June 2022

Did K-12 school closure and reopening policies in response to COVID-19 enlarge the gender employment gap?

Xinyi Wang
wangx2040@gmail.com

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April 27, 2022

Advisor: Felix Friedt

Economics Department

Acknowledgement:

I would like to express my special thanks of gratitude to my advisor Felix Friedt who gave me the golden opportunity to do this honor project on the topic (Did K-12 school closure and reopening policies in response to COVID-19 enlarge the gender employment gap?). I would also like to thank to my committee members Amy Damon and Julie Dolan for their generous suggestions and I came to know about so many new things.

Secondly, I would also like to thank my parents and friends who helped me a lot in finalizing this project within the limited time frame. I would like to thank to Xiaoyan for her emotional support throughout this project.

Thanking you,

Xinyi Wang

April 27, 2022

Abstract:

The COVID-19 pandemic hits female workers the most. This impact on the United States's labor market can be attributed to the limited availability of childcare and schooling options (Stefania and Jiyeon, 2021). With limited resources for childcare and schooling, parents, especially mothers, had to exit the labor force or reduce working hours to stay at home and take care of their children. My study will contribute to understanding the effect of the child penalty, especially under the COVID-19 pandemic and study the impact of school closure and reopening policies. Using data from Current Population Survey (CPS) combined with school closure and reopening data, I conduct both static and dynamic analyses at the extensive (i.e. employed or not) and intensive (i.e. # of hours worked) margins. I find that for a worker, who has at least one child in the household, compared to a worker with the same occupation, in the same industry and similar location is around 76% less likely to be employed when schools are closed while a female worker tends to be 34% more likely to be employed than a male worker after the school has been reopened.

Introduction:

The gender gap index across economic participation, educational attainment, health and survival, and political empowerment subindexes have narrowed over time (World Economic Forum, 2020). However, with the COVID-19 outbreak in Wuhan, China in December 2019, COVID-19 soon grew into a global pandemic within a few weeks. As the impact of the COVID-19 pandemic continues to be felt, the estimated time that is needed to close the whole gender gap has increased from 99.5 years to 135.6 years (World Economic Forum, 2021).

Stefania and Jiyeon (2021) state that unlike other recessions in United States' history, where men usually experience larger employment drops, the COVID-19 recession resulted in larger employment losses for women. This unique impact on the United States's labor market can be attributed to the limited availability of childcare and schooling options (Stefania and Jiyeon, 2021). With such limited resources for childcare and schooling, parents, especially mothers, had to exit the labor force or reduce working hours to stay at home and take care of their children.

My study will contribute to understanding the effect of the child penalty, especially under the COVID-19 pandemic. By examining different phases of school closures and reopening policies and distinguishing between households with and without school-aged children, I will quantify the child employment penalty during the pandemic and differentiate the effects by gender. This study will focus on the different labor outcomes, including the probability of being employed (extensive margin) and the number of hours worked (intensive margin). While the effect of school closure policies has been studied and shown to have an enlarging effect on the gender employment gap, this study will emphasize the effect of school reopening policies and evaluate whether the closure effects are reveresed. This analysis leverages detailed data from the Current Population Survey and attempts to identify the effects at two levels of spatial aggregation. First, at the state-level where I observe school closure/reopening policy data for all states. Second, at the county-level, where I observe school closure/reopening data for California only.

Literature Review:

Gender pay inequality is ubiquitous in society. Hall and Krueger (2012) verified that around one-third of the US working force did not see transparent wages. The gender pay gap is not driven by level of education but by gender discrimination specifically in the labor market. Irimie et. al, (2014) conducted theoretical research which demonstrated gender inequality is a common phenomenon in the labor market, and it is usually caused by discrimination and gender biases. They compared the gender difference between the education period and later career, in which they discovered employers are keen to hire male graduates, regardless of whether a woman would be more appropriate or not. When men are obviously favored in the labor market, women can only work in positions that they are not familiar with, resulting in lower productivity than men, which causes low payment for women.

Although the gender income gap is ubiquitous, COVID-19 made the situation worse. The COVID-19 pandemic shocks the labor market in the US. Based on the experiences during previous recessions in the United States' history, one might have expected men to experience a larger employment drop as usual during COVID-19.

However, the COVID-19 pandemic hit the United States' labor market quite differently, with women being hit the most. Stefania and Jiyeon (2021) studied the effects of the COVID-19 on the labor market of the US, especially from the perspectives of occupation, family, and gender. According to their findings, occupation and the increased childcare factors are two unique factors that may account for the opposite result in the labor market. Since women are mainly employed in the service occupation, which tend to be contact and inflexible jobs, women are more likely to lose their jobs. Plus, the fact that there is a substantial "child penalty" which may reduce women's wages even before they give birth to their first child. This study will focus on the second unique factor, which is the increased childcare factor, and try to explain the gender income and employment gap change during the COVID-19 pandemic.

A new study from the Center for Global Development (2020) suggests that each woman provided up to 173 additional hours in childcare in 2020 through October, compared to only 59 additional hours from men. The reason why I focus on the effect of increased childcare is that it is strongly related to the child penalty. The child penalty has been studied a lot and research suggests that child penalty may contribute a large portion of the gender income gap. Francesca, B, and Helmuth, C, and Chiara, M (2019) constructed a model to study the difference between men and women in informal childcare. They separated informal childcare into two types: basic care (feeding, changing children, baby-sitting) and quality care (activities that stimulate children’s social and cognitive skills). Based on their predictions and real data from Italy, mothers tend to devote more time than fathers in both basic and quality informal childcare. More educated mothers also devote more time to quality informal childcare and also spend more time in the labor market than less-educated mothers. Mark Aguiar and Erik Hurst (2007) use five decades of time-use surveys to document trends in the allocation of time within the United States. They find a clear trend that women have carried a heavier load for childcare than men even before the COVID-19. During COVID-19, this gender gap in childcare intensified. Given such disparities in the time allocation on childcare between men and women, the consequence of such differences draws attention to the gender gap in the labor market as women may not be able to work as many hours as men.

Patricia and Jessica (2018) focused on the role of children in explaining the remaining gender gap in the labor market. In their analysis, they discover that over two-thirds of the gender income gap can be explained by the differential impact of children on men and women. Since children play a huge role in explaining the gender income gap, I focus on the school policies to see whether different school policies will affect the gender gap.

School closure policies have been proven to have different impacts on the working styles of men and women. Eiji, Y, and Yoshiro, T (2021) have studied the impact of closing schools on working from home during the COVID-19 pandemic for the period of school closure from mid-March to mid-April 2020. Specifically, they studied the impact of how the presence of the children affects parents' work and how the effect of their children differs between genders. After controlling various variables, they reached the conclusion that mothers are more likely to work at home in order to keep an eye on their children when their children are in primary school while fathers’ working styles are less likely to change. However, when their children are in junior high school, both parents’ working styles are hardly affected. Such results affirm the heavier burden on mothers of young children compared to fathers. A similar result has been found by Collins C, Ruppanner L, Christin Landivar L, Scarborough WJ (2021). They combined the Elementary School Operating Status database and Current Population Survey to study the effect of remote learning on labor force participation and concluded that the gender gap in labor force participation increased by 5% due to K-12 distance learning.

