The Effect of Parenthood on Employment and Labour Force Participation Rates for Women During the COVID-19 Pandemic

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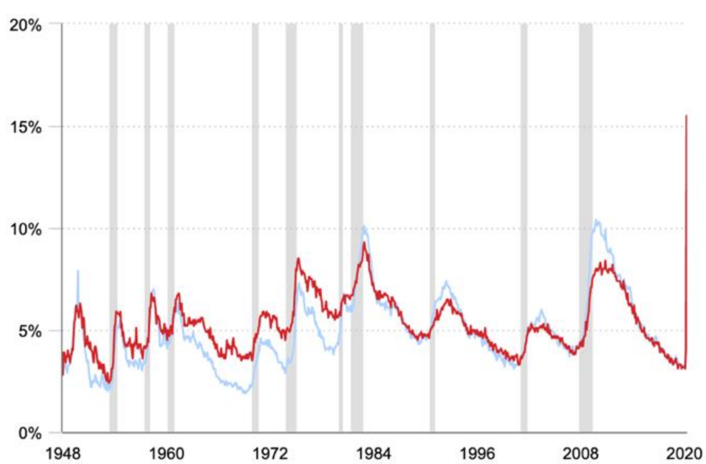
Introduction

During the early 1980s recession, the annual average unemployment rate for women, such that the unemployment rate is defined as "the number of unemployed people as a percentage of the labor force" where the labour force is the sum of the employed and unemployed (U.S. Bureau of Labor Statistics, 2023b), was lower than the annual average unemployment rate for men for the first time since 1947 (Nilsen, 1984). Since that recession, women's unemployment rates started to be the same, if not generally even lower, than men's unemployment rates (U.S. Bureau of Labor Statistics, 2020a). This new difference between women's and men's unemployment rates has become greater during every single recessionary period that has occurred since the early 1980s recession right up until the COVID-19 pandemic (U.S. Bureau of Labor Statistics, 2020a). In the short recessionary period caused by the COVID-19 pandemic, women's unemployment rates suddenly spiked past men's unemployment rates as they were 15.5% and 13% respectively, leading to a gap of 2.5 percentage points in April 2020 (Figure A), which is the largest sex-based employment rate difference compared to any month in any of the previous recessionary periods (U.S. Bureau of Labor Statistics, 2023a).

Figure A. Unemployment Rates of Men and Women, 1948-2020



(U.S. Bureau of Labor Statistics, 2020a)

As women's unemployment rates have decreased over the years, this change has come hand in hand with the gradual increase of women's labour force participation rates (Hipple, 2016). Still, women's labour force participation rates, such that labour force participation rate is defined as "the percentage of the population that is either working or actively looking for work" (U.S. Bureau of Labor Statistics, 2023b), have been significantly lower than men's labour force participation rates even in recent years. This difference becomes particularly pronounced when taking educational attainment levels into account. As of 2015, the labour force participation rate of women who did not complete secondary education was 49.1%, which is over 30 percentage points lower compared to men's 79.5%. Furthermore, the labour force participation rate of women who finished college was 82.3%, which is over 11 percentage points lower compared to men's 93.9%.

In a 2020 paper that followed the US labour market during the COVID-19 pandemic, Cajner et al. found that "employment declines were about 4 percentage points larger for women than for men" (Cajner et al., 2020). Even when factoring in potential causes of this gap such as firm size or industry as some companies and industries have been much harder hit by the COVID-19 pandemic than others, most of the difference in unemployment rates between men and women remained unaccounted for. In a 2021 paper, Albanesi and Kim found that married women without children and married women with children's employment to non-participation flow increased by 0.16 and 0.18 percentage points respectively in the summer of 2020 while in the same timeframe, their male counterparts' employment to non-participation flow increased by 0.06 and decreased by 0.03 percentage points respectively (Albanesi & Kim, 2021).

The purpose of this paper is to find the factors that are causing these unemployment rate differences and labour force participation rates differences during the COVID-19 pandemic compared to right before the COVID-19 pandemic. Namely, I will be looking at if being a parent during the COVID-19 pandemic causes women to have any economically and statistically significant changes in their employment and labour force participation statuses.

Labour force participation rates come into play because declining labour force participation rates can oftentimes hide the true results of how much employment rates have decreased for specific groups of people. Thus, this leads to my research question: after controlling for factors that are proven by prior literature that affect employment or labour force participation, to what extent does being a parent during the COVID-19 pandemic relate to women's employment and labour force participation statuses? Ultimately, if being a parent who is female during the COVID-19 pandemic has a significant relationship with being employed or a part of the labour force, knowing this can guide current governmental action to better support more vulnerable demographic groups during future global pandemics or economic shocks in general.

Literature Review

There are a few main topics of relevant literature that need to be explored to give full context to the research question: to what extent does being a parent during the COVID-19 pandemic relate to women’s employment and labour force participation statuses? These topics can be organised into three broad categories: demographic groups, economic shocks, and childcare. These areas of literature provide important background knowledge regarding parenthood during the COVID-19 pandemic concerning women's employment and labour force participation statuses.

The literature regarding unemployment amongst different demographic groups is fairly robust. Regarding race, a 2013 paper by Michaelides and Mueser found that “unemployment for non-Whites remains much higher than for Whites” (Michaelides & Mueser, 2013). There is still a race gap in unemployment when industry and occupation are accounted for, although it has declined in recent years. Regarding ethnicity, this same paper found that “relative Hispanic unemployment has declined, and industry and occupational differences explain much of the remaining gap”, suggesting that there is still an unemployment gap due to ethnicity (Michaelides & Mueser, 2013). So, based on existing literature, race and ethnicity are both related with unemployment rates.

Regarding educational attainment and unemployment rates, Riddell and Song found that “higher education at the post-secondary level reduces the incidence of unemployment” (Riddell & Song, 2011). This is easily predicted due to the skill development and credentialing that higher education can provide. This relationship still holds when controlling for “survey year, survey month, state of residence, age groups, gender, race, marital status, and metropolitan status”

(Riddell & Song, 2011). So, based on existing literature, educational attainment is related with unemployment rates.

