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Gendered labor market outcomes during COVID-19: Evidence from early withdrawal of Federal Pandemic Unemployment Compensation

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Abstract

Despite their importance in the social safety net, Unemployment Insurance (UI) benefits are expected to increase unemployment duration. I find that males, on average, face a greater drop in unemployment than females when (UI) is no longer offered in their respective state. Male's unemployment rate dropped more by a magnitude of 0.7 percent compared to female's which consists of about 11.5 percent of male unemployment during UI. Females who were married, were in lower family income brackets, or had children saw smaller changes in unemployment when UI programs were exhausted.

1. Introduction:

The global economy shrunk 3.5 percent in 2020, a 7 percent loss as opposed to the 3.4 percent growth forecasted in October 2019, primarily due to the emergence of the global COVID-19 pandemic (Yeyati et al. 2020). The labor force participation rate declined from 63.4% in January 2020 to 60.2% in April 2020. As of August 2021, the labor force participation had yet to fully recover, at 61.7% (Center on Budget and Policies, 2021). The economic downturn hit the U.S labor market quickly and forcefully. The drop in the employment rate in post-outbreak months was driven by mass layoffs rather than workers voluntarily quitting their jobs, thus allowing laid-off individuals to qualify for safety net programs (Dias et al. 2020). In the week ending March 14, 2020, there were a total of 250,000 initial unemployment insurance (UI) claims- a jump of 20% from the week before. Just two weeks later, there were over 6 million claims (Bartik et al. 2020).

In March 2020, the CARES Act passed the Federal Pandemic Unemployment Compensation (FPUC), which added a $600 federal supplement to weekly UI benefits until July 2020. The Lost Wages Assistance (LWA) program, a federal-state unemployment benefit program, aimed to provide $300 to $400 in supplemental unemployment insurance benefits from the beginning of August to December 27th 2020. Unfortunately, funding for the program depleted earlier than expected and the LWA ended early.

The CARES Act partially reinstated the supplement at $300 per week in January 2021 until September 6, 2021. Federal payments to unemployment benefits are supplemental to state unemployment benefits, where state UI benefits are pegged to previous salaries. The Pandemic Emergency Unemployment Compensation (PEUC) also made the UI benefits more generous by extending coverage to those who exhausted standard state benefits. In addition to these extra payments, unemployment benefits became exceedingly accessible through the Pandemic

Unemployment Assistance (PUA), which extended benefits to uncovered workers such as the self-employed, freelancers, and part-time workers. All pandemic-related federal unemployment benefits expired on September 6, 2021.

UI benefits provide a temporary wage replacement to workers who become unemployed. The system was set up so individuals may smooth their consumption by creating a balance between spending and saving at times where they may have no working income. As a response to the historical recessions and unemployment, policy makers responded by extending the total eligible length of UI from 13 weeks to a max of 99 weeks— most states had a total eligible length of 26 weeks.[1] This means people who were laid off have more time than usual to remain unemployed and receive payments while looking for work.

Business owners expressed concern that unemployment benefits would deter job re-entry and reduce worker availability (Buchwald 2021). The rationale follows a neoclassical model of the economy where jobs are taken only to generate the income for optimal levels of consumption and leisure. Workers may "price" themselves into a job by lowering wage demands while benefit eligibility rules are not strictly enforced. Therefore any alternative source of unearned income will reduce individual work incentives and increase unemployment. An individual on UI will need a higher wage available, most likely more than historical wages, to rejoin the workforce. (Howell et al. 2011).

Work and life balance during the pandemic meant very different things between women and men, especially for mothers, as they tend to carry an outsize burden and shoulder the load of closed schools and daycare. In general, women are more likely to be part-time workers (Gould et al. 2020). Working women often choose more flexible work because of family responsibilities as

[1] The state decides the logistics as to how it wants to run the unemployment compensation programs and their own qualification guidelines. In 2021, select states withdrew from the FPUC earlier than its planned end date.

they are still often expected to be the primary caretaker for families. (Alon et al. 2020) During COVID-19 the CARES Act made unemployment insurance more accessible through PUA by extending eligibility to self-employed and part-time workers. Therefore, compared to pre-COVID, more women during COVID are able to claim unemployment benefits.

A wide range of literature points to controversial mechanisms as to whether unemployment benefits slow economic recovery as they incentivize certain individuals to remain unemployed. Once the UI benefits end, there will theoretically be an increase in employment- however, the nature of the pandemic may have impacted labor market outcomes differently among females and males (Coombs et al. 2021).

1.1 Research Question:

My paper examines whether the economic recovery differs by gender, particularly focusing on the effect of the expiration of unemployment benefits. During recovery periods of past recessions, women have undergone a slower and weaker recovery compared to men despite lower job losses. From June 2009 through May 2011, men increased their job count by 768,000 jobs and decreased the unemployment rate by 1.1 percentage points down to 9.5%. Women, during the same period, lost 218,000 jobs and increased the unemployment rate by 0.2 percentage points to a total of 8.5% (Kochhar, 2011). Albanesi and Kim (2021) study employment during COVID and categorize the labor force by high or low flexibility and high or low contact. Investigating the employment rates by gender, they found the slowest recovery in employment was represented by women in the flexible and low-contact sectors.

Although there has been literature using the expiration of federal unemployment benefits to gauge economic recovery, there is no current literature regarding how the lapse of benefits leads to different economic recovery between men and women. My hypothesis is that there is heterogeneity in unemployment between males and females once UI benefits are exhausted due to unproportional household production responsibilities and wage differences. To address the question I will use the Current Population Survey (CPS) survey and Bureau of Labor Statistics (BLS) data to run an analysis quantifying differences in unemployment and labor force participation throughout COVID economic recovery. I will then look at heterogeneity through marital status, status of having children, children's age and income. I find that women have a "slower" recovery compared to men similar to past recessions.

2. Literature Review:

Economists debate the effects between UI levels and the labor market. Several studies point to a correlation between increased UI and decreased labor market activity. Meyer (1988) utilizes a Kaplan Meier specification to estimate the relationship between employment and benefit exhaustion (or end). He finds that higher UI benefits reduce the probability of employment, in particular going from 6 weeks to 1 week until exhaustion triples the probability of employment. This means the more individuals receive from safety net programs the higher unemployment rates we will observe. In support of Meyer's study, Hagedorn et al. (2016) utilizes a county border discontinuity design to estimate the effects of UI benefit.[2] They found a 1% drop in benefit duration leads to a statistically significant increase of employment by 0.019 log points. Tao Zhang et al. (2002) uses a flexible hazard rate model to analyze the effect of unemployment compensation on unemployment duration. They conclude that the escape rate[3] rises sharply in months just to benefit exhaustion, meaning the rate at which people find work rises months prior to benefit exhaustion. Furthermore he notes that men are more responsive than women with respect to changes in unemployment compensation– where women are most responsive with

[2] A country border design looks at counties close to each other geographically but in different states, thus different state policies. The two counties will have similar labor markets since they share many geographic properties.
[3] The escape rate, in this context, is the rate at which people go from unemployment to employment.

respect to benefit exhaustion. This implies that women search harder for jobs at the notice of an upcoming benefit termination, which is supported by a higher escape rate for women compared to men.

To the contrary, other studies point toward a null or weak relationship between UI benefits level and labor market participation and unemployment. Gabriel et al. (2019) uses a Diamond Mortensen and Pisarides model to suggest a small and minimal effect of extending benefits. Specifically, Gabriel et al. found that extending benefits increases the unemployment rate by at most 0.3 percentage points. Ammar Farooq et al (2021) finds a controversial effect, where increasing UI has a positive effect on the labor market by improving job match quality in the re-employment job. Furthermore, they find that these effects are greater for women and less educated workers. Similarly, the Congressional Budget Office released a paper in 2012 suggesting that increased UI generosity actually stimulates employment, thus agreeing with Farooq. They theorize that unemployment benefits will stimulate individual's disposable income, ultimately boosting firms' revenue and job openings for employment (CBO, 2012).

Some studies point to a correlation between UI and unemployment, dependent on group stratification. Raj Chetty et al (2005) examines the effect of UI benefits on unemployment exit hazards between constrained and unconstrained groups in terms of liquidity[4], using nonparametric graphical methods and Cox hazard models. Chetty observes that a 10% increase in UI benefits raises unemployment durations by 6-8% in all the constrained groups but had little to no effect on unemployment duration among unconstrained groups.

Throughout the COVID recession, policy makers extended the length of UI benefits for an additional 39 weeks, loosened eligible requirements, and increased benefits by $600 per week

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[4] A constrained group in Raj Chetty et al's experiment refers to liquidity. For unconstrained group individuals, losing a job will not be too bad on economic health as the individual will be available for debt, savings, and other assets. However, in constrained groups, people will not have access to the above, thus we can look at pure income effects.

in 2020 and $300 per week in 2021, both of which are supplemental to state benefits. UI traditionally has an average income replacement rate at 35-50 percent in most states— however, replacement rates during COVID-19 were estimated to be over 100% for about ⅔ of recipients. The median amount an individual receives amounts to 134 percent[5] of lost wages during COVID-19. Specifically, for the bottom 20% of income distribution, UI benefits were able to more than double their wages (Ganong Et al. 2020).

Several studies examine the $600 dollar federal UI benefits administered from March 2020 to July 2020. Dube (2020) uses a difference-in-difference event study design to estimate the macro employment effects. He finds minimal impact of job gains from the benefit reduction, especially when he focuses on low-income households, who compromise most UI recipients. Altonji et al. (2020) runs a linear probability event study model and found that expanding UI generosity does not depress employment in the aggregate during COVID-19. In fact, workers facing large expansions in UI benefits return to previous jobs at similar rates to those not receiving expansions. A third study by Ganong et al. (2021) finds the negative effects of benefits on employment from discouraged job search were minimal. The job finding rate before and after the $600 supplement led to a reduction in discouraged job search by 0.2-0.4%. There was another round of federal UI benefits at $300 per week taking place at the start of 2021. Vaccines and a healthy labor market were not available in 2020 ; therefore, as unemployment benefits ended, it was exceptionally difficult to become employed or re-employed.

Coombs et al (2021) examine the second round of stimulus in 2021 and find contradicting results to the studies, Dube (2020), Altonji et al. (2020), and Ganong et al (2021), regarding the first round of stimulus. Coombs et al. (2021) studied the $300 dollar supplement round in 2021 and how the early withdrawal of pandemic unemployment insurance affects UI receipt,

[5] Some states saw incredible replacement rates. For example, New Mexico with 177% and Maryland with 129 %

employment and spending. They were able to utilize a natural experiment, as 22 states ended all supplemental pandemic unemployment insurance early. The team found that ending the pandemic UI increased employment by 4.4 percentage points and reduced UI recipiency by 35 percentage points among workers who had UI at the end of April 2021. This paper was published in August 2021, hence did not capture the effects of when UI expired for everyone on September 4th 2021.

2.1 Gender Disparities in the Impact of COVID:

In past American recessions, men typically bear more losses in employment than women. However, in the COVID-19 pandemic, women's unemployment increased by 12.8 percentage points between February and April 2020, opposed to an increase of only 9.9 percentage points for men (Alon et al. 2020). During September 2020, when kids returned to school, the unemployment rate between males and females differed by .3 percentage points. These together imply that having school-aged children placed a disproportionate burden on mothers compared to fathers, especially when schools and day-care centers were closed.

Women have been disproportionately impacted and constitute between 52.2% to 55.8% of unemployment insurance claims (Gould et al. 2020). Women are overrepresented in high-contact and inflexible industries most impacted by the pandemic. A research report conducted by McKinsey estimates that 4.5% of women are at risk of unemployment during COVID, opposed to 3.8% of men given the nature of the industries men and women participate in (Madgavkar et al. 2020). Household production was commonly disproportionately allocated. According to the American Time Use survey, women spent an average of 102 minutes per day while men spent an average of 46 minutes per day caring for and helping household children in 2020 (ATUS, 2021).

Hapkau et al. (2020) conduct a study in Europe and find that women were roughly equally affected in job loss when compared with men, but women in the study provide a larger share of increased unpaid work. Having a greater proportion of home production makes it harder for women to transition back to the workforce as their opportunity cost for work increased throughout COVID-19, providing more incentive to stay unemployed or even leave the workforce. This effect of increased opportunity cost is more for caregivers, particularly married couples with children, and individuals with children under the age of 5 (Heggeness et al 2021). Closures of schools and daycare centers due to COVID-19 have massively increased child care needs, which mostly became the working mother's responsibility despite both parents being home (Landivar et al. 2020).

According to Lee (2021), about one-third of all mothers in the workforce have scaled back or quit their jobs in 2020. This is apparent among heterosexual married couples, where both the mother and father work in telecommuting-capable occupations. Using data from 2017-2018 Current Population Survey, Titan Alon et al. (2020) find only 22 percent of female workers are employed in highly telecommutable occupations as opposed to 28 percent of male workers, thus making it remarkably difficult for women to adapt to new work conditions. To make matters worse, among parents who were able to telecommute to work, mothers saw a greater decrease in labor force compared to fathers. Heggeness and Suri (2021) conclude mothers disproportionately left the labor market at the end of the 2020-2021 virtual school year as opposed to women without children. In fact, mother's labor force participation decreased between 0.1-1.4 percentage points compared to women without dependent children.

