THE IMPACT OF CHILDCARE CENTER CLOSURES AND REOPENINGS DURING COVID-19 PANDEMIC ON EARNINGS OF PARENTS WITH YOUNG CHILDREN

Research Paper

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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 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

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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 aren't just facilities--they're 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? 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 & 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 induced closures further highlighted this vulnerability. Collins et al. (2020) 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%.

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 on 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 aren't 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 of 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. The study that was conducted in the Netherlands uses the multinomial logit model to examine the decision making processes, which shows the positive attitudes for both childcare and work. 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 an area. For example, a study by Bauearnschuter examines the impact of German public care reform on maternal employment rates, using instrumental variables and difference in differences approaches. Another study by Russel investigates the effects of childcare center closures during the COVID-19 pandemic focus on mothers of young children. These studies utilizes econometric methods to assess the impact of childcare policies and availability on women's employment outcomes.

Many studies have employed econometric methods to examine the impact of childcare policies and availability on women's employment outcomes. One paper closely related to this research utilized Labor Supply-Evidence From Two Quasi Experiments (Bauernschuster, 2015). This paper uses the instrumental variable and difference-in-differences (DID) approaches to assess the effects of a German public care reform in 1996. It further investigates 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 within this paper may include potential unobservable factors that could sway the results and the specificity of the German context, which may not be generalized to other countries.

One other notable contribution regarding this subject is from “Effect of Mandatory childcare center closures on women’s labor…” which investigates the impact of childcare center closures during the COVID-19 pandemic on women’s labor outcomes (Russel, 2020). 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 is 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 utilization of certain economic methods, however it goes over the measurement of quality in childcare centers, focusing on the two key aspects of regulatable elements (Scarr, 1994). The significance of this journal is that it generalizes the quality it measures in research, as they impact the children's developmental outcomes and well being.

Our research has the potential to contribute to the existing literature by providing empirical evidence on 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 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 influences 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 of accessible, affordable childcare.

With the COVID-19 pandemic that emerged in late 2019, it presented many challenges to the operation of childcare centers not just in the United States but gloabally. As the virus spread rapidly, many concerns of 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 were intended to be temporary in order to protect the public health however the policy instead created long-lasting implications for the childcare industry and the families it serves.

Many studies were created in order to take a deeper look on the long term effects the policy had created. A study by Lauren Russel and Chuxuan Sun, that summarizes the enduring consequences of impermanent measures of prolonged effects of compelled childcare center shutdowns on parental labor market results, indulges into the long term repercussions of these temporary policy measures (Russell & Sun, 2022). Studies like this are crucial in shedding light on the last consequences of childcare center closures and contribute to the ongoing predicament on childcare policy in the United States.

III. Descriptive Analysis

3.1 Data Overview

Our dataset is compiled by Dr. Klara Peter 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. The data is longitudinal, meaning it tracks the same type of information on the same subjects at multiple points in time. There are 1,588,349 observations.

We have information about family structure characteristics, since they are 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); ethnicities only cover White, Black, American Indian, 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

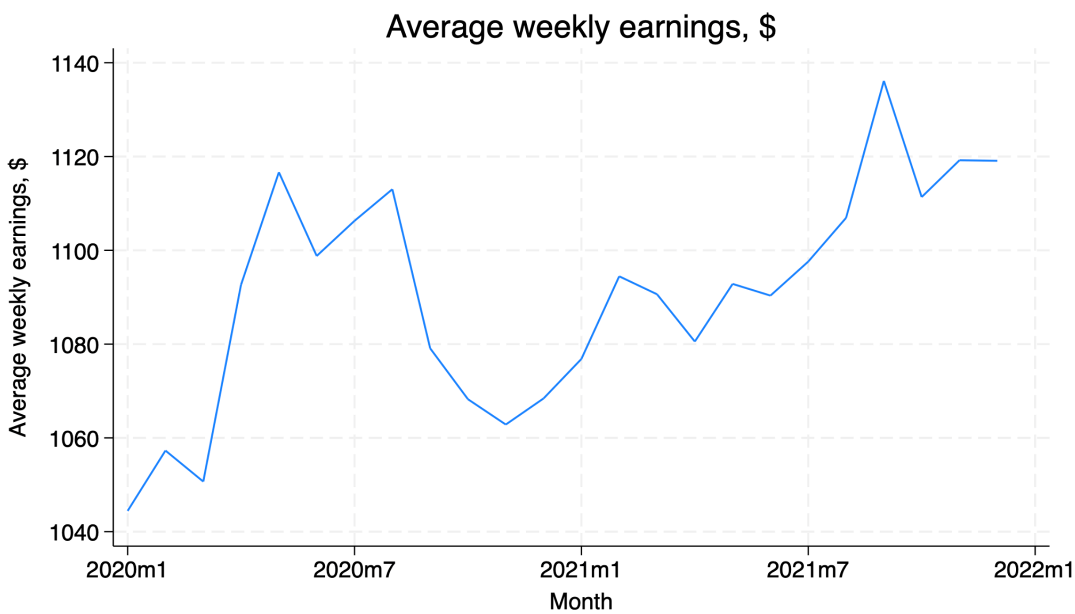
The key variables in our analysis are the policy variable, indicating the stage of childcare centers reopening, the group variable, indicating whether the individual has a child under the age of 5, and the outcome variable, which is weekly earnings. This section will explain the structure of these key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



