MEASURING THE U.S. EMPLOYMENT SITUATION USING ONLINE PANELS:
THE YALE LABOR SURVEY

By

Christopher L. Foote, Tyler Hounshell, William D. Nordhaus,
Douglas Rivers, and Pamela Torola

April 2021

Measuring the U.S. Employment Situation Using Online Panels:
The Yale Labor Survey[1,2,3]
April 15, 2021

Christopher L. Foote, Tyler Hounshell, William D. Nordhaus,
Douglas Rivers, and Pamela Torola

Abstract

This study presents the design and results of a rapid-fire survey that collects labor market data for individuals in the United States. The purpose is to test online panels for their application to social, economic, and demographic information as well as to apply this approach to the U.S. labor market. The Yale Labor Survey (YLS) used an online panel from YouGov to replicate statistics from the Current Population Survey (CPS), the government's official source of household labor market statistics. The YLS's advantages included its timeliness, low cost, and ability to develop new questions quickly to study unusual labor market patterns during the COVID-19 pandemic. Results from the YLS track employment data closely from the CPS during the pandemic. Although YLS estimates of unemployment and participation rates mirrored the broad trends in CPS data, YLS estimates of those two rates were less accurate than for employment. The study demonstrates the power of carefully crafted online surveys to replicate expensive traditional methods quickly and inexpensively.

I. Introduction and Overview

This study presents the design and results of a rapid-fire online survey that collected individual labor market data for the United States using an online panel during the COVID-19 pandemic. The weekly Yale Labor Survey (YLS) was designed to measure the same statistics as the monthly Current Population Survey (CPS), the government's official source of household labor market data.[4] Like the CPS, the YLS asked a battery of questions concerning current and past employment, hours, and income. Unlike the CPS, the YLS was not based on a probability sample of the U.S. population, but instead relied on a large online panel of respondents maintained by YouGov, a survey firm specializing in online surveys.

Because the YLS drew upon an existing panel of potential respondents, it obtained responses inexpensively and quickly (within 24 hours). The YLS is also more flexible than the CPS. Although it drew its major questions from related ones in the CPS, the YLS includes questions related to the unusual nature patterns of work and unemployment during the pandemic. It has been able to develop new questions in the field quickly as labor market circumstances evolved. By relying on the online panel, however, the YLS had to surmount important sample-selection issues if it was to be useful for analysis of the overall U.S. labor market. In this paper, we assess the YLS's performance, in part by comparing its results to official CPS data.

The YLS began with some small pilot surveys during the week of March 29–April 4, 2020, and aside from a three-week hiatus in the fall of 2020, the survey was conducted regularly through mid-March 2021. This report covers 117,000 respondents in 89 waves over 43 weeks ending with the reference week of February 7-13, 2021. Eleven of those weeks were also reference weeks for the CPS, so YLS results can be directly compared with CPS results for April 2020 through February 2021.

The study has three principal purposes. The first is to determine *whether it is feasible* to provide rapid-turnaround estimates of complex socio-economic data such as the state of the national labor market. The second goal is to improve

---

[4] The CPS is a joint product of the Bureau of the Census and the Bureau of Labor Statistics (BLS). It is the source of official monthly household labor market statistics, such as the unemployment rate, labor force participation rate, and employment-to-population ratio.

national economic policy and planning by *providing more timely estimates* of the state of the labor market. The third goal is to *test the accuracy of online panels,* which are a relatively new platform for performing population surveys. The following section discusses the extent to which these goals were met.

II. Major Results and Conclusions

II.A. Goals of the Study

The study has three principal purposes. The first is to determine whether it is feasible to provide rapid-turnaround estimates of socio-economic data such as the state of the national labor market. The second goal is to improve national economic policy and planning by providing more timely estimates of the state of the labor market. The third goal is to test the accuracy of online panels, which are a relatively new platform for performing population surveys. This section reports on the Yale Labor Survey (YLS), its findings, and broader implications.

First, on the goal of feasibility, online surveys are promising because they can be conducted quickly and inexpensively. Online surveys draw from a specific group of people – those willing to take online surveys for modest compensation— so they are not guaranteed to be representative of the entire population. However, with careful selection and weighting of the observations, we attempt to remove as much selection bias in YLS as possible.

Relative to feasibility, the project has proven that a complicated online population survey can be collected regularly both quickly and inexpensively. The YLS has collected weekly data for almost a year on labor market and other population characteristics, with monthly sample sizes about one-tenth those of the CPS. As we show below, results have been broadly similar to those from the CPS, but these results are available in a matter of days and at less than 1% of the cost of the CPS, with a monthly sample size approximately one-tenth of the CPS. So, the first goal of feasibility and low cost has definitely been achieved.

On the second goal, *timeliness*, there is a heightened need for timely economic data in a time of unprecedentedly rapid developments. Unfortunately, there is a significant lag time between when government surveys are conducted and when their results are published. A clear example of a publication lag occurred when the pandemic shock hit the U.S. labor market in March. The monthly Employment Situation reports cover labor market data over reference periods that include the 12th of each month. Thus, the reference week for the March 2020 CPS was March

8–14. The CPS was conducted during the following week, and the results were published on April 3.

The timing of the onset of the COVID-19 turned out to be disastrous given the CPS's schedule. The first state shutdown order came in California on March 19, 2020 – this shutdown came the week after the March CPS reference week. Consequently, the March 2020 CPS did not show how badly the labor market had deteriorated during the last half of March 2020. This deterioration was finally revealed by the April 2020 CPS, which was published in early May 2020 – almost six weeks after the major employment shock took place. In fact, the initial YLS surveys in early April 2020 that the U.S. labor market was showing extreme stress, so the YLS provided information a full month before the official government data. It is clear, then, the YLS has shown the ability to provide important economic information on virtually a real-time basis.

The third aim of this study is to test the *accuracy* of online panels for demographic and labor market information. That is, we study whether the biases of online panels can be removed to produce results that are similar to the CPS. An online panel is a set of individuals who have agreed to complete surveys through the internet. Panelists are recruited online and receive points or money for taking surveys. In the present context, the major advantages of online surveys are that they are inexpensive, can be run continuously, and can produce answers quickly – in a single day if the questions have already been coded into survey software.

Online surveys have become widely used in the last two decades, particularly in market research and election polling, but have seldom been used to measure labor-market activity. There are two types of online panels: opt-in and "probability-based." (In the latter, panelists are randomly selected, though the combination of low cooperation rates and high levels of attrition result in response rates in the low single digits.) In both cases, quota sampling and weighting are used to compensate for selection bias. There is conflicting evidence about the relative accuracy of the different methods, and there is variation between different vendors. (Gittelman et al., 2015; Kennedy et al., 2016) Election prediction provides the most credible measure of accuracy. Online opt-in panels have provided similar results to phone surveys. In the 2020 U.S. election, both approaches had problems, but opt-in panels outperformed traditional phone polls. (Silver, 2021) However, employment and labor market participation are likely to be subject to different types of selection bias. Previous comparisons have

4

not involved standard employment measures, nor have used available labor market variables been used for sample selection, weighting, or estimation.

Because the labor market is tracked using the comprehensive and carefully crafted government CPS, we can obtain estimates of the accuracy of online demographic surveys by comparing the outcomes of the YLS with the CPS. As will be discussed in the next section, the evidence on the accuracy of online panels for labor markets is mixed.

A final conclusion is that the YLS has succeeded in obtaining *independent estimates of the state of the labor market.* Virtually all existing complex demographic and economic surveys are conducted by the government, expensive, and difficult to duplicate. This study shows that it is possible to use alternative techniques to replicate the larger and more expensive demographic surveys.

II.B. Major Results

The Yale Labor Survey (YLS) has conducted studies of the labor market over the period from April 2020 to March 2021. It has succeeded in providing *independent estimates* of the state of the U.S. labor market – ones that parallel and largely replicate the estimates from the federal government's Current Population Survey. The estimates are prepared weekly and are available less than a week after the collection of the survey data. The survey questions are contained in Appendix H of the study.

Four main labor market series are compared. Two series are related to employment. One employment measure is the *work-for-pay ratio* (WFPR), which is our name for series that calculates the share of the population at work during the reference week; a second measure is the more familiar *employment-to-population ratio* (EPR), which includes both persons at work and employed persons who are absent from their regular jobs. We also compare YLS and CPS estimates of the *unemployment rate* (UR) and the *labor force participation rate* (LFPR), which, like the EPR, are defined in the standard way. Here are some key findings.[5]

- The YLS was relatively successful at estimating employment status. The YLS successfully mirrored the CPS-reported drop in the EPR (from pre-

---

[5] These statistics use "final weights" version 2 to weight the respondents. For a discussion of weighting procedures, see Appendix E.

pandemic levels of 63%) to around 52% in April. It also matched the subsequent rise to around 55% in June, the steady increase through October, and the leveling off through early 2021. Similarly, YLS estimates of WFPR tracked those of CPS from their April low (49%) to the more recent levels (around 57%).

- Although the YLS generated an unemployment estimate that broadly tracked the UR from the CPS, the YLS estimate of the UR was consistently too high. Over the entire 11 months, the average unemployment rate from the YLS was 12%, while that of the CPS was 9%. This overestimate was found among most demographic groups and time periods, even breaking down the data across 128 categories of race, gender, age, and education.
- Because YLS estimates of employment matched those from the CPS relatively closely, the YLS overestimate of the UR resulted in an YLS overestimate of the LFPR as well.

Patterns of labor market activity across major demographic groups generally mirrored patterns in the CPS.

- Both the YLS and CPS found higher unemployment rates among Black and Hispanic respondents compared to white respondents throughout the whole period. The same is true for respondents under age 29 and older than 65 years. YLS respondents with college or post-graduate degrees showed much lower unemployment rates, another disparity mirrored in the CPS.
- Estimates for major sectors in the YLS showed the great divide seen in the CPS between those industries that were hard-hit (such as leisure activities) and those that fared well (such as financial services).
- The errors in the employment-population ratio (EPR) are highest in the 65+ age groups. With a few exceptions, other YLS age groups are a close match to the CPS.

One of the remaining puzzles in the YLS is the consistent error in measuring unemployment over the last year – even after applying weights that reflect both demographic characteristics and past labor market status. While the source of this discrepancy has not been resolved, we suspect that part of the problem arises from biases in retrospective measures of earlier labor force status. Because respondents tend to underreport earlier unemployment rates in their retrospective answers (relative to what they reported contemporaneously), this

leads to an over-estimate of current unemployment rates, because the baseline employed group contains persons who should have been classified as unemployed. Other sources of bias – such as difficulties in measuring search or layoff – have not proven to be an important source of bias in our investigations. We plan to follow up with further studies to determine if the persistent bias in estimating unemployment can be better understood and corrected.

The primary lesson of this study is that online surveys of complicated social, economic, and demographic characteristics of the population can be studied using online panels. However, it appears – at least for the questions involved in the labor market – that there are small residual biases in reporting or sample selection that have not been easily identified and corrected. The size of these biases for employment-related measures seems small enough to indicate that future internet panels may provide valuable real-time information on labor markets.

The next two sections describe important aspects of the CPS and YLS, including sample selection, differences in questions across the two surveys, and the construction of sample weights. Section III provides a broad overview of these topics, and section IV goes into somewhat more detail. Readers who would like to skip to the results can begin with section V.

III. Brief Description of Methods

A. Background on the CPS

The following is a description of the CPS, which is sponsored jointly by the Census Bureau and the Bureau of Labor Statistics (BLS). The Census Bureau administers the CPS using a probability-selected sample of about 60,000 occupied households.[6] Questions in the CPS concern labor market activities during the *reference week* that includes the 12th of the month. The fieldwork is typically conducted during the subsequent *survey week* that includes the 19th of the month.

The modern "activity-based" definition of unemployment dates back to the late 1930s, with refinements in that definition continuing through various

---

[6] The CPS is a survey of households and is often called the household survey. The other main government employment survey, conducted by the Current Employment Statistics (CES) program, gathers data from establishments. Monthly results from both the CPS and the CES are released on the same day, typically the first Friday of every month.

revisions in the CPS. The core CPS questions separate the adult civilian non-institutional population (POP) into three groups: employed (E), unemployed (U), and not in the labor force (NILF). These three groups are exhaustive and mutually exclusive, so POP = E + U + NILF. Employed persons are those who work for pay or profit (or are temporarily absent from their jobs), while non-employed persons must be actively looking for work or on temporary layoff to be counted as unemployed. The labor force (LF) is defined as E + U. This study examines four main labor force statistics: the work-for-pay ratio (WFPR) and the closely related employment-population ratio (E/POP), the unemployment rate (U/LF), and the labor force participation rate (LF/POP).[7]

The CPS uses a complex design involving both stratification and multistage selection of housing units. CPS initial contacts were in-person until the pandemic, with some recontacts by phone. Historically, the CPS response rate has been around 90%, but with a declining trend recently. The average response rate for the 12 months ending in February 2020 was 83%. However, the overall response rate declined to 65% in June 2020 and then recovered to 78% in January 2021. (U.S. Bureau of Labor Statistics, 2021a) It is not clear whether the weightings undertaken by the BLS-Census have adequately dealt with the massive non-response issues in recent months.

Before turning to a formal description of the YLS, we would make a preliminary remark about the CPS as a formal point of comparison for our survey. The CPS is rightly considered to be the "gold standard" for household labor market surveys in the United States. This term indicates, according to the Oxford English Dictionary, "something of the highest quality which serves as a point of reference against which other things of its type may be compared; a measure, standard, or criterion of excellence."

There is no doubt that the CPS is a valuable point of reference. But in reality the CPS is unlikely to ever measure unemployment with the same precision that is common in the physical sciences. As an example, social surveys like the CPS

---

[7] Measuring unemployment during the pandemic has been particularly challenging because the CPS was not designed with pandemic-induced lockdowns in mind. Particularly in the early months, the CPS incorrectly classified many unemployed persons as "employed, but temporarily absent from work." Using microdata from the CPS, and following a method suggested in recent BLS publications, we create an alternative unemployment measure, *U3-alt,* to correct for the misclassification. This corrected unemployment rate is conceptually similar to the unemployment rate generated by the YLS. A description of the methods is contained in Appendix C.

regularly overestimate the fraction of people who vote in elections. Comparing survey data on voting to administrative data on voter turnout is useful because voter turnout is as close as we will ever come to an accurately measured population statistic (a point made clear by the very close 2020 election). According to survey experts, the CPS's regular November election supplement has regularly overestimated voter turnout on the order of 10 percentage points. (Matthew DeBell et al., 2020) This fact reminds us that even gold-standard surveys like the CPS cannot hope to attain the standards of measurement we have achieved for the gravitational constant or the mass of the electron.

A similar issue arises with respect to the impact of interviewer error on the discrepancy between YLS and CPS. Re-interview studies often find substantial errors in labor force measures, and some of the errors are introduced by interviews and re-interviews. To the extent that the YLS is anonymous and given to a panel with experience in online panels, this is likely to impart a different kind of error from that associated with the government-run CPS. (Biemer and Forsman, 2021)

B. The Yale Labor Survey

A brief description of the YLS is as follows. The survey is designed to capture the major employment aspects of the CPS and to illuminate unusual aspects of the labor market stemming from the COVID-19 pandemic that shook labor markets beginning in March 2020.

The main differences between the CPS and YLS involve both the *questions asked* in the two surveys and the *sample-selection and weighting methods*. The YLS's questions concerning labor market status are similar but not identical to those in the CPS, as explained below. Also, to better understand special features of the pandemic labor market, the YLS also includes several COVID-related questions. Examples include questions asking whether respondents worked at their normal workplaces or at home, whether they were paid by their employers even though they did not work, and whether they have applied for or are receiving unemployment insurance. We also ask standard questions about recent hours of work, incomes, and when respondents held their last jobs.

More important are the differences between the two surveys in their sample-selection and weighting methodologies. The CPS is designed to be a probability-based sample of the adult U.S. non-institutional population, and its statistical validity relies on its resembling a probability sample of the population to the

greatest degree possible. By contrast, the YLS was administered by YouGov, a UK-based market research and survey firm, and uses an opt-in sample.

Additionally, the CPS and YLS also differ in their sample sizes. After two pilot tests, the YLS survey was conducted weekly in waves of 1500 to 5000 respondents per week. The survey period covered in this report includes 117,000 observations over 43 weeks through the middle of February 2021. The monthly sample size for the CPS is about 60,000 households.

C. The YouGov Panel

The present section provides a brief overview of the YouGov panel and YLS methods, with additional detail provided in the next section. In contrast to the probability-based CPS, the YouGov panel from which weekly YLS samples are drawn is an *opt-in sample*; all interviews are conducted online among people who have previously agreed to complete YouGov surveys for compensation. These features ensure rapid turnaround and low cost, but they also risk imparting selection bias to the resulting sample.

To correct for sample bias, the YLS relies upon adjustments that correct for differences between panel participants and the U.S. population. These adjustments are based on statistical models that are designed to improve the representativeness of the sample. As noted, one motivation for this study is to determine whether the results from a fast, inexpensive survey can provide useful insights before and between waves of expensive, slower, and more established surveys like CPS.

These adjustments involved two critical elements. The first is the procedure that draws a YLS sample as a subset of the YouGov panel. As noted earlier, this panel is populated by people who have previously agreed to fill out YouGov surveys for modest compensation. The YouGov panel turns out to be unrepresentative of the U.S. population along many demographic characteristics (such as age, race, and education). But a more representative sample can be drawn from the YouGov panel through the application of appropriate sampling procedures. For the YLS, *quota sampling* was used to draw samples that are representative of U.S. adults in terms of age, gender, education, and race. Specifically, the sampling frame includes 96 strata, or cells, and respondents were selected from each cell approximately in proportion to the frequency of that cell in the February 2020 CPS. This month was chosen because the economy and the labor market were relatively stable, so we could match summary

statistics from YLS respondents to corresponding averages in the U.S. population.

