Monthly Poverty Rates in the United States during the COVID-19 Pandemic

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**Abstract:** Official poverty estimates for the United States are presented annually, based on a family unit’s annual resources, and reported with a considerable lag. This study introduces a framework to produce monthly estimates of the Supplemental Poverty Measure, based on a family unit’s monthly income, with a two-week lag. We argue that a shorter accounting period and more timely estimates of poverty better account for intra-year income volatility and better inform the public of current economic conditions. Our framework uses two versions of the Current Population Survey to estimate monthly poverty given observed changes in demographic and labor market characteristics. Validation tests demonstrate that our monthly estimates of poverty closely align with observed trends in the Survey of Income & Program Participation from 2004 to 2016 and trends in well-being during the COVID-19 pandemic. We apply the framework to calculate trends in monthly poverty from January 1994 through December 2020. We find that monthly poverty rates generally declined in the 1990s, increased throughout the 2000s, and declined after the Great Recession through the onset of the COVID-19 pandemic. Within-year variation in monthly poverty rates, however, has generally increased, and among families with children, within-year variation in monthly poverty rates is comparable to between-year variation. This is largely due to the average family with children receiving 37 percent of its annual income transfers in a single month through one-time tax credit payments. Moving forward, researchers can apply our framework to produce monthly poverty rates whenever more timely estimates are desired.

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INTRODUCTION

Official estimates of poverty rates in the United States (U.S.) are presented on an annual basis and with a considerable lag. Poverty estimates for the 2019 calendar year, for example, will be the most recent official estimates from the U.S. Census Bureau until autumn 2021.

Moreover, official estimates of poverty are based on a family unit’s annual income. This study argues that a shorter income accounting period and a more timely release of poverty estimates (1) better measure the month-to-month volatility of poverty that many families experience, (2) provide policymakers and scholars real-time data on socio-economic conditions to guide their policy response, and (3) can serve as a useful supplement to annual estimates of poverty.1 We introduce a framework to estimate monthly updates of poverty based on families’ monthly incomes released with a two-week lag time. The framework can also incorporate the introduction of, or changes to, income support programs to produce close-to-real-time estimates of monthly poverty.

Though a 12-month income account period is the norm in the U.S. and abroad when measuring poverty, two sources of high- and rising-income volatility warrant the introduction of a monthly measure of poverty as a supplement to the annual measure of poverty. First, even prior to the COVID-19 pandemic, month-to-month volatility in labor market earnings was particularly high among lower-wage workers (Bania & Leete, 2009; Hill et al., 2017; LaBriola & Schneider, 2020; Morris et al., 2015). Second, we provide evidence that the U.S. tax and transfer system is itself a source of intra-year income volatility. Specifically, we demonstrate that the average family with children receiving income support in 2018 received more than a third of those transfers in a single month through a one-time tax credit payment.

1 We use the term “families” in this study to refer broadly to family units (the measurement unit for assessing the pooling of resources when measuring poverty), regardless of whether children are present in the family unit. We specifically refer to “families with children” when noting results specific to such units.
Given the intra-year volatility in earnings and income from transfers, a focus on annual income when measuring poverty may increasingly mispresent how individuals in the U.S. experience poverty. This became particularly evident in the midst of the COVID-19 pandemic, when rapid rates of job loss and large intra-year volatility in income transfers contributed to large month-to-month variation in living conditions (Bitler et al., 2020; Gassman-Pines & Gennetian, 2020; Han et al., 2020; Parolin, Curran, Matsudaira, et al., 2020; Raifman et al., 2021).

We thus develop a monthly poverty measure following the Supplemental Poverty Measure (SPM) framework using both the U.S. Current Population Survey’s Annual Social and Economic Supplemental (CPS ASEC) and basic monthly files. The CPS ASEC includes annual income components, but also features considerable information to convert most income components to their likely monthly values. The monthly files do not provide comprehensive data on family units’ incomes, but do provide monthly updates of demographic and employment conditions. We apply combined-sample multiple imputation (CSMI) techniques to export the association of observable characteristics and poverty in the ASEC to the updated composition and labor market characteristics of the monthly files. We present a series of validation tests to evaluate the usefulness of a poverty measure based on monthly income and evaluate the likely accuracy of our monthly poverty projections. We find, for example, that our monthly poverty estimates closely align with observed rates of monthly poverty from the Survey of Income & Program Participation (SIPP) from 2004 through 2016, and that our monthly poverty estimates are strongly, positively associated with rates of hardship and well-being during the COVID-19 pandemic.

Our work offers three primary contributions to the demography, poverty, and social policy literatures. First, this study advances the conceptual case for a measure of poverty based on monthly income as a supplement to measures of poverty based on annual income.
We find, for example, that within-year variation in monthly poverty rates is comparable to between-year variation in annual poverty rates for families with children between 1994 and 2019. Second, from an empirical perspective, our monthly updates of poverty estimates serve as timely indicators that can track the economic insecurity of families in the U.S. on a regular basis. We present trends in monthly poverty rates from January 1994 through December 2020, for example, the latter months coming after the onset of the COVID-19 pandemic. Third, our framework is flexible in that it can incorporate specified changes to tax and transfer programs that occur throughout the year (as well as hypothetical changes to project the potential impact of proposed policy changes). We demonstrate this feature through the integration of the Economic Impact Payments (EIPs, or stimulus checks) and expansions to unemployment benefits passed within the CARES Act of March 2020.

Though the framework introduced in this study is particularly timely given the context of the COVID-19 pandemic, we emphasize that it carries relevance beyond the present crisis and can be applied in any circumstance moving forward when more timely estimates of poverty rates are needed.

BACKGROUND

The Usefulness of Poverty Indicators

Poverty rates have long been recognized as a useful indicator of economic performance and, more specifically, of levels of financial insecurity and/or destitution facing families (Atkinson, 1998; Citro & Michael, 1995; Fox, 2020; National Academy of Sciences, 2019; O'Connor, 2001). Conceptually, living in poverty indicates that a given family (or resource-sharing unit) lives with resources that fall short of an agreed-upon needs standard. Though scholars often debate the most appropriate measure of “resources” or “needs,” there exists general consensus that individuals living in poverty tend to face more challenges in consuming basic necessities, greater likelihood of food insecurity and material hardship,
lower levels of subjective wellbeing, more health challenges, and other adverse outcomes (National Academy of Sciences, 2019). Moreover, experiencing poverty during childhood is associated with reduced health, learning, and social mobility outcomes (Aber et al., 1997; Brooks-Gunn & Duncan, 1997; Chaudry & Wimer, 2016; Duncan et al., 1998; National Academy of Sciences, 2019). Given these concerns, researchers, policymakers, and the general public tend to value low and declining rates of poverty.

Official estimates of poverty in the U.S. have traditionally applied the official poverty measure (OPM). Introduced in the 1960s, the OPM threshold was based on the cost of a minimum food diet in 1963 and updated each subsequent year for inflation (Fox & Renwick, 2016; Iceland, 2013; Ruggles, 1990). The OPM uses a pre-tax definition of family resources that excludes near-cash transfers. This means that transfers from programs such as the Supplemental Nutrition Assistance Program (SNAP) and the Earned Income Tax Credit (EITC) are not included. SNAP and the EITC, however, have emerged in recent decades as two of the largest anti-poverty programs in the U.S. (Internal Revenue Service, 2019; U.S. Department of Agriculture, 2017). In contrast, cash transfers from the Temporary Assistance for Needy Families (TANF) program, which are counted in the OPM income definition, have steadily declined throughout the past two decades (Floyd et al., 2017).

To address the shortcomings of the OPM, the Census Bureau began producing estimates of poverty using the Supplemental Poverty Measure (SPM) (Fox, 2020; Fox & Renwick, 2016). Four primary features distinguish the SPM from the OPM (Fox et al., 2015; Wimer et al., 2016). First, the SPM uses a more comprehensive definition of resources. In addition to including transfers from SNAP, the EITC, and other near-cash or tax-based transfers, the SPM also deducts expenditures on work, child care, and medical out-of-pocket spending from a unit’s net resources. Second, the SPM expands the definition of the family to include cohabiting partners and foster children (alongside other small changes) when
determining who in the household shares resources. Third, the SPM thresholds differ from OPM thresholds. They are derived from recent expenditures on a core bundle of goods, which includes food, clothing, shelter, and utilities, plus a little more for extra necessities. And fourth, the SPM thresholds take into account geographic differences in the cost of living, as measured through geographic differences in housing costs.

