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How Does the Dramatic Rise of CPS Non-Response Impact Labor Market Indicators?*

Robert Bernhardt[†] David Munro[‡] Erin Wolcott[§]

February 2021

Abstract

Since 2010 and before the pandemic hit, 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 of the survey’s eight panels—account for most of the rise. Leveraging the labor force status of partially-responding households in the months surrounding their non-response, we find that rising refusals artificially suppressed the labor force participation rate and employment-population ratio but had little discernible effect on the unemployment rate. Factors robustly correlated with state-level refusal rates include a larger urban population, a smaller Democratic vote share (our proxy for sentiment towards government), and the economic and social changes brought about by manufacturing decline.

Keywords: Current Population Survey, Non-Response, Unemployment, Labor Force Participation, Employment-Population Ratio.

JEL Codes: C83, E24, J64

*The views expressed here are those of the authors and do not necessarily reflect those of the Federal Reserve Bank of Chicago, the Federal Reserve System, or any other institution with which the authors are affiliated.

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1 Introduction

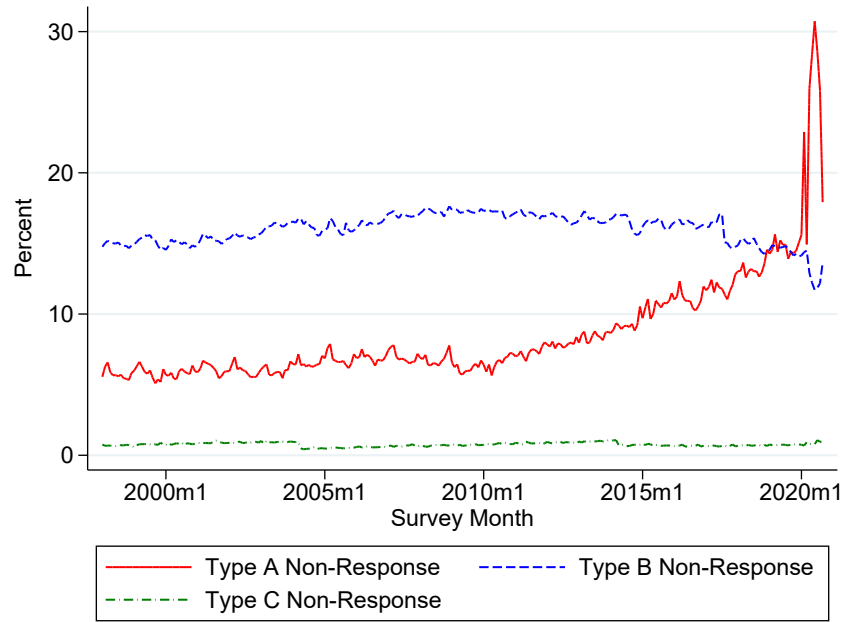
Since 2010 and before the pandemic hit, the share of occupied households in the United States who did not respond to the Current Population Survey (Type A non-interview) more than doubled from 6 percent to 15 percent. This contrasts with temporarily or permanently unoccupied housing units who did not respond (Type B or Type C), which has changed little since the 1990s. Figures 1 and 2 show that the steady increase in Type A non-interview or non-response (we use these terms interchangeably) is driven by households refusing to participate in the survey, and this tripled.¹ This gradual rise in refusals since 2010 is markedly different from trends behind other reasons for non-response such as a language barrier or no one being home.

Given the numerous important labor market indicators derived from the CPS, a rising non-response rate is concerning for the accuracy of these metrics. We document that the increase in missing observations from household non-response is *not* random. It has biased the labor force participation rate and employment-population ratio but has had little discernible effect on the unemployment rate. We offer a correction method to adjust for rising non-response and explore the underlying mechanisms behind rising refusal rates. Although, we report non-response rates through September 2020 in Figures 1 and 2, we do not focus on the recent temporary spike in non-response for “other” reasons related to the Census Bureau suspending in-person interviews in April because of the coronavirus (BLS, 2020; Rothbaum and Bee, 2020).

The influence non-response has on aggregate survey data is difficult to measure because we cannot observe the characteristics of non-responders to see whether there is selection into the non-responding group. But unlike purely cross-sectional surveys, the repeated panel

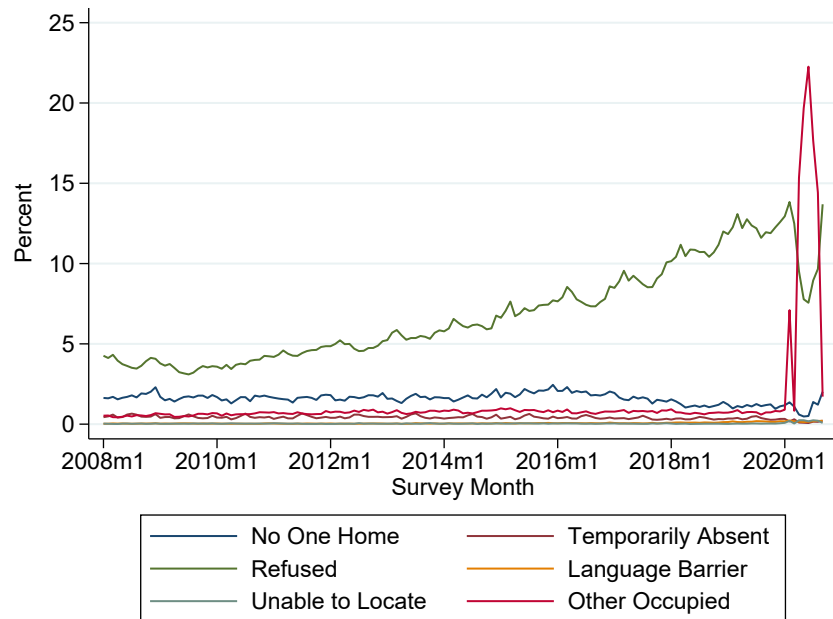
¹Figure 2 shows refusals, as a share eligible households including Type A-C non-response, grew from 4 to 12 percent over the last 10 years. It is also important to note that this paper focuses on unit non-response instead of item non-response, where the latter is when a household responds to the survey but the interviewee fails to answer a specific question.

Figure 1: Non-Response Rates by Type in the CPS



The number of non-interviews by type divided by the number of eligible households.

Figure 2: Type A Non-Response by Reason in the CPS



The number of Type A non-interviews by reason divided by the number of eligible households (including Type A-C non-interviews).

structure of the CPS provides some information about non-responding households. The CPS surveys households for four consecutive months, followed by an eight month break, followed by another four months of survey. Households have the choice not to respond during any of the eight survey months. Thus, a particular household may have any number of responses between 0 and 8, inclusive.

We start our analysis by documenting that since 2010, there has been a growing share of two groups of non-responding households. These include: (1) households who respond to none of the survey months, and (2) households who respond to some but not all of the survey months. Because this second group of non-responding households (i.e. partial responders) contributes to a larger share of total non-response 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*). If drop-outs and drop-ins were identical, we would not need to worry about selective attrition. We show, however, this is not the case for the types of rising non-response in the CPS. There are more drop-ins than drop-outs, and drop-ins are more likely to be out of the labor force once they respond, especially recently. This, in turn, biases the sample towards individuals not participating in the labor force and is one of the reasons why we find the labor force participation rate and employment-population ratio to be artificially low.

We offer a correction method, again, by leveraging the panel structure of the CPS. With a sample of responders, we calculate monthly flow rates between labor force statuses over time. We apply these flow rates to responders in the months surrounding non-response to fill in their missing observations with the likelihood they are employed, unemployed, and out of the labor force. We then recalculate the unemployment rate, labor force participation rate, and

employment-population ratio. This correction method has little effect on the unemployment rate. However, we find that the labor force participation rate and employment-population ratio have been underestimated, particularly in recent years. This result is consistent with our finding that drop-ins are increasingly likely to be out of the labor force. We conclude that the decline in the U.S. labor force participation rate and employment-population ratio calculated from the CPS over the last decade has been exaggerated by at least 40 basis points from rising Type A non-response. Since we can only directly account for partially-responding households, as opposed to never responding households, we view this estimate as a lower bound for the true bias introduced by rising non-response.

In the last part of the paper, we shed light on the mechanisms behind these rising refusal rates. Given that refusal rates are trending upwards, an important and open question involves understanding why this is so. We document substantial state-level heterogeneity in refusal rates and explore whether it correlates with other state-level metrics. We explore how refusal rates correlate with presidential voting (our proxy for government trust), average age, rural versus urban settings, voter turnout (our proxy for civic engagement), Robocall frequency, and loss of manufacturing (which has been identified as an important correlate with many other dramatic economic, health, and social changes). Of these variables, we find that refusal rates decrease with the share of the state’s vote going to the Democratic presidential candidate and decrease with the share of the state’s rural population. We find refusal rates increase with the state’s losses of a manufacturing industry. The only other variable to show some significant correlation with refusal rates is age, with older states tending to have lower refusal rates, but this relationship is not robust to our different measures of refusals.

