How Does the Dramatic Rise of CPS Nonresponse Impact Labor Market Indicators?*

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Abstract

Within a decade, the share of households refusing to participate in the Current Population Survey (CPS) tripled. We show that partially-responding households—households that respond to some but not all survey panels—account for most of the rise. Leveraging the labor force status of partially-responding households in the months surrounding their nonresponse, we find rising refusals suppressed the measured labor force participation rate and employment-population ratio but had little effect on the unemployment rate. Notably, nonresponse bias accounts for 10 percent of the reported decline in the labor force participation rate from 2000 to 2020.

Keywords: Current Population Survey, Unemployment Rate, Labor Force Participation Rate, Employment-Population Ratio, Non-interview, Survey Refusal, Bias.

JEL Codes: C83, E24, J64

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1 Introduction

From 2010 to 2020, the share of occupied households in the United States that did not respond to the Current Population Survey (CPS) increased from 8 to 18 percent. Figure 1 shows the steady increase in nonresponse or non-interview rates (we use these terms interchangeably) is driven by households refusing to participate in the survey.[1] Survey refusals rates, in fact, tripled. Although Figure 1 reports nonresponse rates through July 2021, we do not focus on the recent, temporary spike in nonresponse for "other" reasons related to the Census Bureau suspending in-person interviews in April 2020 because of COVID-19. (BLS, 2020; Rothbaum and Bee, 2020).[23]

Headline labor market statistics are calculated from the CPS. These missing households raise questions about the accuracy of key labor market indicators used to monitor the United States economy and calibrate economic models. We document that the increase in missing observations from household nonresponse is *not* random. It has biased the labor force participation rate and employment-population ratio down but has had little discernible effect on the unemployment rate. We offer a correction method to adjust for nonresponse. Our correction method is an improvement over current methods because it imputes the labor force status of missing observations instead of weighting the sample primarily to make it demographically representative. In doing so, we find measurement error from nonresponse is larger than previously thought and is growing.

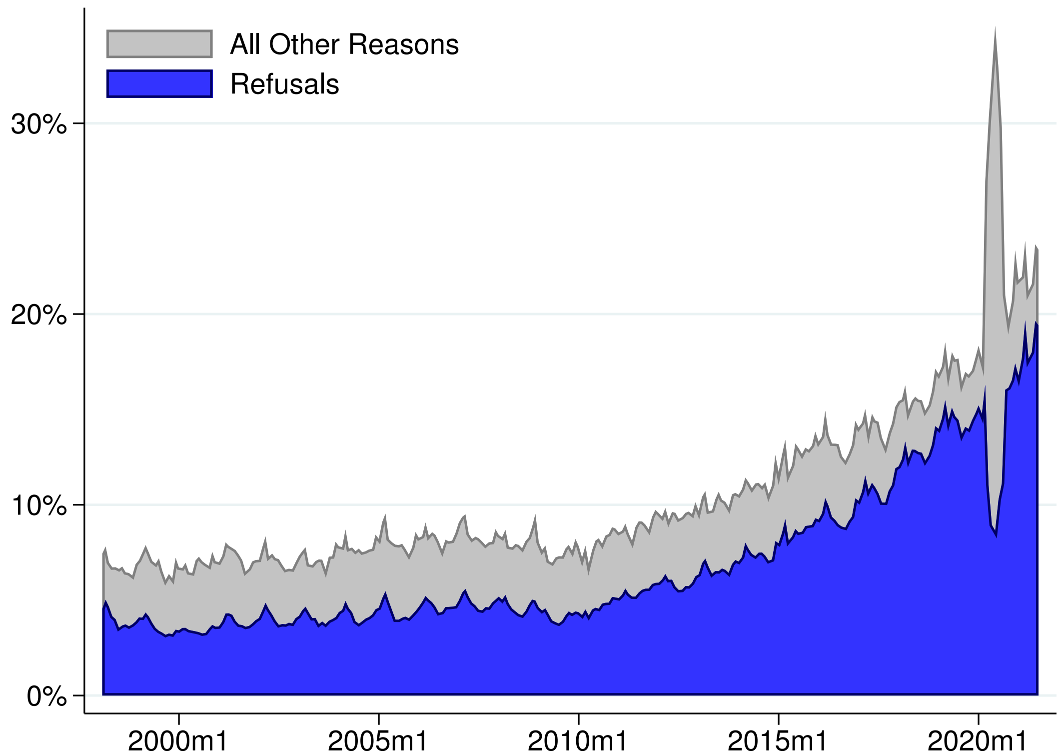
The major challenge researchers face in studying nonresponse is that we cannot observe the characteristics of nonresponders to see whether there is selection into the nonresponding

[1] This paper focuses on Type A unit nonresponse which is where an occupied housing unit does not respond. This is distinct from Type B and Type C unit nonresponse, where the housing unit is temporarily or permanently unoccupied, and it is distinct from item nonresponse, where a household responds to the survey but the interviewee fails to answer a specific question.

[2] Refusals and "other" are sub-categories of Type A nonresponse.

[3] See Bick and Blandin (2020), Foote et al. (2020), Faberman et al. (2022) and for alternative survey data measuring the pandemic labor market.

Figure 1: CPS Nonresponse Rates of Occupied Dwellings



Notes: Authors' calculations using data from the CPS. The number of Type A non-interviewed households divided by the total number of interviewed and Type A non-interviewed households from January 1998 through July 2021. All Other Reasons include: no one home, unable to locate, temporarily absent, language barrier, and other.

group. But unlike purely cross-sectional surveys, the repeated panel structure of the CPS provides some information about nonresponding households. The CPS surveys households eight times, separated by at least a month. Households have the choice to not respond during each of the eight survey months and we leverage this panel structure to learn more about nonresponders.

We start our analysis by documenting that over the last decade, there has been a growing share of two groups of nonresponding households: (1) households that respond to none of the survey months, and (2) households that respond to some but not all of the survey months. Because this second group of nonresponding households (i.e. partial responders) contributes to a larger share of total nonresponse than the first group, and because we have information about this second group during the months they *do* respond, partial responders are the cornerstone of our analysis.

Among partial responders, we define two types of households in a given month: households that leave the survey after responding to a panel (drop-*outs*) and households that enter the survey after failing to respond to a panel (drop-*ins*).[4] If drop-outs, drop-ins, and consecutive responders were identical, we would not worry about selective attrition among partial responders. We show, however, this is not the case in the CPS. Selective response behavior, especially since 2010, has artificially biased the sample away from individuals participating in the labor force.

We offer a correction method by leveraging the panel structure of the CPS. With a sample of consecutive responders, we calculate monthly flow rates between labor force statuses over time. We apply these flow rates to partial responders in the months surrounding nonresponse to fill in their missing observations with the likelihood they are employed, unemployed, and out of the labor force. After testing robustness to the assumption that responders and nonresponders have similar flow rates, we recalculate the unemployment rate, labor force participation rate, and employment-population ratio.

This correction method has little effect on the unemployment rate. However, the labor force participation rate and employment-population ratio are lower than our corrected time series. Using the raw counts of individuals in the CPS, we find the magnitude of our correction has grown by three-fold, to over a percentage point, between 2010 and 2020. This accounts for nearly 20 percent of the decline in the (unweighted) participation rate since the turn of the millennium. The unweighted series, however, is not the official labor force participation rate. The Bureau of Labor Statistics (BLS) weights the sample primarily to ensure it is demographically and geographically representative. Applying these BLS weights

[4] Over the duration of the 16-month survey, it is possible a household can be both a drop-in and a drop-out.

to our corrected data is tricky because we do not want to overcorrect for nonresponse. After a careful multi-step process, we find that the BLS weights correct for some but not all of the growing bias. Nonresponse bias still accounts for 10 percent of the decline in the official (weighted) participation rate since the turn of the millennium. More concerning, however, is if refusal rates continue to increase at the same rate—which they appear to be doing—and the bias becomes more severe.

Our work contributes to a long-standing, yet still growing, literature seeking to understand the rise of nonresponse across household surveys (Harris-Kojetin and Tucker, 1999; Atrostic, Bates, Burt, and Silberstein, 2001; Brick and Williams, 2013; Schoeni, Stafford, McGonagle, and Andreski, 2013; Meyer, Mok, and Sullivan, 2015; Williams and Brick, 2018; Dutz, Huitfeldt, Lacouture, Mogstad, Torgovitsky, and van Dijk, 2021).

This paper complements several recent papers studying nonresponse in the CPS. Korinek et al. (2007), Bee et al. (2015), and Hokayem et al. (2015) study the effect of missing observations on measures of income but do not address measures of labor force status. Heffetz and Reeves (2019) show easy-to-reach and hard-to-reach respondents, as measured by the number of survey attempts, are systematically different. If nonresponders are more similar to hard-to-reach responders, low response rates impede survey accuracy. In concurrent work, Borgschulte, Cho, and Lubotsky (2020) hypothesize that the increase in refusal rates since 2010 is linked to anti-survey rhetoric among Republican or Tea Party supporters. The authors find inconclusive evidence for this hypothesis, but conclude that the political cycle has influenced response rates since the 1990s with individuals more likely to respond to the CPS when the sitting president aligns with their political party.

In work most close to ours, Ahn and Hamilton (2021) highlight and correct for several internal contradictions and sources of bias, including missing observations, within the CPS. Our paper differs in that we exclusively focus on documenting and adjusting for bias from rising nonresponse. Understanding how nonresponse, in particular, impacts important labor market indicators is of paramount and growing importance given the large and steady increase in survey refusals since 2010. In doing so, we find the labor force participation rate and employment-population ratio are most affected by nonresponse bias, while Ahn and Hamilton (2021) find the unemployment rate is most affected by all sources of bias and misclassification between unemployment and not in the labor force plays an outsized role.[5] Another important difference is that we apply the BLS weights to our corrected series in a way that minimizes the risk of overcorrecting the data.

Our work relates to a literature documenting the prevalence of rotation group bias in the CPS (Bailar, 1975; McCarthy, 1978; Solon, 1986; Halpern-Manners and Warren, 2012; Krueger, Mas, and Niu, 2017). Rotation group bias arises in a repeated panel survey when, for instance, the unemployment rate calculated from households in the first month of the survey differs from the unemployment rate calculated from households in the second month.[6] Because of the notable differences across survey months, we condition on survey month when imputing labor market statuses for nonresponders.

The correction method we offer to account for rising nonresponse is similar to Abowd and Zellner (1985), Tucker and Harris-Kojetin (1998), Fujita and Ramey (2006), Nekarda (2009), and Ahn and Hamilton (2021) in that it conditions on survey participants' previous or future responses to learn about their missing responses.

The paper proceeds as follows. Section 2 describes the data. Section 3 shows that partially-responding households drive an important share of rising refusal rates. Section 4 illustrates the ways in which survey refusals are not random and depend on survey drop-in and drop-out behavior. Section 5 corrects for the bias from rising nonresponse; and Section 6 concludes.