For these reasons, this study primarily adopts the SPM framework for measuring poverty. We argue, however, that a once-per-year measure of SPM poverty based on a family’s annual income will by definition miss the considerable intra-year volatility of income and poverty that many family units experience.

The Income Accounting Period

Poverty is most often measured on an annual basis according to a family unit’s annual resources. This is true not only for official measures of poverty in the U.S., but also in the European Union, Canada, Australia, and the United Kingdom (Eurostat, 2020; Francis-Devine, 2020; Parliament of Australia, 2004; Statistics Canada, 2020). The U.S. Census Bureau and its international counterparts, for example, generally release comprehensive data on income once per year with a 12-month reference period (Fox, 2020).

Annual poverty estimates have several potential advantages over shorter or longer accounting periods. Relative to shorter time periods, an annual measure may better reflect a family’s long-run consumption capabilities; families with more income over the course of a year are better able to adapt and maintain their level of wellbeing in the event of a short-term drop in income (Atkinson, 2019). Relative to longer time periods, the annual accounting period more appropriately captures economic fluctuations, such as sustained drops in income during a recession, that affect the wellbeing even of families who are, in the long run, generally well-off. Annual measures of poverty are also more computationally feasible.

Indeed, the Canberra Report on Household Income Statistics explicitly recommends a one-
year accounting period when measuring poverty, though primarily due to the convenience of annual data collection (The Canberra Group, 2001). The report writes (p. 26) that “a twelve-month reference period is the common period for which owners of small enterprises derive a measure of profit or loss for their business if they are operating within the formal sector. If income statistics are compiled from administrative records such as income tax data, the data for wage and salary earners are also likely to be only available with a twelve-month reference period.”

Despite its convenience, the 12-month accounting framework faces several limitations relative to shorter accounting periods. In the context of rapid fluctuations in economic conditions or large intra-year volatility of a family’s income, short-term measures of income and poverty may more accurately represent the level of economic insecurity that a family faces throughout the year. This is especially true for lower-income families, who may not have the resources to smooth consumption over longer periods of unemployment or income loss. A monthly accounting period, rather than annual, may more accurately reflect these families’ experience with poverty. Atkinson (2019, pp. 63-64) makes a similar argument, writing that the choice between a monthly or annual estimate of poverty depends on “the assumptions made about the effect of short-term fluctuations on the economic wellbeing of individuals and households.” If transitory declines in income tend to contribute to higher rates of hardship or lower levels of wellbeing, then an accounting period of less than a year may be warranted.2 A 1976 report on “The Measure of Poverty” from the U.S. Department of Health, Education, and Welfare’s Poverty Studies Task Force makes a similar point, noting that whether poverty is measured over “a week, month, year or lifetime, depends on the particular purpose the definition of poverty is meant to serve… [f]or designing programs which deal

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2 Likewise, a monthly poverty measure, if it more closely tracks fluctuations in hardship and wellbeing relative to an annual measure, might also better fit Peter Townsend’s (1979) conceptualization of relative deprivation (“the lack the resources to obtain the types of diet, participate in the activities and have the living conditions and amenities which are customary”).

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with emergencies or temporary low income, like temporary unemployment, a shorter accounting period is more appropriate.” In turn, this study argues that sufficiently high rates of intra-year volatility of incomes warrant a shorter accounting period for poverty measurement as a supplement to the traditional 12-month measure (Bania & Leete, 2009; Hill et al., 2017; Morris et al., 2015; Shaefer et al., 2015). Specifically, we point to two sources of rising intra-year income volatility: the labor market and the U.S. tax and transfer system. Our purpose is not to argue that monthly poverty estimates are superior to annual or longer-term time periods, but rather they are a critical supplement to such measures in that they better capture intra-year income dynamics that annual and longer-term time periods obscure.

Volatility of Earnings and Income

Studies of earnings or income volatility have often focused more on year-to-year volatility, as opposed to intra-year volatility; nonetheless, these studies consistently find that individuals at greater risk of poverty tend to experience higher rates of volatility. Foundational studies related to earnings volatility, for example, have demonstrated that year-to-year earnings volatility increased among men from the 1970s to the late 1980s, particularly among lower-educated men (Gottschalk & Moffitt, 1994). From the 1990s onward, cross-year earnings volatility remained relatively flat for the working population at large (see Moffitt (2020) for a thorough review), but has remained consistently higher among groups most vulnerable to poverty (lower-educated workers and racial/ethnic minorities, for example) (Moffitt, 2020; Ziliak et al., 2011). Recent scholarship focusing on month-to-month volatility has similarly found that lower-income individuals face particularly high rates of volatility. Morduch and Siwicki (2017) for example, find that lower-income families tend to experience several months throughout the year when their monthly income is at least 25 percent lower than their annual average monthly income. Similarly, Banic and Leete (2009) and Morris et al. (2015) find in the SIPP that intra-year income volatility is high and rising among lower-
income families with children. Focusing on working hours rather than incomes, LaBriola and Schneider (2020) find using the panel component of the CPS ASEC that low-educated workers experience high and rising rates of volatility in work hours relative to higher-educated workers. Put simply, studies using different data sources, measures of volatility, outcome variables, and temporal scopes have aligned on the conclusion that family units at higher risk of poverty are particularly likely to face higher levels of income volatility.

**Volatility of Taxes and Transfers**

Importantly, high levels of volatility are not solely a product of market outcomes; instead, the tax and transfer system is increasingly a source of month-to-month variation in income. Consider, for example, that transfers from the EITC and Child Tax Credit (CTC) are distributed in a single, lump sum payment during tax season (typically February, March, and April). Though these benefits are counted as annual income equivalent to monthly cash payments, consumption data suggest that recipients spend the benefits differently than they would if the benefits were distributed evenly throughout the year. The payments received during tax season are unlikely to sustain greater consumption throughout the end of the year (Goodman-Bacon & McGranahan, 2008; Mendenhall et al., 2012; Michelmore & Jones, 2015). In fact, research related to the receipt of SNAP, which is distributed monthly, suggests that many families struggle to sustain SNAP benefits through the end of a month, let alone a full year (Beatty et al., 2019; Bond et al., 2021; Goldin et al., 2020; Laurito & Schwartz, 2019).

Figure 1 documents the rising share of transfers composed of once-per-year lump-sum payments. Specifically, the figure shows the mean share of annual income transfers among SPM units distributed as lump-sum payments (primarily the EITC and CTC, though this also

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3 This analysis covers a time period concluding in December 2020, prior to the March 2021 passage of the American Rescue Plan Act under which the Internal Revenue Service will delivery half the Child Tax Credit in 2021 in advance monthly payments; as of the time of writing, the remainder will be delivered in a lump-sum payment at tax time in 2022 (Crandall-Hollick, 2021).
includes stimulus checks and temporary refundable tax credits introduced during the Great Recession).

**Figure 1**: Mean share of annual income transfers distributed to families in once-per-year lump-sum payments, 1980-2019

Note: Authors’ findings from the CPS ASEC. Indicator measures share of lump sum transfers (EITC, CTC, and 2008 stimulus check) relative to all income transfers (also including Social Security, TANF cash assistance, SNAP benefits, value of subsidized school lunches, housing subsidies, unemployment insurance benefits, Supplemental Security Income benefits, WIC benefits, and energy subsidies). Non-refundable portion of CTC transfers are excluded. Increase during 2008-2011 is due to distribution of one-time stimulus checks and temporary refundable tax credits as part of the American Recovery and Reinvestment Act of 2009.

Prior to the introduction of the EITC in 1975, no transfers were delivered, by design, as once-per-year lump-sum payments. After 1975, however, the mean share of transfers received as a single payment steadily increased as the EITC expanded, and as especially as the CTC was introduced (1997) and subsequently expanded. By 2018, a year in which federal legislation again increased the value of the CTC, lump-sum transfers accounted for 37 percent of total annual transfers for the average person in a family unit with children receiving any
Among all SPM units, regardless of whether children were present, the mean was 25 percent. Put differently, the average SPM unit receiving income transfers received a quarter of those transfers in a single month (generally February or March) after filing taxes.

