Measuring Poverty Subannually in the United States:

A Methodology Note

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Abstract

Rapid changes in the U.S. economy have made it increasingly important to be able to produce estimates of poverty on a timely and frequent basis. Despite the demand for current and frequent statistics, there is a lag between the reference period and annual publication of poverty statistics. This paper builds on existing studies combining the basic monthly Current Population Survey with the Annual Social and Economic Supplement (CPS ASEC) to create a subannual measure of poverty with reference periods of 1, 3, and 4 months. I present subannual estimates of the Official Poverty Measure (OPM) and the Supplemental Poverty Measure (SPM) for 2009-2022. I also examine various methodological issues around the design of a subannual poverty measure. I also present corroborating results from the Survey of Income and Program Participation (SIPP) and the Household Pulse Survey (HPS). I suggest that a monthly poverty measure, to supplement annual statistics on poverty, may be appropriate for publication as a research series by the U.S. Census Bureau.

Keywords: Frequent Poverty Measurement, Supplemental Poverty Measure, Current Population Survey

JEL codes: I32, C8, O51

[1]Contact: Ani Rudra Silwal (ani.r.silwal@census.gov), U.S. Census Bureau, Social, Economic, and Housing Statistics Division. This paper is released to inform interested parties of ongoing research and to encourage discussion of work in progress. Any views expressed herein are those of the author and not those of the U.S. Census Bureau. The author would like to thank Zach Parolin and Jeehoon Han for generously sharing code and answering questions about it. All comparative statements have undergone statistical testing and are significant at the 90 percent confidence level, unless otherwise indicated. For more information about sampling error, visit <https://www2.census.gov/programs-surveys/cps/methodology/CPS-Tech-Paper-77.pdf> (CPS); <https://www.census.gov/programs-surveys/sipp/methodology/sampling-error.html> (SIPP); and <https://www.census.gov/programs-surveys/household-pulse-survey/technical-documentation.html> (HPS). The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product (Data Management System (DMS) number: D-0000010797, Disclosure Review Board (DRB) approval number: CBDRB-FY23-SEHSD003-032.

1. Introduction

Poverty estimates are an invaluable tool for measuring progress in wellbeing over time and within the United States. Estimates for the Official Poverty Measure (OPM) and the Supplemental Poverty Measure (SPM) are updated each fall. For example, data on poverty in 2021 were collected in Spring 2022 and released in Fall 2022. Estimates for 2022 will not be available until Fall 2023.[2] However, it may be useful to know the magnitude of poverty for shorter time frames and at a higher frequency, especially during periods of turbulence in the broader economy and labor markets.

There has also been increased interest in finding more frequent estimates of poverty since annual estimates do not show important differences in wellbeing within the year.[3] The COVID-19 pandemic and recent recessions have reminded us that employment and earnings can drop rapidly within a span of months or even weeks. Even during economic calm, families may experience wellbeing differently over the course of a year. Government policy, such as the Coronavirus Aid, Relief, and Economic Security (CARES) Act of 2020, can respond to economy-wide disruptions within a short period. Other more frequent measures like the unemployment rate also reveal substantial seasonal variation. For all these reasons, providing preliminary estimates or projections of poverty in between annual releases would be of much public interest and value.

Several recent studies have recognized the value of a poverty measure that would be updated between annual releases (Bergmann and Coder 2010, Chavez et al. 2016, Han et al. 2020, Parolin and Wimer 2020, Parolin et al. 2022). While these studies differ in various ways, all of them agree that researchers should utilize the monthly releases of the Current Population Survey (CPS) to complement the Annual Social and Economic Supplement (CPS ASEC). Combining the rich details in the CPS ASEC, collected annually, with the higher frequency of the basic monthly CPS may be a feasible path to estimate poverty at a subannual frequency. Although several studies agree that the CPS can potentially be used for a more frequent estimate of poverty, they propose different solutions to the many methodological challenges. Should the accounting period for this measure be a month, a quarter, or simply a year? How should we compute the uncertainty around the estimates of poverty? What assumptions should we use to combine data from basic monthly CPS and the CPS ASEC? Addressing these questions is critical for the frequent measure of poverty to be reliable and credible. This paper addresses these questions and other relevant issues to consider if one intends to measure and publish a subannual measure of poverty.

This study attempts to build on the existing literature on measuring poverty subannually to propose a subannual measure of poverty that could be published routinely by the U.S. Census Bureau. I focus on a short-term measure of deprivation: a poverty measure with a reference period of less than a year, building primarily on Parolin et al. (2022), but also Bergmann and Coder (2010).[4] I describe a general methodology that can be implemented to publish subannual estimates of the OPM and the SPM. I implement this

[2] A challenge with the annual production cycle is that OPM and SPM are based on income for each calendar year. The best time to collect this data is each spring, when families are more familiar with their year-end income as they file their taxes.

[3] Studies such as Morduch and Siwicki (2017) and Schneider and Harknett (2021) also document the how low-income households often have volatile intra-year incomes in addition to unstable and unpredictable work schedules.

[4] Han et al. (2020) propose a measure of poverty with an annual reference period that is updated every month based on data from basic monthly CPS. Han et al. (2022) and Parolin et al. (2022) discuss merits and demerits of both approaches.

methodology for January 2009 through December 2022.[5] I also present estimates for a monthly, quarterly, and quadrimesterly[6] reference periods. I also compare my findings with Warren and Silwal (2022), who combine data from basic monthly CPS with data from the Survey of Income and Program Participation (SIPP) instead of the CPS ASEC. Finally, I compare my findings with those from Glassman and Silwal (2023), who construct a measure of financial insecurity from the Household Pulse Survey (HPS).

The findings presented in this paper suggest that it is feasible to publish OPM and SPM estimates subannually using a general but flexible methodology. The combination of a monthly reference period and a monthly update frequency emerges as a natural candidate for routine implementation, primarily because the basic monthly CPS, an important input for subannual poverty, is published in the first half of each month for the previous month by the Census Bureau and the Bureau of Labor Statistics. It should be noted that the estimates presented here are modeled projections of monthly poverty and not as reliable as annual poverty estimates from the CPS ASEC. However, these estimates should add to the body of evidence that informs short-run economic policy decisions.

This paper is organized as follows: Section 2 summarizes the existing literature on measuring poverty subannually in the United States and beyond. Section 3 describes the different sources of data I use for this work before I describe the methodology that I propose for measuring OPM and SPM subannually. Section 4 describes the main results, which include monthly, quarterly, and quadrimesterly estimates of OPM and SPM for 2009-2022. In Section 5, I present results of some sensitivity checks. In Section 6, I discuss some outstanding questions that I believe need to be resolved if the Census Bureau decides to begin publication of a subannual poverty series. The final section summarizes this paper and provides some concluding thoughts. Various appendices include additional detailed information on subannual poverty that I discuss in the paper.

2. Relevant Literature

This section begins with early discussions of the need for a subannual reference period. It then discusses the first studies that measured subannual poverty using CPS data and those that were published during the COVID-19 pandemic.

2.A. Early Literature on Subannual Poverty

Ever since the CPS ASEC began collecting annual data on personal income in 1947, there has been a tension between an annual data collection cycle and federal benefits that were often distributed monthly. The calendar year may have been a natural choice for capturing expenses that vary across the seasons of a year; it may also have been a nod to the annual taxation cycle. However, even prior to the CPS ASEC, a monthly timeframe was used by state-led mothers' pension programs, the first of which was introduced

[5] I selected 2009 since it is the first year for which SPM data are available. Fox et al. (2015) extend the SPM series back to 1967 using certain assumptions.
[6] A quadrimester is a period of four months.

by Illinois in 1911 (Moore 1986). Federal assistance programs introduced in the aftermath of the Great Depression followed suit by distributing benefits every month. The discussion of a federal poverty threshold in the early-1960s revolved mostly around an annual amount, although Orshansky (1963) recognized the inconsistency between an annual budget and monthly benefit distribution by assistance programs.[7]

Ruggles (1990) argued that an annual income measure is not an obvious choice for measuring poverty. She asked: "If someone has inadequate resources for part but not all of a year, is that person 'poor'?" She argued the usefulness of studying poverty using a monthly accounting period to be consistent with the eligibility criteria for government benefits, which often rely on monthly income. Episodes of poverty can be triggered by setbacks that can interrupt one's income stream at any point during the year. This includes personal events such as unemployment spells, childbirth, death, short-term disability of an earner, etc. Ruggles (1990) used the SIPP to define and measure spells of poverty lasting from 1 to 28 months. Building on this work, the landmark 1995 report on poverty (Citro and Michael, 1995) agreed that a subannual accounting period for the poverty measure would serve as a timely indicator of economic distress in the population. It suggested potentially measuring poverty for a reference period one or four months, although the report admitted challenges with evaluating the merits of different reference periods.

2.B. Using the CPS to Measure Poverty Subannually

Although studies based on the SIPP show the value of measuring poverty subannually, we are constrained in how much we can use it to publish subannual poverty estimates. Although it collects data in a monthly format, these estimates can only be released annually because it conducts interviews once a year.[8] Bergmann and Coder (2010) showed the promise of publishing poverty estimates every month for a monthly reference period. Their primary source of data was personal earnings in the basic monthly CPS. The authors supplemented this data with state-level data on unemployment claims. They imputed the remaining components of household income by using data from the most recent CPS ASEC before comparing total income against monthly poverty thresholds that were computed by appropriately inflating the official poverty thresholds from July 1984. Although the authors successfully showed the feasibility of publishing a monthly poverty series relying on data from the CPS and the CPS ASEC, they were concerned by the variability of their estimates across months. They attribute this to sampling variance and modeling challenges in imputing non-wage income. The data on wage earnings they use are based on the outgoing rotation groups (months-in-sample 4 and 8), which restrict the authors to using only a quarter of the full sample. The authors also highlight the difficulty of matching households from the CPS ASEC as "donors" for all income from sources other than wages and salary. The authors concluded that estimates of "other income" deteriorate in quality as the time series extends well beyond March, the month on which their estimates are based.

Chavez et al. (2016) built on Bergmann and Coder (2010) by relying on a question in the CPS that asks for total family income from the previous 12 months. The advantage of this approach is that these studies can use data on all cash income of families, rather than simply wage earnings. A global income question

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[7] This was published prior to her seminal work on "Counting the Poor: Another Look at the Poverty Profile" from 1965.
[8] SIPP conducted interviews once every four months from October 1983 until 2014, when interviews began to be conducted once a year to reduce respondent burden (U.S. Census Bureau 2019).

in CPS also allows these studies to examine a rolling 12-month reference period, which mitigates the concern that Bergmann and Coder (2010) raised about month-to-month variation in estimates. The disadvantage of this method is that the income question in the CPS is only asked to a quarter of the sample (months-in-sample 1 and 5);[9] moreover, the responses are categories of income ranges rather than continuous.[10] Chavez et al. (2016) relied on data from the previous CPS ASEC to convert income ranges to a specific dollar amount. In doing so, they showed that poverty can be estimated and updated every month using the CPS. Chavez et al. (2016) also combined three months of CPS data so that the annual poverty rate can be updated every quarter. This strategy was possibly motivated by the concern that poverty estimates from CPS have large standard errors and a large month-to-month variation.

2.C. Studies Published During the COVID-19 Pandemic

The rapid economic changes during the COVID-19 pandemic and the associated government responses raised the urgency of more timely and frequent statistics on poverty. Han et al. (2020) and Parolin et al. (2020) both rose to this challenge, although they employed different strategies. Han et al. (2020), like Chavez et al. (2016), combined data from the CPS ASEC and basic monthly CPS to update the annual poverty rates every month. Unlike Chavez et al. (2016), Han et al. (2020) did not combine monthly CPS data for each quarter; using CPS data one month at a time allowed them to revise the poverty rate with every new release of the CPS. Although Han et al. (2020) were careful to clarify that their measure of poverty, based on the global income question in CPS, is not the official poverty measure, it effectively is comparable because the authors use the official thresholds to compute the poverty rate.[11]

Estimating the SPM is a little more complex than it is for the OPM since the SPM includes not just cash income but also non-cash benefits and subtracts expenses. Parolin et al. (2022) proposed a methodology to estimate the SPM for a monthly reference period. They begin with the various components of annual SPM resources, which they convert into monthly values. Then they sum the components to obtain the total SPM resources for a given resource unit. These monthly resources are then compared against one-twelfth of the annual value of the SPM threshold to assign a poverty status to every resource unit. The next step is to create a dataset of variables that predict poverty and are available in both the CPS ASEC and the CPS.[12] The final step is to estimate a model of SPM poverty status as a function of its covariates in the CPS ASEC so that the model coefficients can be used to impute the poverty status of the CPS sample.

