

NBER WORKING PAPER SERIES

INCOME AND POVERTY IN THE COVID-19 PANDEMIC

Jeehoon Han
Bruce D. Meyer
James X. Sullivan

Working Paper 27729
<http://www.nber.org/papers/w27729>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2020

This paper was prepared for the Brookings Papers on Economic Activity conference on June 25, 2020. We would like to thank our discussant, Abigail Wozniak and the editors, for helpful feedback, Chris Kelly and Josie Donlon for excellent research assistance, Anna Brailovsky for helpful comments, the NSF for financial support for this project, and the Russell Sage Foundation, Alfred P. Sloan Foundation, Charles Koch Foundation, and the Menard Family Foundation for their support of the Comprehensive Income Dataset Project. We would also like to thank Bill Evans for sharing data on state level COVID-related mortality rates and state policies. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2020 by Jeehoon Han, Bruce D. Meyer, and James X. Sullivan. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Income and Poverty in the COVID-19 Pandemic
Jeehoon Han, Bruce D. Meyer, and James X. Sullivan
NBER Working Paper No. 27729
August 2020
JEL No. H53,I32,J65

ABSTRACT

This paper addresses the economic impact of the COVID-19 pandemic by providing timely and accurate information on the impact of the current pandemic on income and poverty to inform the targeting of resources to those most affected and assess the success of current efforts. We construct new measures of the income distribution and poverty with a lag of only a few weeks using high frequency data from the Basic Monthly Current Population Survey (CPS), which collects income information for a large, representative sample of U.S. families. Because the family income data for this project are rarely used, we validate this timely measure of income by comparing historical estimates that rely on these data to estimates from data on income and consumption that have been used much more broadly. Our results indicate that at the start of the pandemic, government policy effectively countered its effects on incomes, leading poverty to fall and low percentiles of income to rise across a range of demographic groups and geographies. Simulations that rely on the detailed CPS data and that closely match total government payments made show that the entire decline in poverty that we find can be accounted for by the rise in government assistance, including unemployment insurance benefits and the Economic Impact Payments. Our simulations further indicate that of those losing employment the vast majority received unemployment insurance, though this was less true early on in the pandemic and receipt was uneven across the states, with some states not reaching a large share of their out of work residents.

Jeehoon Han
School of Economics
Zhejiang University
Yuhangtang Road No.866
Hangzhou, 310058
China
jeehoonhan3@gmail.com

James X. Sullivan
Department of Economics
3108 Jenkins Nanovic Halls
University of Notre Dame
Notre Dame, IN 46556
James.X.Sullivan.197@nd.edu

Bruce D. Meyer
Harris School of Public Policy
University of Chicago
1307 E 60th Street
Chicago, IL 60637
and NBER
bdmeyer@uchicago.edu

I. Introduction

The start of the COVID-19 pandemic in the United States quickly resulted in an unprecedented decline in economic activity with employment and earnings plummeting. At the same time, the federal government responded with tax rebates in the form of Economic Impact Payments, small business loans, and an unprecedented expansion of unemployment insurance as part of the CARES Act and related stimulus legislation that all told committed more than three trillion dollars to countering the effects of the COVID-19 pandemic. Whether this response has been adequate to offset the losses and what net effect it may have on income and poverty remains unclear. To ensure that the government can track the income changes of the American population overall and by demographic group to target and calibrate its fiscal response most effectively requires timely information on income and poverty. Unfortunately, official estimates of income and poverty for 2020 will not be available until September of 2021. These official statistics will be of little use to federal, state, and local policymakers who need to decide quickly how to allocate scarce resources to minimize COVID-19's impact on vulnerable populations. Thus, this crisis calls for timely and accurate information on the impact of the current pandemic (as well as future shocks) on the economic well-being of individuals and families.

To address the gap in critical, real-time information we construct new measures of the income distribution and income-based poverty with a lag of only a few weeks using high frequency data for a large, representative sample of U.S. families and individuals. We rely upon the Basic Monthly Current Population Survey (Monthly CPS), which includes a greatly underused global question about annual family income. A clear advantage of using the Monthly CPS to estimate changes in income and poverty is that the quick release of these data allows us to understand the immediate impact of macroeconomic conditions and government policies. For example, given data release dates, analyses of income from the Monthly CPS would have revealed the negative impact of the Great Recession a full 14 months before official estimates indicated an increase in poverty. Our approach generates immediately useful income and poverty estimates for the overall population, as well as how these rates vary by demographic groups and geography. We also validate this new and timely measure of family income by comparing estimates that rely on these data to estimates from data on income that have been used much more broadly and that have a long historical track record. Our validations will help other

researchers understand the advantages and limitations of using more timely income data to understand changes in economic well-being.

Our initial evidence indicates that at the start of the pandemic government policy effectively countered its effects on incomes, leading poverty to fall and low percentiles of income to rise across a range of demographic groups and geographies. Our evidence suggests that income poverty fell shortly after the start of the COVID-19 pandemic in the U.S. In particular, the poverty rate, calculated each month by comparing family incomes for the past twelve months to the official poverty thresholds, fell by 1.5 percentage points from 10.9 percent in the months leading up to the pandemic (January and February) to 9.4 percent in the three most recent months (April, May, and June). This decline in poverty occurred despite that fact that employment rates fell by 14 percent in April—the largest one month decline on record. The declines in poverty are evident for most demographic groups, although we find some evidence that poverty declines most noticeably for those who report their race as neither white nor black and those who have a high school education or less.

Our simulations using the detailed and nationally representative CPS data indicate that government programs, including the regular unemployment insurance program, the expanded UI programs, and the Economic Impact Payments, can account for more than the entire decline in poverty, which would have risen by over 2.5 percentage points in the absence of these programs. These programs also helped boost incomes for those further up the income distribution, but to a lesser extent. Evidence based on actual dollars spent on these programs indicates that most eligible families received the Economic Impact Payment, and that the expanded coverage of unemployment insurance reached the vast majority of those desiring to work who were unable to do so. However, the states were slow to reach many without work and some states were still unable to reach a large share of their population even three months after the initial employment decline.

This study generates some of the first evidence on how the COVID-19 pandemic is affecting the economic well-being of individuals and families in the U.S., and which groups are affected most. Economists have long examined the impact of large macroeconomic shocks, such as recessions (i.e. Grusky et al. 2011) or pandemics (i.e. Almond 2006; Almond and Mazumder 2005). However, due to the limited availability of data making it difficult to study major shocks as they evolve, past research has necessarily mostly happened long after the events occurred. Our

study provides a template for the future understanding of large economic shocks as they happen. This paper also addresses important survey methodology questions, such as whether the patterns of annual income from a monthly survey align with the patterns for income from annual surveys that are the source for official statistics, and how responses to a single, global question about income compare to estimates of total income from questions about many income sources. Understanding the validity of survey-measured income is critically important given the prominent role it plays in economic research.

II. Discerning the Impact of COVID-19

The impact of the pandemic on the labor market was swift and severe. Employment rates (Appendix Figure 1) dropped sharply, by more than 8 percentage points (14 percent), in April, the largest one-month decline on record. At the same time earnings fell by more than 10 percent (Appendix Figure 2). Although both earnings and employment bounced back somewhat in May and June, they remain well below the levels at the start of 2020.

The two most direct ways that federal policies worked to offset this sudden decline in earnings were through Economic Impact Payments and the expansion of unemployment insurance benefits. The Economic Impact Payments provided \$1,200 to individuals with income less than \$75,000 and to single parents (heads of household) with income below \$112,500, and they provided \$2,400 to married couples with income less than \$150,000. Recipients were also eligible to receive an additional \$500 for each qualifying child. For those with income above these thresholds, the payments were reduced by 5 percent of the income that exceeded the threshold.

Economic Impact Payments started the second week of April, with the early checks going to those with the lowest adjusted gross income. As shown in Appendix Figure 3, the Internal Revenue Service had sent Economic Impact Payments to nearly 90 million individuals by April 17, and to an additional 63 million individuals over the next 5 weeks. As of June 3rd, 159 million payments had been processed.¹

Additional relief was made available to those who lost their job through expanded unemployment insurance benefits. The CARES Act, which was passed in late March, created the Pandemic Unemployment Compensation (PUC) program, which provided an additional \$600 per

¹ www.irs.gov/newsroom/159-million-economic-impact-payments-processed-low-income-people-and-others-who-arent-required-to-file-tax-returns-can-quickly-register-for-payment-with-irs-non-filers-tool.

week to claimants on top of the usual benefit. These PUC payments expired at the end of July 2020. The CARES Act also extended eligibility for benefits to groups not covered by the traditional UI program, such as the self-employed, part-time workers, and those who did not have a long enough work history to qualify for the traditional program (Pandemic Unemployment Assistance, PUA), and it extended by 13 weeks the duration of UI benefits for a regular claim (Pandemic Emergency Unemployment Compensation, PEUC).

An unprecedented number of individuals have filed for these benefits during the pandemic. As shown in Appendix Figure 4, initial claims shot up starting in mid-March. For the week ending April 4th, 6.2 million initial claims were filed. Between the weeks ending March 21 and June 20, more than 50 million initial claims were filed. According to the Bureau of the Fiscal Service of the U.S. Treasury (U.S. Treasury (2020)), UI payments never exceeded \$3 billion in a single month from February 2019 through February 2020. In March 2020, these payments jumped to \$4.2 billion, and then to \$48.4 billion in April, \$93.7 billion in May, and \$115.7 billion in June.

Together these policies have the potential to significantly boost family incomes and lift many families, at least temporarily, out of poverty. Consider a family of four with two adults and two children whose family income comes entirely from the earnings of the head of the household. If the head's earnings do not change after the start of the pandemic and the family receives the maximum Economic Impact Payments in April, then this family would be lifted out of poverty (i.e. their income for the past 12 months would exceed the poverty threshold for a family of this size and composition) in April as long as their income exclusive of Economic Impact Payment was within 90 percent of the poverty line. Moreover, the one-time Economic Impact Payment would be sufficient to keep such a family's income over the past 12 months above the poverty line for an entire year, through March 2021. Alternatively, if, in addition to the Economic Impact Payment payments, the head of such a family lost his or her job in April 2020 and collected UI benefits as well as the additional \$600 per week through July 2020, then such a family would have income above the poverty line in April and for the following nine months as long as their pre-COVID earnings (and therefore income) were within 80 percent of the poverty line.²

² This calculation assumes that the head collects UI benefits equal to half of pre-separation earnings.

III. Earlier work on Timely Measures of Income and Poverty

While there is an extensive literature that examines income and poverty measurement and trends (summarized in Ruggles 1990; Citro and Michael, 1995; Meyer and Sullivan, 2012 and Burkhauser et al., 2019), none of these studies have addressed the long delay in the availability of nationally representative income data, and very few have used the data from the Monthly Current Population Survey (Monthly CPS). Bergmann and Coder (2010) use the Monthly CPS to construct a poverty measure based on earnings and imputed UI benefits for the period from 2005 to 2009. A few researchers have used the Monthly CPS to generate timely estimates of income and compare these estimates to the CPS Annual Social and Economic Supplement (ASEC). However, this work has focused on median income (Green and Coder, 2020) and provided only very limited validation of its measures. Thus, there is surprisingly little precedent for our timely, validated measure of income and poverty.

IV. Data and Methods

We rely on income to measure poverty in this situation, despite two of us having argued for more than fifteen years that, for historical (as opposed to timely) research, consumption should be preferred. However, we have never argued that consumption should be exclusively used. Income and consumption data are complements and there are situations where each is likely to be more informative than the other. Given that detailed, comprehensive and representative consumption data are not available in a timely fashion, the income data are an important source.³ Furthermore, the short run aspects of this pandemic, in which consumption is likely to move independently of short run changes in income, makes income of interest in its own right. Examining short term changes in income during the pandemic allows us to examine whether the concomitant decline in consumption is due to a shortfall in current income or another explanation, such as a limited opportunity to consume certain goods and services or uncertainty over future income streams.

Our new measures of the income distribution and income-based poverty rely on data from the Monthly CPS, which collects information on labor market outcomes and demographic characteristics from a representative sample of about 40,000 to 50,000 households.⁴ Interviews

³ If the Bureau of Labor Statistics follows the same schedule as in recent years, nationally representative data on consumption for 2020 from the Consumer Expenditure Survey would not be released until September 2021.

⁴ We obtained the Monthly CPS data through IPUMS-CPS (Flood et al. 2020).

are conducted during the calendar week containing the 19th of the month. The survey provides the timeliest nationally representative data available for family income. The Monthly CPS has been collecting information about income for nearly 40 years. Thus, we can observe the cyclical patterns of income and its association with other variables long before the onset of the COVID-19 pandemic, which is helpful for understanding the validity of the income data, as it allows us to compare income and other observable characteristics from these data to those from many other historical data series. To capture changes in income before and after the start of the pandemic, we will focus on data from the January 2020 survey through the June 2020 survey, although for some analyses we also report more historical estimates.

Analysis Sample

Our analyses focus on a subset of individuals from the Monthly CPS because we do not observe family income for all individuals for several reasons. In Appendix Table 1, we report the number of households and individuals that are in the survey for each month of 2020 and how these numbers change as we restrict the sample. First, housing units selected to be in the CPS are typically only asked this question in the first and fifth interview months that they are in the survey (housing units are in the CPS sample for eight months over a 16-month period—four months on, eight months off, and four months on).⁵ Second, the total income question is asked only in reference to the family income of the householder’s family, so we do not observe this income information for individuals in the household who are outside the householder’s family (i.e. unrelated individuals and unrelated subfamilies), which accounts for about 5 percent of individuals in the first or fifth interview month. Finally, during our sample period, between 23 and 28 percent of individuals in the first or fifth months of the survey do not have a response to the family income question. Although the Census Bureau provides imputed values of income for those who do not respond, we do not include these observations in our analysis. As a result of these restrictions, we observe family income from respondents in their first or fifth month in the survey for a monthly sample ranging from 8,999 households and 20,822 individuals in February 2020 to 6,149 households and 14,383 individuals in April 2020.

⁵ CPS households that do not provide an answer to this income question in their first or fifth month are asked this question in subsequent months. Thus, about 3 percent of households in these other months are asked and respond to the family income question. Otherwise, in the public use files, the value of family income in these other months is just carried over from the response in either the first or fifth month.

An important issue to consider for analyses of income before and after the start of the pandemic is that concerns about COVID-19 may have affected survey responses. Due to health concerns, the Census Bureau shifted the survey collection method for the Monthly CPS from in-person to phone interview for some households in March 2020 and for nearly all households in April 2020. Households in their first and fifth interview month are most affected by this change because interviews in these two months are usually conducted in-person, whereas interviews in other months are normally conducted via phone. For example, in January 2020, 66 percent of the households in their first or fifth month were interviewed in person.

In Appendix Table 2, we examine how the change in the survey method affects the survey nonresponse rate as well as the composition of the sample across interview months between February and June 2020. The first row shows that the nonresponse rates in the April, May, and June 2020 surveys were substantially higher than that in February 2020 for all interview months. However, this rise was most noticeable for households in their first month, and to some extent for those in their fifth month. That the rise in survey nonresponse rates is more noticeable for those in their first or fifth month than for those in other months suggests that the shift from in-person to telephone interviews may have had an impact on response rates. We also see a rise in item nonresponse for the family income question, although this rise is much less pronounced than the rise in survey nonresponse.

These patterns might be problematic if survey or item non-response is not random. To consider whether there might be selection into non-response, we examine the observable characteristics of the sample across interview months before and after the onset of the pandemic, restricting the sample to individuals who are included in the householders' families with non-imputed family income. Most of the characteristics that we report in Appendix Table 2 are similar pre- and post-onset of COVID regardless of interview month. However, there is some evidence that individuals in the first interview month in April, May, and June 2020 are slightly more educated and less likely to be in a single parent family than those in the first interview month pre-COVID. These small differences suggest that changes in survey response rates may have resulted in a slightly more advantaged sample of first month responders in the most recent survey months though further analysis suggests the differences are not substantive.⁶

⁶ For our main sample (first and fifth month respondents), we reject the joint hypothesis that the demographic characteristics in Appendix Table 2 (not including income and employment) are the same for those in April, May,

To be cautious, we address concerns about possible changes in sample representativeness in two ways. First, for our main analyses we re-weight the samples from March through June so that observable characteristics—family type, age of head, and education of head—for these months match those in January and February, as explained in Appendix I. As an additional robustness check, we also report results for a sample that includes only individuals in their fifth month interview, as the change in nonresponse rates and demographic characteristics across recent months is smaller for this group.

Family Income in the Monthly CPS

Our primary analyses rely on a global question in the Monthly CPS about total cash income for the householder’s family for the previous 12 months. Specifically, the question asks the respondent to report:

“total combined income during the past 12 months...of all members [of the family]. This includes money from jobs, net income from business, farm or rent, pensions, dividends, interest, social security payments and any other money income received...by members of [the family] who are 15 years of age or older.”⁷

This global family income question from the Monthly CPS aligns closely with the definition of total cash income from the CPS ASEC, which is used for official poverty and income statistics, although family income from the CPS ASEC is calculated as the sum of responses to questions about many different components of income. Because interviews take place in the third week of the month, we assume that the respondent includes income from the interview month in their response to the question. Making this distinction is important for determining when we should expect to see this measure of family income reflect the effects of the pandemic. For example, respondents to the April CPS arguably included negative income shocks that occurred or government payments that were received during the first few weeks of April. During these weeks, unemployment insurance claims grew sharply and the first wave of Economic Impact Payments were distributed.

and June as compared to those in January and February (p-value < 0.01). However, when we regress unemployment on these characteristics for a sample of those in the other interview months, and use the estimates from this model to predict unemployment for our main sample across survey months, the mean predicted values are virtually the same throughout our sample period, differing by less than 0.024 percentage points (0.96 percent). They are also virtually the same as the mean predicted values for the other interview months that did not move from in-person to telephone interviews, suggesting that the change in interview mode did not affect sample composition substantively.

⁷ <https://www2.census.gov/programs-surveys/cps/techdocs/questionnaires/Labor%20Force.pdf>

It is also unclear whether the responses to this question give equal weight to each of the previous 12 months, or whether greater weight is given to income in more recent months. If there is telescoping, i.e. more accurate recall of more recent income, then the most recent responses to the income question in the Monthly CPS are more likely to capture the effects of the pandemic. Investigating whether there is evidence of telescoping in the Monthly CPS family income data is an important area for future research.