[5]There is a separate literature studying misclassification of labor market variables in the CPS. For example, see Poterba and Summers (1986), Chua and Fuller (1987), Elsby et al. (2015), Kudlyak and Lange (2018), and Vom Lehn et al. (2021).

[6]Appendix A shows that rotation group bias for the labor force participation rate has risen alongside nonresponse rates, but the same cannot be said for the unemployment rate.

2 Data

The Current Population Survey is a monthly survey conducted by the U.S. Census Bureau of about 60,000 occupied households (technically housing units), primarily focusing on labor market, educational, and demographic variables. Most famously, it is used to compute the official unemployment rate, labor force participation rate, and employment-population ratio. The CPS uses a 4-8-4 rotating sample design, where selected households are surveyed for a total of eight months. Households are included in the sample for four consecutive months, excluded from the sample for eight months, and then surveyed during the next four months, bringing the total number of survey months to eight for each household. The survey is designed so households are always entering and leaving the survey. By design, one eighth of households are surveyed in the first month, and one eighth are surveyed each month thereafter.

The CPS is a government survey but it is not legally required. Many households do not respond. It is important to note that a household is surveyed for eight months, counting nonresponse months. For example, if a household does not respond for the first two months but responds to all successive surveys, then the CPS will include two nonresponses and six responses for that household.

Our primary sample is the Current Population Survey microdata spanning January 1998 through December 2019 of individuals 16 years and older.[7] Each month of the data contains information on approximately 140,000 individuals in responding households, and approximately 10,000 to 15,000 in nonresponding households (Types A, B, C). For each of these observations we have household response indicators, and where available, personal demographic information and labor market data. We match households and individuals across the eight months of the panel using household, person, and month identifiers. In total, the

[7]We begin the sample in 1998 because that is when the BLS began publishing the final composite weight which we use in Section 5.5.

dataset includes about two million households.

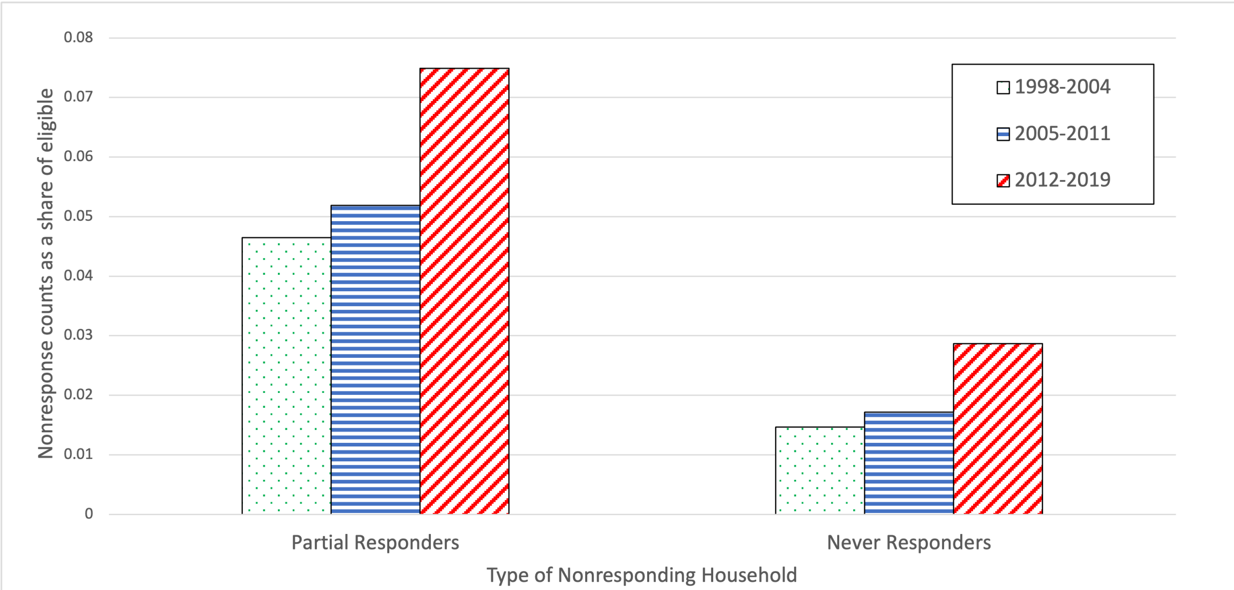
3 Partial- vs. Never-responding Households

For our analysis, it is important to know whether nonresponses originate from partially-responding households (who we have some information about) or never-responding households (who we know little about). To examine this, we compute (1) the number of nonresponses from partially- and never-responding households and (2) the total number of eligible interview months for all households. We then calculate the share of nonresponses relative to eligible interview months for three time bins 1998-2004, 2005-2011, and 2012-2019. As an example, for the households that never respond, we first compute the number of these households and multiply that number by eight (the number of nonresponses they generate) and then divide that number by the total number of eligible interview months of all households in the sample.

Figure 2 is the result. The left group of bars show the prevalence of *partially*-responding households for three periods. The right group of bars show the prevalence of *never*-responding households for the same periods. Regardless of type, the most recent period (diagonal red bars) is larger than the two earlier periods (green dot and blue stripe bars).

Now let us focus on the differences between the two types of nonresponding households. Partially-responding households represent a much larger share of nonresponses in all periods. Most recently, more than seven percent of possible responses were nonresponses from partially-responding households, while only three percent were from never-responding households. Moreover, the increase of nonresponse from the earlier periods to 2012-2019 for partially-responding households is much larger than that for never-responding households. Even though nonresponders from never-responding households nearly doubled, the level change was much smaller than that of partially-responding households. Thus, while

Figure 2: Prevalence of Partial vs. Never Responders



Notes: Authors' calculations from the CPS. Bars represent the counts of Type A nonresponse months as a share of eligible response months. Partial responders are households that nonrespond to at least one but less than eight CPS panels. Never responders are households that nonrespond to all eight CPS panels.

never-responding behavior seems to have the fastest growth rate over the past two decades, partially-responding behavior still represents roughly two-thirds of nonresponses.

In the following sections, we document non-random survey response behavior (conditioning on labor force status) and use information from partial responders to develop corrections for three key labor market indicators.

4 Selective Response Behavior

Partially-responding households give us a glimpse into what nonresponding households look like in the months they answer the CPS. Since most of the recent uptick in nonresponse is driven by partially-responding households, these households are useful to understand the characteristics of who is increasingly refusing the survey.

We define two types of partially-responding households. Drop-*outs* are households that respond in month t but nonrespond in month $t+1$. Drop-*ins* are households that nonrespond in month $t-1$ but respond in month t. The CPS has seen a sizable share of both drop-outs and drop-ins since 1998. If drop-outs, drop-ins, and consecutive responders are identical, we would not worry about selective response behavior from partial responders.[8] Unfortunately, this is not the case in the CPS. There are two margins of selection: (1) drop-out and drop-ins collectively differ from consecutive responders and (2) drop-ins differ from drop-outs and there are more drop-ins that accumulate over the eight panels.

The top panel of Table 1 reports the share and count of responders and drop-*outs* between a household's first month in sample (MIS 1) and their second month in sample (MIS 2), using data from 1998 through 2019. The first entry indicates the share of responders in the second month of the survey (MIS 2) who were employed the month before (MIS 1). The subsequent columns indicate the share of total drop-outs and just refusals in the second month of the survey who were employed the month before. Only 61% of MIS 2 responders were employed the month before, while 66% of both total dropouts and just refusals were employed the month before. The second row of Table 1 focuses on individuals who are unemployed. Here, too, the unemployed make up a larger share of total drop-outs and refusals than responders. The third row of Table 1 focuses on individuals not in the labor force, and the pattern is reversed. Responders are more likely to be not in the labor force (NILF) than total drop-outs or refusals. To summarize, drop-outs, whether all nonresponse or just refusals, are more likely to be in the labor force than consecutive responders.[9,10]

The bottom panel of Table 1 reports similar statistics as the top panel but this time for drop-*ins* between MIS 1 and MIS 2. The first entry indicates the share of responders in the

[8] Nekarda (2009) shows that bias created from people physically moving out (Type B nonresponse) is small because the people moving in have similar characteristics. Our focus is on Type A nonresponse.

[9] Appendix F shows that this pattern for drop-outs generally holds between MIS 1 through MIS 8 on a consecutive pairwise basis.

[10] Table 1 does not use BLS weights. This is common in the nonresponse literature because the BLS only provides a "final" weight so it is difficult to distinguish the effects that nonresponse, sample design, and post-stratification have on these weights (Korinek et al., 2007). Appendix F.1 shows that using BLS weights has little impact on the findings of Table 1.

Table 1: CPS Drop-outs and Drop-ins

MIS 2 Interview Status

MIS 1 Labor Force Status: Percent (Count)	Response	Nonresponse All	Nonresponse Refusal
Employed	61.20% (1,565,731)	66.40% (45,144)	65.94% (22,026)
Unemployed	3.45% (88,345)	3.98% (2,705)	3.96% (1,323)
NILF	35.35% (904,319)	29.62% (20,138)	30.10% (10,052)

MIS 1 Interview Status

MIS 2 Labor Force Status: Percent (Count)	Response	Nonresponse All	Nonresponse Refusal
Employed	60.62% (1,551,328)	65.66% (82,025)	64.49% (31,734)
Unemployed	3.30% (84,457)	3.33% (4,172)	3.35% (1,646)
NILF	36.08% (923,505)	31.00% (38,730)	32.16% (15,827)

Notes: Authors' calculations from linking households and individuals across MIS 1 and MIS 2 in the CPS. Data aggregated over 1998-2019. Each count is a person who lives in a household, where the household either responds or nonresponds. Nonresponse is either all Type A or refusals within Type A. The top panel is the share and count of interview status in MIS 2 that had a labor force status in MIS 1 (drop-outs). The bottom panel is the share and count of interview status in MIS 1 that had a labor force status in MIS 2 (drop-ins). All columns add up to 100%.

first month of the survey (MIS 1) who were employed a month later (MIS 2). The subsequent columns indicate the share of total drop-ins and just refusals in the second month of the survey who were employed the month after. Only 61% of MIS 1 responders were employed the month after, while 66% of total dropouts and 64% of refusals were employed the month after. The second row of Table 1 also shows that the unemployed make up a larger share of drop-ins than responders. The third row shows NILF make up a larger share of responders than drop-ins. In other words, drop-ins, whether all nonresponse or just refusals, are more likely to be in the labor force than consecutive responders.[11]

Taken together, both panels of Table 1 reveal that there are two margins that put downward pressure on the reported labor force participation rate. The first is that drop-ins and drop-outs are both more likely to be *in* the labor force than consecutive responders. By definition, drop-ins and drop-outs respond less than consecutive responders and with "sticky" labor force statuses, this biases the sample away from labor force participation. The second margin at play is that there are more drop-ins than drop-outs in the CPS between MIS 1 and MIS 2, and as shown in Appendix F, this holds more generally for all months in sample.[12] Moreover, drop-ins contain a larger share of NILF than drop-outs: 32% relative to 30% for refusals. Accounting for the additional households that drop into the survey and are disproportionally NILF biases the full-sample participation rate downward relative to a participation rate calculated from only MIS 1 responses.