The difference in women's and men's labor supply explain why men have an easier time recovering from a recession. Men's labor supply elasticity is lower, especially for married men, compared to women. This suggests that when men face unemployment during a recession, they are likely to stay in the labor force and eventually become employed. However, when women become unemployed in a recession, they are likely to drop out of the labor force or seek part-time work. Together, these patterns suggest during economic recovery for a recession where women are disproportionately affected, women will still face more pressure from a decline in aggregate labor supply (Fukuki et al. 2021).

2.2 Labor Market Conditions Since All States Expired:

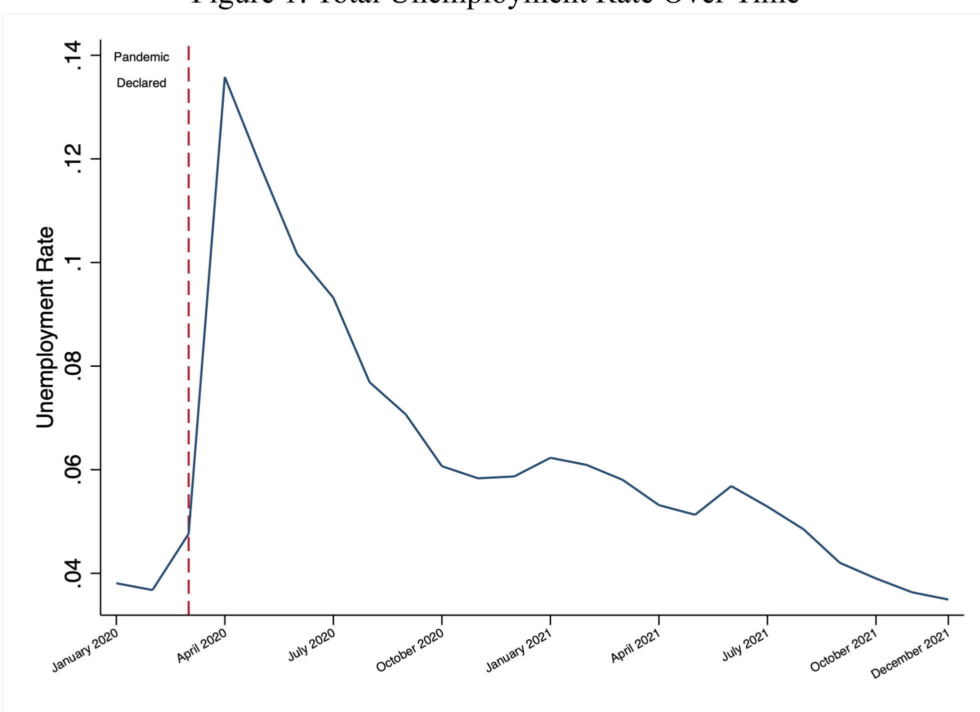
In the 2008 recession, some recipients stayed on UI benefits to improve their careers. At that time, a more generous unemployment insurance program refined the function of the markets by improving efficiency through job matching. Investing in human capital improves the efficiency of the market by boosting productivity, innovation, and general wellbeing. Both workers and employers gain from a generous UI as workers wages and firm productivity both increase (Farooq et al. 2021).

In October 2021, people searched for higher paying and more stable careers, this is reflected by stagnant levels of unemployment throughout the mid months of 2021. Massive layoffs throughout the pandemic prompted individuals, particularly the younger generation, to look for a “stable” job that offers flexibility and external career benefits. Thus, a fraction of the unemployed stayed on UI benefits not because they were incapable of finding a job, but because they would rather take their time to invest in themselves and find a suitable job (Smith, 2021). This effect was more prominent during the $600 dollar round of UI benefit in 2020, as individuals realized the importance of high wages and a stable job (Chalney 2021).

In the month of November 2021, the unemployment rate fell to a pandemic low of 4.2% from 4.6% in October. This drop in unemployment is significant as more than half a million workers, mainly females, returned to the workforce. As mentioned earlier, factors suppressing employment included public health concerns and child-care issues. In November 2021, the labor force participation rose to 61.8 percent, which is the highest level recorded since March 2020. 590,000 workers re-entered the labor force, 304,000 of whom were women.

In December 2021, the unemployment rate declined 0.3 percentage points to 3.9%, approaching the 3.5% unemployment rate in February 2020 before COVID was declared a pandemic. Labor shortages and supply chain worries limited the number of jobs added in December 2021 to 199,000, as opposed to October's 648,000 and November's 249,000. The labor market is still down by 3.6 million jobs from its pre-pandemic levels. The current unemployment rate may be explained by American's unwillingness to settle for lower paying and unstable jobs, as individuals now seek better pay and benefits. Fortunately, the number of initial unemployment claims have fallen below pre-pandemic numbers in recent weeks, implying that companies are holding on to current workers despite the Omicron outbreak (Rosenberg 2022).

Figure 1: Total Unemployment Rate Over Time



3. Theory:

I am going to model the decision of women to stay unemployed once UI expires, among individuals who remain in the labor force. I will do so by explaining the mechanisms and pieces building up to the Duncan model (2003). The decision to be employed will ultimately be a function of reservation wage[6], household production, and personal preferences. The theory behind my paper revolves around the trade-off between goods and time. I split time between leisure, labor, and household production. The foundational mechanics of the theory can be explained by a labor-leisure tradeoff model. Certain individuals face a greater opportunity cost dependent on changes in wage, non-labor income and personal preferences.

I will model the disproportionate impact of unemployment benefit exhaustion through a framework that explains the mechanisms behind market labor supply within a joint household. I do so using the model proposed in Duncan (2003), as this model allows us to examine the interdependence between spouses occupational choices and treat the spouse's characteristics as endogenous, because the spouse's income is considered as non-work income for their partner.

A fundamental difference between a regular labor-leisure trade off and the Duncan model is the household production curve, where we account for joint maximization between partners– ultimately modeling goods and time spent on household production. This production function stems from the idea that consumers often choose not directly from commodities they purchase, but from commodities they transform into goods through production, which takes time. This is crucial to integrate into models of labor supply especially at a time when individuals are staying at home more than usual, thus consuming more home-produced goods.

[6] Reservation wage is the minimum amount of wage for someone to participate in the labor market.

3.1 Labor-Leisure Trade off in context of Unemployment Benefits:

People budget their time across different activities. An individual decides how much he or she "values" their leisure time versus labor time, which can be converted to goods bought using working wages. The more a person works, the more they will tend to value their remaining leisure time and vice versa. The shape of an individual's indifference curves depends on their preference towards leisure and labor.

When someone is laid off they can apply for unemployment insurance. In the labor-leisure tradeoff, the individual is considered unemployed, therefore all of their time is devoted to leisure and their utility curve sits at the corner solution at point B in figure 2.

Because of the government FPUC program, individuals' consumption levels are not at zero, but are at whatever amount is granted by the federal UI program. This is reflected by person B in figure 3. The budget constraint discontinues drops to the left of B in figure 3, because if someone were to start working, they would lose unemployment benefit.

Figure 2: Labor-Leisure

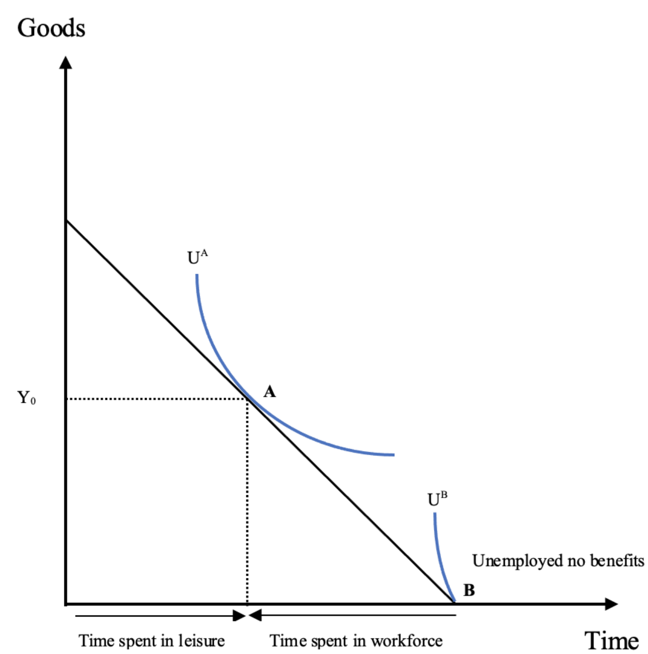
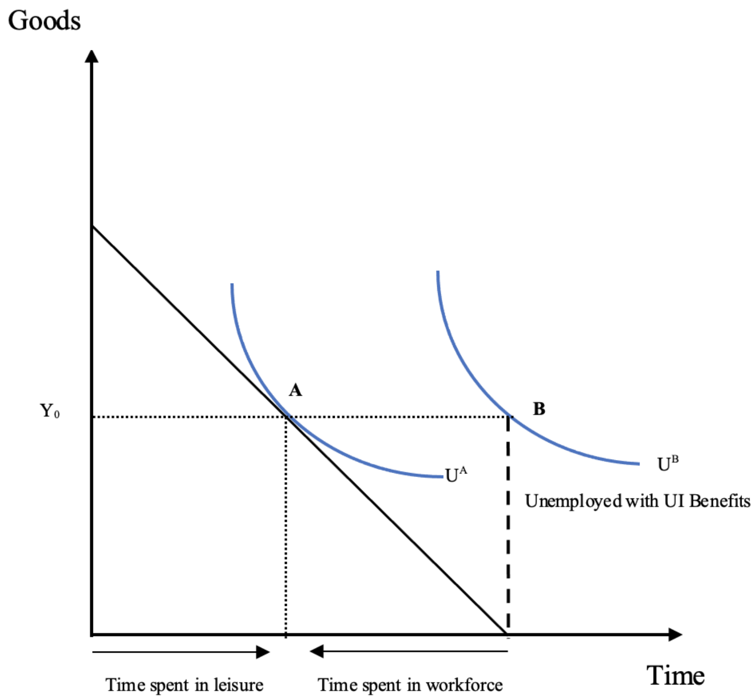


Figure 3: Labor-Leisure with UI Benefits



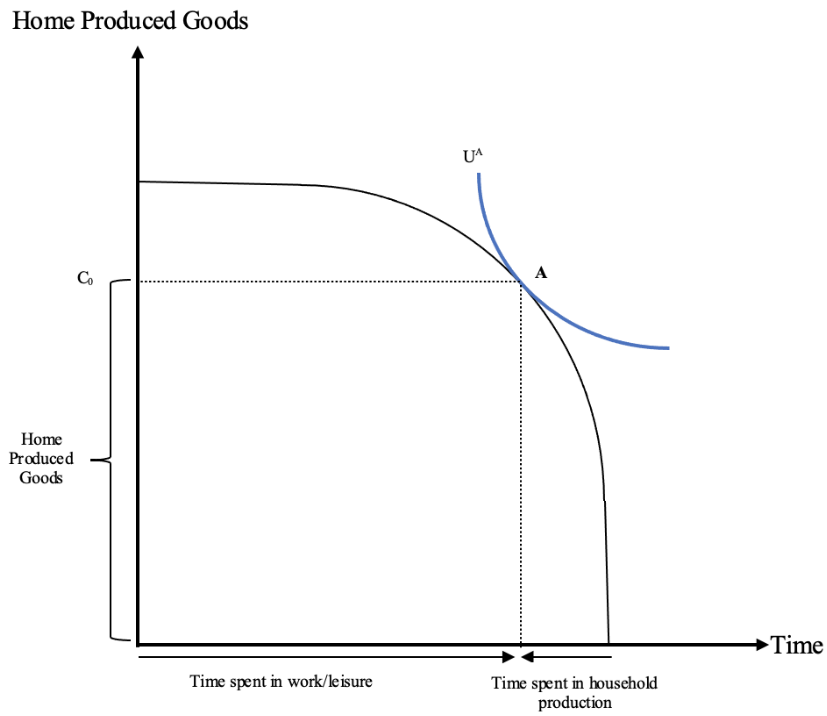
In this particular model, leisure represents all time spent outside of work. This does not necessarily mean the person is unproductive and not producing– as unpaid care is considered under leisure time. This idea is critical to address in the context of COVID as unpaid care was a major burden on households, especially on those with children.

3.2 Duncan Model Household Production Function:

In the Duncan model, there is a household production curve, which models goods and time spent in household production— also referred to as unpaid work. A line with more curvature means the individual tends to gain greater goods from production per unit of time spent on production. A flatter production line with less curvature means the person tends to be less effective in producing household goods, as diminishing returns are more evident.

