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The Parental Labor Gap: The Impact of Daycare Access on the Parental Labor Force during the COVID-19 Pandemic

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1 Introduction

At the height of World War II, the United States government passed the Lanham Act, implementing publicly funded childcare programs across the country to encourage women to join the workforce while their husbands were at war. This program accomplished exactly what it intended – women joined the labor force rapidly. But when the war ended, so did the public preschools [6]. Decades later, no national progress has been made to bring these preschools back. In the United States Congress, a Democrat has introduced a bill creating a universal preschool program every Congressional session since 1999 [11]. Every single one of those bills has failed. In August 2022, the Democrats — the party most commonly fighting for universal preschool — passed the Inflation Reduction Act, a win for climate and healthcare policy. However, this bill notably only passed after the removal of the section of the bill that would have implemented six years of national funding for a universal preschool program across the United States for all three- and four-year-olds [11]. The United States does not seem poised to pass a policy to provide early childcare anytime soon.

Much of the discourse surrounding universal preschool/pre-kindergarten policies focuses on their impact on child development. While this is the most obvious and direct impact of universal preschool, it is not always the most convincing to politicians concerned about the cost of starting a program. In trying to get bipartisan support for a national universal preschool bill, many policymakers have instead turned to exploring the economic benefits of universal preschool programs. This paper aims to explore the effects of public preschool programs on parental labor employment during an economic shock (the COVID-19 pandemic) – with a goal of providing clearer motivation to create national funding for universal preschool.

In many developed countries, universal public school starts for children at a very young age – as early as 3 or 4. The governments of these countries pride themselves on their financial backing of programs that kickstart children's development and provide parents with childcare so they can participate in the workforce [2]. Even in the US, many states and cities have begun to introduce their own universal preschool programs over the past decades. However, these programs are still getting off the ground, and they struggle to survive without federal funding.

The first state-level universal preschool program in the US was implemented in Oklahoma in 1998. Since then, 43 states plus Washington DC have passed some sort of public preschool program, although many

restrict the type of families that are eligible for the programs. Of these 43 programs, only 13 of them accept all three- and four-year old children, while others have various restrictions that limit the reach of the programs [12]. Those 13 states with no restrictions have provided good opportunities for research on the benefits of such programs. Results suggest that access to public childcare does increase labor force participation for mothers by as much as three percentage points [13][12]. Notably, all published papers thus far have focused solely on the maternal labor force rather than the parental labor force, justified by the research that the burden of childcare disproportionately falls on women.

The literature has found positive effects between public preschool and the maternal labor supply, but has always included the caveat that these effects differ across different demographic groups. When preschool programs are available, there are still systemic challenges that may cause differences in access and success. As an example, Washington DC's universal preschool program has received criticism for covering majority white families, despite claims to be "universal" [17]. Nor does the program benefit people from all income groups equally. Interestingly, it is those families in both the highest and lowest income groups who benefit the most [14]. These facts mean that any further research into "universal" childcare programs should always be studied through the lens of different economic factors for different demographic groups.

In the two years since the COVID-19 pandemic began, the landscape for work has shifted dramatically. Many companies and employers switched to telework when the pandemic hit, and many still do not require workers to come into the office. Research suggests these COVID-induced changes have led to a closing of the gap in childcare duties between men and women in households [15]. Heggeness and Suri (2022) have analyzed data on the parental labor supply of parents of school-age children. Comparing parents in positions with telework eligibility versus in-person positions, Heggeness and Suri found that while telework improved the labor participation rate of mothers slightly, there was still a major gap in labor force participation between mothers and women without children.

Heggeness and Suri examined parents with school-aged children. These parents did not need childcare prior to the pandemic due to mandatory public school. They point out that a lack of childcare for preschool age children is a problem for parents that, while exacerbated by the pandemic, existed beforehand. Unlike school-aged children, who were taken care of universally across the United States through mandatory school-

ing starting in kindergarten, most children under the age of 5 were not guaranteed care even prior to the pandemic. The question remains: how did universal preschool programs affect parental labor force participation during the COVID-19 pandemic, and were these effects equal across different demographic groups? Given current research in the field, we would expect that cities or states with public preschool programs likely bounced back more quickly in terms of parental labor force participation as public programs opened up quickly and continued to serve as many people as possible. However, this pattern could well differ in the same directions that the actual programs differ in terms of serving demographic groups — with white, very high or very low income families benefiting the most.

Universal preschool data is still young, small in scope, and not publicly accessible. So, this paper explores the more general question of whether daycare in general increases the parental labor force participation – the idea being that if daycare has a positive impact on the parental labor force, than universal preschool programs would just create more daycare options, therefore increasing the number of parents using daycare.

I use the Survey of Income and Program Participation data set from the United States Census Bureau to examine the effect of daycare on parental labor force participation during the COVID pandemic. The SIPP surveys a sample of participants across the United States – surveying each individual up to 12 times over the course of a year in order to allow for analysis across time. This paper will expand on research already done on the benefits of universal preschool programs to the parental labor force by exploring whether these benefits remain the same in the new working landscape caused by the pandemic. Further, by analyzing who benefits the most from these programs, this research can influence the direction of future universal preschool policies going forward.

