Fall 10-25-2022

The Impact of COVID-19 on Employment Characteristics

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by

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Submitted in partial fulfillment
of the requirements for the degree of
Master of Arts in Economics, Hunter College
The City University of New York

2021

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Abstract:

The following study examines ways in which the COVID-19 pandemic has disrupted the labor market in the United States. The disease resulting from the novel Coronavirus (hereafter, referred to as COVID-19) precipitated the largest global economic slowdown since the Great Depression. The United States has experienced unprecedentedly high levels of jobless claims, the lowest labor force participation rate in decades, declining wage growth, and unparalleled reports of job cuts (Trading Economics 2020). My findings present disproportionately negative effects of COVID-19 on employment, labor force participation, worker absence, and weekly working hours for the female population in my sample, as well as for veterans, disabled persons, and racial minorities.

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1 Introduction

In December 2019, the first case of COVID-19 was reported by officials in the city of Wuhan, China. Many of the earliest known cases were linked to the Huanan Seafood Market in Wuhan, but over the course of the proceeding weeks, the virus spread rapidly throughout Wuhan city and all of greater China. Not long after, this highly-infectious disease began circulating throughout the world. The first positive diagnosis of COVID-19 in the United States occurred on January 20, 2020 in the state of Washington. The stock market crashed and the U.S. recession officially began in February, and on March 11, 2020 the World Health Organization (WHO) declared the COVID-19 outbreak a global pandemic (Cucinotta et al. 2020). The recession had a huge impact on the labor market. Many non-essential workers were laid off while others began working from home, a phenomenon that has forever changed the way business is done around the country. This recession impacted industries that had previously been less effected during previous downturns. Large sectors of the economy, such as transportation, hospitality, and tourism, completely shut down their normal operations (Montenovo et al. 2020). The majority of these sectors employed females and people of color, indicating the possibility of disproportionate losses to employment rates among these demographics. At the same time, many individuals found themselves working from home and were faced with needing to adapt to balancing their domestic responsibilities while maintaining a normal work-day. Following suit, schools and daycare centers began to shut down as well. Parents of young children now had to balance their professional and domestic responsibilities simultaneously, and gender-specific reactions differed. With the absence of available child-care, many parents were compelled to stay at home and provide their own child care, reducing the market's labor supply of available workers (Dingel et al. 2020). This raised concerns over the gender-specific reactions to the labor market supply and how these impacts may continue to effect the female demographic for years to come.

My contribution to the study of the recessionary period following the COVID-19 outbreak includes the gender-specific impact on an individual's transitions between states of work, as well as how the initial effects of COVID-19 on worker transitions have changed over the months between April and October 2020 among certain demographics. These transitions include status of employment, changes to labor force participation, worker absence, and transitions between full-time and part-time work. I will go on to further define these terms in the sections pertaining to the regression analysis. I begin by analyzing how the likelihood of becoming unemployed varies for individuals in my sample depending on his or her characteristics after COVID-19's disruption to the labor market. I do the same analysis for the likelihood that an individual will remain in the labor force, become absent from his or her job, or transition to working part-time after having previously been a full-time worker. The results of this analysis differ among gender, demographic, and point in time. My findings display the ways in which females and people of color experienced disproportionately negative impacts to their labor market states, that do not appear to rebound in the few months following the recessionary fallout of April 2020.

After the initial impact of COVID-19 on the economy, numerous pieces of literature exploring disparities among worker transitions were published. Carli (2020) evaluates the ways in which COVID-19 has exacerbated the gender gap in employment and advancement, and Stevenson (2020) and Alon et al. (2020) similarly warn readers on the potential for persistent or even permanent scarring. My analysis further studies this concern by comparing the true gendered-specific reactions during the months of recovery following the COVID-19 outbreak. Clifford et al. (2020) evaluate the pre-pandemic wage gap between men and women and postulates that in two-earnings households, it becomes more economical for the lower earner to leave the labor force when a domestic caretaker is needed, a category females most frequently fall in to. While this is an important reaction to keep in mind, my analysis fails to find a material effect of having a child in need of full-time care to be a variable in a female's decision to leave the labor force. Montenovo et al. (2020) evaluate employment disparities across various racial, gender, and age groups compared to the employment effects that they experienced during the 2001 and 2008 recessions, in order to highlight the nature of the current recession and its focal targets. This helps us target the unique reactions of COVID-19 on this recessionary period and to understand why many females and people of color were impacted in ways they were not in previous recessions. Cowan (2020) examines how gender, ethnicity, and education disproportionately influence the direction in which individuals transfer between labor-market states (i.e. employed, unemployed, left the labor force, etc.) and hours worked during recessionary periods. Using weekly administered payroll data, Cajner et al. (2020) concludes that employment loss due to COVID-19 have been concentrated among lower-wage workers, and that businesses across the board have cut nominal wages for millions of workers regardless of gender or race. Montenovo et al. (2020) states that workers who are absent from their jobs are important factors in determining the early labor market effects of COVID-19, due to many employers furloughing their employees or employees requesting leave to care for a sick household member; these workers are categorized as absent, not unemployed. Similarly Coibion et al. (2020) estimates that COVID-19 related unemployment is significantly higher than what has been recorded due to prevalent misclassifications of the Current Population Survey (CPS) data regarding job losses, as a result of the influx of absent workers and the nature of many employment dismissals at the time, such as furlough. These classifications are likewise important within my study-sample, as my calculations reveal a greater percentage of individuals in my sample becoming absent from work or leaving the labor force in April 2020 than becoming unemployed. 9.54% of my sample report being unemployed in April, while 11.11% report either becoming absent or having left the labor force (5.23% absent, 5.88% left the labor force). Each state acted independently of the federal government in the months following, declaring differing levels of stringencies for stay-at-home orders. However, by using data from cellphones, Gupta et al. (2020) found that mobility substantially fell in all states, regardless of how severe their social-distancing mandates were. Similarly, Lozano-Rojas et al. (2020) found that the historically unprecedented increase in unemployment claims throughout March 2020 occurred across all states regardless of local epidemiological conditions. This suggests that the labor market slowdown was due primarily to the nation-wide response; indicating that state-level policies had a comparatively modest effect, rendering moot the need to control for state-specific policies in further analyses.

