Employer Reallocation During the COVID-19 Pandemic: Validation and Application of a Do-It-Yourself CPS*

Alexander Bick
Arizona State University

Adam Blandin
Virginia Commonwealth University

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Abstract

Economists have recently begun using independent online surveys to collect national labor market data. Questions remain over the quality of such data. To address these concerns, we introduce a novel online survey built around the Current Population Survey (CPS). By replicating core components of the CPS, we ensure that our measures are comparable, allowing us to weight and validate results using a high-quality benchmark. We provide two applications of our survey approach. First, during the initial year of the COVID-19 pandemic, the survey provided estimates of US labor market aggregates several weeks ahead of the CPS which were closely aligned with official estimates. Second, using data unique to the RPS, we assess the extent of employer reallocation during the pandemic. We document that 36.8% of workers employed just before the pandemic had separated from their employer one year later, nearly double the typical separation rate in recent years, with large differences by pre-pandemic employer tenure. We conclude by discussing several additional applications of our methodology.

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1 Introduction

In response to rapidly evolving data demands amid the COVID-19 pandemic, economists have recently begun using independent online surveys to collect national labor market data (Adams-Prassl et al., 2020; Barrero et al., 2021; Belot et al., 2020; Bell and Blanchflower, 2020; Coibion et al., 2020; Foote et al., 2020). This development represents a potentially important addition to economists' toolkit that could far outlast the pandemic. One advantage of labor market data from online surveys is speed: a single researcher can collect and process several thousand responses in a few days, which is a much more rapid timeline than existing publicly available datasets. Another advantage is flexibility: independent surveys can be tailored to address specific research questions by asking novel questions and strategically sampling desired groups. Moreover, because the costly tasks of administering and recording surveys can be outsourced to commercial survey companies in exchange for a relatively modest fee, this approach does not require operating one's own survey infrastructure, and is therefore widely accessible.

However, important questions remain over the utility of labor market data derived from independent online surveys. One set of questions concerns the *reliability* of such data; in particular, whether survey samples are representative of the underlying population for variables of interest, and whether survey responses contain excessive measurement error. A related set of questions concerns the *comparability* of the data; namely, the extent to which labor market concepts (such as "unemployment" or "earnings") are comparable to concepts in other widely used surveys.[1]

Against this backdrop, the current paper introduces a novel online labor market survey designed to speak to the above concerns. Essentially, we use an existing high-quality dataset, the Current Population Survey (CPS), as the "scaffolding" for the novel survey, which we refer to as the Real-Time Population Survey (RPS). The core of the RPS closely follows key aspects of the CPS, which ensures that survey concepts are *comparable* and allows researchers to weight results against a widely used benchmark with a large sample size. Section 2 provides an overview of the RPS, which was conducted twice per month from late March through September 2020, and monthly since then.[2] We highlight areas of overlap and divergence with the CPS as well as existing institutional online surveys such as the Survey of Consumer Expectations, the Understanding America Survey, and the American Life Panel.

[1] Independent online surveys have been used extensively by experimental economists and other social scientists, see e.g. Bursztyn et al. (2014); Kuziemko et al. (2015); Bhargava et al. (2017); Zimmermann (2020). (Each of these papers distributed their survey through the survey company Qualtrics, which we also use.) What is new is the adaptation of these surveys to collect national labor market data, and in this context the above concerns over the data's representativeness and comparability are particularly acute.

[2] Since late April, the RPS is conducted in collaboration with the Federal Reserve Bank of Dallas.

Next, in Section 3 we use overlapping questions in the RPS and CPS to validate outcomes in the RPS, addressing concerns over the data's *reliability*. Retrospective questions in the RPS about employment, hours worked, earnings, industry, and employer tenure in February 2020 produce statistics in line with the February 2020 CPS. In addition to providing validation, these results suggest that retrospective questions in online surveys can provide accurate quasi-panel information, which we exploit later in the paper. We then show that the RPS was able to provide useful and timely estimates of US labor market aggregates during the first year of the COVID-19 recession. While we note some discrepancies, overall RPS time series for labor force participation, employment, unemployment, hours worked, and earnings are similar in both level and trend to the CPS, but available several weeks earlier and, in the first several months of the survey, twice as often.

Finally, bolstered by the above comparisons, Section 4 uses RPS data on employer tenure to provide novel insights on the extent of employer separations and reallocation during the first year of the COVID-19 pandemic. This information is not available in the CPS because the employer tenure supplement was last run in January 2020 and is only conducted every two years. We document that, among workers employed in February 2020, 36.8% had separated from their pre-pandemic employer one year later, with 25.9% working for a new employer and 10.9% not employed. This is nearly twice the annual separation rate observed over the previous two decades, and confirms predictions by Barrero et al. (2020) that the COVID-19 pandemic would produce large reallocation effects. We also find large differences in labor market outcomes by pre-pandemic employer tenure. Among workers who had been with their pre-pandemic employer less than two years, 61.8% had separated one year later, compared with 15.9% of workers who had been with their pre-pandemic employer for at least a decade. At the same time, conditional on a separation occurring, high-tenure workers were less likely to be working for a new employer one year into the pandemic, and those that did find a new employer were more likely to have experienced a drop in earnings. Collectively, these findings are informative for the calibration and validation of quantitative models of the labor market consequences of the pandemic (Gregory et al., 2020), and suggest a particularly important role of match-specific productivity for labor market outcomes during this recession (Menzio and Shi, 2011; Fujita and Moscarini, 2017; Gregory et al., 2021).

Our approach is similar to contemporaneous work by Foote et al. (2020), who also ran a repeated online survey that followed core aspects of the CPS.[3] From June 2020 through March 2021

[3]The two surveys were initially created without prior knowledge of each other. The first RPS results were made public on April 15, 2020 referencing the week of March 29-April 4, 2020. Foote et al. (2020) shared a preliminary draft with us on April 24, 2020. Their results, with an initial reference week of April 5-11, 2020, were first made public on June 24, 2020, at which point the RPS had released its first six survey reports.

they released weekly labor market estimates for the US, and in weeks that overlapped with the RPS we find similar estimates for most series (one exception is the unemployment rate, for which the RPS and CPS align more closely). We interpret this as an additional validation of our methodological approach, since Foote et al. (2020) use a different commercial survey provider and designed their survey independently from us. Unlike the RPS, to our knowledge their survey does not ask about employer tenure, which forms the basis of our analysis in Section 4, or about live-in spouses or partners. Another related project is Kurmann et al. (2021), who exploit payroll data from Homebase to shed light on small business dynamics and employment during the pandemic. While their data is administrative, rather than survey-based, our projects are related by an attempt to expand the set of labor market data available to researchers, and a focus on better understanding the reliability of these novel data sources through the use of external benchmarks.

We view the RPS as a proof of a more general survey concept, which uses existing large-scale, high-quality surveys as scaffolding to enhance the utility of novel surveys. This concept is not restricted to issues surrounding COVID-19, or to CPS-based questionnaires. Section 5 concludes with a discussion of several additional possible applications of this approach related to better understanding work arrangements (e.g., remote work, non-wage amenities, and "gig work"), as well as specific policy questions lacking relevant nation-wide data.

2 Survey Design and Sampling in the RPS and CPS

The RPS is a national online labor market survey of individuals aged 18-64. The survey is designed to mirror the CPS along key dimensions, while also collecting additional information not available in the CPS. Here we briefly review central aspects of sampling and design in each survey, pointing out areas of overlap as well as key differences. We analyze data from April 2020 through March 2021, for which we have comparable CPS data.

2.1 Sample Selection

The CPS is a monthly survey of roughly 60,000 households, where a household is a residential address. The sample design is a rotating panel: a given household is interviewed for four months in a row, not interviewed for the next 8 months, and then is interviewed again for four more months. Typically, one member of each household reports on behalf of all other members age 15 and over.

While the CPS uses a probability-based sample, the RPS derives its sample from an online panel provided by Qualtrics, a survey company widely used by academics as well as by federal agencies

for survey pre-testing and evaluation.[4] Qualtrics panel members opt-in to receive survey invitations after which they can choose to participate, see Qualtrics (2014).[5] The Qualtrics panel is not a random sample of the US population, even if one would condition on the 94 percent of individuals aged 18-64 living in households with internet access according to the 2019 American Community Survey.[6] However, researchers can direct Qualtrics to target survey invitations to desired demographic groups. In the case of the RPS, the sample was targeted to be nationally representative for the U.S. along several broad demographic characteristics: gender, age, race and ethnicity, education, marital status, number of children in the household, Census region, and household income in 2019.[7] Panel members are not allowed to take the survey twice in a row, but we are unable to verify whether respondents participate more than once in non-adjacent survey waves. According to Qualtrics staff, very few panel members did so.

From April through September 2020, the RPS typically collected 1,500 to 2,000 responses on the Qualtrics platform in interview waves fielded twice per month. In the first waves of June, July and September, the number of respondents was roughly twice as large. In October 2020, the RPS switched to a monthly frequency with approximately 2,200 respondents. As in the CPS, the RPS also asks respondents to answer the same questions on behalf of spouses or any unmarried partners in the same household. This additional information expands the number of individual-level observations by about 60 percent. In total, the RPS features 63,502 valid observations covering April 2020 through March 2021 (see Table C.1 for the details for each wave).

Samples derived from the above procedure may still differ from the CPS in observable characteristics for several reasons. First, targeted moments are never matched exactly. Second, information on spouses and partners are not taken into account by the Qualtrics sampling procedure. Finally, given limitations in sample size, it is infeasible to match very fine breakdowns or combinations of these targets. We address these issues by constructing sample weights using an iterative proportional fitting (raking) algorithm based on Deming and Stephan (1940). To address selection into our sample based on recent labor market history, we also include in our weighting scheme the share of

[4] See Yu (2019) for an overview of online survey methods and their use for testing at U.S. Census Bureau and Bureau of Labor Statistics.

[5] Qualtrics acts as a panel aggregator and distributes the survey to their partners' actively managed market research panels. The panels used for the RPS include about 15 million people in the U.S. Surveys that are completed too quickly are dropped to eliminate respondents that did not answer questions carefully.

[6] Next to the original CPS files from the BLS website, we work with the IPUMS version of the ACS and CPS, see Ruggles et al. (2021) and Flood et al. (2020), respectively.

[7] More specifically, the targets were based on the following categories: Age: 18-24, 25-34, 35-44, 45-54, 55-64; Race and ethnicity: non-Hispanic White, non-Hispanic Black, Hispanic, other; Education: high school or less, some college or associate degree, bachelor's degree or more; Marital status: married or not; Number of children in the household: 0, 1, 2, 3 or more; Census region: Midwest, Northeast, South and West; Annual household income in 2019: <$50k, $50k-100k, >$100k.

individuals who "work for pay or profit" as well as well as the share on layoff in the most recent CPS *prior* to the survey. For additional details on RPS weights, see Appendix C.4.

2.2 Survey Design

The CPS is composed of a core module that is asked each month, and a set of supplemental modules that are asked less frequently. The core CPS asks a host of demographic questions, as well as several questions about household members' labor market status. Labor market questions are used to assign individuals to one of five labor market categories: (1) employed/at work, (2) employed/absent, (3) unemployed/on layoff, (4) unemployed/searching, and (5) not in labor force. This assignment requires over a dozen questions with a combination of yes/no or open-ended answer options, and a nontrivial flow/skip process based on previous answers. The core CPS collects additional work-related information, including hours of work, employer type, occupation, and industry. In a household's fourth and eighth interviews, the CPS Outgoing Rotation Group (ORG) supplement asks about workers' usual earnings.

The RPS follows questions on demographics and labor market outcomes in the core CPS and CPS-ORG as outlined in the CPS Interviewing Manual (US Census Bureau, 2015), using the same word-for-word phrasing when practical. In particular, the survey replicates the intricate sequence of questions necessary to assign labor market status. Appendix C.2-C.3 provide additional details on the assignment of labor market status in the RPS.

A key strength of the CPS is a rotating panel, which allows researchers to study changes in labor market outcomes over time; for example, a large literature uses CPS data to discipline models of labor market flows. While the RPS does not have a panel design, it obtains (quasi-) panel information using retrospective questions. In addition to asking about labor market outcomes last week, as the CPS does, the RPS also asks about outcomes in February 2020, providing a reference point just prior to the COVID-19 outbreak in the US.

Finally, the RPS includes a suite of questions not included in the basic CPS, on topics including remote work, unemployment insurance, and worker expectations. In particular, our analysis in Section 4 makes use of RPS questions on employer tenure, which the CPS did not collect over this time period.

2.3 Comparisons to Other Labor Market Surveys

The RPS is far from the only national online labor market survey. Several research institutions conduct long-run online panels which are intended to be nationally representative and which collect labor market information. Important examples for the US include the RAND American Life Panel (ALP), the University of Southern California's Understanding America Study (UAS), and the Federal Reserve Bank of New York's Survey of Consumer Expectations; examples for other countries include the Longitudinal Internet Studies for the Social Sciences (the Netherlands) or the German Internet Panel. Two strengths of these types of surveys is their panel component, which allows researchers to track individuals over time, and their probability-based sampling design to generate representative samples. A related development is the recent introduction of the U.S. Census Pulse Survey, which exploits the Census's email database to reach a large, representative sample, but which only asks a few labor market questions and which does not have a panel component.

Relative to these institutional surveys, independent online surveys can outsource recruitment and survey collection in exchange for a modest fee. While some of the above institutional surveys do offer independent researchers the opportunity to field novel questions to the institutional panel, the costs are substantially higher. For example, a 10 minute survey with 1,500 respondents costs $39,500 for UAS and ALP, whereas the provider we use, Qualtrics, would charge $7,500.[8] Moreover, independent surveys provide a greater degree of flexibility. For example, the much larger commercial panels allow researchers to strategically over-sample certain populations groups to suit their research interests; to name just a few, this could variously include individuals who have moved recently, who own a business, or who drive an electric car.

These advantages spurred a host of new, independent online surveys during the COVID-19 pandemic, which collected information on a range of issues including remote work, worker expectations, cross-country differences in labor market responses, and variation in the impact of the pandemic across different worker categories (Adams-Prassl et al., 2020; Barrero et al., 2021; Belot et al., 2020; Bell and Blanchflower, 2020; Coibion et al., 2020; Foote et al., 2020). The utility of data from these surveys hinges on three key issues: (1) To what extent are the samples in these surveys representative of the underlying population for the variables of interest? (2) To what extent do survey respondents provide accurate answers? (3) Are the questions asked by these surveys comparable to other historical and contemporaneous datasets widely used by economists?

The "scaffolding" approach behind the RPS is designed to address these issues. By *partially*

[8] The higher cost of UAS and ALP also include services such as survey programming and sample weight construction, which we do ourselves.

overlapping with a high-quality benchmark survey, the survey attempts to strike a balance between comparability, validation, and novelty. It is to these validation exercises that we now turn.

3 Validation of Labor Market Estimates

This section documents the extent to which outcomes in the RPS are consistent with those in the CPS. First, we compare labor market outcomes in the RPS to counterparts in the CPS for February 2020, the month prior to the onset of the COVID-19 pandemic. We then compare contemporaneous labor market estimates in the RPS to those in the CPS during the first year of the pandemic.

Although we note some discrepancies, along most dimensions the two surveys closely agree. We view these comparisons with the CPS as validation tests of our sample. While many variables that we use for sample selection or weighting are of course correlated with current or February 2020 labor market outcomes, we do not explicitly use these moments either for sample selection or weighting. That is, we do not match any moments from Sections 3.1 or 3.2 by construction.

3.1 Pre-Pandemic Comparisons to the CPS

The RPS asks respondents whether they were employed in February 2020, the month before the onset of the COVID-19 pandemic. Respondents were also asked about usual hours of work, usual earnings, and industry in February 2020. Figure 1 compares these outcomes to their CPS counterparts.

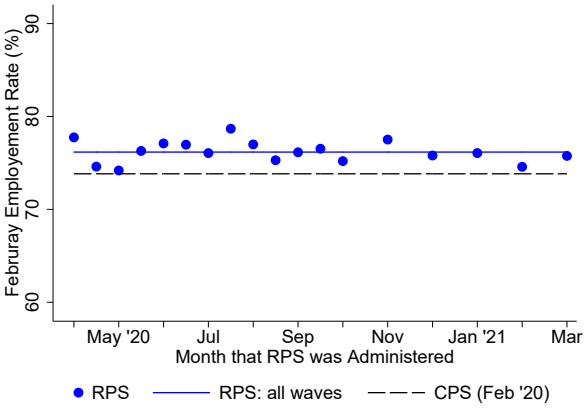
Figure 1a displays February 2020 employment in each RPS wave since April. The mean February 2020 employment rate across RPS surveys is 76.6%, slightly higher than the 73.8% employment rate in the February 2020 CPS. The standard deviation of February 2020 employment across RPS waves is 1.4%.

Figure 1b displays mean usual weekly hours worked in February 2020 in each RPS wave since April 2020, where the sample is restricted to those who were employed in February 2020. The mean usual work week is 40.0 hours, with a standard deviation of 0.4 hours across survey waves. This is close the 39.1 mean hours per week in the February 2020 CPS. Similarly, the standard deviation of usual hours in February 2020 is also somewhat higher in the RPS (13.9 vs. 10.3 hours).

