NBER WORKING PAPER SERIES

SHORT-RUN EFFECTS OF COVID-19 ON U.S. WORKER TRANSITIONS

Benjamin W. Cowan

Working Paper 27315
http://www.nber.org/papers/w27315

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2020

Short-run Effects of COVID-19 on U.S. Worker Transitions
Benjamin W. Cowan
NBER Working Paper No. 27315
June 2020
JEL No. J1,J2,J6

ABSTRACT

I use Current Population Survey Data from February and April 2020 to examine how individual workers have transitioned between labor-market states and which workers have been hurt most by the COVID-19 pandemic. I find not only large effects on workers becoming unemployed but also a decline in labor-force participation, an increase in absence from one's job, and a decrease in hours worked. Generally, more vulnerable populations—racial and ethnic minorities, those born outside the U.S., women with children, the least educated, and workers with a disability—have experienced the largest declines in the likelihood of (full-time) work and work hours.

Benjamin W. Cowan
School of Economic Sciences
Washington State University
103E Hulbert Hall
Pullman, WA 99164
and NBER
ben.cowan@wsu.edu

Introduction

COVID-19 and its fallout have had a staggering effect on the U.S. labor market. 38.6 million unemployment claims were filed in the 9 weeks preceding May 21, 2020.[1] As data has become available, researchers have begun examining the determinants of job loss and its incidence. Several new papers have focused on parsing out the effects of state and local social distancing policies on job loss, with a common finding that individual policies have had a relatively modest effect compared to the universal effects of the pandemic (Rojas et al., 2020; Lin and Meissner, 2020; Baek et al., 2020; Kong and Prinz, 2020). Another set of recent papers have begun to analyze the distributional impacts of the pandemic (Coibon et al., 2020; Kurman et al., 2020; Cajner et al., 2020; Montenovo et al., 2020; Fairlie, Couch, and Xu, 2020; Borjas and Cassidy, 2020). These papers collectively show deep effects of the pandemic on employment using a variety of data sources on firms and workers.

I contribute to this literature by analyzing individual worker transitions between February and April 2020 in the Current Population Survey (CPS). I use the set of individuals age 21 and older interviewed in both of these months to establish several points. First, as shown in Figure 1, in addition to a 6 percentage point increase in the unemployment rate over these 2 months, I observe a 3 percentage point decrease in the labor force participation rate, a 3 percentage point increase in the rate of absence from work, and a more than 2 percentage point increase in the likelihood of working part-time when the worker usually works full time.

Second, as shown in Tables 1 and 2, I examine individual transitions between labor-market states (out of the labor force, employed, absent from work, and unemployed) as well as transitions between full/part time status (working full time, working part time, and not working) from February to April. Workers are considered "unemployed" if they are not working but are available to work and have either been looking for a job or are temporarily laid off from their job.[2] Other individuals who are not working are either employed but absent from their job or out of the labor force. From February to April 2020, more individuals transfer from being at work to out of the labor force/absent from work (8%; roughly 4% each) than to unemployed (6.5%). In addition, 6% of individuals transfer from full-time work (at least 35 hours per week) to part-time work (less than 35 hours) in addition to the 9% who transfer from full-time work to not working. Not surprisingly, there are very few individuals who go from not working to working (full time) over this period. These results highlight the fact that the pandemic has had much deeper labor-market effects than are measured strictly by the unemployment rate.

My third contribution is to examine how individual worker characteristics correlate with specific labor-market transitions. I show that the pandemic has been particularly devastating to the employment outcomes of vulnerable groups. Among those individuals who were at work in February, all racial minorities (blacks, Asians, and members of other races) are less likely than whites to be at work in April. Hispanics are less likely to be at work than non-Hispanics. The

[1] https://www.nytimes.com/2020/05/21/business/coronavirus-stock-market-today.html?type=styln-live-updates&label=economy&index=1&action=click&module=Spotlight&pgtype=Homepage#link-5635d863
[2] https://www.bls.gov/cps/cps_htgm.htm#unemployed

effect for black workers is particularly large (3.5 percentage points) and is not affected by controlling for occupation and industry fixed effects. Roughly half of this effect is due to transitions out of the labor force (as opposed to transitions to absent from work or unemployed).

Workers under age 30 and over age 60 are less likely to be at work in April (conditional on being at work in February). The former effect is explained by differences in occupation and industry, but the latter effect is not. Most of the effect on older workers is explained by transitions out of the labor force. Some of this effect may be due to declining labor supply on the part of older workers given the elevated risk the virus poses to them.[3]

Members of other vulnerable groups who are at work in February also suffer disproportionately large reductions in the likelihood of being at work in April. This includes workers born outside the U.S. (controlling for race and Hispanic ethnicity), disabled workers, and the least educated groups. Individuals with no high-school diploma or only a high-school diploma are roughly 20 percentage points less likely than those with advanced degrees to transition to “at work” without controlling for industry and occupation (and 10 percentage points less likely when controlling for those factors). A substantial part of this reduction is explained by workers leaving the labor force or absence from work in addition to workers becoming unemployed.

