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The COVID-19 She-cession: Has Female Unemployment been Disproportionately Impacted?

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I hereby grant permission for my dissertation to be used for teaching in future years.

Abstract

The outbreak of Covid-19 and subsequent measures and restrictions to contain the virus have had severe economic consequences. Literature exploring the impact the pandemic has had on employment inequalities is rapidly growing. The key interest of this dissertation is to examine the effect of Covid-19 on female unemployment relative to male unemployment in the U.S. and hence determine whether it is has experienced a larger increase. Using difference-in-difference estimations and monthly panel data from the Current Population Survey (CPS) we find that the probability of being unemployed climbed substantially for women relative to men beginning in April 2020; a result which persisted, albeit at a lower magnitude, in subsequent months. Triple-difference estimates suggest that childcare was a major determinant of this difference, while industry-specific difference-in-difference estimates indicate that the disproportionate employment share of females within certain sectors played a role. In contrast, statistical analysis findings suggest that women had more favourable job and skill characteristics, specifically a greater likelihood to telework in their occupations and higher education levels, which likely contributed to lessening the negative impact of Covid-19 for women relative to men. We also discuss possible policy interventions required to prevent female employment permanently lagging behind male employment.

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I. Introduction

The Covid-19 pandemic is an unprecedented global health crisis that struck economies harshly in 2020, continuing into 2021. Governments attempted to combat the outbreak of the highly infectious virus through social distancing and stay-at-home measures which subsequently led to major economic downturns worldwide. The full economic implications hit most western countries in April 2020, with the U.S. unemployment rate hiking up to 14.8 percent - a figure not seen since the Great Depression.

An important distinction between this downturn and previous recessions is that generally men's employment has been most severely impacted in past recessions. This is largely attributed to the highly cyclical sectors that men disproportionately work in. While women have faced fewer infections of coronavirus than men, there is increasing evidence to suggest that they have suffered and continue to suffer harsher economic consequences from the outbreak. According to the Federal Reserve of Economic Data (FRED) (2020), gender unemployment rates were approximately equal in March 2020, but by April the female unemployment rate had climbed 2.7 percent above the male rate. Possible explanations for this differential effect between men and women include the fact that sectors most affected by lockdown measures disproportionately employ women, making females more vulnerable to job losses, and because women traditionally carry most of the burden of childcare responsibilities which increased substantially during lockdown due to school and day-care centre closures.

This dissertation will review existing studies and subsequently use data from the U.S. Current Population Survey (CPS) to analyse statistics and conduct difference-in-difference estimations to uncover whether women's unemployment was disproportionately impacted by Covid-19. We generate such estimates for the earliest stage of the pandemic but also build on existing studies by obtaining results for almost a year on from the initial economic effects. We find that there was a widening in the gap between male and female unemployment of 3 percentage points during the first economically impacted month of the pandemic. This figure reduced to 0.9 percentage points when data is included up until February 2021.

We then conduct further empirical investigations to uncover which factors may have had a significant role in the female unemployment rate being so drastically effected in comparison to the male rate. Triple-difference estimates suggest that childcare responsibilities accounted for approximately 51 percent of the increase in the unemployment gap. We also find that the sectors females tend to work in are likely to have played a major role, as female-dominated industries give the most statistically significant difference-in-difference estimates. However, descriptive statistics imply that gender disparities in educational attainment and the ability to work from home may have helped narrow the gap as women appear to be leaders in both of these areas.

Finally, we explore a range of policy options for economic recovery from the pandemic that ensure women's employment will not suffer long-term consequences. In 2019, women accounted for over half of the U.S. labour force for only the second time in history- it must be ensured that the disparity since the pandemic does not threaten years of female employment progress.

II. Literature Review

In contrast to previous recessions, the employment losses from the Covid-19 crisis have been greater for women than for men. Existing literature identifies two main drivers which explain this 'she-cession'; lockdown measures have disproportionately impacted sectors with a high share of female workers, and the closure of schools and day-care centres has heightened childcare needs forcing many parents, particularly mothers, to choose between remaining employed or looking after children.

A. Childcare Responsibilities

Women are traditionally the primary caregiver of children in households. Alon, Doepke, Olmstead-Rumsey and Tertilt (2020) analyse statistics using U.S. survey data such as the American Time Use Survey to find that before the crisis, among married parents in the U.S. who both work full time, women provided about 60 percent of childcare. They estimate that if the relative distribution of the burden remains at 60-40 and childcare needs rise by 20 hours/week during the crisis, full-time working women would need to increase their childcare hours by 12 hours versus 8 hours for men. Without flexible work arrangements, a likely outcome is that one spouse will temporarily have to quit work and, based on the existing division of labour, this is more likely to be the wife. These predictions are supported by evidence from Zamarro and Prados (2020), who find that, in the U.S., women have carried a heavier load than men in the provision of childcare during the pandemic, even while still working. However, Alon et al. (2020) also infer that some fathers are now taking on the primary caregiver role for their children and certain social norms regarding household duties may be eroded, all of which should ultimately promote gender equality in the labour market. This is supported by Profeta (2020) who argues that fathers who are forced to stay home for work now have the opportunity to extend their hours of domestic work and childcare, especially in dual-earner couples where the mother works outside the home, making the father the only parent at home. This could change the traditional sharing of home responsibilities and help create an equal balance of roles within the family.

Fabrizio, Gomes and Tavares (2021) conduct linear probability model estimations using U.S. monthly CPS data to identify gender differentials in the likelihood of employment during the pandemic, particularly specifying changes due to the presence of children. They find that being a woman with at least one child under 12 years-old reduced the probability of being employed by 3 percentage points compared to a man with similar characteristics during the first nine months of Covid-19. A further decomposition finds that the additional effect on women with young children explains 45 percent of the total male-female employment gap between April and December. They also regard the important economic consequences of this result, calculating that the impact of extra childcare on the employment of women with young children reduced total U.S. output by 0.36 percent between April and November 2020.

Further investigation into the initial stages of the crisis include Heggeness' (2020) work, which examines the impact of the Covid-19 shock on parents' labour supply in the U.S. She conducts a difference-in-difference estimation, exploiting the variations in lockdown timing between states to distinguish a clear control group that has not been affected by the economic shock of Covid-19 (states that closed later) and a treatment group that has been affected (early-closure states). She finds that working mothers in early closure states were 68.8 percent more likely than working mothers in late closure states to have a job but not be working due to early shutdowns. She found no effect on working fathers or working women without school-age children. Covid-19 seems to have prompted a unique immediate juggling act for working mothers. Heggeness' method using state variation in lockdown timings can only be used with March 2020 data as this is the only month in which some states had introduced lockdown measures and others had not. It is therefore not a suitable method for studying early employment losses as the true effects on unemployment only occurred in April 2020, by which time all states had restrictions in place. At the very beginning of the pandemic, the magnitude and duration of closures was still unclear, therefore employers had a delayed reaction to letting staff go, and it also takes time to apply for and receive unemployment. As expected, Heggeness (2020) found that early closures had no effect on unemployment in March for anyone.

Another paper which particularly emphasises the unequal burden of increased domestic and childcare duties on women during Covid-19 is Couch, Fairlie and Xu (2020). They conduct difference-in-difference estimations, as well as triple-difference estimations to analyse whether the pandemic disproportionately impacted female unemployment relative to male unemployment and whether this was largely due to the presence of children. Using U.S. CPS microdata, they find that the employment-to-population ratio for prime-age women with school-aged children declined by 3.7 to 4.8 percentage points relative to comparable men from April to August 2020. Triple-difference estimates indicate that 64 to 89 percent of this difference is attributed to decreased work activity due to their children.

