Covid-19 and the Current Population Survey: Response Rates and Estimation Bias October2020

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Abstract
The Covid-19 pandemic has resulted in sudden and severe changes to data collection procedures in the monthly U.S. Current Population Survey (CPS), including the suspension of personal visit interviews starting in March 2020. Although personal visit interviewing has begun to resume, response rates during the pandemic have fallen across all eight panels in the CPS survey. The decline has been sharpest for households enrolled since collection procedures have been modified, leading to an imbalance between pre- and post-pandemic panels. This paper reviews the impact of imbalanced response rates on major labor force estimates by deconstructing CPS estimation bias into mutually exclusive, observable components.

Key Words: Covid-19; pandemic; Current Population Survey; CPS; response rates; estimation bias

1. Introduction

Toward the end of the March 2020 data collection period, the Current Population Survey took the extraordinary step of indefinitely suspending all personal visit interviews in response to the Covid-19 pandemic. From that point through June 2020, all CPS interviews were conducted by phone, a significant disruption to normal collection operations that had the potential to impact the quality of CPS labor force estimates in unknown ways. Personal visits resumed partially in July and August, based on regional conditions, and nationally in September[2]. In this paper, the effects of these widespread modal changes are analyzed in the context of estimation bias of topside labor force levels and rates.

The CPS is a panel survey that attempts to interview sampled households (HHs) following a 4-8-4 rotation scheme[3]: HHs are in sample four consecutive months; out of sample the next eight months; and they are again in sample the following four months. The first four months (wave 1) are denoted month-in-sample (MIS) 1 – 4, and the final four months (wave

[1] Views expressed are those of the author and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics.

[2] As of September 2020, collection procedures have not completely returned to normal. All interviewers attempt telephone interviews prior to contacting households in person, and the share of interviews conducted by personal visit remains lower than prior to the pandemic.

[3] The 4-8-4 rotation scheme is designed to create an approximate 75 percent overlap in responding HHs for measuring over-the-month change and an approximate 50 percent overlap in responding HHs for measuring over-the-year change in labor force estimates. These overlap rates improve the precision of change estimates compared to an independent samples design.

2, after the eight-month break) are denoted MIS 5 – 8. MIS is also interchangeably referred to as rotation group.

During a typical collection cycle, data are obtained from the majority of MIS 1 and MIS 5 responding households via personal visit interviews while most MIS 2 – 4 and MIS 6 – 8 interviews are conducted by phone. This is particularly important for MIS 1 for both initial enrollment and because contact information is collected during this interview. This creates a circular data collection problem: Phone interviews require accurate contact information to conduct, but contact information is typically collected during personal visit interviews. To mitigate the deleterious effects on response rates, the Census Bureau, who collects the CPS data for the Bureau of Labor Statistics (BLS), provided interviewers with telephone numbers from their contact frame. While this is an imperfect solution, it enables MIS 1 interviews to be conducted by phone when contact frame information is accurate for the sampled HHs.

Inevitably, CPS response rates suffered from the suspension of personal visits during data collection. Declines have been most pronounced in MIS 1 and other post-pandemic panels, which are defined in this paper as HHs that entered the sample in or after March 2020. Historically, each MIS has its own labor force biases relative to the average across all eight MIS (Erkens 2012, 2017). The nonuniformity of the effects on response rates across MIS 1 – 8 and between pre- and post-pandemic panels can cause ripples that influence the current monthly labor force estimates as well as future estimates, due to the CPS composite estimator that utilizes past data to improve the precision of estimates of change over time.

To investigate the severity of these potential disruptions to the labor force time series, this paper mathematically deconstructs the CPS composite estimator of total employed persons and total unemployed persons into mutually exclusive, observable components that have exhibited stable behavior between January 2003[4] and February 2020, the last month of data collection unaffected by Covid-19[5]. The not seasonally adjusted unemployment rate (U3[6]) is decomposed as a derivative series. The behavior of these components is observed during the pandemic months through September 2020, the last month of data available at the time this paper was written, to identify how systematic changes in response rates—specifically, response imbalance across panels—have induced bias into CPS labor force estimates under certain assumptions.

The bias estimates presented in this paper assume no misclassification error. The issue of potential underestimation of unemployment related to misclassification is discussed in *The Employment Situation* news releases published by the BLS and associated pages describing the effects of the Covid-19 pandemic[7].

[4] The CPS composite estimator was adjusted and reset in January 2003 with the introduction of new weighting methods and additional demographic controls (*Design and Methodology, Current Population Survey, Technical Paper 77*).
[5] Personal visits were not completely suspended until March 20, 2020—late in the March collection period—but some geographic areas were not conducting personal visits at the beginning of the week. Geographic areas suspending personal visits expanded each day, and interviewers who were uncomfortable were not required to conduct interviews in person. March response rates (Section 2) demonstrated an immediate decline.
[6] The BLS computes six measures, U1 – U6, of labor force underutilization. U3, seasonally adjusted, is the official unemployment rate.
[7] https://www.bls.gov/covid19/effects-of-covid-19-pandemic-and-response-on-the-employment-situation-news-release.htm

2. Response Rates

The CPS is a multistage probability survey, designed to meet both national and state precision requirements, that samples about 60,000 eligible HHs per month. The ultimate sampling units are clusters of HHs that are assigned a base weight equal to the inverse of the probability of selection.

Each eligible adult in the household is assigned the base weight. A series of one-step ratio adjustments are then applied, including a HH-level nonresponse or "noninterview" adjustment based on geography followed by a series of person-level coverage adjustments to match independent population totals. After the one-step adjustments, the adjusted person-level weights are raked[8] in three dimensions to match detailed, monthly population controls at the following levels:

- State / sex / age
- Ethnicity / sex / age
- Race / sex / age

The resulting "second-stage (SS) weights" reduce the bias and decrease the error in the vast majority of sample estimates[9].

Notably, individual MIS are not distinguished at any stage of weighting. CPS combines primary sampling units of similar size and metropolitan status—generally within state boundaries, although some cross state lines—to create nonresponse adjustment cells. In several coverage steps and in SS weighting, MIS are paired[10]:

- MIS 1 and MIS 5
- MIS 2 and MIS 6
- MIS 3 and MIS 7
- MIS 4 and MIS 8

Pairing MIS enables the creation of more detailed cells in SS weighting, in which respondent weights are adjusted to match external population controls. This has the benefit of increasing precision and reducing bias for subgroup estimates that would otherwise be uncontrolled if individual MIS were instead specified in the calibration steps. Given the four MIS pairs, each pair is weighted to represent one-fourth the control total in the various SS weighting dimensions.

Let MIS pair (i, j) comprise MIS i and MIS j:

$$(i, j), i \in [1,2,3,4], j = i + 4$$

and let π_i, π_j, and π_{ij} denote the response rates of MIS i, MIS j, and MIS pair (i, j), respectively.

[8] Raking is also known as raking ratio estimation or iterative proportional fitting.
[9] Chapter 2-3 of *Design and Methodology, Current Population Survey, Technical Paper 77*.
[10] In some weighting dimensions at the state level, there is not enough sample to support MIS pairing. All eight MIS are combined in these cells.

Assuming missing at random within MIS i and MIS j for any MIS pair (i, j), and noting that the historical labor force biases of (i, j) are unequal (Erkens 2012), labor force estimates based on SS weights are unbiased with respect to the independent population controls if $\pi_i = \pi_j = \pi_{ij}$.

