How has the COVID-19 Pandemic Affected Married Female Labor Force Participation?

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ABSTRACT

SARs-CoV-2 and the coronavirus pandemic have left a lasting impact on the United States and the US economy. Many people were laid off or lost their jobs completely because of the nationwide shutdowns. Yet not every demographic was affected equally. Using the monthly Current Population Survey data published by the US Census Bureau from March 2019 through February 2021, I estimate a probit model of the effect of the pandemic on labor force participation of demographic groups divided by gender, marital status, and having children under 18. This is done by comparing monthly data from during the pandemic to the same month exactly one year prior to the pandemic. The model indicates that every demographic, apart from single males with children, was negatively affected by the pandemic during April and May of 2020. This paper further finds that married and single females with children experience significantly lower probabilities of labor force participation in the Fall of 2020 and Winter of 2021, likely due to females taking on greater carework as children stayed home taking remote classes during the beginning of the new school year. Married males with children did not experience this second round of depressed labor force participation, highlighting the potentially gendered effect. Ultimately, this paper finds that although every demographic group was affected by the pandemic, females with children experienced worse negative effects on their probabilities of labor force participation due to their disproportionate burden of childcare.

How has the COVID-19 Pandemic Affected Married Female Labor Force Participation?

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Table of Contents

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

In February 2021, concerns over the decline in female labor force participation had already begun to rise. Katie Rogers (2021) of the New York Times reports that in an address Vice President Kamala Harris claimed that 2.5 million females had left the labor force during the first year of the pandemic. This is in stark contrast to the apparent decline of only 1.8 million men, as reported by Labor Department data, that left during the same period (as cited in Rodgers, 2021). Many of the concerns brought up by Rogers (2021) over female labor force participation revolved around the burden of childcare and the ability of schools to reopen that spring. Through this paper, I aim to determine if there was an effect of having children on labor force participation for females specifically, and how large that effect was compared to other groups.

The focus of this paper is how the COVID-19 pandemic has affected married female labor force participation in the United States. In the past 18 months, there have been several papers published about the gender inequalities being perpetuated and exacerbated because of the pandemic. Some papers are concerned with how the pandemic's recession disproportionately affects service industry jobs, which are primarily female dominated, while others turn to home and family life as the source of inequalities (Dang and Nguyen, 2020; Landivar et al., 2020; Alon et al., 2020). When the country began shutting down in March of 2020, many states closed their schools because of the risk of transmission between kids and their propensity to spread disease. This meant that many kids were having to take classes at home and their parents took on the extra hours of carework to ensure that their child was attending classes and learning the material she needed to. This extra carework fell to parents, not only because schools closed, but also because childcare centers and other formal and informal forms of childcare had become virtually impossible to arrange given the Center for Disease Control's recommendations regarding social distancing and other state regulations (Alon et al., 2020). This situation affected all families with young children; however, it has been theorized that married women, more than any other demographic, are dropping out of the labor force or severely cutting their working hours to provide extra childcare during the pandemic.

The other reason why people have theorized the pandemic may affect female labor force participation more than it will male labor force participation is because the nature of the SARs-CoV-2 virus has meant many companies in service industry have had to shut down completely or cut their staff. This is because the virus is spread through high contact interactions common in the service industry and, historically, service industry jobs have been dominated by women. Therefore, because the pandemic has had a particularly strong negative affect on the service industry, people speculate that more women have lost their jobs or left the labor force than men have. This combined with the increase in carework at home, likely means there has been a disproportionate decline in the probability of female labor force participation, especially among married women with children, than other demographic groups.

This is a particularly important and concerning issue for governments and economists because in a typical recession, female jobs are more immune to shocks. In fact, some papers and economists suggest that married female labor force participation is "counter-cyclical," meaning they are more likely to work in a recession than before one in order to ensure economic and financial security for their families (Albanesi and Kim, 2021, p. 5). The recession brought on by the COVID-19 pandemic and the data in this paper, however, shows that the jobs typically occupied by women are not immune to all external shocks. Therefore, it is imperative to analyze how the pandemic has affected these demographics to make informed policy decisions in terms of economic recovery. If governments attempt to follow normal recession policies, they may end up pumping money into the wrong sectors of the economy, deepening the economic inequalities the pandemic has exposed even further.

Despite the speculation on the part of many economists, my research shows that the probability of labor force participation for all demographics based on marital status, gender, and having children decreased due to the pandemic. Every demographic group faced a significant decline in their probability of labor force participation at some point during the first year of the pandemic. However, if the probability of a married woman with children participating in the labor force during the pandemic dropped more than the probability of a male participating, then there is still cause for concern as there would be lasting implication for the diversity of the labor market and for societal progress as a whole.

This paper estimates a model to determine the effect that COVID-19 has had on the probability that a married female with children will participate in the labor force compared to other demographics split by gender, marital status, and having children under 18, while controlling for variables such as age, highest level of education, and race. I estimated a probit model with dummy variables for each demographic for each month (March through February) using pooled datasets for labor force participation in that month pre-pandemic and during the pandemic. I use March of 2020 as the first month in the "pandemic" and every month after it, until February 2021, is also considered to be "during the pandemic." I found that the pandemic's effect on the probability that each demographic participated in the labor force varied across the first year of the pandemic. For some demographic groups, such as single males with children, their probability of labor force participation seemed to recover quicker than other demographics, such as single and married women with kids. In particular, females with children, single and married, experienced significantly decreased probabilities of labor force participation from September of 2020 to February of 2021. My results suggest that while there was a negative effect on every demographic's probability of labor force participation due to the pandemic, that there is likely a separate pandemic effect on females, specifically females with children, correlated with gender and having children that is not experienced by married males with children. The combination of these effects has resulted in a different pattern of female labor force participation relative to male labor force participation than is considered to be "typical" during a recession.

The next section of this paper discusses the previous research on how the pandemic has affected labor supply, followed by a section on labor economics and how the labor supply is normally affected by different variables and conditions. From there, this paper will discuss how to model labor force participation decisions during the pandemic followed by a section on the econometric methodology that is used. Then I will discuss the data I have used to run my models, and the results of running these regressions. Finally, there will be a section of analyses of the results, what they suggest about the pandemic, and a concluding section on the importance of this study moving forward.

2 LITERATURE REVIEW

Since the onset of the pandemic, there are relatively few papers that have done an econometric analysis of the gendered effects of the pandemic on monthly labor force participation rates. There are multiple papers that use descriptive statistics to discuss how the COVID-19 pandemic has affected gender roles and specifically what the impact has been for married women with children. There are other papers that discuss the pandemic's effect on gender inequalities in the labor force, some that discuss how to best measure and model changes in labor force participation, specifically amongst married women outside of the pandemic, and finally a paper that discusses the impact that epidemics have on different demographic groups. Overall, they suggest that female labor force participation is traditionally "counter cyclical" (Albanesi and Kim, 2021), but during the pandemic female labor force participation has been declining in part due to their disproportionate numbers in the service industry and due to the increased burden of childcare. These papers suggest that for these reasons the pandemic has had a direct effect on females.

Stefania Albanesi and Jiyeon Kim's (2021) paper "Effects of the COVID-19 Recession on the US Labor Market: Occupation, Family, and Gender" examines how the recession caused by the COVID-19 pandemic has differed from the Great Recession, and what the implications are for the labor market on both the demand and supply-sides. They use data from the U.S. Census Bureau's Current Population Survey for both the impact of the Great Recession on employment and for the effect of the pandemic. Their model of the Great Recession demonstrates that during the recession the change in the employment-to-population ratio across all populations (single without children, single with children, married without children, and married with children) is larger for men than it is for women (Albanesi and Kim, 2021). However, the changes caused by the pandemic's recession are larger for female employment than they are for male employment. Albanesi and Kim (2021) emphasize this model's importance because the results of the pandemic's recession are in direct opposition to what is typically seen during a recession. Historically, the jobs that are predominantly held by women, typically service industry jobs, are impervious to external shocks. Furthermore, Albanesi and Kim (2021) suggest that for married women with kids, in particular, their employment statistics are "counter-cyclical" (p. 5). They are more likely to work during a recession in order to ensure that their family has some income if their partner loses their job. However, during the pandemic, the trends in employment demonstrate just the opposite effect: women's employment-to-population ratios dropped more than men's. Albanesi and Kim (2021) attribute this to both supply and demand side effects: it is in part due to industry and occupation variables and due to social issues (pp. 13-14).

Albanesi and Kim (2021) also ran a model measuring the differences in changes in employment and labor force non-participation between women and men during two phases of the pandemic: phase 1, from March to May 2020, and phase 2, from June to November 2020 (pp. 14-16). The differences in employment and non-participation rates are compared to data from February of 2020. Albanesi and Kim (2021) find that all female demographics "suffer larger losses in employment compared to men at every stage of the pandemic" (p. 15). Furthermore, the group that was disproportionately affected, was married women with children. When Albanesi and Kim (2021) controlled for occupation, they found that only about one third of this difference was explained (pp. 15-16). Therefore, there must be another cause for this gendered effect. One such cause could be the need to care for children. Finally, Albanesi and Kim (2021) also examine the labor flows from employment to non-participation and find that the majority of this shift is made up of single women with children and married women with children. They find this to be an important consequence of the pandemic because, in recent years, the flow rate for women from employment to non-participation in the labor force has been decreasing, converging towards the male flow rate (Albanesi and Kim, 2021). Although when controlling for occupation, most of these differences become insignificant, the difference for married women with children compared to married men with children remains significantly larger, which is the population that my paper is primarily concerned with (Albanesi and Kim, 2021). This means that although there are sectoral reasons why female employment and labor force participation have dropped, there are separate labor-supply side causes as well. My paper will be examining the supply-side effect that having children has on married female participation.

Benjamin Cowan's (2020) paper "Short-Run Effects of COVID-19 on U.S. Worker Transitions" also measures the transitions in the labor market because of the pandemic. Cowan (2020) uses data from the Current Population Survey in February and April of 2020 to run two different models (p. 1). The first model focuses on changes in the employment states of those surveyed in both February and April 2020, while the second model estimates the changes in hours worked. Cowan (2020) finds that from February to April, women are 2% less likely than men to continue at be "at work," and that they don't share the same positive effects on employment status for being married or having children as men do. These effects for women, Cowan (2020) argues, already cause a large gap in labor force participation when not in a recession or pandemic, that the decline in employment and labor force participation as a result of the pandemic is exacerbating this gap (p. 6). Cowan's (2020) model demonstrates that for women having children increases the likelihood that they will go from participating in the labor force in February to not participating in April (Cowan, 2020). Therefore, in our model, we expect that having children will have a negative impact on female labor force participation.

Gema Zamarro, Francisco Perez-Arce and Maria Jose Prados's (2020) paper "Gender Differences in the Impact of COVID-19" looks at the differences in employment, childcare responsibilities and psychological effects that the COVID-19 pandemic has had on different genders, education levels and marital status. Zamarro, et al. (2020) conclude that non-college educated women have lost their jobs more than any other group during the pandemic, and that despite having equal ability to telecommute to work, women have been taking on more childcare responsibilities than men and have reduced their working hours more as well. This paper is important because it uses survey data from the USC Dornslife Center for Economic Research's Understanding Coronavirus in America tracking survey and descriptive statistics to conclude that partnered women have had a greater burden of child rearing responsibilities than any other group during the pandemic (Zamarro et al., 2020). Zamarro et al. (2020) expand to say that females are even reducing their work hours to take care of children during the pandemic. My hypothesis is that, due to the pandemic, married women are less likely to participate in the labor force because they need to take on more childcare duties at home, which draws strongly from the conclusions that Zamarro et al. (2020) make.

Zamarro et al. (2020) is also useful in noting that how much education a woman has does correlate with her labor force participation. This may be because lower education levels may be correlated with jobs in the service industry, or that having attained a graduate degree of some kind works as a proxy variable for wanting to work. Regardless, Zamarro et al. (2020), as well as parts of Alon et al.'s paper (2020), suggest that education level is an important control variable.

Further descriptive evidence of COVID's gendered effect on the labor force is found in the data visualization, "Early Signs Indicate that COVID-19 is Exacerbating Gender Inequality in the Labor Force," by Liana Christin Landivar, Leah Ruppanner, William J Scarborough and Caitlyn Collins (2020). Landivar et al. (2020) use the CPS for February and April of 2020 to examine changes in labor force participation, unemployment and work hours across men and women with and without children. They find that more women with children ages 6-12, roughly elementary and middle school ages, have left the work force than any other group (Landivar et al., 2020). They also found that more women are now unemployed than men are, and that they have cut down telecommuting hours more, while men have cut down all work hours more (Landivar et al., 2020). This short data visualization does not separate out groups based on marital status; however, through descriptive statistics it does support the paper by Zamarro et al. (2020) that the gendered effects of COVID 19 are present and likely linked to having children (Landivar et al., 2020, Zamarro et al., 2020).

In "The Impact of COVID-19 on Gender Equality," Titan Alon, Matthias Doepke, Jane Olmstead-Rumsey, Michèle Tertilt (2020) argue that the COVID-19 crisis will have the largest impact on single mothers. This is likely to be true because of the burden caused by having to take care of children who are studying at home. While this seems to contradict the findings of Zamarro et al. and Landivar et al., Alon et al. (2020) also note that the impact on labor force participation is likely to be particularly apparent in the married female population. What is interesting about this paper for my purposes is that it examines how childcare might be affected by the COVID-19 crisis and how that will likely affect employment and labor force participation of women. Alon et al. (2020) argue that women already have disproportionately large childcare duties, therefore it is to be expected that as the number of needed childcare hours increase because of the closure of schools and other facilities, women will be burdened with having to spend more time caring for their children then men. Alon et al. (2020) hypothesize that if there is more flexibility in the work force with telecommuting options then the inequality may decrease, however, they also mention that there is likely to be a larger number of women either cutting their hours or dropping out of the labor force entirely during the pandemic. This is particularly important to note, because it implies that married women would likely try to return to the labor force after their children are able to return to schools. However, since experience is usually a large factor in wages and ability to get a job, having to drop out of the labor force entirely (or even reduce hours) will likely have a lasting impact on female wages and workplace mobility. This is the third paper to support the theory that women will leave the workforce entirely during the pandemic in order to take care of their children. Although none of them have run regressions, Zamarro et al. (2020), Landivar et al. (2020), and Alon et al. (2020) provide a strong basis for the formation of this paper's hypothesis.