B. Female-dominated Industries

Couch et al. (2020) also discuss another potential reason for the gender unemployment gap during Covid-19 - the industries and occupations that were most harshly impacted were those which require direct contact and subsequently were subject to closures and social distancing measures, and these industries disproportionately employ women. Two main factors determine if certain occupations are exposed to an elevated unemployment risk during the pandemic; whether the occupation is considered “critical” and therefore unaffected by stay-at-home orders, and whether the occupation allows for telecommuting. Using the Oaxaca-Blinder decomposition, Couch et al. (2020) find that women were more likely to work in “non-essential” industries, explaining 0.6 to 1.0 percentage points of the male-female unemployment gap. However, their results also showed that women had a greater likelihood to telework, higher education levels, and a less-impacted occupational distribution which may have all contributed to lessening the negative impacts of Covid-19 for women relative to men.

Similarly, Alon et al. (2020) find that women usually have a higher ability to telecommute. Considering occupations where at least 25 percent of workers are able to telecommute, 49 percent of male employees but a full 63 percent of female employees work in these occupations. While this factor could indicate a narrowing of the gender gap during Covid-19, these telecommuting actions are usually in particular to deal with “personal” issues such as childcare, which once again underlines the uneven existing distribution of labour in the household. Alon et al. (2020) also highlight how women experiencing greater employment losses during the pandemic does not follow the usual pattern of past recessions.

C. Employment Dynamics of Past Recessions

Doepke and Tertilt (2016) summarise evidence on how employment varies over the business cycle for women and men. Women's aggregate labour supply is much less volatile compared to men's. From 1989-2014, men accounted for around three quarters of overall cyclical fluctuations in employment, while women accounted for less than one quarter. They argue an important channel for this is the different sectoral composition of males and females. In past recessions, industries such as construction and manufacturing are hit much harder than, say, healthcare and education. Men's employment tends to be more concentrated in sectors with a high cyclical exposure, whereas women are highly represented in sectors with relatively stable employment over the cycle. A recent paper by Coskun and Dalgic (2020) finds that in two sectors, "Government" and "Education and Health Services," employment is actually countercyclical and these sectors account for 40 percent of women's employment, but only 20 percent of men's. Conversely, the extremely cyclical sectors of "Manufacturing," "Construction," and "Trade, Transportation, Utilities" account for 46 percent of male but only 24 percent of female employment. Other industries that are typically highly concentrated with female employees include retail, hospitality and tourism- sectors which experienced complete shut-downs, particularly in the early months of Covid-19.

This argument is further supported by an analysis from Gent, Khan, and Cloutier (2018) who discuss the determinants of the variation between male and female unemployment in the U.S. during the 2008 Great Recession. Performing pooled OLS regressions, they interact employment share with gender share within industries to find that male employment was much more adversely affected, particularly due to job losses in the financial and manufacturing industries, which disproportionately employed males. We would expect the opposite effect to occur during the economic downturn from the pandemic, given the sectors that suffered the most.

This dissertation will build on this existing literature in several important ways. Firstly, we develop the analyses by looking at a much extended time period, using data until February 2021 to obtain a more long-term view of the effects of Covid-19. Previous studies are based only on the early months of the pandemic, while the labour market experiences of different groups have evolved differently beyond the initial impact of the crisis. Many of the existing studies mentioned have also failed to control for certain important characteristics such as race, even though it is reported that there was a highly disproportionate impact on black workers relative to white workers (Hotchkiss, 2021). Additionally, they do not control for U.S. state variations in unemployment- there was a substantial difference in the longevity and stringency of lockdown between states (Hallas, Hatibie, Majumdar, Pyarali and Hale, 2020). This paper will account for such important variables. It provides a comprehensive study of differences in occupational and skill characteristics and increased childcare responsibilities, how both of these influences impacted the surge in female job losses relative to males, and which factor appears to have had the most significant effect. Most existing literature only focuses on one of these key determinants. Finally, we end by discussing policy ideas that ensure women's employment is not permanently damaged by the pandemic- a vital long-term consideration which many studies do not discuss in great detail.

III. Context and Data

A. Covid-19 in the U.S.

Data from the U.S. was chosen for the analysis because it has been the country most affected by Covid-19 in terms of both virus cases and deaths. It has consequently suffered one of the world's highest unemployment rates during the early months of the pandemic- unemployment spiked from 3.5 percent in February 2020 to 14.8 percent in April according to FRED (2020).

Social distancing measures were quickly enforced as the virus spread across the U.S. By March 23rd, all states had adopted some social distancing measures, notably including closures of non-essential businesses, educational facilities and day-care centres. As of 10th April, most American schools had stopped in-person teaching. These policy reactions were undoubtedly a prime cause of the subsequent sharp increase in unemployment that the country experienced.

B. Data

We use monthly panel data from the Integrated Public Use Microdata Series, Current Population Survey (IPUMS-CPS) (Flood, King, Rodgers, Ruggles and Warren, 2021). The IPUMS-CPS harmonises microdata from the monthly U.S. labour force survey, the CPS, covering the period 1962 to present. The CPS is administered to approximately 60,000 households and when weighted the data represents the civilian non-institutional U.S. population ages 16 and above. It includes various demographic information and employment data.

Data was extracted on a monthly basis from October 2019 up to February 2021. We interpret April 2020 as being the first month where labour market activity was truly disrupted throughout the country. We start by focusing on shifts in employment beginning with April given the timing of the introduction of social distancing measures nationally- in contrast to March, the April data was collected following the implementation of social distancing restrictions by all states (Couch et al., 2020). Following the extraction, the data was cleaned in STATA and additional variables were generated. Table 1 provides a summary of the key variables used in the analyses.

Table 1- Interpretation of key variables:

Variable Name	**Interpretation**
Unemployed	Takes value 1 if individual is unemployed, 0 otherwise
Covid	Takes value 1 if time period is April 2020-February 2021, 0 otherwise
Female	Takes value 1 if individual is female, 0 otherwise
Female*covid	Interaction of ‘Female’ dummy and ‘Covid’ dummy- takes value 1 if individual is female within Covid-19 time period, 0 otherwise.
Has child	Takes value 1 if individual has one or more children, 0 otherwise
Female*covid*haschild	Interaction of ‘Female’, ‘Covid’ and ‘Has child’ dummies- takes value 1 if individual is female with at least one child within the Covid-19 time period, 0 otherwise
Age	Individual’s age
Age squared	The square of individual’s age
Race	Specifies which race category individual falls into: White, Black or Asian
Industry	Specifies which major industry an employed individual works in
Education	Years of schooling of individual
Telework	Categorises individual by whether they worked remotely due to Covid-19 or not
State region	Specifies the state region the individual lives in: Northeast, South, Midwest or West

Respondents below the age of 18 and above the age of 65 were dropped to restrict the sample to a working population. An employment status variable was used to create the dependent variable of the regression equation, "Unemployed". Only respondents who were working or unemployed were taken into consideration; other employment statuses such as "retired" were dropped. The IPUMS-CPS data includes 23 race categories, however, the majority of respondents fall into the groups "White", "Black" and "Asian", so the variable was reduced to only these categories.

The dummy, "Covid", was created for the period of data after and including April 2020. A "Female" dummy was generated and then interacted with the "Covid" dummy to give the term "Female*covid" which will give the parameter of interest in the difference-in-difference estimation. This was then further interacted with the "Has child" dummy to generate "Female*covid*haschild", which will have the parameter of interest in the triple-difference estimation. An age-squared variable was created due to the quadratic, U-shaped relationship between age and unemployment. A variable for state FIP codes was recoded to create "State region" which categorises the U.S. states into "North", "South", "Midwest" or "West". There was clear regional variation in the timing and stringencies of lockdowns in 2020, with the majority of Southern and Midwestern states having less stringent policies than others. Figure 1.1 (see Appendix) illustrates the stringency trend among U.S. states by highlighting the strength of containment measures and how long they were maintained by each state (Hallas et al., 2020).