Acknowledging such differences in childcare for different genders especially with school closure policies, this study will focus on the trade-off between childcare and employment during the COVID-19 pandemic. The study is focused on households with young children. School closure policies have been studied and proven to affect women workers more. However, my study will not only look at the K-12 school closure policies but also the K-12 school reopening policies in order to compare the difference between those with children at home and those without children at home. When comparing the K-12 school reopening policies, my study will try to explain if the gender employment gap caused by the K-12 school closure policy automatically recovers after the K-12 school, or if those K-12 school closures may have a long-term effect on the gender employment gap.

Model:

Theory:

After the CDC confirmed the first laboratory-confirmed case in Washington DC on January 21st 2020, COVID-19 soon spread to all states in the United States within several weeks. COVID-19 spreads when an infected person breathes out the very small particles that contain the virus, and are then breathed in by others or contaminate surfaces. Under such circumstances, people within 6 feet of an infected person are the most likely to be infected (CDC, 2020). Schools, however, fall into the category above of close-contact institutions as most of the activities happen within 6 feet between both students and teachers. Thus, schools have been considered high-risk places where COVID-19 can easily spread. In order to minimize the spread of COVID-19, governors declared states of emergencies and followed the recommendation from the CDC to close the schools.

Under states' orders, K-12 schools had ended in-person instructions in March 2020 and offered remote learning options instead. Students ages 5-18 were forced to stay at home as a result of school closure. This has effects on parents' employment outcomes. In fact, according to Fabrizio, Gomes and Tavares (2021), women with young children, younger than 12 years old, have been disproportionately affected compared with other women and men in terms of employment loss. This can be attributed to the extra childcare that those women have to provide. According to a new study from the Center for Global Development (2020), each woman provided up to 173 additional hours in childcare since COVID-19 has started through October 2020, compared to only 59 additional hours from men. With such a huge difference in the hours for childcare, women are left with shorter time for work. Consequently, they are more likely to be separated from the labor market than men. In addition, COVID-19 hit the service industry the most, which lead to a great reduction in demand for services. Since women are more likely to be employed in a service industry, this compositional effect leads to a greater reduction in demand for female workers.

The employment effects are further complicated by the potential heterogeneity across household income. For example, households with good financial standing will be able to take care of the children if their work is remote. If remote work is unavailable, such household can still afford to pay for a huge amount of money to hire someone to take care of their children or have mom/dad stays at home and take care of the children. On the other hand, these households may be able to afford to take time off work to take care of the children. If it is a mom whose work is not remote and they do not want to hire someone for childcare, then the gender employment gap occurs, while if it is a dad whose work is not remote or they are willing to hire someone for childcare, then there may be no gender employment gap. Although such circumstance rarely happens to a good financial standing household, high-paying jobs are most likely to be remote so that both parents will be able to work at home. In this case, I am expecting a 0 or small effect of school closure on the gender employment gap for those households with good financial standing.

However, things are different for low-income households. They do not have the option to hire others to take care of their children. Moreover, low-paying jobs are less likely to offer a remote work environment when children return home, at least one of the parents needs to reduce working hours or leave the labor market to take care of children. Since females usually work in the service industry and COVID-19 hits the service industry the most, then the demand for female workers decreased a lot. If it is a mom whose work is not remote, then mon has to quit the job for childcare as they cannot leave the child alone at home and the dad has to go to work to support the family. If both parents' works are not remote, then when there is a chance for returning back to work, it is usually the dad who returns back to work and leaves mom at home with children. Thus, it is more likely that the female workers who leave the labor market. In this case, I am expecting a large impact of school closure on the gender employment gap for those households with poor financial standings. Through the above mechanisms, COVID-19 can point to a significant employment penalty for women, especially when schools are closed under the COVID-19 pandemic.

Acknowledging such employment penalty for women under the COVID-19 pandemic, school reopening may counteract such enlarged gender employment gaps. For low-income families, they no longer need to choose between mom and dad who stay at home and take care of the children while the other works. When schools reopen Moms are more likely to be relieved from the extra childcare that usually occurred when their children stay at home and may be able to restart their full-time jobs. However, even if moms are willing to restart their jobs, some of them may be unable to find jobs and remain unemployed. Thus, I am expecting the enlarged gender employment gap to be closed or reduced by the school reopening policies. Similar to the closure effects, school reopening should have a larger effect on the gender employment gap observed for low-income households.

Empirical Model:

To quantify the effect of school closure/reopening on employment, I run two kinds of regression analyses at both the state-level and county-level: one is the static model and the other is the dynamic model. The static model for state from extensive margin perspective for school closure is given as follows:

$$logit(y_{i,k,s,o,t}) = \beta_0 + \beta_1 Female_i + \beta_2 Closure_{s,t} + \beta_3 Closure_{s,t} * Female_{i,t}$$

$$+\gamma * controls + \alpha_k + \alpha_s + \alpha_o \times \alpha_t + \varepsilon_{i,k,s,o,t}$$

Static model for state from extensive margin perspective for school reopening:

$$logit(y_{i,k,s,o,t}) = \beta_0 + \beta_1 Female_i + \beta_2 Open_{s,t} + \beta_3 Open_{s,t} * Female_{i,t}$$

$$+\gamma * controls + \alpha_k + \alpha_s + \alpha_o \times \alpha_t + \varepsilon_{i,k,s,o,t}$$

Where i indexes an individual, k indicates industry, s indicates state, o indicates occupation and t indexes time. The extensive margin is measured via the outcome variable $y_{i,k,s,o,t}$, which indicates the employment status of the individual at time t, in s state and k industry with occupation o. $Closure_{s,t}$ indicates the dummy for the school closure policy within that individual's state at time *t*, with $Closure_{s,t} = 0$ for school has not been ordered closed in that state at time t and $Closure_{s,t} = 1$ for school has been ordered closed in that state at time t. $Open_{s,t}$ indicates the dummy for the school reopening policy within that individual's state at time *t*, with $Open_{s,t} = 0$ for school has been ordered closed in that state at time t and $Open_{s,t} = 1$ for school which is partially opened or fully opened in s state. $Female_i$ indicates the dummy for gender, with $Female_i = 0$ for males and $Female_i = 1$ for females. $controls$ includes a set of controls for age, COVID-19 new cases, vaccine rates, family size, whether the person has difficulty, education attainment, whether the person is white, family income. α_k is the fixed effect term for each industry, α_s is the fixed effect term for each state. $\alpha_o \times \alpha_t$ is the cross fixed effect for occupation and time, which will help control the occupation change throughout the time. By controlling for industry, family income and the cross effect of occupation and time, I will be able to account for most of the difference between different industries and occupations throughout the time. However, this does not take the potential triple-cross fixed effects between time, industry, and occupation into account as this will generates too many levels inside this term, which may not produce statistically insignificant results. And $\varepsilon_{i,k,s,o,t}$ is the error term.

For the school closure effect, this research conducts logistic regression for state level analysis from September 2018 to July 2020[1], which is before the first state that has published any school reopening policy. For the school reopening effect, this research conducts logistic regression from April 2020 to September 2021. By separating the effect of school closure and school reopening policies, this would reduce any potential drawbacks of combining both policies in the same model as the trend caused by school closure or reopening are sperate from each other.

The static model from extensive margin used the difference-in-difference method, and the coefficients of interest are β_2 which captures the effect of school closure or reopening on male workers' employment and β_3 captures the differentiate effect of school policies on female workers' employment other than male workers. Thus, the effect of school closure or reopening policies on female workers' employment would be $\beta_2 + \beta_3$.