In the paper "Gender Inequality during the COVID-19 pandemic: Income, expenditure, savings, and job loss," Hai-Ahn H. Dang and Cuong Viet Nguyen (2020) look at survey data from six different countries from April 2020 and run different regressions on the impact of gender and other observable variables on "changes in employment, income, expenditure and savings due to the COVID-19 pandemic" (Dang and Nguyen, 2020). They determine that women in China, Italy and the United States are more likely to have permanently lost their job due to the pandemic than men are (Dang and Nguyen, 2020). While Dang and Nguyen (2020) also look at differences in what women and men expect their future incomes to be and what their current expenditures and savings rates are, this paper is particularly useful because it looks at what the differences in job losses are between men and women. Dang and Nguyen (2020) note that while temporary job loss seems to be about the same between the two groups, that they also think part of the differences in permanent job loss might be explained by the fact that women hold more service jobs, which were hit harder by COVID lockdowns, than men do. This is important to bear in mind because people who have lost service jobs might not have been able to get them back until lockdowns were lifted. Therefore, they would not be actively searching for new jobs until then and be labeled by the Bureau of Labor Statistics as "not in the work force," thereby lowering the labor force participation rate for a reason not related to childcare, albeit still gendered.

Dang and Nguyen's (2020) paper is also important to note because they ran a regression on individuals as well as country level data. While their primary focus was employment and income levels, they also controlled for age bracket and whether someone lived alone (Dang and Nguyen, 2020). These two variables seem likely to affect labor force participation, as will be discussed in the "Labor Economics and Labor Supply Models" and "Model" sections. The basis for this paper's decision to include controls for these sorts of variables was, in part, drawn from this.

There is another recent paper directly discussing the effects that COVID-19 has had on the labor force participation rate. "Labor Markets During the COVID-19 Crisis: A Preliminary View" by Olivier Coibion, Yuriy Gorodnichenko, and Michael Weber (2020) discusses how the unemployment numbers being reported by the Bureau of Labor Statistics do not represent the true amount of job loss due to the pandemic. This paper uses survey data from the Nielsen Homescan panel to estimate that since the pandemic there has been a roughly 8 percentage point decline in the employment-to-population ratio but only an increase of about 2 percentage points in the unemployment rate (Coibion et al., 2020). Coibion et al. (2020) claim that this difference is explained by a decline in the overall labor force participation rate in the United States. Therefore, when looking at the impact of the COVID-19 pandemic, it is just as important, if not more so, to look at the changes in the labor force participation rate as it is the unemployment rate. Coibion et al. (2020) also claim that from their survey they determined this decrease in labor force participation is because people are retiring earlier. While this appears to be true, they did not control for gender and marital effects, so it is unclear if this statement overgeneralizes all groups. They also do not clearly indicate what age groups they are looking at, so it is possible that this large change in retirement may only be true at the far end of the age spectrum (Coibion et al., 2020). Therefore, in my paper I will be dropping people who are below 25 years of age and may not participate in the labor force because they are students, or above 60 years of age and may be retiring. Additionally, the survey data Coibion et al. (2020) used was limited and from early on in the pandemic, it is important to see that if these numbers persisted as the lockdowns remained in place. I intend to expand on this research by looking at the gendered effects on the labor force participation rate from before during the pandemic by using data from March 2019 to February 2021, to see if their results are still correct.

The paper "Female Labor Force Participation Rates for Nine Ethnic Groups" by Geoffrey Carliner (1981) looks at modeling the labor force participation of nine different ethnic groups (white, Black, Native American, Puerto Rican, Chicano, Cuban, Japanese, Chinese and Filipino) by theorizing that the probability that someone participates in the labor force "is equivalent to the individual's market wage (w_m) being at least as large as the value of time in the home" (p. 286). Carliner (1981) then looked at the regression on labor force participation using a logit model and used a variable for the number of kids someone had and a quadratic term for age to account for experience. Carliner (1981) also looked at different regions where people lived, and while this was significant for the wage regression, it wasn't always for the labor force participation one. I will be leaving out this variable, but further research on the effect of location during the pandemic should be conducted. This is because different states and regions had different social distancing and lockdown policies that impacted businesses reopening and schools returning to in-person instruction. Furthermore, because Carliner's paper looked at minority groups, they also added in a variable for citizenship status (1981). This may be interesting to add in the future, however, since I am not focusing on the racial effects of the pandemic for this particular project, I will not be adding in a citizenship variable nor interaction terms with race.

There is also some pre-existing research on the impact that epidemics generally have had on labor force participation rates, specifically the paper "The Response of the Labor Force Participation Rate to an Epidemic: Evidence from a Cross Country Analysis" by Zhen Yu, Yao Xiao and Yuankun Li (2020). Yu et al. (2020) use data from the International Disaster Database and the World Bank from 1970 to 2015 about epidemic outbreaks and country specific economic indicators. They modeled the labor force participation rate in each of these countries on whether there was an epidemic that year, that country's "Uncertainty Avoidance Index," and other economic indicators (Yu et al., 2020). The important conclusions that they draw are that while epidemics cause a general decrease in the labor force participation rates, there is a larger change in male labor force participation rates than in female rates (Yu et al., 2020). Yu et al. (2020) attribute this to the fact that in many of the countries in their study, male labor force participation rates prior to the epidemic are larger than female rates, so the changes would be more dramatic. Since this study was a cross-country analysis that did not include the COVID-19 pandemic, it will be interesting to see if there is a difference in results when looking at the solely at the effect COVID-19 has had on the United States labor force. This paper also found that there was a larger decline in participation in younger people, and that "[t]he negative impact was more apparent in low- and middle-income countries than in high-income ones" (Yu et al., 2020). So, it is possible that just studying the United States will have different results, as it is a high-income country, but the effect is still expected to be significant as Coibion et al. (2020) discusses that there has already been a sizable change in labor force participation due to COVID-19.

I build on this literature to examine the entire first year of the pandemic and estimate how large the gendered effect of having children was on the probability of female labor force participation during the pandemic. I will also demonstrate the effect that the pandemic had on the probabilities that other demographic groups participated in the labor force during the pandemic, and finally compare the changes in probability with that of married females with children.

3 LABOR ECONOMICS AND LABOR SUPPLY MODELS

The neoclassical model of labor-leisure choice is based on the idea that people make decisions about how to allocate their time between work, or labor, and leisure (Borjas, 1996, p. 17). People want to purchase goods and services, but they also want to consume leisure time. To purchase goods, they must work for a wage or income, but in doing so they give up consuming leisure activities equal to the quantity of time they spend working. The model estimates the balance of this trade-off, how much time is spent in each activity. It is important to note that in this model all waking hours are split between labor and leisure. There is no other option for how to allocate time. Furthermore, any at-home or informal carework that is not a paid job is considered to be "leisure-time" and not "labor" (Ehrenberg and Smith, 1988, pp. 172-173). The terms "labor" and "labor time" in this model are strictly defined as time spent in paid or formal employment. For women the tradeoff is often between housework/leisure and paid work (Borjas, 1996).

Using the definition of "labor" from the neoclassical labor-leisure model, we can now define what the "labor force" is. The labor force is measured as the sum of the total number of people who are employed and the total number of people who are either currently laid off or are unemployed and actively looking for a job (Borjas, 1996 p. 18). All residual individuals are considered "not to be in the labor force." According to the U.S. Census Bureau's Basic Monthly Current Population Survey (CPS) Dictionary, the CPS codes for three different types of people who are "not in the labor force;" those who do not participate because they are disabled, those who are retired, and "other." This paper is focused on the effect that the pandemic had on demographic groups' probabilities of labor force participation based on gender, marital status, and having children, not on the effect of being disabled. Therefore, if an individual is not in the labor force due to disability, then she is not included in this project. In a typical labor supply model, the labor force participation rates are calculated as the total number of people in the labor force divided by the size of the working age population (Borjas, 1996, p. 19). The probabilities of labor force participation in this paper are estimated using the monthly Current Population Survey data collected by the Bureau of Labor Statistics.

This paper will be focusing on labor force participation numbers rather than unemployment rates because many people in service industry jobs were laid off work and may still be "unemployed" and actively looking for a job. This change in employment status, while caused by the pandemic, is not caused by the pandemic's effect on school closures and children remaining at home. Therefore, capturing the sector of the population that is looking for a job but not currently employed would confound the data from individuals who are choosing not to work due to family circumstances. It is still likely that some people will choose to remain "unemployed" during this period despite not wanting to actively search for a job because the CARES act offered higher unemployment benefits making unemployment more desirable to some than leaving the labor force entirely. This phenomenon will likely only affect the data by making changes in the labor force supply seem smaller than they were practically.

An individual's decision to work is based on a number of factors. According to the neoclassical model of labor-leisure choice, people are choosing between spending their time working, or in leisure. The choice to devote time to labor is made because people want to earn a wage to spend on consumption goods or on more leisure time to make them happy (Borjas, 1996). The level of happiness an individual achieves when consuming a certain amount of consumption goods and leisure time is called their utility and is estimated using utility functions. Utility functions model how people are indifferent between a set of different combinations of consumption goods and leisure time, while other combinations will give them more or less utility (Borjas, 1996, pp. 20-28). The indifferent options are generally represented as indifference curves (Borjas, 1996, pp. 24-28). The choice of whether to work is then determined by optimizing an individual's time such that they achieve the highest level of utility given their possible wage rate and time constraints, since there are only so many hours in a day (Borjas, 1996).

Since a person's time can only be split between labor and leisure, she will maximize her utility by optimizing the amount of time she spends working so that she can consume a larger amount of consumption goods at a higher wage, and less leisure time, or more leisure time and work less at a lower wage (Borjas, 1996, pp. 43-46; Ehrenberg and Smith, 1988, pp. 172-177). Basic budget and time constraint equations estimate the only costs to work as being the time not spent in leisure, and the cost of leisure is the lost income by not working (Borjas, 1996, pp. 28-30). However, since an individual can make some money from interest payments from bonds or stock dividends, she may have a basic level of non-labor income (Borjas, 1996, pp. 30-33). Hence, if an individual does not work at all, then she will still receive this income and a certain level of utility. She will therefore not work unless the utility she receives from working is higher than when not working (Borjas, 1996, pp. 30-39). This paper focuses on this decision to stay in or out of the labor force during the pandemic.

There are a lot of other factors beyond time spent in labor or leisure that can impact a person's decision to work. Certain variables, like the costs of commuting to work can serve as barriers to entry because they increase the reservation wage that someone is willing to work for before entering the labor force (Borjas, 1996, pp. 32-33). Another major factor that can affect a person's decision to work is their marital status and their partner's income. If a person is married, then the amount of nonmarket labor, housework or childrearing, that needs to be done can be split between both people (Borjas, 1996, pp. 51-68). With two people in a household, if they have different potential wages then the decision of whether to work gets more complicated. Each of the two partners has a different level of production in the labor market and at home. Together, the two budget constraint lines form one household opportunity frontier, that is used to maximize the household's overall utility function (Borjas, 1996, pp. 52-56; Ehrenberg and Smith, 1988). If one partner is relatively more productive at housework than they are in the labor market, then the household's utility may be maximized best if that partner stays home rather than engaging in the labor force (Borjas, 1996, pp. 56-58). While this does not necessarily mean that only one partner performs all the housework, nor that only one partner is in the labor market, it does mean that if one partner has a lower wage rate, then it is likely that they will spend less time in the labor market than in performing nonmarket labor (Borjas, 1996; Ehrenberg and Smith, 1988).

This household production function is important to consider when looking at changes in labor force participation during the pandemic because I hypothesize that the pandemic has increased the number of hours of nonmarket work that need to be performed each day. Since many schools closed during the first year of the pandemic, children were at home all day. Having children at home during the middle of the day, especially young children, increases the overall number of hours of nonmarket work that need to be performed by parents because many children cannot take care of themselves. Therefore, someone must increase the number of hours being spent on nonmarket work. In a single person's household, that individual must balance both work and the increased nonmarket labor. But in a household with two or more adults, either one or both adults must take on the increased labor (Borjas, 1996; Ehrenberg and Smith, 1988). I hypothesize, that since female wages are on average lower than male wages, and because the pandemic disproportionately affected the female dominated service industry, that married females will be the ones increasing the number of hours that they spend on nonmarket labor. Furthermore, because of this discrepancy in wages and hours, women are more likely to leave the labor force during the pandemic to perform nonmarket or childrearing labor.

Other key factors that are normally associated with variations in work behavior include: years of schooling, race or ethnicity, age, disability, and having children. The highest level of education that a person has obtained, directly correlates to the amount of human capital she has. The higher her human capital, the more desirable a worker she is, and the more likely that jobs will hire her for a higher wage. Thus, if someone has obtained a college degree, and will make over $60,000 a year, then she is more likely to enter the labor force than an individual who has only graduated high school and will therefore have a lower starting salary (Pencavel, 1986 as cited in Ashenfelter et al., 1986). There is also a strong correlation with race and labor force participation. White men between 25 and 54 are more likely to work than black men (Pencavel, 1986 as cited in Ashenfelter et al., 1986, pp. 18-26). Therefore, race is an important factor to consider when estimating labor force participation.

Having a disability can also affect participation because it can eliminate your ability to engage in certain kinds of labor. Because this paper is estimating the effects of the pandemic on changes in labor force participation and not on disabilities, it will be dropping any data labeled as not participating due to disability to eliminate confounding variables.

As it has been hinted at already, having children can impact labor force participation decisions in multiple ways that differ between men and women. According to Ehrenberg and Smith (1988), when a woman gives birth the household's utility maximizing indifference curve becomes much steeper because she becomes more productive at home taking care of the young children (p. 236). This means that it takes a much higher wage for women to justify not working solely at home. As children get older this utility maximizing indifference curve becomes flatter again (Ehrenberg and Smith, 1988). Having children, especially young children, has also been correlated with an increase in male labor force participation, reinforcing Ehrenberg and Smith's (1988) point that female labor force participation is more likely to be negatively affected by having children than male participation (Pencavel, 1986, as cited in Ashenfelter et. al., 1986, p. 21). Because having young children in the non-pandemic environment already decreases female labor force participation due to an increase in productivity at home, I hypothesize that this effect is greater during the pandemic and may extend to older children as schools of all levels closed. The pandemic should not have affected the number of care hours that an infant requires unless the family was receiving outside childcare. However, the pandemic has impacted the number of care hours that toddlers and elementary school age children require. Therefore, Ehrenberg and Smith's (1988) description of the change in indifference curves may not hold during the pandemic because of the changes in the amount nonwage work. A household's indifference curve may take longer to flatten out because the amount of care required during the pandemic is not decreasing. The same indifference curve may also become steeper during the pandemic for similar reasons of increased carework.

Age is another important factor in labor force calculations. According to John Pencavel's *Labor Supply of Men: A Survey* (1986) the probability of working increases until age 25, which is when most people have finished their undergraduate or master's degrees (As cited in Ashenfelter et. al., 1986 pp. 21-25). From 25 to mid-fifties, the probability of labor force participation remains relatively constant and then drops after the age 54 (Pencavel, 1986, as cited in Ashenfelter et. al., 1986, pp. 20-21). This drop in labor force participation is likely due to people beginning to retire as they reach their late fifties or early sixties. Ehrenberg and Smith (1988) suggest that the time allocated to work is more of a curve. When a person hits retirement age, around 60, and can begin collecting their pension or social security, it increases the nonwage income such that their utility is no longer being maximized by working (Ehrenberg and Smith, 1988). Thus, they retire and leave the labor force (Ehrenberg and Smith, 1988, pp. 238-240). Hence, a quadratic functional form is likely the most accurate functional form to use when estimating the effect of age on labor force participation.