Finally, "Telework" is a new Covid-19 variable reporting whether or not the respondent teleworked or worked from home for pay at any time during the previous four weeks specifically due to the pandemic. Those whose telework was unrelated to the pandemic, such as people who worked entirely from home pre-Covid-19 are assigned to the NIU (not in universe) category. This variable cannot be directly used in an unemployment regression to determine how it affects job losses as the question was only asked to employed individuals.

The full nationally representative sample over the extracted time period includes approximately 1.8 million observations, but after cleaning the panel and dropping individuals not in the universe, the final sample includes 774,501 observations. Table 2 provides some summary statistics for the models. The telework measure only begins being observed from

May 2020 onwards, hence the reduced number of observations compared to the overall sample.

Table 2- Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Unemployed	774501	.063	.243	0	1
Covid	774501	.613	.487	0	1
Female	774501	.476	.499	0	1
Female*covid	774501	.291	.454	0	1
Has child	774501	.441	.497	0	1
Female*covid*haschild	774501	.134	.34	0	1
Age	774501	41.889	12.944	18	65
Age squared	774501	1922.25	1094.236	324	4225
Race	774501	143.949	133.091	100	651
Industry	774501	612.045	276.195	0	952
Education	774501	12.583	2.885	1	18
Telework	435113	8.63	25.825	1	99
State region	774501	2.562	1.055	1	4

Figure 1.2 displays the average unemployment rate for the final sample of respondents from January-August 2020. It captures the sudden spike in unemployment in April, when the economic effects of the pandemic first kicked in. This jump from February to April of 3.6 percent to 14 percent closely corresponds with the official FRED rates of 3.5 percent and 14.8 percent respectively. Following April, there was then a downward trend in the unemployment rate, although it still remained high relative to the pre-pandemic rate.

Figure 1.2

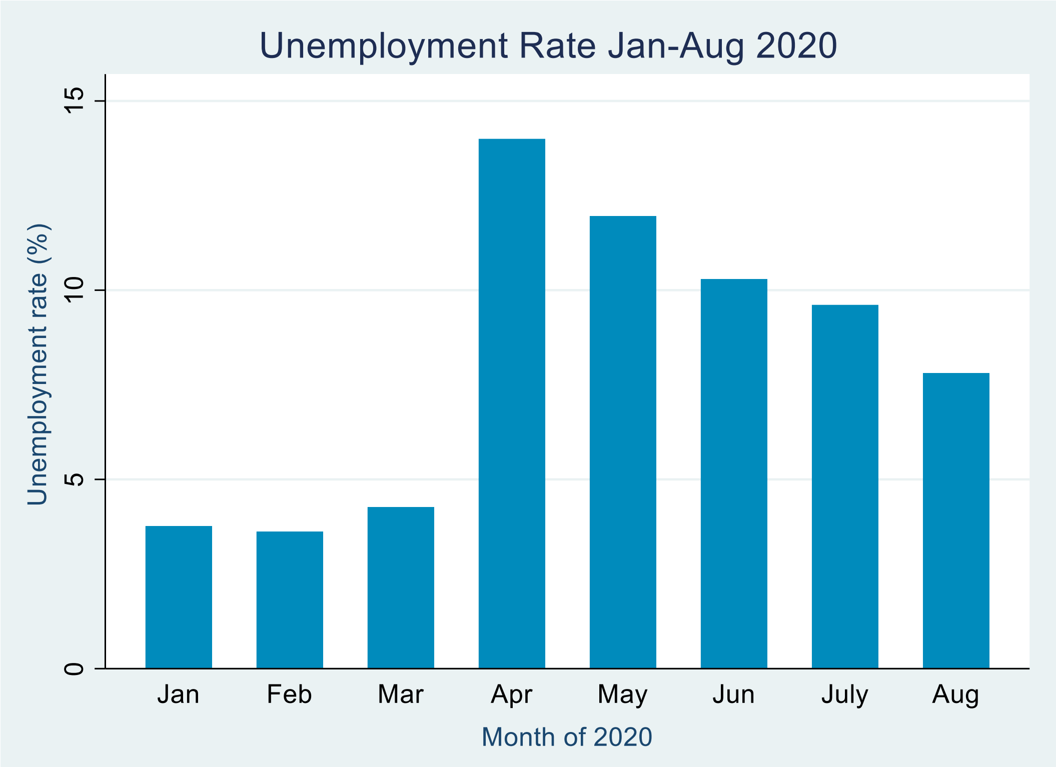
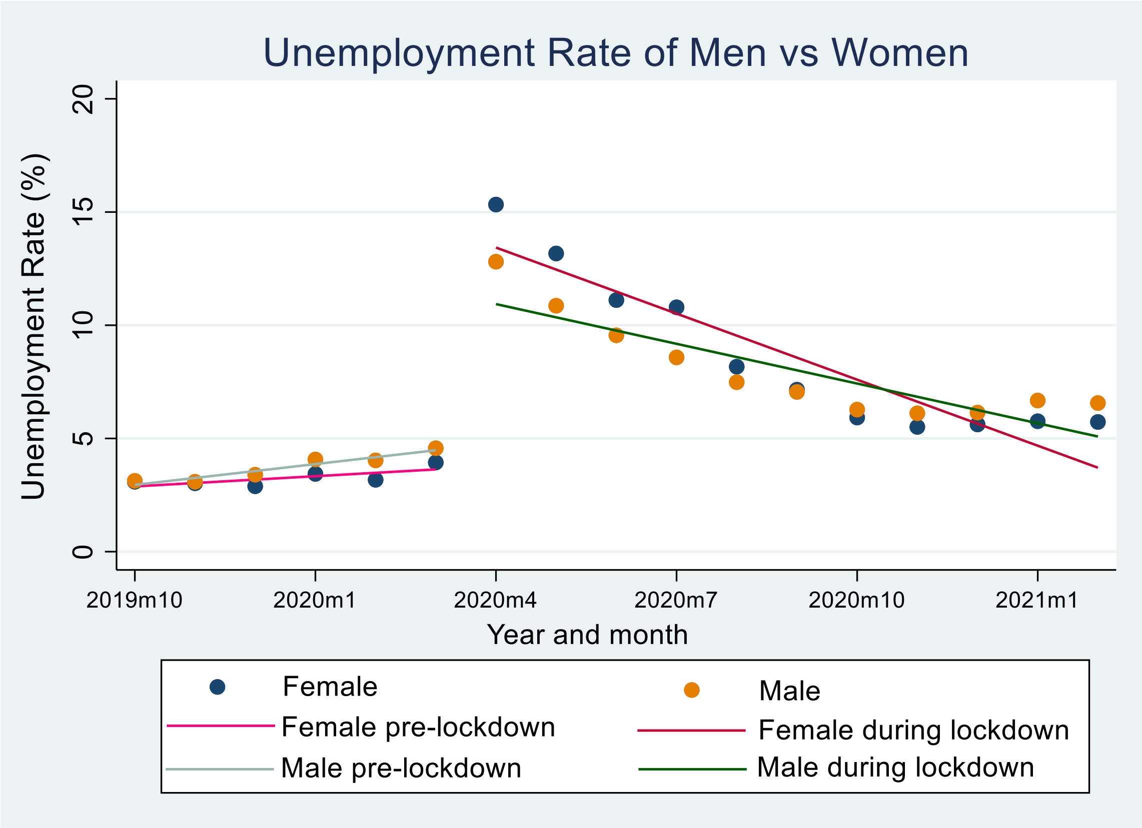


Figure 1.3 is a scatter plot showing the average unemployment rate of men versus women in months before and after the initial economic impacts of the pandemic as well as their fitted values. During the period before April 2020 we can see that the male unemployment rate marginally exceeded the female rate, with both lines following a similar, slightly upward trend. However, after the Covid-19 shock in April, both the unemployment rates of men and women climbed significantly, with the female rate suddenly spiking to 15.3 percent, exceeding the male rate of 12.8 percent.

