

# FORECASTING ESTIMATES of POVERTY during the COVID-19 CRISIS

*Poverty Rates in the United States Could Reach  
Highest Levels in Over 50 Years*

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The COVID-19 (“novel coronavirus”) pandemic has caused a drastic slowdown in economic activity. In recent weeks, record levels of unemployment insurance (UI) claims make clear that the immediate economic consequences of the pandemic are stark. It remains unclear, however, how the ongoing crisis will affect poverty rates in the United States. In this brief, we apply a novel method for forecasting poverty rates in the United States using the Supplemental Poverty Measure (SPM) framework.

Our projections suggest that if unemployment rates increase to 30 percent, as one estimate from the Federal Reserve projects for the second quarter of the year, then SPM poverty rates will increase dramatically.<sup>1</sup> If the 30 percent unemployment rate persists throughout the year, we project that annual poverty rates will increase from 12.4 percent to 18.9 percent. **This projected poverty rate represents an increase of more than 21 million individuals in poverty and would mark the highest recorded rate of poverty since at least 1967, the first year for which we have reliable estimates of SPM poverty.** Even if employment rates fully recover after the summer, we project that poverty rates will increase to 15.4 percent, comparable to levels observed during the Great Recession. Importantly, these projections do not yet take into account new income transfer programs, such as the expanded cash assistance payments, that federal and state governments have enacted to blunt the economic effects of the crisis.

Our analyses suggest that working-age adults and children will face particularly large increases in poverty rates. If a 30 percent unemployment rate were to persist throughout the year, we project that poverty rates among working-age adults will rise by 63 percent (7.4 percentage points). For children, we project that poverty rates will rise by 53 percent (7.3 percentage points). The retirement-age population, in contrast, faces smaller projected increases in poverty rates. Black and Hispanic individuals will also face particularly large increases in their poverty rates, though no racial/ethnic group is likely to be spared.

## Key Findings

- If unemployment rates rise to 30 percent, we project that the annual poverty rate in the United States will increase from 12.4 percent to 18.9 percent, the highest recorded poverty rate since at least 1967.
- Even if employment rates recover after the summer, we project that the annual poverty rate will reach levels comparable to the Great Recession.
- We project that pre-tax/transfer poverty rates will reach a record high if the annual unemployment rate surpasses 10 percent.
- Working-age adults and children will face particularly large increases in poverty.
- Absent a quick recovery in employment rates, substantial income transfers are likely needed to prevent a record-high poverty rate in the United States.

<sup>1</sup> Faria-e-Castro, Miguel (2020). “Back-of-the-Envelope Estimates of Next Quarter’s Unemployment Rate.” Federal Reserve Bank of St. Louis.



We forecast poverty rates under three alternative employment scenarios (10 percent, 20 percent, and 30 percent). Because we do not yet know how long such high levels of unemployment will last, we also forecast poverty rates under different assumptions of the duration of unemployment increases. We provide these forecasts assuming increases in unemployment that last either one quarter or one year, though these assumptions can be easily varied. We forecast poverty rates using two different definitions of poverty, both using an SPM framework (see textbox). The first is the standard SPM poverty measure, which incorporates all taxes and transfers. The second is a pre-tax, pre-transfer measure of SPM poverty using contemporary poverty thresholds.<sup>2</sup> Our goal in using the pre-tax/transfer definition is to forecast the poverty rate delivered by the wider economy. This will then serve as our baseline with which we can understand how existing public policy responses buffer against forecasted increases in poverty, as well as the potential buffering effect of expanded or alternative policy responses going forward.

This forecasting is a work in progress. We hope our estimates will provide policy makers and other stakeholders with much needed “real time” information on the possible extent of suffering among the U.S. population. This brief is our first attempt to develop the infrastructure to routinely monitor the extent of poverty in an up-to-date and timely manner. In future briefs and updates we will seek to refine and improve our methods. We welcome feedback and suggestions for improvements as we further develop this critical infrastructure.

### **The Supplemental Poverty Measure:** *An Improved Poverty Measure for Policy Analysis*

Throughout this brief, we use the Supplemental Poverty Measure (SPM) in our forecasting of poverty rates. The United States has an official measure of poverty that has existed since the 1960s, but the official measure is widely considered to be flawed. For this reason, we use the SPM as our primary poverty measure for these analyses which includes the following improvements:

- Whereas the official measure counts only pretax, cash income in its definition of resources, the SPM counts a more comprehensive measure of resources, which include after-tax income, in-kind or near cash benefits, and a subtraction of non-discretionary expenses like those for medical, work, and child care expenses.
- The SPM uses a broader definition of the “family” than the official measure. Cohabiting couples are treated identically to married couples and are assumed to share resources. Foster children and other youth in the household are assumed to share resources with the primary family in the household.
- The SPM poverty line is based on families’ expenditures on a core basket of necessities: food, clothing, shelter, and utilities, plus a little extra. The official poverty lines are based solely on food costs that prevailed in the 1950s and 1960s.
- The SPM poverty line is adjusted for cost of living across metro areas, whereas the official poverty line is virtually uniform across the country.

2 Fox, Liana (2019), “The Supplemental Poverty Measure: 2018,” *Current Population Reports*, P60-268 (RV), U.S. Census Bureau.

Our methodological appendix details the methods and assumptions underlying our projections. Validation tests from prior years of data demonstrate that our model is largely effective in producing projections of poverty rates that align closely with observed poverty rates. Moreover, our simulations of poverty rates under 10, 20, and 30 percent unemployment align closely with expectations given the past relationship between annual SPM poverty rates and national unemployment rates.

## **Forecasting Estimates of Poverty**

Official estimates of poverty in the United States are presented on an annual basis and with a considerable lag. As of April 2020, for example, the latest estimates of poverty from the U.S. Census Bureau cover the 2018 calendar year. Given the rapid economic change resulting from the COVID-19 pandemic, policymakers require up-to-date information on the economic wellbeing of the most disadvantaged households to help guide their policy responses. This brief applies a novel method for forecasting estimates of SPM poverty rates in the U.S. under specified unemployment scenarios. We present updates of SPM poverty under three scenarios: if unemployment rates rise to 10 percent, 20 percent, or 30 percent. For each unemployment scenario, we present projections for a *one-quarter increase in unemployment* (i.e. unemployment rising to 30 percent from April through June, but recovering to current rates afterward) and an *annual increase in unemployment* (higher unemployment rates lasting throughout the year). The one-quarter simulation projects poverty rates under an optimistic scenario that employment rates will recover to pre-crisis levels during the summer of 2020.