If the relative response rate of $i \in (i, j)$ is defined as π_i^*, unbiasedness implies

$$\pi_i^* = \frac{\pi_i}{\pi_{ij}} = 1.00$$

When $\pi_i^* = 1.00$, the response for MIS pair (i, j) is "balanced;" i.e., it is equally representative of MIS i and MIS j. If $\pi_i^* \cong 1.00\ \forall\ i \in [1,2,3,4]$, then under the prescribed assumptions, the bias induced as a result from response imbalance across the four MIS pairs is approximately zero.

Over the time period January 2003 – December 2019[11], as shown in Figure 1, the historical relative response rates are consistently near one. Some increasing fluctuation occurs toward the end of the series, particularly for MIS pair $(1,5)$, as response rates have trended downward in the CPS in recent years. Overall, the historical time series do not appear to exhibit any problematic response imbalances, indicating that bias resulting from unequal response rates within MIS pairs is negligible.

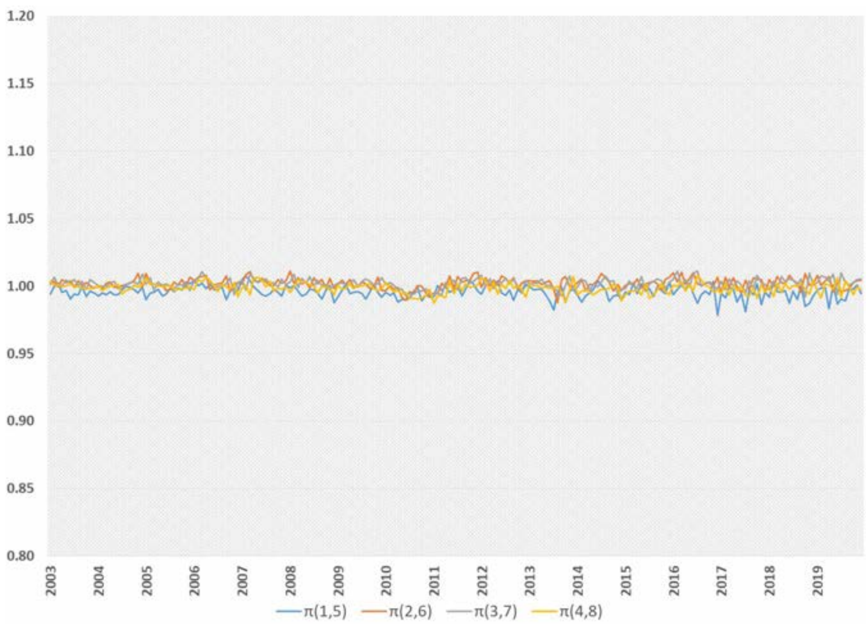

Figure 1: Relative response rates π_i^*, January 2003 – December 2019. In the legend, $\pi(1,5) = \pi_1^*, \cdots, \pi(4,8) = \pi_4^*$.

[11] Prior to 2003, a different weighting structure was used in the CPS. MIS were weighted separately, and there were fewer cells used in second-stage weighting. Since individual MIS were weighted separately, relative response rates were all equal to one, by definition. Formulaically, since there were no MIS pairs, the denominator would be π_i instead of π_{ij}, and $\pi_i^* = \frac{\pi_i}{\pi_i} = 1.00$.

Table 1 displays the base-weighted response rates[12] by MIS since January 2020. The post-pandemic panels (highlighted in gold) were more directly impacted by the lack of personal visits in the early months of the pandemic and experienced heavier declines. Pre-pandemic panels suffered less response attrition between March and August. MIS 1 and MIS 5, which typically utilize personal visits for the majority of completed interviews, lost more response than the other MIS within the same wave. Personal visits were completely suspended April through June but resumed in some regions of the country in July, the first month that wave 1 response rates began to recover. The response rates in September, when personal visits were resumed nationally, almost recovered to the January and February levels.

Table 1: Base-Weighted Response Rates by MIS, Jan-2020 – Sep-2020[13]
(Response rates given as proportions.)

MIS	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*
1	0.80	0.81	0.57	0.46	0.47	0.47	0.53	0.58	0.74
2	0.83	0.84	0.74	0.63	0.56	0.55	0.59	0.64	0.77
3	0.83	0.85	0.77	0.75	0.67	0.60	0.63	0.66	0.77
4	0.84	0.83	0.78	0.78	0.76	0.69	0.65	0.68	0.79
5	0.80	0.81	0.69	0.68	0.69	0.69	0.70	0.72	0.79
6	0.82	0.82	0.76	0.73	0.71	0.71	0.72	0.74	0.82
7	0.82	0.83	0.76	0.76	0.74	0.72	0.74	0.75	0.82
8	0.84	0.84	0.79	0.78	0.78	0.74	0.74	0.77	0.83
All	0.82	0.83	0.73	0.70	0.67	0.65	0.66	0.69	0.79

In January and February 2020, the response rates were balanced within MIS pairs, and the relative response rates π_i^* were all close to 1.00. However, as the Covid-19 pandemic began to affect collection activities in March, response rates declined unevenly across the eight MIS, unbalancing the representativeness of MIS i and $j \in$ MIS pair (i, j).

[12] Weighted response rates are preferable to unit response rates for evaluating estimation bias. Historically and during the pandemic months, the difference between weighted and unit response rates at the MIS level is typically less than one percentage point. Analyses using either set of response rates generate similar results.
[13] None of the MIS 5 – MIS 8 panels are considered post-pandemic because of the 4-8-4 sample rotation utilized by the CPS. The MIS 5 panel in July 2020 first entered the CPS sample in October 2019 and is therefore defined as a pre-pandemic panel in this paper.

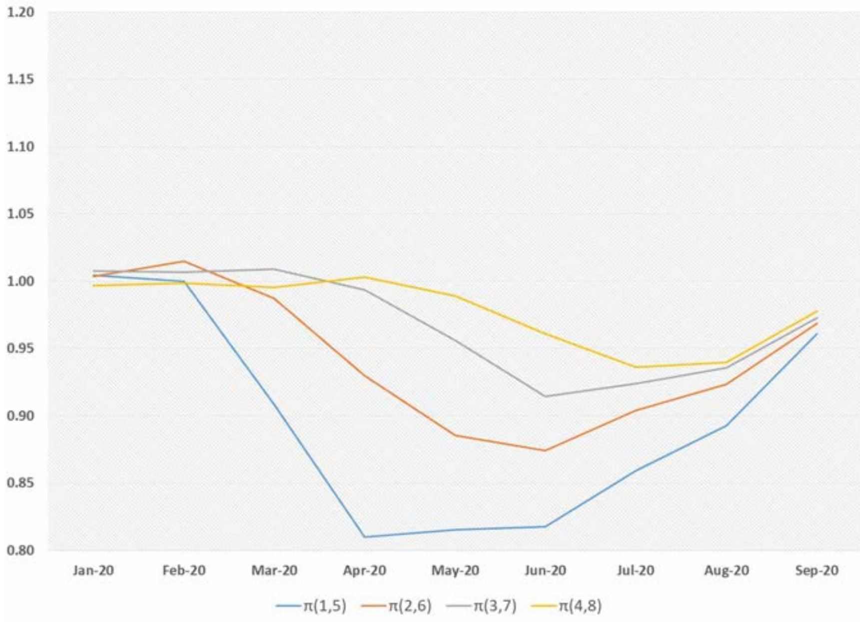

Figure 2: Relative response rates π_i^*, January 2020 – September 2020. In the legend, $\pi(1{,}5) = \pi_1^*, \cdots, \pi(4{,}8) = \pi_4^*$.