While no one was spared from COVID-19's effects on everyday life, certain demographics experienced disproportionate impacts to their labor market status, which continue to reverberate months after the onset of the pandemic. Throughout Section 4, I utilize micro data from national population surveys to further examine the extent of these labor adjustments and how they have specifically impacted females, people of color, veterans, and disabled individuals more than their respective counterparts. Section 5 concludes the analysis and provides insight into further research that may be needed to better understand these inequalities.

2 Data

I use data collected monthly from the Current Population Survey for the months of January, April, and October 2020. The CPS is sponsored jointly by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics. These monthly surveys are conducted using a combination of telephone and in-person interviews to gather data on reported employment characteristics and relevant categorical information for individuals and their households. The survey uses a reference period including the 12th day of the month, and measures the demographic characteristics and employment statuses of all working-age individuals in a responding household. The CPS is structured to record answers from the same individuals for four consecutive months, break for eight consecutive months, then record data from these same respondents over the subsequent four months of their twelve-month cycle. For the purposes of my study, I only analyze the responses from individuals whose answers were recorded in both January and April, or both January and October. By doing so, I am able to study the precise employment transitions of workers in my sample before and after COVID-19 effects the labor market. The nation-wide Unemployment Rate peaked in April at 14.7% of the labor force, a precipitous increase from January's 3.6% and the highest the country has seen since the Great Depression and its recovery period. This factor indicates that April is a good benchmark to measure the peak effects of COVID-19 on employment outcomes, and October, being the most recent CPS data available, becomes the point of reference for any economic amelioration that takes place between April and October. I utilize data from 15,713 persons, 10,806 of whom the CPS recorded in both January and April, and 4,907 individuals the CPS recorded in both January and October. I limit the responses I use to include men and women of working-age, between the ages of 18 and 55, and I ignore responses from those who report being unemployed since before COVID-19 plagued the country, as these individuals would skew the true impact of the recession on unemployment rates.

The relevant independent variables in my sample include binary variables indicating gender, race, marital status, veteran status, if the individual was born outside of the United States, and whether an individual has any recorded personal disability including, but not limited to, hearing, vision, mobility, or memory loss. Two more indicator variables are included relating to the status of one's children: having a child in school and having a child young enough to need child care. I determine that a child is in school if he or she is between the ages that are legally mandated to attend school in the state they reside in. This covers the minimum likelihood of having a child in school, but may not be reflective of the true classifications. New York, for example, requires children between the ages of 6 and 16 to attend elementary and high school. However, there may exist individuals in my sample who have children older than 16 or younger than 6 that are in school, that unfortunately would not be accounted for. Having a child young enough to need child care covers all children 14 years-old and younger. I include these two variables to reflect any influence child care needs have on employment transitions after schools and daycares close. I also include variables such as age, highest educational achievement, family income, and the industry one is currently, or was most recently, employed in.

There are 31,426 observations in my dataset across the relevant 3 months, two observations for each of the 15,713 recorded individuals. 50.57% of the respondents are female and 79.23% classify themselves as white. 55.88% of my sample is between the ages of 30 and 49 years-old, and the majority of respondents reside in California, Texas, Florida, and New York. 65.97% of the sample reports having at least some college education, and the greatest proportion of the sample (11.22%) works in the Health Care and Social Assistance industry. For the purposes of my study I broaden the classification of a couple being married to include unmarried cohabitating partners, as both marriage and cohabitation serve the same purposes of providing two incomes and two individuals who can share domestic labor responsibilities; 59.24% of my sample falls under this definition of marriage. More summary statistics can be found on Table 1.

2.1 Summary of Relevant Variables

The four relevant dependent variables in my sample are unemployment, labor force participation, worker absence, and part-time work. An individual is defined as unemployed if he or she has been fired from his or her job and remains in labor force searching for work. An individual is classified as being a labor force participant if he or she is employed, unemployed, or absent from work. An individual is absent if he or she has not been fired from his or her job but is not present at work. An individual is a full-time worker if he or she works 35 hours or more each week, anything less than 35 working hours is considered part-time work.

The following paragraphs introduce the variables and their relation to the sample population by stating the means and the proportions of the population that fall into these categories for all relevant months. My first dependent variable, unemployed, is a binary variable which is equal to one if the respondent is unemployed and zero if he or she reports being either employed or not in the labor force. The mean for unemployed differs for each month, 2.57% of the entire population sample (not just those in the labor force, which is used as a benchmark in calculating the unemployment rate) is unemployed in January, 9.54% in April, and 3.63% in October. Younger and less educated individuals experience relatively higher levels of unemployment in April that persists through October. The Hispanic demographic in my sample also shows higher proportions of unemployment in April than any other racial demographic, by October, however, the African-American population in my sample is the racial group with the highest reported proportion of unemployed individuals. More detailed statistics on the proportions of the population that are unemployed for each month can be found on Table 2.

My second dependent variable is also a binary variable, labor force participation, equal to one if the respondent records being in the labor force, and zero if he or she is not in the labor force.

81.08% of the population records being in the labor force in January, 77.25% in April, and 79.17% in October. The subgroups that experience the lowest proportions of labor force participation in all relevant months are females, those under 25-years-old or over 50-years-old, individuals with less than a college degree, and individuals with a reported disability. Married persons become less involved in the labor force in April and October, and a smaller proportion of mothers are in the labor force than fathers throughout all relevant months. A more detailed account of labor force participation within the sample can be found on Table 3.

My third dependent variable, absence from work, takes on the value of one if an individual reports being absent from work, and zero if he or she is not absent from work, is unemployed, or is not in the labor force. A person can be absent for a number of reasons, such as familial obligations, medical problems, personal days, maternity leave, and many more. From the start of the pandemic, attending in-person work has presented issues for many workers, as countless lives were put at risk by going into work, and many had to stay at home to care for those who could no longer receive outside care, such as elderly family members or young children. This individual is still employed by his or her employer, he or she is just not currently present at his or her job. In January, 1.87% of the population sample reports being absent from their jobs, 5.23% in April, and 2.02% in October. In April, females experience higher proportions of absence from their jobs, however, by October, this effect reverses as there is a greater proportion of absent males than absent females in the sample. A larger proportion of older persons report being absent from work than younger persons in all relevant months. Asian individuals and foreign born persons in my sample also account for larger proportions of absence in April, which appears to subside by October. For the majority of the sub-samples, the initial increases to the proportions of the population that report being absent from work in April, have mostly decreased toward their January proportions by October. More details on absent workers can be found on Table 4.