The second critical element needed to make YLS results representative is the construction and application of *sample weights*. Quota sampling is intended to generate a sample that is broadly representative of the target population, but in practice it rarely generates samples that exactly match multiple population targets simultaneously. A "raking" procedure is therefore used to construct weights that align the YLS sample across six demographic characteristics (age, gender, education, race, marital status, and the presence of children).[8]

The use of quota sampling and the construction of sample weights ensures that YLS samples mirror the U.S. population along important demographic characteristics. But the YLS sample must also reflect the general labor market attachment of the U.S. population. Accordingly, in addition to demographic information, we also used respondents' past labor market status in the construction of sample weights.

Past labor market experience needs to be incorporated into YLS sample weights because the labor market behavior of people who agree to participate in the YLS survey may not be representative of the U.S. population in terms of their labor market attachment. To see this, consider one cell of the panel – married white women with a college education aged 35–54 with no children. This group represents 1.16% of the YLS sample using the quota sampling and 1.17% after applying the post-stratification weights. These two proportions are similar because, thanks to the quota-sampling procedure, the proportion of the demographic group in relation to the whole sample to be very close to the proportion of the demographic group in the U.S. population. Ideally, rates of employment and unemployment in the sample group would mirror the corresponding rates of the same demographic group in the overall population. If such mirroring occurred for all demographic slices of a YLS sample, then the YLS could produce valid estimates of aggregate labor market data using only the quota-based demographic sampling and weights constructed from demographic data alone.

---

[8] See the next section for details of the raking procedure. The six demographic variables included in this procedure are either collected in the survey, are in the respondent's YouGov user profile, or both.

Unfortunately, in practice, the YLS sample does not closely match the representative sample generated by the CPS for the labor market. More specifically, employment and unemployment rates for narrowly defined demographic groups in YLS samples tend to be different from those rates for the same groups in the general population. Respondents tend to be unemployed more often than their population counterparts. As is shown in Appendix D, more than 90% of the 128 demographic cells over-report unemployment relative to the CPS.

This bias stems from unobserved variables that affect YLS respondents' labor market behavior – variables that may include the respondents' work histories, health statuses, skills, and work attitudes, as well as local labor market conditions. To take one example, the federal government estimates that about 25% of Americans have a disability. (Centers for Disease Control and Prevention, 2020) According to the BLS, in 2020, 18% of persons with a disability were employed compared to 62% without a disability. (U.S. Bureau of Labor Statistics, 2021b) The quota-sampling procedure does not include disability as a demographic variable, nor is disability one of the demographic variables used to construct the sample weights. The omission of disability from these two steps can therefore result in an unrepresentative sample, even after sample weights have been applied.

To address this problem and capture the complex set of unobserved labor market influences, our weighting procedure incorporates data on past labor market status (as well as demographic information). When the weights are constructed, respondents' past labor market status is treated just like a demographic characteristic such as race or age. When past labor market status is included, a weighted sample from a survey taken in (say) February 2021 will match not only the demographic makeup of the U.S. population, but also the rates of employment and unemployment in the previous month when past labor force status is measured (for example, December 2020 or January 2021).

In a sense, past labor market status creates a "quasi-panel," meaning that it allows incorporation of individual unobserved variables that are unchanged over the period since the previous month. It is only a "quasi" panel because the earlier labor market status is a retrospective observation on the part of respondents and is therefore subject to measurement error (such as recall or question error). To the extent that the retrospective labor market status is inaccurate or biased,

this will tend to bias the weights and therefore the current estimates of labor market status. (See the discussion below and in Appendix G.)

We have incorporated prior labor market status into the sample weights in different ways as the project has evolved:

- For the early months of the survey, labor market status was derived from answers provided by the respondent in the October 2019–February 2020 period, collected by YouGov as part of its data collection on its panel participants. Where these data were not available, the YLS asked a recall question about February 2020 labor market status and additional questions about current labor market status.[9]

- As time passed, labor market status in February 2020 status became less predictive of current labor market status. Starting in July 2020, therefore, we added retrospective questions about employment from February to June. We can use these questions to create "final weights" that reflect labor market activity in months closer to survey dates. As an example, the YLS final weights for the December CPS week use labor market status averaged from the October and November 2020 CPS microdata. These final weights roll forward over time as new CPS microdata become available. The weighting procedure is described in Appendix E.

An important question is whether this weighting procedure is likely to adequately address the sample-selection issues inherent in this online survey. Comparisons of probability-based studies are an active area of research.[10] Studies of the relative accuracy of online, non-probability surveys, and probability-based surveys have mixed results. In any case, there is no systematic determination of which approaches are superior for which kind of population information (e.g., pure demographic information, secondary information, economic and social data).

---

[9] Respondents were asked, "During the first two weeks of February 2020, did you do any work for pay or profit?" Those responding "Yes" were deemed employed in February 2020. Those responding "No" or "Not sure" by those currently employed were classified as unemployed in February 2020. Those who responded "No" and were not currently employed were allocated their current situation, with categories being one of employed, unemployed, retired, disabled, student, homemaker, and other.

[10] Potential adjustments include quotas, stratified random sampling from the panel, matching, post-stratification weighting, and propensity-score weighting. Our approach combines quotas and post-stratification weighting.

Moreover, many of the studies comparing different methods are relatively simple – asking questions such as "were you employed" – rather than the approach of the YLS, which involves multiple and overlapping questions. Finally, it is worth noting that even probability-based sampling – often considered the "gold standard" for survey research – has encountered major hurdles in recent years, as the willingness of randomly drawn respondents to participate in surveys has trended down. And more recently, there were additional physical barriers to in-person interviews during the pandemic.

More details on the potential errors for the weights are contained in section IV.F. The questions for the survey are contained in Appendix H. An example that works through the method of using prior labor force status is contained in Appendix G.

IV. Detailed Description of the Panel and Statistical Methods

This section provides additional detail on the source and selection of respondents for the study, how the sample was weighted, the calculation of standard errors, and assumptions needed for valid inferences.

IV.A. Source of Respondents

Respondents were drawn from YouGov's opt-in online panel, which is similar to other access panels commonly used for market research and public opinion polling. (Sudman and Wansink, 2002) YouGov recruits participants using internet-advertising campaigns (primarily Google Adwords, Facebook, and banner ads on popular websites, but also using co-registration, visitors to YouGov's home page, and referrals from existing panelists). After confirming their email addresses ("double opt-in"), the individuals provided personal and demographic information to become registered panelists. There is no well-defined sampling frame or established probabilities of selection for panelists. The panel is simply a pool of respondents available for conducting individual research studies. People who join online panels exhibit biases that are similar to those who answer random telephone surveys (for example, they are older, more likely to be white, and have more schooling). Attitudinal studies have found that online panelists are early adopters, less traditional, and more environmentally concerned. (Gittelman et al., 2020) Unlike in phone surveys, however, online panelists are approximately balanced on gender.

The issue of selection bias has become increasingly severe for both government and private surveys in recent years. We noted above that the CPS had a response rate of only 65% in June 2020, which is below the U.S. government's statistical standard. Pew estimates that response rates in telephone surveys declined from 36% in 1997 to 6% in 2018. (Pew Research Center, 2019)

Additionally, over time it has become increasingly difficult to reach target audiences. Most random-digit-dial phone surveys conducted today do not use random selection to choose respondents within a household. To reduce the number of women and older respondents in the sample, either explicit quotas or other procedures are employed to reduce selection bias. For example, the interviewer might first ask, "Out of all the people age 18 or older who are at home now, may I please speak to the youngest male?" If no male lives in the household, the interviewer might then ask, "May I speak to the youngest female?"

The major point here is that an accurate representation of the population can no longer assume that the responding sample has an equal probability of selection for all members of the target population. Rather, surveys must use procedures to weight individuals in the sample, and therein lies the modern art of survey research.

IV.B. Selection of Panelists for this Study

Samples for individual YouGov studies, like this one, are selected from the YouGov panelist pool that contains the target population (in this case, the U.S. population 18 or older). The size of YouGov's panel is much larger than the sample size needed for any individual study, but the company is conducting many studies simultaneously. At the time of this project, there were almost 200,000 active panelists.[11] YouGov uses quota sampling to select respondents from the panel for receiving invitations and an allocation algorithm to assign responding panelists for particular studies, which we describe now.

For the YLS, panelists were allocated to 96 quota cells, based upon the cross-classification of their age (18–29, 30–44, 45–64, or 65+), gender (male or female), education (high school or less, some college, college degree, post-

---

[11] An active panelist for this purpose is defined as having completed a survey in the last month.

graduate degree), and race (white, black, or Hispanic).[12] For each cell, a target number of respondents was selected that is proportional to the number of adults in the February 2020 CPS. For each panelist, a probability of response is estimated based upon past rates of participation and demographics. Panelists in each quota cell are randomly selected for being sent invitations until the expected number of responses in each cell equals the target number. The invitations do not describe the subject of the study, nor do they guarantee that the panelist will be assigned to any particular study.

Panelists who click on links in their email invitations are routed to one of the available studies according to an algorithm until the target number for the survey is reached or until the field period (say, 24 hours) ends. The algorithm assigns a value to each panelist for each study that the respondent qualifies for. The value is based upon the number of additional respondents needed to fill the respondent's quota cell, divided by the length of time remaining for fielding the survey.

As compensation for participating in this study, panelists receive points that can be converted to cash after a minimum threshold has been reached. For this study, each respondent was awarded the equivalent of $0.50 in points. The median time to complete the survey was 9 minutes.[13]

IV.C. Weighting

Respondents were selected from YouGov's panel to join the study to be representative of all U.S. adults in terms of four demographic variables (age, gender, education, and race). Due to non-response, the realized sample does not match the population targets exactly. We use *post-stratification weighting* to improve the representativeness of the sample. The post-stratification involves two sets of variables: demographic and labor market. In all, we used six demographic weighting variables: the four demographic variables used in the

---

[12] YouGov includes "Hispanic" as an answer option for the question "What best describes your race?" The Current Population survey asks separate questions about the respondents' race and origin. In the CPS, we have grouped whites of Hispanic origin as Hispanic and blacks of Hispanic origin with Blacks. Whites include any non-Hispanics who are not black, including those identifying as Native American, Asian, Middle Eastern, and mixed race.

[13] One interesting feature of the present survey is that respondents might consider that they are working for pay because they are compensated for answering online surveys. As we note in the discussion of "nuggets" below, we correct for a misclassification of this group.

quota-based sampling (age, gender, education, and race) along with marital status and presence of children. Additionally, as noted above, we use variables to represent labor market status (LMS) to capture unobserved variables that represent an individual's labor market propensities. These were either February LMS in the early part of the survey or recent LMS in the later parts (see section III.C. above).

The purpose of weighting in this context is to adjust the sample to better represent the target population. Each respondent is assigned a positive weight, so that the fraction in each cell from the weighted sample matches the fraction of that cell from a census or other reliable estimate. The assumption is that by applying the same weights for computing means and proportions of other sample variables, this procedure will correct for differences in the characteristics between the sample and the target populations.

In the simplest case, both the sample and population can be partitioned into a set of mutually exclusive and exhaustive categories according to some characteristics. For example, if it is known that 52% of adults are female, and 48% are male, while the sample is 60% female, weighting women by 52/60 and men by 48/40 will adjust the sample proportions to match the population proportions for gender. Cell weighting works well so long as the sample fractions in each category are not too small. For example, if a particular age-race-education-gender category has zero people in the sample, it is not possible to use a (finite) multiplicative weighting to attain the population proportion.

The problem of zero-member cells limits the number of demographic characteristics that can be included in a quota-based sampling procedure. For example, consider a survey that must be balanced along multiple demographic characteristics (e.g., age/education/race/region/gender). A naive approach would be to form a cross-classification using all characteristics, and then do cell weighting using the full cross-classification. This high-dimensional plan fails in practice because the number of cells in a cross-classification grows quickly with the number of dimensions. For example, if there are four age categories (18–29, 30–44, 45–64, 65+), four education categories (high school or less, some college, college graduates, and post-graduates), three race categories (white, black, Hispanic), four regions, and two genders, the cross-classification contains $4 \times 4 \times 3 \times 4 \times 2 = 384$ cells. If a sample cell is empty, it is impossible to set its weight as some positive number and match the corresponding population share. Even if there are only one or two sample observations in cells, the corrective

weights can become large, making the resulting sample estimates unstable.

Therefore, for the YLS, we used quota-based sampling using only four categories (gender, race, education, age). We then constructed sample weights that further refine the sample along those characteristics and also incorporate marital status, the presence of children, and labor market status.

IV.D. Raking in the YLS

The general theory of raking (weighting) and its use in the YLS is discussed in Appendix F. The variables included, to begin with, six key demographic variables: Age, gender, race, education, marital status and presence of children. To these was added labor market status, LMS. Several cross-classifications were also used.

Weights were computed for each day's or week's sample. The weights are not exactly equal to the ratio of the population to sample proportion in each cell because we do not weight on all the cross-classifications. In fact, it is impossible using the raking algorithm to match all the cross-classifications with the daily samples because some cells in the full cross-classification are empty on particular days.

An example that works through the method of using prior labor force status is contained in Appendix G.

IV.E. Statistical Properties

There are different methods for estimating the variance of sample means and proportions using raking weights. Little and Wu (1991, p. 90, eq. 19) provide an asymptotic variance formula under non-random selection. Unconditional variance estimates can be obtained by treating raking as a special case of calibration weighting. (Chang and Kott, 2008) Alternatively, Canty and Davison (1999) discuss bootstrapped variance estimates and confidence intervals, which are conceptually simpler if finite population corrections are not necessary.

Statistical inference is another important issue. The primary purpose of post-stratification weighting with opt-in samples is to reduce bias caused by self-selection and non-response. In principle, weighting can remove bias if panel selection and within-panel non-response are conditionally independent of the weighting variables. This is Rubin's "missing at random" condition. (Little and Rubin, 2019)

However, raking weights are based upon a parametric response model that assumes that the log ratio of population proportions to sample selection probabilities obey a main-effects model without interaction. (Little and Wu, 1991, p. 87, eq. 5) That is, the only interactions relevant for selection bias involve variables whose population joint distribution is known. Nonetheless, even if raking does not eliminate all selection bias, it seems to perform reasonably well in practice when selection bias is not severe and sample sizes not too small. (A rule of thumb is to have at least 30 observations per cell.)

It is important to note, however, that raking can only remove bias that occurs because of non-representative samples at the level of the post-stratified cells (e.g., demographic and labor market). If there are biases in responses within the most detailed cells (e.g., demographic characteristics and prior labor market status), then the weighting cannot remove that bias because it arises from unobserved variables.

In practice, post-stratification improves the estimates markedly when labor market variables are used but adds relatively little when only demographic variables are employed. The latter result is not surprising because quota sampling eliminates most of the demographic bias, but there is still a bias that can be removed by weighting on past labor market status.

V. Basic Labor Market Definitions and the COVID-19 Pandemic

V.A. Defining Labor Market Status

Like the CPS, our survey divides the U.S. adult civilian non-institutional population into three groups: employed (E), unemployed (U), and not in the labor force (NILF). Because of survey limitations, we have limited our analysis to the population 20 and over.[14] Figure 1, taken from a BLS description of employment and unemployment concepts, illustrates the sequential rules that the YLS survey also sought to follow.

---

[14] Persons under 18 cannot participate in the YLS because protection of human subjects requires parental consent. See Appendix B and the footnote 16 for the effect of this limit on our choice of the 20+ population.
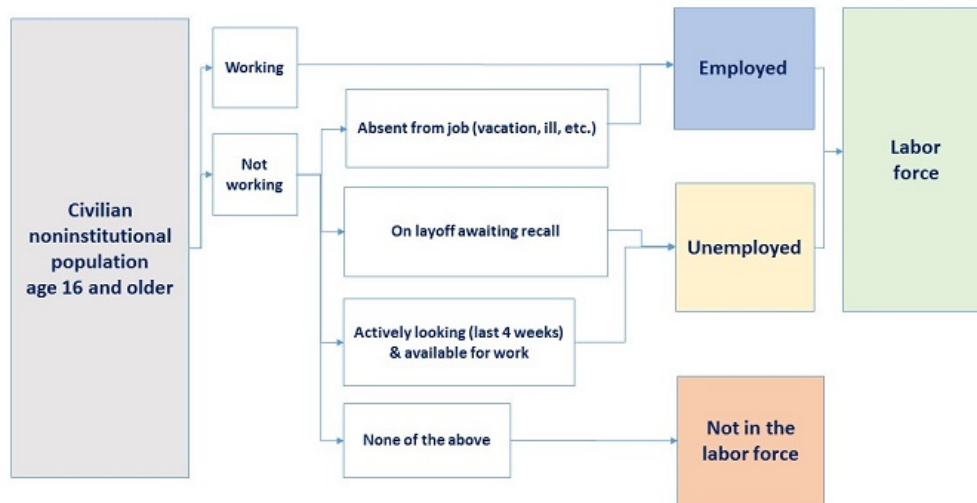
Figure 1. Labor Force Concepts in the Current Population Survey

(Source: BLS. Available at https://www.bls.gov/cps/definitions.htm)

- **Employed** persons worked for either pay or profit during the reference week. We added to this group respondents who answered that they received pay even though they did not work during the reference week (as explained in Appendix A).
- **The work-for-pay ratio** (WFPR) measures the fraction of survey respondents who report that they worked for pay or profit during the reference week. This fraction is adjusted for overreporting due to those whose only jobs are answering online surveys.
- **Unemployed** persons are those who did not work for pay but were on temporary layoff or actively looking for work. In the YLS survey, the unemployment pool is comprised of:
  - Respondents who actively searched for work in the last 4 weeks and were available for work within 7 days, and
  - Respondents who were on layoff or furlough and expected to return to their job.[15]

---

[15] Respondents could signal this expectation in two ways. One survey question asked non-working respondents about their present work situation, to which one possible answer was "laid off or furloughed from a job to which you expect to return." Respondents could also signal a job-recall expectation by answering yes to a separate question: "If you recently lost your job,

- Persons who are **not in the labor force (NILF)** are those who are neither employed nor unemployed.

