The Impact of CARES Act Unemployment Benefits on Employment

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Abstract

This thesis examines the impact of the $600 per week increase in unemployment insurance (UI) benefits from the Federal Pandemic Unemployment Compensation (FPUC) on employment in various industry groups. I build upon the theoretical model developed in Petrosky-Nadeau (2020) that describes how workers weigh accepting a job offer versus staying on unemployment by incorporating the additional risk of contracting COVID-19 at work. I find that the reservation benefit, the level of benefit where job seekers are indifferent between accepting a job offer and remaining unemployed, remains significantly higher than weekly UI benefits provided by the FPUC for most workers. Furthermore, the reservation benefit is relatively inelastic to changes in weekly UI benefits and is instead more responsive to changes in the job finding rate.

In addition, I empirically examine the impact of increased unemployment benefits on employment, job openings, and consumer spending in various industry groups. I use a Bartik-style instrument to find the government spending multiplier of real FPUC dollars with regards to employment and job openings in different industries. I find that states that received more real FPUC dollars relative to other states did not experience a decline in employment for most of the industry groups analyzed. This can be explained by the FPUC also causing a small drop in labor demand, shown by a reduction in job openings and consumer spending, that incentivized workers to remain employed.

JEL Classification: J64, J65, J68

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1 Introduction

While the consequences of the COVID-19 pandemic in the United States will take years to assess, it was immediately clear that the pandemic would have a devastating effect on the economy. The scale of job destruction was far greater and faster than during the Great Recession – the two-month decline in employment between February and April 2020 was 50% larger than the entire decline in employment during the Great Recession in 2008 (Bartik et al., 2020). In response, Congress quickly passed the CARES Act, the largest stimulus bill in history at $2.2 trillion. However, the debate over the effectiveness of funds from the different programs in the CARES Act delayed the passage of the Consolidated Appropriations Act that was passed in December 2020 and was a sharp point of contention during the passage of the American Rescue Plan in March 2021. This paper focuses on the effects of the Federal Pandemic Unemployment Compensation (FPUC), which was part of the CARES Act. The FPUC boosted federal unemployment insurance (UI) benefits for all eligible recipients by an additional $600 per week between March 27th and July 26th 2020.

The question of whether increasing UI benefits improves or hurts general welfare has long been debated. The principal issue at play is the moral hazard effect, where more generous benefits create disincentives for workers that have been laid off to find a job. Tied to the moral hazard effect is the replacement rate, which is the percentage of a worker's previous wages that is covered by UI benefits. Intuitively, a higher replacement rate would lead to a greater moral hazard effect. A classic critique of unemployment insurance is that "UI has a significant moral hazard cost in terms of subsidizing unproductive leisure" (Gruber 2007). However, during times of crisis when millions of people are out of work, policy-makers must weigh the drawbacks of potentially increasing unemployment and slowing economic growth against the benefits of increasing UI to prevent households from sliding into poverty.

The COVID-19 pandemic created a unique situation where various factors both incentivised and discouraged people from working. During the pandemic, individuals experienced lower employment rates, lower hiring rates, and a generally poor economy, which encouraged them to seek jobs or remain employed. At the same time, other factors encouraged people to stay home: workers feared contracting COVID-19 while on the job and the FPUC increased UI benefits by a historic amount. There have been various papers examining the effect of different factors resulting from the pandemic, including higher UI benefits. Recent economic literature such as Petrosky-Nadeau (2020) and Boar and Mongey (2020) find that in theory UI benefits from the FPUC were not large enough to discourage a job seeker from accepting a job offer providing the median wage. This paper aims to answer the following questions: First, what was the effect of the shock from the FPUC providing an additional $600 per week in UI benefits on employment? Second, did additional UI benefits from the FPUC affect employment by changing labor demand?

To answer these questions, this paper first builds upon the theoretical framework introduced by Petrosky-Nadeau (2020) that models how job seekers decide between accepting a job offer or staying unemployed. I build upon the model by incorporating the chance of contracting COVID-19. Doing so decreases the reservation benefit, the level of UI benefits at which a worker is indifferent between accepting a job offer and staying unemployed. I find that even though an individual making the median wage has a replacement rate of 114%, her reservation benefit of $1,577 per week remains significantly higher than the $1,068 per week in UI benefits she would receive. As such, the level of UI benefits provided by the FPUC is nowhere near the amount that would discourage a person making the median wage from working. In order for job seekers to prefer remaining unemployed to accepting a job offer, the weekly wage of the offer must be under $460, less than half of the median wage.

In addition, I calculate the elasticity of the reservation benefit with regard to multiple parameters, including the weekly wage, weekly UI benefit, job finding rate, separation rate, and probability of contracting COVID-19. In this model, the job finding and separation rates are independent from each other, exogenous, and static. I find that the reservation benefit is relatively inelastic to changes in weekly UI benefits, where a 1% increase in benefits only increases the reservation benefit by 0.08%. Thus the main effect of the FPUC is simply increasing the weekly benefit relative to the reservation benefit. In contrast, the reservation benefit is sensitive to permanent changes in the weekly job finding rate, where a 1 percentage point increase in the job finding rate decreases the reservation benefit by almost \$600, around 38%. Ultimately, my model predicts that labor supply in most industries should not be significantly impacted by just an increase in weekly benefits. Furthermore, I show that even a small impact on labor demand from the FPUC can counteract the program's direct effect on labor supply by changing the job finding rate, although the FPUC only changed the job finding rate temporarily. As such, in my model workers value the opportunity to find a job in the future more than they value being able to fall back on higher UI benefits.

I test the predictions from the theoretical model by empirically analyzing the effect of the national-level increase in UI benefits from the FPUC on employment, job openings, and consumer spending at the state level during the duration of the program. I obtain data from Homebase and Opportunity Insights (TrackTheRecovery.org), which provide weekly changes for each statistic in different industry groups relative to the month of January 2020. This data is combined with data from the Bureau of Labor Statistics and the CDC to acquire employment and job opening levels and to control for the impact of COVID-19 on each state.

I identify the effect of FPUC benefits by finding the multiplier of government spending from the FPUC program. I use an empirical technique outlined in Ramey and Zubiary (2018) to run weekly time series regressions estimating the effect of the total amount of real dollars provided by the FPUC on the total number of jobs/job openings per week between the dates of March 27th and July 31st. My source of variation is the differences in the cost-of-living between different states. Due to price parity differences between states, the flat nominal \$600 increase differs in terms of real dollars. I find the total amount of real dollars that the FPUC provided to each state by multiplying the real value of the \$600 by the cumulative number of continued UI claims in the state. To remove the endogenous effect where the economic conditions in a state, such as employment, affect future UI claims and thus FPUC dollars entering the state, I use a Bartik-style instrument. This instrument is the fraction of national UI claims each state had in December 2007. It is plausibly exogenous because UI claims from December 2007 should not affect employment, job openings, or consumer spending in 2020 except via its effects on UI spending in 2020.

My empirical results support the prediction from my theoretical model that employment levels will not significantly decrease because of high UI benefits. I find that the magnitudes of the coefficients estimating the impact of government spending on employment for each week are statistically insignificant for all industry groups except leisure/hospitality. Even in the retail sector, where workers have both a higher than average chance of contracting COVID-19 on the job and a replacement rate of over 150% (Ganong et al., 2020), an increase in real dollars from the FPUC did not have a significant impact on employment. By contrast, an additional $10,000 from the FPUC that entered a state was associated with a decrease of around 5 job-weeks in leisure/hospitality. An explanation for this decline in employment in leisure/hospitality from increased FPUC dollars is that at $407 per week, workers within the supersector have by far the lowest weekly wages of all industry groups analyzed, low enough for UI benefits to exceed the reservation benefit (Bureau of Labor Statistics).

I also analyze the impact of FPUC dollars on job openings and consumer spending to examine the effects of the FPUC program on labor demand. I find that the point estimates for the impact of FPUC dollars on job openings are directionally negative, although not statistically significant, for all industries except for manufacturing for most of the time period. Furthermore, consumer spending in all sectors except for groceries fell in states that received relatively more FPUC dollars in the weeks following the passage of the CARES Act. A 1% increase in FPUC dollars that entered a state is correlated with a 0.1% to 0.2% drop in consumer spending in entertainment, transportation, and restaurants. As such, the decline in job openings and consumer spending suggests that the FPUC generated a small drop in labor demand that decreased the job finding rate. As mentioned, the change in the job finding rate in actuality was temporary rather than permanent as in the model. However, even with a temporary fall in the job finding rate, the drop in labor demand encouraged workers to remain at their jobs and incentivised job seekers to accept offers, thereby counteracting the effect of increased UI benefits disincentivising people from working.

This paper contributes to the existing literature by building upon previous theoretical models and utilizing a different empirical approach to examine the effects of increased UI benefits during the COVID-19 pandemic. I incorporate the probability of contracting COVID-19 into my theoretical model, allowing me to provide a more representative picture of workers' decisions during the pandemic and to put a relative dollar value on the penalty of contracting COVID-19. In addition, I use an empirical approach that allows me to present the impact of the FPUC program on a per-dollar basis. Understanding this impact is important due to both the large amount of UI benefits paid and the concerns over UI benefits hurting the economic recovery. Between March and December 2020, the amount of UI benefits paid was around $138 billion (Department of Labor). Thus, understanding the impact of increasing UI payments during the COVID-19 pandemic on employment may help policymakers decide on the size and duration of UI benefit increases/extensions in future economic crises.

The remainder of this paper is organized as follows. Section 2 outlines a brief background on the U.S. unemployment system and previous stimulus packages. Section 3 reviews the literature on the effects of UI benefits on labor markets. Section 4 presents the theoretical model. Section 5 introduces the data. Section 6 presents empirical strategy while Section 7 discusses the results. Section 8 provides a brief conclusion.

2 Background

The modern federal-state unemployment insurance system in the United States was created by the Social Security Act of 1935. Each state typically administers its own UI program and benefits are funded by a combination of state and federal payroll taxes. UI benefits vary by state, with the average unemployed individual in the United States receiving a weekly payment of $378 in 2020 prior to the CARES Act (Dupor, 2020). The standard maximum duration for receiving benefits is 26 weeks, although during times of high unemployment, the federal government often establishes programs extending and increasing benefits.

Eligibility for UI benefits varies slightly between different states. However, in general, workers who are terminated "without cause" are eligible for UI benefits while those who are laid off for misconduct or quit their jobs without "good cause" are not eligible (Department of Labor). Before the pandemic, there were significant limitations on eligibility for independent contractors and other informal workers. However, eligibility for UI benefits was expanded under the FPUC to cover independent contractors and gig workers, which meant that many people who were historically unable to claim UI benefits were able to do so.

Unemployment insurance has been expanded before, typically in terms of duration. During the Great Recession, the Emergency Unemployment Compensation granted an initial extension of UI benefits of 13 weeks and amended in a tiered system of extensions up to 53 weeks, depending on a state's unemployment levels. In total, there have been nine occurrences since 1958 when UI benefit programs have been temporarily expanded at the federal level. However, compared to previous UI expansions, the increase in UI benefits from the FPUC during the pandemic was much greater in scope. During the duration of the FPUC, eligible UI claimants were entitled to the combination of the federal $600 from the FPUC and standard state-level unemployment insurance. The across-the-board additional $600 in weekly benefits meant that the majority of workers (76%) earned more money from UI benefits than in their previous job, thus having a replacement rate of over 100%. In fact, an average worker in the bottom two deciles of the income distribution had a replacement rate of more than 200% (Ganong et al., 2020).

3 Literature Review

Much of the recent literature analyzing the impact of UI builds upon job search models such as the McCall model and the Mortensen-Pissarides (MP) framework (McCall 1970, Mortensen and Pissarides 1994). In the McCall model, a worker's wage is determined by the reservation wage, the lowest wage a worker is willing to accept. In contrast, in the MP framework, a worker's wage is determined by Nash bargaining while how workers and firms "match" is influenced by the probability that the worker receives a job offer. An abundance of economic research uses these models as a basis for analyzing the impact of various shocks on labor markets.

During the Great Recession, Congress authorized federally-funded extensions of UI benefits through the Extended Unemployment Compensation (EUC) program, which provided up to an additional 53 weeks of benefits to eligible individuals. When the extension was passed, a major concern was whether moral hazard issues would outweigh the benefits of increasing consumption from the unemployed and hurt the economic recovery. Research including the McCall model indicates that higher UI benefits reduce the labor supply via moral hazard, which leads to increased unemployment. Much economic research has investigated the subject, with the majority (Card et al., 2007; Lalive 2007; van Ours and Vodopivec 2008; Krueger and Mueller 2011) presenting evidence that workers expending less effort in the job search process is the source of the moral hazard effect. However, even if programs like the EUC increase moral hazard, whether they negatively affect general welfare is contentious.

For example, Hagedorn et al. (2013) assert that EUC UI benefit extensions hurt general welfare, stating that UI extensions have a significant negative impact on labor demand due to expectations of higher wage growth in the future. Extending UI benefits exerts an upward pressure on the equilibrium wage, thereby lowering the profits employers receive from filled jobs and causing a large decrease in job vacancies. As a result, total spending falls because increased spending by the unemployed does not offset the decline in spending from having fewer people employed. Meyer (2002) and Schmieder et al. (2012) also present evidence supporting the claim that UI benefits increase unemployment durations and may lead to lower welfare. However, these papers claim that UI benefits cause longer unemployment durations by allowing people to take longer to find jobs, not by increasing expected wages.

On the other hand, Chetty (2008) and Marinescu (2017) argue the negative impacts of UI benefits on general welfare are overstated because papers that find such results underestimate search effects. Chetty finds that the extra money that unemployed workers receive is used to search for better matching jobs that fit their skill set. This search effect accounts for 60 percent of the marginal effect of UI benefits on unemployment durations. Thus, better worker-job matches improves general welfare which counteracts the negative effects of longer durations. Marinescu critiques Hagedorn's assertion that UI extensions significantly impact job vacancies and generate a negative labor demand externality. She finds that in equilibrium, a 10% increase in UI durations increases aggregate unemployment by only 0.6%. She states that not taking into account search externalities and spillover effects across counties may lead to an overestimation of the impact UI extensions have on labor demand.