2 Literature Review

The two seminal papers referenced in almost every subsequent paper examining early education and maternal labor force participation come to extremely different conclusions. Gelbach (2002) analyzed data prior to any public preschool programs in the United States. He studies the effect of public kindergarten as the earliest public education option at the time. Using data from the 1980 census, he found positive effects on both the employment status and the amount worked for all mothers who enrolled their children in public kindergarten

[8]. Fitzpatrick (2012) expanded on Gelbach's analysis with census data and included the United States' first public preschool program: Oklahoma in 1998. Using a regression discontinuity approach observing mothers with children right above and below the four year old cut off for the Oklahoma program, Fitzpatrick's study found no increase in maternal labor force participation for any subset of mothers except for single mothers with no younger children [7]. This finding showed that the effects of public preschool programs are likely dependent on whether a mother has other young children and whether other caregivers are available in the household.

Li (2020) expanded on Fitzpatrick's Oklahoma findings by comparing Oklahoma's program to Georgia's public preschool program, which was created in the same year. Georgia's public preschool program was a full day, full week program, while the Oklahoma program only provided childcare for half days. Li echoes Fitzpatrick's findings that the Oklahoma program had no effect on maternal labor force participation. Unlike Oklahoma, Li found statistically significant positive effects on the maternal labor supply from the implementation of the Georgia program [13]. This opens up a new hypothesis suggesting that programs may only have a positive effect on labor force participation if the programs cover the full work day.

Li's paper also documented stark differences in the effects of preschool programs on maternal labor force participation by demographic group – findings that are echoed by Ilin, Shampine, and Terry (2021). These authors take a similar approach to Li in conducting their analysis but expands to more recent data and across the entirety of the United States. Ilin, Shampine, and Terry find that the positive effects of public preschool programs are much larger for mothers of the following demographic groups: "married, college educated, residents of metropolitan areas, and with income either below 200 percent or above 400 percent of the federal poverty level" [12, 2]. In a study of just the public preschool program in Washington, DC, Malik (2018) finds the same result about the importance of income: DC's public preschool program is only correlated with higher maternal labor force participation for the highest and lowest income brackets in DC [14].

Internationally, most programs in European countries have been around for so long that there is little data available on the maternal labor supply pre and post the implementation of universal preschool. However, Luxembourg did not roll out their subsidized preschool program until 2009. Luxembourg provides a good

comparison for US studies on preschool programs rolled out around a similar time. Bousselin (2021) used a differences-in-differences regression to study the effect of Luxembourg's preschool program on the maternal labor force. Luxembourg's program consisted of government vouchers given to parents to use to pay for either public or private childcare programs, making this program different from the state programs across the US. However, it is still relevant to observe the results of Bousselin's study as it examines the immediate effects of the roll out of a new program. Bousselin found that the maternal labor force participation grew by 3 percent, and the average number of hours mothers worked also increased [2].

With the exception of Fitzpatrick's paper, all of the above papers have found positive effects on the maternal labor supply from universal public preschool programs. However, each paper's results have come with caveats noting differences in demographic groups most and least impacted by these programs. [13][12]. In interpreting such results, one needs to be able to extrapolate how much of those differences are due to access of the childcare programs, choice to send their children to those programs, or inability to join the labor force for reasons other than childcare. So, another important group of literature for the purpose of this paper looks at the effects of COVID-19 on the general labor market decisions of these demographic groups.

It is important to note that the world is no longer in the same working environment that it was back when the above studies analyzed employment data. In March 2020, the COVID-19 pandemic changed the parameters of work by shutting down offices, moving people to telework, or laying off many individuals. Interestingly, the literature overwhelmingly finds that this changing environment has lessened the gender gap in the division of childcare and labor force participation between men and women [15][1][4][9]. All papers acknowledge that the COVID-19 pandemic negatively impacted both men and women and led to a lower overall labor force participation rate in the starting months of the pandemic. But, the new work environment is benefitting women more than men, meaning that while there is still a clear gap in labor force participation, that gap is shrinking.

Papers by Sevilla and Smith and Alon et. al were both written right at the start of the pandemic, analyzing the labor shock the pandemic immediately caused. Alon's paper found that in March 2020, women were more negatively impacted by the start of the pandemic than men – the drop in employment due to pandemic closures had a larger impact on sectors dominated by female employees, such as restaurants

and hospitality. Alon notes that this differs from the "standard" employment trends seen during other recessions. In previous recessions, workers in male dominated fields experienced a greater degree of layoffs [1]. These employment trends coupled with the closing of schools led to an immediate difference in the impact of COVID-19 on men and women because the literature has shown that women care for children in a household much more. However, Alon notes that the changing work landscape positively impacts the closing of the gender gap between men and women. While there are more women in fields likely to have shut down due to the pandemic, there are also more women in fields that were considered "essential workers" such as nurses or grocery store workers. Alon also found that many of these women in essential fields were likely to have husbands who were in fields that could work from home. So, the burden of childcare shifted with the start of the pandemic. Alon notes that other literature has shown that when events shift the division of childcare in a household, it is not likely to go back to how it was before the shift [1].