Sex is another factor that affects the rates of unemployment. In a 2002 paper, Rives and Sosin found that within different occupations, “women’s unemployment rates are consistently higher than men’s rates” (Rives & Sosin, 2002). However, the authors of this paper also found that there is a higher proportion of women in occupations that have lower unemployment rates overall, for both men and women. Combined with the previous finding, this means that while women tend to be in occupations that have higher employment rates, women’s unemployment rates are still higher relative to men’s unemployment rates. So, based on existing literature, sex and unemployment rates are related in a variety of ways.

Interestingly, Rives and Sosin also found that there are smaller proportions of women in occupations that are more strongly impacted during recessions (Rives & Sosin, 2002). Although both men and women have higher unemployment rates during economic shocks, men typically have higher unemployment rates than women during recession years (U.S. Bureau of Labor Statistics, 2023a). So, existing literature seems to support historical evidence that sex, economic shocks, and unemployment rates are all related with each other.

In addition, the increased demand for childcare at home could explain the unemployment rate gap that Cajner et al. found (Cajner et al., 2020). Because of COVID-19, there have been “large-scale closures of daycare centers and schools”, which results in a greater proportion of childcare being carried out in the home (Alon et al., 2020). This change impacts women more than men because women spend about twice as much time with children compared to men (Craig, 2006). For couples with children under age 18, men typically provide about 0.9 hours of childcare per day compared to women’s 1.8 hours, but for couples with children under age 6, where men typically provide about 1.4 hours of childcare per day compared to women's 2.7 hours (U.S. Bureau of Labor Statistics, 2020b). Both men and women provide about 50% more childcare when their children are younger, in absolute terms, women provide nearly double the amount of childcare as men do regardless of their children's ages. On top of that, some families are single-parent households, of which single-mother households make up about 70% (US Census Bureau, 2019). So, whether women are parenting jointly with their husbands or parenting by themselves, they are spending much more time on childcare than men. Both existing literature and historical data show that sex, childcare, and unemployment rates are all related with each other.

The impact of the childcare problem on women is particularly relevant because for every additional hour of unpaid care work that women do, on average, there is a five percentage point decrease in women's labour force participation rate (Ferrant et al., 2014). There is significant literature on women's parenthood status and their participation in the labour market. In particular, despite increases in the labour force participation rate for women over time, "mothers are still less likely to work than nonmothers… and employed mothers average fewer work hours than nonmothers" (Kaufman & Uhlenberg, 2000). As a result of this childcare burden, women with children are likely missing out on certain career opportunities and earning less than non-mothers, which can permanently limit their potential career success.

Theory of Equations

In this paper, I am interested in modelling how the COVID-19 pandemic has affected employment rates and labour force participation rates between men and women when taking parenthood into account. I will have two main final logistic models since both of the dependent variables (*employed* and *labourforce*) are categorical and binary. Both models will be built up in three iterations, starting from just the variables of interest, then with their various interaction terms, and finally with all of the control variables.

For my first model, my primary variables of interest will be the interaction terms between sex, parenthood status, and whether COVID-19 was present or not (based on a particular month during the years 2019 to 2021). Thus, some of the variables in the model will be the individual's sex, parenthood status, COVID-19 status, as well as the interaction terms between these three variables. My control variables will be demographic factors such as race, ethnicity, education, marital status, and geography. The outcome for my first model will be whether the person is employed or not, but I will also run a second model with the same variables of interest and control variables, but where the outcome will be whether the person is in the labour force or not.

At the most basic level, my dependent variable *Employed* is an indicator variable that shows whether the individual is employed. For this starting model, my independent variables are sex, parenthood status, and whether COVID-19 was present or not. So, this model will be:

$$Employed_{i,t} = \beta_0 + \beta_1 Female_{i,t} + \beta_2 Parent_{i,t} + \beta_3 Covid_{i,t} + \mu_{i,t}$$

Female is an indicator variable referring to whether the individual is female in that sample. *Parent* is an indicator variable referring to whether the individual is a parent in that sample. *Covid* is an indicator variable referring to whether COVID-19 existed in that sample.

Once the starting model has the base variables, the next step will be to add the interaction terms between these variables:

$$Employed_{i,t} = \beta_0 + \beta_1 Female_{i,t} + \beta_2 Parent_{i,t} + \beta_3 Covid_{i,t} + \beta_4 Female_{i,t} * Parent_{i,t} + \beta_5 Female_{i,t} * Covid_{i,t} + \beta_6 Parent_{i,t} * Covid_{i,t} + \beta_7 Female_{i,t} * Parent_{i,t} * Covid_{i,t} + \mu_{i,t}$$

*Female * Parent* is an interaction term controlling for the general added effect of being a female parent on whether the individual is employed. *Female * Covid* is an interaction term controlling for the general added effect of being a female during the COVID-19 pandemic on whether the individual is employed. *Parent * Covid* is an interaction term controlling for the general added effect of being a parent during the COVID-19 pandemic on whether the individual is employed. *Female * Parent * Covid* is an interaction term accounting for being a female parent during the COVID-19 pandemic's potential added effect on whether the individual is employed and is the primary variable of interest. So, the next step will be to add the control variables for education, marital status, race, ethnicity, and geographic location which gives us our first model:

Model 1 (Employment)

$$Employed_{i,t} = \beta_0 + \beta_1 Female_{i,t} + \beta_2 Parent_{i,t} + \beta_3 Covid_{i,t} + \beta_4 Female_{i,t} * Parent_{i,t} + \beta_5 Female_{i,t} * Covid_{i,t} + \beta_6 Parent_{i,t} * Covid_{i,t} + \beta_7 Female_{i,t} * Parent_{i,t} * Covid_{i,t} + \beta_{10} Education_{i,t} + \beta_{11} Married_{i,t} + \beta_{12} White_{i,t} + \beta_{13} Hispanic_{i,t} + \beta_{14} \boldsymbol{S}_{i,t} + \mu_{i,t}$$

Education is an indicator variable referring to whether the individual attained any post-secondary education or not to control for education's effect on individuals' employment statuses. *Married* is an indicator variable referring to whether the individual is married to control for marriage's effect on individuals' employment statuses. *White* is an indicator variable referring to whether the individual is White or not to control for race's effect on individuals' employment statuses. *Hispanic* is an indicator variable referring to whether the individual is Hispanic or not to control for ethnicity's effect on individuals' employment statuses. $\mathbf{S}_i$ is a vector that represents a set of fixed effects by state, which would be the fifty states of the United States. In the regression, the "base" state is the District of Columbia, in which there are 50 other indicator variables for each of the 50 states to control for any geographic or state-based effect on individuals' employment statuses.

