# The Impact of the Federal Pandemic Unemployment Compensation on Employment: Evidence from the Household Pulse Survey (Preliminary)

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### 1 Introduction

The Federal Pandemic Unemployment Compensation on Employment passed under the CARES Act added a \$600 boost to weekly UI benefits. In this short note, I assess whether FPUC had a negative impact on employment by disincentivizing labor supply (or by reducing job creation), as some commentators have suggested. To do so, I use the high-frequency Census Household Pulse Survey (HPS), which collects data on employment, and look at employment probabilities of those who are of age 18 or over, and do not have a college degree (as this group is highly affected by the UI program). I use state level variation in the median post-CARES earnings-replacement rates as provided by Ganong, Noel and Vavra (2020). I then consider whether the employment rebound after mid-May was stymied by the presence of high replacement rates using an event-study design.

In short, I find that while the replacement rates varied sizably across states (because of very different wage levels of workers without a college degree across states), there is no clear indication that this had an impact on the employment in the data through late July. These conclusions hold after controlling for demographic differences and state-level job loss measures during the pandemic. A similar conclusion obtains when I focus only on individuals whose households have experienced joblessness since March 2020. As an additional check, I considered how employment rate of those without any college degree was affected by the same replacement rates (as we should expect less or no impact there). Reassuringly, college workers' employment was largely unaffected, providing additional validation of the research design. My findings are similar to what Altonjii et al. (2020) found using different data and empirical design. Overall, the weight of evidence seems to suggest that to date, the FPUC—which was very successful in raising consumption among low-income families (—did not have a discernible impact on employment through late July, 2020. Moreover, given the availability of the public high-frequency HPS, the same method used in this paper can be used to keep track of impact on employment going forward.

## 2 Data and Methods

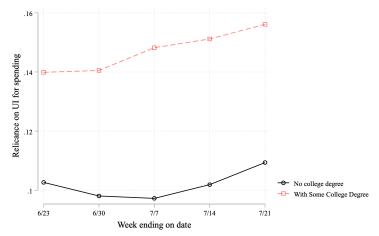
### 2.1 Data

I use the weekly Census Household Pulse Survey, which collects weekly data from an average of around 97,000 respondents per week using email and texts. The details for the dataset can be found here: https://www2.census.gov/programs-surveys/demo/technical-documentation/hhp/2020\_HPS\_Background.pdf. I focus on

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the following variables: whether a person was working in the previous week (ANYWORK), their educational credentials (EEDUC), and what share of their income came from unemployment benefits (SPNDSRC5), whether someone in their household experienced job loss since March 2020 (WRKLOSS), their race (RRACE), hispanic origin (RHISPANIC), year of birth (TBIRTH\_YEAR), gender (EGENDER), and previous year's household income category (INCOME). In particular, I focus on non-college educated workers (those with at most a high school degree) for the primary analysis, as this group has relied much more on the UI boost, but also show results for workers with some college degree (associate or more) as check. As we can see in the figure below, individuals without any college degree report mentioning UI as a source of income to meet spending needs than those with some college degree.

Figure 1: Reliance on Unemployment Insurance Payments as Source of Income to Meet Spending Needs, by Education

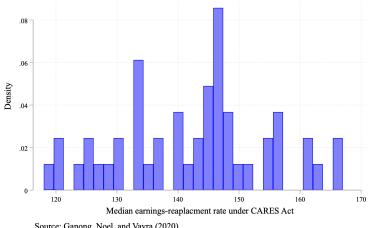


Notes: Analysis of US Census Household Pulse Survey micro-data.

I use the information on the median replacement rate under CARES Act (i.e., what share of one's pre-pandemic earnings are being replaced using FPUC and regular benefits) from Ganong, Noel and Vavra (2020). The figure below shows the distribution of replacement rates across states. In general, the median replacement rate by state varied between 118 (Maryland) and 167 percent (New Mexico), with a median of 137 percent.

Link to the Benefits Calculator here: https://bfi.uchicago.edu/insight/blog/ui-calculator/

Figure 2: Distribution of Post-CARES Median UI Replacement Rates by State



Source: Ganong, Noel, and Vavra (2020) UI insurance calculator at https://bfi.uchicago.edu/insight/blog/ui-calculator/

### 2.2 Research methods

I use variation in the post-CARES median replacement rate  $R_s$  to assess labor supply impacts. The key idea is that a worker deciding whether and how much to search for a job will compare their (weekly) wage rate W and compare it with benefits,  $\min(bW, \overline{B}) + \$600$ , where b is the usual replacement rate and  $\overline{B}$  is the maximum weekly benefit amount. Typically, b is around 50% for lower-wage workers in most states, though there are caps on weekly benefits,  $\overline{B}$ . In general, workers' search intensity will be a function of the effective replacement rate, R, which is approximately equal to:

$$R = \frac{\min(bW, \overline{B}) + \$600}{W} \approx b + \frac{\$600}{W}$$

So states that have higher wages (W) for similar workers (like MA or MD) will have a lower R, as compared to states like NM or WV. This means that as the labor market rebounds starting in early May, the extent to which labor supply is a binding constraint, we would expect to see states with higher R exhibit lower employment growth, other things equal.