As both unemployment rates began to slope downwards following April, the female rate remains above the male rate until around October. Male unemployment then begins to overtake female unemployment as before the pandemic. The occurrence of this sudden switch between women overtaking men but then men later regaining the higher unemployment rate is a key motivation for separately examining the effects of Covid-19 on the gender gap in the initial months of the pandemic and then again in an extended time period.

Figure 1.3



IV. Econometric Models and Estimation Methods

A. Difference-in-Difference Model

To formally test whether females were disproportionately impacted by Covid-19, we specify difference-in-difference models. Difference-in-difference is a tool used to estimate treatment effects by comparing the pre-treatment and post-treatment differences in the outcome of a treatment and a control group. Here, we are interested in estimating the effect of Covid-19 on the outcome of unemployment with the treatment group being females and the control group being males.

The following regression equation for the probability of unemployment is estimated:

$$(2.1)\ U_{it} = \alpha + \gamma female_i + \pi COVID_t + \delta female_i * COVID_t + \theta_{age^2} + \sigma_{educ} + \lambda_{industry} + \phi_{race} + \rho_{statereg} + \varepsilon_i$$

where U_{it} is the unemployment outcome variable being examined- a dummy for whether the respondent is unemployed or not. α is individual fixed effects, $female_i$ is a dummy for whether the individual is female or not and $COVID_t$ is a dummy for the post-covid time period from April 2020 onwards. The parameter of interest is δ as this captures the difference-in-difference or disproportionate effect estimate of the pandemic on female unemployment. Finally, we control for other factors that may influence unemployment such as age-squared, education, industry, race, and state region. ε_i is the error term. Individuals and time are indexed by i and t, respectively.

Equation (2.1) is firstly estimated using only data from the time period October 2019-April 2020 in order to decompose the initial effects of Covid-19. We estimate one basic model with no controls, and another more robust model with all the controls specified above. The robust model is again re-ran using only a subsample of the population with children. Next, we estimate (2.1) using further data; from October 2019-February 2021. The difference-in-difference estimates from the two different time periods are expected to vary considerably, as unemployment decreased substantially after April and many of the industries in which many women presumably lost their jobs reopened. The gap between male and female unemployment should therefore have narrowed, as indicated by Figure 1.3.

B. Triple-Difference Model for the Presence of Children

The wealth of existing literature which identifies increased childcare burdens on women as the key driver of this male-female unemployment gap prompts us to directly estimate the impact of having children. To do this, we run a triple-difference model for the presence of children. Following Couch et al. (2020), we divide this result by the difference-in-difference estimate for the subsample of the population with children to give us an approximate estimate of how much childcare accounts for the observed widening of the male-female unemployment gap.

The triple-difference model of the impact of Covid-19 and the presence of children on the gender unemployment gap is:

$$(2.2)\ U_{it} = \alpha + \gamma female_i + \pi COVID_t + \varphi haschild_i + \delta_1 female_i * haschild_i + \delta_2 female_i * COVID_t + \delta_3 COVID_t * haschild_i + \delta_4 female_i * COVID_t * haschild_i + \theta_{age^2} + \sigma_{educ} + \lambda_{industry} + \phi_{race} + \rho_{statereg} + \varepsilon_i$$

where $haschild_i$ is a dummy variable for whether the individual has any children or not. Other model specifications are the same as in Equation (2.1). The new parameter of interest is

δ_4 as this directly compares the change in the gender gap due to Covid-19 for women and men with children to the change in the gender gap for women and men without children. A positive and statistically significant triple estimate indicates the male-female unemployment gap has been widened more for people with children than for those without children, suggesting childcare responsibilities were largely to blame for the significant increase in female job losses.

As before, Equation (2.2) is first estimated using only data from October 2019-April 2020 and then re-estimated using the longer time period from October 2019-February 2021 to determine whether the initial effects of having children during the pandemic differ in the longer-term. We may expect the triple estimate to be smaller in the extended time period model as day-care centers reopened as early as June 2020, hence less need for mothers to stay home and take care of young children. However, the majority of schools remained shut well into February 2021 which may cause a positive triple-difference estimate to persist.

All specifications are estimated with Ordinary Least Squares (OLS). When using panel data, individual-specific transitory shocks are likely to be correlated across time, so we account for this serial correlation by clustering the standard errors by the units of observations when estimating each regression model.

C. Further Decomposition of the Male-Female Unemployment Gap

As discussed in literature, there are various other reasons besides heightened childcare responsibilities falling on women which may have led to the pandemic's disproportionate impact on female unemployment. The main factors we focus on are differences between men and women in educational attainment, the industry they work in, and whether or not they had the ability to work from home during Covid-19.

The effects of these factors are determined by analysing descriptive statistics and, to particularly decompose how industry may affect the unemployment gap, we run the difference-in-difference regression of (2.1) separately for each industry (absent the industry fixed effects). This will reveal whether the disproportionate effect estimate varies across industries and hence we can assess whether the sectors with the most significant results are those which largely employ females according to our descriptive statistics.

D. Common Trends Assumption

All assumptions of the OLS model apply to these estimation models, but additionally, difference-in-difference relies on the common/parallel trends assumption holding. The validity of this assumption would imply that males and females must have had similar unemployment trends before the pandemic (pre-treatment). It assumes that treatment and control outcomes move in parallel in the absence of treatment, hence a divergence of a post-treatment path from the trend established by a comparison group may signal a treatment effect (Angrist and Pischke, 2014).

While this assumption is inherently untestable, there are several methods for strengthening its validity. By observing the pre-shock period, we can check if the two groups were following a similar trend and were parallel. Figure 1.3 shows that, while not exactly parallel, the male and female unemployment rates were following a similar upward trend in the period coming up to the pandemic shock in April 2020. Had the shock not occurred, we assume they would have followed this trend. Additionally, we can estimate a placebo model by pretending the treatment occurred in some period prior to the shock and running the same difference-in-difference regression based on this pre-shock data alone. If the resulting difference-in-difference estimate is statistically indistinguishable from zero, this would lend support for the validity of the common trends assumption.

V. Results

A. Difference-in-Difference Estimates Relative to Men:

Table 3 reports estimates of Equation (2.1) that vary in the sample time period and controls. Columns (1-4) include only October 2019-April 2020 data, while Columns (5) and (6) use data from October 2019-February 2021. Column 1 includes no controls while all remaining columns control for group differences in individual, occupational and geographical characteristics, as specified in (2.1).