The static model for state from intensive margin perspective would be the same model as the extensive perspective model. The key difference is that $y_{i,k,s,o,t}$ indicates the hours worked last month (rather than if an individual is employed or not) and I use $\ln(y_{i,k,s,o,t})$ to replace $\text{logit}(y_{i,k,s,o,t})$ in the equation. The equations for school closure and school reopening policies will be as follows:

$$ln(y_{i,k,s,o,t}) = \beta_0 + \beta_1 Female_i + \beta_2 Closure_{s,t} + \beta_3 Closure_{s,t} * Female_{i,t}$$

$$+\gamma * controls + \alpha_k + \alpha_s + \alpha_o \times \alpha_t + \varepsilon_{i,k,s,o,t}$$

[1] For the county level, to analyze the school closure effect, I include data from September 2018 to August 2020.

Static model for state from intensive margin perspective for school reopening:

$$ln(y_{i,k,s,o,t}) = \beta_0 + \beta_1 Female_i + \beta_2 Open_{s,t} + \beta_3 Open_{s,t} * Female_{i,t}$$

$$+\gamma * controls + \alpha_k + \alpha_s + \alpha_o \times \alpha_t + \varepsilon_{i,k,s,o,t}$$

The static model from intensive margin also uses the difference-in-difference method, and the coefficients of interest are β_2 which captures the effect of school closure or reopening on male workers' working hours and β_3 captures the differentiated effect of school policies on female workers' working hours. Thus, the effect of school closure or reopening policies on female workers' employment would be $\beta_2 + \beta_3$.

Similarly, both models for county-level analysis from an intensive perspective and an extensive perspective will be the same as the models for state-level analysis but instead of having state-level policies, I am having county-level policy here.

One potential drawback of the state-level analysis is that there are other differences between each state that I can hardly control for. These include, for example, the demographic and other labor market policies differences. Different labor market policies in each state may affect the labor outcome of that state and if these effects are correlated with school policies then the conclusion of this research can be overstated. Also, in the state-level dataset that I am using, only 20 states have mandatory school closure or reopening policies while the rest of them will let the districts decide whether to close or reopen schools on their own, which makes it hard to know the real opening status within that state. Therefore, I also consider the county-level analysis to overcome the disadvantages at the state level. A county-level analysis (within the same state) accounts for the difference in state-level labor market policies and alleviates some of the concerns. However, even at the county-level there may be some unobservable county actions during the pandemic that may confound our results. These actions would have to be correlated with school closure/reopening policies.

In addition to the static analysis, I also develop a county-level dynamic model of the school reopening effects. Specifically, I separate monthly effect of reopening policies before and after the announcement of school reopening policy.

A dynamic model for reopening from extensive margin perspective is given as follows:

$$y_{i,k,c,o,t} = \beta_0 + \beta_1 Female_i + \sum_{z=-12}^{12} \beta_z \, Open_{c,t,z} + \sum_{z=-12}^{12} \gamma_z \, Open_{c,t,z} * Female_i + \tau * controls + \alpha_k + \alpha_c + \alpha_o \times \alpha_t + \varepsilon_{i,k,c,o,t}$$

Where i indexes an individual, k indicates industry, c indicates county, o indicates occupation and t indexes time, $y_{i,k,c,o,t}$ is the dependent variable and indicates the employment status of the individual at time t, in c county and k industry with occupation o. $Open_{c,t,z}$ indicates the dynamic dummy for the school reopening policy within that individual's county, with $z<0$ represents the time before the school has been reopened and $z>0$ represents the time after the school has been reopened, for example, $Open_{c,t,-1}$ represents the dummy for one month before the school ordered open and $Open_{c,t,1}$ represents the dummy for 1 month after the school ordered open. $Open_{c,t,z} = 0$ for school has been ordered closed in that county at time t and $Open_{c,t,z} = 1$ for school which is partially opened or fully opened. $Female_i$ indicates the dummy for gender, with $Female_i = 0$ for males and $Female_i = 1$ for females. $controls$ includes a set of controls for age, COVID-19 new cases, vaccine rates, family size, whether the person has a disability, education attainment, whether the person is white, family income. α_k is the fixed effect term for each industry, α_c is the fixed effect term for each county. $\alpha_o \times \alpha_t$ is the cross fixed effect for occupation and time, which will help control the occupation change throughout the time. And $\varepsilon_{i,k,c,o,t}$ is the error term.

The dynamic model at the county-level from an intensive perspective is similar to the extensive margin model. The key difference is that the outcome variable $y_{i,k,c,o,t}$ captures the hours worked (rather than employment status) and I use $\ln(y_{i,k,c,o,t})$ to replace $y_{i,k,c,o,t}$ in the equation.

Data description

This study uses the Basic Monthly data from Current Population Survey data collected every month during the calendar year from January 2010 to September 2021 and ASEC data from the Annual Social and Economic Supplement of the Current Population Survey from 2010 to 2021. It also combines state-level school closure and reopening data from Education Week and county-level school status data only for California from The Safe Schools For All Hub for California to study the employment status of workers that are in the labor force. I combine these data with information on the cumulative counts of coronavirus cases in the United States from The New York Times as well as the county-level coronavirus infections data from The Los Angeles Times. The closure and reopening policy for schools vary between states in the United States. Since the employment tends to have a delay in reaction to the policy change, I round up the school reopening month. For example, if the school reopened on mid-March 2021, then in my dataset, I count April 2021 as the first month of reopening.

After restricting to individuals that are in the labor force and have at least one child aged from 5-18 years old[2] from March 2019 to Sep 2021, I obtained 650,752 individual-level data for all states in the United States and 38,660 individual-level data for California. The available information includes dependent variables: employment status and hours worked last week; variables of interest: workers' sex (=0 is male, =1 is female), school closure indicator (=0 is open, =1 is closed) and school reopening indicator (=0 is still closed, =1 partially closed, =2 fully opened); and control variables such as: age, state, county, occupation, industry, the number of children they have, the number of own children under age 5, the year and month that the workers reported the data, family income of the household, marital status, worked remotely for pay due to COVID, unable to work due to COVID, COVID-19 cumulative cases, COVID-19 new cases, vaccine rate. I expect someone who has no choice but to keep their children in the household to send their children back to school

[2] Employment status for an individual who is not in labor force will not change with different school policies and school closure or reopening policies will only have very limited effect on the employment status for

if they have such option, which in other words, they will send their children to school when schools are hybrid reopening. So that in our empirical regression, I treat the school reopening indicator as a binary independent variable, with the hybrid reopening to be 1 and closed to be 0.

Table 1 provides summary statistics for our dependent variables and control variables, separating into 3 different time periods. The pre-closure part summarizes the data before any school has been closed (from August, 2018 to February, 2020), the closure part summarizes the data after the first school has been closed and before the first school that has been reopened (from March, 2020 to August,2020) while the reopening part accounts for the data after the first school that has been reopened (from September, 2020 to September, 2021). Control variable “white” is a binary variable that indicates whether the worker’s race is white (=0 is not white, =1 is white). Control variable “education” is a variable that indicates the worker’s education attainment (=0 high school or below, =1 is some college or above). Table 2 offers these summary statistics at the is a county-level.