Whether someone remains in the sample, leaves the sample, or enters the sample after a nonresponse depends on their labor force status. We find that this dependence has become stronger, especially for refusals, since 2010. This motivates our approach in the next section where we condition on a person's previous (and future) labor force status to estimate missing observations of partially-responding households. Our approach is an improvement

[11] Appendix F.2 shows that this pattern for drop-ins generally holds between MIS 1 through MIS 8 on a consecutive pairwise basis.

[12] Atrostic et al. (2001) also points out the net number of CPS responders increases over month in sample.

over current methods because it goes beyond conditioning on demographics, geography, and rotation group. It turns out that directly accounting for the labor force status of missing observations is important for accurately measuring the labor market.

5 Correcting for the Bias

We now turn to correcting for the bias from nonresponse. Because the CPS is a repeated cross section, if a household responds to at least one panel, we can infer information about their nonresponse from the month(s) they respond. Nevertheless, we need to make assumptions about the missing data. It is important to be explicit about the assumptions we make so readers can evaluate their plausibility. In general, our corrections involve estimating flow rates between labor force statuses and filling in missing data from partially-responding households by applying flow rates to individuals' labor force status in the month before or after a nonresponse.[13] This baseline correction assumes that flow rates from responding households are the same as those of nonresponding households. We motivate this assumption below. Our baseline correction does not, however, account for nonresponding households that we cannot match in adjacent months (e.g. never responders). As a secondary correction, we assume that unmatched (nonresponding) households probalistically have the same labor force characteristics as the partially-responding households we can match. Another way of phrasing this assumption is households that nonrespond at some point in their survey lives have the same labor force characteristics. We provide additional evidence for why this is a reasonable assumption. In the last part of this section, we apply our correction methods and the BLS demographic weights so we can evaluate how rising nonresponse have biased the official BLS statistics.

[13]This is similar to logical imputation used in the Survey of Income and Program Participation (SIPP) for item nonresponse (not unit nonresponse) in that it makes an educated guess about a missing observation based on previous responses. See `https://www.census.gov/programs-surveys/sipp/methodology/data-editing-and-imputation.html`.

5.1 Imputing Missing Observations for Partial Responders

We measure aggregate flow rates between labor force statuses by focusing on individuals who respond for two consecutive months.[14] For this population, we calculate flow rates between three labor market statuses: employed (E), unemployed (U), and not in the labor force (N).[15] Let $z_i^s(t)$ represent the number of individuals who are in labor force status i and MIS s in month t for $i = \{E, U, N\}$ and $s \in [1, 8]$. Conditioning on MIS is important because as we show in Appendix B, flow rates vary substantially by the MIS from which they are calculated. We then calculate two types of flow rates: forward flow rates and backward flow rates. Forward flow rates are the likelihood a respondent in labor force status i at t is in labor force status j at $t + 1$. Backward flow rates are the likelihood a respondent in labor force status j at t was in labor force status i at $t - 1$. Because flow rates vary over time, we calculate forward and backward flow rates for every combination of the three labor force statuses between 1998 and 2019. To preserve sample sizes—and since we are interested in long-run trends of nonresponse bias—we calculate flow rates at an annual frequency based on the year of the first MIS.

Let $f_{ij}^s(t)$ be the forward flow rate between labor force status i and j at MIS s and time t:

$$f_{ij}^s(t) = \frac{z_{ij}^s(t)}{z_i^s(t)}, \tag{1}$$

where $z_{ij}^s(t)$ is the number of individuals in labor force status i and MIS s at t who move to labor force status j and MIS $s+1$ at $t+1$. This forward flow rate is the share of individuals, for a given MIS, in labor force status i who a month later are in labor force status j. Let $\bar{f}_{ij}^s(T)$ represent the average monthly forward flow rate for MIS s calculated from individuals in calendar year T.[16]

[14]This group contains individuals from always responding households and individuals from partially-responding households who have a nonresponse in a month other than the two in question.

[15]EE *flow* rates, for example, are distinct from employer-to-employer *transition* rates as in Fujita et al. (2020) because workers do not necessarily switch jobs.

[16]Appendix B plots six annual forward flow rates averaged across all MIS for individuals in households

Let $b^s_{ij}(t)$ be the backward flow rate between labor force status j and i at MIS s and time t:

$$b^s_{ij}(t) = \frac{z^{s-1}_{ij}(t-1)}{z^s_j(t)}, \tag{2}$$

where $z^{s-1}_{ij}(t-1)$ is the number of individuals in labor force status j and MIS s at t who came from labor force status i and MIS $s-1$ at $t-1$. This backward flow rate is the share of individuals, for a given MIS, in labor force status j who the month before were in labor force status i. Let $\bar{b}^s_{ij}(T)$ represent the average monthly backward flow rate for MIS s calculated from individuals in calendar year T.[17]

By assuming flow rates for consecutively-matched individuals are the same for non-consecutively-matched nonresponding individuals, we can condition on the previous (and/or future) labor force status of missing respondents to impute their current labor force status.[18] Let $\mu^s_{kM\ell}(t)$ be a three-element row vector representing our correction probabilities for a Type A missing observation M in MIS s at month t where statuses $k, \ell \in \{U, E, N, M\}$ are survey responses before and after the M in question.

$$\mu^s_{kM\ell}(T) = \begin{cases} \left[\bar{f}^s_{kE}(T), \bar{f}^s_{kU}(T), \bar{f}^s_{kN}(T)\right] & \text{if } \ell = M, k \neq M \\ \left[\bar{b}^s_{E\ell}(T), \bar{b}^s_{U\ell}(T), \bar{b}^s_{N\ell}(T)\right] & \text{if } \ell \neq M, k = M \\ \left[\frac{1}{2}\big(\bar{f}^s_{kE}(T) + \bar{b}^s_{E\ell}(T)\big), \frac{1}{2}\big(\bar{f}^s_{kU}(T) + \bar{b}^s_{U\ell}(T)\big), \frac{1}{2}\big(\bar{f}^s_{kN}(T) + \bar{b}^s_{N\ell}(T)\big)\right] & \text{if } \ell \neq M, k \neq M \end{cases} \tag{3}$$

where, for example, $\bar{f}^s_{kE}(T)$ is the average forward monthly flow rate between $k \in \{E, U, N\}$ and E with MIS $s \in \{2, 3, 4, 6, 7, 8\}$ in year T. Similarly, $\bar{b}^s_{E\ell}(T)$ is the average backward flow rate between $\ell \in \{E, U, N\}$ and E with MIS $s \in \{1, 2, 3, 5, 6, 7\}$ in year T. Each

that respond for two consecutive months.

[17] Appendix B plots six annual backward flow rates averaged across all MIS for individuals in households that respond for two consecutive months.

[18] We weaken this assumption in Section 5.4 by using flow rates calculated from *only* partially-responding households (with at least two consecutive responses around the month in question) and find the detected bias, if anything, is larger than in the baseline specification.

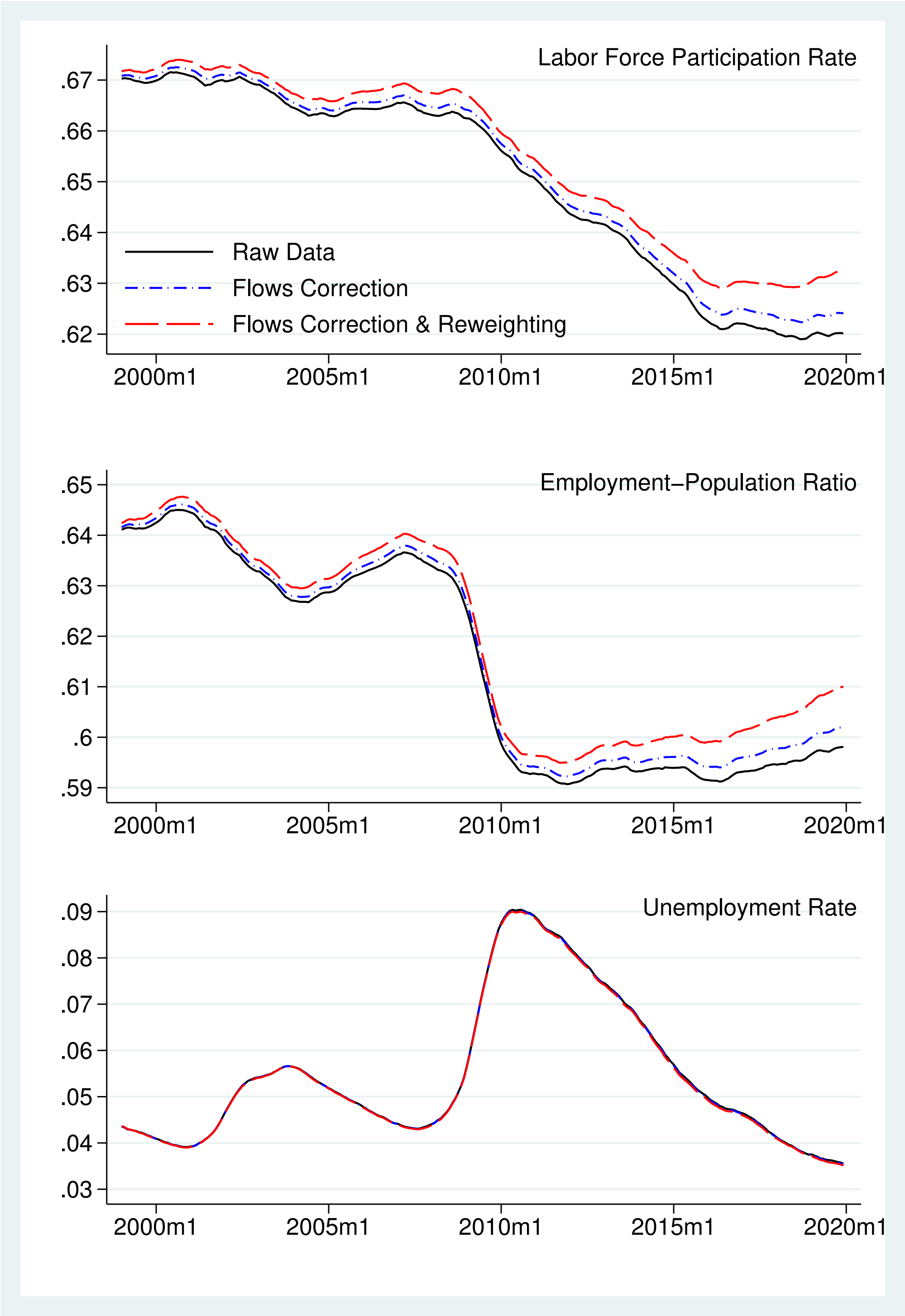
missing observation is filled in with a three-element vector estimating the probability that the nonresponder is employed, unemployed, and not in the labor force.