My final binary dependent variable analyzes the transition from full-time work to part-time work. The binary variable, part-time work, is equal to one if an individual works less than 34 hours a week, and zero if he or she works more than 35 hours or no hours at all. Table 5 displays the average number of hours worked in a week for different groups in each month of my sample. Analyzing the average of weekly hours worked here, as opposed to the frequency of part-time workers, enables insight into which populations have averaged less hours after COVID-19, irrespective of whether the magnitude is large enough to alter a worker's full-time or part-time status. Female, Hispanic, African-American, older, and the less educated individuals in my sample experience the most reduced weekly hours in both April and October on average. Married, foreign born persons, and parents all experience significant losses in hours in April that have mostly been regained by October, though less-so for mothers than for fathers. Individuals who have not completed high school and those under twenty years-old are the only population samples to average more working-hours in October than in January. Disabled workers, on the other hand, are the only population-sample to work less hours in October than in April; while other demographics appear to regain a portion of lost hours between April and October, disabled workers on average continue to lose more.

The analysis of the means for each variable shows disproportionate effects on females, people of color, and disabled individuals in the sample. Further regression analysis will continue to show the true impacts COVID-19 had on the labor market changes experienced by these demographics.

3 Methods of Analysis

After previously reporting the proportions of the populations that appear to be among those most effected by COVID-19, I take my analysis a step further by utilizing more detailed regression analyses to determine the most impacted demographics. I utilize a linear regression model to determine the likelihood of an individual in the sample becoming unemployed, participating in the labor force, becoming absent from work, and transitioning from full-time to part-time work. Individual results vary based on gender, race and ethnicity, disability status, and more. The sum of each unique likelihood provides insight into the overall state of the labor force at this time and which demographics are disproportionately impacted.

4 Results

In this section, I provide detailed takeaways from the regression analyses performed. The unique impacts on unemployment, labor force participation, worker absence, and reduced working hours differ among gender and other demographics. There are a select few groups of individuals that are disproportionately worse off than their counterparts after COVID-19's initial impact on the labor market and the months of recovery that follow.

4.1 An Evaluation of Unemployment

My first regression evaluates the likelihood of an individual becoming unemployed after having previously been employed in January. I evaluate the likelihood in April and October respectively, first for the full population then for only the females in my sample. This regression evaluates how the likelihood of becoming unemployed after COVID-19 is effected by key variables, such as gender, if one has a child in school, if one needs child-care, marital status, race, veteran status, if one was born in a foreign country, and if one has a disability. The regression additionally controls for family income, age, educational achievement, state-specific effects, and industry-specific effects. Table 6 displays these results in marginal percentage point effects.

The female demographic alone experiences an increased likelihood of becoming unemployed in both April and October. While foreign born workers experience an initial increase to the likelihood of becoming unemployed relative to their U.S. born counterparts in April, these effects become insignificant by October. Disabled individuals and African-Americans conversely experience delayed reactions, with significant increases in their likelihood of becoming unemployed in October only.

The likelihood of becoming unemployed in April is 2.69 percentage points higher for females in my sample than their male counterparts; in October, the likelihood of becoming unemployed for females is 1.33 percentage points higher than their male counterparts. Females are continuing to experience an increased likelihood of becoming unemployed after the initial impact of COVID-19 and even throughout the months of recovery preceding October.

Disabled individuals and African-Americans experience delayed reactions to COVID-19, with significant increases in the likelihood of becoming unemployed relative to their respective counterparts in October only. After an initial decrease in likelihood in April, disabled females in my sample now conversely experience an increase of 5.64 percentage points in the likelihood of becoming unemployed in October relative to their non-disabled female counterparts. After insignificant effects in April, African-Americans in my sample experience a 2.19 percentage point increase in the likelihood of becoming unemployed in October relative to their counterparts of other races.

The presence of school-age or very young children has no statistically significant effect on the likelihood of an individual becoming unemployed. Nor does this effect differ for the female and male populations, illustrated in the comparison of the models for the full population and the female population only. I perform a statistical test of joint-significance for the two variables indicating that one has a school-age child and one has a young child in need of child-care to control for any correlation-bias among the variables; I find no statistical significance to report.

When the initial impacts of COVID-19 begin to level out for other population samples in October, African-Americans and disabled females instead endure delayed reactions to their respective likelihoods of becoming unemployed. The delayed effect on African-Americans and disabled females remains unexplained by industry, education, age, or state-specific effects due to higher case-counts or stronger restrictions. Similarly, the consistently higher likelihood of the female population in my sample becoming unemployed relative to their male counterparts remains unexplained by any of the aforementioned variables.

4.2 An Evaluation of Labor Force Participation

My second regression evaluates the likelihood of labor force participation after COVID-19, given labor force participation in January. Once again, I evaluate the likelihood in April and October respectively, first for the full population then for females only. This regression evaluates how the likelihood of being in the labor force post COVID-19-recession is effected by variables such as gender, if one has a child in school, if one needs child-care, marital status, race, veteran status, if one was born in a foreign country, and if one has a disability. The regression additionally controls for family income, age, educational achievement, state-specific effects, and industry-specific effects. Table 7 displays these results in marginal percentage point changes.

Females and disabled individuals experience a significant decrease in the likelihood of remaining in the labor force relative to their respective counterparts through both of our relevant months. Female foreign born workers and African-Americans experience initial decreases to the likelihood of labor force participation in April, which becomes insignificant by October. On the other hand, veterans, female African-Americans, and female Hispanic individuals experience delayed reactions to COVID-19's effect on their labor market participation, with significant negative effects to their likelihoods of participation in October only.

Females experience a 2.37 percentage point decrease in their likelihood of remaining in the labor force relative to their male counterparts in April, and an even larger decrease of 4.6 percentage points in October. Disabled individuals in April experience a 5.77 percentage point decrease of labor force participation, females with a disability experience an even larger decrease of 7.78 percentage points relative to their counterparts. By October, the decreases to the likelihood of labor force participation are even larger for disabled individuals at 7.79 percentage points for the demographic as a whole and 9.48 percentage points for females with a disability in particular. Females and disabled individuals continue to experience the effects of COVID-19's impact on their likelihoods of labor market participation throughout the months of recovery leading up to October, indicating that the delayed impact became more detrimental to their labor force participation months after the outbreak of the pandemic than it even was initially.