Table 1. Summary Statistics at the state-level[3]

	(1)			(2)			(3)				
	pre-closure[4]			closure[5]			reopen[6]			t-test	t-test
	Mean	Std. dev.	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.	Obs	(1)-(2)	(2)-(3)

[3] In this table, I restrict our sample size to individuals that are in the labor force and have at least one child aged from 5-18 years old from March 2019 to Sep 2021 for all states and I also separate this time period into 3 smaller periods and conduct 2 t-tests: (1) between pre-closure period and closure period (2) between closure period and reopen period.

[4] The pre-closure period indicates time from September 2018 to February 2020.

[5] The closure period indicates time from March 2020 to July 2020.

[6] The reopen period indicates time from August 2020 to September 2021.

employed (M)[7]	.978	.148	169,706	.944	.229	52,569	.958	.201	107,192	(+)***	(-)***
employed (F)	.969	.173	165,021	.923	.267	50,983	.951	.216	105,281	(+)***	(-)***
hours worked (M)[8]	175.110	47.309	161,914	170.247	48.204	47,718	171.367	47.02193	99,765	(+)***	(-)***
hours worked (F)	150.785	47.718	154,144	145.283	49.391	43,701	148.174	47.02193	95,579	(+)***	(-)***
female	.493	.500	334,727	.492	.500	103,552	.496	.500	212,473	(0)	(-)**
white[9]	.811	.391	334,727	.8117	.3910	103,552	.800	.400	212,473	(0)	(+)***
education 10	.678	.467	334,727	.706	.456	103,552	.688	.463	212,473	(-)***	(+)***
family income	79060.140	44217.600	334,727	83995.600	44188.04	103,552	82359.910	44804.850	212,473	(-)***	(+)***
family size	1.607	.923	334,727	1.541	.779	103,552	1.534	.774	212,473	(+)***	(+)**

Table 2. Summary Statistics at the county-level[11]

		(1)			(2)			(3)			
		pre-closure[12]			closure[13]			reopen[14]		t-test	t-test
	Mean	Std. dev.	Obs	Mean	Std. dev.	Obs	Mean	Std. dev.	Obs	(1)-(2)	(2)-(3)
employed (M)[15]	.972	.165	11,757	.929	.256	3,472	.940	. 238	7,228	(+)***	(-)**

[7] In this table, employed (M) and employed (F) are the dependent variables from extensive margin. And they indicate employment status for male workers and female workers accordingly.
[8] In this table, hours worked (M) and hours worked (F) are the dependent variables from intensive margin. And they indicate the hours worked last month for male workers and female workers accordingly.
[9] White, education, family income and family size are a set of control variables.
[10] Education indicates education background that the individual has. Education =1 if the individual has a degree of college or above and otherwise it is 0.
[11] In this table, I restrict our sample size to individuals that are in the labor force and have at least one child aged from 5-18 years old from March 2019 to Sep 2021 for California only and I also separate this time period into 3 smaller periods and conduct 2 t-tests: (1) between pre-closure period and closure period (2) between closure period and reopen period.
[12] The pre-closure period indicates time from September 2018 to February 2020.
[13] The closure period indicates time from March 2020 to August 2020.
[14] The reopen period indicates time from September 2020 to September 2021.
[15] In this table, employed (M) and employed (F) are the dependent variables from extensive margin. And they indicate employment status for male workers and female workers accordingly.

employed (F)	.960	.195	10,499	.894	.307	2,908	.922	.268	6,448	(+)***	(-)***
hours worked (M)[16]	167.796	40.829	11,170	160.851	42.250	3,066	163.741	42.275	6,608	(+)***	(-)**
hours worked (F)	147.904	44.124	9,772	141.393	47.078	2,375	145.585	47.277	5,668	(+)***	(-)***
female	.468	.499	22,112	.456	.498	6,380	.471	.499	13,676	(+)**	(-)**
white[17]	.763	.425	22,112	.765	.424	6,380	.751	.432	13,676	(0)	(+)**
education	.607	.488	22,112	.652	.476	6,380	.648	.477	13,676	(-)***	(0)
family income	79585.29	46489.15	22,112	87570.53	47027.23	6,380	83951.45	46838.88	13,676	(-)***	(+)***
family size	1.708	1.183	22,112	1.605	.974	6,380	1.622	1.028	13,676	(+)***	(0)

From the extensive margin, based on the t-test between the pre-closure period and the closure period for the dependent variable: employed, the positive and significant implies that for all workers regardless of their industry or occupations, after school has been closed, their probability of getting employed will be decreased by around 3-4%. The negative sign of the t-test between closure period and reopening period shows that after the school has been reopened, the probability of getting employed will increase. Although the probability of getting employed recovered after, it does not return to the level before the pandemic. There are still plenty workers missing in the labor market due to the COVID-19 pandemic. The number of these missing workers can be even larger as those who lost their jobs may not be accessible

[16] In this table, hours worked (M) and hours worked (F) are the dependent variables from intensive margin. And they indicate the hours worked last month for male workers and female workers accordingly.
[17] White, education, family income and family size are a set of control variables.

for this survey. This will inevitably cause bias to the research that the actual gender employment can be larger, and the effect of school policies can be overstated.

From the intensive margin, based on the t-test between the pre-closure period and the closure period for the dependent variable: hours worked last month, the positive and significant implies that for all workers regardless of their industry or occupations, after school has been closed, their working hours will be reduced by 5-7 hours per month. The negative sign of the t-test between closure period and reopening period shows that after the school has been reopened, the working hours will be increased by 2-4 hours per month. This also suggests that the negative impact on working hours caused by COVID-19 has not been fully removed by the reopening of schools.

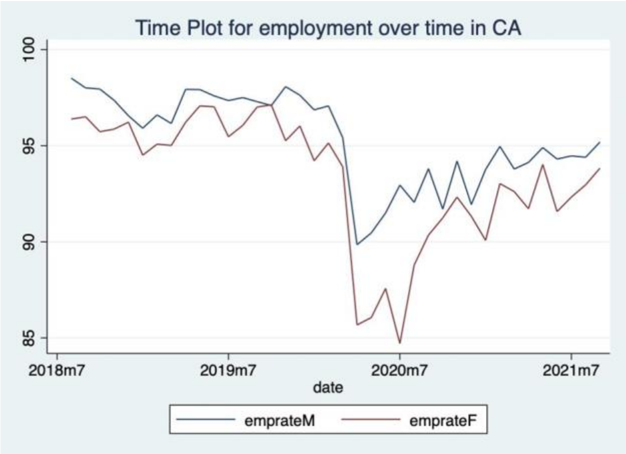
The t-test for female in state-level between pre-closure period and closure period is 0 while it is negative for the t-test between closure and reopening period. This indicates that there are more women in the state-level dataset after the school has been reopened. However, the t-test for female in state-level between pre-closure period and closure period is positive while it is negative for the t-test between closure and reopening period. This shows that, in California, there are fewer female workers after school has been closed and more women after the school has been reopened.

The t-test for our control variables shows that after school has been reopened, there are more white people in the dataset. It also shows that there are more individuals with at least some college education after school has been closed while after school has been closed, this returns to the normal pre-closure level. These two findings can be highly related to the self-selection of labor market in response to COVID-19 that again proves the necessity to control for these variables in the regression.

Figure 1 shows the employment over time in United States for all states and Figure 2 shows the employment over time in California.