V.B. Technical Note on Measuring Employment

The BLS has six "alternative measures of labor underutilization," denoted U1 through U6, which are published each month as part of the monthly jobs report. The standard unemployment rate is U3, defined (perhaps uninformatively) as "total unemployed." The narrowest underutilization measure (U1) includes only the long-term unemployed, while the broadest (U6) is defined as "total unemployed plus all persons marginally attached to the labor force, plus total employed part-time for economic reasons, plus all persons marginally attached to the labor force." In January 2021, U1 was 3.4%, U3 was 6.3%, and U6 was 11.1% (seasonally adjusted).

The YLS attempts to replicate the headline measure, U3. However, during the early part of the pandemic, the BLS noted that it had probably misclassified many workers displaced by the coronavirus as "employed but absent from work," when these workers should have been classified as unemployed. BLS calculations indicated that this misclassification probably lowered the reported unemployment rate (U3) by 5 percentage points in April 2020. Fortunately, improvements in the labor market and in CPS implementation reduced this error over time to around 0.6 percentage points by February 2021.

Because of the misclassification, YLS researchers used CPS microdata to construct an alternative measure of unemployment, moving workers classified as employed but absent from work for "other reasons" into the unemployment pool. The resulting measure, U3-alt, then allowed an apples-to-apples comparison with the unemployment rate in the YLS, where the classification error was less likely to occur. For a further discussion, see Appendix C. While the correction reduced the error in the calculation of labor force status in YLS in the early months, that improvement was smaller in the later months.

---

have you been given any indication that you will be recalled to work within the next six months?"

VI. Results of the Survey

VI.A. Overview

Table 1 and Figure 2 summarize results for the CPS survey months from February 2020 to February 2021. (For the full results by month, see Appendix D.) We have direct comparisons for most months. Our estimates are limited to the population aged 20 and over (see Appendix B).[16] We show both the standard U3 measure of unemployment and the alternative concept, U3-alt, which includes an adjustment for classification errors in the survey as described in the last section.

The major conclusion is that the YLS estimates closely parallels the labor market experience as described by the CPS. The estimates for employment are relatively accurate; those for unemployment tend to be slightly high; and consequently, the labor force participation rate is also higher than the CPS estimates.

Table 1 shows the average values and errors of each of the three major labor force categories for the 11 months, measured as a percent of the adult population. The YLS captures the employment-population ratio closely over the period. However, it systematically overestimates unemployment, with a larger overestimate with the standard U3 than with U3-alt. The fraction of persons not in the labor force is underestimated (that is, the participation rate is overestimated) largely because of the overestimate of unemployment.

---

[16] Persons under 18 are excluded from the sample because the protection of human subjects requires parental consent to participate in a survey. Although persons aged 16–19 years have low labor force participation, they also have high unemployment rates, so there is a non-trivial difference between the 16+ unemployment rate and the 20+ unemployment rate. For the last two decades, the 16+ rate has been about ½ ppt higher than the 20+ rate, although this difference has trended lower since 2013.

	Average monthly value		
	Percent of Population		
	Employed	Unemployed	Not in Labor Force
CPS	57.7	5.4	36.9
CPS-alt	56.7	6.4	36.9
YLS	56.5	8.2	35.4

	Average error		
	Percent of Population		
	Employed	Unemployed	Not in Labor Force
YLS - CPS	-1.3	2.8	-1.5
YLS - CPS-alt	-0.2	1.7	-1.5

Table 1. Average Values and Errors for YLS and CPS

Figure 2 shows monthly and weekly comparisons of the CPS and YLS for different concepts. The CPS-based estimates show both the official U3 rate and our constructed U3-alt rate.

Panels 2(a) and 2(b) show the persistent upward bias in the estimated unemployment rate, while panels 2(c) and 2(d) show that the survey was quite close to the CPS on the employment rate. The error in the unemployment rate increased after October 2020.

2a. Unemployment rate (monthly)

YLS weight used is based on labor history: wt_finwt1.

2b. Unemployment rate (weekly)

YLS weight used is based on labor history: wt_finwt1. Date shown is end of reference week.
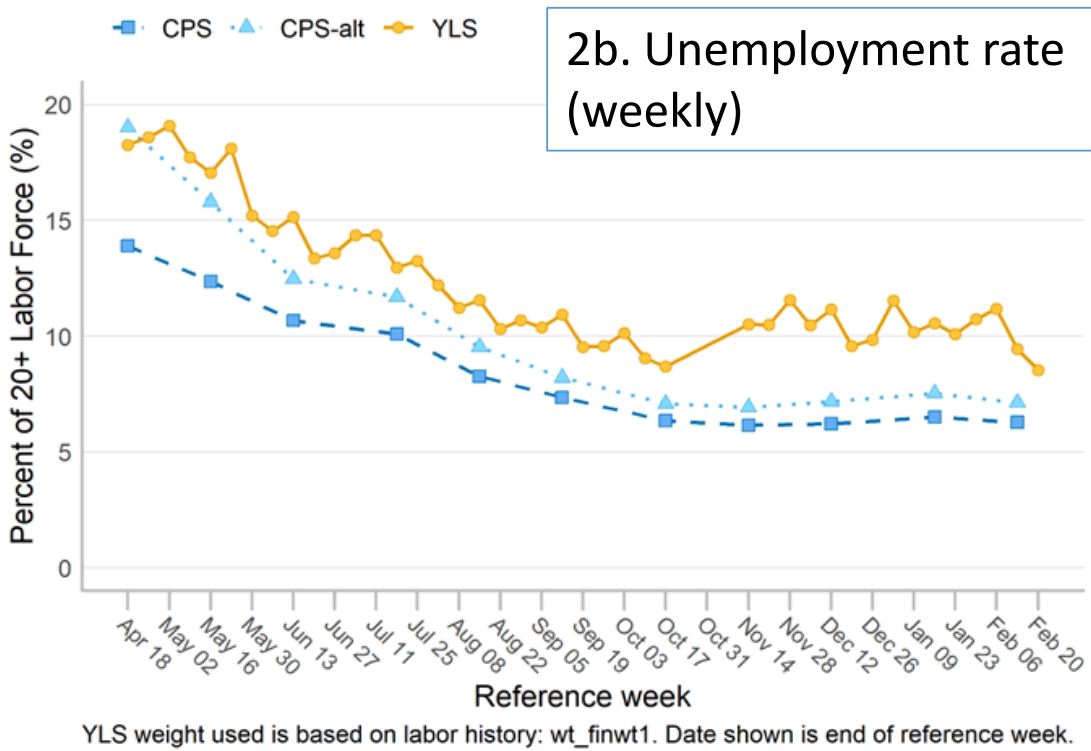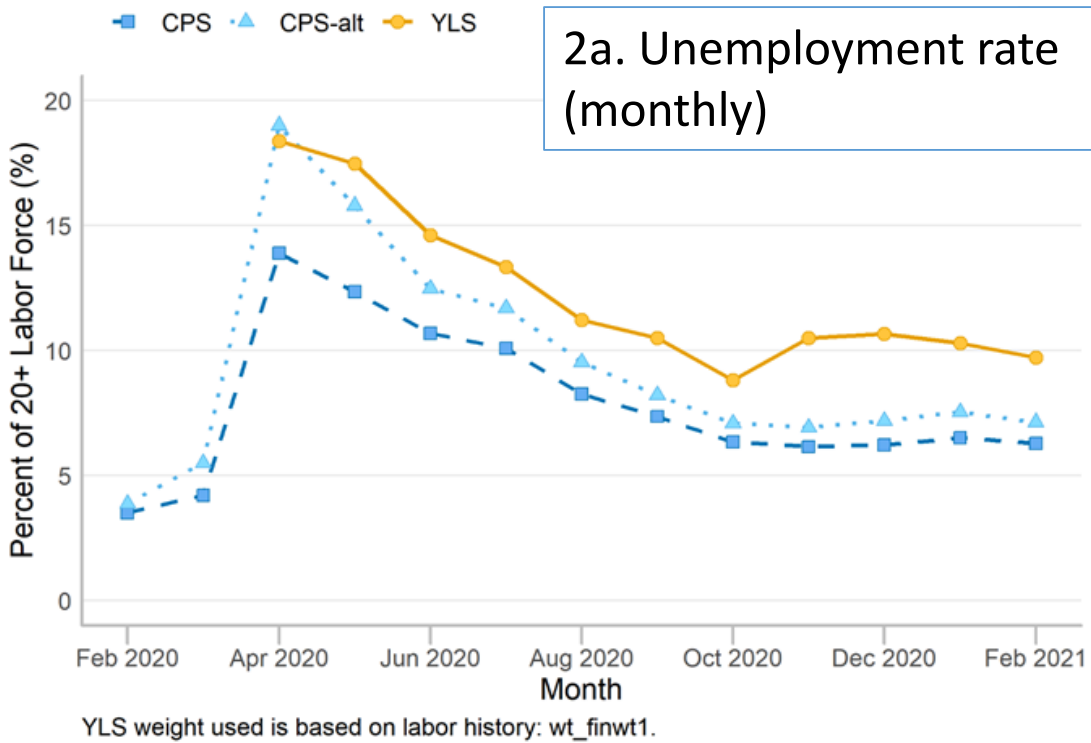
Figure 2(a) and 2(b). Unemployment Rates by Week and Month, CPS and YLS

2c. Employment/pop (monthly)

YLS weight used is based on labor history: wt_finwt1.
YLS EPR is adjusted by -1.4 percentage points.

2d. Employment/pop (weekly)

YLS weight used is based on labor history: wt_finwt1.
YLS EPR is adjusted by -1.4 percentage points.
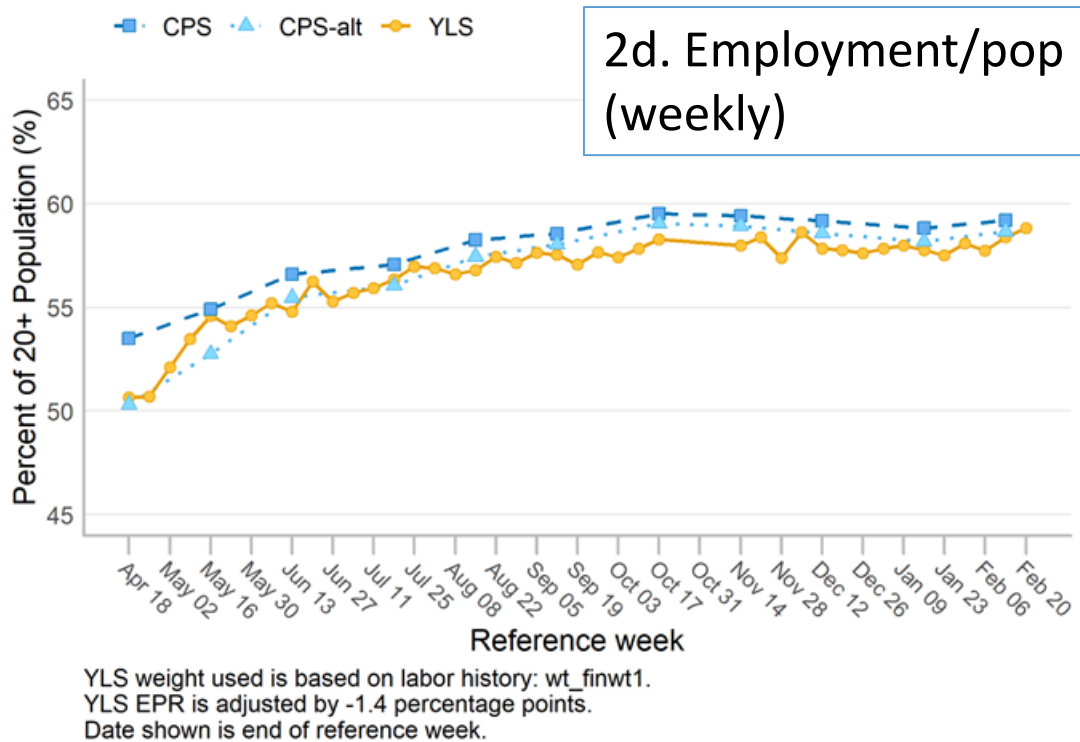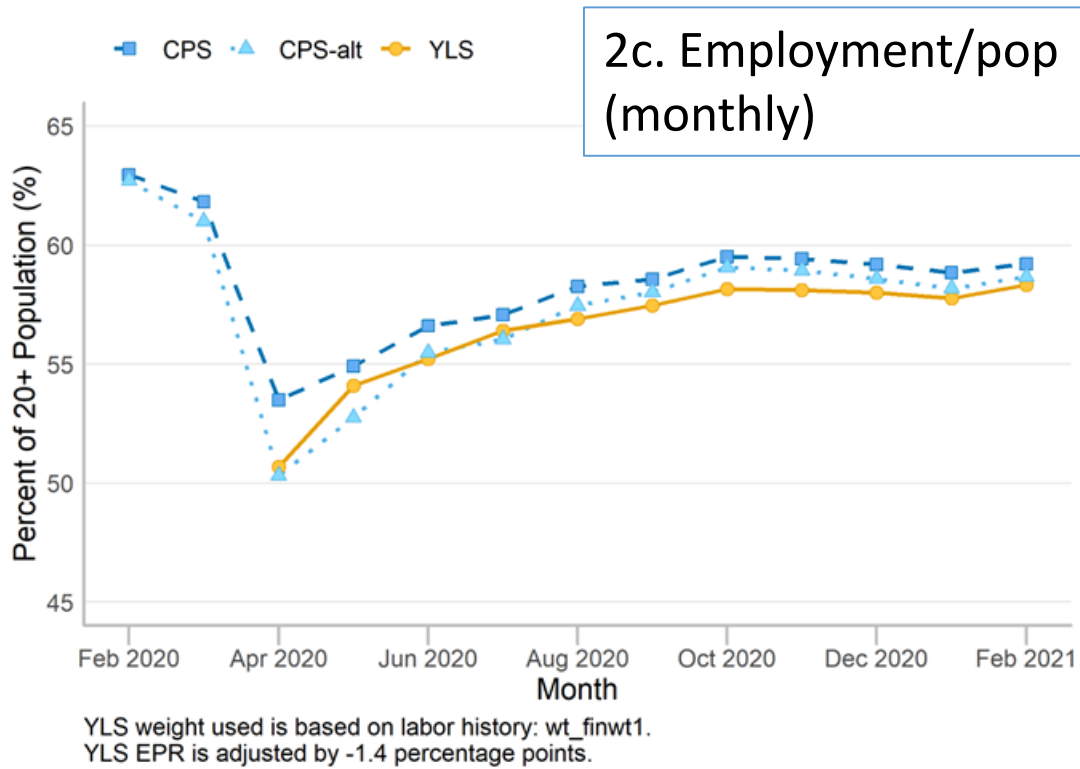Date shown is end of reference week.

Figure 2(c) and 2(d). Employment-Population Ratios by Week and Month, CPS and YLS

The alternative unemployment rate (U3-alt) is closer to the YLS unemployment rate than the standard U3 unemployment rate. The explanation is that many workers were mistakenly classified as employed in the CPS, whereas they were correctly classified as unemployed in the YLS. The difference between U3 and U3-alt declined over the period after April as the pandemic-related absences for "other reasons" declined sharply.

The bottom line on the survey for the aggregates is that the YLS has proven remarkably accurate for employment but has consistently overestimated unemployment.

VI.B. Unemployment Rates for Major Groups

Next, we show the labor market status for different groups. Tables 2 and 3 provide the averages for the entire sample period. The underlying trends indicate, accurately, the following impacts:

- Among age groups, the youngest age groups had the highest unemployment rates during the pandemic.
- Among racial and ethnic groups, Black and Hispanic workers had the highest unemployment rates during the pandemic.
- Among educated groups, lower educated groups had the highest unemployment rates during the pandemic.
- Among occupations, those in service, construction, and transportation occupations were the most severely impacted.
- Among industries, leisure and hospitality were the most severely affected.

Here are some results for demographic groups compared to the CPS:

- The YLS tends to overestimate unemployment among females relative to males.
- Among age groups, the YLS tends to overestimate unemployment primarily among the oldest age group (age 65+).
- There is no significant difference in estimates by racial groupings.
- The YLS tends to overestimate unemployment among groups with lower education relative to those with higher education.
- The YLS tends to overestimate unemployment among widows and divorced as marital status.

Here are some results for economic groupings compared to the CPS:

- Among regions, the YLS tends to overestimate unemployment in the South relative to the Northeast.
- Among occupations, the YLS tends to overestimate unemployment in sales and underestimate in farming, transportation, and services.
- Among industries, the YLS tends to overestimate unemployment dramatically in mining and information and overestimate in leisure and hospitality.