The first component in Equation (3) uses forward flow rates and pertains to missing observations where the survey participant responded last month but failed to respond in the current month and failed to respond next month (or was out of the survey next month), namely $\ell = M$. The second component in Equation (3) uses backward flow rates and pertains to missing observations where the survey participant failed to respond last month (or was not in the survey last month), namely $k = M$, and failed to respond in the current month but responded next month. The third component in Equation (3) uses both forward and backward flow rates and captures missing observations where the survey participant responds both last month $k \neq M$ and next month $\ell \neq M$, but not in the current month. Essentially, this missing observation is flanked by two non-missing, in-sample observations. To address the fact that we have two observations from which we can calculate the respondent's probabilistic labor force status, we use both sets of information by applying forward and backward flow rates and averaging the results.

5.2 Imputing Missing Observations for the Unmatched

Equation (3) cannot account for all missing observations. Missing observations with no responses in adjacent months, such as never responders, are excluded. To address this type of nonresponse, we apply sample weights such that a respondent who satisfies one of the cases in Equation (3) is upweighted. This is our second important assumption. By doing so, we are assuming that partially-responding households filled in by Equation (3) are identical (labor force wise) to nonresponding households not accounted for in Equation (3). The nonresponders unaccounted for by Equation (3) tend to live in households that have a large numbers of nonresponses and thus cannot be matched adjacently. This might be viewed is a strong assumption. To investigate its plausibility, we show that partial responders, regardless

Figure 3: Key Labor Market Indicators



Notes: Authors' calculations using data from the CPS for January 1999 through December 2019. All series are the 12-month historical moving average. The black solid line is the labor force participation rate calculated from the raw counts of respondents in the CPS. The blue dashed line adjusts for missing observations using our flows correction outlined in Equation (3). The red dashed line reweights our corrected series to account for missing observations that are excluded from Equation (3).

of how many times they refuse, are similar to each other (labor force wise), yet distinct from always responders.[19]

Figure 3 plots three estimates of three key labor market indicators from 1999 through 2019.[20] The black solid line represents rates calculated from the raw data without any adjustment. The blue dashed line imputes missing observations using Equation (3). The red dashed line further imputes missing observations by reweighting the sample to account for nonrespondents excluded from Equation (3). For the labor force participation rate and employment-population ratios, the dashed lines continually diverge from the solid line after 2010 which is exactly when nonresponse rates take off. Notably, 20 percent of the decline in the labor force participation rate (as calculated from the raw counts of CPS respondents) since 2000 is due to measurement error from nonresponse. The unemployment rate looks different. All lines closely overlap, suggesting growing nonresponse has not discernably biased the unemployment rate. These findings line up with Section 4 where we document that most of the selective response behavior is between in and out of the labor force and not between employment and unemployment, and the latter is what the unemployment rate is calculated from.

5.3 Composition vs. Treatment

An important question relating to our correction approach is if a change in an individual's labor force status (i.e. "treatment") is itself a cause of nonresponse. We are unable to explore this question directly because it requires information of an individual exactly when they nonrespond, which, of course, we do not have. However, in this section, we discuss two

[19] As an additional check, Appendix D shows that at the state-level, rates of partially-responding households are highly correlated with rates of never-responding households. While we do not observe the underlying causes of nonresponse, it is likely a product of cultural, demographic, political, etc. factors, which themselves are correlated geographically. When we control for geography, we observe a strong correlation between partial and never responders, which provides additional grounding for our assumption that partial and never responders are alike.

[20] At this stage, none of the series in Figure 3 use the final composite weights provided by the BLS. We revisit this issue in Section 5.4.

examples of these “treatment” issues to highlight when our correction leads to an over or underestimate of the bias. We also highlight that the evidence we do have suggests that our approach underestimates the bias.

Example 1:

Suppose a survey participant named Juan records the following statuses for the first three months: (1) employed, (2) nonresponse, (3) employed. While our approach for imputing Juan’s missing observation for MIS 2 is relatively complicated, as a first approximation, let us assume we impute his status as employed. This imputation would increase the employment-population ratio for MIS 2 and—as we generally find in the paper—our “corrected” employment-population ratio would be larger than that calculated from the raw data. Suppose, though, that Juan’s true (unobservable) labor force status in MIS 2 was NILF, and it was factors related to NILF that caused him to nonrespond. If we set Juan’s missing observation to NILF instead of employed, this would mean the true employment-population ratio is lower than our “corrected” series. In this example, our correction approach would overestimate the employment-population ratio. Notice, however, for this to be the case, the likelihood someone responds to the survey must be negatively correlated with NILF. The evidence we do have suggests the opposite is true. In Table 1, we see that individuals who reported NILF in MIS 1 are *more* likely to respond to the survey in MIS 2.

Example 2:

Suppose a survey participant named Jessica records the following statuses for the first three months: (1) NILF, (2) nonresponse, (3) NILF. As a first approximation let us assume we impute her status as NILF. This imputation would lower the employment-population ratio for MIS 2 and our “corrected” employment-population ratio would be smaller than that calculated from the raw data. Suppose, however, that Jessica’s true (unobservable) labor force status in MIS 2 was employed, and that factors related to employment caused her to nonrespond. If we set Jessica’s missing observation to employed instead of NILF, this would mean the true employment-population ratio is larger than our "corrected" series. In this example, our correction approach would underestimate the employment-population ratio. For this to be the case, the likelihood someone responds to the survey must be negatively correlated with employment, which aligns with what we see in the data. In Table 1, we see that individuals who are employed in MIS 1 are *less* likely to respond to the survey in MIS 2. There are also intuitive reasons why being employed might make an individual less likely to respond to the survey. For example, working individuals may have less free time to respond.

Again, we can never say definitively that these "treatment" issues go one way or another because the data does not exist, but the evidence we do have suggests individuals who are employed or unemployed refuse the survey with a higher likelihood. If a change in labor force status occurs during a month where an individual nonresponds, and this correlation between nonresponse and labor force status holds, it would be the case that our "corrected" employment-population ratio and labor force participation rates understate the true upward correction needed and that the downward bias in the official series is worse than what we calculate.

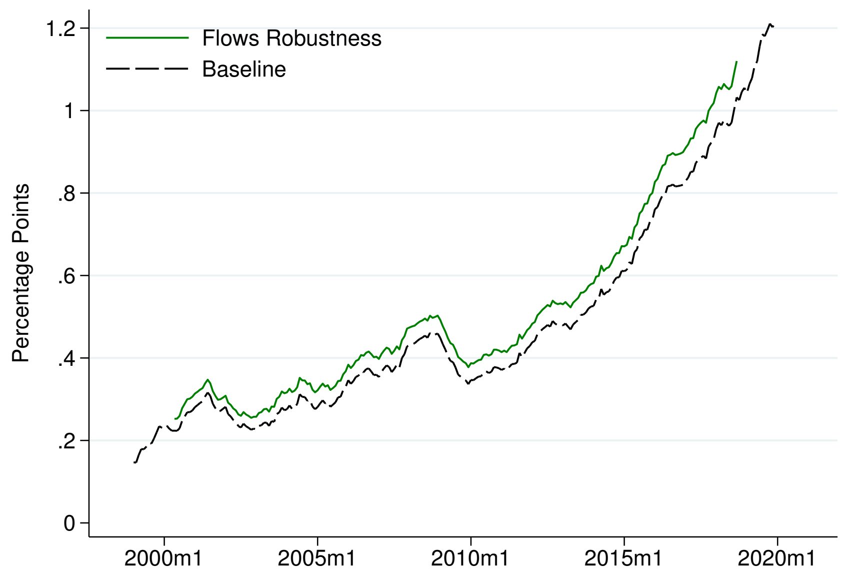
5.4 Robustness

Again, we emphasize that our adjustment procedure above makes two major assumptions. In this section, we investigate the plausibility of these assumptions and the robustness of our results to weakened assumptions. The first assumption we refer to as the *flows* assumption, which assumes the flow rates between labor force statuses are the same regardless if individuals live in a responding or nonresponding household. The second assumption we will refer to as the *reweighting* assumption, which assumes matched and unmatched nonresponders have the same labor force characteristics probablistically. Both of these assumptions pertain to households with higher numbers of nonresponses. Included in this group are never-responding households, who, by definition, we never observe anything about. However, this group is also heavily influenced by partial responders who have a high number of nonresponses, and, by leveraging information about these households when we *do* observe them, we can explore the plausibility of our assumptions.

In the baseline flows assumption, flow rates are calculated from all individuals who register a response in the two months in question. This sample of individuals includes always responders and partial responders whose nonresponse(s) occurred in another panel month. To test the flows assumption, we calculate flow rates using *only* households that have at least one nonresponse, but where the nonresponse occurs in months other than the ones used to compute the flow rates. We view this as a weaker assumption because we are using flow rates only calculated from partial responders to fill in missing observations for the other partial responders. The idea is that partial responders are similar to other partial responders.

With this weakened assumption to compute flow rates, we repeat the same adjustment procedure outlined in Sections 5.1 and 5.2. Figure 4 highlights how our results change by plotting the gaps between our corrected series and the raw participation rate. The black dashed line plots the difference between the Flows Correction & Reweighting series and the Raw series from Figure 3. The solid green line plots this difference, but where the Flows Correction & Reweighting series only uses flow rates from partially-responding households instead of the full sample of households. The Flows Robustness series is truncated at the beginning and end because it requires information on households linked over 16 months of the full survey duration. Notably, both lines start to exponentially increase in 2010 which is precisely when nonresponse rates start to increase dramatically. The Flows Robustness series reports an even higher prevalence of bias than the baseline specification. These results highlight that flow rates do not appear to be systematically different when computed from the restricted sample and that, if anything, doing so leads to an even larger computed bias. We continue to use the Baseline specification in the analysis that follows because it generates

Figure 4: Gap Between Corrected and Uncorrected Labor Force Participation Rate



Notes: Authors' calculations using data from the CPS. The Baseline series is constructed from the "Flows Correction & Reweighting" series and runs from January 1999 through December 2019. The Flows Robustness series is similar to the Baseline but corrects the raw data using flow rates from partially-responding households. The Flows Robustness series is truncated, running from April 2000 through September 2018, because respondents need to be observed for the span of the 16-month survey to determine if they are partial responders. All series are 12-month historical moving averages.