The income supports introduced during the COVID-19 pandemic, not included in the visual above, likely added further intra-year volatility to family units’ incomes. The CARES Act, passed in March 2020, distributed one-time Economic Impact Payments (EIPs) and a $600 per week, nationally-uniform supplement to unemployment benefits to eligible recipients. However, receipt of these payments were concentrated over a four-month period, and access to both the EIPs and unemployment benefits was delayed for many applicants (Parolin, Curran, & Wimer, 2020). As a result, a family could spend multiple months in 2020 with no earnings or government income support, but subsequently receive a large level of income transfers in a single month. From an annual accounting perspective, the income transfers might lift this family above the annual poverty line. Viewed from a monthly perspective, however, it is likely that the family lacked the current resources to meet their monthly expenses while awaiting the income support. For example, those with low or no employment income – including those who had not filed recent taxes and were not otherwise connected to programs such as Veterans Assistance or the Social Security Administration – were disproportionately at risk of missing out on their EIP receipt (Zucker et al., 2020). Put simply, the U.S. welfare state, like the labor market, is an increasing source of month-to-month income volatility, strengthening the case for a shorter income accounting period when measuring poverty.

Accepting the conceptual basis for an income accounting period of shorter than 12 months, however, leads to the question of how short the income accounting period should be.

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4 Including the non-refundable portion of the CTC increases the share to 75 percent in 2019.
One could, for example, make a case for a 4-month accounting period with evidence that many low-income families smooth consumption over multiple months, even if not the entire year. We do not reject this argument, but absent current evidence on the optimal number of days over which to assess income in determining poverty status, we present a measure of poverty based on a 1-month accounting period. The monthly accounting period matches the focus of past research on the intra-year volatility of earnings and incomes and provides an appropriate contrast to the traditional poverty measures based on a 12-month accounting period (Bania & Leete, 2009; Hill et al., 2017; Morris et al., 2015). Equally important, the monthly accounting period, unlike a 4-month accounting period or similar, is possible to produce using available, timely survey data, as we discuss in more detail below.

### Timeliness of Poverty Estimates

A separate challenge relates to the timeliness of publicly-provided poverty estimates. If an estimate of poverty based on monthly income (e.g. for April 2020) is released, say, a year later (April 2021), then its usefulness in informing current economic conditions and potentially informing policy responses is greatly reduced. We argue, instead, that a particularly useful measure of monthly poverty is one that can be produced and made public in (close to) real time.

This approach differs from the Census Bureau’s current practices in releasing official estimates of poverty in the U.S. The Census produces estimates of poverty from the CPS ASEC, which is released annually and collects information on income for the prior calendar year (Fox, 2020). Poverty estimates for a given year (e.g. 2020) are thus released with a considerable lag (September of 2021). While there is no replacement for the quality and thoroughness of the Census Bureau’s data releases, policymakers, academics, and the general public would benefit from more timely estimates of socio-economic conditions. This is particularly true in times of rapid economic change. The months following the onset of the
COVID-19 pandemic, for example, clearly illustrated the need for more timely poverty estimates. As the national unemployment rate approached 20 percent in April 2020, the most recent estimates of poverty from the Census were from 2018 when the annual unemployment rate was under 4 percent (U.S. Bureau of Labor Statistics, 2021).

The central challenge in providing more-timely estimates of SPM poverty, however, is capturing month-to-month changes in demographic, labor market, and social policy conditions. In the U.S., monthly micro-data on demographic and labor market are readily available; the Census Bureau releases monthly CPS files that provide up-to-date, representative information on the demographic and labor market characteristics of the population. However, the monthly files lack detailed information on family incomes.\(^5\) As such, they cannot readily inform the extent to which taxes and transfers affect poverty rates in a given month, a central inquiry in evaluations of poverty and social policy. We argue that a particularly useful framework for projecting monthly poverty rates should, as best as possible, be able account for new or altered income support programs introduced in prior months and to evaluate the effect of these income support programs on monthly poverty rates.

The COVID-19 pandemic again provides a useful case study. In March 2020, the U.S. Congress passed the CARES Act to mitigate some of the economic consequences of the pandemic (Congressional Budget Office, 2020). Included in the CARES Act were two major expansions to income transfer programs: Economic Impact Payments (a one-time cash payment to a large share of the U.S. population) and expansions to unemployment benefits that (1) provided a $600 per week national benefit supplement for 16 weeks, (2) granted access to workers not typically eligible, and (3) extended benefit duration for an extra 13 weeks of receipt past the point at which state benefits are normally exhausted. Additional details on the core features of these income support expansions are provided in Appendix 2.

\(^5\) The only income data in the monthly files are a categorical indicator of family income from the prior year. This indicator is only asked in the respondent’s first and fifth month in the sample (25 percent of the sample).
Our framework accounts for CARES Act when estimating monthly poverty rates throughout 2020 to produce more accurate post-tax/transfer measures of poverty and to demonstrate the flexibility of our poverty estimation framework.

**DATA & METHODS**

Building on the arguments above, we propose a measure of poverty based on monthly income, released on a monthly basis, and with the ability to incorporate recent changes to income transfer programs. In an ideal data environment, comprehensive and real-time survey data would provide these indicators directly. In the absence of such data, we apply a mix of methods and data sources to compute monthly poverty estimates. We describe our methodological approach below in three parts. First, we provide a framework for producing monthly projections of families’ incomes in the CPS ASEC. This includes detail on how specified policy changes, such as the introduction of the CARES Act, can be incorporated in our framework. Second, we describe our approach for projecting monthly poverty rates in the monthly CPS files. Third, we discuss assumptions inherent within our model and present several validation tests to evaluate the potential accuracy and usefulness of our estimates.

**Monthly Estimates of Income**

Among public and nationally-representative income surveys, the Survey of Income and Program Participation (SIPP) is among the few to provide monthly and annual indicators of income and poverty for the same family units over multiple years. As such, it may seem an obvious starting point for projecting poverty rates based on monthly income. However, the SIPP data are not updated regularly (the latest data are from 2018) and do not provide the same breadth of information on sources of income, or geographic location data, as the CPS files. Thus, our framework uses two sources of CPS data: the ASEC and basic monthly files, as defined before. The ASEC is released only annually, but features all the necessary income and poverty data to identify family units in SPM poverty. The monthly files do not have the
same income and poverty information, but do feature more timely information on demographic characteristics and employment rates, to project monthly updates of poverty.

We construct our monthly poverty measure in the ASEC file. In doing so, we use the same components as in the annual SPM framework, but we convert each annual value into an estimated monthly value. To do so we, we use five sets of assumptions, detailed in Table 1, regarding the annual-to-monthly conversions of income components in the ASEC.
**Table 1: Conversion of annual income components to monthly income components**