The relative response rates since January 2020 are displayed in Figure 2. The breakdowns coincide with the post-pandemic panels: for households in the MIS first enrolled in or after March 2020, the relative response rates are below one. All four lines plummet, indicating that MIS 1 – 4 are underrepresented in their corresponding MIS pairs. In terms of response rates: $\pi_i < \pi_j \ \forall \ (i, j)$ pairs. As noted in the introduction, contact information for newly sampled HHs is typically obtained during personal visit interviews, so these relative response declines are intuitive given the emphasis on phone interviews during that period.

As the Covid-19 pandemic began to hinder data collection efforts in March and became more extreme in April, the first panel to have MIS 1 interviewed entirely by phone instead of personal visit, the stability of the relative response rates breaks down rapidly. The π_i^* generally trend downward until July, when the resumption of personal visits in some regions of the country began to ameliorate this problem.

3. Estimation Bias

The deterioration of relative response rates during the pandemic suggests a potential estimation bias, specifically in relation to the historical labor force time series, for several reasons:

- Post-pandemic panels tend to be underrepresented in response composition since they account for less than half the weight of their corresponding MIS pairs.
- Each MIS has its own labor force biases relative to the average of second-stage weights.
- CPS composite estimation utilizes past data and unequally weights each MIS, further complicating bias considerations.

Of particular concern, MIS 1 is known to have a substantially higher tendency toward unemployment than the other seven rotation groups, as demonstrated in Figure 3.

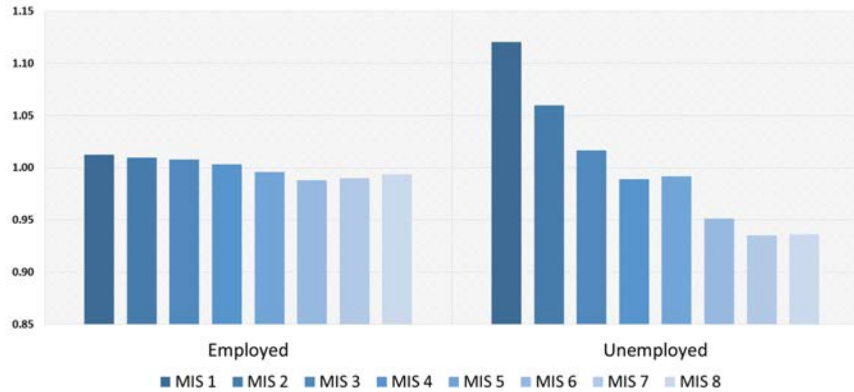

Figure 3: Average multiplicative bias by labor force status and MIS, January 2003 – December 2019. Multiplicative biases are computed using SS weights as ratios relative to the average across all MIS.

As previously shown in Figure 2, MIS 1 is also the most underrepresented. Without considering the other complicating factors, this combination alone is worrisome and suggestive of underestimation of unemployment.

This concern led to the research question: Is the pandemic effect on CPS response rates creating substantial estimation bias in major labor force categories?

Attempting to answer this question, the bias of the CPS composite estimator is deconstructed into a series of components, accounting for relative response rates and the composite weight coefficients on current and past months' SS labor force estimates. It is important to identify the effect of composite estimation, which induces known biases into the historical time series. Any changes due to Covid-19 must be assessed relative to the extant structure of the composite bias to be informative.

A formative assumption of the bias decomposition is that MIS biases with respect to the primary labor force estimates, employed and unemployed, are approximately the same as before the pandemic. This assumption is challenged by accumulating bias results, presented hereafter, and will be discussed in subsequent sections.

3.1 Bias Notation

The bias decomposition is based primarily on second-stage estimates at the MIS level, "adjusted bias" estimates that account for relative response rates, and predicted or modeled bias[14] based on SS labor force estimates for participation rate (for total employed) or unemployment rate (for total unemployed).

The adjusted bias estimate divides the average SS estimate—often treated as the objective or unbiased quantity in literature on CPS estimation—by the relative response rate of the appropriate MIS pair. This is necessary during the pandemic because ignoring the relative response rate in a multiplicative bias estimate would give the false impression that, for example, MIS 1 unemployment bias fell below 1.00 in March 2020, April 2020, etc. This is untrue and simply an artifact of the weighting underrepresentation of MIS 1.

[14] Regression models for EM and UN adjusted bias are given in Table 3 in the Appendix.

$i = MIS;\ i \in [1, \dots, 8]$

$ij = MIS\ pair\ (i, j); i \in [1,2,3,4]; j = (i + 4)$

$t = estimation\ month$

$l = lag\ in\ monthly\ composite\ estimate;\ l \in [0, \dots, L, \dots, \infty)$

$x_{i,t-l} = SS\ labor\ force\ (LF)\ estimate\ of\ MIS\ i\ in\ month\ t - l$

$\bar{x}_{t-l} = \frac{1}{8}\sum_{i=1}^{8} x_{i,t-l} = \ average\ SS\ LF\ estimate\ in\ month\ t - l$

$b_{i,t-l} = \frac{x_{i,t-l}}{\bar{x}_{t-l}} = multiplicative\ LF\ bias\ of\ MIS\ i\ in\ month\ t - l$

$w_{i,t-l}^{S} = total\ base\ weight\ of\ eligible\ sample\ households\ in\ MIS\ i, month\ t - l$

$w_{i,t-l}^{R} = total\ base\ weight\ of\ eligible\ respondent\ households\ in\ MIS\ i, month\ t - l$

$\pi_{i,t-l} = \frac{w_{i,t-l}^{R}}{w_{i,t-l}^{S}} = base\ weighted\ response\ rate\ in\ MIS\ i, month\ t - l$

$w_{ij,t-l}^{S} = total\ base\ weight\ of\ eligible\ sample\ households\ in\ MIS\ pair\ (i, j), month\ t - l$

$w_{ij,t-l}^{R} = total\ base\ weight\ of\ eligible\ respondent\ households\ in\ MIS\ pair\ (i, j), month\ t - l$

$\pi_{ij,t-l} = \frac{w_{ij,t-l}^{R}}{w_{ij,t-l}^{S}} = base\ weighted\ response\ rate\ in\ MIS\ pair\ (i, j), month\ t - l$

$\pi_{i,t-l}^{*} = \frac{\pi_{i,t-l}}{\pi_{ij,t-l}} = relative\ weighted\ response\ rate\ of\ MIS\ i\ to\ MIS\ pair\ (i, j)\ in\ month\ t - l$

$b_{i,t-l}^{ADJ} = \frac{b_{i,t-l}}{\pi_{i,t-l}^{*}} = multiplicative\ LF\ bias\ of\ MIS\ i\ in\ month\ t - l, adjusted\ for\ relative\ response\ rate$

$b_{i,t-l}^{MDL} = model\ predicted\ value\ of\ adjusted\ bias\ b_{i,t-l}^{ADJ}\ in\ MIS\ i, month\ t - l$

$w_{i,t-l} = coefficient\ of\ composite\ LF\ estimator\ in\ MIS\ i, month\ t - l$

$N_t = civilian\ noninstituional\ population\ 16\ plus\ in\ month\ t$

3.2 Monthly Estimates

CPS monthly level estimates, such as total employed (EM) and total unemployed (UN), are produced using an AK composite (CM) estimator, which is a special case of the generalized composite estimator (Breau and Ernst, 1983; Erkens 2012). The CPS composite estimator is essentially a weighted linear combination of current month and past months' SS x MIS estimates. Rates, such as the unemployment rate, are derived as ratios of composited levels[15]. While official estimates are seasonally adjusted (SA), in this paper only the not seasonally adjusted (NSA) estimates are considered.