Overall, the neoclassical model labor-leisure choice finds that while people must decide how to split their time between labor and leisure hours, there are multiple factors that can affect this decision. It is important when modeling labor supply and labor force participation decisions to consider these factors and what effects they have on individual choices. While all of the variables discussed above are important for labor supply models and should be included for control purposes, I hypothesize that a person's marital status and whether they have children will have a larger impact on labor force participation decisions during the pandemic than during other periods.

4 MODEL

Labor force participation decisions and likelihood are based on a number of factors. For example, a person's age is likely to influence whether they are participating in the labor force: if they are younger than 25 then they have a higher likelihood of being in school, but if they are over 65 then they may be retired. In either case the individual is not working. As seen in Ehrenberg and Smith (1988), age also affects labor force participation more when a person is younger and declines as people age. Hence, this paper uses a quadratic functional form to control for the effect of age on a person's probability of being in the labor force. A person's highest level of education is also important in determining whether they participate in the labor force because a higher degree is linked to higher human capital and a longer amount of time spent developing that human capital in school. Therefore, a person with a higher degree is more likely to be working or in the labor force than someone with a lower-level degree (Pencavel, 1986, as cited in Ashenfelter et. al., 1986).

Another factor that can affect both employment rates and labor force participation rates, is race. This is not only an important factor to include because of discriminatory practices, but also because I am looking at the effects of the pandemic on labor force participation and the coronavirus has disproportionately affected black and Hispanic people. Therefore, it is reasonable to believe that there may be race related reasons for changes in labor force participation numbers during the pandemic that are not related to the perpetuation of gender norms.

Finally, three other variables that can have large influences on labor force participation are gender, marital status, and having young children. This paper is primarily concerned with these variables and how the pandemic has affected people based on their gender, marital status, and whether they have children. Gender is an interesting variable because, as Albanesi and Kim (2021) mention, female, specifically married female, employment, and labor force appear to be counter-cyclical (p. 5). This is in part due to the type of employment that is dominated by females, the service industry, and because of utility-maximizing decisions based on security: if there is an economic downturn and the wife starts working as well, then the family is safer if they husband loses his job. This nuance goes together with marital status because married women are, on average, less likely to engage in the labor market than any other demographic. This is likely because of a perpetuation of gender roles, where married women stay at home and their partners are the “bread-winners.” If someone is single, then she is her only source of income, so she is more likely to have to work. Someone with a partner, however, may be able to have an outside source of income, and could be less likely to work. That being said, these decisions and distinctions are more prevalent amongst females than males, especially given that overall female labor force participation is significantly lower than male labor force participation. Therefore, both gender and marital status are crucial elements to labor force participation decisions.

Finally, having children further influences a person’s decisions to join the labor market. If a person has children, then they must provide for those kids. This includes both paid and unpaid expenses. Therefore, if a person has kids and is married, if one partner makes enough money to sustain the entire household, then the other partner is likely to not work and take on the un-paid labor of raising a family (Ehrenberb and Smith, 1988; Borjas, 1996). In heteronormative marriages, it is typically the wife's job to stay at home doing carework, while the husband works. If someone is single, however, and has kids, then she is solely responsible for taking care of the child and must work. Therefore, it is likely that single people with children, on average, are more likely to work than married individuals. Yet again we see a link between marital status, gender, and now having children when it comes to labor force participation decisions.

For the purposes of this paper, the variables that we are most concerned with affecting labor force participation are age, highest level of education, race, gender, marital status, and having children under the age of 18.

5 METHODOLOGY

In this paper I am estimating the probability that a person will participate in the labor force given certain demographic information about them, the number of children they have and whether the data was collected during the pandemic. Because the focus is on the decision to participate in the labor force, the dependent variable only has two values: 0 if they are not in the labor force and 1 if they are. Therefore, I will be using a binary response model to estimate the probability of labor force participation on a given set of factors, x.

The binary response model that this paper uses is a probit model. The basic form of a probit model is that $P(y = 1|\boldsymbol{x}) = G(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots)$ where G(z) can only take on values between 0 and 1 (Wooldridge, 2013). This eliminates the possibility of having a negative probability or a probability greater than 1 as neither case would make sense. For a probit model G(z) represents the cumulative distribution function of the standard normal density as shown below (Wooldridge, 2013). The standard normal CDF takes on an s-shaped curve (Wooldridge, 2013).

$$G(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} * e^{-\frac{z^2}{2}} dz$$

This model, as with other binary response models, is ultimately derived from a latent variable that if the value of $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + e > 0$ then the dependent variable is 1, or a success (Wooldridge, 2013). For this paper, a success means that the individual is participating in the labor force and the function G(z) takes on the following form:

$$P(y = 1|\boldsymbol{x}) = G(\beta_0 + \beta_{1-15} * pandemic * female * married * children + \delta_5 * age + \delta_6 * age^2 + \delta_7 * hsGrad + \delta_8 * someCol + \delta_9 * AssocDeg + \delta_{10} * BachDeg + \delta_{11} * postGrad + \delta_{12} * hispanic + \delta_{13} * black + \delta_{14} * indigenous + \delta_{15} * asian + \delta_{16} * Hawaiian + \delta_{17} * multiRacial)$$

The non-linearity of the probit model means OLS cannot be used to estimate the model, instead I will use a maximum likelihood estimator based on the distribution of the dependent variable given all of the independent variables. The nature of this estimator eliminates the heteroskedasticity found in a linear probability model of the variance of the dependent variable given the independent ones (Wooldridge, 2013). The estimated values for each coefficient and estimate of the standard error can then be used to perform t-tests and construct confidence intervals.

Probit models are not the only forms of binary response models, there are also linear probability models and logit models. A linear probability model (LPM) is a multiple linear regression on a binary dependent variable. While the models can be useful in certain circumstances because they are using a linear regression it is possible to have outcomes that do not make sense. Plugging in certain values into a linear probability model can result in a negative probability or a probability greater than one which contradicts the fact that the dependent variable's range is supposed to only be zero or one (Wooldridge, 2013).

Logit models are similar to probit models, but instead of estimating the cumulative distribution function of the standard normal density function, logit models use a standard logistical distribution (Wooldridge, 2013). This paper is choosing to use probit models because there is no evidence to suggest that the distribution of the error on the latent variable is not normally distributed, although I will run both models for thoroughness.

6 DATA

I used the US Census Bureau's Monthly Current Population Survey data from March of 2019 to February of 2021. I sourced this data from the data.nber.org website. I chose these months to focus on because I want to compare each month from the first year of the pandemic with the same month from the year prior to the pandemic. By comparing the same month one year apart, I will be eliminating most of the seasonal changes in labor force participation allowing me to examine the direct effects the pandemic had on the probability of labor force participation. Overall, about half the data is from before the pandemic, March 2019-February 2020, and half from during the pandemic, March 2020-February 2021. I pooled the two datasets from each month to determine the effect of the pandemic on labor force participation. In Table 1, I provide descriptive statistics of all the variables and omitted categories for the entire two years of data.

I excluded data points from people who are younger than 25 because of the higher likelihood that they are not working because they are in school. I also excluded people over 60 who may not be in the labor force because they are retired instead of because of pandemic factors. Furthermore, the focus of this study is on how having children under the age of 18 impacted labor force participation decisions during the pandemic. It is less likely that a person over the age of 60 has young children that require extra supervision while attending school remotely. Removing individuals who are over 60 years old should help account for the trend that

Table 1: Variable Descriptions and Summary Statistics

VARIABLES	Mean	SD	Min	Max
Demographic Groups				
Prior to the Pandemic				
With Children				
Single Females	0.0328	0.178	0	1
Married Females	0.0871	0.282	0	1
Single Males	0.0126	0.112	0	1
Married Males	0.0845	0.278	0	1
Without Children				
Single Females	0.0794	0.27	0	1
Married Females	0.0764	0.266	0	1
Single Males	0.0934	0.291	0	1
Married Males	0.0664	0.249	0	1
During the Pandemic				
With Children				
Single Females	0.0278	0.164	0	1
Married Females	0.0768	0.266	0	1
Single Males	0.0111	0.105	0	1
Married Males	0.0739	0.262	0	1
Without Children				
Single Females	0.0684	0.253	0	1
Married Females	0.0686	0.253	0	1
Single Males	0.0816	0.274	0	1
Married Males	0.0593	0.236	0	1
Age	42.49	10.42	25	60
Age Squared	1,914	893.8	625	3,600
Highest Degree Obtained				
No College	0.329	0.47	0	1
Some College	0.152	0.359	0	1
Associates	0.114	0.318	0	1
Bachelors	0.258	0.437	0	1
Masters	0.111	0.314	0	1
Professional	0.016	0.125	0	1
Doctorate	0.0215	0.145	0	1
Race				
White	0.801	0.399	0	1
Hispanic	0.15	0.357	0	1
Black	0.1	0.3	0	1

Table 1: Variable Descriptions and Summary Statistics (Continued)

VARIABLES	Mean	SD	Min	Max
Race (Continued)				
Indigenous or Native Alaskan	0.0126	0.112	0	1
Asian	0.0652	0.247	0	1
Hawaiian or Pacific Islander	0.00489	0.0698	0	1
Multiple Races	0.0163	0.127	0	1
Total Observations: N = 1,151,253				

Table 1: This table provides a list of all the demographic and control variables used in the monthly models, including the omitted categories, and their means, standard deviations, minimum and maximum values of all the combined data from each month.

Coibion et al. (2020) suggests, where the pandemic is causing more people to retire, and not confounding this retirement effect with the effect of having children. I have also excluded any other individuals who have marked that they are not in the labor force due to disability since this is likely not related to having children during the pandemic. In this way, my model focuses on the pandemic’s effect on people with young children who would be in the primary workforce age bracket compared to the effect on the demographic groups without children.

7 RESULTS

I ran a separate probit model for every month comparing labor force participation data from before the pandemic to data during the pandemic. Each model used all the demographic groups where the omitted category was married women with children not during the pandemic. I used chi-squared tests to determine if the difference between the probability that each group participated in the labor force during the pandemic than before the pandemic was significant. I further tested if the change in probability during the pandemic was significantly different from the change that married women with children engaged in the labor force during the pandemic. The marginal effects results from the probit models for each month are reported in Table 2, the probit model coefficients are available upon request. Table 3 displays the change in the probability that each demographic participates in the labor force for each month during the pandemic, starting with March through February, by illustrating the difference between the probability calculated from the probit model coefficients for each demographic during the pandemic and prior to the pandemic. Hence, a negative value in Table 3 indicates a decreased probability of labor force participation for that demographic during the pandemic compared to the same month prior to the pandemic. Figure 1 is a visual representation of the data presented in Table 3, graphing all the changes in probability of labor force participation for each demographic starting with March through February.

Table 2: Probit Model Marginal Effects Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Demographic Groups												
During the Pandemic												
With Children												
Single Female	0.0721***	0.0585***	0.0629***	0.0673***	0.0774***	0.0692***	0.0578***	0.0548***	0.0552***	0.0533***	0.0543***	0.0553***
	(0.00356)	(0.00475)	(0.00455)	(0.00445)	(0.00410)	(0.00412)	(0.00424)	(0.00421)	(0.00424)	(0.00435)	(0.00439)	(0.00436)
Married Female	-0.00184	-0.0137***	-0.00980**	-0.00340	0.00565	-0.00466	-0.0151***	-0.0199***	-0.0213***	-0.0172***	-0.0106**	-0.0141***
	(0.00434)	(0.00487)	(0.00480)	(0.00477)	(0.00462)	(0.00466)	(0.00476)	(0.00477)	(0.00485)	(0.00481)	(0.00469)	(0.00475)
Single Male	0.106***	0.105***	0.107***	0.113***	0.117***	0.110***	0.102***	0.103***	0.104***	0.104***	0.107***	0.109***
	(0.00258)	(0.00381)	(0.00342)	(0.00304)	(0.00288)	(0.00304)	(0.00334)	(0.00302)	(0.00294)	(0.00302)	(0.00295)	(0.00277)
Married Male	0.127***	0.131***	0.133***	0.136***	0.138***	0.132***	0.130***	0.127***	0.127***	0.126***	0.130***	0.130***
	(0.00155)	(0.00183)	(0.00171)	(0.00167)	(0.00170)	(0.00168)	(0.00168)	(0.00166)	(0.00167)	(0.00170)	(0.00169)	(0.00165)
Without Children												
Single Female	0.0886***	0.0839***	0.0800***	0.0819***	0.0847***	0.0851***	0.0775***	0.0782***	0.0732***	0.0766***	0.0806***	0.0812***
	(0.00240)	(0.00296)	(0.00300)	(0.00300)	(0.00300)	(0.00280)	(0.00290)	(0.00281)	(0.00296)	(0.00288)	(0.00284)	(0.00280)
Married Female	0.0533***	0.0465***	0.0456***	0.0541***	0.0536***	0.0512***	0.0428***	0.0402***	0.0427***	0.0466***	0.0439***	0.0490***
	(0.00335)	(0.00391)	(0.00387)	(0.00372)	(0.00381)	(0.00369)	(0.00379)	(0.00378)	(0.00375)	(0.00369)	(0.00379)	(0.00365)
Single Male	0.101***	0.0960***	0.0964***	0.103***	0.106***	0.102***	0.0985***	0.0960***	0.0888***	0.0914***	0.0986***	0.0962***
	(0.00207)	(0.00259)	(0.00251)	(0.00240)	(0.00239)	(0.00232)	(0.00235)	(0.00233)	(0.00251)	(0.00245)	(0.00236)	(0.00238)
Married Male	0.112***	0.115***	0.111***	0.112***	0.112***	0.110***	0.112***	0.109***	0.107***	0.106***	0.109***	0.109***
	(0.00178)	(0.00216)	(0.00219)	(0.00221)	(0.00230)	(0.00217)	(0.00204)	(0.00202)	(0.00210)	(0.00211)	(0.00213)	(0.00209)

Table 2: Probit Model Marginal Effects Results (Continued)

VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Demographic Groups												
Prior to the Pandemic												
With Children												
Single Female	0.0684***	0.0796***	0.0779***	0.0765***	0.0789***	0.0805***	0.0744***	0.0710***	0.0710***	0.0724***	0.0771***	0.0721***
	(0.00348)	(0.00360)	(0.00356)	(0.00360)	(0.00364)	(0.00337)	(0.00357)	(0.00360)	(0.00363)	(0.00357)	(0.00350)	(0.00365)
Single Male	0.111***	0.122***	0.121***	0.121***	0.123***	0.116***	0.113***	0.113***	0.112***	0.109***	0.113***	0.107***
	(0.00206)	(0.00224)	(0.00213)	(0.00218)	(0.00219)	(0.00237)	(0.00250)	(0.00229)	(0.00239)	(0.00254)	(0.00247)	(0.00285)
Married Male	0.132***	0.144***	0.143***	0.144***	0.146***	0.142***	0.138***	0.134***	0.135***	0.134***	0.136***	0.134***
	(0.00151)	(0.00164)	(0.00162)	(0.00163)	(0.00164)	(0.00158)	(0.00156)	(0.00154)	(0.00155)	(0.00157)	(0.00160)	(0.00161)
Without Children												
Single Female	0.0854***	0.0933***	0.0929***	0.0937***	0.0966***	0.0909***	0.0891***	0.0854***	0.0847***	0.0899***	0.0921***	0.0933***
	(0.00245)	(0.00266)	(0.00261)	(0.00261)	(0.00263)	(0.00259)	(0.00259)	(0.00261)	(0.00265)	(0.00252)	(0.00254)	(0.00248)
Married Female	0.0567***	0.0617***	0.0593***	0.0567***	0.0585***	0.0553***	0.0511***	0.0474***	0.0537***	0.0539***	0.0572***	0.0536***
	(0.00319)	(0.00346)	(0.00345)	(0.00351)	(0.00356)	(0.00348)	(0.00356)	(0.00358)	(0.00345)	(0.00343)	(0.00343)	(0.00349)
Single Male	0.107***	0.117***	0.115***	0.116***	0.117***	0.112***	0.106***	0.100***	0.101***	0.104***	0.107***	0.107***
	(0.00196)	(0.00214)	(0.00213)	(0.00214)	(0.00219)	(0.00213)	(0.00220)	(0.00224)	(0.00223)	(0.00218)	(0.00218)	(0.00216)
Married Male	0.114***	0.123***	0.119***	0.119***	0.123***	0.119***	0.116***	0.112***	0.114***	0.115***	0.117***	0.117***
	(0.00175)	(0.00195)	(0.00198)	(0.00201)	(0.00199)	(0.00192)	(0.00193)	(0.00195)	(0.00192)	(0.00188)	(0.00191)	(0.00188)
Age	0.0211***	0.0232***	0.0209***	0.0217***	0.0206***	0.0200***	0.0199***	0.0185***	0.0191***	0.0193***	0.0189***	0.0189***
	(0.000966)	(0.00102)	(0.00102)	(0.00103)	(0.00104)	(0.00101)	(0.000979)	(0.000961)	(0.000967)	(0.000977)	(0.000988)	(0.000981)
Age Squared	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(1.13e-05)	(1.19e-05)	(1.19e-05)	(1.21e-05)	(1.22e-05)	(1.18e-05)	(1.15e-05)	(1.13e-05)	(1.13e-05)	(1.14e-05)	(1.16e-05)	(1.15e-05)

Table 2: Probit Model Marginal Effects Results (Continued)

VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Some College	0.0286***	0.0301***	0.0266***	0.0316***	0.0255***	0.0234***	0.0296***	0.0306***	0.0284***	0.0277***	0.0288***	0.0241***
	(0.00273)	(0.00291)	(0.00294)	(0.00293)	(0.00306)	(0.00297)	(0.00280)	(0.00271)	(0.00275)	(0.00280)	(0.00281)	(0.00284)
Associate's Degree	0.0561***	0.0602***	0.0597***	0.0596***	0.0641***	0.0614***	0.0607***	0.0600***	0.0532***	0.0508***	0.0562***	0.0591***
	(0.00263)	(0.00281)	(0.00280)	(0.00285)	(0.00286)	(0.00277)	(0.00267)	(0.00260)	(0.00271)	(0.00277)	(0.00273)	(0.00267)
Bachelor's Degree	0.0660***	0.0693***	0.0683***	0.0659***	0.0619***	0.0607***	0.0647***	0.0657***	0.0665***	0.0644***	0.0687***	0.0718***
	(0.00228)	(0.00243)	(0.00243)	(0.00247)	(0.00254)	(0.00244)	(0.00233)	(0.00228)	(0.00229)	(0.00234)	(0.00233)	(0.00231)
Master's Degree	0.0819***	0.0887***	0.0907***	0.0907***	0.0835***	0.0802***	0.0814***	0.0863***	0.0869***	0.0849***	0.0916***	0.0904***
	(0.00230)	(0.00247)	(0.00240)	(0.00244)	(0.00262)	(0.00252)	(0.00241)	(0.00227)	(0.00228)	(0.00234)	(0.00228)	(0.00227)
Professional	0.0850***	0.0969***	0.0934***	0.0874***	0.0842***	0.0809***	0.0853***	0.0862***	0.0851***	0.0821***	0.0929***	0.0891***
	(0.00430)	(0.00437)	(0.00439)	(0.00477)	(0.00523)	(0.00507)	(0.00456)	(0.00428)	(0.00430)	(0.00448)	(0.00410)	(0.00431)
Doctorate	0.0931***	0.101***	0.100***	0.0933***	0.0922***	0.0979***	0.0974***	0.0962***	0.0948***	0.0869***	0.0892***	0.0966***
	(0.00335)	(0.00371)	(0.00357)	(0.00396)	(0.00413)	(0.00353)	(0.00343)	(0.00331)	(0.00340)	(0.00382)	(0.00384)	(0.00335)
Hispanic	-0.0222***	-0.0307***	-0.0316***	-0.0265***	-0.0288***	-0.0290***	-0.0302***	-0.0260***	-0.0245***	-0.0265***	-0.0229***	-0.0238***
	(0.00320)	(0.00342)	(0.00345)	(0.00345)	(0.00351)	(0.00340)	(0.00327)	(0.00316)	(0.00319)	(0.00326)	(0.00321)	(0.00318)
Black	-0.0136***	-0.0174***	-0.0139***	-0.0151***	-0.0138***	-0.0206***	-0.0214***	-0.0212***	-0.0189***	-0.0204***	-0.0250***	-0.0194***
	(0.00376)	(0.00397)	(0.00398)	(0.00403)	(0.00405)	(0.00396)	(0.00380)	(0.00374)	(0.00375)	(0.00382)	(0.00389)	(0.00383)
Indigenous or Native Alaskan	-0.0772***	-0.0618***	-0.0616***	-0.0387***	-0.0625***	-0.0654***	-0.0644***	-0.0756***	-0.0571***	-0.0600***	-0.0654***	-0.0616***
	(0.0114)	(0.0113)	(0.0116)	(0.0113)	(0.0122)	(0.0116)	(0.0109)	(0.0110)	(0.0106)	(0.0112)	(0.0112)	(0.0108)
Asian	-0.0709***	-0.0854***	-0.0833***	-0.0685***	-0.0596***	-0.0579***	-0.0684***	-0.0614***	-0.0662***	-0.0772***	-0.0745***	-0.0698***
	(0.00538)	(0.00568)	(0.00573)	(0.00560)	(0.00558)	(0.00543)	(0.00536)	(0.00525)	(0.00527)	(0.00549)	(0.00547)	(0.00537)

Table 2: Probit Model Marginal Effects Results (Continued)

VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Hawaiian or Pacific Islander	-0.0260	-0.00600	-0.0320*	-0.0410**	-0.0429**	-0.0645***	-0.0927***	-0.0613***	-0.0330*	-0.0151	-0.000137	0.000678
	(0.0165)	(0.0158)	(0.0170)	(0.0181)	(0.0179)	(0.0180)	(0.0190)	(0.0173)	(0.0169)	(0.0169)	(0.0153)	(0.0149)
Multi-Racial	-0.0111	-0.0162*	-0.0154	-0.0243**	-0.00342	-0.000498	0.00877	0.0145*	0.00277	0.00654	-0.0143	-0.00510
	(0.00873)	(0.00926)	(0.00949)	(0.00962)	(0.00886)	(0.00849)	(0.00789)	(0.00787)	(0.00842)	(0.00831)	(0.00890)	(0.00871)
Observations	96,257	95,459	92,826	90,803	91,091	94,081	98,593	100,188	99,077	96,987	97,905	97,986

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

Table 2: This table reports the marginal effects results obtained from the Probit model for each month (March-February) and the associated standard errors. Probit coefficients available upon request.

Table 3: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic)

VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
With Children												
Single Fem.	0.0037	-0.0211**	-0.015**	-0.0092*	-0.0015	-0.0113**	-0.0166**	-0.0162**	-0.0158**	-0.0191**	-0.0228**	-0.0168**
Married Fem.	-0.00184	-0.0137**	-0.0098**	-0.0034	0.00565	-0.00466	-0.0151**	-0.0199**	-0.0213**	-0.0172**	-0.0106**	-0.0141**
Single Male	-0.005**	-0.017	-0.014	-0.008**	-0.006**	-0.006**	-0.011	-0.01**	-0.008**	-0.005**	-0.006**	0.002**
Married Male	-0.005*	-0.013**	-0.01**	-0.008*	-0.008**	-0.01**	-0.008**	-0.007**	-0.008**	-0.008**	-0.006**	-0.004
Without Children												
Single Fem.	0.0032	-0.0094**	-0.0129**	-0.0118**	-0.0119**	-0.0058*	-0.0116**	-0.0072**	-0.0115**	-0.0133**	-0.0115**	-0.0121**
Married Fem.	-0.0034	-0.0152**	-0.0137**	-0.0026	-0.0049	-0.0041	-0.0083**	-0.0072*	-0.011**	-0.0073**	-0.0133**	-0.0046
Single Male	-0.006**	-0.021**	-0.0186**	-0.013**	-0.011**	-0.01**	-0.0075**	-0.004*	-0.0122**	-0.0126**	-0.0084**	-0.0108**
Married Male	-0.002	-0.008**	-0.008**	-0.007**	-0.011**	-0.009**	-0.004*	-0.003	-0.007**	-0.009**	-0.008**	-0.008**

* p<0.1, ** p<0.05

Table 3: This table displays the difference between the pandemic probabilities and pre-pandemic probabilities of labor force participation and the results of the chi-squared significance tests to determine if the pandemic data is significantly different. Note that negative values indicate a decreased probability of labor force participation during the pandemic than prior to the pandemic for that demographic group.

For most of the first year of the pandemic, every demographic group's probability of labor force participation was below their pre-pandemic probabilities. There are some demographics that were not significantly different during a few months. The exceptions for single and married women with children is that during the summer months, the differences in the probability of participation decreased and were not significantly different from their pre-pandemic probabilities. As shown in Table 3, most demographics did not have a significant change in their probability of labor force participation. In April, all demographics besides single males with children experienced significantly decreased labor force participation. Figure 1 demonstrates that after April there is a general trend upward, where the differences in the probability of labor force participation during the pandemic were smaller in May and June for most demographics, except for single females without children.

The overall trend in the labor force participation probabilities for females with children are similar for both married and single females. The data for married females with kids is not significantly different from their pre-pandemic probability of participating in the labor force during March of 2020 and the summer months, May through August. However, during April 2020 and from September 2020 through February 2021 the probability of married females with children participating in the labor force was significantly lower than the pre-pandemic probability by over 1% each month. As shown in Tables 1 and 2 The largest drop in the probability that married females participated in the labor force was -2.13% in November of 2020. The trend in probability changes, as shown in Figures 1-4, appears to increase slightly after November until January when it reached -1.06%, before dipping again to -1.41% in February of 2021.

Figure 1: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic): All Demographics

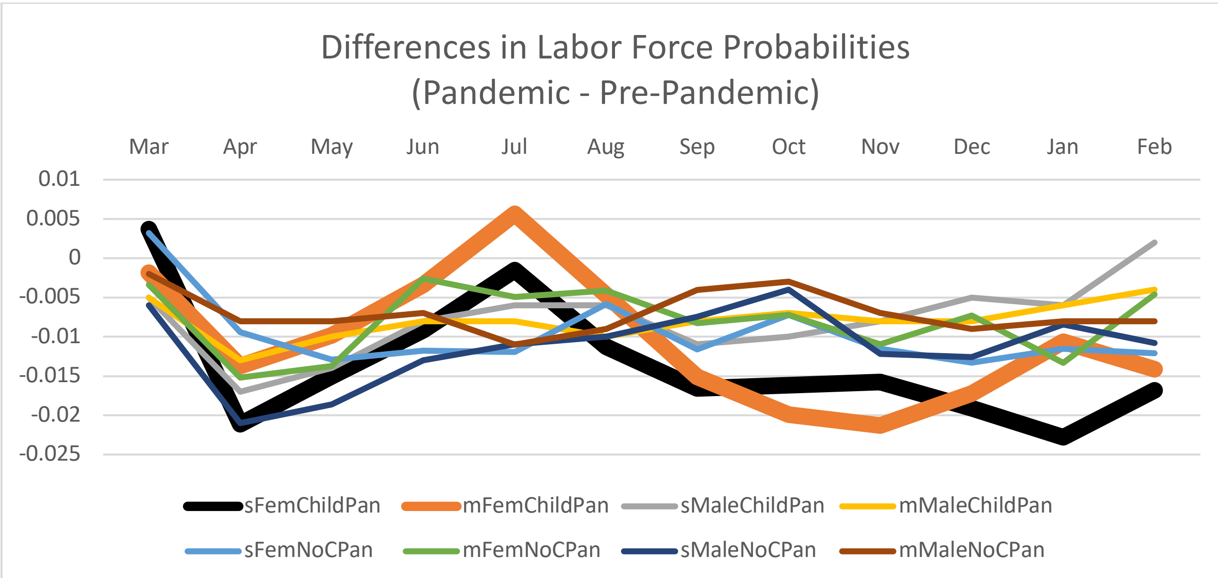

Figure 1: A visual representation of the data presented in Table 3. This graph pictures the changes in the estimated mean probability of labor force participation for each of the eight demographic groups.