Multiple papers have been published examining labor markets during the COVID-19 pandemic. Both the damage the pandemic inflicted and the economic recovery was uneven. Bartik et al. (2020) show that the decline in employment largely occurred between March 14th and 28th, driven by losses in small business, retail, leisure, and hospitality. Forsythe et al. (2020) find that essential jobs had the smallest decline in the number of jobs available, while leisure and hospitality had the largest decline. Furthermore, the pandemic disproportionally impacted low-pay non-essential jobs, especially those that could not translate to a work-from-home environment (Liu and Mai 2020).

Similarly, the labor market recovery was also worse for low income workers. Chetty et al. (2020) find that high-wage workers experienced a recession that only lasted several weeks and largely avoided layoffs. On the other hand, many low-wage workers lost their job or were furloughed because of the pandemic, experienced a sharp recession that lasted for months, and faced a slow job market recovery.

There has been consensus in the literature that the FPUC was effective at improving general welfare. Han et al. (2020) find that the expansion of UI benefits helped reduce poverty during the pandemic. In addition, Faria-e-Castro (2020) shows that increased UI benefits stimulated consumption, leading to a higher GDP than there would have been without the benefits program. The recipients of UI benefits were also well-targeted by the FPUC. Cortes and Forsythe (2020) find that around half of total UI benefit payments went to workers whose earnings were in the bottom third of the income distribution before the pandemic. This outcome helped decrease income inequality that was caused by the pandemic disproportionally destroying low-income occupations, although the researchers also note that there was significant difficulty in reaching the poorest sections of the population.

Because the FPUC increased UI benefits by a historically large amount, the program was both effective and created moral hazard concerns. Gangong et al. (2020) report that expanded UI benefits led to a median replacement rate of 145%. They find that the FPUC provided benefits that were so large that they reversed some sectoral income changes that had arisen from the increase in unemployment due to the pandemic. Under normal UI benefits, the expected income for the median worker in the bottom quintile of the income distribution would have fallen, but due to the FPUC it had instead increased by about 20%.

Petrosky-Nadeau (2020) develops a theoretical model to calculate the reservation benefit for workers during the months of May and June and determines the level of benefit needed for a job seeker to reject the security of a job offer. After grouping the workforce by educational attainment, age, and occupation, he finds that the majority of job seekers would not refuse a job offer, even when replacement rates are significantly higher than 100%. Both he and Boar and Mongey (2020) demonstrate that the duration and magnitude of UI benefits from the FPUC were too small to make it worthwhile for most individuals to reject a return-to-work offer.

The theoretical models of Petrosky-Nadeau and Boar and Mongey have been largely corroborated by empirical evidence. Marinescu et al. (2020) find that the FPUC had no significant effect on the overall decline in job applications from the general population and only a slight negative impact on the quartile with the highest replacement rate change. While applications per vacancy for high replacement rate job seekers decreased after the CARES Act passed, those job seekers were already sending fewer applications before the passage of the CARES Act. Finamor and Scott (2020) examine the impact of expanded UI benefits on small business employment, finding that workers who had different replacement rates did not have a different probability of being employed after the passage of the CARES Act. Therefore, the literature suggests that high UI benefits did not significantly decrease employment among the general labor pool.

This paper builds upon the work of Petrosky-Nadeau (2020) and Boar and Mongey (2020) by incorporating the chance of contracting COVID-19 into people's decision making on whether to work or stay home on unemployment. This inclusion allows for a more accurate representation of conditions during the pandemic. Furthermore, I calculate the elasticity of the reservation benefit with respect to different parameters, allowing me to determine how much each factor affects a person's reservation benefit. Lastly, I utilize a different empirical approach, outlined in Ramey and Zubiary (2018), that lets me to find the government spending multiplier of FPUC dollars. As such, I am able to estimate the per-dollar effect of the FPUC program on employment in various industry groups.

4 Theoretical Framework

4.1 Income and Job Acceptance Decisions

This section describes how an insured risk-neutral job seeker decides between accepting a job offer and remaining unemployed during the COVID-19 pandemic. This model builds upon the framework developed in Petrosky-Nadeau (2020) by introducing the idea that individuals have a higher chance of contracting COVID-19 while working compared to being unemployed at home. The job seeker decides between accepting an offer providing a weekly wage w, which has the value W_E, and being unemployed, which has the value of $W_U(b, t)$, where b is the weekly UI benefit and t is the number of remaining weeks of UI eligibility. The job seeker takes into account the weekly probabilities of finding a job f and being separated from a job s. In this model, s and f are independent from each other, exogenous, and static.

When working, the individual has the weekly probability c of contracting COVID-19 which has the "value" of $Cov(\bar{t})$, where $\bar{t}$ is the number of weeks that a person is sick with COVID-19. The value $Cov(\bar{t})$ represents the *permanent* value of contracting COVID-19 for an individual, meaning that $Cov(\bar{t})$ includes the negative impact of contracting COVID-19 and the value of being employed once the individual returns to work. With these parameters, the value of being employed at a job providing a wage of w is expressed as:

$$W_E = w + \overbrace{\frac{1}{1+r}}^{\text{Discount}}[\underbrace{(1-s)(1-c)W_E}_{\text{Stay employed no COVID-19}} + \overbrace{(1-s)cCov(\bar{t})}^{\text{Catch COVID-19}} + \underbrace{sW_U(b,T)}_{\text{Become unemployed}}] \tag{1}$$

where T is the maximum duration of UI benefits. Thus, when on unemployment, workers have t weeks of UI eligibility remaining where $1 \leq t \leq T$. As such, the value of being unemployed, where an individual receives weekly UI benefits b for a duration of t more weeks is:

$$W_U(b,t) = b + \frac{1}{1+r}[\underbrace{(1-f)W_U(b,t-1)}_{\text{Stay unemployed}} + \overbrace{f * \max[W_E, W_U(b,t-1)]}^{\text{Receive job offer, decide whether to accept}}] \tag{2}$$

In the last week of eligibility, the value of being unemployed is:

$$W_U(b,1) = b + \frac{1}{1+r}[(1-f)W_U(0) + \underbrace{fW_E}_{\text{Accept any job offer}}] \tag{3}$$

$$W_U(0) = \frac{1}{1+r} f W_E \tag{4}$$

The value of contracting COVID-19 $Cov(\bar{t})$ is denoted as:

$$Cov(\bar{t}) = w - \overbrace{k}^{\text{Weekly penalty of COVID-19}} + \frac{1}{1+r}[\underbrace{h\overline{H}}_{\text{Become hospitalized}} + \overbrace{(1-h)Cov(\bar{t}-1)}^{\text{Stay in ``quarantine''}}] \quad \text{for } \bar{t} \leq 2 \tag{5}$$

$$Cov(0) = \underbrace{W_E}_{\text{Return to work once no longer sick}} \tag{6}$$

$$\overline{H} = \zeta W_E \quad \text{for } \zeta \leq 1 \tag{7}$$

where k represents the flow utility of falling ill, h the probability of becoming hospitalized, and $\overline{H}$ the present discounted value of becoming hospitalized. One can think of the difference between $\overline{H}$ and W_E as the dollar value penalty of being hospitalized with COVID-19. I let $\overline{H}$ be fraction ζ of the value of being employed. Thus, a job seeker is indifferent between being hospitalized and losing $1-\zeta$ of their permanent income. An assumption is made that individuals in the COVID-19 state continue to receive their wage and that if an individual is not hospitalized, she is in the quarantine state for at most two weeks.

If the job seeker prefers employment compared to remaining unemployed at time period $t+1$, the value of being unemployed for the maximum duration of T weeks can be expressed as (see Appendix for derivation):

$$W_U(b,t) = B(T) + \left(\frac{f}{r+f}\right) W_E \quad \text{for } 1 < t \leq T \tag{8}$$

$$B(T) = \sum_{i=0}^{t-1} b \left(\frac{1-f}{1+r}\right)^i \tag{9}$$

Equations (8) and (9) demonstrate that the value of being unemployed is a combination of the discounted value of expected UI benefits $B(T)$ and the discounted value of finding a job.

4.2 Reservation Benefit

The reservation benefit, denoted as $b^r(t,w)$, is the level of weekly UI benefits such that a job seeker is indifferent between accepting a job or staying unemployed. To find the reservation benefit we solve for:

$$W_U(b^r(t,w),t) = W_E \tag{10}$$

We can derive the following:

$$b^r(t,w) = \frac{\overbrace{b^r(1,w)}^{\text{Reservation Benefit with 1 week remaining}}}{\underbrace{\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}_{\text{Discount with job finding rate considered}}} \quad \text{for } 1 < t \leq T \tag{11}$$

where

$$b^r(1,w) = \frac{r}{r+f} W_E = \frac{r[(1+r)w + (1-s)cCov(\bar{t}) + sB(T)]}{(1+r)(r+f) - (1-s)(1-c)(r+f) - sf} \tag{12}$$

Individuals will accept an offer to return to their previous wage if $b < b^r(t,w)$.

As the number of eligible weeks on unemployment decreases, the reservation benefit increases to $b^r(1, w)$, the reservation benefit with 1 week of eligibility remaining.

4.3 Parameters

I input values for each parameter to create a baseline reservation benefit for a typical job seeker considering a job offering the median wage. For the weekly wage w, I use the median weekly wage of all occupations in the United States, which is approximately \$936 (Bureau of Labor Statistics). I use an annualized discount rate of 2% and convert it to a weekly discount rate r. For the weekly job separation and job finding rates s and f, I use figures from Petrosky-Nadeau (2020), who converts monthly flow rates from 2009-2010 CPS data for employment and unemployment to a weekly frequency. The weekly UI benefit b is calculated by taking the standard replacement rate before the pandemic, which was 50% of a job's weekly wage, and adding \$600, the amount provided by the FPUC program. I derive the reservation benefit with 16 weeks of UI benefits remaining, such that $1 < t \leq 16$.

To find an estimate of the weekly probability of contracting COVID-19 c, I take the estimated number of COVID-19 cases between February 15th and December 31st 2020 from the CDC and divide by both the population of the United States and by 47, the number of weeks between the two dates. I use this time period because data on estimated cases in more specific time periods was unavailable. While the official number of COVID-19 cases is lower than the estimated number (20 million versus 83 million), estimated cases provide a better picture of the actual probability of contracting COVID-19. I assume that job seekers believe that the probability of contracting COVID-19 while unemployed is zero, as they will be staying at home. I set k, the weekly flow penalty of contracting COVID-19, equal to the weekly wage.

In order to find the probability of being hospitalized once a person has contracted COVID-19, I divide the estimated number of COVID-19 hospitalizations by the estimated number of cases. Because the most severe symptoms typically appear around one to two weeks after symptoms initially begin (Mayo Clinic), I divide by two to obtain the weekly probability of being hospitalized once having contracted COVID-19.

Lastly, I specify $\overline{H}$ by setting ζ at 0.95. Therefore, a job seeker is indifferent between being hospitalized and having their income permanently drop by 5%. This value was chosen because the cost of the average COVID-19 related hospitalization averaged between \$26,000 to \$40,000 with insurance and \$50,000 to \$78,000 without insurance (FAIR Health, 2020). Thus, with median lifetime earnings of \$1.7 million, a disutility of \$85,000 for being hospitalized after taking into account the human cost of falling severely ill is reasonable[1].

While I assume that the median job-seeker is representative of the general population in the baseline scenario, it is probable that she earns a lower wage, is more concerned about contracting COVID-19, and has extenuating circumstances such as having to spend more time on childcare that decreases her reservation benefit. If this is the case, the reservation benefit will be biased high as the typical job-seeker values being employed less. On the other hand, she is also likely to be younger and have a lower chance of being hospitalized. The values of each parameter in the baseline case are shown in Table 1.

With these parameters, I derive a weekly reservation benefit of \$1,577 for a risk-neutral job seeker deciding whether to accept a job offering the median wage. The impact of changing each parameter on the reservation benefit is detailed in Figure 3.

4.4 Elasticity of Reservation Benefit

Using the baseline specifications, I calculate the elasticity of the reservation benefit with respect to different parameters, shown in Table 2. As reflected in the graphs in Figure 3, increases in the weekly wage, weekly benefit, and present value of hospitalization increase the reservation benefit. On the other hand, increases in the job finding rate, separation rate, chance of contracting COVID-19, flow utility of COVID-19, and hospitalization probability decrease the reservation benefit.

Interestingly, increases in both the job finding rate and the separation rate decrease the reservation benefit. An intuitive explanation is that individuals that are currently unemployed feel more secure about staying unemployed if the job finding rate is high,

[1] Ultimately the value of ζ does not matter much as the difference in reservation benefit when ζ is equal to 0.9 versus 0.99 is less than \$80 per week as shown in Figure 3. This is largely because both the weekly chance of contracting COVID-19 and the weekly probability of being hospitalized are quite low.

as they are confident in their ability to find a job in the future. In addition, the risk of contracting COVID-19 is lower while on unemployment. Meanwhile, when the separation rate is high, accepting a job offer becomes less attractive as the probability of keeping the job falls. Ultimately, being employed is less attractive when finding a job is easy and keeping a job is hard.

The reservation benefit is elastic to the job finding rate and the weekly wage, while it is relatively inelastic to the weekly UI benefit, separation rate, and probability of contracting COVID-19 when the parameters are at the baseline values. A 1% increase in the weekly wage increases the reservation benefit by 0.59% and a permanent 1 percentage point increase in the job finding rate causes the reservation benefit to fall by 38%. The elasticity of the reservation benefit with respect to the job finding rate can be explained by the majority of the value of being unemployed being derived from finding a job in the future, as shown in equation 2. Thus, a decrease in the job finding rate significantly decreases the value of being unemployed, leading to a large drop in the reservation benefit which encourages people to be employed. On the other hand, the effect of increasing weekly UI benefits by 1% is small as it increases the reservation benefit by only 0.08%. As such, increasing UI benefits does not change the reservation benefit significantly and simply increases the weekly benefit relative to the reservation benefit. Therefore, a change in labor demand that affects weekly wages or the job finding rate has a far greater impact on job seekers than changes in the size of UI benefits if benefits are sufficiently below the reservation benefit, as it is for a person making the median wage.