Theoretically, the generalized composite estimator is infinitely recursive. In practice, the CPS composite estimator was reset in January 2003, marking a natural starting point, and the exponential decay of the composite weights at increasing monthly lags drives those coefficients near zero rather quickly. For EM estimates, which place greater weight on past months' data due to higher panel correlations over time, the composite coefficients, rounded to two decimal points, drop to zero at lag 16; i.e., the weight on the SS estimates from 16 months prior is negligible. For UN estimates, which have lower panel correlations and therefore lesser weight on past data, the rounded coefficients drop to zero at lag 6. In this research, the coefficients are not rounded but are capped at lag $L = 36$, a sufficiently

[15] If the denominator is an independent population control, only the numerator is composited. For example, the employment-population ratio is the composite estimate of EM divided by the civilian noninstitutional population, 16 years and older.

long history to ensure that all lagged SS estimates with any tangible effect on labor force estimates are included in the composite estimates.

While the AK composite coefficients improve precision for over-the-month change for major labor force estimates by leveraging panel correlations over time, relative to monthly second-stage estimates, the variance reduction comes at the expense of inducing a persistent "drift." To decompose the bias into mutually exclusive components, including the composite drift, several level estimates are computed using the following formulas, which apply to both EM and UN:

$$y_t^{ADJ(SS)} = \sum_{i=1}^{8}\left(b_{i,t}^{ADJ} \cdot \bar{x}_t\right) = SS\ estimate\ in\ month\ t, adjusted\ for\ \pi_{i,t-l}^{*}$$

$$Note: y_t^{ADJ(SS)}\ is\ assumed\ to\ be\ the\ unbiased, objective\ series\ for\ the\ bias\ decomposition$$

$$y_t^{MDL(CM)} = \sum_{l=0}^{36}\sum_{i=1}^{8}\left(w_{i,t-l} \cdot b_{i,t-l}^{MDL} \cdot \bar{x}_{t-l}\right) =$$

$$CM\ estimate\ in\ month\ t, based\ on\ CM\ coefficients\ w_{i,t-l}\ and\ predicted\ MIS\ bias\ b_{i,t-l}^{MDL}\ \forall\ i,l$$

$$Assume: \sum_{l=37}^{\infty}\sum_{i=1}^{8}\left(w_{i,t-l} \cdot b_{i,t-l}^{MDL} \cdot \bar{x}_{t-l}\right) = 0\ since\ w_{i,t-l} \approx 0\ \forall\ i \in [1,\dots,8], l \in [37,\dots,\infty)$$

$$y_t^{ADJ(CM)} = \sum_{l=0}^{36}\sum_{i=1}^{8}\left(w_{i,t-l} \cdot b_{i,t-l}^{ADJ} \cdot \bar{x}_{t-l}\right) =$$

$$CM\ estimate\ in\ month\ t, based\ on\ CM\ coefficients\ w_{i,t-l}\ and\ adjusted\ MIS\ bias\ b_{i,t-l}^{ADJ}\ \forall\ i,l$$

$$Assume: \sum_{l=37}^{\infty}\sum_{i=1}^{8}\left(w_{i,t-l} \cdot b_{i,t-l}^{ADJ} \cdot \bar{x}_{t-l}\right) = 0\ since\ w_{i,t-l} \approx 0\ \forall\ i \in [1,\dots,8], l \in [37,\dots,\infty)$$

$$y_t^{CM} = \sum_{l=0}^{36}\sum_{i=1}^{8}\left(w_{i,t-l} \cdot b_{i,t-l} \cdot \bar{x}_{t-l}\right) =$$

$$CM\ estimate\ in\ month\ t, based\ on\ CM\ coefficients\ w_{i,t-l}\ and\ unadjusted\ MIS\ bias\ b_{i,t-l}^{ADJ}\ \forall\ i,l$$

$$Assume: \sum_{l=37}^{\infty}\sum_{i=1}^{8}\left(w_{i,t-l} \cdot b_{i,t-l} \cdot \bar{x}_{t-l}\right) = 0\ since\ w_{i,t-l} \approx 0\ \forall\ i \in [1,\dots,8], l \in [37,\dots,\infty)$$

$$Note: y_t^{CM}\ is\ the\ CPS\ (NSA)\ level\ estimate$$

3.2.1 Bias decomposition of level estimates

The difference between y_t^{CM} and $y_t^{ADJ(SS)}$ characterizes the total bias of the month t labor force estimate under the assumptions of missing at random within MIS $i\ \forall\ i \in [1,\dots,8]$ and unbiasedness of $y_t^{ADJ(SS)}$. Since the drift of the composite estimator is essentially a structural part of the time series, and given predictive bias models that smooth through some of the natural sampling error, the total bias under the prescribed conditions can be deconstructed into a series of additive components.

To decompose the composite estimate, y_t^{CM} is defined as the unbiased quantity $y_t^{ADJ(SS)}$ plus a series of difference terms:

$$y_t^{CM} = y_t^{ADJ(SS)} + \langle y_t^{MDL(CM)} - y_t^{ADJ(SS)}\rangle + \langle y_t^{ADJ(CM)} - y_t^{MDL(CM)}\rangle + \langle y_t^{CM} - y_t^{ADJ(CM)}\rangle$$

And the difference $\langle y_t^{CM} - y_t^{ADJ(SS)}\rangle$, the additive bias of y_t^{CM}, can be stated as:

$$\langle y_t^{CM} - y_t^{ADJ(SS)}\rangle = \langle y_t^{MDL(CM)} - y_t^{ADJ(SS)}\rangle + \langle y_t^{ADJ(CM)} - y_t^{MDL(CM)}\rangle + \langle y_t^{CM} - y_t^{ADJ(CM)}\rangle$$

The first term, $\langle y_t^{MDL(CM)} - y_t^{ADJ(SS)}\rangle$, is the difference between the composite estimate using model predictions for the adjusted bias terms, $b_{i,t-l}^{MDL}$, and the adjusted second-stage estimate. This difference reflects the composite drift after smoothing through the sampling error. By using $b_{i,t-l}^{MDL}$, the drift is more easily isolated.

The second term, $\langle y_t^{ADJ(CM)} - y_t^{MDL(CM)} \rangle$, represents the error of the prediction models. When the predictive models are unbiased, these residuals capture the monthly sampling errors, which are correlated due to the CPS panel design. Early in the pandemic, the residuals fell within historical bounds, suggesting that the MIS biases were not varying from past behavior in a meaningful way. However, that began to change for total unemployed, indicating some systematic change in MIS biases.

The final quantity, $\langle y_t^{CM} - y_t^{ADJ(CM)} \rangle$, is the difference between the observed biases and the adjusted biases, which correct for relative response rates, and therefore directly measures the effect of response imbalance—unequal representation of individual MIS within MIS pairs—on the NSA composite estimate y_t^{CM}. If the relative response rates of all four MIS pairs in months $t, t-1, \cdots, t-L$ are equal to one, then the response imbalance is equal to zero. Since response imbalance has only become a nontrivial issue since March 2020, this bias is directly attributable to the pandemic.