Figure 2 displays just the changes in the probit model estimated probabilities of labor force participation for married females with children and single females with children. The data labels are color coded where the lighter green boxes, on the line for married females, represents months where the probit coefficient on married females with children was significant, the light red on the same line indicate a difference that was not statistically significant. This line uses the significance tests from the coefficients estimated by the probit model because the omitted category was married females with children not during the pandemic, thus, the significance test of the coefficient already estimates if the effect is significantly different from pre-pandemic numbers. The dark green labels on the single female line represents months where the difference in the probability that single females with children participate in the labor force is significantly different from the probability that married females with children participate according to significance tests comparing the predicted probabilities for each demographic. The red labels on

Figure 2: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic): Single Females with Children Only, Compared with Married Females with Children

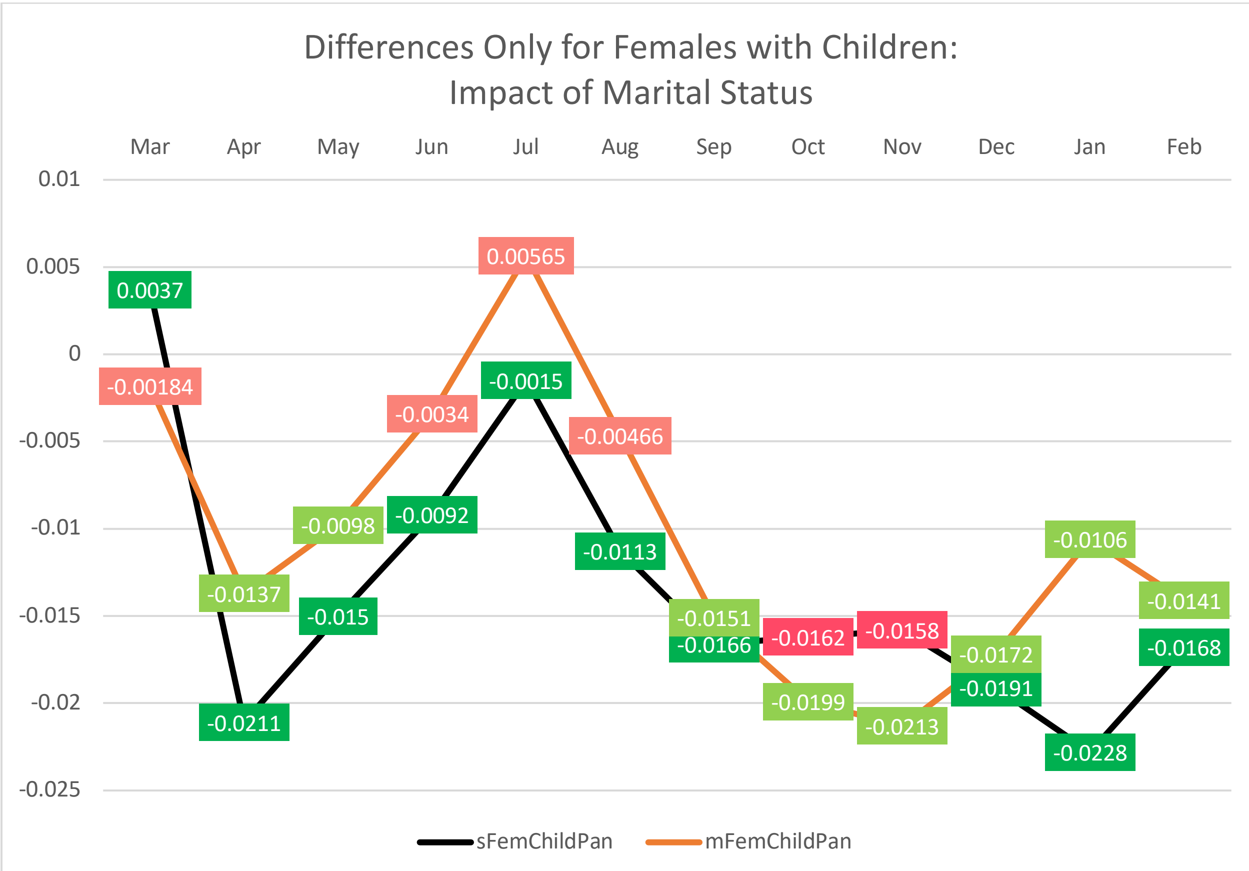

Figure 2: this is a subgraph of Figure 1 depicting only the data for single and married females with children. The light green data labels for married females with children indicate the months where their labor change in probability of labor force participation during the pandemic was statistically significant compared to before the pandemic. The red data labels on the same line indicate the months where the change was not statistically significant. The green data labels on the single female line indicate the months where the difference in labor force participation for single females was significantly different from the difference in probability for married females. The red data labels on the same line indicate the months where this was not statistically significant.

the same line indicate the months where the probabilities were not significantly different from each other.

The probability of single females with children participating in the labor force experienced a similar trend to married females with children. There was no significant difference in probability of participation during March 2020, nor June and July of 2020 at the 5% level,

Figure 3: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic): Females Only, Compared with Married Females with Children

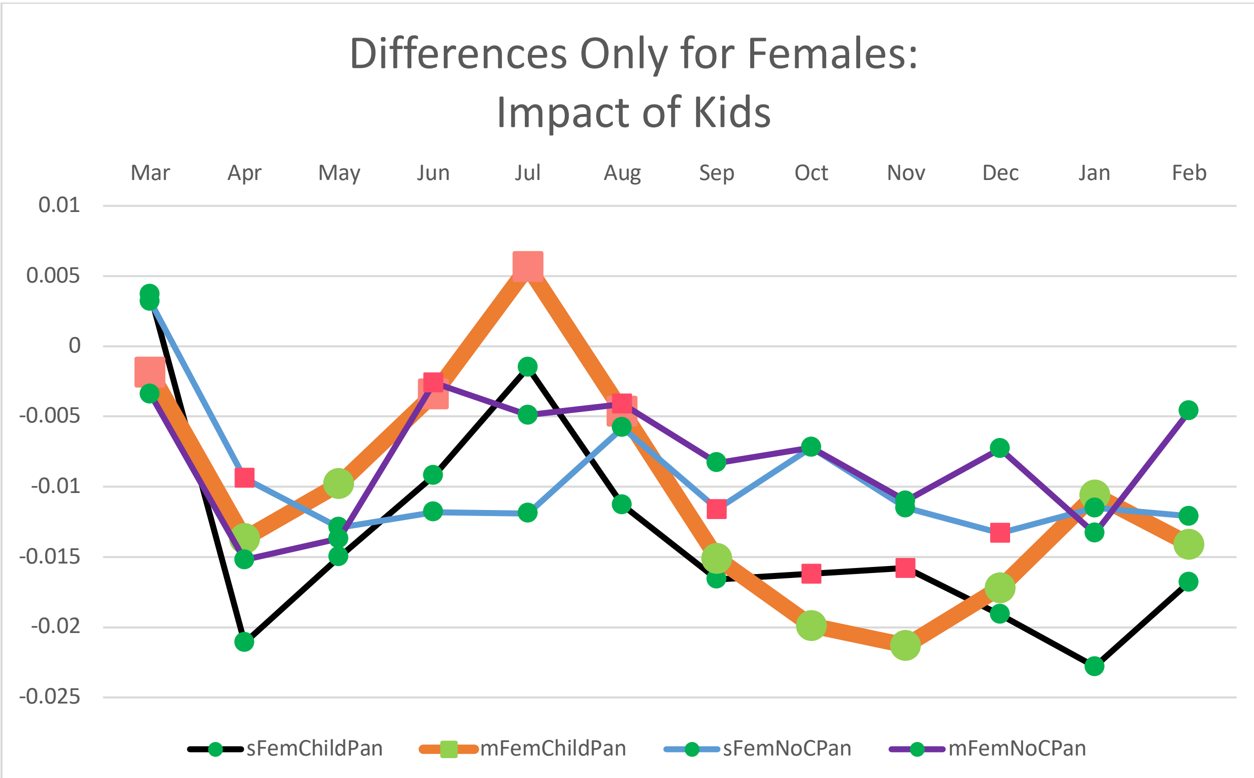

Figure 3: A subgraph of Figure 1 containing only the female demographic groups. As in Figure 2, the green circles on the line for married females with children indicate the months where the change in probability of labor force participation is statistically significant and the red squares indicate the months where they were not. The green circles on the other lines represent when the difference between the change in probability for the given demographic and the change in probability for married females with children is statistically significant, and the red squares are when this difference is not significantly different from zero.

although the difference in June is significant at 10%, compared to their respective pre-pandemic monthly data. Yet, for every other month during the pandemic, the probability that single females with children would participate in the labor force was at least 1.1% lower than it was before the pandemic. Table 3 reports that the largest decline in the probability of single female labor force participation was -2.28% in January of 2021, followed closely by a decline of 2.11% in April of 2020. The smallest statistically significant change in the probability of labor force engagement for single females with children is 1.13% in August of 2020. Both married and single females with children experienced larger declines in their probabilities of labor force participation during the second wave of the pandemic, August through February, than they did from the initial shock in March and April of 2020.

Women without children, single and married, do not appear to experience the same trend as women with children. As shown in Table 3 and Figure 3, their probabilities of participating in the labor force also declined in April. Figure 3 compares all the differences in the probability of female labor force participation with the change in the probability for married females with children. The red squares on the lines for single females with children, single females without children and married females without children indicate months where the differences were not statistically significant compared to married women with children, using a p-value of 0.05, and the green circles indicate months where the differences were statistically significant. This information is according to the significance tests comparing the differences in probabilities for the other female demographics to married females with children. The red squares on the line for married females with children indicate the months where the difference between pandemic and pre-pandemic probabilities were not significant for that month, while the green circles indicate that they were statistically significant according to the significance tests on the probit coefficients using a p-value of 0.05. According to Figure 3, the differences in September and December for married females and October and November for both married and single females are significantly higher, closer to 0, than the difference in probability for married women with children during those months. The probability that married females without children participated in the labor force was only lower than pre-pandemic months during April, May, September, and November through January at the 5% level, and during October at the 10% level. Single females without children, on the other hand, experienced statistically significant declines at the 5% significance level in their probability of participating in the labor force almost every month

Figure 4: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic): Married Females with Children and Married Males with Children Only

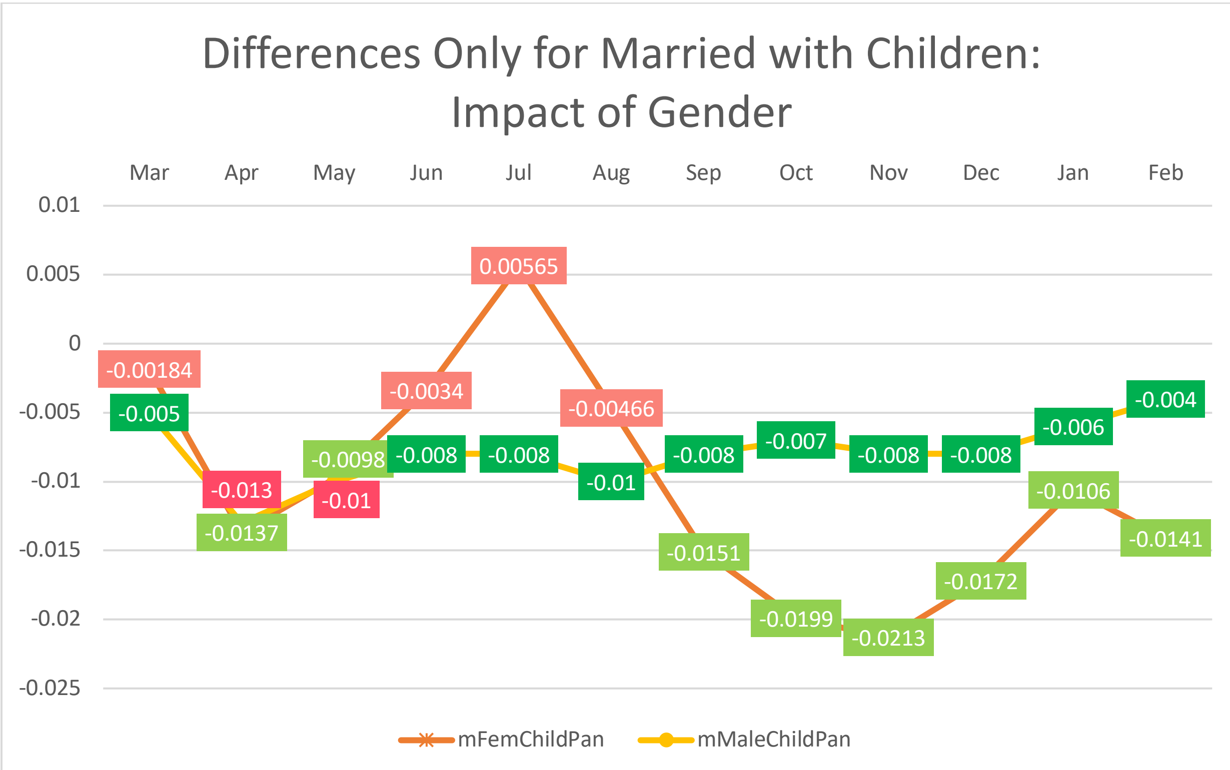

Figure 4: This final subgraph of Figure 1 displays only the data for married females with children and married males with children. As in Figures 2, the green data labels on the line for married females with children indicate the months where the change in probability of labor force participation is statistically significant and the red data labels indicate the months where they were not. The green data labels on the married males line represent when the difference between the change in probability for married males with children and the change in probability for married females with children are statistically significant, and the red data labels are when this difference is not significantly different from zero

during the pandemic with the exceptions of August which was significant only at the 10% level, and March which was not significant. The significant changes were all over a 1% drop in the probability that single females without children participated in the labor force during the pandemic month, except for in August and October where the decline was only 0.58% and 0.72% respectively.

The changes in labor force participation probabilities for females with children, single and married, were lower than the change in the probability of married male labor force participation for each month after August as seen in Figure 1. Figure 4 compares the differences between married males and married females with children. The only months where the differences were not significantly different were April and May, where the differences in the change in probabilities were only 0.0007 and 0.002 respectively. Married men with children also experienced declines in the probability that they would participate in the labor force for most months during the pandemic. For married men with children, these changes were not significant during February of 2021 at the 10% level nor were they significant at the 5% level during March of 2020 and June of 2020. While all other months experienced a statistically significant difference in the probability that married men with children would participate in the labor force, other than the 1.3% drop in April 2020, for every other pandemic month the probability of participation was lower than prior to the pandemic by at most 1%.

Single men with children also experienced lower probabilities of labor force participation during the pandemic. Table 3 shows that the differences in the probability that single men with children participated in the labor force during the pandemic followed a different pattern than many other demographics. Single men with kids did not experience a significant change in their labor force participation probability during April, May and September of 2020. The largest statistically significant decline was only 1% in October 2020, and by February 2021 single men with children were 0.2% more likely to participate in the labor force than in February of 2020, prior to the pandemic. Albeit a small percentage, this is the only statistically significant increase in probability of labor force participation compared to the pre-pandemic probability across all of the demographic groups.

As shown in Table 3, in April 2020 the probability that single men without children participated in the labor force was lower than the pre-pandemic percentage by 2.1%, the second largest difference that month. The difference between the probability of participation during the pandemic and prior was not significant at the 5% level during October of 2020. Furthermore, the difference in labor force participation in September 2020 was only 0.75% and in January 2021 was only 0.84%. However, for every other month the probability of single males with kids participating was lower than the pre-pandemic probability by at least 1%.

Similarly for married men without children, the pandemic months with significantly different probabilities of labor force participation were all lower by less than 1%, apart from July 2020 where the probability that married men without children would participate was lower than the pre-pandemic probability by 1.1%. Overall, every demographic group experienced some declines in the probability of being in the labor force during the pandemic.

The control variables for this model were age, highest level of education and race. All of these variables and their effects on the probability that an individual participates in the labor force can be found in Table 2.

