-0.00509	-0.00507
\$200,000 and above	0.617***	0.615***
	-0.00534	-0.00532
Race		
Black	0.0862***	0.0753***
	-0.00401	-0.00398
Asian	0.108***	0.122***
	-0.00402	-0.00401
Other/mixed	0.0642***	0.0663***
	-0.00451	-0.00448

Table 2: Coefficients from the Simple OLS Models		
	(1)	(2)
Variable	**Simple OLS Model**	**Simple OLS Model with Moderating Variable**
Constant	5.093***	5.129***
	-0.017	-0.017
Observations	719,542	719,542
R-squared	0.072	0.083

Notes: The coefficient for observations with missing income is not reported. Robust standard errors in parentheses *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$. Not all coefficients included, excluded coefficients: Having 2-5+ children, Interactions between receiving food stamps and having 2-5+ children, Marital status (widowed, never married), Education levels: some high school, some college, associate's degree, graduate degree, age coefficient excluded, certain income levels excluded. All coefficients included in full table in appendix.

coefficient in the simple OLS model without the moderating variable having a positive coefficient. Some possible explanations for this are the interaction effect and multicollinearity. The presence of the variable for children under 18 has changed the way food stamp recipiency affects food spending, resulting in a different sign in the coefficient. With regards to multicollinearity, food stamp recipiency could be correlated with the number of children under 18 in the household. This can affect the stability and the interpretation of the coefficient for food stamp recipiency.

VI. DID Model

With our initial empirical model, we hope to estimate the influence of SNAP benefits on food spending, when controlling for various demographic characteristics. The initial hypothesis we have for our treatment variable and our continuous outcome variables is that if an individual receives food stamps, then they will spend more on food. Our treatment variable could have an ambiguous effect on food spending because people who are receiving food stamps may not necessarily increase their food consumption, thus they do not spend more money on household groceries and keep their same dietary preferences regardless of their recipiency of food stamps. It is not necessarily possible that reverse causality can happen from Y to X because increased food spending does not necessarily indicate that an individual is receiving food stamps. Looking into income levels for this would be beneficial to see if reverse causality is possible in lower income levels. We hypothesize that food stamp recipiency is likely to have a positive impact on food sufficiency in the last 7 days because households can afford more food. However, food stamp recipiency could also negatively impact food sufficiency due to people purchasing less nutrient-dense foods with food stamps, causing them to not become more food-sufficient or maintain their current rating. It could also be true that due to some other factors, such as increasing food prices, SNAP benefits have little to no effect on food sufficiency because recipients' diets will not be altered. Our baseline DID empirical equation with two-way time/location fixed effects is:

$$\ln(Y_i) = \beta_0 + \gamma_1 X_{it} + \beta_1 Z_{it} + \theta_t + \mu_s + \varepsilon_i \tag{3}$$

Our Y_{it} is our continuous variable for household food spending on groceries and prepared meals in the past 7 days adjusted for adult equivalency and the consumer price index. The shock variable P_{st} in our empirical equation is monthly food inflation. When we have it as a continuous variable. When food inflation is a categorical variable, it is broken down into 5 categories. Category 1 is for deflation, which occurs when food inflation is less than 0. Category 2 is for low inflation, which occurs when food inflation is between 0 and 34$\%$. Category 3 is for medium inflation (when food inflation is between 35 and 67$\%$). Category 4 is for high inflation (when food inflation is between 68 and 111$\%$). Category 5 is for very high inflation when monthly food inflation is greater than 111$\%$. We observe the effects of food price inflation on food spending for the years 2021-2022. We do not include notable sample constraints for demographics.

Time and location fixed effects are important for our DID model because they help control unobserved differences that might bias the estimates it outputs. Holding time constant, location-based fixed effects can control for factors like different state-level policies. Some examples of state policies that can affect the affordability of food items may be differing sales tax on food and minimum wage. According to research by the Center on Budget and Policy Priorities (CBPP) , sales tax rates on food purchases vary significantly by state. For example, in 2020 Utah had a 3$\%$ sales tax on food while Arkansas only had a 0.125$\%$ sales tax on food. Holding division constant, time-based fixed effects can control for factors like the implementation of new policies that could affect food spending. For example, the American Rescue Plan Act of 2021 which provided a temporary increase to SNAP benefits and expanded eligibility for the program, therefore, likely leading to an increase in food spending among low-income households (U.S Department of Agriculture).

Our DID model breaks the parallel-trend assumption of the classical DID model. Our control (individuals not receiving SNAP benefits) and treatment group (SNAP benefits recipients) already have differing characteristics before the treatment. One example of a way our DID model could break the parallel-trend assumption is because of the differences in income and job stability between our control group and our treatment group. SNAP recipients may be more likely to have low-income jobs or unstable employment therefore during periods of economic downturns, SNAP recipients might be more likely to face job losses or reduced working hours. This decrease in overall income combined with food inflation can lead to a more substantial reduction in food spending for SNAP recipients than non-SNAP recipients who may have more stable jobs and whose income may not be as affected by the economic conditions.

Going further into our analysis, we used the triple difference model to assist in estimating the causal impact of the shock on our outcome of food spending, specifically to see the policy's effect on a specific group over time. The triple difference model looks at time differences, group differences, and policy/shock differences. Typically to set up a triple difference model, researchers will collect data on the outcome variable of interest for control and treatment groups before and after the policy/shock change. The model then estimates the effect of the treatment by looking at the difference in outcomes. For our model, the triple difference model is:

$$\ln(Y_i) = \alpha + \beta Z_{it} + y_1 X_{it} + \gamma_3 (P_{st} \cdot X_{it}) + \mu_s + \theta_t + \varepsilon_i \tag{4}$$

$$X_{it} = \begin{cases} = 0 & \text{if individual receives SNAP benefits} \\ = 1 & \text{if individual does not receive SNAP benefits} \end{cases}$$

P_{st} is our categorical variable for levels of food inflation. The monthly food inflation shock is likely to affect individuals who receive food stamps because those who receive food stamps will likely be impacted by what foods they can afford to purchase due to the increased cost of food.

$$P_{st} = \begin{cases} = 0 & \text{if deflation} \\ = 1 & \text{if low inflation} \\ = 2 & \text{if medium inflation} \\ = 3 & \text{if high inflation} \\ = 4 & \text{if very high inflation} \end{cases}$$

We demonstrate the effects of the monthly inflation shock using our baseline DID model. Looking at the estimates that have been pulled from our baseline DID model, we were able to ascertain that the food stamp recipiency variable is significant in predicting food spending.

When examined as a continuous variable, monthly food inflation demonstrated a statistically significant aggregate effect, resulting in a 0.4% reduction in food spending per unit increase of inflation. We view this as a significant result because, in terms of monthly inflation, a 0.4% decrease is observable in everyday life. However, when analyzing food inflation as a categorical variable, the impact of low inflation did not yield any significant change, registering a 0% effect. For medium inflation, there was a modest decrease, leading to a 0.4% reduction in food spending. High inflation had a minimal effect, resulting in a 0.1% reduction in food spending. In the case of very high inflation, there was a more pronounced impact, with an aggregate effect of reducing food spending by 0.8%. Nevertheless, it is noteworthy that none of the coefficients for the different levels of food inflation are statistically significant.

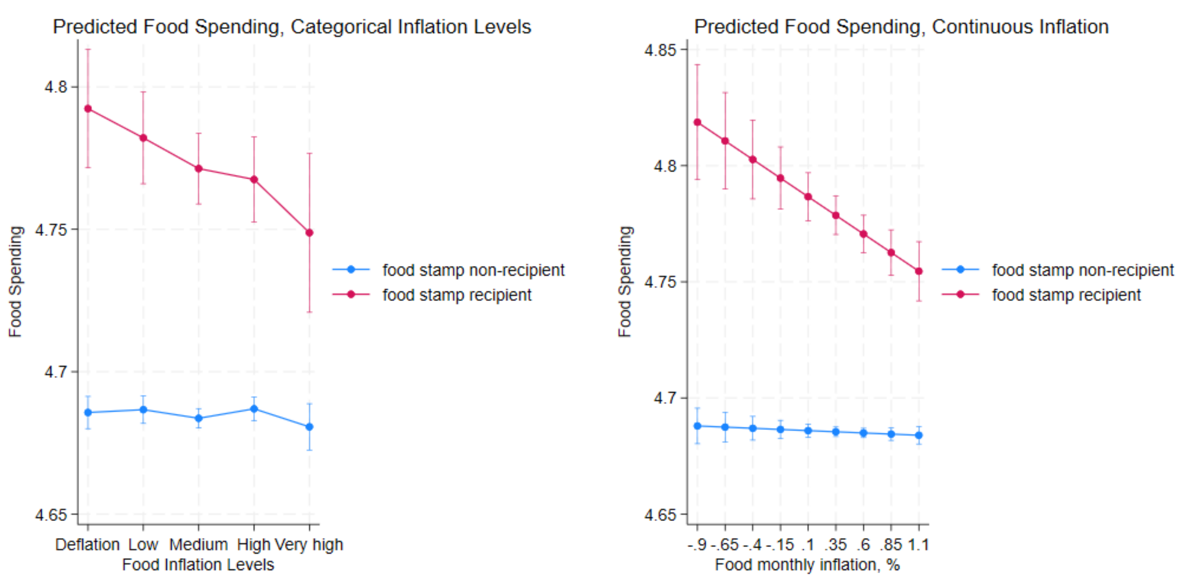
When visualizing our policy effect on food spending and separating for different levels of infla-

Table 3: Baseline DID Model		
	(1)	(2)
Variable	**Inflation-unadjusted**	**Level-unadjusted**
Inflation Levels		
Low Inflation		0
		-0.004
Medium Inflation		-0.004
		-0.003
High Inflation		-0.001
		-0.004
Very High Inflation		-0.008
		-0.005
Food Stamp Recipiency	0.089***	0.089***
	-0.004	-0.004
Marital Status		
Divorced	-0.029***	-0.029***
	-0.003	-0.003
Never married	-0.049***	-0.049***
	-0.003	-0.003
Educational Attainment		
High school graduate or equivalent	-0.165***	-0.165***
	-0.016	-0.016
Bachelor's degree	-0.191***	-0.191***
	-0.015	-0.015
=1 if Female	-0.052***	-0.052***
	-0.002	-0.002
Household Size	-0.178***	-0.178***
	-0.001	-0.001
# of Children under 18 in HH	0.120***	0.120***
	-0.001	-0.001
Income Categories		
$25,000 - $34,999	0.124***	0.124***
	-0.006	-0.006
$50,000 - $74,999	0.261***	0.261***
	-0.005	-0.005
$100,000 - $149,999	0.397***	0.397***
	-0.005	-0.005
$200,000 and above	0.608***	0.608***
	-0.005	-0.005

Table 3: Baseline DID Model		
	(1)	(2)
Variable	**Inflation-unadjusted**	**Level-unadjusted**
Race		
Black	0.067***	0.067***
	-0.004	-0.004
Asian	0.101***	0.101***
	-0.004	-0.004
Other/mixed	0.054***	0.054***
	-0.004	-0.004
Monthly Food Inflation	-0.004*	
	-0.003	
Constant	5.036***	5.037***
	-0.018	-0.018
Observations	719,542	719,542
R-squared	0.091	0.091

Notes: The baseline DID model explores the impact of monthly food inflation on food spending patterns for both SNAP recipients and non-recipients. For Marital Status, "Married" is the base. For Educational Attainment "Less than High School" is the base. For Income Categories, "Less than $25,000" is the base. For Race, "White" is the base. Some coefficients not included are: Marital status (widowed, never married), Education levels: some high school, some college, associate's degree, graduate degree, age coefficient excluded, certain income levels excluded. All coefficients included in full table in appendix. Data: HPS, CPI. Robust standard errors in parentheses *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

Figure 7: Monthly Inflation Visualization on Food Spending



Notes: Figures represent the Monthly Inflation Visualization on Food Spending, providing a visual of how inflation levels influence food spending patterns over time. The x-axis represents food inflation levels as a categorical variable and as a continuous variable, and the y-axis represents food spending percentage. Data: HPS tion, we found that predicted food spending changed for those who receive food stamps. Predicted food spending decreased by 0.07% when looking at monthly food inflation as continuous for food stamp recipients. Looking at the trends between different food inflation levels, food spending decreased at a consistent rate between low and medium inflation levels and then that rate decreased between medium and high food inflation levels. When food inflation went from high to very high, we saw the rate of decrease pick back up for food stamp recipients. For those who did not receive food stamps, the graphs do not show very much differentiation in predicted food spending based on food inflation levels.

VII. Group Balancing using Inverse Propensity Weighting (IPW)

In this section, we refer to Table 1. Upon initial examination, there are noticeable disparities in observed characteristics between the treated group (those receiving food stamps) and the control group (those not receiving food stamps). One striking observation is the significant effect on the variable of marital status, as indicated by the coefficient of 0.898. Another crucial variable to consider is household size, which ranges from one to fifteen, with a statistically significant coefficient of 0.577, illustrating mean differences between the treatment and control groups. The variables related to race also exhibit statistically significant mean differences between these two groups. Similar observations apply to the variable representing the number of children per household and our household income category variables. Notably, all our variables yielded statistically significant results when subjected to t-tests for assessing mean differences between the groups.

In our study, we created a triple difference model with Inverse Propensity Weighting (IPW) to investigate the relationship between food stamp recipiency, inflation levels, and food spending patterns. Our findings demonstrate that food stamp recipients experience an increase in food spending. However, when food inflation is treated as a continuous variable, the interaction with food stamp recipiency showed that SNAP recipients spend less as food inflation increases. The magnitude of this coefficient is small at 0.03. This decrease was not statistically significant (p-value is > 0.1) after addressing biases through IPW balancing. After IPW, this coefficient becomes positive.

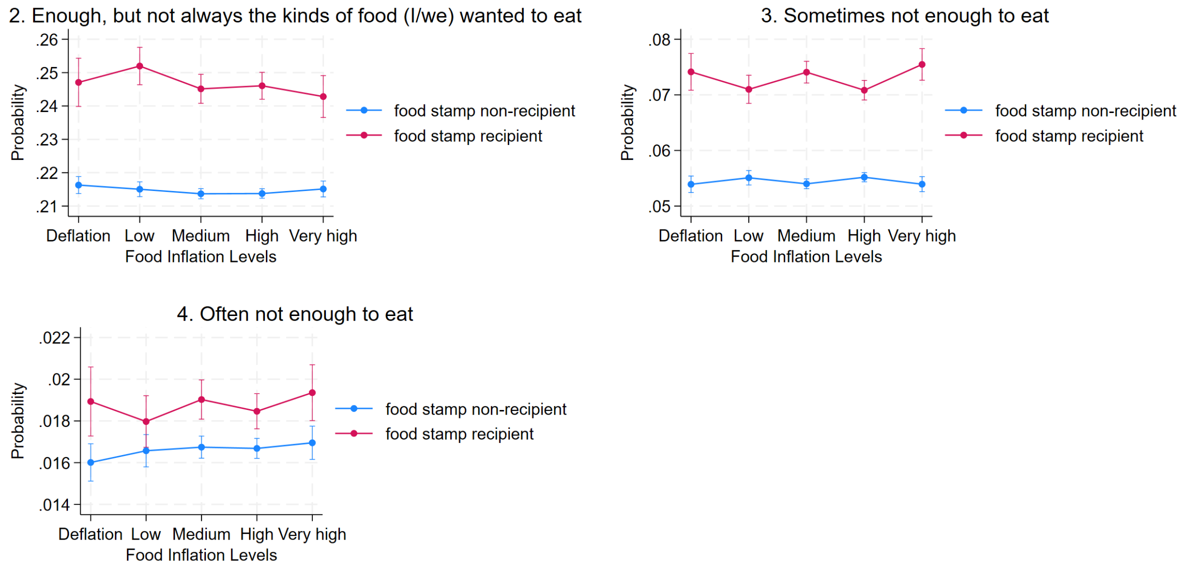
The results from interacting the categorical variable of food inflation and food stamp recipiency show that the shock of inflation did not lead to a significant increase or decrease in food spending for most levels of inflation among both food stamp recipients and non-recipients. We determined that these results among the different inflation levels were insignificant due to the small values of their coefficients and that they were not statistically significant (p-value > 0.1). We do observe that during episodes of high and very high inflation, food stamp recipients demonstrate a decrease in food spending, but again this is not statistically significant after adjusting with IPW.

Table 4: Triple Difference model with IPW

Variable	(1) Continuous Inflation-unadjusted	(2) Continuous Inflation-adjusted	(3) Inflation Level-unadjusted	(4) Inflation Level-adjusted
=1 if Food stamp recipient	0.104***	-0.025	0.107***	-0.052
	-0.006	-0.018	-0.011	-0.041
Food monthly inflation, %	-0.002	0.014		
	-0.003	-0.012		
Continuous Inflation and Food Stamp Recipient	-0.030***	0.032		
	-0.009	-0.025		
Inflation Levels				
Low			0.001	0.01
			-0.004	-0.01
Medium			-0.002	0.004
			-0.003	-0.012
High			0.001	0.019
			-0.004	-0.015
Very high			-0.005	0.015
			-0.005	-0.016
Low Inflation and Food Stamp Recipient	-0.011	0.031		
			-0.013	-0.044
Medium Inflation and Food Stamp Recipient	-0.019	0.049		
			-0.012	-0.047
High Inflation and Food Stamp Recipient	-0.026**	0.066		
			-0.013	-0.047
Very High Inflation and Food Stamp Recipient	-0.039**	0.034		
			-0.018	-0.05
Constant	5.034***	5.100***	5.036***	5.099***
	-0.018	-0.061	-0.018	-0.06
Observations	719,542	719,542	719,542	719,542
R-squared	0.091	0.079	0.091	0.079

Notes: The inclusion of Inverse Propensity Weighting further refines the estimation of causal effects. Excluding control variables used in estimation and some inflation and food stamp recipiency interactions. Data: HPS, CPI. Robust standard errors in parentheses *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

Figure 8: Multinomial Logistic Regression Plot of Food Sufficiency Categories



Notes: Illustrates the results of the Multinomial Logistic Regression analysis examining the relationship between food stamp recipiency, monthly inflation levels, and self-reported food sufficiency categories. The lines represent the predicted probabilities of falling into different food categories, with distinct lines for SNAP recipients and non-recipients. Data: HPS, CPI

VIII. Multinomial Logistic Regression of Food Sufficiency on SNAP Recipiency

To understand the impact of food stamp recipiency on food sufficiency across various levels of monthly food inflation, we employed a multinomial logistic regression. Multinomial logistic regression is a suitable statistical method when the outcome variable is nominal and comprises more than two categories. In our research, the food sufficiency variable consists of four distinct categories, thus making this regression an appropriate choice for modeling our data. Our regression analysis involved regressing food sufficiency on the interaction between monthly food inflation shock levels and food stamp recipiency. The reference or base outcome in our regression analysis corresponds to respondents who reported having enough to eat and consuming the foods they preferred, denoted as category 1. We observed that category 1, signifying self-reported food sufficiency, was the most prevalent observation among both SNAP recipients and non-SNAP recipients in our dataset.

Following the completion of this regression analysis, we generated a line graph that calculates the marginal effects of the interaction on the likelihood of food sufficiency falling into category 2, where respondents have enough to eat but not always the kinds of food they prefer. This line was then visually represented on a graph, with probability on the y-axis and food inflation on the x-axis, as depicted in the top-left corner of Figure 8. The same procedure was replicated for categories 3 and 4 of food sufficiency, as shown in Figure 8. We also created separate lines for SNAP benefit recipients and non-recipients. All the plots reveal minimal fluctuations in the probability of the respective food sufficiency categories for both food stamp recipients and non-recipients. Notably, food stamp recipients displayed a slightly higher likelihood of falling into category 2, especially during periods of low inflation. In Category 3, the probabilities were considerably lower than those in Category 2, with less differentiation between the two treatment groups. Category 4 exhibited an even narrower probability range, ranging from 1.6% to 1.9%, with limited variation between the two treatment groups. From the results of this multinomial logistic regression, we can discern that some differences exist in terms of food sufficiency between SNAP benefit recipients and non-recipients, but these differences do not raise considerable concern.

IX. Conclusion

Throughout our paper, we investigate the relationship between food stamp recipiency, food expenditure patterns, and food sufficiency in the United States. Building on the current literature exploring food inflation and food expenditure, we monitor how food stamp recipiency impacted food spending over varying levels of food inflation. Through different methods, such as OLS, DID, IPW, and multinomial logistic regression, our research has provided new insights into food affordability and sufficiency for SNAP recipients and non-recipients using the HPS. This dataset offers insight into how the COVID-19 pandemic impacted American households. Our treatment variable is food stamp recipiency and we explore the outcomes of food expenditure and food sufficiency. We see differing trends in food expenditure over the 2021-2022 survey period. We saw that most survey respondents were not recipients of SNAP benefits, and most of these respondents reported that they were food-sufficient. We also looked at the substantial regional disparities in food inflation across the continental United States.

Our baseline findings highlight a positive relationship between food expenditure and SNAP recipiency. Looking further into the influence of monthly food inflation on food expenditure, we found that inflation treated as a continuous variable influenced food spending. However, the effects were not consistently significant across different inflation levels when inflation is categorical. By creating a triple difference model with IPW, we investigated the relationship between food stamp recipiency, different levels of inflation, and food spending patterns while addressing potential biases in our analysis. We found that the shock of inflation did not lead to a significant increase or decrease in food spending at most levels among the control and treatment groups. Our food sufficiency investigation identified minimal fluctuations in the probability of differing food sufficiency categories for both food stamp recipients and non-recipients.

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Appendix

Vector	Variable Name	Variable Label	Type	Notes about variable construction
Y_{it}	hhspndfood	Household food spending on groceries and prepared meals in the past 7 days	Continuous	
Y_{it}	hhfoodsuf	HH food sufficiency in past 7 days	Categorical	4 categories: enough to eat what we want to eat, enough to eat, but not always what, sometimes not enough to eat, often not enough to eat
X_{it}	hhsnaprec	=1 if anyone in HH receives benefits from SNAP or the Food Stamp program, rounds	Binary	
P_{st}	food_infl	Food monthly inflation, %	Continuous	
P_{st}	shock	Food monthly inflation categories	Categorical	5 categories: Deflation, Low inflation, Medium inflation, High Inflation, Very High inflation
M_{it}	hhchild	Total number of people under 18 years old in household	Categorical	6 categories: 0 children, 1 child, 2 children, 3 children, 4 children, 5 children

μ_s	division	Regional Division for CPI Merge	Categorical	=1 if Northeast =2 if South =3 if Midwest =4 if West 110 = New England 120 = Middle Atlantic 230 = East North Central 240 = West North Central 350 = South Atlantic 360 = East South Central 370 = West South Central 480 = Mountain 490 = Pacific
θ_t	intmid	Middle of interview period	Continuous	
Z_{it}	hhinccat	Categories for total Household Income before taxes last year	Categorical	8 categories: Less than \$25,000, \$25,000 – 34,999, \$35,000 – 49,999, \$50,000 – 74,999, \$75,000 – 99,999, \$100,000 - \$149,999, \$150,000 – 199,999, \$200,000 or above
Z_{it}	marsta	Marital status	Categorical	5 categories: married, widowed, divorced, separated, and never married
Z_{it}	educ	Educational attainment	Categorical	7 categories: less than high school, some high school, high school graduate or equivalent, some college, associate's degree,

				bachelor's degree, and graduate degree
Z_{it}	age	Age of HH head	Continuous	Age distribution is 18-64
Z_{it}	female	=1 if female	Binary	0 = No 1 = Yes
Z_{it}	hhsize	Total number of people in HH	Continuous	
Z_{it}	race	Race categories	Categorical	1 = White 2 = Black 3 = Asian 4 = Other/mixed

Table 2: Coefficients from the Simple OLS Models		
	(1)	(2)
Variable	**Simple OLS Model**	**Simple OLS Model with Moderating Variable**
=1 if Food Stamp Recipient	0.113***	-0.0147**
	-0.00434	-0.00664
1 Child Under 18		0.122***
		-0.00276
2 Children Under 18		0.220***
		(0.00325)
3 Children Under 18		0.318***
		(0.00496)
4 Children Under 18		0.414***
		(0.00792)
5 Children Under 18		0.525***
		(0.0136)
Receives Food Stamps & 1 Child Under 18		0.127***
		-0.00996
Receives Food Stamps & 2 Children Under 18		0.210***
		(0.0100)
Receives Food Stamps & 3 Children Under 18		0.253***
		(0.0122)
Receives Food Stamps & 4 Children Under 18		0.304***
		(0.0164)
Receives Food Stamps & 5 Children Under 18		0.334***
		(0.0231)
Marital Status		
Widowed	-0.0266***	-0.0416***
	(0.00786)	(0.00782)
Divorced	-0.00747**	-0.0241***
	-0.0031	-0.00309
Separated	0.0381***	0.0109
	(0.00775)	(0.00771)
Never Married	-0.0696***	-0.0468***
	-0.00279	-0.00281

Table 2: Coefficients from the Simple OLS Models		
	(1)	(2)
Variable	**Simple OLS Model**	**Simple OLS Model with Moderating Variable**
Education		
Some high school	-0.0377**	-0.0411**
	(0.0184)	(0.0183)
High school graduate or equivalent	-0.172***	-0.170***
	-0.0158	-0.0157
Some college	-0.200***	-0.196***
	(0.0156)	(0.0155)
Associate's Degree	-0.195***	-0.197***
	(0.0158)	(0.0157)
Bachelor's degree	-0.189***	-0.195***
	-0.0156	-0.0155
Graduate degree	-0.188***	-0.203***
	(0.0156)	(0.0155)
Age of HH head	-0.00378***	-0.00209***
	(9.22e-05)	(9.51e-05)
Female	-0.0517***	-0.0545***
	-0.00189	-0.00188
Total number of people in HH	-0.114***	-0.178***
	-0.00073	-0.00109
Income Categories		
$25,000 - $34,999	0.123***	0.113***
	-0.00581	-0.00578
$35,000 - $49,999	0.183***	0.174***
	(0.00548)	(0.00546)
$50,000 - $74,999	0.257***	0.251***
	-0.00509	-0.00507
$75,000 - $99,999	0.321***	0.318***
	(0.00518)	(0.00516)
$100,000 - $149,999	0.393***	0.391***
	-0.00509	-0.00507
$150,000 - $199,999	0.478***	0.479***
	(0.00536)	(0.00534)
$200,000 and above	0.617***	0.615***
	-0.00534	-0.00532

Table 2: Coefficients from the Simple OLS Models

	(1)	(2)
Variable	**Simple OLS Model**	**Simple OLS Model with Moderating Variable**
Race		
Black	0.0862***	0.0753***
	-0.00401	-0.00398
Asian	0.108***	0.122***
	-0.00402	-0.00401
Other/mixed	0.0642***	0.0663***
	-0.00451	-0.00448
Constant	5.093***	5.129***
	-0.017	-0.017
Observations	719,542	719,542
R-squared	0.072	0.083

Notes: The coefficient for observations with missing income is not reported. Robust standard errors in parentheses *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$. Not all coefficients included, excluded coefficients: Having 2-5+ children, Interactions between receiving food stamps and having 2-5+ children, Marital status (widowed, never married), Education levels: some high school, some college, associate's degree, graduate degree, age coefficient excluded, certain income levels excluded. All coefficients included in full table in appendix.

Table 3: Baseline DID Model		
	(1)	(2)
Variable	**Inflation-unadjusted**	**Level-unadjusted**
Inflation Levels		
Low Inflation		0
		-0.004
Medium Inflation		-0.004
		-0.003
High Inflation		-0.001
		-0.004
Very High Inflation		-0.008
		-0.005
Food Stamp Recipiency	0.089***	0.089***
	-0.004	-0.004
Marital Status		
Widowed	-0.050***	-0.050***
	(0.008)	(0.008)
Divorced	-0.029***	-0.029***
	(0.003)	(0.003)
Separated	0.007	0.007
	(0.008)	(0.008)
Never married	-0.049***	-0.049***
	(0.003)	(0.003)
Educational Attainment		
Some high school	-0.034*	-0.034*
	(0.018)	(0.018)
High school graduate or equivalent	-0.165***	-0.165***
	(0.016)	(0.016)
Some college	-0.190***	-0.190***
	(0.016)	(0.016)
Associate's Degree	-0.189***	-0.189***
	(0.016)	(0.016)
Bachelor's degree	-0.191***	-0.191***
	(0.015)	(0.015)
Graduate degree	-0.200***	-0.200***
	(0.016)	(0.016)
Age	-0.002***	-0.002***
	(0.000)	(0.000)
=1 if Female	-0.052***	-0.052***
	-0.002	-0.002
Household Size	-0.178***	-0.178***
	-0.001	-0.001
# of Children under 18 in HH	0.120***	0.120***
	-0.001	-0.001

Table 3: Baseline DID Model

	(1)	(2)
Variable	**Inflation-unadjusted**	**Level-unadjusted**
<u>Income Categories</u>		
\$25,000 - \$34,999	0.124***	0.124***
	(0.006)	(0.006)
\$35,000 - \$49,999	0.186***	0.186***
	(0.005)	(0.005)
\$50,000 - \$74,999	0.261***	0.261***
	(0.005)	(0.005)
\$75,000 - \$99,999	0.326***	0.326***
	(0.005)	(0.005)
\$100,000 - \$149,999	0.397***	0.397***
	(0.005)	(0.005)
\$150,000 - \$199,999	0.479***	0.479***
	(0.005)	(0.005)
\$200,000 and above	0.608***	0.608***
	(0.005)	(0.005)
<u>Race</u>		
Black	0.067***	0.067***
	-0.004	-0.004
Asian	0.101***	0.101***
	-0.004	-0.004
Other/mixed	0.054***	0.054***
	-0.004	-0.004
Monthly Food Inflation	-0.004*	
	-0.003	
Constant	5.036***	5.037***
	-0.018	-0.018
Observations	719,542	719,542
R-squared	0.091	0.091

Notes: The baseline DID model explores the impact of monthly food inflation on food spending patterns for both SNAP recipients and non-recipients. For Marital Status, “Married” is the base. For Educational Attainment “Less than High School” is the base. For Income Categories, “Less than \$25,000” is the base. For Race, “White” is the base. Some coefficients not included are: Marital status (widowed, never married), Education levels: some high school, some college, associate’s degree, graduate degree, age coefficient excluded, certain income levels excluded. All coefficients included in full table in appendix. Data: HPS, CPI. Robust standard errors in parentheses *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.1$.

Catalyzing Labor Market Participation: A Study of State-Level Earned Income Tax Credit Expansion

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Abstract

The Earned Income Tax Credit (EITC) has garnered extensive attention within the field of labor economics. Nevertheless, there exists a noticeable gap in the literature when it comes to understanding the labor-market impact of the state level EITC, which has seen increased policy activity in recent years. This paper employs a combination of difference-in-difference and triple difference with inverse probability weighting, all grounded in the framework of an individual employment outcome model. Our objective is to investigate how state-level EITC expansions, with varying levels of generosity, affect the labor market. Rotating panel data from the 2010-2019 Current Population Survey provide estimates of this effect. The result of our estimations reveals that state-level EITC expansions have yielded positive effects, particularly for single women with children, a group recognized as primary beneficiaries of the EITC. However, the degree of influence and significance levels associated with different expansion levels exhibit variation.

I. Introduction

Since 1975, the Earned Income Tax Credit (EITC) has been a cornerstone of U.S. anti-poverty policy, effectively supplementing the incomes of low-income working families (Hoynes 2016). This notable tool has consistently encouraged work among disadvantaged workers, with over 25 million eligible tax prepares receiving nearly $60 billion in federal EITC in 2023 (of State Legislatures 2023). The EITC bolsters the earnings of low-income workers, alleviating their tax burden and providing incentives for employment. Tax credits received during the income tax filing process fluctuate based on income levels and family composition.

From 1988, U.S. states gradually introduced their own EITC programs, expanding from a few states to encompass 31 states and Washington, D.C. by 2023. The generosity of these state-level

EITCs varies widely, with refundable percentages ranging from 3 percent in Montana to a nonrefundable 125 percent in South Carolina. State EITC expansion is largely driven by a desire to offer more substantial support to residents, thereby increasing transfer payments to eligible low-income recipients (Markowitz et al. 2017).

Our study aims to investigate the influence of additional state EITC on the beneficiary group and determine if aid level differences correlate with differing impacts. Our empirical approach for estimating the effects of state EITCs on labor market participation aligns closely with previous literature on EITC effects on employment and income across different populations. We distinguish groups more likely to be affected by the EITC, such as single mothers with children, from control groups like married men without children. Our primary data source is the 2010-2019 CPS (Current Population Survey) dataset, which we use to estimate the difference-in-difference (DID) and triple-difference (DDD) model. To establish causality, we assume that the timing of state EITC introduction and expansion is independent of intra-state policy changes, economic conditions, and demographic composition. The independent decision-making of state governments regarding EITC introduction and expansion ensures these policy changes remain free from external influences, allowing us to accurately assess their impact on the employment status, without interference from confounding factors.

We contribute to the existing literature in several ways. Firstly, we explore the impact of changes in the presence and generosity of state EITC programs, a measurement not extensively covered in prior literature. Within our scope, there is a notable absence of studies examining the influence of the state EITC expansion on labor market outcomes, particularly in relation to variations in its generosity. As we will elaborate, it is crucial to account for the varying degrees of state EITC expansion since more substantial expansions can significantly augment recipients' income, creating distinct labor incentives that cannot be adequately captured by a simple binary measure of whether a state implemented the EITC expansion.

Additionally, our study investigates labor market dynamics over a ten-year period, spanning from 2010 to 2019. During this time frame, six states introduced state-level EITC expansions (California, Connecticut, Hawaii, Montana, Ohio, and South Carolina). Given that the most recent post-COVID-19 expansion of the federal EITC occurred in 2009, the chosen time period allows for a one-year buffer after the federal expansion. This minimizes the influence of the federal EITC expansion on the labor market conditions we study, ensuring that the labor-related decisions of our sampled population are primarily influenced by state EITC expansions. Selecting this time period holds another significance because it aligns with the government's pressing need for economic recovery in the aftermath of the pandemic-induced depression. Analyzing the effects of policy expansions predating the epidemic offers valuable insights to inform the government's post-pandemic policy decisions. This research has the potential to uncover lessons and strategies from a pre-pandemic context, which can be highly instructive for policymakers facing the challenges of rebuilding the labor market in the wake of a global crisis. Policymakers can gain a deeper understanding from these consequences and their applicability in the current and future economic landscapes.

Section II provides an in-depth exploration of the relevant literature and the development of state EITC. Section III offers an extensive introduction to the CPS database, providing a comprehensive overview of key statistics. Section IV introduces the empirical model employed to analyze labor market disparities for both our treated and control groups. In Section V, we analyze the impact of state EITC using DID and DDD models. Finally, in Section VI, we summarize our findings and suggest potential directions for future improvements.

II. Literature Review and Background

2.1 Evolution of State EITC

EITC is a federal tax credit aimed at supporting low-income workers. While the federal EITC receives the most attention, states are increasingly implementing their own EITC programs at the state level. Rhode Island led the way by introducing the first state-level version of this tax benefit in 1986. Each state EITC program allows recipients to claim a tax deduction (as a percentage) on their federal EITC against their state income tax obligations. In most states with EITC programs, the credit is fully refundable, meaning that recipients receive a refund from the state if the credit exceeds their tax liability (Bogdanos 2019). By 2023, 31 states in the United States, including the District of Columbia and Puerto Rico, have widely adopted the state EITC.

These state EITCs are designed to assist low-income working families in meeting their basic needs. By promoting employment and alleviating financial hardships for these families and their children, they are seen as building on the success of the federal EITC. Given that people of color, women, and immigrants are disproportionately represented in low-wage jobs and low-income households, this credit serves as important tools for promoting equity. By increasing household incomes, they also contribute to the well-being of local communities and state economies (Williams et al. 2020). While white families receive more EITC services than any other racial or ethnic group due to their population size, people of color, relative to their population, receive these services at a relatively higher rate. The EITC has played a crucial role in reducing poverty rates among people of color. Historical and ongoing racial discrimination has led to many people of color working in low-wage jobs, facing barriers to financial security, and struggling to cover basic living expenses and cope with financial emergencies. The EITC addresses these disadvantages by boosting the incomes of low-wage workers. Research by (Gagnon et al. 2017) indicates that state-level EITC programs provide an average of $120 more in benefits to families of color than to non-Hispanic white families. Additionally, state-level EITC programs have helped more people of color and Hispanics rise above the poverty line.

Refundability is a crucial feature of state EITC, serving as the cornerstone of their effectiveness in increasing income, reducing poverty, and supporting families over the long term. It ensures that, if the state EITC exceeds a taxpayer's tax liability, they receive some or all of the excess credit as a refund. In this way, individuals can receive the full credit amount they qualify for based on their earnings, regardless of their tax obligations. These refundable provisions are vital because they guarantee that even those with the lowest incomes can benefit from these credits, preventing the exclusion of the most economically vulnerable families.

The state EITC, an extended version of the federal EITC, incentivizes workers in a similar manner. The EITC has three key components: the phase-in, plateau, and phase-out. The phase-in region represents the income range where the EITC, as a percentage of earned income, gradually increases. As individuals or families within this range earn more income, their EITC benefit grows, providing additional financial support to those with low incomes. The income effect of the phase-in is that it encourages, and rewards work among individuals with lower incomes. It provides an incentive for people to find and maintain employment, especially in low-paying jobs. Most economists agree that the EITC encourages low-income single mothers to join the workforce, with solid empirical support for this positive effect (Edwards and de Rugy 2015). Consequently, single women with children are often considered the primary beneficiaries of the EITC.

Once individuals reach the maximum credit within the phase-in range, their EITC remains unchanged within a certain income range known as the plateau. During this phase, they continue to receive the highest EITC benefits for which they are eligible, offering them stable financial support. In the phase-out region, beyond the income range eligible for the EITC, the credit gradually decreases as a percentage of earned income. When an individual's or family's income surpasses a certain threshold, their EITC benefits begin to decrease. The income effect of the phase-out is that it discourages individuals from earning above a certain income level since their EITC benefits decline as their income increases. This phase-out mechanism ensures that the EITC primarily targets low- and middle-income individuals.

Despite the positive aspects emphasized by EITC policy proponents, the program has also faced significant criticism. One weakness is the program's elevated error and overpayment rates, stemming from mathematical errors, rule misinterpretations, and fraudulent claims. The EITC has consistently maintained an error rate exceeding 20% since the 1980s, a trend that has persisted for decades. In 2014, a report from the U.S. Internal Revenue Service revealed an error and fraud rate of 27%, resulting in overpayments totaling $18 billion (Edwards and de Rugy 2015). The root of the problem lies in individuals receiving excessive EITC payments due to false information provided about their income levels, filing status, and eligibility for dependent children. The EITC's refundable nature makes it particularly vulnerable to exploitation by dishonest claimants who can easily submit false tax returns and await government-issued checks. Additionally, the EITC application form requires a certain level of English reading and writing proficiency, which further complicates matters. Exploiting this vulnerability, some tax preparation companies have preyed on vulnerable workers, particularly those with limited English proficiency, including many immigrants. These companies assist workers in filing claims and offer loans with the expectation of receiving an EITC refund, but they impose fees for their services. This exploitation of individuals who may not fully understand the EITC process adds to the program's challenges and raises questions about its effectiveness and fairness.

2.2 Previous Literature on Federal and State-Level EITC

Numerous studies have consistently highlighted the poverty-reducing impact of federal programs, such as the EITC (Hoynes and Patel 2018), and their effectiveness in increasing labor force participation (Francis 2006). Hoynes and Patel (2018) use a quasi-experimental approach to examine the EITC effects on poverty and income for single mothers with children, revealing that a $1,000 EITC increase led to an 8.4% reduction in households with income below 100% of the poverty threshold. Francis (2006) claims that 60 percent of the 8.7 percentage point annual increase in single mother employment between 1984 and 1996 can be attributed to the EITC expansion. Single mothers, especially those in their thirties with children and lower educational attainment, constitute the primary beneficiaries of the EITC (Eissa and Liebman 1996).

Prior research on the Federal EITC has focused on its impact on labor market outcomes, primarily concentrated on policy expansions and their effects on different beneficiary groups, considering factors like marriage, race, and education. Such analysis typically centers on the EITC's generational expansion as the primary policy change and the interaction between policy and demographic characteristics, employing policy as a binary indicator. Eissa and Hoynes (2004) introduce the concept of the secondary earner and its influence on the labor force participation of dual-earner families. Second earners led to an increase in labor force participation for married men and a decrease for married women, although the decrease among women outweighed the increase among men. Jiao et al. (2022) explore ethnic differences using pretreatment parallel trend and intention-to-treat impact models, revealing contrasting labor supply effects for married white and Black women.

While the double-difference model has been a valuable tool for analyzing the effects of EITC policies, it falls short in explaining the impact of state EITC expansions on diverse populations due to variations in the timing and intensity of state-level EITC credit expansions. As a result, our study introduces the DDD model to further explore disparities between state policies and beneficiary groups.

In contrast to the extensive research on the federal EITC, limited attention has been given to investigating the consequences of state EITC expansions. This gap may be attributed to the perception that the EITC requirements for eligible low-income individuals have remained relatively unchanged, yielding similar effects on labor market outcomes. A study by Strully et al. (2010) examines the impact of prenatal poverty on infant health, specifically birth weight, using state EITC changes as a natural experiment. The research demonstrates that state EITCs are associated with increased birth weights and reduced maternal smoking during pregnancy. More recent research has delved into the influence of state EITC on participation in the federal EITC program, focusing on low-skilled single filers with children (Neumark and Williams 2020). Using a triple-difference approach, this study suggests that state EITCs may enhance participation in the federal EITC program, especially for single filers with one child and in states with a substantial affected population.

Although extensive research has explored the impact of the federal EITC on the labor market, the state EITC remains an area with considerable potential for investigation. This significance arises from the absence of significant changes in federal EITC since 2009, except for post-pandemic recovery policies. However, the increasing number of states expanding their state-level EITC benefits in recent years indicates a growing trend. To help policymakers effectively support low-income individuals, it is crucial to understand the effects of different expansion policies and variations in labor outcomes among diverse groups.

III. Descriptive Analysis

3.1 Dataset Overview

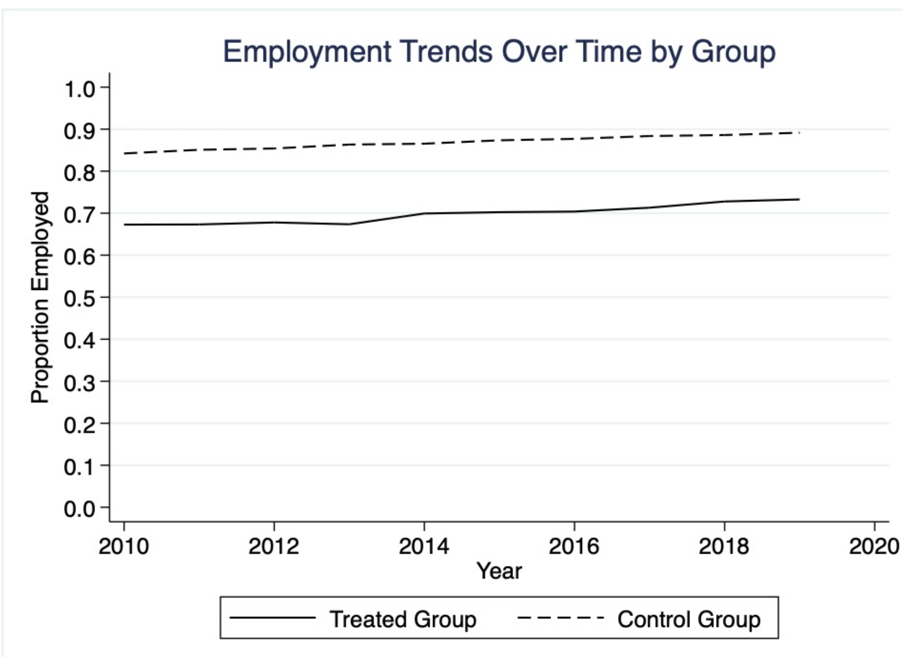
We utilize data from the CPS Annual Social and Economic Supplement (ASEC), also known as the March supplement to CPS. The ASEC, a comprehensive dataset covering income, employment, and household variables, is crucial for comprehending socio-economic patterns in the U.S. Our analysis focuses on the period from 2009 to 2018, offering valuable insights into labor market dynamics and income trajectories. The dataset, initially containing 1,948,983 observations spanning individuals aged 0 to 85, forms the basis of our research.