The paper by Alon et. al analyzes the immediate labor shock from COVID-19 in the US, which pairs well with the paper by Sevilla and Smith about the shifting gender roles due to COVID-19 in the United Kingdom. Like in the US, Sevilla and Smith found that the gender divide amongst childcare shrank at the start of the pandemic and persisted for three subsequent months. They find that this shift was driven almost entirely from the supply side (the availability of men to do childcare due to layoffs or telework) and not from the demand side (the increased need for childcare due to school closures). While there was no correlation between women's decrease in childcare duties and a change in their working environment, men only increased their childcare duties if they were working less. Like Alon, Sevilla and Smith hypothesized that this shrinking of the gender division for childcare would remain into the future, even once schools reopened [15].

More recent research echoes the immediate findings of the above papers at the start of the pandemic and shows that these trends have continued. Goldin (2022) writes, "The real story of women during the pandemic concerns the fact that employed women who were educating their children, and working adult daughters who were caring for their parents, were stressed because they were in the labor force, not because they left" [9, 6]. Goldin notes that contrary to many news sources, the maternal labor force participation rate did not drop considerably due to the pandemic, and the women who stayed in the labor force did not generally decrease their hours worked. Again, Goldin acknowledges that the burden of childcare and the

impacts of the pandemic fell disproportionately on women, but in terms of the childcare division of labor, COVID-19 has made the gap shrink. Couch, Farlie, and Xu completed similar analysis to Goldin, but split their data up between parents with school-age children and parents with children under 5. They found that the gap in the division of childcare was actually only shrinking for parents of children under the age of five [5].

As can be seen through this literature review, there has been significant research done on two large topics: the effect of public preschool on the maternal labor supply, and the effect of the COVID-19 pandemic on household childcare situations. However, very little work has been done to look at the intersection of these two topics. This paper aims to fill that gap. The SIPP allows for analysis of both employment/labor force participation and childcare arrangements during the pandemic. This paper combines these topics into a cohesive research question that will look at the interactions between these two large events/policies and how the pandemic has affected both. Notably, the analysis of this paper will look at the childcare effects on the parental labor force for both men and women, differing from past research that has only focused on the maternal labor supply. The literature has made it clear that in the new work environment following the pandemic, the gender division of labor has begun to change.

3 Data and Methods

3.1 Framework for Hypothesis

Historically, labor force participation of women has been lower than that of men. Further, the labor force participation of parents has been consistently lower than that of those without children. This is due to parents choosing to stay home to care for their children, especially before they are at an age where they are old enough to go to school. The combined effects of these two trends generates labor force participation rates that are lower for mothers than for fathers.

Studies have shown that the labor force participation rate for mothers is statistically higher in areas where daycare is offered. Sevilla and Smith found that women are generally the parent in charge of children for the household [15]. So, I hypothesize that the use of daycare will have a higher effect on labor force

participation for mothers than for fathers.

When the pandemic hit, the employment rate dropped everywhere. While this is different than the labor force participation rate, it is likely that some parents who lost their jobs during the pandemic then left the labor force as the pandemic also led to fewer childcare options. The question remains whether the labor force participation rate dropped evenly for men and women. While studies show that women initially suffered more from labor cuts at the start of the pandemic, Sevilla and Smith found evidence that the child care gap between mothers and fathers shrunk as more fathers took on child care responsibilities [15]. So, I hypothesize that despite the general trend that women were affected more than men by the pandemic, mothers were actually affected less than fathers in terms of labor force participation.

As the work environment changed with the pandemic, the importance of daycare likely did as well. Many parents suddenly found themselves at home for telework which could hypothetically allow for them to also care for their children instead of daycare. However, Heggeness and Suri found that telework was not causing a decrease in need for daycare [16]. I hypothesize daycare became more important for labor force participation as the pandemic hit due to the new lack of barrier between work and home.

I also hypothesize that the effects of daycare on parental labor force participation rate differ for different demographic groups. Ilin, Shampine, and Terry found that "mothers with the following demographic characteristics significantly increase their labor supply as a result of an access to free Pre-K: married, college educated, White non-Hispanic, residents of metropolitan areas, and those with income either below 200 percent or above 400 percent of the Federal Poverty Level (FPL)" [12, 2]. Chien et. al, looking specifically at the universal preschool program in Washington DC, found that although participation is decided through a lottery system, the lottery system itself still favors white, high-income individuals [4]. So, simply the demographic makeup of who utilizes these programs would likely mean that the programs have greater effects on the labor force participation on those populations.

3.2 Data Description

This paper is based on data from the United States Census Bureau's "Survey of Income and Program Participation." This is a nationwide survey that asks respondents questions regarding their demographics,

economic indicators, and participation in various programs such as insurance accounts, government welfare programs, and childcare programs. The Census Bureau describes this survey as:

> "SIPP is a nationally representative longitudinal survey that provides comprehensive information on the dynamics of income, employment, household composition, and government program participation. SIPP is also a leading source of data on economic well-being, family dynamics, education, wealth, health insurance, child care, and food security." [3].