As a way of accounting for the changes in labor force probability as a person age, I used a quadratic functional form. Age displayed a significant quadratic effect on probability of labor force participation, as was expected.

To control for the highest level of education achieved, there are six different dummy variables: some college, Associate's degree, Bachelor's degree, Master's degree, a professional degree, or a Doctorate. The omitted category in this series is no college experience. All these dummy variables have a significant positive effect on the probability of labor force participation, and the degrees that require more time in school have a larger positive effect. This, too, follows the expectations of the labor-leisure model.

In order to control for the effect of race on the probability that a person participates in the labor force, there are five dummy variables for different racial categories with "white" as the omitted category. All other races either have a significant negative effect on the probability of labor force participation, or the effect is not significant. This follows the expected pattern that white people are more likely to participate in the labor force in the United States than all other demographics.

8 ANALYSIS

Every demographic's probability of participating in the labor force was affected by the pandemic at some point between March of 2020 and February 2021. This was likely due to a variety of factors. First, some workers' decisions may have been based on the lack of available jobs in the market and were discouraged from looking for a position after being laid off due to the disproportionate affect that the pandemic had on certain industries. Another factor is the increased burden of childcare during the pandemic when schools closed in late March or early April. Finally, another factor could simply be that some workers were afraid of going back to work due to the virility and mortality of Covid-19.

As shown in Table 3 and Figure 1, the pandemic caused significantly decreased probabilities of labor force participation in every demographic group, except for single males with children, during both April and May of 2020. Many states experienced closures during March of 2020 and did not begin reopening after the first wave of cases until the end of May or beginning of June. Since the closures initially happened during mid-March, the effect of these closures on jobs and labor force participation would likely not show up fully until April, thus explaining why many groups, although some had decreased probabilities of labor force participation, did not experience statistically significant differences in March. Since there is a general trend of significantly lower probability of labor force participation in April and May, there appears to be an overall effect that the initial pandemic shock had on the labor force.

While the pandemic affected, and is indirectly still affecting, all sectors of the economy, the pandemic had a disproportionate effect on the service sector of the economy as social distancing and state mandates closed many restaurants, beauty parlors, and other businesses that required face-to-face contact and were deemed “non-essential.” Unfortunately, the jobs in this sector of the economy are held primarily by women who lost their jobs due to closures. The government did try to mitigate these effects by providing funds to businesses to pay their employees, however, many people still lost their jobs or were laid off. As this happened across the entire service sector, there were no other comparable jobs to be had even if people remained in the labor force to look for them. Hence, despite the fact that single females with children are the primary source of income for their children and have to provide for them, if the industry they work in no longer has jobs they too would be discouraged from working. The same sentiment would explain the decline in the probability that single women without children participated in the labor force. They do not have the same childcare burdens as single women with kids, yet, as seen in Table 3 and Figure 3, their labor force participation declined for most of the first year of the pandemic.

For single women with children, there is likely a combination of factors that affected their labor force participation decisions. As schools and outside childcare options closed, children remained at home to complete school “remotely.” Single women had to make decisions between staying at home to care for their children or look for work. In addition to the disproportionate effect that the pandemic had on the services industry, another factor for the decline in labor force participation is that prior to 2020 females were less likely to work jobs with remote options. Therefore, in order to care for their children and monitor schoolwork, single women would be more likely to have to give up working to take on the added carework. This explains why the difference between the pre-pandemic and pandemic probabilities that single men with kids will participate in the labor force are lower than the difference for single women with kids as demonstrated in Table 3 and Figure 1. As both demographics represent single parents, and likely a single income household, male-dominated industry jobs were less affected by the pandemic than services, and those jobs were more likely to offer remote options anyways. This provided single men with some alternative to leaving the labor force. Figure 1 suggests that this effect is larger during the school year as the change in the probability that single mothers participated in the labor force is not significantly different from the pre-pandemic probability during June and July, and the estimated difference is greater than the change for single fathers. This difference may also be due in part to the possibility that divorced mothers could have an alternate income in the form of alimony payments, however, this would not necessarily explain the changes in the summer months for single mothers.

The theory that single females with children are leaving the labor force to take care of their children is further supported by the trend that their probability of labor force participation are lower during the months that children are in school. As displayed in Table 3 and Figure 2, single females with children experienced a significant decline in the probability of labor force participation, at the 5% level, in April and May of 2020, and most schools throughout the United States made the decision to switch to online classes during March. Hence, for the remainder of the traditional school year, April and May, children would be at home requiring higher amounts of parental care, leading to a decreased probability of working for their caregivers. A similar trend is also exhibited during August 2020 through February 2021 for single females with children. This is in line with the second wave of coronavirus cases in the United States and when children typically return to school for the fall semester. As cases were rising in the United States, many schools again opted for remote learning during these months, which is when single females experienced the greatest decline in their probability of labor force participation: -2.28% in January. Thus, supporting the theory that the probability that single mothers participated in the labor force is negatively correlated with remote schooling.

While most single parents are the main provider for their children and cannot share all the necessary carework with others, especially during the pandemic, married females have a partner that could share the burden of childcare. However, Figure 4 illustrates that married females with children experienced larger differences in labor force participation than married males with children for most of the pandemic. The months where there was no significant difference between the pre-pandemic probability that married mothers engaged in the labor force and the probability during the pandemic also correlate with when summer breaks typically begin and when states started reopening after the first wave COVID cases: June through August. Figure 2 highlights that similarly to single females with children, however, during the typical school periods, April to May and September through February, married female labor force participation was significantly lower during the pandemic than the year prior. This is likely because they were having to take on extra carework when their children were in school remotely due to school closures.

It is important to note that the difference in the changes in probability of labor force participation between married fathers and married mothers is not significantly different during April and May, and the data for married mothers is not significant for June through August. As discussed above, during April and May, all the demographic groups except for single males with children experienced a significantly lower probability of labor force participation than prior to the pandemic. Yet, the probability that married mothers participated in the labor force declined again in September and the change remained significantly lower than pre-pandemic numbers for the rest of the first year of the pandemic. Their change in probability also remained significantly lower than that for married fathers for the remainder of the year, suggesting that, unlike the initial pandemic shock, there is a secondary factor that affected mothers but not fathers. Moreover, since the decline in the probability the labor force participation of mothers, both married and single, is correlated with when school started up remotely again in the fall, it suggests that mothers not participating in the labor force is related to their children attending class from home. Hence, it follows that the duty of care was likely on married women more than it was on married males during remote schooling.

The trends in the probability of married and single mothers participating in the labor force are particularly interesting outcomes because female labor force participation, especially for married females, is considered to be "counter-cyclical" (Albanesi and Kim, 2021). This is in part because service industry jobs are typically more immune to economic shocks, but also because married females are more likely to enter the labor force if they believe that their husband might lose his job or receive a pay cut (Albanesi and Kim, 2021). Yet, the data suggests that the opposite was true during the pandemic. Figure 3 emphasizes this point, as all female labor force participation had declined during April and May, as well as from September 2020 through January 2021, apart from married females without children in October when the difference was only statistically significant at the 10% level as shown in Table 3. For single females without children, especially, their probability of labor force participation was significantly lower than their pre-pandemic probability for all months during the pandemic except for March and August. Thus, highlighting the peculiarities of the pandemic's effect on the economy and the labor force as a whole, especially of the pandemic's effect on female labor force participation. The characteristics of pandemic's recession did not mimic those of other recessions.

While the service industry is primarily female dominated, it does not preclude all men, nor did every job that was lost during the pandemic belong to a female in the service industry. Therefore, some of the effect of the decrease in the probability of married and single males without kids participating in the labor force, as demonstrated in Figure 1 and Table 3, could still be because men without children felt discouraged. It also could simply be a fear of how virulent and deadly the first strain of COVID-19 was prior to vaccines. For both reasons, males without kids were less likely to participate in the labor force during the pandemic.

Overall, the differences in the probability of labor force participation were all under 2.5%, while most of these data points are statistically significant, this difference may not initially seem practically significant. However, a decline in the probability of labor force participation of 2% or even 1% can be millions of people who left the work force. This indicates immense potential losses of GDP, and setbacks to the entire economy. It is also important to note that this difference may not capture the entire effect of the decrease in participation as many people may have opted to remain "in the labor force" as "unemployed" due to the CARES act and the high unemployment benefits that the government distributed during the pandemic. However, as these benefits would impact the "unemployed" population and taking them away would not add more people to the labor force, rather the unemployed population may be more inclined to drop out of the labor force and those already not participating would not be more inclined to join. For the purposes of this study the data provided is sufficient to examine the impact that the pandemic had on labor force participation.

9 CONCLUSIONS

The coronavirus pandemic affected the entire economy. As shutdowns swept the United States, store fronts closed, schools went online, and many parents found themselves having to choose between working or watching over their children's remote learning. While every industry and sector were at least indirectly affected by the coronavirus pandemic, whether through office and shop closures or supply chain backlogs, not every sector was affected equally, nor was every demographic group.

The results of this paper's models suggest that in April and May of 2020, every demographic group apart from single males with children experienced a significant negative effect on their probability of labor force participation. During the first couple months of the pandemic, this affect was prevalent across the economy because of the sudden shock that the nationwide shutdowns created and the uncertainty about the virus and the economy that swept the nation. If these effects were only the result of uncertainty and fear of the virus, then as new information came to light about its spread and declining case rates, the effects would likely decrease, and labor force participation would begin to return to its pre-pandemic numbers. This is what began to happen in May of 2020 through August as businesses began to reopen in the summer of 2020. However, as the second wave of coronavirus hit the United States, only some demographics experienced particularly large declines in their probability of labor force participation again: married women with children and single women with children.

The second wave of the coronavirus pandemic meant that when schools reopened in the fall, August and September, many of them started classes remotely again. Therefore, as in April and May, school-age children were taking online classes in the fall from their own homes. This effectively meant that their parents needed to remain at home to oversee their children's education and hold them accountable to doing their schoolwork and going to class. If a parent's work offered remote capabilities, then, in theory, they could take on the extra carework while also working from home. Since males typically hold jobs that allow for remote work options, I would expect to see little variation in female labor force participation numbers if men, who can work remotely, take on greater carework during the pandemic (Landivar et al., 2020). As the model indicates, however, married females, and single females, with children experienced larger declines in their probabilities of labor force participation during the second round of remote schooling than married males with children. Thus, the model suggests that there is a gendered element to the impact that having children had on labor force participation during the pandemic.

The data for all female demographics suggests decreased labor force participation during the pandemic, but since the effect on females without children is typically significantly less negative than the effect on married females with children, the model suggests that having children has a separate effect during the pandemic than just the overall effect or a gendered effect. The gendered effect on the other female demographics likely arises, at least in part, from the fact that the service industry jobs, which are predominately held by females, was disproportionately affected by the pandemic. This explains why the female labor force participation probabilities do not follow the typical "counter cyclical" patterns as described by Albanesi and Kim (2021).

Ultimately, the coronavirus pandemic has caused far reaching disruptions in the United States economy that are atypical of "recessions" that the United States has experienced in the past. While every demographic group was negatively impacted by the pandemic, the data suggests that during the fall of 2020 females with children were at least 1% if not 1.5% less likely to participate in the labor force. This a large portion of the female work force that left because of the pandemic. According to the New York Times, Vice President Kamala Harris claims that 2.5 million females left the "work force" during the first year of the pandemic (as cited in Rodgers, 2021).

Gender inequalities in labor force participation existed prior to the pandemic, but during 2020, these inequalities worsened primarily because of disproportionately large burdens of childcare and carework created by school closures and the transition to remote learning. This time away from work could also mean that they will be passed over for promotions in favor of their male colleagues who now have one more year of experience. Moreover, large declines in labor force participation are partnered with potentially large declines in GDP, hence, inequalities like this create an inefficient workforce and an inefficient economy. Therefore, it is imperative that the United States government begin examining the gendered effects of the pandemic and target legislation to relieving the childcare and carework burdens shouldered by otherwise working mothers.

APPENDIX

TABLE 1: Variable Descriptions and Summary Statistics

VARIABLES	Mean	SD	Min	Max
Demographic Groups				
Prior to the Pandemic				
With Children				
Single Females	0.0328	0.178	0	1
Married Females	0.0871	0.282	0	1
Single Males	0.0126	0.112	0	1
Married Males	0.0845	0.278	0	1
Without Children				
Single Females	0.0794	0.27	0	1
Married Females	0.0764	0.266	0	1
Single Males	0.0934	0.291	0	1
Married Males	0.0664	0.249	0	1
During the Pandemic				
With Children				
Single Females	0.0278	0.164	0	1
Married Females	0.0768	0.266	0	1
Single Males	0.0111	0.105	0	1
Married Males	0.0739	0.262	0	1
Without Children				
Single Females	0.0684	0.253	0	1
Married Females	0.0686	0.253	0	1
Single Males	0.0816	0.274	0	1
Married Males	0.0593	0.236	0	1
Age	42.49	10.42	25	60
Age Squared	1,914	893.8	625	3,600
Highest Level of Education				
No College	0.329	0.47	0	1
Some College	0.152	0.359	0	1
Associates	0.114	0.318	0	1
Bachelors	0.258	0.437	0	1
Masters	0.111	0.314	0	1
Professional	0.016	0.125	0	1

TABLE 1: Variable Descriptions and Summary Statistics (continued)

VARIABLES	Mean	SD	Min	Max
Highest Level of Education (continued)				
Doctorate	0.0215	0.145	0	1
Race				
White	0.801	0.399	0	1
Hispanic	0.15	0.357	0	1
Black	0.1	0.3	0	1
Indigenous or Native Alaskan	0.0126	0.112	0	1
Asian	0.0652	0.247	0	1
Hawaiian or Pacific Islander	0.00489	0.0698	0	1
Multiple Races	0.0163	0.127	0	1
Total Observations: N = 1,151,253				