African-American individuals and foreign born females experience initial decreases to their likelihoods of labor force participation in April, by October these effects become insignificant. On the other hand, veterans, female African-Americans, and female Hispanic individuals experience delayed negative reactions to COVID-19's impact on their likelihoods of labor force participation. After a positive impact in April for veterans, and no statistical impact on female veterans, female African-Americans, nor female Hispanic individuals, these demographics all experience decreases in the likelihood of labor force participation in October. Notably, African-American females and Hispanic females appear to fare worse in October than the female population as a whole, with a 4.49 percentage point decrease in the likelihood of African-American females remaining in the labor force, and a 3.93 percentage point decrease in the likelihood of labor force participation for Hispanic females in my sample. Veterans experience a 4.74 percentage point decrease in their likelihood of labor force participation relative to their non-veteran counterparts, and female veterans in particular experience the largest percentage point decrease among all population samples, at 13 percentage points, relative to their non-veteran female counterparts.

The presence of children who are in school or who need to be cared for have no statistically significant effect on the likelihood of an individual's labor force participation, nor does this effect differ for the female and male populations. Once again, a statistical test of joint-significant for the two variables indicating that one has a school-age child and one has a young child in need of child-care, yields no statistical significance to report.

Females and disabled individuals in my sample consistently experience significant decreases in the likelihood of labor force participation after COVID-19 effects the labor market. African-American females, Hispanic females, and veteran individuals in my sample all experience delayed reactions to COVID-19 in October only. The large declines in the likelihood of labor force participation for these demographics remains unexplained by the controlled variables, as are the reasons for the delayed effects on particular groups.

4.3 An Evaluation of Worker Absence

My third regression evaluates the likelihood of an individual being absent from his or her job after COVID-19, given that he or she was not absent in January. As I previously mentioned, including the measure of absent workers is integral to understanding the full story of employment-characteristic changes resulting from COVID-19 because of the nature of the layoffs that occurred, as well as the need to cover any relevant CPS misclassifications of employment status. I similarly evaluate the likelihood in April and October respectively, first for the full population then for females only. This regression evaluates how the likelihood of being absent from work is effected by key variables, such as gender, if one has a child in school, if one needs child-care, marital status, race, veteran status, if one was born in a foreign country, and if one has a disability. The regression controls for family income, age, educational achievement, state-specific effects, and industry-specific effects. Table 8 displays these results in marginal percentage point changes.

The married female population alone experiences consistently greater impacts of COVID-19 on their likelihood becoming absent from work in both April and October. The female population as a whole and the Asian population in my sample experience initial increases to their likelihoods of worker absence in April that becomes insignificant by October. Married individuals, veterans, and disabled persons conversely experience delayed increases of COVID-19 on the likelihood of worker absence in October only.

Married females in April experience a 1.29 percentage point increase in the likelihood of becoming absence from work relative to their counterparts; by October, this increase is even greater at 2.97 percentage points higher than their single female counterparts. The female demographic as a whole, along with the Asian population in the sample, experience even larger increases to their likelihoods of worker absence relative to their counterparts in April, females the highest with 1.82 percentage points. By October, females and Asian individuals appear to have recovered from these initial effects, as they do not experience any statistically significant changes to their likelihood of becoming absent from work relative to their male counterparts and counterparts of other races.

By October, the delayed reactions of married individuals, veterans, and disabled individuals in my population sample become significant increases to the likelihood of worker absence. Among all the observed demographic samples in October, female veterans experience the largest increase to the likelihood of becoming absent from work, with a 5.8 percentage point increase relative to their non-veteran female counterparts. Interestingly enough, the married population as a whole, both men and women, experience an increased likelihood of becoming absent from work in October, at 2.97 percentage points higher than their single counterparts, after insignificant effects in April. This may be due to new domestic obligations at home arising, whether it be children or elderly parents, who may require one of these individuals to leave his or her position and become absent from work in order to care for them. Having two married individuals in a single household earning two separate incomes may lead to comfortability with future potential earnings and larger household savings, which may incentivize one to become absent from his or her job if the need arises once the confusion over the initial impact of COVID-19 on daily life has subsided.

Having a child in school or one young enough to be in need of child-care has no statistically significant effect on the likelihood of an individual's absence from work, nor does this effect differ for the female and male populations. There is additionally no joint statistical significance present for these two children-related indicator variables.

The initial impacts of COVID-19 on the likelihood of becoming absent from work appears to level out for the female and Asian populations in my sample by October. Married individuals, veterans, and persons with disabilities conversely experience a delayed impact of COVID-19 on the likelihood of becoming absent from work in October. The influence certain characteristics have on the likelihood of an individual being absent from work appear to have shifted between April and October, as an almost entirely new subset of individuals experience higher likelihoods of absence six months later. Any reasons for the delayed or initial impacts on the likelihood of becoming absent from work for certain demographics remain unclear.

4.4 An Evaluation of Part-Time Workers

The final regression in my analysis measures the transition between full-time workers and part-time workers by evaluating the likelihood of an individual in my sample working part-time in April or October after having worked full-time in January. An individual is considered a full-time worker in January if he or she works at least 35 hours a week, and a part-time worker in April and October if he or she works between 1 and 34 hours. Again this regression is executed in both April and October, first for the full sample then for the female population only, using the same variables mentioned previously. The results are reflected in marginal percentage point changes and can be found on Table 9.

The female population in the sample experience statistically significant increases in their likelihood of becoming a part-time worker in both April and October. Foreign born workers also experience increased likelihood of becoming a part-time worker in April, however these results become insignificant and negative by October. Hispanic females and females in need of child-care interestingly experience and increased likelihood of becoming a part-time worker relative to their respective counterparts in October only, after having insignificant effects in April.

Females in my sample experience a 3.05 percentage point increase in the likelihood of becoming a part-time worker relative to their male counterparts in April, and a steady 3.30 percentage point increase in October. The months of recover preceding October does not appear to have much impact on the increased likelihood among females to become part-time workers. Foreign born workers, however, experience a 2.59 percentage point increase in their likelihood of becoming a part-time worker in April, which subsides and becomes insignificant by October. Foreign born females in particular experience a 4.12 percentage point increase in the likelihood of becoming unemployed relative to their non-foreign born female counterparts, the highest percentage point increase in all of April, which too becomes insignificant by October. This may indicate that the months of recovery were more beneficial to foreign born workers than other demographics.