Han et al. (2022) discussed the strengths and weaknesses of their approach compared to that of Parolin et al. (2022). Han et al. (2022) examine how the differences in methodology – primarily resulting from the choice of reference period – give sharply differing views of changes in poverty since 2020. I build on the methodology proposed in Parolin et al. (2022) for two reasons. First, many readers may expect a monthly measure of poverty also to have a reference period of one month. Second, a transparent accounting of the various components of total SPM resources is more useful for understanding the effect of policies

[9] This means that our effective sample size in basic monthly CPS shrinks by three-quarters.

[10] The current questionnaire has 16 categories of income ranging from "Less than $5000" to "$150,000 or more."

[11] Although the authors call their series "monthly CPS poverty", this may also be misleading since the reference period of their measure is a rolling 12 months; it is monthly only in the sense that it is updated every month. Both studies use the global income question in CPS.

[12] This is likely to be the first study to use a model of poverty estimated from the CPS ASEC to impute the poverty status of everyone in the CPS.

than a global question on cash income whose response is coded in income categories. However, both of these studies present methods to obtain more frequent and timely poverty statistics; they should be seen as complements rather than substitutes.

3. Data and Methodology

In this section, I describe the datasets and research methods used in this study. I first discuss the primary surveys used in my analysis as well as the additional surveys I use for validation. I then describe a general methodology for computing subannual poverty rates. Although much of the methodology described here is from Parolin et al. (2022), I discuss how these studies differ at the end of this section.

3.A. Data Sources

Data from the CPS is a natural candidate for measuring poverty subannually. The CPS is possibly the most widely used household survey for measuring socioeconomic characteristics of the American population. It consists of two components. The first component is the monthly (or basic) component that is conducted every month on a sample of approximately 72,000 housing units (U.S. Census Bureau 2019). The second component comprises various thematic supplements that are conducted throughout the year. Of these, the most well-known is the ASEC, which includes all sample households from the monthly CPS for March of each year and an oversample of certain populations. The CPS ASEC is also the source of data for the official poverty estimates in the United States. Monthly CPS, sponsored jointly by the Census Bureau and the Bureau of Labor Statistics, was designed as the primary source of data on labor force statistics, not poverty. The monthly CPS is not designed to measure annual individual income needed for an annual poverty measure since respondents are only interviewed up to four months in a calendar year and since income data is limited to earnings from the outgoing rotation groups. Instead, the Census Bureau uses the CPS ASEC, with detailed information on various sources of individual income, for the official poverty measure. I downloaded all CPS data from IPUMS (Flood et al. 2022) for this study, although I discuss issues around using data directly from the Census Bureau website.

I use two more data sources to validate results from the CPS ASEC and monthly CPS. The SIPP is a nationally representative panel survey that collects information on a variety of economic and demographic topics. The appeal of this survey is that it collects monthly information on income in a monthly format, although data from this survey is published with a longer lag than the CPS ASEC. The second source is the HPS, an experimental survey conducted by the Census Bureau in collaboration with multiple federal agencies that collects and disseminates survey data within a few weeks of data collection.

3.B. Methodology

The methodology for computing subannual poverty rates builds primarily on Parolin et al. (2022).[13] Section 3.B.iv describes the differences between the approach adopted in this study and Parolin et al. (2022).[14] The procedure for computing subannual rates consists of the following broad steps (refer to Appendix E for an illustrated version of this methodology):

1. The first step (section 3.B.i.) involves working with the CPS ASEC to convert annual resources, thresholds, and poverty status to subannual (monthly, quarterly, or quadrimesterly) values, some of which are assumed to vary across the course of the year.
2. The second step (section 3.B.ii) involves generating variables with common definitions in the CPS ASEC and CPS so they can be used during multiple imputation.
3. The final step (section 3.B.iii) is to conduct multiple imputation of the poverty status among resource units in CPS based on a model of poverty status in the CPS ASEC.

The rest of section 3.B describes the process for computing monthly poverty; section 3c describes how they can be adapted to compute poverty rates for quarterly and quadrimesterly reference periods.

3.B.i. Conversion of Annual Values to Monthly Values in CPS ASEC

Ideally, we would have data on all the income components of everyone in the CPS. In the absence of such data, we need to rely on the best available alternative with detailed data on annual poverty – the CPS ASEC – to realistically estimate the amount of resources each resource unit would have in a given month. Let us say our goal is to measure the monthly rate for December 2022. The most recent CPS ASEC data for doing this would be the one that was published in fall 2022 for the reference year 2021. A starting point for this exercise would be to build a model of poverty in December 2021 using data from the 2022 CPS ASEC (with the reference period of calendar year 2021), which we could then use to predict the poverty status in the CPS for December 2022. In order to compute the poverty status of CPS ASEC households in December 2021 (rather than the full year 2021), we need to make some assumptions about how those resources are allocated throughout the year.[15]

A reasonable method to obtain resources for December 2021 would be to divide the annual resources for 2021 by 12. Dividing a resource unit's 2021 income by 12 to estimate its income for each month in 2021 can be misleading because that unit's incomes and governmental assistance are likely to have varied for each month of 2021. Box 1 describes how I deal with these issues. Group 1 includes various incomes and expenses that can reasonably be assumed to remain constant across all months of the year.

There are three categories of resources that are applicable to some, but not all, months of a year. The first category of adjustments (Group 2) involves accounting for recent unemployment. I reduce their (monthly)

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[13] Han et al. (2020) present an alternative method to update the poverty rate every month by relying more heavily on CPS than the methodology proposed in Parolin et al. (2022). Han et al.'s methodology updates the measure of poverty every month and has a rolling reference period of 12 months, unlike a one-month reference period used in this paper.

[14] An initial step of this exercise involved replicating Han et al. (2020) and Parolin et al. (2020, 2022). The author would like to thank Jeehoon Han and Zach Parolin for providing code and help during the replication process.

[15] Here I make an important distinction between months for which actual CPS ASEC data are available and those for which they are not. For example, if CPS ASEC data for reference year 2022 were available, I would use that dataset to model poverty for all months of 2022. If not, I use the data from the most recent CPS ASEC that is available.

earnings proportionately if they were unemployed for less than four weeks. I also set monthly earnings to zero if an individual was unemployed or if they were not in the labor force at the time of the CPS ASEC interview.

The second category of adjustments (Group 3) includes allocating the Earned Income Tax Credit (EITC) to either March or April, depending on IRS data on the timing of refund as described in Parolin et al. (2022).[16] The final category of adjustments (Group 4) includes the dollar value of school lunch program benefits received by members of the SPM unit as well as income from educational assistance programs such as Pell Grants or other aid from various sources.

Box 1: Rules for Converting Annual Resource Components to Their Monthly Values

- **Group 1**: Resource components that are divided by 12 to obtain monthly values.
  - *Components*: Social Security, income from retirement, Supplemental Security Income, worker's compensation, veteran's benefits, survivor's benefits, income from disability, income from dividends, child support, alimony, income from other sources, WIC, heating assistance, housing assistance, medical out-of-pocket expenses, state and federal taxes (excluding EITC), SNAP/TANF benefits, income from unemployment insurance.
- **Group 2**: Resource components that are adjusted if members of resource unit were unemployed.
  - *Components*: Income from wages, business, farm work; work-related expenses
- **Group 3**: Resource components that are only distributed in a single month.
  - *Component*: EITC
- **Group 4**: Education-related income support that is allocated equally to all months other than June-August.
  - *Components*: value of school lunch program; educational assistance such as Pell Grants

Once the components of annual OPM and SPM resources from the CPS ASEC have been converted into the appropriate monthly values for the month of interest, we are nearly ready to compute the monthly poverty status of all CPS ASEC resource units. We divide the 2021 OPM and SPM thresholds of the CPS ASEC resource units by 12 to obtain the monthly poverty threshold.[17] In our example, comparing the monthly resources against the relevant thresholds will give us the OPM and SPM poverty status of each resource unit in CPS ASEC for December 2021.

3.B.ii. Covariates of Poverty Status for the Imputation Model

The next step of the methodology involves generating a set of variables with a common definition in the CPS and the CPS ASEC so they can be used to impute the poverty status of resource units in CPS. This

[16] Similar to Parolin et al. (2022), I allocate 68.8 percent of payments in March and the remainder in April. Prior to 2017, I allocate 41.4 percent of EITC payments in February, 27.4 percent in March, and the remainder in April. This distribution follows data from Farrell, Greig, and Hamoudi (2018).

[17] This implicitly assumes no inflation during the year. Improvements to the way inflation is incorporated into the threshold could be a topic for future research. Adjusting OPM thresholds by monthly inflation within the year may be more tractable than adjusting the SPM threshold, since SPM threshold revisions are a result of a complex process managed by the Bureau of Labor Statistics.

process is greatly facilitated by the fact that all CPS ASEC households are also a part of the CPS (U.S. Census Bureau 2019, p.17). In other words, the CPS ASEC is only administered to respondents who successfully completed the monthly CPS, thus ensuring that variables in both datasets have the same definition.[18] Box 2 lists primary and derived variables that are used in the imputation exercise as described in Section 3.B.iii.

Box 2: Indicators Used in the Imputation Model

Core Variable from CPS	Indicator Used in Imputation Model
Age	Five-year age category of the household reference person
Sex	Sex of household reference person
Education	Low (high school or less), medium (more than high school, less than college), or high (college degree) education (measured among age 18+ in family unit)
Marital status	Marital status of the household reference person
Race/Hispanic origin	Indicators for White, Black, Asian, Hispanic, or Other
Citizenship and Origin	Indicators for citizenship and whether born outside the U.S.
Family structure	Family structure: indicators 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; number of working-age adults in unit, number of individuals age 65+ in unit, number of children in unit (top-coded at 5)
Marital status	Indicator of whether reference person of family unit is currently married
Employment	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)
Unemployment	Number of weeks unemployed; set to 0 if not unemployed
Disability status	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 limiting mobility
Region of residence	Indicators for Northeast, Midwest, South, and West
Interaction terms	Interactions of: (i) household employment rate with household work intensity, duration of unemployment, household type, household education, age, sex, race/Hispanic origin, disability, and citizenship characteristics; (ii) duration of unemployment with household type; household work intensity, household education, age, sex, race/Hispanic origin, disability, and citizenship characteristics; (iii) household work intensity with household type; and household education, age, sex, race/Hispanic origin, disability, and citizenship characteristics.

Note: Mean values are computed at the household level for the indicators above, unless otherwise noted.

[18] Newhouse et al. (2014) warn that survey-to-survey imputation, like the one used in this study, that relies on variables without the same wording in both surveys will give flawed results.