Our study specifically targets women aged 24 to 65 to avoid eligibility ambiguities as qualifying dependents on parental tax returns. To enhance our exploration of the policy, we introduce a variable representing state EITC percentage levels. Furthermore, we incorporate the unemployment rates obtained from the CPS conducted by the Bureau of Labor Statistics. This inclusion aims to analyze policies by capturing the dynamics of the labor market and effectively controlling for potential confounding factors. Following these modifications, our dataset is refined to a total of 988,552 observations.

3.2 Interpretation of Dependent Variable

The outcome of interest of this study is the employment status, represented as a binary variable equal to one if the observation indicates employment. Figure 1 illustrates distinctive employment patterns between the treated group, consisting of single mothers with children under 14 years old, and the control group, comprising married men with either no children or older offspring, spanning the years 2010 to 2019. Notably, the treated group consistently exhibits employment rates approximately 20% lower than the control group. The employment rate of the treated group remains stable until 2013, experiences a surge in 2014, and subsequently rises steadily until 2019. In contrast, the control group shows a slight, steady increase over the entire period. Despite positive shifts in the labor market throughout the decade, this disparity endures.

Figure 1: Comparative Employment Trend of Treated and Control Groups (2010-2019)

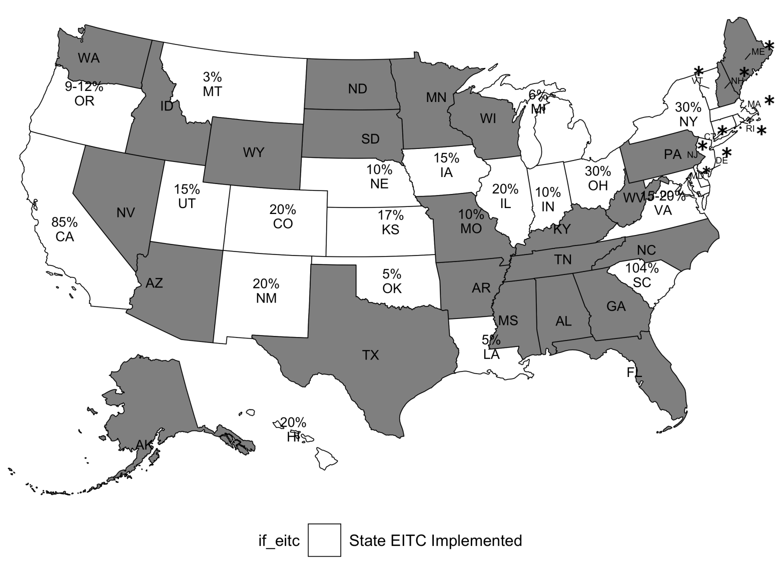


Note: The employment rates for the treated and control groups have been calculated as the mean employment rate for each year spanning from 2010 to 2019.

3.3 State-Level EITC Expansion: Historical Trends and Tax Return Dynamics

In discussing our policy analysis, it is crucial to acknowledge discrepancies between data from the CPS and the actual situation. This is due to the fact that EITC policies in each state may change annually based on states' different economic and financial situations. Additionally, there are technical limitations in setting proportions for five states with proportional tax return levels, including California, Maine, Oregon, Washington, and Wisconsin. This limitations stem from the fact that, for these states, the actual refund ratio may vary based on the number of eligible children an individual has or specific rules in each state. Therefore, in this section, we use actual data from 2019 for each state to visually illustrate the dispersion of EITC expansion levels across states. Our research examines the impact of state-level EITC expansion on labor market participation. The 2009 American Recovery and Reinvestment Act (ARRA09) increased benefits for families with three or more children and modified stipulations for married filers, representing the latest federal EITC change prior to the COVID period. Given our dataset covering 2010 to 2019, there were no substantial federal EITC modifications post-2009 during this period, and we assume that after a one-year adjustment period, labor behavior has already responded to this significant change.

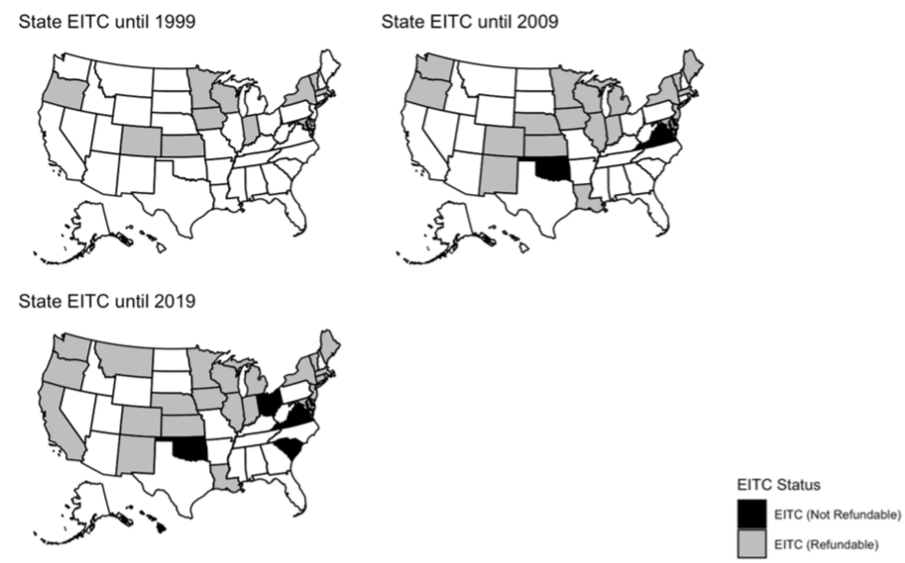
Figure 2: State-wise Distribution of Implementation of EITC and Percent of State EITC



Note: The three states that do not use the federal EITC rules for calculating their state EITC are California, Minnesota, and Washington. The state abbreviations which are labeled with * instead of state EITC percent due to graph dimension constraint are VT, ME, MA, RI, CT, NJ, DE, MD, DC, and their corresponding percent are 38%, 25%, 30%, 15%, 31%, 40%, 4.5-20%, 45-100%, and 70-100%, respectively.

Figure 2 illustrates the implementation status of state EITC across various states. States depicted in gray, such as Alaska and Texas, do not provide state-level EITC, while those in white, such as California and South Carolina, have undergone state-level EITC expansion. The percentages indicated for each state represent the proportion of the state-level EITC relative to the federal EITC. This graph reveals substantial regional disparities in both the adoption and percentage levels of state EITCs, ranging from 3% in Montana to as high as 125% in South Carolina.

Figure 3: EITC Enactment and Refundability Status by State Over Time



Note: The data utilized to create the visual representations were sourced from "State Tax Credits" available at Tax Credits for Workers and Families.

Figure 3 depicts the state-level expansion history over three decades: the 1990s, 2000s, and 2010s. The black blocks represent states that implemented EITC expansion but without refundability. This implies that once a taxpayer's tax obligation reaches zero, they will be unable to receive any remaining amount as a refund. From the graph, we observe a notable increase in states implementing policy expansion, particularly towards the year 2019, and the majority of these are states with refundable EITC.

3.4 Summary Statistics

Table 1: Summary Statistics (Selected Variables)				
Variables	Mean	Std. Dev.	Minimum	Maximum
Dependent Variable:				
Employed (frac.)	0.77	0.42	0	1
Independent Variable(s):				
State EITC Percentage (frac)				
Low State EITC Expansion (<15%)	0.17	0.37	0	1
Medium State EITC Expansion (15-30%)	0.14	0.35	0	1
High State EITC Expansion>30%	0.17	0.37	0	1
No State EITC or Before Enforcement	0.52	0.50	0	1
Marital Status (%)				
Yes	0.62	0.49	0	1
No	0.38	0.49	0	1
Children Number (%)				
No Child	0.43	0.49	0	1
One Child	0.21	0.41	0	1
Two Children	0.22	0.42	0	1
Three and above Children	0.14	0.34	0	1

Table 1 presents summary statistics for key variables in our study. The 'Employed' variable, indicating binary employment status, shows that 77% of the sample is employed. The majority of individuals reside in states with no State EITC or enforcement before 2009, while the remainder is evenly distributed among states with low, medium, or high EITC expansion levels. We reclassified marital status into a binary variable, distinguishing observations as 'Married' or 'Unmarried.' In the EITC context, "qualifying children" are defined by specific criteria. The presence and number of these children significantly impact the credit, with more qualifying children leading to a larger credit. Participants with three or more children were grouped together, influenced by the ARRA09, which provided the highest refund ratio for taxpayers with three children. Table 1 reveals that 62% of participants are married. Regarding the number of children, 43% of participants do not have children, while only 14% have three or more children. Furthermore, we adjusted multiple income metrics to align with 2021 financial values using the Consumer Price Index (CPI). Subsequently, we applied a logarithmic transformation to both family income and personal total income to mitigate issues related to negative income values. In Table 1, the mean of the log-transformed total family real income is $11.11, indicating restricted variability, as evidenced by a standard deviation of $1.04.

IV. Empirical Framework

4.1 Individual Employment Outcomes and Influencing Factors

Before investigating the impact of state EITC expansion, it is imperative to first examine the influence of individual characteristics on employment status. As the primary target group of state EITC comprises middle and low-income individuals, studying the variations in employment outcomes across diverse demographic characteristics can offer valuable insights. This aids in gaining a deeper understanding of the rationale behind implementing state EITC and in accurately identifying its primary beneficiaries. Moreover, it enables us to effectively observe whether policy expansion genuinely impacts the employment outcomes of these beneficiaries or narrows the employment disparities among different groups after introducing the policy variables in the subsequent section.

Our OLS regression model primarily focuses on the number of children an individual has and their employment status. We choose the number of children as the explanatory variable because EITC offers different tax rebate proportions for families with varying numbers of children, with the highest proportion allocated to families with three or more children. This implies that policymakers believe that families with more children are more likely to fall within the middle and low-income groups that require assistance. Therefore, it is reasonable to speculate that the number of children plays a role in shaping individual employment outcomes. When a household needs to care for more children, parents may opt to forgo employment opportunities to stay home and attend to their children. Accordingly, our model predicts individual labor outcomes as follows:

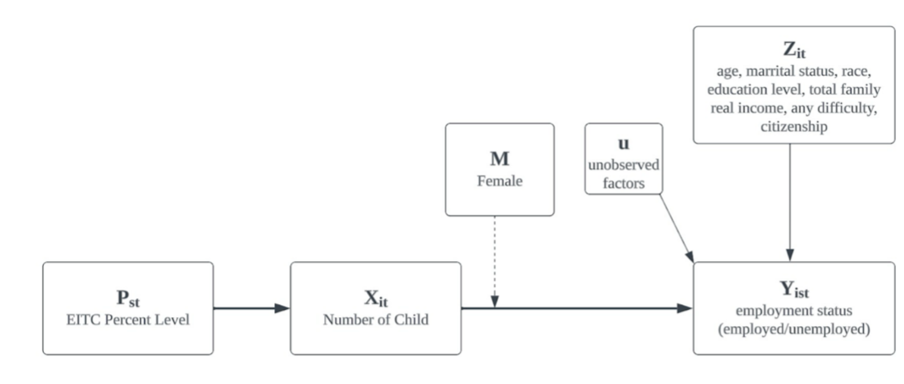
$$E_{ist} = \alpha + \gamma_1 \mathit{Child}_{it} + \beta Z_{it} + \mu_s + \theta_t + \varepsilon_{it} \tag{1}$$

E_{ist} represents the employment status of individual *i* who lives in state *s* at year *t*, as a binary dependent variable. Child_{it} signifies the number of children in the household where individual *i* resides at year *t*. To ensure consistency with EITC's target eligibility criteria, individual *i* with more than three children in the household have three children. In Z_{it}, we incorporate other covariates known to influence individual employment outcomes. These covariates encompass gender, age, age squared, race, marital status, education, household income, disability, and citizenship. The inclusion of these variables in the individual employment outcomes model is warranted by their potential impact on an individual's employment status. For instance, disability and low educational attainment might impede employment participation, while citizenship or being of a certain racial background might positively influence employment outcomes. To address time-invariant differences across states and account for common annual shocks, we introduce state and year fixed effects (μ_s and θ_t). We model the effect of age on employment as nonlinear, recognizing that increasing age may initially bolster employment prospects, driven by greater work experience. However, as individuals approach retirement age, their labor market participation may wane, resulting in a U-shaped or inverted U-shaped relationship between age and employment. The error term ε_{it} captures all the unobserved factors or random variations that affect the individual's employment status but are not explicitly accounted for in the model. It encompasses a wide range of potential influences on employment status, including unmeasured individual traits like motivation, personality, and personal circumstances, which can impact a person's employment status but are not incorporated into our model covariates.

$$E_{ist} = \alpha + \gamma_1 \mathit{Child}_{it} + \gamma_2 \mathit{Female}_i + \gamma_3 \mathit{Child}_{it} \cdot \mathit{Female}_i + \beta Z_{it} + \mu_s + \theta_t + \varepsilon_{it} \tag{2}$$

We further examine the intricate dynamics of family size and labor division's impact on workforce participation. While our initial OLS regression offers insights, we acknowledge that the effects of family size might differ across demographic groups. Specifically, we aim to explore how gender moderates the relationship between the number of children and employment status. The inspiration for introducing this variable came from (Eissa and Hoynes 2004, who introduced the concept of a secondary earner in family income, based on EITC eligibility criteria. They posited that the EITC could reduce the overall labor supply of married couples, particularly affecting women who become secondary earners after marriage. In our study, incorporating female as a moderating variable offers an interesting perspective and allows us to investigate potential differences in employment outcomes for women with children. We hypothesize that factors like childcare responsibilities, family support, and financial incentives drive their decisions to participate in the workforce. Equation (2) introduces the interaction term of Female_i and Child_{it} to explore the combined impact of family size and gender on employment outcomes. In order to display the individual employment outcome model more vividly, we show flowchart in Figure 4. We will explain in detail the impact of introducing policy on this model in the following section.

Figure 4: Flow Chart of Empirical Model



Note: P_{st} represents the Earned Income Tax Credit (EITC) percentage, which influences the number of children X_{it}, reflecting a demographic factor in employment status Y_{ist}. The model accounts for gender *M* as a moderating factor, with unobserved variables *u*, potentially impacting employment outcomes, alongside other control variables Z_{it} such as age, marital status, race, education, income, difficulties, and citizenship.

4.2 Estimation Results for Individual Employment Status

Table 3: OLS Estimates (Selected Variable)

	OLS	OLS with Interaction
One Child•Female		-0.091***
		(0.002)
Two Children•Female		-0.143***
		(0.002)
Three Children and Above•Female		-0.236***
		(0.002)
Female		-0.023***
		(0.001)
One Child	0.009***	0.054***
	(0.001)	(0.001)
Two Children	-0.005***	0.069***
	(0.001)	(0.002)
Three Children and Above	-0.047***	0.077***
	(0.001)	(0.002)

Table 3 presents the regression results for individual employment outcomes. In column (2), we conducted a linear regression with the number of children as the primary explanatory variable. Our findings align with our expectations, demonstrating that the number of children indeed plays a crucial role in influencing an individual's employment status. The statistical significance is robust, with a 1% level of confidence, underscoring the substantial impact of family size on employment outcomes. Having one child slightly increases an individual's likelihood of employment by 0.9%. However, the presence of three or more children hampers a parent's employment prospects, reducing the likelihood of employment by 4.7%. The effects of various other covariates on employment outcomes also conform to our anticipated patterns. Individual characteristics such as holding a higher degree, being male, and belonging to the White racial group enhance the chances of employment. Conversely, having a disability, belonging to a less advantaged racial group, and having lower educational attainment can impede an individual's employment opportunities. The relationship between age and employment outcomes is consistent with our expectations. A positive coefficient for age, coupled with a negative coefficient for age squared, results in a U-shaped relationship. Employment rates tend to increase as individuals transition from youth to middle age. However, as individuals progress from middle age to old age, their employment rates may begin to decline.

When we introduce interaction terms for gender and the number of children, a significant decrease in the employment probability of mothers becomes evident as the number of children increases. Women with only one child are 9.1% less likely to be employed compared to women with similar characteristics but no children. This likelihood decreases to 23.6% for women with three or more children. Interestingly, the number of children has no discernible effect on a man's employment likelihood.

The OLS estimation results affirm our expectations regarding the influence of gender and the number of children on individual employment outcomes. It is clear that family size significantly hinders women's employment opportunities while having no impact on men. This outcome lends support to the inclusion of women with children as a primary beneficiary group within the EITC, emphasizing the policy's potential to address this issue.

V. Examination of State EITC Effect

5.1 Difference-in-Difference Model with Two-Way Fixed Effects

Having comprehended the variations in employment outcomes among distinct demographic subgroups, our next objective was to investigate whether the expansion of the state EITC played a role in reducing the employment disparity between potential beneficiaries and the control group.

However, prior to delving into this analysis, it is imperative that we conduct a thorough examination of the state EITC's impact on employment.

We have selected the DID model as our foundational framework for assessing the impact of the State Earned Income Tax Credit (EITC). The primary advantage of the DID approach lies in its ability to address potential biases inherent in the Single Difference model and some of its enhanced variations. DID is a widely used method for estimating the effects of a specific intervention or treatment policy. It achieves this by comparing changes over time between the outcomes of the population participating in the program (intervention group) and those not partaking in the program (control group).

In our study, we confront the unique challenges posed by variations in the timing of EITC expansion implementation across states. Moreover, not every state implemented the expansion. To address this, we opt for the DID model with two-way fixed effects. This approach allows us to gauge the impact of EITC expansion on employment in subsets of states categorized as "switchers," those introducing the EITC during the sample period. In the period spanning 2010 to 2019, we categorize each state's EITC expansion into three distinct groups: states that never implemented the state EITC and those that expanded it before 2010 (both are control groups); and those that introduced it during the study's time frame (treatment groups). Our DID model significantly enhances the internal validity of our policy research, mitigates the influence of confounding factors, and ensures more accurate and dependable policy effect assessment. Hence, we adopt the DID model as our initial approach to analyze this policy that varies across both time and states.

$$EITC\_Perc_{st} = \begin{cases} 1 & \text{if year of observation is after state EITC enforcement for switchers} \\ 0 & \text{if year of observation is before EITC enforcement for switchers} \\ 0 & \text{for states that never treated or always treated} \end{cases}$$

In the CPS database, we observe significant variation in the extent to which states have expanded their EITC. For example, Montana has the smallest subsidy, with only a 3% expansion of the federal EITC, while South Carolina boasts the largest expansion, increasing the federal EITC by 125%. The divergent levels of EITC expansion generosity among states can be attributed to differences in their financial limitations, political ideologies, and policy priorities. Thus, using a binary variable alone to represent this policy may not provide a comprehensive analysis for accurately testing the effects of state EITC expansion on labor force employment outcomes. To address this, we follow the approach based on the previous DID model and further categorize states that expanded the EITC between 2010 and 2019 into three distinct categories based on the percentage by which they increased their federal EITC. States with expansion levels below 15% are categorized as 'low state-level EITC amount,' those between 15% and 30% as 'medium state-level EITC amount,' and those exceeding 30% as 'high state-level EITC amount.' We hypothesize that these differences in expansion subsidies also impact observable labor market behavior. States with more generous EITC expansions provide higher financial incentives for low-income individuals to work, thereby motivating more individuals to seek and maintain employment.

$$EITC\_Level_{st} = \begin{cases} 3 & \text{if year of observations is after enforcement among high EITC switchers} \\ 2 & \text{if year of observations is after enforcement among medium EITC switchers} \\ 1 & \text{if year of observations is after enforcement among low EITC switchers} \\ 0 & \text{for states that never treated or always treated} \end{cases}$$

After defining the indicator representing state EITC expansion, we employ a DID model within a two-way fixed-effects framework to investigate the employment effects resulting from varying levels of expansion.

$$E_{ist} = \alpha + \beta Z_{it} + \gamma_3 EITC\_Level_{st} + ur_{st} + \mu_s + \theta_t + \varepsilon_{it} \tag{3}$$

The dependent variable, E_{ist}, is an indicator of whether an individual *i* residing in state *s* is employed in year *t*, while $EITC\_Level_{st}$ represents the state EITC indicator coded as described previously. The vector Z_{it} includes individual characteristics such as gender, age (restricted to 24-65), age squared, race, marital status, education level, total family income, disability, and citizenship. Similar to the individual employment outcome model, we hypothesize that specific demographic variables, such as education and marital status, may influence employment disparities among observations. Including control variables enhances the model's internal validity by minimizing the impact of confounding and extraneous variables. This approach facilitates the establishment of a correlational or causal relationship between the variables of interest while reducing research bias. The state fixed effects variable, μ_s, controls for factors that vary across states but remain constant over time. It may include a state's unique economic conditions, industry composition, business environment, and regional economic influences that impact employment rates. The year fixed effects variable, θ_t, helps mitigate bias arising from time-varying yet state-consistent unobserved variables, such as financial crises or major federal policy changes impacting all states. Given the varied policies implemented across states and over time, especially the differing expansion of each state's EITC, employing a two-way fixed effects approach enhances our capability to comprehensively address temporal and geographic disparities. We have also incorporated the annual state-level unemployment rate, ur_{st}, into our model. The unemployment rate is a crucial economic indicator that reflects the labor market's condition within each state. By treating the unemployment rate as an exogenous variable in the context of policy changes, we can separate and identify the direct impact of EITC expansion on employment.

Our DID model relies on several crucial assumptions. The first one is the parallel assumption, which emphasizes that, in the absence of policy, the difference between individuals living in states with EITC expansion and those in states without EITC expansion remains constant over time. This implies that, regardless of whether states receive EITC expansion, both groups exhibit the same employment trend in the absence of the policy. Secondly, we assume that the allocation of state EITC expansion was not influenced by the outcomes. While, in principle, the unemployment rate at the aggregate level may incentivize states to expand EITC as a job creation tool, the low standard deviation of state unemployment rates among all states from 2010 to 2019 allows us to treat it as exogenous. Thirdly, the overlap assumption necessitates that each observation in our sample has a positive probability of receiving state EITC benefits. Furthermore, we assume there are no spillover effects between individuals living in states with enacted EITC and those in states without EITC expansion. This signifies that the employment behavior of one group does not impact the employment outcomes of another group, and vice versa. However, a potential concern with this model is that the policy effect might be influenced by concurrent confounding policies or economic conditions. To address this issue, we attempt to control for the varying state-year unemployment rates in each state to mitigate the potential impact of observed economic conditions.

5.2 Triple Difference Model with Treatment Effect

$$\begin{aligned} E_{ist} = \alpha + \beta Z_{it} + \gamma_2 Group_{it} + \gamma_2 EITC\_Level_{st} \\ + \gamma_3 (Group_{it} \cdot EITC\_Level_{st}) + u_{rst} + \mu_s + \theta_t + \varepsilon_{it} \end{aligned} \quad (4)$$

We then employ a triple difference (DDD) approach to detect the nuanced effects of state EITC expansion more effectively on different population groups. Previous research has consistently identified single women with children as a primary target for the EITC. Consequently, we designate this group as our treated group and select married men without children or with children old enough not qualify for the EITC as the control group. Given the eligibility criteria of the state EITC expansion, we anticipate a more pronounced impact on our treated group. We refrain from designating women with children as the reference group due to the secondary earner theory, which suggests that the expansion of the state EITC may discourage these women from participating in the labor market to secure greater benefits for their families (Eissa and Hoynes 2004). Treating them as the control group could potentially violate the parallel trend assumption. The inclusion of interaction terms in our triple difference model enables us to investigate variations in policy effects between these two groups. This adds an additional layer of analysis beyond the standard DID model, which primarily focuses on average treatment effects. Consistent with the DID hypothesis, we assume no spillover effects between these groups. In other words, the behavioral response of the target group to the EITC expansion has no discernible impact on the non-target group.

5.3 Mitigating Selection Bias with IPW

Our current triple difference analysis, however, may be susceptible to selection bias. The observed disparities between the treated and control groups may not precisely reflect the genuine causal effects of state EITC policies on employment outcomes. Self-selection bias occurs when individuals or groups choose different groups based on specific characteristics or preferences (Nikolopoulou 2022). For instance, individuals with varying educational backgrounds or different racial backgrounds may make dissimilar choices regarding childbearing. This bias can result in variations in both observable and unobservable attributes between the treatment and control groups, impacting the accuracy of treatment effect estimates. To mitigate the influence of this selection bias, we employ inverse probability weighting (IPW) to assign weights to individuals or groups. To compute IPW, we initially conducted probit model estimates for the treatment group (single women with children) to derive propensity scores. Propensity scores aim to encapsulate the likelihood of characteristics influencing entry into the treatment group. Subsequently, we calculated the inverse of the estimated propensity score. This means that the higher the probability of receiving treatment, the lower the weight assigned, and conversely, the lower the probability of receiving treatment, the higher the weight.

The estimated propensity score is:

$$\hat{p} = \text{Prob}(Group_{i,t} = 1) = aZ_{i,t} + \mu_{i,t} \tag{5.1}$$

where $Group_{i,t}$ is defined as:

$$Group_{i,t} = \begin{cases} 1 & \text{if } i \text{ is in treated group} \\ 0 & \text{if } i \text{ is in control group} \end{cases}$$

The estimated inverse propensity weight is:

$$IPW = \begin{cases} \frac{1}{\hat{p}}, & \text{if } Group_{i,t} = 1 \\ \frac{1}{(1-\hat{p})}, & \text{if } Group_{i,t} = 0 \end{cases} \tag{5.2}$$

After determining the weight for each observation, we incorporated IPW into the DDD model. This approach amplifies the contributions of underrepresented individuals while diminishing the impact of those who are overrepresented in our dataset. Table 2 presents the mean differences in covariates between the treated and control groups before and after IPW adjustment. Overall, IPW adjustment effectively reduced or reversed the average disparities between the treatment and control groups across most variables, including race, age, and family income. Although certain variables remain statistically significant after IPW adjustment, indicating ongoing differences between groups (e.g., race, age, real family income, disability, and citizenship), the significance level has been notably reduced. This suggests that the incorporation of IPW mitigates the issue of selection bias, enhances comparability between the treatment and control groups, and bolsters the credibility of subsequent causal inferences.

Table 2: Mean Differences

Variables	**Mean Differences**	
	Adjusted	Unadjusted
High School	0.101***	-0.133
	(0.003)	(0.098)
College and above	-0.136***	0.108
	(0.003)	(0.115)
Black	0.123***	-0.064***
	(0.002)	(0.014)
American Indian	0.015***	-0.001
	(0.001)	(0.008)
Asian	-0.034***	0.017
	(0.002)	(0.042)
Mixed	0.008***	-0.012***
	(0.001)	(0.003)
Age	-15.297***	14.200***
	(0.063)	(0.875)
Age2	-1,345.832***	1,459.384***
	(5.708)	(5.708)
Real Family Income	-1.295***	-0.506*
	(0.007)	(0.274)
Disability	-0.017***	-0.035**
	(0.002)	(0.017)
Citizenship	0.009***	-0.068***
	(0.002)	(0.026)

Note: The table presents unadjusted and IPW adjusted mean differences before and after group balancing. The table omits the base category 'Less Than High School' and 'White'. Age2 is calculated as the square of Age. Total family real income is log of total family real income. Robust standard errors are in parentheses. Statistical significance:***p <0.01, **p <0.05, *p <0.1.

5.4 Estimation Result

Table 3: DID Estimates (Selected Variables)			
	DID Base	DID Triple	DID Triple-IPW Adjusted
Low State EITC Expansion (<15%)	-0.003	0.000	0.068
	(0.004)	(0.008)	(0.068)
Medium State EITC Expansion (15-30%)	-0.001	-0.002	0.052
	(0.005)	(0.007)	(0.108)
High State EITC Expansion (>30%)	-0.005*	-0.003	0.254***
	(0.003)	(0.005)	(0.097)
Group		0.016***	0.03
		(0.003)	(0.028)
Low State EITC Expansion (<15%)•Group		0.009*	-0.092**
		(0.005)	(0.043)
Medium State EITC Expansion (15-30%)•Group		0.024***	0.056
		(0.005)	(0.047)
High State EITC Expansion (>30%)•Group		0.001	0.069*
		(0.005)	(0.039)

Table 3 displays the regression results from the DID and DDD models. In our DID base model, we surprisingly find a negative coefficient for the expansion of state-level EITC, irrespective of the expansion amount, indicating a reduction in employment. This outcome was unexpected. One possible explanation for this unexpected result is that the primary aim of the EITC is to incentivize work by offering financial benefits to low-income individuals, measured on a household basis. When states expand EITC benefits, the financial incentives might lead some individuals to opt not to work or reduce their working hours to access EITC benefits based on family income. Consequently, this can result in decreased employment, even though it contradicts the policy's intent. Therefore, the negative impact on employment suggests that different groups may not respond uniformly to state EITC expansion. To delve deeper into these differential effects, we introduced a DDD model to investigate whether ”single women with children,” considered a key beneficiary group of the EITC, experience distinct effects compared to other groups. This allows us to identify the heterogeneous impacts of EITC expansion. Furthermore, considering that the coefficients for all state EITC expansions are mostly insignificant, except for high expansion amounts at the 10% significance level, it suggests that our initial predictions are not necessarily inaccurate. This may indicate that the current DID models may not entirely capture the intricacies of the relationship between the EITC and employment, underscoring the importance of introducing group indicators.

In the fourth column of table 3, we present the DDD estimation results following IPW adjustment. After this adjustment, the impact of state EITC expansion on employment becomes positive. The coefficient for high state-level EITC expansion is 0.254, signifying that, on average, individuals are more likely to be employed as the state EITC expansion level rises. The significance at the 1% level suggests that this effect is unlikely to be attributed to random chance. This result aligns with the core objective of EITC policy, which is to motivate individuals to participate in or continue their engagement in the labor market, particularly in states with generous EITC expansion benefits.

Additionally, the statistically significant interaction term between state EITC and the treated group implies that state EITC expansion welfare does indeed have differing effects on various demographic groups. In states with lower EITC expansion levels, single women with children exhibit a 9.2 percentage point lower likelihood of employment compared to married men without children. Conversely, in states with moderate EITC expansion levels, individuals with children are 5.6 percentage points more likely to be employed than those in the control group. However, the absence of an asterisk indicates that the coefficient is not statistically significant, implying limited empirical support for this specific effect. High EITC expansion correlates with a noteworthy increase in the probability of employment for the treated group, potentially benefiting single women with children by 6.9 percentage points. This result aligns with the overarching goal of the EITC policy, which aims to encourage labor force participation, especially among disadvantaged groups. While the moderate EITC expansion does not reach statistical significance, the significant impact of high EITC expansion suggests a positive policy outcome, fostering employment opportunities for the targeted group. The mixed significance levels across EITC expansion tiers underscore the need for nuanced policy evaluation to ensure optimal outcomes, while highlighting the potential success of high EITC expansion in promoting employment among single women with children.

VI. Conclusion

State EITC, a labor incentive measure introduced by various states in recent years for low-income groups, has received significantly less attention in research compared to its federal counterpart, the Fed EITC. This study aims to fill this research gap by examining the impact of state EITC on employment incentives in the labor market, utilizing CPS data from 2010 to 2019. Our analysis, accounting for the heterogeneity of different demographic groups in employment, reveals that state EITC does exert varying employment effects on different groups, demonstrating its effectiveness in stimulating employment.

Future research opportunities lie in conducting longitudinal studies to assess the long-term effects of state EITC expansion on employment, income, and overall economic well-being. Additionally, broader investigations into the social and economic implications of EITC expansion, such as its impact on poverty reduction, education access, food security, healthcare, and family dynamics, can provide a more comprehensive understanding of its societal effects. This holistic exploration contributes to a nuanced evaluation of policy effectiveness.

As policymakers navigate the evolving landscape of labor economics, our research offers valuable insights into how state-level EITC expansions influence labor market participation. This understanding equips policymakers with the knowledge needed to implement more effective measures, ultimately contributing to socio-economic prosperity.

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Appendix

Table 1: Summary Statistics (Estimation sample size: 968,301) (Part1)

Variables	Mean	Std. Dev.	Minimum	Maximum
Dependent Variable:				
Employed (%)	0.77	0.42	0	1
Independent Variable(s):				
State EITC Percentage (%)				
Low State EITC Expansion (<15%)	0.17	0.37	0	1
Medium State EITC Expansion (15-30%)	0.14	0.35	0	1
High State EITC Expansion (>30%)	0.17	0.37	0	1
No State EITC or Before Enforcement	0.52	0.50	0	1
Marital Status (%)				
Yes	0.62	0.49	0	1
No	0.38	0.49	0	1
Children Number (%)				
No Child	0.43	0.49	0	1
One Child	0.21	0.41	0	1
Two Children	0.22	0.42	0	1
Three or more Children	0.14	0.34	0	1
Control Variable(s):				
Age	43.11	11.23	24	65
Female (%)	0.52	0.50	0	1
Race (%)				
White	0.78	0.41	0	1
Black	0.12	0.32	0	1
American Indian	0.01	0.12	0	1
Asian	0.07	0.25	0	1
Mixed	0.02	0.13	0	1
Disability (%)				
Yes	0.92	0.27	0	1
No	0.08	0.27	0	1
Age of Youngest Child	10.74	8.41	0	85
Education Level (%)				

High School	0.56	0.50	0	1
Less than high school	0.11	0.31	0	1
College and above	0.34	0.47	0	1
Total Family Real Income ($)	11.11	1.04	0.058114	14.97564

Note: Certain variables related to state EITC policy, such as enactment time, refundability and unemployment rate, are not included in the summary table.

The State EITC Percentage is determined as a percentage of the Federal EITC. As states may vary their subsidy levels or provide different return percentages for observations with multiple children, we have condensed our analysis to encompass the percentage levels within this ten-year dataset.

Table 2: Mean Differences		
Variables	**Mean Differences**	
	Adjusted	Unadjusted
High School	0.101***	-0.133
	(0.003)	(0.098)
College and above	-0.136***	0.108
	(0.003)	(0.115)
Black	0.123***	-0.064***
	(0.002)	(0.014)
American Indian	0.015***	-0.001
	(0.001)	(0.008)
Asian	-0.034***	0.017
	(0.002)	(0.042)
Mixed	0.008***	-0.012***
	(0.001)	(0.003)
Age	-15.297***	14.200***
	(0.063)	(0.875)
Age2	-1,345.832***	1,459.384***
	(5.708)	(5.708)
Real Family Income	-1.295***	-0.506*
	(0.007)	(0.274)
Disability	-0.017***	-0.035**
	(0.002)	(0.017)
Citizenship	0.009***	-0.068***
	(0.002)	(0.026)

Note: The table presents unadjusted and IPW adjusted mean differences before and after group balancing. The table omits the base category 'Less Than High School' and 'White'. Age2 is calculated as the square of Age. Total family real income is log of total family real income. Robust standard errors are in parentheses. Statistical significance:***p <0.01, **p <0.05, *p <0.1.

Table 3: OLS Estimates		
	OLS	OLS with Interaction
One Child•Female		-0.091***
		(0.002)
Two Children•Female		-0.143***
		(0.002)
Three Children and Above•Female		-0.236***
		(0.002)
Female		-0.023***
		(0.001)
One Child	0.009***	0.054***
	(0.001)	(0.001)
Two Children	-0.005***	0.069***
	(0.001)	(0.002)
Three Children and Above	-0.047***	0.077***
	(0.001)	(0.002)
Marital Status	-0.068***	-0.076***
	(0.001)	(0.001)
Unemployment	-0.005***	-0.005***
	(0.001)	(0.001)
Age	0.010***	0.010***
	(0.000)	(0.000)
Age2	-0.000***	-0.000***
	(0.000)	(0.000)
Black	-0.027***	-0.027***
	(0.001)	(0.001)
American Indian	-0.064***	-0.063***
	(0.003)	(0.003)
Asian	-0.036***	-0.037***
	(0.002)	(0.002)
Mixed	-0.023***	-0.024***
	(0.003)	(0.003)
High School	0.088***	0.087***
	(0.001)	(0.001)
College and above	0.122***	0.118***

	(0.001)	(0.001)
Total Family Real Income	0.096***	0.096***
	(0.000)	(0.000)
Disability	-0.420***	-0.420***
	(0.001)	(0.001)
Citizenship	-0.009***	-0.008***
	(0.001)	(0.001)
State Fixed Effects	Yes	Yes
Month Fixed Effects	Yes	Yes

Note: Table reports estimates of equations (1) and (2). Age2 is calculated as the square of Age. Total family real income is the log of total family real income and adjusted with the 2021 price index. ”No child, White, less than high school” are omitted as the base categories. Robust standard errors are in parentheses. *** indicates significant at 1% level; ** 5% level; * 10% level.

Table 4: DID Estimates

	DID Base	DID Triple	DID Triple-IPW Adjusted
Low State EITC Expansion (<15%)	-0.003	0.000	0.068
	(0.004)	(0.008)	(0.068)
Medium State EITC Expansion (15-30%)	-0.001	-0.002	0.052
	(0.005)	(0.007)	(0.108)
High State EITC Expansion (>30%)	-0.005*	-0.003	0.254***
	(0.003)	(0.005)	(0.097)
Group		0.016***	0.03
		(0.003)	(0.028)
Low State EITC Expansion (<15%)•Group		0.009*	-0.092**
		(0.005)	(0.043)
Medium State EITC Expansion (15-30%)•Group		0.024***	0.056
		(0.005)	(0.047)
High State EITC Expansion (>30%)•Group		0.001	0.069*
		(0.005)	(0.039)
Female	-0.106***		
	(0.001)		
Marital Status	-0.068***		

	(0.001)		
One Child	0.009***		
	(0.001)		
Two Children	-0.005***		
	(0.001)		
Three Children and Above	-0.047***		
	(0.001)		
Unemployment Rate	-0.006***	-0.009***	0.080***
	(0.001)	(0.001)	(0.021)
Age	0.010***	0.004***	0.021***
	(0.000)	(0.001)	(0.007)
Age2	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Black	-0.027***	-0.042***	-0.012
	(0.001)	(0.003)	(0.057)
American Indian	-0.064***	-0.061***	-0.339***
	(0.004)	(0.007)	(0.09)
Asian	-0.036***	-0.010***	-0.043
	(0.002)	(0.003)	(0.051)
Mixed	-0.023***	-0.026***	0.114
	(0.003)	(0.006)	(0.106)
High School	0.088***	0.063***	0.115*
	(0.002)	(0.003)	(0.061)
College and above	0.122***	0.074***	0.127**
	(0.002)	(0.003)	(0.059)
Total Family Real Income	0.096***	0.119***	0.117***
	(0.001)	(0.001)	(0.015)
Disability	-0.420***	-0.391***	-0.385***
	(0.002)	(0.004)	(0.072)
Citizenship	-0.009***	0.048***	0.139***
	(0.002)	(0.003)	(0.048)
State Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes

Note: Table reports estimates of equations (3) and (4). Age2 is calculated as the square of Age. Total family real income is the log of total family real income and adjusted with the 2021 price index. ”No child, White, less than high school” are omitted as the base categories. Robust standard errors are in parentheses. *** indicates significant at 1% level; ** 5% level; * 10% level.

Table 5: Description of State Earned Income Tax Credit 2019

State	EITC Year	Refundability	EITC Percent
California	2015	Yes	85% for those earning up to $30,000
Colorado	1999, 2013	Yes	10%
Connecticut	2011	Yes	23%
Delaware	2005	No	20%
District of Columbia	2000	Yes	40%
Hawaii	2017	No	20%
Illinois	2000	Yes	18%
Indiana	1999	Yes	9%
Iowa	1998	Yes	15%
Kansas	1998	Yes	17%
Louisiana	2007	Yes	5%
Maine	2000	Yes	workers without dependent children - 25% all other eligible filers - 12%
Maryland	1987	Yes	28%
Massachusetts	1997	Yes	30%
Michigan	2006	Yes	6%
Minnesota	1991	Yes	34% on average
Missouri	2023	No	10%
Montana	2017	Yes	3%
Nebraska	2006	Yes	10%
New Jersey	2000	Yes	37%
New Mexico	2007	Yes	10%
New York	1994	Yes	30%
Ohio	2013	No	30%
Oklahoma	2002	No	5%

Oregon	1997	Yes	filers with children under the age of three - 12% all other eligible filers - 9%
Rhode Island	1986	Yes	15%
South Carolina	2017	No	125%
Vermont	1988	Yes	36%
Virginia	2004	No	20%
Washington	2008	Yes	Originally scheduled to be 10% or $50 (whichever is greater)
Wisconsin	1989	Yes	One child-4%, Two children-11%, Three children-34%
Utah	2022	No	20%

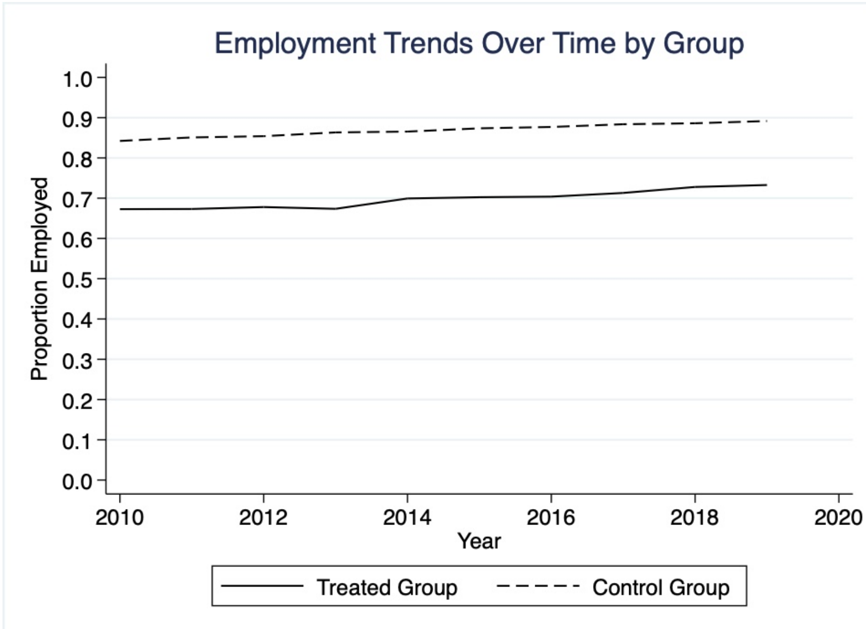
Note: Table displays the state EITC implementation time, refundability, and state EITC percent in states in the U.S, using 2019 data exept for Missouri and Utah which implemented EITC after 2019. Average EITC Percent in Minnesota is calculated as total projected state spending for the Working Family Credit divided by projected federal spending on the EITC in Minnesota as modeled by Minnesota's House Research Department; this average fluctuates from year to year.