Our work relates to a sizable 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. We show that the differential behavior of drop-out and drop-in households is a mechanism through which rising refusal rates have contributed to rotation group bias for the labor force participation rate and employment-population ratio.

Our work complements several recent papers studying non-response in the CPS. Bee et al. (2015) links the CPS with tax records and finds little difference between income levels of responding and non-responding households. This approach, however, cannot speak to differences between employment status of responding and non-responding households. Heffetz and Reeves (2019) shows easy-to-reach and hard-to-reach respondents, as measured by the number of survey attempts, are systematically different. If non-responders are more similar to hard-to-reach responders, low response rates impede survey accuracy. Ahn and Hamilton (2020) highlights and corrects 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 non-response. We believe that understanding how non-response, in particular, impacts important labor market indicators is of paramount and growing importance given the extraordinary and steady increase in survey refusals since 2010. Borgschulte, Cho, and Lubotsky (2020) hypothesizes 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. We too explore the drivers of rising refusal rates and find that at the state-level, it is highly correlated with manufacturing decline.

The correction method we offer to account for rising non-response is similar to Abowd and Zellner (1985), Tucker and Harris-Kojetin (1998), Fujita and Ramey (2006), Nekarda (2009), and Ahn and Hamilton (2020) in that it conditions on survey participants previous or future

responses to learn about their missing responses. Lastly, our work contributes to a growing literature seeking to understand the rise of non-response 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).

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 non-response. Section 6 investigates the mechanisms driving non-response; and Section 7 concludes.

2 Data

The Current Population Survey is a monthly survey of 60,000 households (technically housing units), primarily focusing on labor market, educational, and demographic variables. Most famously, it is used to determine 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.

The CPS is a government survey, but it is not legally required. Many households do not respond. There are many reasons why this can occur, which are categorized into Type A, Type B, and Type C non-responses. These categories are then further subdivided to indicate specific reasons. It is important to note that a household is surveyed for eight

months, counting non-response months. For example, if a household does not respond for the first two months but responds after that point to all successive surveys, then the CPS will include six responses and two non-responses for that household.

Our data are the Current Population Survey microdata beginning in January 1998. Each month of the data contains information on approximately 140,000 individuals in responding households, and approximately 10,000 to 15,000 non-responding households. Due to variation in response rates, fluctuations in household size, and changes in CPS funding, the exact monthly samples vary between 130,000 and 180,000 combined individuals and non-responding households. For each of these observations, we have imported a variety of critical variables. Our list includes household, month and personal identifiers, household response indicators, personal demographic information, and labor market data.²

In total, our matched 8-month panel dataset includes results for just under 2 million households.

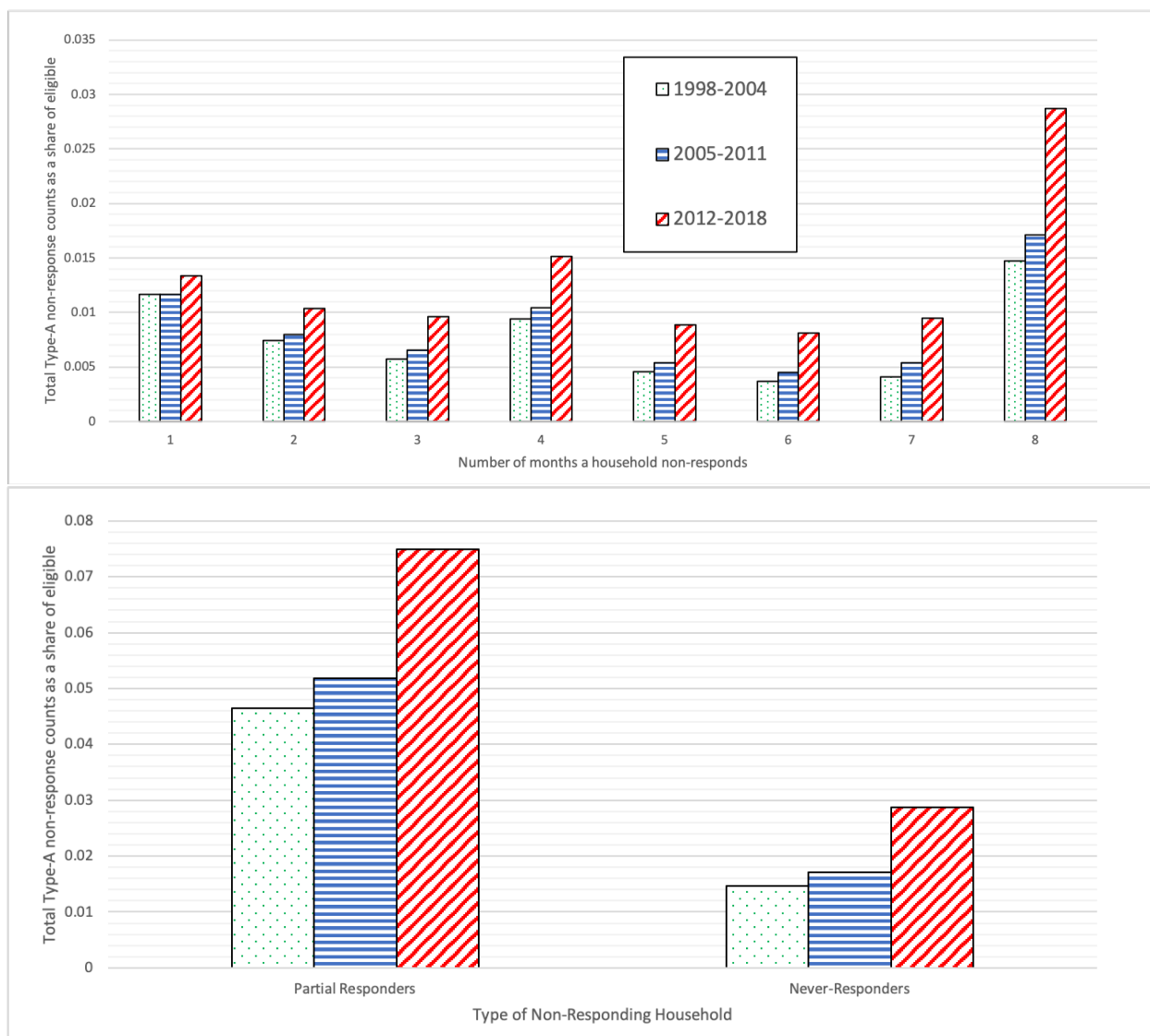
3 Partial vs. Never Responding Households

What type of non-response drives the increase in non-response? Figure 1 and Figure 2 document the increase is driven by Type A non-response, and within Type A, refusals. However, there is an interesting sub-question regarding whether the increase in refusals is driven by the intensive (more refusals per household) or extensive (more households refusing) margin, or both.

To examine the intensive versus extensive margin, we compute (1) the total number of eligible interview months for all households and (2) the number of non-responses from households who non-respond once, twice, etc. We then calculate the share of non-responses

²To protect anonymity, individuals' ages have been modified slightly in the version of the data that we use.

Figure 3: Number of Times Households Non-Respond as a Share of Eligible Interview Months



Authors' calculations from the CPS.

relative to eligible interview months for three time bins 1998-2004, 2005-2011, and 2012-2018.³ Households are binned based on the first month they are in sample. We end the bins in 2018 to exclude households whose last months in sample are during the pandemic. Figure 3 is the result.

The top panel of Figure 3 separately reports the share of non-responding households by the number of months they non-respond. The most recent period (diagonal red bars) always has more non-responders, meaning that households who non-respond once, twice, etc. all increase relative to the earlier periods. However, what we also see is that the size of the increase is largest for higher numbers of non-response, notably for the never responders. This indicates that, relative to earlier periods, it is more likely for a non-responding household to non-respond many times, or even for the entire eight months of interviews. In fact, the share these never-responders nearly doubled between 1998-2004 and 2012-2018.

The bottom panel of Figure 3 groups all partial-responding households together such that the first seven bars of the top panel are reported together and compared to never responders (8-month non-responders). Collectively, partial responders are responsible for more of the increase in Type A non-response from 1998-2004 to 2012-2018. While the percentage increase in the share of non-response stemming from partially-responding households is smaller, its absolute magnitude outweighs the increase from never responders. Thus, while never-responding behavior seems to be growing the fastest over the past two decades, partial responding behavior still represents roughly two-thirds of all Type A non-responses.