The figures in Appendix B present comparisons between the CPS and the CPS ASEC of the mean values of some of the variables in Box 2. Although these series are not entirely comparable because of the frequency of data collection, these figures can help uncover any errors in coding (for variables that were generated from raw variables) and any other anomalies. They may also uncover genuine differences in the underlying data between the two sources. These figures are meant to be descriptive and exploratory to allow analysts to identify any irregularities in the construction of the variables used during multiple imputation. I aggregate variables from Box 2 at the household level rather than at the family level for OPM and SPM unit level for SPM. Doing this means that multiple families or resource units living in the same household will get the same aggregated values even though they should be treated as separate entities for poverty measurement. It is unclear how much error this would introduce. I aggregate variables at the household level primarily to keep the procedure more tractable.[19]

3.B.iii. Multiple Imputation of the Poverty Status

The third and final step of this methodology is to conduct multiple imputation. Following Parolin et al. (2022), I also implement combined-sample multiple imputation (CSMI) to impute the poverty status of resource units in basic monthly CPS.[20] Implementing CSMI in this study entails first appending data from the CPS ASEC (converted into their respective monthly values) with data from monthly CPS, one month at a time. This appended dataset has not only the variables that will be used to model poverty but also the poverty status of resource units in the CPS ASEC. This dataset is arranged at the individual level rather than at the family or SPM unit level.[21]

The underlying prediction model in our multiple imputation is an ordinary least squares (OLS) regression model in which the independent variable is the poverty status of an individual and the regressors are the variables and interaction terms described in Box 2. I run 10 iterations of the multiple imputation model. I then take the mean of 10 separate imputations to compute the probability of poverty for each individual and, in turn, an average poverty rate for the country as a whole.

I follow Lachenbruch (2010) to compute the standard error of the poverty estimate after multiple imputation is conducted.[22] This uses the fact that a regression with no independent variables estimates

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[19] It would be more accurate to aggregate covariates for the multiple imputation model at the family level for the OPM and at the SPM unit level for the SPM. This is difficult to implement since it is very difficult to create SPM units in basic CPS.

[20] This method involves pooling two survey samples: a donor sample that includes a key variable of interest such as poverty status along with its correlates, and a target sample that does not include the key variable but only its correlates. CSMI pools the two samples and treats the lack of the variable of interest in the target sample as a traditional missing data problem that is addressed using standard multiple imputation techniques (Capps et al. 2018).

[21] Arranging the dataset at the family level for OPM and SPM unit level for SPM would be more accurate to be sure that each unit has one poverty status. Arranging the dataset at the individual keeps the workflow simpler and may be sufficient for this methodological note. However, arranging data at the level of the relevant resource unit for multiple imputation may be more appropriate for routine publication. SPM units are units that include the official family definition plus any coresident unrelated children under age 15, foster children under age 22, and unmarried partners (and their relatives) or unrelated individuals (who are not otherwise included in the family definition).

[22] A better method to estimate standard errors in this context may be to use bootstrapping (Schomaker and Heumann 2018). Little and Rubin (2002 p. 87) also recommend a methodology to implement bootstrapped standard errors with multiple imputation.

the mean of the variable.[23] An OLS regression equation with a single predictor variable can be written as: $Y_i = a + bX_i + e_i$. When there are no predictors, this equation reduces to $Y_i = a + e_i$. If we assume that the error term is normally distributed with a mean of zero, then the expected value of the independent variable is: $E(Y_i) = E(a + e_i) = a + E(e_i) = a + 0 = a$. In other words, the constant is the mean of Y_i in this setup and the standard error - which we are primarily interested in - of the constant is the standard error of Y_i. This methodology likely underestimates the standard error since it does not include uncertainty arising from model error. In other words, it assumes that the estimated model is the true model. Future work on this project should try to explore ways to add model error to the standard error computed from the estimated model.

3.B.iv. Differences from Parolin et al. (2022):

Although the methodology I use relies heavily on Parolin et al. (2022), it differs from that study in several ways. The primary goal of that study was to examine the effect of COVID-19 and the associated government response on the SPM rate. The goal of this study is to propose a methodology that could be implemented at the Census Bureau to routinely publish monthly poverty rates in the future. This fundamental difference in objective explains many of the differences in the methodology. Table 1 summarizes the differences between the methodology used in this study and that in Parolin et al. (2022).

Reference year: Parolin et al. (2022) begin with data collected in 2020 for reference year 2019 as the "pre-pandemic" baseline data. Benefits received by families, during the pandemic, such as those from CARES Act and the Advance Child Tax Credit (Advance CTC) payments in 2021 are added explicitly to the baseline model of resources. Instead of using a fixed reference year, I use the most recent CPS ASEC as my baseline data. I take advantage of the fact that these benefits are already incorporated into the relevant CPS ASEC data. In other words, data on Advance CTC payments in the second half of 2021 is already incorporated into the CPS ASEC for the reference year 2021, collected in 2022. Using a rolling baseline, rather than a fixed one, mitigates the need to explicitly model policies that were implemented recently.[24]

SNAP/TANF benefit values: Parolin et al. (2022) also simulate monthly values of SNAP and TANF benefits using state-based rules for the relevant month. They use this value instead of the value found in the CPS ASEC (divided by 12) when they believe a resource unit should get a higher value than that reported in the CPS ASEC. I forgo this methodology and simply assign the one-twelfth of values reported in the CPS ASEC for all months of the year. Accurately simulating state-based rules for SNAP and TANF benefit distribution is difficult, primarily because the information on this is difficult to compile and maintain every

[23] The Stata syntax that Lachenbruch (2010) recommends for estimating the mean and standard error of a multiply imputed variable y is *mi estimate: regress y.*

[24] The key word here is *mitigates*. Explicitly modeling relevant policy changes that were introduced recently would make this exercise more reliable and accurate. For example, the current methodology would assume that the ACTC payments in 2021 were applied equally to all months of 2021, rather than only the second half of the year. My analytical framework allows such adjustments to be incorporated in the future. Incorporating policy changes would mean simulating changes to the relevant resource component. The simulated income component could then replace the baseline value derived from the CPS ASEC. Comparing the estimated poverty rates with and without the simulated policy change would give us the first order effect of the new policy on poverty.

month.[25] In the absence of an accurate simulation, we may end up introducing additional errors in the SNAP and TANF values.[26]

Table 1: Comparison Between this Study and Parolin et al. (2022)

Stage	Issue	Parolin et al. (2022)	This study
Converting annual resources to their monthly values	Pandemic relief (CARES Act, ACTC, etc.) is modeled	Yes	No
	Baseline year for resources	Reference year 2019	Most recent CPS ASEC
	SNAP/TANF benefits	Modeled according to state-based rules	Dispersed evenly throughout the year
	Earnings adjusted if hours worked last week < usual weekly hours	Yes	No
Estimation	Standard errors of poverty computed	No	Yes
	State dummies included in regression	Yes	No
	Multiple imputation type	Chained regression	Unchained regression
All	Reference period for measuring poverty	Monthly	1/3/4 months
	Measurement period	2020-2022	2009-2022

Working hours: Parolin et al. (2022) adjust monthly earnings proportionately downwards if an individual reported that they worked less during the last week compared to their usual weekly hours.[27] I do not do this for a few reasons. The actual hours worked in the last 7 days is also reported on a different scale: it is capped at 199 in the CPS ASEC, but it is only capped 99 in the CPS.[28] An individual could have worked less last week than her usual hours for a variety of reasons (illness, vacation, seasonality of work, temporary unemployment, etc.) but not all of them may result in a loss of income. Without additional information on why people worked less last week than usual, it may not be justifiable to reduce their earnings for an entire month. Another reason why accounting for working hours may not add much value is that we already account for unemployment status in assigning monthly earnings.

Standard errors: Parolin et al. (2022) do not compute the standard errors of their estimates. It is critical to convey to consumers of statistics the uncertainty around poverty estimates in addition to the estimates themselves. I use the methodology described in the previous section (based on Lachenbruch 2010) to compute the standard error of the poverty estimates. The resulting margins of error should be considered

[25] The website for the Center for Budget and Policy Priorities is a good resource on how rules for allocating SNAP and TANF benefits have changed over time. However, this information is not complete and, more importantly, not updated regularly.
[26] Future work on this project could try to obtain administrative data on the historical monthly distribution of SNAP and TANF data so they could be incorporated into this process.
[27] The reference period for usual weekly hours worked is not specified in the survey instrument. Since this question is a part of the basic CPS, it would be fair to assume that it "usual working hours" refers to typical working hours at the time of survey rather than the previous year.
[28] The cap is 199 for usual hours worked in both the CPS ASEC and CPS. Since there are 168 hours in a week, values greater than 168 are clearly invalid and may need to be converted to missing values.

the floor of the actual margins of error, particularly because this methodology does not capture model error, which likely increases as we move further away from the time when the CPS ASEC data were collected.

OPM estimates: I use the methodology from Parolin et al. (2020) to compute monthly estimates of the OPM in addition to SPM.[29] The OPM often provides the reference point for discussions about the SPM. The methodology for computing monthly OPM estimates involves summing the relevant components of cash income and comparing it with one-twelfth of the annual value of the OPM thresholds.[30] This methodology is different from Han et al. (2020) in that it builds the total individual income for a given month from its various components reported in the CPS ASEC, rather than relying on a single global question on the income range of the household in the previous 12 months.

Measurement period: Since the focus of Parolin et al. (2022) is studying the poverty effect of the COVID-19 pandemic and the policy responses to it, their published statistics and methodology are mostly relevant to this period.[31] I generalize their methodology so we can publish a continuous series from 2009 onwards, reflecting the first year for which we have data on the SPM from the Census Bureau.[32]

Multiple imputation type: Parolin et al. (2022) use chained regressions in their multiple imputation methodology, although the only imputed variable is the poverty status. This is conceptually equivalent to an unchained regression since there is no need to run a series of regressions to fill in missing values in multiple variables. I use a single (unchained) regression for multiple imputation.

4. Main Results

4.A. Monthly Poverty Rates

Figure 1 presents monthly OPM and SPM rates computed for January 2009 to December 2022 using methodology described in the previous section. The intra-annual pattern of poverty rates is determined largely by the monthly adjustments to the components of resources. Both the OPM and the SPM series incorporate employment conditions such as employment status as well as the hours worked by all the members of a resource unit. Many components of SPM resources are divided equally throughout the year, although EITC is allocated only to one month, either during February to April prior to 2017 or March to

[29] The OPM is a traditional poverty measure comparing a family's or individual's income to a set of thresholds while the SPM is an alternative poverty measure that uses a broader definition of income than the one used in the OPM. The SPM extends the income definition used in the OPM by considering non-cash benefits such as nutritional and energy assistance programs, tax credits such as the Earned Income Tax Credit (EITC), and geographic differences in housing costs, and subtracting necessary expenses such as work-related expenses, medical expenses, and income and payroll taxes paid. Parolin et al. (2022) present monthly estimates of OPM in Appendix Figure A3.

[30] I do not capture intra-year inflation, although this could be another area of future work.

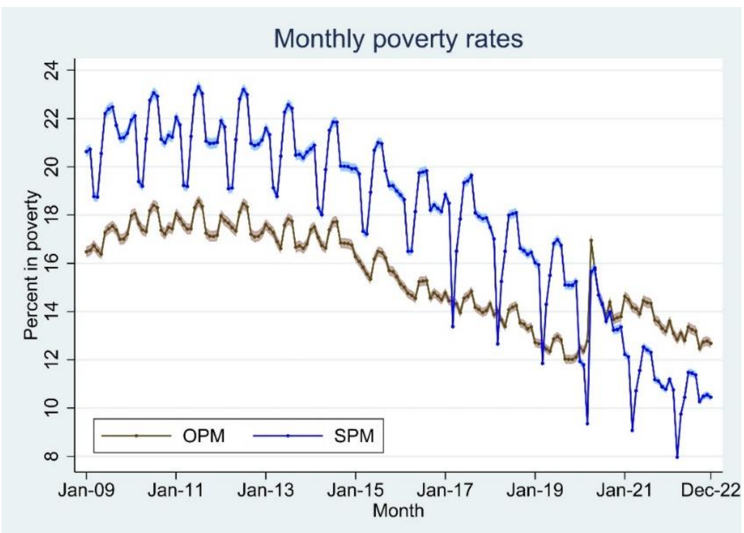
[31] They also publish monthly poverty estimates separately for 1994-2019 (Figure 4), although it is unclear if they use methodology described in their paper to generate these historical estimates.

[32] Variables relevant to SPM are now included in the annual public-use files for the CPS ASEC, but historical abstracts going back to 2009 are also available from the Census Bureau's website.