Rather than reporting a specific amount for total income, respondents in the Monthly CPS choose among 16 categorical income ranges. For the bottom part of the income distribution, the income ranges are fairly small. Below \$15,000 there are five categories, and from \$15,000 to \$40,000 the intervals are \$5,000 wide. To calculate our estimates of poverty and various percentiles of the income distribution, we convert this categorical response into a continuous measure by randomly selecting values of family income from families in the CPS ASEC from the same survey year who have incomes that fall in that same income range and who have some similar demographic characteristics. In Appendix I we provide the details for this imputation procedure, as well as comparisons of family income in the Monthly CPS to family income in the CPS ASEC (see Section VI for additional analyses of the validity of the income measure from the Monthly CPS).

Measures of Income Poverty and the Income Distribution

Our estimates of poverty compare our measure of family income for the 12 months immediately preceding the interview from the Monthly CPS to the official poverty threshold for each family, which varies by family size and composition. We use the official poverty thresholds for the year that aligns with the most recent month of the reference period in the Monthly CPS. For example, since the most recent month of the reference period for respondents to the April 2020 CPS falls in 2020, we use the “official” 2020 poverty thresholds to calculate poverty for these respondents.⁸

There are many limitations of the official measure that numerous studies have noted, such as its adjusting thresholds over time using a price index that overstates inflation, its omission of taxes, tax credits, and in-kind benefits such as food stamps and housing subsidies, and its peculiar equivalence scale (Citro and Michael, 1995; Meyer and Sullivan 2012; Burkhauser et al.

⁸ To obtain “official” thresholds for 2020, we adjust the 2019 thresholds for inflation using the CPI-U, which is the price index the Census Bureau uses to adjust the official thresholds for inflation on an annual basis.

2019). These limitations are less relevant for the short-term changes in poverty that are the focus of this study as long as the errors do not change quickly over time. For example, although price index bias significantly affects estimates of changes in poverty over several decades (Meyer and Sullivan, 2012), such bias is negligible for changes in poverty within a year. While we do not incorporate noncash programs into our analyses because the Monthly CPS does not include data on receipt of such benefits, these programs may play an important role in replacing lost earnings during the pandemic. See Bitler, Hoynes, and Schanzenbach (this issue) for more discussion of the importance of these programs.

Because the sudden disruption in economic activity affected families at all income levels, and many families were eligible to receive government relief benefits, we also investigate how other points in the distribution of income, beyond those near the poverty line, change during the pandemic. In particular, we look at changes in family income for the 10th, 25th, 50th, and 75th percentiles. For these analyses, we adjust the income measures for family size and composition using the Citro and Michael (1995) recommended equivalence scale and account for inflation using the Personal Consumption Expenditures Chain-type Price Index.

V. Changes in Poverty and the Income Distribution During the COVID-19 Pandemic

In Figure 1 we report the poverty rate as well as a 3-month moving average of this rate, for the period from January 2019 to June 2020. Then, in Table 1, we focus in on the estimates for each month between January and June of 2020, as well as the change in poverty between the pre- and post-onset of COVID-19 periods defined as January-February 2020 and April-June 2020, respectively.

The results in Figure 1 indicate that poverty was falling fairly steadily in the period leading up to the pandemic. Between November 2019 and February 2020, poverty fell by 0.9 percentage points. This decline then accelerates once the pandemic hits. Between the pre and post periods poverty fell by 1.5 percentage points (or about 14 percent), and this difference is statistically significant.⁹ The estimates for each month in Table 1 suggest that poverty fell in March, which could be interpreted as surprising given that the CARES Act was passed after the CPS interviews for this month. However, this decline was a continuation of a pronounced

⁹ We find similar results to those discussed in this section when we restrict the sample to only responders in their fifth interview month, but do not re-weight recent months to hold demographic characteristics fixed (Appendix Tables 5 and 7).

downward trend and unemployment had barely started to rise by that point. Furthermore, we caution against making too much of one-month changes given the imprecision of these estimates.

To determine whether the labor market shock and the government response affected certain demographic groups differently, we explore the heterogeneity of poverty rates across groups defined by age (0-17, 18-64, and 65+), race (White, Black, and Other), gender, and the educational attainment of the head of the household (H.S. degree or below and some college or above). Poverty fell for all three groups, with declines of 1.7 percentage points (11.1 percent) for individuals aged 0-17, 1.6 percentage points (16.1 percent) for individuals aged 18-64, and 1.3 percentage points (17.1 percent) for individuals aged 65 and older. The declines in poverty are statistically significant for the two older groups, but they are not significantly different from each other. We also see declines in poverty for all racial and gender groups and all groups defined by the educational attainment of the head. Those in the Other race group (neither white nor black) experienced the largest drop in poverty—a decline of 3.2 percentage points or 25.6 percent—followed by those with low-educated heads who experienced a decline of 2.4 percentage points or 11.3 percent.¹⁰ Both of these changes are statistically significant. However, we cannot reject the hypothesis that the declines in poverty are the same for all race or all education groups.

We also considered how changes in poverty differed depending on how hard states were hit early on from the pandemic or by differences in states' policy responses. For example, we looked at the patterns separately for states with high and low COVID-19 death rates, states that implemented stay-at-home orders early versus late, states that announced a state of emergency early versus late, and states with high versus low reciprocity rates for unemployment insurance. The reciprocity rate, the percentage of unemployed workers who receive UI benefits, is a standard measure of the generosity of state UI programs (see Wandner 2018, for example). The details for how we split these samples are in Appendix I. The results for these subgroups are reported in Appendix Table 6. We find evidence that poverty rates declined for all these groups. The decline is most noticeable for the states that issued initial stay-at-home orders later. Poverty rates for those in this group declined by 2.3 percentage points. And although this decline is statistically significant, we cannot reject the hypothesis that this decline is the same as that for

¹⁰ The Other race group includes American Indian, Alaska Native, Native Hawaiian or Other Pacific Islander (16 percent based on the May 2020 survey), Asian (58 percent), and two or more races reported (26 percent).

those in states that issued these orders earlier. In fact, none of the differences across these groups are statistically significant.

Looking beyond poverty estimates, we also consider how the COVID-19 pandemic affected different points in the distribution of income. In Figure 2 we report estimates of the 10th, 25th, 50th, and 75th percentiles of family income (equivalized to a family with 2 adults and 2 children) for the period from January 2019 to June 2020. Then, in Table 2, we report estimates of the 25th percentile for each month between January and June of 2020, as well as changes in the 25th percentile between the pre- and post-onset of COVID-19 periods. Results similar to those in Table 2 but for the 50th and 75th percentiles are reported in Appendix Tables 8 and 9.

The results in Figure 2 show that income for each of the percentiles we report remains flat for the period from January 2019 through February 2020. Then, incomes start to rise after that. The 25th percentile of family income increased from about \$46,000 in January and February to about \$49,000 in April, May, and June, a statistically significant increase of about \$3,000, or 6.4 percent (Table 2).¹¹ This increase seems reasonable given the government benefits low income families were potentially eligible for, including a \$3,400 Economic Impact Payment (for a married couple with two children) and UI benefits that included a \$600 per week top off.

We also see a rise in income at higher percentiles, although the extent of the rise is smaller as we move up the distribution. Median income (Appendix Table 8) rose by about \$2,500 (2.8 percent) during this period and this rise is statistically significant. At the 75th percentile (Figure 2 and Appendix Table 9), incomes rose more modestly, by about \$1,300 (0.9 percent), and this rise is not statistically significant. A rise in income at the 75th percentile would not be too surprising given that those with incomes at this level would potentially still be eligible for the expanded government benefits. The equivalized income values for the 75th percentile are about \$145,000 for a married couple with 2 children and about \$65,000 for an individual. These values are below the income thresholds for receiving the full amount of the Economic Impact Payment.

As with our results for poverty, we find consistent evidence that income rose between the pre- and post-onset of COVID periods for all of the subgroups that we consider (Table 2 and Appendix Table 10), and in nearly all cases the rise is statistically significant, although the estimates of these changes across groups are not significantly different from each other.

¹¹ The January number is about 1.75 times the federal poverty line for a family of four.

The Effect of Government Policy on Changes in Income

That we find poverty declined and income rose in the first few months after the start of the pandemic, despite the fact that earnings fell sharply, suggests that the government policy response to the pandemic had a substantial effect on income. We can estimate the direct impact of payments to individuals by calculating the differences in poverty and other income statistics relying on measures of family income that alternatively include and exclude the government benefits. Since we directly observed income including the benefits, we only need to calculate a second, counterfactual income measure that subtracts those benefits. Although we do not directly observe receipt of the Economic Impact Payments and the expanded UI benefits, we have sufficient information in the Monthly CPS to calculate the potential benefits that each family could receive—annual income, family size and structure, and unemployment status and duration.

In particular, for our sample from the April, May, and June CPS we impute benefits for the three main government programs that directly transferred cash income to individuals and families—the Economic Impact Payments, the Pandemic Unemployment Compensation (PUC) program and the Pandemic Unemployment Assistance (PUA) program—as well as for regular UI, as these payments also expanded significantly after the start of the pandemic. Our approach will also account for benefits from the Pandemic Emergency Unemployment Compensation (PEUC) program that extended by 13 weeks the duration of UI benefits, although this program affected a small number of claimants during our sample period.

Imputing Economic Impact Payments is straightforward as nearly all income eligible individuals and families received such payments. We calculate the appropriate benefit amount based on family income, size and composition. On aggregate our imputation method accurately captures total Economic Impact Payments paid out, but we cap our imputed benefits to match these aggregates. See Appendix II for a detailed description of our procedure.

Because the expanded UI programs reach well beyond the traditional unemployed, we need to allocate UI benefits to a broad set of individuals who are not currently working. In fact, if we only allocated benefits to those who were unemployed, total benefits would fall far short of the total dollars paid out. Thus, we impute regular UI benefits for a subset of individuals who report being unemployed (not working and looking for work) except those who were previously self-employed. For PUA, we impute benefits for a subset of individuals who were unemployed but were previously self-employed, as well as those who report being absent from work due to

health reasons, family responsibilities, childcare problems, and other reasons; and those who want a job but did not look for work over the past four weeks because: 1) they believed no work was available in their area of expertise, 2) they could not find a job, 3) of family responsibilities, 4) they could not arrange childcare, or 5) of other reasons. While a large fraction of these groups is likely to be eligible for some form of unemployment insurance, there are some individuals who are eligible for UI whom we will miss. For example, we do not observe complete employment histories, so we will miss those who received UI benefits in the twelve months prior to the interview but had already become re-employed by the time of the interview. To ensure that we allocate the appropriate amount of UI benefits paid, we cap the number of individuals (selected at random) to which we impute benefits so that the total dollars of benefits we impute matches administrative totals (U.S. Treasury 2020). Because the likelihood that individuals receive UI conditional on being monetarily eligible differs considerably across states, we allow the cap to vary across states based on state UI reciprocity rates as explained in Appendix II. See Appendix II for more details on our procedure.

Using these imputed benefits, we calculate changes in the share of individuals with family incomes below the poverty line and multiples of the poverty line using income with and without these benefits. In the first row of Table 3 we report our main poverty estimates from Table 1. These estimates are based on reported total annual family income, and therefore, in theory, include Economic Impact Payments and both the expanded and regular UI benefits. We then calculate poverty, subtracting from income these government benefits for our April, May, and June CPS samples. In the last column we report the change in poverty between January 2020 and June 2020 for each measure of poverty. When all of these government policies are excluded, we find that poverty rises by 2.7 percentage points between January and June, and this rise is statistically significant. In other words, not only do the government programs account for the entire decline in poverty that we observe, but in their absence, poverty would have risen sharply.

To determine the relative contribution of these programs in reducing poverty we exclude each of them separately. These calculations indicate that while both UI and the Economic Impact Payments played an important role in staving off a rise in poverty, the Economic Impact Payments played a somewhat larger role. When we exclude these payments, the poverty rate for June is 1.1 percentage points higher than January. If, instead, we exclude all UI programs, but keep the Economic Impact Payments, then the rise in poverty is 0.8 percentage points. If we

exclude only the expanded UI benefits (PUC and PUA), then poverty between January and June falls slightly by 0.1 percentage points, but the poverty rate in June in this counterfactual scenario is still much higher (1.3 percentage points) than the actual estimate for June.

In the remaining panels of Table 3 we consider the effects of these policies on higher points in the income distribution: 200 percent, 300 percent, and 500 percent of the poverty line. As we move up the income distribution, the effect of the policies decreases in percentage terms, which is expected given the targeted nature of these programs and that the fixed value of these payments is a smaller fraction of family income. The estimates in the top panel suggest that the effect of all programs was to reduce poverty by 30.6 percent (from 13.5 percent to 9.3 percent). These combined programs reduced the fraction of families with income below 200 percent of the poverty line by 13.6 percent. Both the Economic Impact Payments and UI contributed to reducing the fraction below 200 percent of the poverty line. Further up the income distribution, government programs increased income, but the effects were smaller. The effect of all programs was to reduce the fraction below 300 percent of the poverty line by 6.2 percent, and the fraction below 500 percent of the poverty line by 1.8 percent.

Our simulations also allow us to provide evidence on other important questions related to how the government response to the pandemic affected individuals and families. In particular, we can examine the extent to which eligible families received benefits and explore which demographic groups were more or less likely to actually receive benefits. Although we don't observe actual receipt of these benefits in our data, we have good information on the total amount of benefits that were given out each month, and we have reasonably good information on who is likely to be eligible from the CPS.

Given the broad eligibility for Economic Impact Payments that was based mainly on income, imputing such benefits is straightforward. Although there was some concern about barriers for certain groups of individuals in receiving these benefits, our simulations suggest that by the third week of June, most eligible individuals and families received such payments. If we allocate payments to all eligible families in the June CPS, the weighted sum of these benefits is \$276 billion, which is only about 3 percent more than the actual amount of payments through June 3, 2020 (\$267 billion) as reported by the IRS.¹²

¹² <https://home.treasury.gov/news/press-releases/sm1025>

For UI, our caps on total benefits imputed are binding in each month, indicating that we have more individuals who are designated as eligible for regular UI or PUA than we impute to receive these benefits, with the gap much more pronounced in the early months. For example, in May, 38 percent of those eligible for PUA were allocated an imputed benefit, while 65 percent of those eligible for regular UI received benefits (Table 4). By June, these receipt rates were much higher— 81 percent for PUA and 86 percent for regular UI—indicating that the majority of those who lost employment received benefits by this point. We should emphasize that many of those that we consider eligible likely are not truly eligible due to having quit, being new entrants or not satisfying the PUA requirements. Thus, the true receipt rate may be higher than these allocation percentages. To double check our assessment of the reach of UI in the pandemic, we compared published counts of UI claims to estimates of those out of work. This analysis corroborates the main takeaways from our simulations (see Appendix II and Appendix Table 15). There was a slow initial response of state UI programs in the pandemic, but by June the vast majority of those out of work were reached by the expanded UI system.

We further break down these receipt rates, separating states into groups defined by terciles of the state-level reciprocity rate from the first quarter of 2020 (Table 5). The reciprocity rate is commonly taken as an indicator of how welcoming the state is to UI claims—those with low rates are thought of as discouraging claims and being more aggressive in disqualifying applicants. These results show that receipt rates differed considerably across these groups. For example, in May, for those in the bottom tercile of reciprocity rates, 23 percent of those eligible for PUA were allocated imputed benefits, while 50 percent of those in the top tercile were allocated benefits. For regular UI, these rates were 46 percent for the bottom tercile and 81 percent for the top tercile. In June, the receipt rates rose for PUA to 54 percent for the bottom tercile and 95 percent for the top tercile, while the corresponding receipt rates for regular UI were 62 percent and 99 percent.

Clearly there are large differences in receipt rates between states that are traditionally unwelcoming to UI claims with a low reciprocity rate and those with a high reciprocity rate. These differences in state reciprocity rates have implications for how well the UI system reaches certain demographic groups. For example, because the low reciprocity rate states have a higher share of the population that is black (17 percent in the lowest tercile compared to 12 percent in

the highest tercile), black Americans have been treated less well by the UI system than white Americans.

VI. Comparisons of Family Income Data from the Monthly CPS to Other Sources

Because the Monthly CPS family income data have been rarely used to measure income or poverty, we benchmark them and examine their accuracy by comparing them to alternative sources of data on income. We consider how these different sources of income align both in levels and in trends. We are also interested in assessing whether monthly updates to an annual measure of income or poverty, which we can do with the Monthly CPS data, anticipate changes that are later revealed by survey data that are only available annually, such as the CPS ASEC. We are further interested in whether within-year variation in family income from the Monthly CPS aligns with data from other sources. These comparisons will provide information that will allow researchers to identify the strengths and weaknesses of these vital, but rarely used, public-use data and aid their use and interpretation.

The most direct comparison for the Monthly CPS is the Annual Social and Economic Supplement (ASEC) to the CPS, as this survey is administered as a supplement to a subset of the Monthly CPS samples from February, March, and April. The CPS ASEC is the source of official income statistics in the U.S. The questions in both surveys are designed to capture a similar concept of income: pre-tax money income. One important distinction between these measures is that the Monthly CPS measure relies on a single, global question about income over the past 12 months from all sources and all individuals in the householder's family, while CPS ASEC income is derived from information on more than 25 different income sources in the household for the previous calendar year for all individuals ages 15 and above. Thus, comparisons of income in the Monthly CPS to income in the CPS ASEC can shed light on the extent to which global questions about income can capture income from many different sources.

To assess the comparability of patterns across these different sources, in Figure 3 we report income poverty using both the Monthly CPS and the CPS ASEC for the period from 2005 through 2020. For the CPS ASEC estimates, we restrict the sample to individuals in householder families only, because this is the sample for which we observe income in the Monthly CPS. For comparison, we also report the official U.S. poverty rate, which is derived from the CPS ASEC data. The only difference between these two measures from the CPS ASEC is that the official measure also includes individuals who are outside the householder's family. Because our sample

from the Monthly CPS is much smaller than that from the CPS ASEC, and is therefore noisier, we also report a 3-month moving average of the Monthly CPS poverty rate. For all measures, the x-axis indicates the most recent month of the income reference period. Thus, we plot the estimates from the CPS ASEC in December of each year because the reference period is the calendar year, but for the Monthly CPS we plot the estimates in the interview month.

