

DISCUSSION PAPER SERIES

IZA DP No. 13643

**Impacts of the COVID-19 Pandemic and
the Cares Act on Earnings and Inequality**

Guido Matias Cortes
Eliza Forsythe

AUGUST 2020

DISCUSSION PAPER SERIES

IZA DP No. 13643

Impacts of the COVID-19 Pandemic and the Cares Act on Earnings and Inequality

Guido Matias Cortes

York University and IZA

Eliza Forsythe

University of Illinois, Urbana-Champaign

AUGUST 2020

Any opinions expressed in this paper are those of the author(s) and not those of IZA. Research published in this series may include views on policy, but IZA takes no institutional policy positions. The IZA research network is committed to the IZA Guiding Principles of Research Integrity.

The IZA Institute of Labor Economics is an independent economic research institute that conducts research in labor economics and offers evidence-based policy advice on labor market issues. Supported by the Deutsche Post Foundation, IZA runs the world's largest network of economists, whose research aims to provide answers to the global labor market challenges of our time. Our key objective is to build bridges between academic research, policymakers and society.

IZA Discussion Papers often represent preliminary work and are circulated to encourage discussion. Citation of such a paper should account for its provisional character. A revised version may be available directly from the author.

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Impacts of the COVID-19 Pandemic and the Cares Act on Earnings and Inequality*

Using data from the Current Population Survey (CPS), we show that the COVID-19 pandemic led to a loss of aggregate real labor earnings of more than \$250 billion between March and July 2020. By exploiting the panel structure of the CPS, we show that the decline in aggregate earnings was entirely driven by declines in employment; individuals who remained employed did not experience any atypical earnings changes. We find that job losses were substantially larger among workers in low-paying jobs. This led to a dramatic increase in inequality in labor earnings during the pandemic. Simulating standard unemployment benefits and UI provisions in the CARES Act, we estimate that UI payments exceeded total pandemic earnings losses between March and July 2020 by \$9 billion. Workers who were previously in the bottom third of the earnings distribution received 49% of the pandemic associated UI and CARES benefits, reversing the increases in labor earnings inequality. These lower income individuals are likely to have a high fiscal multiplier, suggesting these extra payments may have helped stimulate aggregate demand.

JEL Classification: J31, J65, J68, H53, H84, E24

Keywords: COVID-19, earnings inequality, unemployment insurance

Corresponding author:

Guido Matias Cortes
Department of Economics
York University
4700 Keele Street
Toronto, ON M3J 1P3
Canada
E-mail: gmcortes@yorku.ca

* This research has been supported by the Social Sciences and Humanities Research Council of Canada. Anahid Bauer provided excellent research assistance.

1 Introduction

The Covid-19 pandemic has had devastating effects on the American job market. In April 2020, nonfarm payroll fell by 20.5 million jobs compared to March. Although there has been some recovery in recent months, there are still 12.9 million fewer jobs as of July compared to February 2020. The pandemic triggered a multi-trillion dollar policy response through the passing of the Coronavirus Aid, Relief, and Economic Security (CARES) Act. The aggregate and distributional consequences of the pandemic and the associated public policy response, however, are not yet fully understood.

In this paper we investigate these aggregate and distributional consequences using data from the Current Population Survey (CPS), the official source for labor market statistics in the U.S. By exploiting the panel structure of the CPS, we are able to track individual-level earnings changes in order to provide a comprehensive analysis of the impacts of the pandemic and the public policy response throughout the earnings distribution. In particular, we are able to identify individuals who have lost employment during the pandemic and simulate expected unemployment insurance payments to estimate heterogeneity in the impact of these policies across the pre-displacement earnings distribution. Such an analysis is not possible from cross-sectional data or from data collected by state UI agencies on benefit recipients.

We begin by showing that weekly labor earnings per adult fell by around \$95 between February and April 2020, and have only partially recovered over more recent months. These earnings declines translate into aggregate labor earnings losses of over \$250 billion over the course of the pandemic. Interestingly, using our matched data, we find that, contrary to anecdotal evidence regarding pandemic-related pay increases and pay cuts, earnings changes for individuals who remain employed during the pandemic are not atypical during this time period. The decline in labor earnings is entirely driven by the decline in aggregate employment.¹

Job losses, however, are very unequally distributed throughout the earnings distribution. The probability of transitioning out of employment is more than twice as high for individuals who were in the lowest quintile of the earnings distribution before the on-

¹These results are a particularly extreme example of the cyclical composition bias of wages documented by Solon et al. (1994). The literature has been equivocal about whether firms reduce wages during downturns, as is predicted in the Diamond-Mortensen-Pissarides model to facilitate a quick recovery in hiring after downturns. A long literature finds evidence of both cyclical rigidity and flexibility. Most recently, Gertler et al. (2020) find both new hires and continuing workers have downward nominal wage rigidity, although Jardim et al. (2019) finds many continuing workers do receive nominal wage cuts in administrative data, and the frequency of these cuts increases during recessions.

set of the pandemic, compared to those in the top quintile. Hence, while the pandemic led to a reduction in average labor earnings growth rates for workers who were initially employed of around 18 percentage points (p.p.) overall, workers initially in the bottom decile of the earnings distribution experienced a contraction of over 40 p.p. This also implies that inequality in terms of labor earnings (before factoring in unemployment insurance payments) increased dramatically during the pandemic months.

We then proceed to analyze the extent to which the public policy response to the pandemic was able to mitigate the overall loss in labor earnings and the associated increase in inequality. We simulate Unemployment Insurance (UI) benefit receipt at the individual level using pre-displacement weekly earnings and state of residence information from the matched CPS samples. We build off of the state UI benefit database constructed by Ganong et al. (2020), extending the simulator to model benefits provided by the CARES Act. We validate our simulation by contrasting our CPS-based estimates to aggregate data on UI recipients from the Department of Labor.

Since job losses were concentrated among lower-wage workers, the pool of likely claimants is disproportionately low-wage compared to the labor market as a whole. Indeed, while the median weekly earnings for the sample of all workers is \$765, median earnings for workers who were displaced was \$519. We show that the CARES Act was extremely successful in raising average earnings at the bottom of the distribution, completely reversing the regressivity of the labor earnings losses induced by the pandemic by increasing average earnings by over 50% for the bottom 10% of workers, while also inducing small positive increases throughout the rest of the distribution. However, this obscures substantial heterogeneity in UI eligibility, with the bulk of workers who are predicted to be ineligible for UI or CARES benefits concentrated in the bottom deciles of the pre-pandemic earnings distribution.

Using data on actual UI payments from the Department of Labor, we find that \$263 billion has been paid out as of the end of July 2020. Comparing this to our estimate of total pandemic associated wage losses of \$254 billion, this implies that the CARES Act led to excess payments of \$9 billion by the end of July. Nonetheless, we find that these payments are concentrated among workers who were low earners before the pandemic, with the bottom third of pre-pandemic earners receiving 49% of the total payments. Baker et al. (2020) examine consumption behavior from the stimulus checks which were a part of the CARES act, finding 30% of stimulus payments were spent within the month, with lower income individuals driving consumption behavior. Thus, it is likely that the additional UI payments served as crucial additional stimulus

to aggregate demand during the early months of the Covid-19 recession.

It has been well documented that past recessions lead to a rise in wage-based income inequality (see for instance Perri & Steinberg (2012)). However, in the Great Recession, consumption inequality actually fell (Meyer & Sullivan, 2013; Perri & Steinberg, 2012), suggesting that government transfers can mitigate recessionary wage-income losses. In the Covid recession, Cox et al. (2020) use bank account data to show that spending fell for all income groups in March, but had rebounded by April for the lowest income groups.² Since these low income individuals are disproportionately likely to have lost their jobs (see Cortes & Forsythe, 2020), this strongly suggests that unemployment insurance and the Economic Impact Payments checks (distributed beginning April 13th) successfully preserved consumption among these groups.

A rapid literature has developed studying the impact of the Covid-19 pandemic and the CARES Act on the labor market. We highlight a few closely related papers here. Using data from ADP (a large U.S. payroll processing company), and consistent with our results, Cajner et al. (2020) find that lower-wage workers were disproportionately likely to lose employment during the pandemic, and that this composition effect drives the increase in average wages in the cross-section. Early work on the impact of the CARES Act by Ganong et al. (2020) using data from 2019 emphasized how the UI expansion would increase wage replacement rates above 100% for many potential UI recipients.³ This raised the concern that the benefit enhancements may have led to a search disincentive for recipients. However, so far there has been little evidence of this channel, with Marinescu et al. (2020) finding applications-per-vacancy increased on Glassdoor.com during the crisis. Looking at cross-state differences in the average UI replacement rate, Dube (2020) finds no evidence that states with a higher replacement rate had lower employment, while in fact Bartik et al. (2020) find a smaller decline in employment and a faster recovery for small businesses.⁴

To the best of our knowledge, we are the first paper to estimate the impact of the pandemic and the CARES Act on earnings and inequality using nationally-representative longitudinal data covering the pandemic period.

²See also Chetty et al. (2020).

³Ganong et al. (2020) use 2019 ASEC data to estimate replacement rates from the CARES Act across all workers. In contrast, we use individual-level data on job separations from the matched CPS samples in order to identify the impacts among individuals who actually lost employment during the pandemic.

⁴See also Altonji et al. (2020).

2 Data and Methodology

Our analysis uses data from the monthly Current Population Survey (CPS), retrieved from the IPUMS repository (Flood et al., 2020). The CPS has a rotating panel structure, whereby households are surveyed for four consecutive months, then leave the sample for eight months, and are then surveyed for another four consecutive months. To reduce the burden of response, the CPS only collects earnings information during individuals’ 4th and 8th months in the sample. The dataset therefore provides earnings information at up to two points in time for every individual, with the two observations being one year apart. We take advantage of this rotating structure in our analysis and track individuals’ employment status and earnings over time. We match individuals across CPS samples following Madrian & Lefgren (1999).

We restrict our analysis to non-institutionalized civilians aged 16 and older. Most specifications use data from January 2015 through July 2020. The CPS survey is conducted in the week containing the 12th of each month. During the pandemic period, the CPS reported an unusually large number of individuals who were absent from work for unspecified reasons, which the CPS has indicated are better classified as being on temporary layoff.⁵ However, nearly one-quarter of individuals who were absent for “other” reasons in April 2020 report being paid by their employer for their time off. We therefore only re-assign individuals as being on temporary layoff if they appear in the survey as being employed, absent from work for unspecified reasons, and report that they were not paid by their employer for their time off. This adjustment makes little difference in pre-pandemic periods but decreases the employment rate by nearly 2.5 percentage points in April 2020 (see Cortes & Forsythe, 2020).

Our primary measure of labor earnings is usual weekly earnings at the current job, before deductions. We convert earnings in all periods to real June 2020 dollars using the Consumer Price Index (CPI-U) from the Bureau of Labor Statistics. Following Lemieux (2006), we adjust top-coded earnings by a factor of 1.4. We also winsorize the lowest 1% of earnings. We weight individuals using the relevant individual weights for those in the earnings sample (EARNWT in IPUMS).

To understand the impact of the pandemic along the earnings distribution, we classify individuals into ventiles (bins containing 5 percent of workers). Due to noisiness at the tails, we do not sub-divide workers in the bottom or the top decile of the distribution. When analyzing within-individual year-on-year changes across the distribution,

⁵See <https://www.bls.gov/cps/employment-situation-covid19-faq-april-2020.pdf>

we allocate individuals to ventiles based on their position in the earnings distribution in the initial period, but weight them according to their current period weights.⁶

In order to isolate the impact of the pandemic from seasonal and annual patterns we implement a regression approach. For outcomes aggregated to the monthly level, we run regressions of the following form:

$$Y_t = \gamma_t^m + \alpha_t^y + \beta D_t^C + \epsilon_t \quad (1)$$

where Y_t is the outcome variable of interest in period t (e.g. the change in average earnings between month t and month $t - 12$), γ_t^m is a set of calendar month fixed effects, capturing any seasonal patterns in the outcome variable, and α_t^y is a set of year fixed effects. D_t^C is an indicator for the Covid-19 pandemic months – either a vector of dummies for March, April, May, June and July 2020, or a single dummy pooling these months.⁷ Our coefficient of interest, β , captures deviations in our outcome of interest during the pandemic months, once seasonal effects and annual patterns have been accounted for.