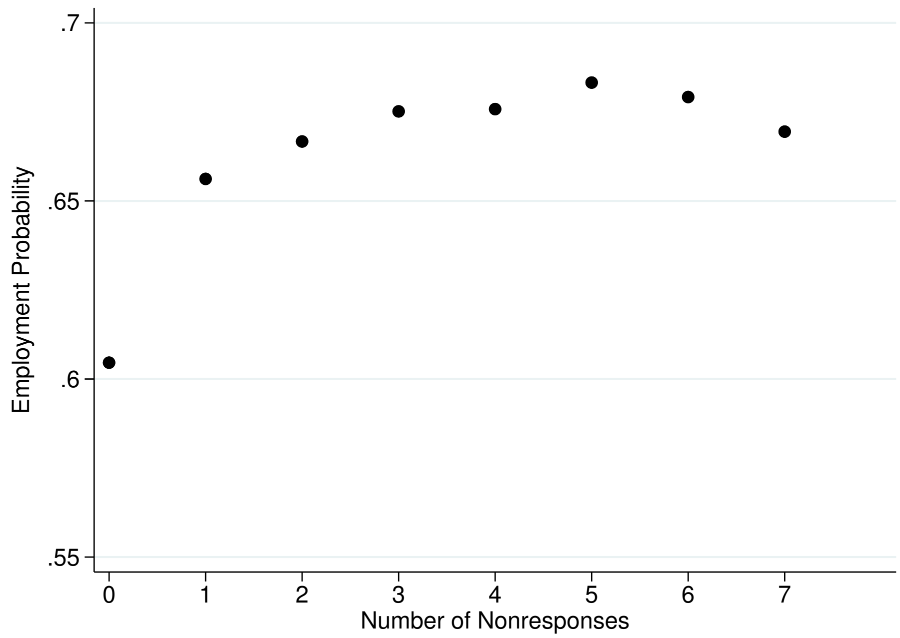
a more conservative estimate of the bias, computes flow rates from a larger sample, and does not face truncation issues.

The second major assumption—the reweighting assumption—is made when constructing the Flows and Reweighting Correction (red line) in Figure 3. Recall, we assume nonresponders we can match to responses in adjacent months are the same, labor force wise, as the nonresponders we cannot match adjacently. To test this second assumption, we explore whether the number of times a household nonresponds matters for labor market indicators. The idea here is that unmatched nonresponders tend to come from households with a higher number of nonresponses. How labor market indicators vary by the number of household nonresponses indicates whether matched nonresponders (i.e. low nonresponse households, on average) are similar to unmatched nonresponders (i.e. high nonresponse households, on average).

Figure 5 plots the average probability a respondent is employed based on the number of times their household nonresponds. Notably, the employment rate of people in an always responding household (i.e. zero nonresponders) is much lower, at 60 percent, than the employment rate of people in a partially-responding household. Moreover, the employment rate of partial responders—whether a one-time or seven-time nonresponder—are similar ranging from 65 to 67.5 percent. In summary, the labor force characteristics of partial responders do not vary much regardless of the number of times they nonrespond, but are distinct from always responders.[21] This suggests that assuming homogeneity among partial responders is reasonable. It is also worth noting that our reweighting assumption may be a conservative one. This can be seen from Figure 5. The probability of being employed for a person in a household with few nonresponses (e.g. 1-3 nonresponses) is lower than for a person in a household with many nonresponses (e.g. 4-7 nonresponses). Since most unmatched households have many nonresponses, using the sample average among partial

[21] Appendix C contains similar charts for the probability of being not in the labor force and the probability of being unemployed.

Figure 5: Employment Rate by Number of Nonresponses



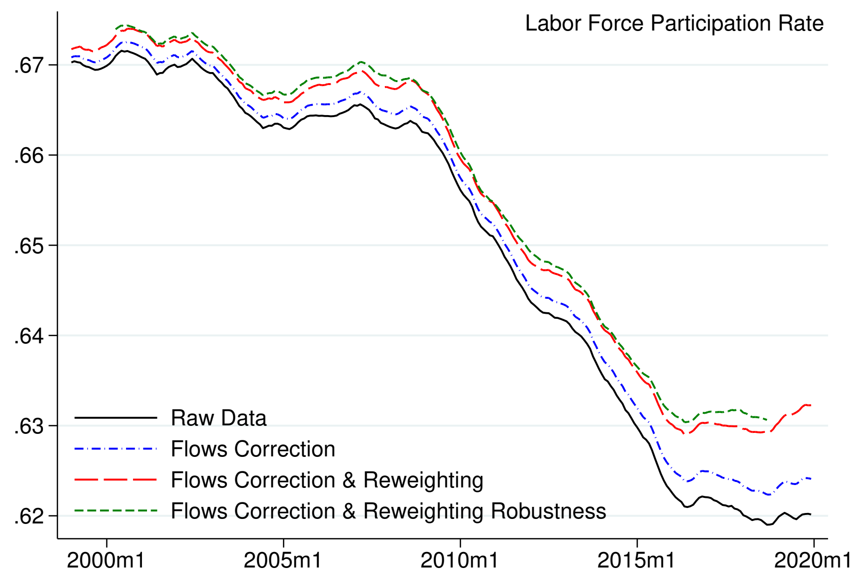
Notes: Authors' calculations using data from the CPS averaged over all months from 1998 through 2019. Probabilities are for individuals 16 years and older. Nonresponses are Type A unit non-interviews.

responders from Figure 5 to upweight these individuals would lead to lower employment rates than using the probability of, say, five-time nonresponding households.[22]

As an alternative and weaker reweighting assumption, Figure 6 applies the labor force characteristics for unmatched nonresponders conditional on their total number of nonresponses. The idea here is that we use information in Figure 5 (and the analogous versions for NILF and unemployment depicted in Appendix C) to fill in labor force characteristics for unmatched nonresponders. This is weaker than our baseline reweighting assumption because it relaxes the assumption that matched and unmatched individuals have identical labor force characteristics regardless of the number of times their household nonresponds. Consistent with the intuition outlined above, Figure 6 highlights that, if anything, our baseline reweighting assumption (red large dashed line) is slightly conservative because our weaker

[22] Indeed, over the inner sample, the average number of nonresponses out of 8 for matched individuals is 2.3 and for unmatched individuals is 5.9.

Figure 6: Robustness Check for Reweighting Assumption



Notes: Authors' calculations using data from the CPS. The first three series run from January 1999 through December 2019. The Flows Correction & Reweighting Robustness series is truncated, running from April 2000 through September 2018, because respondents need to be observed for the span of the 16 month survey. All series are 12-month historical moving averages.

reweighting assumption (green small dashed line) estimates a slightly larger bias for the labor force participation rate. As with our other robustness check, we proceed using our baseline adjustment because it is more conservative, is generated from a larger sample of households, and does not face truncation issues.

5.5 BLS Demographic Weights

An important part of the CPS is the sample weights provided by the BLS to ensure a representative sample. BLS weights target regional demographic information from the U.S. Census.[23] When aggregating individuals in the CPS to produce the official headline statis-

[23]The BLS final composite weight corrects the data in two ways. First, it targets the population within a demographic-region cell. Second, it adjusts for rotation group bias within each cell. Because we aggregate the BLS weights to demographic-region cells—and at this level of aggregation, the weights are orthogonal to the rotation group correction—we do not double correct the data for missing labor force status. See U.S. Census Bureau (2019) for more details.

tics, the BLS applies these weights to respondents. The analysis so far does not use BLS weights and instead uses the raw counts of individuals. This is common in the literature on nonresponse (e.g. Korinek et al. 2007) because applying BLS weights to imputed data can lead to a double correcting of nonresponders. For example, suppose we impute the labor market status of an individual who was missing in a given month using our Flows Correction. It is possible that the BLS weights for the responding population are, at least in part, also derived to account for those who are missing. If nonresponse behavior is strongly correlated with demographic characteristics, individuals who respond to the CPS but who also belong to a demographic group with a high nonresponse rate would be upweighted to match the BLS's demographic targets. If we impute missing individuals from this demographic group using our approach, but also apply the BLS weights to responders, we would end up overcorrecting for the nonresponders.

Nevertheless, it is important to understand how much of the bias we are computing is controlled for by the BLS weights. In an extreme example, if the selective response behavior is perfectly correlated with demographic characteristics, the bias we document would be completely absorbed by the BLS weighting, and the official labor market statistics would, in fact, be unbiased. In this section, we apply both our correction methods and reverse-engineered BLS weights.

To begin, we need the demographic population shares the BLS targets in their weighting approach. Using the demographic and region categories (age, sex, race, ethnicity, and state) described in the technical report by the U.S. Census Bureau (2019), we backward engineer the BLS targets. To save on computation, our demographic categories are broader than what the BLS targets, but consist of over 1,600 demographic cells, and when applied to the raw data generate a remarkably good match with the headline labor market statistics.

We demographically adjust the raw data as follows. Using the BLS weights, we construct the share of the (BLS weighted) population in each demographic cell. Formally:

$$PopShare^{BLS}_{k,t} = \frac{p^{BLS}_{k,t}}{\sum_k p^{BLS}_{k,t}}, \tag{4}$$

where $p^{BLS}_{k,t}$ is the sum of the BLS weights for the population in demographic-region cell k in month t and $\sum_k p^{BLS}_{k,t}$ is the total (weighted) population across cells in month t.[24] Because these population shares are computed using the BLS weights, they should reflect the BLS's desired share of the population in each demographic category. We use these shares as our targets for the demographic shares of the population.