4.5 Theory Discussion

This theoretical model demonstrates that even with replacement rates well over 100% and introducing the probability of contracting COVID-19, the typical risk-neutral job seeker would still prefer to accept a job offer at the median wage rather than stay unemployed. Figure 1 shows the effect of changes in the weekly wage on both UI benefits and the reservation benefit. Holding the other baseline specifications constant, a job offer would need to provide a weekly wage of around $460 in order for a job seeker to be indifferent between accepting the offer and remaining unemployed. Similarly, UI benefits from the FPUC would have to increase to \$1,200 per week for a job seeker to be indifferent, *ceteris paribus*. Therefore, this model predicts that for most industries during the pandemic, higher UI benefits from the FPUC would not deter the majority of job seekers from accepting job offers.

In addition, while the introduction of COVID-19 does decrease the reservation benefit, the effect is modest. The penalty of contracting COVID-19 can be calculated by comparing the value of being employed when the chance of contracting COVID-19 is at the baseline value to when it is zero. I find that the penalty, which is the amount of money the median job seeker would be willing to pay to guarantee that she will never contract COVID-19, to be about \$6,800. Combined with the relatively low probability of falling ill in any given week, the introduction of COVID-19 to the framework leads to a decrease in the reservation benefit of only about \$60 per week.

Another important aspect that the model highlights is the elasticity of the reservation benefit with regards to permanent changes in the job finding rate. This suggests that the labor demand channel has a powerful effect on the reservation benefit, and by consequence employment levels. The effect of an increase in UI benefits from the FPUC on reservation benefits can be mitigated if money from the FPUC also affects labor demand and changes the job finding rate. For example, if weekly UI benefits are greater than the reservation benefit by about 10% (the situation if the FPUC provided \$1,430 per week in additional UI benefits), a permanent drop in the job finding rate of 0.7 percentage points would be enough to increase the reservation benefit to be equal to the weekly UI benefit. While changes in the job finding rate in actuality are temporary, a decrease in the job finding rate would still encourage people to be employed. Thus, a decrease in job openings can increase the reservation benefit significantly and counteract the effect of higher UI benefits disincentivising individuals from working. As such, examining the effect of the FPUC on employment requires not only analyzing its effect on labor supply, but also on labor demand.

5 Data

The data used in this project was obtained from a variety of sources and was compiled on a state-week basis. I use industry specific data for the dependent variables of employment, job openings, and consumer spending. Data for the independent variable (real FPUC dollars) and the control variables (stay-at-home order status, individual mobility, COVID-19 deaths, and total job openings) do not differ between industries. The time period for this data was the 18-week duration of the FPUC program between March 27th to July 31st 2020.

State-level employment data comes from three sources. Data on the daily change in employment was collected from TrackTheRecovery.org and Homebase. Data on professional/business, education/health services, leisure/hospitality, and transportation employment was obtained from TrackTheRecovery.org via Earnin, Intuit, Kronos and Paychex. Daily retail employment change data was obtained from Homebase. These financial services and human capital management firms gather data across NAICS sectors and supersectors from their client companies. For example, Homebase gathers data from 60,000 small businesses, and is largely representative of the general economy in terms of industry breakdown (Bartik et al., 2020).

Both datasets provide rates that describe the daily level of employment relative to the period between January 4th and January 31st 2020. To find the state-wide level of employment for each industry in January 2020, I use the State and Metro Area Employment (SAE) data from the Current Employment Statistics (CES) program at the BLS.

For all industries examined, employment fell sharply in the months of March and April and recovered during the months of May, June, and July. Figure 2 presents the change in total employment for each week between March 27th (week 13) and July 31st (week 31) relative to total employment in the month of January 2020. Total employment was lowest in week 17, in which the level of employment for the median state was 80% of what it was in January. For a state in the 25th percentile and a state in the 75th percentile, the total level of employment relative to January 2020 was 75% and 83% respectively in week 17.

To obtain the real value of the increase in UI benefits for each state, I take the additional $600 per week provided by the program and normalize using the regional price parity for each state. This data was collected from a 2020 news release by the Bureau of Economic Analysis (Real Personal Income by State, 2019). The price parity index covers all consumption goods and services, including housing rents. Figure 4 provides a summary for the regional price parity for each state in 2019.

I use the number of continued weekly UI claims in each state, from the Department of Labor, to find the amount of FPUC dollars entering each state per week. For the Bartik-style instrument, I use unemployment claims data from December 2007. This time period was chosen because it was the first month of the Great Recession, the most recent economic crisis. Figure 5 shows the percentage of national UI claims in December 2007 for each state.

The data used to control for the impact of COVID-19 on different states was collected from the CDC and TrackTheRecovery.org via Google COVID-19 Community Mobility Reports. The dates when each state's stay-at-home order was in effect and the amount of weekly COVID-19 deaths were obtained from the CDC. Weekly COVID-19 deaths are per 100,000 to control for population. TrackTheRecovery.org uses the American Time Use Survey and Google's location tracking data to derive a daily estimate of the total amount of time spent outside the home for each state. I use the time-away-from-home data to represent the strength and level of adherence to a state's shutdown order. Although 44 out of 50 states had implemented a shutdown order during the spring and summer of 2020, the effectiveness of shutdown orders varied widely from state to state. Figure 6 provides a summary of the change in time away from home, with "low" representing the state where time spent away from home changed the least (Montana) and "high" representing the state where time spent away from home changed the most (New Jersey).

Daily consumer spending data and job openings data were also provided by TrackTheRecovery.org via Affinity Solutions and Burning Glass Technologies, which sell proprietary data. Similarly to employment, the data records the daily change in consumer spending/job openings for a state in a given industry relative to the month of January 2020. While the total number of job openings for each state was obtained from the JOLTS program conducted by the BLS, consumer spending figures for different industries at the state level were unavailable. Between industries, the change in consumer spending varied widely. For example, while consumer spending in transportation and entertainment fell by more than 80% in April, groceries and retail spending actually increased slightly. On the other hand, job openings in different industries followed a trajectory similar to employment where job openings for all industries fell sharply in March and April and recovered in the summer months. The summary of the changes in total job openings and changes in consumer spending in different industries for the median state are shown in Figure 7 and Figure 8.

6 Empirical Strategy

6.1 Emprical Strategy for Employment and Job Openings

The baseline specification identifying the effect of UI benefit increases from the FPUC on employment is:

$$\sum_{i=13}^{h} Emp_{ijk} = \alpha_h + \beta_h \sum_{i=13}^{h} Dollars_{ik} + \gamma_h' X_{13jk} + u_{hjk} \tag{13}$$

where $\sum_{i=13}^{h} Emp_{ijk}$ is the cumulative number of jobs normalized by population up to week h since the CARES Act was passed in March 27th 2020 in an industry j and state k. $\sum_{i=13}^{h} Dollars_{ik}$ denotes the cumulative amount of FPUC dollars per capita that entered a state k up to week h. X_{13jk} is the vector of control variables for the respective state and industry that was recorded during the week of March 27th when the CARES Act was passed (week 13). u_{hjk} is the error term.

It can be observed that simply taking the actual number of UI claims for each state to find FPUC dollars per capita would potentially lead to reverse causation. This issue appears because the amount of FPUC dollars entering a state is endogenous to the economy in a state, causing $Dollars_{ik}$ to correlate with the error term. As such, changes in employment within a state would affect the number of UI claims in the future, biasing β_h. To address this problem, I utilize a Bartik-style instrument to estimate weekly FPUC dollars.

I run this regression for each week between March 27th (week 13) and July 31st (week 31). Therefore, i runs from 13 to 31. This technique of regressing cumulative outcome variables on the cumulative amount of government spending is outlined in Wilson (2012) and Ramey and Zubiary (2018). The resulting coefficient β_h can be interpreted as the multiplier of government spending, the number of jobs created or destroyed per dollar of government spending from the FPUC program.

My source of variation is the differences in the cost of living between different states. While the nominal \$600 increase in weekly UI benefits was for all eligible recipients nationwide, the impact of that \$600 varies in real terms. To obtain the real dollar value of the \$600 per week in additional UI benefits, I multiply by the regional price parity for that state. Then to find the number of dollars entering a state in week h, I multiply this cost-controlled \$600 by the number of continued UI claims for that state in that week. I derive the number of continued UI claims by using pre-sample shares and nationwide totals. I then divide by the state's population to account for population differences between states.

I control for a state's stay-at-home order status, individual mobility, COVID-19 deaths, and change in total job openings relative to January 2020 for each state-industry week. COVID-19 deaths and change in total job openings are on a per-capita basis to account for population differences between states. Stay-at-home order status, COVID-19 deaths and individual mobility data are used to control for the different levels of impact the pandemic had on each state. I also control for the change in the total number of job openings in each state relative to January 2020 to take into account the overall level of difficulty for a job seeker to find a job in a state. This is because one can expect states with weaker job markets to also have lower employment and job openings for specific industries.

The inclusion of these control variables resolves some omitted variable concerns, although there are multiple threats to validity. First, state-specific omitted variables can lead to to biases. For example, if there was a state where parents had more children, this could lead to lower employment in the state as parents have a greater incentive to stay home and commit more time to activities such as teaching and childcare. In addition, there is a concern that households experienced long delays in receiving UI benefits after they filed their claims. According to federal timeliness reports, most states did not meet the federal standard of paying out benefits within three weeks for 87% of applicants (Henderson, 2020). However, this delay in UI claims being paid out could be offset by households anticipating UI income in the future, allowing for a smaller drop in consumer spending. In addition, the timeliness rate for 36 out of the 50 states was greater than 50%.

6.2 UI Claims Instrument

I instrument for the number of weekly UI claims in each state by using the fraction of national UI claims during the month of December 2007. I choose this time period because December 2007 was the first month of the Great Recession, the most recent economic downturn. To predict the number of weekly UI claims in 2020 for a state, I take the fraction of national UI claims a state had in December 2007 and multiply by the amount of national UI claims for that week in 2020. Thus, $\widehat{Dollars}_{ik}$ can be expressed as:

$$\widehat{Dollars}_{hk} = \delta_h + \theta_h EstDollars_{hk} + \psi' X_{13jk} + \epsilon_{hk} \tag{14}$$

where

$$EstDollars_{hk} = \frac{D_k * F_{2007,k} * C_h}{P_k} \tag{15}$$

D_k is the price-parity-controlled \$600 for state k, $F_{2007,k}$ is the fraction of national UI claims for that state in December 2007, C_h is the number of national weekly UI claims in week h in 2020, and P_k is the population of the state.

This method assumes that the fraction of national UI claims for each state remains relatively stable over time and is a predictor of future shares of national UI claims. Throughout the time horizon between weeks 13 and 31, the fraction of national UI claims in December 2007 is a strong predictor of the fraction of national UI claims in 2020. Table 3 presents the results of regressing the actual amount of weekly dollars received from the FPUC program on the estimated amount of weekly dollars for each week. All coefficients are statistically significant with $p < 0.001$, indicating a strong first-stage.

As shown in Table 3, for all three types of first-stage regression, the F-statistic for the point estimates during the time horizon exhibit a similar pattern. The F-statistic is stronger for the weeks shortly after the CARES Act was passed and weakens over the course of the time horizon. Moreover, the instrument is weaker with the introduction of controls compared to without controls. The F-statistics for the first stage with only COVID-19 controls are similar to those for regressions with all controls. Likewise, the empirical results for both types of regressions are similar. As such, I only present event study graphs for time series regressions with no controls and all controls.

The premise that the Bartik instrument is plausibly exogenous rests on the assumption that national UI policy was not driven by the needs of any particular state. As such, state-level variation must not have an effect on the amount of UI benefits that enter a state per person. One threat to exogeneity is if there was a systemic trend where a group of states that share similar characteristics increased or decreased their fraction of national unemployment. If that were the case, the requirement of "strict exogeneity" would not be fulfilled (Goldsmith et al., 2018). Thus, the share of the national UI claims for each state in December 2007 multiplied by the real dollar value of the $600 from the FPUC must be uncorrelated to the error term in each regression equation for each state conditional on control variables.

Figure 9 shows 100 times the log point difference of the share of national UI claims between December 2007 and March 2020 for each state. After taking the difference in percentage of national total UI claims from December 2007 to March 2020, I divide by the state's percentage of national UI claims in December 2007 to remove bias from large states. It can be seen that states that experienced an increase in the share of national UI claims are not grouped in any particular manner. Some small states such as New Mexico saw their fraction of UI claims grow, but so did larger states such as Georgia and Texas. In addition, the states that experienced increased unemployment relative the the rest of the country were spread out geographically, not clustered in any one region of the country.

Another threat to exogeneity is that states that were hard hit during the month of March, such as New York, wield significant political influence and advocated for larger bailout packages. However, it can also be observed from Figure 9 that states that saw their fraction of national UI claims rise relative to other states were also diverse politically. The pandemic affected states across the political spectrum, which is reflected in the bipartisan nature of the CARES Act. Thus, it is unlikely that such a broad program was influenced by the political power of any one particular state.

Lastly, if one state or a small group of states is large enough to influence the amount of national UI claims by themselves, then the assumption of exogeneity would be inaccurate. As shown in Figure 10, the fraction of national UI claims largely scales to population, which is not strongly concentrated in any one state in the United States. The largest state, California makes up only 13.3 percent of national UI claims. In addition, omitting any state in each regression does not significantly alter results. As such, this threat to exogeneity, as well as other state-specific threats, is not likely to be an issue for the instrument.