The results in Figure 3 indicate that individuals in householder families have lower poverty than other individuals—the official poverty rate is about 1 percentage point higher than the measure from the CPS ASEC that excludes individuals outside the householder’s family. The poverty estimates from the Monthly CPS are higher than the comparable measures from the CPS ASEC, typically by 1 to 2 percentage points. This difference in levels suggests that the more detailed income questions that are asked in the CPS ASEC capture more income than the single, global questions about family income. For changes over time, however, the patterns are quite similar across these two series. For example, between December 2007 and December 2010, annual CPS ASEC poverty rose by 19 percent, while annual Monthly CPS poverty (3-month moving average) rose by 25 percent. Between December 2014 and December 2018, CPS ASEC poverty fell by 18 percent while CPS Monthly poverty fell by 21 percent. In fact, the annual poverty rates estimated from these two sources—comparing CPS ASEC estimates of poverty to those from the December CPS—are highly correlated. Between 2005 and 2018, the correlation between these two measures of poverty is 0.91.

Figure 3 also shows the advantage of using the Monthly CPS to provide timely estimates. The first evidence of the negative impact of the Great Recession on official poverty did not come until September of 2009, when official poverty estimates (and the CPS ASEC data) were released for calendar year 2008. With the Monthly CPS, however, we see annual poverty rising as soon as June of 2008—an estimate that could have been calculated in July of 2008, a full 14 months before the official estimates became available. The timely Monthly CPS data means that we can already see how poverty was changing in the months leading up to and shortly after the start of the COVID-19 pandemic, and we will continue to get an early look at how economic well-being changes as macroeconomic circumstances evolve over the coming months.

In Figure 4, we report the trends for various percentiles of real family income for both the Monthly CPS and the CPS ASEC for the period from 2005 through 2020. Again, we see that

CPS ASEC income exceeds Monthly CPS income, but for each of the percentiles we report, the changes over time are quite similar for the two data sources.

Another way to consider the accuracy of the Monthly CPS income measure compared to the CPS ASEC income measure is to examine the dispersion of each measure. It is common to model a variable that is measured with error as the sum of a true component plus an error component that is uncorrelated with the true component. In such a case, greater dispersion means more error. The standard deviation, variance and coefficient of variation of the income measures from the two sources can be found in Appendix Table 12. This table indicates that the standard deviation of the Monthly CPS measure is about nine percent lower than the ASEC measure, while the coefficient of variation is about 2 percent higher, suggesting that there is little difference in the amount of measurement error in the two income sources.

We also compare income in the Monthly CPS to income in the Consumer Expenditure Survey (CE). The CE is a nationally representative survey that is the most comprehensive survey of consumption data in the United States. It is a rotating panel survey that interviews about 7,500 families each quarter. While the focus of the survey is spending data, it also collects information on family income. The nice feature of this comparison is that the CE interviews families throughout the year with the reference period for the income questions being the previous 12 months, which aligns with the reference period for the Monthly CPS income question. For the period from the first quarter of 2014 through the end of 2018, we report in Figure 5 estimates of annual income poverty on a quarterly basis using the CE data alongside the estimates from the Monthly CPS, aggregated up to the quarter. As shown in Figure 5, the long-term trends in poverty from the Monthly CPS line up very closely with those from the CE. Between the first quarter of 2014 and the last quarter of 2018, poverty fell by 18 percent using data from the Monthly CPS and by 13 percent using data from the CE. The annual poverty rates estimated from these two sources are highly correlated. During this period, the correlation between these two measures of poverty is 0.84. These patterns suggest that changes in family income that are captured in the Monthly CPS are consistent with other, commonly used, nationally representative data sources.

VII. Relation to Other Information on Income and Well-Being during the Pandemic

In recent months, a flood of near real-time data has shed light on aspects of the changes in economic well-being of the population during the very early stages of the pandemic. At least

two patterns are notable about this research. First, the other sources of evidence, from surveys as well as administrative sources, are largely consistent with, or can be reconciled with, the evidence in this paper. Second, while these other sources provide important information about how the economic circumstances of individuals and families have changed during the pandemic, the evidence we present from the Monthly CPS has important advantages.

Consistent with our results, the Bureau of Economic Analysis (BEA) Personal Income and Outlays data (currently available through June 2020 and shown in Appendix Figure 5) indicate that real disposable personal income fell by 2 percent in March but rebounded to rise by 13 percent in April, calculated as the change from the previous month in both cases. Although it fell in May, personal income remains well above its level in March. The BEA also reported that real personal consumption expenditures fell by 13 percent in April, followed by modest increases in May and June. Cox et al. (2020) and Chetty et al. (2020) also find a decline in April in spending as recorded in bank accounts or aggregated credit records, respectively, though they both find an uptick in May. Cox et al. (2020) also find that savings increased early in the pandemic especially for those with low previous income. They conclude that the initial decline in consumption they observe is not due to a decline in income from labor market shocks. Other evidence suggests credit card debt, personal loans and even borrowing from pawn shops declined.¹³ The rise in income and savings can be reconciled with the initial decline in consumption because the opportunities for spending were limited by stay-at-home orders and travel bans, as well as personal choices to avoid contracting or spreading the virus, and uncertainty about future income streams and other factors. Thus, the income rise that we find is consistent with other evidence.

While aggregated national accounts or financial records yield useful information on aggregate changes in consumption, they do not provide disaggregated estimates of economic well-being by demographic group, which is important for understanding which groups are hurt the most by the pandemic. Distributional statistics such as income percentiles or poverty rates that are needed to assess who is affected by the pandemic also cannot be obtained from these data. Household financial records have the potential to provide disaggregated and distributional detail, but are not representative of the entire population, importantly missing a substantial segment of the population without bank accounts.

¹³ <https://www.wsj.com/articles/consumers-flush-with-stimulus-money-shun-credit-card-debt-11596373201>

There are important and timely new survey sources that provide invaluable information on other domains, but they have little or no information on income. These surveys include the Census Bureau’s Household Pulse Survey, the Federal Reserve Bank’s SHED and the Data Foundation’s COVID Impact survey (see Appendix Table 13 for details on these surveys). These surveys do not collect data on current income. The most recent wave of the SHED does ask about changes in income from the previous month. However, the interviews from this wave occurred in early April, prior to the distribution of most of the government benefits that we consider. The COVID Impact survey (Hamilton Project 2020) finds an increase in food insecurity when compared to a different earlier survey while the Census Bureau’s Household Pulse survey (U.S. Census Bureau 2020) finds high rates of inability to pay rent, for example. These sources, as well as evidence on food bank usage, suggest increased hardship after the pandemic. We should emphasize that the profound disruptions from the pandemic such as the closures of schools, stores, churches and other facilities, the uncertainty about future income streams, concerns about the health of family and friends, and other disruptions could lead to increases in hardship. An uptick in deprivation could be real, though there are reasons to be less certain of the magnitude of any change over time given the different source of the pre and post-pandemic information. In terms of policy, the important fact gained from this paper is that the increase in deprivation is not due to the overall income loss, but rather due to other disruptions of the pandemic, including possibly the unevenness of the income flows. Furthermore, given the evidence that small changes in wording or question order can have large impacts on survey results, having data from a survey that has been fielded in the same form for decades allows us to be more certain about any implications from our evidence than we could when using a new survey without historical benchmarks.

VIII. Discussion and Conclusions

Despite a dramatic slowdown in the labor market, our results indicate that poverty fell, and percentiles of income rose in the early months of the pandemic, using the only available source of representative and timely income data for the U.S. population. We further show that in absence of the stimulus payments and expanded unemployment insurance, poverty would have risen sharply. Although expanded government programs helped stave off a rise in poverty, many of these benefits were one-time or are temporary, so future estimates of income will depend on how the availability of these benefits changes going forward.

While we show that annual income increased at all percentiles, this improvement in the overall distribution of income is still consistent with a share of families experiencing substantial income drops. Given the observed data, a substantial short run fall for a small number of families would have to be combined with small increases for a much larger number.

These changes are based on an annual measure of income. The annual reference period will average out potentially large swings in income from month-to-month because much of the government relief was one-time or temporary. Ideally, we would also examine high quality nationally representative income data for shorter time periods, but these data do not exist. Short run decreases in income for those without savings or another buffer can lead to substantial increases in hardship.

Our simulations also provide evidence on the extent to which eligible families received government benefits. Comparisons to aggregate payments indicate that most eligible families received Economic Impact Payments by June. For UI, many of those who were eligible did not receive benefits in the early months of the pandemic. By June, however, a large majority of those eligible had received benefits. These receipt rates, however, differed noticeably across states, which has important implications for which demographic groups were more or less likely to actually receive benefits. For example, because the low reciprocity rate states have a higher share of the population that is black, black Americans that were eligible for UI were less likely to receive. Examining further the differences in the coverage of UI across demographic groups is an interesting topic for future research.

A number of potential biases in our results are worth noting. We suspect there is some tendency, it is unclear how strong, to emphasize recent income patterns in reporting on the past year. Such a bias would mean that our estimates more closely approximate changes in income over a shorter horizon than the nominal one-year reference period. We also suspect that the shift in income from earnings, a well-reported source of income, to unemployment insurance, a poorly reported source, means that we may have understated any improvements or overstated any declines in income. In recent years, about ninety percent of earnings has been reported in the CPS, as opposed to only about sixty percent of unemployment insurance (Meyer, Mok and Sullivan, 2015).

This study has important implications for both policy and future research. A better, more timely understanding of income and poverty will help federal, state, and local policymakers

allocate scarce resources to minimize the impact of COVID-19 (and future pandemics or other economic shocks) on vulnerable populations. In addition, by assessing the validity of these new measures using several sources of income, this study lays the foundation for future work on timely poverty measurement and allows others to understand the strengths and weaknesses of these vital, but rarely used, public-use data.

References

- Almond, Douglas. 2006. "Is the 1918 Influenza Pandemic Over? Long-term Effects of In Utero Influenza Exposure in the Post-1940 U.S. Population," *Journal of Political Economy*, 114 (4): 672-712.
- Almond, Douglas and Bhashkar Mazumder. 2005. "The 1918 Influenza Pandemic and Subsequent Health Outcomes: An Analysis of SIPP Data," *American Economic Review*, 95 (2): 258-262.
- Burkhauser, Richard V., Kevin Corinth, James Elwell and Jeff Larrimore. 2019. "Evaluating the Success of President Johnson's War on Poverty: Revisiting the Historical Record Using a Full-Income Poverty Measure," NBER Working Paper 26532.
- Bergmann, Barbara and John Coder. 2010. "Developing Monthly Poverty Estimates Based on the Monthly Current Population Survey Labor Force Public Use Files: A Report on Methods and Results," SCSPI Working Paper.
- Citro, Constance F. and Robert T. Michael. 1995. *Measuring Poverty: A New Approach*, eds. Washington, D.C.: National Academy Press.
- Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team. 2020, "Real-Time Economics: A New Platform to Track the Impacts of COVID-19 on People, Businesses, and Communities Using Private Sector Data," working paper, May.
- Cox, Natalie, Peter Ganong, Pascal Noel, Joseph Vavra, Arlene Wong, Diana Farrell and Fiona Greig. 2020. "Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data." Working Paper.
- Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. 2020. *Integrated Public Use Microdata Series, Current Population Survey: Version 7.0* [dataset]. Minneapolis, MN: IPUMS. <https://doi.org/10.18128/D030.V7.0>
- Green, Gordon and John Coder. 2020. "Household Income Trends December 2019," Sentier Research, LLC.
- Grusky, David B., Bruce Western, and Christopher Wimer. 2011. "The Great Recession," New York: Russell Sage Foundation.

- Hamilton Project. 2020. "Blog Post: The COVID-19 Crisis Has Already Left Too Many Children Hungry in America," https://www.hamiltonproject.org/blog/the_covid_19_crisis_has_already_left_too_many_children_hungry_in_america.
- Meyer, Bruce D., Wallace K. C. Mok, and James X. Sullivan. 2015. "Household Surveys in Crisis," *Journal of Economic Perspectives* 29 (4): 199–226.
- Meyer, Bruce D. and James X. Sullivan. 2012. "Winning the War: Poverty from the Great Society to the Great Recession," *Brookings Papers on Economic Activity*, Fall, p. 133-183.
- Ruggles, Patricia. 1990. *Drawing the Line—Alternative Poverty Measures and Their Implications for Public Policy*. Washington, DC: The Urban Institute Press.
- U.S. Census Bureau. 2020. "Household Pulse Survey Interagency Federal Statistical Rapid Response Survey to Measure Effects of the Coronavirus (COVID-19) Pandemic on the United States Household Population." https://www2.census.gov/programs-surveys/demo/technical-documentation/hhp/2020_HPS_Background.pdf
- Wandner, Stephen A. 2018. *Unemployment Insurance Reform: Fixing a Broken System*. W.E. Upjohn Institute.

Appendix I: Some Details on Methods

Imputing a Continuous Measure of Income from Bracketed Income in the Monthly CPS

Rather than reporting a specific dollar amount for family income, respondents in the Monthly CPS choose among 16 categorical income ranges:

- 1) Less than \$5,000
- 2) 5,000 to 7,499
- 3) 7,500 to 9,999
- 4) 10,000 to 12,499
- 5) 12,500 to 14,999
- 6) 15,000 to 19,999
- 7) 20,000 to 24,999
- 8) 25,000 to 29,999
- 9) 30,000 to 34,999
- 10) 35,000 to 39,999
- 11) 40,000 to 49,999
- 12) 50,000 to 59,999
- 13) 60,000 to 74,999
- 14) 75,000 to 99,999
- 15) 100,000 to 149,999
- 16) 150,000 or more

We convert categorical responses into a continuous measure by randomly selecting values of family income from families in the CPS ASEC from the same survey year¹⁴ who have incomes that fall in that same income range and who have some similar demographic characteristics. Specifically, we define the cells from which we draw income values based on the 16 income categories and 15 demographic categories defined by family size, number of children, and whether the age of the household head is 65 or older. For example, we would assign an income value for a 65-year-old single individual in the Monthly CPS who reports having income between \$20,000 and \$24,999 by randomly selecting income values from the CPS ASEC sample of single individuals aged 65 and over who report a total income value that is between \$20,000 and \$24,999. The key assumption for this imputation approach is that the distribution within a given category is the same in the Monthly CPS as in the CPS ASEC, which is reasonable given that both questions refer to a twelve-month period and rely on the same definition of income.

Comparisons of Income from the Monthly CPS to the CPS ASEC

As a preliminary assessment of the validity of the family income measure in the Monthly CPS, we compare income reports in the Monthly CPS to those in the CPS ASEC (see Section VI of the text for additional analyses of the validity of this income measure). Because a majority of CPS ASEC survey participants also participated in the Monthly CPS, we can compare responses to the income questions in the CPS ASEC to those from the Monthly CPS holding constant either the interview date (i.e. looking at respondents who complete both the Monthly CPS and the

¹⁴ In 2020 we use 2019 CPS ASEC as the 2020 data will not become available until September.

ASEC during the same interview) or the reference period, but not both.¹⁵ For these comparisons, we exclude individuals who have imputed income in the Monthly CPS or imputed earnings in the CPS ASEC.

In Appendix Table 3, we report the distribution of the CPS ASEC family income for each Monthly CPS family income bracket holding the reference period constant—i.e for a sample of December or January Monthly CPS respondents who also responded to the CPS ASEC. While there is considerable dispersion in the distribution of CPS ASEC income for a given Monthly CPS income bracket, a substantial share of individuals in a given Monthly CPS income bracket report that their CPS ASEC income falls into that exact same bracket. For example, 34% of individuals who report a family income below \$5,000 in the December or January CPS also report a few months later in the CPS ASEC that their income is below \$5,000, and two-thirds report income in the CPS-ASEC that is under \$15,000. Estimates of the Pearson correlations between CPS ASEC income and Monthly CPS income are well below one, but the rank correlations between the two income measures is over 0.7 (Appendix Table 4, Panel A). The correlations are slightly larger when we hold survey month constant but allow the reference period to differ (Appendix Table 4, Panel B). It is important to note that part of the reason these are below 1 is due to the fact that in the Monthly CPS our income measure is a random draw of an income value from within a bracketed range. We can examine the role of bracketing by looking at the correlation between actual income and a random draw of income from within the respective income bracket for individuals in the CPS-ASEC. For the 2019 CPS-ASEC, this Pearson correlation is 0.85 and the rank correlation is 0.985 (Appendix Table 4, Panel C).

Adjusting Survey Weights

To address concerns about possible changes in sample representativeness we re-weight the samples from April through June so that observable characteristics for these months match those in January and February. Specifically, we first pool the January and February 2020 surveys, and divide our sample into 27 demographic cells defined by three variables: age (18-39, 40-64, 65 or above), education (high school dropout, high school degree or some college, College degree or above), and family type (individual 65 or older, non-elderly married person with/without children, non-elderly unmarried person with/without children). We define these cells broadly enough to ensure that there are no empty cells in any of the survey months. Finally, after imposing the sample restrictions described in the text, we adjust the weights so that the weighted averages of these demographic characteristics are unchanged over time and are equal to the demographic composition of the pooled sample from January and February.

Grouping States for Subgroup Analyses

In our analyses of changes in poverty for subgroups, we considered how the patterns differed depending on how hard states were hit early on from the pandemic or by differences in

¹⁵ CPS ASEC respondents are interviewed in February, March, and April and are asked about income for the previous calendar year. The Monthly CPS interviews individuals and families throughout the year and asks about family income for the previous 12 months. Thus, to compare responses across surveys holding the reference period roughly constant, we focus on the CPS ASEC respondents who participated in the December or January Monthly CPS surveys, because the reference period for the family income question for these Monthly CPS respondents aligns closely with the reference period for their responses to the ASEC (the previous calendar year).

states' policy responses. For example, we looked at the patterns separately for states with high and low COVID-19 death rates, states that implemented stay-at-home orders early versus late, states that announced a state of emergency early versus late, and states with high versus low reciprocity rates for unemployment insurance. Specifically, we divide states into two groups based on each state's COVID-19 death rate as of May 18: "high COVID-19 death rate" states have 10 COVID-19 deaths per 100,000 or more, while "low COVID-19 death rate" states have less than 10 COVID-19 deaths per 100,000. Similarly, we divide states into early and late stay-at-home states based on whether a majority of the population in a state lives in a county that had the stay-at-home order before March 24. We also divide states into early and late state of emergency states based on whether a state declared state of emergency before March 10th. Finally, we split states into two groups defined by the reciprocity rates for regular unemployment insurance, or the insured unemployed as a fraction of the total unemployed, for the first quarter of 2020. The high reciprocity states are those with a rate greater than or equal to 35 percent. Each of these cutoffs is chosen to roughly evenly split the sample based on population in order to maximize sub-sample size and the likelihood that we can discern a difference between the groups.