In figure 4, as we go from right to left on the production function, the slope tangent to the curve becomes less steep and approaches 0, this is because we are experiencing diminishing marginal returns to household labor. The x-axis in figure 4 is inverted for time spent in household production. As we spend more time in household production, we gain less and less home produced goods per additional unit increase in time spent on household production

Figure 4: Production Function



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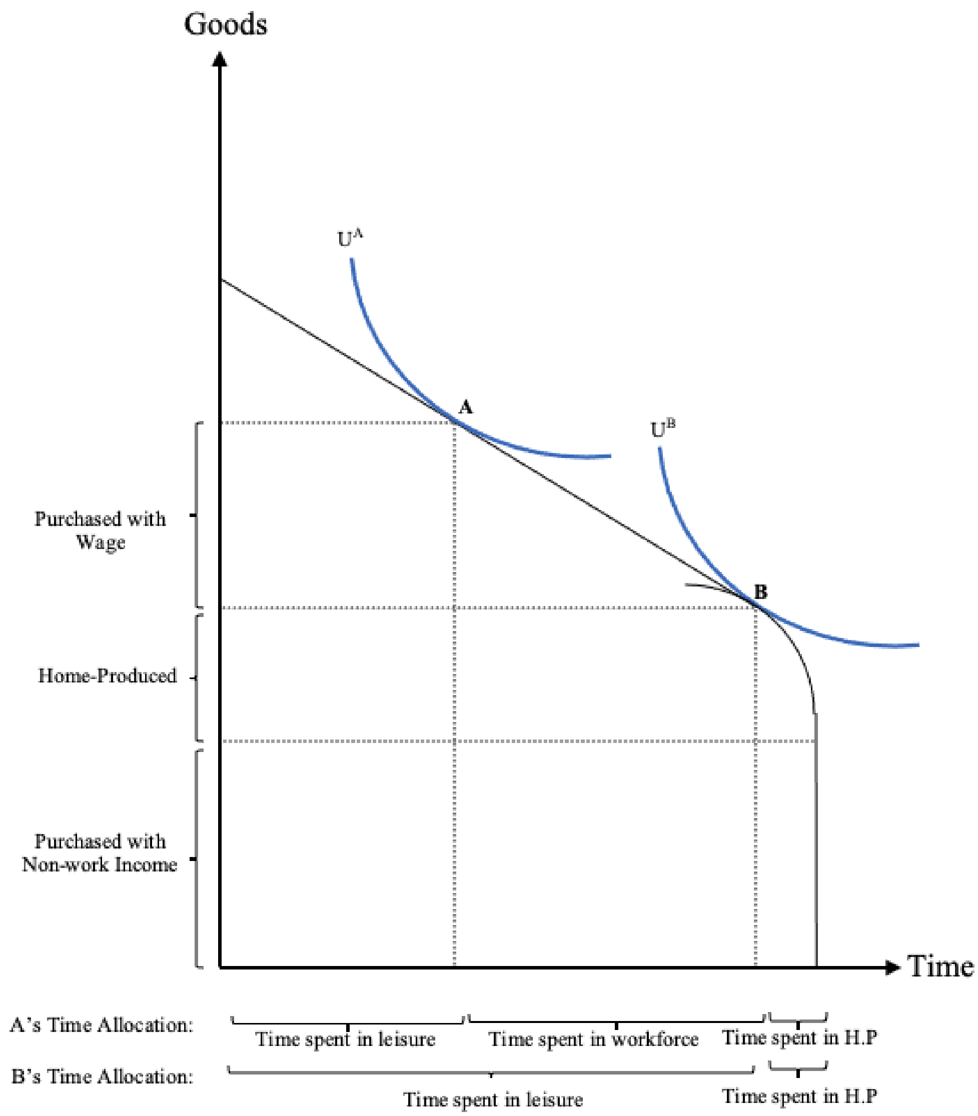
Mentioned earlier, the Duncan model is used to model joint maximization within households between the two partners. Goods within the Duncan model are split into 3 categories: goods purchased from wages, household production, and non-work income. The three categories can be seen below on the both X and Y axes in Figure 5. A person's time spent doing household production is dependent on the steepness of the wage slope, represented by the upper part of the "budget constraint", and curvature of the household production curve. An example of someone unemployed and maximizing household production is Person B in graph figure 5. In this particular case, person A and B are spending equal amounts of time in household production, where B is devoting all time outside of household production to leisure. However, since person A is on the wage slope, person A is able to spend time in the workforce by cutting time out of leisure.

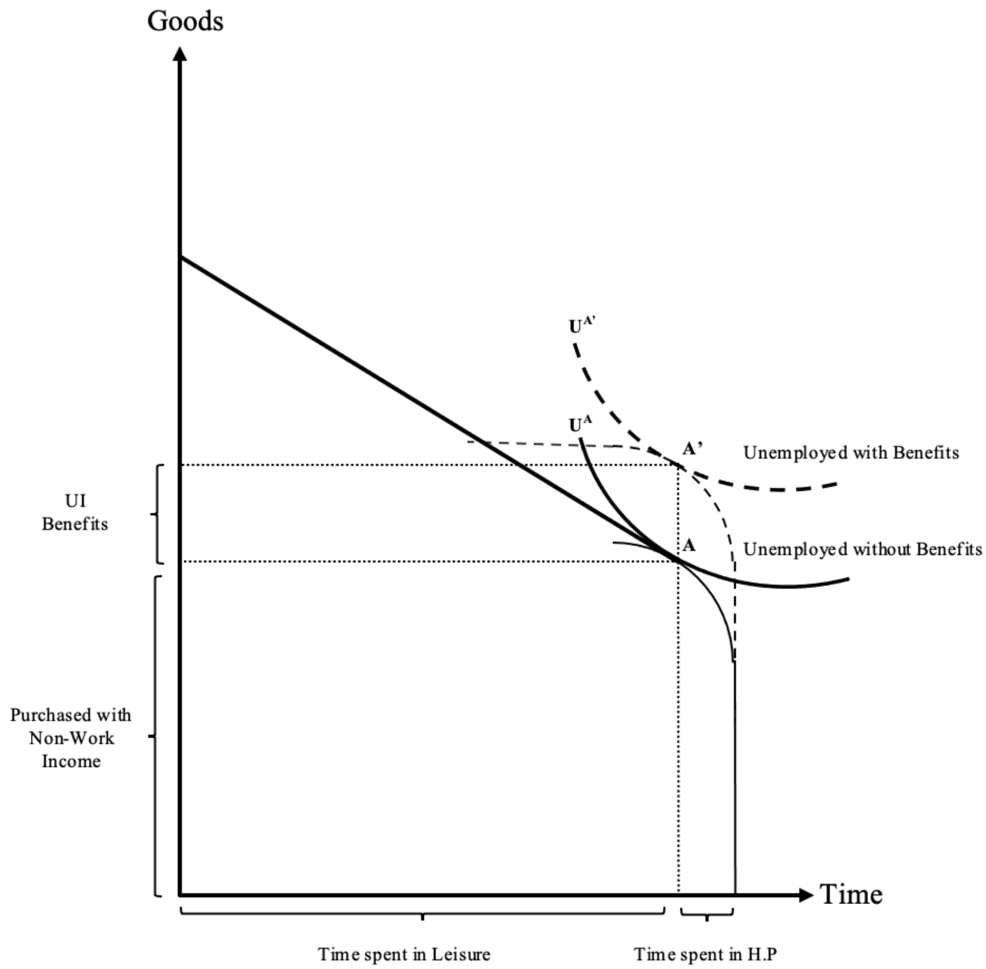
Figure 5: Duncan Model



3.3 Duncan Model During Federal Unemployment Insurance:

Similar to the regular labor-leisure tradeoff, there is a kink when UI is available to the unemployed. However, in the Duncan model, the kink— dotted in Figure 6— includes the household production function, as an individual will still be available for unpaid care while unemployed. Looking at figure 6, Person A is unemployed and splitting time between leisure and household production. However, once unemployment benefits are available, person A can now consume at A'. Person A's indifference curve moves up by the amount of UI benefits offered while keeping the amount of time spent in household production constant.

Figure 6: Duncan Model with Unemployment Benefits

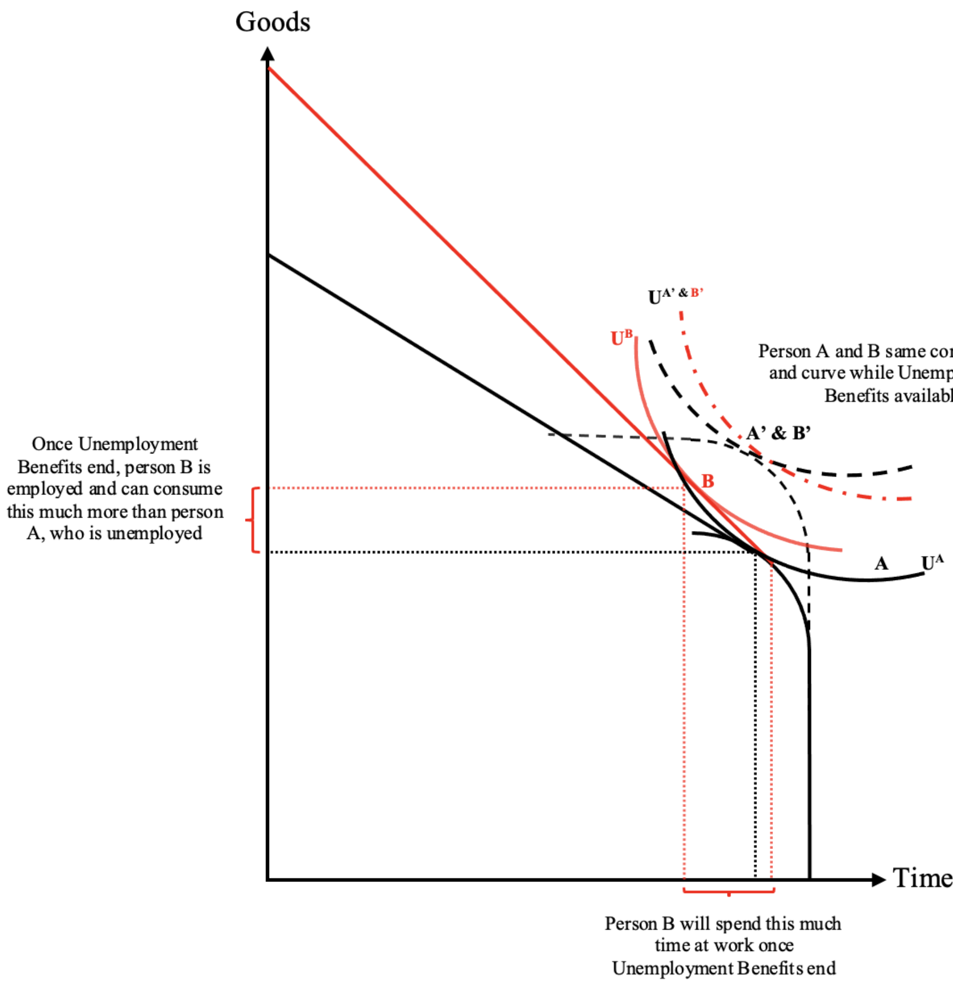


3.4 Duncan Model Different Wages and Production Curves:

An individual's decision to return to work will be dependent on available wages, when off UI, and household production. Throughout COVID-19, household production played an essential role for the working force, especially to parents— as more time spent at home resulted in greater duties and tasks requiring time investment. Once UI benefits are exhausted, we will be able to explain the deciding factors of employment or unemployment.

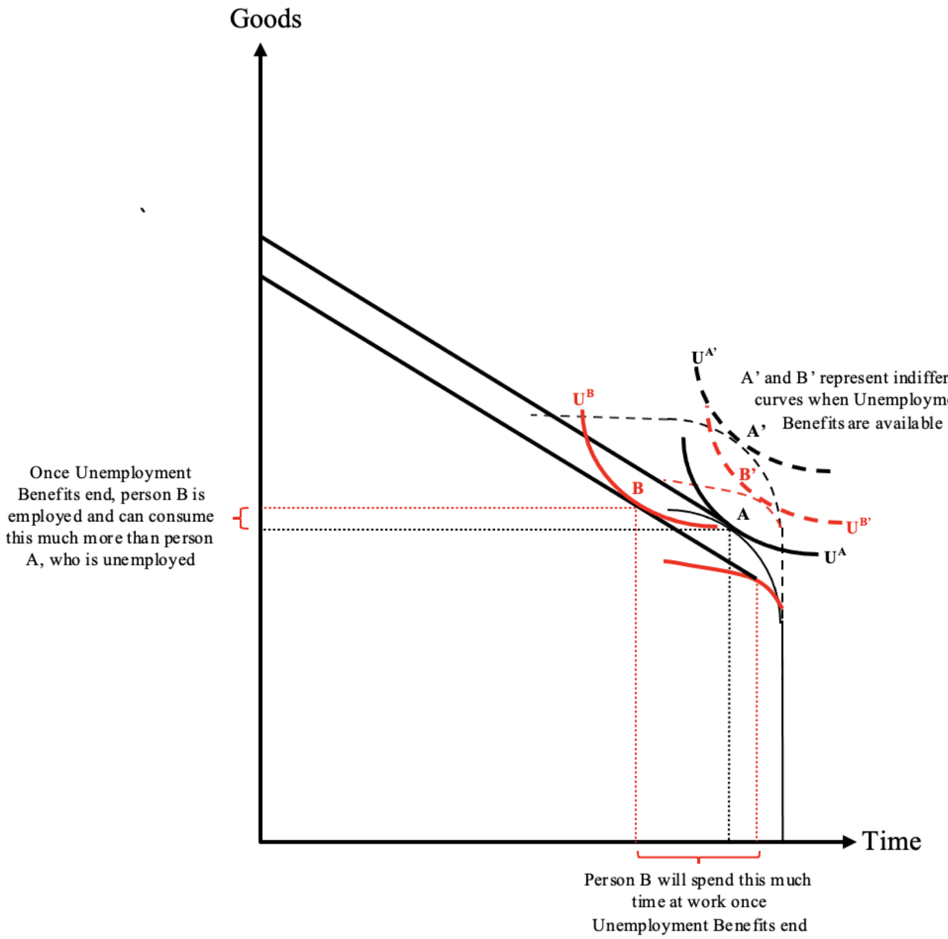
Let us model a situation where A and B have different available wages when off unemployment benefits. In this specific situation, A and B will have the same model except for differentiating wages represented by B having a steeper wage slope. Notice in figure 7, how A and B are consuming the same amount of goods when both are on unemployment benefits at A' and B'. However, once unemployment benefits are exhausted, B's red wage slope prompts the individual to work, while A's wage slope prompts the individual to remain unemployed.