<table>
<thead>
<tr>
<th>Components</th>
<th>Rule</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income components divided by 12 to move from annual to monthly values:</td>
<td>Divide annual values by 12 and apply to each month.</td>
</tr>
<tr>
<td>Components</td>
<td>Rule</td>
</tr>
<tr>
<td>Social Security, income from retirement, SSI, worker's compensation,</td>
<td>Divide annual values by 12 and apply to each month.</td>
</tr>
<tr>
<td>veteran's benefits, survivor's benefits, income from dividends, child</td>
<td></td>
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<tr>
<td>support, alimony, income from other sources, WIC, heating assistance,</td>
<td></td>
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<tr>
<td>housing assistance, Medical Out-Of-Pocket Expenses, state and federal</td>
<td></td>
</tr>
<tr>
<td>taxes (excluding tax refunds).</td>
<td></td>
</tr>
<tr>
<td>Income components that should be adjusted if members of SPM unit are not</td>
<td>(1) Income components are converted to zero for an individual who is</td>
</tr>
<tr>
<td>employed in the given month, but were employed in prior months:</td>
<td>unemployed for five or more weeks. For individuals unemployed for 1-4</td>
</tr>
<tr>
<td>Components</td>
<td>weeks, we pro-rate the earnings to estimate a monthly value based</td>
</tr>
<tr>
<td>(1) Income from wages, business, farm work, work-related expenses, FICA</td>
<td>on average hourly earnings and number of the weeks in the month</td>
</tr>
<tr>
<td>taxes. (2) Standard (non-CARES Act) unemployment insurance benefits.</td>
<td>employed.</td>
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<tr>
<td>(2) Convert unemployment insurance benefits to zero if the individual is</td>
<td></td>
</tr>
<tr>
<td>currently employed. If the individual is currently jobless and reports</td>
<td>(2) Convert unemployment insurance benefits to zero if the individual</td>
</tr>
<tr>
<td>receiving unemployment benefits in the prior year, we pro-rate the</td>
<td>is currently employed. If the individual is currently jobless and</td>
</tr>
<tr>
<td>benefits to match the weeks of unemployment in month (individual UI</td>
<td>reports receiving unemployment benefits in the prior year, we pro-rate</td>
</tr>
<tr>
<td>benefits / weeks of unemployment * max [weeks of unemployment, 4.3]).</td>
<td>the benefits to match the weeks of unemployment in month (individual</td>
</tr>
<tr>
<td>Income components that are only distributed in a single month:</td>
<td>UI benefits / weeks of unemployment * max [weeks of unemployment, 4.3]).</td>
</tr>
<tr>
<td>Components</td>
<td>Rule</td>
</tr>
<tr>
<td>EITC, CTC, ACTC, other refundable tax credits</td>
<td>We project the month of tax filing based on IRS data and allocate the</td>
</tr>
<tr>
<td>refundable tax credits</td>
<td>refundable tax credits accordingly in the given month. In practice,</td>
</tr>
<tr>
<td>Means-tested transfer benefits that are not typically dispersed evenly</td>
<td>this leads to the largest share of refundable tax credits being</td>
</tr>
<tr>
<td>throughout the year:</td>
<td>distributed in February and March, with the remaining benefits</td>
</tr>
<tr>
<td>Components</td>
<td>Rule</td>
</tr>
<tr>
<td>SNAP, TANF</td>
<td>Among all SPM units who report receipt of the SNAP (or TANF) in the</td>
</tr>
<tr>
<td>Education-related income support:</td>
<td>ASEC, we calculate the benefit value that family is eligible for in a</td>
</tr>
<tr>
<td>Components</td>
<td>given month based on state policy rules, family size, monthly</td>
</tr>
<tr>
<td>School lunches and income from education (including Pell Grants or other</td>
<td>earnings. If the projected benefit value is greater than one-twelfth</td>
</tr>
<tr>
<td>aid from government sources, non-governmental scholarships, and grants)</td>
<td>the annual value of SNAP (TANF) but less than the reported annual</td>
</tr>
<tr>
<td>Rule</td>
<td>SNAP (TANF) value, we set the unit’s monthly SNAP (TANF) value as the</td>
</tr>
<tr>
<td>These income components are divided by nine and applied to non-summer</td>
<td>projected benefit value. If the projected monthly benefit value is</td>
</tr>
<tr>
<td>months to account for the fact that they are typically distributed</td>
<td>greater than the reported annual value, we assign the reported annual</td>
</tr>
<tr>
<td>throughout the school year.</td>
<td>annual value as the monthly benefit (by definition, this will be</td>
</tr>
<tr>
<td>Rule</td>
<td>less than the maximum monthly benefit value). If unit reports no</td>
</tr>
<tr>
<td>no annual benefits: we give no monthly benefits, even if they appear to</td>
<td>annual benefits: we give no monthly benefits, even if they appear to</td>
</tr>
<tr>
<td>be eligible.</td>
<td>be eligible.</td>
</tr>
</tbody>
</table>

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In short, the conversions make assumptions regarding the relationship of annual-to-monthly values based on current employment status, duration of unemployment, current month, and more. For individuals who report receiving earnings from employment during the year, but report being currently unemployed for more than four weeks, we set the monthly earnings to zero (see Category 2). We distribute refundable tax credits in the month in which low-income family units are most likely to file taxes, according to IRS data (see Category 3). Prior to 2017, the largest share of refundable tax credits was received in February, followed by March and April. Since 2017, however, the IRS must hold EITC refunds until the start of March as a form of fraud prevention under the Protecting Americans from Tax Hikes (PATH) Act (Aladangady et al., 2018; Berube, 2015; Farrell et al., 2018; Maag et al., 2016). We reflect this change in our allocation of EITC and CTC benefits from 2017 onward. We only include the value of subsidized school lunches in the months in which children tend to attend schools (see Category 5).

We acknowledge that these conversion processes feature limitations and likely include some measurement error. We note, for example, that we do not have sufficient information to identify month-to-month variation in out-of-pocket medical expenses or income from dividends, two components within Category 1. An ideal data environment, as noted, would feature monthly survey (or administrative) data to provide these income measures directly. Despite these limitations, we present a series of validation tests below to corroborate the accuracy and usefulness of our approach; as discussed there, comparisons to the SIPP suggest that our framework generally performs well in accurately tracking monthly income values.

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Prior to 2017, we allocate 41.4% of EITC and CTC payments in February, 27.4% in March, and the remainder in April. After the introduction of the PATH Act in 2017, we allocate 68.8% of payments in March and the remainder in April. We assume that the eligible SPM units with the lowest market incomes are more likely to file first (i.e. February prior to 2017, March from 2017 onward). These assumptions and distributions follow data from Farrell et al. (2018) and Aladangady (2018).
We estimate a monthly poverty measure from January 1994 through December 2020. Data on the duration of unemployment is not consistently available in the monthly files prior to 1994; this explains our initial year of analysis. For our 2020 projections, we include payments from CARES Act income transfers. Unlike the conversion processes above, which adjust observed annual values to projected monthly values, the CARES Act income components must be simulated within the ASEC data. We follow the simulation framework introduced in Parolin, Curran, Matsudaira, et al. (2020). For the distribution of EIP payments (stimulus checks), we follow the distribution schedule of the Department of Treasury and their assumptions on the share of tax units receiving payments through direct deposit (earlier receipt of payments) versus receipt of check by mail (payments over several months depending on tax unit income) (U.S. Department of Treasury, 2020). This approach leads to the majority of EIP payments being distributed in April and May. We follow a conservative estimate from the Urban Institute that participation rates among the eligible were around 70 percent (Holtzblatt & Karpman, 2020). In our assignment of the benefits within the CPS ASEC, we meet the 70 percent participation target (among those eligible) by assuming that lower-income families and non-tax-filers are less likely to receive the benefits than higher-income individuals. This reflects the fact that lower-income individuals are, on average, less likely to have filed taxes and to have provided direct deposit information to the IRS.

For the CARES Act unemployment benefit expansions (PUC, PUA, and PEUC), we follow Bitler et al. (2020) in measuring the share of recently-unemployed individuals who receive unemployment benefits by taking the cumulative number of initial UI payments over the cumulative number of individuals who lost jobs from March 1, 2020 onward. We produce this participation rate by state and month using state-month data on cumulative initial UI claims and cumulative job loss. We assign the benefits in our CPS ASEC data using state-level data on the race/ethnicity and sex composition of the unemployed individuals receiving
the benefits. This information comes from The Century Foundation’s Unemployment Insurance Data Dashboard (The Century Foundation, 2021).

After converting our income components to monthly values within the ASEC, we create a binary monthly poverty indicator equal to 1 if the SPM unit’s monthly income is below one-twelfth the value of the SPM unit’s annual SPM poverty threshold. We use observed SPM thresholds from the ASEC file (i.e. 2020 poverty estimates are based on poverty thresholds observed from the 2019 ASEC), as projecting new poverty thresholds requires more timely consumption data and introduces the possibility of new sources of measurement error. Recall that SPM poverty thresholds vary based on family unit size, geographic location of residence, and whether the family unit owns or rents its residence.