One way to check how well these backward engineered targets do, is to adjust the raw data with these demographic targets and construct labor force statics to compare against the official BLS statistics. We do this as follows. Using the raw individual counts, we compute the share of the population in each demographic cells as:

$$PopShare^{Raw}_{k,t} = \frac{p^{Raw}_{k,t}}{\sum_{k,t} p^{Raw}_{k,t}}, \tag{5}$$

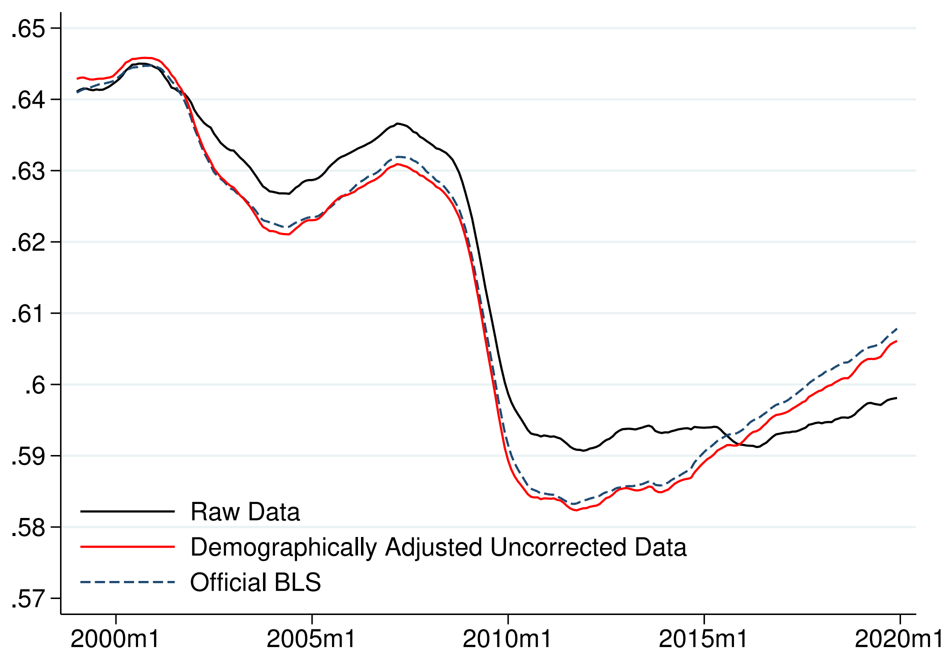
where $p^{Raw}_{k,t}$ is the sum of the (unweighted) population count in demographic cell k in month t and $\sum_k p^{Raw}_{k,t}$ is the total (unweighted) number of individuals in the survey in month t. We then up/down-weight individuals in these demographic cells with the following adjustment factor:

$$AdjustmentFactor^{Raw}_{k,t} = PopShare^{BLS}_{k,t} / PopShare^{Raw}_{k,t}. \tag{6}$$

In other words, if a certain demographic cell k is underrepresented in the raw data, respondents in that group are upweighted so their population share matches those backward engineered from the BLS weights. To be clear, at this stage, we do this only for individuals who respond to the survey. Using these adjustment factors, we then recompute the labor force statistics and compare them to the official BLS series. As an example, Figure 7 plots the

[24]The demographic-region cells include 51 states including the District of Columbia; 4 age groupings, [16,30),[30,50),[50,70),[70,∞); white and non-white; Hispanic and non-Hispanic; male and female.

Figure 7: Demographically Adjusted Employment-Population Ratio



Notes: Authors' calculations using data from the CPS for January 1999 through December 2019. All series are the 12-month historical moving average.

employment-population ratio. The black line in Figure 7 is the same as the black line in the middle panel of Figure 3. It calculates the employment-population ratio from the raw counts of respondents in the CPS. The dashed line plots the official BLS series and the red line plots the demographically adjusted uncorrected data using Equation 6. There are a few points worth highlighting. The difference between the official headline statistic and that computed from the raw data is substantial, suggesting that BLS weights have an important impact on labor market indicators. The second observation is that our demographic adjustment (of the uncorrected data) gets us quite close to the official BLS series. This suggests that our quasi-headline series captures the vast majority of the adjustment resulting from the BLS weights.

We now apply this demographic weighting approach to our corrected data after we have imputed the labor force statuses of the nonresponders. Again, there are two key steps in our adjustment for nonresponders. The first is the Flows Correction where we fill in nonresponders who have a response in the preceding or subsequent month. For the demographic adjustment we also fill in these individuals' demographic and geographic information from the preceding and subsequent month. The second key step is the Reweighting Correction where we upweight these imputed nonresponders to account for the additional nonresponders we cannot match in the preceding or subsequent months. Here, we assume the demographics of the unmatched households are similar to that of the matched. To demographically adjust this data, we now compute the share of the corrected population (responders and imputed nonresponders) in each demographic-region cell as:

$$PopShare_{k,t}^{Corrected} = \frac{p_{k,t}^{Corrected}}{\sum_k p_{k,t}^{Corrected}}, \tag{7}$$

where $p_{k,t}^{Corrected}$ is the sum of the population of responders and nonresponders for our corrected data who are in cell k in month t and $\sum_k p_{k,t}^{Corrected}$ is the total population in our corrected data in month t. This is the same approach as Equation (5), except where we also inlcude the individuals who we have filled in. We then adjust these demographic cells by:

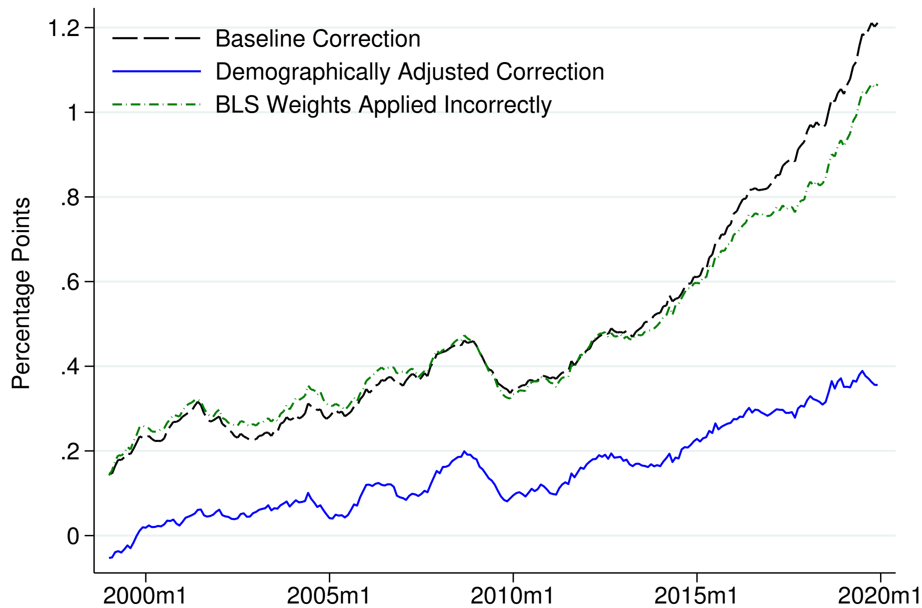
$$AdjustmentFactor_{k,t}^{Corrected} = PopShare_{k,t}^{BLS} / PopShare_{k,t}^{Corrected}. \tag{8}$$

Another way to think about how much the BLS weights control for the nonresponse bias we correct for in the raw data is to look at the magnitude of $AdjustmentFactor_{k,t}^{Corrected}$. If the nonresponse behavior we correct for was perfectly described by differential response behavior across demographic cells, $AdjustmentFactor_{k,t}^{Corrected}$ would equal one for all k cells, and the BLS weights would fully account for nonresponse bias. This is not the case. An easy way to illustrate this is plotting the gap between labor force statistics of a) our corrected data and the raw data and b) our demographically adjusted corrected data and the demographically adjusted uncorrected data.

Figure 8 shows three correction gaps between various series. The dashed black line shows the differences between the labor force participation rate derived from raw CPS counts and our Flows Correction & Reweighting series. This line illustrates the magnitude of the correction from the raw data, and is identical to the "Baseline" series in Figure 4. This gap increased by 104 basis points between 1999 and 2020. The solid blue line is computed analogously but where both the raw count data and the Flows Correction & Reweighting series have been demographically adjusted. This line illustrates the magnitude of the Flows Correction & Reweighting adjustment once demographics are appropriately controlled for in both series. This gap has increased by 41 basis points between 1999 and 2020. In other words, the BLS weights manage to address 60 percent of the increase in nonresponse bias.

These results align with the finding in Borgschulte et al. (2020) that about half of the recent rise in refusal rates in the CPS can be accounted for by demographic controls. In summary, while the demographic adjustments provided by the BLS improve things, they do not eliminate rising bias in our key labor market indicators. Nonresponse bias still accounts for 41 basis points, which is approximately 10 percent of the reported decline in the official

Figure 8: Correction Gaps for the Labor Force Participation Rate



Notes: Authors' calculations using data from the CPS for January 1999 through December 2019. All series are the 12-month historical moving average.

labor force participation rate since the turn of the millennium. On its own, 10 percent is sizable, but this finding is even more consequential considering that nearly half of the decline in the participation rate is from compositional changes in the population (Aaronson et al., 2012). This leaves only two percentage points of the decline to be accounted for by all other factors. The bias we document possibly cuts into the importance of other factors, such as skilled-biased technological change, behind falling participation (Abraham and Kearney, 2020; Wolcott, 2021).

These results also highlight a subtle yet important point related to work examining nonresponse in the CPS. Simply applying BLS weights to responders and nonresponders who have already been accounted for by other means (as in Ahn and Hamilton, 2021) can lead to overcorrecting. The reason is that the BLS weights assigned to individuals who respond to the survey are, in part, determined by those who nonrespond to the survey. If the nonresponders are added back to the data set, the BLS weights applied to the responding individuals are now invalid and risk overcounting the nonresponding population. Refusals are only one of the many measurement issues Ahn and Hamilton (2021) impressively correct for in the CPS, and relative to misclassification issues, they play muted role. Since our focus is on missing observations from refusals, it is even more important to consider the interaction between imputed data and the BLS weights.

To highlight this point, we recompute the participation rate using our Flows & Reweighting corrected data from Section 5.2 but weight individuals by their BLS weight during aggregation. We then plot the gap between the BLS weighted participation rate of the corrected data and the official BLS participation rate as a third line in Figure 8, denoted "BLS Weights Applied Incorrectly." This gap computes an erroneous bias because it applies the BLS weights as-is to the responding population even after nonresponding individuals have been filled in. The result is a gap that is substantially larger than our demographically adjusted Flows & Reweighting correction. Therefore, failing to adjust weights after missing individuals have been imputed risks overcorrecting for the missing population and overestimating the magnitude of nonresponse bias. In sum, an important contribution of the paper is highlighting the care that needs to be given when applying BLS weights to already corrected data. Further, we provide a methodology to address both nonresponse bias and demographic adjustment while avoiding overcorrecting.

6 Conclusion

How does the dramatic rise of nonresponse since 2010 impact labor market indicators? Rising nonresponse in the CPS has artificially suppressed the labor force participation rate and employment-population ratio but has had little discernible impact on the unemployment rate. We document that the rise in nonresponse is driven by households refusing to participate in the survey and that most of the growth in refusals is from households that respond some months but refuse in other months. We leverage the panel structure of the CPS to record the labor force status of nonresponding households in the months surrounding their nonresponse and use aggregate flow rates to impute missing observations. We offer a correction method for indicators calculated by both the raw counts of respondents in the CPS and respondents that have been demographically adjusted by the BLS. All methods point to the problem becoming worse since 2010. Although the BLS weights correct for some of the bias, they do not correct for all of it, and nonresponse appears to be a growing source of bias in labor market indicators derived from the CPS.