With all the control variables accounted for, this will be the first model of this paper. If being a female parent during the COVID-19 pandemic does indeed positively or negatively affect whether the individual is employed or not, I would expect the *Female * Parent * Covid* coefficient to be positive or negative in Model 1 in a statistically significant way, meaning that being female and a parent during the COVID-19 pandemic is correlated with that individual being more likely to be employed or not employed.

Additionally, I will also be running another logistic model where the outcome will be whether the individual is in the labour force or not with the same variables of interest, their interaction terms, and control variables. With the new outcome and the original model, it would look like:

Model 2 (LabourForce)

$$LabourForce_{i,t} = \beta_0 + \beta_1 Female_{i,t} + \beta_2 Parent_{i,t} + \beta_3 Covid_{i,t} + \beta_4 Female_{i,t} * Parent_{i,t}$$
$$+ \beta_5 Female_{i,t} * Covid_{i,t} + \beta_6 Parent_{i,t} * Covid_{i,t} + \beta_7 Female_{i,t} * Parent_{i,t} * Covid_{i,t}$$
$$+ \beta_{10} Education_{i,t} + \beta_{11} Married_{i,t} + \beta_{12} White_{i,t} + \beta_{13} Hispanic_{i,t} + \beta_{14} \boldsymbol{S}_{i,t} + \mu_{i,t}$$

The dependent variable *LabourForce* is an indicator variable that shows whether the individual is a part of the labour force or not. If being female and a parent during the COVID-19 pandemic does indeed positively or negatively affect whether someone is in the labour force or not, I would expect the *Female * Parent * Covid* coefficient to be positive negative in Model 2 in an economically and statistically significant way, meaning that being female and a parent during the COVID-19 pandemic is correlated with that individual being more likely to be in the labour force or not in the labour force.

Data

The data I use in this paper is from the Integrated Public Use Microdata Series (IPUM) online platform, which draws its data from the Current Population Survey (CPS). The CPS is a monthly survey of households in the United States, and it provides a variety of information about households, including individuals' labour force status, employment status, and more general demographic information. The CPS samples with a rotational pattern in which it includes respondents for four months at a time with eight-month gaps.

My sample contains all the months from 2019 through 2021. I refactor all the variables to turn them into the indicator variables as described in the prior section, and I create the *Covid* variable, which shows whether the sample of the individual was taken during the pandemic or not. More specifically, the *Covid* indicator will refer to any sample that was taken during or after March 2020, which is when the World Health Organization officially declared COVID-19 to be a global pandemic, and subsequently, any sample from January 2019 to February 2020 will refer to samples that are "pre-COVID" (U.S. Department of Health & Human Services, 2021).

From this data, I drop all observations that have either empty or irrelevant responses. In this dataset, individuals in the armed forces have NIU for the labour force variable, as the CPS records whether individuals are a part of the civilian labour force or not. To maintain consistency with the literature review that draws from the U.S. Bureau of Labor Statistics, I also drop all individuals who are in the Armed Forces from this dataset as well as all observations where the individual's age does not fall between the years of 25-54 years. As I want to best capture observations where individuals are of working age, I set the lower bound to focus on parents who are a part of the working-age population and I set the upper bound to focus on parents whose children would still be under 18 years old.

After cleaning the data as mentioned, the number of samples shown in my tables end up being under half of the sample amount that the data set initially had. More specifically, the data set went from 3,977,616 observations to 1,479,558 observations after I dropped all of the individuals who were either not in the age range or did not have the necessary information for all of the variables needed (Table 1). For example, Table 1 shows that 86.16% of the individuals sampled are in the labour force, 51.61% of the individuals sampled are female, 54.12% of the individuals sampled are parents, and 55.18% of the samples of individuals were taken during the COVID-19 pandemic.

Table 1. Data Description Table (Overall, Observations=1,479,558)

Variable Name	Mean	Std. Dev.	Min	Max
employed	0.6056	0.7717	-1	1
labourforce	0.8216	0.3828	0	1
female	0.5161	0.4997	0	1
parent	0.5412	0.4983	0	1
covid	0.5518	0.4973	0	1
female_parent	0.3072	0.4613	0	1
female_covid	0.2843	0.4511	0	1
parent_covid	0.2970	0.4570	0	1
female_parent_covid	0.1684	0.3742	0	1
education	0.6655	0.4718	0	1
married	0.5983	0.4902	0	1
white	0.7902	0.4071	0	1
hispanic	0.1599	0.3665	0	1

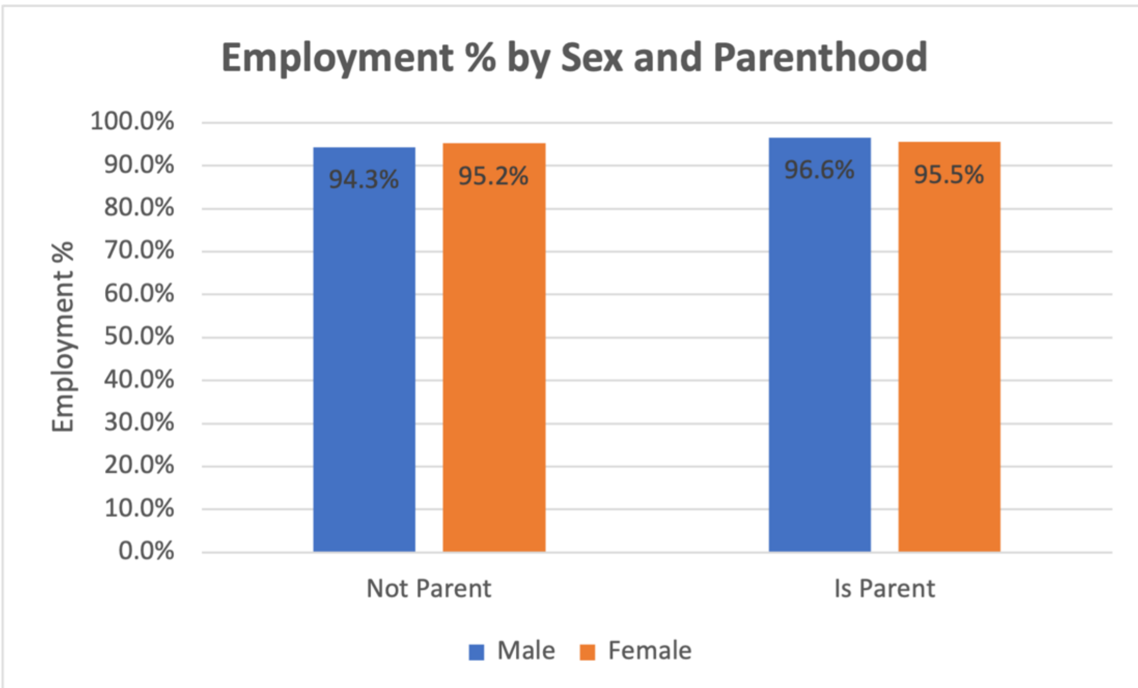
When sorting the data, I recoded some of the data so the eventual regressions will run a bit smoother. For the observations regarding whether the individual was employed or not, not being in the labour force was also a part of the responses, which doesn't fit with the way that employment rates are calculated. However, this makes sense as those who are not in the labour force are not employed nor are they are not actively seeking to be employed (so they are not unemployed). For this, I coded being employed as 1, not employed as 0, and not in the labour force as -1. However, when finding the mean of the employed variable, which represents the percentage of people employed, to give a better visual representation of the employment rates of various groups, if an individual is not in the labour force, then they are not included in those calculations (Table 2). So, we can better see from Table 2 that 95.42% of the individuals sampled are employed.