Appendix II: Simulated Government Benefit Receipt and Comparison to Payment Records

In this appendix we describe how we estimate the distributional effects of federal policies to counter the pandemic and examine who the programs reached and who they did not. To determine the role of government programs, we impute the value of program benefits for the three main new government programs that directly transferred cash income to individuals and families—the Economic Impact Payments, the Pandemic Unemployment Compensation (PUC) program, and the Pandemic Unemployment Assistance (PUA) program—as well as for regular UI, as these payments also expanded significantly after the start of the pandemic.

1. Imputing Economic Impact Payments

Imputing the Economic Impact Payment is straightforward as nearly all income eligible individuals and families received such payments by the end of our sample period, and eligibility was primarily determined by family income, size and composition, all of which we observe in the Monthly CPS. However, to calculate the Economic Impact Payment, in some cases we have to make assumptions about 1) who is in the tax filing unit and 2) how total family income is divided across families with multiple tax filing units.

1.1 Specifying the tax filing unit

To assign individuals in the Monthly CPS to tax filing units we make four assumptions. First, each family unit within a household is a separate tax unit. Because the monthly income question is only asked of the householder's family, we must focus on the 95 percent of the population that this question covers. Fortunately, 97 percent of these individuals are in households that only have one family and no subfamilies. An example of the remaining cases is when a household has a primary family and a subfamily that we would assume file tax returns separately. For a household with multiple subfamilies, each subfamily is a separate tax unit. Second, a married couple files taxes jointly. Third, a person age 23 or below who is not the head of family or the

spouse of family head (i.e. child or other relative of family head) belongs to the family head's tax unit as a dependent. Fourth, a person age 24 or above who is not the head of the family or the spouse of the family head is a separate tax unit.

1.2. Specifying the income of tax filing units

In multiple family households, we first allocate family income in a household assuming that each family's contribution to household income is proportional to the number of adults in the family. Again, this step only applies to households containing three percent of the population. For example, suppose that a household consists of two families where the first family has two adults and the second family has three adults. We assign family income of $2 \times (\text{total household income} / 5)$ to the first family and family income of $3 \times (\text{total household income} / 5)$ to the second family. Similarly, we calculate tax filing unit income as family income multiplied by the percent of adults in a family who belong to the tax filing unit. Overall, 11 percent of people are in households where income is allocated in this way; most of these cases are single family households with other adult family members who are separate tax units.

1.3 Household level Economic Impact Payment

Having the imputed tax filing units and their income, we calculate the amount of Economic Impact Payment for each tax filing unit by applying the Economic Impact Payment eligibility/benefit rules. Specifically, we assign \$1,200 to a single tax unit who has income less than \$75,000. We apply the benefit reduction rate of 5 percent for each dollar in excess of \$75,000. We assign \$2,400 to a married couple tax unit with income less than \$150,000 and apply the benefit reduction of 5 percent for each dollar in excess of \$150,000. For each dependent, we assign an additional \$500 to a tax unit. Finally, we calculate the household-level Economic Impact Payment as the sum of Economic Impact Payments in all tax filing units of a household. When we allocate imputed Economic Impact Payments in this way, the weighted sum slightly exceeds the actual dollars distributed as reported by the IRS¹⁶ in some months.¹⁷ To match the actual amount of benefits distributed, we cap the number of families that receive the Economic Impact Payment. Specifically, we exclude Economic Impact Payments from a random sample of families so that the total dollars of benefits that we impute matches the cumulative total from the IRS up to the end of the interview week for each wave of the Monthly CPS.¹⁸

2. Imputing Unemployment Insurance Program Benefits

¹⁶ See <https://www.irs.gov/newsroom/treasury-irs-deliver-89-point-5-million-economic-impact-payments-in-first-three-weeks-release-state-by-state-economic-impact-payment-figures>
<https://www.irs.gov/newsroom/treasury-irs-release-latest-state-by-state-economic-impact-payment-figures-for-may-22-2020>
<https://home.treasury.gov/news/press-releases/sm1025>

¹⁷ Because our analysis sample is a subsample of the entire CPS sample, we made adjustment to the survey weights so that the sum of the weights in our sample represents the total U.S. population. In particular, we apply an adjustment factor of 5.7 to the survey weight where the adjustment factor is calculated as the sum of the weights in the entire CPS sample divided by the sum of the weights in our analysis sample. This weighting accounts for four sources of sample reduction, the use of two months in sample, the lower response rate in these two months, the restriction to the householder's family, and nonresponse to the income question.

¹⁸ Specifically, we cap the total Economic Impact Payment dollars allocated for the April CPS sample at \$160 billion, for the May sample at \$259 billion, and for the June sample at \$276 billion. See Figure 3 for the source for the two former numbers. The latter number assumes that by June all those eligible have received an Economic Impact Payment.

We calculate Pandemic Unemployment Assistance (PUA) and regular UI benefits separately because these programs differ in terms of who is eligible and the generosity of benefits. Our approach will also account for benefits from the Pandemic Emergency Unemployment Compensation (PEUC) program that extended by 13 weeks the duration of UI benefits, although this program affected a small number of claimants during our sample period. We impute these benefits in three steps. First, we designate who is eligible to receive regular UI or PUA. Second, we impute earnings for potential recipients prior to receipt of benefits. Third, given these values of earnings we calculate the UI benefit amount individuals receive based on program rules, capping the number of recipients in order to match administrative aggregates.

2.a. Designating benefit recipients

We designate all individuals in the Monthly CPS as either regular UI eligible, PUA eligible, or neither. Our regular UI eligible group includes all those who report being unemployed (not working and looking for work) except those who were previously self-employed. Our PUA eligible group includes the unemployed who were previously self-employed, as well as those with a job who report being absent from work due to health reasons, family responsibilities, childcare problems, and other reasons; and those who want a job but did not look for work over the past four weeks because: 1) they believe no work is available in their area of expertise, 2) they could not find a job, 3) of family responsibilities, 4) they cannot arrange childcare, or 5) of other reasons. All other individuals are designated as neither regular UI nor PUA eligible. We take a very broad view of eligibility and include some unemployed who are ineligible because they were fired for cause, quit, or are new entrants, for example. See Appendix Table 14 for the size of these groups by month. Among those employed or not in the labor force, the categories above include some ineligible individuals such as those not at work but still receiving pay (historically about a quarter of this group). As a consequence, our estimated receipt rates probably understate the share of true eligibles who are recipients.

2.b. Imputing pre-separation earnings

Because we do not observe earnings histories in the Monthly CPS, we need to impute the pre-separation earnings for each potential recipient in order to estimate the appropriate weekly benefit amount for which the individual is eligible. For a pooled sample from the April, May, and June CPS surveys, we estimate an OLS regression of usual weekly earnings on observable characteristics including age, gender, education, race/ethnicity, industry, occupation, the state of residence, and survey month indicators for a sample of individuals age 15 and over who are currently employed as wage and salary workers and are in their 4th or 8th month interview, which is when data on usual weekly earnings are collected. We then use the parameter estimates from this regression to predict earnings for those eligible for PUA and regular UI. Because we are making linear predictions, the distribution of our predicted earnings will be under-dispersed compared to the true earnings distribution, which may lead to an overstatement of the weekly benefit amount for individuals with low earnings after accounting for the demographic and job characteristics listed above.

These predicted earnings values, which are based on data for those who are currently employed, are likely to overstate the pre-separation earnings of those who are not employed due to differences in unobservable characteristics. To account for this, we scale down these predicted earnings. In particular, for a sample of individuals who are currently employed, report positive

earnings, and are in their 4th month interview in July, August, or September of 2019, we regress earnings on the same characteristics listed above as well as indicators for whether the individual is designated as regular UI eligible and PUA eligible in the following interview (i.e. in their 5th month interview in April, May, or June of 2020). Estimates from these regressions indicate that among wage and salary workers, those who subsequently are not working and are designated as regular UI eligible (PUA eligible) have earnings that are 12.5 percent (16.4 percent) lower than those who are subsequently designated as neither regular UI nor PUA eligible. We use these estimates to scale down imputed earnings for individuals in each of these groups.

2.c. Calculating the weekly benefit amount

The two key inputs for determining an eligible individual’s UI weekly benefit amount are their earnings history and state of residence. While state-specific benefit amounts can vary based on both the level and changes in individual earnings over up to 4 prior quarters, we do not observe detailed information on earnings histories for our sample. We assume that individuals’ pre-separation earnings are constant for up to 4 quarters prior to applying for benefits. For example, we specify pre-separation annual earnings as 52 times predicted usual weekly earnings. This assumption might lead us to overstate weekly benefits if actual pre-separation earnings are lower.

Given our imputed values of pre-separation earnings, we calculate the weekly benefit amount using each state’s rules on the replacement rate, the maximum benefit amount, and the minimum benefit amount (U.S. Department of Labor, 2020a). In addition, for our PUA-eligible potential recipients, we calculate the weekly benefit amount using the PUA-specific minimum benefit amount for each state, which according to Department of Labor directives should be set as at least 50 percent of the state’s average weekly benefit for regular UI (U.S. Department of Labor, 2020b).

For each individual i in state s that we designate as eligible for regular UI, we calculate a potential weekly benefit amount (WBA) as:

$$WBA_{is} = \max[\text{minimum benefits}_s, (\min((\text{Imputed quarterly earnings}_{is}) * (\text{quarterly replacement rate}_s)), \text{maximum benefits}_s)] + 600.$$

The additional \$600 accounts for Pandemic Unemployment Compensation (PUC) benefits.¹⁹ For individuals that we designate as PUA eligible, we calculate the WBA as:

$$WBA_PUA_{is} = \max[WBA_{is}, \text{PUA minimum benefits}_s] + 600.$$

Using this approach, results in an average WBA for regular UI recipients that is only slightly higher than the national average as reported in the Department of Labor’s Monthly Benefit and Claims data (<https://oui.doleta.gov/unemploy/claimssum.asp>). We report the imputed average weekly benefit amount by month along with the national averages in Appendix Table 11. Despite not including dependents’ allowances, our simulated WBA is higher than the national average, but the differences are small: 1 percent higher in April, 5 percent in May, and 8 percent in June.

¹⁹ As we explain below, when we calculate total benefits, we account for the fact that the \$600 per week PUC benefits was provided retrospectively back to March 29, 2020.

2.d. Calculating total potential UI benefits for each individual

For those we designate as eligible for regular UI, we observe the duration of the unemployment spell in the Monthly CPS data. Thus, we calculate total potential regular UI benefits as WBA_{is} times the number of weeks continuously unemployed²⁰ and set the maximum amount of total benefits for each survey month as WBA_{is} times the number of weeks between the interview week and March 29, 2020. For those we designate as PUA eligible, we only observe the duration of unemployment if they were previously self-employed. Thus, we calculate total potential PUA benefits as WBA_PUA_{is} times the number of weeks continuously unemployed for the self-employed, but for the other PUA eligibles, we calculate the total benefit amount as WBA_PUA_{is} times the average duration of unemployment for the unemployed each month (8 weeks in April, 11 weeks in May, and 13 weeks in June). For each survey month, we set the maximum amount of total potential benefits for those eligible for PUA as WBA_PUA_{is} times the number of weeks between the interview week and the last week of January 2020, because PUA claimants were eligible to receive retrospective benefits back to that point. When calculating the total benefit for those eligible for PUA, however, we only include the \$600 per week PUC benefit for weeks since March 29, 2020, which is the beginning of the first payable week for PUC.

2.e. Matching Administrative Aggregates for UI benefits

While UI benefit receipt expanded dramatically shortly after the start of the pandemic, not all of those whose jobs were disrupted by the pandemic actually received UI benefits. To ensure that we do not overstate the total dollars transferred, we cap the number of individuals to which we impute receipt of benefits so that the total dollars of benefits we impute matches administrative totals. First, because our approach for designating those who are PUA and regular UI eligible in the data would end up overstating the number of PUA recipients relative to regular UI recipients, we randomly select a subset of PUA eligibles so that the fraction of potential recipients in these respective groups matches the distribution of these types among actual recipients in the Department of Labor claims data—in these administrative data, those eligible for PUA account for 10.6 percent of continued claims in April, 32.0 percent in May, and 39.4 percent in June.²¹

Next, for each survey month, we split the sample into 3 groups defined by terciles of the state reciprocity rate for the first quarter of 2020.²² The reciprocity rate is commonly taken as an indicator of how welcoming the state is to UI claims—those with low rates are thought of as discouraging claims and being more aggressive in disqualifying applicants. Within each of these groups we randomly order those eligible for regular UI and PUA, and allocate the imputed benefit amount received to these individuals following that order until the cumulative amount of benefits received reaches the total amount of UI benefits provided according to administrative data from the Daily Treasury Statement (Treasury, 2020).²³

²⁰ Only one state, Oregon, has a waiting week, for which we account. See U.S. Department of Labor (2020a) and <https://www.workplacefairness.org/unemployment-insurance-coronavirus>, which we supplemented with internet searches.

²¹ The claims data from the Department of Labor can include multiple claims for the same claimant in a given week, so these data will not exactly reflect the number of individuals receiving each benefit type.

²² The groups are equally weighted based on state population. The reciprocity rate data are from the Department of Labor's Quarterly UI Data Summary (https://oui.doleta.gov/unemploy/data_summary/DataSum.asp).

²³ The Daily Treasury Statement provides the dollar value for all withdrawals for unemployment-related benefits from the Unemployment Trust Fund as well as the accounts for Federal UI programs that include PUC, PUA, and PEUC benefits. Although states vary somewhat in their procedures for the disbursement of funds, the timing of

In Table 4 we report the total dollars of UI benefits that we impute by program and month. Across all states, once we cap benefits at the administrative total we impute \$32.6 billion through April for regular UI and PUA combined, \$122 billion through May, and \$220 billion through June. Because we cap the number of individuals receiving benefits, many of those we designate as regular UI and PUA eligible do not receive benefits. In Table 4, we also report the fraction of those designated as eligible for these programs who actually receive imputed benefits. These receipt rates indicate that, once we restrict total benefits to match actual dollars paid, many of those who were potentially eligible did not receive benefits, especially in the early months. These receipt rates are subject to a couple of potentially offsetting biases—we miss short unemployment spells that end before a given month, overstating the receipt rate, but we include many ineligibles among those who we classify as eligible, understating the receipt rate.

Our simulations provide one way of examining how well the expanded UI programs in the pandemic have reached those out of work. They indicate that the vast majority of those out of work received UI by June, but in the early months of the pandemic the share was well below one. These calculations employ the accurately measured constraint that total simulated benefits paid should not exceed what we actually know was paid out. A second approach, is to examine the number of individuals without work in a given week compared to the number of weekly UI benefits paid in that week. A version of this approach was employed by Bitler et al. (2020). Unfortunately, information on weeks of benefits paid is available with long and variable lags and reporting by the states has been especially uneven during the pandemic. As a result, one must use weeks claimed rather than weeks paid. In Appendix Table 15 we report estimates from this alternative approach. We see a similar pattern to what we see with our simulation. Initially, in April the ratio is well below one, but by May it is approximately one, and in June greatly exceeds one. Using our two broad definitions of the count of those out of work, the ratio indicates that the number of weeks claimed exceeds the number of those out of work by between 42 and 76 percent. Because not all weeks claimed are in fact paid, this calculation overstates the share of percent or those actually receiving UI, but historically the share of claims not paid has been about 15 percent. Clearly UI has reached well beyond those traditionally considered unemployed and UI eligible and has reached a large share of this group.

withdrawals from the Unemployment Trust Fund should align closely with when UI benefits are actually received (Department of Labor, 1996). To estimate total spending by tercile of state reciprocity rate and month, we take monthly regular UI benefits paid by state, scale these total payments to account for PUC and PUA payments for each state, then rescale the total benefits to match the national aggregate from the Daily Treasury Statement. These state level spending amounts are then aggregated to the reciprocity rate tercile level.

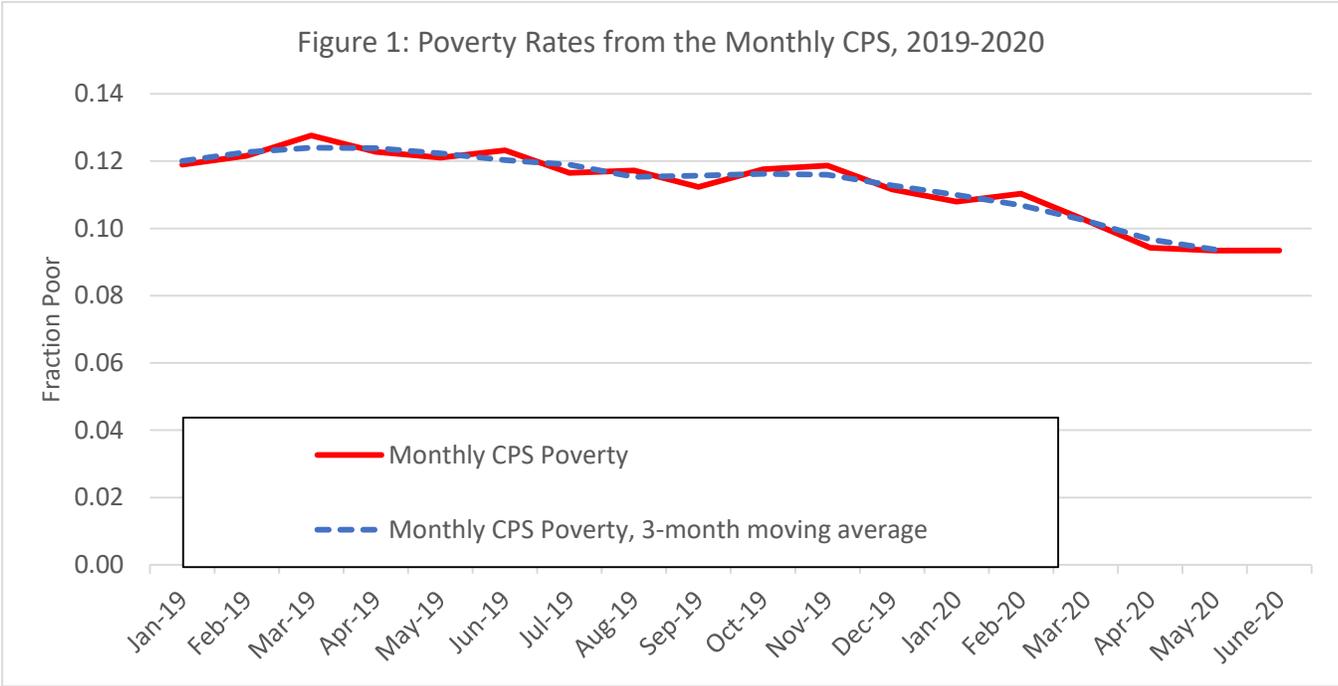
References for Appendices

U.S. Department of Labor (2020a). “Significant Provisions of State Unemployment Insurance Laws, Effective January 2020,” <https://oui.doleta.gov/unemploy/content/sigpros/2020-2029/January2020.pdf>. Retrieved July 24, 2020.