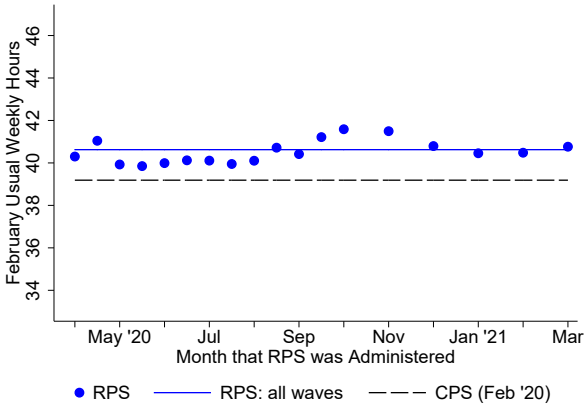
Figures 1c and 1d compare earnings outcomes in the RPS and CPS. Figure 1c displays the share of hourly and salaried workers. Averaging across all RPS survey waves, 65.0% of workers report being paid hourly in February 2020, versus 57.5% in the February 2020 CPS. Figure 1d displays

Figure 1: February 2020 Labor Market Outcomes in the RPS and CPS, Age 18-64

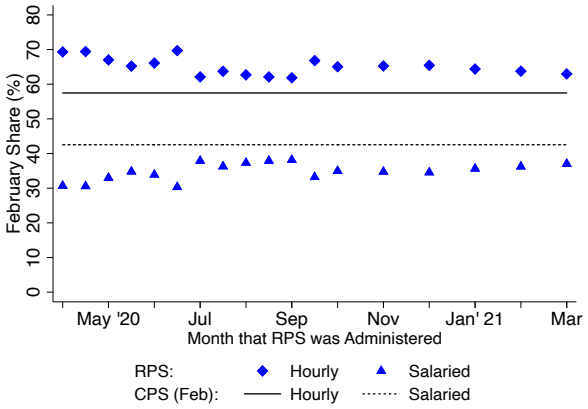
(a) Employment Rate



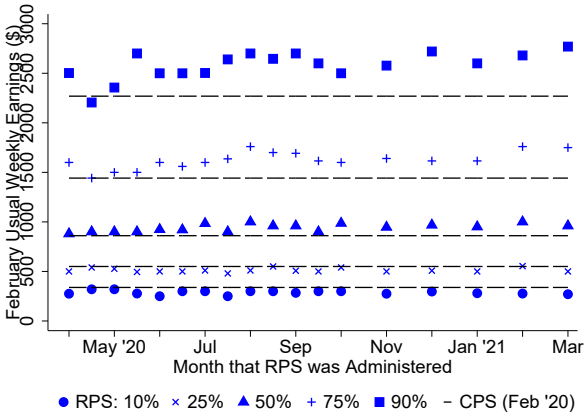
(b) Weekly Hours per Worker



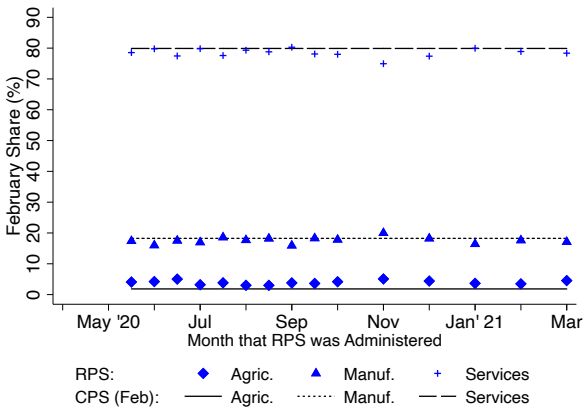
(c) Pay Type: Hourly vs. Salaried



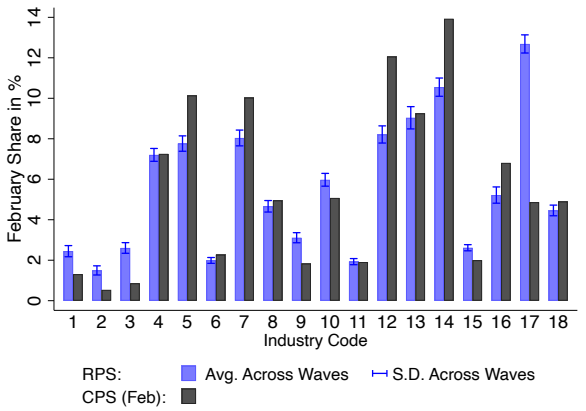
(d) Percentiles of Weekly Earnings



(e) Sectoral Composition



(f) Industry Composition



Notes: Figure contains data from retrospective questions for February 2020 in the RPS, alongside data from the February 2020 CPS. Industries are as follows: 1, Agriculture, forestry, fishing, and hunting, 2, Mining, 3, Utilities, 4, Construction, 5, Manufacturing, 6, Wholesale trade, 7, Retail trade, 8, Transportation and warehousing, 9, Information services, 10, Financial services, 11, Real estate, 12, Professional and business services, 13, Educational services, 14, Health services, 15, Arts, Entertainment, and Recreation, 16, Hotel, Accommodation, and Food Services, 17, Other services, 18, Government (including Armed Forces). The RPS only collected industry results consistently from mid-May onward. In the RPS information on pay type and industry is missing for 1.3% and 2.1% of employed individuals in February 2020, respectively.

the distribution of usual weekly earnings in February 2020.[9] As with hours worked, the earnings distribution is similar between surveys, with somewhat larger dispersion in the RPS. Averaging across all waves, the mean of log earnings in the RPS and CPS is 6.674 and 6.676, respectively; the standard deviation of log earnings is 0.786 and 0.681, respectively. The magnitude of the differences in earnings distributions between the RPS and CPS are comparable to other data sets. For example, Fitzgerald et al. (1998) find that among male household heads mean earnings are 2-5% larger and the log variance is 6-12 log points lower in the PSID than in the CPS-ASEC, respectively.

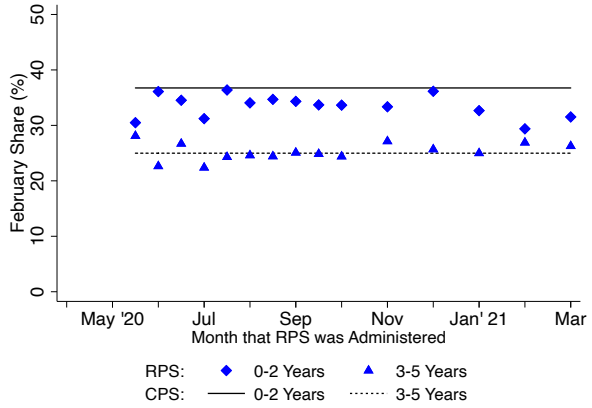
Figure 1e displays the sectoral composition in February 2020 in the RPS and CPS. The RPS only collected information on sector and industry for February 2020 consistently from mid May 2020 onward. The two surveys display nearly identical sectoral compositions for February 2020, and the composition hardly varies across RPS waves. Figure 1f provides a more detailed comparison of the composition across 18 major industries in February 2020. The correlation between RPS and CPS industry shares is 0.79. The industries in which the RPS most undershoots the CPS are professional and business services (8.1% vs. 12.1% in the RPS and CPS, respectively) and health services (10.5% vs. 13.9%); the largest RPS overshoot relative to the CPS is in "other services" (12.8% vs. 4.9%). These disparities may be attributable to some individuals in the service sector not knowing which industry to select, leading to under-counts in particular service industries and an over-count in the "other services" industry. Appendix B.1 shows that the RPS also lines up reasonably well with four broad self-reported industries in the February 2020 CPS.

Figure 2 displays the distribution of employer tenure as of February 2020 in the RPS. While the core CPS module does not collect information about workers' tenure with their employer, it conducts a specialized tenure supplement once every two years. The most recent tenure supplement was in January 2020, which provides a close comparison point to the RPS. Overall, the two surveys display a similar distribution, though the RPS has fewer workers with short tenure. On average across all waves, 33.5% of workers in the RPS have employer tenure of 0-2 years in February 2020, 25.2% have tenure of 3-5 years, 12.8% had tenure of 6-9 years, and 28.5% have tenure of 10 years or more. In the January 2020 CPS tenure supplement, 36.7% have employer tenure of 0-2 years, and each of the higher tenure bins are 0.3 to 1.8 percentage points lower than in the RPS. Because the tenure supplement in the CPS is conducted only every two years, it was not run in 2021, and therefore will not provide a precise picture of how the distribution of tenure changed

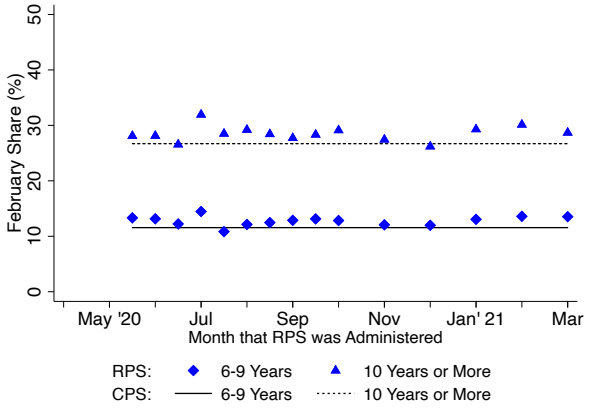
[9] To ensure comparability and minimize concerns over measurement error, we restrict both the RPS and CPS samples to individuals with (i) weekly earnings below the CPS topcode of $2,884.61, (ii) an implied hourly wage exceeding half the federal minimum wage of $3.62, and (iii) no business in the household (Figure B.2a in Appendix B shows that the RPS and CPS contain a similar share of households with a business). In the CPS, 32.7% individuals do not report earnings, 3.1% earn less than $3.62 per hour, and 1.1% earn more than $2,884.61. The respective numbers in the RPS are 6.5%, 6.8%, and 15.5%.

Figure 2: February 2020 Tenure Distribution in the RPS and CPS, Age 18-64

(a) At Most 5 Years of Tenure



(b) At Least 6 Years of Tenure



Notes: Figure contains data from retrospective questions for February 2020 starting with the late May 2020 RPS (wave 5, the first time we asked about job tenure), alongside data from the January 2020 tenure supplement to the CPS. In the RPS, information on February 2020 tenure is based on current tenure in the reference for those holding the same job as in February 2020 and for tenure in February 2020 for anyone else employed in February 2020. The RPS only asks individuals who are neither self-employed nor unpaid family workers about their tenure, and the CPS sample is restricted accordingly. Tenure information is missing for 16.8% of workers in the CPS and for 0.23% in the RPS. We assign employer tenure based on the following question: *When did you start working for this employer? If you had any brief interruptions, like a temporary layoff or unpaid leave, please report when you FIRST started working for this employer.*

during the COVID-19 pandemic. Fortunately, the RPS consistently collected information on tenure throughout the pandemic, and the comparison in Figure 2 makes us confident that this information is broadly nationally representative. In Section 4, we exploit this information to analyze the reallocation of workers across employers during the pandemic.

Collectively, we view the results in this section as validating two central aspects of the RPS design. First, the RPS is broadly consistent with the CPS for several labor market variables of interest. Second, and crucially, this consistency is obtained despite the fact that respondents are answering *retrospective* questions about labor market outcomes that happened several months in the past. This suggests that it is feasible to include a (quasi-) panel aspect even in a single-shot survey like the RPS. Given the centrality of panel data to modern economic research, this opens the door to a much larger set of potential research questions.

3.2 Real-Time Estimates During the COVID-19 Pandemic

Because the CPS is conducted monthly, and requires a three week processing period before results are made public, labor market statistics based on the CPS are perpetually between three and eight weeks out of date. For example, the April 2020 CPS, which found a 14.7% unemployment rate,

was published on May 8; on May 7, one day earlier, the latest CPS statistics referred to the week of March 8-14, which found an unemployment rate of 4.5%. In contrast, one primary benefit of the RPS is the ability to produce high frequency labor market estimates in nearly real-time. Collection of 2,000 valid responses takes 2-3 days, and the results can be processed almost instantly. In this section, we show that the RPS produces labor market estimates that are quantitatively comparable with official CPS measures, but available several weeks earlier and, during the first few months of the sample, updated twice as often.

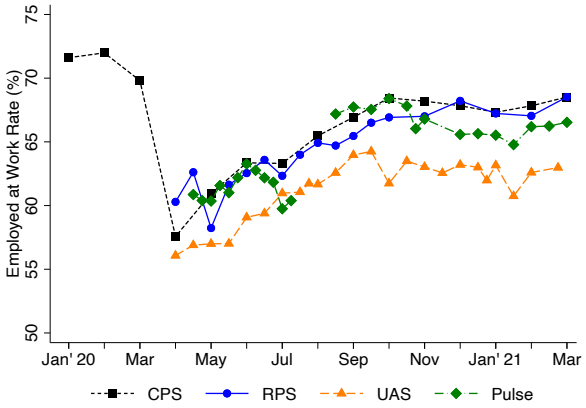
Figure 3 documents RPS and CPS labor market estimates for the US working age population during the first year of the COVID-19 pandemic. The sample weights used to construct these estimates only rely on information from the *prior* month's CPS; as a result, these estimates provide a gauge of the survey's potential to estimate labor market outcomes *ahead of* the CPS. Since survey collection began we have occasionally updated our weighting procedure, but any changes are applied consistently to all survey waves; for details, see Appendix C.4.2. We also note that, for several series, the gap between the RPS and CPS is larger in April and early May 2020 than in subsequent survey waves. We attribute this to changes in the RPS survey questionnaire during these times that brought the RPS more closely in line with the CPS (see Appendix C.3).

Figure 3a displays the employed and at work rate, which is the subset of the employed population that excludes individuals who did not work during the reference week for any reason. This is the simplest measure of labor input available in the CPS, because it mostly relies on asking a single yes/no question: "Last week, did you do any work for pay or profit?"[10] Both the CPS and RPS display a sharply lower employed and at work rate in April 2020 relative to the first few months of 2020. The series then increases substantially through June 2020, and then continues to recover more slowly from July 2020 on. The level of the RPS tends to be below that of the CPS, and as mentioned above the largest gaps occur in April and early May. Because this measure of labor input mainly relies on a single question, several other online surveys ask it as well. Figure 3a also displays estimates from the Pulse Survey (Pulse), a large-scale weekly online survey run by the US Census Bureau, and the Understanding America Survey (UAS), based on a long run probability-based panel maintained by the Center for Economic and Social Research at the University of Southern California. The average absolute percentage point (pp) deviation relative to the CPS in the sample period is 1.1pp, 1.4pp, and 4.1pp for the RPS, Pulse, and UAS, respectively. Based on this we conclude that the RPS provides useful estimates of the employed and at work rate relative to other high frequency

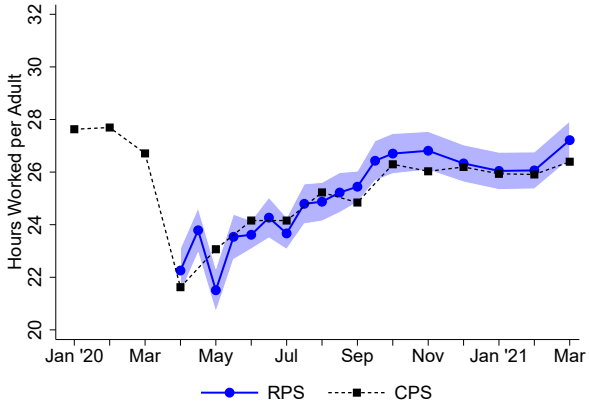
[10] As in the CPS, individuals with a business in the household who answer no to this question are asked whether they did any unpaid work in that business. Those answering yes are then asked again whether they received any payments or profits from the business. Anyone answering yes to this question is categorized as employed at work, as is anyone answering no to this last question but reporting having actually worked at least 15 hours last week.