We analyze the impacts of the pandemic along the earnings distribution following a similar regression approach, but using the individual-level data directly and allowing for heterogeneous patterns at each ventile, i.e.:

$$Y_{it} = \gamma_{pt}^m + \alpha_{pt}^y + \beta_p D_t^C + \epsilon_{it} \quad (2)$$

Here, our outcome variable of interest Y_{it} will be a measure of within-individual year-on-year earnings changes (i.e. between month $t - 12$ and month t). Our sample will therefore be constituted by individuals who were employed and had non-missing earnings in month $t - 12$. p represents the ventile that individual i belongs to (based on his or her position in the earnings distribution in $t - 12$). γ_{pt}^m and α_{pt}^y are fully interacted ventile-month and ventile-year fixed effects, respectively. Depending on the outcome of interest, we either condition on individuals who are also employed in period t , or we include individuals who transition out of employment between $t - 12$ and t . In such cases, we measure earnings changes in percentage terms (rather than log changes), with individuals who are not employed in period t experiencing an earnings change of

⁶This is particularly important during the pandemic period due to the increased incidence of non-response.

⁷The CPS survey in March took place just as the initial impacts of the pandemic were manifesting themselves in the U.S. economy; hence, as seen below, the impacts observed in March are quite muted compared to those observed in subsequent months.

-100%.⁸

Our analysis of the public policy response to the pandemic builds on the Unemployment Insurance (UI) simulator of Ganong et al. (2020) and also uses information from the 2019 American Community Survey (ACS), as discussed in detail in Section 4.

3 Changes in Earnings during the Pandemic

3.1 Impact on Average Earnings

Figure 1 displays the evolution of earnings over time. Panel A shows average real weekly earnings among workers in each cross-section. As has been widely documented, average earnings increased substantially between February and May 2020 (from around \$1,100 to \$1,190) and remain much higher than in the pre-pandemic period. Naturally, this does not translate into higher aggregate labor earnings, given that employment fell dramatically during this time period. As Panel B shows, weekly labor earnings per adult fell substantially at the onset of the pandemic, from around \$670 in February to around \$575 in April, with only a partial recovery thereafter.

The cross-sectional increase in average earnings observed in Panel A of Figure 1 is of course affected by changes in the composition of the workforce due to the large employment contraction at the onset of the pandemic. By exploiting the rotating panel structure of the CPS, we are able to track within-individual changes in earnings in order to determine whether the cross-sectional increase in average earnings is entirely composition driven, or whether it also reflects earnings increases among individuals who remain employed, perhaps because of increases in hazard pay due to the pandemic.⁹

The solid blue line in Panel A of Figure 2 presents raw year-on-year changes in average log real weekly earnings in the cross-section, reflecting the pattern observed in Panel A of Figure 1. The dashed red line, meanwhile, computes average within-individual year-on-year changes in log real earnings for individuals who remain employed. If we consider the patterns typically observed before the pandemic, we see that earnings growth tends to be higher than in the cross-section when following individuals

⁸Alternatively, we could replace zeros with a small positive value in order to continue working with log earnings. However, given how widespread the job losses have been during the pandemic period, the assumed small positive value is not innocuous and can substantially skew the average earnings changes along the distribution.

⁹Amazon, for example, increased hourly wages by \$2 for workers in a number of roles; see https://blog.aboutamazon.com/operations/amazon-opening-100000-new-roles?utm_source=social&utm_medium=tw&utm_term=amznnews&utm_content=COVID-19_hiring&linkId=84444004.

who remain employed. This is because this is a selected sample with stronger labor market attachment. Remarkably, this series remains very stable during the pandemic months. Conditional on remaining employed, earnings changes during the pandemic months were not atypical on average. This implies that the observed increase in mean earnings in the solid blue line is entirely driven by changes in the composition of the workforce.¹⁰

Panel B isolates the impact of the pandemic by implementing the regression approach in Equation (1). The blue and red bars use the same variables as in Panel A. The figure plots the estimated coefficients for the monthly pandemic month dummies, which capture the year-on-year impacts of the pandemic in each month, after controlling for seasonal and annual time effects. The estimated coefficients confirm the substantial and significant increase in mean earnings in the cross-section, and the lack of significant changes in earnings growth among individuals who remain employed.

The green bars in Panel B are based on a specification where the dependent variable is the average within-individual percentage change in real earnings, including individuals whose labor earnings fall to zero due to exit from employment.¹¹ When considering all individuals who were initially employed, including those who exit to non-employment, we observe a dramatic decrease in the average earnings growth rate during the pandemic months – around 18 p.p. year-on-year in April, and around 14 p.p. in May and June. Hence, the increased incidence of job loss led to a dramatic decrease in labor earnings among individuals who were employed in the pre-pandemic period (in line with the decline in earnings per adult documented in Panel B of Figure 1).¹²

3.2 Distributional Impacts

We now turn to the distributional impacts of the pandemic. Figure 3 shows that the distribution of earnings among those who are employed in the cross-section not only

¹⁰This result is consistent with the finding of Cajner et al. (2020), who conduct a similar analysis using payroll data from ADP.

¹¹Note that the dependent variables for the blue and red bars are based on changes in log earnings, rather than percentage changes. Results, however, are nearly identical if we use percentage changes for all specifications.

¹²As we show in Cortes & Forsythe (2020), the vast majority of the decline in employment during the pandemic is driven by an increase in the job separation rate; the decline in the job finding rate is comparatively small. Hence, most of the earnings impact of the pandemic would be felt among individuals who were initially employed.

shifted upwards, but also became much more compressed, with much larger increases in earnings observed at lower percentiles of the distribution, particularly over the 12-month periods to April and May 2020. For reference, the light grey lines at the bottom of the graph indicate the analogous changes over earlier 12-month periods, confirming that this compression is a feature observed only during the early onset of the pandemic.

As with average wages in the cross-section, the distributional changes in Figure 3 are affected by changes in the composition of workers during the pandemic. In Figure 4 we explore the impacts of the pandemic throughout the earnings distribution, focusing on individuals who were employed prior to the pandemic and tracking their outcomes over time, hence accounting for compositional changes. As discussed in Section 2, we isolate the impact of the pandemic throughout the earnings distribution by estimating Equation (2) using individual-level data. The regression incorporates fully interacted ventile-month and ventile-year fixed effects, which allow seasonal and annual patterns to be heterogeneous along the distribution.

Panel A of Figure 4 shows the impact of the pandemic on labor earnings for each percentile bin. A clear pattern emerges: individuals who start off with lower weekly earnings experience dramatically larger declines in their labor income – as high as 38% for individuals in the bottom decile of the distribution.

These changes in earnings may arise due to an extensive margin effect, i.e. a change in the probability of being employed and having *any* labor earnings, and an intensive margin effect, i.e. a change in earnings conditional on remaining employed. Panels B and C separate these two effects. Consistent with our results regarding the impact of the pandemic on average earnings in Figure 2, we find that the impacts of the pandemic along the earnings distribution are driven exclusively by the extensive margin effect. In particular, Panel B of Figure 4 shows that employment losses were much more severe for workers in the lower part of the earnings distribution. While employment probabilities decline by less than 4 p.p. for workers in the top decile of the pre-pandemic earnings distribution, the decline is around 20 p.p. for workers in the bottom decile. This explains the cross-sectional increase in average earnings and the cross-sectional compression of earnings inequality documented in Figures 1 and 3.

Meanwhile, for workers who remain employed, the pandemic does not have a statistically significant impact on earnings, as shown in Panel C of Figure 4. In other words, earnings growth was not atypical for workers who remain employed during the pandemic months, regardless of their initial position in the earnings distribution. Some positive earnings impacts are observed for workers in the lower and middle parts of

the distribution, but these are imprecisely estimated. Appendix Figure A.1 confirms that the lack of significant average changes within each percentile bin does not hide increased propensities of experiencing either earnings increases or earnings declines. The figure shows that the probability of experiencing a decrease (increase) in individual-level nominal weekly earnings of more than \$10 is not systematically impacted by the pandemic. This suggests that reductions in hourly earnings or in paid hours of work have not been widespread among individuals who are still in employment during the pandemic months. Earnings increases for workers who remain employed (who may face an increased risk of exposure to disease) also do not appear to be widespread.^{13,14}

Overall, we can conclude that the increase in mean earnings and the reduction in inequality observed in the aggregate data in Figures 1 and 3 are entirely composition driven, due to the exit of low earners from employment. If we track individuals who were employed in 2019, we see that the pandemic had the effect of dramatically *reducing* labor earnings and *increasing* inequality among these workers. In what follows we analyze the extent to which these negative impacts were mitigated by the public policy response to the pandemic.

4 The Role of Public Policy

The key public policy instrument in the United States to insure against unexpected labor earnings losses is the unemployment insurance (UI) system. Each state has its own requirements and benefit levels. Eligibility typically depends on reaching an earnings threshold before displacement; however, many states also require minimum earnings in more than one quarter, as well as other requirements.

In response to the growing economic threat from the Covid-19 pandemic, the Coronavirus Aid, Relief, and Economic Security (CARES) Act was signed into law on March 27th 2020. This extended UI benefits in three ways. First, the CARES Act created

¹³We find that the entire overall distribution of within-individual year-on-year earnings changes is not very different during the pandemic months compared to the same calendar months in pre-pandemic years, suggesting no evidence of increased dispersion in wage changes among those who remain employed. Results are available from the authors upon request.

¹⁴Using payroll data from ADP, Cajner et al. (2020) find that, when they focus on the firms that typically adjust wages in March, April or May, there is a 20 percentage point increase in wage freezes and a 12 percentage point increase in wage cuts. These firms, however, represent only around ten percent of the businesses in the ADP sample who continuously employed workers during all of 2019 and the first half of 2020. Our results suggest that these patterns are not sufficiently widespread to be detectable in nationally representative data.

a new benefit called Pandemic Unemployment Assistance (PUA), which expands the eligibility universe to individuals who are not typically eligible for UI, including the self-employed, as well as individuals whose earnings or number of weeks worked were too low. Benefits for individuals receiving PUA payments are calculated in the same way as for standard UI recipients, with the exception that the minimum benefit floor is higher, equal to half of the average benefit in the state.¹⁵ Second, the CARES Act created a new program called Pandemic Unemployment Compensation (PUC) which provided a \$600 weekly UI top-up for all UI recipients. Third, the CARES Act extended the maximum duration of benefits by 13 weeks with the Pandemic Emergency Unemployment Compensation (PEUC). The PUA and PEUC are in place until the end of December 2020. PUC payments, however, expired on July 31st.

Below we discuss how we simulate UI benefits received during the pandemic using our matched CPS samples, and how these payments impacted the overall level and distribution of earnings among workers who were employed before the onset of the pandemic.

4.1 Simulating Unemployment Insurance Benefits

The CPS does not collect information on whether an individual is receiving UI benefits. We are, however, able to simulate the benefits that individuals should be eligible to receive using information on their state of residence and their weekly earnings reported in the pre-displacement period. We do this by building on the UI simulator constructed by Ganong et al. (2020).

As above, we focus on individuals observed in month-in-sample 8 who were employed (and had non-missing earnings) in month-in-sample 4 (i.e. one year prior). This ensures that we have a wage observation from which to calculate eligibility and benefits. To be eligible for UI or the CARES Act, an individual generally needs to have been employed and involuntarily lost their job. We can identify individuals who are likely to be eligible for UI or the CARES Act by taking advantage of the panel dimension of the CPS as well as using information on unemployment spell lengths and the reason for unemployment.

Pre-pandemic, we identify individuals as eligible for UI if they were employed one year prior, are currently involuntarily unemployed, and the duration of unemployment is less than the maximal benefit duration of 26 weeks. We also classify individuals as eligible if they are currently employed but absent from work and unpaid.

¹⁵See https://oui.doleta.gov/dmstree/uipl/uipl2k20/uipl_0320.pdf.

This approach identifies individuals who are plausibly eligible for UI, though it will miss individuals who may claim UI but are classified as being out of the labor force by the CPS. Pre-pandemic, this is not of major concern. During the pandemic period, however, there was a substantial increase in flows from employment to non-participation in the CPS (see Cortes & Forsythe, 2020). Most of these individuals likely qualify for UI, but are classified as not-in-the-labor-force because they are not actively searching for work. Thus, we expand our UI eligibility definition beginning in April 2020. In addition to individuals who satisfy our pre-pandemic eligibility criteria, we also deem individuals to be eligible for UI if they are not employed in the current period but were employed at any point in the last three months (i.e. when they were in month-in-sample 5, 6 or 7), regardless of whether they are currently classified as unemployed or out of the labor force in the CPS.¹⁶ In addition, we deem individuals eligible if they are classified as unemployed and have an unemployment spell that started on or after March 1st 2020, regardless of their reported reason for unemployment.