In the following sections, we focus our analysis on partial responders. Partially-responding households are observable and account for most of the rise in non-response. Our methodology focuses on measuring and correcting for the bias due to partially-responding households but should be viewed as a lower bound for the bias because it cannot account for never

³As a simple example, for the households who non-respond eight times, we first compute the number of these households and multiply that number by 8 (the number of non-responses they generate) and then divide that number by the total number of eligible interview months of all households in the sample.

responders.

4 Selective Response Behavior

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

We define two groups of partially-responding households. *Drop-outs* are households that respond in month t but have a Type A non-response in month $t+1$. *Drop-ins* are households with a Type A non-response in month $t-1$ but that respond in month t . The CPS has seen a sizable share of both drop-outs and drop-ins since 1998. If drop-out and drop-in households are identical, then we would not worry about sample bias coming from differences in drop-in and drop-out behavior.⁴ Unfortunately, this is not the case in the CPS. Slight differences in the characteristics of drop-out and drop-in households accumulate over multiple survey months and contribute to biasing the CPS. In what follows we show drop-outs and drop-ins tend to be similar: both have a higher likelihood of being employed and unemployed than consecutive responders, and a lower likelihood of being not in the labor force (NILF), relative to consecutive responders. However, drop-ins do not completely washout drop-outs because there are more drop-ins than drop-outs and the slight, yet important, differences in their labor force status bias the full-sample CPS.

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

⁴Nekarda (2009) shows that bias created from people moving out (and therefore leaving the survey) is small because the people moving in have similar characteristics.

Table 1: Drop-outs: Interview Status in MIS 2 by Labor Force Status in MIS 1 for 1998-2019

MIS 1 Labor Force Status	MIS 2 Interview Status			
	Percent (Count)	Response	non-response All Type A	non-response 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)

Table 2: Drop-ins: Interview Status in MIS1 by Labor Force Status in MIS 2 for 1998-2019

MIS 2 Labor Force Status	MIS 1 Interview Status			
	Percent (Count)	Response	non-response All Type A	non-response 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)

indicate the share of total (Type A) 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 respondents 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 responders not in the labor force, and the pattern is different. Responders are more likely to be out of the labor force than total drop-outs or refusals. To summarize, drop-outs, whether all Type A or just refusals, are more likely to be employed and unemployed, and less likely to be out of the labor force than consecutive responders. This could bias the surviving sample towards non-participation, if this behavior is not balanced by drop-ins.⁵

Table 2 reports similar statistics as Table 1 but this time for drop-*ins* between MIS 2 and MIS 1, also using data from 1998 through 2019. The first entry indicates the share of responders in the 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 2 also shows that the unemployed make up a larger share of drop-ins than responders; however, the third row shows NILF make up a larger share of responders than drop-ins. In other words, drop-ins, whether all Type A or just refusals, are more likely to be employed and unemployed but less likely to be out of the labor force than consecutive responders.⁶

Taken together, Tables 1 and 2 reveal that there are more drop-ins than drop-outs in the CPS between MIS 1 and MIS 2, and as shown in Appendix B, that holds more generally for

⁵Appendix B shows that this pattern for drop-outs generally holds between MIS 1 through MIS 8 on a consecutive pairwise basis.

⁶Appendix B shows that this pattern for drop-ins generally holds between MIS 1 through MIS 8 on a consecutive pairwise basis.

all months in sample.⁷ 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 disproportionately NILF (relative to drop-outs), biases the full-sample participation rate downward relative to a participation rate calculated from only MIS 1 responses.

This bias is more pronounced after 2010 when Type A non-response, and, in particular, refusals increased dramatically. We find pre-2010 that drop-in behavior of all Type A caused the labor force participation rate to fall by 19 basis points over the eight months in sample. Just looking at refusals rather than all Type A non-response, this behavior caused the labor force participation rate to fall by 15 basis points. We find that for 2010 and later, the drop-in/drop-out behavior caused the labor force participation rate to fall by 26 basis points over the eight months in sample.⁸ For just refusals, this caused the labor force participation rate to fall by 25 basis points.⁹ In other words, whether someone remains in the sample or enters the sample after a non-response depends on their labor force status and 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.

The bias we calculate from selective response behavior relates to rotation group bias. Rotation group bias occurs when a survey’s summary statistics differ by the month in sample they are calculated from (Krueger et al., 2017). Appendix A illustrates rotation group bias in the CPS by plotting the participation rate, employment-population ratio, and unemployment rate by month in sample. All three decline as the month in sample increases. Moreover, the difference between the labor force participation rates calculated from MIS 1 and MIS 8

⁷Atrostic et al. (2001) also points out the net number of CPS responders increases over month in sample.

⁸The post-2010 data includes data through 2019; however, to avoid the spike in Type A non-response during the onset of COVID-19, we include only households whose MIS 8 occurred before January 2020.

⁹Appendix B contains the details behind these calculations.

increased since 2010.¹⁰ The patterns of drop-ins and drop-outs described above are consistent with rotation group bias and its evolution over time. Using data from 1998-2019 to measure net drop-ins and drop-outs by labor force status over the eight month-in-samples, we account for 19, 23, and 11 percent of the rotation group bias in the participation rate, employment-population ratio, and unemployment rate, respectively.¹¹

5 Correcting for the Bias

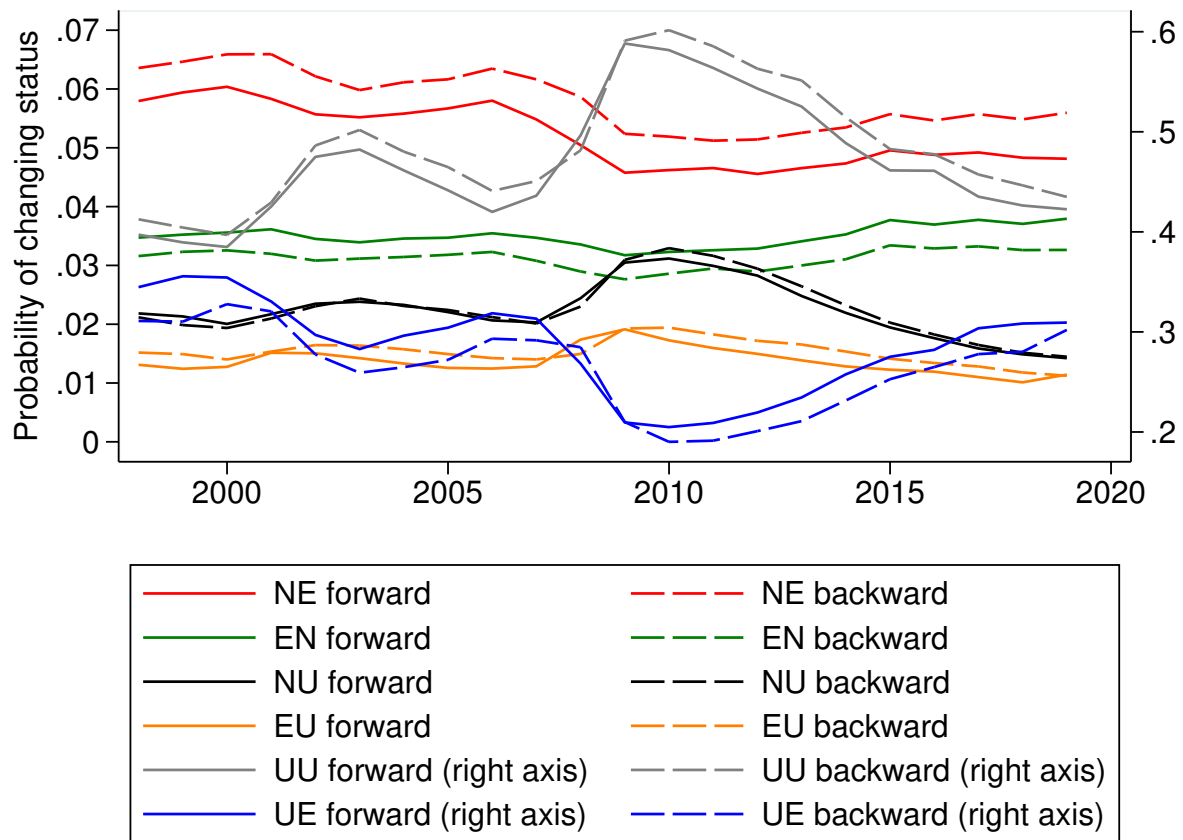
Because the CPS is a repeated cross section, if a household responds to at least one panel, we can infer information about their non-response from the month(s) they respond. Our approach builds on previous correction methods by conditioning on changing—instead of permanent—characteristics of respondents. We then use aggregate flow rates that vary over time and month-in-sample (MIS) to predict missing values. Conditioning on MIS is important because as we show in Appendix A.6, flow rates vary substantially by the MIS from which they are calculated.