Table 2. Data Description Table (In Labor Force, Observations=1,215,665)

Variable Name	Mean	Std. Dev.	Min	Max
employed	0.9542	0.2092	0	1
labourforce	1.0000	0.0000	1	1
female	0.4784	0.4995	0	1
parent	0.5424	0.4982	0	1
covid	0.5488	0.4976	0	1
female_parent	0.2767	0.4474	0	1
female_covid	0.2619	0.4397	0	1
parent_covid	0.2961	0.4566	0	1
female_parent_covid	0.1506	0.3577	0	1
education	0.6978	0.4592	0	1
married	0.6032	0.4892	0	1
white	0.7981	0.4014	0	1
hispanic	0.1537	0.3606	0	1

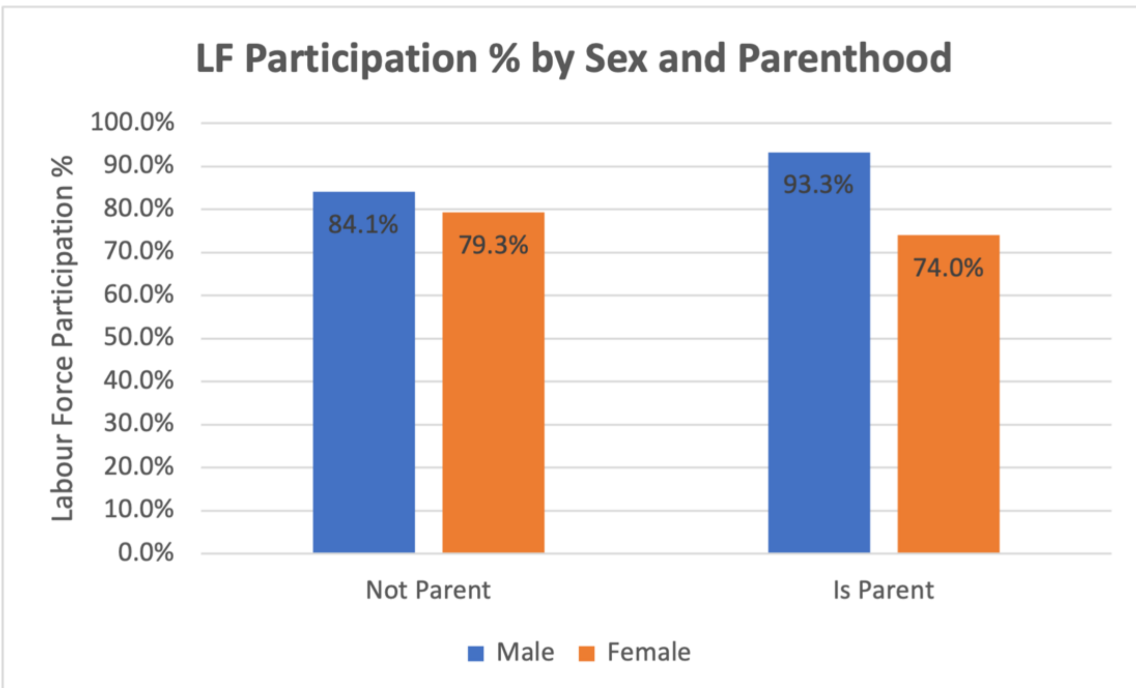
Some other relationships between certain variables depict much larger differences in employment and labour force participation rates, as shown by the figures, which represent the entire dataset from 2019 to 2021. In Figure 1, there appears to be a significant difference in employment rates between men and women with respect to whether they are parents or not. Women who are not parents have a 95.2% employment rate on average, and women who are parents have a similar employment rate of about 95.5% on average. Men who are not parents have a 94.3% employment rate on average, which is 0.9 percentage points lower than their female counterparts, but men who are parents have an employment rate of about 96.6% on average, which is 1.1 percentage points higher than their female counterparts. As shown by the 2.3 percentage point increase for men compared to the 0.3 percentage point increase for women, individuals who are parents are generally more likely to be employed. However, this phenomenon appears to be a lot more prominent for men than for women.