Inserting the level estimates into the bias decomposition terms:

Composite drift: level estimates

$$\begin{aligned}
&\langle y_t^{MDL(CM)} - y_t^{ADJ(SS)} \rangle \\
&= \sum_{l=0}^{36} \sum_{i=1}^{8} \left(w_{i,t-l} \cdot b_{i,t-l}^{MDL} \cdot \bar{x}_{t-l} \right) - \sum_{i=1}^{8} \left(b_{i,t}^{ADJ} \cdot \bar{x}_t \right) \\
&= \sum_{i=1}^{8} \left(w_{i,t} \cdot b_{i,t}^{MDL} - b_{i,t}^{ADJ} \right) \bar{x}_t + \sum_{l=1}^{36} \sum_{i=1}^{8} \left(w_{i,t-l} \cdot b_{i,t-l}^{MDL} \right) \bar{x}_{t-l} \qquad (1)
\end{aligned}$$

Model error: level estimates

$$\begin{aligned}
&\langle y_t^{ADJ(CM)} - y_t^{MDL(CM)} \rangle \\
&= \sum_{l=0}^{36} \sum_{i=1}^{8} \left(w_{i,t-l} \cdot b_{i,t-l}^{ADJ} \cdot \bar{x}_{t-l} \right) - \sum_{l=0}^{36} \sum_{i=1}^{8} \left(w_{i,t-l} \cdot b_{i,t-l}^{MDL} \cdot \bar{x}_{t-l} \right) \\
&= \sum_{l=0}^{36} \sum_{i=1}^{8} w_{i,t-l} \left(b_{i,t-l}^{ADJ} - b_{i,t-l}^{MDL} \right) \bar{x}_{t-l} \qquad (2)
\end{aligned}$$

Response imbalance: level estimates

$$\begin{aligned}
&\langle y_t^{CM} - y_t^{ADJ(CM)} \rangle \\
&= \sum_{l=0}^{36} \sum_{i=1}^{8} \left(w_{i,t-l} \cdot b_{i,t-l} \cdot \bar{x}_{t-l} \right) - \sum_{l=0}^{36} \sum_{i=1}^{8} \left(w_{i,t-l} \cdot b_{i,t-l}^{ADJ} \cdot \bar{x}_{t-l} \right) \\
&= \sum_{l=0}^{36} \sum_{i=1}^{8} w_{i,t-l} \left(b_{i,t-l} - b_{i,t-l}^{ADJ} \right) \bar{x}_{t-l} \qquad (3)
\end{aligned}$$

Equations (1) – (3) are applied to the CPS level estimates of employed and unemployed. A third level estimate, civilian labor force (CLF), is computed as the sum of EM and UN, and consequently the CLF bias terms can be computed as the sum of the corresponding composite drift, model error, and response imbalance terms. Figures 4 – 6 display the results of the bias decomposition for the respective EM, UN, and CLF composite estimates.

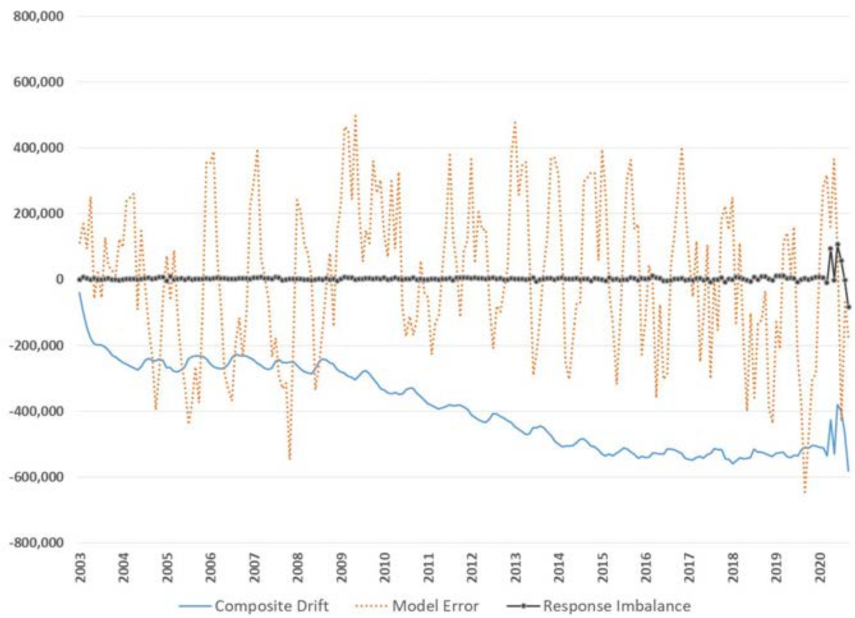

Figure 4: Bias decomposition of NSA composite estimates of total employed, January 2003 – September 2020.

Before Covid-19 affected the ability of the CPS to conduct personal visits during data collection, response imbalance (black dotted line) was consistently near zero, which is expected because historical relative response rates $\pi^*_{i,t-l}$ were all close to one (Figure 1). Beginning in March 2020, there is some fluctuation in the response imbalance due to the underrepresentation of the post-pandemic panels. The imbalance is not consistently biased in either direction and the magnitude is small relative to the magnitude of the model error, which appears unaffected by the pandemic, suggesting no significant bias problems relative to the historical EM time series[16].

[16] The drift in the composite estimator evinces clear bias if the adjusted second-stage estimate is considered approximately unbiased. However, as discussed in Section 3, the primary interest of this paper is identification of bias attributable to the pandemic; the drift is a preexistent consequence of the AK composite estimator.

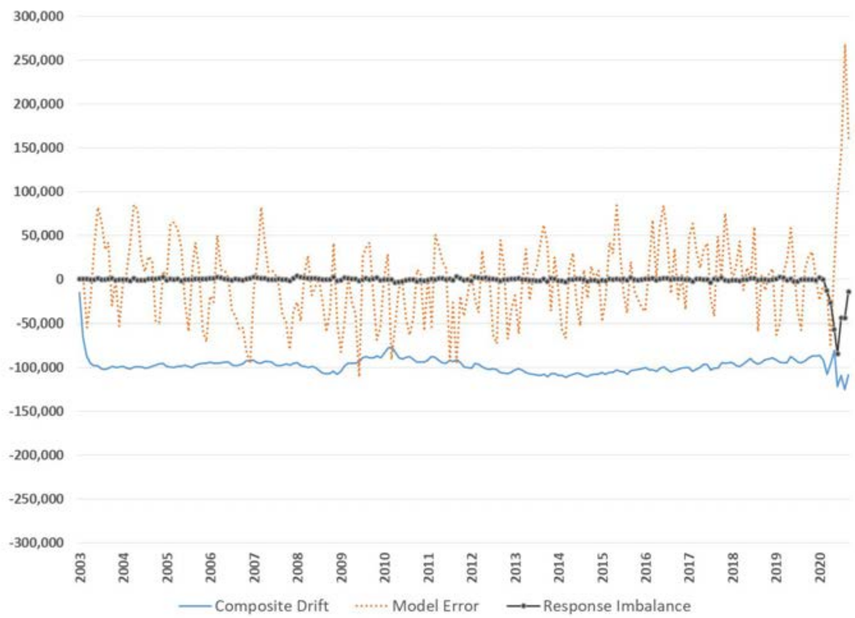

Figure 5: Bias decomposition of NSA composite estimates of total unemployed, January 2003 – September 2020.