Table 6: Definitions of Variables

Variable	Vector	Definition	Source
Employment Status (Binary)	E_{ist}	Binary indicator of individual *i* in state *s* employed or unemployed in year *t*	CPS ASEC
Employment Status (Categorical)	E_{ist}	Three categories for individual i in state s who is employed, unemployed, or OLF (out of labor force) in year *t*	CPS ASEC
Number of Children	$Child_{it}$	Number of child in the household where individual *i*	CPS ASEC
Female	$Female_i$	Binary indicator of gender of individual *i*	CPS ASEC
State EITC Percent Level	$EITC\_Level_{st}$	Categorical indicator of EITC level in state *s* in year *t*	CPS ASEC

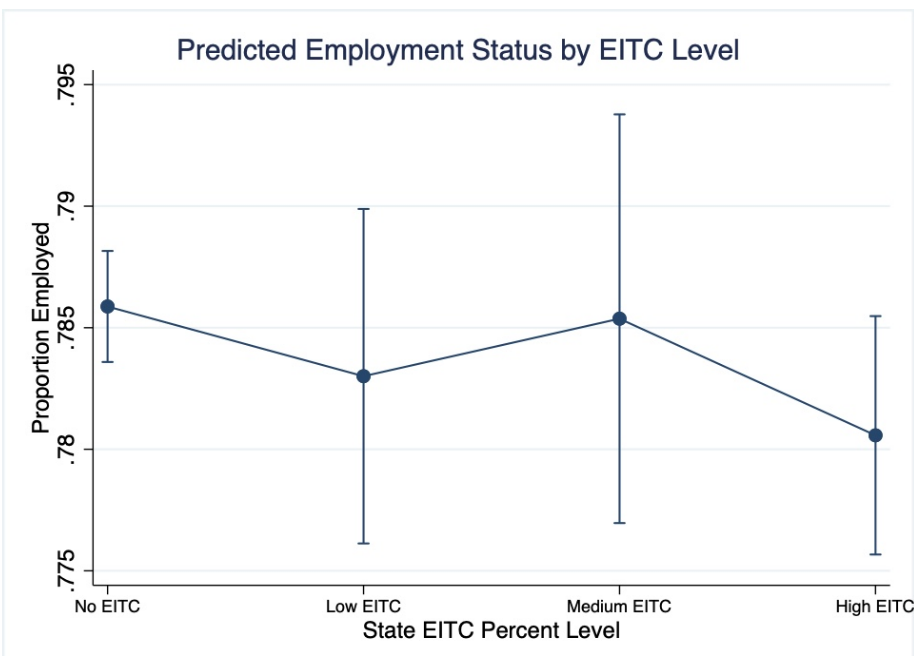
Treated Group	$Group_{i,t}$	Binary indicator of whether an individual i is a single mother with children less than 14-year-old	CPS ASEC
Age	Z_{it}	Number of age of individual *i*	CPS ASEC
Age2	Z_{it}	Squared of Number of age of individual *i*	CPS ASEC
Race	Z_{it}	Five categories for race White, Black, American Indian, Asian, and Mixed	CPS ASEC
Education Level	Z_{it}	Three categories for educational levels Less than High School, High School, and College or above *i*	CPS ASEC
Disability	Z_{it}	Binary indicator of whether individual *i* has any disables	CPS ASEC
Citizenship	Z_{it}	Binary indicator of whether individual *i* is U.S. citizen	CPS ASEC
Unemployment Rate	Z_{it}	Rate of Unemployment *i*	U.S. Bureau of Labor Statistics
Total Family Real Income	Z_{it}	Log of total family real income adjusted with 2021 price index	CPS ASEC

Figure 1. Comparative Employment Trend of Treated and Control Groups (2010-2019)



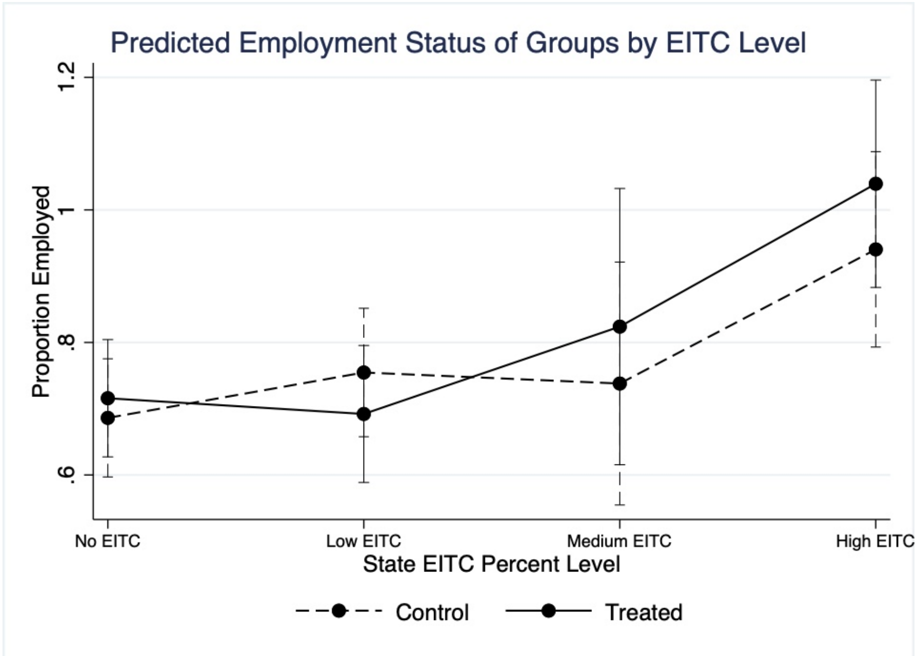
Note: The employment rates for the treated and control groups have been calculated as the mean employment rate for each year spanning from 2010 to 2019.

Figure 2. Impact of EITC Expansion on Employment Status



Note: Figure 2 illustrates the predicted impact of varying EITC levels on employment based on the DID model (Equation 3). Error bars represent 95% confidence intervals.

Figure 3. Proportions of Employment by EITC Level for Treated and Control Groups



Note: Figure 3 illustrates the predicted impact of varying EITC levels on employment based on the Triple DID model (Equation 4) after IPW adjustment. Error bars represent 95% confidence intervals.

Food Choice and Teleworking During the COVID-19 Pandemic

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Abstract

Using new data from the COVID-19 Pandemic, we posit a novel approach to a burgeoning strain of literature understanding the effects of teleworking on individuals. Specifically, we exploit a triple difference model to understand the relationship between working from home, the severity of the COVID-19 Pandemic, and the tradeoff between grocery purchases and away-from-home food expenditures. We find that teleworkers increase grocery spending by as much as 3% relative to non-teleworkers, and that they increase grocery expenditures over away-from-home food expenditures by about 2.6 percentage points. In the presence of a COVID-19 hospitalization shock, this relative increase is 0.29 percentage points. These results are robust to inverse propensity weighting, and may bear important implications for nutrition, health, and productivity outcomes.

Keywords: Remote work, food expenditure, COVID-19

I. Introduction

The COVID-19 pandemic drastically changed the nature of work and health outcomes. As companies and organizations closed their physical offices, many employees, accustomed to a daily commute, had to transition to remote work. At the same time, a mental health crisis induced by tragedy, isolation, and irritation affected millions of Americans. Those suffering from medical conditions unrelated to COVID-19 often failed to receive adequate care, and the pandemic exacerbated existing health inequities. However, the link between the evolving nature of work and health is underexplored.

[*]We would both like to express our gratitude to Klara Peter and Aspacia Stafford for incredible feedback and advisory throughout the research process.

[†]Disclaimer: Decker served as Editor-in-Chief of the Journal, though was not involved in the review of the paper.

Food selection is a key health indicator revealing access and behavioral information. The COVID-19 pandemic upended daily routines, resulting in many Americans embracing novel cooking trends and take-out options. Parsing out a relationship between work mode and food selection can foretell what a changing labor landscape means for this health behavior. The heterogeneous psychosocial impacts of remote work mean its effects on food choice are unclear, but we two potential channels postulate. First, we see an in-office channel, where an individual would commute to work, spending more time of their day in a car or otherwise in transit. This commute will almost certainly expose an individual to several restaurants or coffee shops they might stop at. Moreover, the time spent commuting decreases the free time one has to shop for groceries and prepare food for oneself. Also, offices might provide subsidized cafeterias or free lunches, incentivizing the busy employee to eat there rather than bring their own food, and employers might otherwise provide meals (e.g., during business meetings). Second, there were several trends involving at-home food preparation (baking bread, foamed coffee, etc.) during the pandemic. These were fads, but the point here is a time at-home channel that might take two forms. One form is through cooking as a hobby, where workers might opt to cook to either relax from or potentially shirk work. A second form, especially for multi-person households, is that individuals use cooking (and eating) as a bonding time. The general intuition behind this channel is that people are at home, so we expect they are more likely to stay at home for food preparation. Working from home reduces commuting times, giving more time for grocery shopping and preparing food. However, remote workers who ordinarily shopped for groceries as part of a work commute might rely more on prepared foods.

Since the time-and-place-varying effects of the COVID-19 pandemic are entangled with the decisions to buy groceries or eat out, an effective analysis of this relationship must also consider a causal mechanism. To this end, we introduce a shock in the form COVID-19 hospitalizations. When cases spike, remote workers less exposed to the virus might alter how they acquire their food more than in-person workers, who are already facing high exposure risks. Complicating the analysis is that neither grocery shopping nor prepared meals–as defined by the dataset–is explicitly safer than the other. Although "prepared meals" includes takeout, it also includes dine-in options, which are strictly riskier than grocery shopping. As such, we assume, fairly, that grocery shopping is relatively less risky, especially with the advent of delivery services offering offsetting possibilities for both takeout and grocery shopping.

The main contribution of this research to the literature is in the form of a causal evaluation of work-from-home (and implicitly, the COVID-19 pandemic) on at-home and away-from-home food expenditures We believe a good linkage exists such that there is a relationship worth studying. Previous research has focused on similar but distinct questions, generally centered on time use. Accordingly, to our knowledge, this would be the first study on food expenditure choice stemming from increased telework.

Our estimates provide strong evidence that teleworking indeed increases individual's expenditures on groceries relative to food away from home by about 2.6 percentage points. Moreover, we find that telework increases grocery expenditure alone by as much as 3%. When we consider the presence of a shock in terms of COVID-19 hospitalizations, the difference is much smaller in magnitude, but still significant, at 0.29 percentage points.

Our work is connected to two strands of literature. Foremost, we contribute to a growing literature aimed at understanding the effects of remote work, an increasingly relevant area of study considering the consequences of the COVID-19 Pandemic. Much of the existing literature regarding WFH centers on determining the effects of telework on productivity. As might be expected, the results here are mixed, with some evidence before COVID-19 finding strong benefits to remote work (Bloom et al. 2015), but more recent evidence focused on the Pandemic finding negative effects of teleworking (Barrero et al. 2023). Although the earlier work exploits a randomized control trial, it also examines lower skill workers (call center employees) in China, rather than the US. When wide swathes of workers were forced to telework, rather than optimally choosing to do so, and others in the household were also forced home, the productivity boost turned into a loss. The optimal choice aspect of this dynamic is relevant here, as individuals did not select into working from home, but now must optimally allocate their food expenditures given the new pressures and circumstances. Outside of productivity, prior research has found evidence that WFH increases parents' income more, especially amongst mothers versus fathers (Arntz et al. 2022). Finally, there is evidence that teleworking mitigated the spread of the Coronavirus and lessened work subsidy applications (Alipour et al. 2021). The evidence that teleworking was effective in limiting the spread of Coronavirus is unsurprising, though it is important for our assumptions: we believe that those teleworking will have less exposure to COVID-19, and will continue to manage their risk of exposure in food expenditure allocation.

Second, this research is a more involved study into food choice, especially as it pertains to teleworking. Literature pre-dating the Pandemic is strongly intertwined in the time-use literature. This subset of the literature broadly centers on the time choices of individuals, relevant here studying how individuals allocate time at home to food production (cooking) and consumption (Davis 2014). An important framework of the decision is the trade-off between non-labor productive hours (cooking, chores, etc.) and leisure (Aguiar and Hurst 2007). We assume here that teleworkers will be more likely to delegate time to these non-labor productive hours (namely, at-home cooking) for two reasons: a lack of a commute and convenience. A lack of a commute creates large time savings which individuals can spend cooking, which previous research has noted is more nutritious than food away from home (e.g., Davis 2014). Similarly, the lack of a commute reshapes the convenience of takeout expenditures. Although the proliferation of food delivery services is confounding, the effect of working at home on, for example, coffee expenditures, is not negligible.

Moreover, because it is easier to make lunch and breakfast at home than to get either meal out if teleworking, especially given that many companies offer cafeterias or otherwise provide easy-access to prepared food, then we can expect that the reallocation away from prepared foods will be quite large.

The paper most similar to ours is Restrepo and Zeballos (2020), who synthesize the time use theoretical framework into analysis of time allocations for teleworkers and non-teleworkers before the Pandemic. In particular, they find that remote workers spend more time cooking and eating at home than in-person workers. This result is consistent with our assumptions on teleworkers, and we would expect that the COVID-19 Pandemic might exacerbate such underlying patterns. We diverge from this work, however, in two key ways. First, and obviously, our time frame is exclusively in the later stages of the Pandemic, from April 2021 to the tail of the Omicron wave in February 2022. Second, we track expenditures, rather than actual time use. Two other papers have similar intentions, though we diverge from each in different ways.Marchesi and McLaughlin (2022) provide a more descriptive analysis of food expenditure allocation during the Pandemic; naturally, then, this research marks an improvement over their work in the goal of disentangling a causal relationship. Ellison et al. (2021) conduct their own survey which allowed them to disaggregate food expenditure between grocery stores, takeout, and dine-in. As would be anticipated, dine-in expenditures plummeted, though, important to this analysis, they find that takeout expenditures increased, especially during early stages. Their analysis does not address teleworking, and is also somewhat limited empirically. Thus, while we lack the disaggregation of their data, our focus on teleworking as a separator is again a development in the literature.

The remainder of the paper is organized as follows. Section II overviews the dataset and variables used in estimation, including the characterization of a COVID-19 hospitalization shock. Section III estimates the difference-in-differences models, presents the results, and uses inverse propensity weighting to ensure robustness between teleworkers and non-teleworkers. Section IV concludes.

II. Work and Food Expenditure During COVID-19 Pandemic

2.1 Data Overivew

The survey dataset includes monthly responses from April 2021 to March 2022 from the Household Pulse Survey (HPulse), a project by the US Census and other agency partners that aimed to understand the impact of the COVID-19 pandemic on people's health, work, and mobility. We truncated the sample to the end of the Omicron wave to capture the period where the pandemic would most prominently dictate work and choices decisions. Our subset includes 177,511 responses from households and is nationally representative and partially longitudinal. Respondents are ages 18-64. A key strength is that its monthly collection is sensitive to the quickly changing US COVID landscape. However, it is an experimental survey with a low response rate, giving it a large standard error (The Household Pulse Survey Provides Data Quickly During the Pandemic — HUD USER 2020).

2.2 Trends in Key Variables

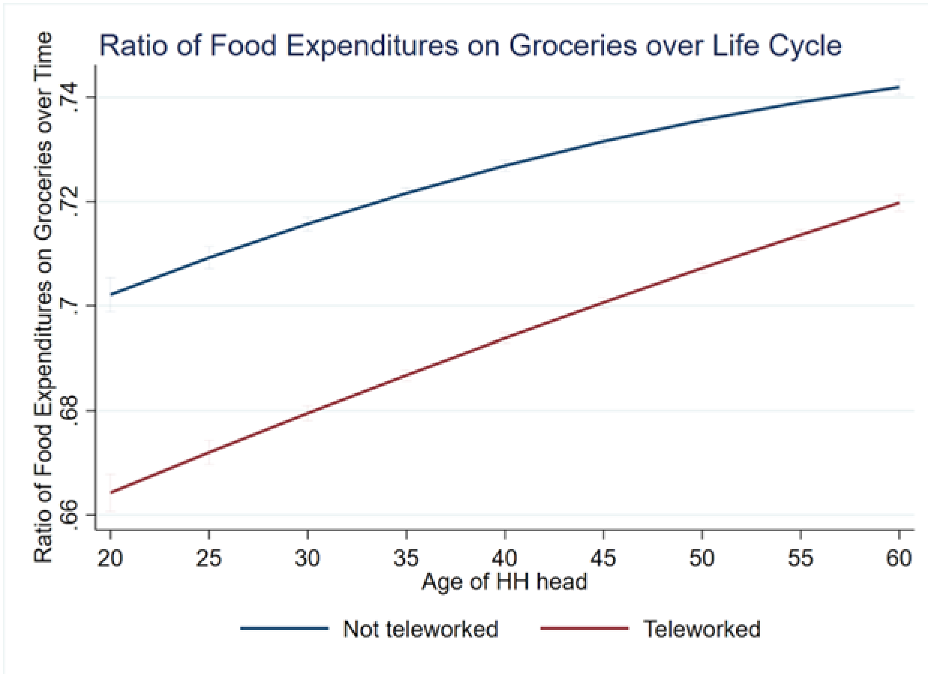
The research primarily examines the proportion of total food expenditure spent on groceries as a continuous. The Household Pulse survey asks respondents about household spending on groceries and prepared meals over the past seven days. This spending is normalized with the June 2019 Food CPI index and by converting responses to adult equivalents to generate real household food spending per adult equivalent. Our agent's choice of interest, teleworking, is an indicator variable where 1 means that a household member did engage in telework and 0 means no household members engaged in telework during the week of the survey. For clarification, we use telework, remote work, and work-from-home interchangeably. As described in more depth in the next section, we define the treatment shock as living in a state with a new COVID-19 hospitalization rate above the 80^{th} percentile during the survey period. To preempt our analysis, we begin by presenting several descriptive figures detailing how our outcomes vary over the life cycle and are generally oriented.

Descriptive data analysis elucidates how grocery food expenditure changed over the lifecycle between the teleworking and non-teleworking respondents (Figure I). For both groups, the grocery expenditure ratio steadily increases over the lifecycle, a trend possibly representative of parents and retired people relying on home-cooked meals to provide for families and to limit transportation costs. The levers explaining why teleworkers spend more of their weekly food expenditures on groceries compared to non-teleworkers are multi-faceted and complex. The empirical model attempts to disentangle the mechanisms underlying this relationship to glean if teleworking has a causal relationship with food expenditure choices.

2.3 Shock Description

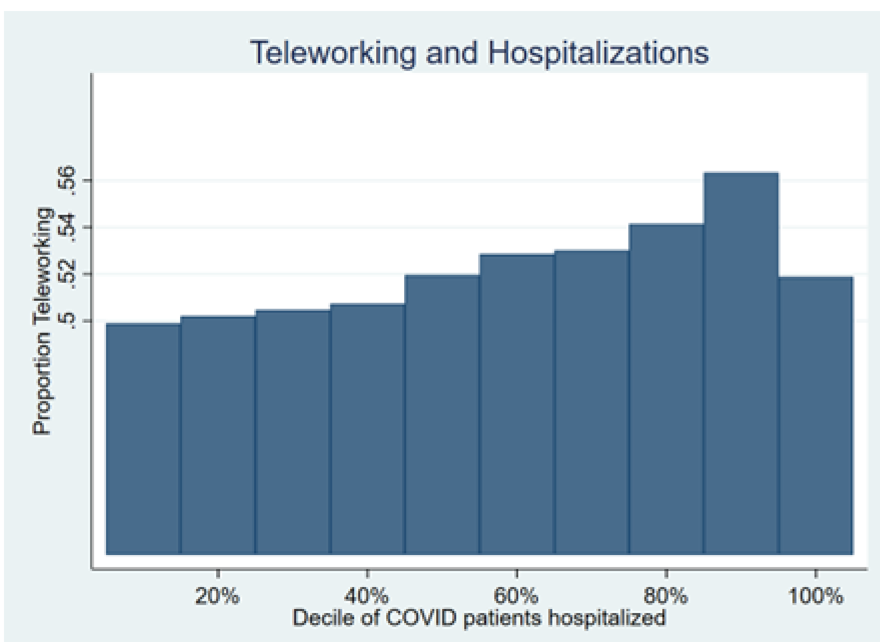
The COVID-19 pandemic's radical shifting of work and the downstream consequences motivate this research. We find a proxy to indicate how the severity of the pandemic relates to teleworking. Plotting COVID-19 hospitalizations against teleworking in Figure II confirms the assumption that higher hospitalizations correspond to a small but noticeable difference in remote work. The deciles are among all the aggregated data across the state and each survey period. The largest jump in remote work occurs at the ninth decile, or between 81-90%, where there was a two percentage point increase from the eigth decile.

Figure 1



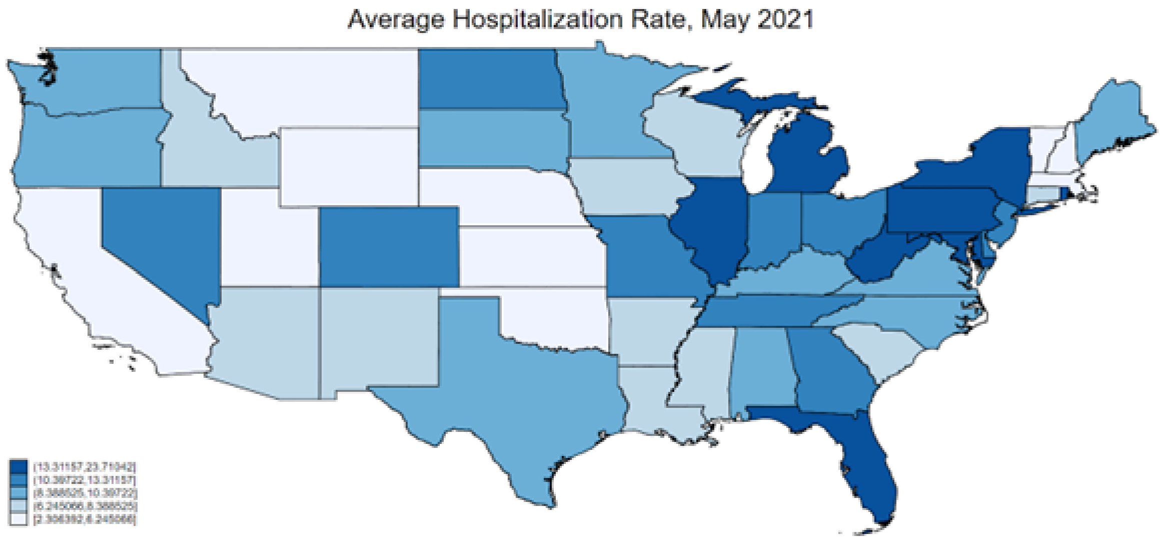
Notes: Red line shows ratio of grocery expenditures to total food expenditures amongst teleworkers over different age groups; blue line is analogous for non-teleworkers

Figure 2



Note: COVID-19 hospitalizations above the 80% percentile are associated with a spike in teleworking.

Figure 3

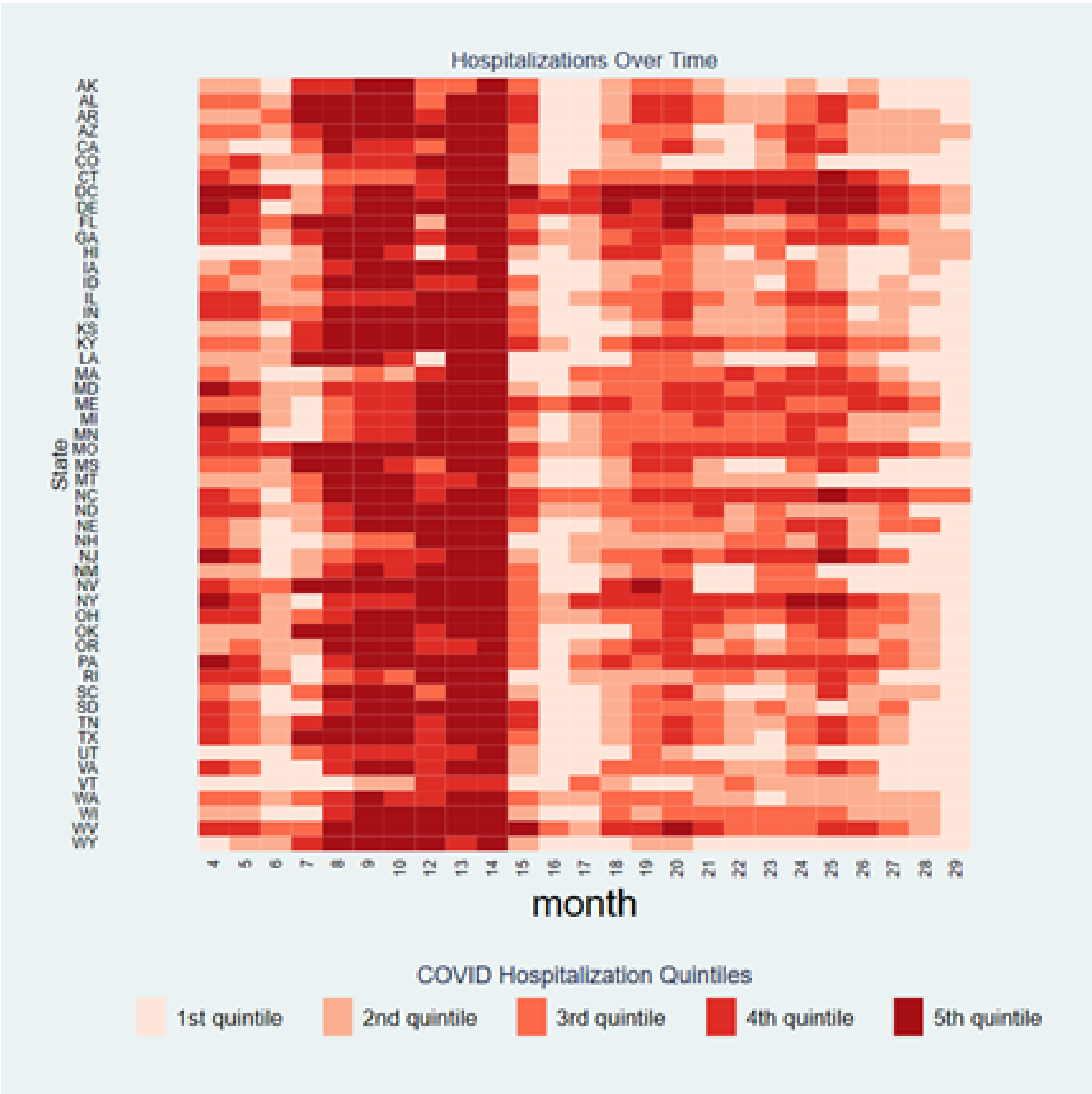


Note: Map shows average hospitalizations by state in May 2021; darker blues indicate relatively more hospitalizations.

This difference, demonstrated in Figure II, signifies the shock analyzed in our research. A survey participant whose state's new COVID hospitalizations are above the 81st percentile, 19.3 hospitalizations per 100,000 people, is considered to be in a pandemic climate that is "teleworking inducive." The map in Figure III shows that new hospitalizations per 100,000 in May 2022 are highest in the Northeast (which makes sense, given this is the most densely populated region of the US) and Midwest. Over 40% of the country is below 9 new hospitalizations per 100,000, which is fairly low. Overall, the magnitude of the new hospitalizations is fairly low compared to what numbers were during 2020–the top value is only 23.7. Generally, neighboring states have similar hospitalization rates. For example, aside from the Northeast and Midwest, the Mountain West (Montana, Utah, etc.) are all similar, as is the South–the major outlier being Florida. This generally makes sense, as climate factors and population density are fairly similar across the clusters of states.

Figure IV demonstrates how COVID-19 hospitalizations have changed over time in different states. The x-axis represents the months of the survey collection that formed the initial sample before it was truncated at the end of the Omicron wave. The values on the x-axis reflect the number of months since January 2021. Because the sample begins in April 2021, the panel visual starts at month 4. According to the visual, there is a significant variation in hospitalizations across states. However, every state experienced a spike in COVID-related hospitalizations during the Omicron with most entering the upper quintile. Later, in 2022 and 2023, there was a wider dispersion of hospitalization rates across states. While generally, COVID-19 hospitalizations were below the fifth quintile after the Omicron wave, some states, such as New York, West Virginia, and Connecticut, crossed the shock threshold.

Figure 4: : Visualization of Hospitalization Severity



Note: Figure shows the relative severity of COVID-19 Hospitalizations for the full sample. Darker reds indicate relatively more cases. Months are since period start, as described above.

III. Difference in Differences Analysis

3.1 The DID Equation Set-Up

Our baseline empirical models highlight the simple OLS relationship between teleworking and our outcome variables, and, separately, a two-way fixed effects approach encapsulating the effects of hospitalizations and telework separately. We anticipate that teleworking might increase grocery expenditure by increasing the time an individual has at home. With more time in the house, individuals would have better chances of preparing food at home, as it is more convenient than leaving home; however, the proliferation of food delivery services might confound our results. Moreover, we expect that as hospitalizations increase, grocery expenditures relative to total food spending will increase, as individuals shift away from any in-person dining, or it becomes fully prohibited. Such policies might in turn affect individuals' abilities to work or their decision on how much to work thus affecting the means they possess to buy food. Formally, we estimate the following baseline two-way fixed effects model:

$$y_{it} = \beta_0 + \beta_1 P_{st} + \gamma_1 Z_{it} + \alpha_s + \theta_t + \epsilon_{it} \tag{1}$$

where Z_{it} is the vector of controls, α_s and θ_t are state and time fixed effects, respectively, it is the error term, and P_{st} represents the measure of hospitalizations. Note that the teleworking-only specification noted above would exclude P_{st} entirely, and teleworking, in the control vector as expressed here, is the variable of interest. We consider two forms of the shock: a continuous variant, defined as the number of new hospitalizations due to COVID-19 per 100,000 residents in state s at time t, and a binary variant. We define the binary shock as equal to one when hospitalizations in a state are in the 80^{th} percentile of hospitalizations over the sample, consistent with the timeline in Section III. The shock was strongest when most states entered the upper quintile of hospitalizations during the Omicron wave from late 2021 to early 2022. Appendix Figure I succinctly visualizes the relationship between the variables.

For controls, we use marital status, education level, whether or not the respondent is female, race, whether or not the respondent is Hispanic, age, sector of employment, household size, income, and a small subset of industry controls. For marital status, we believe that all else equal, having two people who can cook should increase the likelihood of eating at home. Education would predict income, hours worked, and industry, the latter two of which are unobserved or incompletely observed in the data. Accordingly, the effect of education is ambiguous but does hold some key information. We control for gender since we expect that males may be more likely to spend money on eating out due to the persistence of hierarchical gender roles and norms potentially influencing females to eat away from home less frequently. We account for income as we'd expect that as income rises, workers may have more ability to eat out, and their opportunity cost for cooking is higher since their time is worth more. We anticipate that public employment would increase grocery expenditures as public employees should have more flexible and delineated hours than other categories. The vector also includes household size, as more people in the household means more people who might be able to cook and a higher cost of eating out. Finally, we are able to include a reduced set of industries, specifically agriculture, healthcare, social assistance, and education, accounting for about 23% of respondents. Healthcare and agriculture workers would be unlikely to shift to teleworking, though those working in education or social assistance would probably be able to work remotely. In controlling for industry, we are better able to limit the ambiguous bias of the set of industries in the effect of teleworking.

We include state-fixed effects to account for unobserved differences in the states. As it pertains to the COVID-19 pandemic, two such characteristics are aggregate state-level political attitudes and density. Some states, such as Wyoming, are highly rural and have very dispersed populations. Comparatively, areas in the Northeast, such as New Jersey, New York, and Washington D.C., are highly dense. We cannot account for such a factor here, but we nonetheless expect that an individual's behavior might vary if they are likely to encounter people (and many people, at that) when leaving their home. We also expect that state-level political attitudes may vary. While there may be within-state heterogeneity on this front, it follows that the average, modal, and median residents of Massachusetts, for example, will have different attitudes towards the Coronavirus than analogous residents of Oklahoma. Such attitudes were often elite-driven during the height of the pandemic, and may therefore be related to state-level policies, too.

Time-fixed effects are also a facet of the model to account for area-independent shocks and policies. Since the time period we study covers April-June 2021, breaks, and then covers June 2022 until May 2023. National guidance evolved over this time frame, and individuals may garner information from both state-level authorities, as well as national leaders. Similarly, domestic attitudes also might evolve, and other shocks might affect both food spending and food choice, too. High inflation might make individuals less likely to dine out, especially after they have adjusted to account for these higher prices. How these factors affect an individual is a longer process, though accounting for time fixed effects would help mitigate error caused by such variables.

We acknowledge that both the zero-conditional mean and the conditional independence assumptions are likely violated. The primary reason for this is that we believe that industry would be a crucial element in explaining teleworking, and that it would also impact, for example, income. Industry is unfortunately incompletely observed for the subsets of the survey available, and we anticipate this might lead to an understatement of the true impact of teleworking. This intuition stems from the expectation that there may be certain industries, particularly "white-collar" business settings, where meals may be provided or otherwise conveniently available. Such firms might grant employees dollars to spend on takeout, which would similarly bias these results. Furthermore, the lack of disaggregation within types of prepared food spending (takeout versus dine-in) also will produce bias. If individuals begin to substitute from dine-in to takeout in the presence of the shock, then there will not be an observed shift in the food choice decision. Moreover, food delivery companies, such as Doordash, proliferated during the COVID-19 Pandemic, and might have offers that could incentivize individuals to order takeout (e.g., free delivery). At least within states, the parallel trend assumption is not violated, as all individuals face the same virus landscape.

As our baseline model did not include the interaction between teleworking and our COVID measure, the baseline model is useful for a first pass of this relationship, but necessitates a better approach. Accordingly, we exploit a triple difference model by interacting the two. This allows us to see both how teleworking affects grocery expenditure, as well as how teleworking interacts with hospitalizations. In this regard, teleworkers can be seen as receiving a treatment in the sense that they are able to manage their own risk to COVID-19 by deciding how much time to spend outside of their home. Thus, when hospitalizations rise, we might see that teleworkers shift away from dining out and towards grocery shopping so as to limit their exposure to illness. Those who cannot telework are unable to take such measures. There are individuals who might choose between teleworking and in-person, though since this is not a long-term longitudinal survey (individuals are observed at most three times), we feel safe in assuming that they will not change during the period.

Triple differencing permits heterogeneity across groups, so we no longer must impose that all workers are homogenous on account of their work-from-home status. Letting G_{it} represent the indicator variable for those teleworking, we formally estimate:

$$y_{it} = \beta_0 + \beta_1 P_{st} + \beta_2 G_{it} + \beta_3 P_{st} G_{it} + \gamma_1 Z_{it} + \alpha_s + \theta_t + \epsilon_{it} \tag{2}$$

Which is equivalent to the baseline, except for the inclusion of the teleworking interaction. The results of the baseline and triple difference models are contained in Tables 1, 2, and 3 below. Table 4 presents the difference in estimates between the coefficients of interest.

3.2 Estimates and Discussion

While we abridge the main tables of results in the interest of space, we are nonetheless able to observe that our key expectations appear to have some support. In particular, we find strong evidence across specifications that teleworking does indeed increase grocery expenditures by about 2.6 percentage points over AFH food spending.

Our estimates also suggest that the relationship with COVID-19 hospitalizations is best characterized by the continuous shock. Despite the wide range of the fifth quintile, there is only inconsis-

Table 1: Baseline OLS (Food Choice and Teleworking) Estimates

Dependent Variable	Log Grocery Spending	Log AFH
Telework	0.019***	-0.007
	(0.005)	(0.007)
Observations	177,511	177,511

Note: Robust standard errors in parentheses. Controls omitted. *** p<0.01, ** p<0.05, * p<0.1

Table 2: Continuous Hospitalizations Estimates

	2FE Continuous		3D Continuous	
Dependent Variable	Grocery Spending	AFH Spending	Grocery Spending	AFH Spending
Hosp	0.000	-0.002**	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Telework	0.019***	-0.007	0.030***	0.028**
	(0.005)	(0.007)	(0.008)	(0.013)
Telework x Hosp			-0.001	-0.004***
			(0.001)	(0.001)
Observations	177,511	177,511	177,511	177,511

Note: Model includes state and time FE and controls, omitted here for concision. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Spending is log spending.

tent evidence that the quintiles are relevant, and this is independent of teleworkers. These results challenge the framing of a hospitalization threshold triggering a major change in food behavior. We do not find overwhelming evidence that the shock enhances this relationship, though we do find evidence in our triple difference continuous model that a 1 case increase in COVID-19 hospitalizations drives teleworkers to spend 0.3 percentage points more on groceries than AFH food, relative to changes amongst non-teleworkers.

3.3 Group Balancing

As might be expected, there are significant differences between the remote and non-remote groups, particularly in terms of education and income. In the unbalanced sample, remote workers were 12% more likely to receive a bachelor's degree and 20% more likely to obtain a graduate degree than those not remote working. We assume that remote workers, in jobs often requiring higher education, earn more. The difference between the groups increases the higher you rise up the income scale. At the highest income rung–above $200,000–remote workers had a mean difference of 13%. Despite the income differential, it is important to note that those who work in

Table 3: Quantile Shock Estimates

	2FE Cat Shock		3D Cat Shock	
Dependent Variable	Grocery Spending	AFH Spending	Grocery Spending	AFH Spending
2nd Hospitalization Quintile	0.014**	-0.017	0.016*	-0.017
	(0.007)	(0.011)	(0.009)	(0.014)
3rd Hospitalization Quintile	-0.006	-0.028*	-0.002	-0.014
	(0.010)	(0.016)	(0.012)	(0.019)
4th Hospitalization Quintile	-0.013	-0.051**	0.002	-0.020
	(0.015)	(0.023)	(0.021)	(0.032)
5th Hospitalization Quintile	0.015	-0.116**	0.049	-0.043
	(0.035)	(0.055)	(0.047)	(0.078)
Telework	0.019***	-0.007	0.023***	0.001
	(0.005)	(0.007)	(0.007)	(0.011)
Quintile 2 x Telework			-0.004	0.000
			(0.010)	(0.015)
Quintile 3 x Telework			-0.007	-0.027
			(0.012)	(0.018)
Quintile 4 x Telework			-0.025	-0.051
			(0.022)	(0.033)
Quintile 5 x Telework			-0.058	-0.126
			(0.059)	(0.096)
Observations		177,511		

Note: Model includes state and time FE and controls, omitted here for concision. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Spending is log spending.

person are more heterogeneous, as some in-person jobs have minimal educational requirements and others (e.g. doctors) have high requirements. Those working remotely are likely more homogenous in terms of education, as these jobs are likely disproportionately more managerial and require a certain threshold of technology.

Balancing via inverse propensity weight eliminated most differences in observed characteristics. Most significantly, the skews in household income and educational attainment distributions are rectified. The remaining significant mean differences are household income above $200,000 and work in the healthcare industry in which teleworkers are oddly employed in the health field at a 1% higher rate. The comparison of the mean differences between the balanced and unbalanced groups can be found in the appendix.

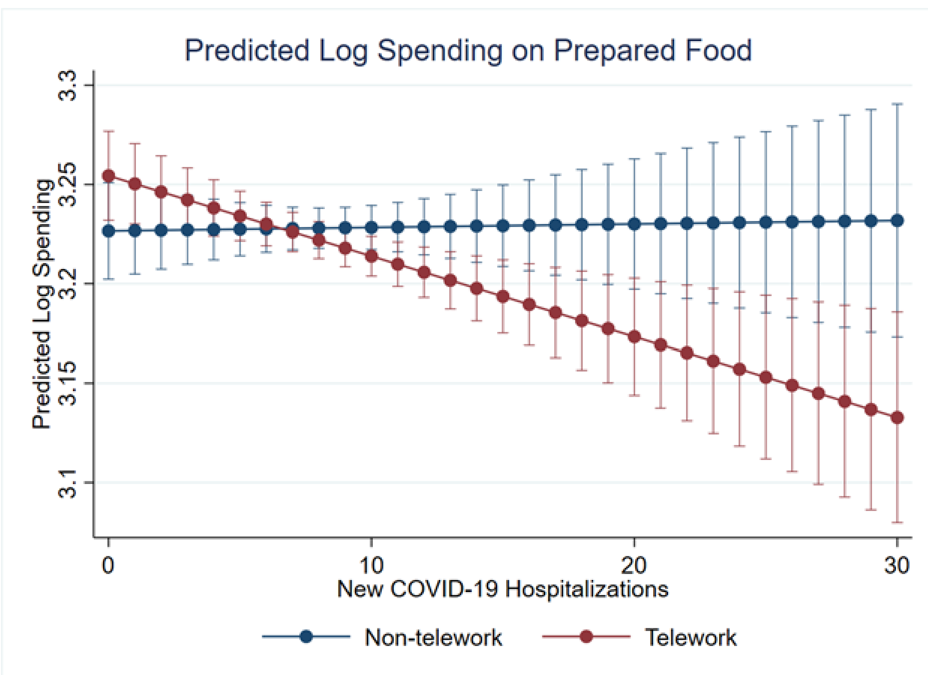
When estimating the triple difference for the balanced groups in the grocery regressions, the interaction terms are in line with the hypothesized relationship and our previous results. The log of real household spending on prepared meals decreased during elevated new COVID-19 hospi-

Table 4: Difference in Estimates

Estimate	Difference	P-value
Telework (Baseline)	-0.02633	0.00105**
Triple Dif Quintile 5 Interaction	-0.06756	0.51417
Triple Dif Quintile 4 Interaction	-0.02625	0.47103
Triple Dif Quintile 3 Interaction	-0.01999	0.30180
Two-Way FE Telework (Quintiles)	-0.02633	0.00104**
Two-Way FE Quintile 5	-0.13102	0.02817*
Two-Way FE Quintile 4	-0.03836	0.12246
Two-Way FE Quintile 3	-0.02267	0.17202
Triple Dif Continuous Interaction	-0.00288	0.03696*
Triple Dif Telework (Continuous)	-0.00248	0.85819
Triple Dif Hospitalizations	-0.00075	0.61689
Two-Way FE Telework (Continuous)	-0.02628	0.00106**
Two-Way FE Hospitalizations	-0.00249	0.04292*

Note: shows difference (AFH Spending - Grocery Spending) with p-values for coefficient estimates. ** p<0.01, * p<0.05

Figure 5



Note: Shows difference in predicted log spending between teleworkers (red) and non-teleworkers (blue) at different levels of the hospitalizations.

Table 5: Triple Difference with Inverse Propensity Score Weighting

Dependent Variable	Grocery Spending	AFH Spending
Hosp	0.001	-0.002
	(0.001)	(0.002)
Telework	0.025***	0.011
	(0.010)	(0.015)
Telework x Hosp	-0.001	-0.003*
	(0.001)	(0.002)
R-squared	0.042	0.063
Observations	175,252	174,329

Note: State and time FE and controls are included in the model but omitted here for concision. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Spending indicates log spending.

talization rates. This result suggests that remote workers, cautioning against contracting the virus, avoided dining out with increased pandemic severity while non-remote workers did not experience an effect. Balancing the sample also reaffirms that remote workers are prone to spending more on groceries (2.5%), suggesting a general lifestyle change induced by choosing to work remotely.

IV. Conclusion

This research attempts to identify how work-from-home drove changes in food expenditures during the COVID-19 pandemic. We leverage national representative data from the Household Pulse survey collected during the beginning of the pandemic to explore changes in weekly food expenditures by month. After accounting for the heterogeneities posed by time-variant and time-invariant confounding unobservables, we develop a triple difference-in-difference specification with inverse propensity weighting. Through this analysis, we identify a negative link between remote work and prepared food expenditure amid worsening pandemic conditions. This result supports the hypothesized channel by which remote workers, guarded from pandemic risk, will reduce viral exposure when acquiring food. Because eating out is perceived as a riskier behavior than grocery shopping, we predicted remote workers would move away from this behavior. Many theories persist about why teleworkers, in a balanced sample, spend more on groceries than non-teleworkers. It appears the factors pointing to an increase in grocery shopping–reduced COVID risk, extra time gained from losing one's commute, and participation in cooking fads–outweighed being more exposed to more food options.

The difference between the two food modes, groceries and prepared meals, is not straightforward, as delivery services can provide both. There are also significant limitations in the estimation strategy. While the models included state-fixed effects, significant geographic heterogeneity within a state could also impact food access outcomes. A prominent example of these limitations is food deserts where people live far away from grocery stores such that food behaviors are less a reaction to the pandemic and more indications of geographic reality. A related limitation is the estimations, even accounting for inverse propensity score weighting, do not directly account for urban and rural differences which could impact food access and responses to the pandemic. Although IPW does attempt to manage unobservables, this is likely imperfect, so further research would ideally disaggregate expenditure categories and include geographic information.

This research lends credence to the notion that, especially in the face of the risk of illness from the Coronavirus, teleworkers mitigated their exposure by substituting away from higher-risk activities brought on by away-from-home food expenditures. The implications of this finding are vast, particularly for physical health outcomes and nutrition among teleworkers. A core insight is that teleworkers tend to spend more at grocery stores, indicating that teleworking can induce healthier food consumption which has downstream impacts on mental and physical health. As teleworking continues to evolve, food expenditure allocation will remain a key behavior of remote workers, whose increasing prominence in the economy will hold increasingly pivotal consequences in consumption and firm decisions.