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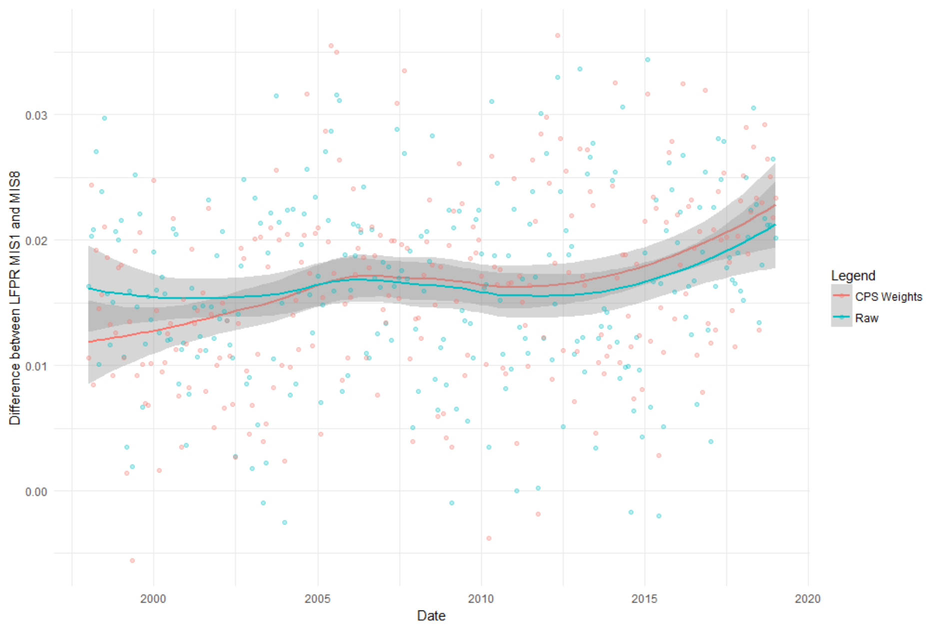
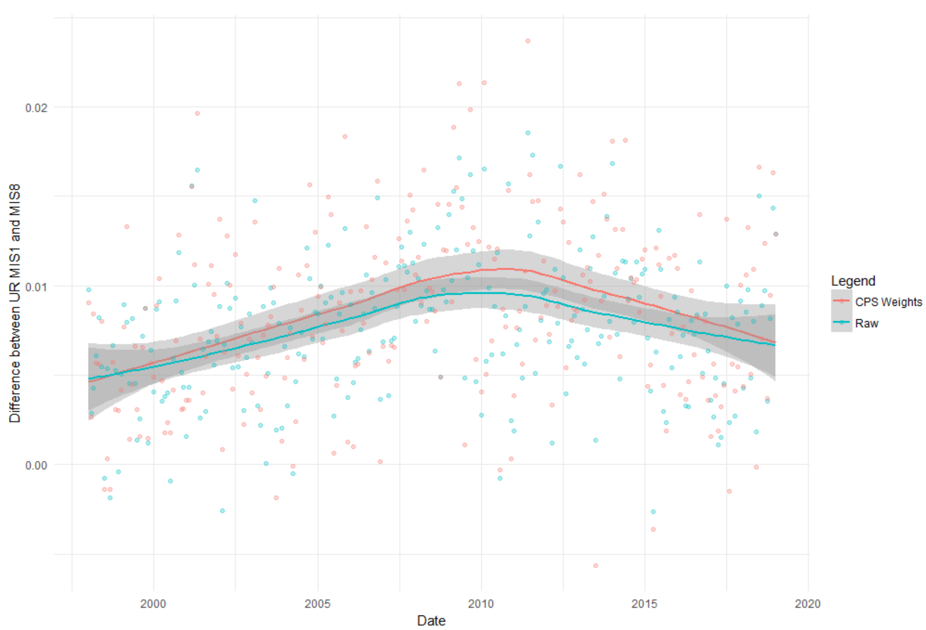
A Trends in Rotation Group Bias

Difference Between MIS 1 and MIS 8 Participation Rate



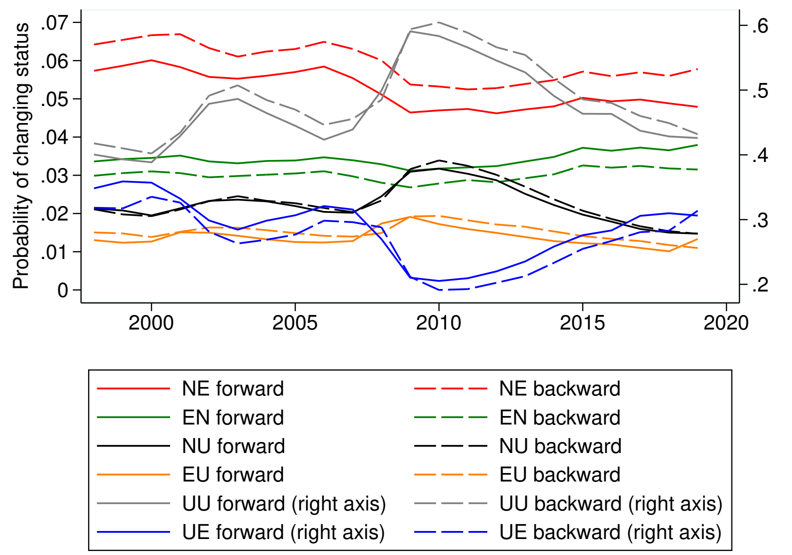
Difference Between MIS 1 and MIS 8 Unemployment Rate



Notes: Authors' calculations using data from the CPS. Difference in labor market indicators by the month-in-sample (MIS) the respondent was the in survey. The CPS weighted series applies the Composited Final Weight used to create BLS published labor force statistics. The raw series is unweighted.

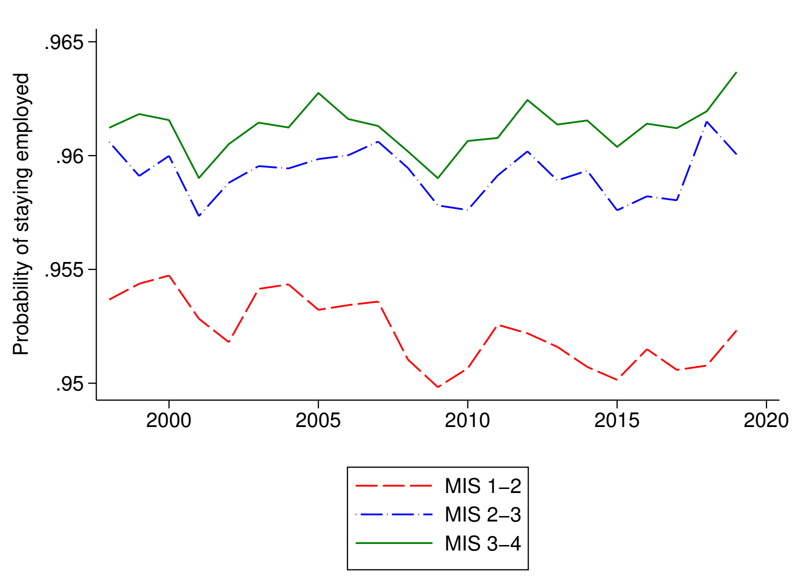
B Labor Force Status Flow Rates

Subset of Flow Rates Averaged Over MIS



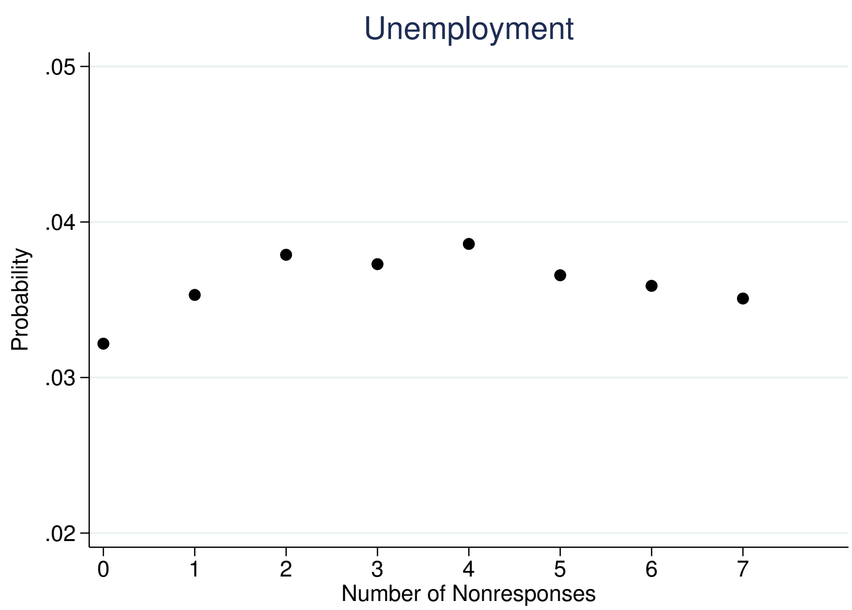
Notes: Authors' calculations using data from the CPS. E represents employed; U represents unemployed and N represents not in the labor force.

Employment-to-Employment Flow Rates by MIS



Notes: Authors' calculations using data from the CPS. Monthly flow rates are from individuals 16 years and older who move between unemployment (U), employment (E), and not in the labor force (N) from the full sample of consecutively responding households. Top panel plots a subset of forward and backwards flow rates. Bottom panel plots EE flow rates for three month-in-sample (MIS) pairs.

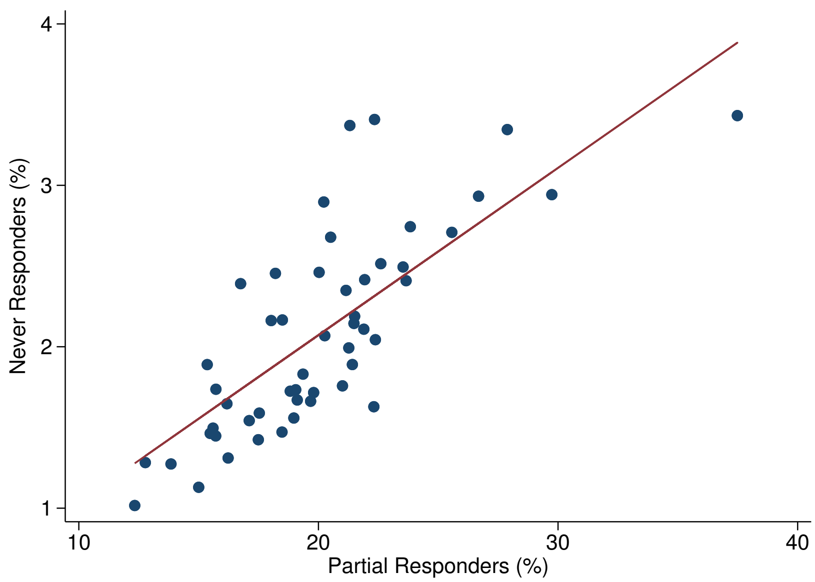
C Labor Market Status by Number of Nonresponses



Notes: Authors' calculations using data from the CPS averaged over all months from 1998 through 2019. Probabilities are for individuals 16 years and older. Nonresponses are Type A unit non-interviews.