Table 2: Probit Model Marginal Effects Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Demographic Groups												
During the Pandemic												
With Children												
Single Female	0.0721***	0.0585***	0.0629***	0.0673***	0.0774***	0.0692***	0.0578***	0.0548***	0.0552***	0.0533***	0.0543***	0.0553***
	(0.00356)	(0.00475)	(0.00455)	(0.00445)	(0.00410)	(0.00412)	(0.00424)	(0.00421)	(0.00424)	(0.00435)	(0.00439)	(0.00436)
Married Female	-0.00184	-0.0137***	-0.00980**	-0.00340	0.00565	-0.00466	-0.0151***	-0.0199***	-0.0213***	-0.0172***	-0.0106**	-0.0141***
	(0.00434)	(0.00487)	(0.00480)	(0.00477)	(0.00462)	(0.00466)	(0.00476)	(0.00477)	(0.00485)	(0.00481)	(0.00469)	(0.00475)
Single Male	0.106***	0.105***	0.107***	0.113***	0.117***	0.110***	0.102***	0.103***	0.104***	0.104***	0.107***	0.109***
	(0.00258)	(0.00381)	(0.00342)	(0.00304)	(0.00288)	(0.00304)	(0.00334)	(0.00302)	(0.00294)	(0.00302)	(0.00295)	(0.00277)
Married Male	0.127***	0.131***	0.133***	0.136***	0.138***	0.132***	0.130***	0.127***	0.127***	0.126***	0.130***	0.130***
	(0.00155)	(0.00183)	(0.00171)	(0.00167)	(0.00170)	(0.00168)	(0.00168)	(0.00166)	(0.00167)	(0.00170)	(0.00169)	(0.00165)
Without Children												
Single Female	0.0886***	0.0839***	0.0800***	0.0819***	0.0847***	0.0851***	0.0775***	0.0782***	0.0732***	0.0766***	0.0806***	0.0812***
	(0.00240)	(0.00296)	(0.00300)	(0.00300)	(0.00300)	(0.00280)	(0.00290)	(0.00281)	(0.00296)	(0.00288)	(0.00284)	(0.00280)
Married Female	0.0533***	0.0465***	0.0456***	0.0541***	0.0536***	0.0512***	0.0428***	0.0402***	0.0427***	0.0466***	0.0439***	0.0490***
	(0.00335)	(0.00391)	(0.00387)	(0.00372)	(0.00381)	(0.00369)	(0.00379)	(0.00378)	(0.00375)	(0.00369)	(0.00379)	(0.00365)
Single Male	0.101***	0.0960***	0.0964***	0.103***	0.106***	0.102***	0.0985***	0.0960***	0.0888***	0.0914***	0.0986***	0.0962***
	(0.00207)	(0.00259)	(0.00251)	(0.00240)	(0.00239)	(0.00232)	(0.00235)	(0.00233)	(0.00251)	(0.00245)	(0.00236)	(0.00238)
Married Male	0.112***	0.115***	0.111***	0.112***	0.112***	0.110***	0.112***	0.109***	0.107***	0.106***	0.109***	0.109***
	(0.00178)	(0.00216)	(0.00219)	(0.00221)	(0.00230)	(0.00217)	(0.00204)	(0.00202)	(0.00210)	(0.00211)	(0.00213)	(0.00209)

Table 2: Probit Model Marginal Effects Results continued

VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Demographic Groups												
Prior to the Pandemic												
With Children												
Single Female	0.0684***	0.0796***	0.0779***	0.0765***	0.0789***	0.0805***	0.0744***	0.0710***	0.0710***	0.0724***	0.0771***	0.0721***
	(0.00348)	(0.00360)	(0.00356)	(0.00360)	(0.00364)	(0.00337)	(0.00357)	(0.00360)	(0.00363)	(0.00357)	(0.00350)	(0.00365)
Single Male	0.111***	0.122***	0.121***	0.121***	0.123***	0.116***	0.113***	0.113***	0.112***	0.109***	0.113***	0.107***
	(0.00206)	(0.00224)	(0.00213)	(0.00218)	(0.00219)	(0.00237)	(0.00250)	(0.00229)	(0.00239)	(0.00254)	(0.00247)	(0.00285)
Married Male	0.132***	0.144***	0.143***	0.144***	0.146***	0.142***	0.138***	0.134***	0.135***	0.134***	0.136***	0.134***
	(0.00151)	(0.00164)	(0.00162)	(0.00163)	(0.00164)	(0.00158)	(0.00156)	(0.00154)	(0.00155)	(0.00157)	(0.00160)	(0.00161)
Without Children												
Single Female	0.0854***	0.0933***	0.0929***	0.0937***	0.0966***	0.0909***	0.0891***	0.0854***	0.0847***	0.0899***	0.0921***	0.0933***
	(0.00245)	(0.00266)	(0.00261)	(0.00261)	(0.00263)	(0.00259)	(0.00259)	(0.00261)	(0.00265)	(0.00252)	(0.00254)	(0.00248)
Married Female	0.0567***	0.0617***	0.0593***	0.0567***	0.0585***	0.0553***	0.0511***	0.0474***	0.0537***	0.0539***	0.0572***	0.0536***
	(0.00319)	(0.00346)	(0.00345)	(0.00351)	(0.00356)	(0.00348)	(0.00356)	(0.00358)	(0.00345)	(0.00343)	(0.00343)	(0.00349)
Single Male	0.107***	0.117***	0.115***	0.116***	0.117***	0.112***	0.106***	0.100***	0.101***	0.104***	0.107***	0.107***
	(0.00196)	(0.00214)	(0.00213)	(0.00214)	(0.00219)	(0.00213)	(0.00220)	(0.00224)	(0.00223)	(0.00218)	(0.00218)	(0.00216)
Married Male	0.114***	0.123***	0.119***	0.119***	0.123***	0.119***	0.116***	0.112***	0.114***	0.115***	0.117***	0.117***
	(0.00175)	(0.00195)	(0.00198)	(0.00201)	(0.00199)	(0.00192)	(0.00193)	(0.00195)	(0.00192)	(0.00188)	(0.00191)	(0.00188)
Age	0.0211***	0.0232***	0.0209***	0.0217***	0.0206***	0.0200***	0.0199***	0.0185***	0.0191***	0.0193***	0.0189***	0.0189***
	(0.000966)	(0.00102)	(0.00102)	(0.00103)	(0.00104)	(0.00101)	(0.000979)	(0.000961)	(0.000967)	(0.000977)	(0.000988)	(0.000981)
Age Squared	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0003***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***	-0.0002***
	(1.13e-05)	(1.19e-05)	(1.19e-05)	(1.21e-05)	(1.22e-05)	(1.18e-05)	(1.15e-05)	(1.13e-05)	(1.13e-05)	(1.14e-05)	(1.16e-05)	(1.15e-05)

Table 2: Probit Model Marginal Effects Results continued

VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Some College	0.0286***	0.0301***	0.0266***	0.0316***	0.0255***	0.0234***	0.0296***	0.0306***	0.0284***	0.0277***	0.0288***	0.0241***
	(0.00273)	(0.00291)	(0.00294)	(0.00293)	(0.00306)	(0.00297)	(0.00280)	(0.00271)	(0.00275)	(0.00280)	(0.00281)	(0.00284)
Associate's Degree	0.0561***	0.0602***	0.0597***	0.0596***	0.0641***	0.0614***	0.0607***	0.0600***	0.0532***	0.0508***	0.0562***	0.0591***
	(0.00263)	(0.00281)	(0.00280)	(0.00285)	(0.00286)	(0.00277)	(0.00267)	(0.00260)	(0.00271)	(0.00277)	(0.00273)	(0.00267)
Bachelor's Degree	0.0660***	0.0693***	0.0683***	0.0659***	0.0619***	0.0607***	0.0647***	0.0657***	0.0665***	0.0644***	0.0687***	0.0718***
	(0.00228)	(0.00243)	(0.00243)	(0.00247)	(0.00254)	(0.00244)	(0.00233)	(0.00228)	(0.00229)	(0.00234)	(0.00233)	(0.00231)
Master's Degree	0.0819***	0.0887***	0.0907***	0.0907***	0.0835***	0.0802***	0.0814***	0.0863***	0.0869***	0.0849***	0.0916***	0.0904***
	(0.00230)	(0.00247)	(0.00240)	(0.00244)	(0.00262)	(0.00252)	(0.00241)	(0.00227)	(0.00228)	(0.00234)	(0.00228)	(0.00227)
Professional	0.0850***	0.0969***	0.0934***	0.0874***	0.0842***	0.0809***	0.0853***	0.0862***	0.0851***	0.0821***	0.0929***	0.0891***
	(0.00430)	(0.00437)	(0.00439)	(0.00477)	(0.00523)	(0.00507)	(0.00456)	(0.00428)	(0.00430)	(0.00448)	(0.00410)	(0.00431)
Doctorate	0.0931***	0.101***	0.100***	0.0933***	0.0922***	0.0979***	0.0974***	0.0962***	0.0948***	0.0869***	0.0892***	0.0966***
	(0.00335)	(0.00371)	(0.00357)	(0.00396)	(0.00413)	(0.00353)	(0.00343)	(0.00331)	(0.00340)	(0.00382)	(0.00384)	(0.00335)
Hispanic	-0.0222***	-0.0307***	-0.0316***	-0.0265***	-0.0288***	-0.0290***	-0.0302***	-0.0260***	-0.0245***	-0.0265***	-0.0229***	-0.0238***
	(0.00320)	(0.00342)	(0.00345)	(0.00345)	(0.00351)	(0.00340)	(0.00327)	(0.00316)	(0.00319)	(0.00326)	(0.00321)	(0.00318)
Black	-0.0136***	-0.0174***	-0.0139***	-0.0151***	-0.0138***	-0.0206***	-0.0214***	-0.0212***	-0.0189***	-0.0204***	-0.0250***	-0.0194***
	(0.00376)	(0.00397)	(0.00398)	(0.00403)	(0.00405)	(0.00396)	(0.00380)	(0.00374)	(0.00375)	(0.00382)	(0.00389)	(0.00383)
Indigenous or Native Alaskan	-0.0772***	-0.0618***	-0.0616***	-0.0387***	-0.0625***	-0.0654***	-0.0644***	-0.0756***	-0.0571***	-0.0600***	-0.0654***	-0.0616***
	(0.0114)	(0.0113)	(0.0116)	(0.0113)	(0.0122)	(0.0116)	(0.0109)	(0.0110)	(0.0106)	(0.0112)	(0.0112)	(0.0108)
Asian	-0.0709***	-0.0854***	-0.0833***	-0.0685***	-0.0596***	-0.0579***	-0.0684***	-0.0614***	-0.0662***	-0.0772***	-0.0745***	-0.0698***
	(0.00538)	(0.00568)	(0.00573)	(0.00560)	(0.00558)	(0.00543)	(0.00536)	(0.00525)	(0.00527)	(0.00549)	(0.00547)	(0.00537)

Table 2: Probit Model Marginal Effects Results continued

VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
Hawaiian or Pacific Islander	-0.0260	-0.00600	-0.0320*	-0.0410**	-0.0429**	-0.0645***	-0.0927***	-0.0613***	-0.0330*	-0.0151	-0.000137	0.000678
	(0.0165)	(0.0158)	(0.0170)	(0.0181)	(0.0179)	(0.0180)	(0.0190)	(0.0173)	(0.0169)	(0.0169)	(0.0153)	(0.0149)
Multi-Racial	-0.0111	-0.0162*	-0.0154	-0.0243**	-0.00342	-0.000498	0.00877	0.0145*	0.00277	0.00654	-0.0143	-0.00510
	(0.00873)	(0.00926)	(0.00949)	(0.00962)	(0.00886)	(0.00849)	(0.00789)	(0.00787)	(0.00842)	(0.00831)	(0.00890)	(0.00871)
Observations	96,257	95,459	92,826	90,803	91,091	94,081	98,593	100,188	99,077	96,987	97,905	97,986

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

Table 4: This table reports the marginal effects results obtained from the Probit model for each month (March-February) and the associated standard errors. Probit coefficients available upon request.

Table 3: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic)

VARIABLES	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb
With Children												
Single Fem.	0.0037	-0.0211**	-0.015**	-0.0092*	-0.0015	-0.0113**	-0.0166**	-0.0162**	-0.0158**	-0.0191**	-0.0228**	-0.0168**
Married Fem.	-0.00184	-0.0137**	-0.0098**	-0.0034	0.00565	-0.00466	-0.0151**	-0.0199**	-0.0213**	-0.0172**	-0.0106**	-0.0141**
Single Male	-0.005**	-0.017	-0.014	-0.008**	-0.006**	-0.006**	-0.011	-0.01**	-0.008**	-0.005**	-0.006**	0.002**
Married Male	-0.005*	-0.013**	-0.01**	-0.008*	-0.008**	-0.01**	-0.008**	-0.007**	-0.008**	-0.008**	-0.006**	-0.004
Without Children												
Single Fem.	0.0032	-0.0094**	-0.0129**	-0.0118**	-0.0119**	-0.0058*	-0.0116**	-0.0072**	-0.0115**	-0.0133**	-0.0115**	-0.0121**
Married Fem.	-0.0034	-0.0152**	-0.0137**	-0.0026	-0.0049	-0.0041	-0.0083**	-0.0072*	-0.011**	-0.0073**	-0.0133**	-0.0046
Single Male	-0.006**	-0.021**	-0.0186**	-0.013**	-0.011**	-0.01**	-0.0075**	-0.004*	-0.0122**	-0.0126**	-0.0084**	-0.0108**
Married Male	-0.002	-0.008**	-0.008**	-0.007**	-0.011**	-0.009**	-0.004*	-0.003	-0.007**	-0.009**	-0.008**	-0.008**

* $p<0.1$, ** $p<0.05$

Table 5: This table displays the difference between the pandemic probabilities and pre-pandemic probabilities of labor force participation and the results of the chi-squared significance tests to determine if the pandemic data is significantly different. Note that negative values indicate a decreased probability of labor force participation during the pandemic than prior to the pandemic for that demographic group.

Figure 1: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic): All Demographics

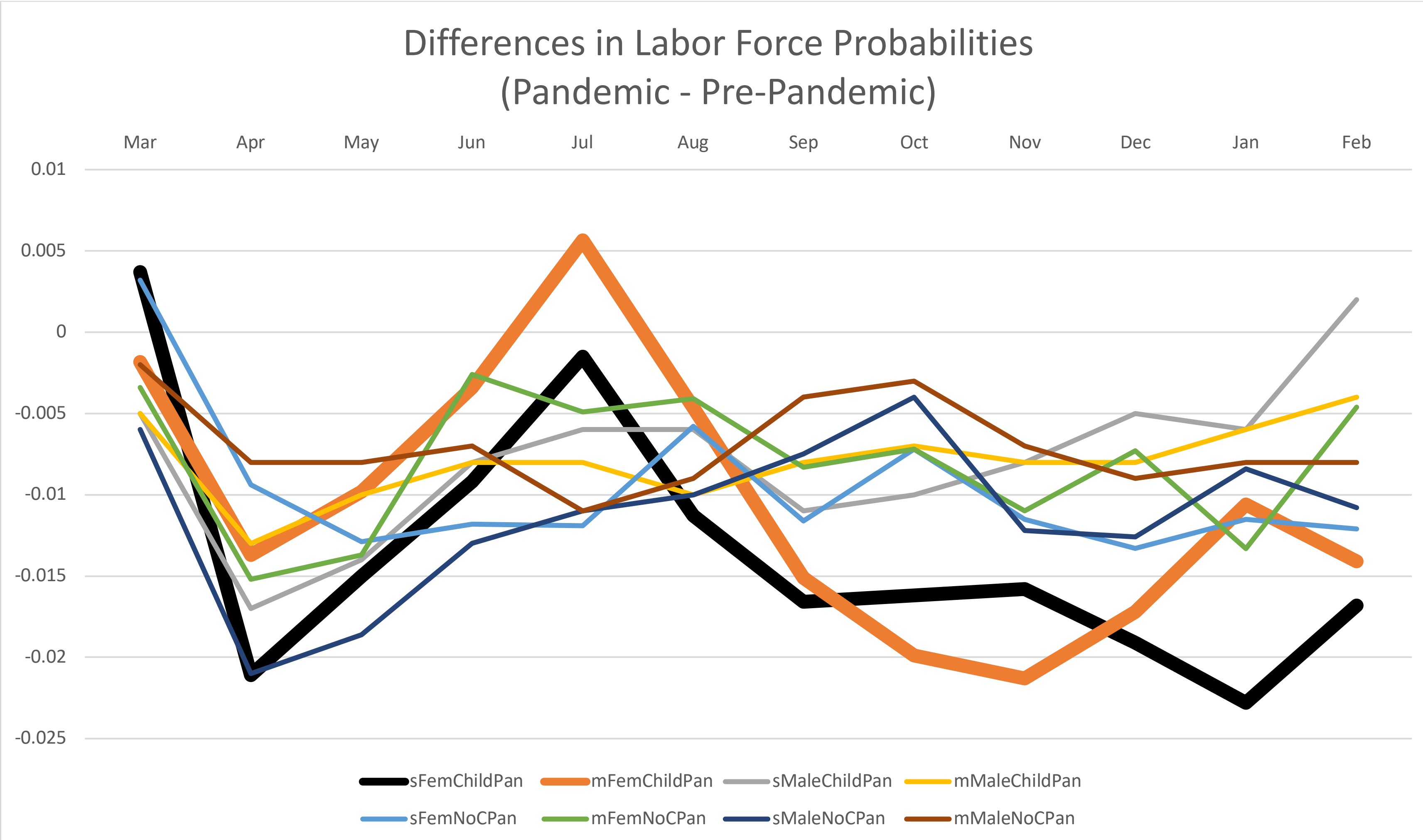

Figure 1: A visual representation of the data presented in Table 3. This graph pictures the changes in the estimated mean probability of labor force participation for each of the eight demographic groups.