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Appendix

Figure I - Visualization of Relationship Between Variables

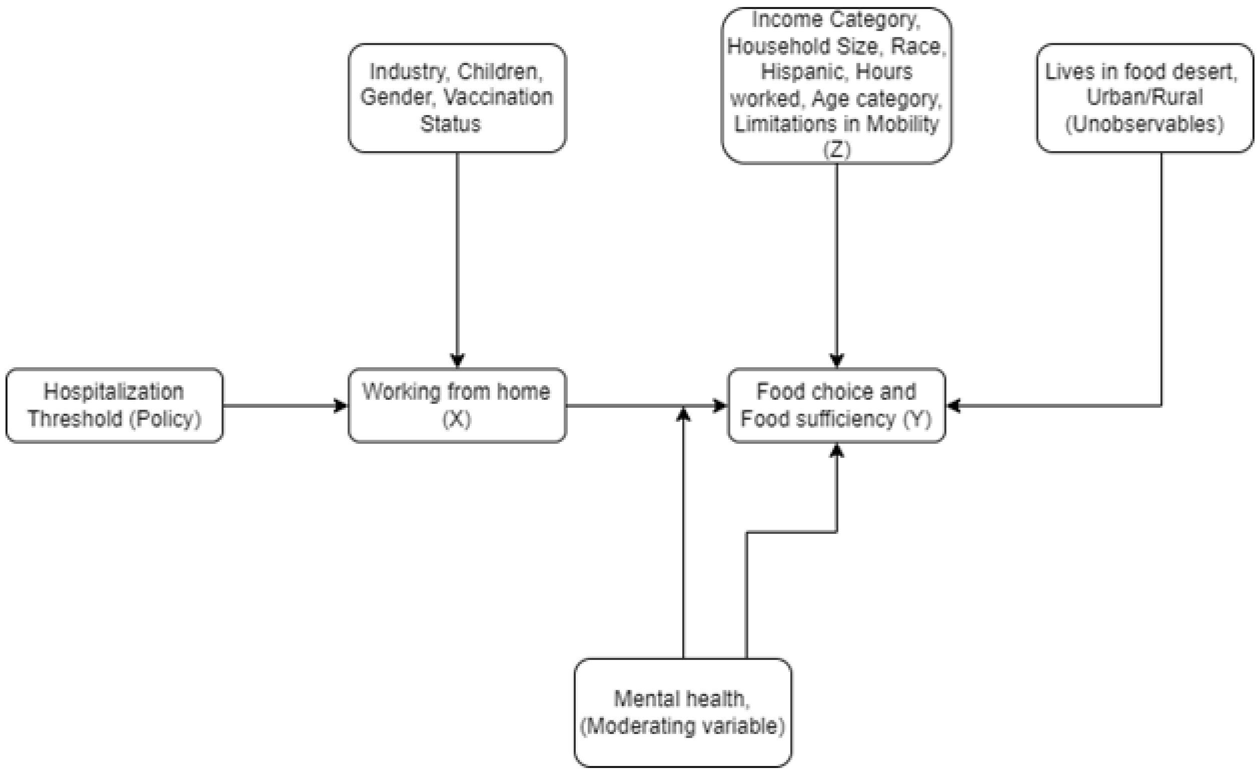

Table I - Descriptive Statistics for Control, Dependent, Mediating, and Explanatory Variables

Variable	N	Mean	SD	Min	Max
Married	978,825	0.583	0.493	0	1
Education category	981,811	2.885	0.836	1	4
Income category	981,811	6.365	3.398	1	13
Female	981,811	0.573	0.495	0	1
Race	981,811	1.352	0.809	1	4
Hispanic	981,811	0.096	0.294	0	1
Age category	981,811	3.478	1.141	1	5
Sector	971,221	2.219	0.912	1	5
HH Size	981,811	2.923	1.463	1	10
Grocery Spending Ratio	520,373	0.714	0.195	0.002	1
Telework	981,811	0.521	0.500	0	1
Hospitalizations (per 100k)	981,811	13.337	12.087	0.343	113
HH Food Insufficiency	939,294	0.053	0.224	0	1

Full Results - 2 Way FE and Triple Differences

Table II - Continuous Hospitalizations

Variables	2FE Continuous		3D Continuous	
Dependent Variable	Grocery Spend	AFH Spend	Grocery Spend	AFH Spend
Hosp	0.000	-0.002**	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Telework	0.019***	-0.007	0.030***	0.028**
	(0.005)	(0.007)	(0.008)	(0.013)
Telework x Hosp			-0.001	-0.004***
			(0.001)	(0.001)
Married	0.078***	0.010	0.078***	0.010
	(0.006)	(0.008)	(0.006)	(0.008)
HS degree	-0.154***	-0.081**	-0.154***	-0.081**
	(0.022)	(0.036)	(0.022)	(0.036)
Bachelor’s degree	-0.185***	-0.036	-0.185***	-0.036
	(0.022)	(0.036)	(0.022)	(0.036)

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Variables	2FE Continuous		3D Continuous	
Graduate degree	-0.160***	-0.108***	-0.159***	-0.108***
	(0.022)	(0.036)	(0.022)	(0.036)
Household income:				
$25,000 - $34,999	0.021	0.115***	0.021	0.115***
	(0.015)	(0.023)	(0.015)	(0.023)
$35,000 - $49,999	0.071***	0.242***	0.071***	0.242***
	(0.014)	(0.021)	(0.014)	(0.021)
$50,000 - $74,999	0.113***	0.383***	0.113***	0.383***
	(0.013)	(0.020)	(0.013)	(0.020)
$75,000 - $99,999	0.162***	0.519***	0.162***	0.520***
	(0.013)	(0.020)	(0.013)	(0.020)
$100,000 - $149,999	0.211***	0.653***	0.211***	0.653***
	(0.013)	(0.020)	(0.013)	(0.020)
$150,000 - $199,999	0.271***	0.803***	0.271***	0.804***
	(0.014)	(0.021)	(0.014)	(0.021)
$200,000+	0.358***	1.047***	0.358***	1.048***
	(0.014)	(0.021)	(0.014)	(0.021)
Income Not reported	0.115***	0.530***	0.115***	0.530***
	(0.015)	(0.021)	(0.015)	(0.021)
Female	-0.021***	-0.154***	-0.021***	-0.154***
	(0.004)	(0.007)	(0.004)	(0.007)
Race:				
Black	-0.038***	0.111***	-0.039***	0.111***
	(0.010)	(0.013)	(0.010)	(0.013)
Asian	0.002	0.100***	0.002	0.100***
	(0.009)	(0.014)	(0.009)	(0.014)

Continued on the next page

Variables	2FE Continuous		3D Continuous	
Other/mixed	0.001	0.055***	0.001	0.055***
	(0.011)	(0.016)	(0.011)	(0.016)
Hispanic	0.114***	0.218***	0.114***	0.218***
	(0.008)	(0.012)	(0.008)	(0.012)
Age:				
25-34	0.143***	0.085***	0.143***	0.085***
	(0.018)	(0.023)	(0.018)	(0.023)
35-44	0.235***	0.009	0.235***	0.009
	(0.018)	(0.022)	(0.018)	(0.022)
45-54	0.219***	-0.057**	0.219***	-0.057**
	(0.018)	(0.022)	(0.018)	(0.022)
55-64	0.164***	-0.277***	0.164***	-0.277***
	(0.018)	(0.023)	(0.018)	(0.023)
Sector:				
Private company	0.011*	0.014	0.011*	0.014
	(0.006)	(0.010)	(0.006)	(0.010)
Non-profit organization	-0.004	-0.015	-0.003	-0.015
	(0.008)	(0.012)	(0.008)	(0.012)
Self-employed	0.055***	0.022*	0.055***	0.022*
	(0.008)	(0.013)	(0.008)	(0.013)
Family business	0.077***	0.095***	0.077***	0.095***
	(0.017)	(0.027)	(0.017)	(0.027)
People in HH				
2	-0.150***	-0.098***	-0.150***	-0.098***
	(0.009)	(0.013)	(0.009)	(0.013)
3	-0.260***	-0.251***	-0.260***	-0.251***
	(0.009)	(0.014)	(0.009)	(0.014)
4	-0.345***	-0.361***	-0.345***	-0.362***
	(0.010)	(0.014)	(0.010)	(0.014)
5	-0.400***	-0.492***	-0.400***	-0.492***
	(0.011)	(0.016)	(0.011)	(0.016)
6	-0.485***	-0.597***	-0.485***	-0.597***
	(0.014)	(0.021)	(0.014)	(0.021)

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Variables	2FE Continuous		3D Continuous	
7	-0.534***	-0.720***	-0.534***	-0.721***
	(0.020)	(0.032)	(0.020)	(0.032)
8	-0.682***	-0.826***	-0.682***	-0.826***
	(0.033)	(0.048)	(0.033)	(0.048)
9	-0.763***	-1.019***	-0.763***	-1.019***
	(0.056)	(0.083)	(0.056)	(0.083)
10+	-0.982***	-1.073***	-0.982***	-1.074***
	(0.067)	(0.075)	(0.067)	(0.075)
Industry:				
Healthcare	0.019***	0.057***	0.018***	0.057***
	(0.007)	(0.010)	(0.007)	(0.010)
Education	-0.019**	0.041***	-0.019**	0.040***
	(0.007)	(0.011)	(0.007)	(0.011)
Social Services	-0.012	0.072***	-0.012	0.072***
	(0.014)	(0.021)	(0.014)	(0.021)
Agriculture	-0.010	-0.112***	-0.010	-0.112***
	(0.023)	(0.036)	(0.023)	(0.036)
Observations	177,511	177,511	177,511	177,511
State & Week FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Spend indicates log spending.

Table III -Categorical Shock Full Results

Variables	2FE Cat Shock		3D Cat Shock	
Dependent Variable	Grocery Spend	AFH Spend	Grocery Spend	AFH Spend
Telework	0.019***	-0.007	0.023***	0.001
	(0.005)	(0.007)	(0.007)	(0.011)

Continued on next page

Variables	2FE Cat Shock		3D Cat Shock	
Hospitalization Quintile				
2nd	0.014**	-0.017	0.016*	-0.017
	(0.007)	(0.011)	(0.009)	(0.014)
3rd	-0.006	-0.028*	-0.002	-0.014
	(0.010)	(0.016)	(0.012)	(0.019)
4th	-0.013	-0.051**	0.002	-0.020
	(0.015)	(0.023)	(0.021)	(0.032)
5th	0.015	-0.116**	0.049	-0.043
	(0.035)	(0.055)	(0.047)	(0.078)
Quintile x Telework			-0.004	0.000
Quintile 2				
			(0.010)	(0.015)
Quintile 3			-0.007	-0.027
			(0.012)	(0.018)
Quintile 4			-0.025	-0.051
			(0.022)	(0.033)
Quintile 5			-0.058	-0.126
			(0.059)	(0.096)
Married	0.078***	0.010	0.078***	0.010
	(0.006)	(0.008)	(0.006)	(0.008)
HS degree	-0.154***	-0.081**	-0.154***	-0.081**
	(0.022)	(0.036)	(0.022)	(0.036)
Bachelor's degree	-0.184***	-0.036	-0.184***	-0.036
	(0.022)	(0.036)	(0.022)	(0.036)
Graduate degree	-0.159***	-0.108***	-0.159***	-0.108***
	(0.022)	(0.036)	(0.022)	(0.036)
Household Income				
$25,000 - $34,999	0.021	0.115***	0.021	0.116***

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Variables	2FE Cat Shock		3D Cat Shock	
	(0.015)	(0.023)	(0.015)	(0.023)
$35,000 - $49,999	0.071***	0.242***	0.071***	0.242***
	(0.014)	(0.021)	(0.014)	(0.021)
$50,000 - $74,999	0.113***	0.383***	0.113***	0.383***
	(0.013)	(0.020)	(0.013)	(0.020)
$75,000 - $99,999	0.162***	0.519***	0.162***	0.520***
	(0.013)	(0.020)	(0.013)	(0.020)
$100,000 - $149,999	0.211***	0.653***	0.211***	0.653***
	(0.013)	(0.020)	(0.013)	(0.020)
$150,000 - $199,999	0.271***	0.804***	0.271***	0.804***
	(0.014)	(0.021)	(0.014)	(0.021)
$200,000+	0.358***	1.047***	0.358***	1.048***
	(0.014)	(0.021)	(0.014)	(0.021)
income Not reported	0.115***	0.530***	0.115***	0.530***
	(0.015)	(0.021)	(0.015)	(0.021)
Female	-0.021***	-0.154***	-0.020***	-0.154***
	(0.004)	(0.007)	(0.004)	(0.007)
Race				
Black	-0.039***	0.111***	-0.039***	0.111***
	(0.010)	(0.013)	(0.010)	(0.013)
Asian	0.002	0.100***	0.002	0.100***
	(0.009)	(0.014)	(0.009)	(0.014)
Other/mixed	0.001	0.055***	0.001	0.055***
	(0.011)	(0.016)	(0.011)	(0.016)
Hispanic	0.114***	0.218***	0.114***	0.218***
	(0.008)	(0.012)	(0.008)	(0.012)
Age				

Continued on next page

Variables	2FE Cat Shock		3D Cat Shock	
25-34	0.143***	0.085***	0.143***	0.085***
	(0.018)	(0.023)	(0.018)	(0.023)
35-44	0.235***	0.009	0.235***	0.009
	(0.018)	(0.022)	(0.018)	(0.022)
45-54	0.219***	-0.057**	0.219***	-0.057**
	(0.018)	(0.022)	(0.018)	(0.022)
55-64	0.164***	-0.277***	0.164***	-0.277***
	(0.018)	(0.023)	(0.018)	(0.023)
Sector				
Private company	0.011*	0.014	0.011*	0.014
	(0.006)	(0.010)	(0.006)	(0.010)
Non-profit organization	-0.003	-0.015	-0.003	-0.015
	(0.008)	(0.012)	(0.008)	(0.012)
Self-employed	0.055***	0.022*	0.055***	0.022*
	(0.008)	(0.013)	(0.008)	(0.013)
Family business	0.077***	0.095***	0.077***	0.095***
	(0.017)	(0.027)	(0.017)	(0.027)
Household Size				
2	-0.150***	-0.098***	-0.150***	-0.098***
	(0.009)	(0.013)	(0.009)	(0.013)
3	-0.260***	-0.251***	-0.260***	-0.251***
	(0.009)	(0.014)	(0.009)	(0.014)
4	-0.345***	-0.361***	-0.345***	-0.361***
	(0.010)	(0.014)	(0.010)	(0.014)
5	-0.400***	-0.492***	-0.400***	-0.492***
	(0.011)	(0.016)	(0.011)	(0.016)
6	-0.485***	-0.597***	-0.485***	-0.597***
	(0.014)	(0.021)	(0.014)	(0.021)
7	-0.534***	-0.720***	-0.534***	-0.721***
	(0.020)	(0.032)	(0.020)	(0.032)
8	-0.682***	-0.826***	-0.682***	-0.826***
	(0.033)	(0.048)	(0.033)	(0.048)

Continued on next page

Variables	2FE Cat Shock		3D Cat Shock	
9	-0.764***	-1.018***	-0.764***	-1.019***
	(0.056)	(0.083)	(0.056)	(0.083)
10+	-0.982***	-1.073***	-0.982***	-1.073***
	(0.067)	(0.075)	(0.067)	(0.075)
Industry				
Healthcare	0.019***	0.057***	0.018***	0.057***
	(0.007)	(0.010)	(0.007)	(0.010)
Education	-0.019**	0.041***	-0.019**	0.041***
	(0.007)	(0.011)	(0.007)	(0.011)
Social Services	-0.012	0.072***	-0.012	0.072***
	(0.014)	(0.021)	(0.014)	(0.021)
Agriculture	-0.010	-0.112***	-0.010	-0.112***
	(0.023)	(0.036)	(0.023)	(0.036)
Observations	177,511	177,511	177,511	177,511
State & Week FE	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Spend indicates log spending.

Table 4-List of Variables

Vector	Variable Name	Variable Label	Type	Notes about Variable Construction
Z_{it}	married	=1 if married	Binary	=1 if married, =0 if single, divorced, or widowed
Z_{it}	educag	Educational attainment	Categorical	Aggregated educational attainment. 4 categories: less than HS =1, HS =2, Bachelor's =3, and Graduate =4
Z_{it}	hhinccat	Categories for income before taxes last year	Categorical	8 categories: ¡25k =1, 25-50k =2, 50k-75k =3, 75k-100k =4, 100k-125k =5, 125k-150k =6, 150k-175k =7, 200k¡= =8, Not reported =13
Z_{it}	female	=1 if female	Binary	Self-explanatory
Z_{it}	race	Race Categories	Categorical	=1 if White, =2 if Black, =3 if Asian, =4 if Other
Z_{it}	hispanic	=1 if Hispanic	Binary	Self-explanatory
Z_{it}	agecat	Age categories	Categorical	=1 if 18-24, =2 if 25-34, =3 if 35-44, =4 if 45-54, =5 if 55-64
Z_{it}	emp_sector	Sector of Employment	Categorical	=1 if Govt, =2 if Private, =3 if Non-profit, =4 if Self-employed, =5 if Family Business
Z_{it}	hhsize	Total number of people in HH	Discrete count/categorical	Values range from 1-10, though ¿ 6 is only 1.83% of respondents
Z_{it}	ind	Industry	Categorical	=1 if Healthcare, =2 if Education, =3 if Social Assistance, =4 if Agriculture

Table 5 - IPW Group Balance Means

Variables	group	SE	Obs.	Variables	group	SE	Obs.
married	0.110***	(0.003)	100,642	married_IPW	-0.003	(0.004)	99,463
educag_2	-0.304***	(0.003)	101,088	educag_2_IPW	0.005	(0.004)	99,463
educag_3	0.122***	(0.003)	101,088	educag_3_IPW	-0.004	(0.003)	99,463
educag_4	0.201***	(0.003)	101,088	educag_4_IPW	-0.002	(0.004)	99,463
hhinccat_2	-0.051***	(0.001)	101,088	hhinccat_2_IPW	0.002	(0.002)	99,463
hhinccat_3	-0.051***	(0.002)	101,088	hhinccat_3_IPW	0.001	(0.002)	99,463
hhinccat_4	-0.053***	(0.002)	101,088	hhinccat_4_IPW	-0.000	(0.002)	99,463
hhinccat_5	-0.010***	(0.002)	101,088	hhinccat_5_IPW	-0.002	(0.002)	99,463
hhinccat_6	0.065***	(0.002)	101,088	hhinccat_6_IPW	-0.003	(0.003)	99,463
hhinccat_7	0.072***	(0.002)	101,088	hhinccat_7_IPW	-0.002	(0.002)	99,463
hhinccat_8	0.130***	(0.002)	101,088	hhinccat_8_IPW	0.005**	(0.003)	99,463
hhinccat_9	-0.057***	(0.003)	101,088	hhinccat_9_IPW	-0.004	(0.003)	99,463
female	-0.035***	(0.003)	101,088	female_IPW	0.003	(0.004)	99,463
race_2	-0.019***	(0.002)	101,088	race_2_IPW	0.001	(0.002)	99,463
race_3	0.035***	(0.002)	101,088	race_3_IPW	0.002	(0.002)	99,463
race_4	-0.016***	(0.001)	101,088	race_4_IPW	0.001	(0.002)	99,463
hispanic	-0.036***	(0.002)	101,088	hispanic_IPW	0.002	(0.002)	99,463
agecat_2	0.000	(0.002)	101,088	agecat_2_IPW	0.001	(0.003)	99,463
agecat_3	0.042***	(0.003)	101,088	agecat_3_IPW	0.002	(0.003)	99,463
agecat_4	0.013***	(0.003)	101,088	agecat_4_IPW	-0.003	(0.003)	99,463
agecat_5	-0.039***	(0.003)	101,088	agecat_5_IPW	-0.001	(0.004)	99,463
hhsize	0.016*	(0.009)	101,088	hhsize_IPW	0.009	(0.012)	99,463
emp_sector_2	-0.004	(0.003)	99,889	emp_sector_2_IPW	0.000	(0.004)	99,463
emp_sector_3	0.022***	(0.002)	99,889	emp_sector_3_IPW	0.000	(0.003)	99,463
emp_sector_4	0.000	(0.002)	99,889	emp_sector_4_IPW	-0.002	(0.003)	99,463
emp_sector_5	-0.013***	(0.001)	99,889	emp_sector_5_IPW	0.002	(0.001)	99,463
indhlth	-0.095***	(0.002)	101,088	indhlth_IPW	0.011***	(0.003)	99,463
indeduc	-0.020***	(0.002)	101,088	indeduc_IPW	0.001	(0.002)	99,463
indsoci	0.009***	(0.001)	101,088	indsoci_IPW	-0.001	(0.001)	99,463
indagri	-0.005***	(0.001)	101,088	indagri_IPW	0.000	(0.001)	99,463

Effects of In-school Health Information on Adolescents' Health Outcomes and Behaviors

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Abstract

Objective: This project evaluated the long-term impact of an in-school health advocacy program on adolescents' health outcomes and behaviors. Study 1 assessed the average treatment effect of health information about the importance of exercise on adolescents' Body Mass Index (BMI). Study 2 evaluated the impact of health information regarding smoking, parental modeling, depressive moods, and environmental cues on individuals' smoking intensities as they transitioned from adolescence into early adulthood. **Methods:** Data were used from the National Longitudinal Study of Adolescent to Adult Health (Add Health), a nationally representative study of American youth. In-school health information and measures of health were based on participant self-report. The correlated random effects estimator (Study 1) and the random effects estimator (Study 2) were used to evaluate the effects of the two distinct pieces of information within the in-school health program. **Results:** Study 1 revealed that in-school health information about the importance of exercise significantly reduced adolescents' BMI. On average, the BMI of adolescents who received information on exercise was reduced by 0.633. Study 2 found that information about smoking, compared to no health information, did not significantly reduce individuals' smoking frequencies. Nevertheless, additional findings from Study 2 underscored the pivotal roles played by mental well-being, parental behaviors, and environmental cues in shaping individuals' smoking habits during the transition from adolescence to early adulthood. **Discussion:** Findings from Study 1 indicate that exposure to in-school health information about the importance of exercise led to a significant reduction in

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adolescents' BMI. Findings from Study 2 highlight the potential efficacy of extending health information delivery to parents, addressing adolescents' mental health needs, and providing appropriate environmental cues in promoting healthy behaviors and discouraging negative ones. These implications could inform policy considerations for comprehensive health interventions targeting this demographic.

Keywords: Adolescents' health outcomes and behaviors; BMI; Smoking; Health interventions

I. Introduction

Healthy lifestyles and behaviors, such as sufficient exercise and sleep, maintaining a healthy weight, and refraining from smoking and binge drinking, have both short-term and long-term benefits. These behaviors promote health and well-being during adolescence and are associated with higher levels of healthy behaviors during adulthood (Frech 2012). In contrast, the lack of these behaviors can contribute to the development of chronic diseases, thereby impacting people's overall well-being and their ability to recover from illness (Strine et al. 2008).

It is crucial that adolescents learn about health information, as adolescence is an optimal time to adopt appropriate attitudes, beliefs, and behaviors related to health. When learned early in life, behaviors that promote good health are more likely to be sustained throughout adulthood (Lau et al. 1990). Additionally, it is preferable to prevent health-damaging behaviors at an early age than to modify an already-established habit later (Alexander 1994). Adolescents are in a critical life transition phase and often initiate decision-making for risky health behaviors, as identified by the Centers for Disease Control and Prevention (CDC 2022b), which include sexual behaviors, tobacco use, unintentional injuries, dietary behaviors, physical activity, and substance use. Trends among high school students have shown an increase in the prevalence of high-intensity drinking, electronic cigarette use, and sexually transmitted diseases (Kratzke et al. 2018. Thus, introducing proper interventions to adolescents that may help develop healthy behaviors and prevent risky behaviors is crucial to both physical and mental health.

Schools serve as optimal platforms to provide health education to adolescents. While community programs aim to address individual and community health, their reach to adolescents is limited (Kratzke et al. 2018). Schools, on the other hand, possess the potential to reach to this demographic on a large scale (Rudd and Walsh 1993). Moreover, health education and academic learning complement each other. Educators and health professionals have long recognized the positive relationship between health and education (Kolbe 2019). Research shows that health issues can limit students' motivation and abilities to learn, hence hindering academic performance (Basch 2011). Therefore, fostering comprehensive school environments that prioritize health, well-being, and academic success among adolescents is crucial (Langford et al. 2014). Delivering health information in schools emerges as a cost-effective and far-reaching strategy to promote the health and well-being of adolescents.

1.1 Literature Gaps

Research focusing on programs dedicated to promoting health and well-being in schools remains limited (Curran et al. 2014). Despite the importance of promoting adolescent health in schools, there is still a disconnect between the health advocacy programs and education systems in the United States that has not been fully addressed (Birch and Auld 2019). Although the CDC (2019) has outlined the desired characteristics of effective health education programs, many schools in the United States fail to offer adequate health education programs in terms of both quality and quantity (Videto and Dake 2019). Thus, it is crucial to conduct more studies to evaluate current health curricula in schools and explore ways to better integrate health and education. Additionally, integrating social psychology theories into the evaluation of in-school health advocacy programs could provide fresh perspectives for designing more effective health interventions tailored for adolescents.

1.2 Theoretical Background

The study relied on relevant health behavior and social psychology theories to help understand the factors that lead to certain health outcome and behaviors. By utilizing a social psychology framework, an economic health model was constructed to statistically analyze pertinent variables.

1.2.1 Theory of Planned Behavior

The Theory of Planned Behavior (Ajzen 1985) posits that behaviors are determined by intentions, which are shaped by three factors: attitudes, subjective norms, and perceived behavioral control. This theory suggests the importance for in-school health advocacy program to deliver effective messages that foster positive beliefs toward healthy behaviors such as physical activities. The importance of subjective norms suggests the need to extend health-attitude interventions to individuals closely connected to adolescents, such as parents, peers, or mentors, as they can significantly impact adolescents' perceptions of norms regarding health behaviors and beliefs. In addition, it is important to assist adolescents in developing perceived behavioral control to engage in healthy behaviors. Within the school context, for instance, physical environments can be redesigned to facilitate health behaviors. Health professionals can provide a diverse range of physical education programs aimed at boosting students' confidence and enhancing their behavioral control in participating in physical activities.

1.2.2 Health Belief Model

The Health Belief Model (Rosenstock 1974) proposes that individual's motivation to undertake health behaviors is influenced by individual perceptions, modifying factors, and the likelihood of action. Individual perceptions include individual's awareness of health consequences, perception of one's susceptibility to illness, and the importance of health behaviors. Modifying factors include environmental cues that affect individuals' intentions to perform health behaviors. Likelihood of action refers to the extent that individuals are willing to actually perform the behaviors, which is determined by perceived benefits and costs. The Health Belief Model suggests potential guidelines for effective in-school health advocacy programs, such as emphasizing the positive consequences of healthy behaviors and the negative consequences of unhealthy ones. Programs that influence individual perceptions, create modifying cues, and remove barriers for individuals to engage in health behaviors may yield long-term benefits in shaping adolescents' health beliefs and behaviors.

1.2.3 Social Cognitive Theory

According to the Social Cognitive Theory (Bandura 2002), cultural and social context play crucial roles in shaping individuals' beliefs and intentions. SCT suggests that social interactions and environmental factors may impact the acquisition and maintenance of behavioral patterns. When applying SCT to the development of health behaviors, interventions should consider cultivating social environments that foster collective self-efficacy, thereby enhancing individual self-efficacy in adopting and maintaining health-related behaviors. Consequently, in-school health programs incorporating social interactions and support, such as collective physical education classes, may prove effective in initiating and sustaining health behaviors.

The theories outlined above offer a structured framework for understanding the determinants of health behaviors, offering valuable guidance in designing effective in-school health advocacy programs. These theories underscore the significance of factors such as attitudes, perceived behavioral control, social influence, and environmental cues in shaping health behaviors. By integrating these elements, in-school health programs have the potential to cultivate positive health beliefs and behaviors in adolescents. Evaluating existing programs within the broader context of social psychology is essential to identify areas for improvement

1.3 Study Objective

The primary aim of this project was to systematically analyze the impact of in-school health information on adolescents' health outcomes and behaviors, drawing upon a combined framework of social psychology and economic health theories. Study 1 specifically investigated the impact of health information regarding exercise on adolescents' Body Mass Index (BMI). Meanwhile, Study 2 delved into the effects of health information about smoking, parental behaviors, depressive moods, and environmental cues on individuals' smoking frequencies throughout the transition from adolescence into early adulthood.

II. Study 1: Information About Exercise and BMI

While prior research has examined the influence of in-school health information on specific health concerns like eating disorders (Kremer et al. 2020), relatively less attention has been dedicated to its impact on broader health indicators, such as Body Mass Index (BMI). BMI serves as a measurable gauge of adolescents' underweight or overweight status, offering an objective and consistent measure for large-scale analysis. Unlike variables like exercise amounts, BMI provides a standardized metric. Given the increasing prevalence of childhood obesity Li et al. (2020) and the lasting health consequences of excessive weight during adolescence Guo and Chumlea (1999), monitoring adolescents' BMI becomes crucial for assessing their health status. Study 1 specifically assessed the average treatment effect of health information about exercise on adolescents' BMI across a one-year period.

2.1 Data and Model

The project used data from the National Longitudinal Survey of Adolescent Health (Add Health). Add Health is a nationally representative study of the health and well-being of US adolescents in grades 7–12 who were enrolled in school during 1994–1995. Study 1 focused on data from Wave 1 and Wave 2. Wave 1 data were collected through an in-school questionnaire administered to students in grades 7 through 12 during the academic year 1994–95. Wave 2 data were obtained from a follow-up study involving a series of in-home interviews approximately one year later, in 1996. Inclusion in the analytic sample for adolescents required valid information regarding exposure to in-school health information.

2.1.1 Variables

Dependent Variable

BMI. Each participant's Body Mass Index (BMI) was computed using self-reported height and weight. Unlike adults, interpreting BMI for children and teens is more complex due to variables like age, sex, weight, and height influencing its assessment (CDC 2022a. For adolescents, a healthy weight status is typically indicated by a BMI falling between the 5th and 85th percentile on the CDC growth charts, rather than specific numerical ranges. It is important to approach BMI as a complementary health measure for adolescents, considering its limitations in isolation. However, leveraging BMI as a standardized scale can still provide valuable insights into the general impacts of health interventions.

Program Variable

Learned Importance of Exercise. Study 1 focused on a specific component of in-school health information: the importance of exercise. This variable was selected due to its potential impact on adolescents' health behavior perceptions and consequent health outcomes. Participants self-reported exposure to this information during Wave 1 interviews through a question addressing their learning experience in school: "Please tell me whether you have learned about the importance of exercise in a class at school."

Control Variables

Demographics. Demographic variables were collected during Wave 1, including adolescents' biological sex, age, race, and school grade level.

Baseline Exercise. To better assess the impact of in-school health information about the importance of exercise on adolescents' weight outcomes, exercise amount was included as an important control variable. In particular, two variables reflecting individual exercise patterns were included as covariates: general exercise times and exercise to lose weight. Regarding general exercise, participants were asked in both waves, "During the past week, how many times did you do exercise, such as jogging, walking, karate, jumping rope, gymnastics or dancing?" Response options include "not at all," "1 or 2 times," "3 or 4 times," and "5 or more times." Participants were also asked about whether they had engaged in exercise with the objective of weight control, "During the past seven days, did you exercise in order to lose weight or to keep from gaining weight?" Response options included "Yes" or "No."

Sleep Hours. Previous research has consistently demonstrated a negative relationship between sleep duration and BMI in both cross-sectional and longitudinal studies, indicating that shorter sleep duration is associated with higher BMI (Garfield 2019. Consequently, sleep hours were included as a covariate to control for in the analysis. In both Wave 1 and Wave 2, participants were asked, "How many hours of sleep do you usually get?" Participants' responses ranged from 1 to 20 hours.

Sedentary Behaviors. Research has shown that sedentary behaviors such as watching TV are associated with obesity (Crespo et al. 2001. With sedentary alternatives replacing physical activities as leisure pursuits (Boone et al. 2007, it is reasonable to expect an inverse relationship between hours of TV viewing and the amount of exercise. Recognizing the potential influence of sedentary hours on participants' BMI, in addition to in-school health information, sedentary behaviors measured in hours were included in the model as a crucial control variable. In both Wave 1 and Wave 2, participants were asked, "How many hours a week do you watch television?" Participants' responses ranged from 0 ("Doesn't watch TV") to 51 hours.

Physical Education. Given the emphasis of Social Cognitive Theory (SCT) on the role of social influence in shaping health behaviors, particularly how peers' behaviors or attitudes may act as reinforcements or punishments, participation in physical education classes becomes a significant factor influencing individual health behaviors such as exercise and beliefs towards health outcomes like BMI. Therefore, adolescents' participation in physical education classes was included in the model as a crucial control variable. It is important to note that the extent of participation in physical education may be endogenous, impacting both attention to in-school health information and the dependent variable, BMI. Participants were asked in both waves, "In an average week, on how many days do you go to physical education classes at school?" Responses ranged from 0 to 5 days.

Learned Consequences of Obesity. According to the Health Belief Model, factors influencing people's awareness of health consequences play a crucial role in shaping their perception of the importance of health behaviors. In addition to information about the importance of exercise, a second component of the in-school health program related to the consequences of overweight was included as a control variable. In Wave 1, participants were asked, "Please tell me whether you have learned about each of the following things in a class at school: The problems of being overweight." Response options included "Yes" or "No."

2.1.2 Analysis

Descriptive analyses were first calculated for the dependent variable, program variable, and control variables in the analytic sample (see **Table 1**). The total number of observations included in the sample was 10,062 (Wave 1 N = 6,008, Wave 2 N = 4,054). Summary statistics were also obtained for the time-variant variables across waves (see **Table 2** for Wave 1 statistics and **Table 3** for Wave 2). The study's model started with the basic statistical specification as follows:

$$Y_{ti} = \beta_1 + \beta_2 X_{ti} + \beta_3 P_i + \delta Z_i + \mu_i + \epsilon_{ti}, \tag{1}$$

where the dependent variable was BMI. X's included time-variant variables at the individual level such as TV hours. P denoted the time-invariant program variable, which was the health information about the importance of exercise. Z's included time-invariant variables such as gender and race. The time-invariant error, μ_i, accounted for unobserved factors such as different levels of motivation among individuals. The time-varying error, ϵ_{ti}, encompassed errors arising from measurement and omitted variables.

OLS with cluster correction was used as the preliminary analysis. However, this method raised several concerns regarding potential biases in the results. First, the participation in the program (i.e., learning about the in-school health information) might be endogenous. It was possible that the unobserved motivation affected both the program participation decision and the outcome (i.e., BMI). Additionally, the frequency of attending physical education classes could similarly be endogenous, affecting both exposure to health information and BMI. Secondly, due to the dataset's longitudinal nature, residual autocorrelation might stem from correlated multiple observations on individuals with unobservable characteristics. Lastly, clustering of schools may impact health behaviors due to social and regional factors. Thus, alternative estimation methods were necessary to address these concerns in a multilevel panel model, ensuring the removal of potential sources of errors and providing a more accurate analysis of the data.

The correlated random effects method was utilized to counter the impact of time-invariant unobservable factors, such as motivation, that could influence both program participation and health outcomes. This approach effectively controlled for potential endogeneity in exposure to the program variable and other control variables. Moreover, it efficiently accounted for the inherent clustering within schools, a common feature in observational data. Building on the basic model specified above, the model of correlated random effects estimator became (T = 2):

$$Y_{ti} = \beta_1 + \beta_2 X_{ti} + \beta_3 P_i + \delta Z_i + \lambda \bar{X}_i + \eta_i + \epsilon_{ti}$$
$$\mu_i = \lambda \bar{X}_i + \eta_i$$
$$\bar{X}_i = 1/T_i \sum_{t=1}^{T_i} X_{ti}$$

In the correlated random effects model, the time-invariant error was assumed to be a function of the average values of the time-variant variables, X_{ti}'s. The model was then estimated by random effects method. A robust version of the Hausman test was conducted to test the endogeneity of the treatment variable. The hypotheses were presented below:

$$H_0 : \lambda = 0$$
$$H_a : \lambda \neq 0$$

2.2 Results

Table 1 illustrates the composition of the full analytic sample, comprising 10,062 adolescents, with a near-equal gender distribution (49% male, 51% female). The majority identified as White (68%), followed by African American (24%). On average, participants were 16 years old during Wave 1, and the mean grade level was 9. On average, participants in the sample spent 14.4 hours per week watching TV and reported an average sleep duration of 7.7 hours per day. Their mean engagement in general exercise was 1.6 times in the week before the questionnaire. Around 44%

#	Variables	Mean (SD / %)
Table 1. Characteristics of Study 1 sample (N=10,062)		
1	Age	16.21 (1.66)
2	Male	4,917 (48.9%)
3	White	6,829 (67.9%)
4	African American	2,379 (23.6%)
5	Asian	417 (4.1%)
6	Grade level	9.76 (1.58)
7	TV hours	14.36 (12.15)
8	Sleep hours	7.72 (1.37)
9	Exercise times	1.65 (1.03)
10	Physical education	2.52 (1.59)
11	Exercise to lose weight	4,391 (43.7%)
12	Learned problem of obesity	5,984 (59.5%)
13	Learned importance of exercise	9,283 (92.2%)
14	BMI	22.55 (4.45)

reported exercising for weight control within that week. They attended physical education classes at school approximately 2.5 days per week. About 60% of participants gained awareness of the consequences of obesity through the in-school health advocacy program. The majority (92%) indicated learning about exercise importance at school. Across the two waves, participant characteristics such as TV and sleep hours, as well as exercise amounts, exhibited minimal differences (see **Table 2** and **Table 3** for detailed statistics).

Table 2. Characteristics of Study 1 sample in Wave 1 (N=6,008)

#	Variables	Mean (SD / %)
1	TV hours	14.81 (12.24)
2	Sleep hours	7.8 (1.40)
3	Exercise times	1.63 (1.05)
4	Physical education	2.66 (1.35)
5	Exercise to lose weight	2,641 (43.9%)

Table 4 presents findings from two models assessing the influence of the in-school health program—specifically, health information emphasizing the importance of exercise—on adolescents' BMI. Model 1, employing OLS, and Model 2, utilizing the correlated random effects method, show compelling results. The analyses indicate a significant treatment effect of health information about exercise on BMI. Specifically, students exposed to information on the importance of exercise experienced a significant reduction of 0.633 ($p < 0.01$) in BMI, on average, compared to those without this exposure during their school experience. While general exercise, TV hours,

Table 3. Characteristics of Study 1 sample in Wave 2 (N=4,054)

#	Variables	Mean (SD / %)
1	TV hours	13.68 (11.91)
2	Sleep hours	7.62 (1.33)
3	Exercise times	1.66 (1.01)
4	Physical education	2.31 (1.89)
5	Exercise to lose weight	1,751 (43.2%)

and sleep hours were significant predictors of BMI in Model 1, their significance disappeared after correcting for standard errors in Model 2. It should be noted that learning about the consequences of overweight and exercising to lose weight had positive effects on BMI, indicating that engaging in these behaviors actually led to weight increase; the counterintuitive results are discussed below.

Table 4. Analyses results

Variables	Model 1	Model 2
Exercise to lose weight	2.523***(0.0869)	0.130**(0.0608)
Exercise times	-0.200***(0.0411)	-0.0173 (0.0278)
Grade level	-0.0736(0.0662)	0.0540(0.104)
TV hours	0.0231***(0.00353)	-0.00252(0.00261)
Sleep hours	-0.0802**(0.0315)	0.0302(0.0225)
Importance about exercise	-0.684***(0.160)	-0.633***(0.198)
Consequences of overweight	0.623***(0.0878)	0.617***(0.109)
Male	0.806***(0.0853)	0.874***(0.106)
Physical education	-0.0335(0.0268)	0.0172(0.0156)
White	-0.857***(0.148)	-0.811***(0.182)
African American	0.0933(0.159)	0.171(0.195)
Asian	-1.697***(0.235)	-1.636***(0.287)
Age	0.514***(0.0626)	0.0789(0.488)

Note: Model 1 presents the results of OLS; Model 2 presents the result of correlated random effects estimator.

2.3 Discussion

The current study investigated the impact of in-school health information regarding exercise on adolescents' BMI. Using the correlated random effects estimator, the results highlighted a significant reduction in BMI among those exposed to information emphasizing the importance of exercise in school. Future research might expand this exploration by examining diverse health indicators beyond BMI, offering a more comprehensive understanding of how exercise-related information impacts adolescent health.

The findings suggest that learning about the consequences of being overweight and engaging in weight loss exercises led to an increase in BMI, which aligns with some concerns raised about potential negative consequences of health programs at school. Some argue that interventions influencing adolescents' eating and physical activity might increase instances of eating disorders by triggering anxiety about body image and promoting dietary restraint (Neumark-Sztainer 2005). To mitigate these potential negative effects, the delivery of health content should be done cautiously, avoiding stigmatization of certain adolescent groups and preventing coercion into undesired health activities (O'Dea 2005). One preventive strategy could involve teaching adolescents critical-thinking skills regarding beauty standards and body images, as suggested by a meta-analysis study (Le et al. 2017). Incorporating this strategy into in-school health advocacy programs could enhance health literacy and correct health-related beliefs.

While Study 1 shed light on the impact of in-school health information about the importance of exercise on adolescents' weight status, it is crucial to delve into other health information and behaviors for a comprehensive evaluation of the health advocacy program at school. Hence, Study 2 was designed to investigate the influence of a distinct component of the health advocacy program on addictive substance use, specifically smoking. Together, these studies aim to provide a more holistic review and a deeper understanding of the program's effectiveness in shaping diverse health outcomes and behaviors among adolescents.

III. Study 2: Health Information and Smoking

Study 2 assessed the impact of in-school health information about smoking on adolescents' smoking frequencies during the transition from adolescence to adulthood. While in-school health information may shape adolescents' attitudes toward smoking and potentially change their behaviors, there are other important factors that lead to addictive substance use. First, the experience of depressive moods has been identified as a potential determinant in adolescents' decision-making regarding smoking. Longitudinal investigations have unearthed evidence suggesting a bidirectional relationship between smoking and depression (Chaiton et al. 2009). Second, as discussed in the Theoretical Background section, social norms may implicitly influence one's attitudes or beliefs toward health behaviors, thereby impacting the likelihood of one engaging in those behaviors. Parents, who have one of the closest relationships to their children, may heavily influence adolescents' perceptions of norms, both through their own actions and the environmental cues present within the family setting.

In short, Study 2 is guided by three primary objectives: 1) to examine the long-term impact of in-school health intervention about smoking on adolescents as they transition into adulthood; 2) to investigate the influence of depressive moods on smoking behaviors; and 3) to assess the extent of parental influence on adolescents' substance use.

3.1 Data and Model

Study 2 also used data from Add Health, focusing on data from Wave 1, 2 ,and 4. Wave 1 data were gathered from an in-school questionnaire administered to a nationally representative sample of students in grades 7 through 12 in 1994–95. Wave 2 data were collected from the follow-up study with a series of in-home interviews of respondents approximately one year later. The Wave 4 interviews were completed in 2008, which consisted of the most recent of four in-home interviews which had followed a sample of adolescents since they were in grades 7-12. Adolescents were included in the analytic sample if they had valid information regarding the exposure to in-school health information about smoking.

3.1.1 Variables

Dependent Variable

Days of Smoking. This study used the number of days smoked as an index to represent the intensity level of the participants' smoking behaviors. Participants were asked "During the past 30 days, on how many days did you smoke cigarettes?" A number was self-reported by each participant.

Program Variable

In-school Health Information About Smoking. Information about smoking was based on participant reports of information collected during Wave 1 interviews. In Wave 1, the participants were asked, "Please tell me whether you have learned about each of the following things in a class at school: Smoking." Response options included "Yes" or "No."

Control Variables

Demographics. Demographic variables were collected during Wave 1. Demographic variables included adolescents' biological sex, age, and race. Depressive Level. Participants' general levels of depressive symptoms were measured across waves. The question on the survey listed as "How often was each of the following things true during the past week? You felt depressed." Participants responded in terms of categorical variables that indicate the level of intensity: "Never/Rarely", "Sometimes", "A lot of the time", "Most/all of the time".

Parents' Educational Levels. Parents' educational levels were measured separately. Participants were asked to indicate the highest levels of education of their moms and dads. Parents' Smoking Behavior. The participants were asked whether their mom/dad ever smoked. The study used this pair of variables as indicators of parents' smoking status.

Evidence of Smoking. This variable was collected by the question, "Was there any evidence of smoking in the household–for example, ashtrays, people smoking, cigarettes, the smell of cigarettes?" This variable is included to indicate the potential environmental factors that were not captured by parent's smoking behavior.

Family Income. In addition to parental behavior, family socioeconomic status can also affect children's health (Case and Paxson 2002). Thus, family income is included to provide additional information. Collected at Wave 4, family income was included in a supplementary analysis due to limited data availability caused by sample attrition. Although its inclusion in the main model could significantly reduce degrees of freedom and potentially introduce bias, income level serves as a crucial indicator of the family's socioeconomic status and is essential for understanding health outcomes.

3.1.2 Analysis

Table 5 presents the descriptive statistics for all variables. The total number of observations included in the sample was 15, 262. OLS regression with cluster correction and sampling weight adjustment was used as the preliminary analysis for the specified model. Due to the surveys' longitudinal nature, it is common to adjust weights at each wave due to sample attrition. However, for this study, only the analytic weights from Wave 1 were used to mitigate potential biases. Please refer to the Methods section in Study 1 for model specification as well as methodological concerns regarding OLS regression. To address errors introduced by heterogeneity, the study utilized the random effects estimator with cluster correction. The model assumed exogeneity of the covariates of interest to optimize the random effects estimator's performance. Any violation of this assumption might lead to biased results.