Figure 1. Employment Percentage by Sex and Parenthood



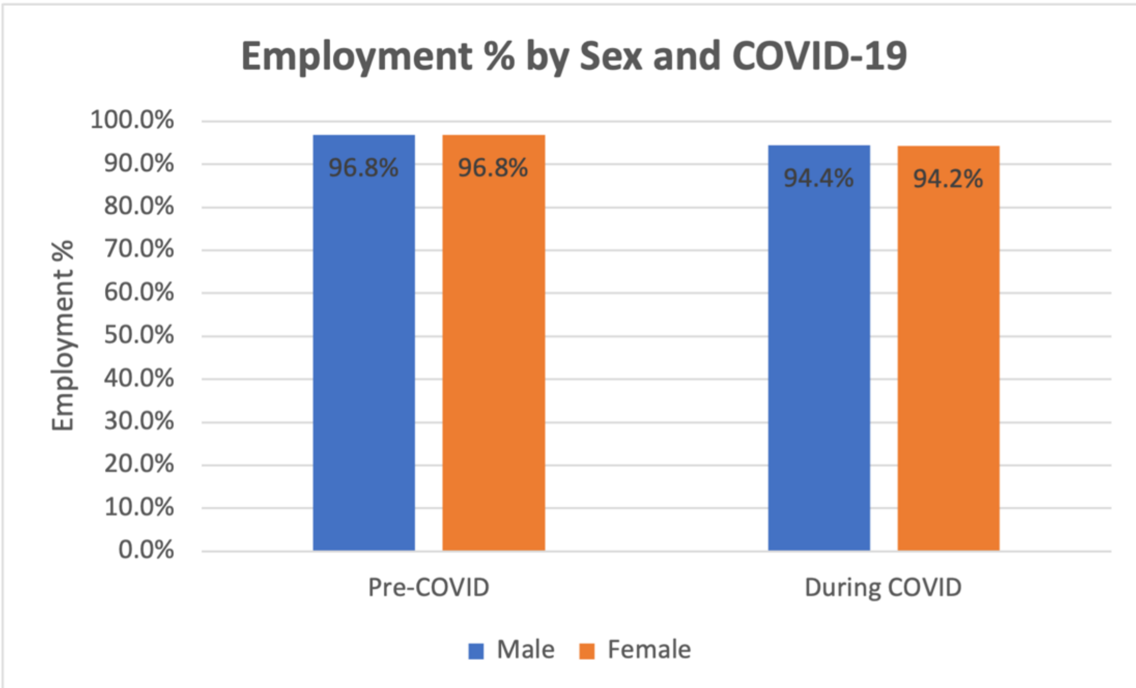
In Figure 2, there is a significant difference in labour force participation rates between men and women with respect to whether they are parents or not. Women who are not parents have a labour force participation rate of 79.3% on average, whilst women who are parents have a lower participation rate of 74.0% on average. Men who are not parents have an 84.1% labour force participation rate on average, which is 4.8 percentage points higher than their female counterparts, whereas men who are parents have a 93.3% participation rate on average, which is 19.3 percentage points higher than their female counterparts. These differences show that regardless of parenthood, men are more likely to participate in the labour force. It is interesting to note that men without children specifically are more likely to participate in the labour force than both women without children and women with children, and this gender gap in labour force participation becomes much more pronounced when comparing men with children to women with children. Men who are parents are the most likely to participate in the labour force by far, whilst women with children are the least likely to be in the labour force.

Figure 2. Labour Force Participation Percentage by Sex and Parenthood



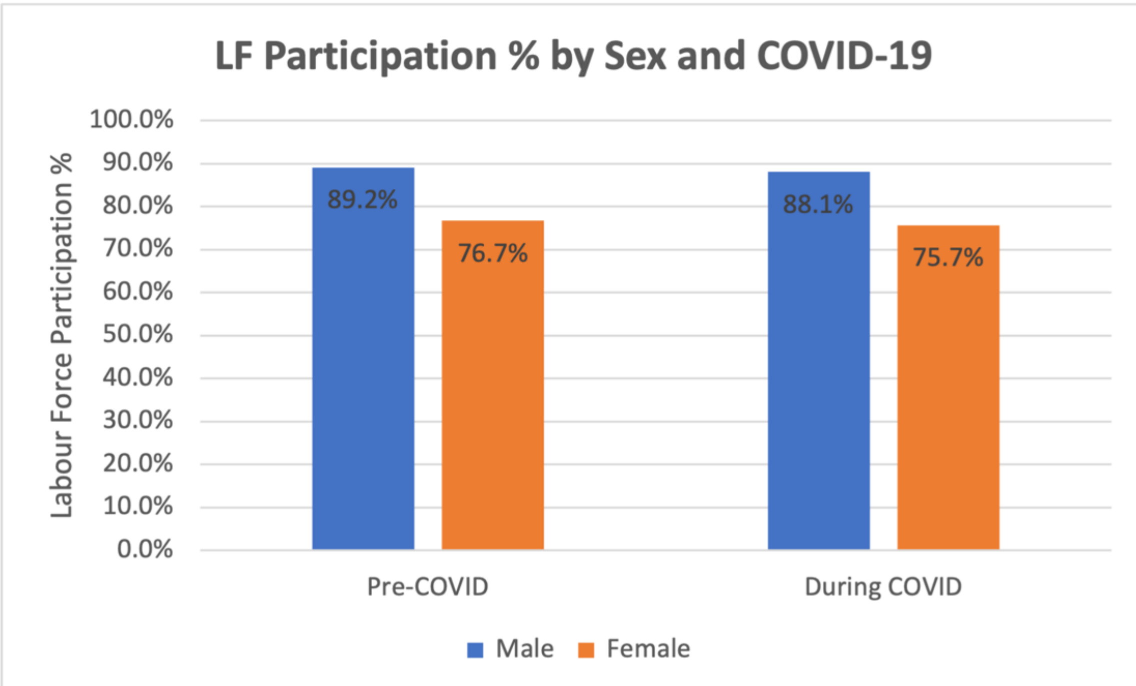
In Figure 3, there appears to be essentially no difference in employment rates between men and women with respect to before or during the COVID-19 pandemic. Before the COVID-19 pandemic, both men and women had the same average employment rate of 96.8%. During the pandemic, the employment rate for men dropped to an average of 94.4%, whereas for women, the employment rate dropped to an average of 94.2%. Men experienced a 2.4 percentage point decrease in employment, and women experienced a 2.6 percentage point decrease in employment. This shows that both men and women were impacted by the COVID-19 pandemic with respect to their employment rates, but the employment rate of women decreased by 0.2 percentage points more than the employment rate of men.