We measure aggregate flow rates by focusing on households who respond for two consecutive months in sample. For this population, we calculate the transition rates between three labor market statuses: employed (E), unemployed (U), and not in the labor force (N). Let $z_{ij}^s(t)$ be the number of individuals who were in labor force status i and MIS $s - 1$ in month $t - 1$ and now are in labor force status j and MIS s in month t for $i, j = E, U, N$ and $s \in \{2, 8\}$. We calculate two types of transition rates: forward flow rates and backward flow rates. Forward flow rates are the likelihood a respondent in labor force status i at $t - 1$, is in j at t . Backward flow rates are the likelihood a respondent in labor force status j at t , was in i at $t - 1$. Because transition rates vary over time, we calculate forward and backward

¹⁰The difference between unemployment rates calculated from MIS 1 and MIS 8 peaked in 2010.

¹¹We calculate counterfactuals estimates of these three key labor market indicators by accumulating net drop-ins and drop-out households by labor force status by over the 8-month panel. We then compare the observed and counterfactual and gap between MIS 1 and MIS 8 to understand the importance of drop-out and drop-in behavior for rotation group bias.

Figure 4: Labor Force Status Flow Rates Averaged Over MIS



Authors' calculations from the CPS.

flow rates between the three labor force statuses between 1998 and 2019. To preserve sample sizes, we calculate annual flow rates.¹²

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

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

where $z_i^{s-1}(t-1)$ is the number of individuals in labor force status i and MIS $s-1$ in month $t-1$. This forward flow rate is the share of individuals for a given MIS in labor force status i who a month later were in labor force status j . Let $\bar{f}_{ij}^s(t)$ represent the annual average of the forward flow rate for MIS s . The solid lines in Figure 4 plot six annual forward flow rates averaged across all MIS for households who respond for two consecutive months.

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

$$b_{ij}^s(t) = \frac{z_{ij}^s(t)}{z_j^s(t)}, \quad (2)$$

where $z_j^s(t)$ is the number of individuals in labor force status j and MIS s in month t . This backward flow rate is the share of individuals in a given MIS in labor force status j who the month before were in labor force status i . Let $\bar{b}_{ij}^s(t)$ represent the annual average of the backward flow rate for MIS s . The dashed lines in Figure 4 plot six annual backward flow rates averaged across all MIS for households who respond for two consecutive months.

By assuming transition rates for non-responding households are the same as responding households, we can condition on the previous (and future) labor force status of missing respondents to impute their current labor force status. Let $\mu^s(t)$ be our correction method

¹²Annual flow rates are calculated by the year of the first MIS.

for Type A missing observation in MIS s at month t .

$$\mu^s(t) = \begin{cases} \sum_i y_{iMk}^s(t) \times \bar{f}_{ij}^s(t), & \text{if } k = M \\ \sum_j y_{\ell Mj}^s(t) \times \bar{b}_{ij}^s(t), & \text{if } \ell = M \\ \frac{1}{2} \left(\sum_i y_{iMk}^s(t) \times \bar{f}_{ij}^s(t) + \sum_j y_{\ell Mj}^s(t) \times \bar{b}_{ij}^s(t) \right) & \text{if } k \neq M, \ell \neq M, \end{cases} \quad (3)$$

where $y_{iMk}^s(t)$ is the number of people with labor force status $i \in \{U, E, N\}$ at $t - 1$, who are missing (M) at MIS $s \in \{2, 3, 6, 7\}$ and t , and are in population $k \in \{U, E, N, M\}$ at $t + 1$. Similarly, $y_{\ell Mj}^s(t)$ is the number of people in population $\ell \in \{U, E, N, M\}$ at $t - 1$, who have a missing observation at MIS $s \in \{2, 3, 6, 7\}$ and t , and are in labor force status $j \in \{U, E, N\}$ at $t + 1$.

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). It then determines the missing observation by the likelihood that labor force status i last month is followed by j in the current month. 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) and failed to respond in the current month but responded next month. It then determines the missing observation by the likelihood that labor force status j next month is preceded by i in the current 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 and 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 applying forward and backward flow rates and average the results.

Equation (3) leaves out three cases of missing observations: (1) instances where a surveyed household fails to respond last month, in the current month, and next month, (2) instances where the surveyed household is in the first month of the survey (MIS 1) or immediately after the break (MIS 5) and fails to respond the following month, and (3) instances where the surveyed household is in the last month of the survey (MIS 8) or immediately before the break (MIS 4) and fails to respond the previous month. For cases like this, we do not have timely information on the previous or future labor force status to condition our prediction on. To account for this type of non-response, we apply sample weights such that a respondent who satisfies one of the cases in equation (3) is up-weighted. By doing so, we are assuming that partially-responding households, that have a missing observation this month but respond a month before or a month later, are identical to households who fail to respond (or are out of sample) for more than two consecutive months. This is of course is a strong assumption, but it is much weaker than standard correction methods assuming non-responding households are identical to responding households, conditional on some permanent characteristics. If the households whose non-responses we cannot infer are different from those we can infer, it seems likely they would differ in the same direction but with plausibly larger magnitudes. Thus, this weighting may even be an underestimate.

Figure 5 plots the labor force participation rate and Figure 6 plots the employment-population ratio. Each figure displays three estimates of these key labor market indicators from 2004 through 2019.¹³ The black solid line plots these key indicators without any adjustment. The blue dashed line adjusts for non-response bias using equation (3). The red dashed line adjusts for non-response using equation (3) and re-weights the sample to account for Type A non-respondents excluded from equation (3). For both the labor force participation rate and employment-population ratio, the dashed lines continually diverge from the solid line after 2010 which is consistent with Type A non-response becoming an

¹³None of the series in Figure 5 and Figure 6 use the final basic weights provided by the BLS since the correction method we propose may correct for some of the problem.

Figure 5: Adjusted Labor Force Participation Rate

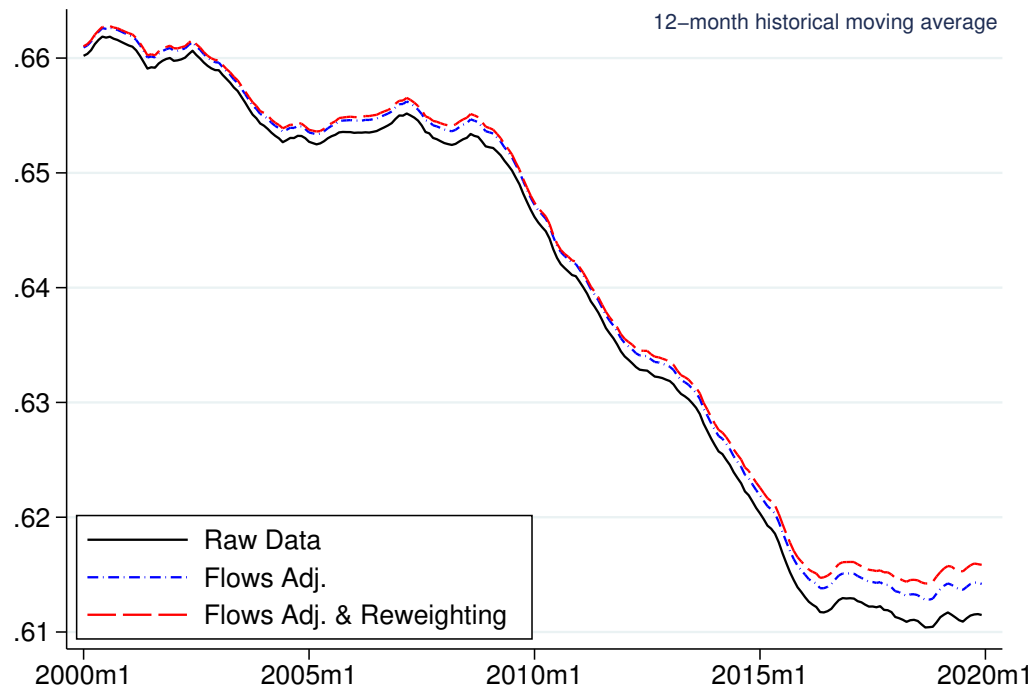
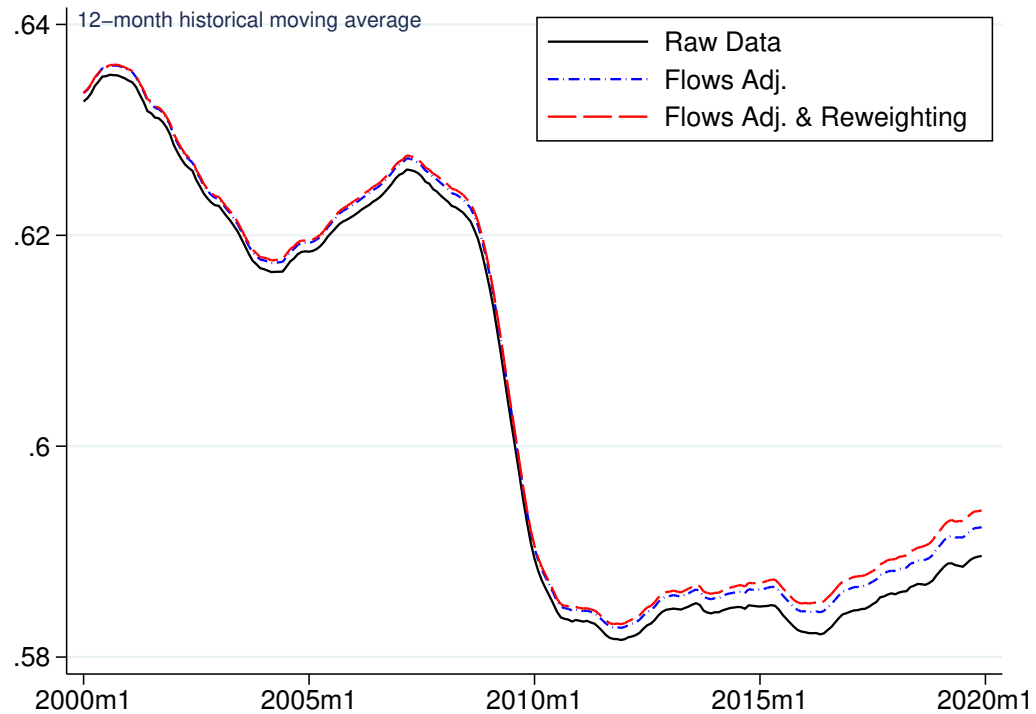