3.2 Results

Table 5 shows that the sample was comprised of 15,262 adolescents which included a relatively similar number of primarily of White (67%) or African American (24%) men (48%) and women (52%), who were an average age of 19 years old. The mean level of parents' education was high school graduate. Most participants indicated that they never/rarely or sometimes felt depressed. 44.8% of the participants indicated that their moms had ever smoked, and 39.7% indicated that their dads had ever smoked. Among the adolescents whose mom smoked, 59% of the adolescents had ever smoked. Among the participants whose dad smoked, 57% of them had ever smoked. In addition, 21% of the participants indicated that they had found evidence of smoking in the

Table 5. Characteristics of the sample (N=15, 262)		
#	Variables	Mean (SD)
1	Age	19.46(5.646)
2	Male	0.475(0.499)
3	White	0.673(0.469)
4	African American	0.241(0.428)
5	Asian	0.0391(0.194)
6	Mom's education	5.749(2.542)
7	Dad's education	5.930(2.658)
8	Depressive moods	0.475(0.740)
9	Mom's smoking behavior	0.264(0.441)
10	Dad's smoking behavior	0.449(0.497)
11	Evidence of smoking	0.397(0.489)
12	Days of smoke	0.210(0.408)
13	Information about smoking	5.570(10.78)

household. On average, all participants smoked for 5.6 days; among smokers, the average was 6.5 days. A large majority received in-school health information about smoking (92%).

Table 6 shows the outcomes from three models evaluating the effects of in-school health information about smoking, depressive moods, environmental cues, and parental smoking behaviors on adolescents' smoking frequency. Model 1 presents OLS estimations, Model 2 employs the random effects method, and Model 3 supplements Model 1 by incorporating family income through OLS regression.

The model was independently applied at each wave to assess the impact of time-variant variables on adolescents' smoking frequency, revealing changes over time. **Table 7** details coefficients of these variables estimated by OLS across each wave. In-school health information on smoking did not significantly predict smoking frequency at any wave. Household environmental factors (e.g., evidence of smoking) most significantly predicted frequency at all waves, and the impact increased as adolescents transitioned to adulthood. Parental smoking behaviors positively predicted adolescents' smoking frequency at all waves, although mom's influence became insignificant at Wave 4.

The study focused on Model 2, while Model 1 served as a comparison and Model 3 provided supplementary analysis. In-school health information about smoking did not exhibit a significant effect on adolescents' smoking behaviors. The strongest predictor was the environmental cues: the presence of evidence of smoking in households predicted an average of 2.7 more days of smoking among adolescents. Parental smoking behaviors also significantly contributed to adolescents' smoking, with an increase of approximately one day in smoking if either mom or dad had ever

Table 6. Days of Smoking on key predictors.			
Variables	Model 1	Model 2	Model 3
Information about smoking	0.203(0.571)	0.148(0.459)	0.0143(0.0416)
Depressive moods	2.150***(0.227)	1.498***(0.172)	0.0823***(0.0176)
Mom's education	X	X	-0.00457(0.00556)
Dad's education	X	X	0.00713(0.00628)
Male	0.636**(0.304)	0.838***(0.260)	0.0747***(0.0242)
White	2.152***(0.521)	1.812***(0.417)	0.0987**(0.0472)
African American	-2.131***(0.574)	-2.107***(0.476)	-0.123**(0.0486)
Asian	-0.710(0.685)	-0.778(0.664)	0.0720(0.0757)
Mom's smoking behavior	1.052***(0.319)	1.076***(0.284)	0.0698***(0.0257)
Dad's smoking behavior	1.158***(0.295)	1.180***(0.262)	0.0844***(0.0246)
Evidence of smoking	2.576***(0.529)	2.693***(0.443)	0.0786**(0.0364)

Robust standard errors in parentheses
*** p < 0.01, ** p<0.05, * p<0.1

Note: 1. Model 1 presents the results of OLS regression without income; 2. Model 2 presents the results of random effects estimator; 3. Model 3 presents the result of OLS regression with income. 4. Detailed reports of estimated coefficients of categorical variables are omitted for brevity.

Table 7. Analyses of the effects of time-variant variables across waves			
Variables	Wave 1	Wave 2	Wave 4
Information about smoking	-.220(.583)	.380 (.683)	.527(1.14)
Mom's smoking behavior	.996*** (.343)	.933** (.413)	1.14 (.706)
Dad's smoking behavior	.846*** (.291)	1.51*** (.421)	1.33** (.531)
Evidence of smoking	2.18*** (.637)	2.03*** (.748)	3.76*** (.868)

Robust standard errors in parentheses
*** p < 0.01, ** p<0.05, * p<0.1

Note: Only variables of interest are presented.

smoked. Additionally, depressive moods were found to significantly predict adolescents' smoking behaviors, with participants tending to smoke an average of 1.5 more days when experiencing higher levels of depressive moods.

3.3 Discussion

Study 2 investigated the influence of in-school health information about smoking, depressive moods, parental behaviors, and evidence of smoking in households on self-reported instances of smoking using a random effects estimator. While the findings showed that health information did not significantly alter smoking behaviors, they highlighted the enduring influences such as adolescents' mental well-being, environmental cues, and parental smoking; across different phases from adolescence to adulthood, these factors consistently affected individuals' smoking behaviors. Even after adjusting for family income, parental modeling and environmental factors remained statistically significant.

IV. General Discussion

This project explored how in-school health information impacted adolescents' health measures. Study 1 showed that information on exercise importance significantly reduced adolescents' BMI. However, Study 2 did not find a significant link between in-school smoking information and smoking behaviors across adolescence to young adulthood. However, Study 2 highlighted lasting effects of parental smoking, depressive moods, and environmental cues on smoking frequencies.

This project explored the potential impact of in-school health advocacy programs on adolescents' well-being, offering four key considerations for policymakers designing interventions in school settings. First, fostering accurate health beliefs among adolescents—positively framing health behaviors like exercise and highlighting the negative consequences of harmful habits like smoking—can encourage healthier choices. Second, in-school health interventions should consider extending the delivery of health information beyond students to include other influential members of their social circles, especially their parents. Individuals who are socially close to adolescents can serve as role models for healthy behaviors. Notably, the health beliefs and behaviors of parents may have a lasting impact on their children. Third, it is crucial for in-school health programs to address mental well-being alongside physical health by providing counseling and support services. The absence of such resources may inadvertently contribute to the development of risky health behaviors (e.g., smoking) linked to depressive moods or stress among adolescents. Lastly, creating effective environmental cues in schools can promote healthy behaviors, such as offering engaging exercise-related content to enhance adolescents' participation in physical activities. These implications provide valuable guidance for policymakers in developing comprehensive health interventions tailored to the unique needs of adolescents, contributing to the promotion of their physical and mental well-being.

4.1 Limitations

This project has several limitations. Firstly, utilizing an existing dataset restricted the inclusion of certain variables that could be vital to the outcomes. For instance, dietary behaviors, unrecorded in Add Health, might significantly affect adolescents' BMI. Additionally, social cues from sources beyond parents, like peers' health behaviors and beliefs, could influence adolescents' health decisions, including smoking. The absence of these key variables might introduce biases when interpreting the results. Second, the Add-Health dataset did not provide a comprehensive account of the in-school health advocacy program. It provided minimal insights into the specific topics covered, such as the importance of exercise. Critical details regarding the program's contextual elements, including the mode of delivery (e.g., posters or class presentations), the duration of the program, and the specific contents covered in each topic, were not available. The absence of this comprehensive knowledge regarding the in-school health program limits the implications drawn from the project's findings for future interventions.

Additional limitations stem from the project's nature. First, sample attrition affected the analyses, with only 74% of initial respondents participated in Wave 2 data collection and 60% in Wave 4. Although imputation methods and sampling weights addressed some misrepresentation due to attrition, the reduced sample size might still impact result accuracy. Second, relying on self-reported data could introduce recall bias among participants, potentially leading to systematic errors. While the statistical methods employed in both studies mitigated recall biases to some extent, this concern still merits careful consideration. Future studies could explore the efficacy of in-school health information more systematically by documenting students' attendance, health behaviors, and outcomes.

4.2 Conclusions

Exposure to health information on the importance of exercise significantly reduced adolescents' BMI. Parental smoking, depressive moods, and environmental cues had enduring impacts on smoking behaviors. The project offers key insights for policymakers designing health interventions in schools, emphasizing four crucial considerations: fostering accurate health beliefs among adolescents, extending health information to influential figures like parents, addressing mental well-being, and creating effective environmental cues. However, the project faces limitations, such as constrained variable inclusion and a lack of comprehensive information about the in-school health program. To overcome these limitations, future studies should conduct detailed evaluations of in-school health programs, contributing to evidence-based interventions that effectively enhance the physical and mental well-being of adolescents in school environments.

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Minimum Wage Policies & Labor Outcomes

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Abstract

We investigated the impact of minimum wage policy on income and employment in various domains. We evaluate the effect of higher minimum wages on the working population using double difference estimation. Then, we compare employment between teenager and young adults, and income between paid-by-hour and salaried workers using triple difference estimation. Finally, we utilized inverse propensity weighting to detect and account for pretreatment differences between individuals. We found that, on average, with increased minimum wages: individuals faced higher incomes and slightly higher unemployment rates, teenagers suffered higher unemployment rates, and paid-by-hour workers earned lower incomes.

Keywords: minimum wage, employment, income, labor outcomes, teenagers v. young adults, paid-by-hour v. salaried workers

I. Introduction

In recent years as Generation Z has begun to enter the workforce, they have sparked fierce debate online about the cost of living. A key argument many individuals make is that the federal minimum wage is not a "livable wage," meaning that the average cost of living for an individual surpasses or barely meets the level of income generated by working a full-time minimum wage job. While minimum wage laws vary widely by state, one thing is certain: costs of living across the United States have risen rapidly over the past years. To name an example, the S&P Case-Shiller U.S. National Home Price Index indicates that average single-family home prices rose by approximately 93.1% between January 2013 and December 2021 (Federal Reserve Bank of St. Louis 2023) . The S&P Case-Shiller index is a popular measure of home prices for single

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family homes, calculated by analyzing differences in sales prices of homes sold multiple times. Furthermore, the U.S. CPI rose by 21.2% during that same period (

One solution to this problem suggested by many is raising the minimum wage. It is evident, however, that the effects of minimum wage policies are ambiguous. Some individuals are winners, receiving more compensation for the time they spend working, while others are losers, as higher employment costs can induce employers to lay off employees or substitute them for more skilled employees. Further still, there are those who feel no direct impact, such as many individuals who work on salaries or are retired. This body of research investigates the impact of three minimum wage policies on two key labor market outcomes: individuals' employment and their total personal income. The policies in question are 1) whether a state has a minimum wage above the federal minimum wage, 2) implementation of a minimum wage increase policy, and 3) the impact of the effective minimum wage.

To analyze how our selected policies impact employment and total personal income, we employ a difference-in-differences, or double differences, approach. For each policy, we split states into treated and control groups based on whether they enacted the policy. For example, states with minimum wages above the federal minimum are treated with respect to that policy while states with minimum wages at or below the federal minimum are control states for that policy. After estimating difference-in-differences models for each of our outcomes and policies, we utilize a triple differences model to test how different groups are affected by each of the policies. We compare the differences in effects on employment each of our policies has on teenagers compared to young adults and the differences in effects on total personal income each of our polices has on paid-by-hour workers compared to salaried workers. Finally, we employ inverse propensity weighting to test for and balance pre-treatment differences across groups. After estimating the base, unbalanced models, we balanced groups using inverse propensity weighting based on pre-treatment differences. The grouping we decided upon to conduct the balancing individuals who earned less than $50,000 in total personal income and those who earned more. We chose this method of grouping because individuals with total income below that threshold are more likely to experience the effects of changing minimum wage policies more than individuals who earn more.

There has been extensive research conducted on what the optimal minimum wage is to maximize income and minimize unemployment. One side claims that with higher minimum wages, people would earn higher incomes and be more motivated to enter the labor force. The other side claims that higher minimum wages, although would allow workers to generate a higher income, would also increase the unemployment rate as businesses' costs of labor would rise, subsequently leading to less job offerings in the labor market.

This body of research contributes to the existing literature primarily by analyzing differences in the policy effects by groups, in addition to measuring the general impact of the policies. The first group we investigate is teenagers compared to young adults. Teenagers are defined as aged 15-21 while young adults are defined as aged 22-29. This is an interesting group to study, as many teenagers work minimum wage jobs, but as minimum wages increase, we expect to see some of these teens lose out to more experienced workers such as young adults. The second group we investigate is currently employed individuals who are paid by the hour compared to employed individuals who are not paid by the hour, or salaried workers. This approach allows us to estimate how individuals who currently work minimum wage jobs are affected by minimum wage policies, which is crucial as it allows us to best estimate the policies' effectiveness.

Our estimations show: on average with higher minimum wages, individuals earn a higher income with slightly negative to no effects on employment rates; teenagers face a higher decrease in employment rates compared to young adults; and workers paid by the hour face a higher decrease in income compared to salaried workers.

The remainder of the paper proceeds as follows. Section 2 provides background on minimum wage policies and an overview of the related literature. Section 3 introduces the data used in our analysis and some key trends and summary statistics for variables of interest. Section 4 lays out the empirical framework of our analysis. Section 5 presents the findings from the estimation of our difference-in-differences and triple differences models. These estimates are then used to assess the differences in impact our policies of interest have upon employment and total personal income between teens and young adults, as well as between hourly wage workers and non-hourly wage workers. After performing the base estimations, we balanced the groups using inverse propensity weighting based on pre-treatment differences and re-estimated our triple differences models using the balanced sample. In Section 6, we summarize the main results of our research and consider potential policy implications.

II. Background and Literature Review

This section opens with a short background on minimum wage policies, summarizing how they have evolved over time as well as providing an overview of some current policy differences across states. We conclude the section by providing a concise summary of existing literature.

Minimum wage laws in the United States originate from the devastation caused by the Great Depression in the 1930s. President FDR fought the economic recession and poor working conditions via the National Industrial Recovery Act, which led to the establishment of the National Recovery Administration. This led to struggles between advocates for businesses and labor rights with some push back on FDR's policies. Finally, the Fair Labor Standards Act (FLSA) was enacted by Congress in 1938. FLSA established the original federal minimum wage and has been amended several times (Neumark and Wascher 2006). The last amendment in 2009 established the federal minimum wage of $7.25. Federal laws have authority over state laws, so state minimum wage laws must set their minimum wage above the federal minimum, with a few exceptions. Tipped workers, who have a federal minimum wage of $2.13, and farm workers are exempt from the federal minimum wage laws. However, employers must cover the difference if tipped workers end up earning less than minimum wage. 30 states and D.C. currently have a minimum wage higher than the federal minimum, whereas 20 states have a minimum wage at or below the federal level. In the states with a minimum wage below the federal minimum, only employers not covered by the FLSA have the ability to pay that wage. These businesses must gross less than $500,000 in annual sales and not engage in interstate commerce (Payne-Patterson and Maye 2023).

In the early 1980s, extensive research concerning minimum wage policies occurred. Brown, Gilroy, and Kohen – BGK – performed an exhaustive analysis on all research done on minimum wage laws. They concluded that a 10% increase in minimum wage results in a 1-3% increase in unemployment rate. This became widely accepted until the end of the 1980s. The topic was revived since a decent number of states had set new wage floors in response to a lack of action by the federal government. This resulted in additional state-level statistical variance to conduct research on and raised questions of legitimacy on the statistical methods used by BGK (MaCurdy 2015). Additional research opportunities arose, which lead to findings on a wide spectrum. Neumark and Wascher conducted research using state and time fixed effects over long sample periods and confirmed BGK's findings. Card used regional variation in one research paper and concluded that minimum wage had no impact on employment. Card focused on states in another research paper and concluded that higher minimum wages had a positive impact on employment. Katz and Kreuger did research by surveying fast-food restaurants before and after a minimum wage increase policy and agreed that the policy had a positive impact on employment (Dube 2019).

These are merely four out of the hundreds of research papers done on the effect of minimum wage laws on employment, but these papers serve as a good representation of the findings. Since doubt was cast on BGK's findings, there has been no clear consensus on how minimum wage policy affects employment. As for minimum wage policy effects on income, there is no shortage in the amount of research done. Macurdy categorizes families by income quintiles, poverty levels, extent of dependence on low-wage earnings, welfare recipient status, and demographic characteristics to analyze the effect of minimum wage policies on income in families, as well as individuals, and concluded that an increase in the minimum wage does not specifically benefit one category more than another (MaCurdy 2015). Medrano-Adán and Salas-Fumás (2023) model an occupational choice economy and found that an increase in minimum wage leads to higher income inequality. A recent review of evidence on the impact of minimum wages on an international level found that an increase in minimum wage lead to increased earnings on income for low-wage workers, while having a minimal impact on employment (Dube 2019). Due to the mixed conclusions on the impact of minimum wage policy changes on income and employment, our research is essential in its contribution to the literature, so progress can be made towards determining the true impact of minimum wage policy.

III. Descriptive Analysis

3.1 Data Overview

The data used in our research originates from the Current Population Survey's Annual Social and Economic Supplement (CPS-ASEC) dataset. The ASEC is a longitudinal study conducted by the U.S. Census Bureau as a supplement to the CPS which reports monthly statistics on labor outcomes such as employment, hours of work, and earnings, as well as additional demographic data such as age, marital status, disability status, educational attainment, and more. The ASEC supplemental dataset includes comprehensive information on work experience, poverty, and the migration patterns of people over 15 years old and is conducted annually from February through March.

Our sample spans from 2013 through 2021 and includes 702,551 observations in total. Since our research focuses on the impact of minimum wage policies on labor outcomes, we restricted our sample to individuals who are most likely to experience these outcomes. First, we restricted our sample by age to individuals between the ages of 15 and 64. Then, we omitted retired individuals. Accounting for these sample constraints, 279,977 observations were deleted, and the following results will be based on the remaining 433,574 observations.

As mentioned above, our two outcomes of interest are total personal income and employment. For each individual in the sample who is 15 years old and over, total personal income is defined as the total amount of income received in the preceding calendar year from the following sources: (1) monetary wages or salary; (2) net income from nonfarm self-employment; (3) net income from farm self- employment; (4) Social Security or railroad retirement; (5) Supplemental Security Income; (6) public assistance or welfare payments; (7) interest (on savings or bonds); (8) dividends, income from estates or trusts, or net rental income; (9) veterans' payment or unemployment and workmen's compensation; (10) private pensions or government employee pensions; (11) alimony or child support, regular contributions from persons not living in the household, and other periodic income.

Employed individuals are either (1) all civilians who, during the survey week did any work at all as paid employees or in their own business or profession, or on their own farm, or who work 15 hours or more as unpaid workers on a farm or a business operated by a member of the family; or (2) all those who have jobs but who are not working because of illness, bad weather, vacation, or labor- management dispute, or because they are taking time off for personal reasons, whether or not they are seeking other jobs. Unemployed individuals are defined as civilians who, during the survey week, have no employment but are available for work, and (1) have engaged in any specific job seeking activity within the past 4 weeks such as registering at a public or private employment office, meeting with prospective employers, checking with friends or relatives, placing or answering advertisements, writing letters of application, or being on a union or professional register; (2) are waiting to be called back to a job from which they had been laid off; or (3) are waiting to report to a new wage or salary job within 30 days (CPS, 2021).

3.2 Minimum Wage Snapshot in Time

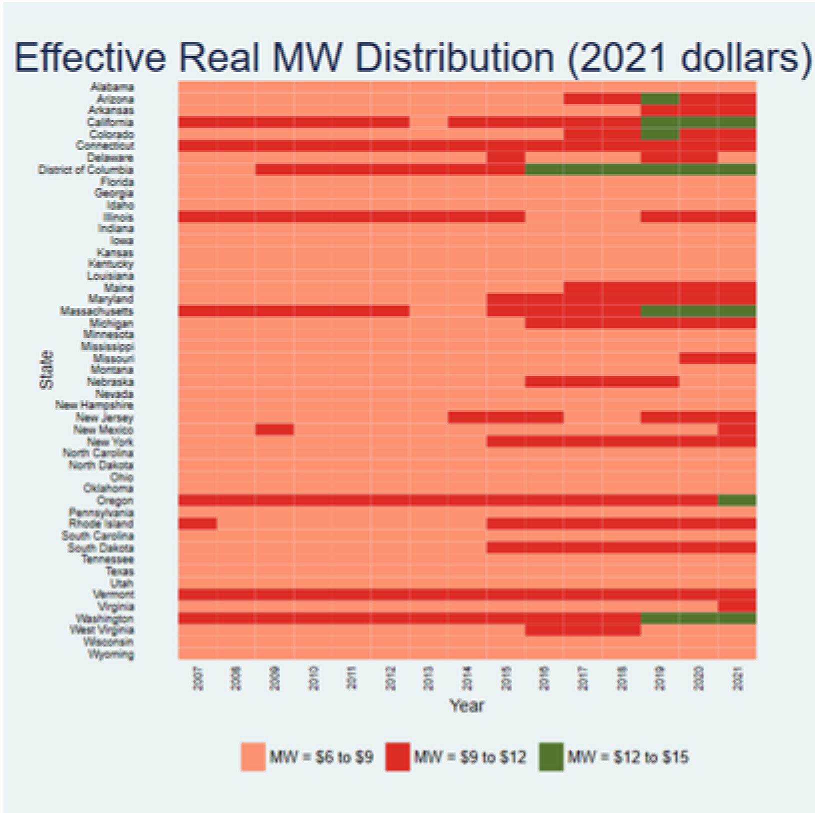
In Figure 1, we display the effective real minimum wage over time for each state in our sample. The effective real minimum wage is broken into three categories: \$6-\$9, \$9-\$12, and \$12-\$15. The figure very clearly illustrates how dynamic minimum wage laws can be, as even with these relatively broad categories, some states exhibit excessive variation between categories. Another interesting thing is that it is unlikely for states to engage in multiple instances of both raising and lowering the minimum wage within a short period. This indicates that states that display a decrease in the effective real minimum wage are unlikely to be lowering their minimum wage; rather, they are failing to update their minimum wage laws to keep pace with inflation. Hence, the figure also shows us how responsive different states are to inflation. For example, California's minimum wage did not keep up with inflation in 2013 and they chose to immediately re-raise the minimum wage in 2014 to account for this. In contrast, states such as New Mexico and Rhode Island took multiple years to adjust their minimum wage for inflation following declines in real effective wages in 2010 and 2008, respectively.

In Figure 2, we map the average personal income for each state with a minimum wage above the federal minimum in 2021, with each shade corresponding to a specific interval of income. It is important to note that this figure also shows the distribution of states that set their minimum wage above the federal level. States in shades of blue are treated, indicating that they have a minimum wage higher than the federal level, while states in the light red are in our control group, with minimum wages at or below the federal minimum.

3.3 Policies That Require Investigation

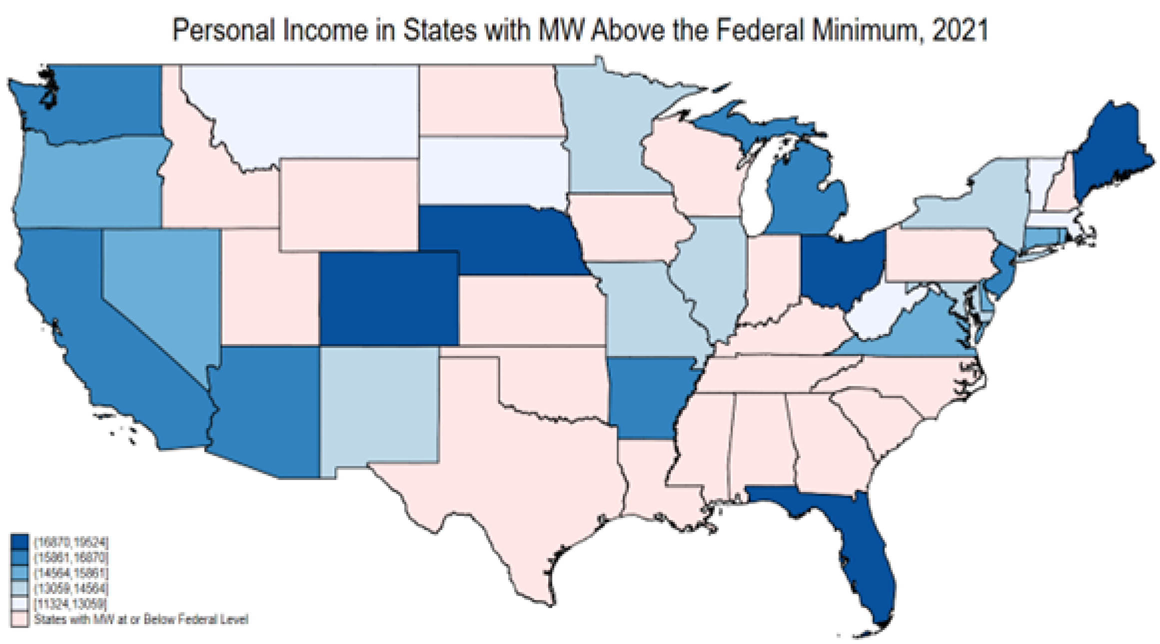
In our analysis, we investigate the impacts of three policy variables: whether a state has a minimum wage above the federal minimum wage, implementation of a minimum wage increase policy, and the impact of effective minimum wage (in 2021 dollars). The rationale behind advocating for a higher minimum wage is grounded in the belief that increased wages can lead to greater consumer

Figure 1: Effective Real Minimum Wage Distribution in 2021 Dollars



Notes: All states and D.C. are included, except Hawaii and Alaska. The real effective minimum wage accounts for inflation using the CPI index.

Figure 2: Mean Personal Income in States with MW above Federal MW, 2021



Notes: All states are shown except Hawaii and Alaska. Darker shades of blue represent higher levels of personal incomes, legend for specific levels is provided in the bottom left corner.

spending, ultimately fostering economic growth.

3.4 Summary Statistics

The summary statistics for our variables of interest and control variables are provided in Table 1 below.

Table 1: Summary Statistics

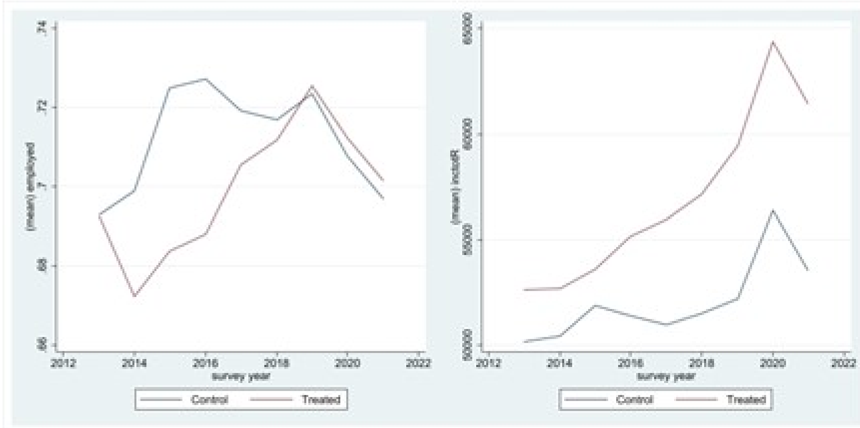
Variable	Obs	Mean	Std.dev.	Min	Max
Total Real Personal Income (in 2021 USD)	370,817	54854.98	77071.64	1	2950301
Employed	433,574	0.705	0.456	0	1
Minimum Wage Increase Policy	433,574	0.346	0.476	0	1
Real Minimum Wage (2021 USD)	433,574	8.916	1.563	6.924	13.5
Indicator for State Minimum Wage Set above the Federal Level	433,574	0.593	0.491	0	1
Race Proportions					
Black	433,574	0.108	0.311	0	1
American Indian	433,574	0.015	0.120	0	1
Asian/Islander	433,574	0.068	0.252	0	1
Mixed Race	433,574	0.020	0.141	0	1
Age					
Age	433,574	38.250	13.955	15	64
Demographics					
Female	433,574	0.513	0.500	0	1
Presence of Children Under 5 years old	433,574	0.143	0.350	0	1
Education Levels					
HS Diploma	433,574	0.431	0.495	0	1
Associate's Degree	433,574	0.094	0.291	0	1
Bachelor's Degree	433,574	0.191	0.393	0	1
Postgraduate Degree	433,574	0.105	0.307	0	1
Industry Proportions					
Agriculture, Forestry, Fishing, and Hunting	433,574	0.014	0.117	0	1

Mining	433,574	0.006	0.078	0	1
Utilities	433,574	0.007	0.081	0	1
Construction	433,574	0.053	0.224	0	1
Manufacturing	433,574	0.075	0.264	0	1
Wholesale Trade	433,574	0.017	0.129	0	1
Retail Trade	433,574	0.079	0.270	0	1
Transportation and Warehousing	433,574	0.032	0.177	0	1
Information	433,574	0.014	0.117	0	1
Finance, Insurance, Real Estate, and Rental and Leasing	433,574	0.048	0.214	0	1
Professional, Scientific, and Technical Services	433,574	0.053	0.224	0	1
Management, Administrative and Support, and Waste Management Services	433,574	0.033	0.178	0	1
Education, Health, and Social Services	433,574	0.173	0.378	0	1
Arts, Entertainment, and Recreation	433,574	0.015	0.123	0	1
Accommodation and Food Service	433,574	0.056	0.230	0	1
Other Services (Except Public Administration)	433,574	0.034	0.182	0	1
Public Administration	433,574	0.036	0.186	0	1
Armed Forces	433,574	0.000	0.011	0	1

Notes: Race, age, sex, education, children, and industry statistics are included as control variables. The real total personal income variable (intotR) has fewer observations because zeros and negatives were dropped to take the log of total real income for the estimations. Base categories for categorical variables omitted from the table.

InctotR is a continuous variable which represents the total personal income of an individual. employed is a binary variable indicating the employment status of an individual. Postminw is a binary variable indicating a period of implementation of a state minimum wage increase policy. EffecmwR is a continuous variable representing the real minimum wage rate. Above is a binary variable indicating if a state set their minimum wage above the federal minimum wage. Race is a categorical variable separated into categories of white (base category), Black, American Indian, Asian/Islander, and Mixed Race. Age is a continuous variable restricted between the ages of 15 and 64. Female is a binary indicator variable for gender. anychld5 is a binary indicator for presence of any children under 5 years old. Education Levels is a categorical variable separated into Less than High School (base category), HS Diploma, Associate's Degree, Bachelor's Degree,

Figure 3: Trends in Outcomes for Treated and Control States



and Postgraduate Degree. Industry Proportions is a categorical variable separated into 18 different categories which are listed out in detail in the Appendix in the description of the ind2 variable.

3.5 Parallel Trends

In this subsection, we present some visualized trends for one of the policies of interest and provide some discussion of the results. One of the key assumptions of utilizing the differences in differences approach is that, in the absence of treatment, the treatment and control groups would experience the same trends in the outcome variable. Figure 3 below displays the trend in both average employment and average total real income for states over time, comparing the trends for states that raised their minimum wages and those that did not.

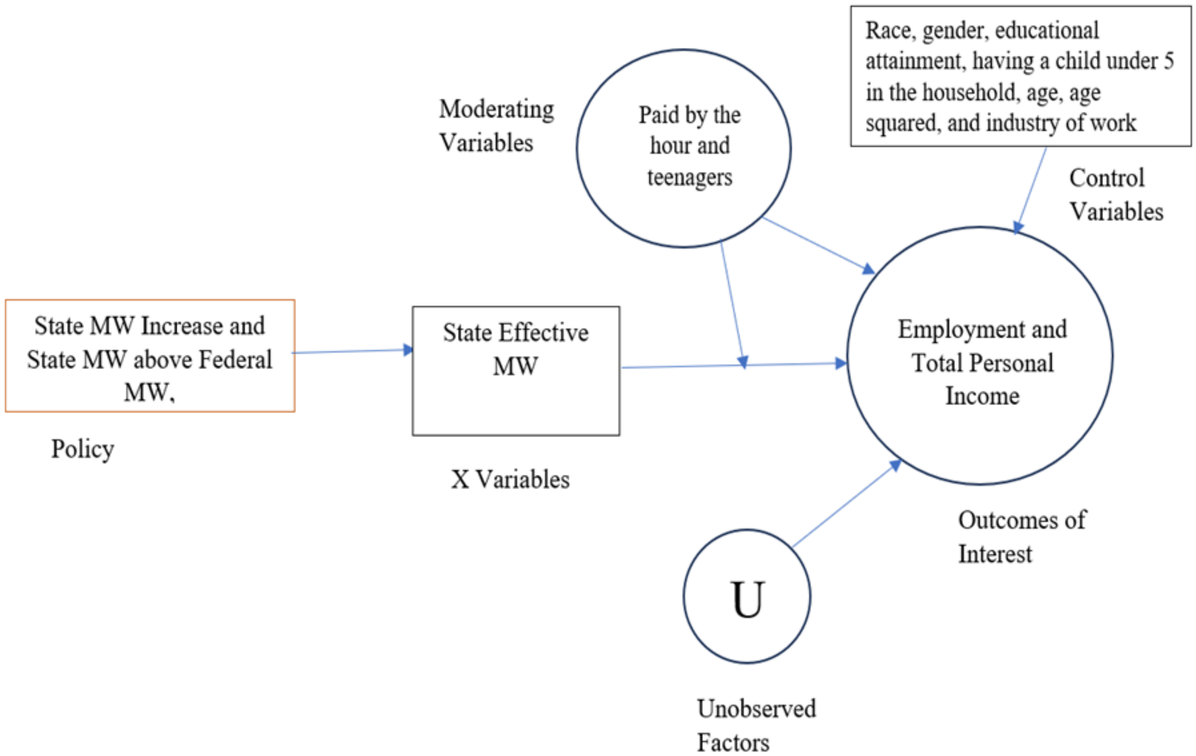
As can be seen, our treated and control states exhibit alternating periods of parallel trends and non-parallel trends. This is due to the staged nature of the policy enactments across states. Years in which the two groups exhibit parallel trends correspond to years in which no states increase their minimum wage. On the other hand, when the two groups behave differently, this signifies that some states enacted the policy, resulting in a breakaway from the current trend.

IV. Empirical Framework

Figure 4:

Figure 4 provides a visual representation of how different variables we selected interact with each other to provide us with our desired estimations. Our outcome variables are total personal income and employment rate. The X variable represented as state effective minimum wage in the graphic is technically treated as a policy in our model. We control our regression of the outcome variables on the policy variables with the control variables listed in the graphic to control for

Figure 4: Visualization of Model Used to Conduct Research



variability caused by race, gender, educational attainment, presence of children under 5, age, and industry. Industry is only used in our income regression as it perfectly correlates with employment, so it would violate the model assumptions if it were included in the employment regression. The moderating variables were used to investigate differences by group in our triple differences models.

V. Impact of Minimum Wage Policy

5.1 OLS Estimates

To start our investigation of the effect of minimum wage policies on labor outcomes, we ran a couple different OLS regressions using 1) log of real total personal income and 2) employment as outcome variables while using both implementation of an increase in minimum wage and residence in a state with a minimum wage above the federal minimum level as the explanatory variables. For both OLS regressions, we controlled for key demographics which were likely to explain our outcome variables including race, age, sex, presence of children under 5, and educational attainment. Additionally, for the OLS with 1) income as the outcome variable, we used industry as a control variable. We could not use industry in the 2) employment OLS because presence of an industry perfectly correlated with an individual's employment status. Table 2 and Table 3 below show the results of the 1) income OLS and 2) employment OLS, respectively.

Table 2: OLS Estimates of Employment

Variables	Estimates	(Standard Errors)
Implementation of an Increase in Minimum Wage	0.00912	-0.0132
Residence in a State with Minimum Wage Above the Federal Level	-0.0178	-0.0128
Constant	16.66^{***}	-0.0223
Observations: 615,751		
R-squared: 0.465		

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: OLS Estimates of Employment

Variables	Estimates	(Standard Errors)
Implementation of an Increase in Minimum Wage	-0.000241	-0.00123
Residence in a State with Minimum Wage Above the Federal Level	-0.0131^{***}	-0.00119
Constant	-0.299^{***}	-0.00202
Observations: 615,751		
R-squared: 0.465		

Notes: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The only significant result from the OLS estimations was that on average, individuals who reside in a state with the minimum wage set above the federal level tend to face 1.31% higher unemployment rates compared to individuals who reside in a state with the minimum wage set at or below the federal level.

5.2 The DID Equation Set-Up

The difference-in-differences model we use to determine the impact of minimum wage policies on employment and total personal income allows us to control for key demographic characteristics. These characteristics are race, age, gender, education level, having at least one child under 5 in their household and industry of work. Note that the industry of work variable is only included in the model with personal income as the outcome variable, as all individuals who have an industry of work are, by definition, employed already. Race and gender can affect the outcomes because there is often discrimination in the labor market. Age affects income and employment status because younger people have less experience and thus are more likely to have trouble finding jobs and earn less when they do become employed. Individuals with children under 5 need to either care for the child themselves or find someone else to. This significantly affects their ability to work, particularly if they cannot afford daycare or a nanny. Finally, your industry of work can be a significant determinant of both your income and your ability to be employed. For example, doctors are likely to earn relatively large amounts of income and are also quite unlikely to be unemployed. The complete model is shown below in Equation 1.

$$Y_{it} = \beta_0 + \beta_1 Z_i + \gamma_0 P_{st} + \theta_s + \mu_t + \epsilon_{it} \tag{1}$$

In our differences in differences model above, Y_{it} is our outcome variable, employment and total personal income. Z_i is our vector of control variables, P_{st} is our post treatment variable. This variable is an interaction variable, as it varies by state and time. θ_s and μ_t are our state and time fixed effects, respectively. These are important to include in our model because each state experiences different unobservable shocks that impact it differently than others, while each year has different economic conditions and events that may impact the data.

Being a difference in differences model, our model has three key assumptions. First, we assume that the control variables are exogenous. We also assume that selection into the treatment group is exogenous and not impacted by any control variables. Finally, we assume that our outcomes have parallel trends between the treated and control group. The most likely assumption to be broken in our data is that selection into treatment is exogenous. This is because people with certain characteristics such as lower education or minimum wage workers might decide to live in a state in which they expect minimum wage increases to be enacted.

5.3 The DID Estimates

The difference in differences model evaluates the effect on income and employment based on three different criteria: 1) implementation of a state minimum wage increase policy, 2) an increase in the effective state minimum wage, and 3) whether a state has a minimum wage higher than the federal level or not. 1) On average, implementation of a state minimum wage increase policy leads to a 1.7% increase in an individual's income, while it shows no statistically significant impact on employment. 2) On average, an increase of $1 in the effective state minimum wage leads to a 1.3% increase in income for individuals, while it shows no statistically significant impact on employment. 3) On average, if a state has a minimum wage higher than the federal level, individuals earn a 2.8% higher income and face a 0.9% higher unemployment rate.

Table 4: Difference in Differences Policy Effects

Policy Name	State MW Increase		Effective State MW		State MW Above Federal MW	
	Income	Employment	Income	Employment	Income	Employment
Policy Effect	0.017**	0.001	0.013***	0.002	0.028**	-0.009**
	(0.008)	(0.002)	(0.005)	(0.001)	(0.014)	(0.004)
Constant	5.239***	-0.259***	5.119***	-0.278***	5.218***	-0.255***
	(0.035)	(0.007)	(0.056)	(0.014)	(0.036)	(0.008)
Observations	370,817		433,574		370,817	
R-squared	0.408		0.209		0.408	

Notes: Standard errors are in parentheses, P-values are interpreted as follows: ***= p¡0.01, **=p¡0.05, *= p¡0.1. MW is short for minimum wage, Income is real total individual income in 2021 prices, employment=1 if employed and 0 if unemployed

5.4 Group Balancing

In this section we present triple differences results from two models. First, we display the results from a model that estimates the impact of our three policies of interest on teen employment compared to employment of young adults. We then display the results from a model that estimates the impact of the policies on total personal income of hourly workers in 2021 dollars compared to the impact on personal income of non-hourly workers. After estimating the base, unbalanced models, we balanced the groups using inverse propensity weighting based on pre-treatment differences. The grouping we decided upon to conduct the balancing was to split the sample into individuals who earned less than $50,000 in total personal income and those who earned more. We chose this method of grouping because individuals with total income below that threshold are more likely to experience the effects of changing minimum wage policies more than individuals who earn more.

Table 5: Triple Differences Results for Teenage Employment

Policy Name	SMW Increase	Effective SMW	SMW Above FMW	SMW Increase	Effective SMW	SMW Above FMW
		Unbalanced Estimates			IPW Balanced Estimates	
Policy Effect on Employment	0.012**	0.007***	0.013	0.012**	0.007**	0.012
	-0.005	-0.003	-0.008	(0.006)	(0.003)	(0.010)
Impact of employment on Teenagers vs. Not	0.028***	0.129***	0.039***	0.033***	0.126***	0.042***
	-0.006	-0.014	-0.006	(0.007)	(0.017)	(0.007)
Policy Effect on Teenage Employment	-0.020***	-0.012***	-0.029***	-0.021***	-0.011***	-0.026***
	-0.005	-0.001	-0.005	(0.006)	(0.002)	(0.006)
Observations		133,619			133,619	
R-squared		0.288			0.269	
State & Year FE		Yes			Yes	
Controls		Yes			Yes	

Notes: Standard errors are in parentheses, P-values are interpreted as follows: ***=p<0.01, **=p<0.05, *=p<0.1, MW is short for minimum wage, Employment=1 if employed and 0 if unemployed, teenage=1 if the individual is aged 15-21 and 0 if the individual is aged 22-29. Unbalanced results are plotted in Figure A1 of the Appendix. Original triple difference estimates shown under "Unbalanced Estimates." IPW balanced pretreatment differences between individuals at the $50,000 total person income mark. SMW Refers to state minimum wage, FMW federal minimum wage.

The results of the triple differences model showcased in Table 5 above evaluates the difference in employment rate for teenagers, defined as individuals aged 15-21, compared to young adults, defined as individuals aged 22-29, based on three different criteria: 1) implementation of a state minimum wage increase policy, 2) an increase in the effective state minimum wage, and 3) whether a state has a minimum wage higher than the federal level or not. 1) On average, implementation of a state minimum wage increase policy leads to a 2% higher unemployment rate for teenagers compared to young adults. 2) On average, a $1 increase in the effective minimum wage leads to 1.2% higher unemployment rate for teenagers compared to young adults. 3) On average, if a state has a minimum wage higher than the federal level, teenagers face a 2.9% higher unemployment rate compared to young adults. The IPW estimates maintained the same sign as the unbalanced estimates and showed minor changes, overall, suggesting a 2.1% instead of a 2% higher unemployment rate in 1), a 1.1% instead of a 1.2% higher unemployment rate in 2), and a 2.6% instead of a 2.9% higher unemployment rate in 3).

Table 6: Triple Differences Results for Log of Personal Income, Hourly vs Non-Hourly Workers

Policy Name	SMW Increase	Effective SMW	SMW Above FMW	SMW Increase	Effective SMW	SMW Above FMW
		Unbalanced Estimates			IPW Balanced Estimates	
Policy Effect on Total Personal Income	0.041***	0.018**	0.017	0.018	0.006	0.008
	(-0.014)	(-0.007)	(-0.023)	(0.017)	(0.009)	(0.026)
Difference in Workers Paid by Hour vs. Salaried Workers	-0.291***	-0.125***	-0.279***	-0.307***	-0.203***	-0.294***
	(-0.009)	(-0.039)	(-0.011)	(0.010)	(0.048)	(0.013)
Policy Effect on Workers Paid by the Hour	-0.044***	-0.020***	-0.047***	-0.014	-0.012**	-0.031*
	(-0.014)	(-0.004)	(-0.014)	(0.017)	(0.005)	(0.016)
R-squared		0.36			0.263	
State & Year FE		Yes			Yes	
Controls		Yes			Yes	

Notes: Standard errors are in parentheses, P-values are interpreted as follows: ***=p¡0.01, **=p¡0.05, *=p¡0.1, MW is short for minimum wage, total personal income is an individual's annual total real personal income in 2021 dollars. Original triple difference estimates shown under "Unbalanced Estimates." IPW balanced pretreatment differences between individuals at the $50,000 total person income mark. Number of observations are equal for each observed outcome: 69,276. SMW Refers to state minimum wage, FMW federal minimum wage.