Hispanic females and females in need of child care, do not fare as well as foreign born females have in October. After insignificant effects in April, Hispanic females experience a 5.5 percentage point increase in the likelihood of becoming a part-time worker relative to their non-Hispanic female counterparts, the largest increase among all demographics in October. Females in need of child care experience a 4.6 percentage point increase in the likelihood of becoming a part-time worker relative to female counterparts without children altogether or without those young enough to need childcare. The variable indicating that an individual has a child young enough to need child care interestingly becomes statistically significant for the first time in this regression only, and only in October. Perhaps this may have become a greater issue in October, as many parents struggled to find after-school care once the 2021 school year began, and many mothers were instead forced to work part-time and provide their own child care. A joint test of statistical significance for having a child in school or needing child care yields no jointly significant effect on the likelihood of a full-time worker's hours being reduced to part-time after January.

The only constant characteristic tied to increased likelihoods of reduced part-time hours in both observed months is linked to the females in my sample. The delayed effect on Hispanic females, and mothers in need of child care remain unexplained by the controlled variables; nor are there explanations for the only initial impact on the foreign born population samples. Being as industry, state, age, and education effects are controlled for, there are no clear explanations as to why these demographics are all impacted in uniquely disproportionate ways throughout the onset of the pandemic and the months of recovery following it.

4.5 The Effects of Other Demographic Characteristics

There are a handful of demographics that have experienced notable effects to their employment characteristics since the COVID-19 outbreak, that are worth discussing. The instance of marriage has a negative effect on the likelihood of becoming unemployed in April, and a positive effect on the likelihood of labor force participation in both April and October. This may give some explanation on the behavior patterns of married people compared to their single counterparts. 67.66% of married people in my sample have at least one child. Having a child to provide for may influence a parent's work ethic or even an employer's decision making. Marriage has a positive effect on the likelihood of being absent from work in October, an effect that is particularly larger for married females compared to single females. The same reasoning may also apply here; as many schools institute remote learning for the fall semester, parents, often mothers, become absent from work so that they may provide child care during the day. This measure may be heavily increased by California residents as they make up 9.57% of the sample's respondents (the largest fraction of all the states), and has roughly 96% of the state's total K-12 students learning remotely (Tadayon 2020) in October 2020, increasing the need for absent-from-work parents.

African-Americans in my sample experience a delayed increase in the likelihood of becoming unemployed in October, and African-American females experience a delayed decrease in the likelihood of remining in the labor force in October. These delays may indicate that African-Americans continue to be hurt by COVID-19's effect on the labor market more than other demographics, despite six months of attempted recovery. Asian individuals in my sample on the other hand seem to experience only initial reactions to COVID-19 in the form of an increase in the likelihood of being absent from work in April, and a decrease in the likelihood of having their hours reduced to part-time work in April, indicating that the Asian population as a whole may have recovered relatively quickly from the labor-market shocks relative to other demographics. Foreign born workers similarly experience only an initial increase in the likelihood of becoming unemployed in April, a decrease in the likelihood of labor force participation in April, and an increase in the likelihood of part-time work in April, effects that become statistically insignificant by October in all cases. This seems to imply that foreign born workers have recovered from COVID-19's initial shocks more than their U.S. born counterparts have. Workers with a reported disability instead experience delayed increases to the likelihood of becoming unemployed and on being absent from work in October; they also endure a constant negative effect on the likelihood of remaining in the labor force in both months, which increases in magnitude by October. Veterans also experience delayed negative effects on the likelihood of labor force participation, and delayed positive effects on the likelihood of being absent in October. While Asian and foreign born individuals seem to recover quickly from the detrimental effects COVID-19 has on their employment characteristics in April, African-Americans, veterans, and disabled persons have not fared as well and appear to be the most in-need of further recovery.

Prevalent in every regression analysis is a theme of undesirable labor market prospects for females since COVID-19 disrupted the economy. The female population in my sample has experienced adverse shocks to all their employment prospects in April, some aspects of which have been alleviated while others exacerbated, six months later. By October, females experience a smaller increase in the likelihood of becoming unemployed relative to their male counterparts than they experience in April, which may indicate a positive step towards recovery. The impact of COVID-19 on the likelihood of females becoming absent from work relative to their male counterparts is also lower in October than it is in April, as well as statistically insignificant. The opposite is true for female's part-time work hours and labor force participation. Relative to their male counterparts, females in October are even more likely to have their hours reduced to part-time work than they were in April. Females also experience a decrease in the likelihood of remaining in the labor force, relative to their male counterparts, that is almost twice as large in October than it is in April. The lasting impact on females does not appear to be explained by the higher concentration of women in many of the industries that have been hit the hardest by COVID-19, due to the inclusion of industry-specific effects in my regression. Nor can it be explained by other plausible reasons, such as age, education, or the state they live in.

I had previously theorized that this outcome is a consequence of many mothers struggling to balance the demands from work and their children, following school and daycare center closures throughout the country. However, the statistically insignificant joint-effects of the indicator variables for school-age children and young children in need of child care, prove otherwise. I have additionally run these same regressions using only one of the indicator variables for children at a time, either the instance of having a child in school or the instance of having a young child that needs to be cared for. I have chosen not to include the results in this paper because all of the cases remain statistically insignificant, except for one. The one statistically significant effect, at the 10% level, is a 1.83 percentage point increase in the likelihood of a parent remaining in the labor force in October if they have a young child, relative to adults who do not need child care. This variable has no significant effects anywhere else and sheds no explanations on female-specific reactions to COVID-19, particularly the increasingly negative effect on labor force participation.