Figure 6: Adjusted Employment-Population Ratio



ever-larger problem. Specifically, the gap between the raw data and the final adjusted data (red dashed lines) increased from about 10 basis points to 45 basis points for both labor market indicators. Appendix C plots the unadjusted and adjusted unemployment rate. The lines closely overlap suggesting growing non-response has not biased the unemployment rate to the same extent it has biased the labor force participation rate and employment-population ratio.

6 What’s Driving Rising Refusal Rates?

Many readers may be interested in understanding the underlying factors contributing to rising refusal rates. To provide some insight, we use state-level heterogeneity in refusal rates and explore how they correlate with various indicators. We first construct two measures of refusals. The first is simply the refusal rate, which is the number of household-level refusals divided by the number of households in the sample. To smooth some of the month-to-month noise when computing this at the state level, we average these refusal rates over two two-year periods: 2008-09 (before the change in trend in refusals) and 2017-18 (at the end of our sample). These state-level refusal rates are reported in columns 2 and 3 of Appendix D. We also construct a second measure of refusals where, using the matched household panel, we compute the share of households who refuse the survey for all eight months. This measure of refusal behavior focuses on the more extreme households who appear to be strongly opposed to completing the survey. To be precise, this is the number of households refusing the survey for all eight months divided by the total number of households.¹⁴ This second metric is computed at the state-level for 2008-09 and 2017-2018 and is reported in columns 5 and 6 of Appendix D.¹⁵ After examining both metrics, two things are obvious. The first is that

¹⁴It is important to emphasize that the first refusal rate measure is the share of survey months recorded as a refusal across all survey months and households, where the second measure is the share of households who refuse the CPS for all 8 months in sample.

¹⁵The sample periods are determined by a household’s first MIS. The later period ends in 2018, yet a respondent’s whose first MIS is in 2018 but latter MIS is in 2019 would be included.

both have increased substantially between 2008-09 to 2017-18, and the second is that there is important heterogeneity across states.

Leveraging this heterogeneity, we explore if any state-level indicators correlate with these measures of non-response. At the outset, it is important to emphasize that our examination of variables which correlate to state-level measures of refusals should not be interpreted causally. However, given that this refusal behavior is intensifying, it is our hope these results provide some clues to future researchers about which factors merit further examination. We investigate these correlations with the following variables.

The first two variables we examine are demographic: median age and the share of the population living in rural areas. Given our results in Section 4, it might be natural to expect younger individuals who are more active in the labor force to refuse the survey more often. Data on median age is from the U.S. Census Bureau for 2018. Additionally, individuals in rural versus urban settings may have different levels of trust or openness to surveys. We examine how refusal rates correlate with the share of a state’s population living in rural settings as recorded by the 2010 Census.¹⁶ Another possible explanation for increases in refusal rates may be related to declines in government trust (Pew Research Center, 2019). Unfortunately, these surveys on trust in government are national, which prevents us from examining state-level heterogeneity. We instead use a proxy for trust in government: the share of each state’s vote going towards the Democratic presidential candidate in the 2016 election, as reported by the Federal Election Commission.¹⁷ Relatedly, another possible explanation for survey refusals could be a lack of civic engagement. We examine civic engagement by including voter turnout in 2016.¹⁸

¹⁶These two variables are things included in the CPS re-weighting procedure to match demographics or the geographic distribution of population. However, if respondents and non-respondents within these demographic and geographic bins are systematically different along other dimensions (as highlighted above), the CPS re-weighting does not necessarily alleviate non-response bias. More importantly, re-weighting aside, our goal here is to provide some insights on what factors correlate with non-response behavior.

¹⁷<https://www.fec.gov/resources/cms-content/documents/federalelections2016.pdf>

¹⁸Data from the United States Elections Project: <http://www.electproject.org/2016g>.

The most recent decade has seen a surge in automated telephone calls (Robocalls), and, as a result, one possible issue for the CPS may be an increased unwillingness to answer the survey. In regards to refusal rates, it can not simply be the fact the households do not answer the phone, this would be coded as a different reason for non-response. However it is plausible that households are overburdened by Robocalls, polls, and surveys which has led to a decline in the willingness to participate.¹⁹ To investigate how Robocalls correlate with state-level refusal rates we compute the average per capita Robocalls received in each state from 2016 to 2019 using data from YouMail: Robocall Index (2020).²⁰

The final variable we include in our analysis is a measure of manufacturing loss. There is growing recognition of the profound impact manufacturing loss can have on local areas. It has been found to have important consequences for employment (Acemoglu et al., 2016), voting behavior (Mutz, 2018; Che et al., 2020), marriage rates (Dorn et al., 2019), mortality and opioid use (Pierce and Schott, 2020), and crime and social trust (Wilson, 2011). We examine the decline in manufacturing’s average share of state GDP from the 1970s (1970-1979) to 2000s (2000-2009) from the Bureau of Economic Analysis. To estimate these simple correlations we run the following regression:

$$\begin{aligned} RefusalRates_s = & \alpha_0 Age_s + \alpha_1 Rural_s + \alpha_2 DemShare_s + \alpha_3 VoterTurnout_s \\ & + \alpha_4 Robocalls_s + \alpha_5 ManuLoss_s + \varepsilon_s, \end{aligned} \tag{4}$$

where $RefusalRates_s$ are either the standard measure of refusal rates by state in 2017-18 (column 3 of Appendix D) or our measure of always refusers by state in 2017-18 (column 5 of Appendix D) for state s . Since smaller states are more susceptible to sampling variability in the CPS, equation (4) is estimated via weighted least squares where state populations are used as weights. Equation (3) does not include a time series dimension because of data constraints. Results are reported in Table 3.

¹⁹Meyer et al. (2015) document the number and breadth of government and private surveys has been rising.

²⁰Historical data only available since 2016.

Table 3: Regression Results for Correlates with State-Level Refusal Rates

Indep. Var.	Refusal Rates 2017-18	Always Refuser Rates 2017-18
<i>Age</i>	-0.364 [†] (0.218)	-0.0625 (0.0496)
<i>Rural</i>	-0.0823** (0.041)	-0.0233** (0.0095)
<i>DemShare</i>	-0.081 [†] (0.056)	-0.0373** (0.0146)
<i>VoterTurnout</i>	-0.065 (0.053)	-0.0052 (0.0143)
<i>Robocalls</i>	-0.0079 (0.0064)	-0.0029* (0.0015)
<i>ManuLoss</i>	0.2591*** (0.0745)	0.0568*** (0.0204)
Adj. R ²	0.2345	0.1316

Estimates are OLS weighted by state population. Robust standard errors are in parentheses.