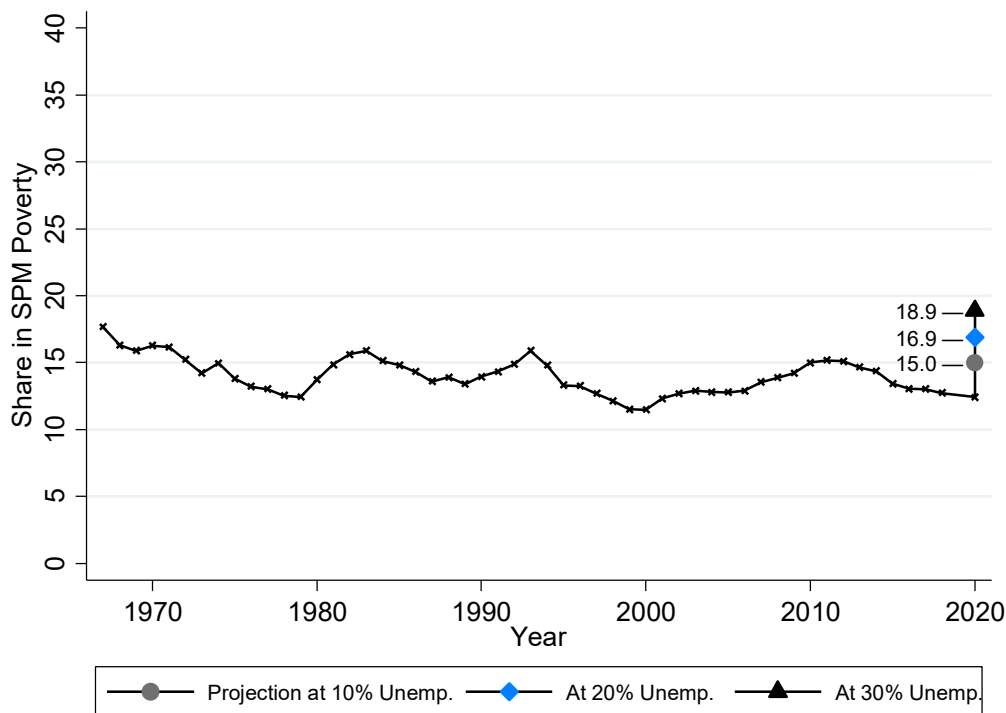
Our simulation strategy, specified in detail in the [Appendix](#), follows two broad steps. First, we produce monthly updates of SPM poverty rates. To do so, we merge demographic data from monthly Current Population Survey (CPS) files (i.e.: February 2020) with detailed data on SPM poverty from the latest CPS ASEC file (i.e.: March 2019). Validation tests using 10 years of prior data demonstrate that this methodology produces estimates of poverty rates that closely track observed poverty rates released nearly 10 months later. Second, we build on our monthly updates of SPM poverty to forecast estimates of poverty given specified assumptions about current or future employment rates. [Appendix B](#) details this process and demonstrates that our projected poverty rates under 10, 20, and 30 percent unemployment align closely with expectations given the relationship between unemployment and poverty rates in prior years.

Importantly, our simulations likely provide a conservative projection of current economic conditions, as our approach provides projections of *annual poverty rates* rather than poverty rates based on monthly income. Estimates of poverty rates based on monthly income, which is more volatile than annual income, are likely to be higher than the estimates presented here.

Our projections of current poverty rates assume that many of the newly-unemployed will receive income transfers from Unemployment Insurance (UI), the Supplemental Nutrition Assistance Program (SNAP), and other programs, **but does not account for an expansion of UI eligibility or the impending emergency cash assistance payments from the federal government.** We hope to build upon the methods outlined here to be able to estimate the effects of these expansions in the near future, as well as potential alternative expansions being considered by policy makers and those recommending various approaches.

As detailed in Appendix B, we simulate changes in unemployment under an assumption that employment losses are concentrated in the following industries: services (accommodation, food services, and other services); arts, entertainment, and recreation; transportation and warehousing; educational services; retail and wholesale trade. These are industries highlighted in state governments' recent UI claims reports. We also project reductions in hours worked among individuals remaining in employment.

**Figure 1. SPM poverty rates projected to reach record high if annual unemployment rate reaches 30%**



Note: Historical SPM data from Columbia University’s Center on Poverty & Social Policy. To facilitate comparisons before and after Census Bureau’s 2019 change in processing system, we subtract 0.9 p.p. from SPM estimates prior to 2019. See Appendix for details on projections.

Figure 1 presents trends in SPM poverty rates from 1967 to 2020. Estimates of poverty from 1967 to 2018 are pulled from the CPS ASEC and the Center on Poverty & Social Policy’s historical SPM series.<sup>3</sup> The baseline estimate for 2020 follows our procedure for updating SPM estimates on a monthly basis (see Appendix A). Our projected estimates of poverty under the three unemployment scenarios follow the process outlined in Appendix B.

We project that the SPM poverty rate was 12.4 percent in February 2020. This is the lowest recorded poverty rate since 2001. Our projections after the onset of the COVID-19 pandemic, however, point to higher poverty rates today. If unemployment rates rise to 10 percent, comparable to the unemployment rate during the peak of the Great Recession, we project that poverty rates would rise to 15 percent.

3 Fox, Liana, Christopher Wimer, Irwin Garfinkel, Neeraj Kaushal and Jane Waldfogel. 2015. “Waging War on Poverty: Poverty Trends Using a Historical Supplemental Poverty Measure.” *Journal of Policy Analysis and Management* 34(3):567-92. doi: 10.1002/pam.21833.

This is approximately the same rate of poverty observed in 2010.<sup>4</sup> If unemployment rates rise to 20 percent, we project a poverty rate of 16.9 percent—the highest rate of poverty since 1967, the first year for which reliable estimates of poverty are available. Finally, if annual unemployment rates rise to 30 percent, we project a poverty rate of 18.9 percent. This would mark the highest rate of poverty over the past 50 years.