	Average unemployment rate		
	CPS	**CPS-alt**	**YLS**
Gender			
Male	8.2	9.8	10.8
Female	8.9	10.8	13.9
Age			
20-29	12.5	13.8	15.8
30-44	7.6	9.0	11.0
45-64	7.3	9.1	10.7
65+	8.3	11.8	15.4
Race			
White	6.9	8.6	10.7
Black	12.2	14.0	15.4
Hispanic	11.1	12.7	15.4
Other	9.8	11.8	12.9
Education			
HS or less	11.4	13.2	16.3
Some college	9.6	11.5	14.5
College grad	6.6	8.1	9.1
Post grad	4.2	5.5	6.2
Marital status			
Married	6.3	7.9	9.0
Widowed	9.3	12.0	14.5
Divorced	8.7	10.7	15.1
Separated	11.6	14.0	14.8
Never Married	12.4	13.9	16.9

Table 2. Average Monthly Unemployment Rates for YLS and CPS, Different Demographic Groups, April 2020–February 2021

	Average unemployment rate		
	CPS	CPS-alt	YLS
Census Region			
Northeast	10.1	12.2	12.5
Midwest	7.7	9.1	11.3
South	7.6	9.2	12.4
West	9.7	11.5	12.8
Occupation			
Management, business, and financial	4.5	6.0	7.4
Professional and related	5.2	6.8	8.5
Service	14.8	17.3	16.0
Sales and related	9.3	11.3	14.4
Office and administrative support	7.9	9.0	10.4
Farming, fishing, and forestry	9.7	10.9	9.6
Construction and extraction	11.1	13.3	14.2
Installation, maintenance, and repair	7.3	8.2	10.6
Production	9.6	10.8	13.7
Transportation and material moving	12.5	14.1	12.9
Industry			
Agriculture, forestry, fishing, and hunting	5.3	6.4	8.7
Mining	14.3	15.6	7.3
Construction	9.1	11.4	11.7
Manufacturing	7.1	7.9	8.9
Wholesale and retail trade	8.8	10.2	11.9
Transportation and utilities	9.6	11.4	9.6
Information	8.8	10.7	7.9
Financial activities	4.4	5.5	5.9
Professional and business services	7.1	8.8	9.5
Educational and health services	6.1	7.7	8.9
Leisure and hospitality	22.9	25.7	29.3
Other services	10.8	14.7	14.6
Public administration	2.9	3.7	7.0

Table 3. Average Monthly Unemployment Rates for YLS and CPS, Different Groups, April 2020–February 2021

VI.C. Estimates of Changes in Labor Market Status

Because the Yale Labor Survey was conducted weekly, it provided near contemporaneous information on the state of the labor market during the pandemic. A good way to assess the YLS's performance is to examine *monthly* changes in YLS data occurring between weeks when CPS data were also available (that is, the weeks containing the 12th of each month). The four panels of Figure 3 display these changes from August 2020 (when the YLS research team began using the "final" survey-weighting strategy) to February 2021.

Figure 3(a) shows the work-for-pay ratio (WFPR). The changes are highly correlated across the two surveys. Both the CPS and YLS capture the strong growth in the WFPR that occurred from August through October 2020, as initial pandemic lockdown orders were relaxed. Both surveys also show mild declines in the WFPR from November through January 2021, with positive growth returning in February.

Figure 3(b) shows the employment-to-population ratio (EPR). The EPR differs from the WFPR in that the EPR includes workers who are absent from their jobs for reasons such as vacation or illness. The CPS-YLS agreement for the EPR is not as close as for the WFPR in the previous panel. This likely arises because WFPR is a simpler concept and easier to measure than EPR. As explained below, subtle differences in how the YLS and CPS both define absences and obtain information on absences allow for more disagreement in EPR measures across the two surveys.

Figure 3(c) displays results for the unemployment rate (UR). Both the CPS and the YLS report large declines in the UR from August through October, when employment was growing rapidly (using the U3-alt definition). The CPS-YLS agreement for the UR is worse than it is for the two employment-related measures. In November 2020, for example, the YLS UR rose by nearly two percentage points, while the CPS UR declined somewhat. The final panel in Figure 3(d) shows that month-to-month changes in the labor force participation rate (LFPR). These line up poorly largely because of discrepancies in measurement of the UR

Why does the YLS match the CPS more closely with the WFPR and EPR than with the UR and LFPR? Part of the UR discrepancy undoubtedly stems from the additional complications that arise when measuring *unemployment* as compared to *employment*. Measuring *unemployment* requires that the survey instrument not

only discern whether a non-employed person is searching for a job, but also whether this search is an *active* rather than *passive* one, because only active searches can lead directly lead to job offers. Additionally, the concept of "layoff" has evolved over time and is particularly ambiguous during a pandemic. When a restaurant shuts down in March 2020 and the employer tells workers that it will be only a short shutdown, does the worker consider this a temporary layoff? To the extent that interview surveys like the CPS and self-administered internet surveys like the YLS treat subtle labor market concepts differently, unemployment rates in the two types of surveys may well differ.

A key innovation of the YLS is that its weights balance the sample with respect to *past labor market status* as well as standard demographic factors such as race and age. The good news is that using previous labor market status goes a long way to correcting the bias from unobserved factors. As we will see, adding the previous labor market status of respondents to the list of factors that determine our sample weights significantly improves the match between the CPS and YLS for all of the main employment series it estimates, including the UR and LFPR. But for the EPR and WFPR, the resulting match is very good, as evidenced by the first two panels of Figure 3.

Work-for-Pay Ratio
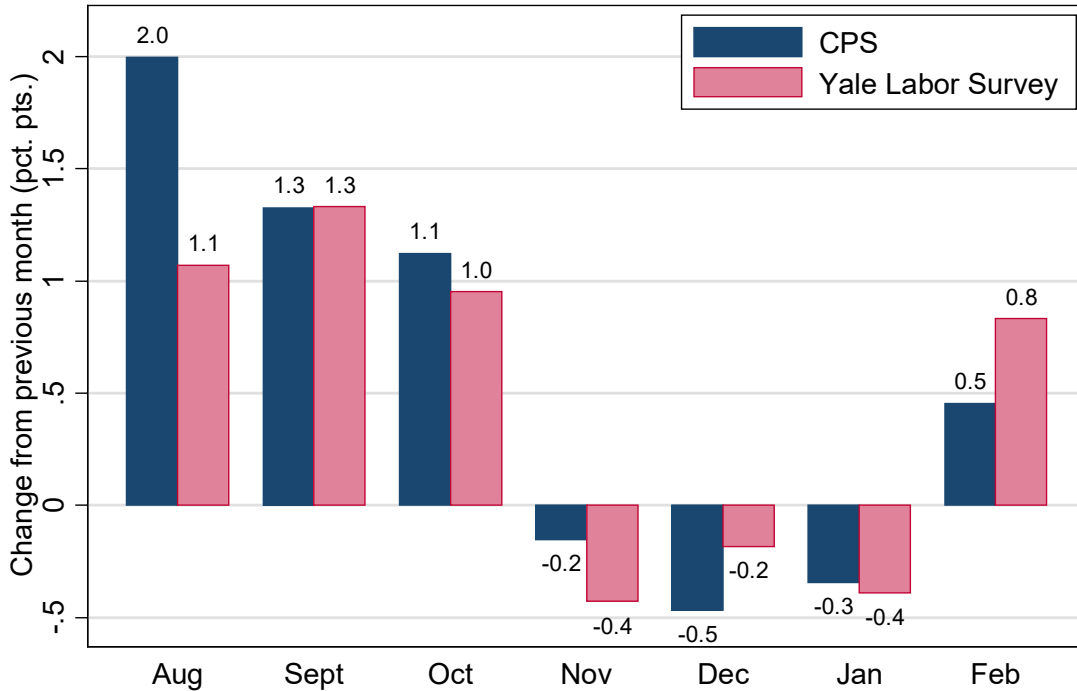
Note: YLS weight is FINWT1. Data are not seasonally adjusted and correspond to ages 20+.

Employment-to-Population Ratio
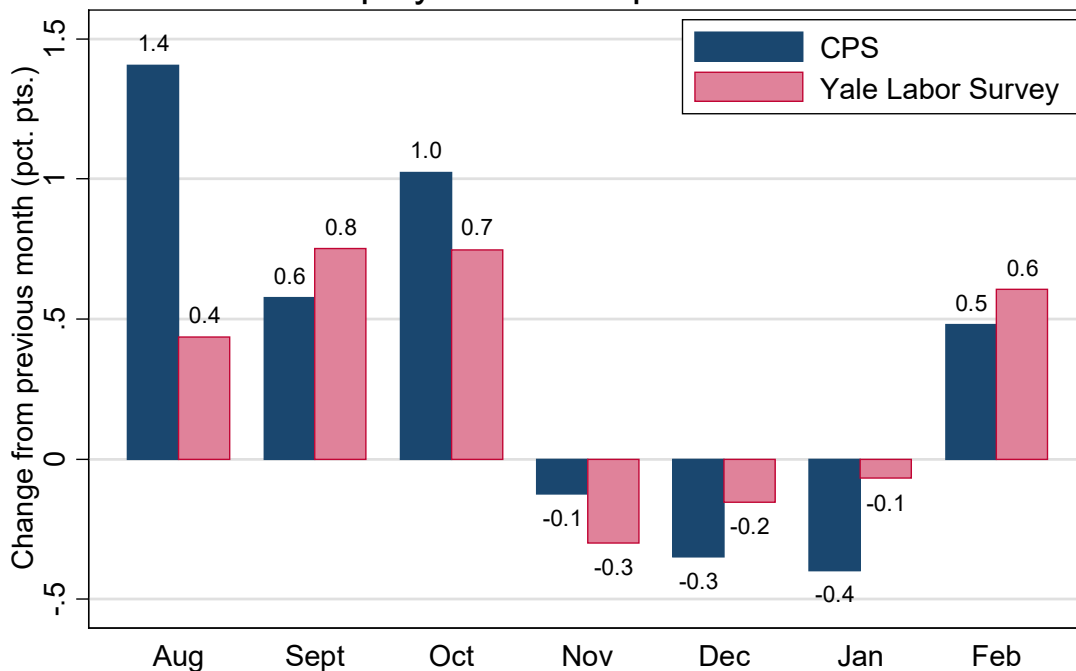
Note: YLS weight is FINWT1. Data are not seasonally adjusted and correspond to ages 20+.
CPS observations classified as employed but 'absent for other reasons' are not included in the CPS results.

Figure 3(a) and (b). Comparison of Changes in Work for Pay and Employment by Month in CPS and YLS
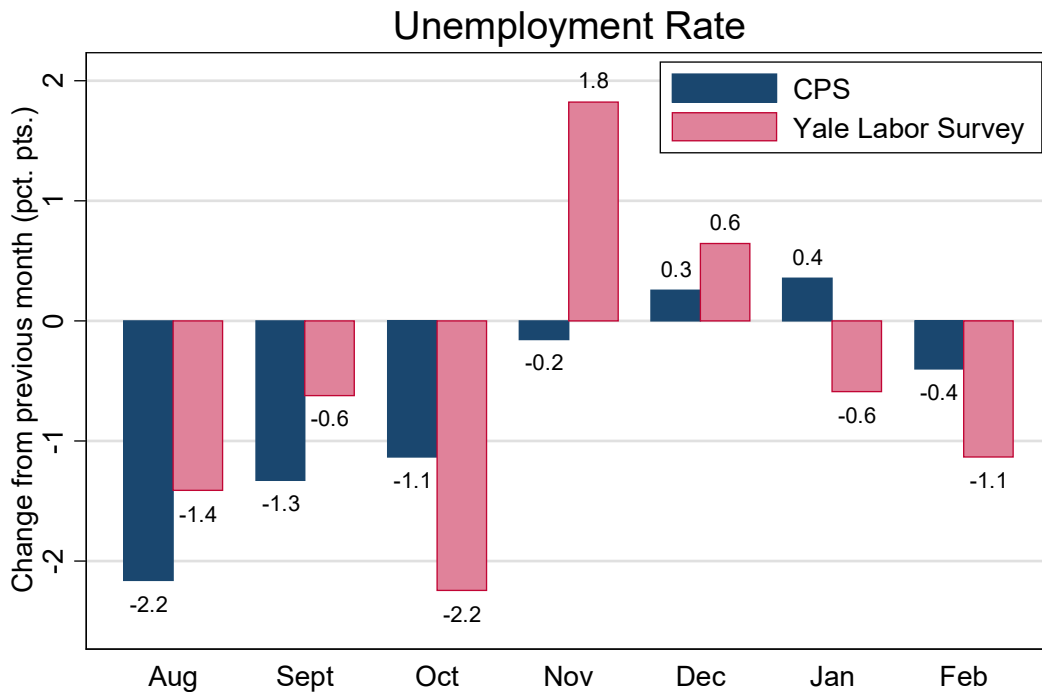
Unemployment Rate

Note: YLS weight is FINWT1. Data are not seasonally adjusted and correspond to ages 20+.
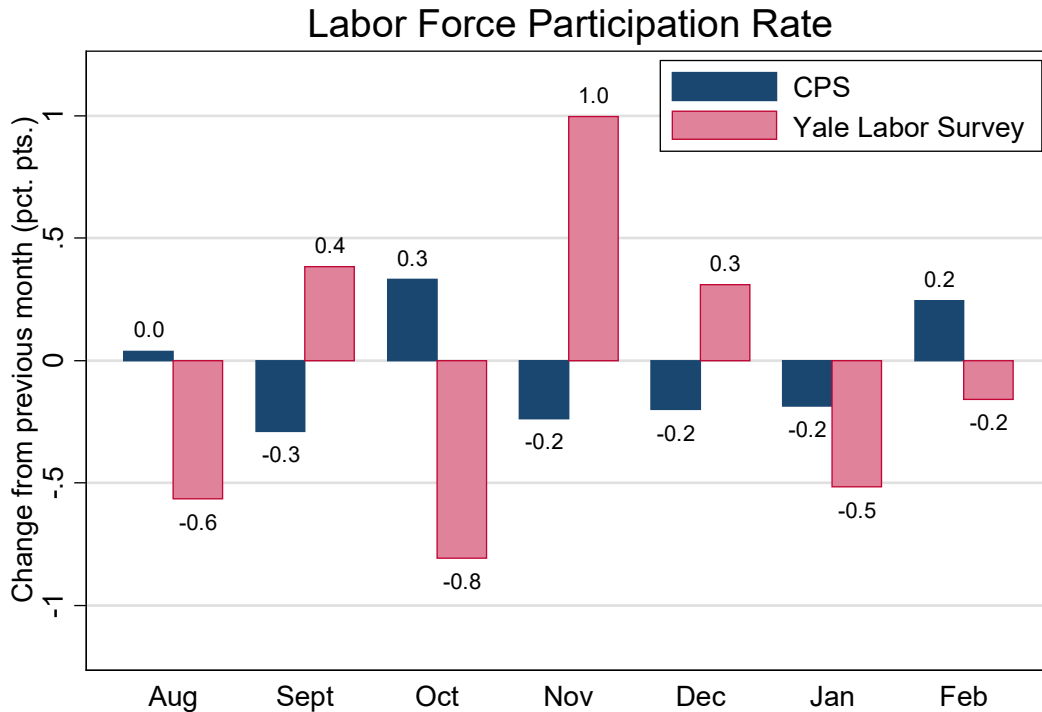CPS observations classified as employed but 'absent for other reasons' are included in the CPS results.

Labor Force Participation Rate

Note: YLS weight is FINWT1. Data are not seasonally adjusted and correspond to ages 20+.

Figure 3(c) and (d). Comparison of Changes in Unemployment and Labor Force Participation by Month in CPS and YLS
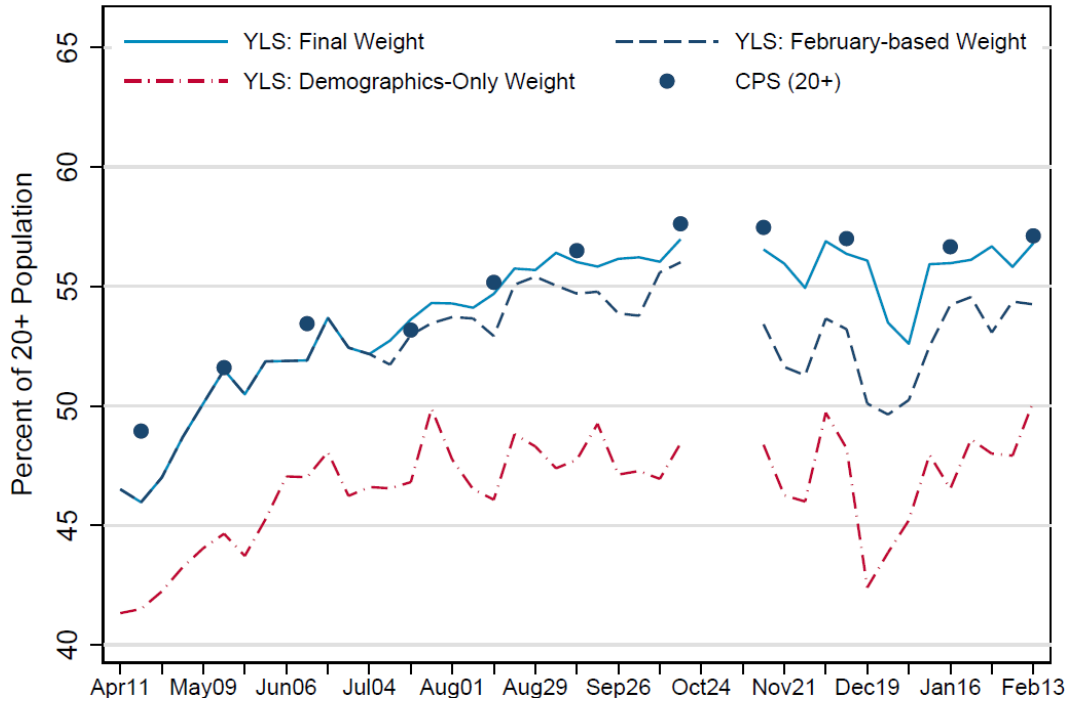
VI.D. Estimates Using Different Weights

We have constructed different weighting models. Figure 4 shows the results using four different weights for the YLS and compares those with the results for the CPS. The four YLS weights are demographic weights and two sets of labor market weights (February and "final" which use recent months). Additionally, these show the standard CPS version of U3 unemployment as well as our modified U3 version.