Table 3- Difference-in-Difference and Triple-Difference Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Covid	0.091***	0.094***	0.073***	0.111***	0.044***	0.050***	
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	
Female	-0.005***	-0.001	0.006***	-0.006***	-0.002***	-0.007***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Female*covid	0.030***	0.030***	0.043***	0.021***	0.009***	0.005***	
	(0.004)	(0.003)	(0.005)	(0.005)	(0.001)	(0.001)	
Age		-0.004***	-0.005***	-0.004***	-0.004***	-0.003***	-0.003***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age Squared		0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education		-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	-0.003***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Black		0.027***	0.029***	0.027***	0.036***	0.036***	0.029***
		(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Asian		0.004***	0.008***	0.004***	0.014***	0.014***	-0.001
		(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
South		-0.007***	-0.007***	-0.007***	-0.017***	-0.017***	-0.006***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Midwest		-0.006***	-0.006***	-0.005***	-0.014***	-0.014***	-0.004**
		(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
West		-0.004***	-0.005***	-0.003***	-0.008***	-0.008***	-0.002
		(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Has Child				-0.007***		-0.005***	
				(0.001)		(0.001)	
Female*child				0.012***		0.011***	
				(0.001)		(0.001)	
Covid*child				-0.038***		-0.015***	
				(0.004)		(0.001)	
Female*covid* haschild				0.022***		0.011***	
				(0.007)		(0.002)	
Placebo							-0.000
							(0.002)
Placebo*female							-0.002
							(0.002)
Constant	0.037***	1.101***	1.136***	1.095***	1.092***	1.081***	1.093***
	(0.000)	(0.004)	(0.011)	(0.004)	(0.003)	(0.003)	(0.007)
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	*3.4e+05*	*3.4e+05*	*1.5e+05*	*3.4e+05*	*7.7e+05*	*7.7e+05*	*1.0e+05*

Notes: The dependent variable is unemployed. Column 1 specification does not control for any variables. All remaining specifications control for differences in occupational, individual and regional characteristics as specified in Equation 2.1. All specifications are estimated using robust standard errors. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

The results of Column (1) show that, for the whole sample population, Covid-19 resulted in a highly statistically significant 9.1 percentage point increase in the probability of being unemployed. Interpreting the difference-in-difference estimate, we can say that the Covid-19 shock in April caused the probability of females being unemployed to rise by 3.0 percentage points compared to males.

Column (2) reports that, even once we control for differences in characteristics, our estimate remains approximately the same and statistically significant. Nevertheless, this is a much more robust estimate with a higher R-squared. Generating an estimate for the population in the sample with at least one child, we find that the gender unemployment gap increased by 4.3 percentage points as shown in Column (3). This estimate will further be utilised when interpreting our triple-difference estimate, but it already indicates that responsibilities associated with having children are a large reason for female unemployment exceeding male unemployment during the pandemic.

The parameters of the controls displayed in Column (2) have some interesting results. Age has an extremely statistically significant and negative coefficient, implying people are less likely to be unemployed as they grow older. However, the relationship between age and unemployment is not linear but rather a quadratic, hence the inclusion of the age-squared term, which also yields a statistically significant result. Interpreting the education coefficient, it appears that one additional year of schooling is associated with a 0.4 percentage point decrease in the likelihood of being unemployed. The race variable indicates that black and Asian people are 2.7 and 0.4 percentage points more likely to be unemployed compared to white people respectively. Individuals living in the southern, mid-western or western states of the U.S. are all less likely to be unemployed compared to those living in north-eastern states. This result makes sense given north-eastern states had more stringent and longer-lasting lockdown measures (BSG, 2020).

Column (5) captures the longer-term consequences of Covid-19, almost a year on from the initial economic impact, by extending the time period until February 2021. We now find that the pandemic caused the probability of females being unemployed to increase by only 0.9 percentage points compared to males. This is 2.1 percentage points below the initial estimate, indicating that the male-female unemployment gap has narrowed in the longer term. There are several potential reasons for this. Many of the female-dominated industries harshly affected by the pandemic had reopened by February in many states such as restaurants, retail and personal care services with some restrictions. As discussed in the next section, children may have had a less significant impact on female unemployment in the longer-run compared to the short-run, also closing the gap slightly. Finally, it is likely that the U.S. CARES Act- a \$2.2 trillion economic stimulus bill signed into law on March 27th 2020- showed true results in the months following March and April. By June, many businesses were eligible for loans, preventing them from closures and letting workers go, and there was relief available to individuals in the form of tax rebates, credits and deductions. These measures would have helped cut job losses from the initial staggering levels which likely also led to a narrowing of the male-female unemployment gap, since businesses that would have faced closures absent the stimuli were largely those that disproportionately employed females.

B. Triple-difference Estimates of Changes Due to Presence of Children:

We now want to decompose the potential causes of the disproportionate impact of Covid-19 on women. Existing literature discussed in Section II implies that the burden of increased childcare responsibilities during the pandemic due to school and day-care centre closures has fallen more on mothers than fathers. We want to examine whether the increase in the gender unemployment gap is different for people who have children and people who do not. To do this, we ran triple difference-in-difference models which directly estimate the impact of the presence of children during Covid-19 on the male-female unemployment gap.

Columns (4) and (6) of Table 3 report estimates of Equation (2.2). Column (4) uses data from October 2019-April 2020 to analyse the initial Covid-19 effects. The triple-difference estimate in this specification reports that there was a greater increase in the gender unemployment gap for women with children compared to women without children. In other words, in April, the male-female unemployment gap was widened 2.2 percentage points more for people with children than for those without children. Dividing the triple-difference parameter in Column (4) by the difference-in-difference parameter in Column (3) suggests that demands associated with having children account for approximately 51 percent of the observed widening in the female-male gap in unemployment.

This result may seem surprising given recent societal efforts towards gender equality. However, most of these efforts focus primarily on labour market participation and advancing women in the workplace, rather than activities within the household. A persistence of gendered inequalities in domestic tasks within households continues to be documented-

Pepin, Sayer and Casper (2018) find that women married to men spend more time on housework than single mothers in the U.S.

The triple-difference result alters when we extend the time period until February 2021, as reported in Column (6). The new estimate is half the size of the original estimate, indicating children are now playing a smaller role in widening the male-female unemployment gap. While the majority of schools remained closed for in-person learning, day-care centres reopened as early as June 2020 which likely lessened childcare responsibilities for women with very young children. It is also possible that fathers took on a greater degree of responsibility in looking after children as Alon et al. (2020) predicted.

C. Descriptive Statistics and Industry-Specific Difference-in-Difference Estimates:

While childcare appears to account for about half of the observed widening in the gender unemployment gap, literature indicates that differential job and skill characteristics among males and females may have also accounted for different unemployment risks during Covid-19. Table 4 reports descriptive statistics in gender composition across industries, educational attainment and whether or not employed individuals worked from home during the pandemic. It also states the unemployment rates for each of these specifications during the pandemic period.

Table 4- Gender Compositions across Education, Teleworking and Industry and Corresponding Unemployment Rates during Covid-19

	Gender Composition (%)			Apr 2020-Feb 2021
	Male	Female	Total	Unemployment Rate (%)
Educational Attainment *(Oct 2019-Feb 2020)*				
High school dropout	7.55	4.98	6.32	13.88
High school graduate	29.84	22.78	26.46	10.41
Some college	16.60	16.97	16.78	8.95
College graduate	33.38	39.20	36.17	6.03
Graduate school	12.63	16.06	14.27	3.76
Worked remotely due to Covid-19 *(Apr 2020-Feb 2021)*				
No	71.98	65.97	69.13	
Yes	20.60	26.35	23.32	
Niu (not in universe)	7.43	7.68	7.55	
Major Industry *(Oct 2019-Feb 2020)*				
Administration	5.25	5.01	5.14	2.62
Agriculture	3.77	1.87	2.86	12.62
Construction	12.49	1.67	7.31	8.92
Education	5.38	14.40	9.70	6.81
Entertainment	2.01	1.84	1.93	25.17
Finance	5.55	7.69	6.58	3.73
Healthcare	4.98	18.08	11.25	4.13
Manufacturing	13.79	6.16	10.14	6.60
Mining	1.23	0.21	0.74	13.9
Personal services	1.56	4.43	2.93	20.46
Professional services	6.69	10.92	8.71	6.15
Repair	9.16	5.93	7.62	8.03
Retail	15.17	16.46	15.79	12.32
Transportation	4.14	1.11	2.69	10.33
Utilities	5.80	2.81	4.36	7.26
Wholesale	3.01	1.42	2.25	5.48

Skills in terms of educational attainment are an important correlate of labour market outcomes (Couch et al., 2020). Table 4 shows that men are more likely to be a high school dropout or a high school graduate than women, while women are more likely to have completed higher education than men such as college or post-graduate degrees. It is likely that these differences in education helped to narrow the unemployment gap between men and women as more educated individuals had lower unemployment rates during the Covid-19 period; high-school graduates experienced a 4.38 percent higher unemployment rate than college graduates.