Figure 2: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic): Single Females with Children Only, Compared with Married Females with Children

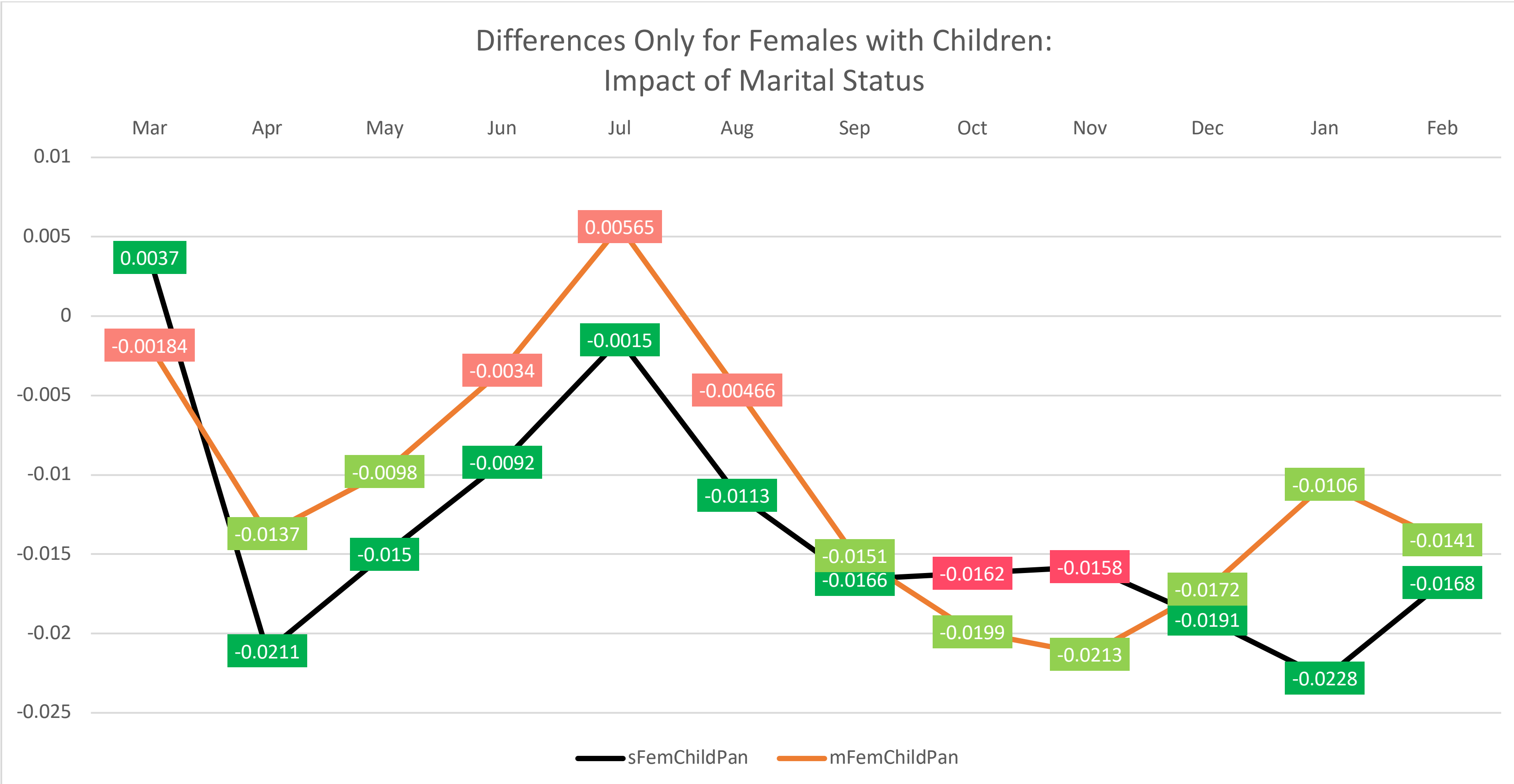

Figure 2: this is a subgraph of Figure 1 depicting only the data for single and married females with children. The light green data labels for married females with children indicate the months where their labor change in probability of labor force participation during the pandemic was statistically significant compared to before the pandemic. The red data labels on the same line indicate the months where the change was not statistically significant. The green data labels on the single female line indicate the months where the difference in labor force participation for single females was significantly different from the difference in probability for married females. The red data labels on the same line indicate the months where this was not statistically significant.

Figure 3: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic): Females Only, Compared with Married Females with Children

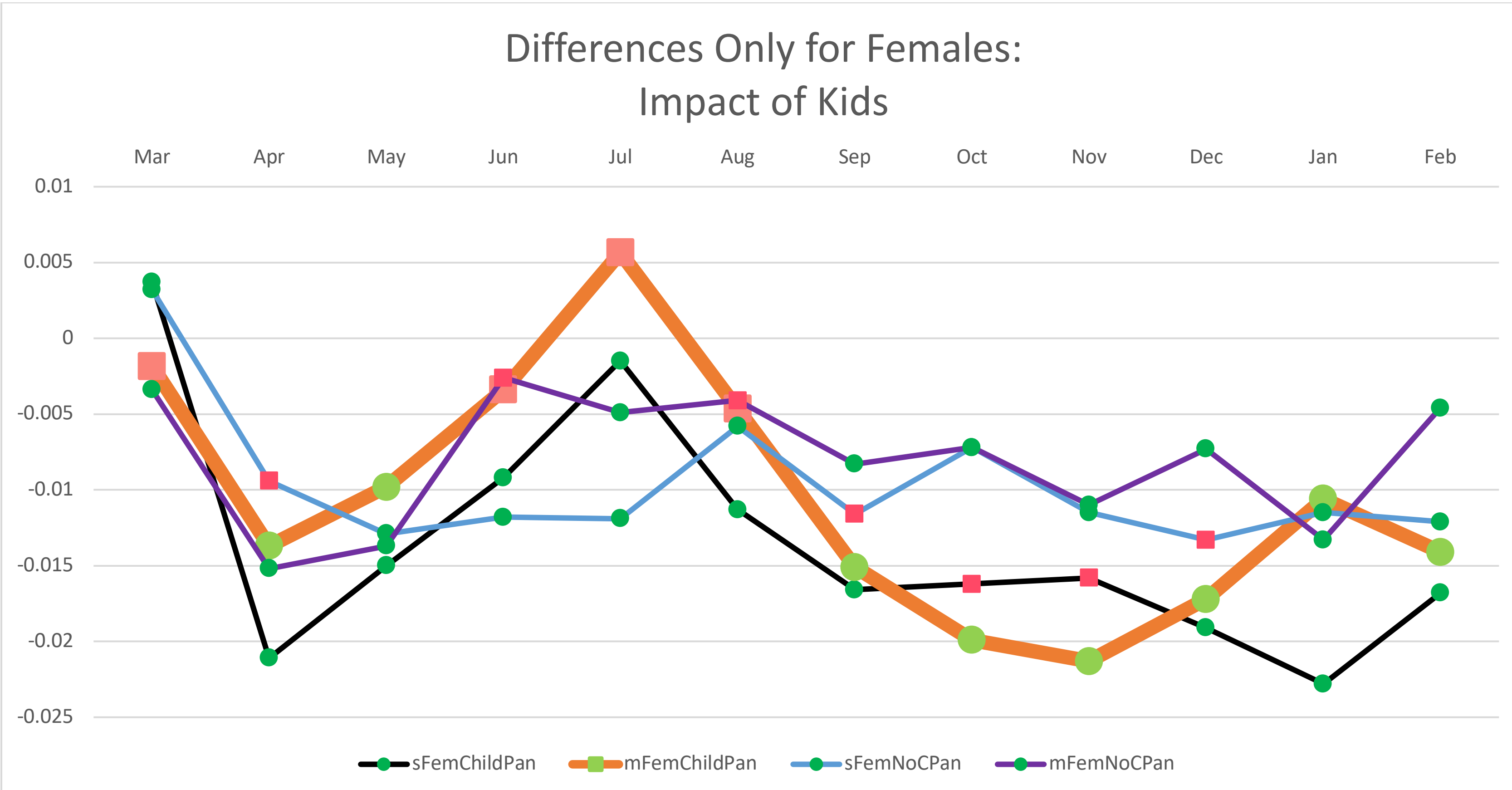

Figure 3: A subgraph of Figure 1 containing only the female demographic groups. As in Figure 2, the green circles on the line for married females with children indicate the months where the change in probability of labor force participation is statistically significant and the red squares indicate the months where they were not. The green circles on the other lines represent when the difference between the change in probability for the given demographic and the change in probability for married females with children is statistically significant, and the red squares are when this difference is not significantly different from zero.

Figure 4: Differences in Labor Force Probabilities (Pandemic - Pre-Pandemic): Married Females with Children and Married Males with Children Only

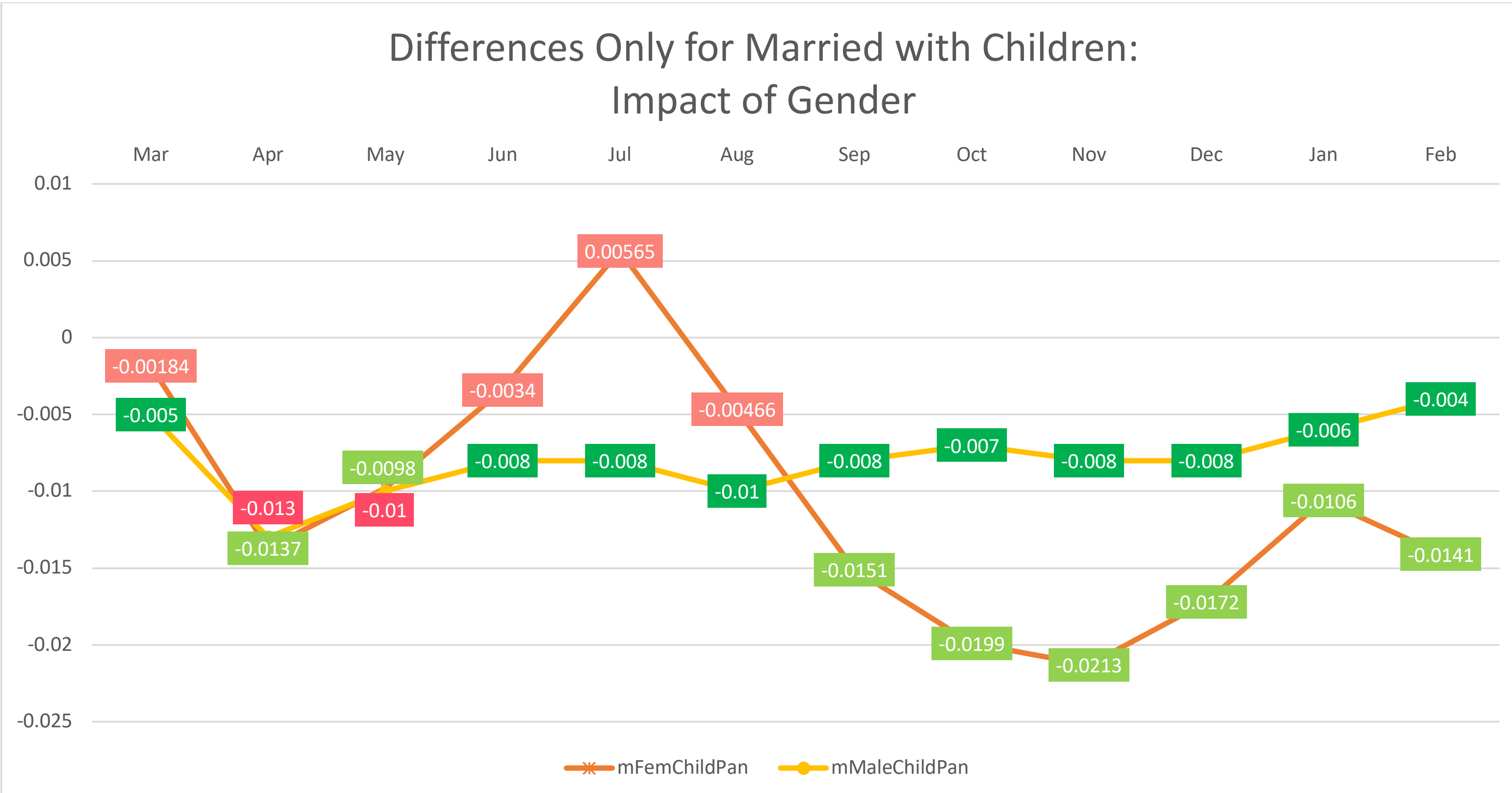

Figure 5: This final subgraph of Figure 1 displays only the data for married females with children and married males with children. As in Figures 2, the green data labels on the line for married females with children indicate the months where the change in probability of labor force participation is statistically significant and the red data labels indicate the months where they were not. The green data labels on the married males line represent when the difference between the change in probability for married males with children and the change in probability for married females with children are statistically significant, and the red data labels are when this difference is not significantly different from zero.

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