6.3 Empirical Strategy For Job Openings

To find the impact of the FPUC on job openings, I run the same regression as with employment, except I regress for the cumulative number of job openings for a state-industry. Because industry-specific job openings were not available on a monthly basis, I use the fraction of total employment for an industry to estimate the level of job openings in January 2020 for an industry group. The derivation of the estimated number of job openings per week in week h, industry$j$, and state k is:

$$JobOpenLvl_{hjk} = \frac{F_{jk} * T_{jk} * \Delta JobOpen_{hjk}}{P_k} \tag{16}$$

where F_{jk} represents the fraction of total employment in an industry-state pair for the month of January 2020 and T_{jk} represents the total number of job openings for the industry-state pair in January 2020. By multiplying the estimated number of job openings by the weekly change in job openings, which is relative to the level of job openings in January 2020, I derive the number of job openings for a state-industry pair in each week. I then divide by the state's population to obtain the weekly number of job openings per capita in order to take into account population differences. Thus, the regression specification for job openings is:

$$\sum_{i=13}^{h} JobOpenLvl_{ijk} = \alpha_h + \beta_h \sum_{i=13}^{h} Dollars_{ik} + \gamma_h' X_{13jk} + u_{hjk} \tag{17}$$

With this approach, I assume that the fraction of total job openings for an industry group is similar to the fraction of total employment for that industry group. If this is not the case, the initial level of job openings for each industry will be inaccurate, although the percent change in job openings is not affected.

6.4 Empirical Strategy For Consumer Spending

For consumer spending, state-level consumer spending figures were unavailable, which meant that I was unable find the initial level of consumer spending to apply daily change data on. As such, I employ a state-level weekly regression model where I regress the weekly change in consumer spending in an industry group in week h relative to January 2020 on the log of the amount of FPUC dollars per capita that entered the state in the week when the CARES Act was passed. Thus, the specification for the consumer spending regressions is as follows:

$$\Delta Spending_{hjk} = \alpha_h + \beta_h log(Dollars_{13k}) + \gamma_h' X_{13jk} + u_{hjk} \tag{18}$$

Therefore, the interpretation of the coefficient β_h is the percent change in consumer spending in week h resulting from a percentage point increase in real dollars that the FPUC provided in week 13 for that state. $Dollars_{13k}$ is derived using the method mentioned previously, although the number of UI claims estimated is only for week 13. Thus, the coefficients when regressing the actual number of weekly dollars on the estimated amount of weekly dollars for week 13 are the same as the coefficients for time horizon zero in Table 3. The results for the regressions are shown in Table 4.

7 Empirical Results

Figure 11 and Figure 12 present graphs displaying the impact of a state receiving an additional 10,000 real dollars from the FPUC program on weekly employment and job openings respectively. Figure 13 shows the effect of a 1% increase in real dollars from the FPUC during week 13 when the CARES Act was passed on the percent change in weekly consumer spending. All graphs display coefficient estimates for each week throughout the duration of the FPUC program and the corresponding 90% and 95% confidence intervals (dark and light shade respectively). The x-axis variable "Week" denotes the number of weeks after the CARES Act was passed on March 27th 2020 (week 13). Each figure presents four industry groups and the results for other industries are shown in Figure 14 and Figure 15.

7.1 Employment Study

Figure 11 presents event study graphs demonstrating that increasing the amount of real FPUC dollars in a state did not lead to a statistically significant change in total employment, retail employment, and education/health employment. Within the leisure/hospitality industry group, additional dollars from the FPUC was correlated with a decrease in employment.

These results reflect the prediction from the theoretical model that increased UI benefits from the FPUC program would not deter most workers from accepting job offers. While the impact of additional FPUC dollars was directionally negative, it was not statistically significant. The supersector that experienced a decline in employment resulting from more FPUC dollars was leisure/hospitality, where an additional 10,000 real FPUC dollars was correlated with a decrease of around 5 job-weeks. This impact was statistically significant between week 3 and week 10 after the CARES Act was passed. Wages offered in the leisure/hospitality sector were the lowest among all industry groups at $407 per week. As a result, workers in the supersector had a replacement rate of over 160% (Ganong et al., 2020). In addition, workers in leisure/hospitality likely had a higher chance of contracting COVID compared to the average worker, which further reduced their reservation benefit.

For industry groups that provide higher wages such as professional/business (Figure 14a), the effect of additional FPUC dollars was minimal. In the health/education sector, the effect of additional FPUC dollars was statistically significant without controls for the first five weeks after the CARES Act was passed, between 5 to 10 jobs created per $10,000. I suspect that there is a large amount of omitted variable bias for this industry group as some states closed schools throughout the spring while others re-opened. Thus, while directionally positive, it is likely there were other variables at play that had a larger effect on employment within the education/health sector.

7.2 Job Opening Study

Figure 12 presents event study graphs detailing the impact of the FPUC program on job openings per week in different industries. I examine job openings to analyze the effect of the FPUC on labor demand. The effect of additional FPUC dollars was not statistically significant for total, retail, and leisure/hospitality job openings. However, the point estimates for total, retail, finance, and professional job openings are directionally negative. The only sector that experienced an increase in job openings as a result of additional FPUC dollars was manufacturing, where increased dollars led to a statistically significant increase in job openings per week once utilizing controls.

Thus, while the impact of FPUC dollars on job openings is not statistically significant for most industries, the fact that the point estimates are directionally negative for almost all industries suggests that there may have been a small drop in labor demand. As shown in the theoretical framework, even a small decrease in job openings affecting the job finding rate can be enough to offset the impact of increased UI benefits from the FPUC encouraging workers to stay home. Within the leisure/hospitality industry group, the impact of FPUC dollars on job openings was consistently around zero throughout the time period. This implies that the impact of the FPUC on employment in leisure/hospitality was not through a labor demand channel.

In the manufacturing sector, an additional 10,000 real FPUC dollars entering a state led to an increase of around 0.5 job openings per week. The point estimates are consistently positive and statistically significant for the first eight weeks. A plausible explanation for this result is that businesses in manufacturing anticipated higher consumer demand in the future from the increase in FPUC dollars and began hiring immediately after the CARES Act was passed. Unlike employment, the median wage of each industry does not appear to have an effect on whether the industry experienced increased or decreased job openings as a result of more FPUC dollars entering the state. The impact of the FPUC program on job openings did not significantly vary between low-paying industries, such as leisure/hospitality and retail, and high-paying industries such as finance and professional/business.

7.3 Consumer Spending Study

Figure 13 presents event study graphs on the effect of increased FPUC dollars on weekly consumer spending. Increasing the amount of real dollars per person in a state did not lead to a consistently statistically significant change in consumer spending for most of the industry groups analyzed. However, the point estimates were negative with statistical significance in the weeks immediately after the passage of the CARES Act for several industry groups and then increased over the course of the time period.

For most of the industry groups analyzed, there appears to be an upward trend in the point estimates moving further into the time horizon. For example, the impact of FPUC dollars on retail spending was zero immediately after the CARES Act was passed, but increased until a statistically significant positive impact was observed in week 18 of the time horizon. A 1% increase in real FPUC dollars entering a state was correlated with retail consumer spending increasing by 0.15%. Thus, there appears to be a disconnect as more FPUC dollars was correlated with increased retail consumer spending over time but not job openings. One explanation is that the increase in retail spending was largely through online shopping rather than in stores, meaning that there was less of an incentive to hire more workers.

However, in the weeks immediately after the CARES Act was passed, the impact of increased FPUC dollars on many types of consumer spending was directionally negative. In the cases of total, entertainment, transportation, and restaurant spending, there is at least one week where the point estimates were negative with statistical significance. These industry groups were among the most negatively impacted by the pandemic. An explanation for this observation is that states that received more FPUC dollars relative to other states also experienced a greater impact from the COVID-19 pandemic that was not captured in the control variables. Another possibility is that people living in states that received more real FPUC dollars (i.e. where the cost of living is lower and unemployment was high), saved money at a higher rate compared to the rest of the country.

In this respect, the event graphs show that immediate impact of the FPUC program on consumer spending was mostly negative, although over time the negative effect disappears and in some industries becomes positive. This provides supporting evidence of a small drop in labor demand caused by higher FPUC dollars reducing consumer spending in the weeks right after the passage of the CARES Act.

7.4 Results Discussion

Ultimately, the results from this empirical analysis support the predictions from the theoretical model. Overall employment did not experience a decline, although for leisure/hospitality, the lowest paying industry group, more FPUC dollars was correlated with a decrease in employment. With regards to job openings, the impact of larger amounts of FPUC dollars was not statistically significant, although for all industries except for manufacturing the point estimates are directionally negative. Thus, it is possible that the impact of increased UI benefits disincentivising workers was mitigated by a reduction of job openings and the job finding rate as a result of businesses anticipating difficulties in hiring workers and lower consumer demand.

This explanation is supported by the directionally negative coefficients when regressing consumer spending on FPUC dollars, especially in the weeks immediately after the CARES Act was passed in areas such as transportation and restaurants. As such, even though the decrease in labor demand was small, it incentivised workers who were employed to stay at their jobs rather than risk being on unemployment. Therefore, small changes in labor demand and industry-specific conditions can explain why a large increase in UI benefits did not significantly affect employment in most industries.

One limitation when interpreting the results is that while in the theoretical model changes in the job finding rate and separation rate are permanent, it is not the case in actuality. However, even a temporary drop in the job finding rate will still likely increase reservation benefits and encourage people to be employed. Thus, the interpretation that a decrease in the job finding rate raised reservation benefits during the weeks analyzed remains valid.

8 Conclusion

This paper investigates the impact of the FPUC on employment in various industry groups. I expand upon the theoretical model developed by Petrosky-Nadeau to incorporate the chance of falling ill from coronavirus. I find that even with expanded UI benefits from the FPUC, the vast majority of job seekers would accept a job offer rather than remain unemployed. As demonstrated, increasing UI benefits does not change the reservation benefit; it simply increases the weekly benefit relative to the reservation benefit. Instead, the reservation benefit is responsive to changes in the job finding rate, which is affected by labor demand. A permanent 1% decrease in the job finding rate causes the reservation benefit to rise by about $600. Furthermore, the negative impact of COVID-19 on the reservation benefit was modest. The difference in the reservation benefit between taking into account and not taking into account the chance of contracting COVID-19 is only $60 per week. Thus, any negative impact of the FPUC on labor supply by increasing weekly benefits relative to the reservation benefit can be offset if the program leads to even a small drop in the job finding rate.

I test this theoretical hypothesis by using an empirical approach outlined in Ramey and Zubiary (2018) to find the multiplier of government spending with regards to employment and job openings per week in different industries. For total employment and for employment in most of the industry groups analyzed, the effect of additional real FPUC dollars was not statistically significant even with the massive increase in the replacement rate to 114% for a worker making the median wage. The results of my empirical analysis support the idea that the effect of the FPUC program on labor supply was minimal in most industries and any negative influence was likely mitigated by the program also causing a directionally negative drop in job openings.

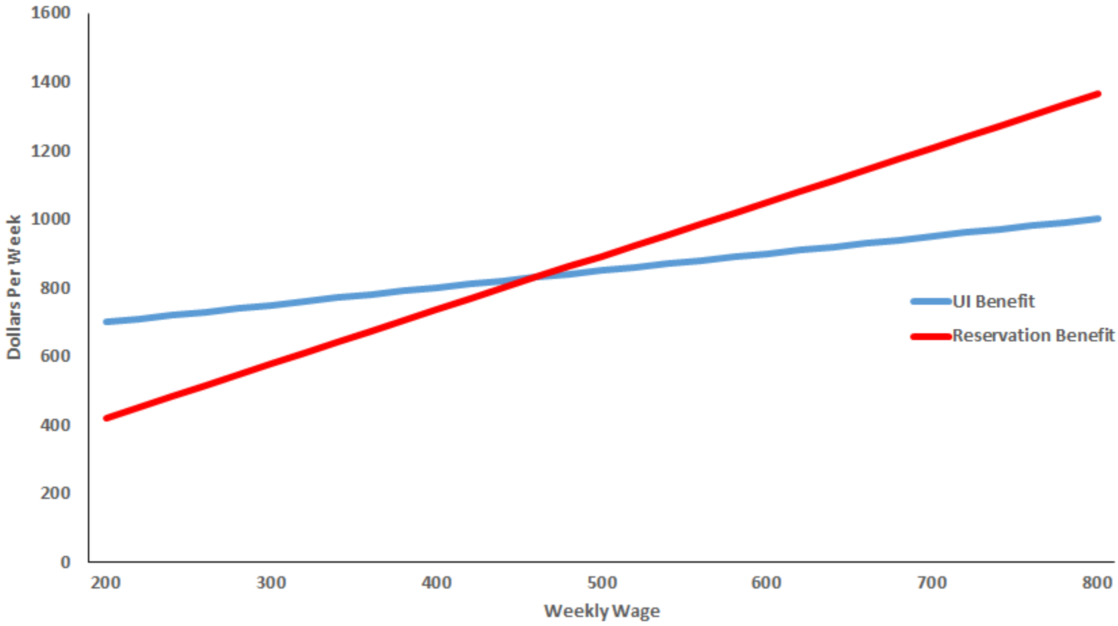
A fall in job openings suggests a drop in the job finding rate, which makes being unemployed less attractive compared to being employed. While changes in the job finding rate in actuality are not permanent as in the theoretical model, even a temporary drop in the job finding rate would likely increase the reservation benefit. Thus, the decrease in job openings incentivised employed workers to stay at their jobs and encouraged job-seekers to accept job offers. A small decrease in labor demand is further supported by my analysis of consumer spending, where in several industry groups such as transportation, healthcare, and restaurants, consumer spending fell as a result of additional FPUC dollars in the weeks immediately after the CARES Act was passed. Therefore, except for leisure/hospitality, a small drop in labor demand was enough to prevent weekly benefits from exceeding reservation benefits for most individuals, which would have disincentivised people from working.

These results are consistent with the findings of most of the literature that report that increased UI benefits from the FPUC did not hurt overall employment rates in states with higher replacement rates compared to states with lower replacement rates (Finamore and Scott, 2020; Bartik et al., 2020, Dube 2020). While employment in leisure/hospitality did fall as a result of more generous UI benefits, this drop can be explained by the uniquely low weekly wages within the supersector.

Looking forward, government policies in the economic recovery from the COVID-19 pandemic provide an opportunity to examine the impact and the effectiveness of various relief programs. In particular, the extension of additional UI benefits of $300 per week until September 2021 from the American Rescue Plan can be examined to find the impact of extending higher UI benefits in a recovering economy. In addition, additional research must be done on whether the effectiveness of state governments in distributing UI benefits affects employment levels within the state. This is left to future work.