Figure 3: Labor Market Outcomes in the RPS and CPS, Age 18-64

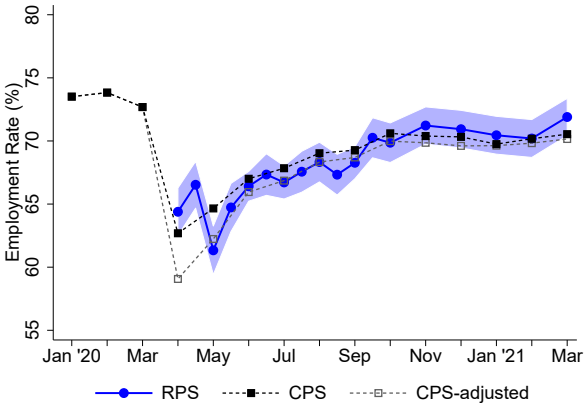
(a) Employed and at Work Rate



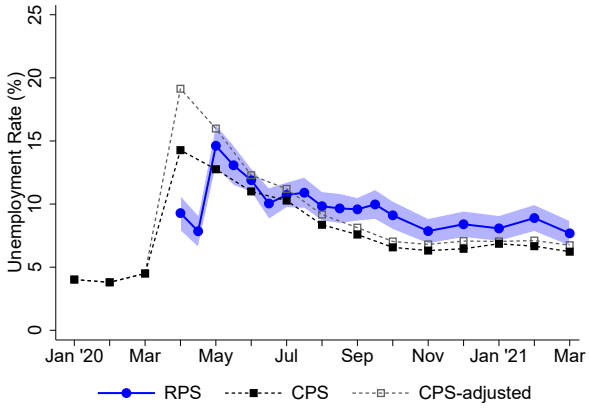
(b) Hours Worked per Working Age Adult



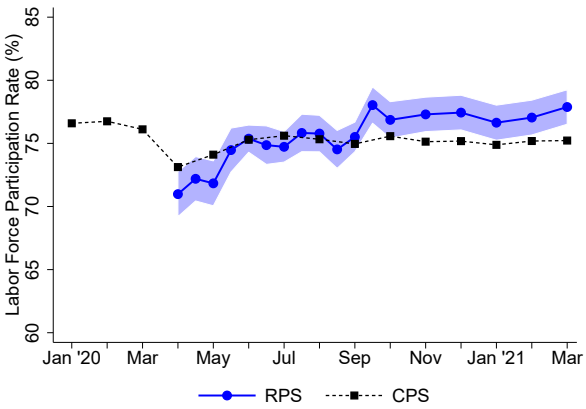
(c) Employment Rate



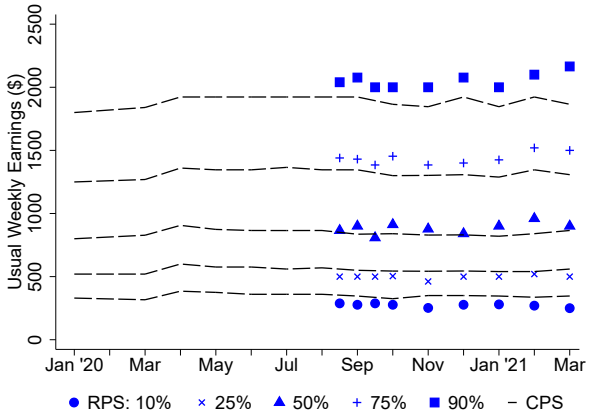
(d) Unemployment Rate



(e) Labor Force Participation Rate



(f) Mean log Weekly Earnings



Notes: Figure contains data from the RPS, CPS, and for the employed and at work rate from the Census Pulse Survey (which was not conducted between mid-July to mid-August) and the Understanding America Survey (UAS). The adjusted CPS data (in gray) for the employment and unemployment rates reflect BLS estimates that in the April CPS up to 7.5 million individuals who were misclassified as employed but absent, should have been classified as unemployed. For details, see the April FAQ report by the BLS. We quantify the impact of misclassification by constructing the adjusted employment and unemployment rates following the discussion in the FAQ report. Specifically, in April we subtract 7.5 million from the employed and add them to the unemployed. For the figures in the main text, which reflect ages 18-64, we reduce the adjustment (e.g. 7.5 million in the case of April) by 5% to reflect the fact that only 95% of the employed are younger than age 65. We conduct an analogous process for later months. Earnings, which were only collected consistently in the RPS beginning in August 2020 are the 10th, 25th, 50th, 75th, and 90th percentiles in the reference week.

surveys. Since Foote et al. (2020) cover a different age group, we do not include their time-series here. We compare our results to theirs in Appendix C.5, and find the two surveys produce comparable estimates for most series relative to the respective age-group-specific benchmark in February 2020. The most notable exception is the unemployment rate, for which the RPS and CPS more closely align.

Figure 3b displays average hours worked per working age adult. This is also a relatively straightforward measure of labor input, in the sense that it only requires one additional question asked of the employed and at work: "How many hours did you actually work last week?" The RPS and CPS display quite similar levels and trends in average hours worked throughout the sample period, with the exception of late April and early May mirroring the deviations for the employed at work rate in these two surveys.

The next three measures of labor market outcomes—employment, unemployment, and labor force participation—are more challenging to assess, as they require many more questions and a nontrivial skip/flow logic. The employment rate is displayed in Figure 3c. In addition to the official CPS rate (in black), the figure also displays an adjusted CPS rate (in gray) reflecting potential misclassification issues at the onset of the pandemic discussed by the BLS in a supplement to their monthly report; see the figure note for details on how we construct this adjustment. The RPS is typically within 1-2 percentage points of both the official and adjusted CPS series, with the exception of April and early May.

The unemployment rates for the RPS and CPS (official and adjusted) are displayed in Figure 3d. The RPS unemployment rate is well below both the adjusted and unadjusted CPS unemployment rate in April; however, the two series are much more similar from May-onward, with the RPS unemployment rate lying on average 1.6 percentage points above the official CPS unemployment rate since May. Both series show a steep decline in unemployment from May to November 2020, a pause in the decline from November 2020 to February 2021, and a resumption of the decline in March 2021. Since the fall of 2020, the higher unemployment rate in the RPS was primarily due to a higher labor force participation rate (see Figure 3e).

We can think of two potential reasons why an online survey like the RPS may report a somewhat higher unemployment rate and labor force participation rate than the CPS, despite having similar employment rates. First, while both the RPS and CPS ask non-employed workers about their job search activities, respondents report these activities differently in each survey. In the CPS, respondents volunteer search activities orally, and these activities are manually categorized later; in the

RPS, we provide these categories as a list which respondents select from. It is possible that individuals are more likely to select activities which qualify as "active search" when they are presented with options rather than when they are required to recall and state these activities themselves. Second, Ahn and Hamilton (2021) point out that the unemployment rate among individuals in their final CPS interviews is often substantially lower than the corresponding rate for the first interview. This could reflect either issues of selection, if unemployed or non-participating individuals are less likely to continue with the CPS, or strategic reporting, if individuals learn over time that they can answer fewer questions if they report being employed. Either effect would bias the overall unemployment rate downwards, which should not be present in a one-shot survey like the RPS.

Finally, Figure 3f displays mean the distribution of weekly earnings. Prior to August 2020, the RPS asked some workers only about earnings changes relative to before the pandemic, which makes it somewhat difficult to compare to earnings levels in the CPS. Beginning in August, however, the RPS began asking all workers about their current usual earnings, following the same methodology as in the CPS. As with the retrospective question about February 2020 earnings, the distribution is similar between surveys, with somewhat larger dispersion in the RPS.

Appendix B.2 shows that over the same time period the RPS also lines up reasonably well with the prevalence of businesses in the household, pay type, sector, self-reported broad industry, and detailed industry. Overall, these results indicate that an online survey in the style of the RPS is capable of providing useful labor market forecasts well ahead of the CPS. Particularly during fast-moving crises such as the COVID-19 pandemic, this suggests that online surveys like the RPS represent a valuable addition to the toolkit of researchers and policymakers.

4 Application: Employer Separations and Reallocation During the COVID-19 Pandemic

The decline in employment in the spring of 2020 represents the largest rate of job loss in the US since the CPS began collecting data in 1940. Yet, by March 2021, employment among working age individuals had recovered roughly 75% of its initial losses. One possibility is that many workers who lost employment early in the pandemic simply returned to their old employers over the course of the year, in which case the labor market disruption caused by the pandemic may have been a violent yet short-lived phenomenon with relatively modest long-run impact. An alternative possibility is that much of the employment recovery was the result of workers finding new employers. In this case, shocks in the initial months of the pandemic may have permanently destroyed a large share of employer-worker matches, many of which may have been highly productive. Because highly pro-

ductive matches are costly to find (Jovanovic, 1979, 1984; Moscarini, 2005; Menzio and Shi, 2011; Fujita and Moscarini, 2017; Gregory et al., 2020), the economic disruption induced by COVID-19 may have induced persistent reductions in productivity and employment as separated workers are forced to search for new productive and stable matches (Fujita et al., 2020).

To assess these alternative scenarios, this section documents trends in employer separations and employment outcomes conditional on separation during the first year of the COVID-19 pandemic. We document outcomes both overall and conditioning on pre-pandemic employer tenure, which theory suggests is a proxy for the expected productivity of an employer-worker match. Because the CPS employer tenure supplement last ran in January 2020 and will not run again until 2022, we primarily rely on the RPS to provide this information.[11]

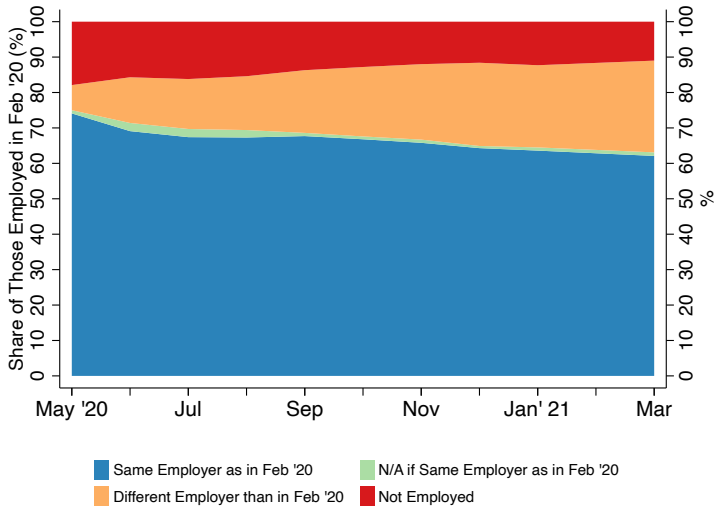
4.1 Aggregate Rates of Employer Separation and Reallocation

To begin, Figure 4 shows that the disruption caused by the COVID-19 pandemic did indeed result in a large rate of employer-worker separations. Our sample is all individuals who report being employed in February 2020, just before the onset of the pandemic. We partition this sample into three main categories: (i) those who are still working for the February 2020 employer, (ii) those working for a new employer, and (iii) those currently not employed. A smaller, fourth category contains workers for whom tenure information is missing, which prevents us from assigning them to either category (i) or (ii). In May 2020, 25.0% of workers had separated from their February 2020 employer, either because they were no longer employed (17.9%) or because they were working for a new employer (7.1%). The separation rate continued to increase in the ensuing months, reaching 36.8% in March 2021, roughly one year out from the onset of the pandemic. At the same time, employment recovered rapidly, driven entirely (in net terms) by a growing share working for a new employer; by March 2021, 25.9% of those employed just before the pandemic were working for a new employer.

Before putting the separation rates in Figure 4 into historical context, we briefly pause to validate one piece of that figure. While one cannot use the CPS to compute the one-year separation rate

[11] The core CPS does ask whether individuals are working for the same employer as in the previous month in interview months 2-4 and 6-8. One issue is that in recent years this information is missing for about 9% of workers (Fujita et al., 2021). More importantly, however, the core CPS does not ask about employer changes between interview months 4 and 5, which means the core CPS cannot speak to spells of employer tenure longer than three months at a time. Attempts to partially impute employer tenure in the core CPS using changes in occupation/industry over time are problematic due to three limitations: (i) they will not capture employer moves within industry/occupation, (ii) they may mistakenly assign employer changes if a change in job tasks (e.g. a promotion) is recorded as a change in occupation, and (iii) there is substantial measurement error in industry and occupations, which results in many erroneous changes in these variables (Moscarini and Thomsson, 2007).

Figure 4: Rates of Separation from Pre-Pandemic Employers: May 2020–March 2021

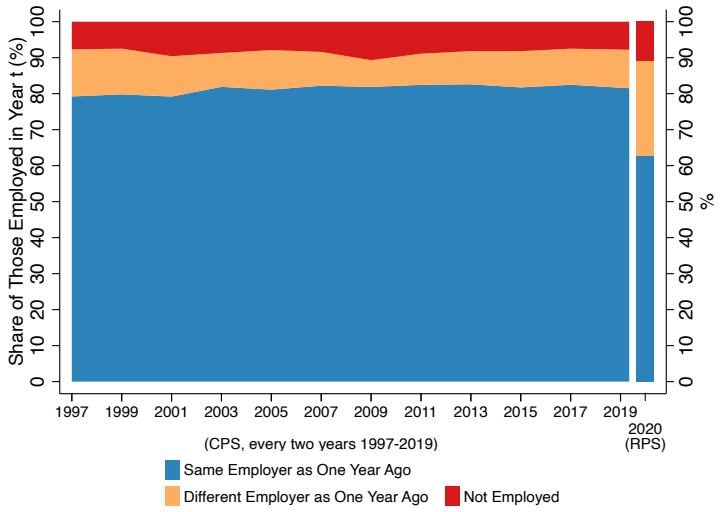


Notes: Figure contains data from the May 2020 - March 2021 waves of the RPS. We omit data from February 2021 out of concern that some respondents confused February 2020 with February 2021. Sample is everyone employed in February 2020. For employed individuals, we assign "same" versus "different" employer as in February 2020 based on the following question: *When did you start working for this employer (or for yourself if you are self-employed)? If you had any brief interruptions, like a temporary layoff or unpaid leave, please report when you FIRST started working for this employer.* The first answer option is *February 2020 or earlier* followed by each month since then *(March 2020, April 2020, ...)*.

during the pandemic, we can use the panel component of the CPS to observe the fraction of February 2020 workers who were also employed one year later, in February 2021. In the CPS, 88.8% of those employed in February 2020 were employed in February 2021, compared to 89.7% in the RPS (this is the sum of the bottom three shades for February 2021 in Figure 4), with a 95% confidence interval of 88.5% to 90.8%. We conclude that the two surveys deliver a consistent message with respect to the transition rate to non-employment for individuals employed just prior to the pandemic.

It is well known that, even in normal times, the US labor market exhibits substantial "churn", with a large share of workers moving in and out of the labor force and across employers (Farber, 1999). Was the reallocation during the first year of the pandemic documented in Figure 4 unusually large? To answer this question, we compare one-year separation rates in the 2020-2021 RPS to CPS tenure supplements over the previous two decades. We construct separation rates in the CPS as follows, focusing on the year 2020 to fix ideas. CPS respondents whose 5th-8th CPS interviews took place in January 2020 took part in the 2020 tenure supplement, and were also observed one year earlier, in January 2019, during their 1st-4th interview. We can therefore compute the share of individuals employed in January 2019 who one year later were (i) working for the same employer, (ii) working for a new employer, or (iii) not employed. Note that because the tenure supplement

Figure 5: One-Year Employer Separation Rates: 1997–2021



Notes: Figure contains data from the 1997-2019 core CPS, the 1998-2020 CPS employer tenure supplement, and the March 2021 wave of the RPS. The sample is all individuals employed in January (or, depending on the year, February) of year t, and who are observed one year later. See text for details on how we construct the CPS statistics. For RPS statistics, see notes to Figure 4. For both data sets, for individuals employed in both years but for which it can not be determined whether they still work for the same employer (on average across years 11.8% individuals in the CPS, and 1% in the RPS for March 2021) we impute this status via "missing at random". Fujita et al. (2021) show that this procedure underestimates the share of employer switches between two subsequent months in the CPS suggesting that our assumption puts a lower bound on the rate of employer switches.

only runs in even years, and the CPS only tracks individuals for 15 months, these separation rates are only available starting in odd years (e.g., the separation rate for workers employed in 2019, 2017, etc.). This means that even when the 2022 CPS tenure supplement becomes available, it will not be able to speak to separation rates during roughly the first year of the pandemic, which began in the spring of 2020 in the US.

Figure 5 displays the results of the above computation for odd years 1997-2019, which make use of CPS tenure supplements for even years 1998-2020, alongside the analogous computation for the RPS (the RPS bars in Figure 5 are equivalent to the March 2021 bar in Figure 4).[12] The figure makes clear that employer separations were much higher during the pandemic than any other year since at least the late 1990s. Specifically, the average separation rate from 1997-2019 was 18.7%, compared to 36.8% during the pandemic. Notably, the one year rate of separation-to-non-employment during the pandemic stands out less by historical comparison, and is essentially on par with the rate in 2009 during the Great Recession. By contrast, the most striking difference during the pandemic was that the share working for a new employer was 25.9% almost twice as large as

[12] We start with the 1998 CPS tenure supplement because the 1996 supplement cannot be linked to the 1995 January CPS due to changes in the system for numbering households in the CPS.

the next highest rate of 13.1%, observed in 1997.

To summarize, the one-year separation rate in the first year of the COVID-19 pandemic was quite high by recent historical comparisons. Coupled with the rapid recovery in employment that occurred from May 2020-March 2021, this implies that roughly one in four employed individuals just before the pandemic was working for a new employer one year later, which is almost double the rate of employer reallocation that occurs in a typical year in the US.

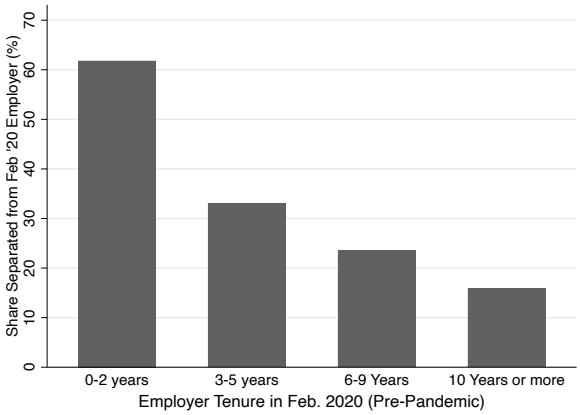
4.2 Employer Tenure and Labor Market Outcomes During the Pandemic

Not all employer-worker matches are equally productive. Through the lens of matching models based on Jovanovic (1979) and Jovanovic (1984), employers and workers agree to enter into an employment contract before fully knowing the productivity of the match. Over time, both sides learn about the match's productivity, with unproductive matches tending to dissolve and productive matches tending to endure. This implies that the loss of productive capacity from separations are heterogeneous, and that the loss in aggregate productive capacity from a given quantity of separations depends on the average productivity of destroyed matches (Fujita and Moscarini, 2017; Gregory et al., 2020; Fujita et al., 2020).