[†] p<0.10 one-sided, *p<0.10, **p<0.05, ***p<0.01

Here we summarize the results in the first column of Table 3. Both *Age* and *Rural* have negative and significant correlations with refusal rates. This suggests that younger and more urban states are more likely to refuse the survey. There is a negative and weakly significant correlation between the share of the vote received by the Democratic candidate in 2016 in a state and the refusal rate, suggesting refusal rates are higher in more Republican leaning states.²¹ Both voter turnout and per capita Robocalls have insignificant relationships with refusal rates. Finally, manufacturing loss has a positive and highly significant relationship with refusal rates. A 10 percentage point decline in manufacturing as a share of GDP is associated with a 2.6 percentage points increase in the refusal rate. The average decline in manufacturing from the 1970s to 2000s was 7.8 percent and the largest decline was Delaware with 26 percent, suggesting that a 10 percentage point decline is not atypical. However, a 2.6 percentage point increase in refusal rates is sizable—the average during 2017 and 2019 was 7.9 percent.

Moving to the results for the Always Refuser Rate, *Age* is no longer significant and *Rural*

²¹Borgschulte et al. (2020) find the state-level growth in refusals of “red state” versus “blue state” depends on who is in the White House.

remains negative and statistically significant. The share of the vote going the Democratic candidate remains negative and becomes larger and more strongly significant. A 10 percentage point increase in the Democratic vote share is associated with a 0.37 percentage points decline in the the never responder rate, which is especially sizable since the mean of this second non-response metric is only 1.4 percent. The Always Refuser Rate may have a stronger (negative) relationship than the simple refusal rate because people who are ideologically against the survey (or more anti-government) may be even more likely to never participate, whereas occasionally refusing households may be refusing for reasons other than ideology. Lastly, manufacturing loss remains positively and significantly correlated with the Always Refuser Rate. A 10 percentage point decline in manufacturing is associated with a 1.38 increase in the Always Refuser Rate. In sum, factors robustly correlated with refusal behavior include a smaller share of the population living in rural areas, a smaller Democratic vote share (our proxy for sentiment towards government), and the economic and social changes brought about by manufacturing decline.²²

7 Conclusion

How does the dramatic rise of non-response since 2010 impact labor market indicators? Rising non-response 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 non-response 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 non-responding households in the months surrounding their non-response and use aggregate flow rates to impute missing observations. To under-

²²Another state-level correlate we tried was polling error from the 2016 presidential election. Appendix E shows that states with higher never-responding rates tended to have higher polling error, but the relationship is not statistically significant.

stand the possible reasons for rising refusal rates, we look across states. Factors robustly correlated with state-level refusal rates include a smaller share of the population living in rural areas, a smaller Democratic vote share (our proxy for sentiment towards government), and the economic and social changes brought about by manufacturing decline. We wish to emphasize again that these are merely correlations, but our hope is that these results point future researchers seeking to understand the causes of survey refusals in productive directions.

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Appendix A Evidence of Rotation Group Bias

Figure A.1: Labor Force Participation Rate by Month in Sample (1998-2019)

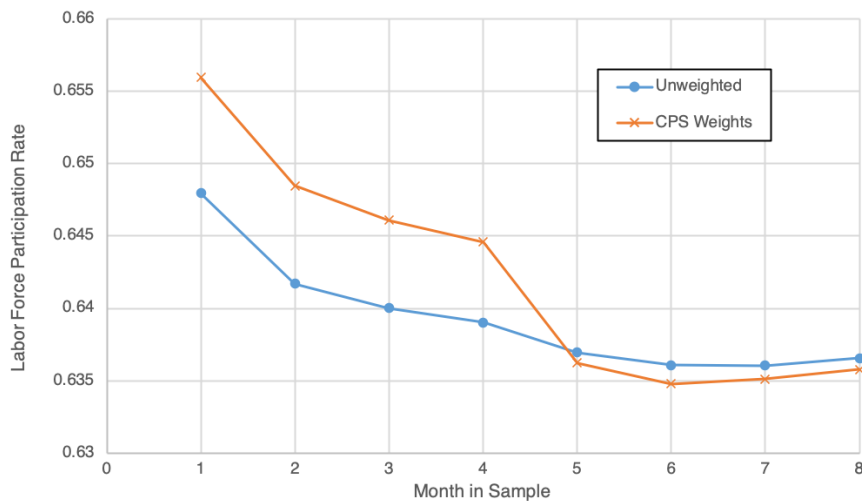


Figure A.2: Employment-Population Ratio by Month in Sample (1998-2019)

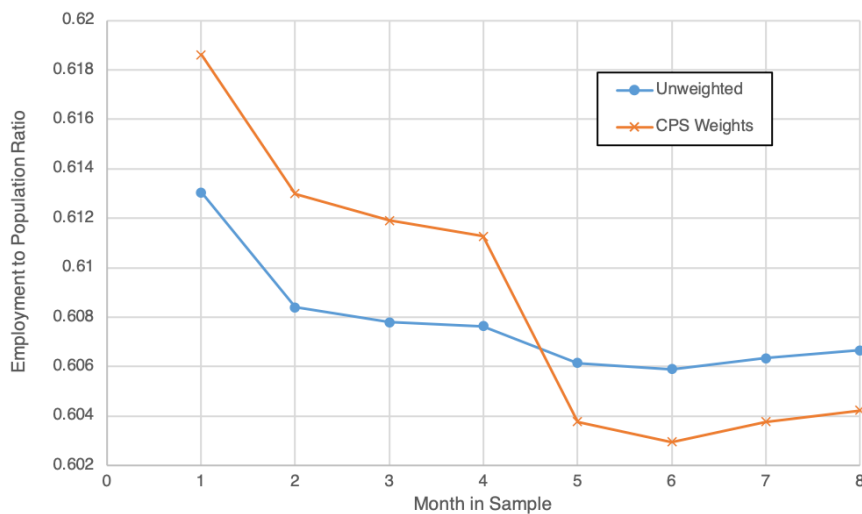


Figure A.3: Unemployment Rate by Month in Sample (1998-2019)