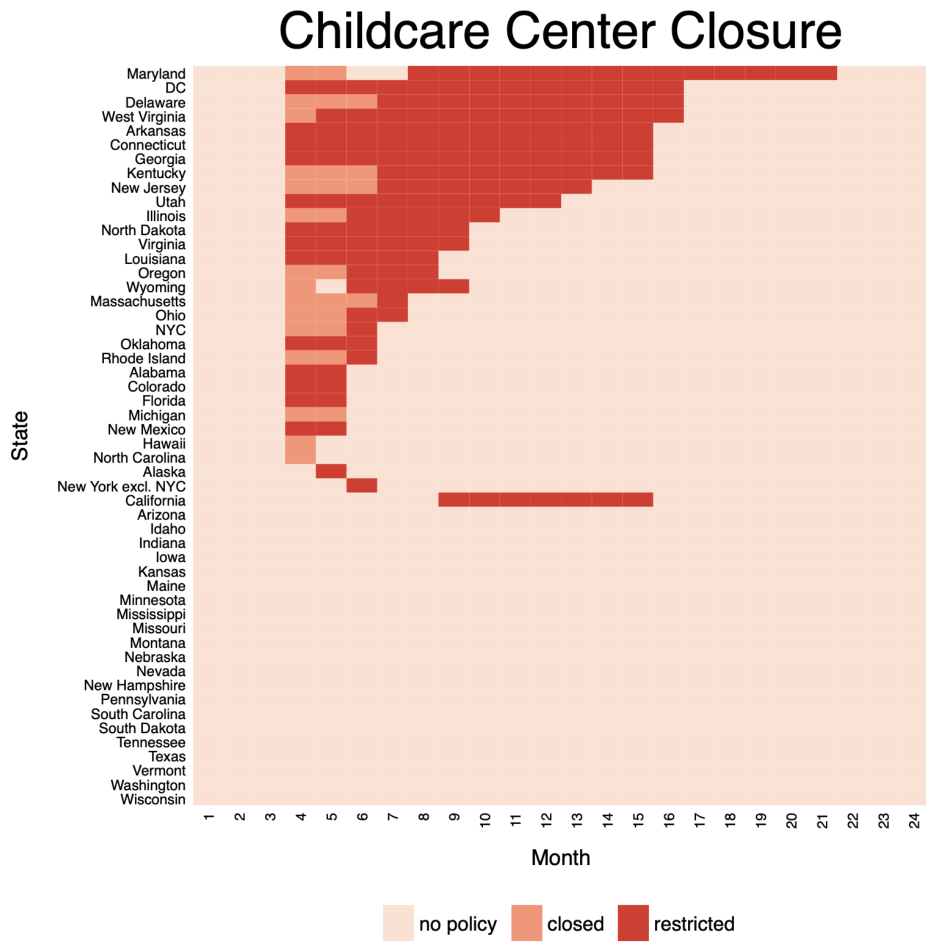
Note: Figure 1 displays the trends in average weekly earnings from January 2020 to January 2022.