**Producing Monthly Updates to Estimates of Poverty**

To produce our estimates of poverty on a monthly basis, we combine our ASEC monthly poverty estimates with up-to-date data on demographic, employment, and household characteristics from the monthly CPS files. To produce an estimate of poverty for January 2020, for example, we combine the January 2020 monthly file with the most recent ASEC file (2019). We treat the lack of poverty status in the monthly files as a missing data problem and borrow methodological tools from the statistics literature for imputing the missing data. Specifically, we apply combined-sample multiple imputation (CSMI), a “data fusion” technique commonly applied in the statistics and social science literatures (Capps et al., 2018; Rendall et al., 2013; Royston, 2004; Schafer, 1999; Van Hook et al., 2015). Here, we apply the method to estimate poverty status in the monthly CPS files. To apply the CSMI, we merge the two samples and construct a common set of indicators that are likely to be useful in estimating a family unit’s poverty status. Table 2 provides the list of indicators.
Table 2: Overview of indicators included in imputation models

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Operationalization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>Five-year age bins from 0 to 85</td>
</tr>
<tr>
<td>Sex</td>
<td>Female or male</td>
</tr>
<tr>
<td>Education</td>
<td>Low (high school degree or less), medium (more than high school, less than college), or high (college degree) level of education</td>
</tr>
<tr>
<td>Race/Ethnicity</td>
<td>Indicators for White, Black, Asian, Hispanic, or Other race/ethnicity</td>
</tr>
<tr>
<td>Citizenship &amp; Origin</td>
<td>Indicators for citizenship and whether born outside U.S.</td>
</tr>
<tr>
<td>Family Structure</td>
<td>Family structure: dummies for single with no kids, single with kids, two adults with no kids, two adults with kids, three or more adults with no kids, three or more adults with kids, retirement-age adults only; indicator of whether more than one family lives in unit; count variables of number of working-age adults in unit, number of individuals age 65+ in unit, number of children in unit (top-coded at 5)</td>
</tr>
<tr>
<td>Marital Status</td>
<td>Indicator of whether head of family unit is currently married</td>
</tr>
<tr>
<td>Employment</td>
<td>Indicators of share of working-age adults in household currently employed; whether in labor force; indicator of 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 for employed adults (11 binary indicators, including an indicator for non-employed)</td>
</tr>
<tr>
<td>Unemployment</td>
<td>Number of weeks unemployed, set to zero if not unemployed</td>
</tr>
<tr>
<td>Disability Status</td>
<td>Indicator of whether at least one working-age person in the unit has any physical or cognitive disability related to hearing, vision, difficulty remembering, physical difficulty, personal care limitation or disability limiting mobility</td>
</tr>
<tr>
<td>State of Residence</td>
<td>Dummy variables for all states</td>
</tr>
<tr>
<td>Metropolitan Central City Status</td>
<td>Indicators of whether unit is not in metro area, is in central city, is outside central city, if central city status is unknown (but in metro area), or if metro status is missing/unknown</td>
</tr>
<tr>
<td>Interaction Terms</td>
<td>Interactions of household employment rate with: household work intensity; duration of unemployment; household type; household education, age, sex, race/ethnicity, disability, and citizenship characteristics; and state of residence. Additional interactions of duration of unemployment with: household type; household education, age, sex, race/ethnicity, disability, and citizenship characteristics; and state of residence. Additional interactions of household work intensity with household type; and household education, age, sex, race/ethnicity, disability, and citizenship characteristics.</td>
</tr>
</tbody>
</table>

Note: All indicators, except unit-level count variables (number of children in unit, number of weeks unemployed, etc.), are operationalized as mean values at the family-unit level to ensure that each family unit receives the same predicted likelihood of poverty.

We then apply multiple imputation using chained equations to estimate SPM poverty status in the monthly data. In addition to the indicators identified in Table 2, we apply a large number of interaction effects to increase the predictive power of the model. The CSMI estimates run 10 iterations of the model. We take the mean of 10 separate imputations to

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compute the likelihood of poverty for each family unit and, in turn, an average poverty rate for the country as a whole. Results are robust when using an alternative approach that estimates the conditional likelihood of poverty using logistic regression in the ASEC and subsequently producing out-of-sample predictions in the basic monthly files.

**Assumptions and Validation Tests**

Our framework relies on an assumption that the conditional likelihood of poverty for a family unit with a given set of observable characteristics will remain constant from one year to the next. The primary mechanism through which this assumption can be violated is through the introduction of new income transfers that alter the association between, say, unemployment and the likelihood of poverty. As one example, the $600 per week unemployment benefits introduced in March 2020 will have reduced the association between unemployment and poverty among recipients of the benefits. If we were not to account for such transfers, our framework would overstate the likelihood of poverty for unemployed adults, as it would assume the conditional likelihood of poverty had not changed from 2019. However, our framework simulates these new policies in the ASEC and thus explicitly accounts for their effects on poverty.

Nonetheless, we present four validation tests to evaluate the potential accuracy of our framework. First, we provide evidence that our process for converting SNAP benefits and earnings from annual to monthly values in the ASEC closely aligns with observed means from the SIPP (see Appendix I, Figure A1). Specifically, we compare the annual means of monthly SNAP benefits and earnings from the SIPP to our projections in the ASEC. The SIPP and ASEC trends evolve in parallel; SNAP benefits rise during the Great Recession, for example, and subsequently fall during the recovery in both samples, with levels largely overlapping.
Second, we perform a Kitigawa-Oaxaca-Blinder (KOB) analysis within the SIPP to estimate the extent to which observed month-to-month changes in OPM poverty from 2007 through 2010 can be attributed to changes in demographic and labor market composition (as opposed to unexplained effects, or the coefficients in the KOB models). This analysis relates directly to the assumption noted above that, given a fixed set of policy rules, changes in monthly poverty can be wholly explained by changes in the share of the population in the various demographic and labor market statuses described in Table 2. Indeed, as documented in Figure A2, changes in composition (or the endowments within the KOB framework) explain nearly all of the observed change in poverty from 2007 through 2010 in the SIPP. That these findings hold during the onset of the Great Recession adds confidence that our framework can perform well in the context of the COVID-19 pandemic or other periods of rapid economic change.

Third, building on the prior two tests, we apply our framework to project monthly OPM poverty rates in the ASEC from January 2004 through December 2016 and compare our projections to observed estimates from the SIPP. As visualized in Figure 2, our projections closely align with levels and trends observed in the SIPP (r=0.87 across all months). The mean difference between the SIPP estimates and ASEC projections is 0.2 percentage points (smaller than the range of the confidence intervals in any month); the largest difference is 1.4 percentage points in May 2008, the first month of the 2008 SIPP wave. In short, the initial three validation tests provide confidence that our framework generally performs well in producing monthly projections of OPM poverty that align with observed estimates in the SIPP.

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7 We assess the OPM rather than the SPM here as the SIPP does not include measures of the latter.

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Figure 2: Monthly OPM poverty rate observed in the SIPP and projected in the CPS (2004-2016)

Note: SIPP data missing from January 2008 to April 2008. R = 0.87 among SIPP and ASEC estimates.

Given that the SIPP does not feature estimates of monthly SPM poverty, which our primary framework uses, we add one additional validation test to evaluate whether our estimates of monthly SPM poverty in 2020 align with alternative indicators of material hardship or economic well-being in 2020. Specifically, we compare state-month means of monthly SPM poverty, as projected using our framework, with state-month means of (1) food insufficiency, (2) missed rent or mortgage payments, (3) feelings of anxiety, (4) feeling down, (5) lacking interest, and (6) frequent worrying as observed within the Census Household Pulse Survey (CHPS). The CHPS was introduced in April 2020 to collect regular estimates of material hardship, economic insecurity, and other indicators of interest. We provide more information on the survey, as well as precise wording for each of the well-being indicators, in Appendix 4.
Figure 2 presents the bivariate correlations of state-level means of our monthly SPM poverty rates with state-level means of the well-being indicators from April to December 2020.

**Figure 3:** Correlation of mean state-level monthly SPM poverty rate (April-December 2020) and mean state-levels of food insufficiency, missed/delayed rent payments, frequent anxiety, feeling down, lacking interest, and frequent worrying (April-December 2020)

The results demonstrate that our monthly estimates align closely with each of these indicators. Put differently, states with higher means of monthly poverty rates in 2020 also tend to feature higher rates of food insufficiency ($r=0.62$), missed or rent mortgage payments ($r=0.48$), feelings of frequent anxiety ($r=0.44$), feelings of being down ($r=0.42$), feelings of lacking interest ($r=0.48$), and feelings of frequent worrying ($r=0.54$). While Figure 1 provides cross-state correlations, Table 3 summarizes the within-state (over time) associations of our monthly SPM poverty indicator and the well-being indicators. The associations are measured here as the log-log relationship from a simple OLS estimate regressing state-month means of
monthly poverty on state-month means of well-being from April to December 2020 with state fixed effects included.