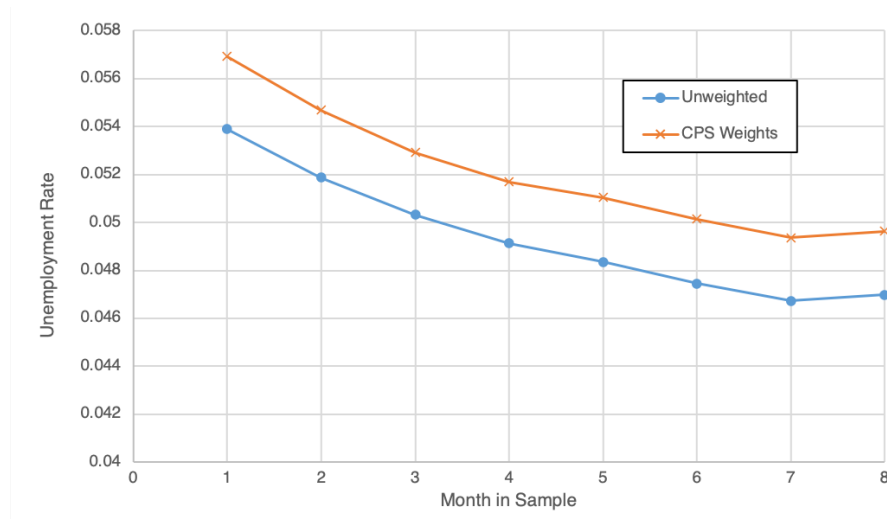


Figure A.4: Difference Between Unemployment Rate in MIS 1 and MIS 8

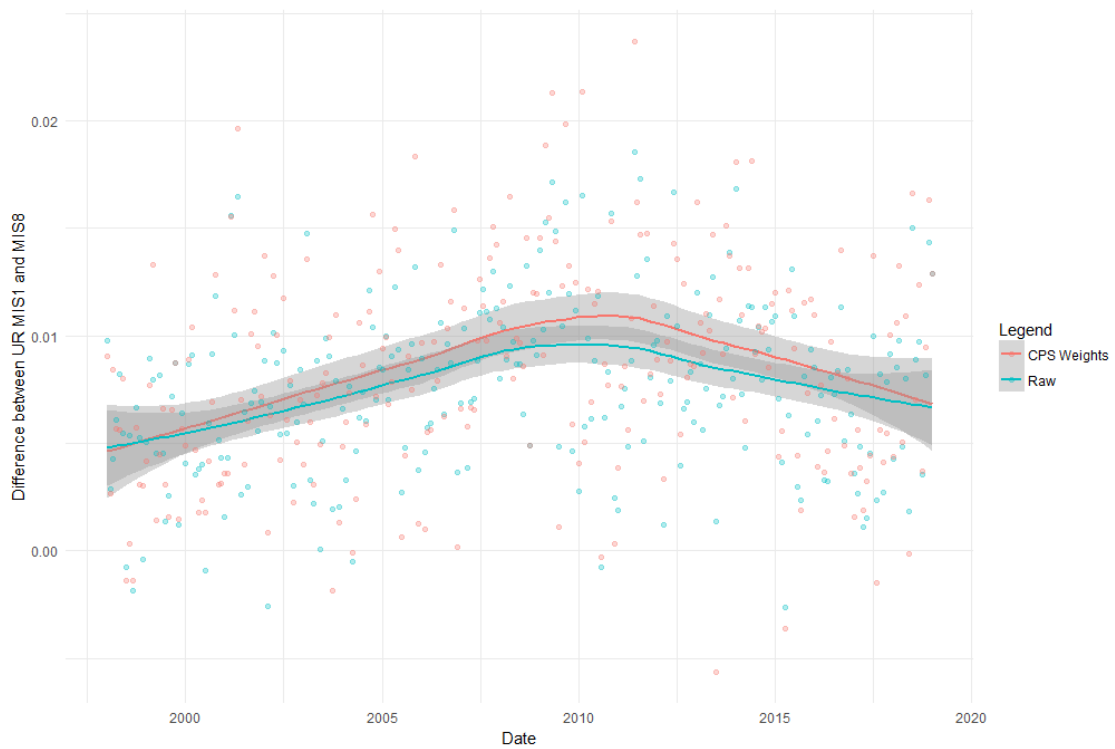


Figure A.5: Difference Between Participation Rate in MIS 1 and MIS 8

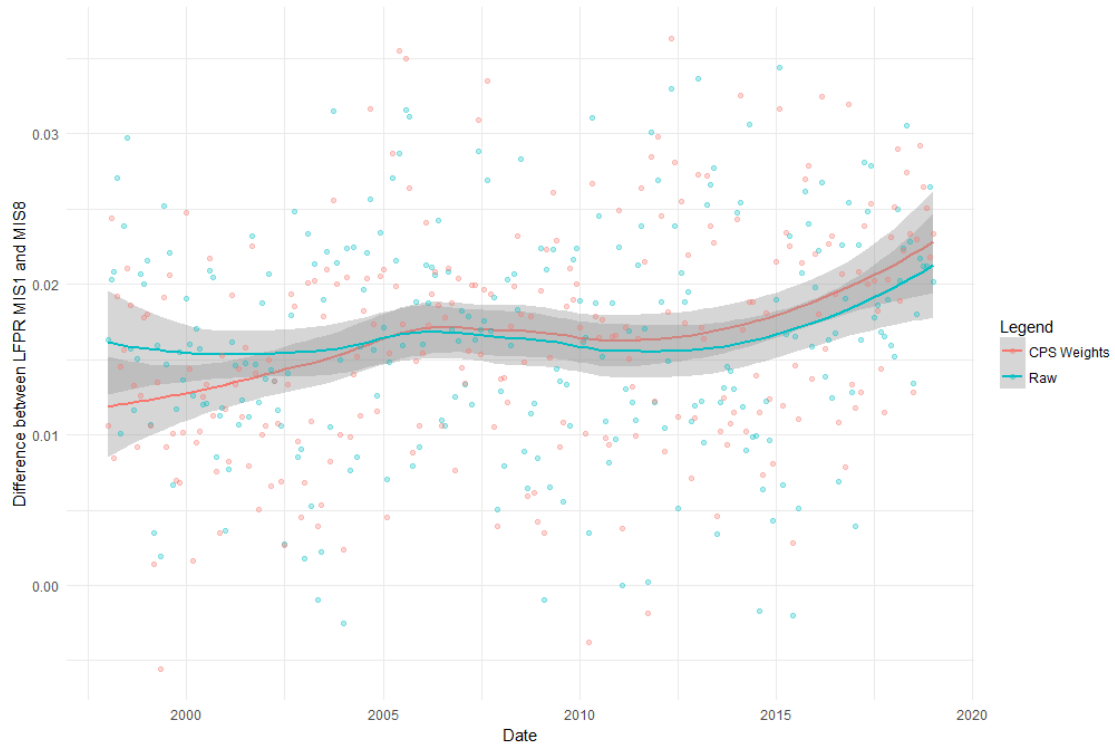
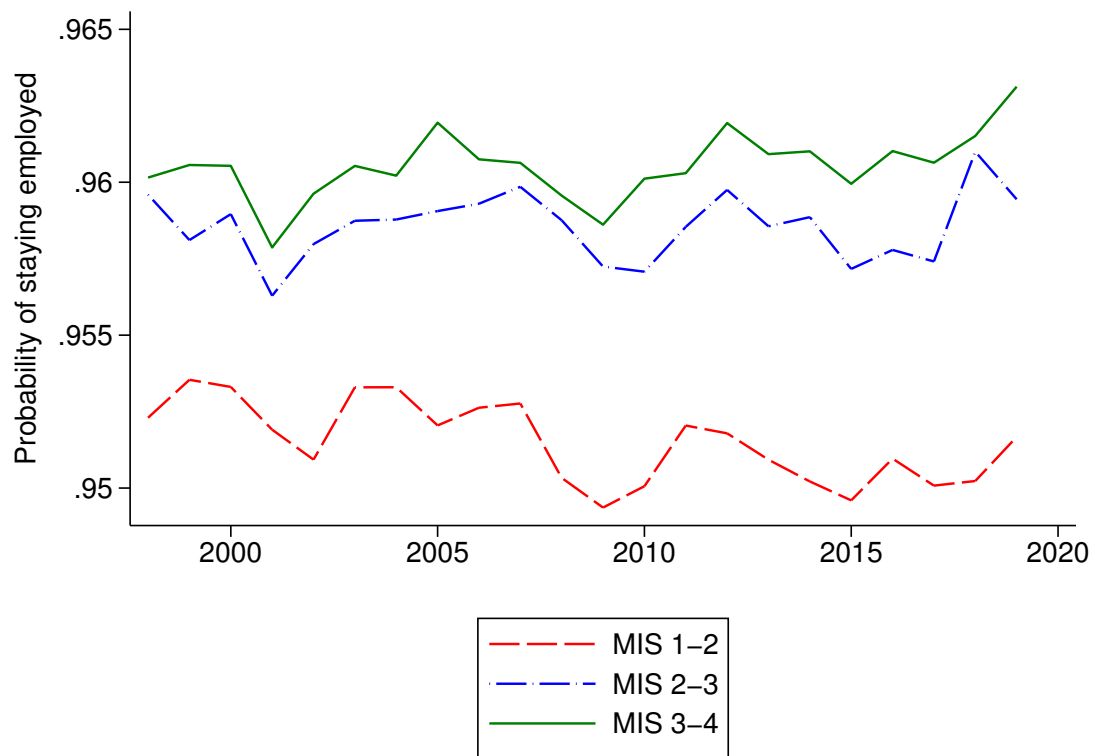


Figure A.6: Employment-to-Employment Flow Rates by MIS



Appendix B Evidence of Selective Response Behavior

B.1 1998-2009

MIS 2 Interview Status					MIS 1 Interview Status				
MIS 1 Labor Force Status	Percent (Count)	Response	Non- response Type A	Non- response Refusal	MIS 2 Labor Force Status	Percent (Count)	Response	Non- response Type A	Non- response Refusal
	Employed	62.78% (9,27,048)	66.97% (20,255)	66.36% (7,563)		Employed	62.23% (919,160)	66.93% (42,292)	64.97% (12,465)
	Unemployed	3.21% (47,395)	3.77% (1,141)	3.67% (418)		Unemployed	3.09% (45,626)	3.16% (1,995)	3.28% (629)
	NILF	34.01% (502,125)	29.25% (8,847)	29.97% (3,416)		NILF	34.69% (512,368)	29.91% (18,902)	31.75% (6,091)
MIS 3 Interview Status					MIS 2 Interview Status				
MIS 2 Labor Force Status	Percent (Count)	Response	Non- response Type A	Non- response Refusal	MIS 3 Labor Force Status	Percent (Count)	Response	Non- response Type A	Non- response Refusal
	Employed	62.33% (943,635)	67.74% (21,224)	68.30% (8,218)		Employed	62.27% (942,931)	66.28% (22,605)	65.52% (7,277)
	Unemployed	3.08% (46,627)	3.66% (1,146)	3.26% (392)		Unemployed	3.00% (45,454)	3.28% (1,119)	3.10% (344)
	NILF	34.59% (523,722)	28.60% (8,962)	28.45% (3,423)		NILF	34.73% (525,839)	30.43% (10,379)	31.39% (3,486)
MIS 4 Interview Status					MIS 3 Interview Status				
MIS 3 Labor Force Status	Percent (Count)	Response	Non- response Type A	Non- response Refusal	MIS 4 Labor Force Status	Percent (Count)	Response	Non- response Type A	Non- response Refusal
	Employed	62.27% (946,461)	67.60% (19,948)	67.16% (7,006)		Employed	62.25% (946,181)	66.16% (19,232)	65.55% (6,359)
	Unemployed	3.00% (45,576)	3.55% (1,049)	3.46% (361)		Unemployed	2.95% (44,845)	3.34% (970)	3.35% (325)
	NILF	34.73% (527,883)	28.85% (8,513)	29.38% (3,065)		NILF	34.80% (529,024)	30.50% (8,866)	31.10% (3,017)