Although the SIPP is a longitudinal survey, the circumstances of the particular subset needed for this project resulted in high non-response rates. When looking at the data, I found that very few parents during the pandemic answered the survey monthly as is advertised. When comparing September 2019 and September 2020 (six months pre- and post- the start of the pandemic), only 46 out of 4126 individuals answered the survey in both months. So, I chose to use these two months and treat them as separate samples, dropping the 46 people who answered both months from the data set. I ran t-tests on the makeup of the two samples in terms of demographics. The results are shown in Table 1, and show that there is no significant difference in the makeup of the 2019 and 2020 samples except for in education. This process is important to ensure that I could use these two samples to look at the effect of the pandemic. If the samples were significantly different in makeup, I can not make conclusions that any changes in regression results are due to the pandemic and not another factor.

This paper focuses on the parental labor force, so the data was filtered to only include respondents who identified as a "parent" and having a "child under 5 in the household." Three sections of the SIPP are utilized in this paper: "Demographics", "Employment and Labor Force", and "Child Care." The "Demographics" and "Employment and Labor Force" sections are person specific variables. All members of each household answer these questions individually.

The "Childcare" section of the SIPP is a household specific section. This means that only one member of each household answers this section of the SIPP. These members are called "reference parents" and are generally the mother of the household, unless there is not a mother present. The SIPP provides unique ID numbers for each individual surveyed as well as a household ID number. By joining the "Childcare" responses from the reference parents with other members of their household by the household ID number, I

created a data set of all parents with children under 5 with their individual demographic and employment information as well as their household childcare information.

The demographics section of the SIPP consists of many categorical questions. I split each categorical variable into a series of indicator variables, each representing a categorical option. For example, I created a "white" variable from responses that answered "white" on the race question of the SIPP. I used a similar process for education level and marital status. For age and number of children, I kept these variables as is due to the responses being numerical.

From the "Employment and Labor Force" section, the SIPP provides multiple questions in which the response environment is classified as "in the labor force." I calculated my labor force participation variable by classifying a response in these questions as "in the labor force" and a non-response as "out of the labor force."

From the "Childcare" section, the SIPP asks about use of child care in five different categories: "program," "center," "headstart," "nursery," and "non-relative." For the purpose of this paper, I combined all of these together to form a "daycare" variable that denotes whether or not a family uses childcare services.

Notably, the SIPP does not include data on household or individual income, as it only records "participation" in various programs. Income is another demographic that likely impacts both labor force participation and daycare participation, and therefore would be important to include in further research into this topic.

3.3 Descriptive Statistics

Table 1 shows the percentage of respondents in each demographic group in the data, for both the pre-covid sample and the post-covid sample. For example, the % in the White row and Female column shows the percentage of the data set that is white women. Along with these calculations, I ran t-tests by sex for each demographic to identify statistically significant differences. The highest proportion of both male and female groups fall into white, non-hispanic, middle-age, high school educated, married, with two children.

As noted in the data description, Table 1 showed that there were not significant differences between the makeup of the pre- and post- covid samples. So, the key points of note in table 1 are those demographics in which there is a large difference between the percentage of men and women of that demographic. The

percentage of women who are Black is significantly higher than for men. There is a significantly greater percentage of white men versus women in the data. The female group is also younger on average than the male group. Men are more often in the middle age group, while the older age group has a similar percentage for both groups.

A larger portion of women are divorced, separated, or single. This is likely due to the format of reference parents in the data set. The default for a reference parent is the female adult in the household unless one is not present, so if those reference parents are divorced or separated women, the corresponding fathers are likely not in the household and therefore not in the data set.

Table 2 shows the labor force participation rate of differing demographic groups in the data set, again for the pre- and post- covid samples. In terms of variables of importance, the labor force participation rate of those families that use daycare is higher than that of the overall parental population. This is true of both men and women who use daycare as well. The number of children also has a large effect on labor force participation - with the gap between male and female labor force participation growing exponentially as the number of children increases.

The differences in labor force participation by race, ethnicity, and age are consistent with the results of previous literature. Both men and women have higher labor force participation rates associated with more education, but men start off with a much higher labor force participation for the lowest level of education than women and have less of an increase with each subsequent level of education.

The labor force participation rates for marital status indicate that women are more likely to be in the labor force if they are single than if they are married, divorced, or separated. This supports the idea that single mothers must work to care for their children themselves whereas once they are married there becomes to option to stay home to care for the children while the other parent of the household works. This is likely why the labor force participation rate for men does not hold this same result.

The likelihood of being in the labor force for mothers drops with each additional child born. This pattern does not hold for fathers - in fact, male labor force participation increases with the first three children. This is likely because while mothers need to leave the labor force to care for more children, men then need to work more to support more people.

Pairing Table 2 with the descriptive statistics of Table 1, demographic groups with large differences in labor force participation are also groups in which the percentages of men and women differ. More women are young and more men are middle age, and the younger age group has a much lower labor force participation for both populations. Combined, these differences in both labor force participation for demographic groups and percentage of sex in demographic groups contribute to the large difference in labor force participation rate between mothers and fathers.