The results of the triple differences model showcased in Table 6 above evaluates the difference in personal income for workers paid by the hour compared to salaried workers based on three different criteria: 1) implementation of a state minimum wage increase policy, 2) an increase in the effective state minimum wage, and 3) whether a state has a minimum wage higher than the federal level or not. 1) On average, implementation of a state minimum wage increase policy leads to 4.44% lower personal income for workers paid by the hour compared to salaried workers. 2) On average, a $1 increase in the effective minimum wage leads to 2% lower personal income for workers paid by the hour compared to salaried workers. 3) On average, if a state has a minimum wage higher than the federal level, workers paid by the hour face a 4.7% lower personal income compared to salaried workers. The IPW estimates maintained the same sign as the unbalanced estimates, suggesting a 1.2% instead of a 2% lower personal income in 2) and a 3.1% instead of 4.7% lower personal income in 3). The IPW estimates for 1) were insignificant.

VI. Conclusion

The findings of our research suggest that individuals generally earn a higher income with a higher minimum wage and face slightly negative to no impact on employment rates. The comparison between teenagers and young adults in terms of employment rates showed that teenagers generally face a higher unemployment rate than young adults with a higher minimum wage. The comparison between workers paid by the hour and salaried workers suggests that workers paid by the hour in terms of income suggests that workers paid by the hour generally earn less income with a higher minimum wage.

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Appendix

Table 7: Full OLS Estimates of Log of Real Total Personal Income

Variables	Log of Real Total Personal Incon
Implementation of an Increase in Minimum Wage	0.00912
	(-0.0132)
Residence in a State with Minimum Wage Above the Federal Level	-0.0178
	(-0.0128)
Races	
Black	-0.297***
	(-0.0164)
American Indian/Aleut/Eskimo	-0.173***
	(-0.0412)
Asian/Islander	-0.539***
	(-0.021)
Mixed Race	-0.00665
	(-0.0314)
Age	-0.706***
	(-0.00119)
Age Squared	0.00767***
	(-1.55E-05)
Female	-0.524***
	(-0.0105)
Presence of Children Under 5	-0.694***
	(-0.0175)
Educational Attainment	
HS Diploma	6.794***
	(-0.0157)
Associate's Degree	6.149***
	(-0.0242)
Bachelor's Degree	6.476***
	(-0.0206)
Postgrad Degree	7.194***

Continued on next page

Table 7 – Continued from previous page

VARIABLES	Log of Real Total Personal Incon
	(-0.0246)
Industries	
Agriculture, Forestry, Fishing, and Hunting	2.762***
	(-0.0487)
Mining	3.277***
	(-0.0763)
Utilities	3.252***
	(-0.0729)
Construction	3.350***
	(-0.0288)
Manufacturing	3.235***
	(-0.025)
Wholesale Trade	3.023***
	(-0.0466)
Retail Trade	1.694***
	(-0.0236)
Transportation and Warehousing	2.845***
	(-0.0348)
Information	2.704***
	(-0.0513)
Finance, Insurance, Real Estate, and Rental and Leasing	2.987***
	(-0.0297)
Professional, Scientific, and Technical Services	2.950***
	(-0.0292)
Management, Administrative and Support, and Waste Management Services	2.888***
	(-0.0344)
Educational, Health, and Social Services	2.610***
	(-0.0197)
Arts, Entertainment, and Recreation	1.506***
	(-0.048)
Accommodation and Food Service	1.339***
	(-0.0271)
Other Services (Except Public Administration)	2.410***

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Table 7 – Continued from previous page

VARIABLES	Log of Real Total Personal Incon
	(-0.0332)
Public Administration	3.100***
	(-0.0336)
Armed Forces	-0.0171
	(-0.515)
Constant	16.66***
	(-0.0223)
Observations	615,169
R-squared	0.602

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; ”White” omitted from Races, ”Less than HS Diploma” omitted from Educational Attainment, ”Unspecified Industry” omitted from Industries.

Table 9: Summary Statistics

Table 9: Full Results of Differences in Differences Models

Policy Name	SMW Increase		Effective SMW		SMW Above FMW	
	Income	Employment	Income	Employment	Income	Employment
Policy Effect	0.017**	0.001	0.013***	0.002	0.028**	-0.009**
	(0.008)	(0.002)	(0.005)	(0.001)	(0.014)	(0.004)
Black	0.041***	-0.058***	0.041***	-0.058***	0.041***	-0.058***
	(0.007)	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)
American Indian/Aleut/Eskimo	-0.008	-0.102***	-0.008	-0.102***	-0.008	-0.102***
	(0.021)	(0.006)	(0.021)	(0.006)	(0.021)	(0.006)
Asian/Islander	-0.084***	-0.062***	-0.084***	-0.062***	-0.084***	-0.062***
	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)
Mixed Race	0.001	-0.028***	0.001	-0.028***	0.001	-0.028***
	(0.018)	(0.005)	(0.018)	(0.005)	(0.018)	(0.005)
Age	0.113***	0.041***	0.113***	0.041***	0.113***	0.041***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Age Squared	-0.001***	-0.000***	-0.001***	-0.000***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.505***	-0.105***	-0.505***	-0.105***	-0.505***	-0.105***
	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
Any child under age 5 in household	-0.015**	-0.019***	-0.015**	-0.019***	-0.015**	-0.019***
	(0.007)	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)
HS Diploma	0.584***	0.219***	0.584***	0.219***	0.584***	0.219***
	(0.009)	(0.002)	(0.009)	(0.002)	(0.009)	(0.002)
Associate’s Degree	0.690***	0.302***	0.690***	0.302***	0.690***	0.302***
	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)
Bachelor’s Degree	0.909***	0.335***	0.909***	0.335***	0.909***	0.335***
	(0.010)	(0.002)	(0.010)	(0.002)	(0.010)	(0.002)

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Table 9 – Continued from previous page

Policy Name	SMW Increase		Effective SMW		SMW Above FMW	
	Income	Employment	Income	Employment	Income	Employment
Postgraduate Degree	1.217***	0.371***	1.217***	0.371***	1.217***	0.371***
	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)
Agriculture, Forestry, Fishing, and Hunting	1.935***	1.935***	1.935***			
	(0.021)	(0.021)	(0.021)			
Mining	2.583***	2.583***	2.583***			
	(0.021)	(0.021)	(0.021)			
Utilities	2.496***	2.496***	2.496***			
	(0.020)	(0.020)	(0.020)			
Construction	2.165***	2.165***	2.165***			
	(0.013)	(0.013)	(0.013)			
Manufacturing	2.311***	2.311***	2.311***			
	(0.013)	(0.013)	(0.013)			
Wholesale Trade	2.302***	2.302***	2.302***			
	(0.016)	(0.016)	(0.016)			
Retail Trade	2.002***	2.002***	2.002***			
	(0.013)	(0.013)	(0.013)			
Transportation and Warehousing	2.156***	2.155***	2.156***			
	(0.014)	(0.014)	(0.014)			
Information	2.328***	2.328***	2.328***			
	(0.018)	(0.018)	(0.018)			
Finance, Insurance, Real Estate, and Rental and Leasing	2.460***	2.460***	2.460***			
	(0.014)	(0.014)	(0.014)			
Professional, Scientific, and Technical Services	2.436***	2.436***	2.436***			
	(0.014)	(0.014)	(0.014)			
Management, Administrative and Support, and Waste Management Services	1.970***	1.970***	1.970***			
	(0.015)	(0.015)	(0.015)			
Educational, Health, and Social Services	2.170***	2.170***	2.170***			
	(0.013)	(0.013)	(0.013)			
Arts, Entertainment, and Recreation	1.827***	1.827***	1.827***			
	(0.020)	(0.020)	(0.020)			
Accommodation and Food Service	1.842***	1.842***	1.842***			
	(0.014)	(0.014)	(0.014)			
Other Services (Except Public Administration)	1.919***	1.918***	1.918***			
	(0.015)	(0.015)	(0.015)			
Public Administration	2.378***	2.378***	2.378***			
	(0.014)	(0.014)	(0.014)			
Armed Forces	1.900***	1.900***	1.900***			
	(0.254)	(0.254)	(0.254)			
Constant	5.239***	-0.259***	5.119***	-0.278***	5.218***	-0.255***
	(0.035)	(0.007)	(0.056)	(0.014)	(0.036)	(0.008)
Observations	370,817	433,574	370,817	433,574	370,817	433,574
R-squared	0.408	0.209	0.408	0.209	0.408	0.209

Notes: These results are from the estimation of equation 2.Standard errors are in parentheses, P-values are interpreted as follows: ***= p<0.01, **=p<0.05, *= p<0.1. MW is short for minimum wage, Income is real total individual income in 2021 prices,employment=1 if employed and 0 if unemployed

Figure A1: Predicted Probabilities of Employment for Teens and Young Adults

Table 8: Full OLS Estimates of Employment

Variables	Employed
Implementation of an Increase in Minimum Wage	-0.000241
	(-0.00123)
Residence in a State with Minimum Wage Above the Federal Level	-0.0131***
	(-0.00119)
Races	
Black	-0.0502***
	(-0.00152)
American Indian/Aleut/Eskimo	-0.0688***
	(-0.00384)
Asian/Islander	-0.0479***
	(-0.00195)
Mixed Race	-0.0188***
	(-0.00293)
Age	0.0398***
	(-9.52E-05)
Age Squared	-0.000402***
	(-1.32E-06)
Female	-0.0786***
	(-0.000933)
Presence of Children Under 5	0.0314***
	(-0.00162)
Educational Attainment	
HS Diploma	0.149***
	(-0.00144)
Associate's Degree	0.270***
	(-0.00221)
Bachelor's Degree	0.306***
	(-0.00182)
Postgrad Degree	0.334***
	(-0.00213)
Constant	-0.299***
	(-0.00202)
Observations	615,751
R-squared	0.465

Notes: Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1; "White" omitted from Races, "Less than HS Diploma" omitted from Educational Attainment.

Table 10: Full Results of Triple Differences Models for Teen Employment

Policy Name	State MW Increase	Effective State MW	State MW Above Federal MW
Policy Effect on Employment	0.012**	0.007***	0.013
	(0.005)	(0.003)	(0.008)
Teens	0.028***	0.129***	0.039***
	(0.006)	(0.014)	(0.006)
Policy Effect on Teens	-0.020***	-0.012***	-0.029***
	(0.005)	(0.001)	(0.005)
Black	-0.061***	-0.061***	-0.061***
	(0.004)	(0.004)	(0.004)
American Indian/Aleut/Eskimo	-0.100***	-0.100***	-0.100***
	(0.010)	(0.010)	(0.010)
Asian/Islander	-0.123***	-0.123***	-0.123***
	(0.005)	(0.005)	(0.005)
Mixed Race	-0.003	-0.003	-0.003
	(0.007)	(0.007)	(0.007)
Age	0.193***	0.193***	0.193***
	(0.004)	(0.004)	(0.004)
Age Squared	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Female	-0.036***	-0.036***	-0.036***
	(0.002)	(0.002)	(0.002)
Any child under age 5 in household	-0.066***	-0.065***	-0.065***
	(0.004)	(0.004)	(0.004)
HS Diploma	0.141***	0.142***	0.142***
	(0.004)	(0.004)	(0.004)
Associate's Degree	0.244***	0.245***	0.244***
	(0.006)	(0.006)	(0.006)
Bachelor's Degree	0.263***	0.262***	0.263***
	(0.005)	(0.005)	(0.005)
Postgraduate Degree	0.277***	0.276***	0.277***
	(0.008)	(0.008)	(0.008)
Observations	133,619	133,619	133,619
R-squared	0.288	0.288	0.288
State & Year FE	Yes	Yes	Yes

Standard errors are in parentheses, P-values are interpreted as follows: ***=p<0.01, **=p<0.05, *=p<0.1, MW is short for minimum wage, Employment=1 if employed and 0 if unemployed, teenage=1 if the individual is aged 15-21 and 0 if the individual is aged 22-29.

Table 11: Full Results for Triple Differences Models for Personal Income of Hourly Workers

Policy Name	State MW Increase	State Effective MW	State MW Above Federal MW
Policy Effect on Total Personal Income	0.041***	0.018**	0.017
	(0.014)	(0.007)	(0.023)
Difference in Workers Paid by Hour vs. Not	-0.291***	-0.125***	-0.279***
	(0.009)	(0.039)	(0.011)
Policy Effect on Workers Paid by the Hour	-0.044***	-0.020***	-0.047***
	(0.014)	(0.004)	(0.014)
Black	-0.123***	-0.123***	-0.123***
	(0.012)	(0.012)	(0.012)
American Indian/Aleut/Eskimo	-0.119***	-0.119***	-0.118***

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Table 11 – Continued from previous page

Policy Name	State MW Increase	State Effective MW	State MW Above Federal MW
	(0.032)	(0.032)	(0.032)
Asian/Islander	-0.031**	-0.032**	-0.031**
	(0.014)	(0.014)	(0.014)
Mixed Race	-0.114***	-0.114***	-0.114***
	(0.027)	(0.027)	(0.027)
Age	0.127***	0.127***	0.127***
	(0.002)	(0.002)	(0.002)
Age Squared	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Female	-0.395***	-0.395***	-0.395***
	(0.007)	(0.007)	(0.007)
Any child under age 5 in household	0.123***	0.123***	0.123***
	(0.009)	(0.009)	(0.009)
HS Diploma	0.596***	0.596***	0.596***
	(0.015)	(0.015)	(0.015)
Associate's Degree	0.750***	0.750***	0.750***
	(0.018)	(0.018)	(0.018)
Bachelor's Degree	0.998***	0.998***	0.998***
	(0.016)	(0.016)	(0.016)
Postgraduate Degree	1.238***	1.237***	1.238***
	(0.017)	(0.017)	(0.017)
Observations	69,276	69,276	69,276
R-squared	0.360	0.360	0.360
State & Year FE	Yes	Yes	Yes

Notes: Standard errors are in parentheses, P-values are interpreted as follows: ***=p<0.01, **=p<0.05, *=p<0.1, MW is short for minimum wage, total personal income is an individual's annual total real personal income in 2021 dollars

Table 12: Full Results for IPW Balanced Triple Differences Models for Teen Employment

Policy Name	State MW Increase	Effective State MW	State MW Above Federal MW
Policy Effect on Employment	0.012**	0.007**	0.012
	(0.006)	(0.003)	(0.010)
Impact of employment on Teenagers vs. Not	0.033***	0.126***	0.042***
	(0.007)	(0.017)	(0.007)
Policy Effect on Teenage Employment	-0.021***	-0.011***	-0.026***
	(0.006)	(0.002)	(0.006)
Black	-0.064***	-0.064***	-0.064***
	(0.005)	(0.005)	(0.005)
American Indian/Aleut/Eskimo	-0.112***	-0.112***	-0.112***
	(0.013)	(0.013)	(0.013)
Asian/Islander	-0.125***	-0.125***	-0.125***
	(0.006)	(0.006)	(0.006)
Mixed Race	-0.002	-0.002	-0.002
	(0.009)	(0.008)	(0.009)
Age	0.163***	0.163***	0.163***
	(0.004)	(0.004)	(0.004)
Age Squared	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Female	-0.050***	-0.050***	-0.050***

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Table 12 – Continued from previous page

Policy Name	State MW Increase	Effective State MW	State MW Above Federal MW
	(0.003)	(0.003)	(0.003)
Any child under age 5 in household	-0.067***	-0.066***	-0.067***
	(0.005)	(0.005)	(0.005)
HS Diploma	0.120***	0.121***	0.120***
	(0.005)	(0.005)	(0.005)
Associate's Degree	0.244***	0.245***	0.245***
	(0.007)	(0.007)	(0.007)
Bachelor's Degree	0.267***	0.267***	0.267***
	(0.006)	(0.006)	(0.006)
Postgraduate Degree	0.240***	0.239***	0.240***
	(0.011)	(0.011)	(0.011)
Observations	133,619	133,619	133,619
R-squared	0.269	0.269	0.269
State & Year FE	Yes	Yes	Yes

Notes: Standard errors are in parentheses, P-values are interpreted as follows: ***=p<0.01, **=p<0.05, *=p<0.1, MW is short for minimum wage, Employment=1 if employed and 0 if unemployed, teenage=1 if the individual is aged 15-21 and 0 if the individual is aged 22-29.

Table 13: Full Results for IPW Balanced Triple Differences Models for Personal Income of Hourly Workers

Policy Name	State MW Increase	State Effective MW	State MW Above Federal MW
Policy Effect on Total Personal Income	0.018	0.006	0.008
	(0.017)	(0.009)	(0.026)
Difference in Workers Paid by Hour vs. Not	-0.307***	-0.203***	-0.294***
	(0.010)	(0.048)	(0.013)
Policy Effect on Workers Paid by the Hour	-0.014	-0.012**	-0.031*
	(0.017)	(0.005)	(0.016)
Black	-0.073***	-0.073***	-0.073***
	(0.014)	(0.014)	(0.014)
American Indian/Aleut/Eskimo	-0.083**	-0.083**	-0.083**
	(0.040)	(0.040)	(0.040)
Asian/Islander	-0.040**	-0.040**	-0.040**
	(0.020)	(0.020)	(0.020)
Mixed Race	-0.054*	-0.055*	-0.054*
	(0.030)	(0.030)	(0.030)
Age	0.131***	0.131***	0.131***
	(0.002)	(0.002)	(0.002)
Age Squared	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Female	-0.214***	-0.214***	-0.214***
	(0.009)	(0.009)	(0.009)
Any child under age 5 in household	0.101***	0.101***	0.101***
	(0.011)	(0.011)	(0.011)
HS Diploma	0.678***	0.678***	0.678***
	(0.017)	(0.017)	(0.017)
Associate's Degree	0.754***	0.754***	0.754***
	(0.019)	(0.019)	(0.019)
Bachelor's Degree	0.843***	0.843***	0.843***
	(0.019)	(0.019)	(0.019)

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Table 13 – Continued from previous page

Policy Name	State MW Increase	State Effective MW	State MW Above Federal MW
Postgraduate Degree	0.883***	0.883***	0.883***
	(0.023)	(0.023)	(0.023)
Mining	0.284***	0.281***	0.282***
	(0.059)	(0.059)	(0.059)
Utilities	0.109*	0.108*	0.109*
	(0.061)	(0.061)	(0.061)
Construction	0.228***	0.227***	0.228***
	(0.038)	(0.038)	(0.038)
Manufacturing	0.187***	0.185***	0.186***
	(0.037)	(0.037)	(0.037)
Wholesale Trade	0.143***	0.142***	0.142***
	(0.041)	(0.041)	(0.041)
Retail Trade	0.038	0.037	0.037
	(0.038)	(0.038)	(0.038)
Transportation and Warehousing	0.102***	0.101***	0.102***
	(0.039)	(0.039)	(0.039)
Information	0.171***	0.169***	0.170***
	(0.043)	(0.043)	(0.043)
Finance, Insurance, Real Estate, and Rental and Leasing	0.171***	0.170***	0.170***
	(0.039)	(0.039)	(0.039)
Professional, Scientific, and Technical Services	0.159***	0.157***	0.158***
	(0.041)	(0.041)	(0.041)
Management, Administrative and Support, and Waste Management Services	0.118***	0.116***	0.117***
	(0.040)	(0.040)	(0.040)
Educational, Health, and Social Services	0.039	0.038	0.038
	(0.037)	(0.037)	(0.037)
Arts, Entertainment, and Recreation	0.003	0.002	0.002
	(0.050)	(0.050)	(0.050)
Accommodation and Food Service	-0.036	-0.037	-0.037
	(0.041)	(0.041)	(0.041)
Other Services (Except Public Administration)	-0.053	-0.055	-0.054
	(0.041)	(0.041)	(0.041)
Public Administration	0.092**	0.091**	0.092**
	(0.040)	(0.040)	(0.040)
Observations	69,276	69,276	69,276
R-squared	0.263	0.263	0.263
State & Year FE	Yes	Yes	Yes

Notes: Standard errors are in parentheses, P-values are interpreted as follows: ***=p<0.01, **=p<0.05, *=p<0.1, MW is short for minimum wage, total personal income is an individual's annual total real personal income in 2021 dollars.

Table 14: Variables Used in Study

Vector	Variable Name	Variable Label	Type	Notes About Variable Construction
Y_{it}	lninctot	Log of Total Personal Income	Continuous	Log of real total personal income in 2021 dollars
Y_{it}	employed	Employment Status	Categorical	0 if unemployed, 1 if employed
P_{st}	above	Residing in state with minimum wage increase	Binary	1 if residing in state with MW above federal MW, 0 if not residing in state with MW above federal MW
P_{st}	effecmwR	Real effective minimum wage	Continuous	Real effective minimum wage of the state in 2021 dollars

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Table 14 – Continued from previous page

Vector	Variable Name	Variable Label	Type	Notes About Variable Construction
P_{st}	postminw	After MW increase	Binary	1 if after MW increase, 0 if before MW increase or state never raised MW
Z_{it}	race	Race	Categorical	0 if White, 1 if Black, 2 if American Indian/Aleut/Eskimo, 3 if Asian/Islander, 4 if Mixed
Z_{it}	age	Age	Continuous	
Z_{it}	sex	Female	Binary	1 if Female, 0 if Male
Z_{it}	educ	Educational attainment recode	Categorical	0 if less than high school diploma, 1 if high school diploma, 2 if associate's degree, 3 if bachelor's degree, 4 if graduate, doctorate, or professional degree
Z_{it}	anychlt5	Any of own children under 5 in the household	Binary	1 if yes, 0 if no
ind	Industry	Industry	Categorical	0 if Unspecified Industry, 1 if Agriculture, Forestry, Fishing, and Hunting, 3 if Mining, 4 if Utilities, 5 if Construction, 6 if Manufacturing, 7 if Wholesale Trade, 8 if Retail Trade, 9 if Transportation and Warehousing, 10 if Information, 11 if Finance, Insurance, Real Estate, and Rental and Leasing, 12 if Professional, Scientific, and Technical Services, 13 if Management, Administrative and Support, Educational, Health, and Social Service, 14 if Arts, Entertainment, and Recreation, 15 if Accommodation and Food Service, 16 if Other Services (Except Public Administration), 17 if Public Administration, 18 if Armed Forces

Notes: All variables were obtained from the CPS-ASEC dataset from the time period of 2013 through 2021
Log File Link: https://acrobat.adobe.com/link/review?uri=urn:aaid:scds:US:2a8e738e-0ab7-3085-baaf-f1098edd9a02

The Impact of Childcare Center Closures and Reopenings During COVID-19 Pandemic on Earnings of Parents with Young Children

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Abstract

This paper examines the economic impact of childcare center reopenings during the COVID-19 pandemic, with a focus on parents with children under the age of 5. As childcare centers play a fundamental role in supporting working parents and child development, the study analyzes the disproportionate impact on family incomes and the gender gap in work hours and earnings. The research employs robust empirical difference-in-differences models and a comprehensive dataset while also recognizing potential long-term effects beyond the immediate consequences of the pandemic. The study's findings reveal that the phased reopening of childcare centers during the COVID-19 pandemic had a substantial positive impact on the earnings of parents with children under the age of 5. Restricted reopenings actually increased the weekly earnings of parents with young children more than full reopenings, results that could be explored in future research.
Keywords: DID, childcare center closures, COVID-19, earnings, labor

I. Introduction

In today's fast-paced society, where two-thirds of U.S. children under the age of 6 have both parents active in the workforce, childcare centers are not just facilities – they are the backbone that holds many families together. With such widespread reliance on these centers, what happens when they suddenly close, and equally important, what are the consequences when they reopen?

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This paper examines the impact of childcare center reopenings during the COVID-19 pandemic on individuals' earnings, with a particular focus on parents with children under the age of 5.

Childcare centers have always been pivotal in aiding parents' work lives and promoting child development (Lee and Parolin 2021). Without reliable childcare, many parents, especially mothers who are often primary caregivers, may find themselves reducing hours or settling for lower-paying jobs. This not only impacts individual and family earnings in the short-term but also career paths and overall financial stability in the future for both the parents and the child. The 2020 COVID-19 pandemic induced closures further highlighted this vulnerability. Collins et al. (2021) found a troubling trend during these closures: mothers with young children reduced work hours four to five times more than fathers, causing the gender work gap to increase by 20-50% (Collins et al. 2021).

While many studies have centered on the ramifications of childcare center closures, our paper takes a distinct angle by focusing on their reopenings – the subsequent phase of the closure policy. In doing so, we introduce a more critical approach by breaking down the treatment effects into stages of reopenings rather than merely presenting it as a binary factor. Our paper is also unique in that it specifically focuses on parents with children under the age of 5. This distinction provides a targeted view of how younger children's care situations contrast with those of older children or households without children.

Preliminary findings suggest that parents with young children may see a marked increase in earnings as childcare centers reopen. This rise can be attributed to the lifted responsibility of home childcare and a restored ability to fully participate in the labor market. An analysis of childcare center reopenings by state can offer insights into policy decisions and their potential consequences on family incomes. With this understanding, policymakers are better positioned to ensure families with young children are not disproportionately affected by disruptions such as childcare center closures and can help narrow the gender gap in work hours and earnings.

The rest of the paper is structured as follows. Section 2 details a comprehensive literature review and background, where we combine findings from other studies and explain key childcare policies. Section 3 gives a brief overview of our data and childcare closure policy. Section 4 includes our empirical framework. Section 5 estimates the effects of the childcare center closure policy through a DID approach. Finally, we conclude with section 6 where we will summarize important findings.

II. Past Literature and Background

The impact of childcare accessibility and closures on parental labor market outcomes has been a subject of growing interest in recent years. The studies on this particular topic have been predominantly focused on the consequences of temporary childcare closures during the COVID-19 pandemic. Past economic literature considers both economic factors and attitudes in mothers' decisions regarding labor force participation and childcare use. The literature highlights traditional economic models that typically focus on financial incentives, such as income and childcare costs, while not considering the impact of individual attitudes and societal norms. Broadly, the literature underscores the complexity between economic incentives and psychological factors in the shaping of mothers' choices and focuses on the need for more of a holistic approach to understanding these decisions.

Research on this topic is not limited to a narrow area. For example, a study by Bauernschuster and Schlotter 2015 examines the impact of German public care reform on maternal employment rates, using instrumental variables and difference-in-differences approaches. Another study by Russell and Sun (2020) investigates the effects of childcare center closures during the COVID-19 pandemic focusing on mothers of young children. These studies utilize econometric methods to assess the impact of childcare policies and availability on women's employment outcomes.

Many studies have examined the impact of childcare policies and availability on women's employment outcomes. For example, Bauernschuster and Schlotter (2015) use instrumental variable and difference-in-differences (DID) approaches to assess the effects of a German public care reform in 1996. They investigate how expanded access to highly subsidized public childcare for three- and four-year-old children influenced maternal employment rates. The strength of this paper is the constant econometric methods that are being utilized allowing for casual reference, showing a significant increase in maternal employment, especially in areas where capacity constraints in public childcare were addressed by the reform. Limitations to this paper include potential unobservable factors which could bias the results and the specificity of the German context, which may not generalize to other countries.

One other notable contribution on this subject is from Russell and Sun (2020), who look at the effect of the COVID-19 pandemic on women's labor outcomes. The study incorporates difference-in-differences analysis to investigate the link between childcare availability and women's employment particularly focusing on mothers of young children aged from 0 to 5. The paper finds substantial effects on mothers' labor supply outcomes while also highlighting the importance of childcare availability and utilization of DID. Limitations that could lie within this paper are the generalizability of findings beyond the unique circumstances of the pandemic and the potential influence of unobserved factors on the outcomes.

Lastly, a journal related to early childhood development of quality in childcare centers does not seem to cover the use of certain economic methods; however, it goes over the measurement of quality in childcare centers, focusing on two key aspects of regulatory elements (Scarr et al. 1994). The significance of this journal is that it generalizes the quality it measures in research, as it impacts the children's developmental outcomes and well-being.

Our research has the potential to contribute to the existing literature by providing empirical evidence on the consequences of childcare center closures at the state level, offering policy insights to reduce gender disparities in labor force participation, and recognizing the broader economic and career implications for families. The research aligns with the current societal focus on childcare in both a sense of economic stability and of gender equity.

Childcare quality is a very significant topic in the United States, where millions of children receive aid or guidance in these so-called childcare centers that ultimately influence their early development. This childcare quality has many traits that have been linked within the centers such as the children's safety, well-being, and cognitive, social, and emotional growth. Aspects such as caregiver-child ratios, age-appropriate activities, health, safety, caregiver-child interactions, and staff training contribute to the overall quality of care. childcare quality in the United States is shaped by a complex policy landscape involving federal, state, and local governments. These policies were created for the sole purpose of balancing quality standards with the need for accessible, affordable childcare.

The COVID-19 pandemic that emerged in late 2019 presented many challenges to the operation of childcare centers not just in the United States but globally. As the virus spread rapidly, many concerns about the safety of children, caregivers, and families became the top priority. In response to these concerns, various states in the United States created and implemented policies that mandated temporary closures of childcare centers to weaken the spread of the virus. The intention of these closures was intended to be temporary to protect public health however the policy instead created long-lasting implications for the childcare industry and the families it serves.

Several studies have taken a deeper look at the long-term effects the policy had created. Russell and Sun (2022) summarize the enduring consequences of impermanent, compelled childcare center shutdowns on parental labor market results, noting the long-term repercussions of these temporary policy measures. Such studies are crucial in shedding light on the lasting consequences of childcare center closures and contribute to the ongoing predicament of childcare policy in the United States.

III. Data: Descriptive Analysis

3.1 Data Overview

Our longitudinal dataset is compiled from Current Population Survey Datasets from the years 2020-2021, and the purpose of this dataset is to collect information about individuals across the nation. Data on childcare center closures is gathered from legal state government documents. There are 3 stages of childcare center reopenings: complete closure, reopening with restrictions, and reopening with no restrictions.

We have 1,588,349 observations, containing key information about family structure characteristics– very likely to affect our outcome variables based on the policy we are studying (age, marital status, number of other children, educational attainment, etc). Some sample constraints are: ages span from 15-64; educational attainment has 4 categories (less than HS, HS degree, bachelor's degree, graduate degree); race/ethnicity covers White, Black, Native American, Asian, other/mixed, and Hispanic. These constraints correspond mainly to the variables we will be using in our model.

A strength of this dataset is we have a very large number of observations, supporting the strength of the conclusions we can draw from our results. Our dataset also spans many states, allowing us to compare the differences between states. A potential limitation is the time period only spans 2020-2021, meant to demonstrate the period around COVID in which the policies were enacted and removed. However, the effects of such policies may span years into the future, and we cannot see the more long-term effects of a policy like this.

In terms of the main variables, the binary treatment variable is called haschild5. This variable takes on the value 1 if the household has a child aged 5 or younger, and the value 2 if not. The continuous outcome variable is earnweek, which stands for weekly earnings in dollars.

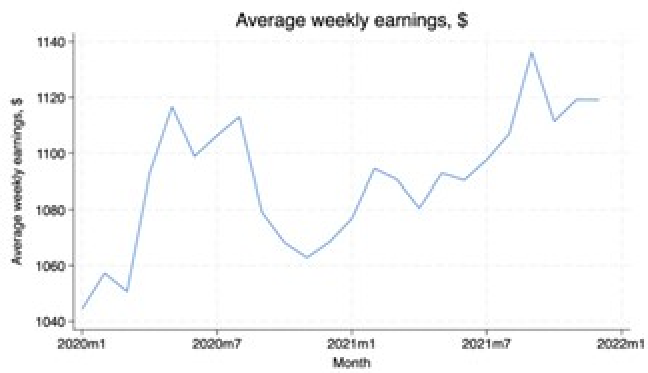
3.2 Structure of Key Variables, Trends in Weekly Earnings

The key variables in our analysis are the policy variable, indicating the stage of childcare centers reopening, the group variable, indicating whether the individual has a child under the age of 5, and the outcome variable, which is weekly earnings. This section will explain the structure of these key variables and trends in our outcome variable.

Our policy variable P_{st} is a categorical variable representing the stage of childcare centers reopening. This variable is created from state government legal documents on childcare center policies during the pandemic. There are 3 possible values: 0 if childcare centers in the state are fully closed in the month of observation, 1 if childcare centers in the state are in restricted reopening stage in the month of observation, and 2 if childcare centers in the state are fully reopened in the month of observation. The variable also takes on the value of 0 if the state never implemented a closure policy. This is because our "treatment" is childcare centers reopening, not closing. In order to distinguish states that reopened childcare centers fully or partially from states that never closed their childcare centers, we code observations in states that never closed their childcare centers the same as observations in which the childcare centers were fully closed. Our group variable G_{it} represents whether a household has preschool-aged children under the age of 5. This variable is determined by looking at the composition of the household. It takes on two possible values: 0 if the household does not have any preschool-aged child under the age of 5, and 1 if the household does not have any preschool-aged child under the age of 5.

Our outcome variable Y_{it} is a continuous variable representing weekly earnings in dollars. It measures the amount of money an individual earns in a typical week from their employment or other income sources. The creation of this variable involves summing up an individual's income sources for a week, including wages, salaries, bonuses, and any other sources of income all being expressed in dollars. This variable captures the continuous variation in earnings, allowing for precise or relative measures of income levels. Figure 1 displays the trends in weekly earnings from the beginning of 2020 to the end of 2021.

Figure 1: Trends in Average Weekly Earnings



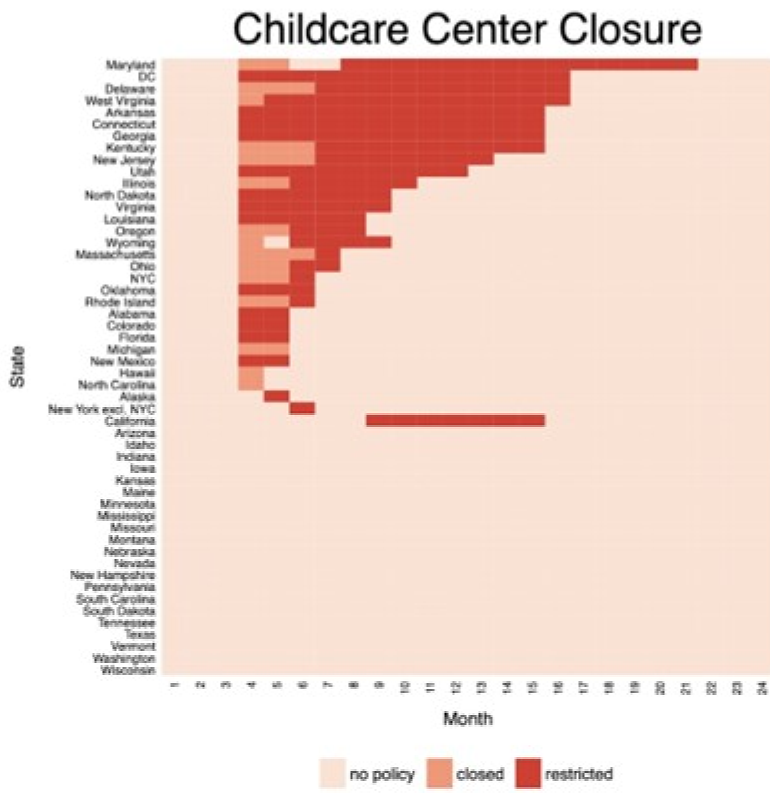
Note: This figure displays the trends in average weekly earnings from January 2020 to January 2022.

Weekly earnings increased during the first half of 2020, which can be attributed to several factors such as a seasonal trend or economic policies that led to a boost in earnings. Despite a slight drop in May, earnings pick back up from June to August. As 2020 continued, there was a significant downturn in the latter part of 2020, which can be attributed to the economic repercussions of the COVID-19 pandemic, which affected many businesses and jobs. Earnings start to recover in 2021 with some dips along the way. Overall, weekly earnings have been volatile during the 2020-2022 time period due to the instability caused by the pandemic.

3.3 Childcare Center Closures and Reopenings

Childcare center closure in the U.S. from 2020 to 2022 was a direct policy response to the global COVID-19 pandemic. The primary objective behind these closures was to limit the spread of the virus among children, staff, and their families. Each state implemented various measures to combat the spread of the virus. Specific provisions under this policy include complete shutdown and partial openings with restrictions, such as limited capacity. Target groups primarily affected by these closures were children, parents, and childcare providers. The initiation of childcare closures began in early 2020 as the virus became a global concern. By April 2020, many states had either advised or enforced the shutting down of childcare centers. To this end, Barnett et al. (2020) show the complete shutdown of both public and private childcare facilities by June 2020. However, the end of 2020 and early 2021 saw wide variability of childcare center closure among states due to differing levels of COVID-19 exposure risk, public guidelines about reopenings, and other social and political factors. Figure 2 displays the timeline of childcare center closures and reopenings by state chronologically.

Figure 2: Timeline of Childcare Center Closures



Note: This figure displays the timeline of childcare center closures across different states starting in January 2020 to the end of December 2021. The lighter shade of red represents childcare center closures, while the darker shade denotes periods of restricted operations.

Different regions had varied timelines and strategies for their closure and reopening plans. For instance, states like Maryland, Delaware, and West Virginia were the first to shut down and experienced the longest periods of restricted reopenings, while other states such as Alabama and Florida saw only two months of restricted childcare centers. There were also many states that did not implement a childcare center closure policy at all. These states were typically in the southern and midwest regions of the U.S. The states that initially shut down were only closed for two to three months maximum, before they reopened with restrictions (e.g. Ohio, Oregon, and Rhode Island). Of the states that shutdown or had limited capacity, California was the last to implement a childcare center closure policy, restricting childcare centers around September 2020, while most other states began closure in April 2020.

3.4 Summary Statistics

In this section, we present a comprehensive overview of the key summary statistics and descriptive measures underpinning our economic analysis. Table 1 displays the tabulation of our policy variable. From the table, we see that no policy or CCC closed and post-policy make up large portions of our dataset. Restricted openings only constitute a small portion of our observations.

Table 1: Stage of Childcare Center Reopening

Stage of Reopening	Freq.	Percent	Cum.
No policy or CCC closed	355171	40.08	40.08
CCC restricted	129412	14.60	54.68
Post-policy	401553	45.32	100.00
Total	886136	100.00	

Table 2: Variable Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Weekly earnings	204584	1102.942	727.108	52.5	2884.61
Own children age ≤ 5	886136	-0.142	-0.349	0	1
Hours worked per week	826977	39.939	-10.859	-1	-140
Number of own children in household	886136	-0.839	-1.148	0	-9
Essential Occupation	886136	-0.438	-0.496	0	-1
Female	886136	479	5	0	1
Married	886136	0.547	-0.498	0	1

Table 2 displays the summary statistics for the outcome, group, and control variables, excepting the categorical variables. Table 3 shows the tabulations of ethnicity and educational attainment, our categorical controls. Weekly earnings have the least number of observations, significantly constraining our dataset. Earnings range broadly from \$52.50/week to \$2884.61/week. 14.2% of observations in our dataset (125,831 observations) are people with children under the age of 5 – these are the observations we expect to be most affected by the policy. The mean number of children in the household is below 1 despite the range of values being from 0 to 9, indicating most people in the dataset have very few children. 43.8% of observed individuals have essential occupations, 47.9% are female, and 54.7% are married.

From Table 3 we see that the majority of observations are non-Hispanic white people, constituting 67.86% of our dataset. Hispanic people make up the next largest ethnicity category at 14.44%, followed by Black and Asian people. In terms of educational attainment, the majority of people have earned a high school degree (52.69%). As expected, the proportion of people decreases as the degree attainment level increases. However, only 6.97% of all individuals earned less than a high school degree.

Table 3: Race-Ethnicity Categories and Educational Attainment

Racial Group	Freq.	Percent	Cum.	Highest Education	Freq.	Percent	Cum.
NH White	601322	67.86	67.86	Less than HS	61795	6.97	6.97
NH Black	81031	9.14	77.00	HS degree	466887	52.69	59.66
NH Native American	7467	0.84	77.85	Bachelor's degree	224376	25.32	84.98
NH Asian	55688	6.28	84.13	Graduate degree	133078	15.02	100.00
NH Other	12684	1.43	85.56				
Hispanic	127944	14.44	100.00				
Total	886136	100.00		Total	886136	100.00	

IV. Empirical Framework

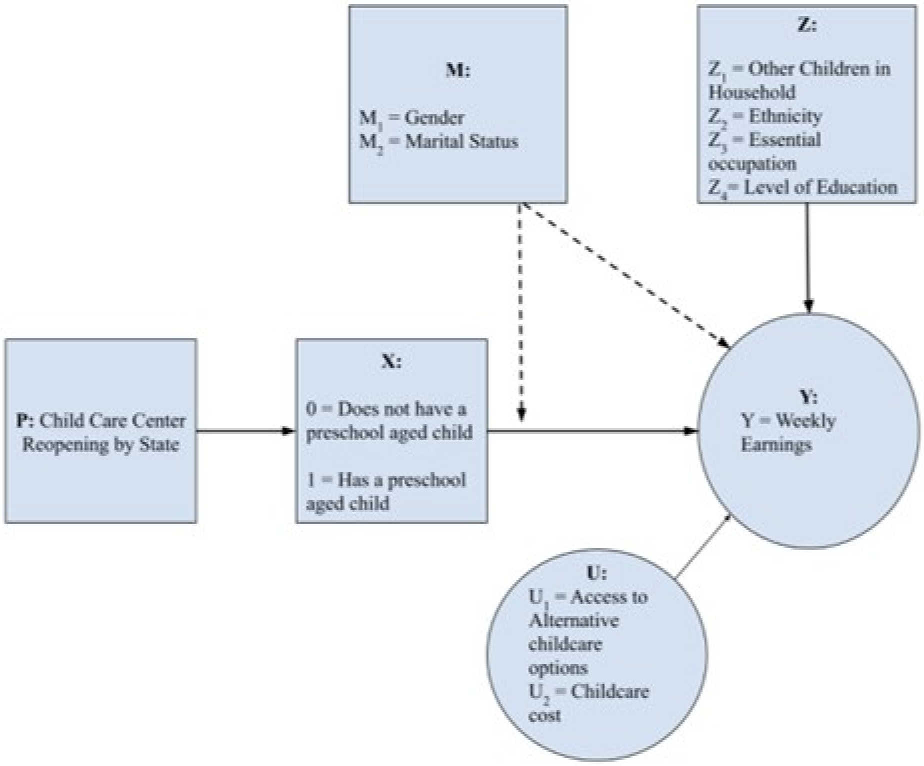
4.1 Flowchart

Figure 3 is a flowchart demonstrating our empirical model As illustrated, our treatment variable, X, is having a preschool-aged child under the age of 5. This is a binary variable: it takes the value 1 when the household has a child under the age of 5, and 0 when the household does not have a child under the age of 5. Our outcome variable, earnweek, focuses on weekly earnings, which is continuous. We hypothesize that households with preschool-aged children (X = 1) will experience lower earnings compared to those with no preschool-aged children (X = 0). The effect of having a preschool-aged child on earnings can be ambiguous because the presence of a preschool-aged child may not affect a parent's earnings. Older children also bring substantial costs, such as clothing, schooling, and extracurricular activities, which could potentially offset any earnings differences between parents of preschool-aged children versus parents of older children. With such ambiguous effects, it is possible for reverse causality where weekly earnings can feed back into decisions related to having a preschool-aged child.

Our control variables include other children in the household, ethnicity, essential occupation, and level of education. The more children that are in the household, the higher earnings may be to support all of them adequately. White and Asian ethnicities typically have higher earnings compared to their Black, Native American, and Hispanic counterparts. Individuals with essential occupations will typically earn more due to a higher need for their jobs. Finally, we expect that more educated an individual is, the higher their earnings will be.

Finally, our two moderating variables include gender and marital status. Our policy variable is childcare center (CCC) reopenings by state. We will be examining the effect of three policies: CCC opening with no restrictions, CCC opening with restrictions on size, and CCC closure. Delaware implemented CCC closure on April 6th, 2020, but then implemented CCC opening with restrictions on size on June 15th, 2020. Hawaii also implemented CCC closure on March 23rd, 2020,

Figure 3: Empirical Model Flowchart



but then reopened with size restrictions on May 19th 2020. On June 9th, 2020 there were no restrictions on size. Kentucky and Massachusetts followed a similar approach to Hawaii where they implemented CCC closure on March 20th and March 23rd, 2020 (respectively) then reopened with size restrictions, and eventually returned to traditional group sizes with no COVID restrictions.