The results for unemployed are more noteworthy. Figure 6 shows two clear effects of the pandemic on the CPS composite estimate of UN:

1) The underrepresentation of wave 1 MIS resulted in a steep decline in the response imbalance metric, reaching a magnitude of nearly -100,000 unemployed persons in June 2020. The partial resumption of personal visits in July and the national resumption of personal visits in September reversed this trend.

2) After an initial dip, a spike in model error accumulated from May through August, indicating that the UN labor force bias patterns across the MIS changed in some substantial way during the late spring and summer months[17]. As the relative response rates were not too far below 1.00 in September (Figure 2), this spike reversed course and began to drop.

The sizable model residuals combined with reduced response imbalance indicate, according to the assumptions of the bias decomposition, that the unemployment is overestimated to a degree beyond the usual bounds of sampling error. In other words, it appears unlikely that the overestimation is due to natural variation in sample composition and instead reflects some systematic change in MIS unemployment bias.

Further investigation revealed that the post-pandemic, MIS 4 panels had positive residuals for unemployment for five consecutive months: May 2020 – September 2020. The nature of the AK composite estimator and its correlational structure places the heaviest weight on the MIS 4 and MIS 8 panels. The succession of positive MIS 4 model errors and the recursion of the composite estimator created the spike, peaking in August 2020 when the model residual reached its maximum.

[17] A related interpretation is that the bias prediction models are no longer unbiased for UN and that the model error component indistinguishably captures both sampling error and model bias.

Relative to historical expectation for each MIS, post-pandemic panels tended to have an increasing unemployment tendency as their time in sample increased. The decomposition equations can highlight this sort of change, picking up the signal at the estimation level and working backward through the component calculations, but cannot identify the root cause of the shift itself.

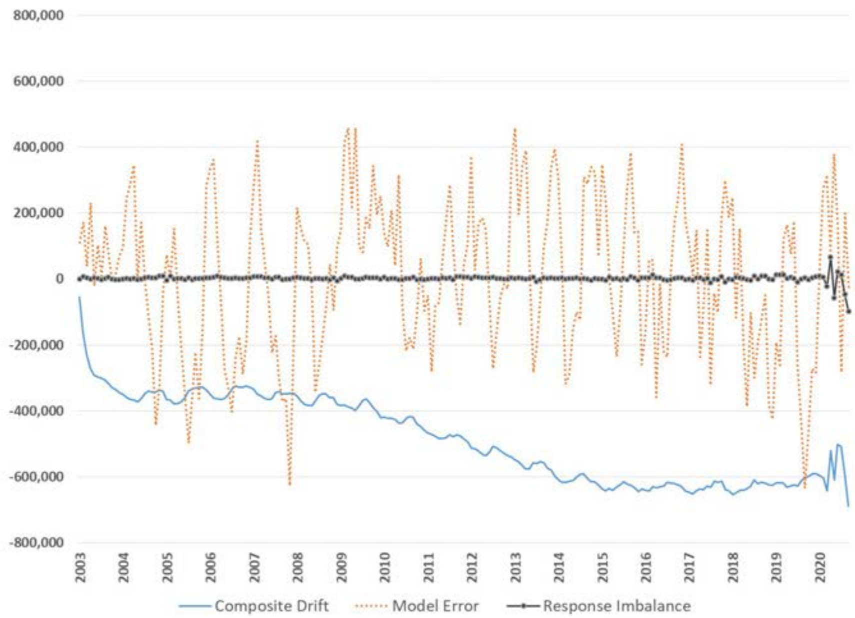

Figure 6: Bias decomposition of NSA composite estimates of civilian labor force, January 2003 – September 2020.

Since the total number of employed persons in the U.S. is much larger than the number of unemployed persons—on average, about 94 percent of the civilian labor force is employed from January 2003 through September 2020—the decomposition in Figure 6 is similar to Figure 4. The response imbalance for EM tends to be slightly more positive than for CLF, but overall, the conclusions are the same: The pandemic has created some fluctuation due to changing collection conditions, but the resultant estimation bias for both EM and CLF appears to be minor.

3.2.2 Bias decomposition of rate estimates

Additive bias components for rates are derived from the level estimates by computing the differences in the rates at each stage of the decomposition. Using the resulting equations, two of the most significant rates computed by the CPS, labor force participation rate (PR) and the unemployment rate (U3), are deconstructed into bias components. As with levels, all computations are based on data that have not been seasonally adjusted.

Unlike the level equations (1) – (3) given in Section 3.2.1, the rate equations are presented separately due to differences in the form of the denominators. For U3, the denominator is the estimated civilian labor force; whereas for PR, the denominator is the civilian noninstitutional population, 16 years and older (CNP), an independent population control with zero sampling variability.

Analogous to the monthly estimates computed in Section 3, the U3 estimates, including notation to distinguish between EM and UN levels, are defined as:

$$p_t^{ADJ(SS):U3} = \frac{y_t^{ADJ(SS):UN}}{y_t^{ADJ(SS):EM} + y_t^{ADJ(SS):UN}}$$

$$p_t^{MDL(CM):U3} = \frac{y_t^{MDL(CM):UN}}{y_t^{MDL(CM):EM} + y_t^{MDL(CM):UN}}$$

$$p_t^{ADJ(CM):U3} = \frac{y_t^{ADJ(CM):UN}}{y_t^{ADJ(CM):EM} + y_t^{ADJ(CM):UN}}$$

$$p_t^{CM:U3} = \frac{y_t^{CM:UN}}{y_t^{CM:EM} + y_t^{CM:UN}}$$

To decompose U3, $p_t^{CM:U3}$ is defined as the assumed unbiased quantity $p_t^{ADJ(SS):U3}$ plus a series of difference terms:

$$p_t^{CM:U3} = p_t^{ADJ(SS):U3} + \langle p_t^{MDL(CM):U3} - p_t^{ADJ(SS):U3} \rangle + \langle p_t^{ADJ(CM):U3} - p_t^{MDL(CM):U3} \rangle + \langle p_t^{CM:U3} - p_t^{ADJ(CM):U3} \rangle$$

And the difference $\langle p_t^{CM:U3} - p_t^{ADJ(SS):U3} \rangle$, the additive bias of $p_t^{CM:U3}$, can be stated as:

$$\langle p_t^{CM:U3} - y_t^{ADJ(SS):U3} \rangle = \langle p_t^{MDL(CM):U3} - p_t^{ADJ(SS):U3} \rangle + \langle p_t^{ADJ(CM):U3} - p_t^{MDL(CM):U3} \rangle + \langle p_t^{CM:U3} - p_t^{ADJ(CM):U3} \rangle$$

The unemployment rate bias terms are interpreted analogously to Section 3.2.1 as composite drift, model error, and response imbalance.