Lastly, as predicted in Alon et al. (2020), the experience of men and women has been different during the early part of the COVID-19 recession. Conditional on being at work in February, women are less likely to be at work in April. Men who are married and men who have children are more likely to stay “at work” over these two months, but this is not the case for women. There are also important gender differences in the likelihood of transitioning from full-time work in February to full-time work in April. Women with children are less likely to make this transition, and this effect is not explained by differences in industry and occupation. Women in this situation are more likely to transition to part-time work, suggesting that both demand and supply-side factors may play a role in their experience. I discuss this further in the Results section.

Related Literature

Coibion et al. (2020) use the Nielsen Homescan survey to show large effects of the pandemic on job losses that exceeded even unemployment claims by the first week of April. In particular, since many individuals in the survey are not looking for new work following job loss or layoff, they estimate that the decrease in the labor force participation rate (8 percentage points) dwarfs the effect on the unemployment rate (which requires an individual to be looking for work) of 2 percentage points. Kurmann et al. (2020) use data from worker scheduling and time clock software (Homebase) to show enormous employment effects in the Leisure & Hospitality and Retail Trade sectors from mid-February to the end of April, with effects occurring both at the extensive (temporary or permanent job layoffs) margin (60%) and intensive (hours reductions for workers still employed) margin (10%). One-third of the former reduction is due to business

[3] https://www.cdc.gov/aging/covid19-guidance.html

dropping employment to zero, which is missed by surveys that only consider employment changes at continuing establishments. These papers do not, however, break down how employment outcomes have changed by individual worker characteristics.

Cajner et al. (2020) use payroll data from ADP (covering about 20% of U.S. private employment) to find that from mid-February to mid-April, private-sector employment declined by around 22% and hours worked for continuously employed workers fell by 4.5%. The brunt of this decrease has fallen on low-wage workers: 36% of the estimated job losses were in the lowest quintile of the wage distribution. Though this data have many advantages, a weakness is the inability to track workers once they leave a firm and limited number of worker characteristics for heterogeneity analysis.

Fairlie, Couch, and Xu (2020) use CPS data to focus on how the labor-market shock due to the pandemic has affected racial and ethnic minorities compared with whites. Their findings indicate that compared with the Great Recession of 2007-09, blacks did not experience a disproportionately large increase in unemployment compared with whites, but Latinx workers did. The authors note, however, that when considering “absent” workers and workers who are “out of the labor force but would like a job” to also be unemployed, the April 2020 unemployment rate for both black and Latinx workers is staggering (and much higher than for whites): more than 31% for each group. Borjas and Cassidy (2020) focus on the labor-market experience of immigrants relative to native-born workers and find that the former group were disproportionately hurt by the COVID-19 shock, which has already reversed the employment advantage previously held by immigrant men relative to native-born men.

The paper most closely related to ours is Montenovo et al. (2020), which also uses CPS data to analyze the consequences of COVID-19. Rather than analyze individual employment transitions, the authors focus on recent unemployment as measured by being unemployed for 10 weeks or fewer in the April CPS.[4] They find larger recent unemployment for women, young workers (ages 20-24), Hispanics, and middle education categories (those with a high-school diploma or some college). The authors also examine how differences in industry and occupation characteristics—particularly with respect to their need for face-to-face interaction, flexibility in allowing work from home, and “essential” status—affect unemployment on their own and to what extent they explain the discrepancies by individual demographics and other characteristics described above.

The analysis in Montenovo et al. (2020) provides much insight into heterogeneity in recent unemployment due to COVID-19. However, it neglects transitions from work to leaving the labor force, neither does it account for transitions from full-time to part-time work (or more generally reductions in hours). Both of these are demonstrated to be economically meaningful in other papers (and in my subsequent analysis). Furthermore, while the authors show that their measure of recent unemployment is similar to the one estimated by looking at within-worker

[4] The authors also examine being employed but absent from work, noting that some workers who were laid off due to the pandemic appear to have been recorded as “employed but absent” rather than laid off by BLS surveyors.

changes in employment between February and April, they do not perform their analysis using individual worker transitions.

My contribution relative to these papers is to examine all possible employment status transitions due to COVID-19 and the individual factors that are correlated with them using the rich set of demographic and socioeconomic variables available in the CPS. The only paper I know of in this nascent literature that exploits the panel dimension of the CPS to analyze individual worker job-market transitions is Borjas and Cassidy (2020); however, their focus is on immigrant vs. non-immigrant labor, while my purpose is more general in scope. In addition, my paper is among the first using recent CPS data to analyze changes in work hours via full/part-time status in addition to analyzing extensive margin effects of COVID-19.

Data

I use data on individuals who were interviewed in both the Basic Monthly February and April CPS.[5] CPS respondents are interviewed for 4 consecutive months, not interviewed for the next 8 months, and then interviewed again for the following 4 months. Because of my sample selection rule, in February I observe individuals in their 1st, 2nd, 5th, and 6th interview months, and in April I observe these individuals in their 3rd, 4th, 7th, and 8th interview months, respectively. I compare individual outcomes in April (the latest month of publicly available data) to those in February because the U.S. economy was largely unaffected until the very end of that month (for example, the decline in the U.S. stock market, which led the surge in unemployment claims, only began to decline after February 21st).[6] My sample includes 38,099 individuals age 21 and older each interviewed twice (once in February, once in April). Summary statistics from February on these individuals are included in Table 3.