**Figure 2. Pre-tax/transfer SPM poverty rate projected to reach record high if annual unemployment rate surpasses 10%**

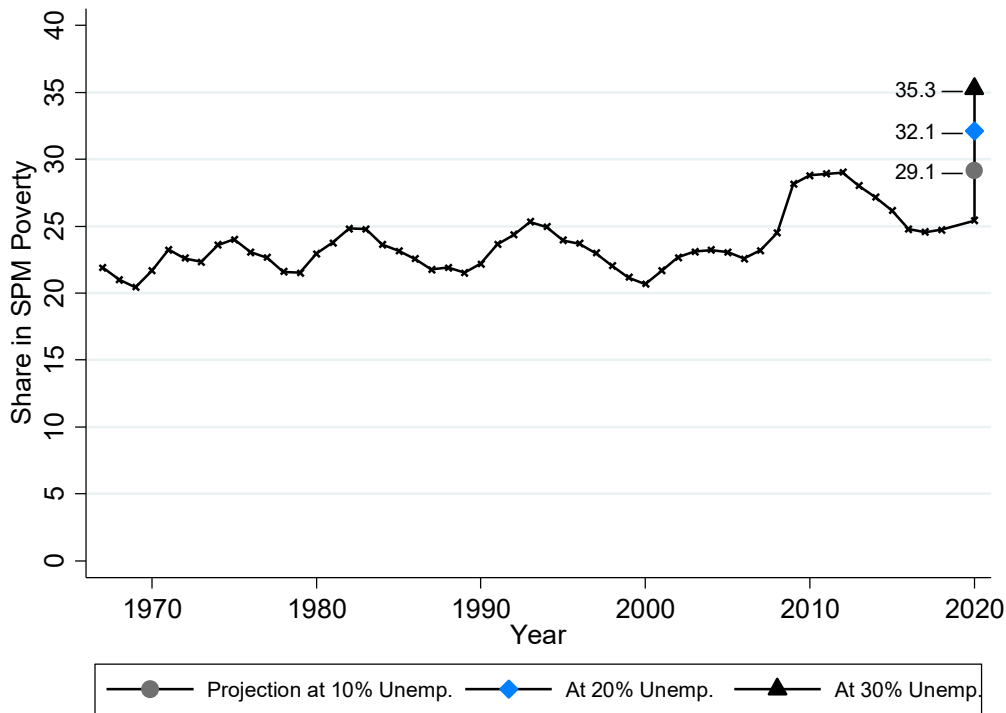


Figure 2 presents similar trends and projections, but for pre-tax/transfer poverty rates. These estimates remove all taxes, transfers, and expenses from a family unit’s resources before calculating their poverty status. As such, they provide an approximation of poverty rates based on market incomes alone. We estimate that the pre-tax/transfer SPM poverty rate was 25 percent as of February 2020, not dissimilar from observed estimates in 2018. If annual unemployment rates increase to 10 percent, however, we project that the pre-tax/transfer poverty rate will rise to 29.1 percent, which is higher than the reported estimates recorded during the peak of the Great Recession. Notably, even an increase to 10 percent unemployment would lead to the highest recorded rate of pre-tax/transfer poverty in the U.S. since at least 1967. If unemployment rises to 30 percent, pre-tax/transfer poverty rates would rise to 35.3 percent in our projections, an unprecedented high. This would mark an increase of more than 33 million U.S. residents living in pre-tax/transfer poverty.

<sup>4</sup> The reported poverty rate in 2010 was 15.9 percent. After accounting for the Census Bureau’s change in processing system in 2019, this is comparable to a 15 percent poverty rate today. *Renwick (2019)* notes that “improvements made in the imputation of medical-out-of-pocket expenses, housing subsidies and school lunch receipts” during the 2019 change in processing system are largely responsible for the 0.9 percentage point reduction in SPM poverty rates. The processing changes do not affect estimates of pre-tax/transfer SPM poverty rates. Our projection of SPM poverty rates at 30% unemployment still surpasses all observed poverty rates from 1967 onward even without applying the 0.9 p.p. reduction due to Census processing changes.



**Figure 3. Deep SPM poverty rates projected to reach record highs if annual unemployment reaches 30%**

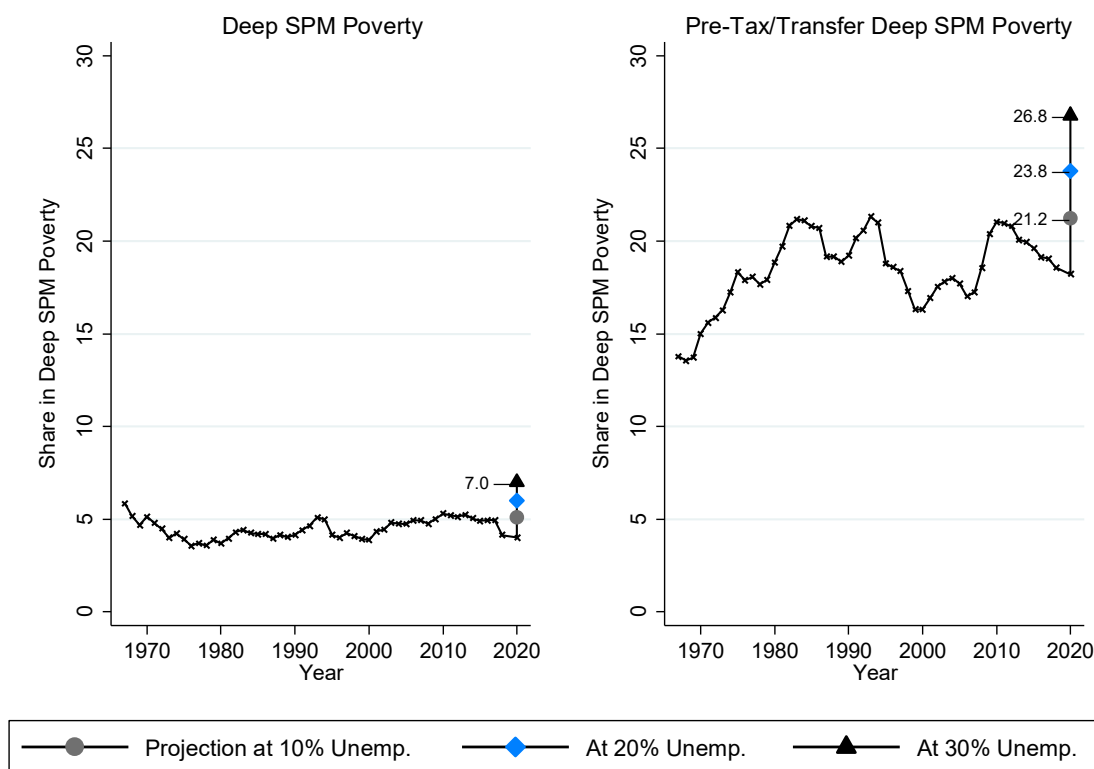
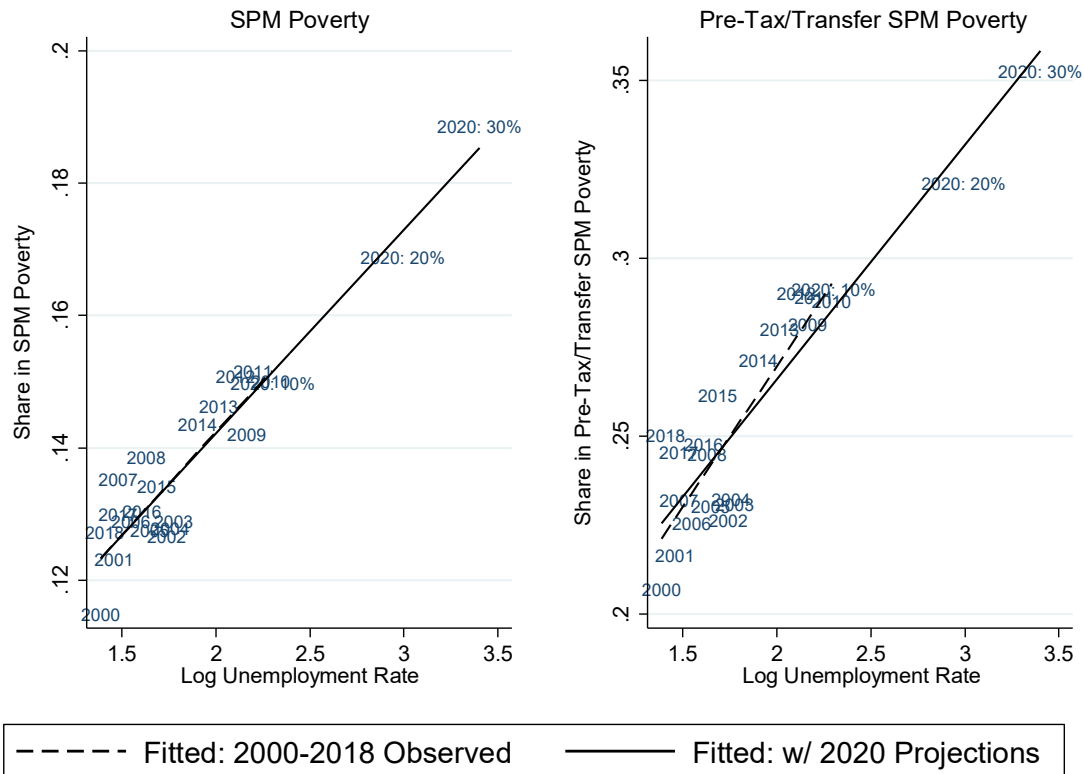