Table 4 also reports the percentage of males and females who have worked from home during the pandemic. This measure was limited to employed people, hence there is no average unemployment statistic based on this variable. However, we do find that women tend to be more concentrated in jobs where they can work remotely than men (26.4% versus 20.6%). This may have offered some protection against job losses for women compared to men.

The final section of Table 4 includes the proportion of males and females employed in major industries in the pre-pandemic period, along with the average unemployment rate for each sector following the beginning of the pandemic. After the arrival of state closure policies in March 2020, the unemployment rate since April has been remarkably high in industries that were considered "non-essential" and had to close during lockdown; many were forced to shut permanently, leading to rapid job losses. By August, 2020, 43 retailers based in the U.S. had filed for bankruptcy (Repko and Thomas, 2020). The results show that several of the sectors which experienced high unemployment rates from April 2020-February 2021 employed more women than men such as personal services and retail, possibly contributing to an increase in female relative to male unemployment.

As literature implies gender compositions across industries may have been a major contributing factor to the pandemic's disproportionate impact on women, further analyses are made using the difference-in-difference equation (2.1). Running the regression separately for each major industry (absent the industry fixed effects) produces the results in Table 5. This shows some clear cross-industry variation in the difference-in-difference estimate. The highly statistically significant results lie in the following sectors; retail, personal services, healthcare, education and professional services. Comparing these results to those in Table 4, we see that these are all sectors which employ more women than men. For example, the professional services sector employs 4.23 percent more females than males prior to the pandemic, and the regression results specifically for this industry in Column (15) show that the pandemic widened the gender unemployment gap by 5.5 percentage points.

Table 5- Industry-Specific Difference-in-Difference Estimates

	(1) Agriculture	(2) Mining	(3) Construction	(4) Manufacturing	(5) Transport	(6) Utilities	(7) Wholesale	(8) Retail
Female	0.037***	0.014	0.003	0.007***	0.007	0.006*	-0.002	0.007***
	(0.008)	(0.012)	(0.005)	(0.002)	(0.005)	(0.003)	(0.004)	(0.002)
Covid	0.004	0.071***	0.109***	0.099***	0.107***	0.067***	0.053***	0.174***
	(0.011)	(0.020)	(0.007)	(0.006)	(0.012)	(0.008)	(0.011)	(0.008)
Female*Covid	0.003	-0.060	-0.025	0.004	0.034	0.020	0.013	0.049***
	(0.022)	(0.042)	(0.021)	(0.012)	(0.030)	(0.016)	(0.021)	(0.011)
Constant	1.158***	0.224***	0.193***	0.185***	0.224***	0.133***	0.190***	0.178***
	(0.041)	(0.069)	(0.020)	(0.016)	(0.033)	(0.021)	(0.032)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9689	2535	24679	34587	9069	14967	7643	53059

	(9) Finance	(10) Repair	(11) Personal Services	(12) Entertainment	(13) Healthcare	(14) Education	(15) Professional Services	(16) Administration
Female	-0.003	0.011***	-0.010*	0.003	-0.005***	-0.002	-0.008***	-0.000
	(0.002)	(0.003)	(0.005)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
Covid	0.020***	0.075***	0.403***	0.385***	0.025***	0.090***	0.038***	0.022***
	(0.006)	(0.007)	(0.031)	(0.025)	(0.007)	(0.009)	(0.007)	(0.006)
Female*Covid	0.013	0.016	0.064*	0.017	0.055***	0.027**	0.055***	0.009
	(0.008)	(0.013)	(0.036)	(0.037)	(0.008)	(0.011)	(0.010)	(0.009)
Constant	0.089***	0.212***	0.247***	0.317***	0.115***	0.157***	0.181***	0.160***
	(0.016)	(0.019)	(0.033)	(0.035)	(0.012)	(0.014)	(0.016)	(0.021)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22512	25833	9630	6502	38240	32941	29835	17667

Notes: The dependent variable is unemployed. Each specification controls for individual and regional characteristics as specified in Equation (2.1), but not controlling for industry fixed effects. All specifications are estimated using robust standard errors. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$.

While such significant results in retail and professional services make sense, given the proportion of women employed in these sectors and the fall in employment they experienced due to closures and social distancing measures, a somewhat surprising result was healthcare. Healthcare had an extremely statistically significant estimate which saw a widening of the unemployment gap by 5.5 percentage points. One may think the healthcare sector would be protected from unemployment during a pandemic considering their services are greatly needed, and this sector has typically been insulated from job loss during periods of economic recession in the past. However, many non-emergency or routine medical services were delayed or cancelled during the pandemic out of concern that hospitals would be overwhelmed by Covid-19 cases, and some people did not seek out medical care out of concern of contracting the virus. As a result, healthcare revenue fell sharply and it is reported that women endured more job losses in the sector than men, as women make up three-quarters of the healthcare workforce and an even greater share of lower-paid positions (U.S. Census Bureau American Community Survey, 2019). From May 2019 to May 2020, the unemployment rate among women working in hospitals increased at a rate roughly equivalent to the increase for men. However, the unemployment rate for women who work in non-hospital healthcare settings increased from 3.0 percent to 11.2 percent, much higher than the rate increase for men (1.7 percent to 6.8 percent) (McDermott and Cox, 2020). This helps to explain our significant difference-in-difference estimate for the healthcare industry.

D. Limitations and Robustness Checks:

It is possible that other characteristic differences between males and females are driving these results even after controlling for important characteristics such as education, age, industry and race. We therefore conduct a robustness check to test whether this may be true by re-running the regression Equation (2.1) on the unemployment outcome variable with all the specified controls using data only from January and February 2020- months that occur before the economic downturn driven by Covid-19. Column (7) of Table 3 reports these results. We see that there is no statistically significant difference between the probability of men and women being unemployed in the months of January and February prior to the pandemic. This result adds assurance that the original analysis correctly identifies the immediate impact of the pandemic on job losses rather than other characteristic differences between men and women in the sample.

There are limitations to using the linear probability model (LPM). Due to the binary nature of the dependent variable, the LPM violates one of the Gauss-Markov assumptions in that the model contains heteroscedasticity. However, as discussed in Section IV, we adjusted for this by obtaining heteroscedasticity-robust standard errors (Wooldridge pg.205, 2013). However, a more concerning issue of using the LPM is that OLS estimated probabilities are not bound within the unit interval i.e. the predicted probability of the dependent variable may be greater than 1 or less than 0. To overcome this limitation, we could instead use more sophisticated binary response models such as logit and probit; these models are specifically made for binary dependent variables and always result in $0 < \hat{y} < 1$. However, after conducting a goodness of fit measure to determine the percent of predicted dependent variable observations that lie outside of the $\{0,1\}$ range, we find it to be less than 6 percent. While this shows a degree of lack of robustness to our results, it is a relatively small percentage of inaccuracy.