Weekly earnings increase during the first half of 2020, which can be attributed to a number of 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 from 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 US 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. A study by Barnett et al. shows the complete shutdown of both public and private childcare facilities by June 2020 (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: Figure 2 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 US. 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: Tabulation of Policy Variable (Stage of Childcare Center Reopening)

Stage of Childcare Center Reopening	Freq.	Percent	Cum.
[0] No policy or CCC closed	355171	40.08	40.08
[1] CCC restricted	129412	14.60	54.68
[2] Post-policy	401553	45.32	100.00
Total	886136	100.00	

Table 2: Summary Statistics of Outcome, Group, and Control Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Weekly earnings	204584	1102.942	727.108	52.5	2884.61
Own children age <= 5	886136	.142	.349	0	1
Hours worked per week	826977	39.939	10.859	1	140
Number of own children in household	886136	.839	1.148	0	9
Essential Occupation	886136	.438	.496	0	1
Female	886136	.479	.5	0	1
Married	886136	.547	.498	0	1

Table 3: Tabulations of Ethnicity and Educational Attainment (Categorical Controls)

Race-ethnicity categories	Freq.	Percent	Cum.	Educational attainment	Freq.	Percent	Cum.
[1] NH White	601322	67.86	67.86	[1] Less than HS	61795	6.97	6.97
[2] NH Black	81031	9.14	77.00	[2] High school degree	466887	52.69	59.66
[3] NH American Indian	7467	0.84	77.85	[3] Bachelor's degree	224376	25.32	84.98
[4] NH Asian	55688	6.28	84.13	[4] Graduate degree	133078	15.02	100.00
[5] NH other/mixed	12684	1.43	85.56				
[6] Hispanic (any race)	127944	14.44	100.00				
Total	886136	100.00		Total	886136	100.00	

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

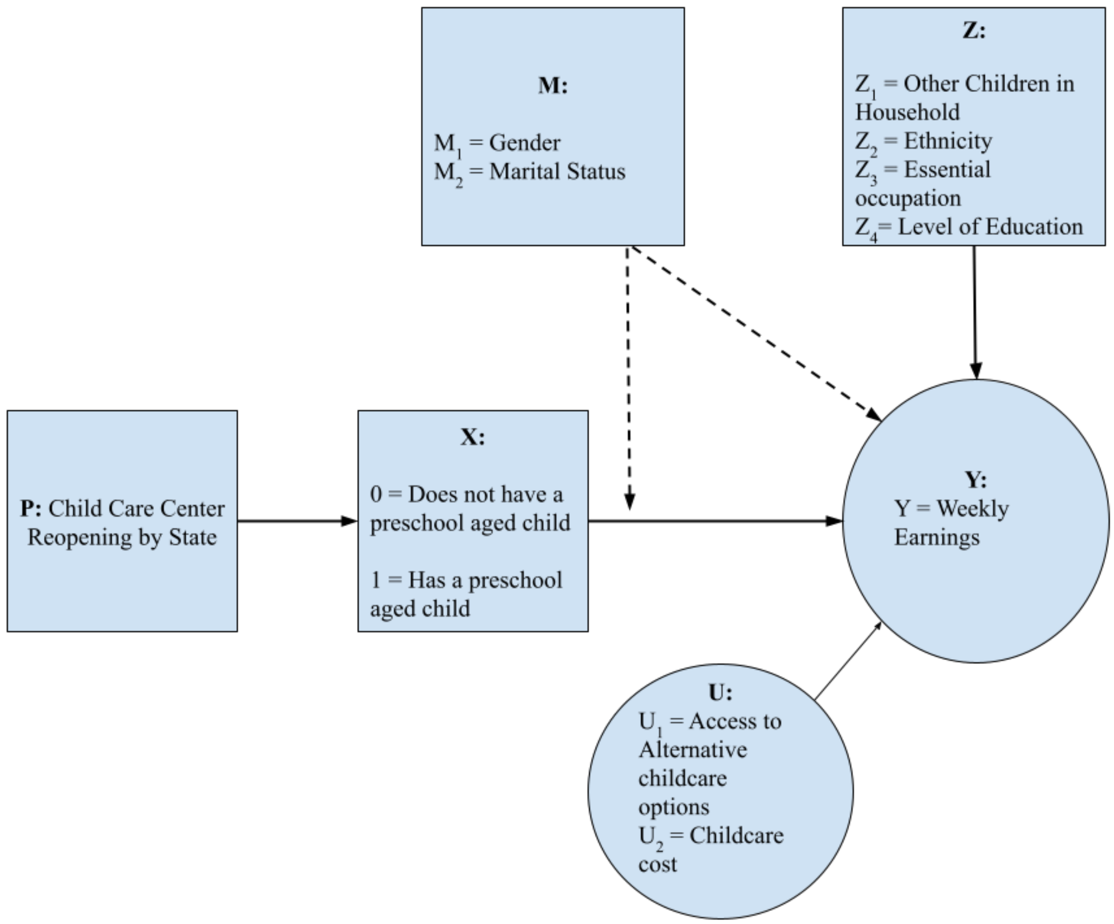
$2884.61/week. 14.2% of observations in our dataset (125,831 observations) are people with children under the age of 5 – these are the observations we expect to be most affected by the policy. The mean number of children in the household is below 1 despite the range of values being from 0 to 9, indicating 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.