Figure 3 presents trends in the SPM deep poverty rate. Deep poverty is defined as having resources below half the SPM poverty threshold and represents an acute form of poverty associated with more severe destitution. The left panel projects standard SPM estimates (after taxes and transfers), while the right panel projects pre-tax/transfer estimates.

We project that the deep poverty rate was 4 percent in February 2020, immediately prior to the worst of the COVID-19 crisis. Our projections after the onset of the COVID-19 pandemic forecast much higher poverty rates today and in the immediate future. If annual unemployment rates rise to 10 percent, comparable to the unemployment rate during the peak of the Great Recession, we project that deep poverty rates would rise to 5.1 percent. If unemployment rates rise to 20 percent, deep poverty would increase to 6 percent, the highest level since 1967. Finally, if unemployment rises to 30 percent, we project that deep poverty rates would rise to 7 percent, the highest rate observed since at least 1967. Put differently, the number of U.S. residents living in deep poverty would rise from around 13 million to 23 million.

The right panel shows pre-tax/transfer deep poverty rates. Under the 10 percent unemployment scenario, we project that pre-tax/transfer deep poverty rates would rise to 21.2 percent, comparable to levels observed during the Great Recession. An increase to 20 or 30 percent unemployment would mark record-high levels of pre-tax/transfer deep poverty. At such high levels of unemployment, between 20 and 30 percent of all Americans would be in deep poverty absent government transfers and tax credits.

**Figure 4. Bivariate relationship between SPM poverty rate and log of unemployment rate**



Note: 2020 values reflect projected poverty rates based on specified level of unemployment. Annual employment rates presented. Bivariate relationships used only for comparing our estimates to past estimates and are not for projecting current poverty rates.

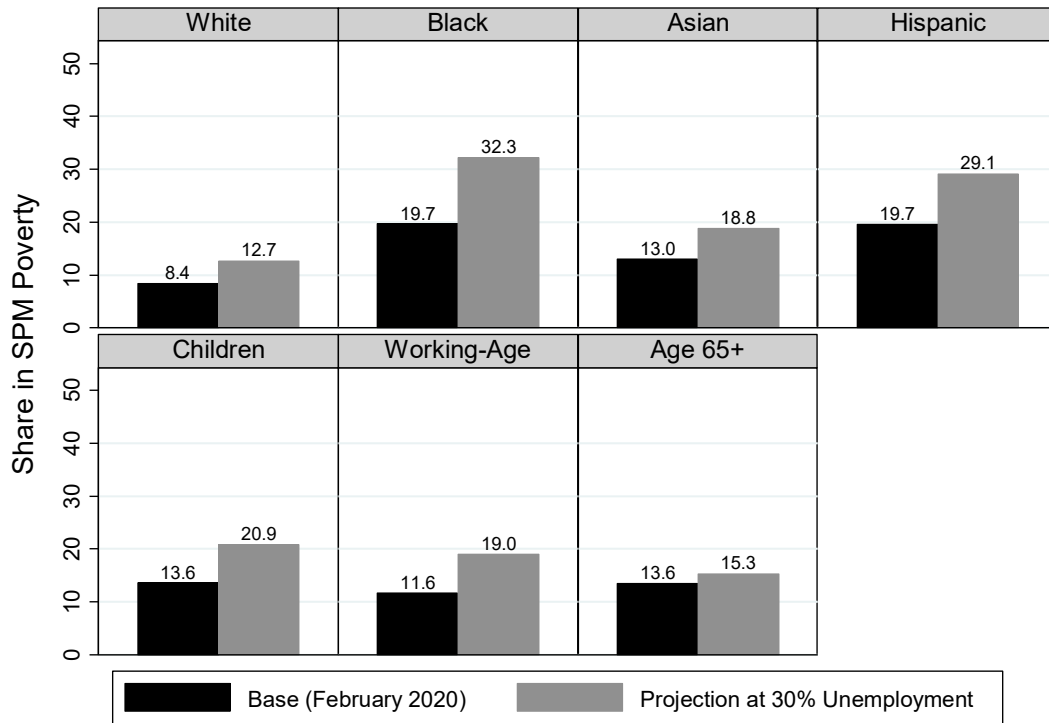
What level of confidence can we have in our projections of poverty rates? In Figure 4, we show that our projected poverty rates align squarely with expectations given the observed relationship between unemployment and poverty rates from 2000 to 2018.<sup>5</sup>