We simulate three layers of UI benefits, based on recent public policy. First, we estimate individuals' expected weekly standard UI benefit, building on the UI simulator of Ganong et al. (2020), which is based on UI guidance provided by the Department of Labor.¹⁷ The simulator generates estimated unemployment benefits based on individuals' state of residence and pre-displacement quarterly earnings. Since information on the number of weeks worked per quarter is not available in the monthly CPS, we use information from the 2019 American Community Survey (ACS). Specifically, in the ACS data, we classify individuals into earnings ventiles as we do in the CPS, and compute the fraction in each ventile-state cell that are above the state's weeks worked threshold for eligibility, and the average number of weeks worked conditional on being above the threshold. We calculate this separately for regular employees and self-employed individuals. We then compute expected individual-level unemployment benefits as the product of the probability of being above the weeks worked threshold and the expected weekly standard UI benefit from the simulator conditional on being above the threshold. Note that the inputs for the simulator are the individual's observed weekly earnings and state of residence from the CPS, as well as the average weeks worked for individuals above the threshold in the same percentile bin and state from the ACS. Some individuals will

¹⁶In Appendix Figure A.2 we show that employment losses during the onset of the pandemic are concentrated among individuals who were employed in the last three months. This supports our focus on these individuals as potential UI recipients.

¹⁷See <https://oui.doleta.gov/unemploy/content/sigpros/2020-2029/January2020.pdf>.

have zero expected standard UI benefits due to low earnings. Individuals who report being self-employed are also excluded from eligibility for standard UI.¹⁸

Second, we simulate the expanded eligibility from the PUA provision in the CARES Act. PUA recipients include individuals who are self-employed, and those that do not qualify for standard UI because their earnings are too low or they did not work enough weeks of the prior year to qualify. PUA benefits are based on the same formula as the state’s standard benefits; however, earnings minimums and weeks worked requirements are waived. In addition, there is a weekly benefit floor defined for each state, which is calculated as half of the average weekly benefit paid by the state. For individuals whose expected standard UI benefits would be zero due to earnings being too low, we set PUA benefits equal to the weekly benefit floor in their state. For other individuals who were not self-employed, we compute the expected benefits as above, and add the probability of being below the weeks worked threshold multiplied by the weekly benefit floor in the individual’s state. For the self-employed, we compute their predicted PUA payments as the maximum between their predicted UI benefits using the UI simulator (based on their individual earnings and state of residence from the CPS, along with imputed weeks worked from the ACS) and the PUA benefit floor in their state of residence.

Third, we add in the \$600 PUC benefit to all UI recipients identified as eligible for the standard UI or PUA UI benefits.

There are several caveats to our approach. First, we do not observe whether individuals meet other requirements for eligibility, such as employment by a covered employer and being discharged rather than quitting. We may incorrectly label some individuals as UI eligible if they retired or otherwise left the labor market.¹⁹ Conversely, we would omit individuals who happened to not be employed in the reference week a year prior, but are otherwise eligible. Second, we do not know if the individual actually claimed UI. Bitler et al. (2020) find that during the pandemic, only 42% of unemployed individuals with a high school degree or less were receiving unemployment benefits, compared with 52% of those with a college degree. Although we do not know if this gap is due to eligibility or claiming behavior, this suggests that lower-income workers may be less likely to claim even when eligible. Finally, we do not observe whether individuals are undocumented immigrants, who are ineligible to receive UI benefits. Bitler et al. (2020) estimate 4% of workers are undocumented, and these individuals are more likely to be

¹⁸We measure self-employment by status in the most recent month worked.

¹⁹We do not define eligibility on whether or not the worker reports being retired or disabled, because they could still claim UI even if they do not intend to return to employment.

low-wage workers.

In order to assess the reliability of our estimates, in the next section we compare our estimated claims and payments with data from the Department of Labor.

4.2 Benchmarking to Department of Labor Data

We begin by comparing the characteristics of predicted UI claimants from the CPS data during the pandemic period to the characteristics of actual UI recipients provided by states to the Department of Labor (DoL).²⁰ As shown in Appendix Table A.1, the share of women and Hispanics are similar. The CPS data, however, predicts a smaller share of black claimants than in the UI data (12% vs 21%). There are also some differences in the age distribution, with a higher share of workers 55 and up in the CPS data compared with actual recipients (30% versus 22%). This suggests that we may be classifying some retirees as potential UI claimants. Finally, the industry distribution is similar between the two data sources. Overall, while we cannot know if a particular individual claims UI, the characteristics of our predicted claimants is quite similar to that of actual UI recipients.

Next, we compare the total estimated number of claimants and payments. There has been a variety of issues with states reporting data on UI recipients, leading to large over-counts in the number of claims. Thus, we instead use data on actual weeks of claims paid and the total amount paid through the two main programs: the standard UI, and the PUA program.²¹ Unfortunately, the PUA data remains incomplete with about 20 states each month failing to report.

We begin by comparing the number of estimated UI claimants in the CPS with actual UI claims paid from March through July 2020 in Panel A of Table 1. To do this, we first compute total outflows from employment (in person-months) in the CPS by multiplying the year-on-year outflow rate with employment in the corresponding month in 2019. This gives us total job separations of 136 million (or approximately 30 million per month). Many of these job separations would have occurred naturally even in the absence of the pandemic, due to normal rates of firings, quits and retirements, for example. In order to estimate the number of pandemic-induced job separations, we estimate Equation (1) using the year-on-year job separation rate as the dependent

²⁰The DoL data is derived from ETA 203 reports submitted monthly by states, and covers the period up to June 2020.

²¹These numbers are reported monthly by each state UI system on forms ETA5159 and ETA902p.

variable. The estimated coefficients are displayed in Appendix Figure A.3. We use these estimates for the excess job losses during the pandemic to construct the total number of pandemic-induced person-month job separations. As shown in Table 1, these amount to 71 million.

This group of individuals who have left employment can be divided into three groups: those we predict to be eligible for standard UI (75 million person-months), those we predict to be eligible for PUA (20 million), and those we predict not to be eligible for either program (41 million). We estimate that the pandemic led to an increase in 70 million separators who are eligible for standard UI. We also find that the number of ineligible job separators fell by 20.6 million person-months during the pandemic. This is slightly smaller than our estimate for the total PUA claims of 20.1 million, suggesting that the vast majority of the decline in ineligible separations is associated with the expansion of eligibility provided by the PUA program.

The columns on the right of Table 1 display the actual number of claims paid through each of these programs (as well as the PEUC), with the caveat that this is an undercount of the PUA program due to state non-reporting.

The total number of individual-months we estimate are eligible for standard UI are 75 million, compared to 66 million who have received benefits through either standard UI or the PEUC, which extends the duration of standard UI. Comparing the PUA numbers, we see that we predict 20 million person-months are eligible for PUA, while at least 25 million have received these benefits. These discrepancies may be related to the caveats of our approach discussed above, which does not perfectly predict eligibility. Moreover, some of the individuals who we predicted would be eligible for standard UI may not have been eligible and hence gone through the PUA program instead. The DoL UI numbers may also be imprecise due to processing or reporting delays. Overall, however, our total estimate of 94.65 million person-month eligible claimants from the CPS is not far off from the 90.31 million person-month claims that have actually been reported as paid.

In Panel B of Table 1, we tally the total dollars in benefits we predict have been received by claimants, and compare these to the amounts that have actually been paid, according to DoL data.²² Although the data on the \$600 PUC payments have not yet been released, we assume that all standard UI, PEUC, and PUA recipients receive this

²²We aggregate predicted weekly benefits in the CPS to the monthly level by assuming that an individual who we deem to be eligible for UI during the CPS reference week would claim unemployment benefits during all weeks in that month.

benefit from April through July. This yields a total of \$263 billion in actual benefits paid between March and July 2020. In contrast, we calculate that \$300 billion would have been paid if all individuals we predicted would be eligible were able to receive benefits. This amounts to a 12% underpayment rate.

We can compare the total payments made through the different UI programs to the total volume of labor earnings losses experienced during the pandemic months. Panel C of Table 1 shows that the total year-on-year change in aggregate labor earnings between March and July amounted to \$124 billion.²³ This raw change, however, is an under-estimate of the impact of the pandemic if one considers the fact that aggregate labor earnings would have normally been expected to increase during this time period, due to normal rates of population, employment, and wage growth. If we once again implement the approach of estimating Equation (1), now using aggregate labor earnings as the dependent variable, we can obtain estimates of the impact of the pandemic in each month. Aggregating these monthly impacts, we estimate total pandemic-induced labor earnings losses to be \$254 billion. Comparing this number to the total UI benefit payments made during this time period, we see that the total benefits paid were \$9 billion more than the pandemic-associated earnings loss.

Below we analyze how these UI payments impacted earnings growth across individuals, on average and according to their initial position in the earnings distribution. We show results based on our benchmark eligibility simulation, corresponding to the left-hand columns of Table 1. We also use the gap between our simulated eligibility figures and the DoL data in order to provide estimates that match the information on actual claims paid. In particular, based on the information in Panel A of Table 1, and in order to match the number of claims from the DoL data, we assume that individuals that we predict to be eligible for standard UI in the CPS have a 6% probability of receiving PUA instead, and a 6% probability of receiving no benefits at all.

4.3 Effect of UI Policies on Average Earnings

Figure 5 shows how standard UI, the PUA, and the PUC affect average within-individual earnings growth. As we saw in Figure 2, individuals employed before the pandemic experienced a 18 p.p. decrease in their weekly labor earnings growth rate in

²³This amount is obtained by multiplying year-on-year changes in aggregate weekly earnings by the number of weeks per month, and adding up the total obtained for the five pandemic months (March through July).

April; the year-on-year decline was smaller, at 7 p.p., by July. Here we see that standard UI is able to counteract only a portion of these earnings losses, with average losses of 13p.p. in April and 3p.p. by July. By expanding eligibility, PUA was able to shrink the average losses to 7p.p. in April. Finally, the full CARES Act, which combines standard UI, PUA expanded eligibility, and the PUC additional \$600 payments would have successfully increased average earnings growth rates by 26p.p. in April and 17p.p. in July, if all individuals that we estimate to be eligible had claimed and received payment. The final set of bars in Figure 5, which is our preferred specification regarding actual benefits paid, adjusts benefits based on the gap between our estimates and the DoL payment data. This adjustment cuts the earnings increases, leading to a 24p.p. increase in the earnings growth rate in April, 19p.p. in May, 13p.p. in June, and 16p.p. in July.²⁴

4.4 Effect of UI Policies by Pre-Pandemic Wage Percentile

Next we want to understand the distributional impacts of these policies. Recall from Figure 4 that the pandemic induced declines in employment that disproportionately affected individuals in the bottom half of the pre-pandemic earnings distribution. Further, eligibility for UI varies dramatically across the earnings distribution. In Appendix Figure A.5, we show that individuals who were in low-earning jobs before the pandemic are much less likely to be employed during the pandemic months, and much more likely to be ineligible for any UI programs, compared to individuals who were in higher-earning jobs. Almost one quarter of pandemic job-losers in the bottom 10% of the earnings distribution would not qualify for their state’s standard unemployment insurance program, but do qualify for the PUA. Thus, the expansion of UI eligibility from the CARES Act primarily increased access to unemployment insurance for low-income workers.²⁵

In Figure 6, we combine the estimates for March through July 2020 from Figure 5, but look at the effect across ventiles in the previous year’s distribution of weekly labor earnings. As in Figure 4, we estimate the change in the earnings growth rate during the pandemic months, after controlling for year and month fixed effects, using the regression approach in Equation (2).

²⁴In Appendix Figure A.4 we show the level changes in earnings.

²⁵Appendix Figure A.6 provides information on the reasons for ineligibility for displaced workers from each earnings decile.

In the top left panel of Figure 6 we show the impacts on earnings growth rates during the pandemic months after factoring in baseline simulated UI benefits, before the CARES Act provisions. Here we see that the UI system does a modest job of replacing lost income. Without UI, the bottom third of the income distribution would have their weekly earnings growth rate fall by more than 15 percentage points; with standard UI, this reduction is halved. Nonetheless, we see that these UI benefits are not enough to counteract the increased regressivity in the earnings distribution induced by pandemic job loss.

We next add the PUA benefits, shown in the top right of Figure 6. This primarily increases benefits to individuals at the bottom of the wage distribution, who do not have sufficient earnings or quarters of employment to qualify for their state’s UI program. Nonetheless, earnings losses remain larger at the bottom of the wage distribution, and almost all ventiles have average losses.