Montenovo et al. (2020) demonstrate that there is a large drop in response rates in the March and April CPS (by around 13 percentage points). Part of this may be due to the fact that BLS had to change its interviewing procedure and timing due to the pandemic, while part may be due to individuals having a more difficult time completing the survey due to the same. An important question is the extent to which this non-response is random with respect to employment outcomes. The authors provide some evidence that the non-response is correlated with individual socio-demographics. However, the elevated non-response happens to be particularly concentrated among individuals in their 1st, 2nd, 5th, or 6th interview month in the survey. Because our sample requires individuals to be interviewed in both February and April of 2020, it only includes individuals interviewed in their 3rd, 4th, 7th, or 8th response month in April. This mitigates, but does not eliminate, the possibility that my sample is selected on characteristics that affect employment outcomes. In addition, however, average sample characteristics of all

[5] I obtain the data from IPUMS-CPS: Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles and J. Robert Warren. Integrated Public Use Microdata Series, Current Population Survey: Version 7.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D030.V7.0
[6] The CPS reference week each month includes the 12th of the month.

CPS individuals interviewed in February are very similar to those of our analysis sample, as shown in the second panel of Table 3.

Individuals are defined as being in the labor force if in the previous week they were at work, held a job but were temporarily absent, were looking for work, or were temporarily laid off from a job. Individuals are classified as “at work” if they did work for pay or profit or worked at least 15 unpaid hours in a family business/farm in the previous week. Individuals are “absent” if they held a job in the previous week but were away from it for various reasons (e.g., illness). As noted in Montenovo et al. (2020), some workers who were temporarily laid off due to the pandemic appear to have been recorded as absent rather than laid off (unemployed) by BLS surveyors, highlighting the importance of tracking this occurrence in my analysis. Lastly, individuals are classified as “unemployed” if they had been looking for work or were temporarily laid off from a job. The employment categories “out of the labor force,” “at work,” “absent,” and “unemployed” are disjoint and cover all individuals in the data.

I measure the hours an individual works as the total number of hours she actually worked in the previous week (at all jobs). Following CPS’s definition, I classify individuals as “full time” if they worked at least 35 hours in all jobs in the previous week. “Part time” workers work a positive number of hours but less than 35 in the previous week.

Methodology

I examine how individual characteristics affect employment transitions using regression analysis. In particular, I estimate models of the following form:

$$Trans_i^{j(feb),k(apr)} = X_i^{feb}\beta + u_i,$$

where $Trans_i^{j(feb),k(apr)}$ is the job-status transition for individual i between state j (in February) and state k (in April). These states either represent employment status (at work, not in labor force, absent from work, or unemployed) or “hours” status (full time, part time, or not working). The vector X_i^{feb} contains individual characteristics (measured in February) including dummies for gender, age category, race, Hispanic ethnicity, whether born in the U.S., presence of a disability (at least one limitation of the following types: hearing, seeing, cognitive, physical, mobility, or personal care), marital status (and its interaction with female), presence of children in the home (and its interaction with female), veteran status, urban status, and state of residence. Including state fixed effects is meant to control for the different state-level policies and infection/death realizations from COVID-19 over this time period. I also include dummies for educational attainment (based on highest grade or degree completed), and in some specifications I include dummies for occupation and industry.[7]

[7] There are 515 distinct occupations and 263 distinct industries among individuals in our sample. Occupation and industry codes are 4-digit codes that correspond with the individual’s primary job in the previous week (if they had a job in the previous week). If the individual did not have a job, their most recent job was used to code their occupation and industry.

All regressions are weighted by the final basic person weight in the February survey, and standard errors in all regressions are robust to heteroscedasticity.

Results

I. Transitions between employment states

Because very few individuals transition from not working to “at work” between February and April 2020 (a little over 2% of my sample; see Table 1), in this analysis I focus on the 22,785 individuals in my sample who were “at work” in February. Only about 76% of these are at work in April. I examine, in turn, the likelihood of transitioning from “at work” in February to “at work” (columns 1 and 2), to “out of the labor force” (columns 3 and 4), to “absent from work” (columns 5 and 6), and to “unemployed” (columns 7 and 8), all in April. The regression results are contained in Table 4. Individuals from certain backgrounds may be disproportionately represented in certain occupations and industries that have been most affected by the COVID-19 crisis (Montenovo et al., 2020). In the first column pertaining to each dependent variable, I do not include industry and occupation fixed effects; in the corresponding second column, I do. The coefficients from these two specifications are of course important for answering different questions.

The results from the first column of Table 4 indicate that women are 2 percentage points (significant at the 10% level) less likely to transition from “at work” in February to “at work” in April. Furthermore, positive effects of being married and having children in the home on this transition for men are nonexistent for women (see the coefficients on the interactions between “female” and “married” and “female” and “children”). Inclusion of industry and occupation fixed effects eliminates the difference in outcomes for single women without children relative to childless single men (the coefficient on “female”) but does not change the discrepancy between men and women when it comes to marriage or the presence of children in the home. Looking at transitions to other labor-market states (columns 3 through 8), it is apparent that transitions to out of the labor force, absence from work, and unemployment each contribute to the overall decrease in the likelihood of remaining at work for married women (relative to married men) and women with children at home (relative to men with children at home).