Figure 1. Time plot for employment over time in US

Figure 2. Time plot for employment over time in CA



Figures 1 and 2 are visualizations for dependent variable from extensive margin: employment. The blue line represents male workers and red line represents female workers. From September 2018 to September 2021, male workers are more likely to be employed than female workers. Both figures show that when COVID-19 hit the labor market, the probability for both male workers and female workers dropped significantly. However, there is a notable difference in the pandemic effect between male and female workers. The impact is much greater for female workers.

Figure 3 shows the # of hours worked over time in United States for all states and Figure 4 details this information for California only.

Figure 3. Time plot for hours worked last month over time in US

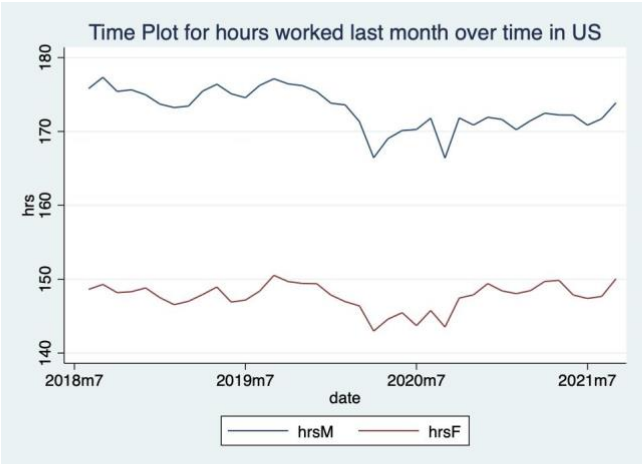
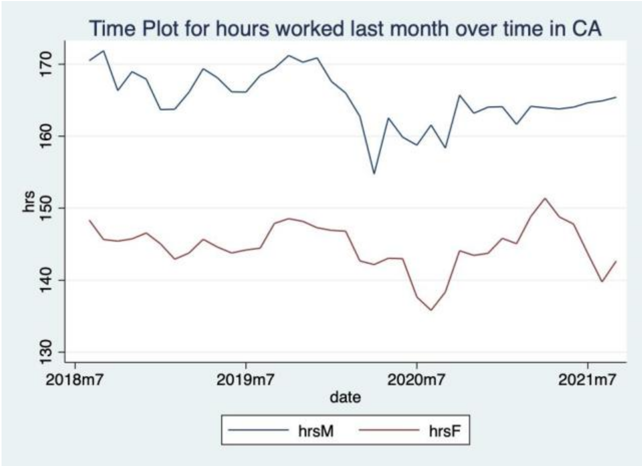


Figure 4. Time plot for hours worked last month over time in CA



Figures 3 and 4 are visualizations for dependent variable from intensive margin: hours worked last month. The blue line is for male workers and red line is for female workers. From September 2018 to September 2021, male workers tend to work more hours each month than female workers while from intensive margin, there is no clear drop in working hours caused by COVID-19 pandemic.

Table 3 below is a detailed timetable of school closure for the states that have a clear state-level closure/reopening policy. It excludes the states that delegate the decision to individual school districts. Input "C" implies that in that month, the schools in that state were ordered to close while Input "O" implies that in that month, the schools were ordered to at least reopen in a hybrid format or fully open that month. For example, for state Texas, all schools were closed from March 2020 until August 2020 when the schools reopened.

Table 3. A timetable of school policies for selected States with exact information[18]

	2020										2021					
State	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
CA	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O

[18] Other states that are not in this table do not have state-level closure or reopening policies and each school districts can decide on their own whether to open or close the schools in its area.

DC	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
HI	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O
NM	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O
VT	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O
WV	C	C	C	C	C	C	C	O	C	O	O	O	O	O	O	O
OR	C	C	C	C	C	O	C	O	O	O	O	O	O	O	O	O
KY	C	C	C	C	C	O	O	O	C	O	O	O	O	O	O	O
AR	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
IA	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
MO	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
TX	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
FL	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
AZ	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
NH	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
MA	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
NC	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
SC	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
WA	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O
KS	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O	O

From Table 3 I see that many states implemented statewide school closure mandates starting in March 2020. However, it also demonstrates a large degree of variation in the timing of reopening. Texas, for example, was the first to reopen in August 2020, while Washington DC was the last to reopen in February 2021.

Table 4 below is a detailed timetable of school closure for all countries in California. For example, for county Alameda, all schools have been closed from March 2020 until February 2021 when the schools have been reopened.

Table 4. A timetable of school policies for counties in California

	2020										2021					
County	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun
Alameda	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Butte	C	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O
Contra Costa	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O	O
El Dorado	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O
Fresno	C	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O
Humboldt	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Imperial	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Kern	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
King	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Los Angeles	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Madera	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Marin	C	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O
Merced	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O
Monterey	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Napa	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O
Orange	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Placer	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Riverside	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Sacramento	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
San Bernardino	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
San Diego	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O	O
San Francisco	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
San Joaquin	C	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O
San Luis Obispo	C	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O
San Mateo	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Santa Barbara	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Santa Cruz	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Shasta	C	C	C	C	C	C	C	O	O	O	O	O	O	O	O	O
Solano	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O

Sonoma	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Stanislaus	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Tulare	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Ventura	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O
Yolo	C	C	C	C	C	C	C	C	C	C	C	O	O	O	O	O

From Table 4, I see less variation in the timing for reopening in California. With county Merced and San Diego being the first two counties that open in September 2020, most other counties reopen around February 2021.

Results:

In this section, I provide and discuss the empirical results. I begin with the static state-level analysis followed by the static county-level analysis and ended with the dynamic county-level analysis and

Table 5: Static State-level logistic regression (hybrid opening[19])[20]

	Extensive		Intensive	
	(1)	(2)	(3)	(4)
VARIABLES	closure	reopen	closure	reopen
female	-0.407***	-0.438***	-0.188***	-0.187***
	(0.0262)	(0.0364)	(0.00182)	(0.00467)
school closure	-1.728***		-0.0747***	
	(0.181)		(0.0199)	
female*closure	0.00753		0.00118	
	(0.0413)		(0.00390)	
school reopening		-0.0203		0.000243
		(0.0697)		(0.00816)
female*reopening		0.216***		0.0193***
		(0.0429)		(0.00514)
age	0.249**	0.115	-0.0130	-0.0310***
	(0.100)	(0.101)	(0.00856)	(0.0112)
new cases	-5.408***	-0.697	-0.220	0.0131
	(1.144)	(0.440)	(0.137)	(0.0498)

[19] Table for static model with full reopening is attached in the appendix.

[20] In this model, I conduct logistic regression from both extensive and intensive margin and include state fixed effect, industry fixed effect and occupation*time fixed effect.

vaccine rate		-0.00268*		-0.000233
		(0.00152)		(0.000155)
family size	-0.0629***	-0.0672***	0.00169**	0.00208*
	(0.00831)	(0.00982)	(0.000795)	(0.00122)
income	15.09***	15.11***	0.544***	0.731***
	(0.269)	(0.266)	(0.0186)	(0.0244)
difficulty	-0.640***	-0.580***	-0.0847***	-0.0681***
	(0.0398)	(0.0427)	(0.00463)	(0.00618)
education	0.0250	-0.0356*	-0.0141***	-0.0155***
	(0.0200)	(0.0202)	(0.00178)	(0.00237)
white	0.355***	0.310***	-0.0186***	-0.0174***
	(0.0207)	(0.0209)	(0.00189)	(0.00244)
Constant	3.008***	2.677***	5.253***	5.246***
	(0.183)	(0.168)	(0.0127)	(0.0155)
Observations	425,051	276,736	395,627	250,406
R-squared			0.078	0.071
State FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Occupation*Time FE	YES	YES	YES	YES

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

Table 5 shows the static state-level logistic regression from both extensive and intensive perspectives, which includes two separate models: one for the effect of school closure, one for the effect of school reopening.