Specifically, Figure 4 shows that national unemployment rates are strongly associated with national poverty rates. Before including our projected poverty rates in 2020, the unconditional correlation between the log of unemployment and SPM poverty rates from 2000 to 2018 is 0.87. The left panel shows that our three projections (poverty rates at 10, 20, and 30 percent unemployment) align very closely with expectations given the past relationship between poverty and unemployment. There is no observable difference between the fitted line of the 2000 to 2018 and the fitted line that includes our three projections. Put simply, our projections of poverty rates align closely with what we should expect given the past relationship between unemployment and poverty rates.

The right panel of Figure 4 presents similar results, but for pre-tax/transfer SPM poverty rates. Again, our projections of pre-tax/transfer poverty align closely with expectations given the past relationship between unemployment and poverty rates. These diagnostic results give us a fair degree of confidence in our forecasting models, though caution is nonetheless warranted in interpreting our projections given the unprecedented nature of the current economic slowdown.

<sup>5</sup> Specifically, we take the log of unemployment rates to account for the non-linear relationship between unemployment rates and poverty rates.

Figure 5. Projected changes in SPM poverty rates by demographic group



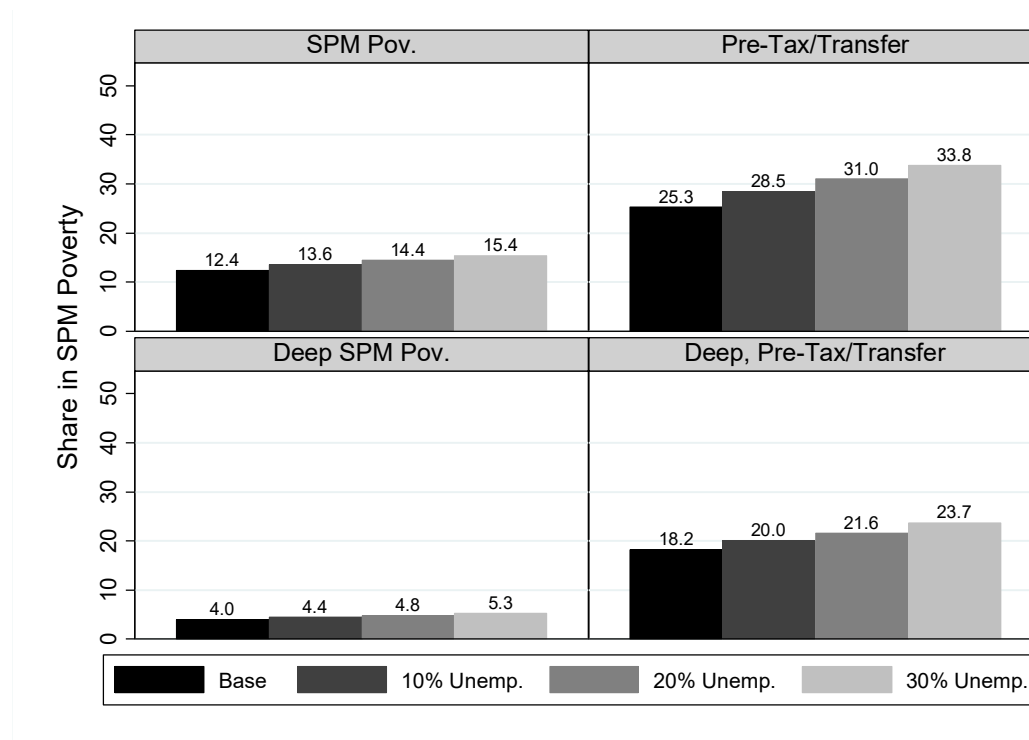
Note: Baseline represents estimated poverty rates as of February 2020. See Appendix for details on projections. Unemployment simulations represent annual poverty rates.

Figure 5 presents projected changes in SPM poverty rates by demographic group if annual unemployment rises to 10, 20, or 30 percent. The estimates make clear that no racial/ethnic group is likely to be spared, though Black and Hispanic individuals appear to face the greatest increases in poverty. White individuals face a 4.3 percentage-point increase in poverty rates, whereas Black individuals face an increase of 12.6 percentage points and Hispanics face an increase of 9.4 percentage points. Asians face a 5.8 percentage-point increase in poverty rates. Note that these projections by race/ethnicity rely on the assumption that the racial composition of the unemployed in the present crisis is comparable to the composition of the unemployed during the peak of the Great Recession. If racial/ethnic minorities face greater employment disadvantages in the current crisis, then racial/ethnic disparities may be even greater than we project. We intend to further refine these estimates by race and ethnicity as we continue to improve our modeling.

The figure also shows that working-age adults (a 63 percent relative increase in poverty) and children (54 percent relative increase) will face substantial increases in poverty rates if unemployment rates rise to 30 percent. The retirement-age population, in contrast, faces much smaller increases in poverty rates (13 percent relative increase).



**Figure 6. Projected changes in SPM poverty rates under quarterly increase in unemployment**



Note: Baseline represents estimated poverty rates as of February 2020. See Appendix for details on projections. Unemployment simulations represent quarterly increase in unemployment followed by recovery to pre-crisis levels for duration of the year.

Figure 6 presents estimates of poverty under a scenario in which the unemployment rate increases only for a three-month period, before recovering to pre-crisis rates. This optimistic scenario of course results in lower SPM poverty rates relative to more prolonged scenarios such as an increase in unemployment that occurs over a full year. If quarterly unemployment rates increase to 30 percent before recovering, we project that SPM poverty rates will increase to 15.4 percent. We project that pre-tax/transfer poverty rates will increase from 25.3 to 33.8 percent under this scenario.