Figure 7: Duncan Model with Different Wage Slope with UI



We proceed by constructing a model dependent on an individual's household productivity. Let A be more productive and face less diminishing returns to home-produced goods than B.[7] When on UI, A' has greater goods compared to B'– as being unemployed will result in more time spent at home and increase home production. However, as unemployment benefits end, B becomes employed while A does not as B's production function is flatter and the wage slope will be able to catch B.

Figure 8: Duncan Model with Different Production Function with UI



In conclusion, using the Duncan model, we will tend to see individuals with lower available wages and more convex production curves to remain unemployed. The nature of

[7] Person A will have a more convex production function compared to person B, meaning that person A will consume at levels yielding greater home produced goods.

different wages and household roles are the main driving mechanisms resulting in a higher unemployment rate for women throughout the pandemic. As states go off federal unemployment benefits, individuals unearned income reduces, and the wage rate or household production income will be the ultimate determinant regarding employment status according to theory and these models (Fry 2022).

Looking at both figure 7 and 8, I hypothesize the ending of UI benefits to impact the change of male unemployment more than the change of female unemployment. For my paper, person A will be a female while person B will be a male, since empirical evidence points towards females experiencing lower wages and more time spent in households. I have a null hypothesis where the difference between male and female unemployment will be zero, thus if my coefficient is statistically significant, we will be rejecting the null hypothesis and conclude the exhaustion of unemployment benefits heterogeneously impacts sexes differently.

4. Data Description:

I use the Current Population Survey (CPS) to identify the change of unemployment and labor participation rates during periods with and without unemployment insurance benefits. I use the UI initial claims data from the Bureau of Labor Statistics (BLS) to provide further state-wide background information regarding total UI claims in each state throughout the pandemic.

4.1 Current Population Survey:

The CPS is a monthly survey of individuals living in households conducted by the Census Bureau. The CPS is currently used to produce estimates on monthly statistics regarding workforce participation, employment, and unemployment that are closely watched by businesses, investors, and policymakers. The dataset uses a rotating panel structure, with households resurveyed for a number of months.

The survey provides detailed economic and demographic data representing everyone age 15 and over in the U.S who is employed, unemployed, or not in the labor force. For my study, I extracted every month from January 2020 to December 2021, which covers both rounds of the FPUC and periods of time before and after benefits. However, for my empirical analysis, I will only look at the year 2021. Each observation has a year, month, and state variable; allowing me to construct a dummy variable indicating if a respondent lived in a state with Federal UI in a given month.

The survey collects observational data from all 50 states, including several other territories. It follows individuals living in a household for 4 months, takes an 8 month break, then interviews them for another 4 months, meaning households follow a 4-8-4 pattern. Therefore, each observation is an individual who is repeated in the survey for a maximum of 8 observations in 8 different months. There are a few rare cases where households only appear once throughout the dataset, hence, I have a combination of both unique and repeated observations. Using the demographic information, I can subcategorize my observations into females, males, low income, race, mothers and fathers. This is critical for heterogeneous analysis on the effects of removing UI.

4.2 Bureau of Labor Statistics UI initial Claims Data:

The Bureau of Labor Statistics is a federal agency that collects data regarding the U.S economy and labor market. Relevant to my research, the BLS collects data on initial UI claims at a state-level and monthly frequency. The report segregates the initial claims by age, industry and sex. Since the CPS data does not include UI data, I will use the BLS data to depict trends in total UI claims throughout the scope of my study to visualize how male and female total UI claims correlate to one another.

4.3 Industry UI Statistics:

Looking at the gendered nature of work across industries, the top five industries by concentration of females were disproportionately impacted by COVID-19 compared to male dominated industries[8].

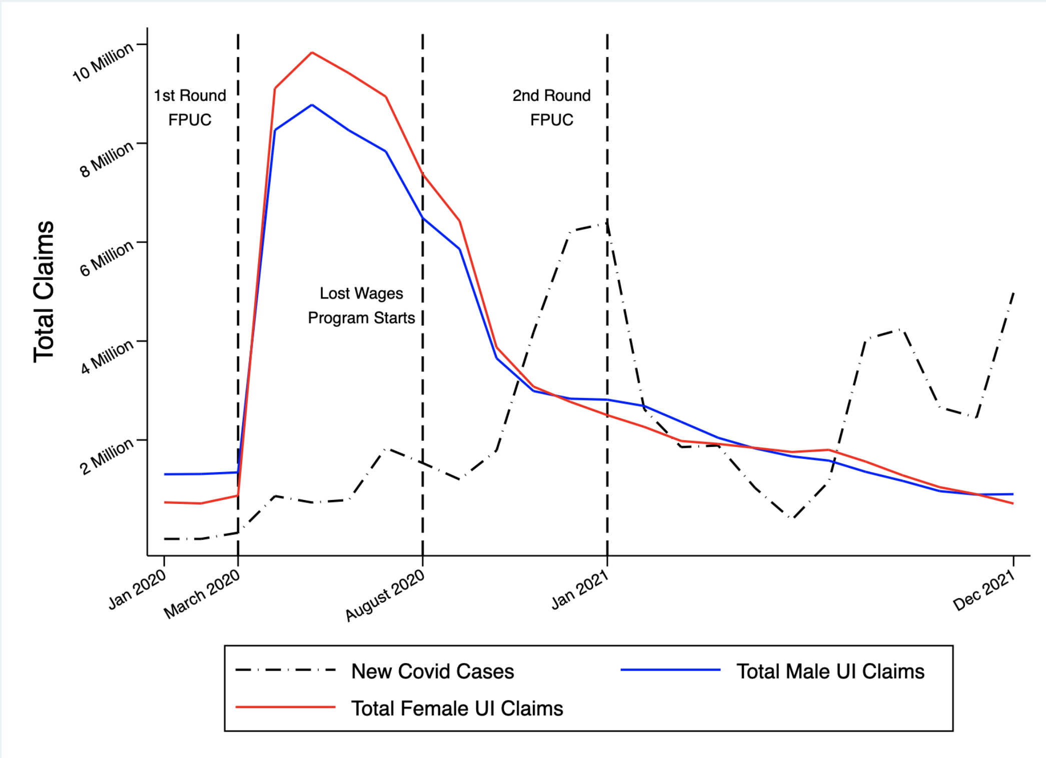
Figure 9: Industries by Percent Female February 2020

Percent Female	Industry
9%	Automotive Repair and Maintenance
11%	Construction
12%	Truck Transportation
24%	Architectural, Engineering, and Related Services
26%	Computer Systems Design and Related Services
76%	General Medical and Surgical Hospitals
76%	Educational Services
77%	Outpatient Care Services
80%	Individual and Famility Services
96%	Child Day Care Services

Child daycare services and schools were immediately shut due to shelter in place orders- most of which had trouble setting up telecommuting work in initial months of the pandemic. Male dominated industries, engineering and computer systems roles were able to transition more smoothly to telecommutable work while construction and truck transportation temporarily halted but gradually continued through the pandemic. This is supported by the trends in UI claims by sex during the first few months of COVID-19 using the BLS data in figure 11.

[8] COVID affected industries differently, as certain industries require more face-to-face interaction. I sort relevant industries by highest and lowest female employment in Table 1 using employment data in February 2020.

Figure 11: Unemployment Claims by Sex

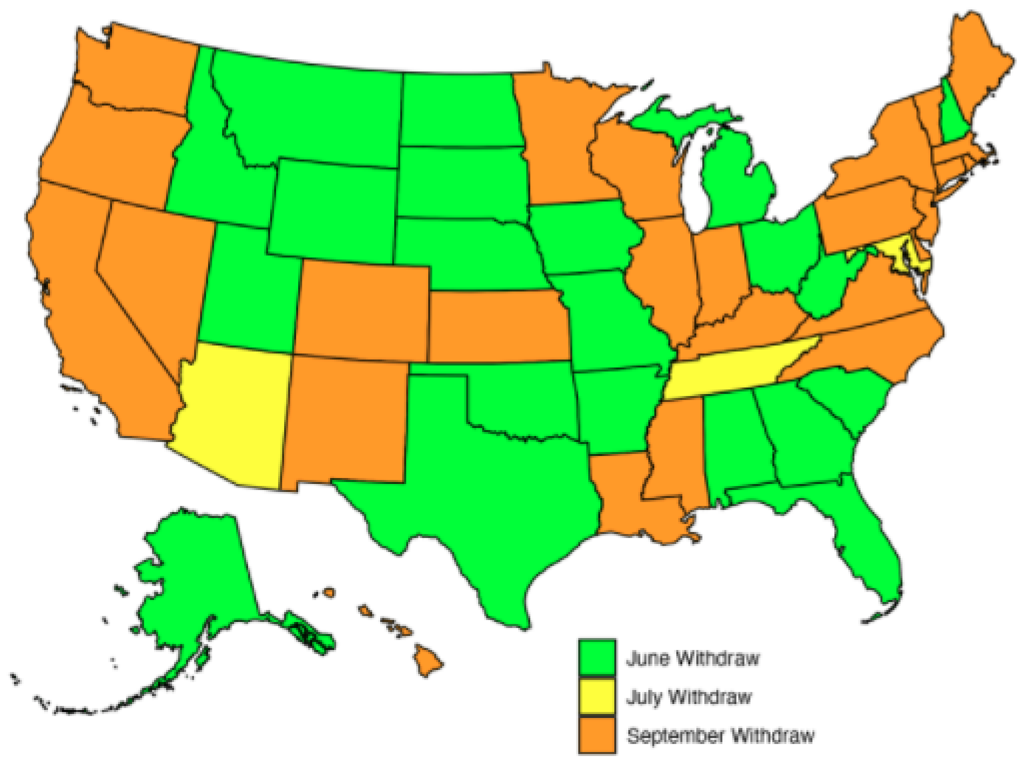


At the start of 2020, total male claims were significantly greater than total female claims, likely due to labor force composition as some industries have more turnover than others. In March 2020, total female UI claims outpaced total male UI claims when the FPUC started, meaning more females were laid off and filed for UI benefits in the early months of the pandemic. When the extra federal payments end in July 2020, we see the number of male and female UI claims become increasingly similar in trend characteristics. A Lost Wages program utilized FEMA funding to smooth consumption between the two rounds of stimulus payments.

I plot the total number of new covid cases within the US along with male and female claims. A spike in December 2020, attributed to the delta variant, led to a gap in male and female claims going into January 2021. The gap suggests that COVID decreased total female UI claims relative to males, which may be a result of many factors, from females dropping out of the labor force to an increased male unemployment rate.

During the second round of federal UI benefits in 2021, contrary to the $600 stimulus round, select states withdrew from the program earlier by cutting off the weekly installments of $300 2-3 months earlier. Below in Figure 12 I map out when each state withdrew from the program.

Figure 12: Federal Pandemic Unemployment Compensation Cutoffs



The June and July states made a decision to withdraw early after making claims that unemployment benefits are encouraging laid-off workers to stay at home instead of looking for jobs. Figure 13 depicts how many people are in UI states each month within the CPS dataset.