**Table 3:** Within-state associations of monthly SPM poverty rates with well-being indicators from the Census Household Pulse Survey (April to December 2020)

<table>
<thead>
<tr>
<th></th>
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<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Insufficiency</td>
<td>32.4%</td>
<td>-67.0%</td>
<td>-80.0%</td>
<td>-6.9%</td>
</tr>
<tr>
<td>Missed Rent/Mortgage</td>
<td>-18.9%</td>
<td>-9.8%</td>
<td>-22.3%</td>
<td>53.9%</td>
</tr>
<tr>
<td>Anxious</td>
<td>24.3%</td>
<td>-43.5%</td>
<td>-56.7%</td>
<td>-10.7%</td>
</tr>
<tr>
<td>Down</td>
<td>25.1%</td>
<td>-43.4%</td>
<td>-72.1%</td>
<td>14.3%</td>
</tr>
<tr>
<td>Lacking Interest</td>
<td>20.0%</td>
<td>-42.4%</td>
<td>-59.6%</td>
<td>15.6%</td>
</tr>
<tr>
<td>Frequent Worrying</td>
<td>29.7%</td>
<td>-38.6%</td>
<td>-62.6%</td>
<td>4.0%</td>
</tr>
</tbody>
</table>

Note: Associations represent coefficients from OLS estimate regressing log of state-level mean of well-being indicator on log of state-level mean of SPM poverty rates from April through December 2020 (n= 459, or 50 states + DC over 9 months) including state dummies.

Table 3 shows that within-state variation in our monthly SPM poverty measure (which includes the CARES Act income support) is positively associated with within-state variation in five of the six well-being indicators (the one exception being missed rent or mortgage payments). Notably, our primary measure of monthly poverty features a stronger, positive association than a measure of monthly poverty that excludes the CARES Act income support (Column 2), a measure that excludes all taxes and transfers (Column 3), and a measure of a state’s non-employment rate (the one exception again being missed rent/mortgage payments). While poverty, material hardship, and well-being are conceptually distinct (Atkinson, 2019; Nolan & Whelan, 2011), the stronger association of our measure of monthly poverty with the CHPS indicators nonetheless provides further confidence of the usefulness and potential accuracy of our framework. We now turn toward our projection of trends in monthly SPM poverty.

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8 The mismatch between poverty and missed rent or mortgage payments may be attributable to the eviction moratorium in place much of 2020.

9 The non-employment rate is defined as 1 minus the state’s employment rate (the share of all adults between age 18 and 65 who are employed). State-month estimates of non-employment are estimated from the basic monthly CPS files. Results are similar if we use the state-month unemployment rate instead.
FINDINGS

We first present trends in the monthly SPM poverty rate for 2019 to illustrate the “typical” month-to-month variation in poverty rates revealed by our framework. We then present an analysis of long-run trends in monthly poverty (1994 through 2019), and then show estimates of monthly poverty in 2020, the year of the onset of the COVID-19 pandemic.

Figure 4: Trends in Monthly SPM Poverty in 2019

Figure 4 displays monthly poverty rates for each month in 2019 for the full population. The solid black line includes all taxes and transfers, whereas the dashed gray line represents the pre-tax/transfer measure. In January 2019, we estimate that 30.2 percent of all individuals lived with pre-tax/transfer incomes below the monthly poverty threshold, and 15.8 percent when accounting for taxes and transfers. In March, a month in which a large share of refundable tax credits is administered, the monthly poverty rate falls to 12 percent, its lowest value of the year. April remains low compared to other months (13.9 percent) for similar
reasons. In the summer months, however, the poverty rate rises to up to 16.9 percent in August. Recall that our framework does not include education-related income support, including the value of subsidized school lunches, during June through August given that most students are not attending schools during these months. By December 2019, the monthly poverty rate falls to 15.2 percent, slightly lower than the January 2019 rate. This decline can largely be attributed to the decline in the pre-tax/transfer poverty rate, which fell to 29.6 percent in December 2019.

**Historical Trends in Monthly Poverty**

**Figure 5:** Trends in Monthly SPM Poverty, 1994 to 2019

Note: Lowest point estimates in monthly SPM poverty measure largely represent monthly reductions in poverty upon receipt of once-per-year refundable tax credits.

Figure 5 places the 2019 estimates into historical context. Specifically, the figure visualizes the monthly poverty rate from January 1994 through December 2019. In broad terms, the monthly poverty rates declined from 1994 through the early 2000s, then
subsequently increased, particularly during the Great Recession. From January 2007 to August 2011, for example, the monthly poverty rate climbed from 16.9 percent to 22.8 percent. From 2011 through 2019, however, poverty rates gradually declined and reached 15.2 percent by December 2019 (compared to a rate of 22.2 in January 1994).

Switching focus from levels to volatility, the pre-tax/transfer measure (gray triangles) clearly shows less \textit{intra-year} volatility relative to the post-tax/transfer measure (black circles). However, the pre-tax/transfer measure does feature more \textit{between-year} variation relative to the post-tax/transfer measure. During the Great Recession, for example, the pre-tax/transfer measure increases from around 28 percent in May 2008 to 36 percent in January 2011, an increase of 8 percentage points. The increase is unsurprising given the decline in employment rates that occurred during those years. The monthly SPM rate that includes transfers, however, does not increase at the same rate during this timeframe, reflecting the role of increases in income transfers in preventing further increases in poverty (Bitler et al., 2017). From May 2008 to January 2011, the monthly SPM poverty rate rises to 17.3 percent to 21.7 percent, an increase of 4.4 percentage points.

That said, the monthly poverty rate does vary considerably across months \textit{within} years, attributable primarily to the lump-sum provision of many income transfers (i.e. Figure 1). From 1994 through 2019, the intra-year range (maximum value minus minimum value) in monthly poverty rates varied from a low of 2.8 percentage points in 2005 to 5.1 percentage points in 2011; the mean intra-year range from 1994 through 2019 was 3.7 percentage points. This is around two-thirds the value of the range of \textit{between-year} means in monthly poverty, which is 5.8 percentage points between 1994 to 2019 (ranging from a high of 21 percent in 1994 to a low of 15.2 percent in 2019).\footnote{Results are similar when measuring variation using the coefficient of variation (COV). The mean within-year variation using the COV is 0.07 and between-year variation is 0.10.}

10 Results are similar when measuring variation using the coefficient of variation (COV). The mean within-year variation using the COV is 0.07 and between-year variation is 0.10.
The figure above looks at the population as a whole. Given that refundable tax credits through the EITC and CTC are concentrated among family units with children, however, between- and within-year differences in poverty may vary for units with and without children. Figure 6 thus presents trends in our post-tax/transfer measure of monthly SPM poverty over the same time period, but segmented by family type.

**Figure 6:** Monthly SPM Poverty Rates by Family Type (all taxes and transfers included)

Notable findings stand out. First, levels of poverty are consistently higher among families with children, except in the months in which the EITC and CTC are distributed. From 1996 onward, families with children experience lower or comparable poverty rates relative to childless families during tax season (February and March), yet feature higher poverty rates in

Note: Low point estimates in monthly SPM poverty measure for family units with children largely represent monthly reductions in poverty upon receipt of once-per-year refundable tax credits.

The black circles represent the monthly poverty rate among family units with children, while the gray triangles represent the monthly poverty rate among childless families. Two notable findings stand out. First, levels of poverty are consistently higher among families with children, except in the months in which the EITC and CTC are distributed. From 1996 onward, families with children experience lower or comparable poverty rates relative to childless families during tax season (February and March), yet feature higher poverty rates in

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nearly every other month. This is consistent with evidence from annual poverty rates that finds that refundable tax credits are the largest poverty-reduction transfers for families with children (Fox, 2020).