Composite drift: unemployment rate

$$\langle p_t^{MDL(CM):U3} - p_t^{ADJ(SS):U3} \rangle = \frac{y_t^{MDL(CM):UN}}{y_t^{MDL(CM):EM} + y_t^{MDL(CM):UN}} - \frac{y_t^{ADJ(SS):UN}}{y_t^{ADJ(SS):EM} + y_t^{ADJ(SS):UN}} \quad (4)$$

Model error: unemployment rate

$$\langle p_t^{ADJ(CM):U3} - p_t^{MDL(CM):U3} \rangle = \frac{y_t^{ADJ(CM):UN}}{y_t^{ADJ(CM):EM} + y_t^{ADJ(CM):UN}} - \frac{y_t^{MDL(CM):UN}}{y_t^{MDL(CM):EM} + y_t^{MDL(CM):UN}} \quad (5)$$

Response imbalance: unemployment rate

$$\langle p_t^{CM:U3} - p_t^{ADJ(CM):U3} \rangle = \frac{y_t^{CM:UN}}{y_t^{CM:EM} + y_t^{CM:UN}} - \frac{y_t^{ADJ(CM):UN}}{y_t^{ADJ(CM):EM} + y_t^{ADJ(CM):UN}} \quad (6)$$

Similarly, but with the CNP as the denominator, the PR estimates are defined as:

$$p_t^{ADJ(SS):PR} = \frac{y_t^{ADJ(SS):EM} + y_t^{ADJ(SS):UN}}{CNP_t}$$

$$p_t^{MDL(CM):PR} = \frac{y_t^{MDL(CM):EM} + y_t^{MDL(CM):UN}}{CNP_t}$$

$$p_t^{ADJ(CM):PR} = \frac{y_t^{ADJ(CM):EM} + y_t^{ADJ(CM):UN}}{CNP_t}$$

$$p_t^{CM:PR} = \frac{y_t^{CM:EM} + y_t^{CM:UN}}{CNP_t}$$

To decompose PR, $p_t^{CM:PR}$ is defined as the assumed unbiased quantity $p_t^{ADJ(SS):PR}$ plus the series of difference terms:

$$p_t^{CM:PR} = p_t^{ADJ(SS):PR} + \langle p_t^{MDL(CM):PR} - p_t^{ADJ(SS):PR} \rangle + \langle p_t^{ADJ(CM):PR} - p_t^{MDL(CM):PR} \rangle + \langle p_t^{CM:PR} - p_t^{ADJ(CM):PR} \rangle$$

And the difference $\langle p_t^{CM:PR} - p_t^{ADJ(SS):PR} \rangle$, the additive bias of $p_t^{CM:PR}$, can be stated as:

$$\langle p_t^{CM:PR} - y_t^{ADJ(SS):PR} \rangle = \langle p_t^{MDL(CM):PR} - p_t^{ADJ(SS):PR} \rangle + \langle p_t^{ADJ(CM):PR} - p_t^{MDL(CM):PR} \rangle + \langle p_t^{CM:PR} - p_t^{ADJ(CM):PR} \rangle$$

As with U3, the participation rate bias terms are interpreted as composite drift, model error, and response imbalance.

Composite drift: participation rate

$$\langle p_t^{MDL(CM):PR} - p_t^{ADJ(SS):PR} \rangle = \frac{\left(y_t^{MDL(CM):EM} + y_t^{MDL(CM):UN}\right) - \left(y_t^{ADJ(SS):EM} + y_t^{ADJ(SS):UN}\right)}{CNP_t} \quad (7)$$

Model error: participation rate

$$\langle p_t^{ADJ(CM):PR} - p_t^{MDL(CM):PR} \rangle = \frac{\left(y_t^{ADJ(CM):EM} + y_t^{ADJ(CM):UN}\right) - \left(y_t^{MDL(CM):EM} + y_t^{MDL(CM):UN}\right)}{CNP_t} \quad (8)$$

Response imbalance: participation rate

$$\langle p_t^{CM:PR} - p_t^{ADJ(CM):PR} \rangle = \frac{\left(y_t^{CM:EM} + y_t^{CM:UN}\right) - \left(y_t^{ADJ(CM):EM} + y_t^{ADJ(CM):UN}\right)}{CNP_t} \quad (9)$$

Figures 7 – 8 show the results of applying equations (4) – (6) and equations (7) – (9) to the NSA composite estimates of unemployment rate and participation rate, respectively.

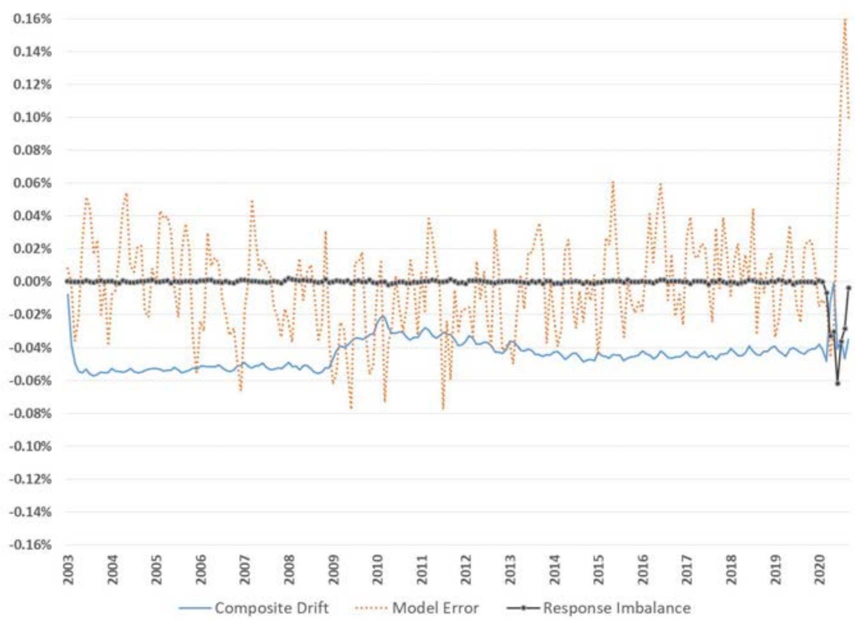

Figure 7: Bias decomposition of NSA composite estimates of the U3 unemployment rate, January 2003 – September 2020.

Resembling the UN plot in Figure 5, the decomposition of U3 in Figure 7 exhibits a sharp, accumulating increase in model error over the course of the summer, followed by a 0.06 percentage point drop in September, suggesting a return to historical MIS bias patterns may be imminent. After a V-shaped disruption, the response imbalance has nearly returned to zero bias, which was the historical rule before the pandemic drastically affected the ability of CPS interviewers to conduct personal visits.

In the extrema, the model error component peaked at an overestimation bias of 0.16 percentage points, while the response imbalance bottomed out at 0.06 percentage point underestimate. Combining model error and response imbalance in Table 2 provides an estimate of how the pandemic, highlighted in gold, affected the NSA unemployment rate.

Table 2: Estimated Bias of NSA Unemployment Rate, Jan-2020 – Sep-2020
(Bias reported in percentage points. Excludes composite drift.)

	Jan	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*
Bias	-0.01	-0.01	-0.02	-0.08	-0.05	-0.01	0.08	0.13	0.10

It should be noted that the estimated bias of the NSA U3 rate is not directly applicable to the seasonally adjusted U3. That is, one cannot modify the SA unemployment rate by the amounts in Table 2 and expect to obtain results unbiased under the aforementioned assumptions due to the additional complexity of the seasonal adjustment procedure. Accounting for seasonal adjustment in the bias decomposition would be a nontrivial extension. (Estimates of bias for EM, UN, CLF, and PR are reported in Tables 4 – 7 in the Appendix.)

An interesting mathematical result in the composite drift occurs early during the pandemic when the blue line shoots up toward the origin. Indeed, in April 2020, the drift is effectively zero, meaning that the composite estimator is not inducing any noticeable bias relative to the adjusted second-stage estimates at that point in the time series. This coincided with skyrocketing unemployment figures that topped 22 million in April; after, the drift immediately returned to its historical magnitude.