4.2 The Relationship Between Having a Child Under 5 and Individual Earnings

Using the variables outlined above, we estimate the relationship between having a child under the age of 5 and individual earnings. Equation 1 below represents our ordinary least squares (OLS) model, where Y_{it} = $earnweek_{it}$, X_{it} = $haschild5_{it}$, S_s = state fixed effects, and θ_t = time fixed effects.

$$Y_{it} = \beta_0 + \beta_1 * X_it + \beta_2 * Z_{it} + S_s + \theta_t + u_{it} \tag{1}$$

S_s captures unobserved factors that are constant within a state, but might vary across different states, such as state-specific tax policies and average cost of living. On the other hand, θ_t captures factors that change over time but are generally consistent across all individuals in all states at a given point in time. Examples include national economic conditions, such as recessions, and changes in federal policies or laws that affect all states. Some unobserved factors in the error term that could be influencing the Y variable are access to alternative childcare options and how expensive the childcare available to the parent is. Equation 2 below represents the same OLS model but with the following moderating variables (M) included: mar$_{it}$ (marital status) and fem$_{it}$ (gender of parent, 1 if parent is female).

$$Y_{it} = \beta_0 + \beta_1 * X_i t + \beta_2 * Z_{it} + \beta_3 * \text{fem}_{it} + \beta_4 * \text{mar}_{it} + X_{it}(\beta_5 * \text{fem}_{it} + \beta_6 * \text{mar}_{it}) + S_s + \theta_t + u_{it} \quad (2)$$

Our results from both the basic OLS model and the OLS model with moderating variables are presented in Table 4.

Table 4: Race-Ethnicity Categories and Educational Attainment

Variable	Obs	Mean	Std. Dev.	Min	Max
Race-ethnicity categories					
NH White	601322	67.86	67.86		
NH Black	81031	9.14	77.00		
NH Native American	7467	0.84	77.85		
NH Asian	55688	6.28	84.13		
NH Other	12684	1.43	85.56		
Hispanic	127944	14.44	100.00		
Total	886136	100.00			
Educational attainment					
Less than HS	61795	6.97	6.97		
High school degree	466887	52.69	59.66		
Bachelor's degree	224376	25.32	84.98		
Graduate degree	133078	15.02	100.00		
Total	886136	100.00			

We find interesting results when comparing the two models. The coefficient on X ("own children age 5 or younger in hh") in OLS Model 1 is -30.14, indicating that individuals with pre-school age children will on average earn \$30.14 less than individuals without pre-school age children. However, the coefficient on X in OLS Model 2 is 48.00, meaning that individuals with pre-school aged children make \$48.00 more than those without pre-school aged children on average. This differs in direction from Model 1, which does not include the moderating variables. The coefficient on female in OLS Model 2 is -314.1, meaning that women, on average, are expected to make \$315.20 less than men, *ceteris paribus*. On the other hand the coefficient on married in OLS

Model 2 is 192.2, indicating that being married on average, means one will make \$192.20 more than an unmarried individual. The coefficient on "Has child under 5 X female" in OLS Model 2 is -79.35, meaning that a woman with a preschool aged child will make \$79.35 less than a man without a preschool aged child. The coefficient on "Has child under 5 X female" in OLS Model 2 is -74.59, meaning that a married individual with a preschool aged child will make \$74.59 less than an unmarried individual without a preschool aged child. These results are consistent with our initial hypothesis.

V. Analysis and Findings

5.1 DID Equations

The DID empirical model provides an approach to estimate the causal effects of a policy or shock. Using this model, we can compare the impact in the outcome variables over time between a group exposed to a policy, which is the treated group, and a group that was not exposed, which is the control group. In the context of our research question, we use the DID model to analyze the impact of childcare reopenings on the earnings of individuals. We hypothesize that individuals in states where childcare facilities were reopened (either from being restricted or completely closed), which are the treated states, will experience a more significant increase in earnings after removing completely closed policy than individuals in states where childcare facilities did not implement a policy and remained open, which are the control states. Since the month of policy enactment varies by states, we include fixed effects for the state-specific timeline and fixed effects for time. Our baseline DID empirical equation with two-way time and state fixed effects is reflected in Equation 3:

$$Y_{it} = \alpha + \beta Z_{it} + \gamma Pst + S_s + \theta_t + \epsilon_{it} \tag{3}$$

Our key dependent variable, Y_{it}, represents weekly earnings for an individual i during time t. We identify the effect of childcare center reopening on the subset of switchers, or states that implemented childcare center reopening. Our policy treatment variable Pst is a categorical variable that represents what stage of the childcare center closure policy an individual i is experiencing. The control group takes on the value of 0 for the entirety of the time period, because they never implemented a closure policy, nor reopened. The treated group takes on values of 0, 1, or 2 corresponding to whether childcare centers were closed, open with restrictions, or fully open, respectively. Z_{it} is a vector representing our control variables: the number of children in the household, if the individual works in an essential occupation, ethnicity, and educational attainment. S_s and θ_t represent state and time fixed effects, which are included to control for conditions that vary by state but not over time, and vary by time but not by location, respectively.

The policy was enacted mainly in April 2020, shortly after the COVID-19 pandemic hit the United States. The time period of the childcare closure policy spans 2020-2021 to analyze the impacts of COVID-19 in the immediate time period of childcare closures and reopenings. In our study, the ages of individuals span from 15-64. Educational attainment has 4 categories (less than HS, HS degree, bachelor's degree, graduate degree). Racial/ethnic groups are defined as: White, Black, Native American, Asian, other/mixed race individuals, and Hispanic.

Our control variables (number of children in the household, ethnicity of the individual, if the individual is working in an essential occupation, and educational attainment) are listed in Appendix Table 1. These variables were chosen as controls because of their assumed correlations on the outcome variable, weekly earnings. The number of children in a household is likely to impact our outcome variable of weekly earnings. Generally, households with more children may require higher earnings to adequately support their larger family size. Ethnicity also plays a role in weekly earnings, with White and Asian demographics often earning higher than their Black, Native American, and Hispanic counterparts. Those in essential occupations will typically earn more due to the increased demand for their roles. Lastly, higher educational attainment often correlates with higher earnings.

In the classic DID model, we assume that our control variables are exogenous ($cov(Z_{it}, \epsilon_{it}) = 0$). This means that they do not correlate with unobserved factors and are not easily affected by the policy. We further assume parallel trend between the groups ($cov(P_{st}, \epsilon_{it}) = 0$), meaning that absent the treatment, the treated group will have the same outcomes as the non-treated group. The conditional independence assumption is violated since our treatment (states that implemented a childcare center reopening policy) is not random. To account for this violation, we include a host of control variables and fixed effects.

The triple difference method offers causal inference by comparing changes in outcomes over a selected time period in treated and control groups, mitigating selection bias, and improving control for time trends. With the triple difference model, we are able to more intensely discern the difference in effect for people within a group more likely to be affected by the policy. The group variable, G_{it}, is a binary variable indicating whether or not the individual has a child under the age of 5. Childcare centers closing, being restricted, or reopening are more likely to impact the earnings of individuals who have preschool age kids because the accessibility of childcare will affect the number of hours the individual has to work. The triple difference equation is shown in equation 4:

$$Y_{it} = \alpha + \beta Z_{it} + \gamma_1 Pst + \gamma_2 G_{it} + \gamma_3 (P_{st} * G_{it}) + S_s + \theta_t + \epsilon_{it} \tag{4}$$

We include P_{st} and G_{it} as independent terms to observe their individual effects. By interacting P_{st} and G_{it}, we are able to see the effect of our policy treatment on the earnings of our group of interest, which is parents with preschool aged children. Because of this structure, we isolate the effects of the specific policy of childcare centers closing and reopening because we are looking at the group most likely to be affected. Therefore, other policies enacted during COVID-19 that might be impacting earnings and other measures included in this research will not influence our model's results.

5.2 DID Equation Estimates

Our results are presented in the following tables. Table 5 shows the results from estimating Equation 3, our simple DID model, as well as the results from estimating Equation 4, our triple differences model. Equation 4 incorporates our group variable, indicating the group we presume to be most affected by the policy (parents with a preschool aged child).

In the DID model, we find that individuals' earnings went up during periods in which childcare centers were restricted $(P_{st} = 1)$ compared to when childcare centers were fully closed, and those earnings decreased very slightly during periods in which childcare centers reopened fully $(P_{st} = 2)$ compared to when childcare centers were fully closed. However, neither of these coefficients were statistically significant. Our control variables had statistically significant coefficients; a higher number of children in the family correlated with higher earnings, increasing educational attainment led to increased earnings. Each of these coefficients were expected – parents would need to earn more to support more children, and having a higher education level increases one's qualifications and subsequently one's earnings.

In our triple differences model, we again find that the coefficients on our policy variable P_{st} are not statistically significant. However, we find some interesting results on the coefficients of our group variable and our interaction term. The coefficient on our group variable indicates that individuals with preschool-aged children earn \$42.59 less on average than individuals without preschool-aged children, significant at the 1 percent level. This may be because these individuals have to spend time caring for their young children, reducing the number of available hours they have to earn income. We also find statistically significant coefficients on the interaction terms. Parents with preschool-aged children earned \$31.42 more on average during periods of restricted childcare center openings than when those childcare centers were closed, significant at the 5 percent level. When childcare centers were completely reopened, parents with preschool-aged children earned \$17.34 more on average than parents with preschool-aged children when those childcare centers were closed, significant at the 5 percent level. This may be because when childcare centers are partially or fully open, parents can leave their children and spend more time working, increasing their earnings. These results align with our hypothesis, as we expected the policy to affect parents with preschool-age children more intensely than those without. It is interesting thatthe magnitude of the increase in earnings is greater during restricted childcare center openings than it is for full reopenings.

Table 5: Race-Ethnicity Categories and Educational Attainment

Variable	Obs	Mean	Std. Dev.	Min	Max
Race-ethnicity categories					
NH White	601322	67.86	67.86		
NH Black	81031	9.14	77.00		
NH Native American	7467	0.84	77.85		
NH Asian	55688	6.28	84.13		
NH Other	12684	1.43	85.56		
Hispanic	127944	14.44	100.00		
Total	886136	100.00			
Educational attainment					
Less than HS	61795	6.97	6.97		
High school degree	466887	52.69	59.66		
Bachelor's degree	224376	25.32	84.98		
Graduate degree	133078	15.02	100.00		
Total	886136	100.00			

Notes: This table reports the results for estimation equations 3 and 4. The dependent variable is weekly earnings. The numerical values next to variable names represent the coefficients of those variables, and the numbers in parentheses represent the corresponding standard errors.

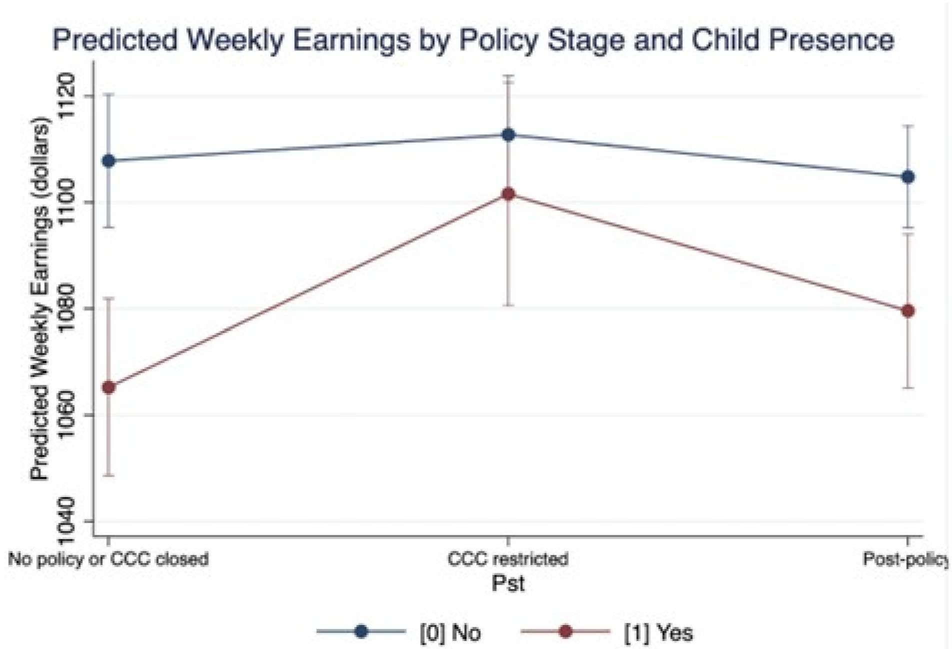
Figure 4 illustrates the variation in weekly earnings among parents with children under 5 compared to those without it, across three phases of our policy: closure, restricted reopening, and full reopening. It is clear that parents with a child under the age of 5 experienced a notable rise in earnings following childcare center restricted reopenings, and then a slightly lower increase in earnings after full reopenings. Earnings for parents without a child under 5 remained relatively constant.

5.3 Group Balancing

We apply group balancing to our model in order to achieve some level of balance in observed characteristics. To do this, we begin by dividing the dataset into groups based on our group variable, G_{it}, indicating whether or not the individual has a child under the age of 5. Table 6 shows the differences in the two subgroups by the characteristics of interest.

For "number of children in the household," the treated group has a mean of 2.091, while the control group has a mean of 0.621. The t-test shows a significant difference with a very high t-value (319.350), indicating a substantial difference in the number of children.

Figure 4: Predicted Weekly Earnings by Policy Stage and Child Presence



Note: [0] represents individuals without a child under the age of 5, while [1] represents parents with a child under the age of 5.

Table 6: Group Balancing by Presence of Child

	Mean			t-test		
Variable	Treated	Control	%bias	t	p>t	V(T)/C(T)
Number of children in HH	2.091	0.621	139.100	319.350	0.000	
NH Black	0.090	0.101	-3.600	-7.810	0.000	
NH American Indian	0.013	0	-11	-36	0.000	
NH Asian	0.080	0.075	0.9	0.430	0.666	
NH other/mixed	0.018	0.017	0.1	-0.490	0.624	
Hispanic	0.171	0.149	-6	-0.270	-0.783	
Essential Occupation	0.437	0.436	-0.1	-0.280	-0.783	
High school degree	0.467	0.528	-12	-26	0.860	
Bachelor’s degree	0.274	0.253	-4	-0.270	-0.783	
Graduate degree	0.201	0.149	-13	-0.450	-0.000	
*If variance ratio outside $[0.98, 1.02]$						
PsR^2	LR X^2	P>X^2	Mean Bias	B	R	%Var
0.231	75163.84	0.000	18.4	4.1	1.19	100
* if B>25%, R outside $[0.5, 2]$						

The race and ethnicity categories have some standout results. Non-Hispanic Black and Hispanic individuals have relatively larger t-values and percentage biases compared to the rest of the ethnicity categories. For non-Hispanic Black individuals, the t-value is -7.81, while the percentage bias is -3.6%, and for Hispanic individuals, the t-value is 13.7, while the percentage bias is 6.1%. This indicates some substantial differences for the treated and control groups for those two ethnicity categories.

For the variable "essential occupation," the treated and control groups have very similar means for essential occupation. Both showed the numbers of 0.437 vs 0.436, with the t-test showing no significant difference (p-value of 0.783).

The variable "edattain" represents different educational attainment categories. All categories actually show significant differences between the treated and control groups. The attainment category for a graduate degree has the t-value with greatest magnitude at 31.45 and a percentage bias of 13.7%. The high school degree category has a t-value with another large magnitude, -26.86, and a percentage bias of -12.2%.

The variance ratio compares the variance of the treated group to the variance of the control group. For our data, variances ratios outside the range of [0.98,1.02], could indicate a significant difference. Number of children in the household has a variance ratio (V(T)/V(C)) outside of this range, at 1.26.

In terms of the other measures at the bottom of Table 6, we find that the LR X2 test is very large and significant, indicating that the model is a good fit. However, the B-statistic (141.2%) is well outside the 25% threshold, indicating substantial differences between the treated and control groups. The R statistic is within the range of [0.5, 2], indicating that the model may be appropriate. %Var indicates that the model accounts for 100% of the variation in the data.

Overall, the table shows that there are significant differences between the treated and control groups in the variables of number of children, ethnicity, and educational attainment. Essential occupation showed no significant difference in distribution. The model seems to be a good fit, however there is substantial bias, especially in the B statistic.

Given the values in Table 6, using the IPW procedure eliminated differences in many observed characteristics. However, it failed to eliminate differences in some key variables: number of children in the household, non-Hispanic Blacks, and Hispanics. These variables all have significantly high percentage biases of 139.1%, -12.2%, and 13.7%, respectively. This means that even after using IPW, the treated and control groups for these variables are still distinct with respect to all observed characteristics.

Table 7 shows the results of our triple difference model with and without balanced groups. The coefficient on our group variable is 31.649 which is the estimated policy/treatment effect. Having young children in the household is associated with an increase of 31.649 units in weekly earnings, which is a significant change from -42.59, the coefficient on the group variable in the model in which the two groups were not balanced.

Table 7: Triple Difference estimates with and without group balancing (IPW)

variables	Without IPW	With IPW
Pst = 1, CCC restricted	4.937	
	(10.40)	
Pst = 2, Post-policy	-3.016	
	(10.73)	
Own children age 5 or younger in household	-42.59***	31.649***
	(6.533)	(8.756)
Has child under 5 X CCC restricted (Pst = 1)	31.42**	
	(12.26)	
Has child under 5 X post-policy (Pst = 2)	17.34**	
	(8.684)	
Number of own children in household	64.58***	15.470***
	(1.440)	(5.978)
Constant	634.8***	
	(14.03)	
Observations	204,584	92,387
R-squared	0.258	0.277
State FE	Yes	Yes
Month FE	Yes	Yes

Notes: This table reports the results for our model with and without group balancing. The dependent variable is weekly earnings. The numerical values next to variable names represent the coefficients of those variables, and the numbers in parentheses represent the corresponding standard errors. The race and educational attainment regressors are omitted from this table. The full version can be found in the Appendix Table 2.

VI. Conclusion

This paper emphasizes the critical and multifaceted issue of childcare center closures and reopenings during the COVID-19 pandemic, focusing on how these events impact the earnings of parents with children under the age of 5. With childcare centers playing an important role of facilitating parents' careers and fostering early childhood development, the paper not only considers the closures of these centers but also the phased reopenings. The study adopts a robust empirical framework, including DID models, to estimate the causal effects of childcare reopenings on earnings, while the triple difference method implemented further enhances the depth of analysis by focusing on parents with preschool aged children. The findings indicate that as childcare centers reopen in any capacity, parents with young children tend to experience a significant increase in earnings. However, we see that parents received more earnings when childcare centers were restricted in their openings compared to when they fully reopened, which is an interesting result. Although the research benefits from the comprehensive dataset that incorporates multiple states and a large number of observations, it has the limitation of a relatively short time period in its analysis. Future studies could explore the long-term consequences of childcare policies, as time goes on more effects could be revealed that are beyond the immediate post-pandemic that this paper has discussed.

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Appendix

Table 1: Control Variables

Variable Name	Variable Label	Type	Notes about variable construction
nchild	Number of own children in HH	Categorical	0-8 children hold own numerical value, families with 9+ children coded as 9
ethnicity	Race-ethnicity categories	Categorical	Categories: NH White; NH Black; NH Native American; NH Asian; NH Other/mixed; Hispanic (NH = non-Hispanic)
essenocc	=1 if essential occupation	Binary	1 if individual works in essential occupation, 0 if individual works in non-essential occupation
edattain	Highest educational attainment	Categorical	Categories: Less than HS; High school degree; Bachelor's degree; Graduate degree

Table 2: Triple Difference estimates with and without group balancing (IPW), full version

Variables	Without IPW	With IPW
Pst = 1, CCC restricted	4.937	
	(10.40)	
Pst = 2, Post-policy	-3.016	
	(10.73)	
Own children age 5 or younger in household	-42.59***	31.649*** (8.756)
	(6.533)	(8.756)
Has child under 5 X CCC restricted (Pst = 1)	31.42**	
	(12.26)	
Has child under 5 X post-policy (Pst = 2)	17.34**	
	(8.684)	
Number of own children in household	64.58***	15.470*** (5.978)
	(1.440)	
NH Black	-197	14
	(14)	(0.03)
NH American Indian	-124	45

Table 2: Triple Difference estimates with and without group balancing (IPW), full version

Variables	Without IPW	With IPW
	(0.02)	(0.01)
NH Asian	-32	25
	(0.01)	(0.01)
NH other/mixed	-11	43
	(0.01)	(0.01)
Hispanic (any race)	-166	66
	(0.01)	(0.01)
Works in essential occupation	-11	17
	(0.01)	(0.01)
HS degree	279	
	(0.01)	
Bachelor's degree	695	
	(0.01)	
Graduate degree	973	
	(0.01)	
Constant	634	
	(0.01)	
Observations	204584	
R-squared	0	
State FE	Yes	Yes
Month FE	Yes	Yes

Trends in Labor Productivity During the COVID-19 Pandemic: An Econometric Analysis of the Labor Market

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Abstract

In the wake of the COVID-19 pandemic, the labor market underwent a seismic transformation, with a surge in telework becoming a hallmark of this era. This study is driven by the compelling question of how telework influenced labor productivity, specifically in the context of the pandemic. As teleworking remains a prevalent mode of work, even post-vaccination efforts, an in-depth analysis of its productivity holds incredible significance for both employers and employees. To unearth insights, we harnessed Current Population Survey data spanning from May 2020 to December 2021. Employing the Difference in Difference regression technique, we designated the threshold of vaccination rates exceeding fifty percent as our binary shock variable. Our analysis unveils compelling evidence that teleworking individuals, the treated group, experienced increased productivity and higher wages in the aftermath of this shock.

Keywords: labor productivity, vaccination shock, difference in difference model, inverse propensity weight

I. Introduction

At the height of the COVID-19 pandemic, American state governments across the nation issued stay at home orders resulting in many businesses closing down for months. For many industries,

*We would like to thank our research guide and professor Dr. Klara Peter. Without her help and guidance, this project would not have been possible. We also thank Miller Ray for providing valuable feedback throughout the research.

this meant shifting their labor into telework. As such, employees had to work from home, an environment foreign to many long-time labor force participants. On one hand, concerns loomed over decreased productivity due to home-related disruptions. On the other, the elimination of commutes and other office-related tasks promised the potential for heightened efficiency. By eliminating non-work-related activities, more time could be dedicated to focusing on work, increasing sleep, and more. This paradox framed the core inquiry of this study: how did teleworking impact labor productivity during the COVID-19 period? Moving forward, this question assumes paramount significance as employers and employees strive to optimize their performance, making the varying productivity levels associated with one's teleworking status exceedingly pertinent.

When deciding on a specific research question, we viewed previous research papers that had covered similar topics. We analyzed a paper focused on worker productivity in the United Kingdom, a paper that analyzed survey results regarding worker productivity from over twenty-five countries, and a paper that highlighted numerous factors that influence worker productivity. Through this, we found evidence that both workers and managers were more productive while teleworking, suggesting more telework may be offered in the future (Criscuolo et al. 2021). We also found evidence that though there may be similar productivity on average, there are some industry factors that result in major differences in productivity among different industries (Etheridge et al. 2020). Lastly, we found evidence that there are factors, such as children, we must consider when coming to conclusions about teleworking productivity (Ban et al. 2020). By analyzing these published papers, we were able to add important variables and ideas to our research, while also finding a way to bring forth new contributions to this question.

To answer this question, we perform regression analysis on Current Population Survey (CPS) data between May 2020 and December 2021. Since there is no direct variable that measures worker productivity, we created a wage rate variable to use as our outcome variable. This was done by dividing average weekly earnings by average hours worked per week. Once this variable was created, a shock variable was formulated. This was simply done by creating a binary variable that equals zero if vaccination rates are below fifty percent, or one if vaccination rates are greater than or equal to fifty percent. The study incorporates state vaccination rates as a shock variable in its analysis to explore potential correlations between public health measures, particularly COVID-19 vaccination rates, and the impact of teleworking on labor productivity. The choice of vaccination rates as a shock is motivated by the idea that regional variations in vaccination coverage might influence the prevalence and severity of the pandemic's disruptions. By including this variable, the research aims to uncover whether regions with higher vaccination rates experienced different patterns in teleworking productivity compared to those with lower rates. This approach enables a nuanced examination of how public health factors, represented by vaccination rates, may interact with teleworking dynamics, and contribute to variations in labor productivity during the critical period of the COVID-19 pandemic.

After the creation of these variables, a difference in difference (DID) regression was performed to help us analyze our research question. Our model took previous literature into account, helping us create our control vector and look out for the trends we saw in another research. It was important for us to look for similar trends as two of the papers we reviewed were published in 2020. This is important because our data spans until the end of 2021 and uses a shock variable dependent on vaccination rates. This, as well as our utilization of a DID model, illustrates how our research will contribute new information to the question of teleworking productivity.

After running our DID regressions, we found statistically significant evidence that our treated group of teleworkers were more productive after the shock. After this regression, we also used Inverse Propensity Weighting (IPW) to balance the control and treatment groups. Using IPW, we ran the same regression yielding similar results. Though the effect was smaller, there was still statistically significant evidence that our treated group was more productive after the shock. Through graphs and models, we illustrate the trends in vaccination, wages, and their relationship. This, paired with our equations, provides the evidence that helped us reach these conclusions.

The remainder of this paper consists of five sections. The second section is a review of pre-existing literature on the subject matter and identifies the contribution our research seeks to make. The third section is a descriptive overview of our data, including how we formed our variables and our summary statistics. The fourth section is our empirical framework, describing the relationship between our variables. The fifth section is where we perform our estimates, showing the DID and IPW constructions. The sixth and final section summarizes our findings and concludes the paper.

II. Literature Review

We read multiple sources that used surveys and different regressions to come to their conclusions. The first of these papers discusses teleworker productivity based on survey results from twenty-five different countries (Criscuolo et al. 2021). These surveys were conducted on managers and workers, often citing studies that suggest conflicting conclusions regarding the effects of teleworking on productivity during the COVID-19 pandemic. In response, they "ran firm-level regressions linking initial productivity levels to telework intensities, controlling for size and country-sector fixed effects" (Criscuolo et al. 2021). The results suggested that both managers and workers had more productive experiences teleworking. This led the authors to believe there would be more telework offered in the future, as there were more positive experiences across the board. We also read a similar paper focused on a self-reported analysis of labor productivity over the course of lockdown. This paper utilized the UK Household Longitudinal Survey (UKHLS) to determine if and how productivity changed during the pandemic (Etheridge et al. 2020). The result of their analysis is that, on average, most individuals' productivity did not significantly change. However, this undermines very significant industry differences (Etheridge et al. 2020). Thus, the researchers found causal evidence that individuals in industries better suited for telework were more productive, and those in industries not suited for telework were less productive. Taking these first two papers into account, we were cautious when choosing our control variables and making our conclusions. These papers were influential in how we organized our research and helped us best approach our research question.

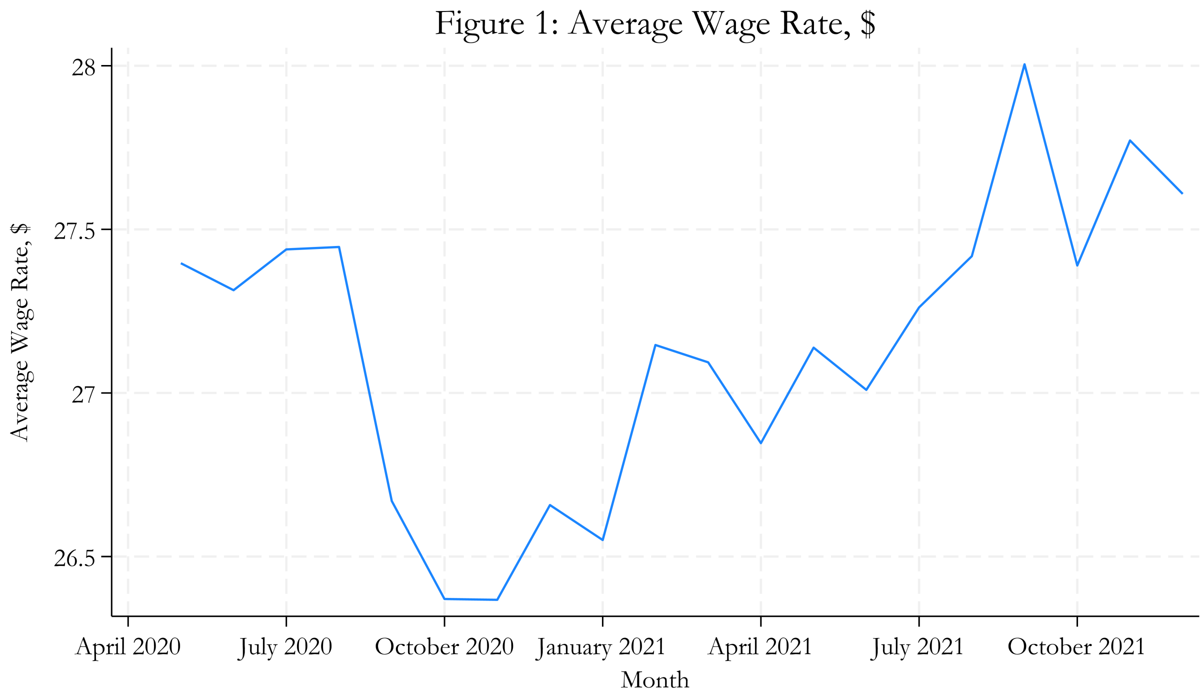
Ban et al. (2020), they incorporated Partial Proportional Odds (PPO) models when performing their statistical analysis. This paper was more focused on the factors that directly influenced teleworker productivity, rather than just productivity in general. This was still quite an important influence on our research, as it helped us narrow down our list of control variables for our regression. The study was done on individuals who work from home in four select counties in Seattle, Washington. There were 2174 responses from adults, none of whom were financially compensated for their participation. After using their PPO analysis, they came to some interesting conclusions. These findings include that respondents with no children are more likely to report neither a change nor an increase in productivity, and even those who spend more time "on personal hobbies, [were] linked to maintaining the same level of productivity, or to increasing productivity" (Ban et al. 2020). Additionally, those with longer driving trips to work were more likely to report no changes or increase in productivity, but those with longer walking trips were more likely to report a decrease in productivity. This was important to consider when performing our analysis, as the researchers' outlined variables would need to be included in a control variable vector. Overall, this paper was influential in deciding how we utilized the variables within our data set, even if the research question they used was more focused on the direct variables that influence productivity.

III. Data and Model

For our data set we are using the Current Population Survey (CPS) between January 2020-December 2021. We chose this time period to reflect the rise of teleworking during the COVID-19 pandemic. Additionally, we chose this time period because after December 2021, COVID-19 restrictions were more relaxed. This data set takes monthly data from the US labor force survey. This is a cross sectional data set consisting of 1,588,349 observations. We restricted the age of observations to those between 15-64 years old and removed unemployed individuals from our data set. This then resulted in 886,136 observations. Some limitations of this data set are that there are variables excluded that would influence productivity and there were lower response rates for this survey during the COVID-19 period. The use of the telework variable ultimately leads to some limitations as well. For example, we have no way of concluding whether these teleworking hours were productive because they were unsupervised. Unfortunately, there are no variables in our data set to test if these hours were productive or not, so we are assuming that these were productive hours. This is an overall strong data set because there are many observations during our selected time period, and there are numerous variables that directly impact the effects we are studying. Additionally, there are some important details about our main variables within the data set. Our research analyzes how teleworking affects worker productivity, with a moderating variable of industry. We also plan to use COVID vaccination rates as different periods of "shocks" to our data. These periods will be from the COVID outbreak to before the COVID vaccine was released, when vaccination rates were at 0-50%, and lastly when vaccination rates were above 50%. These rates will vary from state to state. Our industry variable includes fourteen of the main industries within the US, from agriculture to the Armed Forces. Lastly, we will recode missing values within our wage rate, our variable measuring productivity, to account for outliers that skew our data. We will create this wage rate variable by dividing weekly earnings by hours usually worked per week.

Our two key variables in this study are wage, our dependent outcome variable and COVID-19 teleworking status, our binary treatment variable. The dataset we are using includes variables for both weekly earnings as well as hours worked each week. We have obtained our hourly wage variable by simply dividing weekly earnings by weekly work hours. Our teleworking status variable is binary with a value of "1" indicating remote work and a "0" indicating on-site work. The collection of the teleworking variable by surveyors was temporary in nature, as it was only done in the context of the COVID-19 pandemic. The variable was no longer a part of the CPS after December 2021, which is why our period of sampling does not continue beyond that date. Another worthwhile consideration is that this binary variable offers no option for hybrid work, which we would define as working both on-site and remotely depending on the circumstances of a given workday. For our given timeframe, however, this might not be too disruptive of an issue. Remote work during the pandemic was ultimately done out of the desire to reduce the spread of the virus in workplaces. Hybrid work would ultimately defeat that purpose, assuming that remote work policies were implemented to reduce virus spread. If we find that the dynamics of hybrid work may have ramifications for our findings, we will address it as needed.

When examining the average hourly wage rate over the course of the May 2020 to December 2021 period, there are a few observations that stand out. As expected, there is a sharp decline in average wages beginning in the summer of 2020 and lasting throughout the remainder of the year. Considering that data points of zero were eliminated from these calculations, the massive dip suggests actual wage decreases more than it does mass layoffs. It is also worth noting the timing of this. When mass COVID-19 related lockdowns began in April and May of 2020, estimations of the duration of the pandemic were rather unclear. By July and August, it would have been evident that the pandemic would be a long-term phenomenon, thus indicating a decline in wage. After



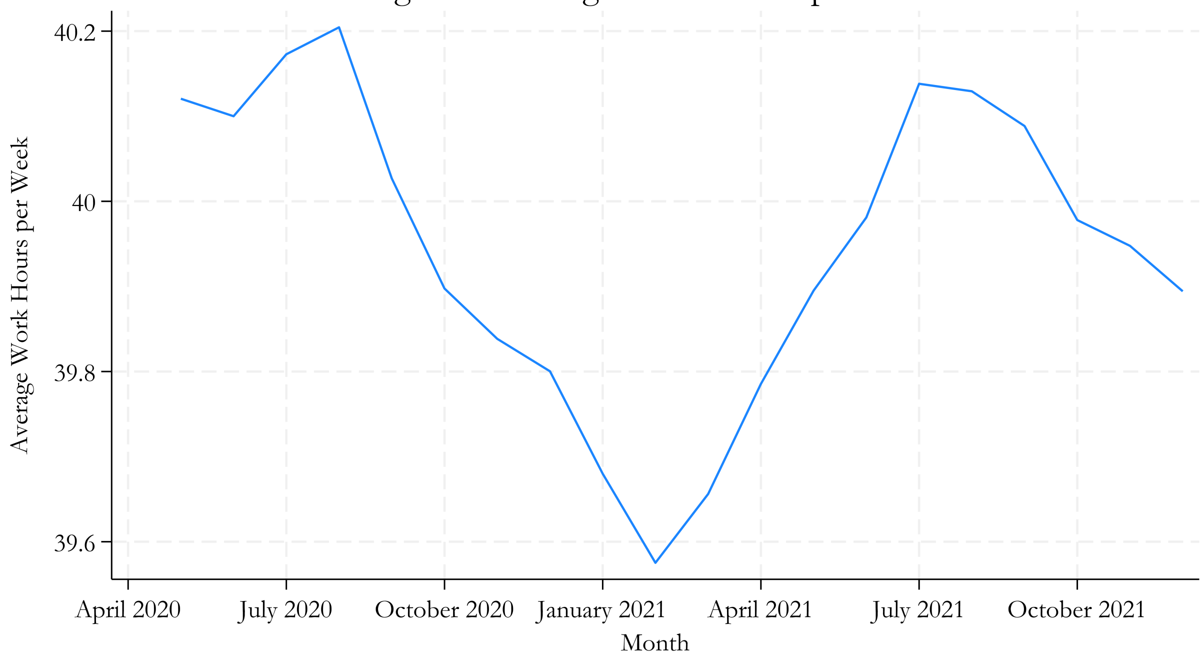
Wage Trends During COVID-19 Pandemic

losing revenue due to the pandemic, firms likely implemented as many cost saving measures as possible. Another possibility is that individuals were put out of work and were willing to seek out temporary lower paying jobs for the sake of stability. After this large dip, average wages steadily trended upwards until the end of our observation period of December 2021. This could have been influenced by any number of factors under the umbrella of economic growth post-lockdowns.

Upon immediate examination, predicted wage rates for remote workers appear to be significantly higher than those who work on-site. Of course, this is without controlling for any of the other variables. One thing to consider is the nature of industries with remote work options. Lower wage jobs such as retail and food service positions have no feasible remote work alternative to them. We hypothesize that we will find that most jobs that are able to be worked remotely tend to be white collar jobs in industries that generally pay higher and require higher levels of education. Should this be true, it makes sense why there would be such an immediately noticeable difference between the two modes of work in the above graph. It is important to consider why this gap widens as age increases. One preliminary theory for this could be that there may not be as many remote jobs for people in their early 20s, so the number of observations in that segment of the line could be insufficient.

The shock variable, ”vaccination coverage,” captures the extent to which a population has completed the COVID-19 vaccination series during the study period. It represents a critical indicator

Figure 2: Average Work Hours per Week



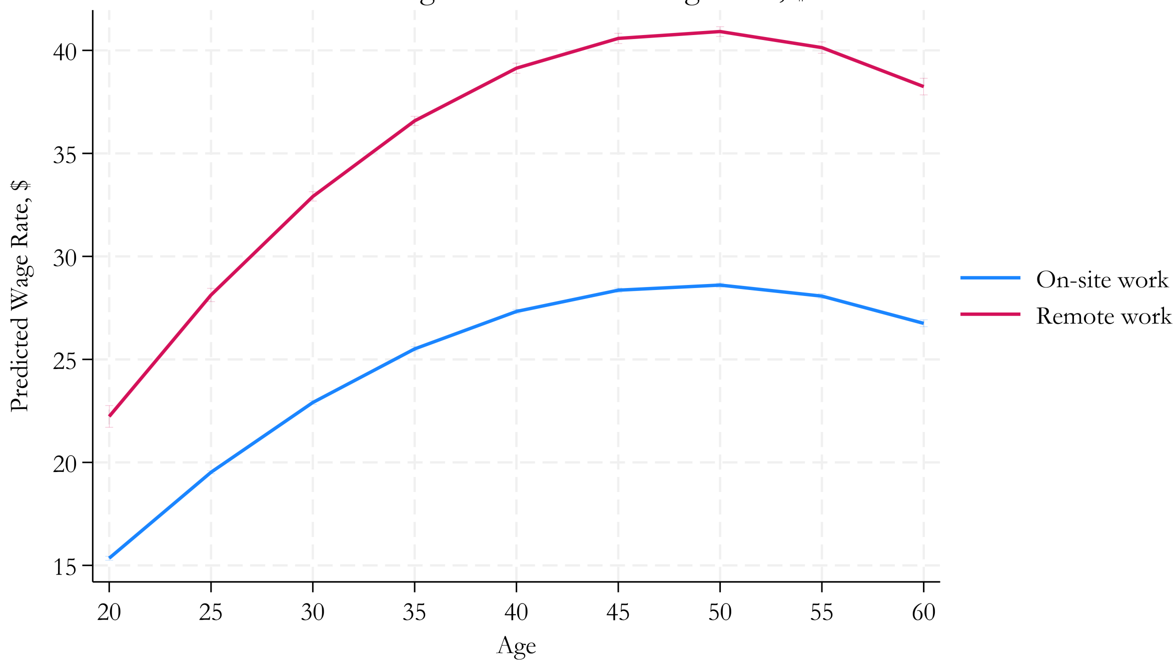
Hours Worked Trends During the COVID-19 Pandemic

of public health and reflects the progress made in vaccinating individuals against the COVID-19 virus. This shock is sourced from official vaccination records and data collected by health authorities and agencies at both national and regional levels. It measures the percentage of individuals who have received the full COVID-19 vaccination series per 100 people.

Throughout the sample period, this shock variable exhibited significant temporal and geographical variations. In the early stages of the pandemic, vaccination coverage was minimal, with most regions reporting values close to zero. As vaccine distribution efforts ramped up, coverage rates began to rise, but the pace and extent of this increase varied across states and regions. Some areas experienced more rapid vaccination rollout, while others lagged due to logistical challenges or differing vaccination strategies. The shock reached its most severe magnitude during mid-2021 when some states achieved near-complete vaccination coverage, while others were still in the early stages. The consequences of these variations in vaccination coverage have significant implications for public health, economic recovery, and policy decision-making.

Specific states or regions may have stood out in terms of their vaccination coverage trajectories. For example, states with robust healthcare infrastructure and efficient vaccination campaigns may have achieved higher coverage rates earlier in the sample period, whereas regions with limited resources or vaccine hesitancy issues may have lagged. Understanding the dynamics of this shock variable is essential for evaluating the effectiveness of vaccination strategies, identifying areas of

Figure 3: Predicted Wage Rate, $



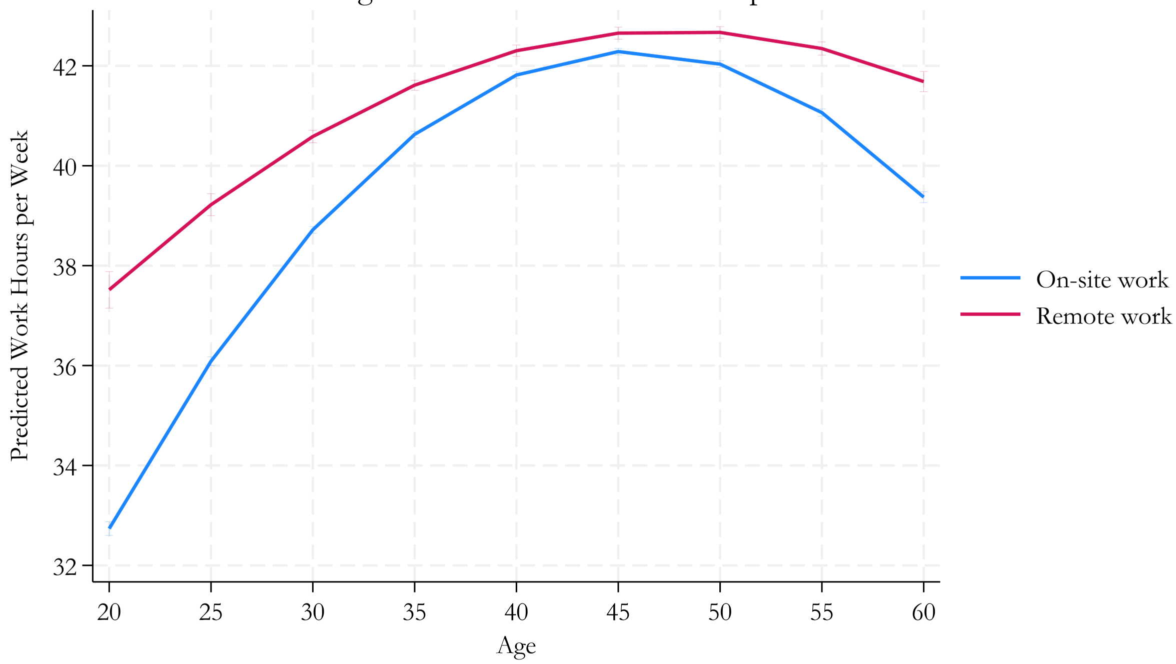
Predicted Wage as Age Increases

concern, and informing future public health policies and interventions.

The three maps above show cumulative vaccination rates by state for three different time periods. These periods are May 2021, December 2021, and May 2022. Note that the key used for each time snapshot is different, as the range of vaccination rates changed greatly over time. However, one clear finding is that vaccination rates were certainly not consistent between states. States in the Northeast (most of New England and New York) routinely led the country in vaccination rates throughout all three figures. California, Washington, and Oregon are also notable leaders. There are a couple of outliers that can be observed. For example, in the first snapshot of May 2021, New Mexico seems to emerge as a leader in vaccination rates. However, this anomaly seems to fade away as time continues. Another noteworthy one is West Virginia, which starts out with a low vaccination rate, but by December 2021 has one of the higher vaccination rates in the country. Then by May 2022, their lead against other states seems to level out significantly.

The above panel data shows vaccination rates by state across the period from 2020 throughout 2022. Once again, it becomes obvious that vaccination rates were by no means uniform across the country. Select states, such as Rhode Island, Vermont, and Massachusetts, managed to achieve over 71% vaccination by as early as Summer 2021. However, there are several states that did not even achieve those vaccination levels by the end of 2022. Despite these differences, all states reached at least 28% vaccination during March 2021, due to this being the first time in which vaccines

Figure 4: Predicted Work Hours per Week



scriptsizePredicted Hours as Age Increases

were made available. Although widespread adoption varies among the states, it seems that every state had a sizable enough portion of residents who were willing to receive the vaccine as soon as it came out. One anomaly that is worth further research is West Virginia, which appears to have exceeded 71% or higher in December of 2021, but then reverts to below 71% immediately after.