April since 2017.[33] Appendix C plots the estimated monthly series with the respective annual values for various population sub-groups. The annual poverty rates in these figures is often higher than the monthly poverty rate because the monthly rates take into account the fact that workers may go through spells of unemployment during the year that will lower their earnings.

The SPM rate is higher than the OPM rate for each month between Jan 2009 and January 2020, except for March 2017, March 2018, and March 2019. The SPM rate was lower than the OPM rate from January 2020 to April 2020 and September 2020 to December 2022. In interpreting this result, it is important to bear in mind that the monthly series is measuring short-term deprivation, in particular the deprivation that arises when monthly income falls below one-twelfth of the annual poverty threshold. Although it is important to monitor such short-term deprivation, some of the families who count as poor under this monthly measure will compensate for the income shortfall in the balance of the year and end up with annual incomes that surpass the annual poverty threshold.

Figure 1: Monthly OPM and SPM, January 2009 – December 2022



Source: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022. Shaded areas represent 90 percent confidence intervals.

4.B. Quarterly Poverty Estimates

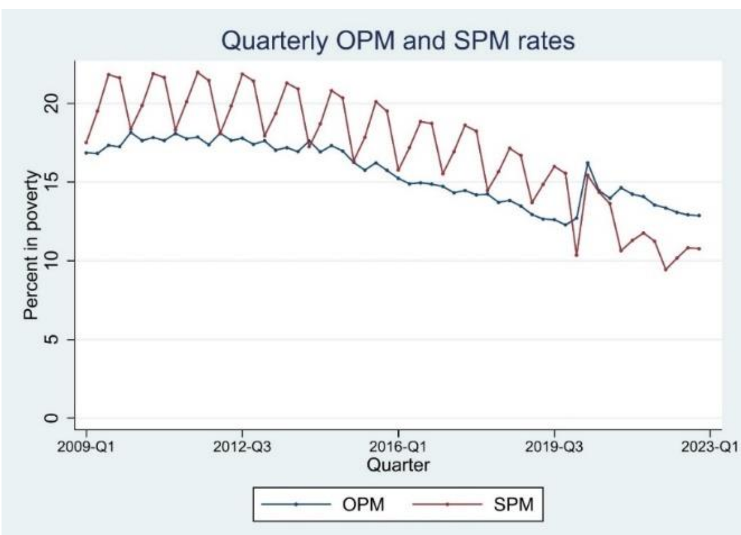
The primary advantage of a quarterly reference period over a monthly one is that a longer reference would get rid of some of the noise in the estimates arising from sampling variability. A longer reference period would also mean less-frequent updates, which would not only put less burden on staff resources but also allow for more careful vetting of results prior to publication. Using a quarterly reference period rather than a monthly one would also allow removal of some idiosyncratic changes in variables in the CPS

[33] This timing is a result of the change to the timing of EITC refunds (described in Section 6) and also possibly due changes to the Child Tax Credits as a part of the Tax Cuts and Jobs Act of 2017.

such as employment status. For example, someone who receives weekly paychecks may receive five paychecks some months; this may mean that income one month is 25 percent higher than the previous month (without any changes to weekly earnings). If income were measured every quarter for this person, there may still be differences across quarters, but those differences would be smaller.

The methodology for computing quarterly poverty estimates closely follows the methodology for computing monthly poverty estimates. We begin with the various components of annual OPM or SPM resources in the CPS ASEC. We then convert the annual value of each component to a quarterly value according to the rules outlined in Box 1. I then aggregate the components of OPM and SPM resources and compare these resources against one-quarter of the poverty threshold for each OPM or SPM unit. This will give us the quarterly OPM poverty status for every family and SPM poverty status for each SPM unit. I then use multiple imputation to assign the poverty status for everyone in CPS based on a model of poverty in CPS ASEC. Figures 2 presents OPM and SPM rates for a quarterly reference period. The quarterly OPM series appears smoother than the monthly series. This makes intuitive sense since combining three months of data should reduce sampling variability between the periods. Similar to the monthly OPM and SPM series, we still see spikes in the poverty rates in the quarterly series. This is because of our methodology for allocating SPM resources unevenly across the months; in particular, the EITC is only allocated to March or April.

Figure 2: Quarterly OPM/SPM, January 2009 – December 2022



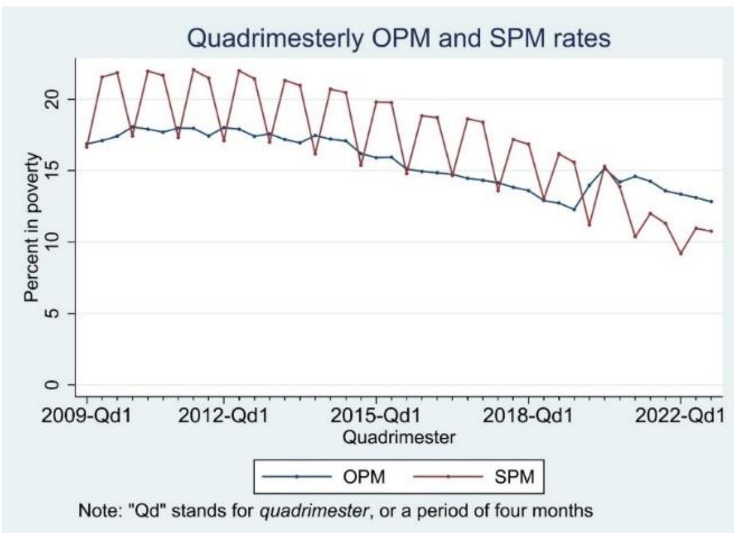
Source: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

4.C. Quadrimesterly Poverty Estimates

The 1995 NAS report on poverty (Michael and Citro 1995) mentions the possibility of publishing subannual poverty statistics with a reference period of one or four months. A reference period of four months, rather than three months, is a little unusual. This is especially the case since the estimates of Gross Domestic

Product (GDP), an important economic indicator, are published every quarter. Not many economic indicators are published at four-month intervals. The NAS report may have proposed this as an alternative since SIPP, which was used for many early studies on subannual poverty, was conducted every four months. Quadrimesterly poverty rates could be computed in a manner similar to quarterly poverty estimates. The only difference is that the resources and thresholds will be aggregated for a four-month reference period. Figures 3 presents OPM and SPM the series for a quadrimesterly reference period. At first glance, Figure 3 is visually similar to Figure 2. The OPM series is smoother than the SPM series for the same reason as the quarterly series: combining four months of data to predict poverty removes some of the sampling variation that exists in monthly CPS. Similar to the quarterly series, we still see that the SPM estimates vary across quadrimesters. This is again primarily because we allocate the EITC to the first quadrimester (January-April), thus reducing the poverty rate in that period compared to the remaining two quadrimesters of the year.

Figure 3: Quadrimesterly OPM/SPM, January 2009 – December 2022



Source: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

There are many reasons to prefer a reference period of longer than one month. A lower frequency of publication allows for more careful vetting of estimates in addition to putting a smaller strain on staff resources. However, a longer reference period does not necessarily result in a smoother series and may still need to be accompanied with an explanation for the potentially large changes since the previous estimates.

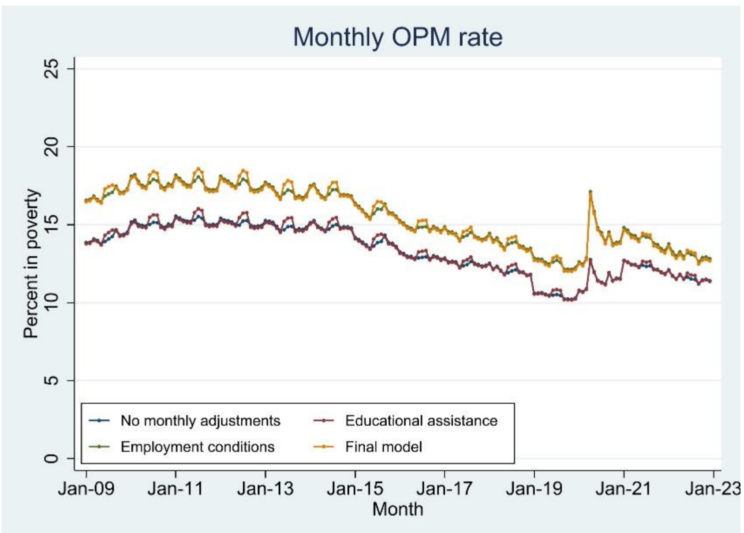
5. Sensitivity Checks

This section first attempts to understand the factors that determine the shape of the OPM and SPM series. It then explores the possibility of alternative sources of data that could be used to validate estimates based solely from the CPS. It finally presents some results of alternative modeling assumptions.

5.A. Comparisons to an Annual Model

An obvious question one could ask is what are the consequences of allowing OPM and SPM resources to vary from month to month? In other words, what would the results look like if we simply allocated resources equally across months? We begin with a model in which OPM and SPM resources of CPS ASEC units are distributed equally across the months during the first stage of the described in Section 3. We then add month-specific adjustments to this "baseline" model to see their impact on the overall OPM and SPM rates.

Figure 4: Breaking Down the Various Adjustments to the Monthly OPM Rates



Source: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

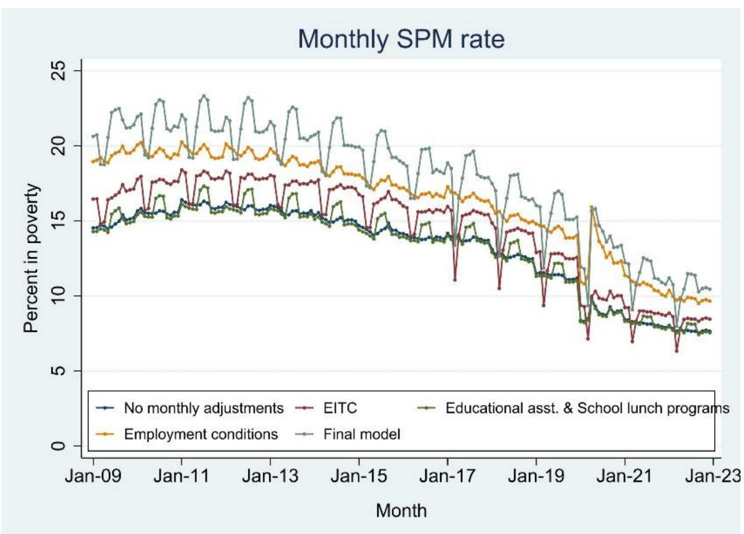
Figure 4 breaks down the various adjustments to the monthly OPM series to understand the effect of unevenly allocating resources in CPS ASEC across different months of the year. The baseline model in this figure is the "No monthly adjustments" series, in which all the components of OPM resources are divided by 12 to obtain the resources for a given month. The thresholds are also divided by 12 to compute the poverty status of each resource unit in CPS ASEC. Since both the resources and thresholds are divided by 12, the poverty status of all families is the same as in CPS ASEC. In other words, this is equivalent to using data on annual poverty status from the CPS ASEC to build a model of poverty so the resulting model coefficients can be applied to the CPS for the month of interest.

Adding educational assistance has minimal effect on the OPM series compared to the baseline series without monthly adjustments. The mean monthly poverty rate for the 2009-2022 period increases from 13.32 percent to 13.36 percent after allocating education assistance only to non-summer months, rather than spreading them out equally across all months. Incorporating recent employment conditions has a large effect on the poverty rate: its inclusion increases the mean monthly poverty rate to 15.49 percent.

This increase makes sense because we allow monthly earnings to be lower than one-twelfth of respondents' annual earnings if they recently experienced unemployment. Incorporating both monthly adjustments to the OPM resources increases the mean monthly poverty rate from 13.32 percent to 15.48 percent, although this increase is not statistically significant.