Alon et al. (2020) discuss how the 2020 recession associated with COVID-19 is different (due to social distancing measures) from recent past recessions in terms of which sectors of the economy are most affected. Many of those taking the biggest initial hit have larger-than-average female shares. This would be one explanation for the negative effect on “female” that is present without industry and occupation controls but is eliminated once they are included in my model. Part of the gender difference in effects related to children may be due to school and daycare closures that have accompanied social distancing, a point I return to in the next section. Since the presence of children magnifies the gap in male and female labor supply in normal times (Juhn and McCue, 2017); the results in Table 4 imply that COVID-19 has exacerbated this pattern, at least in the short run.

Workers in the 31-40, 41-50, and 51-60 age categories are about 3 percentage points more likely than 21-30 year-olds to stay "at work" between February and April without controlling for industry/occupation effects. Older workers are less likely than 21-30 year-olds to make the transition. For those over age 70 who were at work in February, the effect is huge at almost 17 percentage points. The positive effects for middle-age workers relative to young workers is mostly explained by the inclusion of industry and occupation controls, but the effects for older workers is not. The majority of the effect for older workers is explained by transitions out of the labor force (columns 3 and 4 of Table 4), which may be partly due to a reduction in labor supply for this group given their elevated risk associated with contracting the virus.

Blacks, Asians, and members of other races who were at work in February all experience a lower likelihood than white workers of maintaining that status in April.[8] Inclusion of industry and occupation fixed effects explains part of the effect for Asians and members of other races, but none of the effect for blacks. The latter results is consistent with the analysis in Fairlie, Couch and Xu (2020), who find that industry/occupation explains little of the black unemployment change in a decomposition analysis. Transitions to specific labor-market states other than "at work" (Table 4, columns 3-8) indicate that while the negative "at work" effect can be explained almost entirely by an increase in the probability of unemployment for Asians and other races, a decrease in labor-force participation is an important component of the overall effect for blacks. They are about 1.5 percentage points more likely than whites to transition from "at work" to "out of the labor force." This is consistent with the tendency of blacks to leave the labor force altogether, likely as discouraged workers, in prior recessions (Fairlie, Couch, and Xu, 2020).

Table 4 also shows that individuals born inside the U.S. experience a much higher probability of staying "at work" and Hispanic individuals a lower one, consistent with Borjas and Cassidy (2020), Montenovo et al. (2020), and Fairlie, Couch and Xu (2020). The full effect on Hispanics manifests itself through an increase in unemployment, while the predominant effect for non-native workers is via absence from work. More work is needed to understand the differing effects on transitions away from "at work" by race/ethnicity/nativity during the COVID-19 crisis.

Though many new papers analyze distributional effects of the COVID-19 pandemic on labor-market outcomes, few if any have focused on the case of workers with a disability prior to the crisis. My regression results suggest that those with a disability who were at work in February are about 7 percentage points less likely than those without a disability to be at work in April. This effect is barely explained by inclusion of the industry/occupation controls. Furthermore, since there is essentially no effect of having a disability on transitioning to unemployment as it is defined by the BLS (columns 7 and 8), an analysis focused exclusively on this narrow definition of unemployment would miss these large effects. Workers with a disability are both significantly

[8] The "other race" category in this analysis includes many groups combined due to relatively small sample sizes among each of them. They include American Indian/Aleut/Eskimo, Hawaiian/Pacific Islander, and many categories in which the respondent marks more than one race. Altogether, this category makes up about 3% of my sample.

more likely to exit the labor force (columns 3 and 4) and be absent from work (columns 5 and 6) than workers with no disability.

Finally, very large effects of educational attainment on worker transitions from February to April 2020 are evident in Table 4. The reference group is individuals with advanced (beyond a bachelor's) degrees, the highest education group. The coefficients associated with various education categories are monotonically increasing (in absolute value) as education levels fall. This pattern differs somewhat from the one found in Montenovo et al. (2020), who find the worst effects of the pandemic recession on middle education categories when it comes to more narrowly defined recent unemployment. In my analysis, those with less than a high-school diploma are a staggering 23 percentage points less likely to transition from "at work" in February to "at work" in April (column 1 of Table 4). Adding industry and occupation controls cuts the education effects roughly in half, but they remain economically large (between about 5 percentage points for college graduates to about 11 percentage points for those with less than a high-school diploma). There are large effects of education category on all three transitions away from "at work," as seen in the remaining columns of Table 4.

II. Transitions between hours states

Table 5 examines a different dimension of the employment effects of the COVID-19 labor-market shock: hours worked. In particular, I examine how individuals transition not just to being out of work but to lower hours (part-time) as a result of the crisis. Again, because transitions from part-time or out-of-work to full-time work are rare over this time period, I focus on the portion of my sample who were full-time workers in February (17,880 individuals). Only 69% of these were employed full-time (at least 35 hours worked last week) in April. Columns 1-2 pertain to the probability of "full time to full time" transitions, Columns 3-4 pertain to "full time to part time" transitions, and Columns 5-6 pertain to "full time to no work" transitions. As was the case in Table 4, odd columns do not have industry/occupation fixed effects while even columns do.

For some of the groups discussed in the previous section who experienced large "at work" reductions, transitions away from full-time work are largely explained by transitions to no work (zero work hours in the previous week). This is the case for differences by education group and for Hispanics. Asians—as well as blacks and other races, to a lesser extent—are actually less likely than whites to transition to part-time work but much more likely to transition to no work at all. On the other hand, the large effect of "native born" on full-time to full-time transitions is explained in part by transitions to part-time work as well as transitions to no work.