Table 1: Summary Statistics

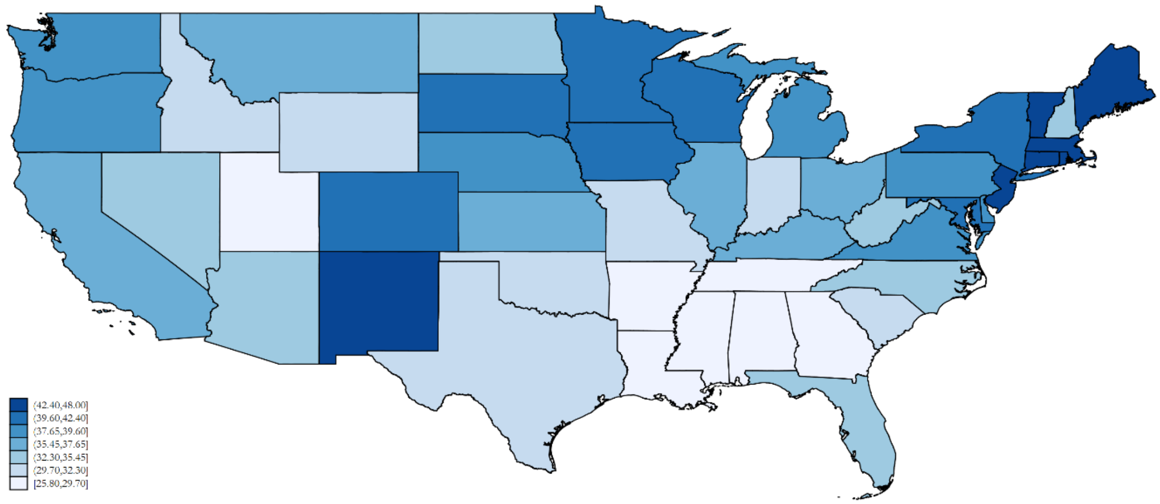
Variables	**Teleworking Mean**	**Non-Teleworking Mean**
Hourly Wage Rate	36.931	24.837
	(17.634)	(14.487)
Essential Occupation	0.086	0.523
	(0.280)	(0.499)
Children	0.459	0.434
	(0.498)	(0.496)
Age	41.909	40.515
	(11.507)	(13.197)
Educational attainment		
Less Than a High School Degree	0.006	0.082
	(0.079)	(0.274)

High School Degree	0.241	0.594
	(0.428)	(0.491)
Bachelor's Degree	0.417	0.217
	(0.493)	(0.412)
Graduate Degree	0.335	0.108
	(0.472)	(0.310)
Race		
White	0.779	0.808
	(0.415)	(0.394)
Black	0.084	0.106
	(0.277)	(0.308)
American Indian	0.007	0.013
	(0.083)	(0.111)
Asian	0.113	0.056
	(0.317)	(0.230)
Mixed	0.017	0.018
	(0.130)	(0.132)
Female	0.537	0.476
	(0.499)	(0.499)
Married	0.604	0.520
	(0.489)	(0.500)
Observations	38,150	153,614

IV. Empirical Framework

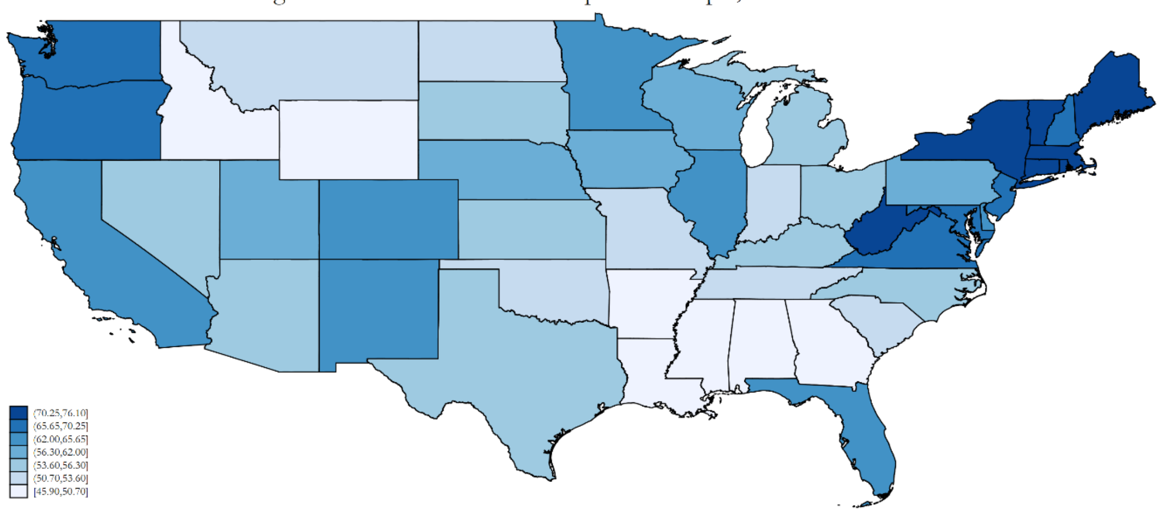
Our treatment variable is teleworking during COVID. This variable is binary and describes whether the person recorded worked remotely or in person. The outcome variables we are tracking are earnings per week and hours worked per week. The amount earned per week is a proxy for the productivity of the worker and is the continuous variable that we will be focusing on. The hours worked per week is categorical but will still be tracked to see the relationship between teleworking and hours worked. Our hypothesis is that working remotely will lower productivity and therefore increase the number of hours worked. It is possible that since productivity is being measured through a proxy as income per week, there may be a reverse causality from Y, the wage rate and hours worked to X, the binary variable for teleworking. It is possible that the higher income jobs can be done through remote teleworking while lower income jobs, such as construction, can only be done in person. We hope to remove the effect of the types of jobs to effectively compare

Figure 5: Individuals Vaccinated per 100 People, May 2021



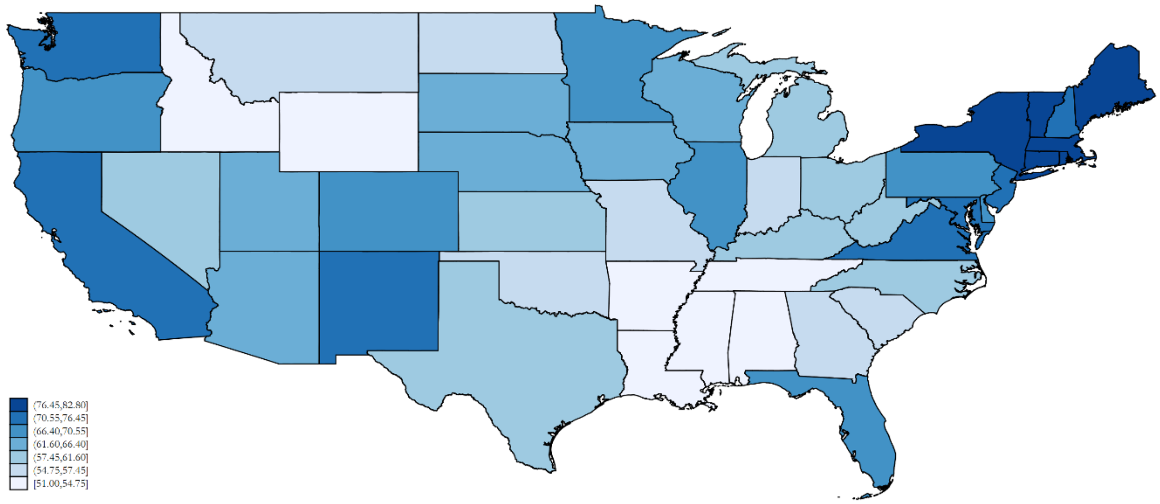
This shows state vaccination rates per 100 people. The darker shades correspond to higher vaccination rates.

Figure 6: Individuals Vaccinated per 100 People, December 2021



This shows state vaccination rates per 100 people. The darker shades correspond to higher vaccination rates.

Figure 7: Individuals Vaccinated per 100 People, May 2022

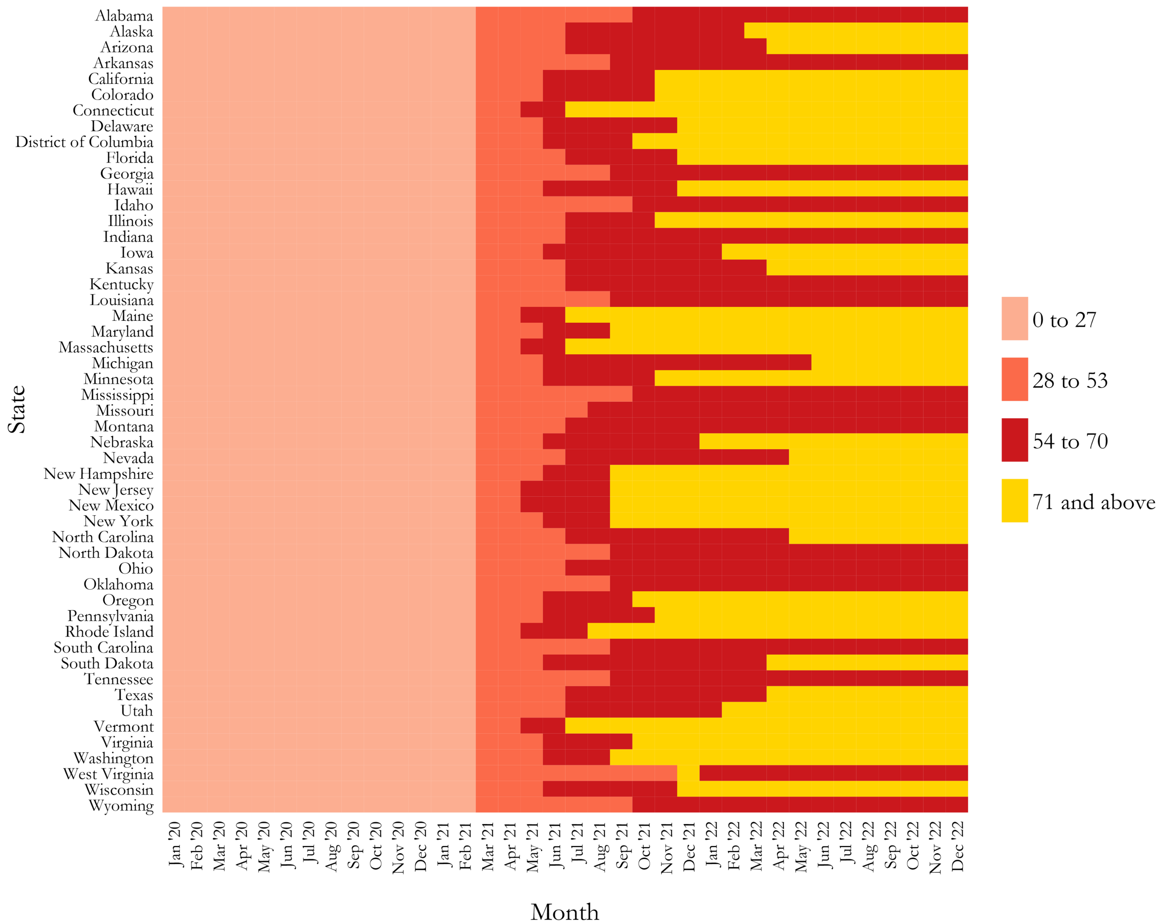


This shows state vaccination rates per 100 people. The darker shades correspond to higher vaccination rates.

the impact of teleworking. The variables we are using for control are education, children, gender, age, and race. Education is chosen because higher levels of education, such as college and graduate schools will impact the salary of each person. Therefore, the proxy for productivity will be affected. The number of children and having children could affect the type of job that someone could have, thereby impacting productivity and increasing the number of hours worked due to external distractions. Industry, gender, age, and race are all common factors that are known to determine and correlate with salary. However, this must be accounted for when comparing productivity levels. We are using an essential worker vs non-essential worker variable as our moderating variable. When accounting for the effect of teleworking on productivity/salary, having an essential job will decrease the income level. Essential jobs require less education and have a lower barrier to entry. Therefore, in a capitalist society and a free job market, there are more workers that can complete essential jobs, and a lower compensation level as a result. Our shock indicator variable is vax_50, a binary shock indicator of the percentage of the population having all vaccinations. In different states this shock variable is met at different points on our timeline throughout 2020 and 2021.

In our econometric analysis, we introduce the following linear equation to investigate the relationship between teleworking during the COVID-19 pandemic (covidtelew), individual characteristics such as education, gender, age, the presence of children, race, and occupation type (essential or non-essential), and the shock variable of COVID-19 vaccination rates (vax_50) on individual wage levels. The equation, wage, is structured to account for state fixed effects, time fixed effects, and unobserved factors that may impact wage outcomes, allowing us to explore the multifaceted

Figure 8: Cumulative Vaccinate Rate per 100 People



This figure shows the different stages of vaccination rates and how they varied in time by state.

influences on labor productivity during this transformative period.

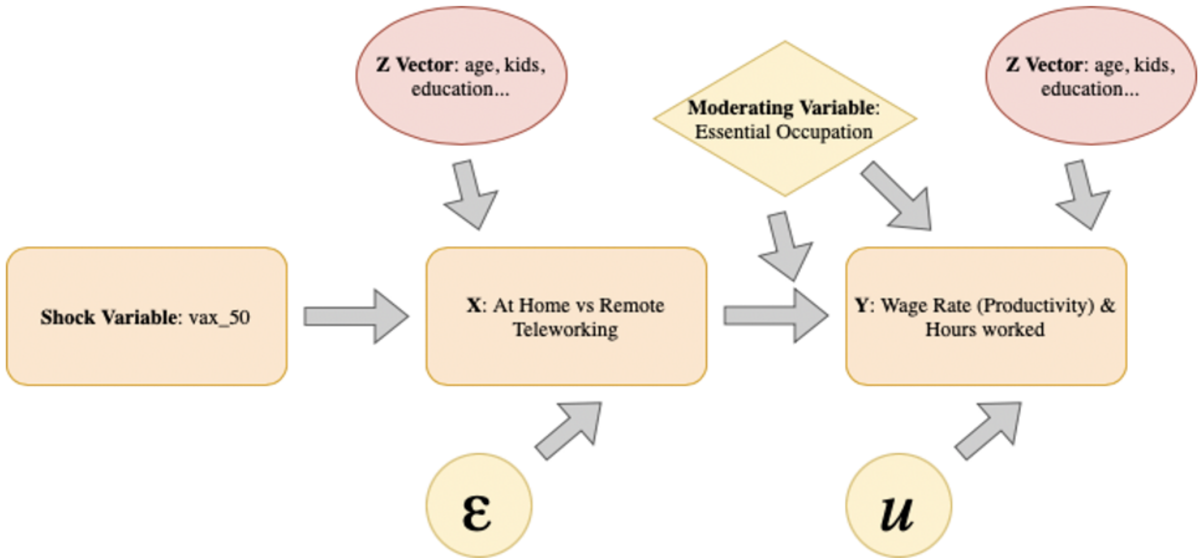
$$\text{wage}_{it} = \beta_0 + \beta_1\text{covidtelew}_{it} + \beta_2\text{educ}_{it} + \beta_3\text{female}it + \beta_4\text{age}_{it} + \beta_5\text{child}it$$
$$+ \beta_6\text{race}_{it} + \beta_7\text{essenocc}_{it} + \beta_8\text{married}_{it} + \beta_9 vax50_{it} + \alpha_i + \gamma_t + \varepsilon_{it}$$

In our expanded econometric analysis, we introduce the following linear equation that incorporates a moderating variable to explore how essential occupation status (essenocc) interacts with teleworking during the COVID-19 pandemic (covidtelew) to influence individual wage levels.

$$\text{wage}_{it} = \beta_0 + \beta_1\text{covidtelew}_{it} + \beta_2\text{educ}_{it} + \beta_3\text{female}_{it} + \beta_4\text{age}_{it}$$
$$+ \beta_5\text{child}_{it} + \beta_6\text{race}_{it} + \beta_7\text{essenocc}_{it} + \beta_8\text{married}_{it}$$
$$+ \beta_9 vax50_{it} + \beta_{10}(\text{essenocc}_{it} \cdot \text{covidtelew}_{it}) + \alpha_i + \gamma_t + \varepsilon_{it}$$

The equations presented includes wage, representing individual wage levels, as the dependent

Figure 9: Empirical Framework



This flowchart illustrates how we modeled our research and how each variable influences our model.

variable with the subscript "it" is denoting individual observations over time. In both equations, the main effects encompass teleworking during the COVID-19 pandemic, education, female, age, child, race, essential occupation status, and vax_50 (COVID-19 vaccination rate shock) as independent variables. The interaction term, essential occupation status * teleworking, captures how the moderating variable (essential occupation status) influences the relationship between teleworking and wages. The z vector, denoted as Z, comprises control variables such as education, gender, age, the presence of children, race, and occupation type. State fixed effects (α) and time fixed effects (γ) account for unobserved factors specific to states and time periods, while the error term (ϵ) encompasses other unobserved influences on wage outcomes.

In the first linear equation, which includes the main effects without the interaction term, several key findings emerge. Teleworking during the COVID-19 pandemic (covidtelew) is positively associated with wages, suggesting that individuals who worked remotely tended to have higher wages. Education (educ) exhibits a strong positive relationship with wages, emphasizing the importance of higher levels of education in boosting income levels. Being female (female) is negatively correlated with wages, indicating a gender wage gap, while age (age) and the presence of children (child) positively influence wages. Essential occupation status (essenocc) negatively impacts wages, reflecting lower income levels for those in essential jobs. Additionally, higher COVID-19 vaccination rates (vax_50) are associated with increased wages. The R-squared value suggests that the model explains a substantial portion of the wage variation, and robust standard

Table 2: Combined Effects of Remote Work and Essential Work

Variables	Teleworking status (1)	Teleworking status (1)
Teleworking status	5.868***	4.591***
	(0.0957)	(0.259)
Essential worker	-2.495***	-2.385***
	(0.0672)	(0.0688)
Works remotely & essential worker	-	1.445***
	-	(0.276)
Educational attainment	7.049***	7.055***
	(0.0437)	(0.0437)
Female	-6.041***	-6.024***
	(0.0617)	(0.0618)
Age	0.186***	0.186***
	(0.00237)	(0.00237)
Has children	2.098***	1.493***
	(0.0703)	(0.0669)
Race	1.492***	0.0722**
	(0.0669)	(0.0345)
Married	0.0751**	2.101***
	(0.0345)	(0.0703)
Vaccination rate over 50%	2.113***	2.113***
	(0.0765)	(0.0765)
Constant	-4.486***	-4.573***
	(0.180)	(0.180)
Observations	192,720	192,720
R-squared	0.322	0.322

errors are employed to account for potential data issues. In the second equation, which includes the interaction term between essential occupations and teleworking, the findings largely align with the first equation, with the added insight that essential occupation status interacts positively with teleworking in influencing wages. This demonstrates that individuals in essential jobs who worked remotely tended to earn more. Overall, these results provide valuable insights into the factors affecting labor productivity during the COVID-19 pandemic.

V. Analysis and Findings

Our baseline empirical model aims to test how teleworking affects worker productivity. We use industry as a moderating variable and have a shock variable that uses vaccination rates among states. We have two stages for this shock variable: when less than 50% of the population was vaccinated and when over 50% of the population was vaccinated. Our initial model is a Difference in Difference (DID) Model, which considers different periods of our shock as well as our different groups. Our initial hypothesis is that teleworkers will make more money when vaccination rates are zero, and then the wages will slowly start to decrease. This is because occupations that are already virtual are more likely to be high paying. However, once the pandemic hit, there were more occupations switching to virtual set ups.

$$\text{wage}_{it} = \delta Z_{it} + \beta_3 P_{st} + \mu_s + \theta_t + \varepsilon_{it}$$

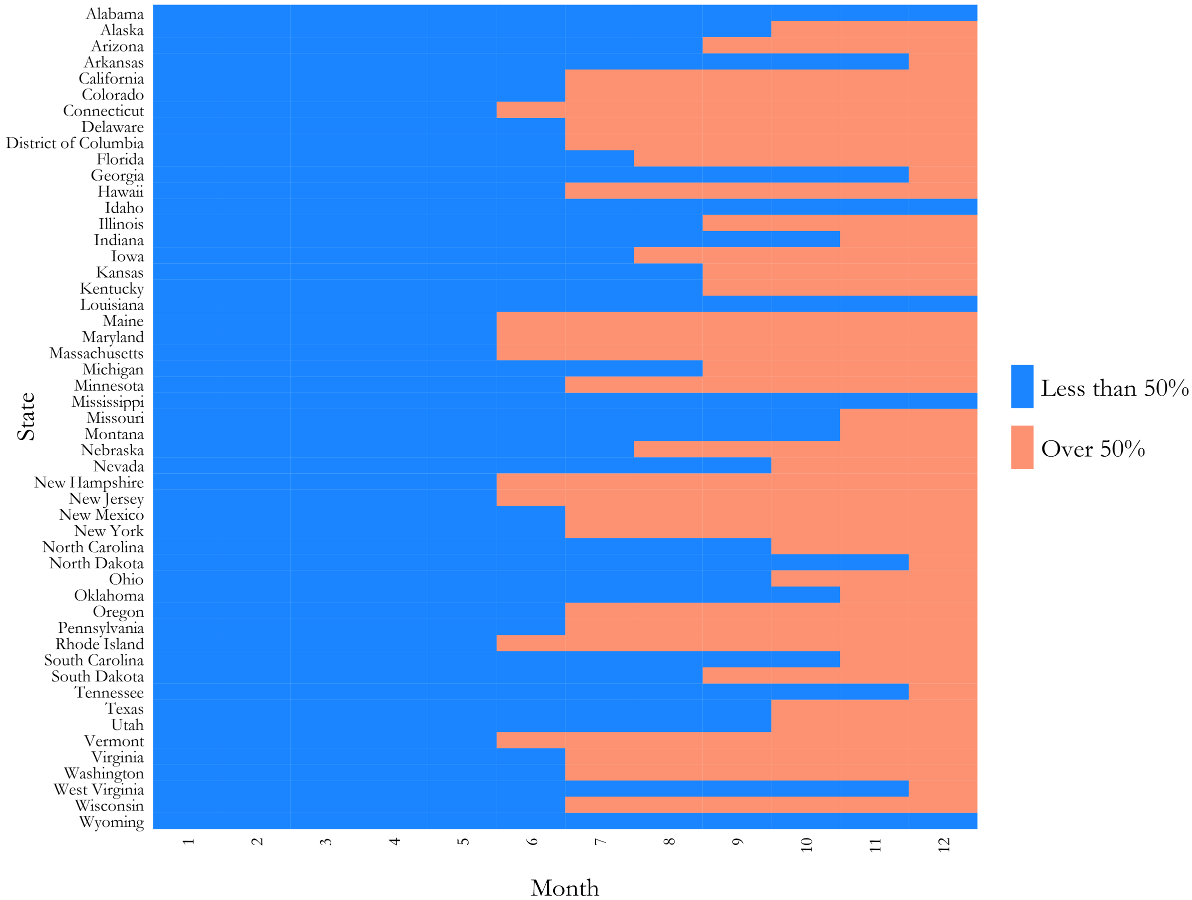
Where Z_{it} is a vector of control variables including variables like gender and race. P_{st} is our binary shock variable, μ_s is our variable for state fixed effects, and θ_t is our variable for fixed time effects. Our continuous outcome variable is wage rate, which we are using as a measure of productivity.

The shock variable, "Vaccine Series Completed per 100 people" captures the extent to which a population has completed the COVID-19 vaccination series during the study period. It represents a critical indicator of public health and reflects the progress made in vaccinating individuals against the COVID-19 virus. This shock is sourced from official vaccination records and data collected by health authorities and agencies at both national and regional levels. It measures the percentage of individuals who have received the full COVID-19 vaccination series per 100 people. For our model, we have chosen to measure this as a binary variable that measures vaccination rate within the state that the observed person resides in.

Throughout the sample period, which spans from January 2020 to December 2021, this shock variable exhibited significant temporal and geographical variations. In the early stages of the pandemic, vaccination coverage was minimal, with most regions reporting values close to zero. As vaccine distribution efforts ramped up, coverage rates began to rise, but the pace and extent of this increase varied across states and regions. The shock reached its most severe magnitude during mid-2021 when some states achieved near-complete vaccination coverage, while others were still in the early stages of the vaccination process. This is why we have included state fixed effects, so the difference of shock timing is accounted for. As seen in the figure below, the timing at which each state reached a 50% threshold of vaccination varied greatly throughout 2021. Some had achieved this milestone by June, whereas others did not even achieve it by the end of the year. The consequences of these variations in vaccination coverage have significant implications for public health, economic recovery, and policy decision-making.

Our analysis encompasses a broad age range, spanning from 16 to 64, reflecting the diverse demographic of our study population. This inclusivity ensures that we do not inadvertently constrain our dataset, allowing us to comprehensively examine the effects of various characteristics on our

Figure 10: Cumulative Vaccinate Rate per 100 People (2021)



This is a representation of our shock variable of vaccination rates per 100 people being over 50% by state.

outcome variable. The rationale for including these specific control variables lies in their potential to significantly impact our primary outcome variable. Our control variables consist of a continuous age variable, which recognizes the influence of age-related factors on outcomes, a categorical education variable that acknowledges the role of educational attainment in shaping earnings, a binary children variable that accounts for family dynamics, a binary gender variable recognizing potential gender-based wage disparities, a categorical race variable to explore the impact of racial identity, and a binary variable indicating essential worker status, a pivotal consideration in light of the COVID-19 pandemic. The selection of these variables aligns with previous research that has highlighted their relevance in understanding the complexities of productivity and income within the context of a rapidly evolving labor market.

In employing the DID model, we operate on the basis of three fundamental assumptions. Firstly, we assume that the vector of control variables is exogenous, meaning that these variables are unrelated to unobserved factors influencing the outcome. Secondly, we assert that the shock variable maintains exogeneity, signifying that it is not influenced by unobservable traits. Our third assumption, known as the Conditional Independence Assumption, posits that an individual's selection into the treatment group is a random process, independent of the error term, under the conditions of control variables, the shock, and fixed effects. However, it's important to acknowledge that, in the context of our model, these assumptions may face violations. The first assumption may be compromised since the observable differences within the controls might exhibit correlation with the error term. The second assumption may falter due to potential correlations between unobservable traits and the shock variable. Lastly, the third assumption may be transgressed as unobservable characteristics could directly impact an individual's inclusion in the treatment group. These nuanced considerations underscore the complexity of our modeling framework and potential limitations in the assumptions' application.

The triple difference model allows us to run a similar regression to the DID model, but it also allows us to include a variable indicating if an individual is likely to be in the treated group or not. This variable will help create a more accurate equation across the board. Our treated group is those who telework. The policy is likely to affect this group because once vaccination rates increased, in-person work started to open up again. This means that our treated group was directly affected.

$$\text{wage}_i t = \delta Z_{it} + \beta_3 (P_{st} \cdot G_{Lt}) + \mu_s + \theta_t + \varepsilon_{it}$$

Table 3: Triple Difference and DID Compared

Variables	**Triple Difference**	**DID**
Vaccination rate over 50%	-0.284**	0.0160
Post shock		
	(0.134)	(0.132)
Worked remotely	4.511***	–
	(0.103)	
Vaccination rate over 50% & worked remotely	2.483***	–
	(0.238)	
Age	0.216***	0.216***
	(0.00221)	(0.00223)
Has children	2.322***	2.332***
	(0.0618)	(0.0623)
Educational attainment		
High school diploma	5.189***	5.340***
	(0.0791)	(0.0797)

College	14.29***	15.17***
	(0.107)	(0.106)
Graduate degree	19.18***	20.47***
	(0.131)	(0.129)
Race		
Black	-3.127***	-3.142***
	(0.0956)	(0.0963)
American Indian	-1.646***	-1.672***
	(0.242)	(0.243)
Asian	0.732***	1.084***
	(0.146)	(0.148)
Mixed	-0.544**	-0.428**
	(0.214)	(0.216)
Female	-6.003***	-6.043***
	(0.0607)	(0.0613)
Married	-2.304***	-3.268***
	(0.0668)	(0.0656)
Essential worker	9.523***	10.65***
	(0.263)	(0.264)
Observations	192,720	192,720
R-squared	0.340	0.328

Notes: Less than a High School Degree is the omitted category for education, and White is the omitted category for race.

After seeing the results of our triple difference model, we can provide a comprehensive interpretation of the estimation results, aiming to discern the effects of policy-driven shocks on outcomes. Then, we can focus on the primary effects and interaction terms. Moreover, we will briefly discuss the influences of additional control variables, seeking to establish their alignment with prior research and expectations. Lastly, we will explore whether the policy or shock impacted the two groups, namely teleworkers and in-person workers.

In the baseline equation, our central inquiry revolves around the effect of the 50% vaccination rate shock variable on worker productivity, as represented by the dependent variable ”wage.” The coefficient for this shock variable is -0.284, signifying a statistically significant, negative influence on wages ($p<0.05$). These findings imply that, on average, worker productivity declined as vaccination rates exceeded the 50% threshold. This outcome aligns with our initial hypothesis, which speculated a decline in wages as vaccination rates rose. This interpretation suggests that the shock, along with increased vaccination rates, might have contributed to a reduction in worker productivity, possibly due to a transition away from teleworking as in-person work resumed.

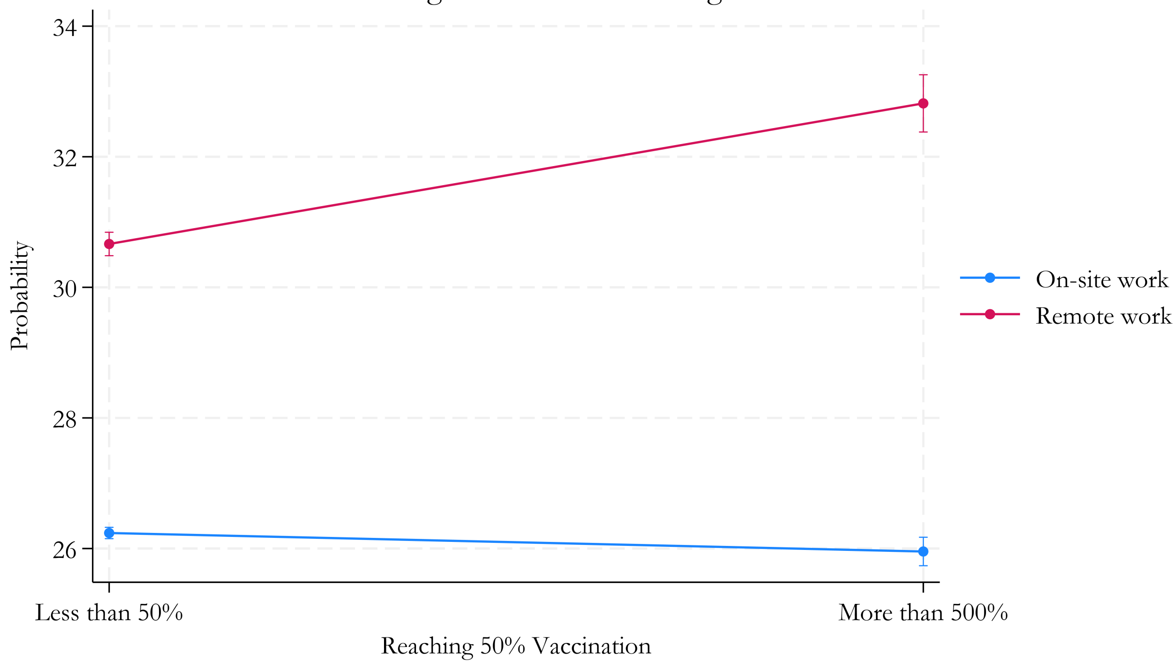
Our triple difference model includes three key components: Over 50% vaccination, telework status, and the interaction term between them. The coefficient for over 50% vaccination is 0.016 and is not statistically significant. In isolation, the shock variable exhibits a negligible effect on wages, in contrast to the baseline equation. This observation suggests that the influence of vaccination rates on wages may be contingent on whether individuals are engaged in telework. The teleworking coefficient is 4.511 ($p<0.01$), indicative of a noteworthy and positive impact on wages. This implies that individuals engaged in telework tend to enjoy higher wages relative to their in-person counterparts. The interaction term yields a coefficient of 2.483 ($p<0.01$). This result is of particular significance as it intimates that the impact of vaccination rates on wages diverges for teleworkers and in-person workers. When vaccination rates exceed 50%, teleworkers experience an incremental wage boost in comparison to the baseline effect of the shock. This discovery suggests that teleworking, within the context of elevated vaccination rates, might enhance worker productivity and income.

The influence of control variables, encompassing age, education, gender, and essential worker status, is also evident in their significant effects on wages. These results resonate with previous research, reiterating the influence of these factors on worker productivity and income.

Our analysis reveals that the shock, shown by the over 50% vaccination variable, has a negative effect on wages in the baseline equation. Nonetheless, within the triple difference model, a more nuanced narrative emerges. Teleworking, as a primary effect, exerts a positive impact on wages, and its combination with the shock augments worker productivity, suggesting that teleworkers experienced an income boost when vaccination rates surpassed 50%. This preliminary analysis of the triple difference model opens discussion and further analysis into alternative factors such as external shocks to study worker productivity. Additionally, this highlights the necessity for policies to be enacted which address different groups of workers.

The two graphs presented in this analysis offer valuable insights into the impact of the shock variable, vax_{50}, on wage rates and hours worked within the framework of the DID model. As depicted in the first graph, which illustrates the predicted wage rates, we can discern distinctive trends for remote workers (red line) and on-site workers (blue line) concerning the shock variable. The red line experiences a gradual increase, starting around 31 and rising to approximately 32.5. In contrast, the blue line exhibits a subtle decrease, commencing at roughly 26.2 and slightly declining to 26. These trends are indicative of the different responses of these two groups to the shock of vaccination rates exceeding 50%. Remote workers appear to benefit from this shock with higher wage rates, while on-site workers observe a marginal decline. This contrast underscores the influence of the shock on the wage rates and the role of remote work in mitigating the potential negative effects.

Figure 11: Predicted Wage Rate

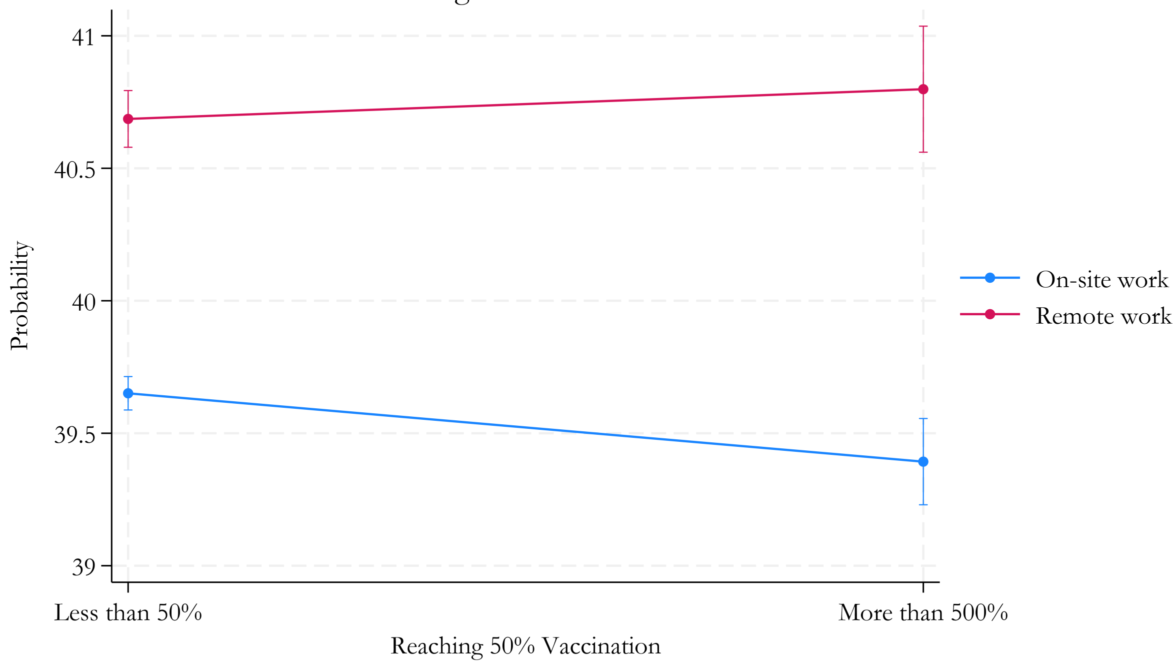


This figure illustrates predicted wage before and after our shock variable.

Moving on to the second graph depicting predicted hours worked, the deeper impact of the vax_{50} shock is further highlighted. The red line representing remote workers maintains a relatively steady line, implying that the shock does not significantly alter their working hours. It starts at approximately 39.75 and concludes at around 39.4, indicating a minor reduction. Meanwhile, the blue line representing on-site workers shows a gradual decline in hours worked, commencing at 39.75 and diminishing to about 39.4. These patterns emphasize the differential impact of the shock on the working hours of these two groups. Remote workers appear to maintain their working hours, whereas on-site workers experience a modest decrease. In the context of the DID model, these observations underscore the role of telework in buffering the effects of external shocks, such as the increase in vaccination rates, and its influence on wage rates and hours worked for different groups of workers.

The two groups (those who telework and those who do not) have many significant differences in observed characteristics. One of the most noticeable is the difference in essential worker status. The results suggest that remote workers are less likely to be essential workers, with around 9% of remote workers being essential. This observation is interesting due to the nature of essential work. It is hard to imagine that any essential workers would be able to work remotely at all, and 9% almost seems surprisingly low. Another observation that is significant, although not necessarily surprising, is that those that telework are much more likely to be those who have higher levels of

Figure 12: Predicted Hours



This figure illustrates predicted hours before and after our shock variable.

education (meaning college and beyond) compared to those who do not. It also seems that those who telework are more likely to be older, though only by a couple years on average. Race seems to also play a factor, specifically for Asian individuals, however only by a few percentage points.

The inverse propensity weighting procedure seems to have eliminated major differences. Differences in race categories have reduced to near zero levels across the board. In terms of age, the group of those that telework are likely to be older only by around half a year, a figure that is impressive considering that we already have found that the younger ages in our sample tend to be more likely to be in the control group compared to those that do not telework. Previously, education was another factor that was vastly different from the control and treatment groups. The IPW procedure has brought these differences down to around zero across all education levels.

Table 6: DID Model with IPW Procedure

Variables	**DID Base Model (1)**	**DID IPW (2)**
Vaccination rate over 50% Post shock	-0.289**	-0.093
Post shock		
	(0.133)	(0.426)
Worked remotely	4.497***	4.090***

	(0.103)	(0.164)
Vaccination rate over 50% & worked remotely	2.487***	1.629***
	(0.238)	(0.381)
Age	0.194***	0.213***
	(0.002)	(0.006)
Has children	1.614***	1.729***
	(0.066)	(0.168)
Educational attainment		
5-12 grades, no diploma	2.648***	2.814***
	(0.287)	(0.987)
High school diploma	7.593***	9.107***
	(0.280)	(0.900)
College	16.540***	18.104***
	(0.290)	(0.895)
Graduate degree	21.333***	22.706***
	(0.299)	(0.897)
Race		
Black	-2.788***	-3.554***
	(0.096)	(0.283)
American Indian	-1.468***	-1.447***
	(0.242)	(0.417)
Asian	0.649***	0.617***
	(0.146)	(0.220)
Mixed	-0.371*	-0.197
	(0.214)	(0.570)
Female	-5.880***	-6.337***
	(0.061)	(0.148)
Married	1.975***	2.001***
	(0.070)	(0.183)
Essential worker	-2.239***	-2.363***
	(0.067)	(0.147)
Observations	192,720	192,720
R-squared	0.342	0.326

Notes: White is the omitted category for race. State and Time Effects included.

After using an inverse propensity weighting procedure, the difference in observed character-

Table 4: Mean Comparison of Two Groups

Variable	Treated	Control	% Bias	t	p ¿ t	V(T)/V(C)
Age	42.344	40.957	11.1	36.19	0.000	0.76*
Has child	0.46483	0.43737	5.5	18.67	0.000	
Educational attainment						
5-12 grades, no diploma	0.00789	0.08054	-35.9	-99.64	0.000	
High school diploma	0.25627	0.60387	-75	-245.09	0.000	
College	0.40675	0.20994	43.6	156.14	0.000	
Graduate degree	0.32866	0.10047	57.9	225.45	0.000	
Race						
Black	0.08179	0.10326	-7.4	-24.30	0.000	
American Indian	0.008	0.0119	-3.9	-12.56	0.000	
Asian	0.09999	0.04944	19.3	72.32	0.000	
Mixed	0.01709	0.01767	-0.4	-1.48	0.138	
Female	0.53525	0.46413	14.3	48.16	0.000	
Married	0.61473	0.53502	16.2	54.23	0.000	
Essential worker	0.09764	0.52795	-104.8	-312.26	0.000	

Notes: White is the omitted category for race. * if variance ratio outside [0.99; 1.01]

istics does seem to change for some variables. Most notably, the wage rate of those who have experienced the shock is still negative but is much closer to zero than previously. If the person works remotely, their wage rate still seems to be higher on average, but not as much as before the IPW weighting procedure. If the observed individual was a teleworking individual and had experienced the 50% vaccination rate shock, then their wage also still increased, but by almost a whole dollar amount less on average. This is by far the largest noticeable difference between the two models.

VI. Conclusion

In this paper, we explored the relationship between telework and productivity through wage rate. Using CPS data, we performed regression analysis using DID modeling to implement a vaccination shock variable. Through this, we saw that after our shock, workers were more productive. This result stayed consistent after we used IPW to balance our control and treatment groups. This is significant because it has heavy implications for the future of the labor market. Employers may be more inclined to offer remote work and employees may be more inclined to search for remote work. Arguably our most significant finding from our research is that teleworkers made higher wages. This is significant because it represents a labor supply shock as vaccination rates increased. With higher vaccination rates, in-person jobs were reopening. This resulted in an influx of indi-

Table 5: Balancing of the Two Groups

Variables (IPW)	**Regression on teleworking status**	**R-squared**
Age	0.428***	0.000
	(0.118)	
Has child	0.012***	0.000
	(0.004)	
Educational attainment		
5-12 grades, no diploma	0.043***	0.006
	(0.005)	
High school diploma	0.001	0.000
	(0.004)	
College	-0.033***	0.002
	(0.002)	
Graduate degree	-0.015***	0.000
	(0.001)	
Race		
Black	0.012***	0.000
	(0.003)	
American Indian	-0.000	0.000
	(0.001)	
Asian	-0.009***	0.000
	(0.001)	
Mixed	-0.000	0.000
	(0.001)	
Female	0.010**	0.000
	(0.004)	
Married	0.008*	0.000
	(0.004)	
Essential worker	0.067***	0.005
	(0.004)	
Observations	705,024	

Notes: White is the omitted category for race. State and Time Effects included.

viduals searching for these jobs, meaning the price of labor was cheaper for in-person workers. Though the data was collected over a limited period, our statistically significant results offer optimism regarding the future of teleworking. These results also build on the previously published literature. The increase in productivity but decrease in wages for in-person wages offers new insight into how productivity and wages varied during the COVID-19 pandemic. In summary, our research provides some insight on the relevant question of worker productivity during and after the height of the COVID-19 pandemic. The yielded results suggest that teleworking will continue to be relevant in the future.

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Appendix

Table 7: Appendix: Definition of Variables

Variable	Vector	Description	Type	Notes
wage	Y_{IT}	Productivity metric	Continuous	Hourly wage
hours	Y_{IT}	Hours usually worked per week at all jobs	Categorical	1 if not working, 2 if part-time, 3 if full-time, 4 if over-time
covidtelew	X_{IT}	Worked remotely for pay due to COVID-19	Binary	1 if worked remote, 0 if not
vax_50	S_{IT}	Shock Variable for Stages of Vaccination	Binary	0 if ¡50% vaccinated, 1 if $\geq 50\%$ vaccinated
essenocc	M_{IT}	Essential occupation	Binary	1 if essential, 0 if non-essential
educ	Z_{IT}	Educational attainment	Categorical	Includes grades, diplomas, and degrees
child	Z_{IT}	Has children	Binary	1 if yes, 0 if no
female	Z_{IT}	1 if female	Binary	1 if female, 0 if male
age	Z_{IT}	Age	Continuous	Age of observed individual
race	Z_{IT}	Race	Categorical	Includes White, Black, American Indian, Asian, Mixed
married	Z_{IT}	1 if married	Binary	1 if married, 0 if not