Figure 5 presents results of a similar analysis in which monthly adjustments to annual SPM resources are incrementally added to the baseline model in which resources are allocated equally across all months of a year. The mean monthly poverty rate for 2009-2022 when we make monthly adjustments to educational assistance and school lunch programs is 13.20 percent, compared with 13.14 percent for the baseline model. Allocating the EITC to a single month in either March or April (since 2017) and February-April (prior to 2017) increases the mean poverty rate to 14.50 percent. Incorporating employment conditions to the baseline model increases the mean poverty rate to 16.38 percent. Incorporating all these adjustments to the baseline model increases the mean poverty rate from 13.14 percent to 17.81 percent. None of these differences are statistically significant.

Figure 5: Breaking Down the Various Adjustments to the Monthly OPM Rates



Source: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

Breaking down the monthly adjustments to annual resources is useful in understanding how much each of them contributes to the average poverty level and the shape of the series. We see that much of the within-year variation for the subannual SPM estimates is driven by the EITC, although incorporating employment conditions has a larger effect on the average monthly OPM rate. Another benefit of this type of exercise is that it will allow us to examine any future changes to the rules (described in Box 1) for converting annual resource components to their monthly values.

5.B. Using Alternative Datasets to Measure Subannual Poverty

Although this study has examined only data from the CPS ASEC and CPS, there is a potential to use other sources of data. This section examines the possibility of using the SIPP and the HPS to validate the findings based on CPS data as well as provide alternatives for a suite of poverty measures that are published in a timely and frequent manner.

5.B.i. Using SIPP Data to Model Monthly OPM Rates

Warren and Silwal (2022) describe a methodology that could be used to project monthly poverty rates from the SIPP (instead of the CPS ASEC) into basic CPS. In some ways, SIPP is an ideal candidate for measuring monthly poverty rates. Since the original 1984 panel, the SIPP has collected the various inputs necessary to construct OPM poverty status for each month of data collection. Both SIPP and CPS share a person-month format that provides demographic data for each reference month; this differs from the CPS ASEC, in which data on demographics are taken at the time of interview (February-April) and assumed to be constant for the previous calendar year. The panel nature of the SIPP allows for longitudinal poverty estimates such as chronic and episodic poverty rates (Warren and Tettenhorst 2022).

The methodology for imputing poverty status from SIPP into CPS generally follows Parolin et al. (2022) but is limited to cash income and the OPM. The first step of this methodology – converting annual resources into their monthly values – is not necessary in the SIPP since it already collects data in a monthly format. The next step of the process is to select predictors of poverty that are available in both SIPP and CPS. Finally, a model of poverty status and income is estimated. Appendix F presents a figure of monthly OPM rates that are estimated by using the monthly data on cash income from SIPP as the source data rather than CPS ASEC. This assumes that the model of poverty (built using SIPP data) from 12 months earlier is still valid for the month of interest and can be used to impute the poverty status of families in CPS.

Warren and Silwal (2022) first impute the poverty status of families in CPS using taking the average of ten multiple imputations, following Parolin et al. (2022). They also model total family income rather than its poverty status as an alternative way to estimate monthly poverty in the CPS. A concern with estimating income is that it does not follow a normal distribution that is often assumed in OLS estimation. The income distribution typically has long thin tails and may be skewed. Warren and Silwal (2022) implement the log-shift transformation, a common solution which entails adding a constant value to the entire distribution (the minimum value, in this case) before taking the log. This allows them to use all of the observations in the dataset while preserving their relative ranks. A critique of this method, however, is that the constant shifting parameter is arbitrary. Despite the log transformation, the income data may still be far from resembling a normal distribution.[34]

Although the SIPP has provided monthly poverty rates for the U.S. since the 1980s, these are often released with a significant lag, much longer than the CPS ASEC. For example, poverty rates from the 2021 SIPP, for reference year 2020, were collected between January-June 2021 and publicly released by the Census Bureau in August 2022. This significant lag between the reference period and public data release

[34] The authors also implement the Inverse Hyperbolic Sine (IHS) transformation, which preserves the relative ranks between the observations while yielding a transformed distribution that is closer to the normal distribution.

currently limits the value of the SIPP for timely and frequent poverty statistics. However, a SIPP-based model of income seasonality could potentially be a part of future subannual estimates that are mostly based on the CPS ASEC and monthly CPS.

5.B.ii. Comparison with Data from the HPS

The HPS is another resource that can be potentially used to create a subannual measure of wellbeing.[35] Glassman and Silwal (2023) propose a measure of financial insecurity based on the HPS that could complement the subannual poverty series described in this study based on the CPS. The HPS is an experimental online survey created in April of 2020 by the Census Bureau, in collaboration with various federal agencies, to measure the real-time effects of the COVID-19 pandemic on peoples' lives. It is conducted every month[36] with data that are publicly released within a few weeks of the survey. This survey collects data on the U.S. population that is 18 years and older.

The HPS has its limitations. Its sampling frame is limited to households with a known email address or cell phone number. It collects detailed information on the respondent but only limited information on other household members. It is a relatively new and evolving survey with some questions that have changed over time. It also has a low response rate of about 7.5 percent on average throughout the period covered in this study. Despite these limitations, its timeliness and high frequency make this an appealing source of data. In particular, the HPS contains a question that could be used to measure financial insecurity.[37] Glassman and Silwal (2023) define respondents as financially insecure if they report having a "very difficult" time paying household expenses. Although the measure of financial insecurity is not comparable to the subannual OPM and SPM measures described in this paper, it can be used to corroborate the findings of those measures. In that sense, it serves a purpose similar to that of the SIPP discussed in the previous section.

Appendix G presents national poverty estimates for the U.S. population age 18 years and over for the OPM and the SPM from the CPS, as well as the financial insecurity measure from the HPS from April 2020 through June 2022. Glassman and Silwal (2023) report that the three rates presented in Appendix G are within approximately two to six percentage points of each other during April 2020 – June 2022. They suggest these differences could be partly explained by differences in sample composition, differences in the unit of measurement (families, SPM units, and households), and the difference between an objective income measure and a subjective financial difficulty measure. Despite these differences, the estimates show a large degree of similarity during the period examined. The overall takeaway is that these measures could be a part of a suite of measures that can inform us about the monthly change in income poverty and subjective financial insecurity.

[35] For more information on the HPS, refer to https://www.census.gov/programs-surveys/household-pulse-survey/technical-documentation.html.

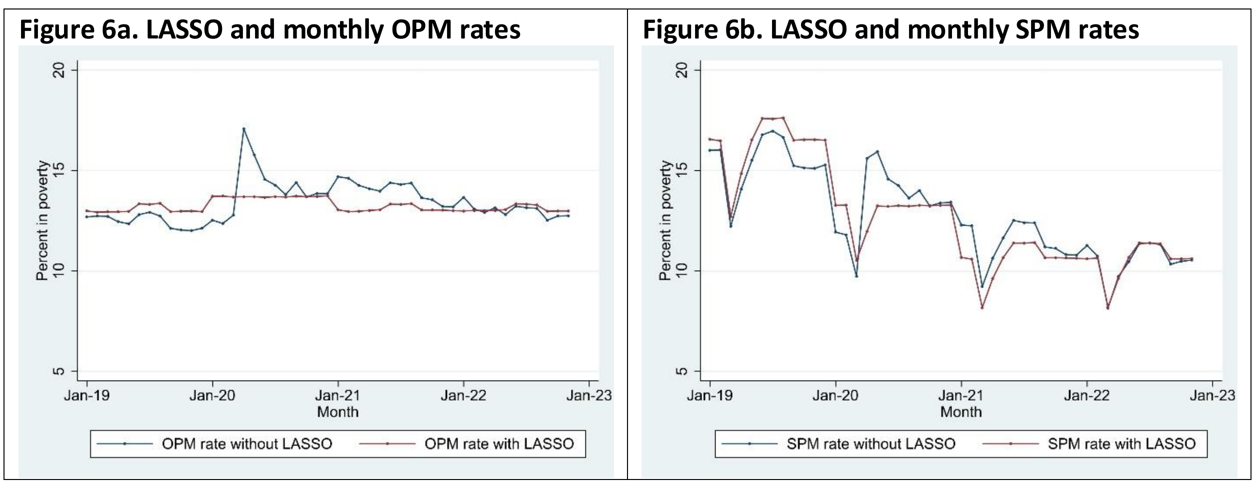
[36] As of February 2022, the survey is conducted on a two-weeks on, two-weeks off cycle, although the data collection cycle has varied from one to four weeks in the past.

[37] The survey question is: "In the last 7 days, how difficult has it been for your household to pay for usual household expenses, including but not limited to food, rent or mortgage, car payments, medical expenses, student loans, and so on? Select only one answer. 1) Not at all difficult 2) A little difficult 3) Somewhat difficult 4) Very difficult."

5.C. Model Selection Techniques

The specification of the imputation can have a large effect on poverty estimates. In producing the main results in Section 4, covariates of poverty in the imputation model were selected by generally following Parolin et al. (2022). I was also limited by the list of variables that were available in both CPS ASEC and CPS. This section examines what the estimates would look like if we used only selected a subset of variables that are most correlated with poverty status. One technique for selecting variables from a list of candidate variables is the Least Absolute Shrinkage and Selection Operator (LASSO). The LASSO allows us to select a set of predictive variables while avoiding over-fitting the model to a sample (Tibshirani 1996). This method involves regressing all candidate variables on the outcome of interest, which in our case is the OPM or SPM poverty status. The resulting estimates include zero coefficients for some variables, which are excluded in the subsequent estimation. The remaining variables with non-zero coefficients are then included in the multiple imputation model. LASSO is a convenient and somewhat intuitive tool for selecting a subset of predictor variables without sacrificing unbiased estimates.

Figure 6: Monthly OPM and SPM Rates with and Without LASSO



Source: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

Figures 6a and 6b present estimates of monthly OPM and SPM rates with and without LASSO to select the covariates of the imputation model. The mean monthly OPM rate for this period with LASSO is 13.24 percent with a standard deviation of 0.31 percent; without LASSO, the mean and the standard deviation are 13.41 percent and 1.01 percent, respectively. What is striking is that the jump in the OPM rate in early 2020 is unobservable in the estimates without LASSO.[38] This suggests that LASSO may select variables that are generally important, but also throw out important information in a prediction model. For example, some age-related variables may have been excluded by LASSO but were important predictors of OPM status in early 2020. The SPM series in Figure 6b has higher volatility compared to the OPM series because

[38] This also coincides with the start of the COVID-19 pandemic, which led to many people losing jobs.

of the modeling decisions in allocating taxes and benefits. Despite this, we see a jump in the monthly SPM rate in early 2020 in the series without LASSO; we do not see a similar jump in the series with LASSO. The mean value of the SPM series without LASSO is 12.62 percent (with a standard deviation of 2.60 percent) compared with the series with LASSO, which has a mean of 12.76 percent and a standard deviation of 2.27 percent. This suggests, similar to the OPM series, that using the LASSO leads to a predicted series that has a lower standard deviation compared to the results without LASSO.

LASSO sets the coefficients to zero for variables that are not strongly correlated with the outcome variable, effectively letting us drop them from the regression model. An alternative to LASSO is ridge regression, which does not set the coefficients of some variables to zero but does shrink them significantly; this effectively lets us keep all variables in the model but gives higher weights to variables that are more correlated with the outcome variable. Elastic net regularization is a broader technique that encompasses LASSO and ridge regression. Implementing these techniques is possible in many statistical software packages, although interpreting the results is not always straightforward. These techniques are also computationally intensive and may be limited in value for routine publication at this time.

Stepwise selection is another popular method to reduce the number of covariates in a regression model. I attempted to implement stepwise regression, but the computational burden was prohibitive because of the need to sequentially process nearly 200 variables for each month. One possibility worth exploring is to use variance inflation factors (VIF) to select covariates (Corral et al. 2022). The VIF of a variable is proportional to the R^2 from the model in which all other right-hand side variables are regressed on that variable. The greater the variation in a variable that can be explained by other covariates, the higher its VIF and the less it will add to the model's explanatory power. Corral et al. (2022) suggest dropping variables with a VIF of 10 or more.

The takeaway from this discussion is that there may not be a huge benefit to model selection methods for estimating subannual poverty rates. However, we also know that model specification has consequences for coefficients and prediction. Further research may be necessary on this issue.