IV. Empirical Framework

4.1 Flow Chart

As illustrated in Figure 3 below, 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.

Figure 3: Empirical Model Flowchart



Our Z 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, American Indian, and Hispanic counterparts. Individuals with essential occupations will typically earn more due to a higher need for their job. The more educated you are, the higher your earnings will most likely 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, 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_i = state fixed effects, and θ_t = time fixed effects.

$$Y_{it} = \beta_0 + \beta_1 * X_{it} + \beta_2 * Z_{it} + S_s + \theta_t + u_{it} \quad (1)$$

S_i 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: $married_{it}$ (marital status) and $female_{it}$ (gender of parent).

$$Y_{it} = \beta_0 + \beta_1 * X_{it} + \beta_2 * Z_{it} + \beta_3 * female_{it} + \beta_4 * married_{it}$$

$$+ X_{it}(\beta_5 * female_{it} + \beta_6 * married_{it}) + S_s + \theta_t + u_{it} \quad (2)$$

Our results from both the basic OLS model and the OLS model with moderating variables are presented in the following table below.

Table 4:OLS Model Estimates

VARIABLES	(1) OLS Model	(2) OLS Model 2
Own children age 5 or younger in household	-30.14***	40.80***
	(4.571)	(8.485)
Female		-314.1***
		(2.912)
Has child under 5 X female		-79.35***
		(7.719)
Married		192.2***
		(3.084)
Has child under 5 X married		-74.59***
		(8.090)
Number of own children in household	64.54***	37.51***
	(1.440)	(1.438)
NH Black	-197.5***	-132.9***
	(4.519)	(4.469)
NH American Indian	-124.1***	-83.38***
	(12.92)	(12.41)
NH Asian	-32.89***	-40.79***
	(6.784)	(6.573)
NH other/mixed	-111.3***	-67.67***
	(11.43)	(11.06)
Hispanic (any race)	-166.5***	-149.1***
	(4.083)	(3.919)
Essential Occupation	-111.8***	-152.0***
	(2.973)	(2.920)
HS degree	279.2***	270.0***
	(3.965)	(3.737)
Bachelor's degree	695.5***	679.9***
	(5.121)	(4.894)
Graduate degree	973.0***	952.9***
	(6.082)	(5.888)
Own children age 5 or younger in hh	-30.14***	
	(4.571)	
Constant	634.5***	715.2***
	(11.81)	(11.43)
Observations	204,584	204,584
R-squared	0.258	0.323
State FE	Yes	Yes
Month FE	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: OLS Model 1 represents just the relationship between having a child under the age of 5 and the individual's earnings. OLS Model 2 represents the same relationship but with moderating binary variables, female and married, included.

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 doesn't include the moderating variables. The coefficient on female in OLS Model 2 is -314.1, meaning that being a woman means on average, you make $315.20 less than a man. On the other hand the coefficient on married in OLS Model 2 is 192.2, indicating that being married on average, means you will make $192.20 more than an unmarried individual. The coefficient on haschild5*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 haschild5*married 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. Difference-in-Differences Models

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 will 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):

$$Y_{it} = \alpha + \beta Z_{it} + \gamma P_{st} + S_s + \theta_t + \varepsilon_{it} \quad (3)$$

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 P_{st} is a categorical variable that represents what stage of the childcare center closure policy an individual i is experiencing. The control group will take on the value of 0 for the entirety of the time period, because they never implemented a closure policy, nor reopened. The treated group will take on values of 0, 1, and 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, ages of individuals span from 15-64. Educational attainment has 4 categories (less than HS, HS degree, bachelor's degree, graduate degree). Ethnicities cover White, Black, American Indian, Asian, other/mixed, 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 the Appendix, Table A. 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, American Indian, 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 classical DID model, we assume that our control variables will be exogenous ($cov(Z_{it}, \varepsilon_{it}) = 0$). This means that they do not correlate with unobserved factors and are not easily affected by the policy. We also make the parallel trend assumption ($cov(P_{st}, \varepsilon_{it}) = 0$), which states that the absence of treatment implies the treated group will have the same outcomes as the non-treated group. The conditional independence assumption will be violated since our treatment (states that implemented a childcare center reopening policy) is not random. To account for this violation, we will need to include control variables and many 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 below:

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

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).