In the bottom left panel of Figure 6, we add in the extra \$600 per week PUC program. Here we see earnings changes are positive throughout the bottom half of the distribution, and close to zero in the top half. As discussed above, however, this baseline estimation overestimates the number of individuals receiving benefits, relative to the DoL numbers. Thus, in the bottom right panel, we provide the estimates adjusted for the fraction that actually received UI payments. Note that we do not know where in the wage distribution these non-claimants fell, and we thus apply the transformation uniformly. Although most ventiles show small positive earnings increases, these increases are concentrated in the bottom of the distribution, with the bottom quarter receiving average weekly earnings growth rate increases of 20 percentage points or more.

It is important to emphasize that, although these policies led to larger earnings replacement rates at the bottom of the distribution, when we look at level changes in earnings (rather than percentage changes), losses and benefits are much more uniform. These results can be found in Appendix Figure A.7.

To put these numbers in context, in Figure 7 we compare weekly earnings and benefit amounts along the earnings distribution. In the top panel, we compare the weekly earning levels across deciles for all individuals employed during the pre-pandemic period (blue bars) and those that lost employment (red bars). As a consequence of the fact that job loss was concentrated in low earning workers, here we see that while the previous year’s median wage of the potentially displaced set (i.e. across all workers) is \$765, for the actually displaced the median wage was \$519.

In the bottom graph, we restrict our analysis to these workers that were displaced

during the pandemic, and again estimate the average benefit under various UI provisions. The red bars reproduce the earnings levels across deciles for these displaced workers, as shown in the top panel. The gray bars show the average benefits under standard UI. The lowest earning third would receive weekly benefits of under \$200 per week. For the whole distribution, average standard UI benefits max out at approximately \$480 per week.

The green bars show the estimated average benefit with expanded eligibility under the CARES Act, through the PUA program. As mentioned above, this primarily helps the bottom of the wage distribution, who have a high rate of ineligibility for standard UI. Given the minimum payments, this brings up average benefits to above average wage losses for the bottom decile of displaced workers.

Finally, the yellow bars estimate the total benefits from the CARES Act, which adds the additional \$600 per week on top of the benefits in the green bar. Here we see that total benefits are higher than earnings for 80% of displaced workers; however, note that these workers are displaced from jobs in the bottom 60% of the pre-displacement earnings distribution.

4.5 Discussion

The CARES Act, and in particular the \$600 PUC payments, ended up providing more economic stimulus than as initially conceived. The \$600 figure was chosen to provide the median full-time earner a 100% replacement rate when combined with standard UI replacement rates of about 40%.²⁶ However, the policy overshot for two reasons. First, the median weekly pay in 2019 was only \$765, because many workers do not work full time. This would push the median replacement rate to 118%. Even more importantly, pandemic job loss was concentrated among low-earning individuals, with median weekly earnings of job losers of only \$519. The median job loser has a projected replacement rate of 156%. In Appendix Figure A.8, we show how benefits are distributed across deciles of the pre-displacement earnings distribution. Almost half of the benefits go to the bottom earning one-third of workers.

As we estimated above, CARES Act payments (in conjunction with standard UI payments) exceeded total pandemic earnings losses by \$9 billion. This amounts to less than 3% of the Economic Impact Payments (EIP) in the CARES Act, which took the form of payments of \$1200 per adult and \$500 per child. Baker et al. (2020) found these

²⁶See <https://www.washingtonpost.com/business/2020/08/06/600-dollar-unemployment-benefit/>

direct payments led to a strong spending response, concentrated among people with low account balances, low earnings and large income drops, concluding that targeting stimulus to households with low levels of liquidity will have the largest fiscal multipliers. In particular, they find multipliers of 0.33 for individuals who earn under \$1000 per month, which comprise 20% of our sample of separators and who received replacement rates of over 300%. In contrast, they find the lowest fiscal multipliers for individuals who earn over \$3000 per month, which corresponds to the top 20% of separators, and coincidentally are the only group who face replacement rates below 100%. In addition, they find larger multipliers for households experiencing earnings drops. Thus, by expanding UI beyond the replacement rates for displaced low earners, the targeted aid provided by the CARES Act may have had a stronger fiscal multiplier than the EIP stimulus checks. Moreover, the combination of the EIP stimulus payments and the CARES benefit expansion was likely responsible for the remarkable finding from Han et al. (2020) that poverty rates have fallen during the pandemic.

Nonetheless, we estimate that around 5% of individuals that we predict to be eligible for UI or PUA did not receive benefits. Further, about 30% of individuals who lost employment during the pandemic period do not meet our screen for UI eligibility. These workers are much more likely to be low-earning, and hence in most need for stimulus payments. Thus, although the PUA and PUC were very successful in replacing income and increasing consumption for recipients, many individuals were ineligible for this aid.

5 Conclusions

The Covid-19 pandemic has had a dramatic impact on the U.S. labor market. By exploiting the rotating nature of the CPS samples, we provide an account of the impact of the pandemic and the associated public policy response on earnings, focusing on a consistent and nationally-representative sample of workers who were employed before the onset of the pandemic.

We find that low-earning individuals were disproportionately likely to lose their jobs during the pandemic. In the absence of the public policy response through the CARES Act, earnings inequality would have experienced a dramatic increase. The PUA and PUC provisions of the CARES Act were able to offset these impacts. The PUA UI eligibility expansion primarily benefited low-income workers, while the \$600 PUC payments led to a larger percentage increase in income for individuals in the bottom

third of the wage distribution. Given consumption patterns of low-income individuals, this likely produced a substantial fiscal multiplier, helping to reduce the fall in aggregate demand from the recession.

On August 1st, 2020, the \$600 PUC benefits expired, while UI claims remain historically large.²⁷ If the PUC benefits had not been available in July, on average workers would have experienced decreases in weekly earnings growth rates of 3 percentage points, compared with the increases of 11 percentage points they actually received. This would amount to a total loss of \$15 billion, with workers in the bottom third of the earnings distribution absorbing nearly half of this loss. These workers, who earned less than \$500 a week before the pandemic, are less likely to have savings and other income sources to weather a sustained loss in income. Thus, not only was the loss of benefits personally disastrous for many individuals, it also cut off an important source of aggregate demand while the economy remains in the depths of the worst recession since the Great Depression.

²⁷<https://www.dol.gov/ui/data.pdf>

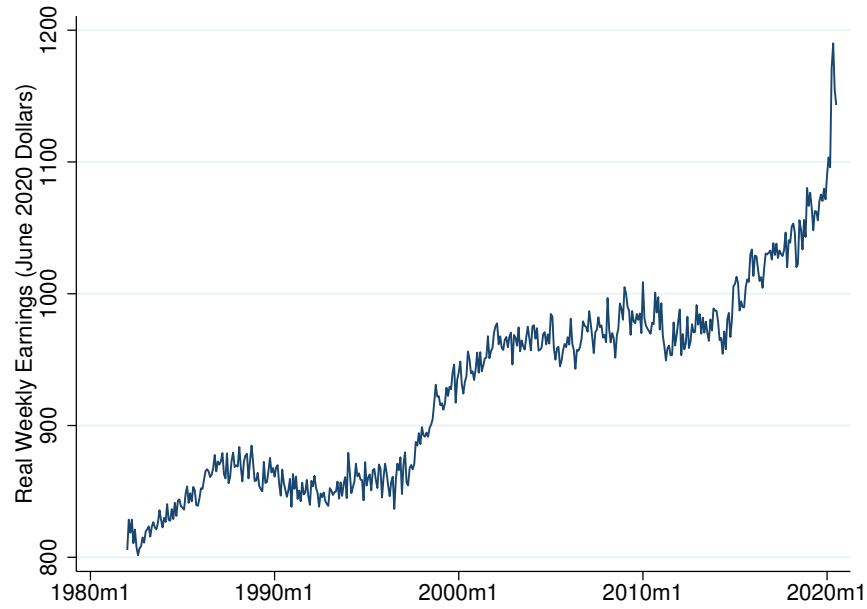
References

- Altonji, J., Contractor, Z., Finamor, L., Haygood, R., Lindenlaub, I., Meghir, C., O'Dea, C., Scott, D., Wang, L., & Washington, E. (2020). Employment effects of unemployment insurance generosity during the pandemic. *Working Paper*.
- Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., & Yannelis, C. (2020). Income, liquidity, and the consumption response to the 2020 economic stimulus payments. *NBER Working Paper No. 27097*.
- Bartik, A. W., Bertrand, M., Lin, F., Rothstein, J., & Unrath, M. (2020). Measuring the labor market at the onset of the COVID-19 crisis. *NBER Working Paper No. 27613*.
- Bitler, M. P., Hoynes, H. W., & Schanzenbach, D. W. (2020). The social safety net in the wake of COVID-19. *Brookings Papers on Economic Activity Conference Drafts*.
- Cajner, T., Crane, L. D., Decker, R. A., Grigsby, J., Hamins-Puertolas, A., Hurst, E., Kurz, C., & Yildirmaz, A. (2020). The U.S. labor market during the beginning of the pandemic recession. *Brookings Papers on Economic Activity Conference Drafts*.
- Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., & The Opportunity Insights Team (2020). How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data. *NBER Working Paper No. 27431*.
- Cortes, G. M. & Forsythe, E. (2020). The heterogeneous labor market impacts of the Covid-19 pandemic. *Upjohn Institute Working Paper 20-327*.
- Cox, N., Ganong, P., Noel, P., Vavra, J., Wong, A., Farrell, D., & Greig, F. (2020). Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data. *Brookings Papers on Economic Activity Conference Drafts*.
- Dube, A. (2020). The impact of the federal pandemic unemployment compensation on employment: Evidence from the Household Pulse Survey. *Working Paper*.
- Flood, S., King, M., Rodgers, R., Ruggles, S., & Warren, J. R. (2020). Integrated Public Use Microdata Series (IPUMS), Current Population Survey: Version 7.0 [dataset].

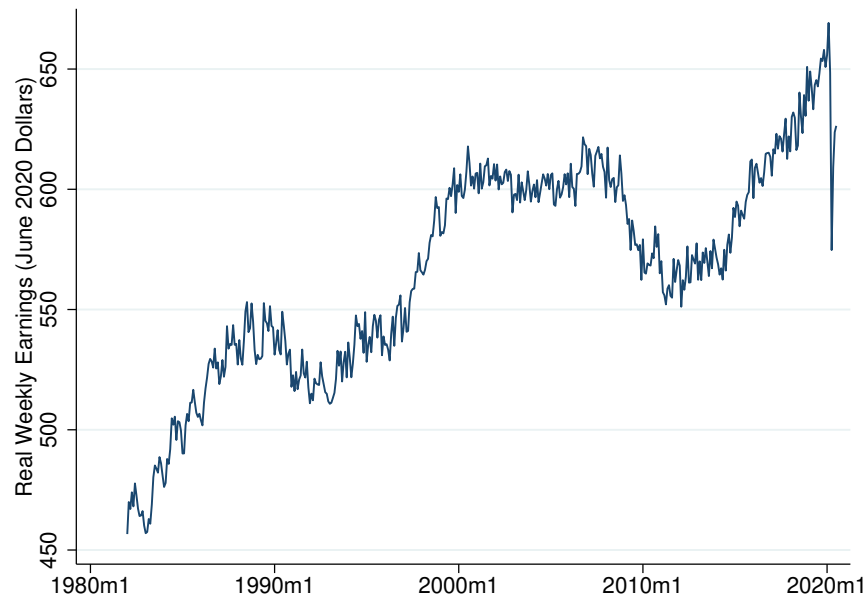
- Ganong, P., Noel, P. J., & Vavra, J. S. (2020). US unemployment insurance replacement rates during the pandemic. *NBER Working Paper No. 27216*.
- Gertler, M., Huckfeldt, C., & Trigari, A. (2020). Unemployment fluctuations, match quality, and the wage cyclical of new hires. *The Review of Economic Studies*, 87(4), 1876–1914.
- Han, J., Meyer, B. D., & Sullivan, J. X. (2020). Income and poverty in the COVID-19 pandemic. *Brookings Papers on Economic Activity Conference Drafts*.
- Jardim, E. S., Solon, G., & Vigdor, J. L. (2019). How prevalent is downward rigidity in nominal wages? Evidence from payroll records in Washington state. *NBER Working Paper No. 25470*.
- Lemieux, T. (2006). Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? *The American Economic Review*, 96(3), 461–498.
- Madrian, B. C. & Lefgren, L. J. (1999). A Note on Longitudinally Matching Current Population Survey (CPS) Respondents. *NBER Working Paper No. 247*.
- Marinescu, I. E., Skandalis, D., & Zhao, D. (2020). Job search, job posting and unemployment insurance during the COVID-19 crisis. *Working Paper*.
- Meyer, B. D. & Sullivan, J. X. (2013). Consumption and income inequality and the Great Recession. *American Economic Review*, 103(3), 178–83.
- Perri, F. & Steinberg, J. (2012). Inequality and redistribution during the Great Recession. *Economic Policy Paper 12-1, Federal Reserve Bank of Minneapolis*.
- Solon, G., Barsky, R., & Parker, J. A. (1994). Measuring the cyclical of real wages: how important is composition bias? *The Quarterly Journal of Economics*, 109(1), 1–25.