All estimates show a negative relationship between being female and getting employed. For example, when I look at column 2, the coefficient = -0.407 (SE=0.0262) indicates that the female group has $e^{-0.407} = 0.67$ times odds of the male group being employed. Female workers tends to be 33% less likely to be employed than the male workers within the same state and in the same industry and same occupation at the same time. When isolating the school closure effect, the coefficient= -1.728 (SE=0.181) indicates that after the school closure policy has been released, it has $e^{-1.728} = 0.17$ the odds of employment before the school closure policy has been released for male. In other words, it means that a worker tends to be 83% less likely to be employed when the school has been closed than a worker within the same state and in the same industry and same occupation at the same time before the school has been closed. The effect of the school closure policy on female employment will be similar to male while it is not statistically significant. When isolating the school reopening effect, the coefficient= -0.0203 indicates that after the school closure policy has been released, it has $e^{-0.0203} = 98\%$ the odds of employment before the school closure policy has been released for male. And this is not statistically significant which means that the school reopening does not have a significant effect on male employment. While the effect on female employment is different as the coefficient=0.216 (SE=0.0262) suggests that the female group has $e^{0.216} = 1.22$ times the odds of the being employed after school reopened. This means that compared to a male worker in the same state with same industry and occupation under the same time, female workers tend to be 22% more likely to be employed. This result proves that with the reopening policy, women are more likely to get employed and the gender employment gap will be reduced.

At the intensive margin, this study uses linear regression model with log transformation for state-level intensive margin analysis. From Column 3 the coefficient= -0.188 (SE=0.00182) suggests that being a female tends to work around $e^{-0.188} = 82\%$ of the hours that a male worker within the same state and in the same industry and same occupation at the same time. When isolating the effect of school closure, it shows a significant negative effect on males working hours per month. When looking at Column 4 the coefficients show that with school reopening policy has negligible effects on male and female working hours.

Table 6: Static County-level logistic regression (hybrid opening[21])[22]

	Extensive		Intensive	
	(1)	(2)	(3)	(4)
VARIABLES	closure	reopen	closure	reopen
female	-0.661***	-0.626***	-0.166***	-0.163***
	(0.0904)	(0.0957)	(0.00646)	(0.0124)
school closure	-1.413**		-0.0427	
	(0.630)		(0.0838)	
female*closure	-0.130		0.0115	
	(0.146)		(0.0144)	
school reopening		-0.221		-0.0135
		(0.194)		(0.0221)
female*reopening		0.294**		0.00823
		(0.132)		(0.0160)
age	-0.675*	-0.703**	-0.0528*	-0.0108
	(0.348)	(0.342)	(0.0308)	(0.0433)
new cases	-2.559	-0.263	-0.399	0.0232
	(3.551)	(0.748)	(0.410)	(0.0934)
vaccine rate		0.501		0.0309
		(0.978)		(0.120)
family size	-0.108***	-0.0511*	0.000157	0.00414
	(0.0232)	(0.0281)	(0.00231)	(0.00369)
income	13.41***	14.26***	0.528***	0.889***
	(0.935)	(0.902)	(0.0680)	(0.0977)
difficulty	-0.838***	-0.805***	-0.0737***	0.0520
	(0.169)	(0.179)	(0.0199)	(0.0321)
education	0.0109	-0.191***	-0.0245***	-0.0218**
	(0.0792)	(0.0735)	(0.00679)	(0.00977)
white	0.230***	0.376***	0.0168***	-0.00497
	(0.0796)	(0.0719)	(0.00647)	(0.00896)
Constant	2.143***	2.915***	5.108***	5.075***

[21] Table for static model with full reopening is attached in the appendix. I found that with hybrid reopening, it is enough for the female employment to rise that counting full-reopening as 1 is the analysis will eventually mess up the results.

[22] In this model, I conduct logistic regression from both extensive and intensive margin and include county fixed effect, industry fixed effect and occupation*time fixed effect.

	(0.542)	(0.551)	(0.0467)	(0.0606)
Observations	24,995	16,741	25,595	15,414
R-squared			0.079	0.081
County FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Occupation*Time FE	YES	YES	YES	YES

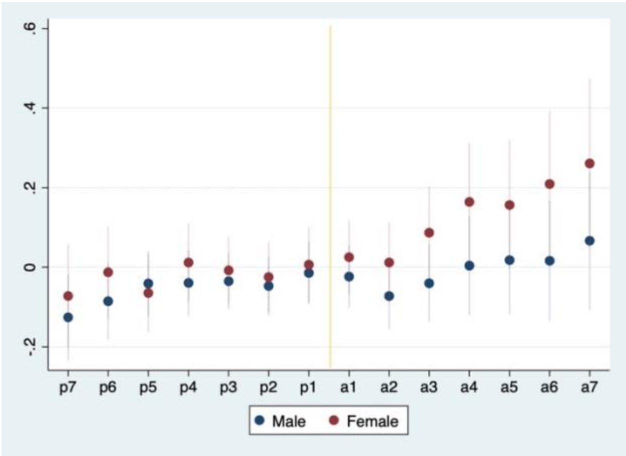
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6 shows similar static results as Table 5 at the county-level. When isolating school closure/reopening effects, both models show a statistically significant negative relationship between being female and getting employed. For example, when I look at column 2, the coefficient =-0.661 (SE=0.0904) indicates that the female group has $e^{-0.661} = 0.53$ times the odds of the male group being employed. Thus, I find that female workers to be 47% less likely to be employed than the male workers in the same state, with same industry and occupation at the same time. The effect of the school reopening policy on male employment is negative with the coefficient from Column 3 =-0.221 (SE=0.194) and the effect will be positive for female employment as the coefficient =0.294 (SE=0.132) and is statistically significant. This means that the log odds of female workers being employed are $e^{0.294} = 1.34$ the odds for male workers. This means that compared to a male worker in the same county with same industry and occupation under the same time, female workers tend to be 34% more likely to be employed after schools reopen.

The linear regression model with log transformation is used for state-level intensive margin analysis. From Column 3, the coefficient = -0.166 (SE=0.00646) suggests that being a female tends to work around $e^{-0.166} = 84\%$ of the hours that a male worker worked per month. When isolating the effect of school closure, it shows a significant negative effect on males working hours per month. When looking at Column 3, the coefficients show that with school closure policy in effect, it generates a negative effect on males working hours and is statistically significant while it generates an almost 0 and non-significant positive for female * school closure on working hours. This means that the school closure policy shows a negative effect on male workers and there is no difference between female and male workers according to this. Similarly, based on the standard errors from the results, the sample mean is an accurate reflection of the actual population mean while the standard errors for the county-level analysis are bigger than the ones from state-level analysis, which can be due to the sample size difference between these two analyses.