Table 5: Model Estimates (DID and Triple Differences)

VARIABLES	Equation (3) DID Model	Equation (4) Triple Differences Model
Pst = 1, CCC restricted	9.453	4.937
	(10.26)	(10.40)
Pst = 2, Post-policy	-0.436	-3.016
	(10.67)	(10.73)
Own children age 5 or younger in household		-42.59***
		(6.533)
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	60.36***	64.58***
	(1.271)	(1.440)
NH Black	-197.3***	-197.4***
	(4.520)	(4.518)
NH American Indian	-123.9***	-124.1***
	(12.93)	(12.93)
NH Asian	-33.01***	-32.85***
	(6.780)	(6.784)
NH other/mixed	-112.0***	-111.3***
	(11.44)	(11.43)
Hispanic (any race)	-166.8***	-166.6***
	(4.083)	(4.083)
Works in essential occupation	-112.3***	-111.8***
	(2.973)	(2.973)
HS degree	278.2***	279.2***
	(3.960)	(3.966)
Bachelor's degree	693.9***	695.6***
	(5.111)	(5.121)
Graduate degree	971.1***	973.1***
	(6.073)	(6.082)
Constant	633.6***	634.8***
	(14.02)	(14.03)
Observations	204,584	204,584
R-squared	0.258	0.258
State FE	Yes	Yes
Month FE	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

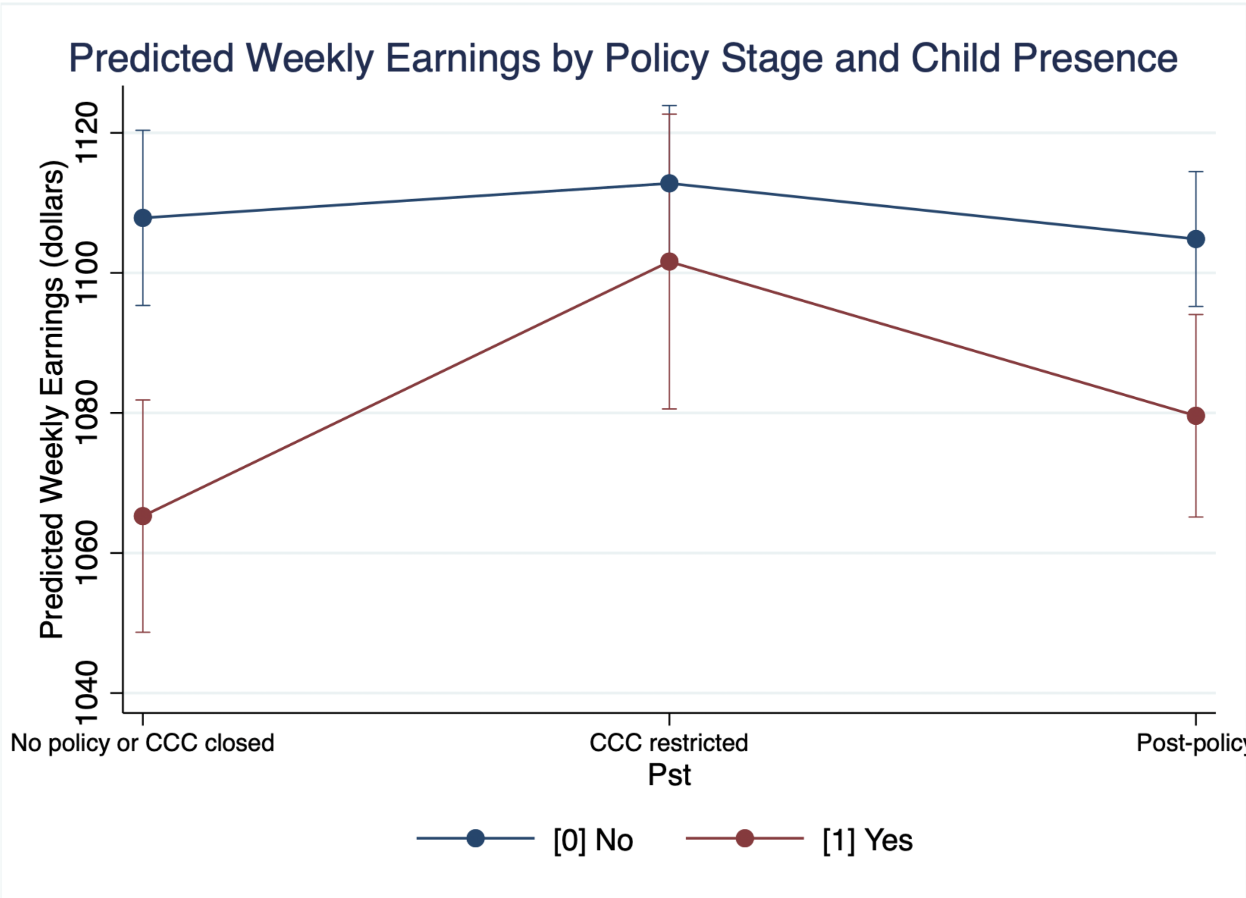
Notes: This table reports the results for estimation equations (3) and (4). The dependent variable is weekly earnings. The numerical values next to variable names represent the coefficients of those variables, and the numbers in parentheses represent the corresponding standard errors.