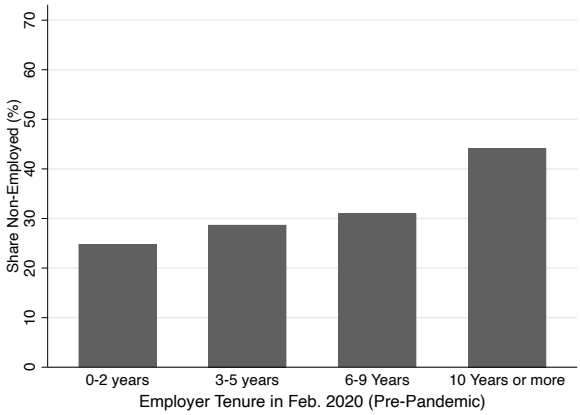
The above argument suggests that employer tenure is a useful proxy for a match's expected productivity, and that looking at the incidence of separations by pre-pandemic employer tenure can shed light on the aggregate loss in productive capacity due to the COVID-19 shock. Analyzing employer separations separately by pre-pandemic tenure requires observing employer tenure at two points: once in the base period, to classify workers by pre-pandemic tenure, and once in the later period, to identify separations. As before, the CPS is not a viable option because it only tracks individuals for up to 15 months and only runs the tenure supplement every two years. We therefore again rely on the RPS to provide this information. Figure 6a displays the separation rate of workers from their February 2020 employers one year into the pandemic (this includes both workers who are no longer employed and those who are working for a new employer relative to February). Recall that the overall separation rate among February 2020 workers was 36.8% (see Figure 4). Strikingly, Figure 6a shows that this rate was 63.4%, for workers who had 0-2 years of tenure before the pandemic. The separation rate declines monotonically with pre-pandemic tenure, falling to only 16.5% for workers with tenure of 10 years or more (Table A.1 verifies that a similar pattern continues to hold after controlling for a host of worker observables). Even this rate is quite high, implying that roughly one in six workers with ten years of tenure or more separated from their employers. Nevertheless, the results suggest that the loss in aggregate productive capacity was lower than the hypothetical scenario in which separations were uniform by employer tenure.

Figure 6: Separation and Re-employment One Year into COVID-19, by Employer Tenure

(a) Employer Separation Rate



(b) Share Not Employed c/o Separation

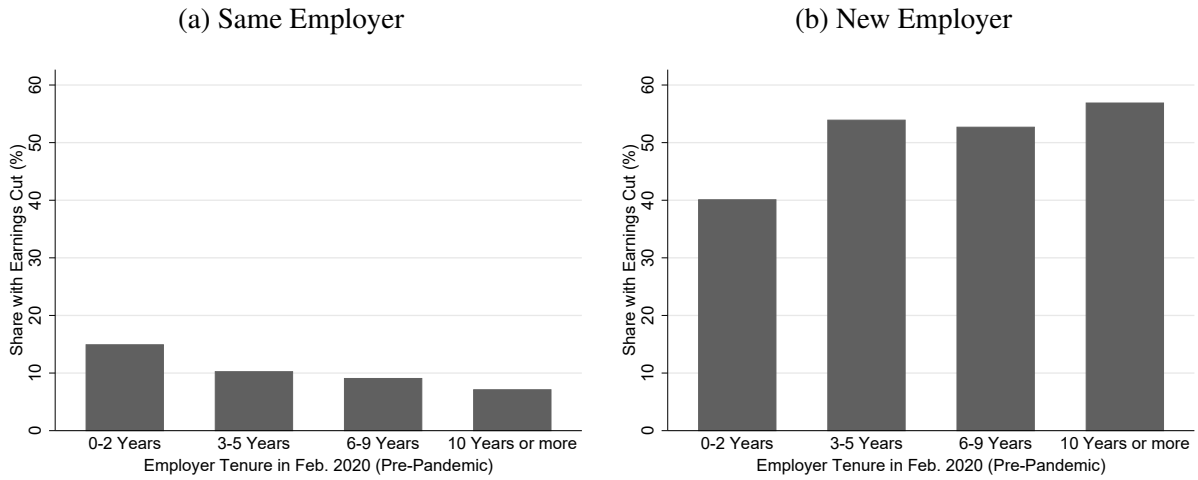


Notes: Figure contains data from the March 2021 wave of the RPS. "Pre-pandemic employer" refers to the individual's employer in February 2020, and "pre-pandemic employer tenure" refers to the worker's tenure with that employer as of February 2020. In Figure (a), the sample is all February 2020 employees, excluding the self-employed and unpaid family workers. In Figure (b), the sample is all February 2020 employees, excluding the self-employed, who were not working for the same employer in March 2021.

Although the probability of separation is strongly decreasing in pre-pandemic employer tenure, Figure 6b shows that, conditional on separation, the probability of non-employment is *increasing* in pre-pandemic tenure. That is, low tenure workers were more likely to separate from their employers during the pandemic, but *conditional on separating* they were also more likely to have matched with a new employer one year into the pandemic (Table A.2 verifies that a similar pattern continues to hold after controlling for a host of worker observables). One possibility is that high tenure workers have higher reservation wages, and so remain non-employed for longer; Hogan (2004) finds that workers' reservation wages are increasing in their previous wage. Another possibility is that this reflects heterogeneity in the job-finding propensity of workers which is correlated with their likelihood of remaining with a given employer (Hall and Kudlyak, 2019; Gregory et al., 2021).

Pre-pandemic employer tenure is also strongly correlated with changes in earnings during the first year of the pandemic, but the sign of this relationship changes depending on whether the worker has experienced a separation. Figure 7a shows that, conditional on remaining with the same employer as in February 2020, high-tenure workers were less likely to experience an earnings cut: 14.7% of workers with 0-2 years of pre-pandemic tenure earned less in March 2021, compared with 7.1% of workers with at least 10 years of tenure. Alternatively, Figure 7b shows that, unsurprisingly, workers who had a new employer were much more likely to experience an earnings cut. Moreover, conditional on working for a new employer, previously high tenure workers were *more likely* to

Figure 7: Share Experiencing Earnings Cut One Year into COVID-19, by Employer Tenure



Notes: Figure contains data from the March 2021 wave of the RPS. "Pre-pandemic employer tenure" refers to the worker's tenure with that employer as of February 2020. In Figure (a), sample is all employees, excluding the self-employed and unpaid family workers, working for the same employer in February 2020 and March 2021. In Figure (b), sample is all employees, excluding the self-employed, working for different employers in February 2020 and March 2021. Earnings cut refers to a decline in earnings of at least 10%.

experience an earnings cut: 41.2% of workers with 0-2 years of pre-pandemic tenure earned less in March 2021, compared with 59.9% of workers with at least 10 years of tenure. (Tables A.3 and A.4 show similar patterns after including worker and industry controls, though the estimates are somewhat imprecise).

Collectively, the findings throughout this section are informative for the calibration and validation of quantitative labor market models of the pandemic (Gregory et al., 2020). Slightly more than one third of workers separated from their pre-pandemic employer in the first year of the pandemic. This is roughly twice the annual separation rate observed over the previous two decades, and lends support to the prediction by Barrero et al. (2020) that the COVID-19 pandemic would produce large reallocation effects. Our findings point to an especially important role for match-specific productivity for labor market outcomes in this recession compared to recent recessions (Menzio and Shi, 2011; Fujita and Moscarini, 2017; Gregory et al., 2021; Goensch et al., 2021). Separations were most common among workers with short employer tenure, suggesting that the average level of match capital destroyed by separations may have been low. Consistent with this notion, over three quarters of short tenure workers who experienced separations were again employed one year into the pandemic, and a majority of these workers report earning at least as much as they did one year ago, just before the pandemic. At the same time, roughly one in six workers with a decade or more of tenure also separated from their employer, which theory suggests were highly productive matches on average. Long-tenure workers who experienced separations were less likely to be

working for a new employer one year into the pandemic, and conditional on having found a new employer were more likely to experience earnings losses than short tenure workers. We conclude that, while many separated workers quickly transitioned into new jobs which pay comparably well, a subset of separated workers may experience longer-lasting scarring effects in employment and earnings.

5 Concluding Remarks and Additional Applications

This paper evaluates data from the RPS, a national online labor market survey which has run regularly throughout the first year of the COVID-19 pandemic in the US. The central idea underlying the RPS is to closely follow the core of an existing high-quality survey, the CPS, which allows us to weight and validate RPS data using a trusted and widely used benchmark survey. Overlapping questions reveal that the distribution of a host of labor market variables in the RPS are quite similar to the CPS, both before and during the pandemic, which we take as direct evidence of the reliability of RPS data. At the same time, the RPS allows for more rapid data collection than the CPS, which is especially valuable during rapidly evolving crises such as the COVID-19 pandemic. The RPS also allows us to ask novel questions not contained in existing datasets: in particular, questions on employer tenure in the RPS reveal that 36.8% of workers experienced an employer separation during the COVID-19 pandemic, which is nearly double the separation rate in the US in recent decades.

We view these results as a proof of concept of our "scaffolding" approach, which attempts to strike a useful balance between comparability and novelty. We believe this approach is applicable to a wide array of research questions beyond those in the current paper. We conclude by discussing a few other promising examples.

Another application of RPS data is Bick et al. (2021), which leverages novel questions about commuting and remote work just prior to and during the COVID-19 pandemic. We find that the aggregate commuting patterns in the RPS align very precisely with with high frequency commuting behavior from cellphone data. Unlike cellphone data, however, RPS data allows us to decompose changes in commuting into changes in employment versus changes in remote work, to separate workers according to commuting frequency (e.g., full time, occasional, or fully remote), to observe the characteristics of workers who have continued to commute versus those who are commuting less, to link changes in commuting behavior to changes in other labor market outcomes, and to elicit worker expectations about commuting in the future. This analysis provides key facts to help understand the nature of the labor market disruptions caused by the pandemic, including both quantitative models of the short-run economic crisis, e.g. Baqaee et al. (2020), and longer-run effects

such as permanent changes in remote work.

There are many other potential applications of our survey concept beyond questions currently asked in the RPS. First, in addition to the ability to work remotely, jobs vary widely in their provision of other non-wage amenities. Amid rising earnings inequality in recent decades, does heterogeneity in these amenities exacerbate or dampen the inequality in the overall return to work (Kaplan and Schulhofer-Wohl, 2018)? An online survey built around the CPS could help address this issue by including supplemental questions on access to a workplace office, gym, or company car; flexible versus inflexible hours; quantity of required or actual travel for work; number of paid parental leave, vacation and sick days; and non-wage compensation such as stock options and employer contributions to pensions. To facilitate historical comparisons, a subset of these questions could be borrowed from the CPS work schedule supplement, which has not been run since 2004.

Another topic broadly related to better understanding work arrangements is the recent rise in "gig work" for services related to ride-sharing (e.g. Uber, Lyft), food-delivery (e.g. Uber Eats, DoorDash, Instacart), or odd jobs (e.g. TaskRabbit). The CPS has occasionally run a contingent worker supplement (most recently in 2017) which may capture a subset of this work, but these questions are only directed towards a worker's main job, and therefore will not capture supplemental or occasional gig work (Abraham et al., 2019). An online survey build around the CPS could include supplemental questions on gig work to help answer questions related to which types of individuals participate in gig work, what share of income is provided by gig work, how much gig work is not captured by the CPS, and to what extent gig work helps insure workers against shocks, such as the loss of a job, or an unexpected expense.

Finally, our approach could also help address specific policy-related questions for which no nation-wide data are available. To give one specific example, the optimal design of taxes and subsidies on renewable energy products, such as electric vehicles and solar panels, will depend on the characteristics of individuals who own these products, especially the incidence by age and income. Questions related to this issue would be straightforward to include in an online survey built around the CPS or ACS. To the extent that the owners of renewable energy products are a relatively small share of the national population, researchers could over-sample these individuals, but still construct sample weights in such a way that the sample is nationally representative.

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Appendix (For Online Publication Only)

A Additional Results on Employer Tenure and Separations

Table A.1: Conditional Probabilities of Employer Separation

Constant	0.508^{***}
	(0.036)
Employer Tenure: 3-5 Years	-0.247^{***}
	(0.027)
Employer Tenure: 6-9 Years	-0.293^{***}
	(0.028)
Employer Tenure: 10+ Years	-0.334^{***}
	(0.029)
Female	0.018
	(0.019)
Age 18-29	0.102^{***}
	(0.026)
Age 50-64	-0.062^{***}
	(0.022)
Education: High School or Less	0.041
	(0.026)
Education: Bachelors or More	−0.009
	(0.023)
Industry Effects	*X*
Obs.	2182
R^2	0.17

Source: March 2021 wave of Real-Time Population Survey, ages 18-64. Estimates the probability of separating from pre-pandemic (February 2020) employer by March 2021, based on a linear probability model. The sample is all individuals employed in February 2020 with non-missing employer tenure information. The regressions are weighted based on sample weights.

Table A.2: Conditional Probabilities of Non-employment After Employer Separation

Constant	0.262^{***}
	(0.054)
Employer Tenure: 3-5 Years	0.045
	(0.037)
Employer Tenure: 6-9 Years	0.055
	(0.044)
Employer Tenure: 10+ Years	0.149^{***}
	(0.053)
Female	0.049
	(0.031)
Age 18-29	0.041
	(0.036)
Age 50-64	0.203^{***}
	(0.043)
Education: High School or Less	-0.061
	(0.039)
Education: Bachelors or More	-0.067^{*}
	(0.038)
Industry Effects	*X*
Obs.	839
R^2	0.10

Source: March 2021 wave of Real-Time Population Survey, ages 18-64. Estimates the probability of being non-employed in March 2021 conditional on having separated from pre-pandemic (February 2020) employer, based on a linear probability model. The sample is all individuals employed in February 2020 with non-missing employer tenure information. The regressions are weighted based on sample weights.

Table A.3: Conditional Probabilities of Earnings Cut: Same Employer

Constant	0.095**
	(0.047)
Employer Tenure: 3-5 Years	−0.043
	(0.028)
Employer Tenure: 6-9 Years	−0.048
	(0.032)
Employer Tenure: 10+ Years	−0.068**
	(0.028)
Female	0.032*
	(0.019)
Age 18-29	0.000
	(0.030)
Age 50-64	−0.006
	(0.020)
Education: High School or Less	0.041
	(0.026)
Education: Bachelors or More	−0.015
	(0.022)
Industry Effects	*X*
Obs.	1030
R^2	0.04

Source: March 2021 wave of Real-Time Population Survey, ages 18-64. Estimates the probability of experiencing a cut in earnings in March 2021 relative to February 2020. Earnings cut is defined as a decline of at least 10%. The sample is all individuals still working for their February 2020 employer with non-missing employer tenure information, hourly wages at least half the federal minimum wage, and usual weekly earnings below the CPS topcode value of $2,885. The regressions are weighted based on sample weights.

Table A.4: Conditional Probabilities of Earnings Cut: New Employer

Constant	0.243**
	(0.110)
Employer Tenure: 3-5 Years	0.152**
	(0.059)
Employer Tenure: 6-9 Years	0.038
	(0.084)
Employer Tenure: 10+ Years	0.070
	(0.078)
Female	0.067
	(0.050)
Age 18-29	0.054
	(0.055)
Age 50-64	0.296***
	(0.068)
Education: High School or Less	−0.089
	(0.058)
Education: Bachelors or More	0.028
	(0.059)
Industry Effects	*X*
Obs.	476
R^2	0.10

Source: March 2021 wave of Real-Time Population Survey, ages 18-64. Estimates the probability of experiencing a cut in earnings in March 2021 relative to February 2020. Earnings cut is defined as a decline of at least 10%. The sample is all individuals working for a different employer than in February 2020 with non-missing employer tenure information, hourly wages at least half the federal minimum wage, and usual weekly earnings below the CPS topcode value of $2,885. The regressions are weighted based on sample weights.

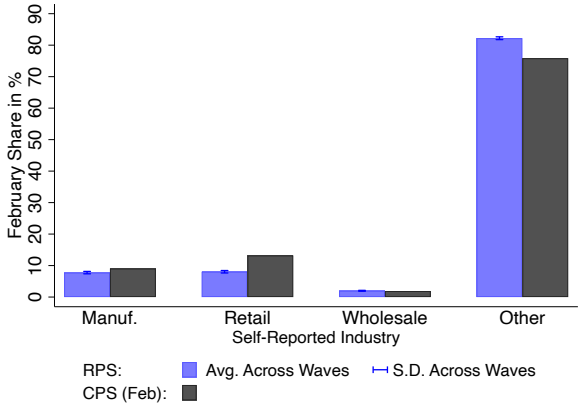
B Additional Validation Results

In the following we present additional validation results, both for February and for "last week", i.e. the reference week in the RPS and CPS, respectively.

B.1 Additional Validation for February

This section presents an additional validation result for February. While the detailed industry of employment in the CPS is not self-reported, the CPS asks about the categories displayed in Figure B.1. Similar to the not-self-reported sector in the CPS, the RPS and CPS closely line up for this measure.

Figure B.1: Self-Reported Broad Industry in February



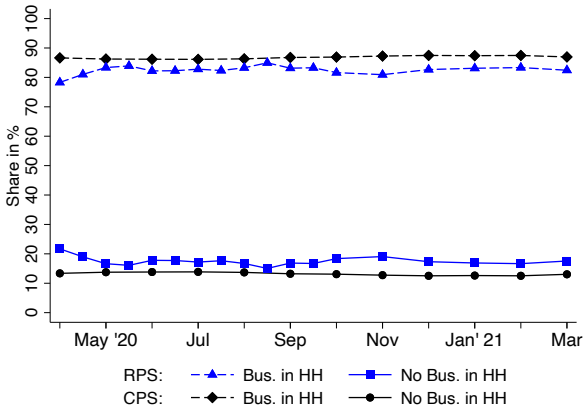
Notes: *Self-reported Industry* 1, Manufacturing, Retail Trade, 3, Wholesale Trade, 4, Missing. In the RPS this information for February is only available from wave 5 (May)-onward.