5.D. Ordinary Least Squares vs. Maximum Likelihood Estimation

This study uses a linear probability model[39] within a multiple imputation framework to model poverty status, which is a dichotomous variable. The appeal of the linear probability model is methodological simplicity. Using a logit or probit model using maximum likelihood estimation would be, in theory, more appealing since they are suited to modeling dichotomous outcome variables. I explored the possibility of using a logit model to model poverty status but was not able to successfully do so since the model did not successfully converge for all months. The lack of convergence is sometimes due to multicollinearity, which I addressed by dropping not only dropping collinear variables but also removing variables that had VIF of more than 3. This is presumably because of the large set of variables that I use in the multiple imputation model. Even if I were successfully able to implement a logit model for this exercise, it is not obvious that doing so would be a good choice (Friedman 2012).[40]

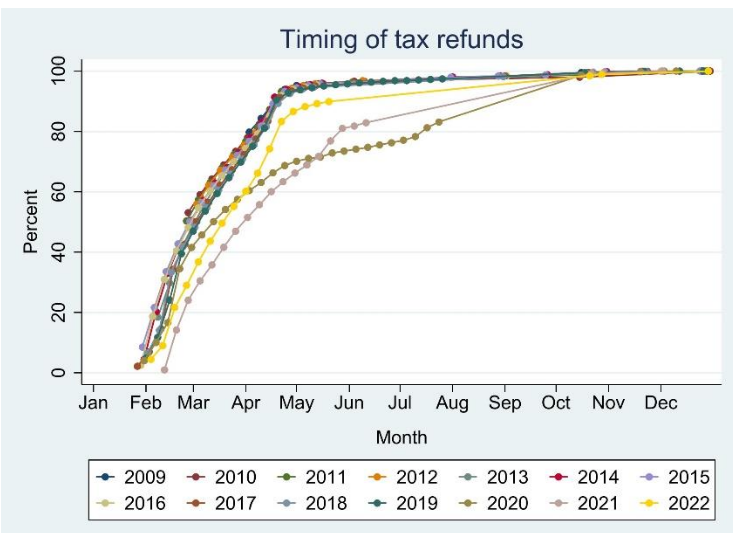
[39] The linear probability model is ordinary least squares estimation applied to a dichotomous outcome variable, rather than a continuous outcome variable.
[40] I ruled out using the probit model since it is not available in Stata's implementation of multiple imputation.

6. Further Research

This section discusses some outstanding questions for discussion and consideration if the subannual poverty measures described are going to be published routinely by the Census Bureau.

Should we revise the timing of EITC refunds? Figure 5 illustrates how we allocate EITC refunds throughout the year on subannual SPM rates. The formula for distributing EITC refunds is mostly based on a single study by a commercial bank published in 2018 and based on checking account data from 2016 (Farrell et al. 2018). Distributing EITC refunds to families to specific months lowers the poverty rate in those specific months but increases it for other months. Aladangady et al. (2022) document a sizeable and speedy spending response to the timing of EITC refunds on household spending. Although this study uses the finding from Farrell et al. (2018) that households receive EITC refunds in predominantly in March (and assumes that this pattern has not changed since 2017), estimates on the timing of tax refunds from the Internal Revenue Statistics (IRS) in Figure 7 show that the pattern may be more complex and varies by year. Figure 7 shows the cumulative share of total refunds distributed by the IRS at different times during the year.

Figure 7: Timing of IRS Tax Refunds, 2009-2023



Source: Internal Revenue Statistics, Filing Season Statistics, Weekly Data, 2009–2023.[41]

Households have delayed filing taxes since 2020 in the aftermath of COVID-19, although it is unclear how permanent this change is. Moreover, timing of tax refunds overall likely differs from the timing of EITC refund due to regulations preventing early EITC refunds as well as likely differences in filing timing by income, which Figure 7 does not address. Accounting for this annual variation in the timing of tax

[41] The weekly numbers from the IRS need to be interpolated to obtain monthly estimates. Downloaded on February 7, 2023, from https://www.irs.gov/newsroom/filing-season-statistics-by-year.

refunds has implications for how much the poverty rates will drop in some months of the year and may be an important issue for further study.

Should the monthly estimates be revised once newer CPS ASEC data become available? The methodology proposed in this study entails using the most recent CPS ASEC to model poverty status. For example, the monthly poverty estimate for February 2023 (which can be published in March 2023 using monthly CPS for February 2023) will be based on a model of poverty based on the 2022 CPS ASEC for reference year 2021. But comparable CPS ASEC data for 2023 will not be available until fall 2024, meaning that there will be opportunities to revise the February 2023 poverty estimate when the next two CPS ASECs are released. The question then arises: should the monthly poverty estimates be revised for February 2023 in fall 2023 using data from CPS ASEC for reference year 2022 and again in fall 2024 using data from CPS ASEC for reference year 2023? In releasing subannual poverty statistics, we could either follow the practice for unemployment rates (which are not revised after they are published each month) or quarterly GDP rates (which are revised multiple times as newer data become available).[42]

How should the Census Bureau operationalize the production of subannual estimates? Once the ideal reference period and frequency of publication of subannual poverty estimates are chosen, a detailed plan for routine publication that includes data acquisition, data analysis, and dissemination will need to be created. Although this study uses data from IPUMS, being able to acquire CPS data directly from the Census Bureau should speed up this process.[43] Ingesting new CPS data or CPS ASEC data requires care since variable names and categories may change over time. Being able to work with variables in the IPUMS format would allow for easier collaboration with external researchers and facilitate any replication efforts.

What are the outstanding methodological issues? Several methodological issues related to estimating subannual poverty remain to be resolved. First, more work needs to be done to compute more accurate standard errors of the estimates. The current estimates of standard errors assume that the chosen imputation model is the true model. In particular, we need to more accurately capture uncertainty in the estimates arising from sampling and non-sampling error. Second, we should further explore modeling resources instead of poverty status. Simulating the full income distribution would allow for estimates beyond just poverty and mean welfare. Using wages from the CPS should also be explored, although we will be limited by the fact that wage earnings will only be available on a quarter of the full CPS sample. Finally, although the unit of analysis assumed in this study is the individual, we possibly need to estimate the model of poverty at the family level for OPM and SPM unit for SPM. This will ensure that all members of the resource unit receive the same poverty status.

What are potential future improvements to the methodology? The historical accuracy of subannual poverty estimates will be improved if major policy changes are modeled explicitly. In particular, the timing of pandemic-era policies such as the stimulus payments and ACTC in 2020 and 2021 were concentrated during certain months of the year. The methodology proposed in this paper, in an attempt to make it applicable to all years, distributes all tax credits (other than EITC) equally throughout the year. This decision likely overstates the monthly poverty rate for the months during which these benefits were

[42] We could get a sense of the magnitude of these changes by looking at how monthly estimates would have been different in the past if they were based on CPS ASEC data from the previous year instead of two years ago.

[43] CPS data are typically released a week after unemployment estimates are released (usually, the first Friday of each month). IPUMS makes harmonized data available on its website about a week after raw data are posted on Census Bureau's website.

available. Modeling these programs for future SPM monthly estimates is possible, although this will require making assumptions about the timing of receipts.

Can we use data other than the CPS for this effort? We should explore the possibility of incorporating additional sources of data for this exercise.[44] Quarterly data from Longitudinal Employer-Household Dynamics (LEHD) may be a useful addition. Administrative records on incomes and program participation should also be considered, although care may need to be taken regarding the completeness and timeliness of this data. Additional sources of data that could be useful are the quarterly Consumer Expenditure Survey (CE), state-level unemployment insurance claims, non-farm payroll employment, Weekly Economic Index, Google Trends, and private sector data such as those used by Opportunity Insights and SafeGraph. Many of these are experimental, do not always have broad spatial or temporal coverage, or are not publicly available. However, these have the potential to augment the data sources used more-reliably estimate poverty subannually.

7. Conclusion

Higher-frequency measures of poverty can serve as a useful economic indicator in times of economic change, like the COVID-19 pandemic. The current annual data collection cycle of the CPS ASEC does not allow for us disseminate statistics on a timely or frequent basis. Although the need for more frequent reporting of data on poverty is clear, this does not imply that such a need can be easily met. The long-run solution may be to collect the data underlying the OPM or SPM on a more regular basis. To do so would be costly; besides, any major changes in data collection are not likely in the near term. Admittedly, there are many sources of data on higher-frequency measures of economic health such as employment, GDP, and consumer sentiment. However, these indicators either refer to the economy as a whole or do not give a complete picture of the resources available to households. Therefore, it is useful to experiment with ways of exploiting existing data for the purpose of creating a more frequently updated series. A strategy such as the one presented in this paper – to combine existing sources of data we already have – may give us a valuable tool to supplement the existing annual poverty statistics. Another benefit of this method is that it acts as a filter through which to project multivariate streams of data, on labor markets and other demographics, into an easily understood index of deprivation until more complete annual data are available from the CPS ASEC.

This paper examined the possibility of combining the CPS ASEC with monthly CPS to create subannual measures of poverty that could be released faster and at a higher frequency than annual poverty measures coming from the CPS ASEC or the American Community Survey. Although this study relies heavily on the methodology in Parolin et al. (2022), these studies differ in important ways. The focus of Parolin et al. (2022) was to propose a method to capture the effect of COVID-19 and its associated government response on the SPM. This study generalizes that methodology so it can be published routinely to capture short-term changes in economic circumstances and government policy. The

[44] Albright and Asiala (2016) describe the challenges, despite its promise, of using the American Community Survey (ACS) for the routine production of monthly poverty estimates.

generalizations also allow for flexibility to adapting to any production constraints at the Census Bureau that may dictate the frequency of releases in routine production.

There may also be reasons against shorter-term measures of poverty. Income measured over short periods may appear volatile for coincidental reasons: someone with bi-weekly paychecks will receive three paychecks in two months out of a year. A shorter accounting period would also mean that the circumstances observed may be temporary and that households found below the poverty threshold may have escaped in the following period. Income measured over longer periods may be a better indicator of the longer-term potential consumption if households can tap into savings, borrow from other sources, and delay expenditures. Despite these concerns, I argue that a subannual measure of poverty is a useful addition to the suite of measures of the wellbeing of the U.S. population.

Although this paper finds that it is feasible to routinely publish a subannual series of OPM and SPM for different reference periods, a monthly series is most consistent with the data production cycle of the CPS. What remains to be determined is whether a monthly production and publication cycle will be feasible for the Census Bureau. Further research is still needed to improve the credibility of these estimates. The modeling decisions made during computation of the monthly OPM and SPM may need to be revisited as they can affect the level and trend of poverty. For example, how the EITC is allocated within the year affects the SPM rate. If poverty data were reported subannually, it would be possible to add it to the body of evidence upon which short-run economic policy decisions are based. In the end, these measures would supplement the annual measures of poverty. They will inform us of the extent and nature of short-term deprivations as well as the intra-year volatility in poverty, providing another lens on the hardships that families face.