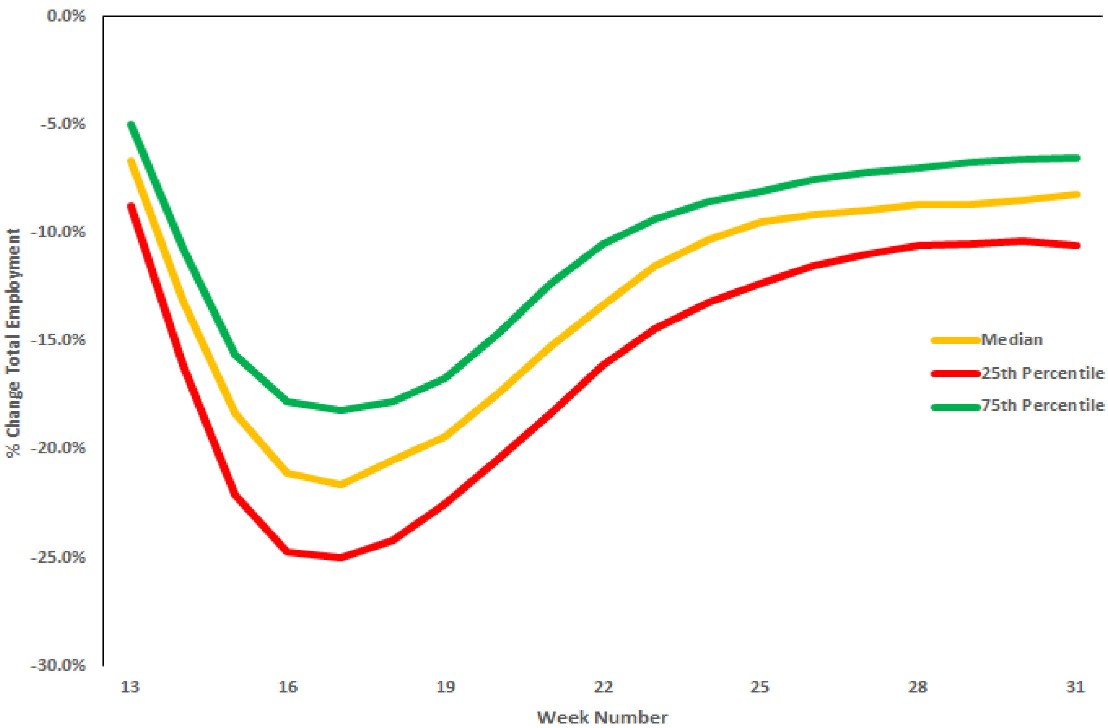
9 Figures

Figure 1: Effect of Weekly Wages On UI Benefit and Reservation Benefit



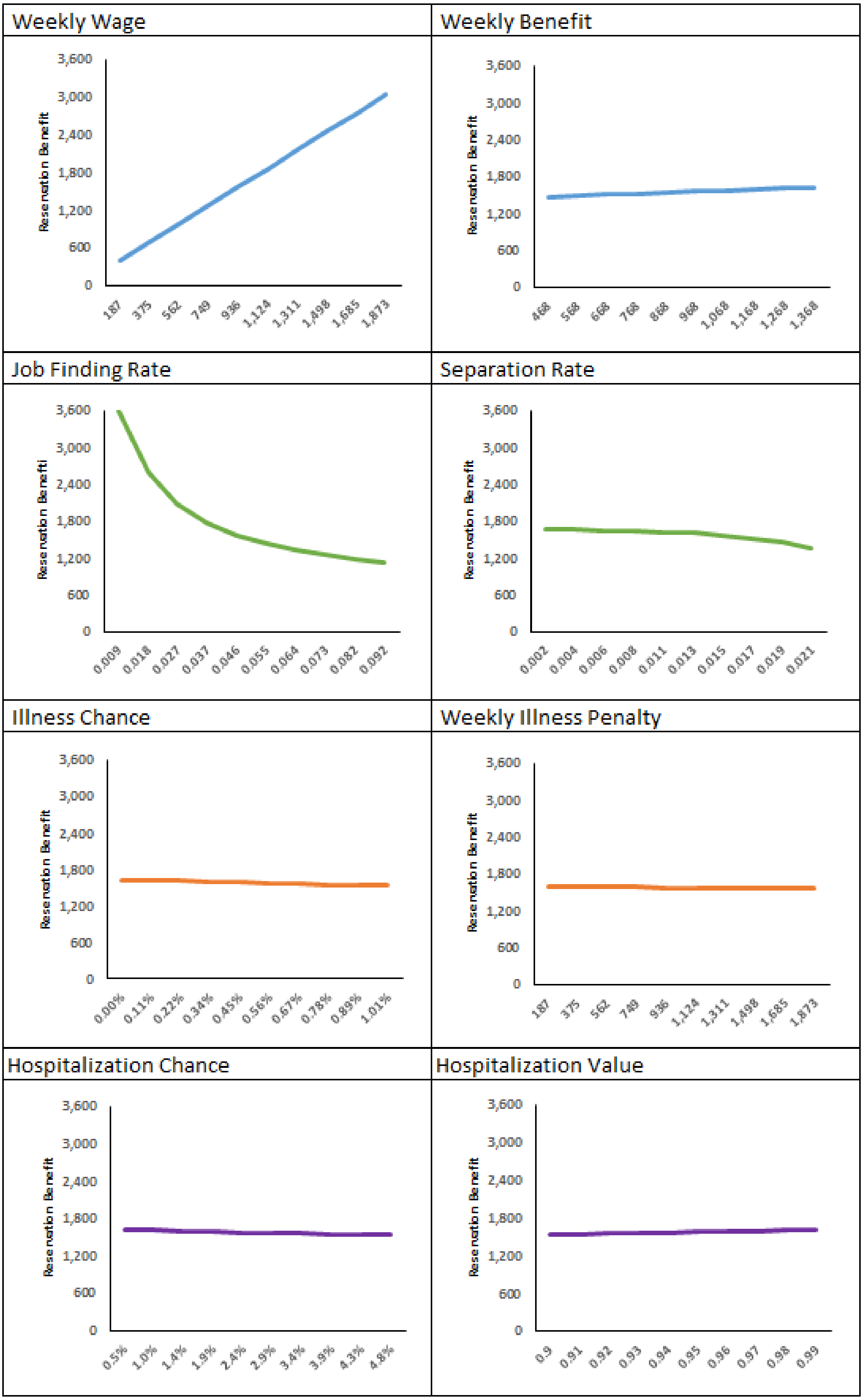
Note: All other parameters held to baseline specification.

Figure 2: Weekly Change in Employment Relative to January 2020



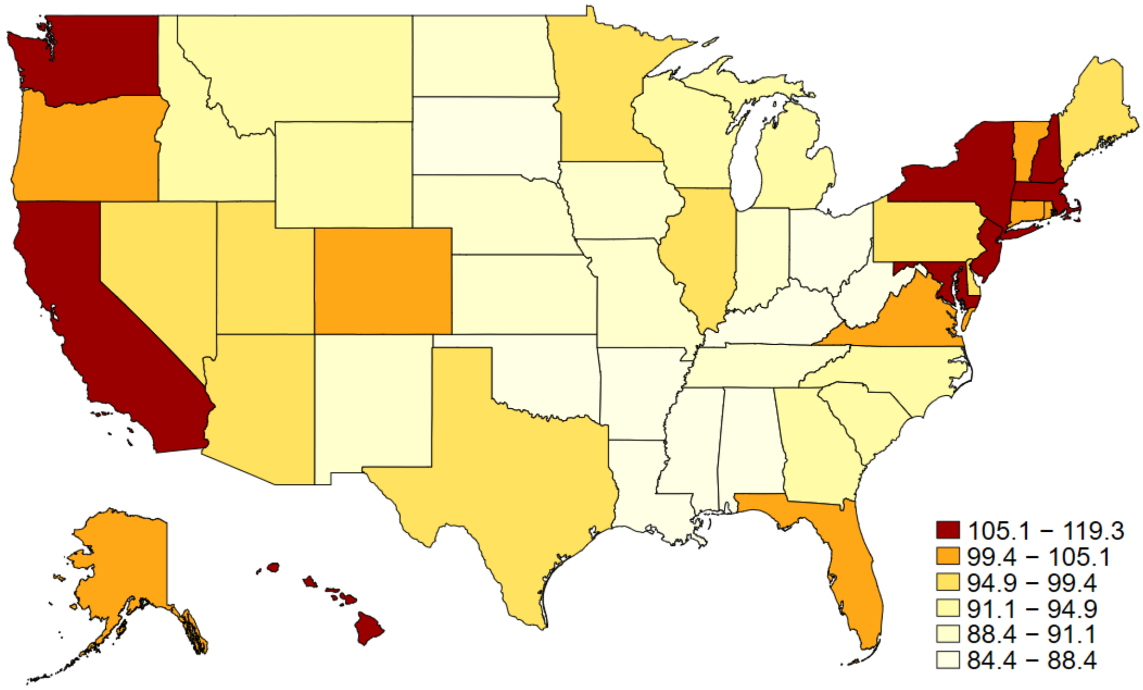
Note: Weekly change derived by averaging daily change in employment for each week relative to January 2020. Percentile refers to the state in the 25th or 75th percentile for each week, which differs between weeks.

Figure 3: Impact of Parameters on Reservation Benefit



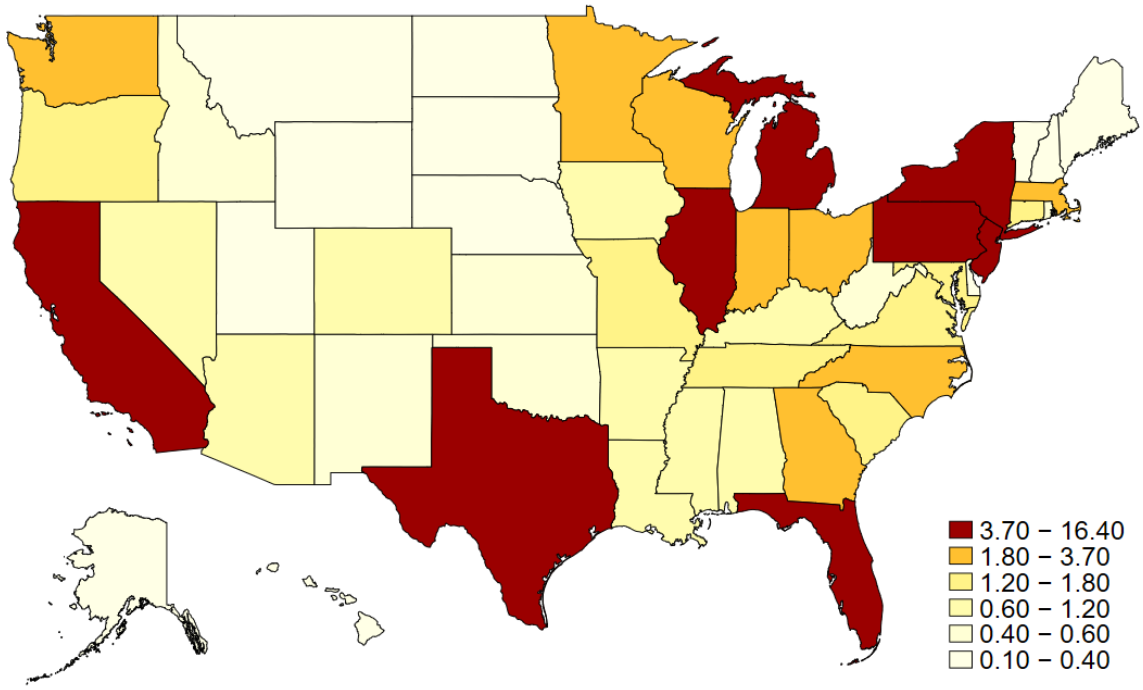
Note: All other parameters held to baseline specification.

Figure 4: Regional Price Parity Compared National Baseline



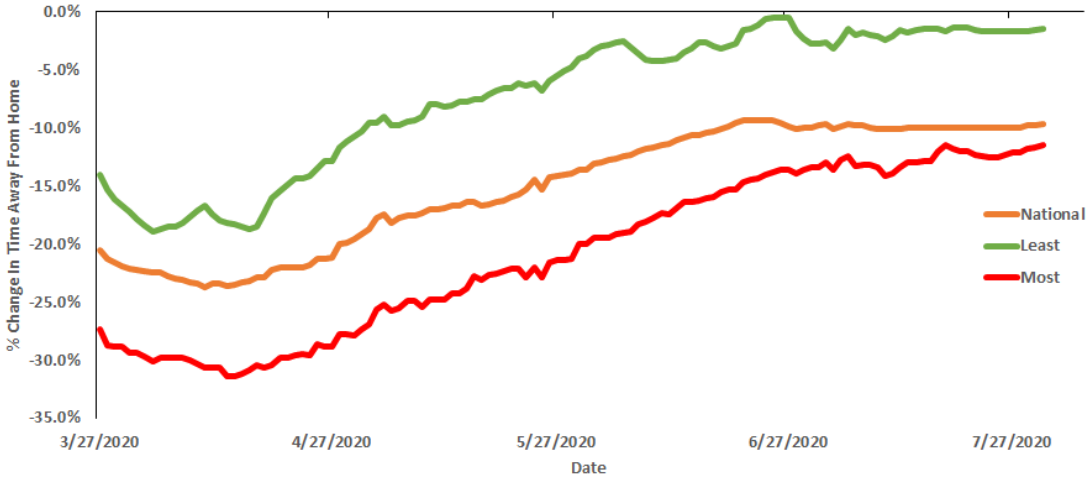
Note: Compared to national baseline of 100. Data from 2019.

Figure 5: Percent of National Total UI Claims December 2007



Note: Percentage of continued claims for month of December 2007.