5 Conclusions

I have mainly focused my attention on female veterans, females with a disability, Asian females, and females with the least amount of education because these are groups that have been disproportionately impacted by COVID-19, while their male counterparts have mostly experienced more subdued effects. Understanding which groups in my sample have recovered the least from COVID-19's initial shocks to the labor market helps to identify which demographics continue to experience disproportionate outcomes and are in need of further assistance in the United States. For example, Asian females between the ages of 18 and 55 years-old do not have the highest unemployment rate relative to other demographics in October, however they do experience the steepest increase in their unemployment rate between January and October; Asian females experience a 126% increase in their unemployment rate, white females experience a 72% increase, Hispanic females a 60% increase, and African-American females a 44% increase. Analyzing the growth of the unemployment rate helps to uncover the magnitude of impact for each demographic relative to where they started off, and the population of Asian females in my sample seems to be in need of more recovery than other subgroups. The absence of sufficient recovery may indicate a need for reapportioned funds targeted towards reemploying more disadvantaged groups. However, the growth of the unemployment rate does not explain why Asian females and Asian males have experienced COVID-19's labor-market changes with such extreme differences.

The pattern of disproportionately negative effects on the employment characteristics of the female population, veterans, disabled persons, and racial minorities since COVID-19 disrupted the labor market has been established in this paper. These demographics experience delayed reactions to COVID-19 during the months when other population samples appear to be recovering from any initial effects. Future researchers now bear the responsibility of determining why this is the case and what, if any, are the commonalities between these subgroups. Perhaps these disparities are a reflection of the system and culture of the U.S. labor market. Perhaps it is merely a distinction between the differing lifestyle preferences for the males and females in my sample. Additionally, between April and October of 2020, the U.S. Small Business Association provided hundreds of billions of dollars to various establishments in need of federal relief. Recipients of this loan were given the option to have it forgiven if the funds were distributed towards eligible expenses, one of them being payroll expenses. It is conceivable that employment at one of the companies that received this form of aid, and used it to pay its employees, may have affected an individual's labor market transitions that are not accounted for in this analysis. The disproportionate effects on the employment characteristics of females and minority demographics as a result of COVID-19 remains unexplained, though I introduce numerous possible explanations I believe may be worth examining.

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Table 1: Basic Statistics

VARIABLE	MEAN	STD	SUM
Female	0.5057	0.5000	15,893
White	0.7923	0.4057	24,898
African-American	0.0995	0.2994	3,128
Asian	0.0682	0.2520	2,142
Hispanic	0.1632	0.3696	5,130
Age 18-20	0.0637	0.2442	2,001
Age 21-24	0.0856	0.2797	2,689
Age 25-29	0.1198	0.3248	3,766
Age 30-39	0.2873	0.4525	9,028
Age 40-49	0.2715	0.4447	8,531
Age 50-55	0.1722	0.3775	5,411
Less Than HS Degree	0.0836	0.2767	2,626
High School Degree	0.2568	0.4369	8,070
Some College	0.2903	0.4539	9,122
Bachelor's Degree	0.2438	0.4294	7,662
Master's Degree & Up	0.1256	0.3314	3,946
Married	0.5924	0.4914	18,616
U.S. Veteran	0.0389	0.1934	1,223
Foreign Born	0.1702	0.3758	5,348
Disability	0.0611	0.2395	1,919
Child In School	0.3263	0.4689	10,253
Need Child Care	0.3680	0.4823	11,564
Agriculture, Forestry, Fishing & Mining	0.0186	0.1353	586
Construction	0.0602	0.2379	1,892
Manufacturing	0.0826	0.2752	2,595
Wholesale Trade	0.0195	0.1384	614
Retail Trade	0.0878	0.2830	2,759
Transportation & Warehousing	0.0379	0.1910	1,192
Utilities	0.0077	0.0874	242
Information	0.0163	0.1266	512
Finance & Insurance	0.0391	0.1939	1,229
Real Estate, Rental & Leasing	0.0150	0.1216	472
Professional, Scientific & Technical	0.0705	0.2560	2,216
Administration & Management	0.0343	0.1820	1,078
Education	0.0845	0.2782	2,656
Health Care & Social Assistance	0.1122	0.3156	3,525
Arts, Entertainment & Recreation	0.0157	0.1243	493
Accommodation & Food Services	0.0572	0.2321	1,796
Other Services	0.0238	0.1525	749
Public Administration	0.0531	0.2243	1,669
Military	0.0122	0.1097	383

Table 2: Percent of Sample That Is Unemployed

Sample	January	April	October
Full	2.57	9.54	3.63
Female	2.23	9.96	3.75
Male	2.92	9.10	3.51
White	2.31	9.21	3.01
African-American	4.09	9.56	6.69
Asian	2.43	9.64	4.10
Hispanic	3.55	11.01	4.53
Age 18-20	6.17	12.59	5.47
Age 21-24	4.10	14.01	6.49
Age 25-29	3.42	9.78	4.67
Age 30-39	2.21	8.84	3.16
Age 40-49	1.81	8.39	3.46
Age 50-55	1.57	8.88	2.29
Less Than HS Degree	4.91	11.41	2.82
High School Degree	3.63	12.45	4.81
Some College	2.34	11.15	4.27
Bachelor's Degree	1.64	6.95	2.91
Master's Degree & Up	1.12	3.67	1.55
Married	1.58	7.98	2.83
U.S. Veteran	2.29	8.25	3.19
Foreign Born	2.91	10.17	3.82
Disability	3.36	5.07	2.45
Mother	1.90	9.23	3.07
Father	1.60	7.25	2.93
Agriculture, Forestry, Fishing & Mining	5.17	4.15	7.77
Construction	4.24	12.36	3.65
Manufacturing	2.30	11.62	4.05
Wholesale Trade	2.25	8.54	1.92
Retail Trade	4.32	14.22	5.08
Transportation & Warehousing	2.86	9.79	3.35
Utilities	0.00	4.40	0.00
Information	1.16	11.04	3.33
Finance & Insurance	2.13	4.49	3.05
Real Estate, Rental & Leasing	2.87	7.69	1.69
Professional, Scientific & Technical	2.15	5.11	3.58
Administration & Management	6.86	13.08	5.52
Education	2.08	11.16	1.38
Health Care & Social Assistance	1.83	7.72	3.05
Arts, Entertainment & Recreation	1.92	28.40	9.52
Accommodation & Food Services	4.54	27.46	14.74
Other Services	3.23	22.36	5.30
Public Administration	1.81	4.73	1.11
Military	0.51	0.74	0.00