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Appendix

Appendix A: Monthly OPM and SPM Rates (January 2019 to December 2022) for All People[1]

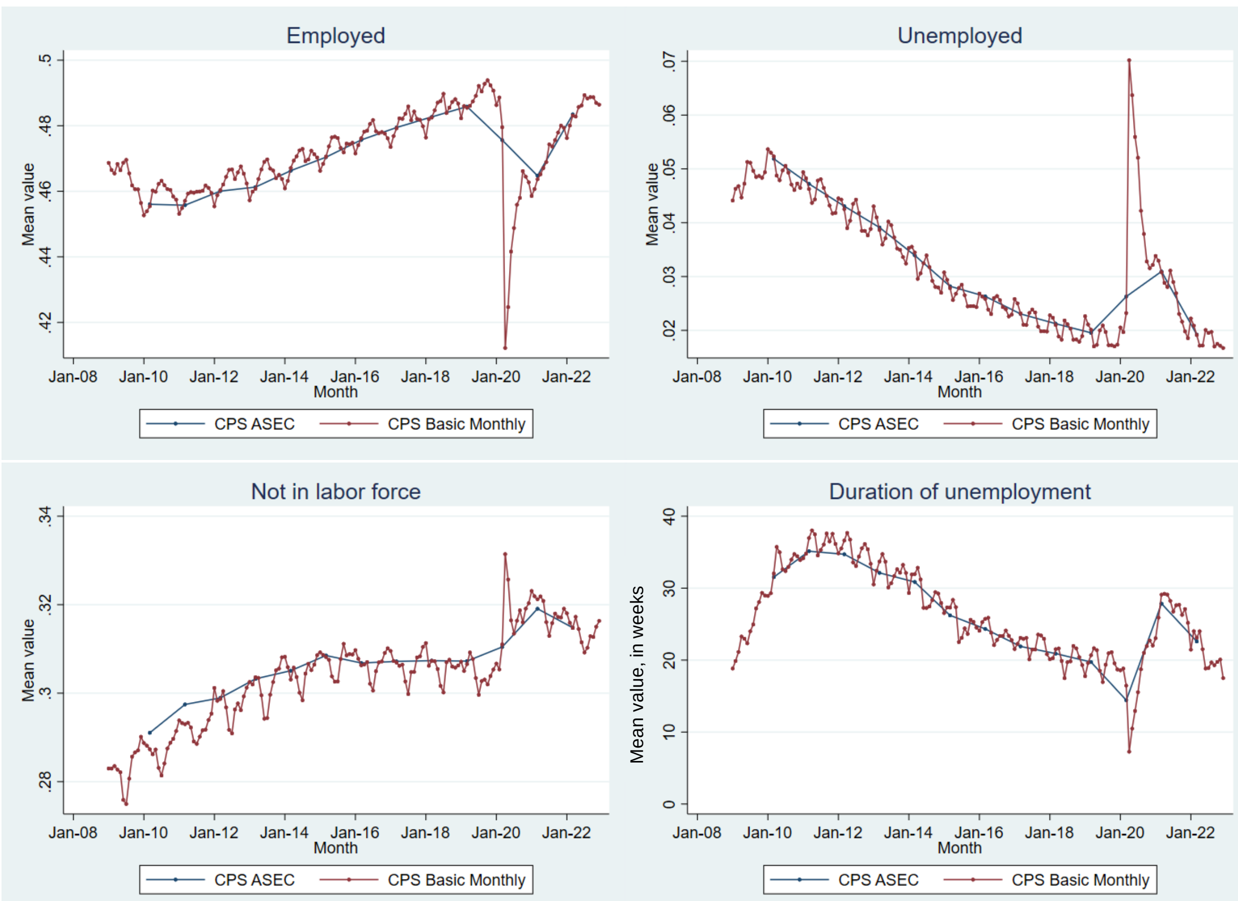
(Margins of error in percentage points. Information on confidentiality protection, sampling error, nonsampling error, and definitions is available at <https://www2.census.gov/programs-surveys/cps/techdocs/cpsmar21.pdf>.)

	Monthly OPM Rate		Monthly SPM Rate	
	Percent	Margin of error[2] (±)	Percent	Margin of error[2] (±)
Jan-2019	14.3	0.2	17.5	0.2
Feb-2019	13.9	0.2	17.0	0.2
Mar-2019	14.0	0.2	12.7	0.2
Apr-2019	13.6	0.2	15.2	0.2
May-2019	13.4	0.2	16.5	0.2
Jun-2019	14.1	0.2	18.0	0.2
Jul-2019	14.2	0.2	18.0	0.2
Aug-2019	14.2	0.2	18.1	0.2
Sep-2019	13.5	0.2	16.6	0.2
Oct-2019	13.5	0.2	16.5	0.2
Nov-2019	13.3	0.2	16.4	0.2
Dec-2019	13.4	0.2	16.5	0.2
Jan-2020	12.7	0.2	16.0	0.2
Feb-2020	12.7	0.2	15.9	0.2
Mar-2020	12.7	0.2	11.9	0.2
Apr-2020	12.4	0.2	14.3	0.2
May-2020	12.4	0.2	15.5	0.2
Jun-2020	12.9	0.2	16.8	0.2
Jul-2020	13.0	0.2	17.0	0.2
Aug-2020	12.8	0.2	16.7	0.2
Sep-2020	12.0	0.2	15.1	0.2
Oct-2020	12.0	0.2	15.1	0.2
Nov-2020	12.0	0.2	15.1	0.2
Dec-2020	12.1	0.2	15.2	0.2
Jan-2021	12.5	0.2	11.9	0.2
Feb-2021	12.4	0.2	11.8	0.2
Mar-2021	12.8	0.2	9.4	0.1
Apr-2021	17.0	0.3	15.7	0.2
May-2021	15.7	0.3	15.8	0.2
Jun-2021	14.7	0.2	14.7	0.2
Jul-2021	14.3	0.2	14.3	0.2
Aug-2021	13.8	0.2	13.6	0.2
Sep-2021	14.4	0.2	14.0	0.2
Oct-2021	13.7	0.2	13.2	0.2
Nov-2021	13.7	0.2	13.3	0.2
Dec-2021	13.8	0.2	13.4	0.2
Jan-2022	14.6	0.2	12.2	0.2
Feb-2022	14.5	0.2	12.1	0.2
Mar-2022	14.2	0.2	9.1	0.1
Apr-2022	14.1	0.2	10.7	0.2

May-2022	13.9	0.2	11.6	0.2
Jun-2022	14.5	0.2	12.5	0.2
Jul-2022	14.4	0.2	12.4	0.2
Aug-2022	14.3	0.2	12.3	0.2
Sep-2022	12.5	0.2	10.3	0.1
Oct-2022	12.7	0.2	10.5	0.1
Nov-2022	12.8	0.2	10.5	0.1
Dec-2022	12.7	0.2	10.5	0.1

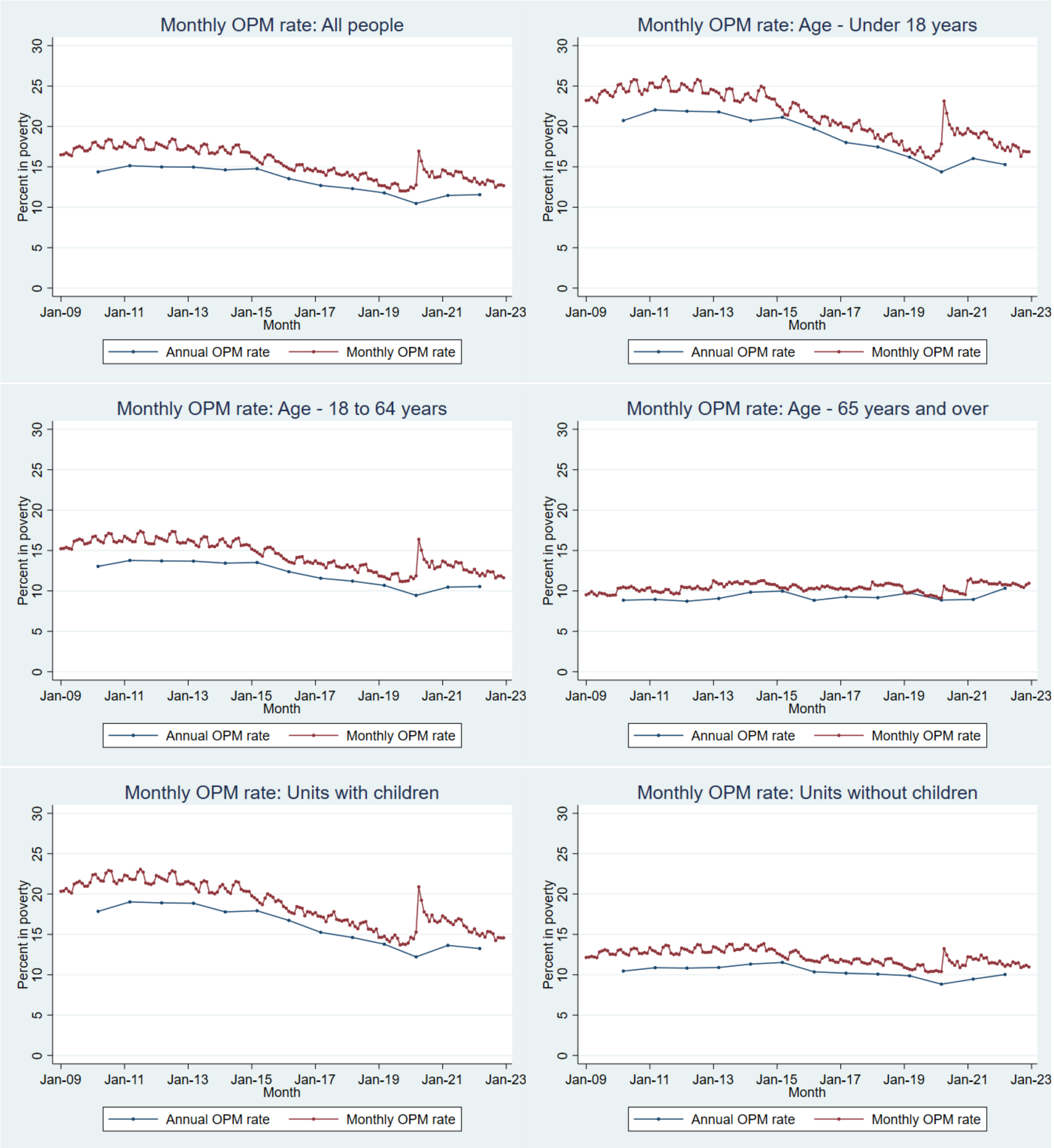
[1] Monthly poverty rates were computed for January 2009 to December 2022 and are available from the author upon request, if not presented in this table.
[2] A margin of error (MOE) is a measure of an estimate's variability. The larger the MOE in relation to the size of the estimate, the less reliable the estimate. This number, when added to and subtracted from the estimate, forms the 90 percent confidence interval. MOEs shown in this table are based on standard errors calculated without using replicate weights.
Source: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009-December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