Figure 1: Evolution of Real Weekly Earnings

Panel A: Real Weekly Earnings per Worker



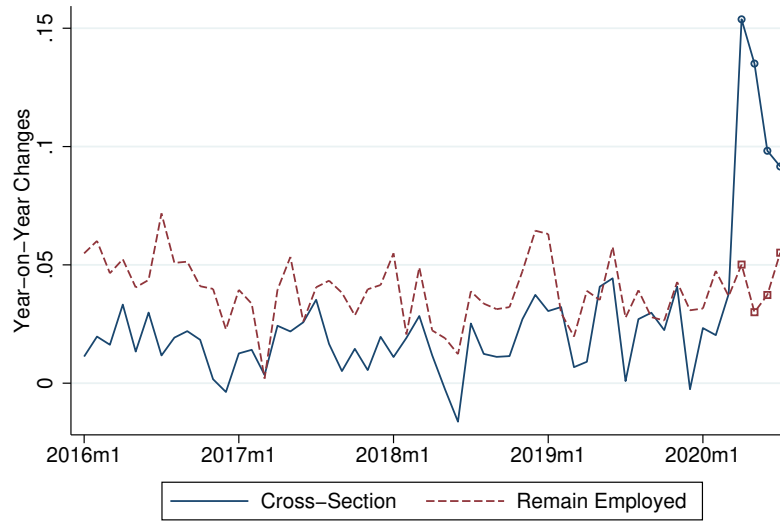
Panel B: Real Weekly Earnings per Adult



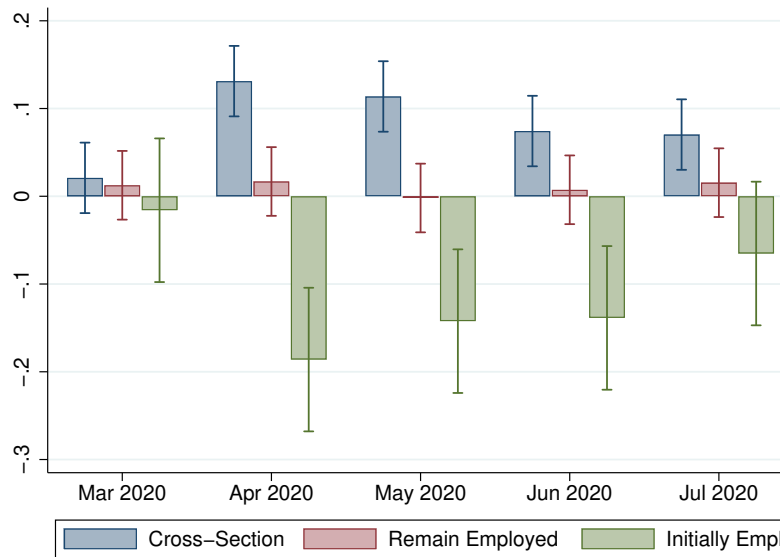
Note: The figure is based on CPS data on usual earnings in the current job, converted to June 2020 dollars. Following Lemieux (2006), top-coded earnings are adjusted by a factor of 1.4. The lowest 1% of earnings are winsorized.

Figure 2: Changes in Mean Earnings: Overall vs Within Individuals

Panel A: Year-on-Year Changes in Real Weekly Earnings

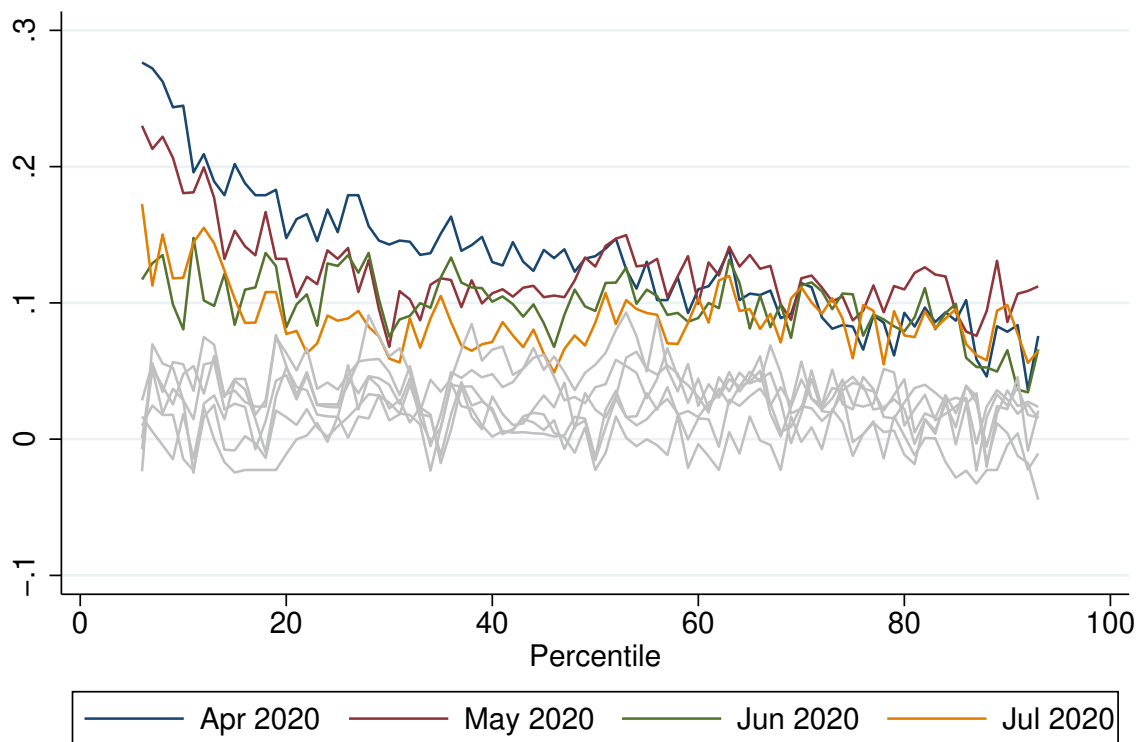


Panel B: Pandemic Impact on Real Weekly Earnings



Note: Panel A plots changes in average log real weekly earnings in the cross-section of workers in the solid blue line, and among workers who remain employed (with non-missing earnings) in the dashed red line. Panel B plots the estimated coefficients and 95% confidence intervals from Equation (1) using monthly data on year-on-year changes since January 2015 (55 observations). The coefficients capture the effects of the pandemic after controlling for seasonal and year effects. The dependent variables for the “Cross-Section” and the “Remain Employed” specifications are the series from Panel A. The dependent variable for “Initially Empl” is the average within-individual percentage change in earnings for all individuals who were employed (and have non-missing earnings) one year earlier, including those who transition out of employment.

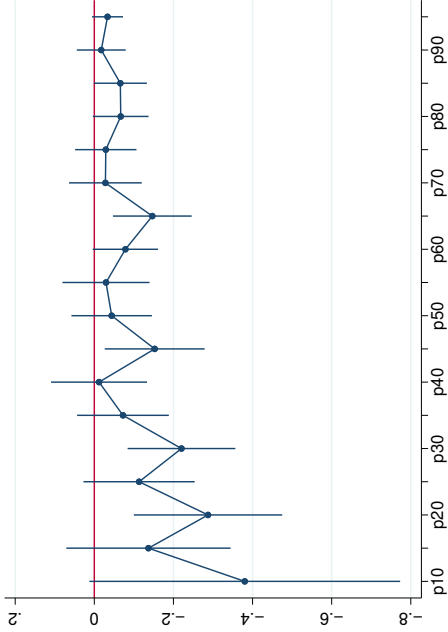
Figure 3: Year-on-Year Changes in the Cross-Sectional Distribution of Real Weekly Earnings



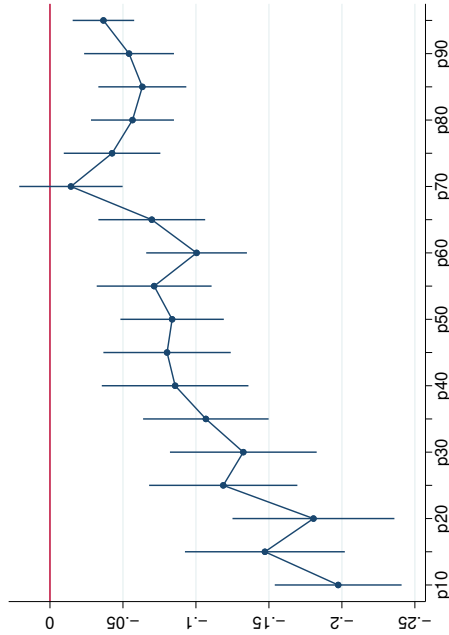
Note: The figure plots the year-on-year changes in real weekly earnings at each percentile, based on cross-sectional CPS data on usual earnings in the current job, converted to June 2020 dollars. The bottom 5% and the top 6% of the distribution are omitted, given that low earnings are winsorized and high earnings are censored due to top-coding. The 12-month periods to April, May, June and July 2020 are highlighted; the light grey lines correspond to earlier 12-month periods (October 2019 onwards).

Figure 4: Distributional Impact of the Pandemic

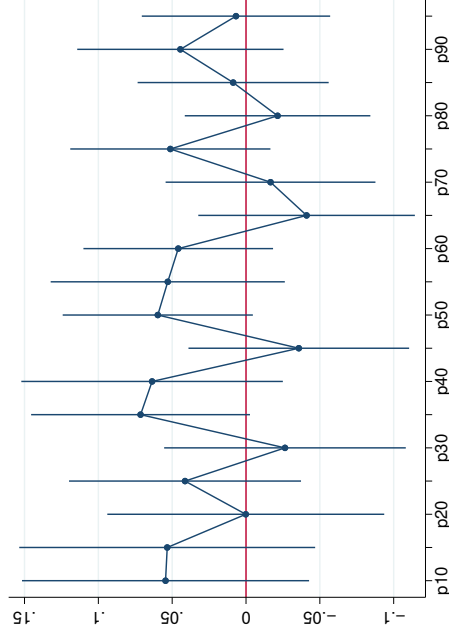
Panel A: Impact of the Pandemic on Labor Earnings (% Change)



Panel B: Impact on Probability of Remaining Employed (Extensive Margin)

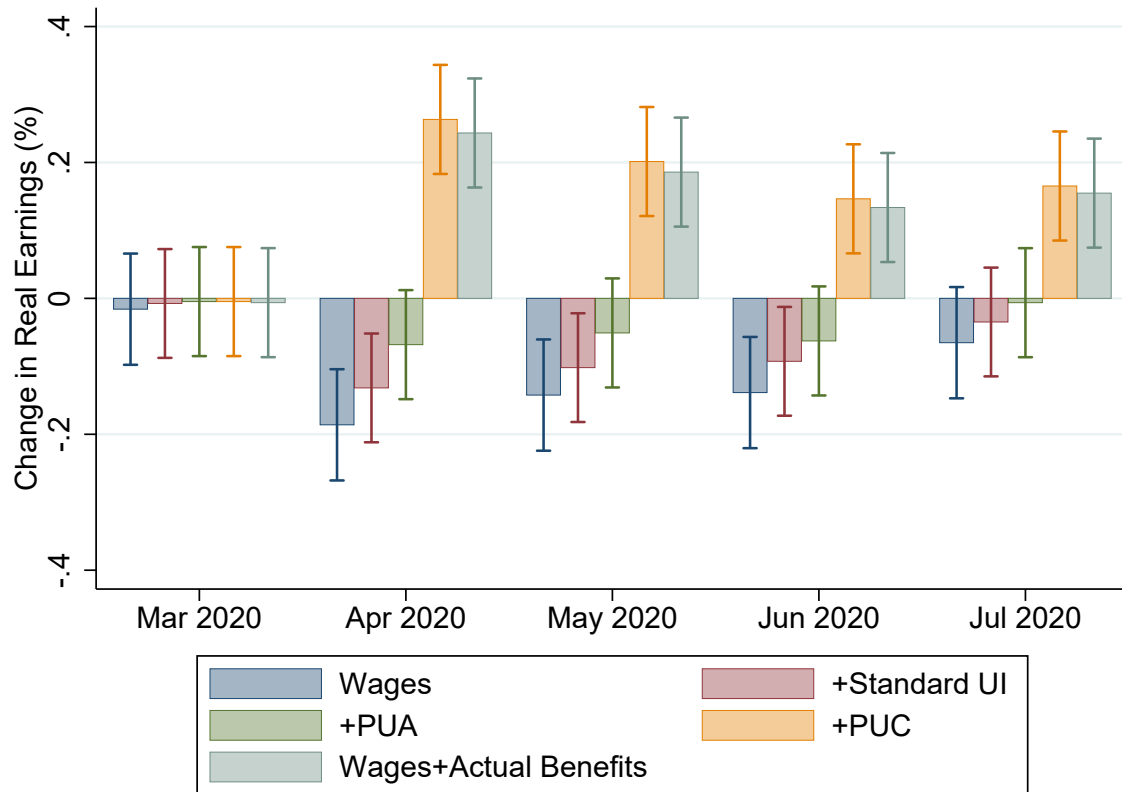


Panel C: Impact on Earnings Conditional on Remaining Employed (Intensive Margin)