D State-Level Correlations

Share of Partial vs. Never Responders



Notes: Authors' calculations using data from the CPS. Each data point represents state-wide average over 1998-2019.

E Demographically Adjusted Correction Gaps

Notes: Authors' calculations using data from the CPS.

F Evidence of Selective Response Behavior

F.1 Impact of BLS Weights

Table 2: CPS Drop-outs and Drop-ins

MIS 1 LF Status	MIS 2 Interview Status			
Percent		Response	Nonresponse All	Nonresponse Refusal
Employed		61.75%	67.06%	66.82%
Unemployed		3.69%	4.15%	4.12%
NILF		34.56%	28.79%	29.05%

MIS 2 LF Status	MIS 1 Interview Status			
Percent		Response	Nonresponse All	Nonresponse Refusal
Employed		61.05%	66.25%	65.17%
Unemployed		3.52%	3.51%	3.49%
NILF		35.43%	30.24%	31.34%

Notes: Authors' calculations from linking households and individuals across MIS 1 and MIS 2 in the CPS. Data aggregated over 1998-2019. Each count is a person within a household, where the household either responds or non-responds. Nonresponse is only Type A. The top panel is the share of interview status in MIS 2 that had a labor force status in MIS 1 (drop-outs). The bottom panel is the share of interview status in MIS 1 that had a labor force status in MIS 2 (drop-ins). This table is equivalent to Table 1 in the paper except that it uses BLS weights instead of raw individual counts.

F.2 1998-2009 Average for All Consecutive Pairs, Not BLS Weighted

MIS 1 Labor Force Status	MIS 2 Interview Status			
Percent (Count)		Response	Non-response All	Non-response Refusal
Employed		62.78% (9,27,048)	66.97% (20,255)	66.36% (7,563)
Unemployed		3.21% (47,395)	3.77% (1,141)	3.67% (418)
NILF		34.01% (502,125)	29.25% (8,847)	29.97% (3,416)

MIS 2 Labor Force Status	MIS 1 Interview Status			
Percent (Count)		Response	Non-response All	Non-response Refusal
Employed		62.23% (919,160)	66.93% (42,292)	64.97% (12,465)
Unemployed		3.09% (45,626)	3.16% (1,995)	3.28% (629)
NILF		34.69% (512,368)	29.91% (18,902)	31.75% (6,091)

MIS 3 Interview Status

MIS 2 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	62.33% (943,635)	67.74% (21,224)	68.30% (8,218)
Unemployed	3.08% (46,627)	3.66% (1,146)	3.26% (392)
NILF	34.59% (523,722)	28.60% (8,962)	28.45% (3,423)

MIS 2 Interview Status

MIS 3 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	62.27% (942,931)	66.28% (22,605)	65.52% (7,277)
Unemployed	3.00% (45,454)	3.28% (1,119)	3.10% (344)
NILF	34.73% (525,839)	30.43% (10,379)	31.39% (3,486)

MIS 4 Interview Status

MIS 3 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	62.27% (946,461)	67.60% (19,948)	67.16% (7,006)
Unemployed	3.00% (45,576)	3.55% (1,049)	3.46% (361)
NILF	34.73% (527,883)	28.85% (8,513)	29.38% (3,065)

MIS 3 Interview Status

MIS 4 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	62.25% (946,181)	66.16% (19,232)	65.55% (6,359)
Unemployed	2.95% (44,845)	3.34% (970)	3.35% (325)
NILF	34.80% (529,024)	30.50% (8,866)	31.10% (3,017)

MIS 5 Interview Status

MIS 4 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	62.15% (883,918)	68.78% (50,861)	68.64% (22,307)
Unemployed	2.86% (40,608)	3.23% (2,386)	3.19% (10,38)
NILF	35.00% (497,776)	27.99% (20,695)	28.16% (9,152)

MIS 4 Interview Status

MIS 5 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	61.81% (879,251)	65.25% (26,051)	64.34% (12,380)
Unemployed	2.96% (42,087)	3.69% (1,475)	3.82% (735)
NILF	35.24% (501,260)	31.05% (12,398)	31.84% (6,127)

MIS 6 Interview Status

MIS 5 Labor Force Status	Percent (Count)	Response	Non-response All	Non-response Refusal
	Employed	61.95% (918,022)	66.98% (21,061)	66.31% (7,690)
	Unemployed	3.08% (45,645)	3.43% (1,078)	3.29% (381)
	NILF	34.97% (518,116)	29.59% (9,303)	30.40% (3,526)

MIS 5 Interview Status

MIS 6 Labor Force Status	Percent (Count)	Response	Non-response All	Non-response Refusal
	Employed	61.82% (916,083)	67.33% (33,565)	66.02% (10,818)
	Unemployed	3.01% (44,678)	3.19% (1,588)	3.22% (527)
	NILF	35.17% (521,172)	29.49% (14,701)	30.76% (5,040)

MIS 7 Interview Status

MIS 6 Labor Force Status	Percent (Count)	Response	Non-response All	Non-response Refusal
	Employed	61.93% (933,437)	67.77% (19,897)	67.62% (6,960)
	Unemployed	3.03% (45,707)	3.54% (1,033)	3.33% (343)
	NILF	35.04% (528,143)	28.71% (8,431)	29.05% (2,990)

MIS 6 Interview Status

MIS 7 Labor Force Status	Percent (Count)	Response	Non-response All	Non-response Refusal
	Employed	61.96% (933,933)	66.51% (21,126)	65.91% (7,194)
	Unemployed	2.98% (44,882)	3.32% (1,056)	3.48% (380)
	NILF	35.06% (528,538)	30.17% (9,584)	30.61% (334)

MIS 8 Interview Status

MIS 7 Labor Force Status	Percent (Count)	Response	Non-response All	Non-response Refusal
	Employed	62.00% (94,1055)	68.10% (15,867)	67.25% (4,657)
	Unemployed	2.99% (45,370)	3.62% (844)	3.77% (261)
	NILF	35.01% (531,366)	28.28% (6,589)	28.98% (2,007)

MIS 7 Interview Status

MIS 8 Labor Force Status	Percent (Count)	Response	Non-response All	Non-response Refusal
	Employed	61.97% (940,672)	66.10% (20,316)	64.95% (7,537)
	Unemployed	3.02% (45,780)	3.31% (1,017)	3.08% (357)
	NILF	35.01% (531,378)	30.59% (9,402)	31.97% (3,710)

F.3 2010-2019 Average for All Consecutive Pairs, Not BLS Weighted

MIS 2 Interview Status

MIS 1 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	59.04% (638,683)	65.94% (24,889)	65.73% (14,463)
Unemployed	3.79% (40,950)	4.14% (1,564)	4.11% (905)
NILF	37.18% (402,194)	29.91% (11,291)	30.16% (6,636)

MIS 1 Interview Status

MIS 2 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.42% (632,168)	64.36% (39,733)	64.18% (19,269)
Unemployed	3.59% (38,831)	3.53% (2,177)	3.39% (1,017)
NILF	37.99% (411,137)	32.12% (19,828)	32.43% (9,736)

MIS 3 Interview Status

MIS 2 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.54% (650,552)	65.33% (24,931)	65.07% (14,397)
Unemployed	3.58% (39,736)	3.83% (1,460)	3.70% (818)
NILF	37.89% (421,101)	30.85% (11,771)	31.23% (6,909)

MIS 2 Interview Status

MIS 3 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.47% (649,866)	64.61% (23,904)	64.42% (12,483)
Unemployed	3.43% (38,178)	3.46% (1,279)	3.34% (647)
NILF	38.10% (423,484)	31.93% (11,812)	32.25% (6,249)

MIS 4 Interview Status

MIS 3 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.50% (652,867)	64.84% (22,343)	64.68% (12,742)
Unemployed	3.43% (38,291)	3.69% (1,273)	3.62% (713)
NILF	38.07% (424,844)	31.46% (10,842)	31.70% (6,244)

MIS 3 Interview Status

MIS 4 Labor Force Status

Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.49% (652,750)	64.65% (21,732)	64.30% (11,662)
Unemployed	3.33% (37,157)	3.35% (1125)	3.18% (576)
NILF	38.19% (426,186)	32.00% (10,757)	32.53% (5,900)

MIS 5 Interview Status

MIS 4 Labor Force Status: Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.36% (606,481)	65.52% (50,075)	65.40% (31,466)
Unemployed	3.23% (33,602)	3.63% (2,777)	3.46% (1,663)
NILF	38.41% (399,094)	30.85% (23,580)	31.15% (14,987)

MIS 4 Interview Status

MIS 5 Labor Force Status: Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.36% (606,541)	63.58% (28,315)	62.95% (17,962)
Unemployed	2.91% (30,341)	3.56% (1,585)	3.61% (1,029)
NILF	38.72% (402,464)	32.87% (14,638)	33.44% (9,543)

MIS 6 Interview Status

MIS 5 Labor Force Status: Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.50% (632,967)	65.82% (24,534)	65.66% (14,920)
Unemployed	3.02% (32,682)	3.33% (1,240)	3.32% (754)
NILF	38.48% (416,391)	30.86% (11,503)	31.02% (7,049)

MIS 5 Interview Status

MIS 6 Labor Force Status: Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.36% (631,470)	65.61% (32,029)	65.34% (17,957)
Unemployed	2.93% (31,739)	2.86% (1,397)	2.72% (746)
NILF	38.71% (418,935)	31.53% (15,389)	31.94% (8,778)

MIS 7 Interview Status

MIS 6 Labor Force Status: Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.47% (643,396)	66.16% (22,434)	66.54% (13,724)
Unemployed	2.93% (32,229)	3.29% (1116)	3.21% (661)
NILF	38.61% (424,846)	30.55% (10,360)	30.26% (6,241)

MIS 6 Interview Status

MIS 7 Labor Force Status: Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.47% (643,467)	65.60% (23,027)	65.23% (13,304)
Unemployed	2.88% (31,652)	2.95% (1,034)	2.98% (608)
NILF	38.65% (425,404)	31.45% (11,039)	31.79% (6,484)

MIS 8 Interview Status

MIS 7 Labor Force Status: Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.57% (651,157)	65.47% (16,783)	65.83% (9,771)
Unemployed	2.88% (32,010)	3.31% (847)	3.39% (461)
NILF	38.55% (428,526)	31.22% (8,004)	31.05% (4,580)

MIS 7 Interview Status

MIS 8 Labor Force Status: Percent (Count)	Response	Non-response All	Non-response Refusal
Employed	58.58% (651,200)	65.28% (22,297)	65.25% (13,706)
Unemployed	2.88% (32,042)	2.75% (939)	2.66% (558)
NILF	38.54% (428,486)	31.97% (10,918)	32.10% (6,742)