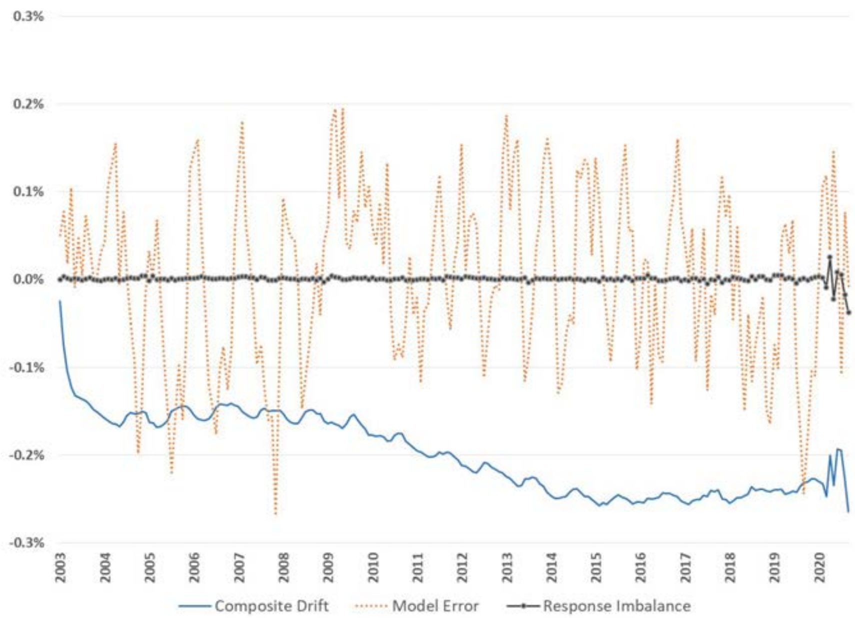

Figure 8: Bias decomposition of NSA composite estimates of labor force participation rate, January 2003 – September 2020.

The decomposition of participation rate is the simple equivalent of the decomposition of civilian labor force converted into a percentage basis, where the CNP is the denominator. Thus, Figure 8 depicts the same components as Figure 4, and the same interpretation applies: There is little concern for estimation bias resulting from Covid-19 on the estimate of the labor force participation rate.

4. Conclusions

As Covid-19 gripped the U.S. in March 2020, the CPS indefinitely suspended personal visits, a primary method of interview for MIS 1 and MIS 5 households. From April through June, no personal visits were conducted, impinging on the ability of the CPS to collect contact information and complete interviews with households enrolled during the pandemic. Wave 1 response rates declined, and the respondent composition fell out of its usual equilibrium across all eight rotation groups. Post-pandemic panels were underrepresented, and these were concentrated in the early MIS groups, which tend to have different labor force biases compared to later MIS groups. In particular, MIS 1 households have a high unemployment tendency, and they were the most underrepresented; thus, underestimation of unemployment and the unemployment rate were a concern.

A novel decomposition of the AK composite estimator into mutually exclusive bias quantities was constructed to isolate the effects of the pandemic on CPS topside labor force estimates. The bias of the current form of the composite estimator, also known as drift, stretches back to January 2003 and was separated out to avoid conflating pandemic effects and the structural composite bias. The decomposition is based on the assumption that the post-pandemic labor force biases within rotation groups are consistent with the historical time series. The results for total employed, civilian labor force, and the labor force participation rate showed no evidence of violating this assumption and no significant estimation bias resulting from the pandemic.

For total unemployed and the U3 unemployment rate, the decomposition signaled a change in MIS bias during the late spring and summer months of 2020. Predictive bias models failed to account for an emergent relationship between unemployment tendency and time in sample within the post-pandemic panels. In terms of bias, the research presupposition of underestimating the unemployment rate was initially true, dropping about 0.08 percentage points below the unbiased estimate of U3 in April. However, the systematic shift in MIS bias reversed the trend, leading to a peak overestimate of about 0.13 percentage points in August. While these bias estimates are noticeable in the figures and tables and likely represent some real statistical phenomenon, they are not alarming in practical terms.

It bears repeating that all CPS estimates in this paper are not seasonally adjusted, and the separate issue of potential misclassification error is not considered here.

Continuing research objectives may include: monitoring recent trends; investigation of unusual bias results; reexamination of the assumptions underpinning the decomposition equations; accounting for post-pandemic indicators in predictive bias models; and broadening understanding of how response patterns may change during shocks to data collection procedures.

Fortunately, if the trends in recent months continue, the CPS response rates are returning to balance, and the change in unemployment response patterns may be an aberration during a time of upheaval.

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Appendix 1

Employed (EM) Model

$PR_{t-l}^{SS} = second\ stage\ NSA\ labor\ force\ participation\ rate\ in\ month\ t-l$

$b_{i,t-l}^{ADJ} = \beta_{i,0} + \beta_{i,1} \cdot PR_{t-l} + \varepsilon_{i,t}$

$b_{i,t-l}^{MDL} = \hat{b}_{i,t-l}^{ADJ} = \hat{\beta}_{i,0} + \hat{\beta}_{i,1} \cdot PR_{t-l}$

Unemployed (UN) Model

$UR_{t-l}^{SS} = second\ stage\ NSA\ U3\ unemployment\ rate\ in\ month\ t-l$

$b_{i,t-l}^{ADJ} = \beta_{i,0} + \beta_{i,1} \cdot UR_{t-l} + \varepsilon_{i,t}$

$b_{i,t-l}^{MDL} = \hat{b}_{i,t-l}^{ADJ} = \hat{\beta}_{i,0} + \hat{\beta}_{i,1} \cdot UR_{t-l}$

Table 3: EM and UN coefficients[18] for adjusted bias, Jan-2020 – Sep-2020

	EM Coefficients		*UN Coefficients*	
MIS	$\hat{\beta}_{i,0}$	$\hat{\beta}_{i,1}$	$\hat{\beta}_{i,0}$	$\hat{\beta}_{i,1}$
1	1.13	-0.17	1.19	-1.11
2	1.05	-0.07	1.07	-0.28
3	1.03	-0.04	1.00	0.30
4	1.01	-0.00	0.96	0.53
5	0.97	0.04	1.00	-0.17
6	0.94	0.08	0.93	0.29
7	0.92	0.11	0.93	0.06
8	0.94	0.08	0.91	0.46

[18] Coefficients were estimated using ordinary least squares regression.

Appendix 2

Table 4: Estimated Bias of NSA Total Employed, Jan-2020 – Sep-2020[19]
(Bias reported in thousands. Excludes composite drift.)

	Jan	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*
Bias	48	285	307	253	363	170	-374	-72	-266

Table 5: Estimated Bias of NSA Total Unemployed, Jan-2020 – Sep-2020
(Bias reported in thousands. Excludes composite drift.)

	Jan	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*
Bias	-23	-8	-23	-101	-44	12	105	224	143

Table 6: Estimated Bias of NSA Civilian Labor Force, Jan-2020 – Sep-2020
(Bias reported in thousands. Excludes composite drift.)

	Jan	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*
Bias	26	278	284	153	319	182	-269	152	-123

Table 7: Estimated Bias of NSA Labor Force Participation Rate, Jan-2020 – Sep-2020
(Bias reported in percentage points. Excludes composite drift.)

	Jan	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*
Bias	-0.01	0.11	0.11	0.06	0.12	0.07	-0.10	0.06	-0.05

[19] Months affected by the Covid-19 pandemic are highlighted in gold.