Several points are clear in the figures:

- The demographic weights fare poorly in most cases. This is, as explained above, likely to arise because of unobserved variables that are important for labor market behavior, such as disability.
- The February labor market weights do reasonably well in the early part of the period but diverge increasingly from the CPS in the later part of the year. The reason is that February status becomes increasingly obsolete as time passes.
- The final labor market weights (reflecting labor market status in each of the cells in the last two months) track the actual CPS relatively closely. This is particularly true for the employment and work-for-pay data. However, the final weights tend to overestimate the CPS U3 throughout most of the period, although they are reasonably accurate at tracking U3-alt in the early months of 2020.
- The results for the labor force participation rate (LFPR) are parallel to the results for unemployment, tending to overpredict because of the overestimate of the unemployment rate.

The clear conclusion of the data shown in Figure 4 is the critical importance of including labor market experience in raking the data. Demographic data alone do a relatively poor job in tracking the CPS.
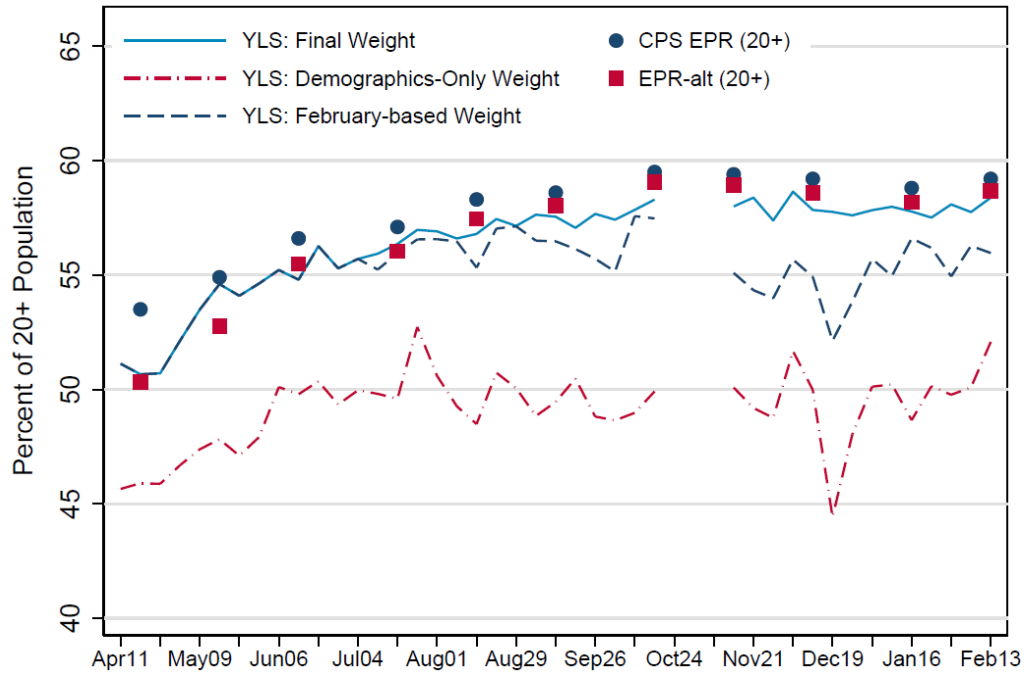
Figure 4(a) and 4(b). Comparison of Estimates on Employment for Different Weights

Unemployment Rate
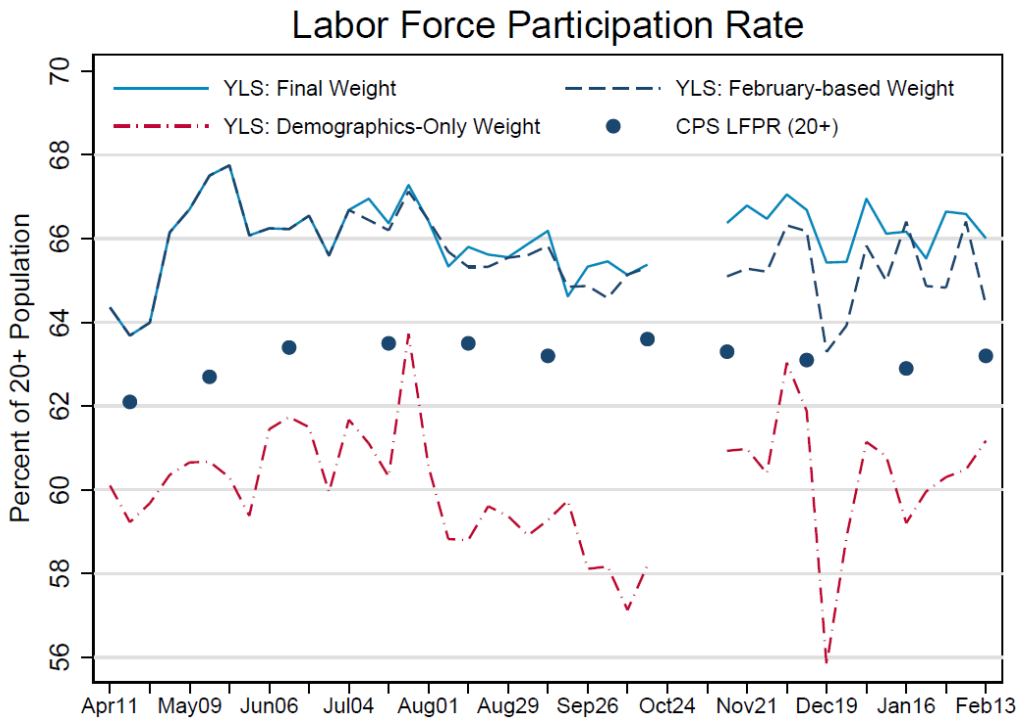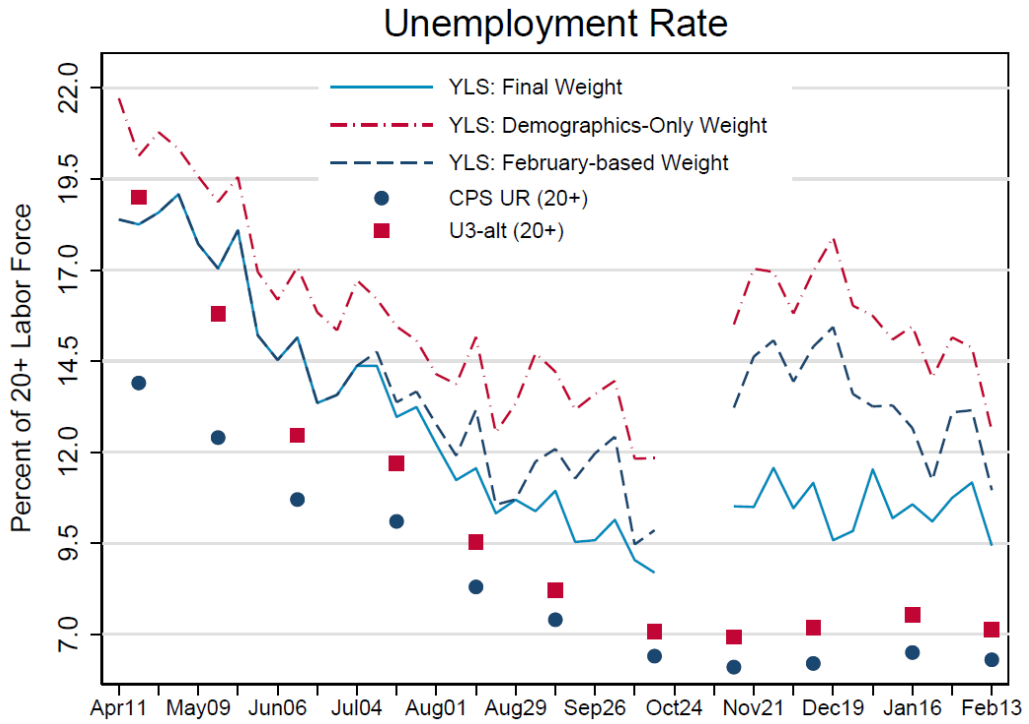
Labor Force Participation Rate

Figure 4(c) and 4(d). Comparison of Estimates on Unemployment and Labor Force Participation for Different Weights

VII. Further Results

The YLS has many interesting findings for the pandemic period. Section A samples a few of the nuggets from the surveys. Subsequent sections discuss the gig economy.

VII.A. Some Nuggets from the YLS

The YLS contains many interesting nuggets that illustrate the impact of the 2020 pandemic on the labor market. Here are a few.

Work at home or the office? Many workers who normally worked outside the home started to work remotely as the effects of the pandemic spread. How large were the numbers? We asked where respondents worked during the survey year. We found that only 54% responded that they worked entirely outside the home, while another 11% responded they work both home and outside.

Why absent from job? The YLS asked respondents about the reasons they were absent from work, adding pandemic-related questions to the normal ones in the CPS. It was interesting that only a small fraction of respondents listed child-care problems as a reason for absence. However, close to 40% listed, "I was temporarily absent from a job due to the coronavirus." Additionally, 6% said they were absent because of illness in their family, and 12% said they were absent because of their own illness.

When last worked? Several questions queried people about when they lost their last jobs. About 1% of respondents who had ever worked replied that they last worked in each month from May 2019 to February 2020, though 5% lost their job in February 2020. There was a huge jump in job losses in March 2020, when about 24% of respondents reported losing their jobs. Since that time, the rate of job loss has been about 3% per month, declining from 6% in April 2020 to 1.3% in January 2021.

Why lost job? The YLS asked people why they lost their jobs if they were employed prior to the onset of the pandemic. Of those who responded in April of 2020, 70% of workers said they lost their job because their firm reduced workers or hours because of COVID-19. That sharply decreased to 50% by August of 2020 and has steadily decreased to about 44% as of February 2021.

Answering internet surveys as a job. One of the issues with the YLS is that people might think that answering surveys represents "work for pay or profit." While this is a reasonable answer, we know that respondents are definitely biased toward people who respond to internet surveys (since they all do!). To test the extent to which this might bias the responses, we directed respondents that they should not consider internet surveys as a job. Starting in wave 21, we queried respondents on this issue. With targeted questions, we determined that the fraction of the population which responded "yes" to the work-for-pay answer increased consistently by 1.4% from respondents whose only job was answering internet surveys. We were unable reliably to classify these individuals as unemployed or not in the labor force, but we note that the number of employed is slightly overestimated in the survey and apply a -1.4% correction to our employment measures to diminish the bias.

Gender. There have been concerns that the CPS does not incorporate current views of gender. We therefore asked about both binary gender and a larger group of gender categories (N = 54,000). We found that 96.8% reported consistent binary gender on both the "Gender" and the "Gender7" question. Of the sample, 0.79% reported non-binary gender, and 1.11% reported inconsistent binary gender (all weighted values). Experience with the panel suggests that this level of inconsistency is about the same as that found for the traditional two-category gender question. The labor force status of the non-binary gender groups tended to have higher labor force participation, but that was largely due to the younger age of that group.

Hours yesterday. One interesting calibration question was the query to ask how many hours each respondent worked yesterday, which was asked of those who worked for pay. The mean response over the year was 7.2 ($\pm$ 0.2) hours for those working for pay. This is 3.8 hours per adult when corrected for those not working for pay. The American Time Use Survey (ATUS) for 2019 reported an average of 3.6 hours per adult (U.S. Bureau of Labor Statistics, 2020). This is a remarkably close figure given the simplicity of the YLS question.

VII.B. Self-employment and "Gig-Economy" Work

We also investigated the number of self-employed workers in the YLS sample. The CPS includes a "class of worker" characterization that includes wage and salary workers, self-employed workers, and unpaid family workers. Counting both the incorporated and unincorporated self-employed in the self-employment

category, slightly more than 10% of employed persons have been self-employed over the last several years in the CPS.

This figure is close to the rates of self-employment in the YLS data, which we measured by asking people who worked for pay about their type of employer. We asked respondents whether they were "self-employed," and 13% of weighted respondents selected this answer, a figure slightly above the CPS self-employment rate.[17]

A separate YLS question asked workers to classify themselves using different categories than the class-of-worker question in the CPS. Respondents could note that they were working "for myself in my own firm," that they were a "contract or gig economy worker," or that they were "working for a wage or salary at a firm or other employer." For all waves that included this question, 15% of working respondents said they were working for themselves in their own firm, while another 11% said they were gig-economy workers.

As other researchers attempting to measure the "gig economy" have found, it can be difficult to match up workers conceptions of their jobs with CPS concepts. Many workers might consider themselves gig-economy or self-employed when presented with one set of potential answers, but call themselves wage-and-salary workers when presented with a different set of answers. Even the legal definitions and tax-law definitions regarding employment are complex and may not easily be understood by those who are not typical W2 employees.

VIII. Comparison with Other Studies

Many studies are forecasting U.S. labor market characteristics, but few are tracking labor market responses in real-time. As of the date of the report, other than the CPS and the present study, we are aware of six other surveys that examine labor-market dynamics in the COVID period.

The three main other studies published to date are by Olivier Coibion, Yuriy Gorodnichenko, and Michael Weber (2020, CG&W), which relies on the Nielsen Homescan panel; a survey by Alexander Bick and Adam Blandin (2021, RPS), which relies on a Qualtrics panel; and a Census Bureau panel, the Household Pulse Survey (2021, HPS), which began April 23.

---

[17] For more on the effects of high self-employment and multiple-jobholding rates in online surveys of the labor market, see Katz and Krueger (2019).

1. The CG&W study relies on a panel that was fielded earlier in 2020 with employment questions and then was administered over the period April 2–6, 2020. The employment-population ratio in the CG&W study in April 2020 was 52%, similar to the 52.1% in the YLS (20+) and close to the April CPS estimate of 53% (ages 18+, not seasonally adjusted). The CG&W-estimated LFPR dropped by 7.5 percentage points between January and April, and the unemployment rate in the CG&W study in early April 2020 was 6.3%, far below both the YLS and the CPS. The discrepancy may result from CG&W's definition of unemployment (those on layoff not looking for work are all classified as NILF). There has been no update to CG&W at the time of writing.

2. *The Real-Time Population Survey* (RPS) by Bick and Blandin, in collaboration with the Federal Reserve Bank of Dallas, covers virtually the same period as the YLS. RPS reports results among those aged 18–64. In October 2020, RPS introduced a new weighting procedure which greatly improved the accuracy of their estimates.

Both YLS and RPS have on average overestimated unemployment. In April 2020, the YLS estimated unemployment at 17.7% (18–64), slightly under the CPS U3-alt estimate of 19.1%, while RPS underestimated by 7.5 percentage points. Both the YLS and RPS tracked the ensuing decrease in unemployment throughout 2020, albeit with positive error: from May to October, the YLS overestimated CPS U3-alt by an average of 1.4 percentage points, while RPS overestimated CPS U3-alt by an average of 2.2 percentage points. RPS's unemployment rate error has been widening since roughly August, and YLS's unemployment error jumped in November. From November 2020 to January 2021, RPS's average unemployment rate has been 11.1%; YLS has averaged 10.3%; both are well above CPS' U3-alt average of 7.2%.

In April 2020, RPS found a 62% employment-population ratio (18–64) compared to 61% in YLS and 63% (59% using the U3-alt definition) among those aged 18–64 in CPS. As the CPS the employment-population ratio increased from its April low to its current level around 69–70% (18–64), both YLS and RPS have tracked this increase relatively closely. YLS has come closer to CPS in most months, undershooting EPR (alternate definition) by an average of 0.5 percentage points since June; RPS estimates of EPR fall just below those of YLS in most months, thus undershooting CPS by an average of 0.7 percentage points. The EPR estimated by the CPS and YLS leveled out or even fell slightly since October, averaging 70% (69.5% alt) and 69.0%, respectively; RPS-estimated EPR jumped

to 70% in November, then decreased to a near-constant 68.6%, averaging 68.9% in the same period overall.

3. The Census-administered *Household Pulse Survey* (HPS) of the population age 18+ has been published for 24 weeks since April 23–May 5 and has been through three revisions. The third phase of the survey concluded on March 1, 2021. The HPS tracks several variables and is particularly useful in rapid estimation of employment (disregarding those absent from a job). It has posed a "work for pay" question similar to the CPS and the YLS since its inception. The estimates of the work-for-pay ratio in the HPS are close to those of the CPS for the CPS survey weeks (within 1% to 1.5% on average). HPS estimates also closely track YLS estimates throughout the period. Its Phase 2 deployment, from August 19, 2020 till October 28, 2020, showed the most deviation from the CPS and YLS. The proportion of the total population that worked for pay was consistently about 2% higher than the CPS and YLS during this period.