U.S. Department of Labor (2020b). “U.S. DOL Answers Questions From States About PUA Unemployment Program,” www.lawandtheworkplace.com/2020/04/u-s-dol-answers-questions-from-states-about-pua-unemployment-program/. Retrieved July 24, 2020.

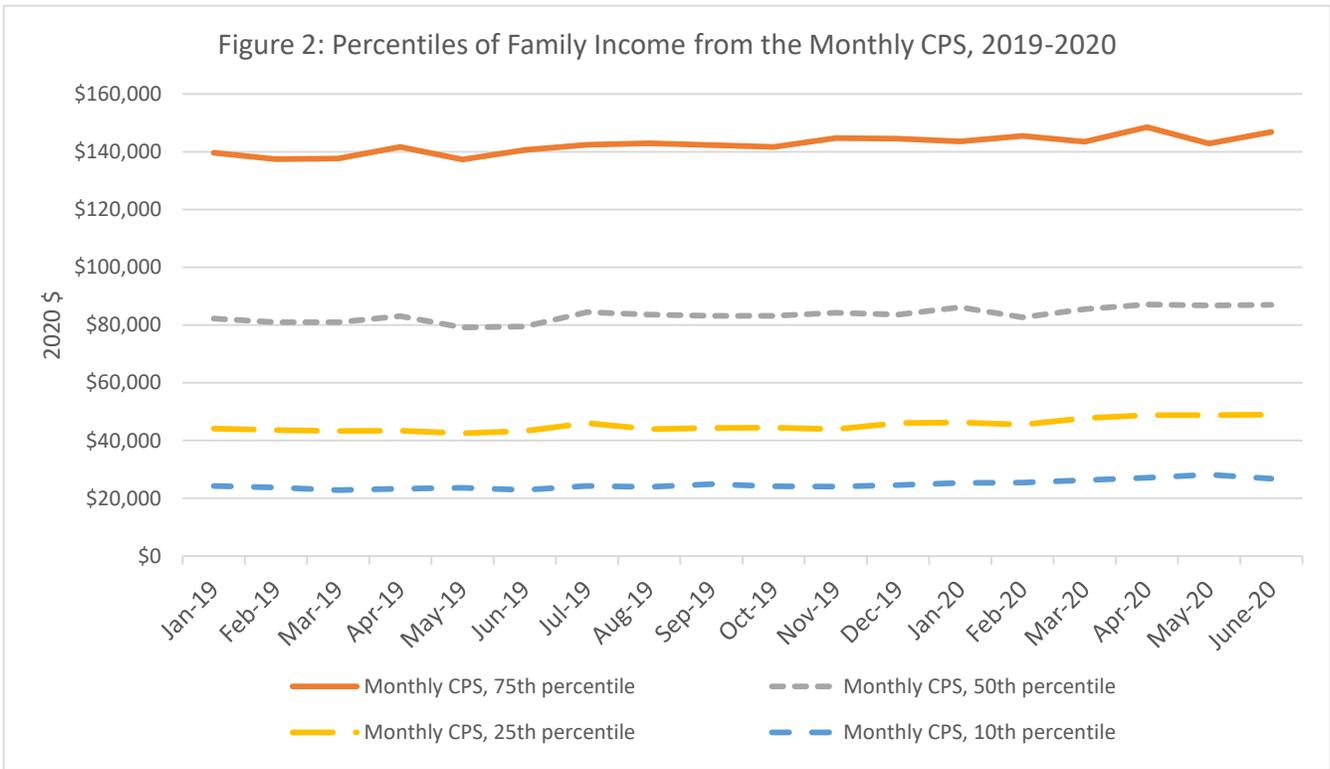
U.S. Department of Labor (1996). “Unemployment Insurance Program Letter No. 22-96,” https://oui.doleta.gov/dmstree/uipl/uipl96/uipl_2296.htm. Retrieved July 24, 2020.

U.S. Treasury (2020), Daily Treasury Statement:
<https://datalab.usaspending.gov/dts/?start=20050609&end=20200617&frequency=mtd&category=Unemployment%20Insurance%20Benefits>. Retrieved July 23, 2020.



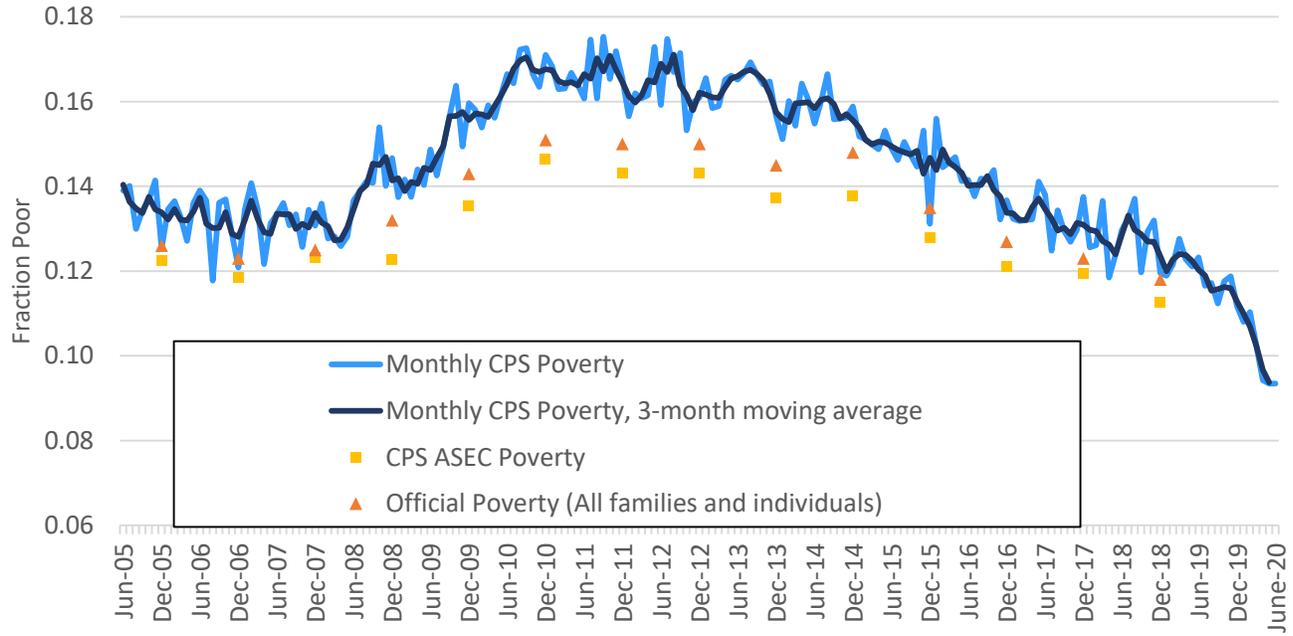
Notes: The sample includes individuals who are included in the householders' families and those in their 1st or 5th month in the survey. Individuals who have imputed income in the Monthly CPS are excluded. The three-month moving average is calculated as the unweighted average of poverty rates in month t-1, t, and t+1. The statistics are weighted using fixed demographic weights since March 2020.

Figure 2: Percentiles of Family Income from the Monthly CPS, 2019-2020



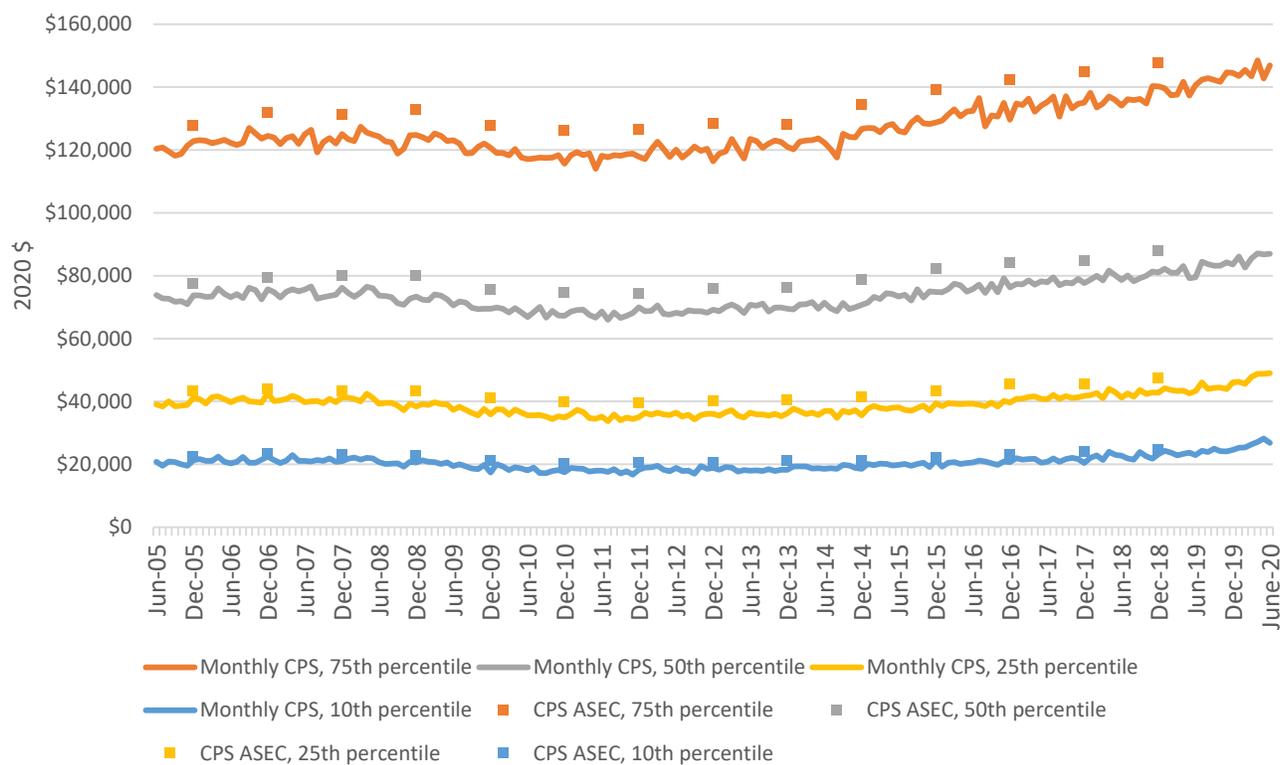
Notes: The sample includes individuals who are included in the householders' families and those in their 1st or 5th month in the survey. Individuals who have imputed income in the Monthly CPS are excluded. The family income is equivalence-scale adjusted and equivalized to a family with 2 adults and 2 children. The income is adjusted over time using the Personal Consumption Expenditures Chain-type Price Index and is expressed in May 2020 dollars. The statistics are weighted using fixed demographic weights since March 2020.

Figure 3: Poverty Rates from the Monthly CPS and the Annual Social and Economic Survey of the CPS, 2005-2020



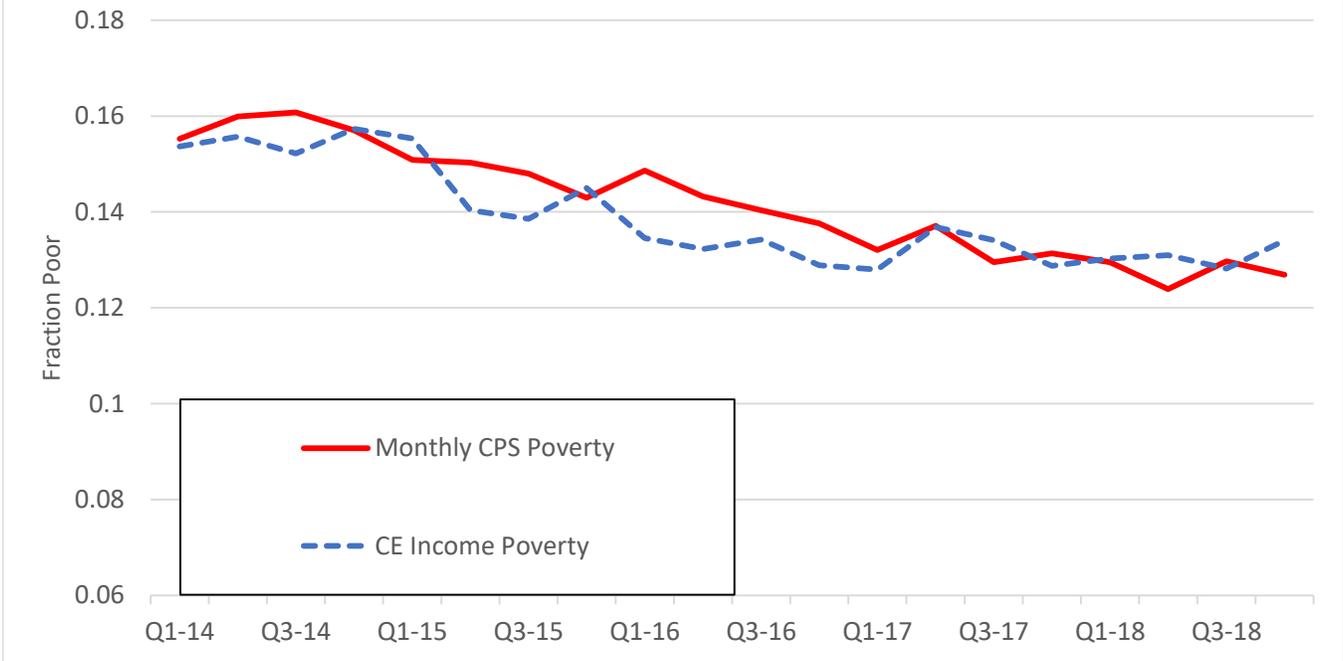
Notes: The Monthly CPS and CPS ASEC samples include individuals who are included in the householders' families. The Monthly CPS sample is restricted to individuals with non-imputed income who are in their 1st or 5th month in the survey. The three-month moving average is calculated as the unweighted average of poverty rates in month t-1, t, and t+1. The statistics are weighted using fixed demographic weights since March 2020.

Figure 4: Percentiles of Family Income from the Monthly CPS and the Annual Social and Economic Survey of the CPS, 2005-2020



Notes: The Monthly CPS and CPS ASEC samples include individuals who are included in the householders' families. The Monthly CPS sample is restricted to individuals with non-imputed income who are in their 1st or 5th month in the survey. The family income is equivalence-scale adjusted and equivalized to a family with 2 adults and 2 children. The income is adjusted over time using the PCE Chain-type Price Index and is expressed in May 2020 dollars. The statistics are weighted using fixed demographic weights since March 2020.

Figure 5: Poverty Rates from the Monthly CPS and the The Consumer Expenditure Surveys, 2014-2018



Notes: Poverty rates are calculated for each survey quarter. The Monthly CPS sample includes individuals who are included in the householders' families and those in their 1st or 5th month in the survey. Individuals who have imputed income in the Monthly CPS are excluded. The CE income is calculated as the before-tax income less food stamps.

Table 1. Poverty Rates, Monthly CPS, 2020

Month	January	February	March	April	May	June	(Apr+May+Jun)- (Jan+Feb)
Full Sample	10.8%	11.0%	10.2%	9.4%	9.3%	9.3%	-1.5%
	(0.5)	(0.5)	(0.5)	(0.6)	(0.6)	(0.6)	(0.5)
Number of individuals	20,020	20,822	16,733	14,383	14,236	14,391	
Age							
Age 0-17	15.3%	15.3%	16.3%	14.4%	13.2%	13.1%	-1.7%
	(1.0)	(1.0)	(1.2)	(1.4)	(1.4)	(1.3)	(1.0)
Age 18-64	9.8%	9.9%	8.5%	8.0%	8.4%	8.4%	-1.6%
	(0.4)	(0.4)	(0.5)	(0.6)	(0.6)	(0.5)	(0.4)
Age 65+	7.7%	8.7%	7.6%	7.1%	6.6%	7.1%	-1.3%
	(0.6)	(0.6)	(0.6)	(0.6)	(0.6)	(0.7)	(0.6)
Race							
White	9.4%	9.2%	8.7%	7.8%	8.3%	7.9%	-1.3%
	(0.5)	(0.5)	(0.6)	(0.6)	(0.6)	(0.6)	(0.5)
Black	18.2%	20.8%	21.3%	18.7%	16.1%	18.2%	-1.9%
	(1.6)	(1.7)	(2.1)	(2.5)	(2.2)	(2.2)	(1.8)
Other	12.4%	12.1%	9.0%	9.5%	9.1%	8.6%	-3.2%
	(1.5)	(1.6)	(1.4)	(1.9)	(2.2)	(1.7)	(1.6)
Gender							
Male	10.3%	10.1%	8.7%	8.7%	8.5%	8.8%	-1.5%
	(0.5)	(0.5)	(0.5)	(0.7)	(0.6)	(0.7)	(0.5)
Female	11.3%	11.9%	11.7%	10.1%	10.1%	9.9%	-1.6%
	(0.5)	(0.5)	(0.6)	(0.7)	(0.7)	(0.7)	(0.6)
Head Education							
H.S. Degree or below	20.9%	20.3%	20.5%	19.5%	18.1%	17.0%	-2.4%
	(1.1)	(1.1)	(1.3)	(1.6)	(1.4)	(1.3)	(1.1)
Some College or above	6.0%	6.4%	5.3%	4.7%	5.3%	5.9%	-0.9%
	(0.4)	(0.4)	(0.4)	(0.5)	(0.6)	(0.6)	(0.4)

Note: The sample includes individuals who are included in the householders' families and who are in their 1st or 5th month in the survey. Individuals with imputed income are excluded from the sample. The statistics are weighted using fixed demographic weights since March 2020. Standard errors are clustered at the household level.