Second, and relatedly, the intra-year volatility of poverty rates clearly varies for families with and without children. Among families with children, the mean within-year range in monthly poverty rates (maximum minus minimum poverty rate in a year) is 7 percentage points. In contrast, the between-year range is 8 percentage points. Put simply, families with children experience similar levels of intra-year variation in monthly poverty rates relative to between-year variation in monthly poverty rates over the period of 1994 through 2019. Families without children, in contrast, do not. Their mean within-year range in monthly poverty rates is 1.3 percentage points, while their between-year range is 5.1 percentage points. Childless families thus not only feature lower between-year variation in monthly poverty relative to families with children, but also feature a mean within-year range of monthly poverty rates that is around 19 percent (1.3 p.p. / 7 p.p.) of the rate experienced by families with children.

**Trends in Monthly Poverty in 2020**

The estimates presented in Figures 4 to 6 all use observed distributions of income transfers from the given year’s ASEC files. A useful addition to our framework, however, is its ability to project more-recent estimates of monthly poverty while incorporating new or altered income support programs, such as those introduced in the CARES Act. Figure 7 visualizes estimates of 2020 poverty with and without the CARES Act’s income supports.

Specifically, Figure 7 shows that the monthly poverty rate in January and February 2020 was similar to the rates observed at the end of 2019 (see Figures 4 and 5). The COVID-

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11 Results are similar when measuring variation using the coefficient of variation (COV). The mean within-year variation for families with children is 0.11 compared to between-year variation of 0.12. For families without children, the within-year variation is 0.03 and between-year variation is 0.10.
19 pandemic began to affect employment rates in March 2020, though produced its largest consequences for employment rates in April. The April 2020 unemployment rate increased to around 15 percent (or up to 19 percent when accounting for misclassification errors, see U.S. Bureau of Labor Statistics (2021)), the highest rate observed in the U.S. since the Great Depression. As a result, the pre-tax/transfer poverty rate climbed to 37.5 percent in April, the highest rate observed since at least 1994 (see Figure 3).

**Figure 7**: Projected trends in monthly SPM poverty rates in 2020

Note: The large distribution of EITC benefits in March largely accounts for the observed drop in that month. Prior to accounting for the EITC, the pre-CARES monthly SPM rate was 16.1 percent in March and 21.4 percent in April. The CARES Act’s Economic Impact Payments and expanded unemployment benefits (see Appendix 2) account for the declines from April through July, when the Pandemic Unemployment Compensation expired. Pandemic Unemployment Assistance primarily accounts for the declines from August through December.

The monthly poverty rate that includes pre-pandemic income transfers but excludes the CARES Act (see solid black line) likewise increased; from January to May 2020, this pre-CARES Act monthly poverty rate increased from 15.5 percent to 19.9 percent. Accounting for...
the CARES Act income transfers (the EIPs and expanded unemployment benefits), however, alters the trends. From January to April 2020, the monthly poverty rate accounting for all transfers declined from 15.5 percent to 13.9 percent. In April, CARES Act transfers reduced the poverty rate by around 5.6 percentage points; put differently, the income support lifted around 18 million individuals out of poverty, our estimates suggest. These results are consistent with studies using alternative approaches to assess the influence of the CARES Act on poverty rates (Giannarelli et al., 2020; Han et al., 2020).\textsuperscript{12}

In June and July 2020, however, the post-CARES Act poverty rates began to rise despite the pre-CARES rates declining slightly. The reduced poverty reduction effect of the CARES Act from mid-summer on is largely attributable to the fact that the majority of stimulus checks had already been distributed by this time. As such, the June and July poverty rates climbed to around 16 percent, higher than pre-crisis levels, even when taking the CARES Act’s $600 per week unemployment supplement into account.

At the end of July, the $600 per week unemployment supplement expired.\textsuperscript{13} Rising employment rates contributed to a decline in the pre-CARES poverty rate from July to September, but the post-CARES poverty rate nonetheless increased to 16.7 percent. In September, the CARES Act contributed only to a 1.3 percentage point reduction in poverty rates, primarily through the CARES Act’s expansion of unemployment benefits to individuals who might not have qualified in the past (i.e., the Pandemic Unemployment Assistance program). Put differently, the CARES Act only lifted around 4.3 million individuals out of poverty in September, down from 18 million in April. Thus, while the combination of the stimulus checks and $600 per week unemployment supplements appear to have blunted the

\textsuperscript{12} These alternative approaches to estimating poverty rates in the pandemic use an annual income framework and thus are not directly comparable to our monthly estimates.

\textsuperscript{13} Our analysis does not include short-term unemployment benefits that may have been delivered through the Lost Wages Assistance program, part of the Presidential Memoranda issued in August 2020 that directed the Federal Emergency Management Agency (FEMA) to provide disaster relief funds for a temporary COVID-19-related lost wages payment fund. See Parolin, Curran, Matsudaira, Waldfogel, & Wimer (2020).
rise in poverty in April and May, their expiration subsequently contributed to a rise in poverty throughout the summer and autumn. In December 2020, the monthly poverty rate was 16.1 percent when including the CARES Act, 0.6 percentage points higher than observed rate in January 2020. In Appendix 3, we also present trends in 2020 poverty rates (with all transfers and the CARES Act included) by age group and by race/ethnicity.

**DISCUSSION & CONCLUSION**

Official estimates of poverty are produced annually, focus on annual income, and are released to the public with a considerable lag. This study, in contrast, introduces a framework to estimate monthly estimates of poverty based on a family unit’s monthly income. Combining the ASEC and basic monthly versions of the CPS, our framework produces close-to-real-time estimates of monthly poverty rates. Validation tests show that our estimates of monthly poverty closely align with observed estimates in the SIPP from 2004 through 2016, and are more closely aligned with state-month patterns of hardship and well-being in 2020 relative to the employment rate or measures of poverty that do not account for new income transfers. Particularly in contexts of rapid economic change, the monthly poverty rate can inform scholars, policymakers, and the general public of the socio-economic conditions of families across the U.S.

We reiterate that a monthly poverty measure features advantages and disadvantages relative to an annual measure of poverty; as such, it is best understood as a supplement to, rather than substitute for, for the traditional annual measure. The annual accounting period may more appropriately capture families’ long-term consumption capabilities; the monthly accounting period, in contrast, more appropriately captures intra-year volatility in incomes and families’ experiences of poverty. Indeed, even prior to the COVID-19 pandemic, intra-year volatility in incomes appears to be high and rising. First, prior studies have sufficiently demonstrated that intra-year earnings volatility is particularly high for families that experience povertycenter.columbia.edu
poverty (Bania & Leete, 2009; Hill et al., 2017; LaBriola & Schneider, 2020; Morris et al., 2015; Shaefer et al., 2015). Second, we presented evidence that income transfers are increasingly concentrated into lump-sum, once-per-year payments, further exacerbating the intra-year volatility of incomes. In 2018, for example, more than a third of total annual transfers distributed to families with children were concentrated in a single month. These transfers, which primarily include the EITC and CTC, have strong effects on annual income poverty and are the largest direct contributors to reductions in child poverty (Fox, 2020; Jones & Ziliak, 2019). Viewed from a monthly perspective, however, they reveal substantial poverty reduction in a single month (February or March, in particular) and the introduction of large intra-year volatility. While many families may use these transfers to smooth consumption over subsequent months, past research suggests that many families do not and/or cannot (Beatty et al., 2019; Bond et al., 2021; Goldin et al., 2020; Goodman-Bacon & McGranahan, 2008; Laurito & Schwartz, 2019; Mendenhall et al., 2012; Michelmore & Jones, 2015; Shaefer et al., 2015). Thus, consistent with arguments acknowledged in Atkinson (2019); Edin and Shaefer (2016); Morduch and Schneider (2017), and elsewhere, the high month-to-month variation in incomes warrants exploration of higher-frequency (monthly) measures of poverty, and further analyses of the consequences of short-term exposure to poverty on important social outcomes.