All models, regardless of extensive or intensive, state-level or county-level returned similar coefficients for other variables. Age has a positive relationship with employment or working hours and it makes sense that companies tend to hire or use experienced workers for the state-level analysis while for the county-level analysis, it is negative. This can be due to the difference in the industry structure between California and other states. New cases have a negative effect on employment or working hours as people are not able to work or work as many hours as they used to be because of the severe situation of COVID-19. And with a larger family size, the possibility of being employed will decrease. It is also true that with higher family income, people would be less likely to be unemployed. Workers with a disability will be more likely to be unemployed and there is an advantage for white people in finding jobs.

Figure 5: Dynamic county-level linear regression from an extensive perspective (hybrid opening)[23]



Figures 5 and 6 below showed the results from the dynamic county-level analysis. The yellow line in the middle represents the cutting line for reopening policy. p-x represents x months before the event and a-x represents x months after the event. Figure 5 shows that there is no significant difference between males and females before the event (school reopening in this case). While a significant disparity of employment can be seen after the school reopening policy has been in effect: female workers are more likely to be employed than male workers.

Figure 6: Dynamic county-level linear regression from an intensive perspective[24]

[23] This uses the dynamic model mentioned earlier in the paper. The dependent variable here is employed. It contains county fixed effect, industry fixed effect and occupation*time fixed effect.
[24] This uses the dynamic model mentioned earlier in the paper. The dependent variable here is hours worked last month. It contains county fixed effect, industry fixed effect and occupation*time fixed effect.

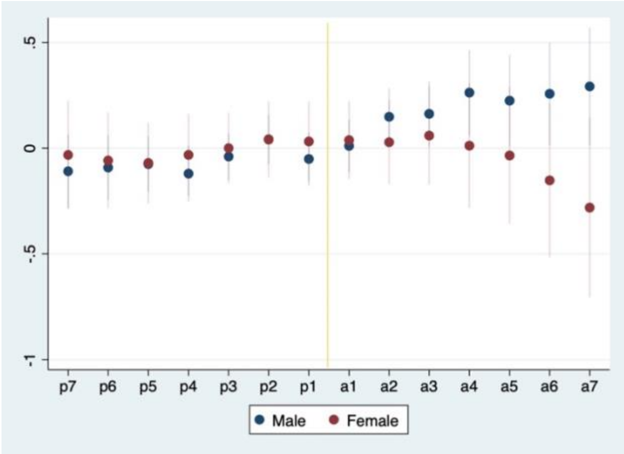


Figure 6 illustrates the dynamic effects at the intensive margin and shows that there is no significant difference between males and females before the event (school reopening in this case). While a significant disparity of working hours can be seen after the school reopening policy has been in effect: female workers work fewer hours than male workers.

Heterogeneity test:

Table 7: A heterogeneity test based on different income levels has been performed

	Extensive Margin-Income levels					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	low[25]	medium[26]	high[27]	low	medium	high
female	-0.244***	-0.312***	-0.417***	-0.199	-0.269***	-0.556***
	(0.0663)	(0.0430)	(0.0395)	(0.151)	(0.0647)	(0.0464)
school closure	-0.464	-1.415***	-2.330***			
	(0.549)	(0.319)	(0.247)			
female*closure	0.130	0.0639	-0.139**			
	(0.140)	(0.0706)	(0.0571)			
school reopening				-0.333	0.0151	-0.000839
				(0.253)	(0.116)	(0.0942)
female*reopening				0.160	0.115	0.350***
				(0.165)	(0.0742)	(0.0571)

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Constant	1.108**	3.177***	4.918***	1.054	2.337***	3.986***
	(0.473)	(0.319)	(0.274)	(0.738)	(0.314)	(0.252)
Observations	16,113	91,749	316,667	9,088	56,563	210,710

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 shows how different income groups react to the school closure and reopening policies. From an extensive margin, female workers with high-income levels are the most affected group by the school closure while they are also the group which recovered the most after the school has been reopened.

Table 8: A heterogeneity test for different income levels from an intensive margin

	Intensive Margin-Income levels					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	low	medium	high	low	medium	high
female	-0.187***	-0.150***	-0.198***	-0.274***	-0.151***	-0.189***
	(0.0120)	(0.00400)	(0.00208)	(0.0419)	(0.0120)	(0.00509)
school closure	-0.0655	-0.0739*	-0.0805***			
	(0.131)	(0.0426)	(0.0234)			
female*closure	-0.0337	-0.0122	0.00855**			
	(0.0301)	(0.00935)	(0.00436)			
school reopening				-0.0369	0.0172	-0.00407
				(0.0659)	(0.0191)	(0.00906)
female*reopening				0.0961**	0.00484	0.0192***
				(0.0449)	(0.0130)	(0.00562)
Constant	5.134***	5.278***	5.299***	5.376***	5.133***	5.278***
	(0.0871)	(0.0318)	(0.0146)	(0.139)	(0.0433)	(0.0173)
Observations	13,366	83,339	298,922	6,690	48,361	195,355
R-squared	0.128	0.066	0.076	0.140	0.068	0.066

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Similar results can be found from Table 8, high-income group is still the most negatively affect group, with female workers decreasing their working hours the most. However, after the school has been reopened, female workers from the low-income group increase their working hours even more than the high-income groups. This can be due to the low threshold for entering the low-income jobs than the high-income jobs.

Discussion:

In conclusion, I found that for a worker, who has at least one child in the household, compared to a worker with the same occupation, same county, same industry, he/she is around 76% less likely to be employed when school has been closed while a female worker tends to be 34% more likely to be employed than a male worker after the school has been reopened. Based on our results, both state-level and county-level regression with our assumption that with school reopening policy in effect, women will benefit more than men. More women will return to the labor market and back to work, thus I have seen a significant positive effect on female works employment. This study also confirms the negative effect of school closure, and this effect does not differentiate between female workers and male workers.

However, the school closure or reopening seems to be too large. One potential explanation to this is that this study restricts to individuals with at least one child at home, which would automatically amplify the effect. Also, this study fails to incorporate other Covid-19 issues as it only includes Covid-19 cases and vaccine rate to account for the Covid-19 effects on employment. The effect from other uncontrolled Covid-19 issues will be buried under the effect of school policies thus the conclusion can be overstated for this study.

Interestingly, unlike the employment has been increased significantly for female workers, the working hours per month has been reduced after the school has been reopened. This can be due to more women are being employed after school has been reopened, thus those who remained at the labor market may not be able to work as many hours as they used to be. Also, I sometimes see the small negative effect of school reopening on males, this can be due to the development cost for females. According to Naila Kabeer (2020), there is no free lunch for gender development. Women workers' development can sometimes build up at the cost of male workers.

Although this study qualitatively demonstrates that school reopening policy has a significant positive effect on women's employment from an extensive perspective, it limits its county-level analysis to California. Unlike other states in the United States, California plays a unique role in United States as its advantageous industries include traditional agriculture, cutting-edge high-tech industries, and extremely developed tourism. It is also the technology and cultural center of the United States and the world's film and television center. It is also a state highly engaged in international trade as international trade accounts for 25% of California's GDP, and 45% of U.S. imports pass through California ports. The uniqueness of California made it hardly able to represent United States. So that the conclusion drawn from the county-level analysis should be checked before applying to other states in United States.