A major finding of the analysis shown in Table 5 pertain to the different experiences of men and women during the first two months of the pandemic. Single women without children at home are less likely to keep their full-time status and more likely to switch to part-time status when industry and occupation controls are not in the model. However, this effect disappears with these controls included, suggesting that these women are more likely to be in industries and occupations that have been particularly hard-hit by the crisis and resulting public health policies. Women with children, however, have seen a large reduction in the probability of full-time employment compared to men with children (roughly 4 percentage points), and this effect is not mediated by the industry/occupation dummies. Furthermore, women in this situation are about 2.3 percentage points more likely to transition to part-time work than men with children. Because these effects are largely impervious to controlling for industry and occupation, they may be a result of labor supply factors resulting from the combination of 1) school and daycare closures resulting from the spread of the virus and 2) women generally shouldering a larger part of the childcare burden than men (as posited in Alon et al., 2020). Whatever the reason, COVID-19 has caused at least a temporary increase in the gender gap in (full-time) employment, particularly for those with children at home.

Conclusion

This paper examines the labor-market transitions of all workers interviewed in both the February and April 2020 CPS over these two months, which have been characterized by the unprecedented COVID-19 pandemic. Examining transitions to all possible employment states reveals important differences in the experience of workers who belong to different groups, both as it pertains to the reduction in those who are “at work” and where those workers wind up in official categories (unemployed, absent from work, or out of the labor force). Examining transitions to different “hours” states (full-time work vs. part-time work) further reveals important sociodemographic differences.

In general, I find that workers in traditionally vulnerable groups have been especially hard hit by the economic crisis associated with the first two months of the COVID-19 pandemic. This includes racial and ethnic minorities, those born outside the U.S., women with children, the least educated, the youngest and oldest workers, and workers with a disability. Policies that focus resources on such groups may have the biggest “bang for the buck” in terms of ameliorating the effects of the crisis, and careful attention is needed to examine how the initial large reduction in employment for these groups responds to changing economic and public health conditions as the pandemic evolves.

References

Alon, Titan M., et al. *The impact of COVID-19 on gender equality*. No. w26947. National Bureau of Economic Research, 2020.

Baek, ChaeWon, et al. "Unemployment Effects of Stay-at-Home Orders: Evidence from High Frequency Claims Data." *VoxEU. org, April* 30 (2020).

Borjas, George, and Hugh Cassidy. *The Adverse Effect of the Covid-19 Labor Market Shock on Immigrant Employment.* No. w27243. National Bureau of Economic Research, 2020.

Cajner, Tomaz, et al. *The US Labor Market during the Beginning of the Pandemic Recession*. No. w27159. National Bureau of Economic Research, 2020.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. *Labor Markets During the COVID-19 Crisis: A Preliminary View*. No. w27017. National Bureau of Economic Research, 2020.

Fairlie, Robert W., Kenneth A. Couch, and Huanan Xu. *The Impacts of COVID-19 on Minority Unemployment: First Evidence from April 2020 CPS Microdata*. No. w27246. National Bureau of Economic Research, 2020.

Juhn, Chinhui, and Kristin McCue. "Specialization then and now: Marriage, children, and the gender earnings gap across cohorts." *Journal of Economic Perspectives* 31.1 (2017): 183-204.

Kong, Edward, and Daniel Prinz. "The Impact of Non-Pharmaceutical Interventions on Unemployment During a Pandemic." *Available at SSRN 3581254* (2020).

Kurmann, Andre, Etienne Lale, and Lien Ta. "The Impact of COVID-19 on US Employment and Hours: Real-Time Estimates with Homebase Data." *May). http://www. andrekurmann. com/hb_covid* (2020).

Lin, Zhixian, and Christopher M. Meissner. *Health vs. Wealth? Public Health Policies and the Economy During Covid-19*. No. w27099. National Bureau of Economic Research, 2020.

Montenovo, Laura, et al. *Determinants of Disparities in Covid-19 Job Losses*. No. w27132. National Bureau of Economic Research, 2020.

Rojas, Felipe Lozano, et al. *Is the Cure Worse than the Problem Itself? Immediate Labor Market Effects of COVID-19 Case Rates and School Closures in the US*. No. w27127. National Bureau of Economic Research, 2020.

Figure 1:

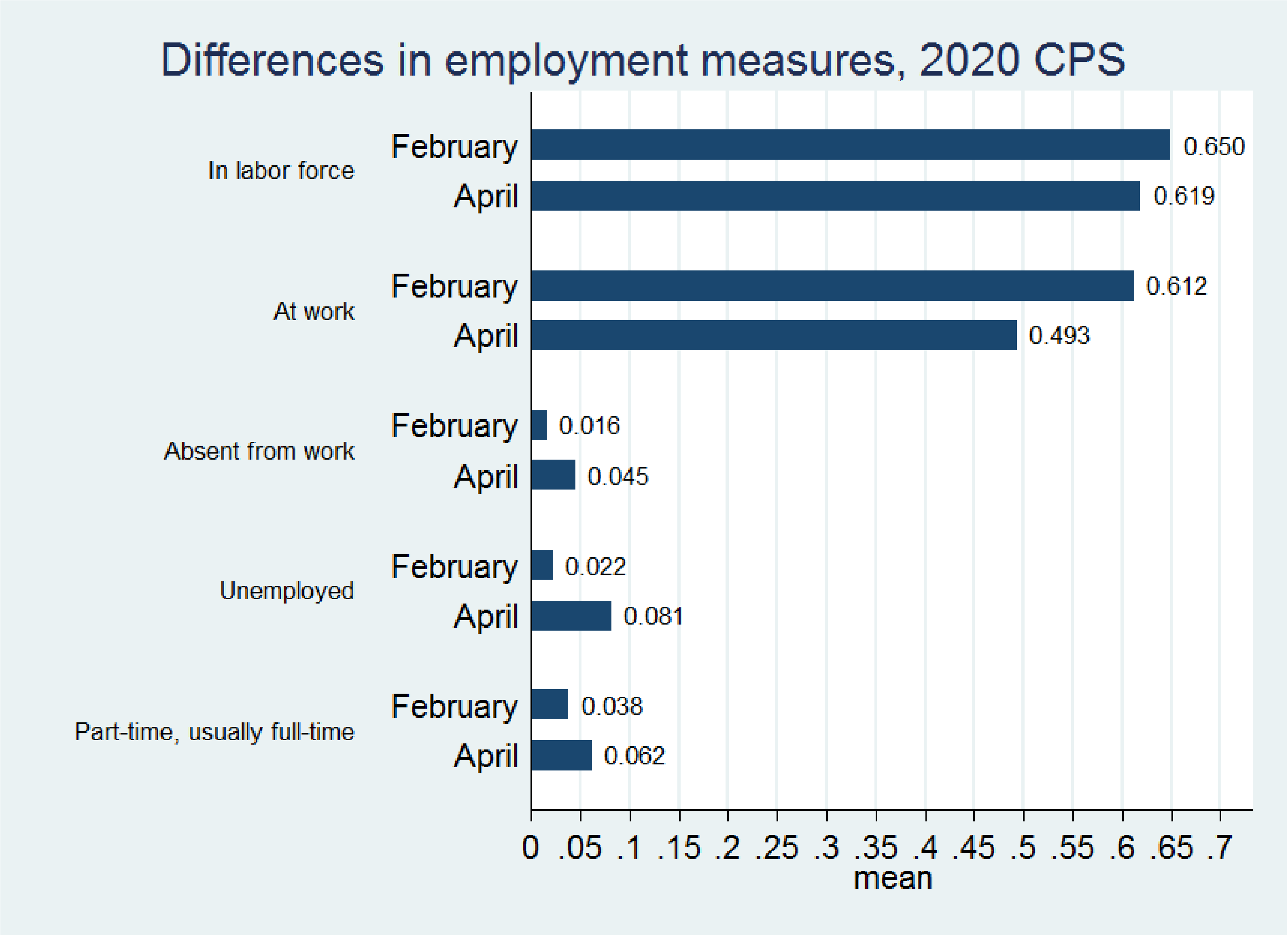
Differences in employment measures, 2020 CPS
In labor force
February
0.650
April
0.619
At work
February
0.612
April
0.493
Absent from work
February
0.016
April
0.045
Unemployed
February
0.022
April
0.081
Part-time, usually full-time
February
0.038
April
0.062
0 .05 .1 .15 .2 .25 .3 .35 .4 .45 .5 .55 .6 .65 .7
mean

Table 1:

Transitions among labor market states, 2020 CPS				
	Out of labor force	At work	Absent	Unemployed
Out of labor force	33.38	0.98	0.18	0.48
At work	4.07	46.74	3.90	6.50
Absent	0.31	0.79	0.29	0.21
Unemployed	0.81	0.43	0.09	0.84

Notes: cells show the percentage transititioning from column categories (February) to row categories (April). The study sample consists of all individuals interviewed in both the February and April 2020 CPS (N=38,099). All statistics were calculated using the final basic CPS person weight from February.

Table 2:

Transitions among labor market states, 2020 CPS			
	Full time	Part time	No work
Full time	33.16	5.97	9.17
Part time	2.78	4.83	5.30
No work	1.35	0.86	36.58

Notes: cells show the percentage transititioning from column categories (February) to row categories (April). The study sample consists of all individuals interviewed in both the February and April 2020 CPS (N=38,099). All statistics were calculated using the final basic CPS person weight from February.

Table 3:

Summary statistics for study sample vs. full sample, February 2020 CPS

	Study sample		Full sample	
	mean	std. dev.	mean	std. dev.
In the labor force	0.65	0.48	0.65	0.48
At work	0.61	0.49	0.61	0.49
Absent from work	0.02	0.13	0.02	0.13
Unemployed	0.02	0.15	0.02	0.15
Work hours last week	24.08	21.58	24.09	21.39
Rural	0.17	0.38	0.17	0.37
Female	0.52	0.50	0.52	0.50
Age 21-30	0.17	0.38	0.18	0.39
Age 31-40	0.18	0.38	0.18	0.38
Age 41-50	0.16	0.37	0.17	0.37
Age 51-60	0.18	0.38	0.17	0.38
Age 61-70	0.16	0.37	0.16	0.36
Age 71+	0.15	0.36	0.14	0.35
White	0.78	0.41	0.78	0.42
Black	0.12	0.33	0.13	0.33
Asian	0.06	0.24	0.06	0.24
Other race	0.03	0.17	0.03	0.18
Married	0.55	0.50	0.54	0.50
Veteran	0.08	0.27	0.08	0.26
Children in household	0.38	0.48	0.38	0.48
Born in U.S.	0.81	0.39	0.81	0.39
Hispanic ethnicity	0.15	0.36	0.16	0.37
Has disability	0.13	0.33	0.13	0.33
Less than high school diploma	0.09	0.28	0.09	0.28
High school diploma	0.27	0.45	0.28	0.45
Some college	0.27	0.44	0.27	0.44
College degree	0.23	0.42	0.23	0.42
Advanced degree	0.14	0.34	0.13	0.34