Figure 13: Observations in CPS Dataset

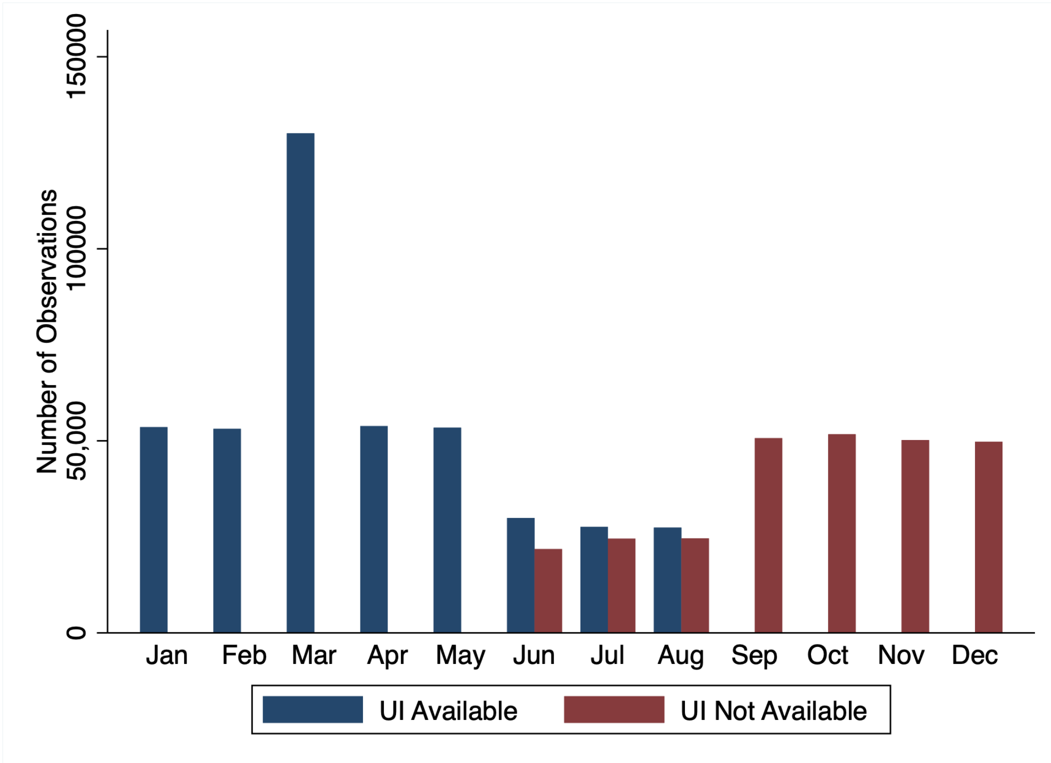
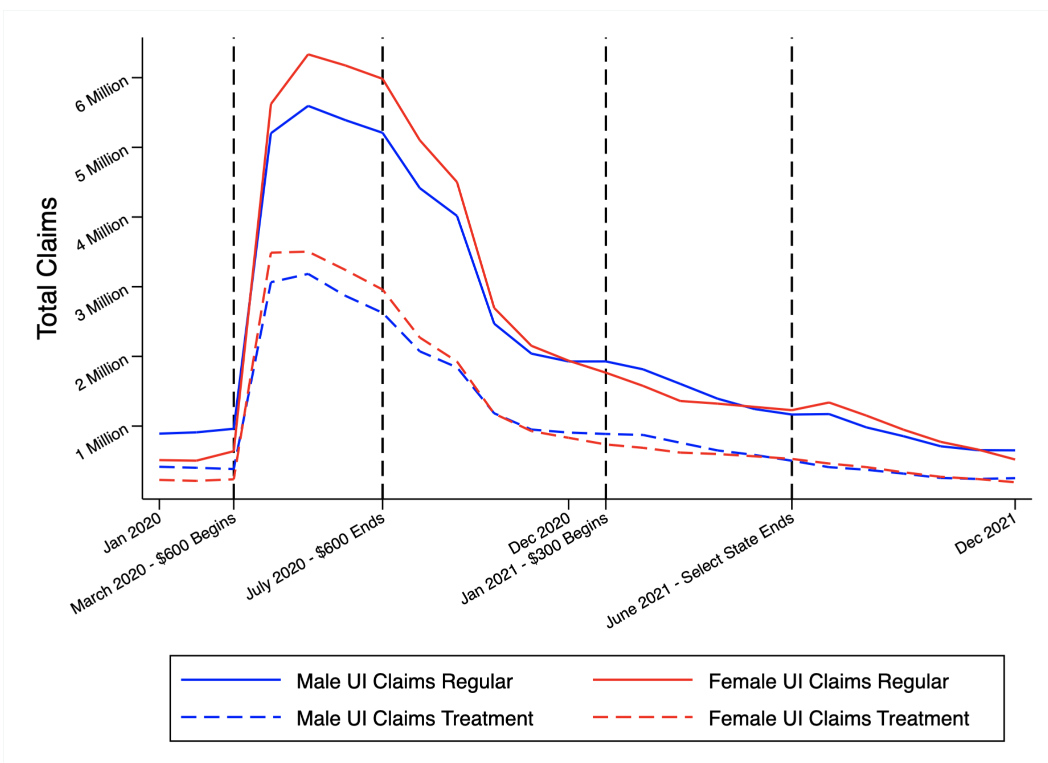


Figure 14: UI claims by Gender and Treatment

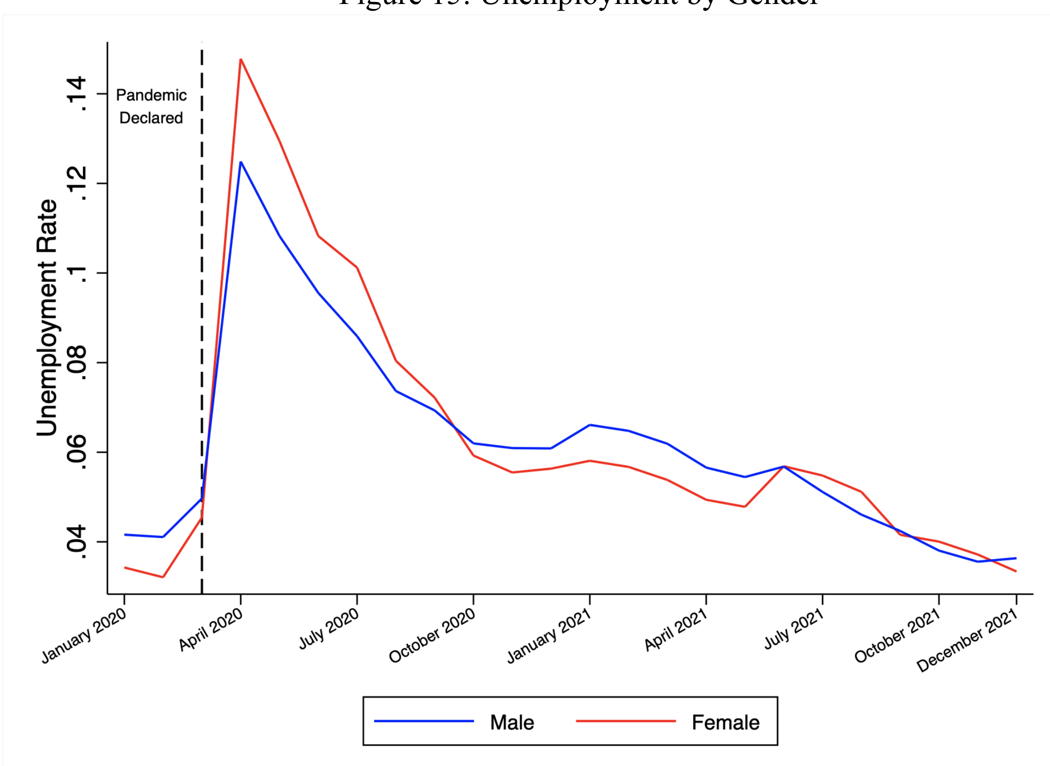


4.4 Unemployment Graphs:

In figure 14, I graph trends in total UI claims by gender and treatment status. "Female control" and "Male control" represent individuals in states that let UI expire at its original date in September rather than withdrawing from the program earlier in June. As treatment states withdrew in June 2021, we note a decrease in both male and female total UI claims, with males claims declining slightly more than females. Meanwhile, states that kept federal UI claims saw a continued growth in claims, more evident among females, the same period treatment group had a drop in claims.

Theoretically there should be a time lag between unemployment and filing for a claim as unemployment should lead to UI claims. Since my data is at a monthly frequency, we may not see this lagged observation, thus unemployment follows a similar trend to total UI claim trends. The overall unemployment trends by gender are displayed in figure 15 below.

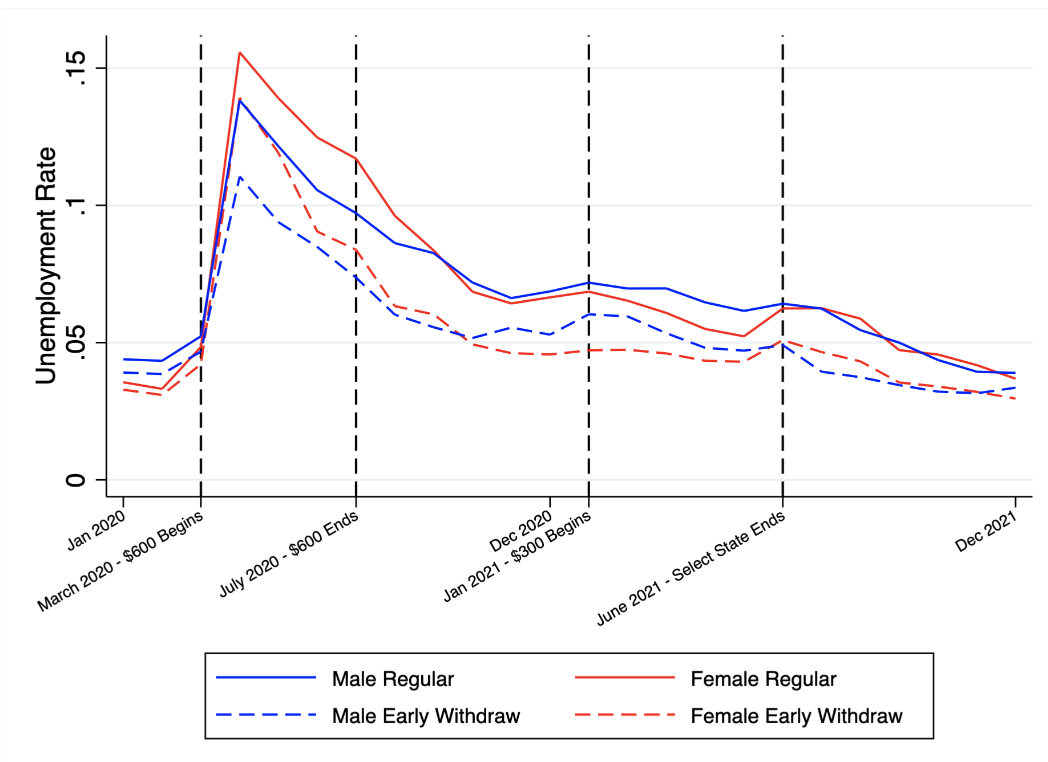
Figure 15: Unemployment by Gender



At the start of 2020, male and female unemployment rates were both below 5%, with male initially being higher than female unemployment. As soon as the pandemic hit, female unemployment jumped to 16% while men's increased to 13.6%. The gender difference disappeared gradually and both rates fell down around 6% in December 2020, this is surprising as some schools stayed closed so I would expect a gap to persist. However, during this time, women labor force participation dropped, leading to a lower unemployment rate.

We can see how gender played a role in determining trends. I plot treatment group vs control group by sex in figure 16.

Figure 16: Unemployment by Gender and Treatment

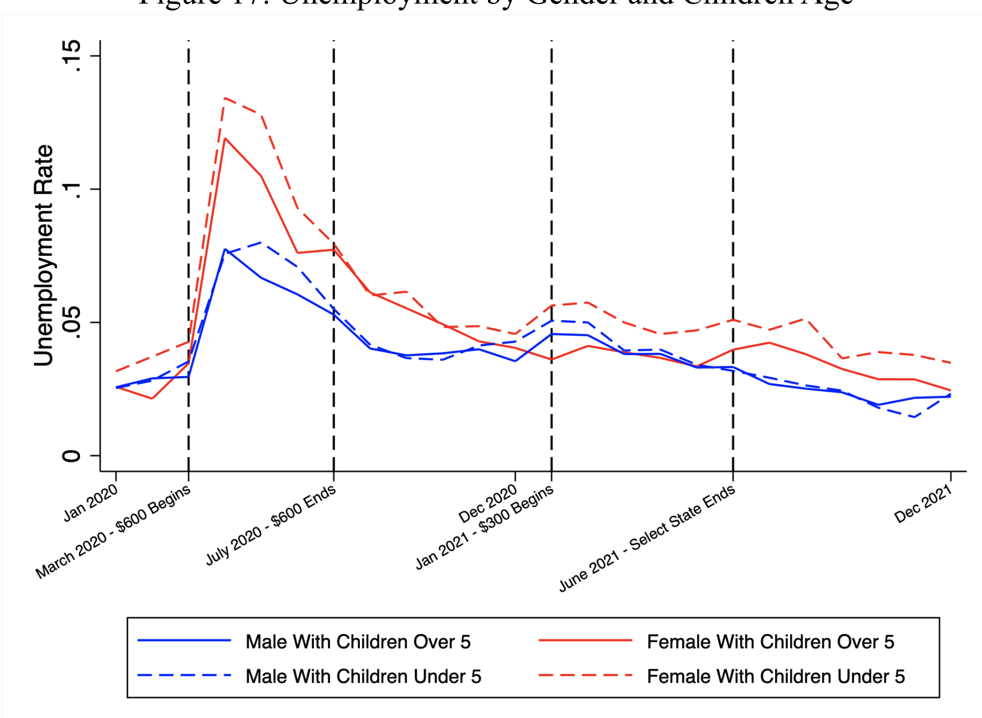


Within early withdrawal states, when UI expires, we note a greater decrease in male unemployment compared to female unemployment. While regular withdrawal states see nearly no significant change in unemployment between male and females, this graph suggests that when individuals have no access to additional federal UI benefits, males see a greater drop in unemployment than females.

We can see the differences in unemployment are small among the four groups at the start of 2020. However, as COVID-19 weakens the economy, female unemployment skyrockets the most in September withdrawal states, which are mostly democratic states by state legislature. Both female and male unemployment in control states are consistently higher than early withdrawal states. An anecdote explaining this mechanism is the harsh and more stringent protocols taken by states under Democratic party control- which ultimately lead to restricted economic activity and higher chance of unemployment among industries that have difficulty going remote (Goolsbee et al. 2020).

In figure 17, it seems that females with children under 5 consistently have higher unemployment rates than females with children over 5. Males seem to have unemployment rates independent of children's age.