3.4 Economic Specification

To analyze my research question, I performed a logit analysis with the following estimating equation:

$$LaborForceParticipation = \beta_0 + \beta_1 female + \beta_2 daycare + \beta_3 female * daycare + (\beta_4 - \beta_{26}) demographics + (\beta_5 - \beta_{27}) female * demographics + \mu$$

The above econometric specification estimates the effects of daycare utilization on labor force participation. As this does not include a time period variable, only the sample from 2019 was used for this regression analysis. I chose the 2019 sample over the 2020 sample because that data is more likely to match historical data and was not affected by the pandemic. Controls for age, race, education level, marital status, and number of children are included in "demographics." I employ a logit estimation to study the impact on labor force participation as the dependent variable, lfp, is a binary variable. So, the results of this regression only provide a direction (positive or negative) that each independent variable affects the likelihood of labor force participation, but not the magnitude of that effect. For this reason, I have put the standard regression results in the appendix and will focus on the marginal effects, which show the change in probability of being in the labor force for a one unit change in the independent variable.

The key variables of interest are sex and daycare participation. However, I also include demographic characteristics that likely affect labor force participation of an individual. These are in seven categories: age, race, disability status, education level, marital status, and number of children. The omitted category for race is white, for education level is less than high school, and for marital status is single. These variables will ideally eliminate some omitted variable bias from the error term.

For specification 2, I repeat regression analysis on equation 1 but with the addition of a time period

variable to denote pre-covid (September 2019) or post-covid (September 2020). By including the same variables and format as my first regression, this allows for easier analysis.

$$LaborForceParticipation = \beta_0 + \beta_2 daycare + \beta_3 daycare * female + \beta_4 timeperiod + \beta_5 daycare * timeperiod + (\beta_6 - \beta_{28}) demographics + (\beta_7 - \beta_{29}) daycare * demographics + \mu$$

Finally, I run analysis on a second equation that looks at the interaction terms between using daycare and different demographics and their effects on labor force participation. For this analysis, I split the data into men and women and ran the regression on both groups. This allows for comparison between male and female labor force participation. Paired with equation 1, these interactions will help tell the full story of the effects of daycare and COVID-19 on parental labor force participation.

4 Results and Analysis

4.1 Regression 1: Interactions with Sex

Table 7 (in Appendix) presents logit estimation results based on equation 1, showing both specification 1 without the time period variable and specification 2 with the inclusion of the time period variable. For ease of presentation, results are shown using one column for the key variables and another column for their interaction with sex. With these results, I next calculated the marginal effects of each variable, controlling for male and female. The directions (positive or negative effect) of these marginal effects are the same as the signs on the coefficients from the logit model, but the numbers themselves are easier to interpret as they show the percent increase in the probability of joining the labor force for a one unit increase in the independent variable. These marginal effects are shown in Table 4.

Results in Table 4 show that daycare positively affects all parental labor force participation, but has much greater effects on maternal labor force participation. The inclusion of the time period variable in specification 2 does not dramatically change these effects. Additionally, the time period variable had no statistically significant effect on labor force participation for men. This was a surprising result, and a look back at the data confirmed that there was very little change within the six months surrounding the pandemic for men. Table 5 looks at the descriptive statistics of labor force participation split up into men and women

and by time period. This confirms the regression result that being pre- or post- the start of the COVID-19 pandemic had no significant effect on labor force participation for men. Dr. Heggeness had similar non-results in her paper using data immediately following the start of the COVID-19 pandemic [10].

For women, the pandemic actually increased the likelihood of labor force participation slightly. This is shown in both Tables 4 and 5 with a statistically significant increase in labor force participation with a p-value less than 0.1. This difference is not large, but nevertheless caused surprise and led me to do more research into newer papers about female labor force participation post-pandemic.

Dr. Goldin had a larger subset of data available through the Current Population Survey rather than the SIPP [9]. Her data went through the end of 2021 whereas this paper's data stopped in September of 2020. With this longer collection of data, her results show the same direction as this paper but with higher statistical significance: the labor force participation rate for women has actually increased post-pandemic. She notes that at at smaller time frame (the two months surrounding the start of the pandemic), the labor force participation of women and mothers did drop by almost 4 percentage points, echoing the results in previous literature. But, this sharp decline did not last long, and Goldin found that maternal labor force participation has increased.

In terms of other standard determinants of labor force participation, the results of Table 4 are consistent with the literature. The coefficient on female is negative, meaning that being female is negatively correlated with labor force participation. With this baseline, the coefficients on the majority of interaction terms with female are positive, meaning that being in these demographic groups compared to the reference groups is more positively impactful for women than men. For example, being more educated positively impacts likeliehood of labor force participation for both men and women, but with the positive interaction coefficients, it shows that women are more positively affected by each additional degree. The negative interaction coefficients on married, separated, and number of children show that while these characteristics are positively correlated with labor force participation for the overall population in the data, they are all negatively correlated with the labor force participation of women. This shows that determinants of labor force participation for mothers and fathers vary greatly, which likely attributes to the large difference in the labor force participation rate between mothers and fathers in the data.