In addition, we can show that estimating the LPM using a subsample that yields only predictions that lie on the unit interval does not change our main findings. Horrace and Oaxaca (2005) put forth the idea of a "trimming estimator" where one first estimates the LPM using the full sample, predicts the fitted values, drops observations whose predictions lie outside the unit interval and then re-estimates the model with the remaining observations. Through conducting this test by running the regression (2.1) for the subsample that only predicts values within the interval, we obtain a difference-in-difference estimate of 0.031. This subsample result is extremely similar to the full sample result of 0.030 reported in Table 3, strengthening the case of using the LPM.

While the analysis detailed in this paper discusses limited variables, it would be interesting to review how other factors have been affected by Covid-19, particularly those linked to females. For example, determining how hours of work were affected alongside unemployment would give a stronger indicator of the effects of childcare on female labour force activity, as presumably many women reduced their working hours to care for children rather than became unemployed. Couch et al. (2020) generate estimations for this using early data, but it would interesting to see the updated hours of work effect across a longer time period.

Finally, a potential issue with reviewing the unemployment rate is that it requires workers to be on temporary layoff or to have searched for work in the past four weeks to be counted in the “unemployed” data. With Covid-19 inducing stay-at-home restrictions and the shut-down of entire industries, it is possible that many workers who have lost their jobs are not actively seeking employment and therefore are not included in the unemployment data.

VI. Policy Measures

Policy measures for economic recovery in the U.S. must be carefully considered in terms of whether they are gender neutral or promote or challenge gender equality.

Since it is clear that increased childcare responsibilities are a large determinant of the disproportionate impact on female unemployment, the government should prioritize measures that could alleviate such a burden such as early reopening of schools. This requires investing in infrastructure and procedures to ensure a safe and sustainable reopening, as well as decisions about vaccination priority groups (Fabrizio et al., 2021).

Alternatively, many OECD countries have introduced periods of special leaves as a possible solution. If these extra leave periods are shared equally among men and women, they may help to promote gender equality within families. However, if they are taken mostly by women, they risk pushing women out of the labour market for a prolonged period. Therefore, it is important to monitor that both genders benefit equally from these programs (Profeta, 2020).

As previously discussed, working from home may also have important consequences. It is likely that many sectors will have permanent shifts in the amount of work that requires in-person attendance versus work that can be completed at home. Flexible work arrangements have proved to be particularly beneficial for women struggling to balance their professional and personal life. Working from home has enormous potential to lessen work-family trade-offs for women and to induce a greater participation in domestic work. Nevertheless, it is again vital to ensure that men and women will continue to equally use the work flexibility that has been introduced during lockdown. Although many countries had pre-existing teleworking and flexible work arrangements, take-up rates were relatively low; only 16 percent of workers in the U.S. used telecommuting in 2019 (U.S. Bureau of Labour Statistics, 2019).

There could also be direct interventions to address unpaid childcare. A report by McKinsey Global Institute (2020) estimates the value of unpaid care work done by women to be $10 trillion, or 13 percent of global GDP. Potential interventions could include employer- or state-funded provision of childcare or tax policies that encourage both spouses to work and family-friendly policies such as flexible or part-time programs to support workers experiencing an increased childcare burden during the pandemic and beyond. Crucial measures are also required to change social norms about the equality in bearing childcare responsibilities. Finally, for industry implications, the government could prioritise the recovery of "non-essential" industries that disproportionately employ women and led to subsequent female job losses such as in hospitality, retail and professional services. Such actions are already taking place through the introduction of the American Rescue Plan Act which, effective from 11th March 2021, provides emergency grants, lending, and investment to hard-hit small businesses so they can rehire and retain workers and purchase the health and sanitation equipment they need to keep workers safe.

VII. Conclusion

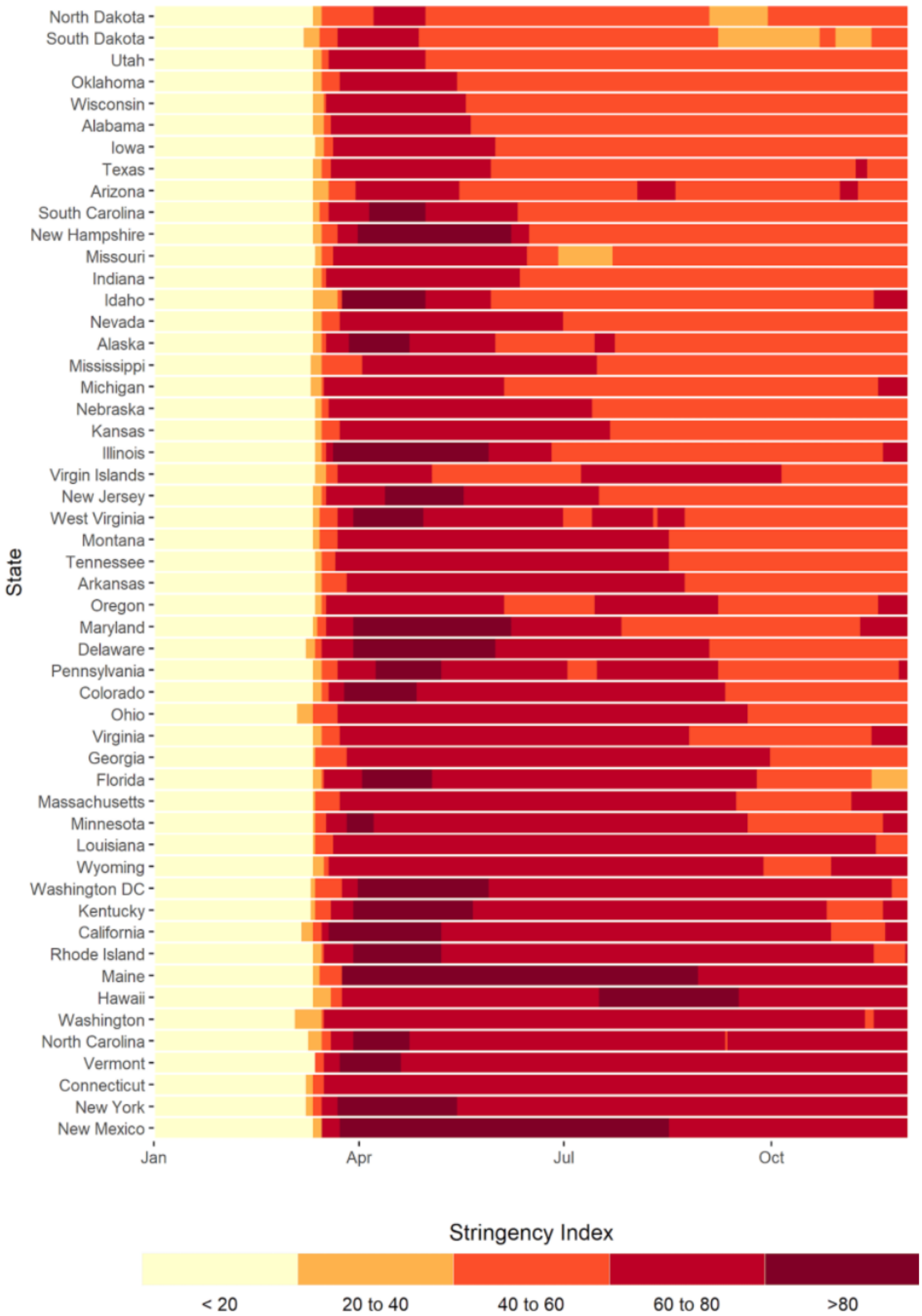
The Covid-19 pandemic has undoubtedly impacted the U.S. economy substantially and caused an unemployment shock with the potential to amplify existing inequalities. Difference-in-difference estimations using CPS data and controlling for individual characteristics found that Covid-19 widened the male-female unemployment gap by 3 percentage points in April 2020. The type of industry appears to have had a role to play, with industry-specific difference-in-difference estimates showing the most significant results for sectors which disproportionately employed females.