Figure 17: Unemployment by Gender and Children Age



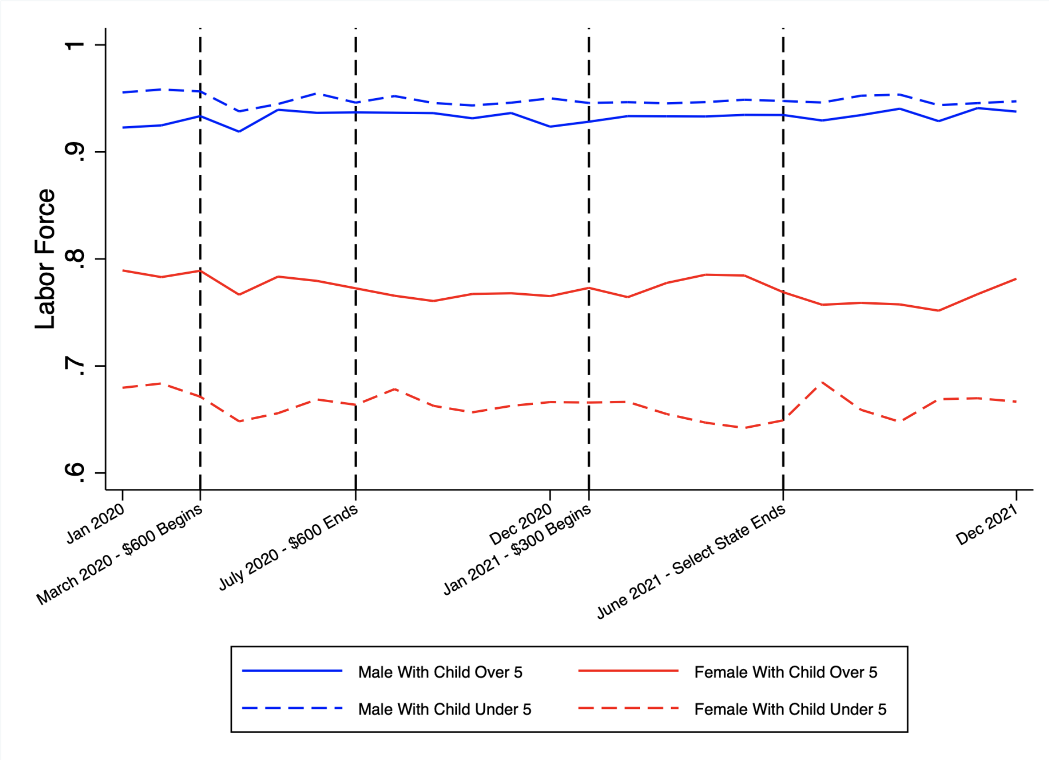
In the U.S, it is standard practice to send children under the age of 5 to daycare. Males are not sensitive to whether they had a child under 5 or not, while females with children under 5 saw greater unemployment rates throughout the pandemic compared to females with children over 5. In fact, males with children under and over 5 behave nearly the same as unemployment benefits end. This is similar to the graph above regarding labor participation by gender and children's age. Before the pandemic, females with children under 5 saw the greatest unemployment out of the four groups. Again, this implies females had an disproportionate amount of unpaid care that ultimately left them voluntarily or obligated to quit their jobs.

4.5 Labor Force Participation Graphs:

It is important to consider labor force participation as employment and unemployment rates are divided by labor force. Throughout the pandemic, women's labor force participation has been declining as a result of additional burdens in the form of needed caregiving and household responsibilities. In order to claim UI, the claimant must be in the labor force actively looking for a job.

Several strong predictive factors in deciding labor participation are children and age of children. Figure 18 analyzes how labor force outcomes sex are dependent on children's age among parents. It is interesting to see how male labor force participation is not influenced by children's age, as both "male with child over 5" and "male with child under 5" hardly differ in labor force participation rate, similar to figure 18 above. Household and childcare responsibilities increased for many during the pandemic, but gender inequalities were most evident among those with children. The gap between "female with child over 5" and "female with child under 5" stays consistent throughout the duration of the pandemic.

Figure 18: Labor Force Participation on Gender and Child Age



4.6 Control Variables:

Control variables are necessary to parse out a casual relationship between individuals and periods on and off of UI. This is because control variables will be able to reduce potential bias caused by omitted variables. The control variables used in my study are age, income, race, and education, all of which may affect employment status and unemployment benefits. Other studies have used similar control variables when measuring labor force outcomes (Aaronson et al. 2021).

4.7 Wage and Work Gap During Pandemic:

Male and females were exposed to different wages throughout the pandemic. Looking at data from 2020 to the end of 2021, females, on average, made 2.31 dollars less in hourly wages. This is important in the context of returning to work after UI programs expire as higher wages will prompt individuals to be more inclined to work. Table 2 below highlights the overall difference in hourly wage between males and females (CPS, 2021).

Table 2: Differences in Wage

	Male	Female	Difference	Standard Error
Average Hourly Wage	21.13	18.82	2.31***	0.0541

Note: *,**,*** mean significance at the 1, 5, and 10 percent level. Standard error is the standard error of the difference.

According to the American Time Use Survey, in terms of providing secondary childcare, which refers to childcare while doing something else, men averaged 4.9 hours per day while women averaged 7.1 hours per day in 2020. The Annual American Time Use Survey also states that men spent an extra 16 minutes per day on housework in 2020, compared to 2019. However, women spent an average of 2.4 hours per day on household work and unpaid care as opposed to 1.6 hours spent by men (MacLellan 2021). Women had to scale back work hours to tend to responsibilities within the household, this effect is more apparent among married individuals. This is shown as we summarize work hours per week below based on marriage status throughout the year 2020 in table 3.

Table 3: Hours Worked

Average Hours Worked per Week	Mean	Standard Error	Total
Married Male	42.74	0.017	365,587
Non Married Male	39.43	0.022	272,772
Married Female	37.78	0.020	305,236
Non Married Female	36.99	0.022	281,577

Note: All Data is from the years 2020-2021 from the CPS.

The gap between married male and females is much greater than between non-married females and males. Furthermore, the standard deviation is greater for married females compared to married males, implying that their hours fluctuate more from the mean throughout the pandemic.

Furthermore, we can see that a disproportionate number of the cases for why women are absent from work are due to “family responsibilities”, “child care problems”, and “maternity” in table 4. The difference in household production and unpaid care is reflected in the Duncan Model by a flatter production function curve in figure 8.

Table 4: Reasons for Absence from Work

Reason for Absence from Work	Male	Female	Difference	Standard Error	Total
Child Care Problems	17%	83%	65%***	0.0336	508
Maternity/Paternity	13%	87%	74%***	0.0120	2,947
Other Family/Personal	34%	66%	32%***	0.0186	2,585
Vacation Personal Day	44%	56%	12%***	0.0074	17,867
Own Illness/Injury	48%	52%	4%***	0.0088	12,745
School/Training	42%	58%	16%***	0.0312	1,006
Other	48%	52%	5%***	0.0080	15,539
Total	24,239	30,380			54,619

Note: *,**,*** mean significance at the 1, 5, and 10 percent level. Standard error is the standard error of the difference. Standard errors are clustered at the state-level.

5. Empirical Strategy and Results:

We need to understand the mechanisms connecting changes in unemployment rate to the expiration of federal unemployment benefits. Specifically, how gender plays a role between exhausting UI and unemployment. I use two specficiations of statistical models to explain how sex plays a role in unemployment rates once states are off federal programs. The following effects I find are consistent with Albanesi et al (2021). Females have slower “recovery” rates in periods of economic recovery than males. A recovery period defined in this study is defined as periods after UI is terminated.

It is important to reiterate how I do not have individual data on who is on unemployment insurance or not, however, I do have individual data on who is unemployed. My OFFUI300 variable indicates when an individual is in a state with federal unemployment benefits at the specific month rather than when the individual is enrolled in the UI benefits.

5.1 Regression -Two Way Fixed Effect:

I will use a two-way fixed effect model to see how being in a state during periods with federal UI benefits impacts labor market activity. My model takes the general form below:

$$Y_{it} = \beta_0 + \beta_1(OFFUI300_{it}) + \beta_2(Female_i) + \beta_3(OFFUI300_{it}\, X\, Female_i) + \gamma_t + \rho_i + \sigma X_{it} + \epsilon_{it}$$

Y_{it} is an individual i's employment outcome at month *t* within the year of 2021. The independent variable will take a value of 1 if unemployed and 0 if employed. β_1 is the difference in unemployment rate between men on and off unemployment insurance. β_2 represents the marginal effect of being female for being in states when UI is offered.

My coefficient of interest is β_3, an interaction of two dummy variables: access to federal unemployment insurance and female. β_3 represents the marginal effect of being female and off UI, or in other words how transitioning off UI will impact females differently than males. A positive value for β_3 implies that females saw a smaller decrease in unemployment compared to males after transitioning out of unemployment insurance.

The month fixed effect, γ_t, is the indicator for each month of the year within 2021. This controls for variations caused by shocks in different months in 2021. The state fixed effect, ρ_i, is an indicator for each of the 50 states in my sample. This controls for different state level policies, other than UI300, that would influence unemployment levels. A rich set of controls, σX_{it}, account for the individuals age, race, education and industry of current or most recent employment. The purpose of these controls is to remove other possible observable explanations for change in labor market activity throughout the pandemic. My data is at the individual level where we are informed of the individual's state of residency, thus we are able to aggregate unemployment up to a state level unemployment rate to use state fixed effects. ϵ_{it} is the stochastic error term, representing variation not explained by my model, most noticeably state-level policies.

The OFFUI300 dummy variable is 1 for all periods when an individual was in a state without extra UI benefits. Female is a dummy variable taking on a value of 1 if the individual classified themselves as a female and 0 if not.

The focus of the model is to isolate how labor market outcomes changed among males compared to females as federal benefits exhausted. The coefficient β_3, should theoretically be zero if females and males were equally affected when UI programs expired. My alternative hypothesis is that the β_3 coefficient is not equal to zero[9].

5.2 Two Way Fixed Effect Results:

In this section, I look at the regression results from the two way fixed effect difference-in-difference model. In table 5, I run the model with and without controls.

[9] In particular I believe the coefficient to take on a value greater than zero as increase in female unemployment is expected to be higher than increase in male unemployment explained by the premises of the Duncan model.

Table 5: Two Way Fixed Effect Results

Female Change in Unemployment Compared to Males	No Controls	Controls
After FPUC Withdraw	0.00711***	0.00715***
	(0.00107)	(0.00149)
Observations	702,317	702,317
R-squared	0.002	0.045

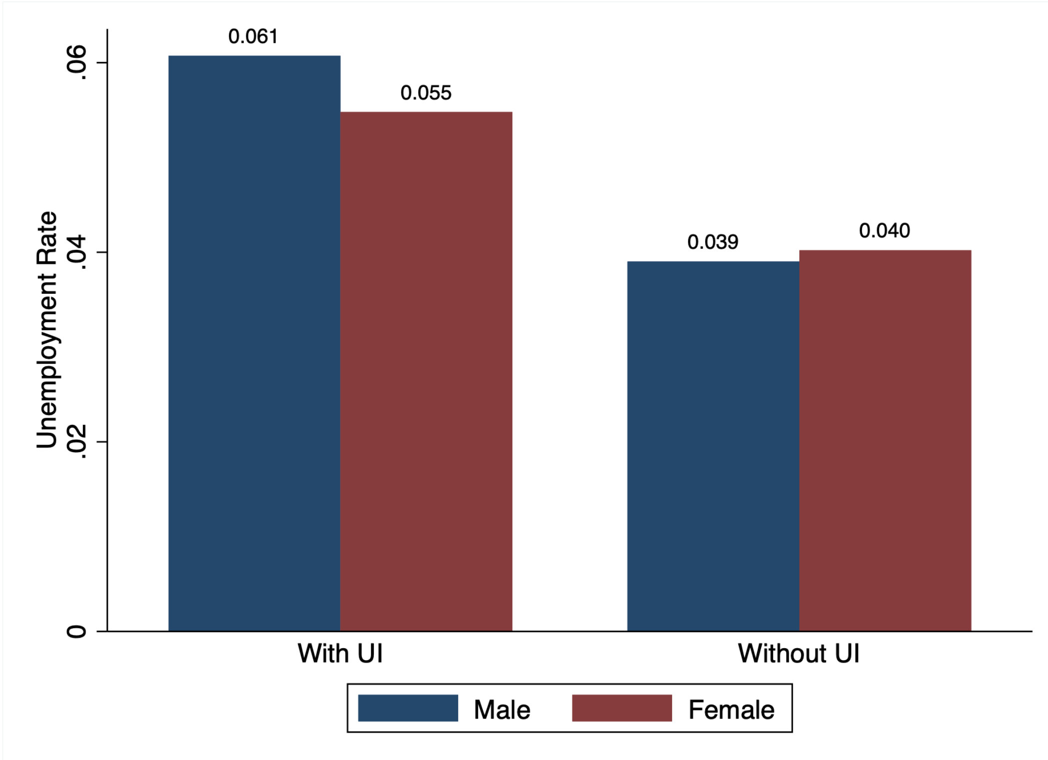
Note: *,**,*** mean significance at the 1, 5, and 10 percent level. Standard Error are clustered at State-level. After FPUC withdraw is the β_3 coefficient from model 1.

When I regress unemployment on an interaction between sex and UI, we can see the expiration of UI impacts female unemployment differently than males. The regression states the difference between female and males off UI and the difference in female and males on UI is 0.715 percentage points, the β_3 coefficient for the regression with controls. This suggests that male unemployment dropped more than the drop in female unemployment by 0.715 percentage points. Although 0.715 percentage points may seem like a small number, relative to the male unemployment of 6.10%, the effect is 11.71% of the male unemployment rate during UI. The effect can be visually represented in Figure 19 and calculated in table 7. With UI, male unemployment was greater than female unemployment, however, without UI, overall unemployment levels dropped, but males dropped more than females to the point where overall male unemployment is lower than overall female unemployment.