Notes: There are 38,099 individuals in the study sample and 88,167 individuals in the full sample. The study sample consists of all individuals interviewed in both the February and April 2020 CPS. The full sample consists of all individuals interviewed in the February 2020 CPS. All statistics are from the February 2020 survey and were calculated using the final basic CPS person weight.

Table 4:

Correlates of Individual worker transitions, February to April 2020 CPS				
	At work--> at work	At work--> at work	At work--> not in LF	At work--> not in LF
	1	2	3	4
Female	-0.020*	0.005	0.007	0.002
	(0.011)	(0.011)	(0.007)	(0.007)
Age 31-40	0.027**	0.008	-0.018***	-0.008
	(0.011)	(0.010)	(0.006)	(0.006)
Age 41-50	0.031***	0.011	-0.016**	-0.006
	(0.011)	(0.010)	(0.006)	(0.006)
Age 51-60	0.032***	0.005	-0.016**	-0.004
	(0.011)	(0.010)	(0.006)	(0.006)
Age 61-70	-0.028**	-0.045***	0.024***	0.031***
	(0.013)	(0.012)	(0.008)	(0.008)
Age 70+	-0.166***	-0.155***	0.109***	0.108***
	(0.022)	(0.020)	(0.017)	(0.017)
Black	-0.034***	-0.036***	0.016**	0.014*
	(0.012)	(0.011)	(0.008)	(0.008)
Asian	-0.035**	-0.026*	-0.005	-0.004
	(0.015)	(0.014)	(0.009)	(0.009)
Other race	-0.027	-0.010	-0.006	-0.007
	(0.021)	(0.019)	(0.011)	(0.011)
Born in U.S.	0.056***	0.032***	-0.018***	-0.008
	(0.011)	(0.010)	(0.007)	(0.007)
Hispanic	-0.021*	-0.011	0.004	0.002
	(0.011)	(0.011)	(0.007)	(0.007)
Disability	-0.072***	-0.067***	0.049***	0.043***
	(0.018)	(0.017)	(0.013)	(0.012)
Veteran	0.026**	0.006	-0.010	0.000
	(0.013)	(0.012)	(0.008)	(0.008)
Married	0.051***	0.020**	-0.015**	-0.009
	(0.010)	(0.010)	(0.006)	(0.006)
Female*married	-0.051***	-0.025*	0.014*	0.011
	(0.014)	(0.013)	(0.009)	(0.009)
Children	0.026***	0.020**	-0.012**	-0.007
	(0.010)	(0.009)	(0.006)	(0.006)
Female*children	-0.031**	-0.023*	0.014*	0.010
	(0.013)	(0.013)	(0.008)	(0.008)
Rural	0.019**	0.013	-0.007	-0.004
	(0.009)	(0.008)	(0.005)	(0.005)
Less than HS diploma	-0.230***	-0.114***	0.072***	0.043***
	(0.017)	(0.018)	(0.011)	(0.013)
HS diploma	-0.194***	-0.103***	0.046***	0.022***
	(0.010)	(0.012)	(0.006)	(0.007)
Some college	-0.162***	-0.082***	0.037***	0.016**
	(0.009)	(0.011)	(0.005)	(0.007)
College degree	-0.072***	-0.047***	0.022***	0.015***
	(0.008)	(0.009)	(0.005)	(0.006)
Industry and occupation fixed effects	No	Yes	No	Yes
Mean of dependent variable	0.764	0.764	0.067	0.067
R-squared	0.069	0.243	0.029	0.095

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. N=22,785. All regressions were weighted using the final basic CPS person weight from February and include state fixed effects (not shown). Dependent variables represent individual worker labor-market transitions from February to April. Omitted categories are as follows: for age dummies: "Age 21-30"; for race dummies: "White"; for education categories: "Advanced degree."