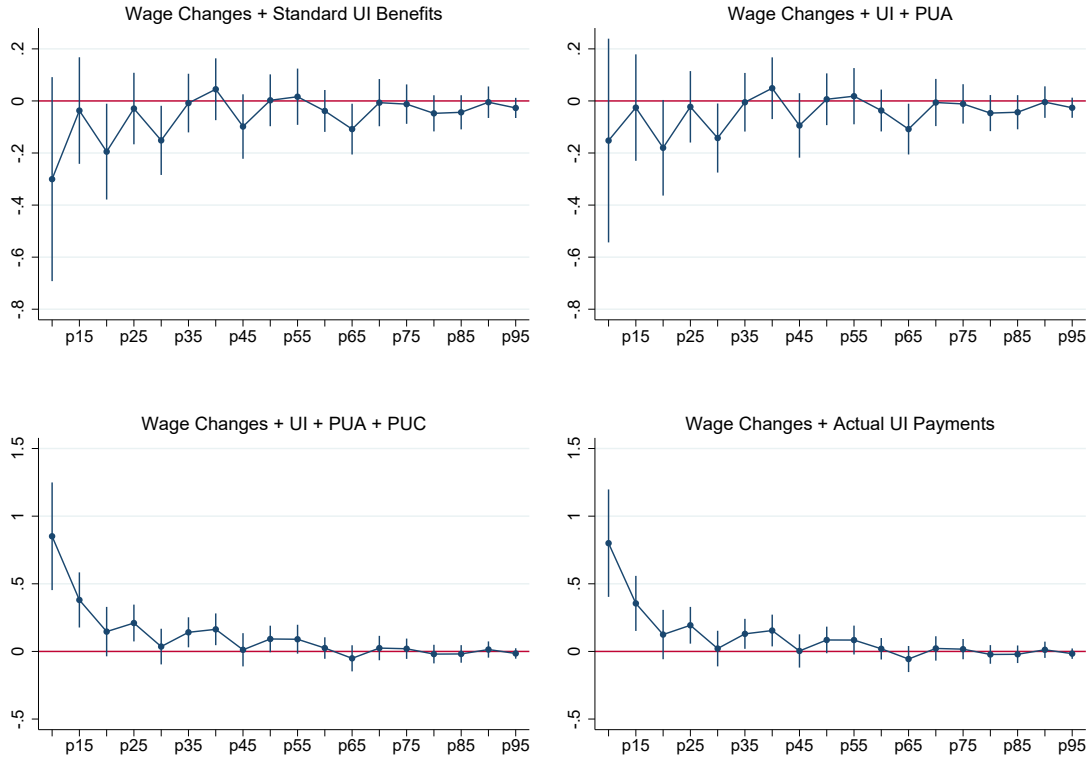
Note: The figure plots the estimated coefficients and 95% confidence intervals for the impact of the pandemic throughout the earnings distribution, based on the estimation of Equation (2) using individual-level data on year-on-year changes from January 2015 until July 2020. The dependent variable in Panel A is the within-individual percentage change in real weekly earnings. The sample includes all individuals who were employed (and have non-missing earnings) in their fourth month-in-sample, including those who transition out of employment (263,023 observations). Panel B uses the same sample; the dependent variable is the probability of remaining employed between month-in-sample 4 and month-in-sample 8. The sample in Panel C only includes individuals who are employed in both month-in-sample 4 and month-in-sample 8 (237,838 observations). The dependent variable is the within-individual change in log real weekly earnings.

Figure 5: Impact of the Pandemic on Year-Over-Year Percentage Change in Labor Earnings and Simulated Benefits by Program



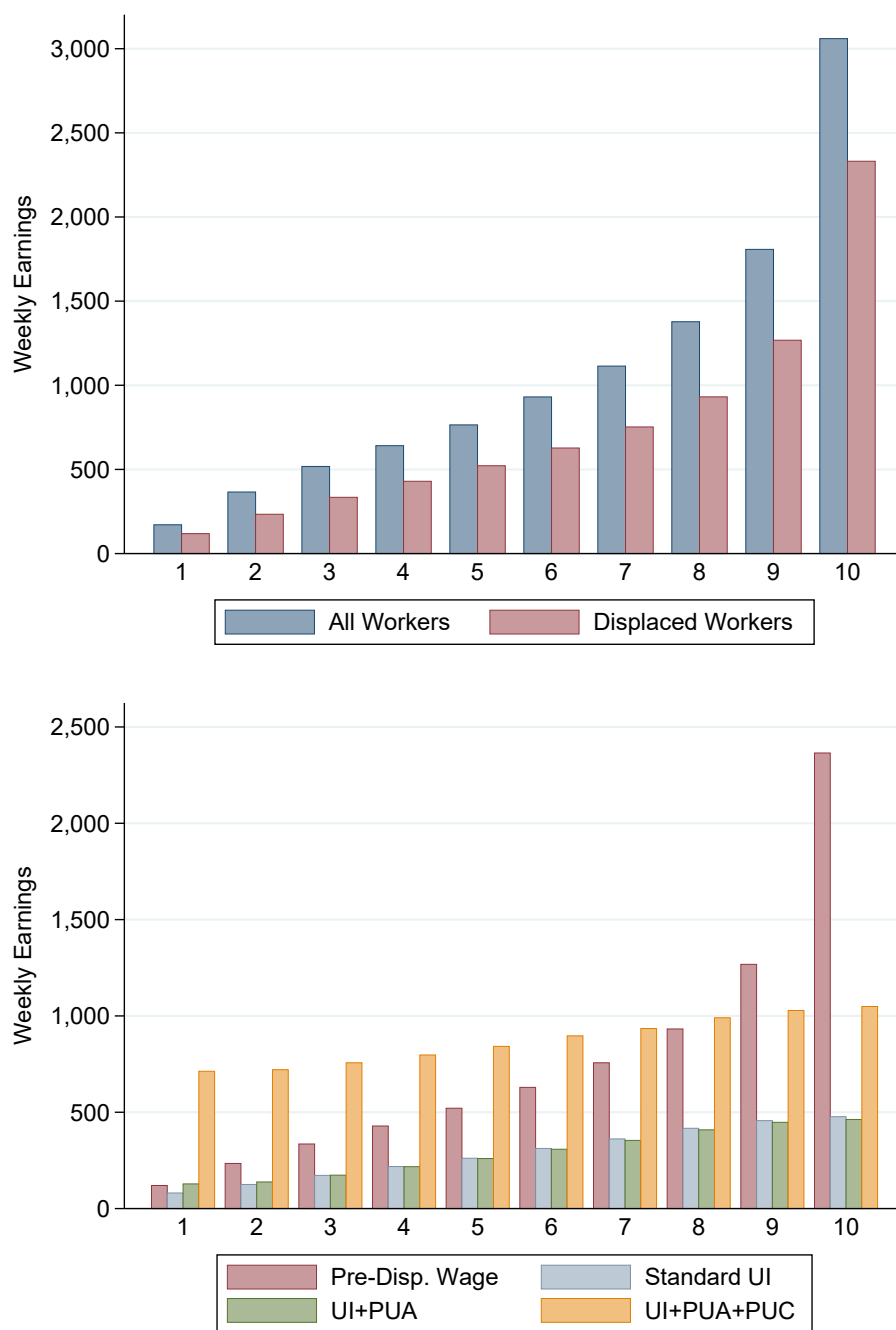
Note: PUA = Pandemic Unemployment Assistance (eligibility expansion), PUC = Pandemic Unemployment Compensation (additional \$600 per week). This graph plots the estimated coefficients and 95% confidence intervals for the impact of the pandemic on the year-over-year percentage change in real weekly earnings among previously employed individuals based on the estimation of Equation (1). The earnings measures are: (1) actual earned wages (including zeros), (2) wages plus estimated standard UI benefits, (3) the above plus estimated PUA benefits, (4) the above plus PUC benefits, and (5) wages plus all benefits, adjusted for the probability of receiving benefits based on our benchmarking exercise in Section 4.2.

Figure 6: Distributional Impacts of UI Policies on Earnings Growth during the Pandemic Period



Note: PUA = Pandemic Unemployment Assistance (eligibility expansion), PUC = Pandemic Unemployment Compensation (additional \$600 per week). The figure plots the estimated coefficients and 95% confidence intervals for the impact of the pandemic throughout the earnings distribution, based on the estimation of Equation (2) using individual-level data on year-on-year percentage changes in earnings from January 2015 until July 2020. Each panel uses a different measure of earnings: (1) actual earned wages (including zeros) plus estimated standard UI benefits, (2) the above plus estimated PUA benefits, (3) the above plus PUC benefits, and (4) wages plus all benefits, adjusted for the probability of receiving benefits based on our benchmarking exercise in Section 4.2.

Figure 7: Pre-Pandemic Earnings versus UI Benefits



Note: PUA = Pandemic Unemployment Assistance (eligibility expansion), PUC = Pandemic Unemployment Compensation (additional \$600 per week). The top figure shows average real weekly earnings in 2019 across deciles for all individuals (blue) versus individuals who lost employment during the pandemic (red). The bottom panel shows average earnings and average benefits by decile of the displaced worker distribution.

Table 1: CPS Job Losses and Predicted Claims vs. Department of Labor Unemployment Insurance Claims Data

Panel A: Job Losses and UI Claims During Pandemic Months					UI claims			
CPS job separations					(person-months, millions)			
(person-months, millions)								
	Standard UI	PUA	Ineligible	Total	Standard UI	PEUC	PUA	Total
Total	74.59	20.06	41.02	135.67	63.83	1.79	24.69	90.31
Pandemic-Induced	69.78		-20.58	71.06	47.73			

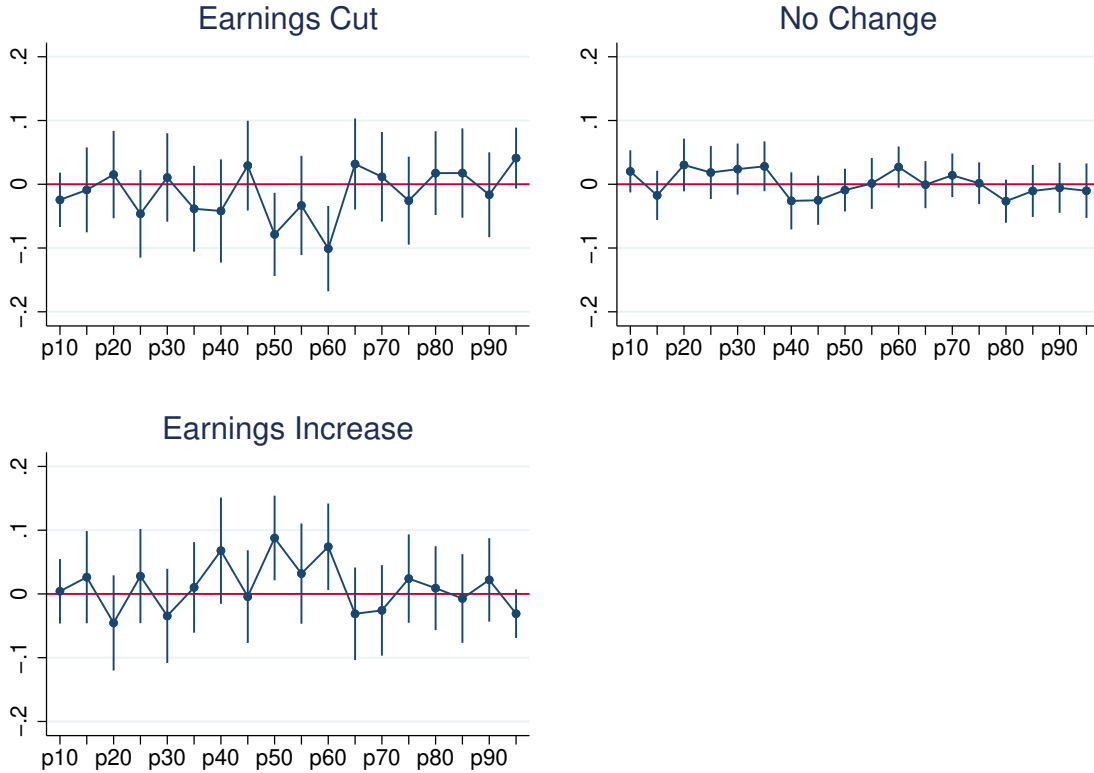
Panel B: Unemployment Insurance Payments During Pandemic Months					UI, dollars paid (billions)			
CPS, predicted dollars paid (billions)								
	Standard UI	PUA	PUC	Total	Standard UI	PEUC	PUA	Total
Total	90.40	9.34	200.37	300.11	76.91	1.73	12.80	174.95
Pandemic-Induced	76.31				59.66			