4.2 Regression 2: Interactions with Daycare

Table 8 (in Appendix) presents logit estimation results for equation 2, which is set up similarly to equation 1 but with daycare interactions instead of interactions with sex. This changes the analysis slightly to look at the effects of daycare not only on male and female labor force participation, but on differing effects for every demographic group. As I could no longer look at interactions with sex, I ran this regression on the male and female subsets of my data separately. As with equation 1, I used the results of Table 8 to calculate the marginal effects of each variable, holding daycare/no daycare constant. These marginal effects are shown in Table 6.

There is a statistically significant and positive marginal effect post-covid for females who use daycare. This means that the probability of this group being in the labor force actually increases post-pandemic. This echos the findings in Table 4 as well as in Goldin's paper. For women with children in daycare, the pandemic has actually increased their likelihood of being in the labor force. The marginal effects for the other three groups, men and women without daycare and men with daycare, were not statistically significant.

Higher education levels have statistically significant positive marginal effects for women who utilize daycare and women who do not. However, the marginal effects are greater in magnitude for those women who do utilize daycare. For men, educational levels do not significantly affect labor force participation for either the daycare or no daycare subsets. I hypothesize that these significant effects for women and not men are due to the fact that men already have a much higher labor force participation rate on average than women - they do not have as big of a gap to improve on. The results of regression 1 showed that both daycare and higher education had positive effects on female labor force participation, so this is likely why the marginal effect of higher education for women who utilize daycare is greater.

The marginal effects of race and ethnicity when controlling for utilization of daycare are not statistically significant, and the magnitudes of these effects are slightly ambiguous. This is likely due to other systemic differences in racial and ethnic groups that affect both their likelihood of being in the labor force and their utilization of daycare.

5 Conclusion

From the results above, a full answer to the research question comes together. During the pandemic, mothers actually increased their labor force participation on average, especially those who utilized daycare. With work moved to telework, having children under 5 at home may have become even more difficult as the boundaries between work and home were blurred. The National Institute of Early Education Research found that while most preschools closed their doors in March 2020, many states helped their preschools quickly open back up - often even before schools for older children who were considered more able to learn remotely. So, women were now either able to work from home while caring for their children, or send their children to daycare and remain in the workforce from home without the double work of also providing childcare at the same time.

The difference in labor force participation between mothers and fathers is striking, but not surprising. From the literature review, it is clear there is a large gap in childcare work between mothers and fathers with mothers taking on the majority of work caring for children. The larger marginal effect of daycare for females vs males aligns with this childcare gap, showing that being able to send your children to daycare has a much higher effect on the probability of women to be in the labor force than men.

The policy and research area of early education remains of utmost importance, and this paper added to the literature showing that daycare programs do not just positively benefit children, but parents and the overall economy as well. These results show a positive effect of daycare for parental labor force participation, and while this project did not look specifically at publicly funded programs, federal funding for preschool would increase the overall amount of preschool access available, therefore allowing more and more parents to utilize daycare and be in the labor force.

This study could be expanded in many ways, but the ones most of note are the lack of a socioeconomic status variable and the short time frame post the start of the pandemic. The latter issue can be solved as we continue to collect data in our new post-pandemic environment, and it would be interesting to run these tests again with more data in the future. Other data sets have clearer income data, and it would be interesting to match that data with the SIPP daycare data to factor in the effect of socioeconomic status into analysis.

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Table 1: Descriptive Statistics

	All	Pre-Covid	Post-Covid
Labor Force Participation	0.667	0.657	0.677
Male	0.439	0.432	0.446
Female	0.561	0.568	0.554
White	0.774	0.788	0.760
Black	0.109	0.101	0.117
Asian	0.075	0.067	0.083
Other (race)	0.042	0.044	0.040
Hispanic	0.244	0.247	0.240
Young (<30)	0.236	0.249	0.222
Middle-age (31-45)	0.615	0.606	0.624
Older (>45)	0.150	0.145	0.154
Disability	0.035	0.04	0.03
Less than high school	0.135	0.155	0.114**
High school	0.257	0.271	0.243
Some College	0.255	0.253	0.257
College	0.223	0.208	0.238
Professional	0.130	0.113	0.147*
Married	0.746	0.731	0.761
Divorced	0.069	0.078	0.06
Separated	0.048	0.056	0.039
Single	0.138	0.135	0.14
1 Child	0.275	0.274	0.276
2 Children	0.337	0.337	0.337
3 Children	0.210	0.217	0.203
4 Children	0.108	0.103	0.113
5 Children	0.038	0.036	0.039
6 Children	0.033	0.033	0.032
Daycare	0.478	0.488	0.467
No Daycare	0.523	0.512	0.533
N	4080	2237	1843

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 2: Descriptive Statistics (Split into Men and Women)