Figure 6: Daily Change in Time Spent Away From Home

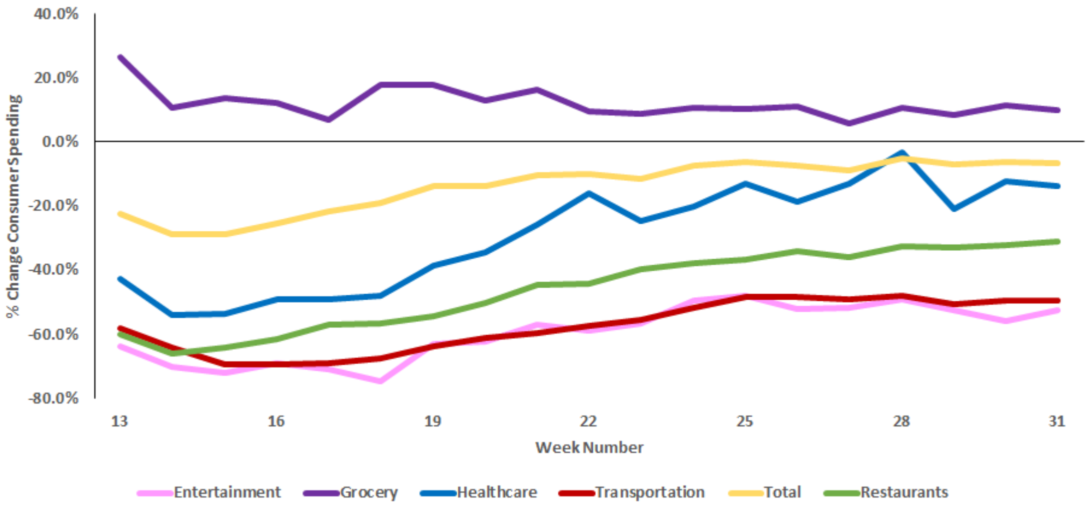


Note: GPS mobility data indexed to Jan 3-Feb 6 2020 from Google COVID-19 Community Mobility Reports. "Least" refers to the state of Montana, while "Most" refers to the state of New Jersey.

Figure 7: Weekly Change in Job Openings Relative to January 2020

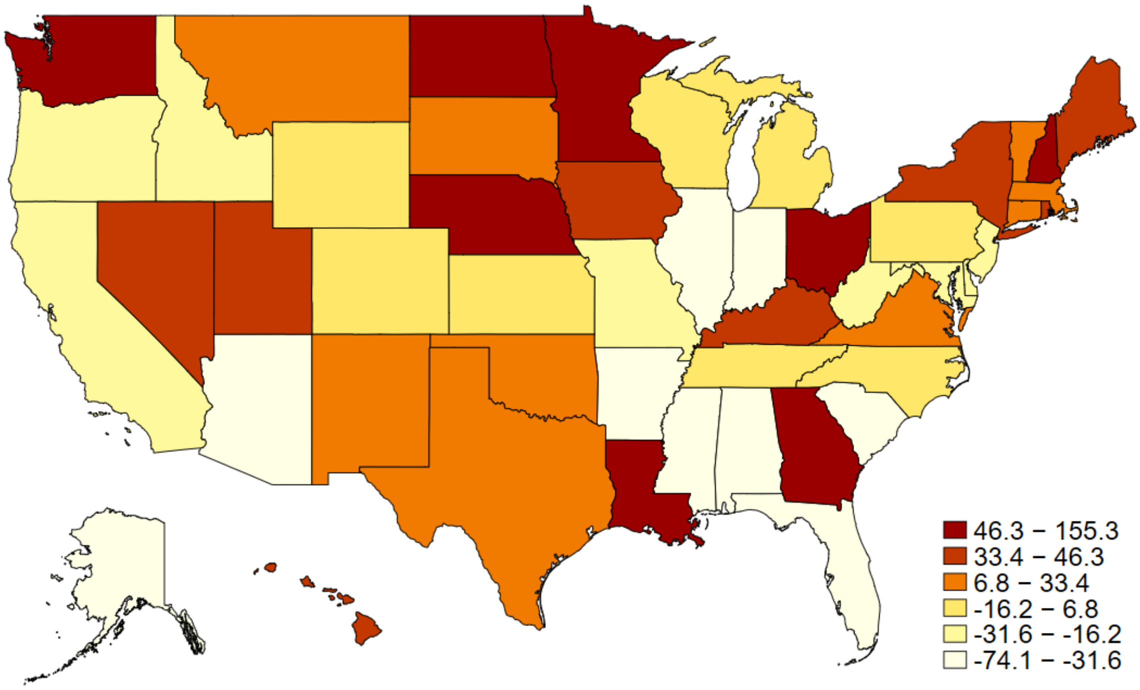
Note: Average level of job postings relative to January 4-31 2020. Percentile refers to the state in the 25th or 75th percentile for each week, which differs between weeks.

Figure 8: Weekly Change in Consumer Spending Relative to January 2020



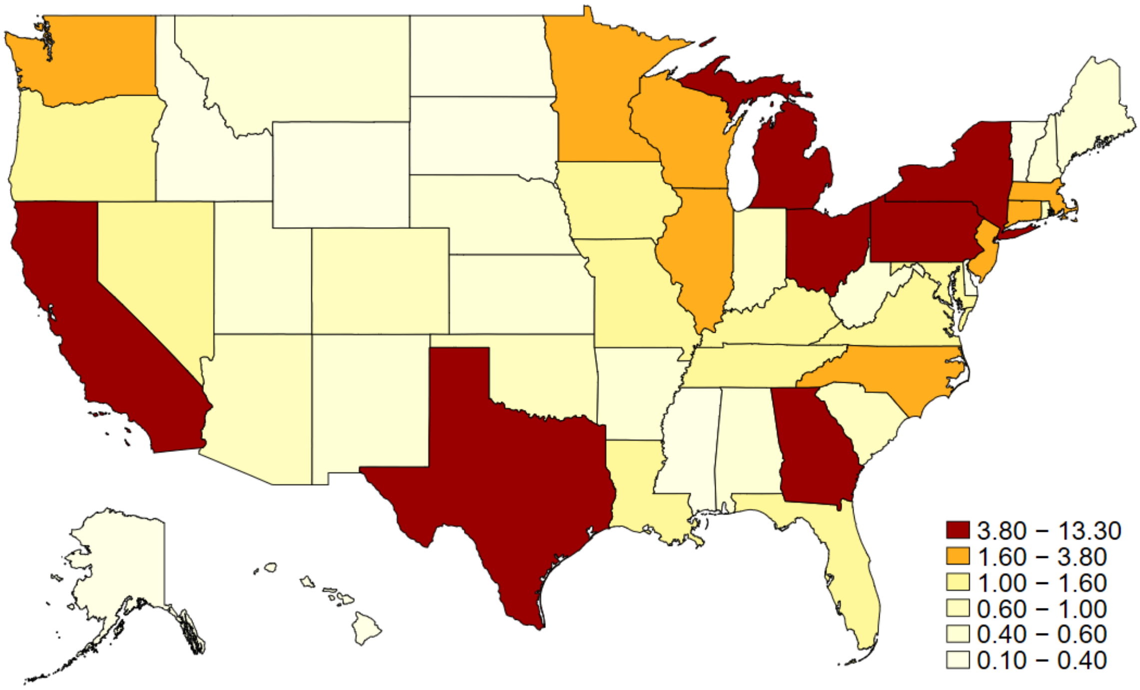
Note: Weekly change derived by averaging daily change in consumer spending for each week relative to January 2020. Change in consumer spending for the median state in an industry group shown.

Figure 9: % Change in Percentage of National UI Claims Between December 2007 and March 2020



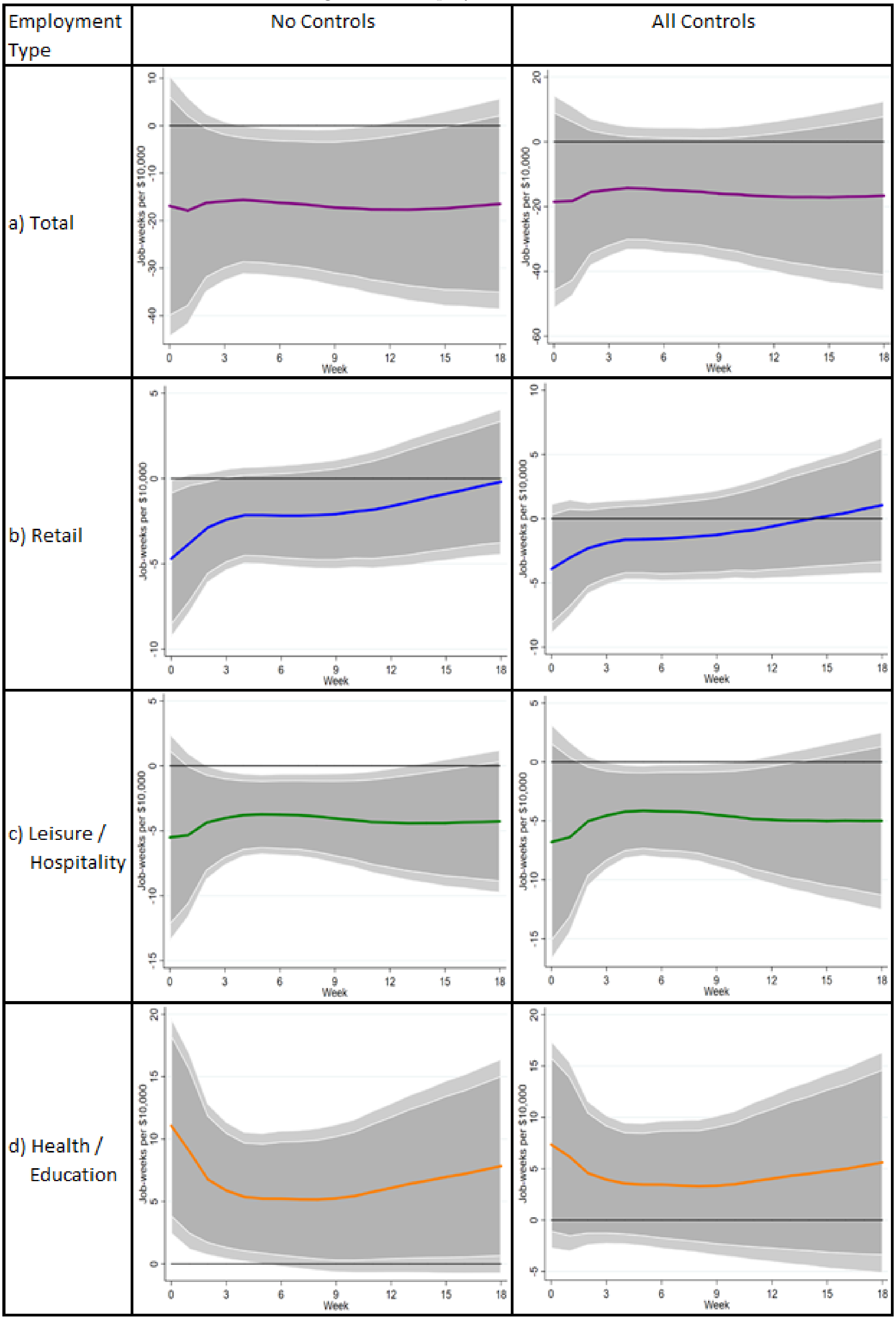
Note: Figure shows the percentage change in the percentage of national continued UI claims between December 2007 and March 2020.

Figure 10: Percentage of National UI Claims 2020



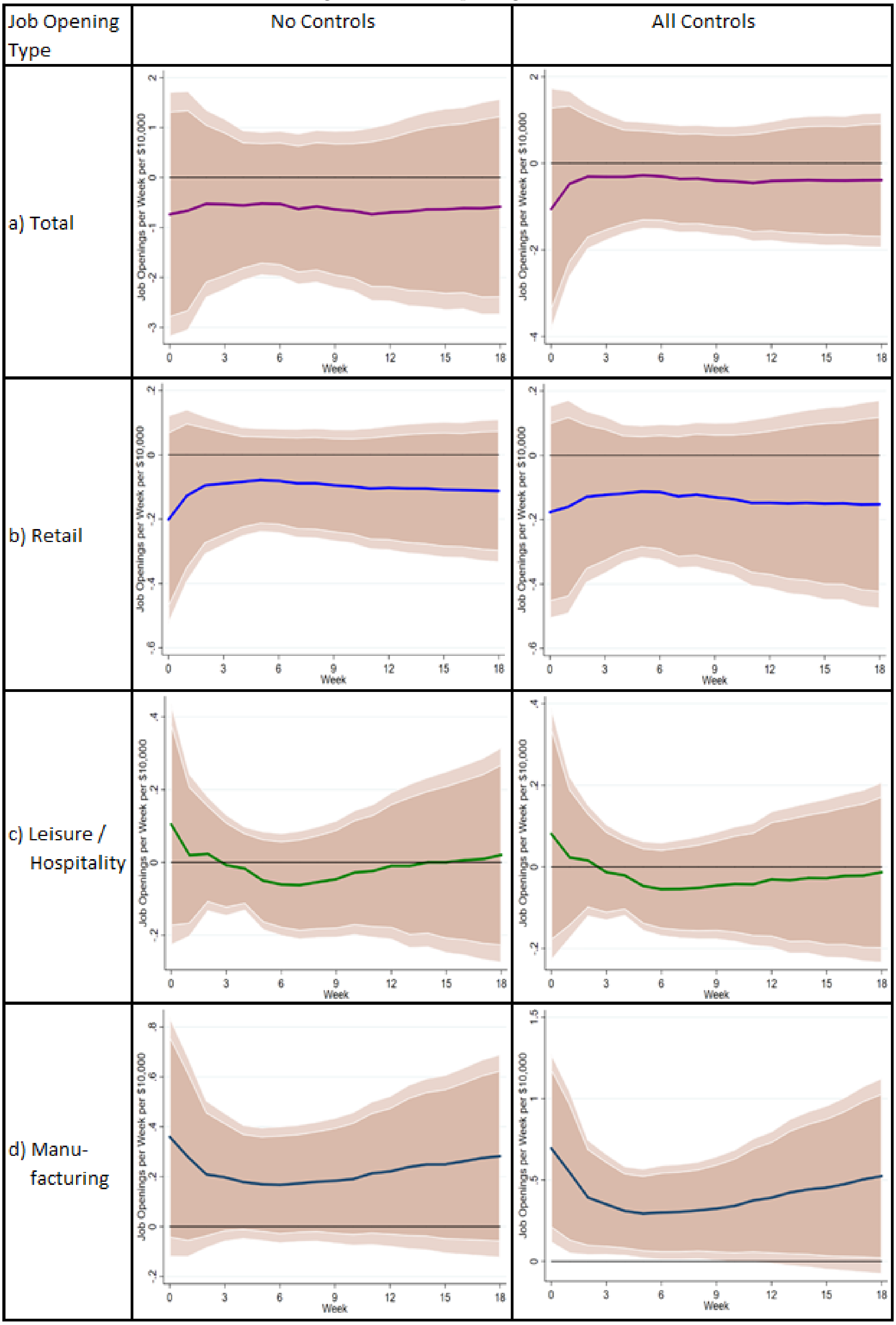
Note: Figure shows the percentage of national continued UI claims in March 2020.