Table 6: Calculating Difference in Difference

	Difference in Unemployment (WithOutUI - WithUI)	Difference	Difference in Difference (Female Diff - Male Diff)
Male	0.039-0.061	= -0.022	0.007
Female	0.040-0.055	= -0.015	

Figure 19: Difference in Difference



I combined the effect of coefficients to obtain the overall effect of gender and UI availability status. I tested the three coefficients and tested to see if they were equal to males on UI. Being female, while conditioned on being in a state with UI, generally reduces the chance of being unemployed by 0.706 percentage points compared to males on UI, as seen in table 7 below. However, in our regression, the interaction term assumes going off UI will affect females differently than males. The difference between females and males off UI is 0.005 percentage points. The interaction term's coefficient is 0.711 percentage points, which almost effectively cancels out the female "advantage" during UI. When there is no longer access to federal UI benefits, the gap between men and women closes relative to men. This implies that men may be more motivated to return to work when benefits end, than females are. The overall effects of combining coefficients along with standard errors are displayed below in table 7.

Table 7: Linear Combinations of Coefficient

Overall Effect - Compared to Male & On UI				
	Coefficient	Std. err.	[95% Confidence Interval]	
Male & Off UI	-0.00677***	0.00149	-0.00970	-0.00384
Female & On UI	-0.00706***	0.00086	-0.00876	-0.00537
Female & Off UI	-0.00669***	0.00148	-0.00959	-0.00378

Note: *,**,*** mean significance at the 1, 5, and 10 percent level.

5.3 Two-way Fixed Effect - Heterogeneity Analysis:

I now examine certain characteristics that might influence the magnitude of change in unemployment among females. I do so by including a triple interaction on OFFUI300 x Female with one of the 5 different dummy variables. The coefficient on the triple interaction terms are displayed below in table 8. The regression value of 0.00465 in equation 1 is interpreted as follows: This suggests that female, without children, unemployment dropped more than the drop in female, with children, unemployment by 0.465 percentage points— 11.6% of average female unemployment off UI.

The most notable effect is how interacting income levels affect unemployment change among females, where lower income households saw greater magnitude in change of unemployment than higher income households. More people from low-income households make up UI recipients, as replacement rates will be more attractive to them. Lower wage females experience a 1.18 percentage point change compared to females in high income households, where they only experience a .0912 percent point in change. The difference is consistent with theory as lower wage families will tend to have flatter wage slopes available to them once UI expires, ultimately choosing the household production curve rather than employment in the Duncan Model. Having greater leisure and household production time will be more beneficial for women who face lower wage jobs in the labor market.

Table 8: Heterogeneity Analysis

Change in Unemployment Compared to Females	Children	Children Under 5	Bottom 20th Percentile	Top 20th Percentile	Married
Children	0.00465**				
	(0.00205)				
Children Under 5		0.00530			
		(0.00328)			
Bottom 20th Percentile			.0118***		
			(0.00451)		
Top 20th Percentile				0.000912	
				(0.00212)	
Married					0.00435**
					(0.00162)
Observations	702,317	702,317	702,317	702,317	702,317
R-squared	0.045	0.045	0.045	0.045	0.046

Note: *,**,*** mean significance at the 1, 5, and 10 percent level. Standard errors are clustered at the state-level.

Children's age also impacts female unemployment rates once UI expires- where females with children 5 and under have a greater increase compared to having children in general. There is a great demand for time and resources when families have a child under 5. Higher levels of time investments can be reflected by a more convex household production curve or a flatter wage slope– a reflection of change in opportunity cost. When federal UI benefits expire for everyone, the percentage of unemployment among females with children under 5 decreased by .530 percentage points less than the change in unemployment among females with no children under 5. The standard error for the coefficient is relatively high compared to the estimate, however, this may be a result of the under-represented portion of females with children under 5 in our dataset.

Married individuals have a noticeably lower difference in unemployment rate compared to the average effect among all females. Previous studies point to single adults staying with their parents during Covid-19, contributing to a greater unemployment number (DePaulo, 2018). This effect is prominent among unmarried women, as they have historically dealt with greater unemployment levels and longer unemployment duration (Boushey 2010).

Table 9: Income Sensitivity Analysis

Sensitivity Analysis Difference from Female Average	Bottom 10th Percentile	Bottom 20th Percentile	Top 40th Percentile	Top 20th Percentile
Bottom 10th Percentile	0.0180**			
	(0.00718)			
Bottom 20th Percentile		0.0118***		
		(0.00451)		
Top 40th Percentile			0.00538***	
			(0.00145)	
Top 20th Percentile				0.000912
				(0.00212)
Observations	702,317	702,317	702,317	702,317
R-squared	0.037	0.035	0.024	0.021

Note: *,**,*** mean significance at the 1, 5, and 10 percent level.

Income has a prominent effect on how individuals react when going off UI. We can see that females in the bottom 10th percentile of family income see their unemployment levels increase 1.8 percentage points higher than the average female off UI. This effect decreases in magnitude as we go towards the top 20th percentile. The top 20th percentile of family income has an insignificant coefficient of .09 percentage points at the 10% level. Unfortunately, we cannot model trends prior and after treatment with this specification.

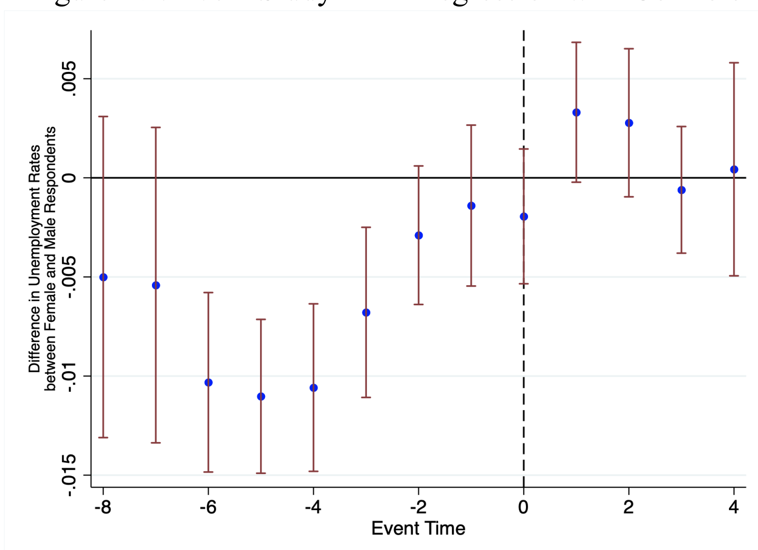
5.4 Event Study Specification:

Mentioned earlier, states experience the withdrawal of unemployment benefits at different times. A majority of the states were treated in June, 3 in July, and the rest in September, therefore we have a staggered treatment effect. An advantage of using an event study regression as opposed to the earlier specification above is that I can disaggregate the beta coefficient effect and can see the magnitude and trend for differences in unemployment prior and after expiration of federal UI benefits.

$$Y_{it} = \alpha + \sum_{\tau=-8}^{4} \beta_{\tau}(FEMALE_{i} X\, MONTH_{t}) + \gamma_{t} + \rho_{i} + \sigma X_{it} + \epsilon_{it}$$

In the equation above, I have information regarding months from 8 months prior to UI expiration to 6 months after expiration. I plot the difference between female and male unemployment along with their standard errors below in my event study results. Similar to my first specification, I have state and month fixed effects. The coefficients are displayed in regression result tables along with their standard errors. The main regression with controls is in table 10 in appendix A as well as graphical representation in figure 20.

Figure 20 : Event Study Main Regression with Controls



Note: Standard Errors are shown above with the 95% confidence interval graphed above. This is the same for all graphs

In the main event study of regression with controls, we do not have a stagnant trend before the event date, rather we can see an upward trend in differences as we approach the event date and onwards. The difference in unemployment becomes significant at the 10% level 1 month after UI exhausts. The results suggest that during periods when states have access to federal unemployment insurance benefits, male unemployment rates were greater than female unemployment rates, the most notable magnitude difference being 6-4 months before UI exhaustion. However, as we approach the event date, the difference becomes smaller and eventually becomes positive once UI expires, suggesting that female unemployment rates gradually increased to a point greater than males once past UI expiration.