Nevertheless, even accounting for the fact that women and men work in different sectors, women's employment is dropping faster than average. This leads us to believe that the factor having the biggest effect on this widening of the gender unemployment gap is the increased childcare burden falling disproportionately on mothers. It has led to forced attritions from women being unable to meet their productivity goals, and voluntary resignations from women who face too much pressure from juggling both their paid and unpaid responsibilities. Triple-difference estimates support this theory, as the male-female unemployment gap was widened 2.2 percentage points more for people with children than for those without children during Covid-19. We calculated that the presence of children accounted for over half of the observed widening in the gender unemployment gap. The only factors that may be helping the U.S. achieve a more equal employment share are the high education levels attained by women and women's greater ability to telecommute in their occupations. However, again, if these telecommuting options are mostly used by women for the purpose of childcare, they may end up having a negative effect on female labour participation, working hours and female advancement in the workplace in the long-run.

The initial difference-in-difference estimates dropped by 2.1 percentage points when we examined a longer time period, indicating unemployment levels between men and women are once again converging, likely due to the reopening of many sectors and daycare centers. While this is a promising starting result, McKinsey Company Public and Social Sector (2021) predict that it will take until 2024 for women's employment in the U.S. to return to pre-pandemic levels, while men's employment will return to the pre-pandemic level one year earlier. To help speed up the journey towards low U.S. unemployment levels as well as equality between the sexes, economic recovery policy measures must consider the reasons for a higher female unemployment rate and help combat these obstacles, particularly the disproportionate childcare responsibilities falling on mothers. If nothing is done to maintain and advance gender parity, the economic and social lives of women could be permanently negatively affected, as well as economic growth more broadly. By contrast, recovery measures that invest in women represent significant opportunities to strive for gender equality and inclusive economic growth.

VIII. Appendix

Figure 1.1: Chart showing time periods states spent under different stringency index values, ordered by length of time spent at stringency index > 60 (Hallas et al., 2020) (Source: OxCGRT)



IX. Bibliography

Alon, T., Doepke, M., Olmstead-Rumsey, J. and Tertilt, M. (2020). The Impact of Covid-19 on Gender Equality. *Covid Economics, Vetted and Real-Time Papers*, Vol. 1(4), 62-86

Angrist, J.D and Pischke, J. (2014). *Mastering 'Metrics: The Path from Cause to Effect*. Princeton University Press, p.178.

Coskun, S., and Dalgic, H. (2020). "The Emergence of Procyclical Fertility: The Role of Gender Differences in Employment Risk." *CRC TR 224 Discussion Paper Series* No. 142.

Couch, K., Fairlie, R.W. and Xu, H. (2020). Gender and the COVID-19 Labor Market Downturn. *Stanford Institute for Economic Policy Research*, Working Paper No. 20-037

Doepke, M., and Tertilt, M. (2016). "Families in Macroeconomics." *National Bureau of Economic Research*, Working Paper No. 22068

Dua, A., Ellingrud, K., Lazar, M., Luby, R., Srinivasan, S. and Aken, T.V. (2021) *Achieving an inclusive US economic recovery*. [online] McKinsey and Company-Public and Social Sector. Available at: https://www.mckinsey.com/industries/public-and-social-sector/our-insights/achieving-an-inclusive-us-economic-recovery [Accessed 1 May 2021]

Fabrizio, S., Gomes, D.B.P., and Tavares, M.M. (2021). COVID-19 She-Cession: The Employment Penalty of Taking Care of Young Children. *IMF Working Papers* No. 2021/058

Federal Reserve of Economic Data (2020). Unemployment Rate (UNRATE). Available at: https://fred.stlouisfed.org/series/UNRATE [Accessed 10 January 2021]

Flood, S., King, M., Rodgers, R., Ruggles, S., and Warren, J.R. (2021). *Integrated Public Use Microdata Series, Current Population Survey*: Version 8.0 [dataset]. Minneapolis, MN: IPUMS. Available at: https://doi.org/10.18128/D030.V8.0 [Accessed 10 January 2021]

Gent, T.V., Khan, F. and Cloutier, N. (2018). Industrial Effects on Male and Female Unemployment Over the Great Recession: An Interurban Analysis. *The American Economist*, 64(1), pp.19-30.

Hallas, L., Hatibie, A., Majumdar, S., Pyarali, M, and Hale, T. (2020). Variation in US states' responses to COVID-19 2.0, *Blavatnik School of Government Working Paper*, No. 2020/034.

Heggeness, M. (2020). Estimating the immediate impact of the COVID-19 shock on parental attachment to the labor market and the double bind of mothers. *Review of Economics of the Household*, 18(4), pp.1053-1078.

Horrace, W. and Oaxaca, R. (2005). Results on the bias and inconsistency of ordinary least squares for the linear probability model. *Economics Letters*, 90(3), pp.321-327.

Hotchkiss, J.L. (2021). Will COVID-19 Erase Black Workers' Labor Market Gains?, *Federal Reserve Bank of Atlanta, Policy Hub* No. 2021-2.

Madgavkar, A., White, O., Krishnan, M., Mahajan, D. and Azcue, X. (2020). *COVID-19 and Gender Equality: Countering the Regressive Effects*. [online] McKinsey and Company. Available at: https://www.mckinsey.com/featured-insights/future-of-work/covid-19-and-gender-equality-countering-the-regressive-effects [Accessed 1 May 2021].

McDermott, D. and Cox, C. (2020). What impact has the coronavirus pandemic had on healthcare employment? [online] *Peterson-KFF Health System Tracker*. Available at: https://www.healthsystemtracker.org/chart-collection/what-impact-has-the-coronavirus-pandemic-had-on-healthcare-employment/#item-start [Accessed 1 May 2021].

Pepin, J., Sayer, L. and Casper, L. (2018). Marital Status and Mothers’ Time Use: Childcare, Housework, Leisure, and Sleep. *Demography*, 55(1), pp.107-133.

Profeta, P. (2020). Gender Equality and Public Policy during COVID-19, *CESifo Economic Studies*, Volume 66, Issue 4, Pages 365–375

Repko, M. and Thomas, L. (2020). As pandemic stretches on, retail bankruptcies approach highest number in a decade. [online] *CNBC.* Available at: https://www.cnbc.com/2020/08/03/with-pandemic-retail-bankruptcies-approach-highest-number-in-a-decade.html [Accessed 1 May 2021].

US Bureau of Labour Statistics (2019). *Job Flexibility and Work Schedules*. Available on: https: //www.bls.gov/news.release/flex2.nr0.htm [Accessed 10 January 2021]

US Census Bureau (2019). *American Community Survey (ACS).* [online] The United States Census Bureau. Available at: https://www.census.gov/programs-surveys/acs.html [Accessed 1 May 2021].

Wooldridge, J.M. (2013). *Introduction to Econometrics: EMEA Edition*. Cengage Learning EMEA, pg. 205

Zamarro, G. and Prados, M.J. (2020). Gender Differences in Couples' Division of Childcare, Work and Mental Health During COVID-19. *CESR-Schaeffer Working Paper Series*, Paper No: 2020-003