Figure 3. Employment Percentage by Sex and COVID-19



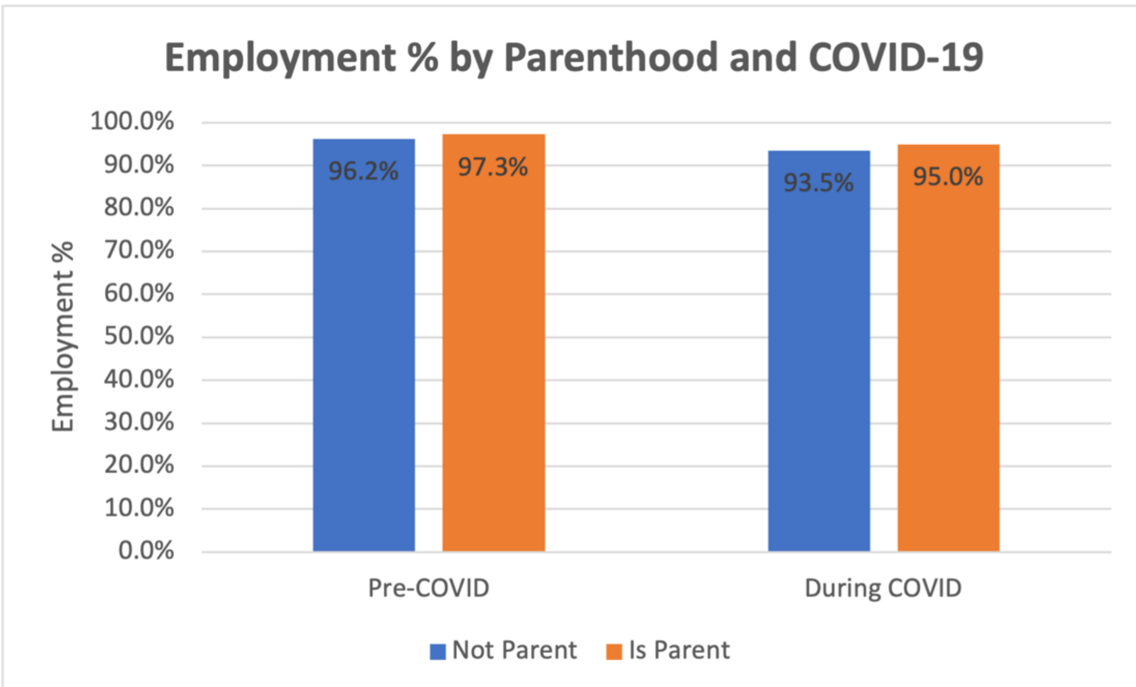
In Figure 4, there are differences in labour force participation rates with respect to gender and the COVID-19 pandemic. Before the pandemic, men had an average labour participation rate of 89.2% and women had an average labour participation rate of 76.7%. During the pandemic, men had a labour participation rate of 88.1% on average, while women had a labour participation rate of 75.7% on average. Comparing pre-COVID to during COVID, both men and women experienced a nearly identical decrease in labour force participation rates; men experienced a 1.1 percentage point decrease and women experienced a 1% decrease. However, while men and women are similar with respect to the impacts of COVID-19 on labour force participation, men and women have significantly different labour force participation rates compared to each other, with a 12.5 percentage point difference pre-COVID and a 12.4 percentage point difference during the pandemic. This shows that while the pandemic decreased labour force participation rates, it did not have a strong impact on the labour force participation percentage differences between men and women.

Figure 4. Labour Force Participation Percentage by Sex and COVID-19



In Figure 5, there are small differences in employment rates with respect to parenthood and COVID-19. Parents before the pandemic had employment rates of 97.3% on average, whereas parents during the pandemic had employment rates of 95.0% on average, which is a difference of 2.3 percentage points. On the other hand, non-parents before the pandemic had employment rates of 96.2% on average, whereas non-parents during the pandemic have employment rates of 93.5% on average, which is a difference of 2.7 percentage points. This shows that both parents and non-parents experienced decreases in employment rates between before and during the pandemic, but non-parents experienced a slightly greater decrease by 0.4 percentage points. Additionally, parents generally have higher employment rates than non-parents, both before and during the COVID-19 pandemic, although the gap is slightly smaller pre-pandemic with a 1.1 percentage point difference compared to during the pandemic with a 1.5 percentage point difference.

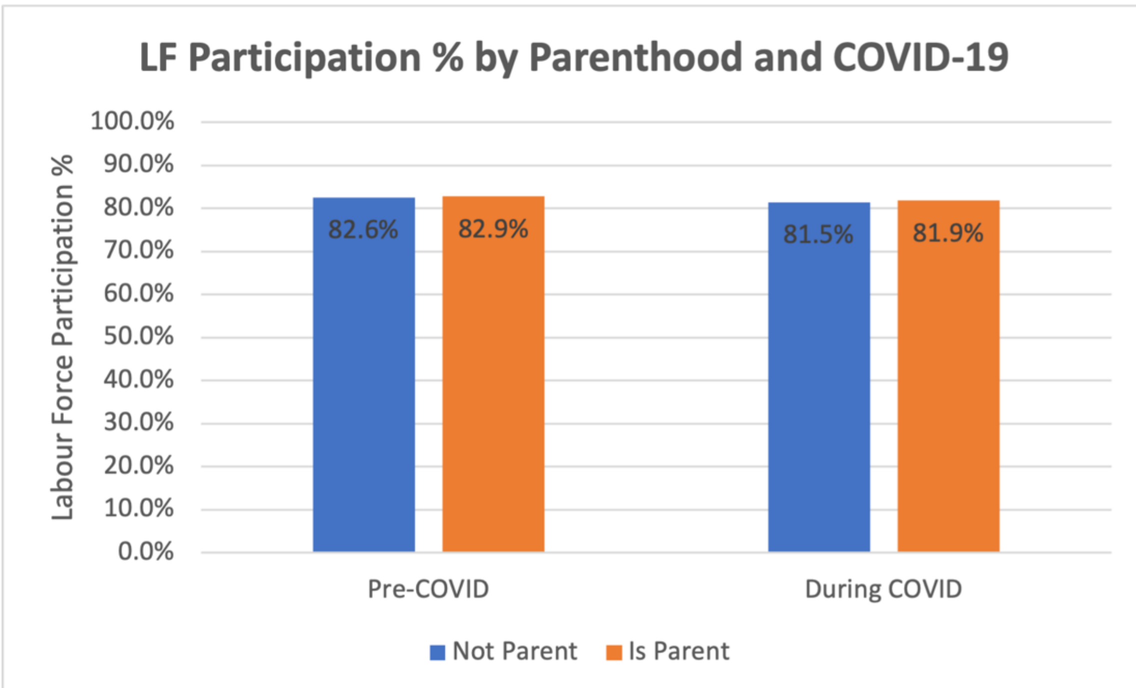
Figure 5. Employment Percentage by Parenthood and COVID-19



In Figure 6, there appear to be no major differences in labour force participation rates with respect to parenthood and the COVID-19 pandemic. Before the pandemic, parents had labour force participation rates of 82.9% on average and non-parents had labour force participation rates of 82.6% on average, which is a small 0.3 percentage point difference. During the pandemic, parents had average labour force participation rates of 81.9% and nonparents had average labour force participation rates of 81.5%, which is a 0.4 percentage point difference. Additionally, the parents' participation rate pre-COVID (82.9%) and during COVID (81.9%)

only show a decrease by 1 percentage point, which is very similar to the 1.1 percentage point decrease in nonparents' participation rate pre-COVID (82.6%) and during COVID (81.5%). This shows that parents have a slightly higher labour force participation rate than nonparents both before and during the pandemic, but the difference is extremely minor. Additionally, this shows that the COVID-19 pandemic is only very slightly negatively related with labour force participation rates for both parents and nonparents.