Our estimates of trends in monthly poverty rates show declining levels of poverty, on average, from 1994 through the early 2000s. In the 2000s, however, poverty rates steadily increased, particularly after the onset of the Great Recession. From January 2000 through January 2011, for example, the monthly poverty rate increased from 15.7 percent to 21.7 percent. As employment recovered following the Great Recession, the monthly poverty rate fell to around 15 percent in February 2020, the month before the COVID-19 pandemic began to spread rapidly across the U.S.
An added feature of our framework, as noted, is its ability to incorporate new or revised income transfers in close-to-real-time. We demonstrated this feature through an incorporation of the CARES Act, the package of income support policies (and more) introduced in March 2020 to cushion the economic consequences of the pandemic. We found that the income supports lifted more than 18 million individuals out of poverty in April and May 2020; however, the effects of the CARES Act faded as the year went on. After the expiration of the $600 per week federal unemployment supplement in July 2020, the poverty-reduction effect of the CARES Act narrowed to around 1 percentage point and the monthly poverty rate subsequently increased. While our framework produces estimates of monthly poverty throughout the pandemic in close to real time, official estimates of annual poverty for 2020 will not be available until the autumn of 2021.

Moreover, intra-year variation in monthly poverty rates are particularly striking. Among families with children, the mean within-year range in poverty rates from 1994 through 2019 (maximum minus minimum poverty rate in a year) was 7 percentage points, comparable to the between-year range of 8 percentage points. Families without children, in contrast, experience small intra-year volatility, as they are not eligible for the CTC and are potentially eligible for significantly smaller levels of EITC benefits. That within-year differences in poverty are comparable to between-year differences for families with children further warrant the introduction of a monthly poverty measure as a supplement to the standard annual measure.

In closing, we emphasize several limitations of our framework and opportunities for future research. First, we reiterate that an ideal data environment would not require the measurement procedures that we introduce in this study. If monthly administrative or survey data were available, our adjustments and projection framework would not be needed. In the absence of such data, however, our framework appears generally adequate in producing
estimates of monthly poverty that align with observed rates in the SIPP in prior years. Nonetheless, there are several sources of potential measurement error within our framework that may affect our results. Our conversion of annual to monthly income components, for example, may bias the projected monthly incomes of family units who do not fit neatly within the assumptions we listed in Table 1. Moreover, our projections of the CARES Act income transfers in 2020 are based on external data of benefit distribution, but introduce a new source of potential measurement error that affect our findings. Similarly, our 2020 estimates use the 2019 SPM thresholds and do not project the potential increase in poverty thresholds, which could slightly bias our 2020 estimates.

While validation tests again support the general accuracy and usefulness of our estimates of monthly poverty rates, future efforts should ideally work toward the incorporation of monthly survey or administrative data on incomes into estimates of monthly poverty. Moreover, we recommend that the U.S. Census Bureau consider the possibility of formally measuring and releasing monthly estimates of poverty as a supplement to their annual estimates of poverty. In the meantime, researchers can apply our framework for projecting monthly poverty rates whenever more timely estimates of poverty are desired.
REFERENCES


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160-million-stimulus-checks-but-marginalized-and-vulnerable-americans-are-still-disproportionately-left-out/
APPENDIX 1: Validation Tests

Figure A1: Average monthly SNAP benefits (left panel) and earnings (right panel) in CPS vs. SIPP, 2004-2018

Note: SPM-unit means. Nominal values. Monthly earnings top-coded at $50,000 per month in both samples. Negative values bottom-coded at zero. SIPP panel ends in 2016. The figure compares our projected average, monthly SNAP benefits (left) and earnings (right) in the ASEC relative to the observed means in the SIPP. Recall that we compute the monthly values of each in the ASEC, but in the SIPP, the values are actually observed over 12 months.
Figure A2: Kitigawa-Oaxaca-Blinder estimation of change in OPM poverty rate due to compositional differences (2007 through December 2010; SIPP)

Notes: SIPP sample limited to respondents who are present in all months within a year. Anchored poverty threshold applied. The base sample is all months in 2007; the comparison sample is each month from May 2008 through December 2012. See Table 1 for full list of demographic and labor market covariates included in “compositional change” measure.
### APPENDIX 2: The CARE Act

Table A1: Overview of income support expansions introduced in the CARES Act

<table>
<thead>
<tr>
<th>Program</th>
<th>Target Population</th>
<th>Benefit Amount &amp; Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Economic Impact Payments</td>
<td>Individuals with adjusted gross income below $75,000 in single filer households, below $112,500 for those who file as heads of household, and below $150,000 in joint filer households; rebate phases out by 5% above these thresholds</td>
<td>Maximum of $1,200 per tax filer and $500 per qualifying child aged 16 and under; one-time payment</td>
</tr>
<tr>
<td>Pandemic Emergency Unemployment Compensation (PEUC)</td>
<td>UI recipients who surpass standard benefit duration (typically 26 weeks)</td>
<td>13 additional weeks of UI benefits through December 31, 2020</td>
</tr>
<tr>
<td>Pandemic Unemployment Assistance (PUA)</td>
<td>Jobless adults generally excluded from regular UI (self-employed, part-time, freelance work, etc.)</td>
<td>Benefit will be at least half of state's regular minimum payment (may be higher); up to 39 weeks of receipt</td>
</tr>
<tr>
<td>Pandemic Unemployment Compensation (PUC)</td>
<td>All unemployment insurance (UI) recipients (including PUA and PEUC recipients)</td>
<td>$600/week for 4 months (ends after July 2020)</td>
</tr>
</tbody>
</table>

Note: The undocumented foreign-born population is excluded from CARES Act income support.
APPENDIX 3: Trends in monthly poverty rates in 2020 by age group and race/ethnicity

Figure A3: Trends in monthly poverty (with CARES Act transfers) by age group (2020)

Note: Monthly SPM rate accounts for income received in the given month. The large distribution of EITC benefits in March largely accounts for the observed dip in that month.
Figure A4: Trends in monthly poverty (with CARES Act transfers) by race/ethnicity (2020)

Note: The monthly SPM rate accounts for income received in the given month. The large distribution of EITC benefits in March largely accounts for the observed drop in that month.
APPENDIX 4: The Census Household Pulse Survey

The Census Household Pulse Survey (CHPS), provides nationally-representative estimates of food insufficiency and housing hardship from April through early 2021. The Census randomly selects addresses to participate in the CHPS, then sends either an email or a text message to the contact information associated with the household, prompting the recipient to participate in a 20-minute online survey asking questions related to education, employment, food security, housing, and more. Combined, the surveys include more than 1 million unique respondents. The CHPS surveys were initially conducted weekly, but switch to a biweekly framework between July and August. We convert the (bi-)weekly data to months to remain consistent with our other indicators, such as the coverage of unemployment benefits (discussed below). Most surveys are conducted within a given month; some, however, overlap slightly. For example, the Week 18 survey was conducted between October 28 and November 9. In these cases, we assign the week’s data to the month that features the larger number of days (November, in this case). Table A2 presents the definitions for the six hardship and well-being indicators that we incorporate into our validation test.

Table A2: Overview of primary hardship indicators

<table>
<thead>
<tr>
<th>Type of Hardship</th>
<th>Prompt</th>
<th>Qualifying Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food</td>
<td>In the last 7 days, which of these statements best describes the food eaten in your household?</td>
<td>Sometimes or often not enough to eat</td>
</tr>
<tr>
<td>Housing</td>
<td>Did you pay your last month’s rent or mortgage on time?</td>
<td>No.</td>
</tr>
<tr>
<td>Anxiety</td>
<td>Over the last 7 days, how often have you been bothered by the following problems: Feeling nervous, anxious, or on edge?</td>
<td>More than half the days or nearly every day.</td>
</tr>
<tr>
<td>Worrying</td>
<td>Over the last 7 days, how often have you been bothered by the following problems: Not being able to stop or control worrying?</td>
<td>More than half the days or nearly every day.</td>
</tr>
<tr>
<td>Lacks Interest</td>
<td>Over the last 7 days, how often have you been bothered by the following problems: having little interest or pleasure in doing things?</td>
<td>More than half the days or nearly every day.</td>
</tr>
<tr>
<td>Feeling Down</td>
<td>Over the last 7 days, how often have you been bothered by the following problems: feeling down, depressed, or hopeless?</td>
<td>More than half the days or nearly every day.</td>
</tr>
</tbody>
</table>
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