Table 3: Percent of Sample That Is In The Labor Force

Sample	January	April	October
Full	81.08	77.25	79.17
Female	76.17	71.79	73.96
Male	86.10	82.90	84.39
White	82.19	78.52	80.39
African-American	77.37	71.31	75.20
Asian	76.19	73.26	74.40
Hispanic	77.74	72.39	75.31
Age 18-20	54.02	46.07	51.17
Age 21-24	74.79	69.53	67.57
Age 25-29	83.95	79.53	82.94
Age 30-39	84.17	80.60	82.84
Age 40-49	84.86	81.64	82.97
Age 50-55	81.80	78.67	77.95
Less Than HS Degree	60.01	54.90	60.45
High School Degree	77.76	73.88	73.34
Some College	80.03	75.43	76.56
Bachelor's Degree	87.50	84.26	87.25
Master's Degree & Up	92.21	90.04	92.41
Married	85.07	81.83	83.70
U.S. Veteran	82.00	82.78	79.26
Foreign Born	77.48	72.66	75.86
Disability	42.06	39.17	30.07
Mother	75.18	70.38	72.40
Father	93.60	91.64	93.16
Agriculture, Forestry, Fishing & Mining	94.83	92.75	93.20
Construction	95.55	93.51	91.36
Manufacturing	96.40	93.18	94.68
Wholesale Trade	98.71	97.49	97.12
Retail Trade	93.56	87.73	88.98
Transportation & Warehousing	94.78	92.84	93.85
Utilities	97.46	92.31	93.94
Information	97.30	93.87	93.33
Finance & Insurance	96.72	95.27	93.40
Real Estate, Rental & Leasing	96.31	91.12	89.83
Professional, Scientific & Technical	96.15	94.23	94.63
Administration & Management	93.33	84.87	92.64
Education	96.95	92.82	91.72
Health Care & Social Assistance	96.16	93.37	92.20
Arts, Entertainment & Recreation	89.66	84.62	84.13
Accommodation & Food Services	91.48	84.09	85.26
Other Services	94.07	85.77	84.09
Public Administration	96.49	93.35	95.20
Military	99.49	98.52	94.23

Table 4: Percent of Sample That Is Absent From Work

Sample	January	April	October
Full	1.87	5.23	2.02
Female	2.03	5.77	1.92
Male	1.71	4.67	2.12
White	1.76	5.12	2.19
African-American	2.24	5.40	0.79
Asian	2.61	6.43	2.05
Hispanic	1.33	5.25	1.64
Age 18-20	1.96	3.70	0.78
Age 21-24	1.72	6.03	0.54
Age 25-29	1.84	5.19	1.97
Age 30-39	1.72	5.30	2.46
Age 40-49	1.88	5.09	2.02
Age 50-55	2.18	5.48	2.29
Less Than HS Degree	2.31	4.63	1.98
High School Degree	1.70	7.04	1.45
Some College	2.05	5.53	2.45
Bachelor's Degree	1.72	4.43	1.88
Master's Degree & Up	1.78	2.85	2.48
Married	1.95	5.33	2.46
U.S. Veteran	0.98	4.25	4.26
Foreign Born	2.46	6.24	1.85
Disability	1.53	4.15	2.45
Mother	2.11	6.21	1.78
Father	1.75	4.85	2.40
Agriculture, Forestry, Fishing & Mining	3.10	4.66	4.85
Construction	3.07	8.19	2.66
Manufacturing	1.69	3.35	2.78
Wholesale Trade	1.29	2.01	0.00
Retail Trade	1.90	7.17	2.12
Transportation & Warehousing	3.20	9.55	3.35
Utilities	0.85	1.10	0.00
Information	3.09	7.36	5.56
Finance & Insurance	0.82	3.31	3.55
Real Estate, Rental & Leasing	2.87	8.28	1.69
Professional, Scientific & Technical	1.97	3.41	1.79
Administration & Management	2.29	7.18	1.84
Education	2.76	6.38	1.61
Health Care & Social Assistance	2.58	6.55	2.20
Arts, Entertainment & Recreation	0.77	13.02	4.76
Accommodation & Food Services	1.99	7.49	0.80
Other Services	2.70	14.23	1.52
Public Administration	1.81	4.20	2.95
Military	1.53	3.70	3.85

Table 5: Average Weekly Hours Worked

Sample	January	April	October
Full	31.00	24.92	29.94
Female	27.50	21.24	26.18
Male	34.61	28.72	33.75
White	31.61	25.62	30.81
African-American	28.93	22.03	27.14
Asian	28.95	23.14	27.62
Hispanic	28.41	21.43	26.59
Age 18-20	12.34	8.45	13.16
Age 21-24	24.26	17.83	21.29
Age 25-29	31.48	25.44	30.46
Age 30-39	33.15	27.02	31.92
Age 40-49	34.18	27.78	32.79
Age 50-55	32.83	26.43	30.55
Less Than HS Degree	20.13	14.08	21.99
High School Degree	28.81	21.88	26.78
Some College	29.65	22.72	27.83
Bachelor's Degree	34.67	29.34	34.25
Master's Degree & Up	38.86	34.73	37.65
Married	33.96	27.98	32.80
U.S. Veteran	33.47	30.36	32.24
Foreign Born	29.19	22.24	27.79
Disability	13.55	10.61	9.40
Mother	27.08	20.61	25.74
Father	40.28	34.42	39.18
Agriculture, Forestry, Fishing & Mining	41.36	38.24	43.34
Construction	37.43	30.36	36.51
Manufacturing	39.98	32.72	37.79
Wholesale Trade	40.38	35.43	39.84
Retail Trade	33.42	26.20	32.03
Transportation & Warehousing	38.56	31.83	36.51
Utilities	42.97	36.66	39.24
Information	40.16	32.74	36.02
Finance & Insurance	39.28	36.80	36.22
Real Estate, Rental & Leasing	34.89	28.74	36.24
Professional, Scientific & Technical	39.09	35.20	36.64
Administration & Management	32.46	26.18	33.49
Education	36.33	27.81	36.77
Health Care & Social Assistance	36.44	31.19	34.13
Arts, Entertainment & Recreation	31.31	16.71	24.92
Accommodation & Food Services	29.93	16.69	24.05
Other Services	35.20	19.71	30.33
Public Administration	39.00	35.42	38.38
Military	37.22	36.16	31.60