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 that the magnitude of the increase in earnings is greater during restricted childcare center openings than it is for full reopenings.

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.

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.

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 began 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.

With “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) and low p-value (0.000), indicating a substantial difference in the number of children. The percentage bias is at 139.1% suggesting a significant difference.

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.

Table 6: Group Balancing by Presence of Child

	Mean			t-test		
Variable	Treated	Control	%bias	t	p>t	V(T)/ V(C)
Number of children in HH	2.091	0.621	139.100	319.350	0.000	1.26*
NH Black	0.090	0.101	-3.600	-7.810	0.000	.
NH American Indian	0.013	0.011	1.6	3.670	0.000	.
NH Asian	0.080	0.075	1.9	4.130	0.000	.
NH other/mixed	0.018	0.017	1.1	2.490	0.013	.
Hispanic	0.171	0.149	6.1	13.710	0.000	.

Essential Occupation, [1] Yes	0.437	0.436	.1	0.280	0.783	.
High school degree	0.467	0.528	-12.200	-26.860	0.000	.
Bachelor's degree	0.274	0.253	4.6	10.270	0.000	.
Graduate degree	0.201	0.149	13.700	31.450	0.000	.

* if variance ratio outside [0.98; 1.02]

Ps R^2	LR X^2	$P > X^2$	MeanBias	B	R	%Var
0.231	75163.84	0.000	18.4	4.1	1.19	100

* if B > 25%, R outside [0.5;2]

In terms of the other measures at the bottom of Table 6, we find that the LR X^2 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 % 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 not similar enough 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: Model estimates with and without group balancing (IPW)

VARIABLES	(1) Triple Differences Without IPW	(2) Triple Differences 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)
NH Black	-197.4***	-235.578***
	(4.518)	(12.170)
NH American Indian	-124.1***	-93.616***
	(12.93)	(25.541)
NH Asian	-32.85***	-15.623
	(6.784)	(14.794)
NH other/mixed	-111.3***	-91.738***
	(11.43)	(22.973)
Hispanic (any race)	-166.6***	-194.760***
	(4.083)	(11.991)
Works in essential occupation	-111.8***	-117.292***
	(2.973)	(7.824)
HS degree	279.2***	209.622***
	(3.966)	(11.281)
Bachelor's degree	695.6***	661.459***
	(5.121)	(13.189)
Graduate degree	973.1***	923.640***
	(6.082)	(15.605)
Constant	634.8***	
	(14.03)	
Observations	204,584	92,387

R-squared	0.258	0.277
State FE	Yes	Yes
Month FE	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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.

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 A: Control Variables

Descriptive Statistics

Variable Name	Variable Label	Type	Notes about variable construction
nchild	Number of own children in household	Categorical	0-8 children holds own numerical value, families with 9+ children coded as 9
ethnicity	Race-ethnicity categories	Categorical	Categories: 1) NH White 2) NH Black 3) NH American Indian 4) NH Asian 5) NH other/mixed 6) 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	Educational attainment level	Categorical	Categories: 1) Less than HS 2) High school degree 3) Bachelor's degree 4) Graduate degree

Link to log file:
https://drive.google.com/file/d/1TY2rrKXniRJa1tm8iOdqb8Y7MvK1_IUB/view?usp=drive_link