To test this, I use an event-study approach that plots the evolution of employment differentially in states with high versus low median replacement rate,  $R_s$ . I estimate the following regression:

$$Emp_{it} = \alpha + \sum_{\tau=1}^{12} \beta^{\tau} \left( I_t^{\tau} \times R_{s(i)} \right) + \Gamma X_{it} + \rho_{s(i)} + \phi_t + e_{it}$$

$$\tag{1}$$

Here  $Emp_{it}$  is an indicator for if the person i worked in the previous week at all,  $I_t^{\tau}$  is an indicator for  $\tau^{th}$  week, s(i) is the state of individual i,  $X_{it}$  is a vector controls (worker's race, hispanic origin, quartic in age, gender, 2019 income, state-level share of households experiencing job loss since March 2020). Since states wages may be correlated with how hard the state was hit by the pandemic-induced job losses in March and April, inclusion of the state-level measure of pandemic job loss may be important. I estimate the regression both with and without these additional controls,  $X_{ist}$ . I plot the coefficients  $\beta^{\tau}$ , normalizing  $\beta^{1}$  as zero, which trace out changes in employment since the first sample week (ending in May 5, 2020). Regressions use the sampling weight provided in the dataset, and standard errors are clustered by state.

.5 .49 .48 .47 .48 .47

Figure 3: Share of individuals 18+ who are employed, no college degree

Notes: Analysis of US Census Household Pulse Survey micro-data

# 3 Findings

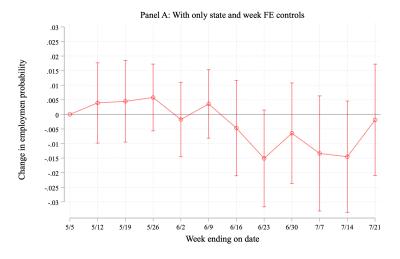
First, as shown in Figure 3, employment for non-college educated workers rebounded after mid-May consistent with evidence from other sources like the Current Population Survey. We also see an employment decline starting in late June, as a second peak in South and Western states led to greater restrictions and consumer reactions. The key question for us is whether having a relatively high replacement rate (e.g., 121 in MA versus 166 in WV) explain the pace of the employment change over this period.

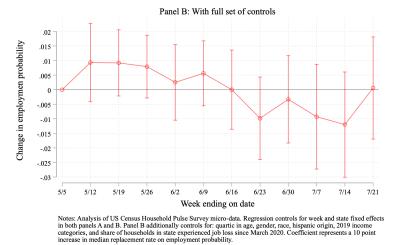
6/9 6/16 Week ending on date

In Figure 4, I show the key results from our estimates using equation (1). The plotted coefficients represent the impact of a 10 point higher replacement rate,  $R_s$ , on employment probabilities of workers without a college degree. In the top panel A, I show the results with only the time and state fixed effects as controls, while in the bottom panel B, I include the full set of individual and state-level controls.

In both panels, there is no statistically significant relationship between employment changes between week ending on 5/5 and later weeks in the sample. The point estimates are positive for other weeks in May and early June and negative in late June and July and close to zero by the most recent week. Use of controls (including the extent of job losses across states, and individual level demographic controls) tends to make the coefficients slightly more positive but the patterns are quite similar. In other words, employment changes from early May (which was the trough in employment) to later periods seem largely unrelated to differences in the likely replacement rate faced by workers without any college degree.

Figure 4: Impact of a 10 Point Increase in Median Replacement Rate on Employment Probability: Individuals 18+ Without Any College Degree

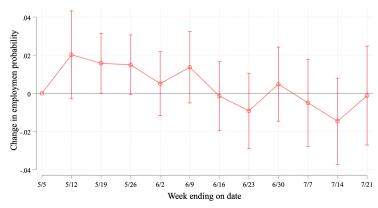




What if we specifically focus on individuals who report that they (or someone in their household) experienced some employment loss ("loss of employment income" to be precise) since March, 2020. This group may be particularly useful to consider if returns from unemployment have been held back by the policy. In Figure 5, we see that there is little relationship between employment probabilities conditional on employment loss and the median

replacement rate.

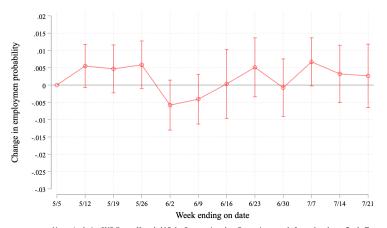
Figure 5: Impact of a 10 Point Increase in Median Replacement Rate on Employment Probability: Individuals 18+Without Any College Degree in Families Experiencing Employment Loss since March 2020



Notes: Analysis of US Census Household Pulse Survey micro-data. Regression controls for week and state fixed effects, and additionally controls for: quartic in age, gender, race, hispanic origin, 2019 income categories, and share of households in state experienced job loss since 2019. Coefficient represents a 10 point increase in median replacement rate on employment probability. Sample includes individuals in households that have experien loss in employment income since March 2020

As a final check, I estimate the same regression (with controls) but now for those who have some college degree. Again, we expect less impact on this group given the relatively less reliance on UI reported by them. As shown in Figure 6, here too, there is little impact on the employment trajectories.

Figure 6: Impact of a 10 Point Increase in Median Replacement Rate on Employment Probability: Individuals 18+ With a College Degree



Notes: Analysis of US Census Household Pulse Survey micro-data. Regression controls for week and state fixed effects, quartic in age, gender, race, hispanic origin, 2019 income category, and share of households in state experienced job since March 2020. Coefficient represents a 10 point increase in median replacement rate on employment probability.

Overall, these findings do not provide evidence supporting the claim that the FPUC has held back the labor market recovery. At some point, when the pandemic subsides and demand for labor grows strongly, labor supply constraints are likely to matter as we have seen in other periods. However, there seems little indication that this is the case so far.

# References

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- 3. Ganong, P., Noel, P.J. and Vavra, J.S., 2020. "US Unemployment Insurance Replacement Rates During the Pandemic." National Bureau of Economic Research Working Paper No. w27216.