However, the HPS does not attempt to calculate unemployment. So there is no comparison between the HPS and other surveys on the labor force or the unemployment rate.

In addition, three other surveys offer useful points of comparison: the COVID Impact Survey, sponsored by the Federal Reserve Bank of Minneapolis and the Data Foundation (Abigail Wozniak, Joe Willey, Jennifer Benz, and Nick Hart, 2020); a survey by Abi Adams-Prassl, Teodora Boneva, Marta Golin, and Christopher Rauh (2020); and one by the Pew Research Center (2020).

4. The COVID Impact Survey, sponsored by the Federal Reserve Bank of Minneapolis and the Data Foundation, found for April 2020 that 47% of people worked for pay, close to the YLS result of 46% from the same week. At the beginning of May 2020 and June 2020, COVID Impact finds work-for-pay rates of 49% and 51%, respectively; YLS results are similar, with 51.3% in May and 51.8% in June 2020. In addition, COVID Impact estimates that 21% of those who did not work for pay were temporarily laid off/furloughed and 44% are retired, compared to 19% and 37% in YLS, respectively.

5. Adams-Prassl et al. conducted the second wave of their U.S. survey on April 9–11, 2020, in which 18% of respondents (unweighted) report having lost their jobs within the last four weeks due to the coronavirus. In YLS for the same reference period, 18% (weighted) of respondents stopped working in March or April 2020 at the time.

6. The 2020 Pew Research Center's American Trends Panel's 65th wave was recorded on April 7–12, 2020. In that survey, 54% of respondents described themselves as employed full-time or part-time, compared to the 52% employment-population ratio of YLS. To our knowledge, Pew has not fielded questions assessing labor force status since.

Reviewing the main studies finds the following summary. The CG&W uses a simpler definition of unemployment (must be looking for work) and thus likely classifies as NILF many people which CPS and YLS would count as unemployed. We believe that the major differences among YLS, RPS, and HPS arise from the weighting of the different panels. The RPS uses a Qualtrics panel, while the HPS uses a rotating panel with person-level weights. The weights in the HPS were adjusted for non-response and housing unit occupancy and then raked to match population controls from the American Community Survey and Census data. However, while the HPS has a well-designed sample frame, the response rate was so low (about 4% of invitations) that the results are likely to contain substantial non-response error.

Moreover, the sample size varies among the studies. The sample size of the RPS is roughly 2,000 per wave for 18 waves; the sample size of CG&W was 13,895; the HPS has collected between 70,000 and 110,000 responses per "week" for 18 weeks (collection periods); and the YLS has a total of 117,000 respondents. COVID Impact has 2,100 nation-level observations per wave, while the Pew Research Center April 7–12 survey has a sample size of 4,917.

IX. Accuracy of the Estimates

IX.A. Total Survey Error

As with other surveys, there are several reasons why unemployment and participation estimates generated by YLS could differ from underlying population values. Often called "total survey error," they come from several sources: sampling error, non-response error, errors from differences in questionnaires and question wording, errors from interviewer vs. self-administered survey, and respondent error. (Lohr, 2010) The first type, sampling error, is easily calculated. The standard error of the estimate of the

unemployment rate for weeks ranges from 0.7% for the CPS survey weeks to 2.8% for non-survey weeks.[18]

However, as in most surveys, non-sampling error, or bias, is likely to be a more important concern. A particular issue for online surveys is potential unrepresentativeness of the panel. Weighting adjustments attempt to remove selection bias related to observed variables.[19] For the YLS survey, weighted estimates exhibited substantially less bias than unweighted estimates. For all surveys through February (N = 117,000), the unemployment rate averaged 16.4% for the unweighted sample and 12.1% for the weighted sample. Similarly, the employment-population ratio is 9 percentage points higher in the weighted than the unweighted sample.

This difference between weighted and unweighted estimates reflects the fact that the respondents in the YouGov online panel tend to have relatively more people unemployed and relatively fewer people employed than the weighted panel, even after controlling for demographics and recalled past employment status. The weighting procedure described in section III is designed to correct for such biases.

A third source of error in comparing the YLS to the CPS is survey-design error, or the extent to which the survey questions and procedures accurately reflect those in the CPS. The team has performed extensive testing, particularly for the components of unemployment, and has found no major errors in the questions or responses. For example, we have probed the search numbers and techniques, and these have been reasonably close to the details provided in the CPS.

IX.B. Internal Consistency on Retest

A useful and easily calculated measure of survey error is the stability of the surveys, sometimes called reliability. Technically, we are measuring the reliability of recall in terms of the consistency of answers on retest. (See Lohr 2010, Chapter 13) The YLS has 25,018 duplicate responders, accounting for 77,637 of the 117,000 responses through wave 90. We tested the consistency of the responses for those age 20 and over. We expect some to be relatively accurate (age and

---

[18] The present document uses standard statistical language. Often survey researchers use the term "margin of error," which is two times the standard error of estimate.
[19] Post-stratification weighting can also improve efficiency, but the main motivation is to remove bias.

gender), while others are more taxing (such as retrospective employment status). Table 4 provides a tabulation of major variables for the duplicates. Most of the elementary answers are consistent. However, occupation and industry are highly inconsistent.

A key question is whether the recall of labor force status is accurate. Retrospective questions about work for pay in previous months are surprisingly consistent, reporting a different answer about 7% of the time. By contrast, those reporting "did not work" had higher error rates, between 12% and 15% in the cases examined. Errors in recall status pose problems because the raking/weighting of respondents is based in part on the retrospective estimates of labor force status. Preliminary estimates indicate a downward bias in the retrospective estimate of unemployment compared to the current estimate in the month of recall (these being calculated for duplicate respondents). This would lead to an upward bias in the estimated YLS unemployment rate because the retrospective labor force status is used to calculate the weights.

Appendix G shows how a bias in retrospective labor market status will bias the estimates in the YLS. It suggests that, for a highly simplified analysis, the bias in the retrospective responses may lead to a systematic upward bias of around 1½ percentage points in the YLS survey. Further research is needed to determine if this bias can explain the systematic bias and whether it can be corrected.

Question	Inconsistent answers
Demographics	
Gender	0.4%
Race	3.5%
Age	4.8%
Religion	5.4%
Education	6.7%
Location and occupation	
State	1.8%
Device	9.2%
City / suburb / town/ rural	9.6%
Income bracket	10.1%
Industry	33.1%
Occupation	34.3%
Recalled status	
Worked for pay - Feb 2020	6.8%
Worked for pay - Jun 2020	7.0%
Worked for pay - Jul 2020	6.4%
Worked for pay - Aug 2020	6.1%
Worked for pay - Sep 2020	5.9%
Status if did not work Feb 2020	11.8%
Status if did not work Jun 2020	15.3%
Status if did not work Jul 2020	15.2%

Table 4. Consistency of Test-Retest

The table shows the fraction of the time that the same question was answered differently by the same respondent.

References

Aaronson, Daniel, Scott A. Brave, R. Andrew Butters, Daniel Sacks, and Boyoung Seo (2020). "Using the Eye of the Storm to Predict the Wave of Covid-19 U.I. Claims." Federal Reserve Bank of Chicago, Working Paper no. 2020-10. https://doi.org/10.21033/wp-2020-10.

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh (2020)."Inequality in the impact of the coronavirus shock: Evidence from real time surveys." IZA – Institute of Labor Economics, Discussion Paper no. 13183. http://ftp.iza.org/dp13183.pdf.

Bernstein, Joshua, Alexander W. Richter, Nathaniel A. Throckmorton (2020). "COVID-19: A View from the Labor Market." Federal Reserve Bank of Dallas, Working Paper no. 2010 (April). https://doi.org/10.24149/wp2010.

Bick, Alexander, and Adam Blandin (2021). "Real-Time Labor Market Estimates During the 2020 Coronavirus Outbreak." Unpublished Manuscript, Arizona State University. https://sites.google.com/view/covid-rps/home.

Biemer, Paul P. and Gosta Forsman. "On the Quality of Reinterview Data with Application to the Current Population Survey." *Journal of the American Statistical Association* 87, no. 420 (1992): 915-23. Accessed March 5, 2021. doi:10.2307/2290627.

Brynjolfsson, Erik, John Horton, Adam Ozimek, Daneil Rock, Garima Sharma, and Hong Yi Tu Ye (2020). "COVID-19 and Remote Work: An Early Look at U.S. Data." NBER, Working Paper no. 27344 (June). https://doi.org/10.3386/w27344.

Canty, Angelo J. and Anthony C. Davison (1999). "Resampling-Based Variance Estimation for Labour Force Surveys." *Journal of the Royal Statistical Society,* Series D, vol. 48 (September), pp. 379-391.

Castro, Miguel Faria (2020). "Fiscal Policy during a Pandemic." Federal Reserve Bank of St. Louis, Working Paper no. 2020-006G. https://doi.org/10.20955/wp.2020.006.

Centers for Disease Control and Prevention (2020). "Disability Impacts All of Us." https://www.cdc.gov/ncbddd/disabilityandhealth/infographic-disability-impacts-all.html.

Chang, Ted and Phillip S. Kott (2008). "Using Calibration Weighting to Adjust for Non-response under a Plausible Model." *Biometrika*, vol. 95 (September), pp. 555-571.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber (2020). "Labor Markets during the COVID-19 Crisis: A Preliminary View." NBER, Working Paper no. 27017 (April). https://doi.org/10.3386/w27017.

DeBell, Matthew, Jon A. Krosnick, Katie Gera, David S. Yeager, and Michael P. McDonald. "The turnout gap in surveys: Explanations and solutions." *Sociological Methods & Research* 49, no. 4 (2020): 1133-1162.

Deming, W.E., and Frederick F. Stephan (1940). "On a Least-Squares Adjustment of a Sampled Frequency Table When the Expected Marginal Totals are Known." *The Annals of Mathematical Statistics*, vol. 11 (December), pp. 427-444.

Gittelman, Steven H., Randall K. Thomas, Paul J. Lavrakas, and Victor Lange (2015). "Quota controls in survey research: a test of accuracy and intersource reliability in online samples." *Journal of Advertising Research*, vol. 55 (December), pp. 368-379.

Foote, Christopher, William D. Nordhaus, and Douglas Rivers (2020). "The U.S. Employment Situation Using the Yale Labor Survey." Cowles Foundation Discussion Paper 2243, July, New Haven, CT.

Ireland, C. Terrance, and Solomon Kullback (1968). "Contingency Tables with Given Marginals." *Biometrika,* vol. 55 (March), pp. 179-188.

Katz, Lawrence F. and Alan B. Krueger (2019). "Understanding Trends in Alternative Work Arrangements in the United States," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, no. 5 (2019): 132-146.

Kennedy, Courtney, Andrew Mercer, Scott Keeter, Nick Hatley, Kyley McGeeney and Alejandra Gimenez (2016). *Evaluating Online Nonprobability Surveys*, Pew Research Center.

Little, Roderick J.A., and Donald B. Rubin (2019). *Statistical Analysis with Missing Data,* 3rd ed. Hoboken, NJ: Wiley.

Little, Roderick J.A., and Mei-Miau Wu (1991). "Models for Contingency Tables with Known Margins When Target and Sampled Populations Differ." *Journal of the American Statistical Association*, vol. 86 (March), pp. 87-95.

Lohr, Sharon L. (2010). *Sampling: Design and Analysis (Advanced Series),* 2nd ed. Boston: Brooks/Cole.

Pew Research Center (2019). "Response rates in telephone surveys have resumed their decline." https://www.pewresearch.org/fact-tank/2019/02/27/response-rates-in-telephone-surveys-have-resumed-their-decline/.

Pew Research Center (2020). "About Half of Lower-Income Americans Report Household Job or Wage Loss Due to COVID-19." https://www.pewresearch.org/social-trends/2020/04/21/about-half-of-lower-income-americans-report-household-job-or-wage-loss-due-to-covid-19/.

Şahin, Ayşegül, Murat Tasci, and Jin Yan (2020). "The Unemployment Cost of COVID-19: How High and How Long?" *Economic Commentary* (Federal Reserve Bank of Cleveland) (May 7), pp. 1-7. https://doi.org/10.26509/frbc-ec-202009.

Silver, Nate (2021). "The Death of Polling is Greatly Exaggerated," retrieved March 25, 2021 (https://fivethirtyeight.com/features/the-death-of-polling-is-greatly-exaggerated/).

Sudman, Seymour and Brian Wansink (2002). *Consumer Panels*, 2nd ed. Chicago: American Marketing Association.

U.S. Bureau of Labor Statistics (2020). "CPS and COVID-19," February, 2020, downloaded from https://cps.ipums.org/cps/covid19.shtml.

U.S. Bureau of Labor Statistics (2020). "Table A-1. Time spent in detailed primary activities and percent of the civilian population engaging in each activity, averages per day by sex, 2019 annual averages." https://www.bls.gov/tus/a1-2019.pdf.

U.S. Bureau of Labor Statistics (2021a). "Household survey response rates." https://www.bls.gov/osmr/response-rates/household-survey-response-rates.htm.

U.S. Bureau of Labor Statistics (2021b). "Persons With Disability: Labor Force Characteristics – 2020." https://www.bls.gov/news.release/pdf/disabl.pdf

U.S. Census Bureau (2019). *Current Population Survey Design and Methodology: Technical Paper 77*. https://www2.census.gov/programs-surveys/cps/methodology/CPS-Tech-Paper-77.pdf

U.S. Census Bureau (2021). "Household Pulse Survey: Measuring Social and Economic Impacts during the Coronavirus Pandemic." https://www.census.gov/programs-surveys/household-pulse-survey.html.

Wozniak, Abigail, Joe Willey, Jennifer Benz, and Nick Hart (2020). "COVID Impact Survey: Version 3 [dataset]." Chicago: National Opinion Research Center.

Yeager, David S., Jon A. Krosnick, LinChiat Chang, Harold S. Javitz, Matthew S. Levendusky, Alberto Simpser, and Rui Wang (2011). "Comparing the accuracy of RDD telephone surveys and internet surveys conducted with probability and non-probability samples." *Public opinion quarterly*, vol. 75 (November), pp. 709-747.

Measuring the US Employment Situation Using Online Panels:
The Yale Labor Survey
April 14, 2021
[YLS-Report-April-041421-appendix.docx]

APPENDICES

Appendix A. Details on Methods for Calculating Unemployment

This appendix describes the approach used by the YLS to assign respondents to E (employed), U (unemployed), and NILF (not in the labor force). Like the CPS, our survey divides the US population into these three groups through a series of sequential rules. The key questions and responses are contained in Appendix F.

- **Employed** persons either worked for pay in the reference week (WORKFORPAY = YES) or answered that they still received pay even though they did not work during the reference week (WORKSITUATION_WORKING = 3 or 4). The "work-for-pay" question is common with the CPS and represents the bulk of employed workers.

- **Unemployed** persons are those that did not work for pay during the reference week but still met two alternative conditions for the CPS's definition of unemployment. To be unemployed, someone who did not work for pay must satisfy one of the following requirements:

  - *Active search:* These respondents actively searched in the last four weeks (FINDWORK = 1) and were available for work within 7 days (AVAILABLE = 1),

  - *On layoff or furlough and expecting to return to job:* Respondents could signal this expectation in two ways: (1) One question (WORKSITUATION) asked non-working respondents to characterize their work situation. Respondents could signal recall expectation by selecting option 1: "Laid off or furloughed from a job to which you expect to return." Additionally, (2) respondents would need to respond "yes" to a separate question (RECALL), which asked, "If you recently lost your job, have you been given any indication that you will be recalled to work within the next 6 months?"[1]

- Persons who are **not in the labor force (NILF)** were neither employed nor unemployed.

---

[1] For a respondent selecting this option, we used another question to verify that the respondent did in fact lose a job within the past 12 months. This restriction had no material impact on the results.

Appendix B. Difference between BLS headline unemployment Rate and 20+ Rate

The YLS reports results for respondents 20 years and over, whereas the CPS also includes persons aged 16 to 19. Because 16 - 19 year-olds generally have high unemployment rates, the CPS's headline 16+ rate is always higher than its 20+ rate. This difference peaked in the 1970s and 1980s, and since that time has averaged about 0.4 percentage point. During the pandemic, the difference peaked in April and May 2020 at 0.5 and 0.6 percentage points, respectively. After May 2020, the gap between the 16+ and 20+ URs declined, equaling 0.3 percentage points in five of the six months from September 2020 to February 2021. Therefore, a reasonable correction would be to add 0.3 percentage points to the YLS unemployment rate for any direct comparison between this rate and the headline CPS rate.

Appendix C. The Problem of Measuring Absence from Work

In the first months of the pandemic, a significant issue arose in the CPS regarding workers *who are employed but absent from work*. Absent workers in the CPS are persons with jobs who do not work during the reference week because they are on vacation, sick at home, prevented from getting to work by bad weather, etc. Such absences can be either paid or unpaid.

Unfortunately, during the early months of the pandemic, many people considered themselves with jobs but "absent from work" because their employer has temporarily shut down. These people should not have been considered employed, but the structure of the CPS questionnaire caused millions of these workers to be included in the official employment category. Because these ostensible employment absences did not arise from usual reasons such as vacation or illness, they were grouped into an "other reasons" category.