### Preventing Record Increases in Poverty Rates

The COVID-19 (“novel coronavirus”) pandemic has led to a drastic slowdown in economic activity. As a result, unemployment rates are expected to climb to as high as 30 percent for at least a quarter of 2020, and perhaps longer. Our framework for forecasting estimates of poverty suggests that SPM poverty rates could reach record highs throughout the year. Even with an increase to 10 percent unemployment, we project that pre-tax/transfer SPM poverty rates will reach their highest level since at least 1967.

Under an optimistic scenario, in which employment rates return to pre-crisis levels during the summer of 2020, annual SPM poverty rates are still projected to reach levels comparable to the Great Recession.

As mentioned earlier, validation tests presented in the Appendix suggest that our projections methods are reliable. Given the dynamic and unprecedented nature of the current economic slowdown, however, we urge caution in interpreting our projections. Large expansions in income transfers would lead to lower post-tax/transfer SPM poverty rates than we present. Moving forward, we plan to adapt our models to project the poverty-reduction effect of the emergency cash assistance payments passed as part of the [CARES Act](#), as well as any other expansions to income transfer programs. Conversely, if unemployment rates continue to rise, the official SPM estimates may be higher than the poverty rates we project.

Our projections emphasize the urgent need for the provision of income assistance to all U.S. residents, **with a particular focus on children and working-age adults who we find are at the greatest risk of falling into poverty.** Without large expansions in income transfers or a quick recovery in employment rates, SPM poverty rates will likely reach their highest level in recent U.S. history.

## Data Appendix

### Appendix A: Simulation Methods for Producing Monthly Updates of SPM Poverty

#### Data Sources

The Census Bureau releases two primary versions of the U.S. Current Population Survey (CPS): a “basic monthly” file released each month and the Annual Social and Economic Supplement (ASEC) released each year. The monthly files feature a broad range of demographic, employment, geographic, and household information, but do not provide comprehensive data on earnings, income, or poverty status.

In contrast, the ASEC features the same information as the monthly files plus a broad range of earnings and income data. The ASEC is thus used to produce annual estimates of U.S. poverty rates. Respondents in the ASEC report their income for the prior year. However, data on current employment status and current demographic/household characteristics are provided in both the ASEC and monthly files.

#### Updating Estimates of Poverty on a Monthly Basis

To produce new estimates of poverty on a monthly basis, we combine up-to-date data on demographic, employment, and household characteristics from the *monthly files* with information from the latest *annual ASEC files* on the association of those observed characteristics with SPM poverty.

For example, say we are looking to produce an estimate of poverty in February 2020. The basic monthly CPS dataset is available for this month. However, the most recent estimates of SPM poverty are from the 2019 ASEC. The objective is to update the 2019 ASEC to take into account the demographic profile of the February 2020 sample to produce an updated estimate of poverty (and, more broadly, an updated income distribution).

Two assumptions underlying this approach to updating poverty rates should be noted. First, the approach relies on the assumption that the likelihood of poverty associated with observed characteristics does not change significantly within a single year. In the example provided above, we are assuming that the likelihood of poverty associated with, say, employment status, as observed in the 2019 ASEC, will not be notably different in February 2020. This assumption could be violated in the event of a large policy change, such as an expansion of income transfers, that affects the association of employment status with SPM poverty. We present steps for overcoming this limitation in [Appendix B](#).<sup>6</sup> Usefully, we can test whether this assumption generally holds using prior years’ data. We test the assumption and find that it generally holds in the [Validation Checks](#) section below.

Second, this new poverty estimate should not be understood as a monthly evaluation of a household’s resources relative to its needs; it is not a *monthly poverty rate* in the pure sense. Instead, the new poverty rate is akin to an annual poverty rate presented on a monthly basis to take into account changing employment and demographic conditions throughout the year.

<sup>6</sup> Updating the projections to explicitly model the observed policy changes is the most direct way to overcome this limitation. To do so, we would update the latest ASEC file with the given policy change and re-create the SPM poverty indicators before merging in the demographic profile of the monthly sample of interest.

To produce monthly updates of poverty rates, we apply a reweighting technique to update the latest ASEC file with the demographic composition of the monthly file of interest.<sup>7</sup> (Note that we use “demographic composition” as shorthand for observable demographic, employment, and household characteristics of the monthly sample). To continue with the example presented in the prior section, we describe the empirical approach for updating the 2019 ASEC with demographic data from the February 2020 monthly file to produce projections of poverty rates in February 2020.

The reweighting approach used in this analysis is perhaps most comparable to the semi-parametric decomposition techniques introduced in [DiNardo, Fortin, and Lemieux \(1996\)](#). It also features parallels with inverse probability weighting, propensity score matching, and related tools. In short, the technique uses a reweighting function to adjust the composition of a given sample (in this case, the ASEC) to match the composition of an alternative sample (the February 2020 monthly).

Specifically, the reweighting function,  $\Psi_{(x)}$ , is defined as:

$$\Psi_{(x)} = \frac{\Pr(t_x = \text{ASEC} | x)}{\Pr(t_x = \text{Monthly} | x)} \cdot \frac{\Pr(t_x = \text{Monthly})}{\Pr(t_x = \text{ASEC})}$$

In this equation,  $\Pr(t_x = \text{ASEC} | x)$  represents the probability that an individual with a vector of observed characteristics,  $x$ , is found in the ASEC sample relative to the monthly sample. To obtain this, we simply estimate a probit model to compute the conditional probability of being in the ASEC relative to the monthly sample. The probit model allows us to directly estimate  $\Pr(t_x = \text{ASEC} | x)$ . Given the sample construction, we can compute  $\Pr(t_x = \text{Monthly} | x)$  as  $1 - \Pr(t_x = \text{ASEC} | x)$ . The unconditional probability of being in the ASEC,  $\Pr(t_x = \text{ASEC})$ , is straightforwardly calculated as the weighted number of observations in the ASEC relative to the weighted number of observations in the monthly sample. The unconditional probability of being in the monthly sample,  $\Pr(t_x = \text{Monthly})$ , is calculated similarly. (These should be nearly identical given that sample weights sum to the aggregate U.S. population).

The resulting reweighting factor,  $\Psi_{(x)}$ , is multiplied by the SPM-unit weights provided in the CPS ASEC. When these revised weights are applied, the composition of the sample now matches that of the February 2020 monthly sample, but within the ASEC sample that includes information on SPM poverty rates. The new weights can be applied to produce estimates of SPM poverty rates for February 2020.<sup>8</sup> For distributional analyses beyond binary poverty status, the weights can be applied to produce a full income distribution for the February 2020 sample.