Table 2. 25th Percentile, Monthly CPS, 2020

Month	January	February	March	April	May	June	(Apr+May+Jun)- (Jan+Feb)
Full Sample	\$46,246 (785)	\$45,546 (916)	\$47,763 (912)	\$48,796 (1,081)	\$48,821 (1,340)	\$48,977 (1,206)	\$2,965 (897)
Number of individuals	20,020	20,822	16,733	14,383	14,236	14,391	
Age							
Age 0-17	\$38,577 (1,213)	\$37,417 (1,142)	\$35,598 (1,699)	\$39,311 (2,222)	\$40,996 (1,222)	\$41,163 (2,124)	\$2,669 (1,145)
Age 18-64	\$49,928 (1,305)	\$49,691 (1,026)	\$53,605 (1,284)	\$54,844 (1,307)	\$54,274 (1,357)	\$54,165 (1,582)	\$4,689 (1,047)
Age 65+	\$47,398 (1,017)	\$46,477 (958)	\$49,074 (1,015)	\$48,437 (1,448)	\$50,499 (1,430)	\$48,391 (1,326)	\$2,045 (1,154)
Race							
White	\$50,216 (1,133)	\$49,050 (985)	\$51,934 (1,172)	\$52,927 (1,277)	\$52,754 (1,328)	\$53,162 (1,478)	\$3,184 (958)
Black	\$31,051 (1,578)	\$30,280 (1,454)	\$29,289 (2,105)	\$35,359 (3,826)	\$34,836 (1,909)	\$32,864 (2,148)	\$3,460 (1,833)
Other	\$44,044 (3,309)	\$43,970 (2,110)	\$48,199 (2,056)	\$52,727 (3,653)	\$45,574 (3,733)	\$49,314 (4,309)	\$5,344 (3,035)
Gender							
Male	\$47,469 (806)	\$47,976 (937)	\$50,707 (1,125)	\$51,886 (1,525)	\$50,969 (1,357)	\$50,451 (1,445)	\$3,258 (995)
Female	\$45,378 (899)	\$43,588 (901)	\$45,391 (1,099)	\$47,221 (920)	\$46,705 (1,110)	\$47,367 (1,149)	\$2,600 (827)
Head Education							
H.S. Degree or below	\$29,323 (746)	\$30,082 (906)	\$29,713 (867)	\$30,186 (1,469)	\$33,144 (1,376)	\$31,896 (1,276)	\$2,160 (1,006)
Some College or above	\$62,750 (1,512)	\$61,390 (1,321)	\$64,412 (1,618)	\$66,108 (1,892)	\$64,360 (1,661)	\$64,033 (1,341)	\$2,850 (1,318)

Note: The sample includes individuals who are included in the householders' families and who are in their 1st or 5th month in the survey. Individuals with imputed income are excluded from the sample. The family income is equivalence-scale adjusted and equalized to a family with 2 adults and 2 children. The income is adjusted over time using the PCE Chain-type Price Index and is expressed in May 2020 dollars. The statistics are weighted using fixed demographic weights since March 2020. The standard errors are bootstrapped and clustered at the household level.

Table 3. Poverty Rates with and without COVID19 related Government Payments, Monthly CPS, 2020

Month	January	February	March	April	May	June	June-January
Panel A. Income<100% Poverty							
Actual Poverty	10.8%	11.0%	10.2%	9.4%	9.3%	9.3%	-1.5%
	(0.5)	(0.5)	(0.5)	(0.6)	(0.6)	(0.6)	(0.8)
w/o EIP and All UI Programs				11.1%	11.6%	13.5%	2.7%
				(0.7)	(0.7)	(0.7)	(0.8)
w/o EIP and PUC/PUA				11.0%	11.4%	13.3%	2.5%
				(0.7)	(0.7)	(0.7)	(0.8)
w/o EIP				10.8%	10.7%	11.9%	1.1%
				(0.7)	(0.7)	(0.7)	(0.8)
w/o All UI Programs				9.6%	9.9%	11.6%	0.8%
				(0.6)	(0.6)	(0.7)	(0.8)
w/o PUC/PUA				9.5%	9.8%	10.9%	0.1%
				(0.6)	(0.6)	(0.6)	(0.8)
Panel B. Income<200% Poverty							
Actual Poverty	29.1%	29.3%	27.8%	27.4%	27.4%	26.9%	-2.1%
	(0.7)	(0.7)	(0.8)	(0.9)	(0.9)	(0.9)	(1.1)
w/o EIP and All UI Programs				28.9%	30.4%	31.2%	2.1%
				(0.9)	(0.9)	(0.9)	(1.1)
w/o EIP and PUC/PUA				28.9%	30.2%	30.6%	1.5%
				(0.9)	(0.9)	(0.9)	(1.1)
w/o EIP				28.9%	29.3%	29.4%	0.3%
				(0.9)	(0.9)	(0.9)	(1.1)
w/o All UI Programs				27.6%	28.4%	28.5%	-0.6%
				(0.9)	(0.9)	(0.9)	(1.1)
w/o PUC/PUA				27.5%	28.1%	28.3%	-0.8%
				(0.9)	(0.9)	(0.9)	(1.1)
Panel C. Income<300% Poverty							
Actual Poverty	45.0%	46.7%	45.0%	43.8%	44.5%	45.1%	0.1%
	(0.7)	(0.7)	(0.8)	(0.9)	(0.9)	(0.9)	(1.2)
w/o EIP and All UI Programs				45.0%	47.6%	48.0%	3.0%
				(0.9)	(0.9)	(0.9)	(1.2)
w/o EIP and PUC/PUA				44.9%	47.3%	47.7%	2.7%
				(0.9)	(0.9)	(0.9)	(1.2)
w/o EIP				44.9%	46.6%	46.6%	1.6%
				(0.9)	(0.9)	(0.9)	(1.2)
w/o All UI Programs				44.0%	45.4%	46.4%	1.4%
				(0.9)	(0.9)	(0.9)	(1.2)
w/o PUC/PUA				43.9%	45.1%	46.1%	1.1%
				(0.9)	(0.9)	(0.9)	(1.2)
Panel D. Income<500% Poverty							
Actual Poverty	69.9%	69.5%	69.3%	68.3%	69.6%	69.7%	-0.2%
	(0.6)	(0.6)	(0.7)	(0.8)	(0.8)	(0.8)	(1.0)
w/o EIP and All UI Programs				69.2%	71.5%	71.0%	1.1%
				(0.8)	(0.8)	(0.8)	(1.0)
w/o EIP and PUC/PUA				69.1%	71.5%	70.9%	1.0%
				(0.8)	(0.8)	(0.8)	(1.0)
w/o EIP				69.0%	71.0%	70.6%	0.7%
				(0.8)	(0.8)	(0.8)	(1.0)
w/o All UI Programs				68.5%	70.1%	70.2%	0.3%
				(0.8)	(0.8)	(0.8)	(1.0)
w/o PUC/PUA				68.4%	70.0%	70.1%	0.2%
				(0.8)	(0.8)	(0.8)	(1.0)

Notes: The sample includes individuals who are included in the householders' families and who are in their 1st or 5th month in the survey. Individuals with imputed income are excluded from the sample. The statistics are weighted using fixed demographic weights since March 2020. Standard errors are clustered at the household level. See Appendix II for the details on the imputation of EIP and UI payments.

Table 4. Imputed Cumulative Stimulus and UI Payments (billion \$) and Receipt rates

Month	Program	Simulated Eligible Amount	Payments from Administrative Data	Simulated Receipt Amount	Dollar Receipt Rate	Person Receipt Rate
April	EIP	274	160	162	59%	59%
	PUA	47.5		2.7	6%	5%
	Regular UI	25.9		10.0	39%	37%
	PUC	90.2		19.9	22%	23%
	Total UI	164	32.4	32.6	20%	23%
May	EIP	279	259	260	93%	93%
	PUA	53.6		20.9	39%	38%
	Regular UI	40.6		27.5	68%	65%
	PUC	142		73.8	52%	52%
	Total UI	237	122	122	52%	52%
June	EIP	278	267 ^a	278	100%	100%
	PUA	48.4		39.8	82%	81%
	Regular UI	49.3		42.8	87%	86%
	PUC	164		138	84%	84%
	Total UI	261	224	220	84%	84%

Notes: EIP = Economic Impact Payments. The Simulated Eligible Amount is the weighted total cumulative dollars of benefits that we would impute if all eligibles received benefits. Payments from Administrative Data reflect the total cumulative dollars paid out based on data from the IRS or U.S. Treasury (2020). Simulated Receipt Amount reflects the total imputed benefits capped to match the administrative data totals (except for the EIP in June). The person receipt rate is calculated as the fraction of those designated as eligible that were allocated imputed benefits for that program.

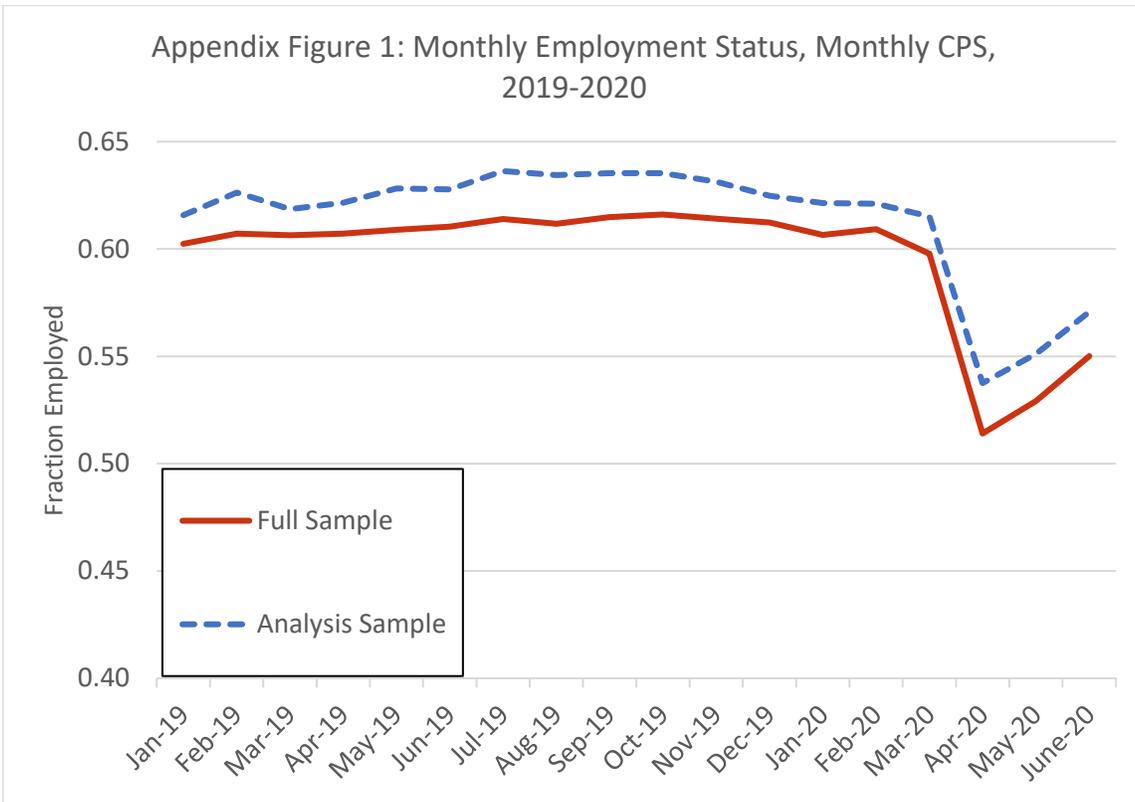
^aThis amount is through June 3, 2020.

Table 5. Imputed UI Receipt rates by Reciprocity Rate Tercile and Month

Month	UI Type	Reciprocity rate tercile	Receipt rate
April	PUA	1	6%
		2	5%
		3	6%
	Regular UI	1	33%
		2	38%
		3	40%
May	PUA	1	23%
		2	40%
		3	50%
	Regular UI	1	46%
		2	65%
		3	81%
June	PUA	1	54%
		2	91%
		3	95%
	Regular UI	1	62%
		2	95%
		3	99%

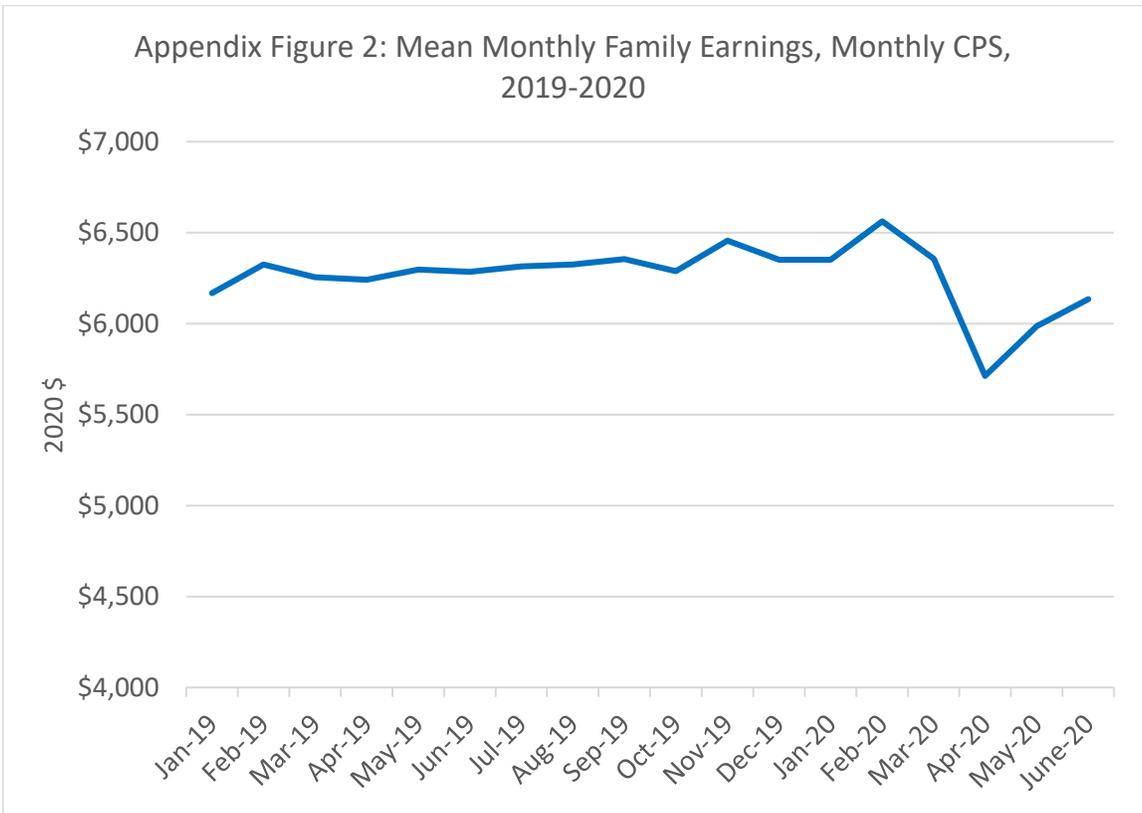
Notes: Terciles of state reciprocity rate are determined using regular UI reciprocity rates by state for the first quarter of 2020.

Appendix Figure 1: Monthly Employment Status, Monthly CPS, 2019-2020



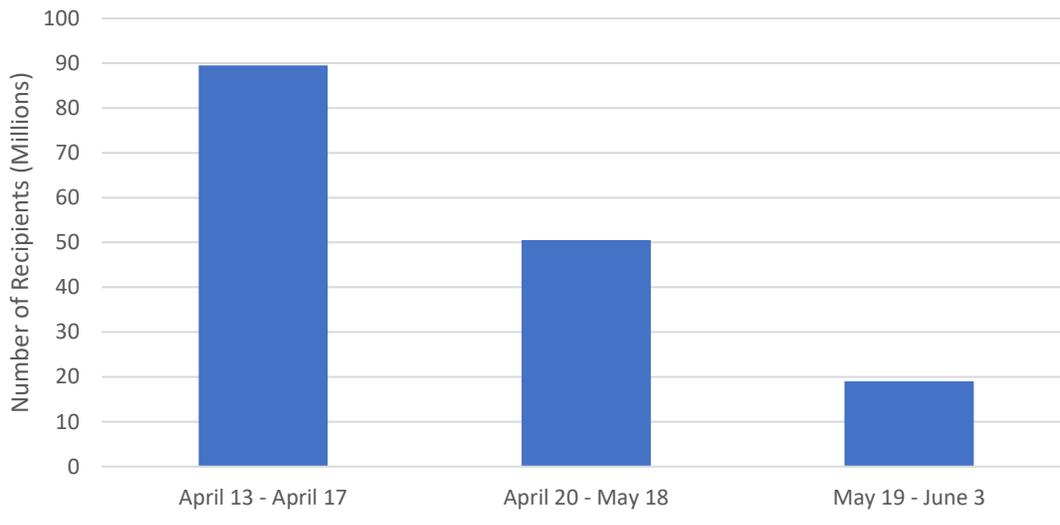
Notes: The full sample includes individuals 16 and older in any months in the survey, while the analysis sample is restricted to individuals 16 and older with non-imputed income who are included in the householders' families and are in their 1st or 5th month in the survey. The statistics for the analysis sample are weighted using fixed demographic weights since March 2020.