To see how this misclassification arose, note that the CPS first asks respondents whether they worked for pay during the survey week. Respondents who answer "no" to the initial work-for-pay question are then asked whether they "had a job" during the survey week, including a job from which they were temporarily absent. Many persons displaced by the pandemic answered "no" to the initial work-for-pay question but "yes" when asked whether they had a job. These answers caused them to be classified as employed but absent from their jobs. An additional CPS question on the *reason* for absence should have prevented these displaced workers from being classified as employed-but-absent. Unfortunately, the unique nature of the coronavirus pandemic prevented this check from working as well as it should have. As a result, the coronavirus displacements were classified as employed but absent for "other reasons."

Because the YLS employment classification has a different structure, it is less susceptible to this classification error. The YLS first asks a work-for-pay question like the one in the CPS. It then follows up by asking all respondents to characterize their work situation. The YLS's "work-situation" question asks respondents if they worked in their usual place, if they worked at a different location, if they did not work but still got paid, or if none of these situations applied. Persons are classified as employed in the YLS if they answer yes to the initial work-for-pay question or if they indicate in the work-situation question that they either worked for pay or received pay. The YLS definition therefore avoids the ambiguity of whether someone who did not work and did not get paid should be counted as employed because they had a job from which they were temporarily absent.

In FAQs published with employment reports for March through June 2020, the BLS suggested that one way to assess the degree of CPS classification error is

to reclassify as unemployed those persons who are recorded as employed but absent from their jobs for other reasons. The following is taken from the FAQ on the April 2020 CPS:

> Of the 11.5 million employed people not at work during the survey reference week in April 2020, 8.1 million people were included in the "other reasons" category, much higher than the average of 620,000 for April 2016–2019 (not seasonally adjusted). BLS analysis of the underlying data suggests that this group included workers affected by the pandemic response who should have been classified as unemployed on temporary layoff. Such a misclassification is an example of non-sampling error and can occur when respondents misunderstand questions or interviewers record answers incorrectly.[2]

We followed this suggestion (with some minor differences) to create the CPS U3-alt rate. Because the constructed CPS U3-alt rate corrects for the CPS classification error, it provides a more direct comparison with the unemployment rate in the YLS, where the CPS classification error is much less likely to occur.

In the early months of the pandemic, our estimated YLS unemployment rate tracked U3-alt closely. However, the size of the gap between the BLS calculation of U3 and U3-alt narrowed from around 5 percentage points in April 2020 to less than 1 percentage point by February 2021.

---

[2] The FAQ for the April Employment Situation Release can be accessed here: http://www.bls.gov/cps/employment-situation-covid19-faq-april-2020.pdf.

Appendix D. Detailed Results and Results by Demographic Group

1. Detailed results by week

Table D.1 shows the detailed results for months of the survey.

2. Results by demographic group

We have examined the summary statistics for the 128 demographic groups to compare the YLS and the CPS for months from February 2020 to January 2021. The results contain some surprises. The first and most important result is that the under-reporting of employment and over-reporting of unemployment is virtually universal across all demographic groups. Focusing only on the demographically weighted results, 93% of cells over-report unemployment. By contrast, the over- and under-reporting of employment is virtually equally balanced among the 128 cells.

Figures D-1 and D-2 provide some visual evidence on these points for the 10 most populous demographic groups. Figure D-1 shows that none of these groups over-report employment, while Figure D-2 indicates a widespread over-reporting of unemployment. Additionally, college graduates of both genders provide relatively reliable responses to both employment and unemployment. By contrast, persons in the high-school-or-less category tend to underreport employment substantially, yet are not particularly out of line on unemployment.
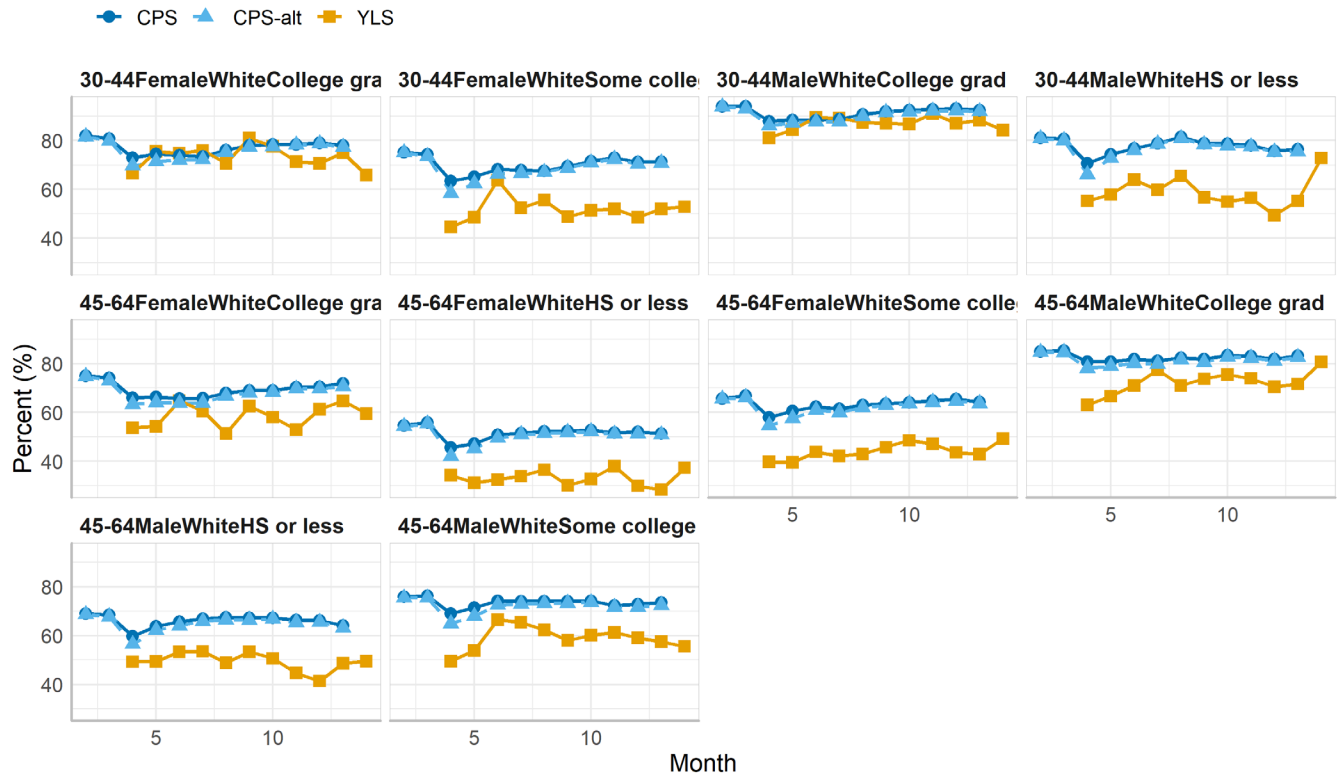
Summary Statistics, 20 years and over (Not Seas Adj), 2020-21

Month	Fraction of Population			Labor Market Status Rates		
	Employed	Unemployed	Not in Labor Force	Unemployment	Employment/ Population	Labor Force Participation
February						
CPS	63.0	2.3	34.8	3.5	63.0	65.2
CPS-alt	62.7	2.5	34.8	3.9	62.7	65.2
YLS-X	na	na	na	na	na	na
March						
CPS	61.8	2.7	35.5	4.2	61.8	64.5
CPS-alt	61.0	3.5	35.5	5.5	61.0	64.5
YLS-X	na	na	na	na	na	na
April						
CPS	53.5	8.6	37.9	13.9	53.5	62.1
CPS-alt	50.3	11.8	37.9	19.0	50.3	62.1
YLS-X	52.1	11.6	36.3	18.3	50.7	63.7
May						
CPS	54.9	7.7	37.3	12.4	54.9	62.7
CPS-alt	52.8	9.9	37.3	15.8	52.8	62.7
YLS-X	56.0	11.5	32.5	17.0	54.6	67.5
June						
CPS	56.6	6.8	36.6	10.7	56.6	63.4
CPS-alt	55.5	7.9	36.6	12.5	55.5	63.4
YLS-X	56.2	10.0	33.8	15.1	54.8	66.2
July						
CPS	57.1	6.4	36.5	10.1	57.1	63.5
CPS-alt	56.0	7.4	36.5	11.7	56.0	63.5
YLS-X	57.8	8.6	33.6	13.0	56.4	66.4
August						
CPS	58.3	5.2	36.5	8.3	58.3	63.5
CPS-alt	57.5	6.1	36.5	9.5	57.5	63.5
YLS-X	58.2	7.6	34.2	11.6	56.8	65.8
September						
CPS	58.6	4.7	36.8	7.4	58.6	63.2
CPS-alt	58.0	5.2	36.8	8.2	58.0	63.2
YLS-X	58.9	7.2	33.8	10.9	57.5	66.2
October						
CPS	59.5	4.0	36.4	6.4	59.5	63.6
CPS-alt	59.1	4.5	36.4	7.1	59.1	63.6
YLS-X	59.7	5.7	34.6	8.7	58.3	65.4
November						
CPS	59.4	3.9	36.7	6.1	59.4	63.3
CPS-alt	58.9	4.4	36.7	6.9	58.9	63.3
YLS-X	59.4	7.0	33.6	10.5	58.0	66.4
December						
CPS	59.2	3.9	36.9	6.2	59.2	63.1
CPS-alt	58.6	4.5	36.9	7.2	58.6	63.1
YLS-X	59.2	7.4	33.3	11.2	57.8	66.7
January						
CPS	58.8	4.1	37.1	6.5	58.8	62.9
CPS-alt	58.2	4.7	37.1	7.5	58.2	62.9
YLS-X	59.2	7.0	33.8	10.6	57.8	66.2
February						
CPS	na	na	na	na	na	na
CPS-alt	na	na	na	na	na	na
YLS-X	59.8	6.2	34.0	9.4	58.4	66.0

YLS-X estimates are for the CPS reference week. YLS Employment/Population is adjusted by -1.4 percentage points.

Table D-1. Basic results and comparison with CPS, March 2020 – February 2021

Employment-population ratio according to YLS and CPS (%),
top 10 populous demographic groups

- CPS   CPS-alt   YLS

30-44FemaleWhiteCollege gra **30-44FemaleWhiteSome colle** **30-44MaleWhiteCollege grad** **30-44MaleWhiteHS or less**

45-64FemaleWhiteCollege gra **45-64FemaleWhiteHS or less** **45-64FemaleWhiteSome colle** **45-64MaleWhiteCollege grad**

45-64MaleWhiteHS or less **45-64MaleWhiteSome college**

Percent (%)

Month

YLS weight used is based on demographics: wt_demo_20.
YLS EPR is adjusted by -1.4 percentage points.

Figure D-1. Monthly results for demographic weighting for employment-population ratio for 10 most populous of 128 demographic groups under age 65.

Unemployment rate according to YLS and CPS (%),
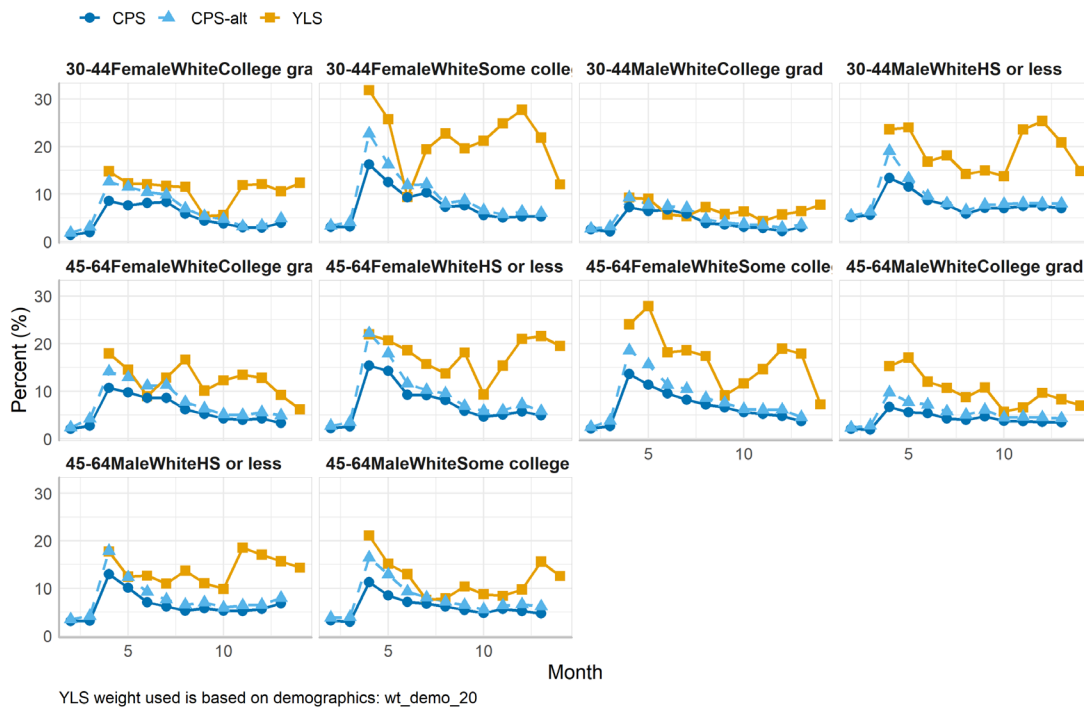top 10 populous demographic groups under age 65

YLS weight used is based on demographics: wt_demo_20

Figure D-2. Monthly results for demographic weighting for unemployment rate for 10 most populous of 128 demographic groups under age 65.

Appendix E. Construction of Weights Using Labor Market Status

The definition of demographic weights (age, education, race, marital status, gender, and children) is largely conventional. However, incorporation of labor market status into these weights requires data that are not easily obtained as well as decisions on how to use them.

The basic approach is to assume that prior labor market status (LMS) proxies for unobserved individual factors that help determine current LMS. For example, if an individual was retired in February 2020, we assume that it is likely that the person remains retired in later months. A similar assumption holds for disability, school attendance, and other reasons for being out of the labor force. Similarly, if a person was employed despite low employment probabilities in her demographic group, her relatively strong labor force attachment would be represented by higher-than-average employment status in the prior LMS, and therefore in the current month as well.

At the same time, it should be recognized that the value of prior LMS will erode over time. This erosion is most likely for students who graduate and enter the labor force. Similarly, some may change the LMS as the economy transitions from tight to weak labor markets, or the reverse in mid-2020.

We constructed two variants of prior LMS: February and later. In the early months of the survey, February labor market status was derived from answers provided by the respondent in the October 2019–February 2020 period, collected by YouGov as part of its data collection on its panel participants. Where these data were not available, the YLS asked a recall question about February 2020 labor market status and additional questions about the current status.

As time passed, the February 2020 status was becoming less relevant due to the erosion of information discussed above. Therefore, in July 2020, the YLS added questions on labor market status in months after February 2020 as well as February 2020. Starting in July 2020, we constructed "final weights" that reflect labor market activity in months that are closer to the survey period. As an example, the YLS weights for the December CPS week use labor market status in each cell averaged from the October and November 2020 CPS microdata. These final weights roll forward over time as new CPS microdata become available.

Table E-1 shows how updated information on labor market status in prior months was incorporated into the "final weights" used in YLS. The column labeled "Feb-based weights" are ones that balance the YLS respondents' labor market attachment in February 2020 to official CPS data for that month. The other

columns refer to weights that balance labor market status in June through November 2020 (months after November were incorporated in a similar way). The final weight for any given YLS week was a weighted average of two month-specific weights, with the importance of each month in this average reported in the appropriate row.

Reference Week Date	Feb-based weight	Jun-based weight	Jul-based weight	Aug-based weight	Sep-based weight	Oct-based weight	Nov-based weight
11-Apr-20	1.00						
18-Apr-20	1.00						
25-Apr-20	1.00						
2-May-20	1.00						
9-May-20	1.00						
16-May-20	1.00						
23-May-20	1.00						
30-May-20	1.00						
6-Jun-20	1.00						
13-Jun-20	1.00						
20-Jun-20	1.00						
27-Jun-20	1.00						
4-Jul-20	1.00						
11-Jul-20	0.75	0.25					
18-Jul-20	0.50	0.50					
25-Jul-20	0.25	0.75					
1-Aug-20		1.00					
8-Aug-20		0.75	0.25				
15-Aug-20		0.50	0.50				
22-Aug-20		0.25	0.75				
29-Aug-20			1.00				
5-Sep-20			0.75	0.25			
12-Sep-20			0.50	0.50			
19-Sep-20			0.25	0.75			
26-Sep-20				1.00			
3-Oct-20				0.75	0.25		
10-Oct-20				0.50	0.50		
17-Oct-20				0.25	0.75		
24-Oct-20					1.00		
31-Oct-20					1.00		
7-Nov-20					0.75	0.25	
14-Nov-20					0.50	0.50	
21-Nov-20					0.25	0.75	
28-Nov-20						1.00	
5-Dec-20						0.75	0.25
12-Dec-20						0.50	0.50
19-Dec-20						0.25	0.75
26-Dec-20							1.00

Table E-1. Construction of Final Weights in the Yale Labor Survey.

This table shows the weights used in FINWT1. FINWT2 uses the most recent weight available, not a weighted average of the past two months. For example, for the survey for November 7, 2020, FINWT1 uses a combination of September and October CPS microdata, with a 75% and 25% weight, respectively. FINWT2 is simply the October-based weight itself.

Appendix F. Raking in Theory

The procedure used to create weights is iterative proportional fitting or "raking," which was proposed by Deming and Stephan (1940) to balance samples on multiple characteristics. Raking requires only the marginal distributions of the control totals and can be computed quickly using the iterative proportional fitting (IPF) algorithm. This section describes the raking procedure followed here.