Figure 11: Employment Results



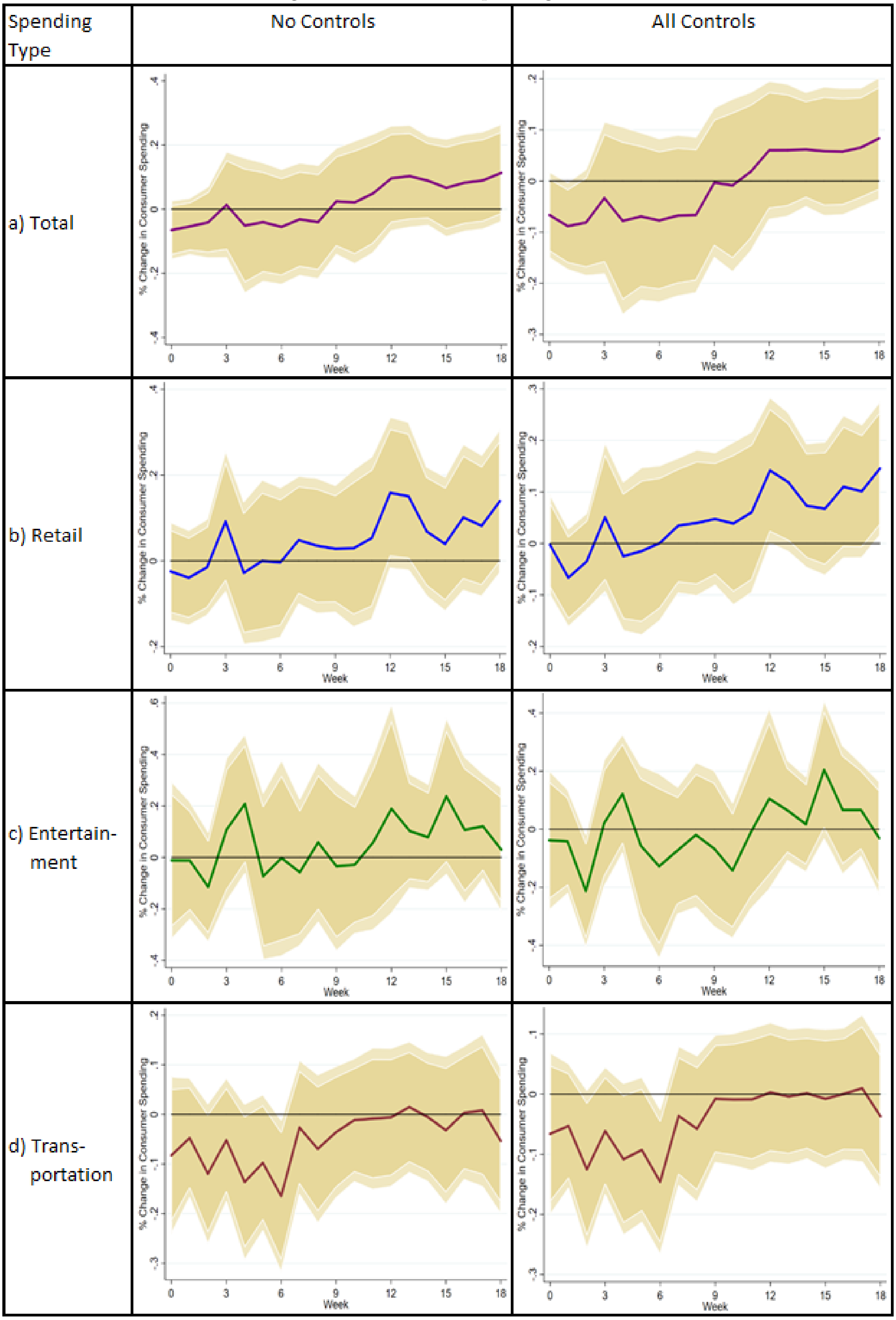
Note: All estimates are in total job-weeks per 10,000 real FPUC dollars.

Figure 12: Job Opening Results



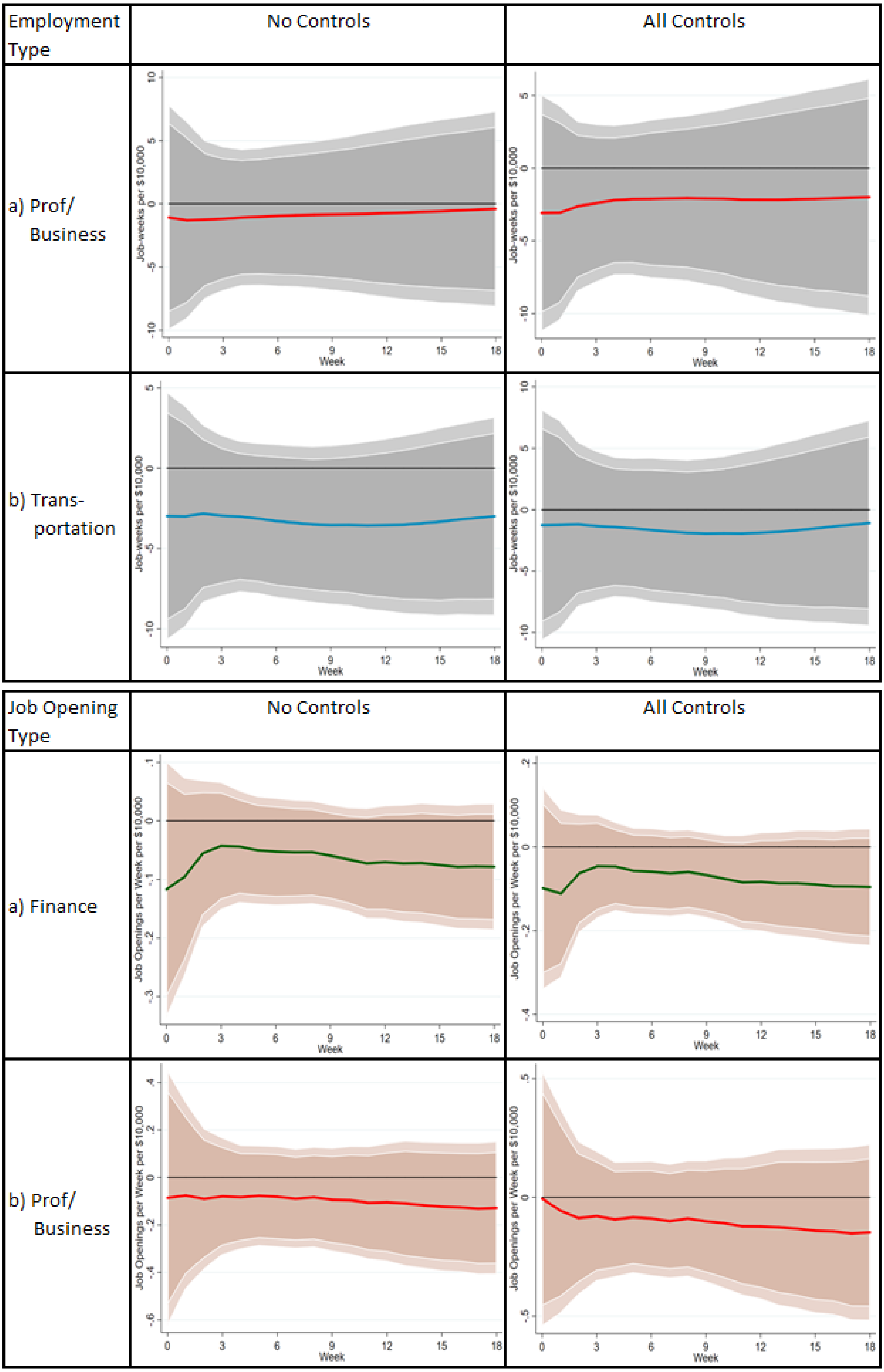
Note: All estimates are in total job openings per week per 10,000 real FPUC dollars.

Figure 13: Consumer Spending Results



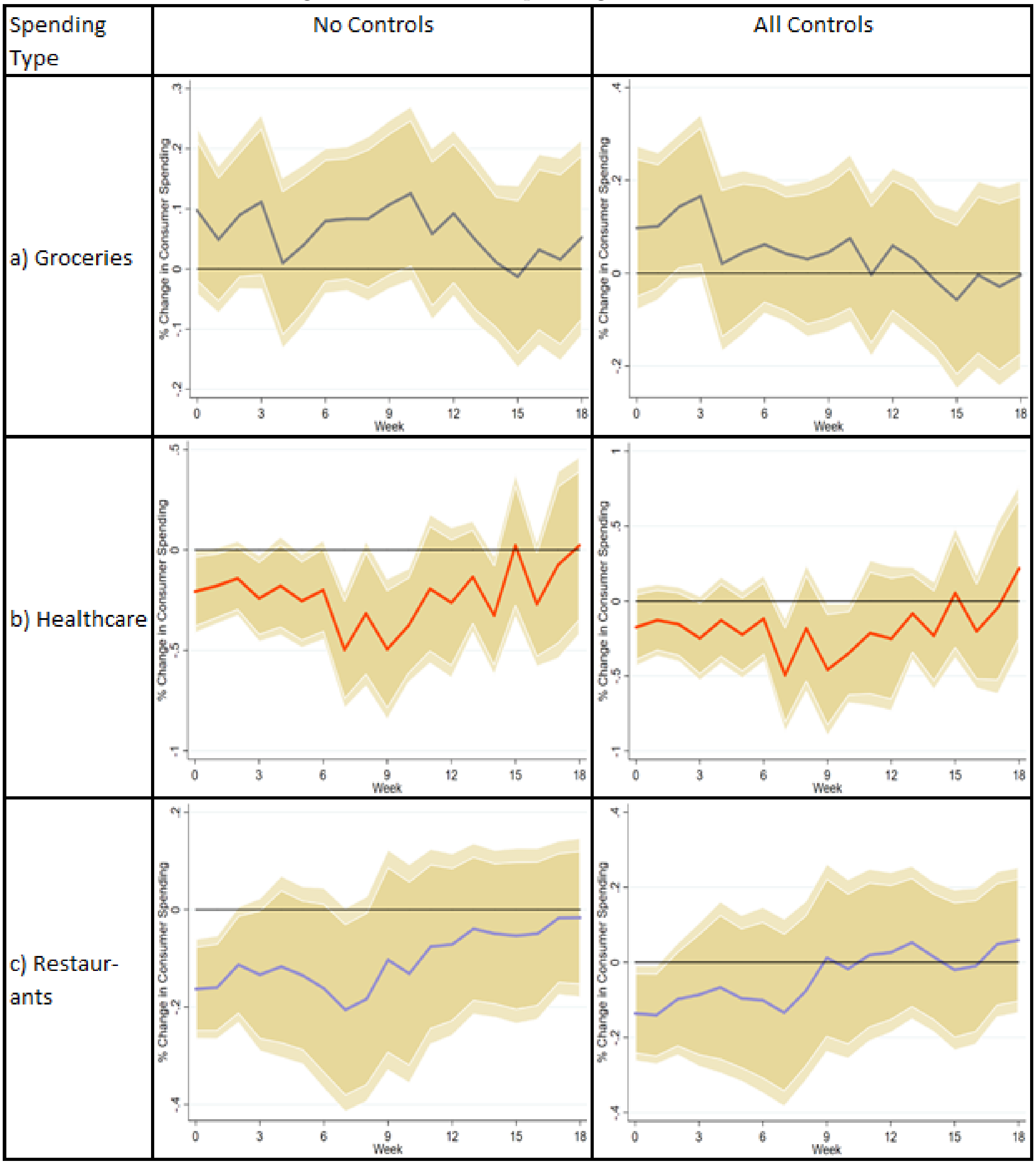
Note: All estimates are in percent change in consumer spending per 1 percent increase in real FPUC dollars.

Figure 14: Employment/Job Opening Results Cont.



Note: All estimates are in total job-weeks/job openings per week per 10,000 real FPUC dollars.

Figure 15: Consumer Spending Results Cont.



Note: All estimates are in percent change in consumer spending per percent increase in real FPUC dollars.

10 Tables

Table 1: Baseline Parameter Values

Value Parameter	Value	Rate Parameter	Value
Weekly wage *(w)*	$936.25	Discount rate *(r)*	0.000385
Weekly Benefit *(b)*	$1,068.13	Job Finding Rate *(f)*	0.0458
Maximum UI duration *(T)*	16 weeks	Separation Rate *(s)*	0.0106
Flow utility of COVID-19 *(k)*	-$936.25	Weekly COVID-19 chance *(c)*	0.00559
Present Value of Hospitalization Relative to Employment *(ζ)*	0.95	Weekly hospitalization chance *(h)*	0.0241

Note: All figures are on a per-week basis except for the present value of hospitalization relative to employment. ζ is static in the model.