	All	Pre-Covid		Post-Covid	
		Men	Women	Men	Women
Labor Force Participation	0.675	0.807	0.508***	0.832	0.552***
White	0.777	0.813	0.769***	0.779	0.745***
Black	0.107	0.080	0.117***	0.090	0.139***
Asian	0.076	0.069	0.066	0.088	0.079
Other (race)	0.042	0.038	0.048*	0.043	0.037
Hispanic	0.243	0.247	0.247	0.231	0.246*
Young (<30)	0.242	0.211	0.314***	0.180	0.261***
Middle-age (31-45)	0.608	0.625	0.555***	0.664	0.587***
Older (>45)	0.151	0.164	0.131**	0.156	0.152
Disability	0.034	0.039	0.041	0.023	0.034
Less than high school	0.133	0.151	0.158	0.098	0.126*
High school	0.259	0.291	0.255***	0.252	0.236*
Some College	0.253	0.219	0.279***	0.250	0.263*
College	0.224	0.219	0.199*	0.239	0.238
Professional	0.131	0.120	0.108*	0.160	0.137*
Married	0.761	0.847	0.658***	0.851	0.689***
Divorced	0.067	0.061	0.090*	0.037	0.079**
Separated	0.044	0.028	0.077***	0.005	0.066***
Single	0.128	0.064	0.175***	0.107	0.166***
1 Child	0.276	0.280	0.269	0.282	0.272
2 Children	0.337	0.342	0.333	0.340	0.334
3 Children	0.210	0.206	0.226*	0.205	0.201
4 Children	0.108	0.110	0.098*	0.109	0.116
5 Children	0.037	0.036	0.037	0.029	0.047
6 Children	0.032	0.026	0.037*	0.035	0.030
Daycare	0.477	0.489	0.487	0.460	0.473
No Daycare	0.523	0.511	0.513	0.540	0.527

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 3: Labor Force Participation

	All	Pre-Covid		Post-Covid	
		Men	Women	Men	Women
All	0.675	0.807	0.508***	0.832	0.552***
White	0.689	0.830	0.518***	0.850	0.557***
Black	0.588	0.628	0.524***	0.647	0.553***
Asian	0.647	0.811	0.413***	0.878	0.486***
Other (race)	0.671	0.750	0.541***	0.813	0.580***
Hispanic	0.660	0.803	0.536***	0.781	0.521***
Young (<30)	0.705	0.806	0.583***	0.815	0.616***
Middle-age (31-45)	0.724	0.918	0.545***	0.861	0.571***
Older (>45)	0.533	0.568	0.424***	0.772	0.367***
Disability	0.023	0.047	0.034	0.010	0.000
Less than high school	0.496	0.667	0.279***	0.751	0.288***
High school	0.611	0.750	0.452***	0.778	0.463***
Some College	0.693	0.854	0.520***	0.820	0.577***
College	0.752	0.897	0.607***	0.900	0.603***
Professional	0.833	0.875	0.763***	0.883	0.812***
Married	0.703	0.861	0.536***	0.859	0.556***
Divorced	0.558	0.515	0.508***	0.642	0.568***
Separated	0.544	0.667	0.500***	0.550	0.459***
Single	0.600	0.682	0.445***	0.700	0.571***
1 Child	0.722	0.813	0.592***	0.821	0.662***
2 Children	0.704	0.825	0.547***	0.836	0.609***
3 Children	0.689	0.836	0.472***	0.883	0.564***
4 Children	0.574	0.712	0.391***	0.804	0.388***
5 Children	0.530	0.684	0.346***	0.727	0.364***
6 Children	0.503	0.857	0.240***	0.770	0.143***
Daycare	0.771	0.843	0.614***	0.911	0.715***
No Daycare	0.598	0.772	0.408***	0.775	0.437***

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4: Marginal Effects - Equation 1

	No Covid-19 Variable		**Covid-19 Variable**	
Variable	Male	Female	Male	Female
daycare	0.057**	0.146***	0.057***	0.150***
age	−0.004***	−0.003**	−0.004*	−0.003***
asian	−0.035	−0.148***	−0.035	−0.148***
Black	−0.105***	0.047	−0.106**	0.043
hispanic	−0.008	0.019	−0.008	0.018
disability	−0.568***	−0.823***	−0.568***	−0.818***
high_school	0.018	0.112**	0.018	0.109**
some_college	0.081*	0.180***	0.081*	0.178***
college	0.090*	0.230***	0.089*	0.226***
professional	0.072	0.416***	0.072	0.411***
married	0.108***	0.012	0.108**	0.007
divorced	−0.009	0.174***	−0.009	0.173*
separated	0.024	0.104	0.024	0.104
num_children	0.013	−0.040***	0.013	−0.040***
post_covid			0.001	0.047*

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Labor Force Participation

	All	**Pre-Covid**	**Post-Covid**	**Difference**
All	0.667	0.657	0.677	0.020
Men	0.819	0.807	0.832	0.025
Women	0.530	0.508	0.552	0.044*
Difference	0.289***	0.299***	0.280***	−0.019

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: Marginal Effects - Equation 2

	Male		**Female**	
Variable	No Daycare	Daycare	No Daycare	Daycare
age	-0.003^{**}	-0.003^{*}	-0.003	-0.004^{**}
asian	-0.033	-0.018	-0.142^{*}	-0.142^{*}
Black	-0.162^{***}	-0.022	0.075	-0.018
hispanic	-0.029	0.038	0.074	-0.046
disability	-2.275	-0.360^{***}	-0.724^{***}	-3.092
high_school	0.042	0.019	0.120^{*}	0.126
some_college	0.096^{*}	0.091	0.178^{***}	0.209^{***}
college	0.067	0.124^{**}	0.237^{***}	0.252^{***}
professional	0.062	0.102	0.395^{***}	0.448^{***}
married	0.126^{***}	0.086	0.043^{***}	-0.047^{*}
divorced	-0.030	0.011	0.236^{***}	0.117
separated	0.093	-0.026	0.076	0.161
num_children	0.022	0.004	-0.043^{***}	-0.038^{**}
post_covid	-0.037	0.048	0.015	0.083^{**}