To fix ideas, first, consider cell weighting by a single covariate with K categories. The population proportion in category k is t_k and the number of sample respondents in category k is n_k, where $n_1 + \cdots + n_K = n$. The proportion of sample respondents in category k is $s_k = n_k/n$, so the ratio of population to sample proportions is $w(k) = t_k/s_k$. If respondent i is in category $x_i = k$, then they are assigned weight $w_i = w(x_i) = t_{x_i}/s_{x_i}$. It follows that

$$\sum_{i=1}^{n} w_i = \sum_{k=1}^{K} n_k \, w(k) = n \sum_{k=1}^{K} t_k = n$$

and the weighted proportion of sample observations in category k is

$$\hat{t}_k = \frac{\sum_{i=1}^{n} w_i \, \mathbf{1}(x_i = k)}{\sum_{i=1}^{n} w_i} = \frac{n_k \, w(k)}{n} = t_k,$$

so the weights w_i do indeed adjust the sample margins to the control totals. Note that the function "$\mathbf{1}(x_i = k)$" is an indicator function which takes the value = 1 when $x_i = k$ and = 0 otherwise.

Raking extends this procedure to balance multiple variables to their control totals simultaneously. We seek a set of non-negative weights $w_i = w(x_{1i}, \ldots, x_{Ji})$ ($i = 1, \ldots, n$) which sum to sample size and satisfy the *marginal constraints,*

$$\hat{t}_{jk} = \frac{\sum_{i=1}^{n} w_i \, \mathbf{1}(x_{ji} = k)}{\sum_{i=1}^{n} w_i} = t_{jk} \quad \text{for } j = 1, \ldots, J \text{ and } k = 1, \ldots, K_j$$

J of these constraints are redundant, since both the sample and population proportions sum to one. If the marginals t_{jk} are consistent and none of the sample marginals is zero when the corresponding population marginal is non-zero, there will be multiple solutions that satisfy the marginal constraints. Thus, we desire weights that are "close" to the unweighted sample while satisfying the marginal constraints. Different definitions of closeness lead to different solutions. Ireland and Kullback (1968) argue for weights that minimize the Kullback-Leibler (KL) divergence between the weighted and unweighted sample distributions,

$$\text{KL}(\hat{p}^w, p) = \sum_{x_1,\dots,x_J} \hat{p}^w(x_1,\dots,x_J)\log\frac{\hat{p}^w(x_1,\dots,x_J)}{p(x_1,\dots,x_J)}$$

subject to the marginal constraints, where $\hat{p}^w(x_1,\dots,x_J)$ and $p(x_1,\dots,x_J)$ are the weighted and unweighted sample proportions in cell $(x_1,\dots,x_J)$. A result from information theory implies the existence of a unique minimizer obeying the marginal constraints that is of the form

$$p^*(x_1,\dots,x_J) = p(x_1,\dots,x_J)\prod_{j=1}^{J}\lambda_{j,x_j} = p(x_1,\dots,x_J)w^*(x_1,\dots,x_J),$$

where

$$w^*(x_1,\dots,x_J) = \prod_{j=1}^{J}\lambda_{j,x_j} = \frac{p^*(x_1,\dots,x_J)}{p(x_1,\dots,x_J)} \quad \text{for } j = 1,\dots,J \text{ and } x_j = 1,\dots,K_j$$

This shows that the effect of weighting by w^* is to balance the sample, since p^* satisfies the marginal constraints.

Iterative proportional fitting (IPF) is a simple iterative algorithm to calculate w^*. Initially, take each weight equal to one. Starting with the first marginal constraint, calculate the ratio $\lambda_{1k}^{(1)}$ of the control total t_{1k} to the weighted sample proportion for that margin (using the current weights). Adjust the weight by multiplying by the weights by $\lambda_{1k}^{(1)}$. This is referred to as *raking* the first sample margin; $\lambda_{j,x}^{(1)}$ is the multiplier which adjusts the first margin to its control total. Using the updated weight, rake the second sample margin to its control variable and cycle through the remaining margins to obtain a set of J raking factors $\lambda_{1,x_j}^{(1)},\dots,\lambda_{J,x_J}^{(1)}$. Iterate this process until all of the raking factors $\lambda_{jk}^{(N)} \overset{N\to\infty}{\to} 1$. Ireland and Kullback show that the rate of convergence is geometric. The name "raking" derives from the picturesque analogy of raking sand first horizontally and then vertically and repeating until it is evenly distributed.

Appendix G. A Simple Example of Weighting for Prior Labor Market Status

Because the weighting is complex, this appendix uses a simple example to explain it. It also shows how a persistent bias in recall labor force status leads to an upward bias in the estimate of the unemployment rate.

For this example, we assume there are only two kinds of labor market status, unemployment (U) and not unemployed (NU). Further, we show the technique for the most disaggregated cell (of gender, education, age, etc.). For the appendix, we use the following terminology:

- ***"Current LF status"*** is the status calculated for "last week" using the full set of CPS questions (e.g., work for pay, absence, layoff, etc.). These estimates are compared each month to the CPS survey.
- ***"Retrospective LF status"*** is calculated using a streamlined and simplified set of questions that inquires as to *past* labor market status in prior months.

We take two months, *M* and *(M+1)*. To begin with, we assume that the actual labor market situation and the surveys are identical each month, with identical errors or biases in each month. Table G-1 shows the illustrative data for the CPS in part [A], the unweighted YLS survey for both months in part [B], and the YLS retrospective survey for month *M* looking back from month *(M+1)* in part [C]. The total sample is assumed to be 100.

	[A] CPS actual		[B] YLS survey		[C] YLS Retrospective	
	U	NU	U	NU	U	NU
Month M	20	80	20	80	10	90
Month (M+1)	20	80	20	80		

[A] = CPS data
[B] = YLS unweighted survey, current response
[C] = YLS unweighted retrospective data

Table G-1. Basic data for representative months

The next step is to construct the weights for month *(M+1)*. These are constructed using the CPS data for month *M* and comparing those to the retrospective LF status for month *M*. The weights are 20/10 for U and 80/90 for NU. These are shown in part [D] of Table G-2, which adds three columns to Table G-1.

	[A]		[B]		[C]		[D]		[E]		[F]	
	CPS actual		YLS survey		YLS Retrospective		YLS weights		YLS weighted survey		Error (% points)	
	U	NU	U	NU	U	NU	U	NU	U	NU	U	NU
Month M	20	80	20	80	10	90	2.000	0.889				
Month (M+1)	20	80	20	80					36	64	16	(16)

[A] = CPS data
[B] = YLS unweighted survey, current response
[C] = YLS unweighted retrospective data
[D] = weights using CPS for M relative to YLS retro for M.
[E] = YLS current, month (M+1), times YLS weights, normalized to sum to 100.
[F] = error from YLS estimates

Table G-2. Construction of YLS weights and weighted survey

The key calculation comes in columns [E]. To calculate the weighted YLS sample for month *(M+1)*, we multiply the weights in [D] by the YLS survey results for month *(M+1)* in column B. These sum up to more than 100 and are then normalized so that they sum to the survey total of 100.

The weighted sample has a larger U and a smaller NU because the retrospective looking back to month *M* underreports U relative to the CPS actual in month *M.* The error is shown in columns [F]. Note that the error is [the actual CPS in month *(M+1)*] minus [the weights times the unweighted YLS survey results for month *(M+1).*]

Not surprisingly, if YLS is accurate, it will produce the correct result. Another case would be where the YLS is consistently biased in the current and the retrospective, shown in Table G-3. Here, the weighting produces the correct result.

	[A] CPS actual		[B] YLS survey		[C] YLS Retrospective		[D] YLS weights		[E] YLS weighted survey		[F] Error (% points)	
	U	NU	U	NU	U	NU	U	NU	U	NU	U	NU
Month M	20	80	10	90	10	90	2.000	0.889				
Month (M+1)	20	80	10	90					20	80	0	0

[A] = CPS data
[B] = YLS unweighted survey, current response
[C] = YLS unweighted retrospective data
[D] = weights using CPS for M relative to YLS retro for M.
[E] = YLS current, month (M+1), times YLS weights, normalized to sum to 100.
[F] = error from YLS estimates

Table G-3. Consistent errors in YLS are fixed using the weighting technique

Results with actual YLS results

We can use the same approach as shown in Table G-2 using the actual estimates from the YLS. We have gathered the full set of duplicate responses – i.e., those where a respondent has both a current LF status and a later retrospective LF status for the same month that can be used for comparison (N = 54,949). Our tabulation found that the retrospective estimate of U (7.7% of the population) was lower than the current estimate (9.3% of the population). Table G-4 uses the same calculation as in earlier tables. The errors in the retrospective find a calculated upward bias for U of 1.02% of the population or 1.61% of the labor force. Note that this is just suggestive because it does not allow for differences by demographic group or by month and assumes a constant LF status over time.

If the same approach is used for the three-way labor force classification, the estimates of the error are virtually the same.

	[A] CPS actual		[B] YLS survey		[C] YLS Retrospective		[D] YLS weights		[E] YLS weighted survey		[F] Error (% points)	
	U	NU	U	NU	U	NU	U	NU	U	NU	U	NU
Month M	4.90	95.10	9.28	90.7	7.72	92.28	0.635	1.031				
Month (M+1)	4.90	95.10	9.28	90.7					5.92	94.08	1.02	-1.02

[A] = CPS data
[B] = YLS unweighted survey, current response
[C] = YLS unweighted retrospective data
[D] = weights using CPS for M relative to YLS retro for M.
[E] = YLS current, month (M+1), times YLS weights, normalized to sum to 100.
[F] = error from YLS estimates

Table G-4. Correct estimates when consistent YLS bias

Appendix H. Major Questions in YLS Survey from March 2020

Yale Questionnaire March 2020
Survey Designed by Staff of Yale Labor Survey
Survey Conducted by YouGov
Survey Approved by Yale IRB [Initial approval #2000027860 and subsequent approvals for revisions to survey]

The following is the text of the survey with coding removed. Note that this includes primarily the questions that are used to determine labor market status and excludes other less relevant questions.

_____

This survey asks about your activities last week. For example, do you work, or on the other hand are retired, going to school, or taking care of family. The questions are detailed, and we appreciate your effort to answer them accurately.

We know that you sometimes take online surveys and may earn pay or rewards for participating. This survey is not about that. When we ask about your work and job, please do NOT include taking surveys as your work for pay.

WORK FOR PAY/ABSENT SECTION

Next are a few questions about work-related activities last week. "Last week" means the seven-day week beginning on Sunday January 31st and ending Saturday February 6.

"LAST WEEK, did you do any work for pay or profit?
<1> Yes
<2> No

"When you said you worked for pay or profit, were you referring to a job answering online surveys?
 <1> Yes
 <2> No

"Aside from answering online surveys, did you have ANY OTHER job where you worked for pay or profit?
 <1> Yes
 <2> No

"LAST WEEK, did you have a job, either full-or part-time? Include any job from which you were temporarily absent.
<1> Yes
<2> No

"What was the main reason you were absent from work LAST WEEK?
 <1> On layoff (Temporary or indefinite)
 <2> Slack work/business conditions

<3> Waiting for new job to begin
<4> Vacation/personal days
<5> Own illness/injury/medical problems
<6> Child care problems
<7> Other family/personal obligations
<8> Maternity/paternity leave
<9> Labor dispute
<10> Weather affected job
<11> School/training
<12> Civic/military duty
<13> Other reason [absent_reason_other]

"Which of the following statements describe why you were absent from your job LAST WEEK. Check all that apply."
<1> I was temporarily absent from a job due to my own illness
<2> I was temporarily absent from a job due to an illness in my family
<3> I was temporarily absent from a job due to a vacation (paid or unpaid)
<4> I was temporarily absent from a job due to bad weather
<5> I was temporarily absent from a job due to a labor dispute (for example, a strike)
<6> I was temporarily absent from a job due to the coronavirus
<7> None of the above

"What best describes your employment situation LAST WEEK?"
<1> I worked for pay or profit at my usual place of work
<2> I worked for pay or profit, not at my usual place of work but at home or at another workplace
<3> I did not work, but still earned pay (for example, personal or sick leave)
<4> I did not work, but my employer is still paying me (but not for the usual reasons for time off such as personal time or sick leave)
<5> I did not work and was not paid

"In your job, what type of employer did you work for last week?"
<1> Federal, state, or local government
<2> Private-for-profit company
<3> Non-profit organization (including tax-exempt or charitable organizations)
<4> Self-employed

"In your job, do you work for yourself (including working as a contractor, freelancer, or "gig economy" worker) or do you work for a firm or other employer?"
<1> I work for myself or my own firm
<2> I am a contractor, freelancer, or "gig-economy" worker
<3> I am paid a wage or salary

"In which month did you start working for your current employer?"
<2102> February 2021
<2101> January 2021
…
<2001> January 2020
<8888> Before January 2020

"How many hours did you ACTUALLY work for pay LAST WEEK?"

HAS NOT WORKED FOR PAY IN LAST WEEK
(only asked of people who have NOT worked for pay last week)

"You said that you did NOT work last week for pay or profit. What best describes your situation at this time?"
 <1> Laid off or furloughed from a job to which you expect to return
 <2> Looking for work
 <3> Disabled
 <4> Ill
 <5> In school
 <6> Taking care of house or family
 <7> Retired
 <8> Something else

Current Employment Status
 <1> Employed
 <2> Unemployed - ILF
 <3> NILF
 <4> Student

 "Regardless of the reason you did not work LAST WEEK, did you earn any pay (or profit) for your time away from work?"
 <1> Yes
 <2> No

"When did you last work at a job or business?"
 <2102> February 2021
 <2101> January 2021
 <2012> December 2020
 …
 <2001> January 2020
 <1900> Before January 2020
 <1899> Never worked
 <1898 if 0> Not in labor force

"Have you been given any indication that you will be recalled to work within the next 6 months?"
 <1> Yes
 <2> No

"Have you been doing anything to find work during the last 4 weeks?"
<1> Yes, I have actively searched for work by doing things like submitting resumes to potential employers, answering employment advertisements, or asking friends and relatives about jobs
<2> No, I have not been actively searching, but I have occasionally checked job listings
<3> No, I have not been doing anything to find work within the last four weeks

"We now ask further questions about your job searches. During the past two months, have you used any of the following methods to search for a job?"
 Please check all methods that apply. If you have not searched at all, check "none of the above."
 <1> Sent out a resume or filled out an application
 <2> Contacted an employer directly or had an interview
 <3> Looked at ads
 <4> Contacted friends or relatives
 <5> Contacted a public employment agency
 <6> Contacted a private employment agency
 <7> Checked union or professional registers
 <8> Placed or answered ads
 <9> Contacted a school employment center
 <10> Attended job training programs or courses

<11> None of the above

"If someone offered you a job today, could you begin work within the next 7 days?"
<1> Yes
<2> No

"Do you currently want a job, either full or part time?"
 <1> Yes
 <5> Maybe/it depends
 <2> No, I am retired
 <3> No, I am disabled or unable to work
 <4> No, I do not want a job for other reasons

"You indicated that you were not actively looking for work over the last 4 weeks. What is the MAIN REASON that you did not look for work?"
 <1> No work is available in my line of work or area because of the current Covid-19 pandemic
 <2> No work is available in my line of work or area because of other reasons
 <3> I tried to find work, but could not find any
 <4> Lack of child care, or other family or personal responsibilities
 <5> Ill health or physical disability
 <6> Some other reason

PAST EMPLOYMENT

"In which of the following months did you do any work for pay or profit?"
January 2021
December 2020
…
January 2020

"You said that you did not do any work for pay during <x>. What best describes your work status during <x>?"
 <1> Available to work, but not looking for a job
 <2> Available to work and actively seeking a job
 <3> On layoff or furloughed from a job to which you expect to return
 <4> Disabled or ill
 <5> Retired
 <6> In school
 <7> Taking care of house or family
 <8> Other

[Asked for relevant month]

EARNINGS/INDUSTRY

"Counting all of your sources of EARNED INCOME (wages, salaries, tips, and commissions, but before taxes and excluding government benefits), how much did YOU earn in 2020?"
<1> Less than $10,000
<2> $10,000-$19,999
…
<15> $140,000-$149,999
<16> $150,000 or more
<17> Prefer not to say

"What is your occupation?"

<1> Management, business, and financial occupations
<2> Professional and related occupations
<3> Service occupations
<4> Sales and related occupations
<5> Office and administrative support occupations
<6> Farming, fishing, and forestry occupations
<7> Construction and extraction occupations
<8> Installation, maintenance, and repair occupations
<9> Production occupations
<10> Transportation and material moving occupations
<11> Armed Forces

"Please tell us the industry of the organization that you worked for."
<1> Agriculture, forestry, fishing, and hunting
<2> Mining
<3> Construction
<4> Manufacturing
<5> Wholesale and retail trade
<6> Transportation and utilities
<7> Information
<8> Financial activities
<9> Professional and business services
<10> Educational and health services
<11> Leisure and hospitality
<12> Other services
<13> Public administration
<14> Armed Forces

"Which of the following best describes your current employment status?"
<1> Full-time
<2> Part-time
<3> Temporarily laid off
<4> Unemployed
<5> Retired
<6> Permanently disabled
<7> Homemaker
<8> Student
<9> Other

PROFILES

In addition, the survey asked for basic demographic information such as gender, education, age, race, state of residence, political preferences, voting behavior, and other. The panels were also asked about their experience with online panels.