Table 6 : Logit Regression: Becoming Unemployed

Model	1	2	3	4
Month	April	April	October	October
Sample	Full	Females Only	Full	Females Only
Female	0.0269		0.0133	
	[0.0073]***		[0.0072]*	
Child In School	-0.0045	-0.0002	-0.0118	-0.0285
	[0.0108]	[0.0156]	[0.0099]	[0.0178]
Need Child Care	0.0048	0.0116	0.0110	0.0214
	[0.0105]	[0.0152]	[0.0095]	[0.0170]
Married	-0.0225	-0.0122	-0.0024	-0.0057
	[0.0078]***	[0.0115]	[0.0080]	[0.0141]
African-American	-0.0155	-0.0241	0.0219	0.0036
	[0.0125]	[0.0185]	[0.0104]**	[0.0219]
Asian	-0.0115	-0.0199	0.0022	0.0074
	[0.0154]	[0.0229]	[0.0157]	[0.0283]
Hispanic	-0.0252	-0.0252	-0.0045	-0.0234
	[0.0112]**	[0.0170]	[0.0108]	[0.0210]
Veteran	0.0076	0.0610	-0.0226	
	[0.0185]	[0.0403]	[0.0265]	
Foreign Born	0.0195	0.0232	-0.0054	0.0059
	[0.0110]*	[0.0171]	[0.0107]	[0.0196]
Disability	-0.0310	-0.0787	0.0321	0.0564
	[0.0200]	[0.0345]**	[0.0167]*	[0.0261]**
N	8,167	3,890	3,271	1,256

* p<0.1; ** p<0.05; *** p<0.01

Table 7 : Logit Regression: Staying In The Labor Force

Model	1	2	3	4
Month	April	April	October	October
Sample	Full	Females Only	Full	Females Only
Female	-0.0237		-0.0460	
	[0.0059]***		[0.0090]***	
Child In School	0.0064	0.0154	0.0039	0.0165
	[0.0092]	[0.0133]	[0.0125]	[0.0193]
Need Child Care	-0.0010	-0.0194	0.0159	-0.0039
	[0.0087]	[0.0127]	[0.0121]	[0.0191]
Married	0.0154	-0.0058	0.0244	0.0015
	[0.0064]**	[0.0098]	[0.0093]***	[0.0157]
African-American	-0.0216	-0.0174	-0.0093	-0.0449
	[0.0088]**	[0.0140]	[0.0127]	[0.0208]**
Asian	-0.0039	0.0152	-0.0161	0.0087
	[0.0120]	[0.0193]	[0.0201]	[0.0387]
Hispanic	-0.0058	-0.0109	-0.0005	-0.0393
	[0.0084]	[0.0134]	[0.0126]	[0.0212]*
Veteran	0.0343	0.0418	-0.0474	-0.1300
	[0.0194]*	[0.0465]	[0.0217]**	[0.0480]***
Foreign Born	-0.0104	-0.0238	-0.0044	0.0084
	[0.0084]	[0.0134]*	[0.0128]	[0.0227]
Disability	-0.0577	-0.0778	-0.0779	-0.0948
	[0.0110]***	[0.0176]***	[0.0168]***	[0.0312]***
N	8,740	4,117	3,963	1,750

* p<0.1; ** p<0.05; *** p<0.01

Table 8 : Logit Regression: Becoming Absent From Job

Model	1	2	3	4
Month	April	April	October	October
Sample	Full	Females Only	Full	Females Only
Female	0.0182		0.0034	
	[0.0047]***		[0.0056]	
Child In School	-0.0018	-0.0023	-0.0108	-0.0197
	[0.0066]	[0.0094]	[0.0074]	[0.0129]
Need Child Care	0.0057	0.0082	0.0054	0.0162
	[0.0064]	[0.0092]	[0.0073]	[0.0125]
Married	0.0039	0.0129	0.0194	0.0297
	[0.0050]	[0.0073]*	[0.0072]***	[0.0135]**
African-American	0.0009	-0.0020	-0.0133	-0.0205
	[0.0075]	[0.0109]	[0.0127]	[0.0213]
Asian	0.0168	0.0129	-0.0003	-0.0208
	[0.0090]*	[0.0139]	[0.0132]	[0.0234]
Hispanic	-0.0101	-0.0049	-0.0072	-0.0180
	[0.0071]	[0.0107]	[0.0091]	[0.0163]
Veteran	-0.0016	-0.0428	0.0229	0.0580
	[0.0120]	[0.0374]	[0.0100]**	[0.0250]**
Foreign Born	0.0045	0.0038	0.0003	0.0108
	[0.0068]	[0.0105]	[0.0092]	[0.0156]
Disability	0.0059	0.0159	0.0294	0.0284
	[0.0106]	[0.0151]	[0.0107]***	[0.0223]
N	10,596	5,288	3,639	1,473

* p<0.1; ** p<0.05; *** p<0.01

Table 9 : Logit Regression: Reduced to Part-Time

Model	1	2	3	4
Month	April	April	October	October
Sample	Full	Females Only	Full	Females Only
Female	0.0305		0.0330	
	[0.0091]***		[0.0124]***	
Child In School	0.0129	0.0205	-0.0063	-0.0357
	[0.0125]	[0.0197]	[0.0160]	[0.0267]
Need Child Care	-0.0090	0.0022	0.0076	0.0460
	[0.0124]	[0.0195]	[0.0161]	[0.0268]*
Married	-0.0096	0.0103	0.0068	0.0061
	[0.0095]	[0.0148]	[0.0138]	[0.0224]
African-American	-0.0043	-0.0016	-0.0544	-0.1116
	[0.0151]	[0.0228]	[0.0234]**	[0.0412]***
Asian	-0.0421	-0.0870	0.0143	0.0152
	[0.0205]**	[0.0356]**	[0.0287]	[0.0518]
Hispanic	0.0127	0.0121	0.0207	0.0550
	[0.0134]	[0.0221]	[0.0196]	[0.0318]*
Veteran	-0.0179	-0.0955	-0.0477	
	[0.0230]	[0.0896]	[0.0380]	
Foreign Born	0.0259	0.0412	-0.0165	-0.0466
	[0.0132]*	[0.0225]*	[0.0200]	[0.0354]
Disability	0.0114	-0.0325	-0.0969	-0.1512
	[0.0268]	[0.0509]	[0.0600]	[0.1243]
N	6,503	2,882	3,050	1,322

* *p*<0.1; ** *p*<0.05; *** *p*<0.01