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

6 Appendix

Table 7: Equation 1 - Regression Results

	Specification 1		Specification 2	
	All	Interaction with $female$	All	Interaction with $female$
$female$	-1.834^{***}		-1.132^{***}	
	(0.121)		(0.240)	
$daycare$	0.429^{***}	0.174^{***}	0.510^{***}	0.166
	(0.049)	(0.058)	(0.090)	(0.105)
age	-0.044^{***}	0.031^{***}	-0.032^{***}	0.014^{***}
	(0.002)	(0.003)	(0.004)	(0.005)
$asian$	-0.625^{***}	0.016	-0.089	-0.529^{***}
	(0.077)	(0.095)	(0.159)	(0.190)
$Black$	-0.599^{***}	0.849^{***}	-0.549^{***}	0.739^{***}
	(0.067)	(0.081)	(0.128)	(0.152)
$hispanic$	-0.049	0.14	-0.049	0.055
	(0.055)	(0.066)	(0.102)	(0.121)
$disability$	-5.193^{***}	1.974^{***}	-6.480^{***}	3.595^{***}
	(0.309)	(0.351)	(1.006)	(1.036)
$highschool$	0.380^{***}	0.231^{***}	0.268^{**}	0.113
	(0.066)	(0.082)	(0.123)	(0.152)
$somecollege$	0.684^{***}	0.389^{***}	0.670^{***}	0.278^{*}
	(0.074)	(0.089)	(0.135)	(0.162)
$collegedegree$	0.940^{***}	0.489^{***}	0.846^{***}	0.191
	(0.082)	(0.099)	(0.152)	(0.181)
$professional$	1.020^{***}	0.919^{***}	0.885^{***}	0.937^{***}
	(0.095)	(0.116)	(0.173)	(0.210)
$married$	1.047^{***}	-1.397^{***}	0.964^{***}	-1.121^{***}
	(0.061)	(0.073)	(0.114)	(0.137)
$divorced$	0.346^{***}	0.062	0.075	0.587^{***}
	(0.112)	(0.130)	(0.189)	(0.224)
$separated$	0.444^{***}	-0.427^{***}	0.308	-0.024
	(0.145)	(0.160)	(0.285)	(0.312)
$numberofchildren$	0.104^{***}	-0.225^{***}	0.111^{***}	-0.258^{***}
	(0.019)	(0.023)	(0.037)	(0.043
$precovid$			0.127	-0.172^{*}
			(0.085)	(0.100)
$constant$	1.835^{***}		1.397^{***}	
	(0.100)		(0.201)	
Observations	2079		4080	

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 8: Equation 2 - Regression Results

	Male		Female	
	All	Int. with *daycare*	All	Int. with *daycare*
daycare	1.742***		1.027***	
	(0.467)		(0.299)	
age	−0.029***	−0.008	−0.015***	−0.004
	(0.005)	(0.009)	(0.004)	(0.006)
asian	−0.018	−0.195	−0.676***	0.235
	(0.187)	(0.368)	(0.133)	(0.222)
Black	−0.863***	0.944**	0.295**	−0.328*
	(0.162)	(0.295)	(0.107)	(0.174)
hispanic	−0.012	−0.112	0.174*	−0.420**
	(0.124)	(0.225)	(0.082)	(0.113)
disability	−17.760	12.119	−2.215***	−14.009
	(213.554)	(213.556)	(0.253)	(142.551)
highschool	0.486**	−0.397	0.397***	0.067
	(0.152)	(0.291)	(0.110)	(0.202)
somecollege	0.699***	0.215	0.915***	0.250
	(0.161)	(0.337)	(0.110)	(0.205)
college	0.779***	0.270	1.011***	0.231
	(0.195)	(0.352)	(0.128)	(0.221)
$professional$	0.874***	0.201	1.619***	0.569*
	(0.228)	(0.389)	(0.160)	(0.262)
married	1.089***	−0.361	−0.015	−0.404*
	(0.139)	(0.252)	(0.096)	(0.161)
divorced	0.081	−0.214	0.857***	−0.451*
	(0.257)	(0.401)	(0.154)	(0.251)
separated	0.714*	−0.140*	0.221	0.192
	(0.375)	(0.061)	(0.157)	(0.273)
numchildren	0.159***	−0.123	−0.180***	0.081*
	(0.046)	(0.078)	(0.029)	(0.046)
precovid	0.367***	−0.632***	0.045	−0.216*
	(0.106)	(0.186)	(0.069)	(0.109)
Constant	0.914***		0.056	
	(0.256)		(0.173)	
Observations	1843		2237	

Note: *p<0.1; **p<0.05; ***p<0.01