B.2 Additional Validation for Reference Week

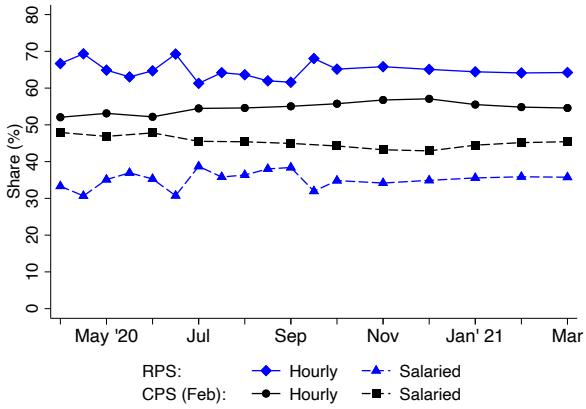
This sections presents additional validation results for "last week", i.e. the reference week in the RPS and CPS, respectively. Figure B.2a shows that in the RPS there are only slighlty more respondents living in a household with somebody owning a business than in the RPS. For all other variables in Figure B.2, the RPS-CPS comparison for the reference week is very similar to February. This is also true for the more detailed industry composition, see Figure B.3.

Figure B.2: Validation for the Reference Week, Age 18-64

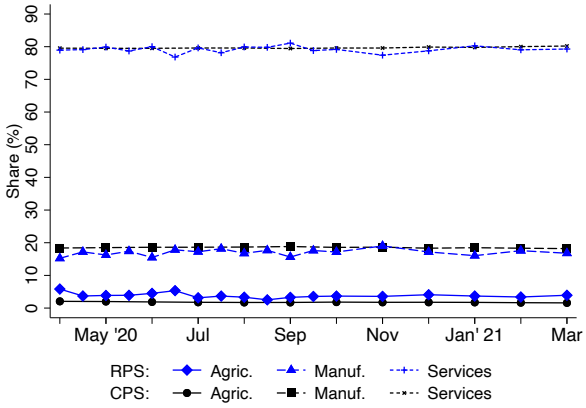
(a) Individuals Living in a HH with a Business



(b) Pay Type



(c) Sector



(d) Self-Reported Industry

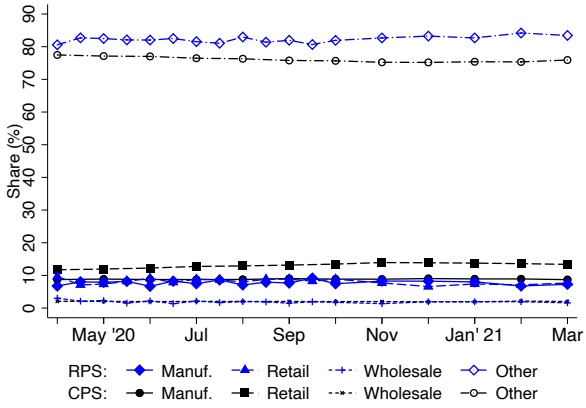
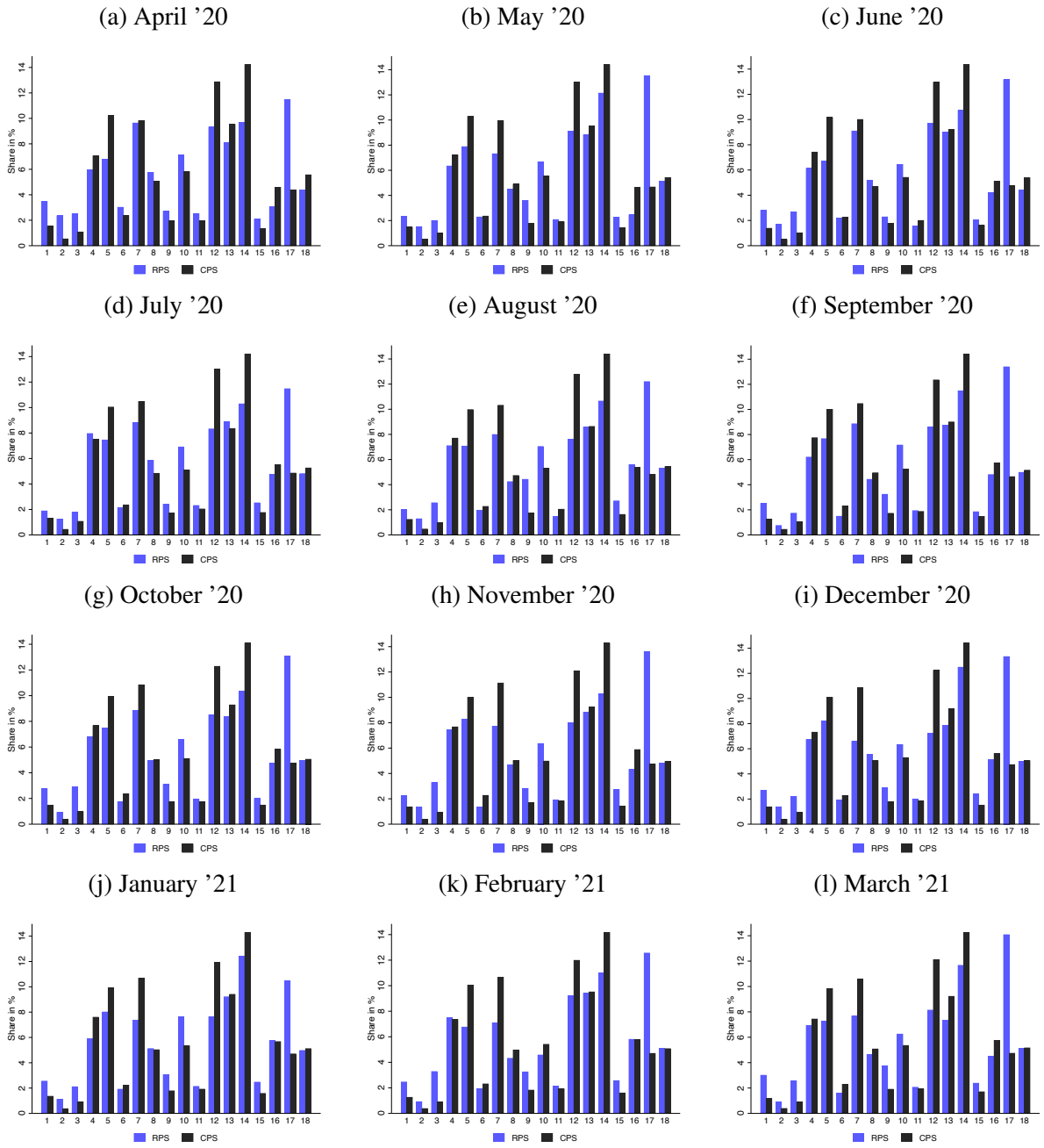


Figure B.3: Industry Composition



Notes: Figure contains data from retrospective questions in the RPS, alongside data from the February 2020 CPS. Industries are as follows: 1, Agriculture, forestry, fishing, and hunting, 2, Mining, 3, Utilities, 4, Construction, 5, Manufacturing, 6, Wholesale trade, 7, Retail trade, 8, Transportation and warehousing, 9, Information services, 10, Financial services, 11, Real estate, 12, Professional and business services, 13, Educational services, 14, Health services, 15, Arts, Entertainment, and Recreation, 16, Hotel, Accommodation, and Food Services, 17, Other services, 18, Government (including Armed Forces).

C Details on Samples, Variable Construction, and Weighting

All data labeled "RPS" in this paper were collected by an online survey designed by the authors, which we refer to as the Real Time Population Survey (RPS). The survey was constructed using Qualtrics software and administered by Qualtrics.

C.1 Sample Collection and Selection

To be eligible to participate in the study, participants had to reside in the US, be at least age 18 or older, and speak English. In wave 1 and from wave 6 onwards, we imposed an upper age limit of 64. In waves 2 through 5 we also collected data on the age group 65 and older. The results in this paper only pertain to the age group 18-64 and only uses data from wave 2 onwards. We exclude wave 1 (covering the week of March 29 through April 4) from our analysis here because we neither consistently collect information on spouses and partners living in the household, nor on employment in February.

Table C.1 provides an overview for each survey. The first column reports the reference weeks, where weeks including 12th coincide with the CPS reference week in a given month. The surveys always started fielding on the Monday after the reference week ended, with the exception of wave 17 (January 2021), which started fielding on the Tuesday after the respective reference week ended. The full data collection was completed within two to three days. The only exception is wave 6 (early June 2020). We ran two parallel surveys in wave 6, one started fielding on Sunday morning, the other started fielding on Monday morning. Fielding was completed for both surveys on Wednesday. We wanted to investigate whether there were systematic differences if fielding started on a weekend day rather than a weekday. For example, it could have been that respondents who are employed are more likely to participate in the survey on a weekend day than on a weekday. However, the two surveys yielded very similar outcomes with regard to all labor market variables.

In general, we aimed for 2,000 to 2,200 final final responses. In waves 2-5 we included the age group 65+. Since we focus on the age group 18-64, the final number of respondents reported here is only about 80% of the originally collected sample. Wave 6 has about twice the size because of the two parallel surveys described above, where each had a sample size of about 2,000 respondents. In waves 8 and 12 we also ran two surveys in parallel to experiment with differences in the survey questionnaire. We will discuss this in detail in Appendix C.3. Each parallel survey aimed for 1,600 final responses. Columns 6 through 8 Table C.1 report statistics on how long it took respondents to take the survey. The median survey completion time was about 5 minutes in wave 2 and 8 minutes and 29 seconds in wave 19. This increase results from a) an increase in employment (employed

Table C.1: Overview for Each Survey Wave

Wave	Dates		Respondents	Valid Observations		Survey Duration in Seconds		
	Reference Week	Survey Fielding		Feb' 2020	Ref. Week	25th Perc.	Median	75th Perc.
		2020						
2	04/12-04/18	04/22-04/23	1541	2485	2491	210	299	438
3	04/26-05/02	05/04-05/06	1600	2498	2501	210	311	466.5
4	05/10-05/16	05/18-05/19	1558	2458	2462	219	307.5	433
5	05/24-05/30	06/01-06/02	1513	2414	2414	237	335	486
6	06/07-06/13	06/14-06/17	3927	6167	6170	251	357	511
7	06/21-06/27	06/29-07/01	1964	3112	3113	246	344.5	503
8	07/12-07/18	07/20-07/22	3117	4957	4964	269	385	552
9	07/26-08/01	08/03-08/04	2016	3199	3202	267.5	376	535
10	08/09-08/15	08/17-08/18	2110	3370	3372	270	381	548
11	08/23-08/29	08/31-09/01	2048	3240	3244	267	385	562
12	09/06-09/12	09/14-09/15	3241	5168	5173	273	398	598
13	09/23-10/03	10/05-10/07	2024	3199	3200	268	398	576
14	10/11-10/17	10/19-10/20	2045	3292	3294	284	406	604
15	11/08-11/14	11/16-11/18	2193	3625	3626	294	419	622
16	12/06-12/11	12/14-12/17	2244	3562	3565	296	427	623
		2021						
17	01/10-01/16	01/19-01/21	2248	3565	3569	310	453.5	652.5
18	02/07-02/13	02/15-02/16	2246	3580	3581	302	439.5	638
19	03/07-03/13	03/15-03/16	2247	3555	3561	334	509	753

individuals are asked more questions) and b) the addition of new questions. With a few exceptions these questions were added at the end of the survey in order to not alter the flow of the core questionnaire and thus maintain comparability across survey waves.

Qualtrics uses a quota-based sampling approach. At the beginning of the survey respondents are asked a host of demographic questions. For some of these characteristics (sex, education, race and ethnicity, marital status, residing with children, geographic region, and household income in 2019), we provide Qualtrics the corresponding shares from the CPS from January through March 2020, for example the fraction of men and women, or the fraction of those with less high school education or less, some college or an associate degree, bachelor degree or more. Once sufficiently many women have filled out the survey (e.g., in a survey with 2,000 final respondents about 1,000 women), new respondents reporting being female are not able to continue with the survey. The quotas are determined only for one group and not cross-combinations, e.g. only by sex and education separately, but not by the joint distribution of sex and education. Table C.2 shows the breakdown for the different background characteristics we provided to Qualtrics. The first column reports the corresponding fractions in the CPS from January through March 2020, and the subsequent columns the composition for each survey wave. The distribution of household income is taken from the 2020 Release of the CPS ASEC (also often referred to as the March supplement), which reports total household income for the year 2019. Prior to wave 13, the 2020 CPS ASEC was not yet available. We therefore provided Qualtrics with the same distribution from 2019 Release of the CPS ASEC,

which reports total household income for the year 2018. Before constructing the earning bins we increased household earnings by 3.5% to account for nominal earnings growth between 2018 and 2019. The corresponding distribution was then 33.8% reporting $0-$50,000 per year, 29% reporting $50,000-$100,000 per year, and the remaining 37.2% reporting more than $100,000 per year.

Table C.2: Targeted Statistics: CPS vs. RPS

		RPS Wave																	
	CPS	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Gender																			
Men	49.2	45.9	48.0	47.4	46.3	46.8	47.0	45.9	48.1	47.9	49.1	49.0	48.4	49.0	47.7	49.1	49.0	48.9	49.0
Women	50.8	54.1	52.0	52.6	53.7	53.2	53.0	54.1	51.9	52.1	50.9	51.0	51.6	51.0	52.3	50.9	51.0	51.1	51.0
Age																			
18-24	14.6	15.2	14.7	14.6	15.6	15.2	15.1	15.4	15.7	16.4	15.3	14.6	14.9	15.1	15.4	15.7	15.5	14.9	14.9
25-34	22.7	22.2	21.4	19.8	21.6	22.8	23.2	24.1	23.6	23.2	24.5	23.3	24.0	25.1	25.0	25.3	26.2	22.9	23.5
35-44	20.9	22.4	22.5	23.9	21.3	19.8	21.8	22.1	20.2	21.3	19.4	22.6	23.1	25.9	22.9	21.4	24.1	22.3	23.3
45-54	20.3	16.5	18.5	18.2	17.3	19.9	17.5	15.9	18.0	17.4	15.6	17.6	16.8	16.1	16.3	15.7	16.0	18.1	16.2
55-64	21.4	23.6	23.0	23.6	24.2	22.3	22.4	22.5	22.5	21.8	25.2	22.0	21.2	17.8	20.2	21.8	18.2	21.8	22.2
Race/Ethnicity																			
Non-hispanic White	59.2	56.9	58.1	57.1	57.9	59.2	57.7	57.1	60.1	60.3	58.2	59.4	57.7	59.7	56.5	57.1	55.5	59.0	65.1
Non-hispanic Black	12.7	13.7	12.9	13.7	15.1	13.1	13.2	13.4	12.4	12.7	13.5	12.6	12.9	13.2	13.8	13.8	13.9	12.8	11.8
Hispanic	18.8	20.3	20.9	19.8	16.5	18.3	19.6	19.5	18.0	17.8	17.8	18.4	19.3	17.4	19.4	19.3	19.0	18.5	13.3
Other	9.3	9.1	8.1	9.4	10.5	9.4	9.5	10.0	9.5	9.2	10.5	9.6	10.0	9.7	10.3	9.8	11.6	9.6	9.9
Education																			
Highschool or less	36.8	37.1	37.7	37.3	31.0	38.0	38.2	38.9	36.9	37.2	36.5	36.7	37.0	36.4	37.5	36.8	37.3	37.1	36.7
Some college/Associate's degree	28.4	26.6	27.6	27.6	29.3	25.3	25.4	24.2	27.2	27.0	28.2	25.7	27.4	28.2	26.8	28.4	24.4	25.2	27.5
Bachelor's or Graduate degree	34.9	36.3	34.7	35.0	39.7	36.7	36.4	37.0	35.8	35.7	35.3	37.6	35.6	35.4	35.8	34.8	38.3	37.7	35.8
Marital Status																			
Married	51.3	50.7	49.7	48.7	51.0	51.0	51.4	52.8	52.3	52.2	51.0	53.7	52.0	55.6	57.5	51.2	51.5	54.3	53.5
Non-Married	48.7	49.3	50.3	51.3	49.0	49.0	48.6	47.2	47.7	47.8	49.0	46.3	48.0	44.4	42.5	48.8	48.5	45.7	46.5
Number of children																			
0	68.2	66.8	66.2	67.1	67.2	66.8	66.8	66.4	67.1	66.2	68.2	66.3	64.8	60.6	58.3	64.4	63.7	66.0	65.1
1	13.4	13.8	14.2	13.5	14.0	13.9	14.0	14.2	14.0	14.8	13.3	14.0	15.0	16.3	17.0	15.1	15.5	14.3	14.8
2	12.0	13.1	13.0	12.7	12.5	12.7	12.5	12.6	12.5	12.4	12.1	13.1	13.5	15.8	17.0	13.3	13.8	13.2	13.2
3+	6.4	6.3	6.6	6.6	6.3	6.6	6.7	6.8	6.5	6.7	6.4	6.6	6.7	7.3	7.6	7.1	7.0	6.5	6.8
Region																			
Midwest	20.7	18.7	19.3	20.3	19.7	19.7	21.4	20.6	20.2	20.2	17.7	17.7	22.5	20.0	18.2	21.3	19.3	21.7	20.9
Northeast	17.2	18.4	20.5	19.8	17.4	19.0	18.3	18.6	18.9	19.1	21.2	21.6	19.1	20.6	23.0	19.2	20.0	17.9	17.9
South	38.0	38.3	39.1	38.1	39.8	38.3	37.7	39.1	39.5	37.7	40.9	40.7	38.4	42.6	41.2	41.2	39.9	39.5	39.6
West	24.1	24.6	21.0	21.7	23.1	23.0	22.6	21.6	21.4	23.0	20.2	19.9	20.0	16.9	17.6	18.4	20.8	20.9	21.6
Household Income in 2019																			
$0-$50,000	31.7	36.8	38.7	36.3	36.1	36.6	37.8	36.7	34.9	35.2	34.8	34.5	35.3	34.8	32.8	35.1	32.6	32.1	32.2
$50,000-$100,000	28.7	29.9	33.5	29.6	31.2	30.4	31.7	27.3	28.4	25.6	29.8	29.3	30.2	29.8	29.0	30.6	29.6	28.6	27.6
$100,000+	39.6	33.3	27.8	34.1	32.7	33.0	30.5	36.0	36.7	39.2	35.4	36.2	34.6	35.4	38.2	34.2	37.8	39.3	40.3

Note: The statistics from the CPS are for the Basic Interviews from January through March 2020. Household Income is taken from 2020 Release of the CPS ASEC (also often referred to as the March supplement), which reports total household income for the year 2019.