Figure 6. Labour Force Participation Percentage by Parenthood and COVID-19



Results

Table 3: Regression with Employed as Dependent Variable

VARIABLES	(1) employed	(2) employed	(4) (fixed effects) employed
Observations	1,215,665	1,215,665	1,215,665
Pseudo R-Squared	0.0125	0.0141	0.0434
female	-0.0385	0.2615	0.144
	(<0.001)	(<0.001)	(<0.001)
parent	0.2959	0.6131	0.3209
	(<0.001)	(<0.001)	(<0.001)
covid	-0.6048	-0.5348	-0.546
	(<0.001)	(<0.001)	(<0.001)
female_parent		-0.577	-0.4068
		(<0.001)	(<0.001)
female_covid		-0.1084	-0.1115
		(<0.001)	(<0.001)
parent_covid		-0.1272	-0.1301
		(<0.001)	(<0.001)
female_parent_covid		0.1527	0.1441
		(<0.001)	(<0.001)
education			0.6172
			(<0.001)
married			0.5465
			(<0.001)
white			0.4122
			(<0.001)
hispanic			-0.1423
			(<0.001)
Constant	3.2754	3.1322	2.3798
	(<0.001)	(<0.001)	(<0.001)

Note: p-values in ()

Starting with Model 1, in which Table 3 shows the effect of being a female parent on employment rates during the COVID-19 pandemic, Column 1 describes the initial regression of just sex, parenthood status, and COVID-19 timing status on the likelihood of an individual being employed. All three variables, which are *female*, *parent*, and *covid*, are statistically significant at the 1% level. The variable *female* is related with an individual being 3.78% less likely to be employed. The variable *parent* is related with the increased likelihood of an individual being employed by 34.43%, which appears to be fairly economically significant. The variable *covid* is related with an individual being 45.38% less likely to be employed, which appears to be more economically significant. However, the pseudo r-squared value with these three control variables is 0.0125, suggesting that the model does not have good explanatory power.

Table 3 Column 2 adds the additional variables of the interaction terms between *female* and *parent*, *female* and *covid*, *parent* and *covid*, and *female* and *parent* and *covid*, and all of these variables, along with the initial variables of interest, are statistically significant at the 1% level. Out of the three initial variables of interest, the variable *parent* appears to be the most economically significant as it is now related with an individual being 84.61% more likely to be employed, which means that being a parent is related with almost double the likelihood of an individual employed. For the interaction terms, the variable *female_parent* appears to be the most economically significant as it is related with an individual being 43.84% less likely to be employed, which means that an individual who is a parent and also female is that much less likely to be employed. However, the pseudo r-squared value with these additional variables is 0.0141, suggesting that the model still does not have good explanatory power.

The results of Column 3 of Table 3 provide a bit more information as the control variables get added, including controlling for all of the states. All of the control variables (*education, married, white, hispanic*), along with the initial variables of interest and their interaction variables, are statistically significant at the 1% level. To start with the initial variables of interest, the variables *female* and *parent* affect the likelihood of an individual being employed by 15.49% and 37.84% respectively. The variable *covid* is related with an individual being 42.07% less likely to be employed.

Moving onto the interaction terms, the variable *female_parent* is related with an individual being 33.42% less likely to be employed. The variable *female_covid* is related with an individual being 10.55% less likely to be employed. The variable *parent_covid* is related with an individual being 12.20% less likely to be employed. Finally, the main interaction term of interest *female_parent_covid* is related with an increased likelihood of an individual being employed by an additional 15.50%. Based on this, being a female parent seems to have the strongest relationship with an individual's employment likelihood (though it is negative) and being a female parent during the COVID-19 pandemic seems to be the only interaction term that is positively related with an individual's employment likelihood.

Then, looking at the control variables, it appears that *education, married, and white* are all relatively economically significant. The control variable of *education* is related with an individual being 85.37% more likely to be employed, which means that an individual having any post-secondary education is associated with that individual being almost twice as likely to be employed. The control variable of *married* is related with an individual being 72.72% more likely to be employed, which means that an individual being married is also associated with that individual being nearly twice as likely to be employed. The control variable of *white* is related with an individual being 51.01% more likely to be employed, which is also pretty economically significant. Finally, the control variable of *hispanic* is related with an individual being 13.26% less likely to be employed, so it is relatively much less significant than all of the other control variables. However, the final version of Model 1 yields an r squared value of 0.0434, suggesting that even with all the control variables regarding education, marital status, race, ethnicity, as well as the fifty different geographical states and District of Columbia, it appears that Model 1 still does not have very good explanatory power.

Table 4: Regression with Labour Force as Dependent Variable

VARIABLES	(1) labourforce	(2) labourforce	(3) (fixed effects) labourforce
Observations	1,479,558	1,479,558	1,479,558
Pseudo R-Squared	0.0294	0.0419	0.0745
female	-0.9007	-0.3499	0.01
	(<0.001)	(<0.001)	(<0.001)
parent	0.1265	0.9721	0.01
	(<0.001)	(<0.001)	(<0.001)
covid	-0.0729	-0.0978	0.01
	(<0.001)	(<0.001)	(<0.001)
female_parent		-1.266	0.01
		(<0.001)	(<0.001)
female_covid		0.0447	0.01
		(<0.001)	(<0.001)
parent_covid		-0.0173	0.01
		(0.293)	(<0.001)
female_parent_covid		0.0086	0.01
		(0.667)	(<0.001)
education			0.01
			(<0.001)
married			0.01
			(<0.001)
white			0.01
			(<0.001)
hispanic			0.01
			(<0.001)
Constant	2.0284	1.7244	0.01
	(<0.001)	(<0.001)	(<0.001)

Note: p-values in ()

For Model 2, in which Table 4 shows the effect of being a female parent on labour force participation rates during the COVID-19 pandemic, Column 1 starts with the initial regression of sex, parenthood status, and COVID-19 timing status on the likelihood of an individual being a part of the labour force. All three variables, which are *female*, *parent*, and *covid*, are statistically significant at the 1% level. The variable *female* is related with an individual being 59.37% less likely to be a part of the labour force, which appears to be fairly economically significant. The variable *parent* is related with the increased likelihood of an individual being a part of the labour force by 13.48%. The variable *covid* is related with an individual being 7.03% less likely to be a part of the labour force. However, the pseudo r-squared value with these three control variables is 0.0294, suggesting that the model does not have good explanatory power.