Appendix Figure 2: Mean Monthly Family Earnings, Monthly CPS, 2019-2020



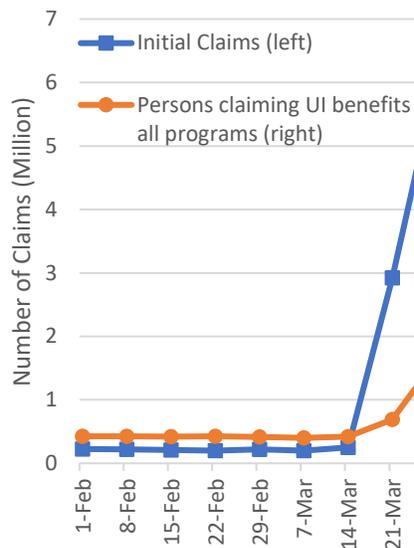
Notes: The sample includes individuals 16 and older in their 4th or 8th month in the survey who are included in the householders' families. The monthly family earnings is calculated as the total weekly earnings for the respondent's family multiplied by 4.3. The family earnings is equivalence-scale adjusted and equalized to a family with 2 adults and 2 children. The earnings is adjusted over time using the PCE Chain-type price index and is expressed in May 2020 dollars.

Appendix Figure 3: Number of Recipients of Economic Impact Payments



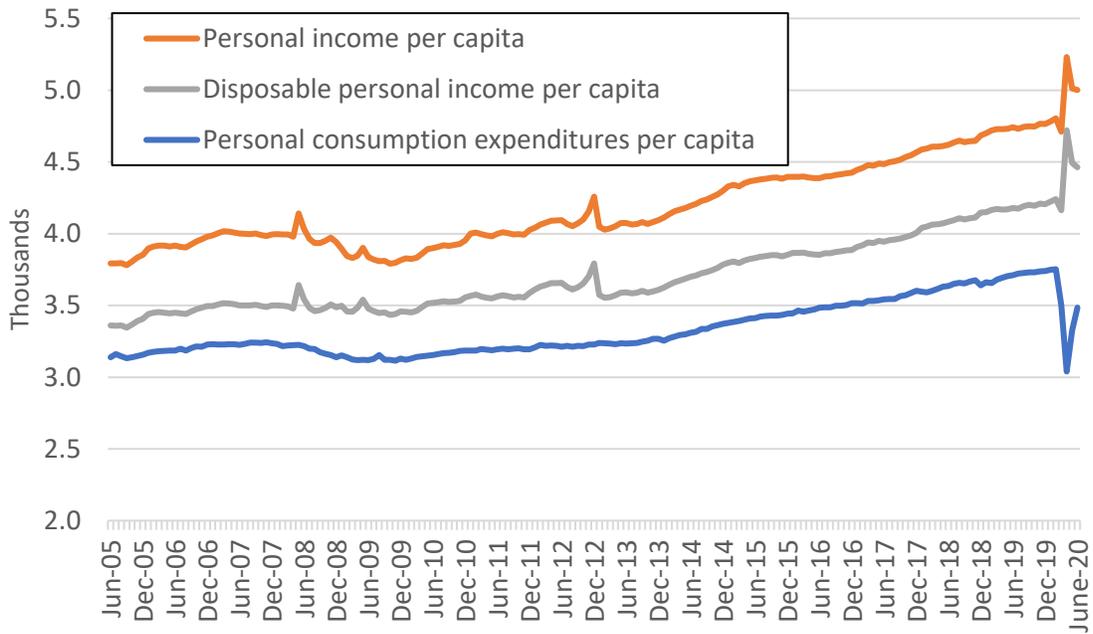
Notes: Recipients are measured at the individual level rather than family level. Data are from the IRS website (<https://www.irs.gov/newsroom/news-releases-for-current-month>).

Appendix Figure 4: Numbers of UI Weekly Claims



Notes: Initial claims are the non-seasonally adjusted claims that include regular state programs, the federal Pandemic Unemployment Assistance (PUA) program, and the programs for federal employees (UCFE), and newly discharged veterans (UCX). All programs include the regular state program, PUA, UCFE, UCX, Pandemic Emergency UC, Extended Benefits, State Additional Benefits, STC/Workshare. Data are from the USDOL ETA website.

Appendix Figure 5: Monthly NIPA Personal Income and Consumption, 2005-2020



Notes: Data are taken from the Bureau of Economic Analysis' National Income and Product Accounts (NIPA) Data Archives, Section 2- Personal Income and Outlays. Original data is annualized, therefore each data point is divided by 12 to obtain a monthly estimate. The income and expenditures are adjusted over time using the PCE Chain-type Price Index and is expressed in May 2020 dollars.

Appendix Table 1. Sample Size, Monthly CPS, 2020

Survey Month	January	February	March	April	May	June
Number of Individuals						
Full sample	116,837	117,477	104,520	101,278	97,437	93,237
1st or 5th month	28,578	28,818	22,756	20,678	20,760	21,057
1st or 5th month, householder's family	27,069	27,253	21,671	19,754	19,800	20,091
1st or 5th month, householder's family, non-missing income	20,020	20,822	16,733	14,383	14,236	14,391
Number of households						
Full sample	48,720	48,872	43,443	42,065	40,568	39,016
1st or 5th month	11,885	11,904	9,390	8,601	8,779	8,860
1st or 5th month, householder's family, non-missing income	8,712	8,999	7,166	6,149	6,165	6,245

Notes: This table reports the number of individuals and households from the Jan-June 2020 Monthly CPS surveys.

Appendix Table 2. Characteristics of the Monthly CPS samples by Interview Month, 2020

Survey month	Feb-20			Mar-20			Apr-20			May-20			Jun-20		
	1	5	2-4,6-8	1	5	2-4,6-8	1	5	2-4,6-8	1	5	2-4,6-8	1	5	2-4,6-8
Survey Nonresponse Rate	0.20	0.20	0.17	0.43	0.31	0.24	0.53	0.31	0.26	0.52	0.32	0.29	0.52	0.32	0.33
Missing Income Rate	0.20	0.28		0.20	0.26		0.26	0.28		0.26	0.29		0.27	0.30	
Male	0.48	0.49	0.49	0.48	0.49	0.49	0.48	0.50	0.49	0.49	0.49	0.49	0.49	0.49	0.49
White	0.77	0.77	0.77	0.79	0.77	0.77	0.76	0.76	0.77	0.76	0.77	0.77	0.78	0.76	0.76
Black	0.13	0.12	0.13	0.11	0.13	0.13	0.12	0.13	0.13	0.12	0.12	0.13	0.12	0.13	0.13
Age	38.3	38.6	38.3	38.5	37.9	38.3	38.9	36.9	38.3	38.1	37.5	38.2	39.1	37.5	38.0
Family Size	3.27	3.22	3.23	3.23	3.31	3.25	3.25	3.37	3.26	3.27	3.27	3.29	3.27	3.26	3.28
Number of Children	1.06	1.07	1.06	1.06	1.08	1.07	1.07	1.13	1.07	1.08	1.06	1.07	1.07	1.09	1.07
Single Parent	0.12	0.12	0.12	0.12	0.12	0.12	0.10	0.12	0.12	0.11	0.11	0.12	0.10	0.12	0.12
Married Parent	0.36	0.38	0.36	0.37	0.37	0.37	0.38	0.41	0.37	0.38	0.38	0.37	0.38	0.38	0.37
Single Individuals	0.15	0.15	0.15	0.13	0.14	0.15	0.14	0.13	0.15	0.14	0.14	0.14	0.13	0.14	0.14
Married w/o Children	0.18	0.18	0.18	0.19	0.20	0.18	0.19	0.18	0.18	0.20	0.20	0.19	0.19	0.18	0.19
Head 65 and Over	0.19	0.18	0.18	0.19	0.17	0.19	0.20	0.17	0.18	0.18	0.17	0.18	0.19	0.18	0.18
H.S. Dropout	0.32	0.31	0.31	0.32	0.32	0.32	0.30	0.33	0.32	0.30	0.31	0.32	0.28	0.31	0.31
H.S. Degree	0.21	0.21	0.20	0.20	0.20	0.20	0.20	0.19	0.20	0.19	0.20	0.20	0.19	0.19	0.20
Some College	0.21	0.21	0.21	0.21	0.22	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.21	0.20	0.21
College Degree or Above	0.26	0.27	0.27	0.27	0.27	0.27	0.29	0.27	0.27	0.30	0.27	0.27	0.31	0.29	0.28
Employed	0.49	0.49	0.49	0.48	0.48	0.48	0.42	0.42	0.41	0.44	0.44	0.43	0.45	0.45	0.45
Income Under \$10,000	0.04	0.04		0.04	0.03		0.02	0.03		0.01	0.03		0.03	0.02	
Income \$10,000 - 19,999	0.06	0.06		0.06	0.06		0.04	0.05		0.05	0.05		0.06	0.05	
Income \$20,000 - 29,999	0.08	0.07		0.06	0.08		0.07	0.07		0.06	0.07		0.06	0.07	
Income \$30,000 - 39,999	0.09	0.10		0.09	0.09		0.08	0.09		0.08	0.09		0.08	0.10	
Income \$40,000 - 49,999	0.07	0.07		0.07	0.07		0.07	0.07		0.06	0.07		0.07	0.07	
Income \$50,000 - 59,999	0.08	0.08		0.07	0.07		0.06	0.08		0.09	0.08		0.08	0.09	
Income \$60,000 - 74,999	0.10	0.12		0.11	0.10		0.12	0.10		0.11	0.11		0.10	0.10	
Income \$75,000 - 99,999	0.13	0.13		0.15	0.14		0.15	0.13		0.15	0.15		0.14	0.15	
Income \$100,000 - 149,999	0.15	0.15		0.16	0.18		0.18	0.17		0.18	0.17		0.17	0.17	
Income \$150,000 and Over	0.19	0.17		0.19	0.17		0.22	0.20		0.20	0.17		0.21	0.18	
Number of individuals	10,812	10,010	64,992	7,707	9,026	61,245	6,031	8,352	60,637	6,089	8,147	57,123	6,092	8,299	52,487

Notes: The sample includes individuals who are included in the householders' families. Individuals with imputed income are excluded in estimating statistics in rows 3-27. The survey non-response rate data come from <https://cps.ipums.org/cps/covid19.shtml>.

Appendix Table 3. CPS ASEC income by Monthly CPS income bracket, CPS ASEC 2005-2019

Monthly CPS income bracket	CPS ASEC Income																Share Pop.
	Under \$5,000	\$5,000 - 7,499	\$7,500 - 9,999	\$10,000 - 12,499	\$12,500 - 14,999	\$15,000 - 19,999	\$20,000 - 24,999	\$25,000 - 29,999	\$30,000 - 34,999	\$35,000 - 39,999	\$40,000 - 49,999	\$50,000 - 59,999	\$60,000 - 74,999	\$75,000 - 99,999	\$100,000 - 149,999	\$150,000 and over	Monthly CPS income bracket
Under \$5,000	0.34	0.10	0.09	0.08	0.05	0.08	0.06	0.04	0.03	0.02	0.03	0.02	0.02	0.02	0.01	0.01	0.03
\$5,000 - 7,499	0.17	0.13	0.16	0.10	0.06	0.11	0.07	0.04	0.03	0.03	0.03	0.02	0.02	0.02	0.01	0.01	0.02
\$7,500 - 9,999	0.12	0.06	0.22	0.15	0.08	0.11	0.07	0.04	0.03	0.02	0.03	0.02	0.02	0.02	0.02	0.01	0.03
\$10,000 - 12,499	0.09	0.04	0.08	0.18	0.13	0.15	0.10	0.06	0.04	0.03	0.03	0.02	0.02	0.02	0.01	0.01	0.04
\$12,500 - 14,999	0.08	0.03	0.05	0.08	0.14	0.21	0.11	0.07	0.05	0.04	0.04	0.03	0.02	0.02	0.02	0.01	0.03
\$15,000 - 19,999	0.06	0.02	0.04	0.05	0.06	0.25	0.17	0.09	0.06	0.04	0.05	0.03	0.03	0.02	0.02	0.01	0.05
\$20,000 - 24,999	0.05	0.02	0.02	0.03	0.03	0.10	0.22	0.16	0.10	0.06	0.08	0.04	0.04	0.03	0.02	0.01	0.06
\$25,000 - 29,999	0.04	0.01	0.02	0.02	0.02	0.07	0.11	0.19	0.14	0.09	0.11	0.06	0.05	0.03	0.02	0.01	0.06
\$30,000 - 34,999	0.03	0.01	0.01	0.02	0.02	0.05	0.06	0.09	0.18	0.14	0.16	0.09	0.07	0.04	0.03	0.01	0.06
\$35,000 - 39,999	0.03	0.01	0.01	0.01	0.01	0.04	0.05	0.06	0.09	0.16	0.21	0.12	0.09	0.06	0.04	0.02	0.06
\$40,000 - 49,999	0.02	0.01	0.01	0.01	0.01	0.03	0.04	0.04	0.05	0.07	0.27	0.17	0.13	0.09	0.05	0.02	0.09
\$50,000 - 59,999	0.02	0.00	0.01	0.01	0.01	0.02	0.02	0.03	0.03	0.04	0.11	0.24	0.23	0.15	0.07	0.03	0.08
\$60,000 - 74,999	0.01	0.00	0.00	0.00	0.00	0.01	0.02	0.02	0.02	0.02	0.06	0.09	0.29	0.27	0.12	0.04	0.10
\$75,000 - 99,999	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.04	0.04	0.10	0.38	0.29	0.08	0.11
\$100,000 - 149,999	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.11	0.51	0.25	0.10
\$150,000 and over	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.02	0.03	0.05	0.15	0.70	0.08
Share Pop. CPS ASEC Income	0.04	0.01	0.02	0.02	0.02	0.05	0.05	0.05	0.05	0.05	0.08	0.07	0.10	0.12	0.14	0.11	

Notes: Each cell reports the percent of individuals who report that their CPS ASEC income falls into a given CPS ASEC income category (column) for a given Monthly CPS income bracket (row). The CPS ASEC mod for a given Monthly CPS income bracket is highlighted in green. The sample includes individuals who report their family income in the December or January CPS and also responded to the CPS ASEC. Individuals with imputed income in the Monthly CPS or those with imputed earnings in the CPS ASEC are excluded from the sample.

Appendix Table 4. Correlation between the CPS ASEC and Monthly CPS income, CPS ASEC 2019

Correlation Type	Pearson	Spearman (Rank)
Panel A. Fixed reference month		
Coefficient	0.421	0.737
Number of individuals	66,106	
Panel B. Fixed survey month		
Coefficient	0.444	0.755
Number of individuals	33,071	
Panel C. Correlation between the actual and Imputed CPS ASEC income		
Coefficient	0.848	0.985
Number of individuals	66,106	

Notes: The correlations are between the natural logarithms of the income measures. An income value of one is assigned to individuals who report zero or negative family income. Individuals with imputed income in the Monthly CPS or those with imputed earnings in the CPS ASEC are excluded. The sample in Panel A and C includes individuals who report their family income in the December or January CPS and also responded to the CPS ASEC. The sample in Panel B includes individuals who report their family income in the March CPS and also responded to the CPS ASEC.

Appendix Table 5. Poverty Rates, 5th month only, original weight, Monthly CPS, 2020

Month	January	February	March	April	May	June	(Apr+May+Jun)- (Jan+Feb)
Full Sample	10.9%	10.9%	10.6%	10.1%	9.5%	8.8%	-1.4%
	(0.7)	(0.7)	(0.7)	(0.9)	(0.8)	(0.7)	(0.7)
Number of individuals	9,490	10,010	9,026	8,352	8,147	8,299	
Age							
Age 0-17	15.8%	14.2%	16.8%	14.7%	13.4%	12.1%	-1.6%
	(1.5)	(1.3)	(1.6)	(1.7)	(1.6)	(1.6)	(1.4)
Age 18-64	9.7%	10.0%	8.7%	8.8%	8.7%	7.7%	-1.4%
	(0.6)	(0.6)	(0.6)	(0.8)	(0.7)	(0.7)	(0.6)
Age 65+	8.5%	9.4%	7.8%	7.5%	6.5%	7.3%	-1.8%
	(0.9)	(0.9)	(0.9)	(0.9)	(0.8)	(0.9)	(0.8)
Race							
White	9.5%	8.9%	8.9%	8.3%	8.6%	8.4%	-0.8%
	(0.7)	(0.7)	(0.8)	(0.9)	(0.8)	(0.9)	(0.7)
Black	18.2%	22.7%	21.7%	20.6%	17.1%	12.3%	-3.8%
	(2.3)	(2.6)	(2.8)	(3.4)	(2.8)	(2.2)	(2.4)
Other	13.1%	11.7%	9.0%	10.0%	7.6%	7.4%	-4.1%
	(2.4)	(2.1)	(1.9)	(2.6)	(2.1)	(1.9)	(2.0)
Gender							
Male	10.3%	9.9%	9.0%	9.8%	8.6%	8.8%	-1.0%
	(0.8)	(0.7)	(0.8)	(0.9)	(0.8)	(0.9)	(0.7)
Female	11.5%	11.9%	12.0%	10.5%	10.4%	8.7%	-1.8%
	(0.8)	(0.8)	(0.9)	(0.9)	(0.9)	(0.7)	(0.7)
Head Education							
H.S. Degree or below	22.2%	19.8%	20.6%	21.8%	18.1%	16.5%	-2.1%
	(1.7)	(1.5)	(1.8)	(2.2)	(1.7)	(1.7)	(1.6)
Some College or above	5.8%	6.4%	5.9%	4.8%	5.8%	5.3%	-0.8%
	(0.6)	(0.7)	(0.7)	(0.6)	(0.8)	(0.7)	(0.6)

Notes: The sample includes individuals who are included in the householders' families and who are in their 5th month in the survey. Individuals with imputed income are excluded from the sample. Standard errors are clustered at the household level.