Panel C: Labor Income Changes During Pandemic Months		CPS (billions of dollars)	
Total		-124.13	
Pandemic-Induced		-254.07	

Note: PUA = Pandemic Unemployment Assistance (eligibility expansion), PUC = Pandemic Unemployment Compensation (additional \$600 per week), PEUC = Pandemic Emergency Unemployment Compensation (benefit duration extension). In the left-hand columns of Panel A, we report the total number of person-month job separations in the CPS over the pandemic period (March through July), broken down by their predicted eligibility status for the different UI programs based on our approach described in Section 4.1. Pandemic-induced estimates are obtained by estimating Equation (1). The right-hand columns present data from the Department of Labor (DoL) on claims paid by program. Panel B presents corresponding dollar amounts of benefits. The DoL figures are based on monthly reports by each state UI system on forms ETA5159 and ETA902p. The PUA data remains incomplete, as not all states have reported this data in all months. The dollar amount for actual PUC payments is based on the assumption that all standard UI, PEUC, and PUA recipients receive this benefit from April through July. Panel C computes the total change in labor income over the pandemic period based on CPS data.

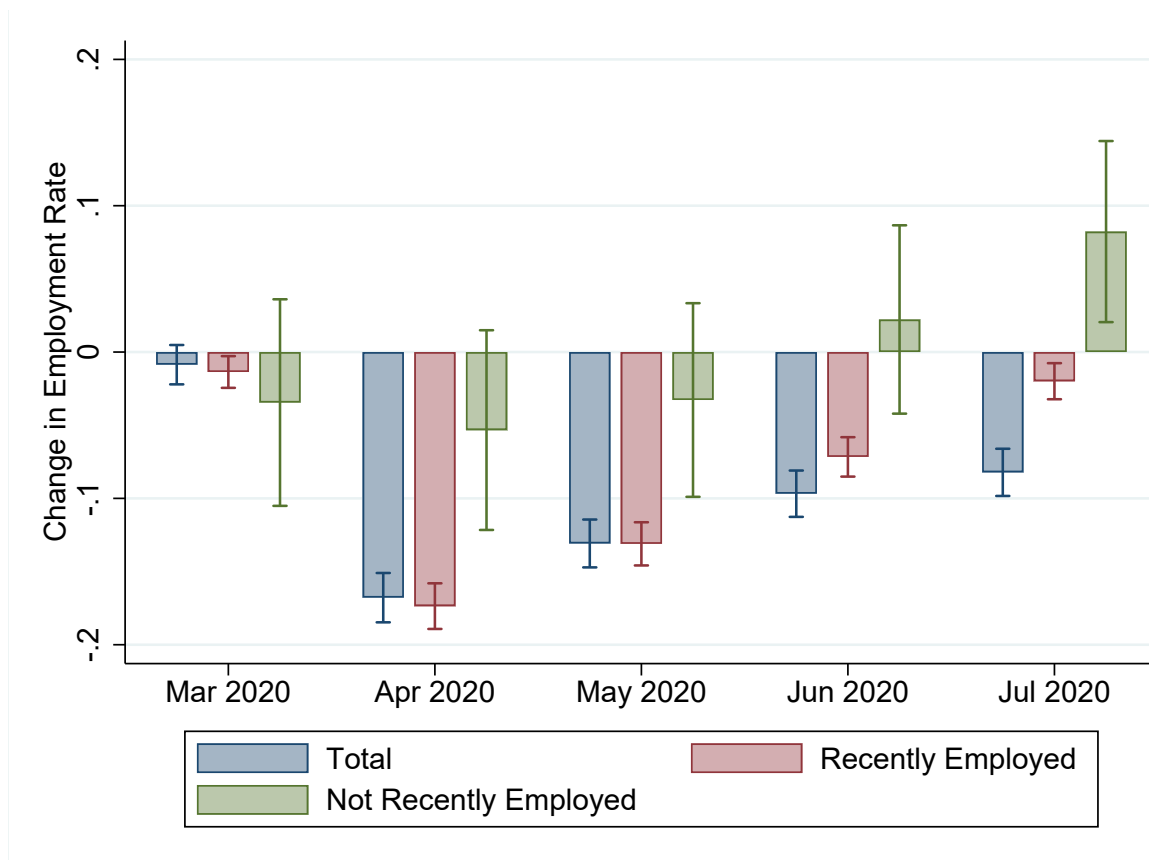
A Appendix

Figure A.1: Pandemic Impact on Nominal Weekly Earnings Changes



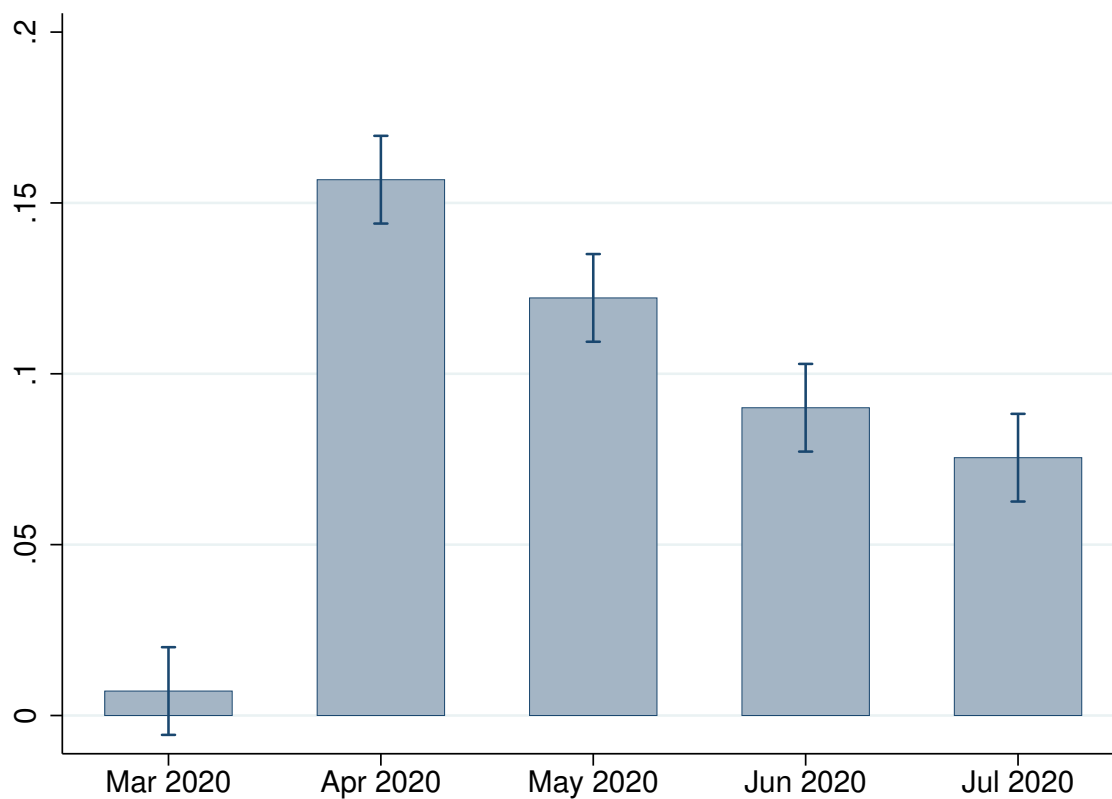
Note: The figure plots the estimated coefficients and 95% confidence intervals from Equation (2) using individual-level data on year-on-year changes in nominal earnings from January 2015 until July 2020. The panels provide estimates of the impact of the pandemic on the probability of experiencing an earnings cut, an earnings increase, or no change in earnings, respectively. Earnings cuts and increases are based on changes of at least \$10 in weekly earnings. The sample includes individuals who are employed in both month-in-sample 4 and month-in-sample 8 (237,838 observations).

Figure A.2: Change in Employment Rate by Employment History



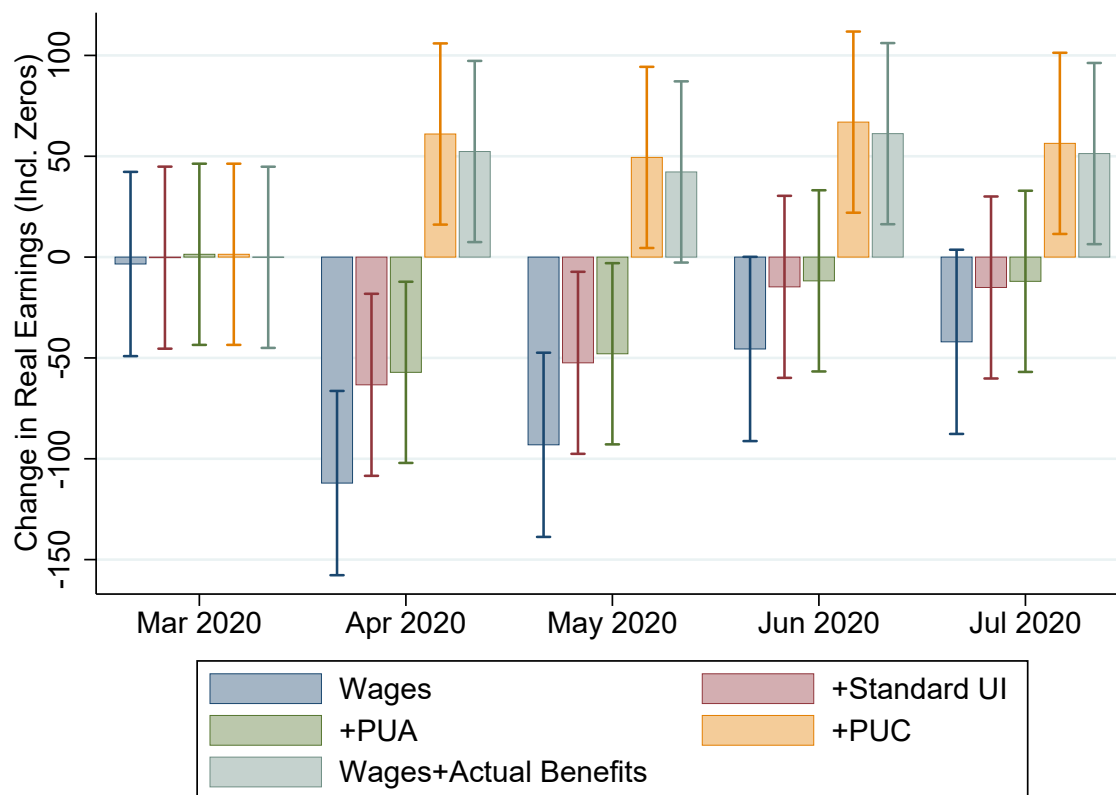
Note: The figure plots the estimated impact of the pandemic (along with 95% confidence intervals) on the employment rate for different groups of workers. Recently employed are individuals who were employed at some point in the last three months, while not recently employed are the balance.