<sup>7</sup> Rather than importing endowments from the monthly file, we achieve similar results when estimating a model of poverty in the ASEC and exporting the coefficients to the monthly file. Among the advantages to applying the reweighting approach presented here is its ability to produce alternative income distributions in addition to updated estimates of poverty.

<sup>8</sup> In Stata syntax terms, one simply needs to summarize the SPM poverty indicator while applying the revised weights. The resulting mean is the SPM poverty rate as of February 2020.

The list of covariates we currently include in the reweighting model are:

- Age: dummy variables for five-year age bins from 0 to 80+; operationalized as household means
- Sex: binary indicator of whether female; operationalized as household mean
- Education: binary indicators for low (HS or less), medium (more than HS, less than college), or high (college degree); household means among adults
- Race/Ethnicity: separate indicators for mean of household members who are White, Black, Asian, Hispanic, or Other race/ethnicity
- Citizenship/Birthplace: binary indicator for citizenship, binary indicator for whether born outside U.S.; household means
- Household structure: dummies for single with no kids, single with kids, two adults with no kids, two adults without kids, three or more adults with no kids, three or more adults without kids, retirement-age adults only; indicator of whether more than one family live in household unit; count variable of number of working-age adults in HH; count variable of number of pensioners in HH; count variable of number of children in HH
- Marital status: dummy variable for whether anyone in household is currently married with spouse present
- Employment indicators: household employment rate among non-disabled working-age adults, in labor force (binary), household work intensity (hours worked per week among working-age adults in household relative to number of working-age adults in household), one-digit occupation codes (nine binary indicators), duration of unemployment in weeks (set to zero for non-unemployed)
- Metro status: binary indicators of whether in city center, near city center, outside city center, or unidentifiable
- State of resident: dummy variables for all states

Note that we primarily aggregate these indicators at the household level, rather than the SPM unit level, as SPM units are not readily available within the monthly CPS files. In practice, SPM units and households are identical in all but a small number of households. Other observed characteristics of individuals and households could be added in future iterations of the model.

### *Validation Checks Using Past Data*

To test the efficacy of the reweighting approach presented above, we apply the method to data from prior years and evaluate whether the mean of the predicted monthly poverty rates align with the observed poverty rate in the subsequent year's ASEC. Given that the ASEC measures income and poverty status for the preceding year, the mean poverty rate in the 11 monthly files should approximately match the observed poverty rate in the subsequent March ASEC file. The legend presented in Table A1, perhaps, provides the clearest explanation of the diagnostic test.

**Table A1: Validation check: SPM poverty rates in ASEC and monthly files**

	Test A		Test B	
	2017	2018	2018	2019
January		13.9%		13.6%
February		13.7%		13.6%
March ASEC	<b>13.94%</b>	13.91%	<b>13.91%</b>	13.63%
April	13.8%		13.7%	
May	13.7%		13.6%	
June	13.8%		13.7%	
July	13.7%		13.7%	
August	13.8%		13.8%	
September	13.8%		13.7%	
October	13.7%		13.7%	
November	13.8%		13.6%	
December	13.8%		13.6%	
Average: April to Feb		13.77%		13.66%
March ASEC		13.91%		13.63%

Legend:

- ASEC used to predict future months
- Monthly samples with estimated poverty rates from prior ASEC
- ASEC used to evaluate accuracy of prior months

In the columns labeled “Test A,” we use the 2017 ASEC file to estimate poverty rates in monthly files from April 2017 to February 2018, applying the reweighting techniques described in the prior section. We then compare the mean poverty rate in the monthly files to the 2018 ASEC. As shown, the monthly files closely match the 2018 ASEC file (13.9 percent compared to 13.8 percent). The difference between the two estimates is not statistically significant.

In Test B, we replicate the same exercise, but for the following year. Specifically, we use the 2018 ASEC to produce monthly estimates of poverty from April to February. We compare the monthly estimates to the observed poverty rate in the 2019 ASEC. Again, the estimates align closely, and the difference between the two estimates is not statistically significant. These patterns provide initial evidence that the reweighting techniques presented before are generally suitable for projecting monthly updates of poverty rates using the ASEC and monthly files.

In Table A2, we replicate the exercise for each month and year since 2010, when data on SPM poverty were first made publicly available. The table also includes the projected poverty rates for April 2019 to February 2020 based on the 2019 ASEC.



**Table A2: Projected SPM Rates by Month** (observed ASEC rates in bold)

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
January		15.3	15.9	16.0	15.9	15.6	15.1	14.2	13.9	13.6	12.5
February		15.2	15.8	15.9	15.9	15.5	15.1	14.1	13.7	13.6	12.4
<b>ASEC</b>	<b>15.2</b>	<b>16.0</b>	<b>16.1</b>	<b>16.0</b>	<b>15.7</b>	<b>15.3</b>	<b>14.3</b>	<b>13.9</b>	<b>13.9</b>	<b>13.6</b>	
April	15	15.8	15.9	15.9	15.5	15.1	14.2	13.8	13.7	12.6*	
May	15	15.8	15.9	15.8	15.5	15.0	14.2	13.7	13.6	12.6	
June	15.1	15.9	15.9	15.9	15.5	15.1	14.2	13.8	13.7	12.7	
July	15.1	16.0	16.0	16.0	15.6	15.1	14.2	13.7	13.7	12.6	
August	15.1	15.9	16.0	16.0	15.6	15.1	14.3	13.8	13.8	12.6	
September	15.1	15.8	15.9	15.9	15.6	15.3	14.2	13.8	13.7	12.5	
October	15.2	15.8	16.0	15.9	15.6	15.2	14.3	13.7	13.7	12.5	
November	15.2	15.8	16.0	15.9	15.6	15.2	14.3	13.8	13.6	12.5	
December	15.2	15.8	16.0	15.9	15.6	15.1	14.2	13.8	13.6	12.5	
Apr – Feb		15.14	15.85	15.95	15.88	15.57	15.12	14.23	13.77	13.66	12.54
<b>ASEC</b>		15.96	16.09	16.00	15.66	15.28	14.35	13.94	13.91	13.63	
<i>Difference</i>		<b>-0.82</b>	<b>-0.23</b>	<b>-0.05</b>	<b>0.22</b>	<b>0.29</b>	<b>0.78</b>	<b>0.29</b>	<b>-0.14</b>	<b>0.03</b>	

Note: \*Census attributes a 0.9 p.p. difference between ASEC 2019 and subsequent monthly files to change in processing system. ASEC = Observed poverty rate from annual ASEC file. Monthly estimates based on estimation procedure presented in Equation (1)

Table 2 shows that for seven of the nine years in which monthly estimates of poverty can be compared to subsequent ASEC poverty rates, the differences in estimates are not statistically significant. The two exceptions are 2011 and 2016. In 2011, the mean of the monthly poverty rates comes in at eight-tenths of a percentage point lower than the observed ASEC. In 2016, the mean of the monthlies is eight-tenths of a percentage point higher. These differences could be a product of policy changes during the given years (see note before on how changes to income transfer policies during the year could affect the efficacy of the model), of changes to Census sampling procedures (as in 2019), or of measurement error. As noted earlier, this brief is our first effort at producing monthly forecasts, and we seek to continuously improve the forecasting going forward.