Appendix:

Appendix table 1: Static State-level logistic regression (full opening)

	Extensive			Intensive		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	closure only	reopen only	closure+reopen	closure only	reopen only	closure+reopen
female	-0.407***	-0.299***	-0.313***	-0.188***	-0.178***	-0.184***
	(0.0262)	(0.0220)	(0.0187)	(0.00182)	(0.00229)	(0.00148)
sch_reopen		-0.0475	-0.0514		-0.0237***	-0.0221***
		(0.0479)	(0.0418)		(0.00484)	(0.00366)
female_reopen		0.0700	0.0969*		0.0350***	0.0398***
		(0.0503)	(0.0495)		(0.00488)	(0.00452)
age	0.00249**	0.00115	0.00189**	-0.000130	-0.000309***	-0.000181***
	(0.00100)	(0.00101)	(0.000765)	(8.56e-05)	(0.000112)	(6.97e-05)
new_cases	-5.408***	-0.662	-2.149***	-0.220	0.0214	-0.0213
	(1.144)	(0.441)	(0.379)	(0.137)	(0.0499)	(0.0399)
fully_vacc_rate		-0.00276*	-0.000675		-0.000236	-0.000358***
		(0.00152)	(0.00142)		(0.000155)	(0.000130)
pernum	-0.0629***	-0.0674***	-0.0624***	0.00169**	0.00205*	0.00191***
	(0.00831)	(0.00981)	(0.00674)	(0.000795)	(0.00122)	(0.000678)
income	1.51e-05***	1.51e-05***	1.60e-05***	5.44e-07***	7.30e-07***	6.06e-07***
	(2.69e-07)	(2.66e-07)	(2.07e-07)	(1.86e-08)	(2.44e-08)	(1.52e-08)

difficulty	-0.640***	-0.580***	-0.641***	-0.0847***	-0.0684***	-0.0779***
	(0.0398)	(0.0427)	(0.0307)	(0.00463)	(0.00618)	(0.00379)
education	0.0250	-0.0356*	-0.00967	-0.0141***	-0.0155***	-0.0146***
	(0.0200)	(0.0202)	(0.0153)	(0.00178)	(0.00237)	(0.00146)
white	0.355***	0.309***	0.346***	-0.0186***	-0.0174***	-0.0175***
	(0.0207)	(0.0209)	(0.0158)	(0.00189)	(0.00244)	(0.00153)
sch_clo	-1.728***		-0.0850	-0.0747***		-0.0147**
	(0.181)		(0.0661)	(0.0199)		(0.00742)
female_clo	0.00753		-0.0692*	0.00118		-0.00117
	(0.0413)		(0.0360)	(0.00390)		(0.00367)
Constant	3.008***	2.605***	3.252***	5.253***	5.241***	5.258***
	(0.183)	(0.167)	(0.168)	(0.0127)	(0.0154)	(0.0114)
Observations	425,051	276,736	650,752	395,627	250,406	602,688
R-squared				0.078	0.071	0.075

Standard errors in parentheses

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

Appendix table 2: Static County-level logistic regression (full opening)

	Extensive			Intensive		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	closure only	reopen only	closure+reopen	closure only	reopen only	closure+reopen
female	-0.661***	-0.452***	-0.476***	-0.166***	-0.154***	-0.161***

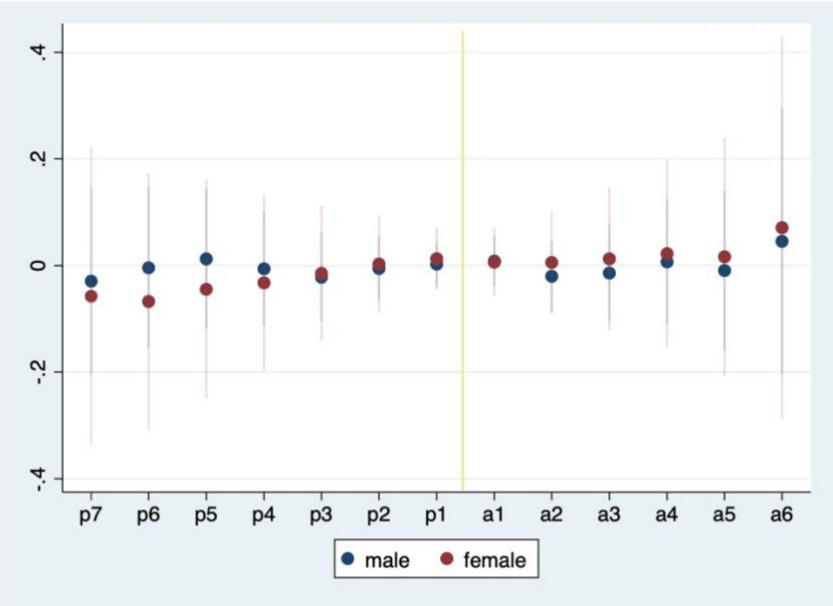
	(0.0904)	(0.0753)	(0.0701)	(0.00646)	(0.00920)	(0.00583)
sch_clo	-1.413**		0.266	-0.0427		0.0146
	(0.630)		(0.195)	(0.0838)		(0.0204)
female_clo	-0.130		-0.189*	0.0115		-0.00153
	(0.146)		(0.109)	(0.0144)		(0.0114)
age	-0.00675*	-0.00698**	-0.00820***	-0.000528*	-0.000118	-0.000228
	(0.00348)	(0.00342)	(0.00257)	(0.000308)	(0.000433)	(0.000258)
new_cases	-2.559	-0.235	-0.186	-0.399	0.0476	-0.0427
	(3.551)	(0.730)	(0.690)	(0.410)	(0.0922)	(0.0780)
fully_vacc_rate	748,497	0.466	-0.248	16,174	0.0217	0.0234
	(1.890e+06)	(0.972)	(0.862)	(41,232)	(0.120)	(0.0937)
pernum	-0.108***	-0.0488*	-0.0769***	0.000157	0.00406	0.00159
	(0.0232)	(0.0280)	(0.0188)	(0.00231)	(0.00369)	(0.00201)
income	1.34e-05***	1.42e-05***	1.44e-05***	5.28e-07***	8.87e-07***	6.45e-07***
	(9.35e-07)	(9.01e-07)	(6.98e-07)	(6.80e-08)	(9.76e-08)	(5.74e-08)
difficulty	-0.838***	-0.809***	-0.829***	-0.0737***	0.0511	-0.0483***
	(0.169)	(0.179)	(0.129)	(0.0199)	(0.0321)	(0.0175)
education	0.0109	-0.188**	-0.102*	-0.0245***	-0.0220**	-0.0247***
	(0.0792)	(0.0735)	(0.0570)	(0.00679)	(0.00977)	(0.00571)

white	0.230***	0.378***	0.278***	0.0168***	-0.00514	0.00771
	(0.0796)	(0.0718)	(0.0569)	(0.00647)	(0.00896)	(0.00539)
sch_reopen		0.240	0.295*		-0.0139	-0.00708
		(0.175)	(0.171)		(0.0185)	(0.0165)
female_reopen		-0.185	-0.143		-0.0205	-0.0157
		(0.179)	(0.177)		(0.0194)	(0.0173)
Constant	2.133***	3.014***	2.627***	5.132***	5.094***	5.111***
	(0.554)	(0.560)	(0.508)	(0.0476)	(0.0623)	(0.0445)
Observations	24,995	16,741	38,660	25,595	15,414	38,495
R-squared				0.079	0.081	0.077

Standard errors in parentheses

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

Appendix Figure 1: Dynamic county-level linear regression from extensive perspective (full opening)



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