C.2 Variable Construction

This section details how we use responses to our survey to construct a set of key variables: employment status, layoff status, actual hours worked last week, and usual weekly hours worked. Our procedure for variable construction closely follows the instructions in CPS Interviewing Manual (US Census Bureau, 2015), using the same word-for-word phrasing when practical, as well as the special guidelines provided in the FAQs by the BLS about the impact of the Coronoavirus on the employment situation.[13]

Employment Status. Employment status has four possible values, all referring to last week: (1) employed and at work, (2) employed and absent, (3) unemployed, (4) not in the labor force.

1. Employed - at work:
    - Respondents who reported that last week they worked for pay or profit.
    - Respondents who worked worked at least 15 unpaid hours at a business owned by someone in their household.
2. Employed - absent:
    - Respondents who reported that last week they (i) had a job from which they were temporarily absent (excluding unpaid work), and (ii) were not on temporary or indefinite layoff from a job.
3. Unemployed - on layoff:
    - Respondents who reported that last week they (i) had a job (excluding unpaid work) and did not work positive hours for pay at that job OR did not have a job, (ii) were on *temporary* layoff (or furlough/unpaid leave) from a job, and (iii) could have returned to work last week if they had been recalled. Individuals satisfying these criteria do not have to look actively for work in the last four weeks.
4. Unemployed - looking:
    - Respondents who reported that last week they (i) did not have a job, (ii) were neither on *temporary* nor *indefinite* layoff (or furlough/unpaid leave), (iii) had actively looked for work in the last four weeks, and (iv) would be available to work if they had been offered a job last week.

[13]The CPS Interviewing Manual is available on the BLS website, as are the FAQs for March, April, May, June, July, August, September, and October .

- Respondents who reported that last week they (i) had a job (excluding unpaid work) and did not work positive hours for pay at that job OR did not have a job, (ii) were on *temporary* layoff (or furlough/unpaid leave) from a job, and could have *not* returned to work last week if they had been recalled OR were on *indefinite* layoff (or furlough/unpaid leave), (iii) had actively looked for work in the last four weeks, and (iv) would be available to work if they had been offered a job last week.

5. Not in the labor force

    - Respondents who reported that last week they (i) did not have a job OR were on *temporary* layoff (or furlough/unpaid leave) and could and and could have *not* returned to work last week if they had been recalled OR were on on *indefinite* layoff (or furlough/unpaid leave), and (ii) were either not actively looking for work in the previous four weeks, and/or would not be available to work if they had been offered a job last week.
    - Respondents who worked at a household business and reported that last week they (i) did not work positive hours for pay, and (ii) worked less than 15 unpaid hours.

Layoff Status. Among those on layoff (or furlough/unpaid leave), we distinguish between temporary layoffs (who either have a date to return to work, or who have been given an indication they will be recalled within the next six months) and permanent layoffs (who have not been given an indication they will be recalled within the next six months).

Recall Status. Starting with wave 8 (July), we asked whether those with a job last work experienced a "work interruption" since they started the job or since March 2020 (whichever is more recent), defined as a period lasting at least one full week where they did not work at that job. We classify anyone as a recall who a "work interruption" because of one of the following: (i) a temporary layoff or furlough, (ii) slow work or business conditions, or (iii) other disruptions related to the pandemic.

Actively Looking for Work. The CPS asks individuals to report all of their job search activities, and then categorizes them. These categories can be summarized as follows: (1) contacted employer(s), employment center(s), or friends/relatives about a job; (2) sent out resumes/filled out applications; (3) checked union/professional recommendations; (4) placed or answered ads; (5) looked at ads; (6) attended job training program/courses; (7) nothing. In our survey, we asked respondents to select all activities that apply to them from this list. Anyone who selected at least one of the options (1) through (4) is then classified as *actively* looking for work.

Usual weekly hours worked prior to March. All respondents were asked about their labor market status and hours worked prior to March of this year (2020). This was done in two slightly different

ways depending on whether the respondent worked at a job last week that they had started prior to March.

- For respondents who had a job last week, and who reported that they worked at that job in February, we asked "before March, how many hours per week did you usually work at this job?"
- For respondents who either did not have a job last week, or who reported that they were not working at this job in February, we first asked them "In February, which of the following best describes your work experience? (i) work for pay or profit, (ii) unpaid work at a business owned by someone in my household, or (iii) not working." If they selected either (i) or (ii), we asked them "Before March, how many hours per week did you usually work at your job from February?"

Usual weekly hours worked. All respondents who were classified as employed and at work last week were asked and who did not work at this job in February were asked "How many hours did you actually work at your main job?". Beginning in August, we also directly ask those who already had this job in February about their usual hours.

Actual hours worked last week. All respondents who were classified as employed and at work last week were asked "last week, how many hours did you actually work at your job?" Respondents who reported working multiple jobs last week were asked both "last week, how many hours did you actually work at your main job?" and "last week, how many hours did you actually work at your all other jobs?", where main job was defined as the job in which they usually worked the most hours.

Earnings. For individuals who had a job last week, and who began that job prior to March 2020, we asked them to report their usual earnings at that job, where usual was specified to mean prior to March 2020. We followed the CPS in by first asking (i) which period was easiest for respondents to report their usual earnings before taxes or deductions (hourly, daily, weekly, every other week, monthly, or yearly), then asking (ii) how much they usually earned per period. Respondents who report the earnings yearly are also asked how many weeks per year they are are paid for.

We also ask workers about their current usual earnings. For workers who did not work started their job after February, we directly ask about their usual earnings in their new job, and record a wage cut if wages decline by at least 10%. For job-stayers relative to February, we ask how their current usual weekly earnings compare to their usual weekly earnings from February—(i) about 25%, (ii) about 50%, (iii) about 75%, (iv) about the same, (iv) more. Beginning with wave 12 (August), we also directly ask job-stayers about their current usual earnings.

February Employment Status. Since the BLS's full sequence of questions for last week's labor market status is too time consuming to ask for February, we construct an indicator for being employed or not employed in February as follows. In this context, when we refer to someone being on layoff from a job last week it is irrelevant whether that individual expects to be recalled within the next six months or not.

1. Employed in February:

    - Last week was employed
    - On layoff from a job which began in February 2020 or earlier (e.g. 2019), and last time worked at the job in February 2020 or later (e.g. in March 2020)
    - Last week was neither employed nor on layoff, or was employed or on layoff from a job that began after February 2020. Then, for the question "In February of this year (2020), which of the following best describes your [spouses's/partner's] work experience?", answered either of the following:
        (a) "worked for pay or profit"
        (b) "self-employed" or "worked in a business owned by someone else in my household" and reporting to have worked usually at least 15 hours in February.

2. Not Employed in February:

    - On layoff from a job which began in February 2020 or earlier (e.g. 2019), and last time worked at the job was before February 2020 (e.g. in January 2020)
    - Last week was neither employed nor on layoff, or was employed or on layoff from a job that began after February 2020. Then, for the question "In February of this year (2020), which of the following best describes your [spouses's/partner's] work experience?", answered either of the following:
        (a) "not working"
        (b) "self-employed" or "worked in a business owned by someone else in my household" and reporting to have worked usually less than 15 hours in February.

C.3 Modifications Across Survey Waves

In waves 3, 4, 8, and 12 we modified our survey questionnaire in an attempt to get as close as possible to the methodology used by the CPS. In waves 8 and 12, we ran parallel surveys, one with the initial questionnaire and one with the new questionnaire. We use comparisons between these parallel surveys to adjust the weighting scheme for earlier waves to maintain consistency across waves. In Bick and Blandin (2021) we publish the results of each new RPS release and gather all previous reports on the project website. While it would have been ideal to start out without any need for modifications, we view these improvements as a natural process of running a novel survey.

C.3.1 Wave 3 Update

Beginning in wave 3, we asked workers whether they were temporarily laid off in two separate places throughout the survey, rather than just once. This resulted in a larger share of people reporting being temporarily laidoff in wave 3 relative to wave 2. Since we did not run a parallel survey that wave with the initial and new structure, we cannot not make any adjustments to wave 2.

C.3.2 Wave 4 Update

Beginning in wave 4, we followed guidelines in BLS FAQ's related to the impact of the Coronavirus on the employment situation for March and April. Respondents who report having a job but who were absent last week, were given the option to choose "Because of other disruptions related to the Coronavirus Pandemic" as a reason for being absent. Anyone choosing this option was asked the same questions as respondents who said they were laid off from a job. As in the CPS, anyone labeled "laid off" who has not been given a date by their employer to return is asked whether they have been given an indication to be recalled to work within the next six months. In addition to "Yes" and "No", we added the answer option "Unsure because of disruptions related to the Coronavirus Pandemic". Following the BLS guidelines, anyone choosing this option is treated as if they said "Yes". Since we did not run a parallel survey that wave with the initial and new answer options, we cannot not make any adjustments to waves 2 and 3.

C.3.3 Wave 8 Update

Starting with wave 8, we changed the order and phrasing of the first questions of our core labor module to better align our survey with the CPS. Initially, the survey asked individuals whether they had a job last week, including any jobs from which they were temporarily absent. Anyone answering yes to this question was asked whether they worked any hours at this job last week. Those not working any hours were asked about the reasons for why they did not work last week.

Based on this (in addition to questions about unpaid work in a business owned by someone in the household), we defined employment as follows:

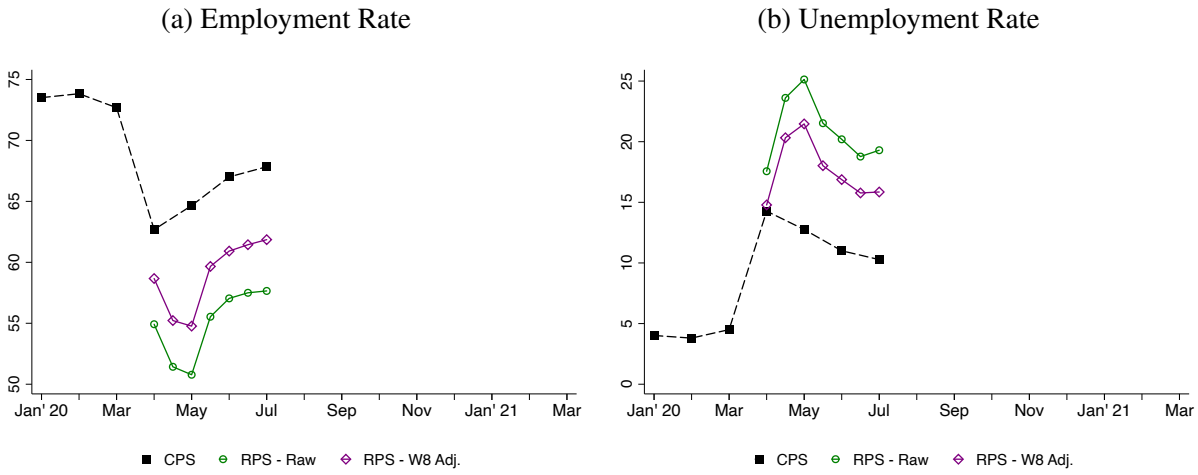
1. Employed - at work:
    - Respondents who reported that last week they (i) had a job (excluding unpaid work), and (ii) worked positive hours for pay at that job.
    - Respondents who worked worked at least 15 unpaid hours at a business owned by someone in their household.
2. Employed - absent:
    - Respondents who reported that last week they (i) had a job (excluding unpaid work), (ii) did not work positive hours for pay at that job for any reason, and (iii) were not on temporary or indefinite layoff from a job.

Starting with wave 8, we instead first asked individuals whether they did any work for pay or profit in the previous week using the exact phrasing from the CPS. Respondents who answered no to this question were then asked whether they had a job last week from which they were temporarily absent. Those answering yes to the absent question were asked about the reasons why they were absent. Based on this (in addition to questions about unpaid work in a business owned by someone in the household), we define employment as follows (see also Appendix C.2):

1. Employed - at work:
    - Respondents who reported that last week they worked for pay or profit
    - Respondents who worked worked at least 15 unpaid hours at a business owned by someone in their household.
2. Employed - absent:
    - Respondents who reported that last week they (i) had a job from which they were temporary absent (excluding unpaid work), and (ii) were not on temporary or indefinite layoff from a job.

Based on the comparison with the parallel survey under the old survey methodology, the results from the previous RPS surveys were adjusted for consistency. In particular, we construct this adjustment factor such that the distribution of employment (0 for not working, 1 for being employed independent of whether the respondent was at work last week or absent from work) and joint distribution of employment and other demographic characteristics matches the same distribution between

Figure C.1: The Effect of Wave 8 Adjustment



the two parallel surveys.[14] The adjustment factor is then applied to the wave 8 survey with the old methodology and all prior surveys.

Figure C.1 shows the effect of changing the order of questions and the adjustment for the employment rate and unemployment rate, respectively. The line labeled as "RPS - Raw Data" uses the actual raw data, where those respondents with a spouse/partner living in the household and the spouse/partner receive a weight of 0.5 and everyone else a weight of 1. The reason for this weighting is that the initial survey targets already resemble correctly the share of those with and without a spouse present. The line labeled as "RPS - W8 Adj." shows for wave 8 the corresponding rates from the survey with the new ordering and phrasing of questions and yielded a higher employment/lower unemployment rate than the initial questionnaire. Accordingly, applying the adjustment discussed above in waves prior to July also increased employment/lowered unemployment.

C.3.4 Wave 12 Update

We made two additional modifications to the RPS questionnaire in wave 12. The first modification centered around a question related to employed but absent respondents. Prior to wave 12, respondents were asked "Last week, did you have a job from which you were temporarily absent?" Starting with wave 12, we used an alternative phrasing, matching the CPS: "Last week, did you have a job, either full- or part-time? Include any job from which you were temporarily absent".

Individuals who answered yes to this question are then asked a follow-up question to determine

[14] These demographics are sex, age (below 40, 40 or older), race (non-Hispanic White, other), education (less than an associate's degree [including some college], associate's degree or more), broad marital status (married + spouse present, other)

whether they are employed/absent or not employed. The second modification was a change in the answer options to this question.

1. "Vacation/personal days", "Own illness/injury/medical problems", and "Quarantine or self-isolation due to the Coronavirus Pandemic" instead of "Vacation/personal/sick days".

2. "Other family obligations" was added as an answer option.

Individuals choosing the new answer option "Quarantine or self-isolation due to the Coronavirus Pandemic" are classified as employed - absent. Previously, they might have chosen the answer option "Because of other disruptions related to the Coronavirus Pandemic", which would have sent them to the "layoff" path, see Appendix C.3.2. We again evaluated the impact of this modification by running two parallel surveys: one using the old form of both questions, and one using the updated questions. From this comparison we find that, with the new phrasing, more individuals report having a job despite also reporting that they did no work last week. Next, conditional reporting no work but having a job, more individuals were classified as employed and at work (as opposed to being classified as a layoff).

For consistency, we use the difference in labor market outcomes between the two parallel surveys to adjust results from previous RPS surveys. To do so, we construct two variables. The first partitions the sample into three bins:

1. No work for pay or profit last week, reported having a job last week, classified as employed absent.

2. No work for pay or profit last week, reported having a job last week, classified NOT as employed absent.

3. Everyone else

The second variable partitions the sample into two bins:

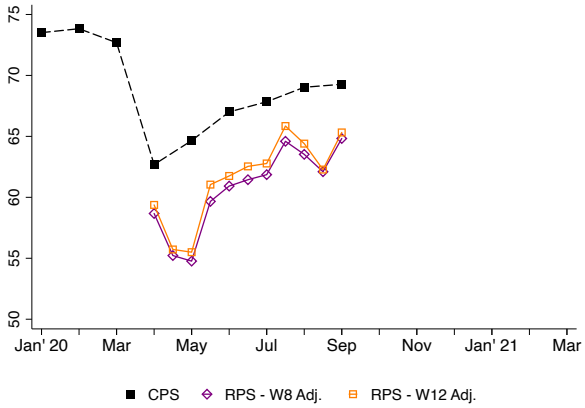
1. Unemployed

2. Everyone else

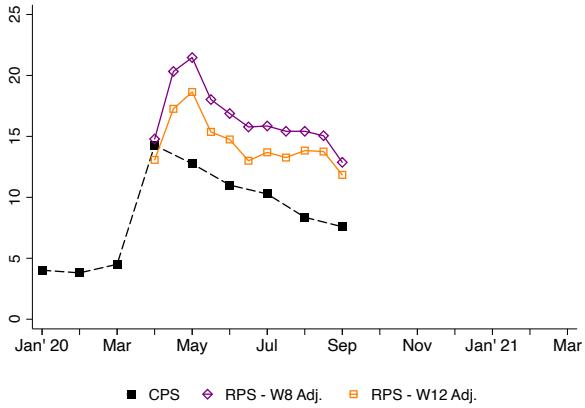
There are six different combinations of these two variables. For each combination we take the ratio of the share of people from the new and old survey and use it additional adjustment factor in

Figure C.2: The Effect of Wave 12 Adjustment

(a) Employment Rate



(b) Unemployment Rate



previous waves for a given realization before applying the actual weighting scheme.