Note that with the 2019 ASEC, the Census Bureau switched to a new sampling and data processing system. These changes contribute to a mechanical reduction in poverty rates of around 0.9 percentage points. In Table A2, we have added those 0.9 percentage points to the 2019 ASEC estimate to facilitate reliable comparison with the prior year’s monthlies. This change, however, means that monthly poverty rates from April 2019 to February 2020 must be compared to prior months and years with caution. Using the methods introduced in this section, we estimate that the SPM poverty rate as of February 2020 is 12.4 percent.

## **Appendix B: Simulation Methods for Forecasting Current and Future Rates of Poverty**

Appendix A presented our strategy for using monthly CPS files to produce updated estimates of SPM poverty throughout a given year. Appendix B builds on this approach to discuss how we use the latest monthly estimates (i.e. February 2020) to forecast estimates of annual poverty rates given inputted assumptions of changes in employment.

Our primary simulation estimates poverty rates based on an unemployment rate of 30 percent, close to a projection of quarterly unemployment rates from the Federal Reserve. We also produce estimates for two alternative scenarios: a 10 percent unemployment rate and 20 percent unemployment rate. For context, 10 percent is approximately the unemployment rate observed at the peak of the Great Recession in 2010. We project poverty rates under scenarios in which, first, the unemployment rates persist throughout the year and, second, the unemployment rates last for one quarter before a subsequent recovery in employment rates.

### *Adjusting Employment Rates & Hours Worked*

Recent reports from state government on UI claims suggest that employment losses in the past month have been concentrated in the following industries: services (accommodation, food services, and other services); arts, entertainment, and recreation; transportation and warehousing; educational services; retail and wholesale trade. In our simulations, we concentrate employment losses in these industries. Specifically, we assign 85 percent of the projected employment losses to occur within these industries, and 15 percent of the projected employment losses from all other industries. We then select the employed adults within these industries to be sent to unemployment until our target rate of unemployment is reached. Rather than randomly selecting the employed-to-unemployed movers, we weigh the group according to the racial composition of the unemployed in 2010, the peak of the Great Recession. In practice, this leads to an increase in non-white workers being sent to unemployment relative to a simulation in which we randomly select the transition group without weighing by race/ethnicity. That racial/ethnic minorities would be disproportionately affected is consistent with evidence of employment transitions from prior recessions. We set the duration of unemployment to 13 weeks in our quarterly unemployment simulations, and one year for our annual employment simulations.

Evidence from prior recessions suggests that reductions in employment occur not only on the extensive margin (employment rates), but also on the intensive margin (hours worked among the employed). Thus, among individuals in these industries who remain employed after our simulations, we reduce the hours worked of the employed until the means of two weekly hours-worked bins (0-30 and 31-40+) for each industry match the means from 2010, the peak of the most recent economic crisis.

After adjusting the employment and hours status of the individuals, we re-create the indicators of employment to be included on our models of poverty: household employment rates, household work intensity, and mean duration of unemployment.

### *Addressing the Composition of the Unemployed*

Our estimation strategy borrows the relationship between household employment (and all other included covariates) and SPM poverty from the latest ASEC file to compute current poverty rates in the monthly CPS files. An assumption underlying this strategy is that the relationship between household employment and SPM poverty will not meaningfully change from month to month. In the present simulation, this assumption is likely to be violated if the composition of the unemployed in February 2020 (when national unemployment rates were under 4 percent) is notably different from the composition of the unemployed in a scenario in which unemployment increase to 10, 20, or 30 percent.

We incorporate two adjustments to improve the model's treatment of the newly unemployed. First, for each of the seven family types included our estimation strategy (see [Appendix A](#)), we reweight the newly-unemployed individuals to match the distribution of the categorical family income bins of their already-jobless counterparts. In practice, this reweighting approach acknowledges that those simulated to unemployment will experience a loss in family income and have a higher likelihood of poverty. Second, we include a broad range of interaction effects in our estimation of current poverty rates to account for the heterogeneous effects of household employment on poverty across several comparatively-stable covariates: family structure, number of children in the household, duration of unemployment, number of working-age adults in the household, by race/ethnicity of the household head, and age of the household head. As a result, our model takes into account that household (un)employment might lead to a different likelihood of poverty for different groups of individuals.

### *Forecasting Estimates of Poverty Rates*

After applying the changes in employment described above to our February 2020 sample, we have what we refer to as our *forecasted sample* with our projected changes in unemployment. To produce estimates of poverty for our forecasted sample, we follow a similar approach described in producing our February 2020 estimates; however, rather than importing the composition of the February 2020 sample into the CPS ASEC, we now export the coefficients from a model of SPM poverty in the ASEC to our forecasted sample. Specifically, we estimate a model predicting SPM poverty status in the ASEC sample using the covariates described before, as well as the (un)employment interactions described in the prior section. We then export these coefficients to our forecasted sample to produce a current estimate of poverty.

### *Validation Checks*

The validation checks presented in Appendix A demonstrate that our method for producing monthly updates to the SPM appear to be largely reliable. However, these monthly updates use demographic and employment information provided in the monthly CPS samples. In contrast, our projections of forecasted poverty rates rely on inputted assumptions of changes in employment rates. We lack “true” estimates of poverty under our simulated unemployment rates to cross-check our projected poverty rates, which is exactly the point of the exercise. We thus compare the relationship between our simulated annual unemployment rates and projected poverty rates to same relationship from the prior 20 years of data. Specifically, we ask: do our projected poverty rates at 10, 20, and 30 percent unemployment rates align with the relationship of unemployment and poverty rate from prior years? [Figure 4](#), presented in the main part of this document, shows the bivariate relationship between SPM poverty (Y-axis) and the log of unemployment rates (X-axis) for the given year. As discussed, our projected poverty rates align closely with expectations given the relationship between the log of employment and poverty in prior years.

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