5.5 Event Study Heterogeneity Analysis:

Figure 21: Event Study Children

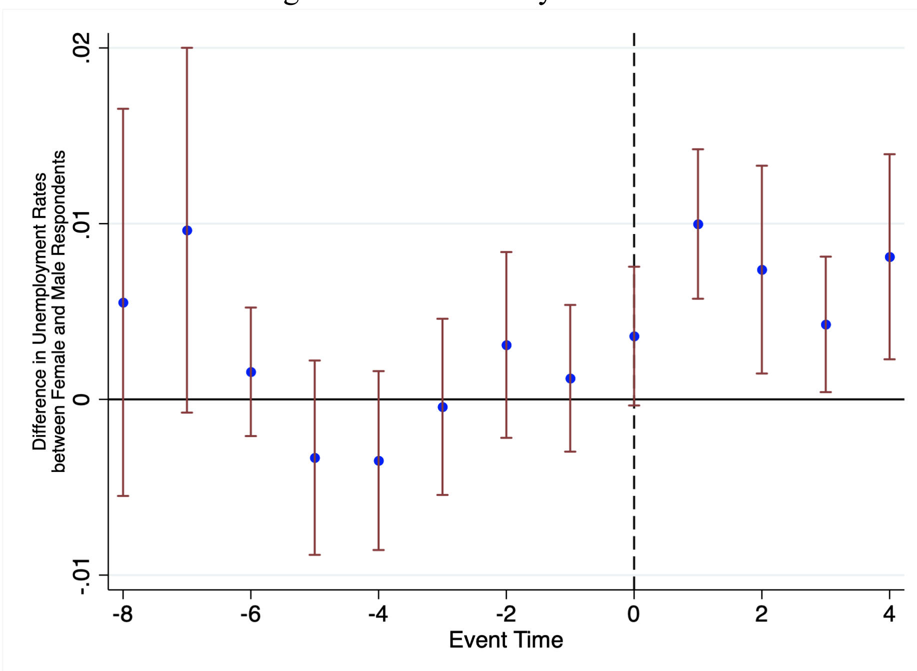


Figure 22: Event Study Children Under 5

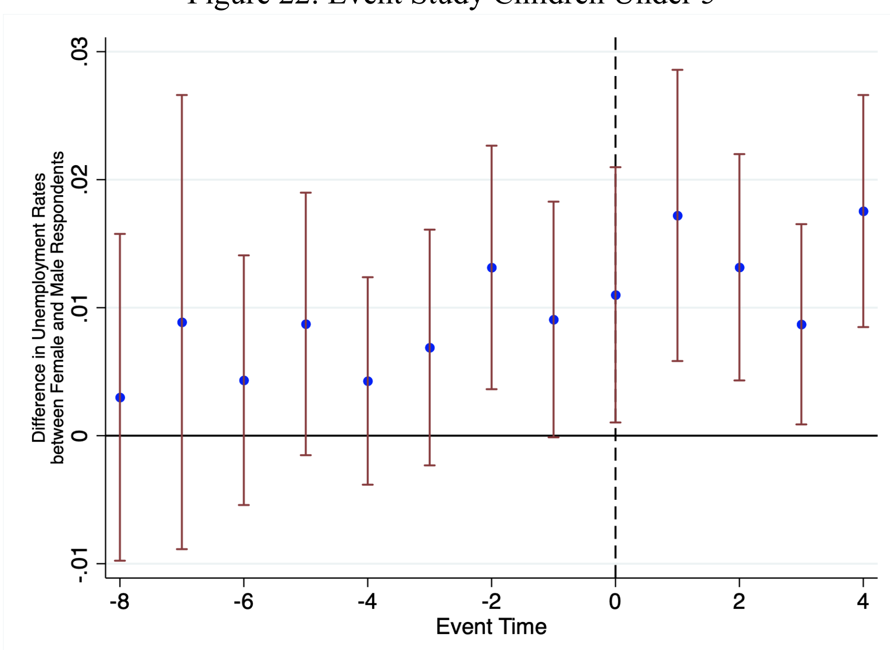


Figure 23: Event Study Bottom Family inc

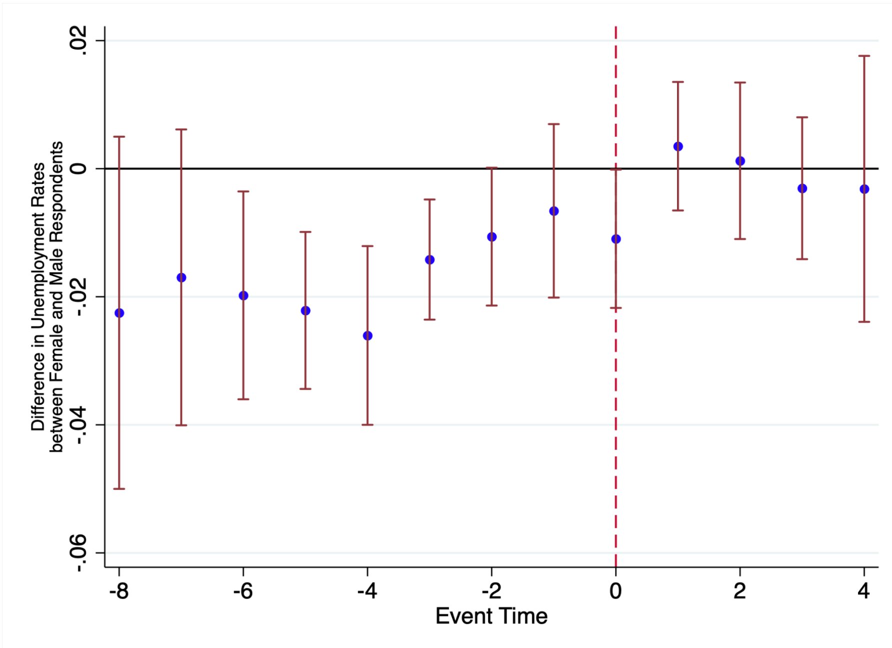


Figure 24: Event Study Top Family inc

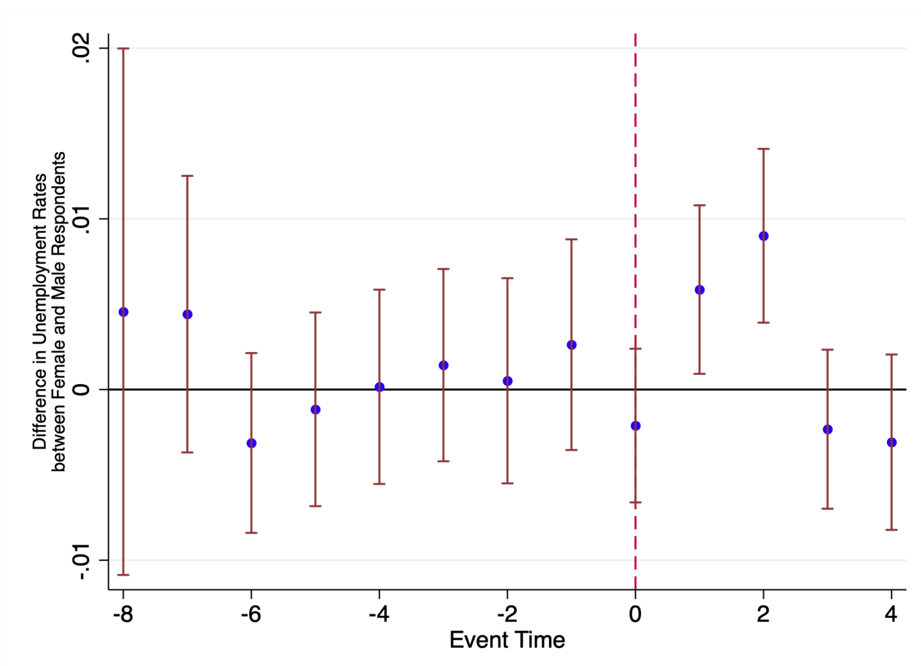
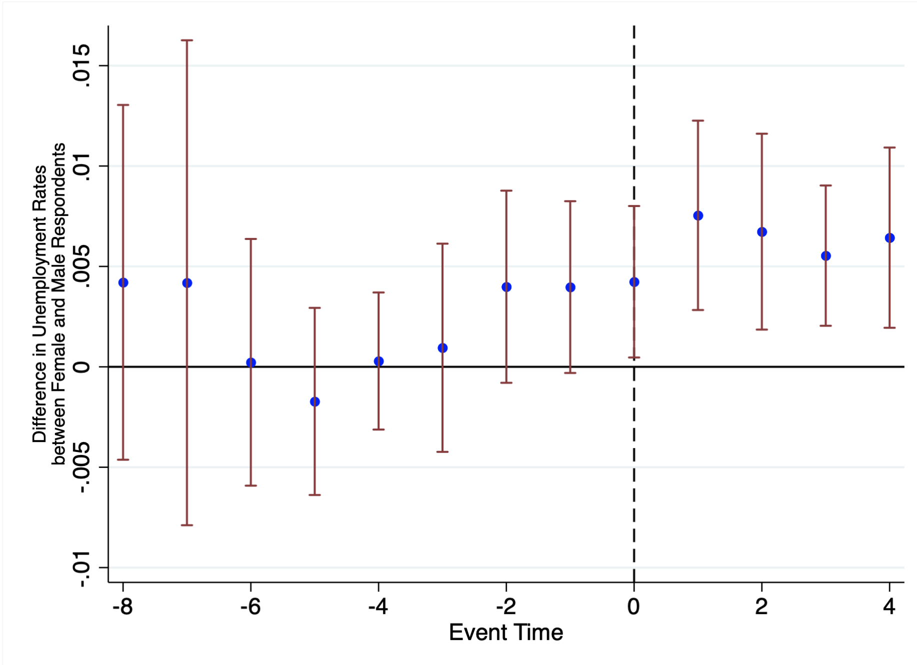


Figure 25: Event Study Married Individuals



Using the same heterogeneous analysis approach as our fixed effect specification, we can break down interesting trends around UI expiration for specific subpopulations. The coefficients for all heterogeneous regression models are displayed in appendix A table 11.

Among the regressions run on children, children under 5, and married individuals, all four months after UI withdrawal lead to a significant difference between female and male unemployment at the 5% level. In the context of the Duncan model, individuals with children, especially under the age of 5, tend to have an unproportional burden of household production and unpaid care placed on females. In married households, stereotypes and roles are more prevalent. Persistent social norms of mothers as primary caregivers contributing to different production functions between males and females. Due to different structural changes in the labor-leisure tradeoff, females will experience a smaller flow of unemployment to employment once UI is unavailable.

Within lower and higher income households, interesting patterns of differences emerge once UI benefits expire. Lower income households have a near 0 difference in unemployment among females and males, however, higher-income households have significantly greater female unemployment. If you are unemployed around expiration date and the other person makes a high level of income, you are more likely to be a female. On the other hand, if you are unemployed and the other person makes a low-level of income, you are equally likely to be female or male.

5.6 Limitations:

Although I have information regarding which states have UI, I do not have information regarding who has UI. Therefore I am capturing the effect of an individual being in a state that offers federal benefits rather than an individual enrolled in the program. Since I do not have a measure of UI at state-level , we can only regress unemployment on an indicator if the state is offering federal benefits. I do not have any data on whether the individuals in my sample are aware of the policy changes and are responding specifically to them. Therefore, it is difficult to infer direct causality between FPUC expiration and unemployment because I assume the majority of people in the state are aware of policy changes and act accordingly because of the policy change.

Using a fixed effect approach, it is difficult to parse out heterogeneous treatment effects due to the difficulty accounting for how states react to the policy differently. If the expiration of federal UI benefits has effects that are constant across states and over months, I will then have an unbiased effect. However, it is unlikely that UI programs impacted all states the same way. For example, without the CARES Act, Massachusetts has weekly unemployment benefits of $823 while Missisispi’s weekly benefits are around $235. It is a fair assumption that the extra $300 dollars a week will have a much greater impact on unemployment rates in Mississippi than it would in Massachusetts (Chaisemartin et al. 2019). Future research should limit the empirical approach to states with similar characteristics to control for heterogeneous treatment effects.

Another drawback for both regressions would be endogeneity caused by state specific shocks, as there are always state specific policies that affect unemployment, such as shelter in place orders and minimum wage. States may potentially implement policies related to unemployment during the pandemic that may be a significant driver in variation of unemployment within the state. For example, daycares may have opened up in the state of Michigan in the month of June, the same date as the state's FPUC withdrawal. The event study model will not be able to subtract out the effect of daycares opening on unemployment.

The states that withdrew first also tend to be republican states. Future research should implement a placebo test. What if the government had announced the withdrawal date earlier? We can then question if individuals exhibit the same return to work and spending behavior. A placebo test will often allow us to observe the differential trends in each state of a person who is unemployed. Fixed effects can only get us so far to control for different state governing policies.

6 Discussion:

There has still been a wide-debate with different papers drawing conflicting conclusions as to whether UI programs disincentivize employment. I use the Duncan model to explain how differences in wage and household production can dictate whether an individual returns to work after being on government income. Throughout the pandemic, females have dealt with the longstanding problem regarding wage gap and disproportional unpaid work load. In addition to these disparities, industries highly represented by females were most affected by the nature of the pandemic. COVID-19 evidently negatively impacted females greater than males, as we can measure via labor market outcomes.

How do UI withdrawals impact men and women differently during COVID? From our empirical results above, it seems that during periods of FPUC and UI, both males and females tend to experience high unemployment rates. However, UI was offered during the downturns of the economy, thus may not be the real driver of low unemployment rates— although a body of literature points to controversies in quantifying the extent to which UI motivates unemployment rates. After UI programs expired, both male and female unemployment dropped.

The drop in unemployment was driven by males, as male's drop in unemployment was greater by 0.7 percentage points. This effect is greatest among families with combined income lower than 150,000. Families with lower income may be more motivated to apply for UI. Furthermore, in the context of the Duncan model, households with low income have less luxury in terms of dealing with home production in addition to a flatter wage slope, both of which unproportionately burden females. Therefore as states withdraw from UI, females in lower income households see a substantially smaller decrease in unemployment compared to males. The results of my study are consistent to those of Coombs et al (2021) and Heggeness et al (2021).

Females suffered a greater unemployment rate initially and a slower "recovery" as benchmarked by unemployment compensation expiration. COVID-19 is often referred to as a "SHESESSION" due to the nature of overrepresentation of females in high-contact and low-flexibility jobs. Mentioned throughout my paper, a great deal of this disproportionate decrease in unemployment roots from the fact that females have different wages and unpaid care workloads than males. As necessary when striving closer to gender employment equality, we must support social norms encouraging females to pursue stable and skillfully demanding jobs. We should also encourage households to proportionally split unpaid care, as this will relieve major burden suppressing females. With a higher wage and proportionate household work, we can strive for gender parity.

Appendix A: Event Study Coefficients

Table 10: Event Study Main Analysis

Difference in Unemployment Male - Female	No Control	Controls
6 Months Before Benefits End	-0.00923***	-0.0103***
	(0.00217)	(0.00231)
5 Months Before Benefits End	-0.0105***	-0.0110***
	(0.00204)	(0.00198)
4 Months Before Benefits End	-0.00992***	-0.0106***
	(0.00219)	(0.00216)
3 Months Before Benefits End	-0.00562**	-0.00679***
	(0.00218)	(0.00219)
2 Months Before Benefits End	-0.00178	-0.00289
	(0.00174)	(0.00178)
1 Month Before Benefits End	0.000616	-0.00140
	(0.00212)	(0.00207)
Month of Benefits End	-0.000538	-0.00194
	(0.00182)	(0.00173)
1 Month After Benefits End	0.00468**	0.00331*
	(0.00185)	(0.00180)
2 Months After Benefits End	0.00373*	0.00278
	(0.00203)	(0.00191)
3 Months After Benefits End	-0.000125	-0.000606
	(0.00161)	(0.00163)
4 Months After Benefits End	0.00136	0.000432
	(0.00269)	(0.00274)
Observations	702,317	702,317
R-squared	0.020	0.045

Note: *,**,*** mean significance at the 1, 5, and 10 percent level. Standard Errors are clustered at state-level.

Table 11: Event Study Heterogeneity

Difference in Unemployment Male - Female	(1) Children	(2) Children Under 5	(3) Bottom 20th Percentile	(4) Top 20th Percentile	(5) Married
6 Months Before Benefits End	0.00157	0.00434	-0.0198**	-0.00313	0.000225
	(0.00187)	(0.00498)	(0.00828)	(0.00269)	(0.00313)
5 Months Before Benefits End	-0.00332	0.00873	-0.0221***	-0.00116	-0.00172
	(0.00282)	(0.00523)	(0.00625)	(0.00289)	(0.00238)
4 Months Before Benefits End	-0.00348	0.00428	-0.0260***	0.000160	0.000288
	(0.00260)	(0.00413)	(0.00712)	(0.00290)	(0.00174)
3 Months Before Benefits End	-0.000425	0.00689	-0.0142***	0.00143	0.000949
	(0.00256)	(0.00470)	(0.00479)	(0.00287)	(0.00265)
2 Months Before Benefits End	0.00310	0.0131***	-0.0106*	0.000514	0.00399
	(0.00270)	(0.00485)	(0.00549)	(0.00307)	(0.00244)
1 Month Before Benefits End	0.00120	0.00908*	-0.00659	0.00263	0.00397*
	(0.00213)	(0.00470)	(0.00691)	(0.00315)	(0.00218)
Month of Benefits End	0.00360*	0.0110**	-0.0109*	-0.00211	0.00424**
	(0.00201)	(0.00509)	(0.00551)	(0.00230)	(0.00192)
1 Month After Benefits End	0.00998***	0.0172***	0.00351	0.00586**	0.00754***
	(0.00217)	(0.00580)	(0.00512)	(0.00252)	(0.00241)
2 Months After Benefits End	0.00739**	0.0132***	0.00123	0.00901***	0.00673***
	(0.00302)	(0.00451)	(0.00623)	(0.00260)	(0.00249)
3 Months After Benefits End	0.00427**	0.00870**	-0.00305	-0.00232	0.00554***
	(0.00197)	(0.00399)	(0.00565)	(0.00238)	(0.00178)
4 Months After Benefits End	0.00812***	0.0175***	-0.00315	-0.00308	0.00643***
	(0.00298)	(0.00462)	(0.0106)	(0.00262)	(0.00229)
Observations	295,695	79,970	143,942	140,343	369,261
R-squared	0.050	0.079	0.024	0.016	0.030

Note: *,**,*** mean significance at the 1, 5, and 10 percent level. Standard Errors are clustered at state-level.

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