MIS 4 Labor Force Status	MIS 5 Interview Status			
	Percent (Count)	Response	Non- response Type A	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 5 Labor Force Status	MIS 4 Interview Status			
	Percent (Count)	Response	Non- response Type A	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 5 Labor Force Status	MIS 6 Interview Status			
	Percent (Count)	Response	Non- response Type A	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 6 Labor Force Status	MIS 5 Interview Status			
	Percent (Count)	Response	Non- response Type A	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 6 Labor Force Status	MIS 7 Interview Status			
	Percent (Count)	Response	Non- response Type A	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 7 Labor Force Status	MIS 6 Interview Status			
	Percent (Count)	Response	Non- response Type A	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 7 Labor Force Status	MIS 8 Interview Status			
	Percent (Count)	Response	Non- response Type A	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 8 Labor Force Status	MIS 7 Interview Status			
	Percent (Count)	Response	Non- response Type A	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)

B.2 2010-2019

		MIS 2 Interview Status		
MIS 1 Labor Force Status	Percent (Count)	Response	Non- response Type A	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 Type A	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 Type A	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 Type A	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 Type A	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 Type A	Non- response Refusal
	Employed	58.49% (652,750)	64.65% (21,732)	64.30% (11,662)
	Unemployed	3.33% (37,157)	3.35% (1,125)	3.18% (576)
	NILF	38.19% (426,186)	32.00% (10,757)	32.53% (5,900)

MIS 4 Labor Force Status	MIS 5 Interview Status			
	Percent (Count)	Response	Non-response Type A	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 5 Labor Force Status	MIS 4 Interview Status			
	Percent (Count)	Response	Non-response Type A	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 5 Labor Force Status	MIS 6 Interview Status			
	Percent (Count)	Response	Non-response Type A	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 6 Labor Force Status	MIS 5 Interview Status			
	Percent (Count)	Response	Non-response Type A	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)

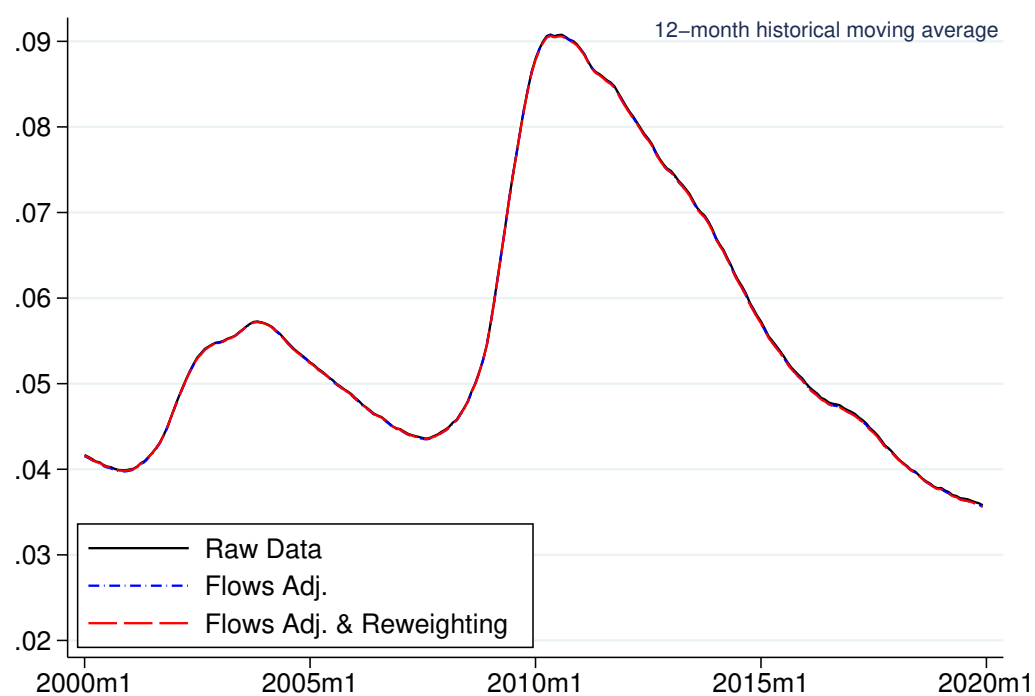
MIS 6 Labor Force Status	MIS 7 Interview Status			
	Percent (Count)	Response	Non-response Type A	Non-response Refusal
	Employed	58.47% (643,396)	66.16% (22,434)	66.54% (13,724)
	Unemployed	2.93% (32,229)	3.29% (1116)	3.21% (661)
	NILF	38.61% (424,846)	30.55% (10,360)	30.26% (6,241)

MIS 7 Labor Force Status	MIS 6 Interview Status			
	Percent (Count)	Response	Non-response Type A	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 7 Labor Force Status	MIS 8 Interview Status			
	Percent (Count)	Response	Non- response Type A	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 8 Labor Force Status	MIS 7 Interview Status			
	Percent (Count)	Response	Non- response Type A	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)

Appendix C Adjusted Unemployment Rate



Appendix D State-Level Heterogeneity in Refusal Rates

State	Avg. Ref. Rate (%) 2008-09	Avg. Ref. Rate (%) 2017-18	Avg. Always Ref. Rate (%) 2008-09	Avg. Always Ref. Rate (%) 2017-18
AL	1.2	4.6	0.09	0.67
AK	4.0	7.0	0.73	0.81
AZ	3.5	10.5	0.40	2.05
AR	2.3	4.9	0.42	0.51
CA	5.1	7.5	0.82	0.93
CO	3.3	6.1	0.43	0.92
CT	5.2	9.3	0.79	1.57
DE	2.9	10.5	0.15	2.09
FL	1.7	4.8	0.08	0.82
GA	2.2	6.9	0.16	1.13
HI	5.6	6.1	0.57	0.66
ID	3.6	8.0	0.91	2.05
IL	2.4	6.4	0.11	0.54
IN	1.8	7.0	0.14	0.94
IA	3.0	4.4	0.64	0.71
KS	3.9	8.4	0.76	1.84
KY	2.0	9.3	0.25	2.02
LA	3.3	6.2	0.42	0.75
ME	3.6	7.0	0.59	1.47
MD	6.2	12.3	0.85	2.12
MA	5.9	10.4	1.10	2.35
MI	3.9	9.0	0.52	1.13
MN	2.9	6.4	0.64	0.97
MS	3.2	7.1	0.65	1.13
MO	4.2	7.6	0.85	1.00
MT	1.9	6.9	0.69	1.79
NE	3.6	8.8	0.48	1.99
NV	3.1	7.9	0.25	0.86
NH	4.0	9.2	0.82	1.59
NJ	4.9	11.8	0.55	1.95
NM	3.3	6.1	0.48	0.84
NY	5.4	8.4	0.89	1.15
NC	1.9	5.2	0.19	0.71
ND	2.2	7.3	0.33	1.13
OH	4.8	11.8	1.33	2.59
OK	3.2	7.7	0.71	1.43
OR	4.7	8.5	0.88	1.57
PA	3.8	10.8	0.65	2.09
RI	5.4	11.0	1.12	2.08
SC	1.6	5.2	0.10	0.89
SD	2.5	6.6	0.43	1.19
TN	2.9	9.0	0.11	1.75
TX	4.2	11.1	0.65	1.99
UT	3.4	8.5	0.72	1.77
VT	3.8	8.8	0.85	1.88
VA	1.9	8.5	0.10	1.17
WA	4.9	9.7	0.99	2.61
WV	2.0	7.4	0.49	1.07
WI	1.5	5.9	0.13	0.97
WY	2.9	7.1	0.26	0.90
Avg.	3.4	7.9	0.54	1.38

Appendix E Polling Error and Always-Refusal Rates