Figure C.2 shows the effect of adjusting the survey questionnaire for the employment rate and unemployment rate, respectively. The line labeled as "RPS - Wave 8 Adj." is the same line as in Figure C.1 but continues it through wave 12 (September). For the data points after wave 8 the raw data are shown, and respondents with a spouse/partner living in the household and the spouse/partner receive again weight of 0.5 and everyone else a weight of 1. For wave 12, this line only includes the parallel survey with the initial questionnaire. The line labeled as "RPS - Wave 12 Adj." shows for wave 12 the corresponding rates from the survey with the new questionnaire and yielded a higher employment/lower unemployment rate than the initial questionnaire. Accordingly, applying the adjustment discussed above in waves prior to July also increased employment/lowered unemployment.

C.4 Weighting

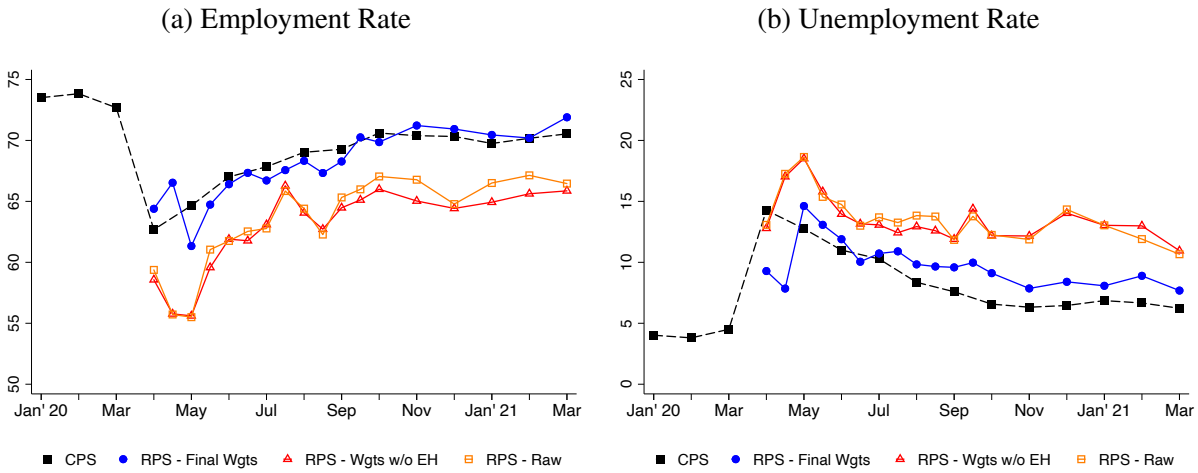
We recommend the interested reader to first read Section 3.2 in the main text and the accompanying Appendix C.2, where we introduce the key labor market concepts.

C.4.1 Construction of Weights

As described in the Section C.1, we asked Qualtrics to administer the survey to a sample of respondents who match the US population along a few broad demographic characteristics: sex, five age bins (18-24, 25-34, 35-44, 45-54, 55-64), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, other), education (high school or less, some college or associate degree, bachelor degree or more), married or not, number of children in the household (0, 1, 2, 3 or more), three annual household income bins (<\$50k, \$50k-100k, >\$100k) and four census regions. While Qualtrics is able to roughly match these shares, the fit is never exact, and there is fluctuation from wave to wave. Further, our final sample also includes spouses and partners of respondents, but the characteristics of these individuals are not incorporated into Qualtrics' sample design. Finally, given limitations in sample size, the survey company does not attempt to match combinations of these targets.

We address these issues by constructing weights using a raking procedure based on Deming and Stephan (1940). Intuitively, imagine each respondent would only be described by two variables, each with two attributes: age (younger than 40 vs. 40 and older) and education (no college vs. some college or more) and the joint distibution of both characteristics would be different from the distribution in the CPS. In that case, it would be straightforward to manually construct weights for each individual with given attributes such that the weighted joint distribution replicates the CPS. As the number of variables and attributes increases this becomes infeasible because some combination of attributes simply do not exist. The raking algorithm simply tries to find weights to achieve the best match along the desired dimensions. In particular, we match the distribution of targets provided to Qualtrics and finer categories for some variable. Specifically, we use sex, age (18-24, 25-34, ..., 55-64), race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, Other), education (less than high school, high school graduate or equivalent, some college but no degree, associate's degree in college, bachelor's degree, graduate degree), marital status (married + spouse present, divorced, never married, other), relationship status (spouse living in the same household, partner living in the same household, other), number of children (none, 1, 2, 3 or more), and the four major Census regions. We interact those with sex, which ensures that there at least 30 observations in each cell in each wave in the RPS. One could have also considered more combinations of variables but there are some practical limits regarding the convergence of the raking algorithm. We did not include last

Figure C.3: The Effect of Weighting



year's household income in the weighting scheme since doing so led to virtually the same aggregate labor market statistics as without including it (results not reported here).

Figure C.3 compares the employment and unemployment rate using the raw data (RPS - Raw) and using the weighting scheme above (RPS - Wgts w/o EH).[15] As one can see the extra weighting has only very little effect on the estimates for the employment and unemployment rate.

We also ask respondents about whether they worked for pay or profit in the first full week of the previous month for survey waves covering the CPS reference week or at the start of the current month for survey waves conducted in the end of month. This week either is one week prior to or the same as reference week of the most recently conducted CPS. For most waves, in the raw data the implied employed at work rate falls short by several percentage points relative to the corresponding CPS number. Even when conditioning on this, the fraction of individuals on layoff exceeds the corresponding fraction in the current CPS by several percentage points.[16] This suggests negative selection into our survey based on recent employment history.

To account for this negative selection into the sample, we expand the weighting scheme discussed beforeas follows. First, we also include the employed at work status at the time of the most

[15]These are not the "true" raw data because they already include adjustments made to reflect changes in the survey questionnaire, which we discuss in Appendix C.3. In fact, the time-series "RPS - Raw" in Figure C.3 correspond to the time-series "RPS - W12 Adj." in Figure C.2. Here we extend it through wave 19 (March 2021). For the data points after wave 12 the raw data are shown, and respondents with a spouse/partner living in the household and the spouse/partner receive a weight of 0.5 and everyone else a weight of 1.

[16]A layoff here is defined as someone who is on layoff, whether temporarily or permanently, and whether they could have returned to work if asked or not. Put differently, these individuals can show up in any of the following labor market states: unemployed on layoff, unemployed looking, or not in the labor force.

recent CPS into our weighting scheme (also interacted with sex, age, race, education, marital status and region).[17] Second, we also weight on the share of individuals on layoff in the previous month, again interacted with demographics.[18] While we do not explicitly ask for whether someone was on layoff at the beginning of the previous months as this would involve multiple questions, we know the start month of the layoff and thus can approximate the share of individuals on layoff in the previous month. It is only an approximiation because it misses individuals on layoff last month, who are no longer on layoff this month (either because they are employed, or they are non-employed and do not any longer report being on layoff), but in contrast includes individuals whose layoff started after the CPS reference week but in the previous month. Including these two adjustment yields the lines "RPS - Final Wgts" in Figure C.3 and was used to construct the estimates in Figures 3 and 3. This adjustment closes the gap with the CPS as well somewhat reduces the volatility of the time-series.[19]

Table C.3 compares the demographic categories (without any interactions) included in the weighting scheme in the CPS and the RPS. Overall, the match is very close. In addition, we report the final number of observations for respondents and spouses/partners if living in the same household for who we could construct a weight. For example, in each survey wave a small number of respondents skipping a question. If as a consequence of this, we cannot determine their labor market status, we also do not assign a weight.

As described earlier, we also include the interaction of these variables with gender as well the statistics for the employed at work rate and share on layoff in the previous CPS in the weighting scheme. To visualize the goodnes of fit, we plot in Figures C.5 and C.6 for each wave for all statistics used in the weighting scheme the fraction of individuals with the respective characteristics in the RPS (on the y-axis) and the CPS (on the x-axis). The fact that there are no noticeable deviations from the 45 degree line documents how well the weighting procedure works.

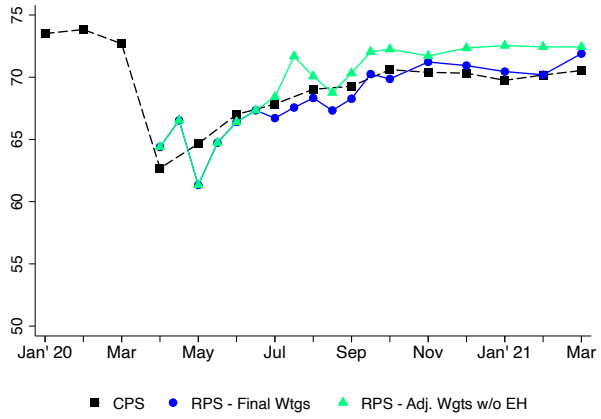
[17] Specifically, we use age (18-24, 25-34, ..., 55-64), race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, Other), education (less than high school, high school graduate or equivalent, some college but no degree, associate's degree in college, bachelor's degree, graduate degree), more broadly defined marital status (married + spouse present, never married, other), relationship status (spouse living in the same household, partner living in the same household, other), and the four major Census regions. We drop the number of children and use a more broadly defined marital status to ensure that each cell in the RPS has at least 30 observations.

[18] Specifically, we use broad groups for age (18-39, 40-64), race/ethnicity (non-Hispanic White, everyone else), education (at most some college, associate's degree in college or more), more broadly defined marital status (married + spouse present, never married, other), relationship status (spouse living in the same household, other). We resort to this smaller set of very broadly defined groups to ensure that each cell in the RPS has at least 30 observations.

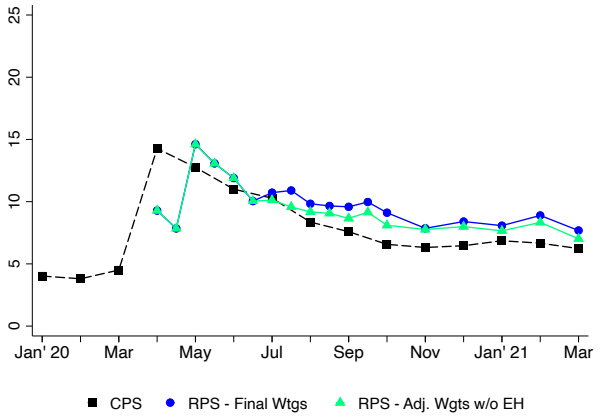
[19] As we show in Figure 1a, our sample is not negatively selected based on employment status in February. In the raw data the February employment rate is even closer to the CPS than in the weighted data. Using February employment status rather than the employed at work status at the time of the most recent CPS into our weighting scheme also reduces the volatility of the time-series but leaves the level unchanged.

Figure C.4: Comparing the Weighting Scheme with the Adjustment Scheme for Waves 8 Onwards

(a) Employment Rate, Age 18-64



(b) Unemployment Rate, Age 18-64



While we consistently collected the information needed to determine the layoff status in the previous month as described above, we only started asking about employed-at-work status during the previous CPS from wave 8 onwards. Therefore, we cannot target employed and at work rates in our raking algorithm for waves prio to wave 8. For these early waves, we add an adjustment factor as follows. First, in wave 8 we implement the full raking procedure including employed-at-work status during the previous CPS. Second, again using the data in wave 8, we construct an adjustment factor such that the distribution of employment and joint distribution of other demographic characteristics matches the same distribution from step 1 but this time the employed at work status at the time of the previous CPS is not included.[20] Intuitively, this adjustment assigns more weight to currently employed people with given characteristics to match employment in wave 8 when we also condition on the employed at work status at the previous CPS. We then apply this adjustment factor to all waves prior to wave 8.[21] After applying this adjustment factor, we choose weights for waves prior to wave 8 without including employed at work status at the respective previous CPS in the weighting scheme, i.e. we only target demographics. To check how will this procedure works, we can compare our key statistics for waves 8 onwards4 when using the actual weights including employed at work status at the respective previous CPS and the one with the adjustment factor. Figure C.4 compares the employment rate and unemployment rate when using the actual weights including employed at work status at the respective previous CPS (RPS - Final Wgts) and an alternative weighting scheme with the adjustment factor but not using the employed at work status at the respective previous CPS (RPS - Adj. Wgts w/o EH). Overall the procedure works well, but suggests that our estimates prior

[20] These demographics are sex, age(below 40, 40 or older), race (non-Hispanic White, other), education (less than an associate's degree [including some college], associate's degree or more), broad marital status (married + spouse present, other) Again, we can use only a restricted set of variables to ensure a sufficient cell size.

[21] Note that we apply this adjustment after the adjustments discussed in Appendix C.3.

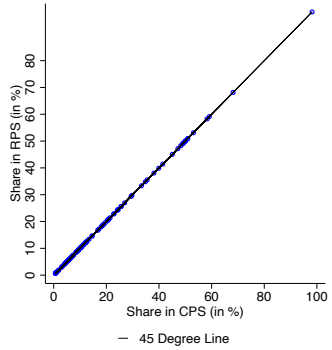
Table C.3: Detailed Statistics Weighting: CPS vs. RPS

		RPS Wave																	
	CPS	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Gender																			
Men	49.2	49.2	49.2	49.2	49.2	49.2	49.2	49.3	49.2	49.2	49.2	49.2	49.2	49.2	49.2	49.2	49.2	49.2	49.2
Women	50.8	50.8	50.8	50.8	50.8	50.8	50.8	50.7	50.8	50.8	50.8	50.8	50.8	50.8	50.8	50.8	50.8	50.8	50.8
Age																			
18-24	14.6	14.6	14.6	14.6	14.6	14.6	14.6	14.6	14.5	14.6	14.6	14.6	14.6	14.6	14.6	14.5	14.6	14.6	14.5
25-34	22.7	22.7	22.7	22.7	22.7	22.7	22.7	22.8	22.8	22.8	22.8	22.8	22.8	22.8	22.8	22.8	22.8	22.8	22.8
35-44	20.9	20.9	20.9	20.9	20.9	20.9	20.9	21.0	21.0	21.0	21.0	21.0	21.0	21.0	21.1	21.1	21.1	21.1	21.2
45-54	20.3	20.3	20.3	20.3	20.3	20.3	20.3	20.3	20.3	20.2	20.2	20.2	20.2	20.2	20.2	20.2	20.2	20.2	20.2
55-64	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4	21.4
Race/Ethnicity																			
Non-hispanic White	59.1	59.3	59.3	59.3	59.3	59.3	59.3	59.0	59.1	58.9	58.9	58.9	58.9	58.9	58.8	58.8	58.8	58.8	58.8
Non-hispanic Black	12.7	12.6	12.6	12.6	12.6	12.6	12.6	12.7	12.7	12.7	12.7	12.7	12.6	12.6	12.7	12.8	12.7	12.8	12.7
Hispanic	18.8	18.8	18.8	18.8	18.8	18.8	18.8	18.9	18.9	18.9	18.9	18.9	19.0	19.0	19.0	19.0	19.1	19.1	19.1
Other	9.3	9.3	9.3	9.3	9.3	9.3	9.3	9.4	9.4	9.5	9.5	9.5	9.5	9.5	9.4	9.4	9.4	9.4	9.4
Education																			
No highschool degree	9.4	9.3	9.3	9.3	9.3	9.3	9.3	8.8	7.7	7.9	7.9	7.9	8.6	8.6	8.5	8.9	9.1	9.3	8.8
Highschool graduate or the equivalent	26.9	27.6	27.6	27.6	27.6	27.6	27.6	26.9	27.6	27.8	27.8	27.8	28.5	28.5	28.5	28.4	28.2	27.9	27.9
Some college but no degree	18.0	18.1	18.1	18.1	18.1	18.1	18.1	17.9	17.8	17.8	17.8	17.8	17.6	17.6	18.1	17.8	17.4	17.5	17.4
Associate's degree in college	10.5	10.2	10.2	10.2	10.2	10.2	10.2	10.1	10.3	10.1	10.1	10.1	9.9	9.9	10.1	10.1	10.1	10.0	10.1
Bachelor's degree	22.9	22.8	22.8	22.8	22.8	22.8	22.8	23.5	23.8	23.6	23.6	23.6	23.2	23.2	22.8	22.8	23.0	23.1	23.4
Graduate degree	12.2	12.0	12.0	12.0	12.0	12.0	12.0	12.8	12.8	12.8	12.8	12.8	12.1	12.1	12.0	12.1	12.2	12.1	12.5
Marital Status																			
Married, spouse present	50.0	49.5	49.5	49.5	49.5	49.5	49.5	50.6	50.6	50.4	50.4	50.4	49.4	49.4	49.4	49.0	49.0	49.1	49.2
Married, spouse absent	1.4	1.7	1.6	1.9	2.3	2.0	2.0	1.9	1.7	1.7	2.1	2.0	2.0	2.5	2.2	2.3	1.9	2.5	1.9
Separated	1.9	2.3	1.8	1.7	1.3	1.9	1.3	1.2	1.5	1.5	1.1	1.2	1.2	1.4	1.1	1.4	1.3	0.8	1.2
Divorced	9.4	9.6	9.6	9.6	9.6	9.6	9.6	9.3	9.2	9.4	9.4	9.4	9.5	9.5	9.6	9.6	9.6	9.4	9.3
Widowed	1.7	1.2	1.8	1.6	1.6	1.4	1.9	1.5	1.5	1.6	1.5	1.6	1.8	1.1	1.7	1.5	1.7	1.8	1.8
Never Married	35.5	35.8	35.8	35.8	35.8	35.8	35.8	35.5	35.5	35.5	35.5	35.5	36.1	36.1	36.0	36.3	36.5	36.4	36.5
Relationship Status																			
Spouse/Partner living in same household	58.6	58.4	58.4	58.4	58.4	58.4	58.4	58.9	59.3	58.9	58.9	58.9	58.8	58.8	58.7	58.6	58.5	58.3	58.4
No Spouse/Partner living in same household	41.4	41.6	41.6	41.6	41.6	41.6	41.6	41.1	40.7	41.1	41.1	41.1	41.2	41.2	41.3	41.4	41.5	41.7	41.6
Number of children																			
0	68.2	68.4	68.4	68.4	68.4	68.4	68.4	68.6	68.3	68.4	68.4	68.4	68.7	68.7	68.4	68.5	68.3	68.5	68.6
1	13.4	13.3	13.3	13.3	13.3	13.3	13.3	13.3	13.3	13.5	13.5	13.5	13.1	13.1	13.3	13.3	13.6	13.3	13.0
2	12.1	12.0	12.0	12.0	12.0	12.0	12.0	11.8	12.1	11.8	11.8	11.8	11.9	11.9	11.8	11.8	11.8	11.7	12.0
3+	6.3	6.4	6.4	6.4	6.4	6.4	6.4	6.3	6.3	6.3	6.3	6.3	6.3	6.3	6.4	6.5	6.4	6.5	6.3
Region																			
Midwest	20.6	20.6	20.6	20.6	20.6	20.6	20.6	20.7	20.8	20.8	20.8	20.8	20.7	20.7	20.6	20.7	20.6	20.6	20.5
Northeast	17.2	17.1	17.1	17.1	17.1	17.1	17.1	17.2	17.2	17.2	17.2	17.2	17.2	17.2	17.1	17.0	17.0	16.9	16.9
South	38.1	38.0	38.0	38.0	38.0	38.0	38.0	37.9	37.7	37.7	37.7	37.7	37.8	37.8	37.9	38.0	38.2	38.3	38.3
West	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.2	24.3	24.3	24.3	24.3	24.4	24.4	24.3	24.3	24.3	24.2	24.3
Number of Observations	61932	2512	2533	2463	2414	6171	3113	4965	3220	3380	3244	5207	3250	3333	3665	3598	3620	3626	3615