Table 4 Column 2 adds the additional variables of the interaction terms between *female* and *parent*, *female* and *covid*, *parent* and *covid*, and *female* and *parent* and *covid*. The interaction terms *female_parent* and *female_covid*, along with the initial variables of interest, are statistically significant at the 1% level, and the interaction terms *parent_covid and female_parent_covid* are not statistically significant at all. Out of the three initial variables of interest, the variable *parent* appears to be the most economically significant as it is now related with an individual being 164.35% more likely to be a part of the labour force, which means that being a parent is related with almost tripling the likelihood of an individual being in the labour force. For the interaction terms, the variable *female_parent* appears to be the most economically significant as it is related with an individual being -71.80% less likely to be a part of the labour force, which means that an individual who is a female parent is almost doubly less likely to be a part of the labour force. It is interesting to note that both of the economically significant variables (*parent* and *female_parent*) are also very economically significant for the model regarding employment status, though these variables seem to be even much more pronounced in the labour force model. Still, the pseudo r-squared value with these additional variables is 0.0419, similarly suggesting that the model still does not have good explanatory power.

The results of Column 3 of Table 4 provide a bit more information as the control variables get added, including controlling for all of the states. All of the control variables (*education, married, white, hispanic*), along with the initial variables of interest and their interaction variables (with the exceptions of *parent_covid* and *female_parent_covid)*, are statistically significant at the 1% level. To start with the initial variables of interest, the variable *female* is related with an individual being 36.64% less likely to be a part of the labour force, which appears to be fairly economically significant. The variable *parent* is related with the increased likelihood of an individual being a part of the labour force by 171.15%, which means that being a parent is related with almost tripling the likelihood of an individual being in the labour force. The variable *covid* is related with an individual being 10.26% less likely to be a part of the labour force.

Moving onto the interaction terms, the variable *female_parent* is related with an individual being 71.23% less likely to be a part of the labour force, which means that an individual who is a female parent is almost doubly less likely to be a part of the labour force. The variable *female_covid* is related with an individual being 4.13% more likely to be a part of the labour force. The variable *parent_covid* is related with an individual being 1.66% less likely to be a part of the labour force, so it is both not economically significant nor statistically significant. Finally, the main interaction term of interest *female_parent_covid* is related with an increased likelihood of an individual being employed by an additional 0.59%, so it is also both not economically significant nor statistically significant. Based on this, being a female parent still seems to have the strongest relationship with an individual's labour force participation likelihood, though it is quite negative.

Then, looking at the control variables, it appears that *education* is by far the most relatively economically significant. The control variable of *education* is related with an individual being 135.91% more likely to be a part of the labour force, which means that an individual having any post-secondary education is associated with that individual being more than twice as likely to be in the labour force. The control variable of *married* is related with an individual being 4.78% less likely to be a part of the labour force. The control variable of *white* is related with an individual being 21.06% more likely to be employed, which is also somewhat economically significant. Finally, the control variable of *hispanic* is related with an individual being 1.76% less likely to be employed, so it is still relatively much less significant than all of the other control variables. However, the final version of Model 2 yields a pseudo r-squared value of 0.0745. This suggests that even with all the control variables regarding education, marital status, race, and ethnicity, as well as the fifty different geographical states and the District of Columbia, it appears that although the final iteration of Model 2 has the strongest explanatory power compared to any iteration of Model 1 or Model 2, it still does not have very good explanatory power.

Conclusion

In this paper, I find that being a female parent during the COVID-19 pandemic is related with whether the individual is employed in both an economically significant and statistically significant way (15.50% at $p<0.001$). However, being a female parent during the COVID-19 pandemic does not affect whether the individual is a part of the labour force in an economically significant or statistically significant way (0.59% at $p=0.29$).

From Model 1, this paper finds that being a female parent during the COVID-19 pandemic has a negative relationship with whether the individual is employed (-33.42% at $p<0.001$), whereas just being a woman or just being a parent both be related with an increased likelihood with whether the individual is employed (15.49% at $p<0.001$ and 37.84% at $p<0.001$ respectively). Education and marital status are found to be the two most economically significant control variables that are related with whether the individual is employed, with both variables being correlated with nearly double the likelihood of whether an individual is employed (85.37% at $p<0.001$ and 72.72% at $p<0.001$ respectively). However, Model 1's explanatory power is relatively weak, as evidenced by the low pseudo r-squared value.

From Model 2, the analysis shows that being a parent is related with an individual being nearly triply as likely to be a part of the labour force, which is extremely economically significant (171.15% at $p<0.001$). Like Model 1, being a female parent during the COVID-19 pandemic is negatively related with whether an individual is a part of the labour force, which is the opposite effect of just being a parent. Education status is once again the most economically significant control variable, and it is found to be related with an individual being more than doubly as likely to be a part of the labour force (135.91% at $p<0.001$). However, similar to

Model 1, Model 2's explanatory power is relatively weak, as evidenced by the low pseudo r-squared value.

Regardless, it is interesting to note that for the most part, sex, COVID-19 timing status, and parenthood status both individually and together generally cause a statistically significant added effect on an individual's employment status and labour force participation status. However, the models' low explanatory power indicates that other factors not included in the analysis may also be affecting employment status and labour force participation status. Perhaps more can be done with the methodology to see if the economic effect is higher than what is currently found, such as adding control variables for different occupation sectors based on existing literature. Ultimately, it is certain that more will be done with this data in the future as we further explore the economic impacts of the COVID-19 pandemic.

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