Appendix Table 6. Poverty Rates, state group, Monthly CPS, 2020

Month	January	February	March	April	May	June	(Apr+May+Jun)- (Jan+Feb)
COVID19 Death Rate							
High Death Rate (>=10 per 100k)	9.4%	10.9%	10.1%	9.1%	8.7%	8.7%	-1.4%
	(0.6)	(0.7)	(0.7)	(0.9)	(0.8)	(0.8)	(0.6)
Low Death Rate (<10 per 100k)	12.1%	11.2%	10.3%	9.8%	10.0%	10.0%	-1.7%
	(0.7)	(0.7)	(0.8)	(0.9)	(0.9)	(0.9)	(0.7)
Date of Stay at Home Order							
Early Stay at Home (3/23 or before)	10.2%	10.6%	10.3%	10.0%	9.3%	9.8%	-0.7%
	(0.7)	(0.7)	(0.8)	(1.0)	(0.9)	(0.9)	(0.7)
Late Stay at Home (after 3/23)	11.3%	11.4%	10.2%	8.9%	9.3%	8.9%	-2.3%
	(0.6)	(0.6)	(0.7)	(0.8)	(0.9)	(0.8)	(0.7)
Date of State of Emergency Order							
Early State of Emergency (3/9 or before)	10.3%	10.6%	9.7%	9.7%	8.9%	9.5%	-1.1%
	(0.7)	(0.7)	(0.8)	(1.0)	(0.9)	(1.0)	(0.7)
Late State of Emergency (after 3/9)	11.3%	11.4%	10.8%	9.1%	9.8%	9.2%	-2.0%
	(0.6)	(0.6)	(0.7)	(0.8)	(0.9)	(0.7)	(0.7)
Reciprocity Rate							
High Reciprocity Rate (>=35%)	9.5%	10.1%	8.5%	8.3%	8.7%	8.9%	-1.2%
	(0.6)	(0.7)	(0.7)	(0.8)	(0.9)	(0.9)	(0.7)
Low Reciprocity Rate (<35%)	12.0%	11.9%	11.9%	10.5%	10.0%	9.8%	-1.9%
	(0.7)	(0.7)	(0.8)	(0.9)	(0.9)	(0.8)	(0.7)

Note: The sample includes individuals who are included in the householders' families and who are in their 1st or 5th month in the survey. Individuals with imputed income are excluded from the sample. The statistics are weighted using fixed demographic weights since March 2020. Standard errors are clustered at the household level.

Appendix Table 7. 25th Percentile, 5th month only, original weight, Monthly CPS, 2020

Month	January	February	March	April	May	June	(Apr+May+Jun)- (Jan+Feb)
Full Sample	\$46,757 (1,200)	\$45,634 (1,205)	\$46,696 (1,398)	\$47,885 (1,485)	\$47,997 (1,591)	\$49,928 (1,831)	\$2,216 (1,253)
Number of individuals	9,490	10,010	9,026	8,352	8,147	8,299	
Age							
Age 0-17	\$38,783 (1,491)	\$38,631 (2,047)	\$35,607 (2,572)	\$37,936 (2,913)	\$41,301 (1,925)	\$43,409 (2,388)	\$2,378 (1,884)
Age 18-64	\$52,512 (1,803)	\$48,505 (1,330)	\$52,670 (1,874)	\$53,805 (1,745)	\$52,188 (1,862)	\$55,265 (1,905)	\$3,655 (1,606)
Age 65+	\$45,690 (1,303)	\$46,544 (1,775)	\$48,006 (1,604)	\$47,885 (2,003)	\$48,944 (1,733)	\$48,215 (1,610)	\$2,445 (1,602)
Race							
White	\$51,874 (1,486)	\$49,035 (1,387)	\$51,006 (1,710)	\$51,404 (1,762)	\$50,760 (1,744)	\$52,625 (2,002)	\$974 (1,564)
Black	\$31,336 (1,960)	\$29,814 (2,593)	\$29,308 (3,362)	\$33,006 (4,745)	\$34,646 (2,871)	\$40,607 (4,185)	\$4,801 (2,798)
Other	\$39,604 (4,530)	\$43,970 (2,983)	\$45,891 (4,106)	\$57,853 (4,703)	\$50,820 (5,639)	\$49,811 (5,540)	\$9,247 (4,220)
Gender							
Male	\$47,625 (1,699)	\$47,734 (1,271)	\$48,859 (1,651)	\$50,550 (2,079)	\$49,695 (1,812)	\$50,004 (2,210)	\$2,320 (1,480)
Female	\$45,690 (1,210)	\$43,970 (1,214)	\$44,546 (1,531)	\$46,363 (1,386)	\$46,581 (1,781)	\$49,549 (1,761)	\$2,326 (1,279)
Head Education							
H.S. Degree or below	\$28,167 (1,039)	\$30,634 (1,235)	\$28,932 (1,765)	\$28,287 (1,393)	\$33,429 (1,368)	\$32,337 (1,526)	\$2,012 (1,387)
Some College or above	\$64,291 (1,768)	\$60,840 (2,093)	\$63,366 (2,247)	\$66,698 (2,820)	\$63,585 (2,249)	\$63,931 (1,892)	\$2,187 (1,905)

Note: The sample includes individuals who are included in the householders' families and who are in their 5th month in the survey. Individuals with imputed income are excluded from the sample. The family income is equivalence-scale adjusted and equalized to a family with 2 adults and 2 children. The income is adjusted over time using the PCE Chain-type Price Index and is expressed in May 2020 dollars. Standard errors are bootstrapped and clustered at the household level.

Appendix Table 8. 50th Percentile, fixed demographic weight, Monthly CPS, 2020

Month	January	February	March	April	May	June	(Apr+May+Jun)- (Jan+Feb)
Full Sample	\$86,120 (1,220)	\$82,620 (1,278)	\$85,469 (1,447)	\$87,115 (1,668)	\$86,795 (1,471)	\$86,991 (1,565)	\$2,450 (1,054)
Number of individuals	20,020	20,822	16,733	14,383	14,236	14,391	
Age							
Age 0-17	\$71,223 (1,784)	\$66,456 (1,817)	\$69,744 (2,174)	\$72,643 (2,322)	\$70,179 (2,000)	\$71,640 (1,963)	\$2,403 (1,622)
Age 18-64	\$94,082 (1,224)	\$92,467 (1,635)	\$93,903 (1,750)	\$96,697 (2,038)	\$95,306 (1,661)	\$95,198 (1,366)	\$2,014 (1,221)
Age 65+	\$80,763 (1,880)	\$77,903 (1,893)	\$81,874 (1,592)	\$83,115 (2,738)	\$82,344 (1,631)	\$78,499 (1,831)	\$1,975 (1,560)
Race							
White	\$90,446 (1,354)	\$87,625 (1,371)	\$90,146 (1,446)	\$92,124 (1,867)	\$90,475 (1,758)	\$91,650 (1,603)	\$2,520 (1,205)
Black	\$58,571 (2,934)	\$56,241 (2,369)	\$55,935 (2,438)	\$57,639 (4,192)	\$60,780 (3,795)	\$57,556 (2,610)	\$1,217 (2,499)
Other	\$88,848 (5,088)	\$84,902 (4,237)	\$91,084 (5,923)	\$102,133 (7,177)	\$91,858 (5,502)	\$96,034 (5,156)	\$10,104 (4,773)
Gender							
Male	\$89,131 (1,447)	\$86,095 (1,300)	\$90,006 (1,438)	\$91,738 (1,806)	\$89,309 (1,624)	\$90,334 (1,675)	\$2,753 (1,209)
Female	\$82,762 (1,506)	\$79,247 (1,419)	\$81,082 (1,530)	\$83,809 (1,530)	\$84,574 (1,526)	\$83,792 (1,693)	\$3,128 (1,240)
Head Education							
H.S. Degree or below	\$52,425 (1,335)	\$50,430 (1,070)	\$52,635 (1,394)	\$52,676 (1,659)	\$54,274 (1,799)	\$55,727 (1,861)	\$3,127 (1,492)
Some College or above	\$105,428 (1,495)	\$104,462 (1,547)	\$106,279 (1,631)	\$109,628 (1,855)	\$105,784 (1,783)	\$103,962 (2,133)	\$1,456 (1,444)

Note: The sample includes individuals who are included in the householders' families and who are in their 1st or 5th month in the survey. Individuals with imputed income are excluded from the sample. The family income is equivalence-scale adjusted and equivalized to a family with 2 adults and 2 children. The income is adjusted over time using the PCE Chain-type Price Index and is expressed in May 2020 dollars. The statistics are weighted using fixed demographic weights since March 2020. Standard errors are bootstrapped and clustered at the household level.

Appendix Table 9. 75th Percentile, fixed demographic weight, Monthly CPS, 2020

Month	January	February	March	April	May	June	(Apr+May+Jun)- (Jan+Feb)
Full Sample	\$143,546 (1,675)	\$145,440 (1,911)	\$143,432 (2,455)	\$148,508 (2,287)	\$142,791 (2,032)	\$146,895 (2,297)	\$1,265 (1,431)
Number of individuals	20,020	20,822	16,733	14,383	14,236	14,391	
Age							
Age 0-17	\$121,444 (3,421)	\$120,018 (4,108)	\$121,503 (4,348)	\$125,108 (3,910)	\$120,288 (4,068)	\$124,180 (4,855)	\$2,662 (3,444)
Age 18-64	\$153,155 (2,116)	\$157,517 (2,840)	\$156,848 (2,373)	\$160,138 (3,022)	\$153,816 (2,259)	\$159,486 (3,088)	\$2,103 (2,377)
Age 65+	\$129,147 (2,465)	\$129,913 (4,102)	\$130,231 (2,636)	\$139,098 (4,349)	\$130,526 (2,660)	\$130,266 (2,420)	\$2,876 (2,538)
Race							
White	\$145,564 (1,867)	\$149,880 (2,191)	\$145,509 (2,716)	\$153,223 (2,918)	\$144,967 (1,800)	\$151,749 (2,386)	\$1,576 (1,852)
Black	\$111,212 (6,407)	\$102,337 (4,304)	\$101,727 (5,800)	\$106,016 (5,727)	\$109,125 (7,847)	\$98,288 (4,852)	(\$492) (4,278)
Other	\$151,989 (5,580)	\$163,674 (7,499)	\$165,411 (7,535)	\$167,618 (7,080)	\$167,682 (10,695)	\$166,782 (10,362)	\$11,747 (7,241)
Gender							
Male	\$146,873 (1,663)	\$150,717 (2,175)	\$150,883 (2,660)	\$153,312 (3,183)	\$145,134 (2,060)	\$150,055 (2,493)	\$631 (1,736)
Female	\$139,695 (2,339)	\$140,510 (2,062)	\$137,849 (1,957)	\$143,122 (2,322)	\$139,695 (2,758)	\$143,019 (2,363)	\$1,952 (1,850)
Head Education							
H.S. Degree or below	\$89,472 (2,646)	\$84,902 (1,859)	\$86,880 (2,740)	\$84,892 (2,305)	\$89,262 (2,308)	\$91,460 (2,934)	\$1,564 (2,210)
Some College or above	\$165,157 (2,946)	\$171,636 (2,716)	\$166,704 (3,583)	\$175,151 (3,210)	\$166,410 (2,809)	\$173,456 (2,990)	\$2,817 (2,764)

Note: The sample includes individuals who are included in the householders' families and who are in their 1st or 5th month in the survey. Individuals with imputed income are excluded from the sample. The family income is equivalence-scale adjusted and equivalized to a family with 2 adults and 2 children. The income is adjusted over time using the PCE Chain-type Price Index and is expressed in May 2020 dollars. The statistics are weighted using fixed demographic weights since March 2020. Standard errors are bootstrapped and clustered at the household level.

Appendix Table 10. 25th Percentile, state group, Monthly CPS, 2020

Month	January	February	March	April	May	June	(Apr+May+Jun)- (Jan+Feb)
COVID19 Death Rate							
High Death Rate (>=10 per 100k)	\$50,776 (1,453)	\$47,692 (1,188)	\$52,320 (1,724)	\$52,440 (2,141)	\$52,625 (1,341)	\$51,102 (1,590)	\$3,394 (1,231)
Low Death Rate (<10 per 100k)	\$42,437 (1,184)	\$43,970 (979)	\$44,745 (1,343)	\$47,041 (1,076)	\$45,757 (1,266)	\$46,599 (1,681)	\$2,914 (1,015)
Date of Stay at Home Order							
Early Stay at Home (3/23 or before)	\$50,142 (1,590)	\$46,821 (1,256)	\$52,083 (1,627)	\$50,451 (2,305)	\$48,730 (1,748)	\$51,815 (1,779)	\$2,209 (1,338)
Late Stay at Home (after 3/23)	\$43,973 (1,108)	\$44,577 (1,088)	\$44,693 (1,236)	\$48,227 (1,157)	\$48,821 (1,964)	\$46,759 (1,353)	\$3,593 (1,120)
Date of State of Emergency Order							
Early State of Emergency (3/9 or before)	\$48,009 (1,290)	\$45,234 (1,196)	\$49,665 (1,495)	\$49,163 (1,943)	\$49,926 (1,472)	\$51,810 (2,194)	\$3,432 (1,243)
Late State of Emergency (after 3/9)	\$44,620 (1,160)	\$46,039 (1,192)	\$45,965 (1,439)	\$48,726 (1,303)	\$47,074 (2,060)	\$47,000 (1,321)	\$2,625 (1,176)
Regular UI Reciprocity Rate							
High Reciprocity Rate (>=35%)	\$50,934 (1,380)	\$48,581 (1,281)	\$53,837 (1,457)	\$52,802 (2,047)	\$49,393 (1,787)	\$55,108 (1,625)	\$2,507 (1,375)
Low Reciprocity Rate (<35%)	\$42,764 (1,311)	\$43,241 (1,166)	\$42,271 (1,103)	\$47,387 (1,011)	\$47,937 (2,006)	\$45,025 (1,297)	\$3,844 (1,120)

Note: The sample includes individuals who are included in the householders' families and who are in their 1st or 5th month in the survey. Individuals with imputed income are excluded from the sample. The family income is equivalence-scale adjusted and equalized to a family with 2 adults and 2 children. The income is adjusted over time using the PCE Chain-type Price Index and is expressed in May 2020 dollars. The statistics are weighted using fixed demographic weights since March 2020. Standard errors are bootstrapped and clustered at the household level.

Appendix Table 11. Comparison of the actual and imputed average WBA

Month	Actual WBA	Imputed WBA	Imputed/Actual-1
April	330.7	333.7	0.01
May	325.4	342.3	0.05
June	316.0	341.3	0.08

Note: This table reports the national average weekly benefit amount (WBA) from the Department of Labor’s Monthly Benefit and Claims data and the imputed average WBA from our simulation for regular UI recipients. To impute the average WBA, we first impute the pre-separation earnings for UI eligibles. We then apply each state’s UI formulas to the imputed earnings.

Appendix Table 12. Income Measures in the Monthly CPS and CPS ASEC, Fixed Reference Month, CPS ASEC 2019

	Monthly CPS	CPS ASEC
Mean	\$87,975	\$98,198
Standard Deviation	101,698	111,236
Variance	10,342,448,245	12,373,449,434
Coefficients of variation	1.16	1.13
Number of individuals	66,106	

Note: The sample includes individuals who report their family income in the December or January CPS and also responded to the CPS ASEC. Individuals who have imputed income in the Monthly CPS or imputed earnings in the CPS ASEC are excluded.

Appendix Table 13. Features of Household Surveys that Collect Income Data During the COVID-19 Pandemic

Survey Name	Monthly CPS	FRB SHED ^a	Household Pulse	COVID Impact
First year of survey	1982 ^b	2013	2020	2020
Number of surveys	462	8	4	3
Survey months in 2020	Jan-June	April	April-June	April-June
Reference period of income question	Last 12 months	Last 12 months	Last calendar year	Last calendar year
Survey mode ^c	In-person (3%), phone (97%)	online	online	online (94%), phone (6%)
Number of income brackets below 25K ^c	7	7	1	2 (under 20k)
Number of income brackets below 50K ^c	11	11	3	5
Survey nonresponse rate ^c	0.47	0.98	0.97	0.97
Missing income rate ^c	0.28	N/A	0.15	0.02
Number of households ^c	8,860	1,030	101,215	7,505

Note: ^aIncome data in the FRB SHED survey is carried over from an initial demographic profile survey. Information about the month of the initial survey is not available. ^bFirst year of survey with income question. ^cData from the most recent survey data available. Respondents of Household Pulse survey are contacted by email or text. The number of households includes those with missing income.

Appendix Table 14. Number of UI eligibles as % population by reasons not working

UI Type	Category	April	May	June
PUA eligible	Unemployed, self-employed	0.54	0.53	0.33
	Absent from work, health	0.90	0.60	0.45
	Absent from work, family	0.04	0.04	0.04
	Absent from work, childcare	0.09	0.14	0.15
	Absent from work, other	3.17	2.17	1.20
	Didn't look for work, no job available	0.26	0.25	0.13
	Didn't look for work, could not find	0.28	0.16	0.22
	Didn't look for work, family	0.20	0.28	0.32
	Didn't look for work, childcare	0.07	0.05	0.08
	Didn't look for work, other	1.65	1.76	1.40
Regular UI eligible	New entry, search full-time job	0.07	0.16	0.20
	New entry, search part-time job	0.03	0.09	0.15
	Experienced, search full-time job	6.14	5.27	4.79
	Experienced, search part-time job	2.55	1.61	1.47
Total		16.1	13.1	10.9

Note: This table reports the number of individuals who were designated as UI eligible for our UI benefit simulation by reasons for not working as a percent of the total number of individuals 16 and above.

Appendix Table 15. Ratio of Continuing UI Claims to Those out of Work

Week	Total UI claims	Unemployed	YoY change in has job/not at work	YoY change in NILF	Definition 1, out of work	Claims/ (def 1)	Definition 2, out of work	Claims/ (def 2)
1/18/2020	2,108,515	5,892,000	-569,014	-201,000	5,322,986	0.40	5,121,986	0.41
2/15/2020	2,092,483	5,787,000	-307,870	-126,000	5,479,130	0.38	5,353,130	0.39
3/14/2020	2,105,265	7,140,000	1,339,134	1,243,000	8,479,134	0.25	9,722,134	0.22
4/18/2020	18,919,431	23,078,000	11,568,470	7,268,000	34,646,470	0.55	41,914,470	0.45
5/16/2020	30,167,170	20,985,000	4,074,007	5,741,000	25,059,007	1.20	30,800,007	0.98
6/20/2020	32,436,335	17,750,000	673,080	4,368,000	18,423,080	1.76	22,791,080	1.42

Notes: The definition 1 of out of work includes the unemployed and year-over-year change in jobholders who are absent from work. The definition 2 of out of work includes the unemployed, year-over-year change in jobholders who are absent from work, and year-over-year change in persons not in labor force. The UI claims data are from the USDOL UI weekly claims reports (https://oui.doleta.gov/unemploy/claims_arch.asp). The number of persons unemployed and the number of persons not in labor force are from the BLS's employment situation reports (<https://www.bls.gov/news.release/empsit.toc.htm>). The number of persons who have a job but absent from work are from the author's calculations using the 2019-2020 Monthly CPS data.