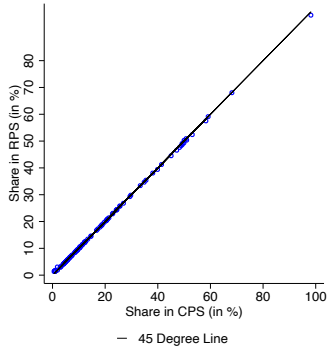
Note: Column 1 reports the statistics for the CPS for the Basic Interviews from February 2020. For waves 2 through 7 we use those for weighting. From wave 8 onwards, we always use the last available CPS because we also aim at matching the employed at work rate and the share of individuals on layoff (as defined in the text) at the time of the last available CPS.

Figure C.5: Weights in CPS vs. RPS for Moments in Raking Procedure for – Waves 2 through 9

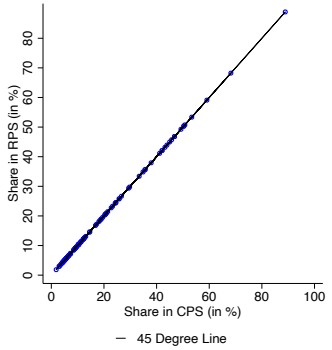
(a) Wave 2



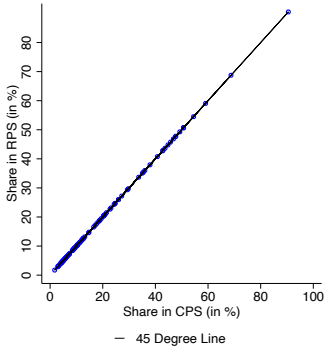
(b) Wave 3



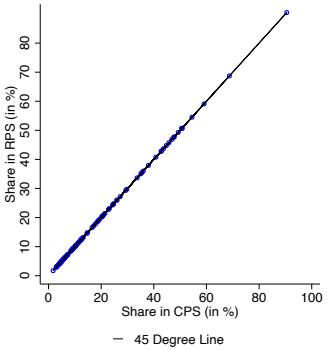
(c) Wave 4



(d) Wave 5



(e) Wave 6



(f) Wave 7

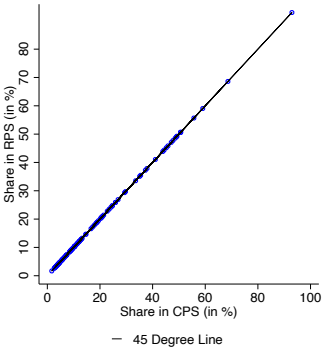
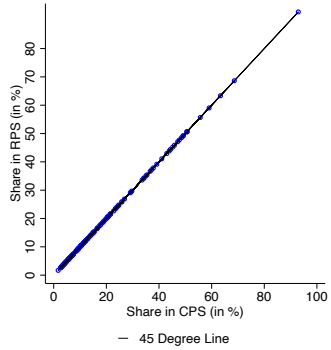
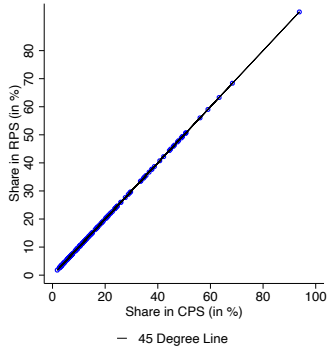


Figure C.6: Weights in CPS vs. RPS for Moments in Raking Procedure for – Waves 8 through 19

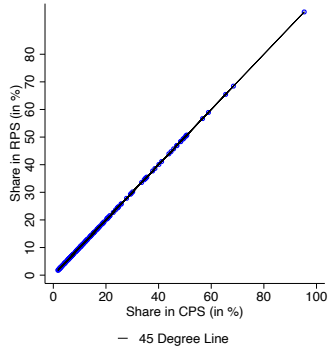
(a) Wave 8



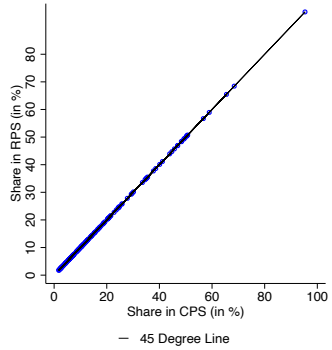
(b) Wave 9



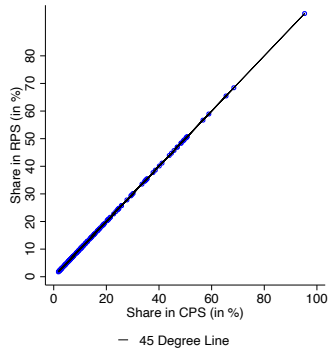
(c) Wave 10



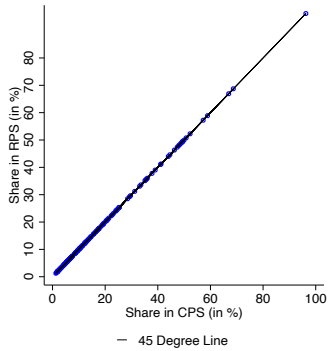
(d) Wave 11



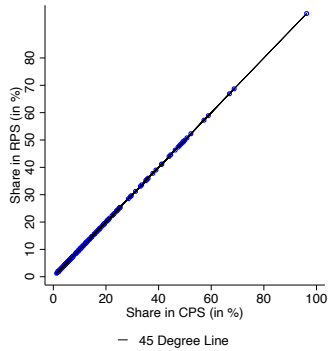
(e) Wave 12



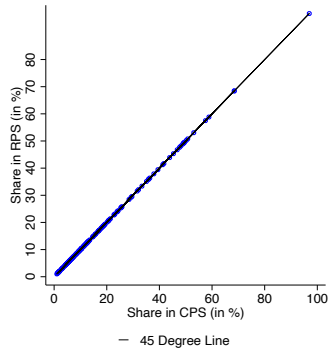
(f) Wave 13



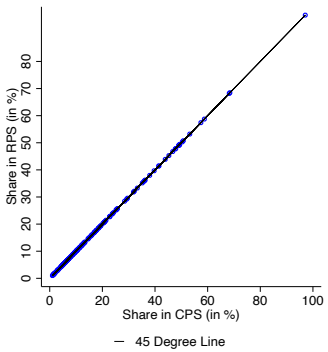
(g) Wave 14



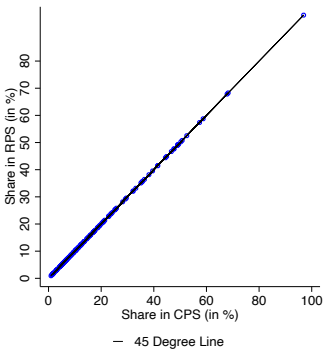
(h) Wave 15



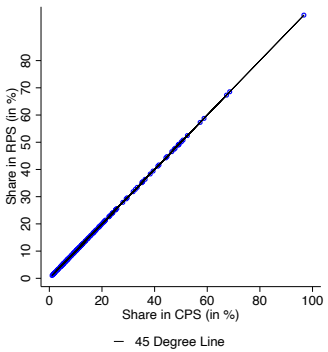
(i) Wave 16



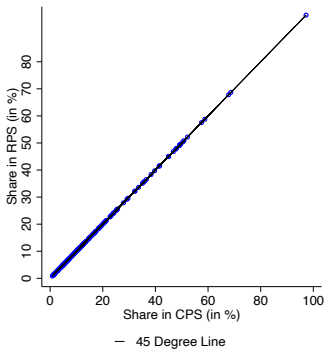
(j) Wave 17



(k) Wave 18



(l) Wave 19



to wave 8 for the employment rate would be slightly lower and for the unemployment rate slightly higher if we would be able to condition on the employed at work status at the previous CPS as well.

C.4.2 Modifications to the Survey Weighting Scheme Over Time

We have occasionally updated our weighting procedure to produce more reliable estimates.

When initially releasing results from our first 3 survey waves, we did not use any weights other than assigning a weight of 0.5 to respondents with a spouse/partner living in the household and to the spouse/partner, with a weight of 1 for everyone else. The motivation behind this weighting scheme was that the initial survey targets already resemble correctly the share of those with and without a spouse present, and without this adjustment the latter group would have been underrepresented.

Starting with wave 4 (early April 2020), we re-weighted the sample to match the share of individuals by household income (at most $50,000, between $50,000 and $150,000, more than $150,000), age (18-34, 35-49, 50-64), and relationship status (whether spouse/partner lives in the household or not). Starting with wave 14 (early October 2020), we implemented the raking procedure discussed in the previous section but without including the share of individuals on layoff in the previous month. We added the share of individuals on layoff to the weighting scheme starting with wave 20 (March 2020). In each case, we retroactively implemented the newly adopted weighting scheme to prior waves as well. In Bick and Blandin (2021) we publish the results of each new RPS release and gather all previous reports on the project website, which allow one to track the estimates released at each point in time.

C.5 Comparison with Foote et al. (2020)

Foote et al. (2020) also ran a repeated online survey that follows the CPS's core labor market module, which they refer to as the Yale Labor Survey (YLS). The two surveys were initially created without prior knowledge of each other. The first RPS results were made public on April 15, 2020 referencing the week of March 29-April 4, 2020. Foote et al. (2020) shared a preliminary draft with us on April 24, 2020. Their results, with an initial reference week of April 5-11, 2020, were first made public on June 24, 2020, at which point the RPS had released its first six survey reports. From June 2020 through March 2021 they released weekly labor market estimates for the US.

The YLS covers the population aged 20+, while the RPS covers the population aged 18-64. Since the level of the employed at work rate varies a lot across age groups, we did not include the YLS in our comparison in Figure 3a. In Figure C.7 we draw a comparison between the two surveys and the CPS not only for the employment at work rate, but also for the employment rate, unemployment rate and labor force participation rate.[22] We display these variables for the CPS for both age groups 18-64 and 20+ as the percentage deviation from the respective February value. We also express the RPS and the YLS time series as deviations from the respective February value in the CPS. Next to including standard demographics, the weighting scheme in the YLS and RPS differ in one important regard: the RPS conditions on employed at work and layoff status in the previous month, whereas the YLS conditioned through November 2020 on employment in February 2020 and from December 2020 onwards on employment, unemployment, and participation status in the previous month, see the description posted on the Boston Fed's project website.

Figure C.7a shows that the CPS employed at work rate in April dropped by 20 percent, independently of the age group. This compares to a decrease of 16.2 % in the RPS and to a decrease of 25.1% in the YLS. The change in the May 2020 employment at work rate relative to February 2020 in the CPS and YLS are fairly similiar to each other, whereas the RPS implied a further decrease in employment relative to April 2020. From then onwards, both surveys track the CPS similarly well although through November and December 2020 the YLS estimates vary quite a bit. This pattern is not visible for the employment rate, see Figure C.7b, suggesting that these are primarily seasonal effects (Thanksgiving, Christmas). From June 2020 onwards, the RPS tends to have a smaller gap with the CPS estimates than the YLS.

With the exception of April 2020, both the YLS and RPS overpredict the changes in the unemployment rate relative to February 2020, see Figure C.7c. Mirroring the comparison with the

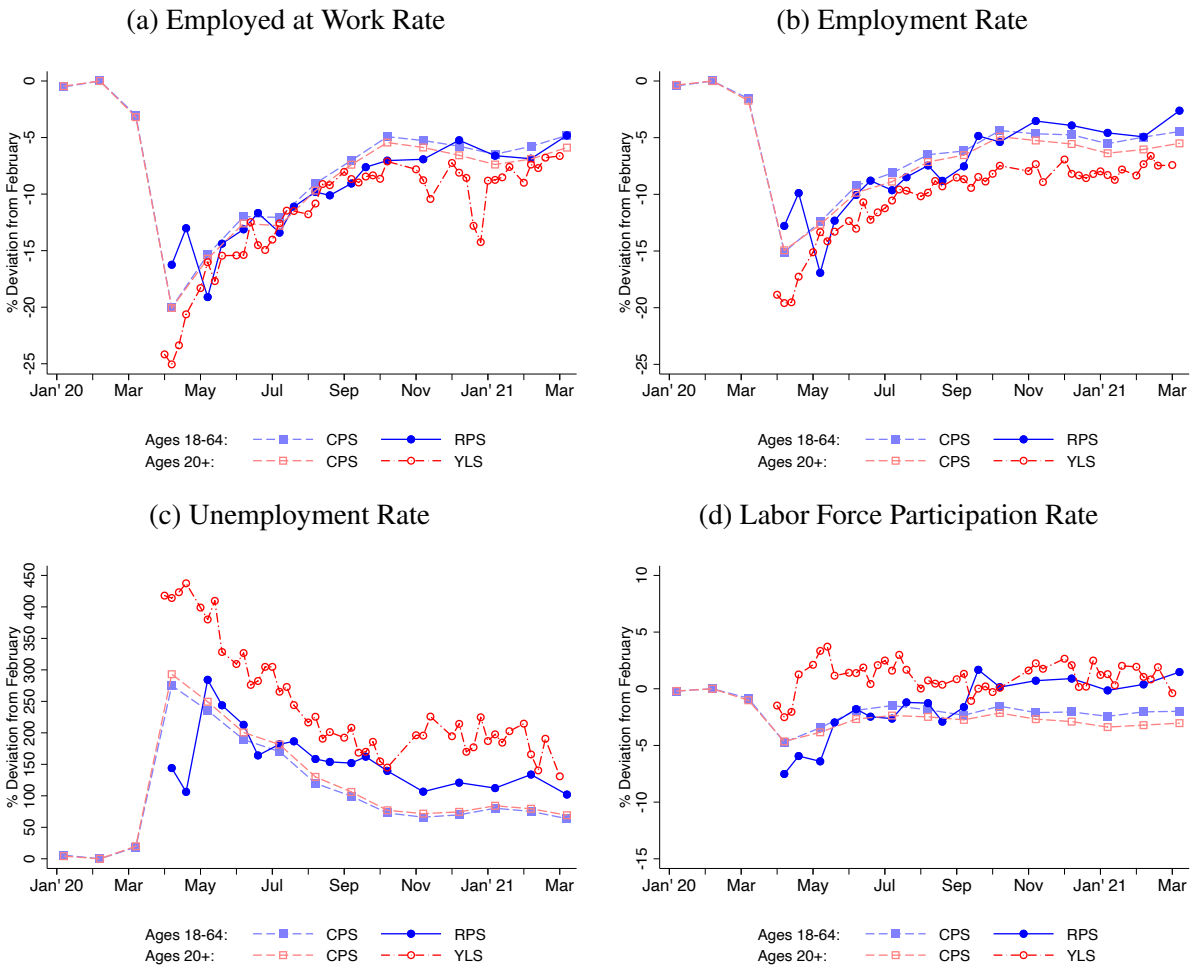
[22] While Foote et al. (2020) also collect data on hours and earnings, they have not yet published the corresponding time-series.

employment rate, the gap with the CPS unemployment rate is larger for the YLS.

Through September 2020, the RPS tracks the labor force participation rate more closely than the YLS. From October onwards the match is similarly close, see Figure C.7d.

To sum up, our assessment is that the two surveys produce fairly comparable estimates of the state of the labor market with the most notable exception being the unemployment rate.[23] We interpret this as an additional validation of our methodological approach.

Figure C.7: Labor Market Outcomes in the RPS, YLS and CPS



Notes: Figure contains data from the RPS and YLS, alongside data from the 2020 CPS. Each data series is shown as percentage deviation from February 2020 in the CPS for the respective age coverage.

[23]For the weighting scheme used for the RPS releases betweeen October 2020 and March 2021, the differences between the YLS and RPS were smaller than in Figure C.7.