Appendix B: Comparison of Means of Selected Variables in CPS ASEC and CPS



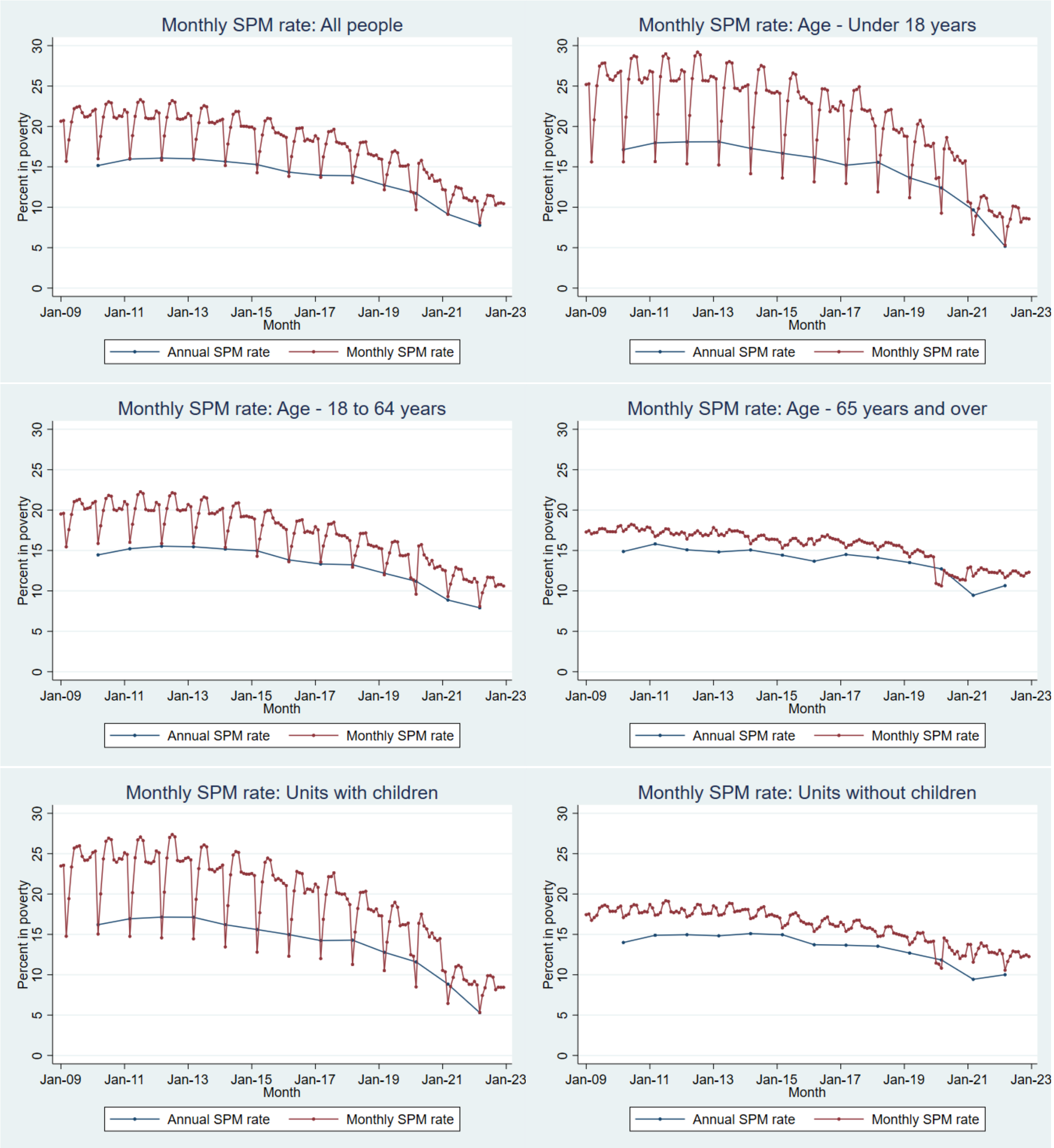
Note: The CPS ASEC values are assigned to the March of the survey year. Similar figures are available for sex, marital status, age, race, Hispanic origin, householder status, disability status, citizenship, nativity, and education.
Source for all figures above and those mentioned in the note: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

Appendix C: Comparison of Annual vs. Monthly Poverty OPM Estimates for Selected Subgroups



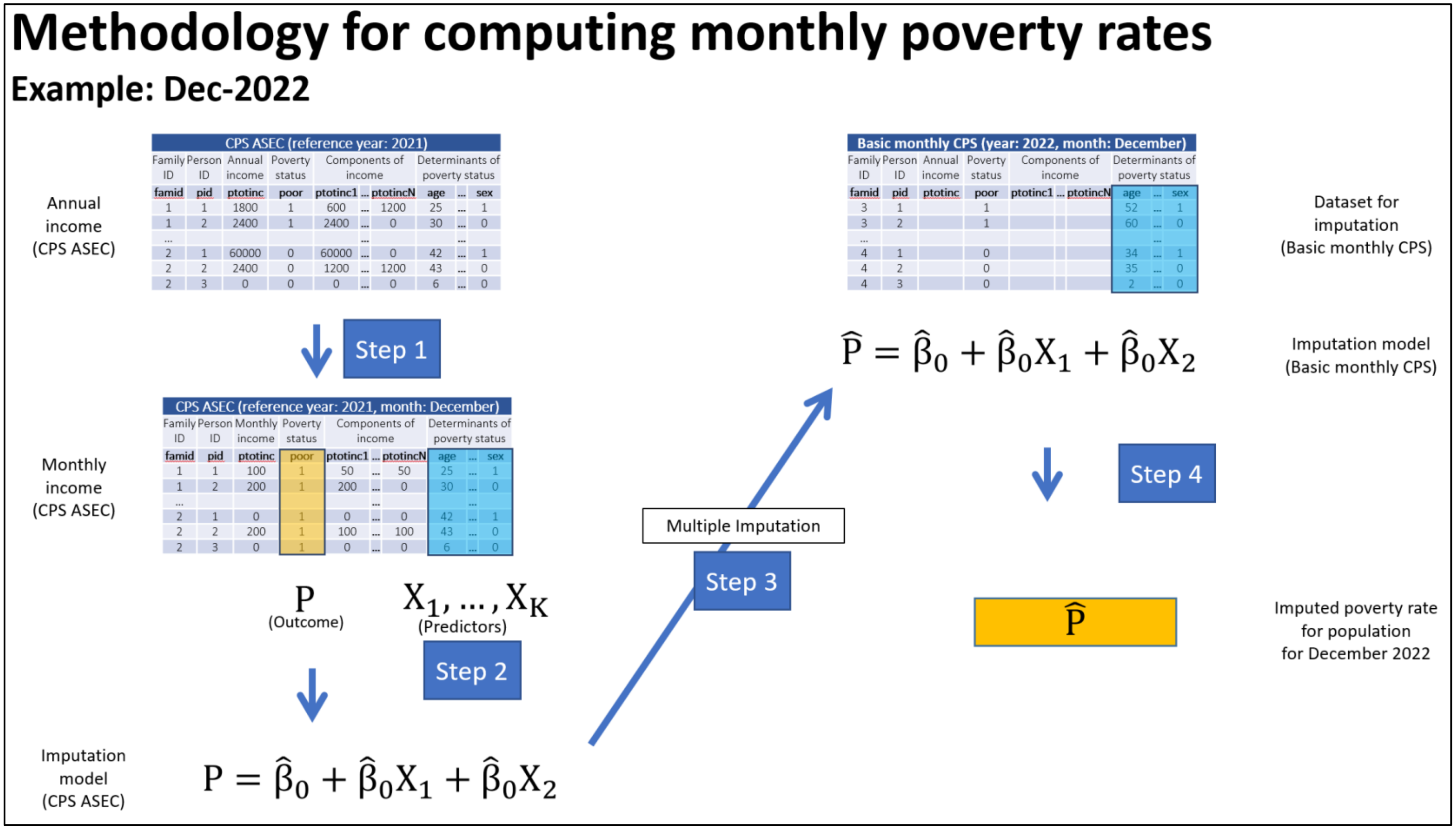
Note: The CPS ASEC values are assigned to the March of the survey year. Similar figures are available for sex, marital status, age, race, Hispanic origin, householder status, disability status, citizenship, nativity, education, units with and without children, and region of residence.
Source for all figures above and those mentioned in the note: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

Appendix D: Comparison of Annual vs. Monthly Poverty SPM Estimates for Selected Subgroups



Note: The CPS ASEC values are assigned to the March of the survey year. Similar figures are available for sex, marital status, age, race, Hispanic origin, householder status, disability status, citizenship, nativity, education, units with and without children, and region of residence.
Source for all figures above and those mentioned in the note: U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022.

Appendix E: Illustrated Methodology for Computing Subannual Poverty Rates (Example: Monthly Poverty Rate for December 2022)



Methodology:

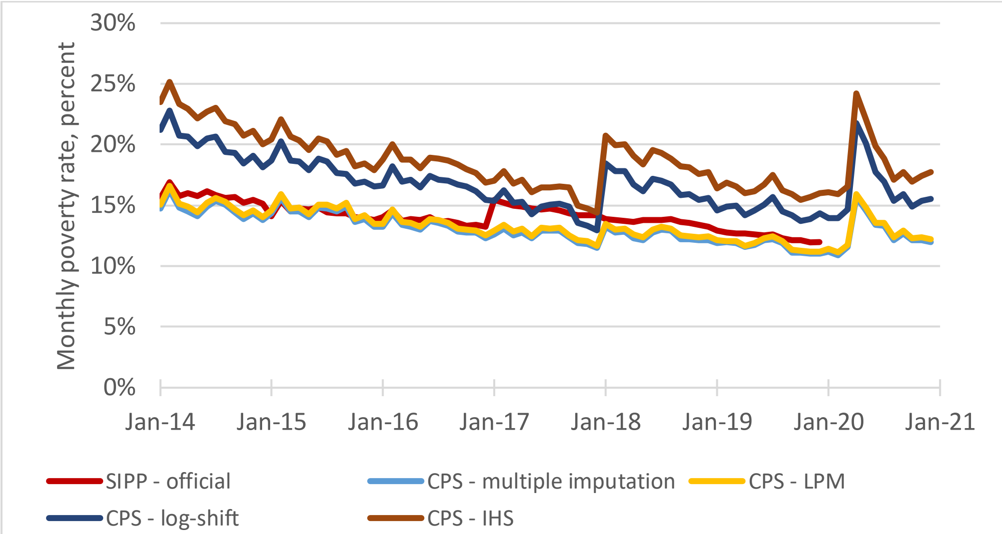
Step 1: Convert components of 2021 annual resources from the CPS ASEC to values for December 2021. Assign monthly poverty status for December 2021 to everyone in the CPS ASEC for 2021.

Step 2: Generate variables in the CPS ASEC (for 2021) and CPS (for December 2022) for multiple imputation model.

Step 3: Conduct multiple imputation of poverty status in CPS for December 2022 based on model of poverty status in the CPS ASEC in December 2021.

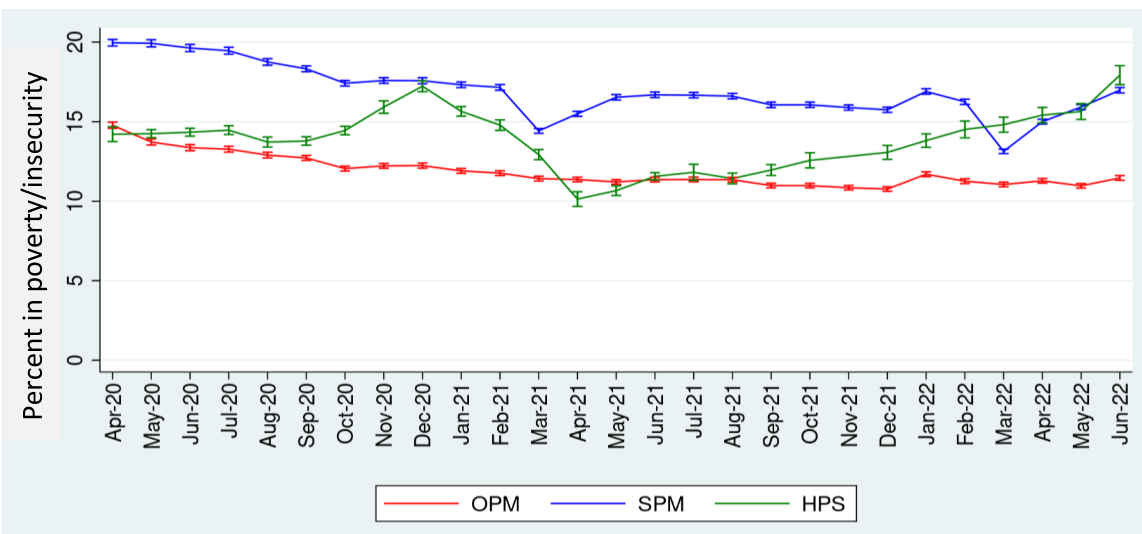
Step 4: Compute poverty rates for all people and relevant subgroups from imputed poverty status in CPS for December 2022.

Appendix F: Monthly OPM Rates Computed Using the SIPP, January 2014 – December 2020



Source: Warren and Silwal (2022). U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022, public-use SIPP data for survey years 2014-2021. Note: LPM stands for the linear probability model, log-shift stands for the log-shift transformation, and IHS stands for the inverse hyperbolic sine transformation.

Appendix G: Monthly Poverty Rates from the CPS and Monthly Insecurity Rates from the HPS



Source: Glassman and Silwal (2023). U.S. Census Bureau, public-use Household Pulse Survey data for Weeks 1 through 46; U.S. Census Bureau, public-use Current Population Survey (CPS) data for January 2009 – December 2022, public-use Annual Social and Economic Supplements (CPS ASEC) for survey years 2010-2022. Error bars represent 90 percent confidence intervals.