Table 2: Elasticity of Weekly Reservation Benefit

Dollar Parameter	**% Change in Reservation Benefit from 1% Increase in Parameter**	
Weekly Wage *(w)*	0.588%	
Weekly Benefit *(b)*	0.081%	
Value of contracting COVID-19	0.918%	
Rate Parameter	**Change in Reservation Benefit from 1% Point Increase in Parameter**	
	$	**%**
Separation Rate *(s)*	($56.93)	-3.61%
Job Finding Rate *(f)*	($597.90)	-37.91%
COVID-19 Contraction Rate *(c)*	($66.05)	-4.19%

Note: Calculated with parameters at baseline values. Value of contracting COVID-19 represents permanent value.

Table 3: First-stage regression: Actual Cumulative Dollars Per Capita on Estimated Cumulative Dollars Per Capita

	No Controls		COVID Controls		All Controls	
Horizon	Coefficient	F-stat	Coefficient	F-stat	Coefficient	F-stat
0	0.662	18.74	0.544	7.43	0.548	5.99
1	0.586	18.79	0.476	7.91	0.479	6.35
2	0.608	23.82	0.505	10.3	0.507	8.14
3	0.596	24.51	0.497	10.68	0.498	8.37
4	0.563	25.68	0.473	11.51	0.474	9.02
5	0.528	24.52	0.443	11.60	0.444	9.08
6	0.484	21.86	0.405	11.39	0.404	8.91
7	0.470	20.31	0.393	10.74	0.392	8.41
8	0.455	18.97	0.383	10.04	0.382	7.89
9	0.438	17.88	0.366	9.95	0.365	7.82
10	0.423	17.01	0.352	9.99	0.351	7.85
11	0.405	15.74	0.332	9.89	0.331	7.78
12	0.392	14.81	0.320	9.83	0.318	7.74
13	0.380	13.90	0.307	9.80	0.306	7.72
14	0.370	13.18	0.298	9.81	0.297	7.73
15	0.361	12.38	0.288	9.73	0.287	7.69
16	0.355	11.78	0.282	9.76	0.280	7.73
17	0.348	11.11	0.273	9.73	0.272	7.72
18	0.342	10.51	0.267	9.63	0.265	7.66

Note: All estimates in real 2020 dollars. All coefficients are statistically significant with $p < 0.001$.

Table 4: First Stage Regression: Actual Weekly Dollars per Capita on Estimated Weekly Dollars per Capita

	No Controls	COVID Controls	All Controls
Estimated Weekly Dollars	0.662***	0.544***	0.548***
	(0.15)	(0.15)	(0.15)
Stay-at-home status		2.135	2.145
		(1.87)	(1.88)
T_home		-56.67	-54.532
		(27.41)	(27.71)
Weekly COVID Deaths		0.391	0.509
		(1.86)	(1.88)
Job Openings			4.432
			(6.07)
Constant	5.678*	-3.689	-2.973
	-2.43	-4.87	-4.99
F-stat	18.74	7.43	5.99
R-sqr	0.2851	0.4033	0.4106

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: All estimates in real 2020 dollars. All variables are in terms of FPUC dollars received by a state in week 13 2020.

11 Appendix

11.1 Reservation Benefit Derivation

If employment is preferred to remaining unemployed at time $t+1$ (Petrosky-Nadeau 2020):

$$W_U(b,t) = B(t) + \left(\frac{f}{r+f}\right) W_E \tag{19}$$

$$B(t) = \sum_{i=0}^{t-1} b \left(\frac{1-f}{1+r}\right)^i \tag{20}$$

Reservation benefit:

$$W_U(b^r(t,w),t) = W_E \tag{21}$$

$$b^r(t,w) = \frac{b^r(1,w)}{\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i} \quad \text{for } 1 < t \leq T \tag{22}$$

For following derivations let $\phi(t) = \sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i$. Solve for $b^r(1,w)$:

$$W_U(b^r(1,w),1) = W_E \tag{23}$$

Reservation benefit with 1 week of UI eligibility remaining:

$$b^r(1,w) = W_E\left(\frac{r}{r+f}\right) \tag{24}$$

From (1):

$$W_E = \frac{(r+f)[(1+r)w + sB(T) + (1-s)cCov(\bar{t})]}{(1+r)(r+f) - (1-s)(1-c)(r+f) - sf} \tag{25}$$

Using (24):

$$b^r(1,w) = \frac{r[(1+r)w + sB(T) + (1-s)cCov(\bar{t})]}{(1+r)(r+f) - (1-s)(1-c)(r+f) - sf} \tag{26}$$

For following derivations let $\psi = (1+r)(r+f) - (1-s)(1-c)(r+f) - sf$

11.2 General Form of Cov($\bar{t}$)

General form of $Cov(t)$:

$$Cov(1) = w - k + \frac{1}{1+r}[h\overline{H} + (1-h)W_E] \tag{27}$$

$$Cov(2) = w - k + \frac{1-h}{1+r}(w-k) + \frac{1}{1+r}h\overline{H} + \frac{1-h}{(1+r)^2}h\overline{H} + \left(\frac{1-h}{1+r}\right)^2 W_E \tag{28}$$

Following this pattern we can express the general form as:

$$Cov(\bar{t}) = (w - k + \frac{h\overline{H}}{1+r})\sum_{i=0}^{\bar{t}-1}\left(\frac{1-h}{1+r}\right)^i + \left(\frac{1-h}{1+r}\right)^{\bar{t}} W_E \tag{29}$$

Let $\eta(\bar{t}) \equiv \sum_{i=0}^{\bar{t}-1}\left(\frac{1-h}{1+r}\right)^i$ and $\tau(\bar{t}) \equiv \left(\frac{1-h}{1+r}\right)^{\bar{t}}$

Using (25) for W_E:

$$Cov(\bar{t}) = \left(w - k + \frac{h\overline{H}}{1+r}\right)\eta(\bar{t}) + \tau(\bar{t})\left[\frac{r+f}{\psi}\left[(1+r)w + sB(T) + (1-s)cCov(\bar{t})\right]\right] \tag{30}$$

$$Cov(\bar{t}) = \frac{\psi\left(w - k + \frac{h\overline{H}}{1+r}\right)\eta(\bar{t}) + \tau(\bar{t})(r+f)[(1+r)w + sB(T)]}{\psi - \tau(\bar{t})(r+f)(1-s)c} \tag{31}$$

11.3 Elasticity of Reservation Benefit With Respect To Weekly UI benefit

Elasticity

$$\epsilon_{(b^r(t,w),b)} = \frac{1}{\phi(\bar{t})} * \frac{\partial b^r(1,w)}{\partial b} * \frac{s\phi(t)}{b^r(1,w)} = \frac{\partial b^r(1,w)}{\partial b} * \frac{s}{b^r(1,w)} \tag{32}$$

From (26) and (31):

$$b^r(1,w) = \frac{r[(1+r)w + sB(T) + +(1-s)c\left[\frac{\psi(w-k+\frac{h\overline{H}}{1+r})\eta(\bar{t}) + \tau(\bar{t})(r+f)[(1+r)w+sB(T)]}{\psi - \tau(\bar{t})(r+f)(1-s)c}\right]}{\psi} \tag{33}$$

$$\frac{\partial b^r(1,w)}{\partial b} = \frac{rs\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}{\psi} + \frac{\frac{r(1-s)c*s\tau(\bar{t})(r+f)\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}{\psi-\tau(\bar{t})(r+f)c(1-s)}}{\psi} \tag{34}$$

$$\epsilon_{(b^r(t,w),b)} = \left(\frac{rs\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}{\psi} + \frac{\frac{r(1-s)c*s\tau(\bar{t})(r+f)\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}{\psi-\tau(\bar{t})(r+f)c(1-s)}}{\psi}\right) * \frac{s}{b^r(1,w)} \tag{35}$$

11.4 Elasticity of Reservation Benefit With Respect To Weekly Wages

Elasticity:

$$\epsilon_{(b^r(t,w),w)} = \frac{\partial b^r(t,w)}{\partial w} * \frac{s}{b^r(t,w)} = \frac{\partial b^r(1,w)}{\partial w} * \frac{s}{b^r(1,w)} \tag{36}$$

Use (26) for $b^r(1,w)$:

$$\frac{\partial b^r(1,w)}{\partial w} = \frac{rs\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}{psi} + \frac{\psi r(1-s)c*s\tau(\bar{t})(r+f)\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}{\psi - \tau(\bar{t})(r+f)(1-s)c} \tag{37}$$

$$\epsilon_{(b^r(t,w),w)} = \left[\frac{rs\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}{\psi} + \frac{\psi r(1-s)c*s\tau(\bar{t})(r+f)\sum_{i=0}^{t-1}\left(\frac{1-f}{1+r}\right)^i}{\psi - \tau(\bar{t})(r+f)(1-s)c}\right] * \frac{w}{b^r(1,w)} \tag{38}$$

11.5 Elasticity of Reservation Benefit With Respect To Separation Rate

Elasticity:

$$\epsilon_{(b^r(t,w),s)} = \frac{\partial b^r(t,w)}{\partial s} * \frac{s}{b^r(t,w)} = \frac{\partial b^r(1,w)}{\partial s} * \frac{s}{b^r(1,w)} \tag{39}$$

Use (26) for $b^r(1,w)$:

$$\frac{\partial b^r(1,w)}{\partial s} = \frac{\psi(rB(t) + \left(\frac{\partial ACov(\bar{t})}{\partial s}\right) - (r(1+r)w + rsB(T) + ACov(\bar{t}))(r - cr + cf)}{\psi^2} \tag{40}$$

where

$$\frac{\partial Cov(\bar{t})}{\partial s} = \frac{(\psi - A\tau(\bar{t}))(BC + D\tau(\bar{t})) - (A(B\psi + E\tau(\bar{t})))(c(\tau(\bar{t}) - 1)(r+f) + r)}{(\psi - A\tau(\bar{t}))^2} \tag{41}$$

$A = r(1-s)c$
$B = \left(w - k + \frac{h\overline{H}}{1+r}\right)\eta(\bar{t})$
$C = cf(2c(s-1)(r+f) - r(r+f+2s-1))$
$D = -cr(r+f)(2sB(T) - B(T) + rw + w)$
$E = (r+f)[(1+r)w + sB(T)]$

11.6 Elasticity of Reservation Benefit With Respect To Job Finding Rate

Elasticity:

$$\epsilon_{(b^r(t,w),f)} = \frac{\partial b^r(1,w)}{\partial f} * \frac{f}{b^r(1,w)} \tag{42}$$

Use (26) for $b^r(1,w)$:

$$\frac{\partial b^r(1,w)}{\partial f} = \frac{\psi(G + H\left(\frac{\partial Cov(\bar{t})}{\partial f}\right)) - (r[(1+r)w + sB(T)] + HICov(\bar{t}))}{\psi^2} \tag{43}$$

where

$$\frac{\partial Cov(\bar{t})}{\partial f} = \frac{IJ + \tau(\bar{t})(w + rw) - Gs\tau(\bar{t})}{\psi - H\tau(\bar{t})} - \frac{(J\psi + (K+L)\tau(\bar{t}))(I - \tau(\bar{t})(1-s)c)}{(\psi - A\tau(\bar{t}))^2} \tag{44}$$

$G = -rs\sum_{i=1}^{t-1} i\frac{(1-f)^{i-1}}{(1+r)^i}$
$H = r(1-s)c$
$I = c + r - cs$
$J = \left(w - k + \frac{h\overline{H}}{1+r}\right)\eta(\bar{t})$
$K = (r+f)(1+r)w$
$L = s(r+f)B(T)$

11.7 Elasticity of Reservation Benefit With Respect To Probability of Contraction COVID-19

Elasticity:

$$\epsilon_{(b^r(t,w),c)} = \frac{\partial b^r(1,w)}{\partial c} * \frac{c}{b^r(1,w)} \tag{45}$$

Use (26) for $b^r(1,w)$:

$$\frac{\partial b^r(1,w)}{\partial c} = \frac{\psi + \frac{\partial NCov(\bar{t})}{\partial c} - (NCov(\bar{t}) + M)O}{\psi^2} \tag{46}$$

where

$$\frac{\partial NCov(\bar{t})}{\partial c} = \frac{(\psi - N\tau(\bar{t}))(r(1-s)(QR+P)) - N(O\psi + P)(1-s)S}{(\psi - N\tau(\bar{t}))^2} \tag{47}$$

$M = r[(1+r)w + sB(T)]$
$N = r(1-s)c$
$O = (s-1)(-(r+f))$
$P = (r+f)\tau(\bar{t})[(1+r)w + sB(T)]$
$Q = \left(w - k + \frac{h\overline{H}}{1+r}\right)\eta(\bar{t})$
$R = f(r + 2(1-s)c + r(r - 2sc + s + 2c))$
$S = (1-s)(-\tau(\bar{t})(r+f) + r + f)$

11.8 Elasticity of Reservation Benefit With Respect To Value of Contracting COVID-19

Solve for partial derivative:

$$b^r(t,w) = \frac{b^r(1,w)}{\phi(t)} = \frac{r}{\phi(t)} * [\frac{(1+r)w}{\psi} + \frac{(1-s)cCov(\bar{t})}{\psi} + \frac{sB(T)}{\psi}] \tag{48}$$

$$\frac{\partial b^r(t,w)}{\partial Cov(\bar{t})} = \frac{1}{\phi(t)} * \frac{r(1-s)c}{\psi} \tag{49}$$

Solve for $\frac{Cov(\bar{t})}{b^r(t,w)}$:

$$\frac{Cov(\bar{t})}{b^r(t,w)} = \frac{Cov(\bar{t})}{\frac{b^r(1,w)}{\phi(t)}} \tag{50}$$

$$= \frac{Cov(\bar{t})\phi(t)\psi}{r[(1+r)w + (1-s)cCov(\bar{t}) + sB(T)]} \tag{51}$$

Multiply for elasticity:

$$\epsilon_{(b^r(t,w),Cov(\bar{t}))} = \frac{\partial b^r(t,w)}{\partial Cov(\bar{t})} * \frac{Cov(\bar{t})}{b^r(t,w)} = \frac{(1-s)cCov(\bar{t})}{(1+r)w + (1-s)cCov(\bar{t}) + sB(t)} \tag{52}$$

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