Figure A.3: Estimated Impact of the Pandemic on the Year-on-Year Job Separation Rate



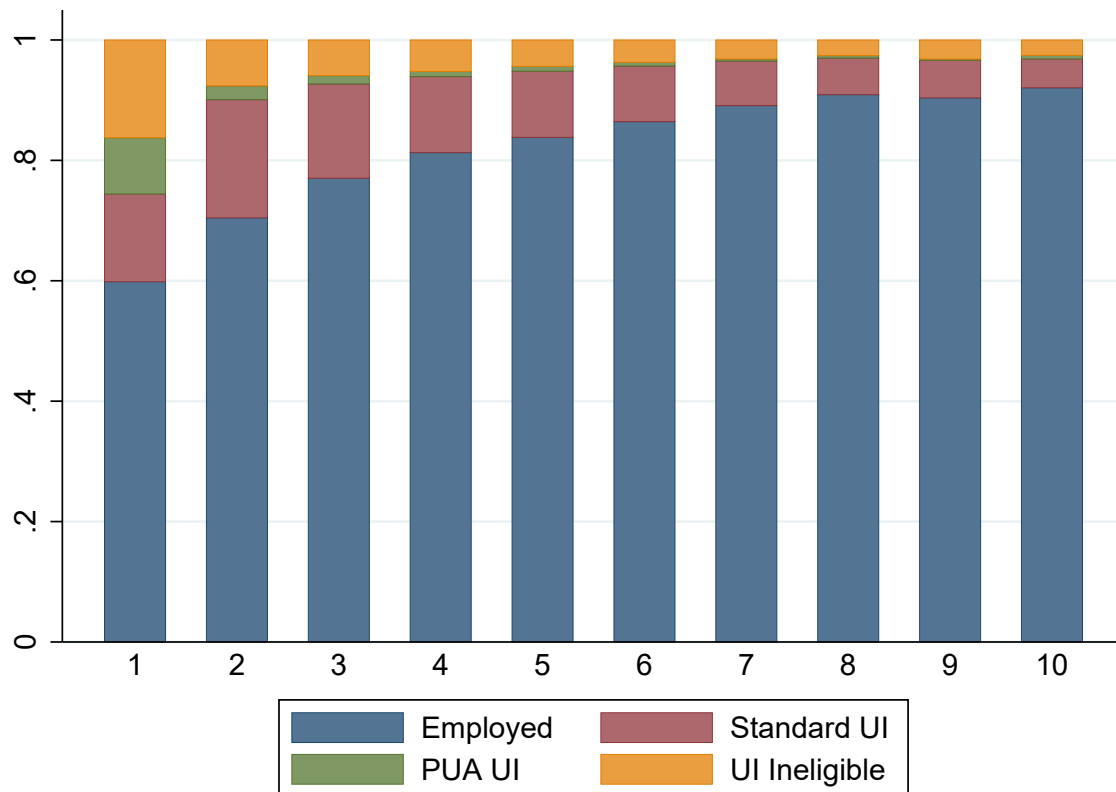
Note: The figure plots the estimated coefficients and 95% confidence intervals obtained from the estimation of Equation (1) using the year-on-year job separation rate as the dependent variable.

Figure A.4: Impact of the Pandemic on Year-Over-Year Dollar Change in Labor Earnings and Simulated Benefits by Program



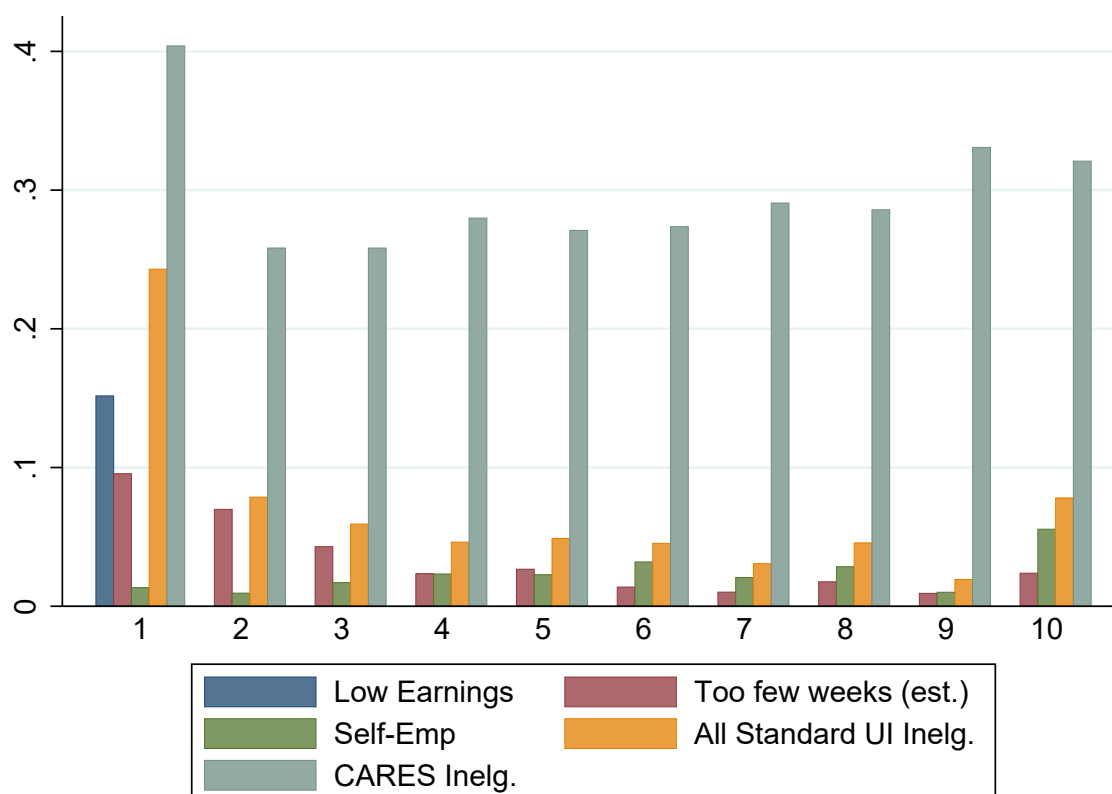
Note: PUA = Pandemic Unemployment Assistance (eligibility expansion), PUC = Pandemic Unemployment Compensation (additional \$600 per week). This graph plots the estimated coefficients and 95% confidence intervals for the impact of the pandemic on the year-over-year dollar change in real weekly earnings among previously employed individuals based on the estimation of Equation (1). The earnings measures are: (1) actual earned wages (including zeros), (2) wages plus estimated standard UI benefits, (3) the above plus estimated PUA benefits, (4) the above plus PUC benefits, and (5) wages plus all benefits, adjusted for the probability of receiving benefits based on our benchmarking exercise in Section 4.2.

Figure A.5: Distribution of Employment and UI Eligibility Status during the Pandemic Period, by Decile of the Pre-Pandemic Earnings Distribution



Note: PUA = Pandemic Unemployment Assistance (eligibility expansion). This figure shows the fraction of individuals in each pre-pandemic wage decile that were either: (a) employed during the pandemic months, (b) eligible for standard UI, (c) eligible only for the CARES PUA UI expansion, or (d) ineligible for UI. Individual's UI eligibility status is predicted based on our approach described in Section 4.1. Note that these are raw shares of individuals, and thus show a larger number of separations than the estimates in Figure 4, which remove typical transition rates.

Figure A.6: Share of Individuals Displaced during the Pandemic who are Ineligible for UI



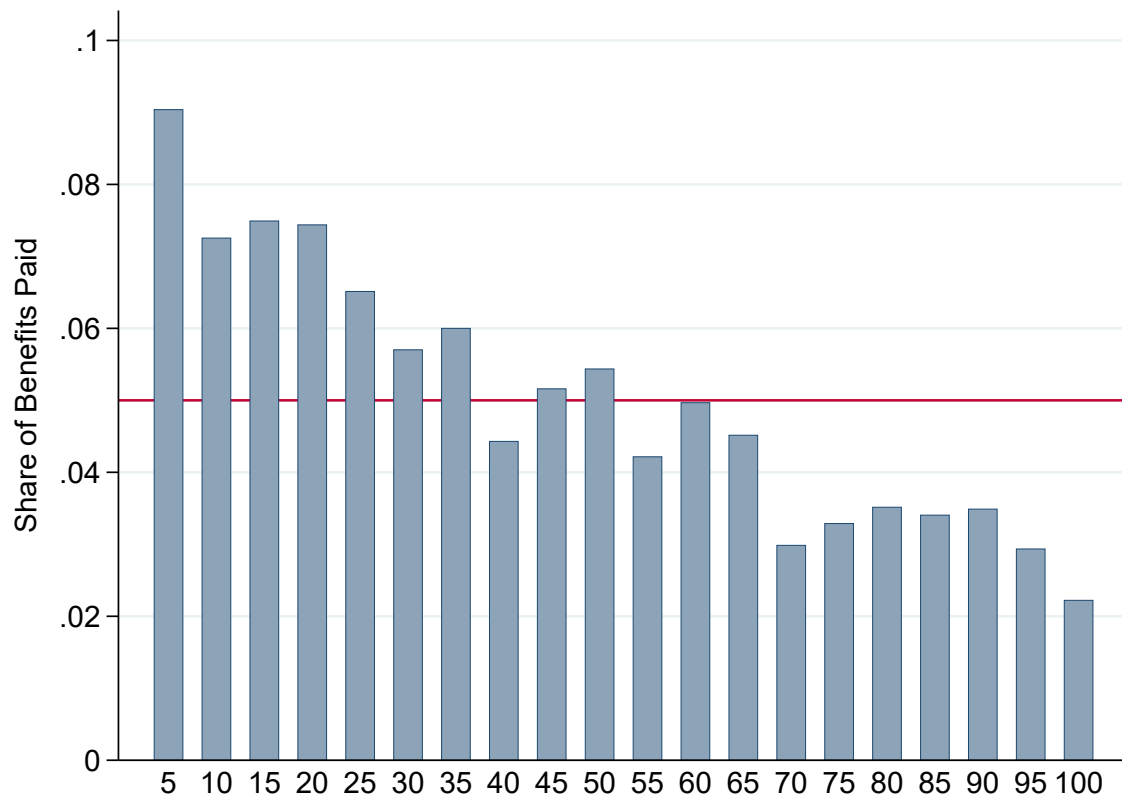
Note: This figure shows the fraction of individuals who were employed one year prior and were displaced during the pandemic but are ineligible for standard UI for one of three reasons: earnings did not pass the state earnings threshold, weeks of employment did not pass the state threshold (estimated from ACS data), or the worker was self-employed in his or her most recent month of employment. Note that all of these workers are eligible for PUA (Pandemic Unemployment Assistance) instead. The grey bar shows the share that we estimate are ineligible for the PUA provision in the CARES Act because they were not recent job losers.

Figure A.7: Impact of the Pandemic on Year-Over-Year Dollar Change in Labor Earnings and Simulated Benefits by Program



Note: PUA = Pandemic Unemployment Assistance (eligibility expansion), PUC = Pandemic Unemployment Compensation (additional \$600 per week). The figure plots the estimated coefficients and 95% confidence intervals for the impact of the pandemic throughout the earnings distribution, based on the estimation of Equation (2) using individual-level data on year-on-year dollar changes in earnings from January 2015 until July 2020. Each panel uses a different measure of earnings: (1) actual earned wages (including zeros) plus estimated standard UI benefits, (2) the above plus estimated PUA benefits, (3) the above plus PUC benefits, and (4) wages plus all benefits, adjusted for the probability of receiving benefits based on our benchmarking exercise in Section 4.2.

Figure A.8: Share of Total UI Benefits by Wage Ventile



Note: This graph plots the share of total benefits paid across standard UI and the CARES Act by ventile in the pre-displacement wage distribution.

Table A.1: Characteristics of UI Recipients versus CPS Predicted Recipients

	Actual UI Recipients	CPS Predicted Recipients
Female	53%	53%
Hispanic	20%	22%
Black	21%	12%
White	70%	75%
Other	10%	13%
Under 25	14%	15%
25-35	27%	18%
35-55	38%	36%
55+	22%	30%
Agriculture	1%	0.4%
Mining	1%	0.6%
Construction	7%	7%
Manufacturing	11%	8%
Trade	16%	13%
Transportation and utilities	4%	6%
Information	2%	2%
Financial activities	1%	3%
Professional and business services	4%	9%
Educational and health services	15%	20%
Leisure and hospitality	22%	19%
Other services	5%	8%
Public administration	1%	2%

Note: This table compares the demographic and industry characteristics among predicted UI claimants from the CPS and actual characteristics of UI recipients reported to the DOL. The data span March through June 2020.