Table 4 (continued):

Correlates of Individual worker transitions, February to April 2020 CPS				
	At work--> absent	At work--> absent	At work--> unemployed	At work--> unemployed
	5	6	7	8
Female	0.009	-0.002	0.005	-0.005
	(0.006)	(0.007)	(0.008)	(0.008)
Age 31-40	0.004	0.005	-0.014*	-0.005
	(0.006)	(0.006)	(0.008)	(0.008)
Age 41-50	0.002	0.002	-0.017**	-0.006
	(0.006)	(0.006)	(0.008)	(0.008)
Age 51-60	0.001	0.003	-0.017**	-0.005
	(0.006)	(0.006)	(0.008)	(0.008)
Age 61-70	0.014*	0.014*	-0.010	-0.000
	(0.007)	(0.008)	(0.009)	(0.009)
Age 70+	0.046***	0.039***	0.011	0.008
	(0.014)	(0.014)	(0.015)	(0.015)
Black	0.005	0.004	0.013	0.018*
	(0.007)	(0.007)	(0.009)	(0.009)
Asian	0.011	0.010	0.029**	0.019*
	(0.009)	(0.009)	(0.011)	(0.011)
Other race	0.001	-0.011	0.033**	0.028*
	(0.012)	(0.012)	(0.016)	(0.016)
Born in U.S.	-0.024***	-0.020***	-0.013	-0.004
	(0.007)	(0.007)	(0.008)	(0.008)
Hispanic	-0.009	-0.010	0.026***	0.019**
	(0.006)	(0.007)	(0.009)	(0.009)
Disability	0.024**	0.028**	-0.001	-0.004
	(0.011)	(0.011)	(0.012)	(0.012)
Veteran	-0.010	-0.008	-0.006	0.002
	(0.007)	(0.007)	(0.009)	(0.009)
Married	-0.011*	-0.004	-0.025***	-0.006
	(0.006)	(0.006)	(0.008)	(0.007)
Female*married	0.019**	0.013	0.018*	0.001
	(0.008)	(0.008)	(0.010)	(0.010)
Children	0.002	0.002	-0.016**	-0.016**
	(0.006)	(0.006)	(0.007)	(0.007)
Female*children	-0.003	-0.006	0.020**	0.019*
	(0.008)	(0.008)	(0.010)	(0.010)
Rural	-0.002	-0.000	-0.010	-0.008
	(0.005)	(0.005)	(0.007)	(0.006)
Less than HS diploma	0.054***	0.037***	0.104***	0.034**
	(0.010)	(0.012)	(0.013)	(0.014)
HS diploma	0.053***	0.041***	0.095***	0.041***
	(0.006)	(0.007)	(0.007)	(0.009)
Some college	0.045***	0.035***	0.079***	0.031***
	(0.005)	(0.007)	(0.007)	(0.008)
College degree	0.021***	0.020***	0.030***	0.013**
	(0.005)	(0.005)	(0.006)	(0.006)
Industry and occupation fixed effects	No	Yes	No	Yes
Mean of dependent variable	0.064	0.064	0.106	0.106
R-squared	0.015	0.090	0.031	0.161

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. N=22,785. All regressions were weighted using the final basic CPS person weight from February and include state fixed effects (not shown). Dependent variables represent individual worker labor-market transitions from February to April. Omitted categories are as follows: for age dummies: "Age 21-30"; for race dummies: "White"; for education categories: "Advanced degree."

Table 5:

Correlates of Individual worker transitions, February to April 2020 CPS						
	Full time--> full time	Full time--> full time	Full time--> part time	Full time--> part time	Full time--> not working	Full time--> not working
Female	-0.026**	-0.001	0.019*	0.008	0.008	-0.007
	(0.013)	(0.013)	(0.010)	(0.010)	(0.012)	(0.012)
Age 31-40	0.029**	0.009	-0.019**	-0.010	-0.010	0.000
	(0.013)	(0.012)	(0.010)	(0.010)	(0.011)	(0.011)
Age 41-50	0.021	0.005	-0.012	-0.005	-0.009	0.000
	(0.013)	(0.013)	(0.010)	(0.010)	(0.011)	(0.011)
Age 51-60	0.034***	0.014	-0.026***	-0.018*	-0.008	0.004
	(0.013)	(0.013)	(0.009)	(0.010)	(0.011)	(0.011)
Age 61-70	-0.014	-0.033**	-0.001	0.003	0.014	0.030**
	(0.016)	(0.016)	(0.012)	(0.012)	(0.014)	(0.014)
Age 70+	-0.101***	-0.098***	0.046**	0.051**	0.055**	0.047*
	(0.030)	(0.029)	(0.023)	(0.023)	(0.026)	(0.025)
Black	-0.026*	-0.021	-0.014	-0.013	0.040***	0.034***
	(0.014)	(0.014)	(0.010)	(0.010)	(0.013)	(0.012)
Asian	0.013	0.013	-0.056***	-0.041***	0.044***	0.028*
	(0.018)	(0.017)	(0.012)	(0.012)	(0.016)	(0.015)
Other race	0.003	0.019	-0.034*	-0.036**	0.032	0.017
	(0.026)	(0.024)	(0.018)	(0.018)	(0.022)	(0.020)
Born in U.S.	0.081***	0.055***	-0.025***	-0.023**	-0.057***	-0.032***
	(0.013)	(0.013)	(0.009)	(0.009)	(0.012)	(0.011)
Hispanic	-0.035**	-0.017	0.011	0.003	0.024*	0.014
	(0.014)	(0.013)	(0.010)	(0.010)	(0.012)	(0.012)
Disability	-0.058**	-0.072***	0.021	0.025	0.037*	0.047**
	(0.023)	(0.022)	(0.017)	(0.017)	(0.020)	(0.020)
Veteran	0.038**	0.005	-0.006	0.003	-0.032**	-0.009
	(0.016)	(0.016)	(0.012)	(0.012)	(0.013)	(0.013)
Married	0.058***	0.031***	-0.011	-0.009	-0.046***	-0.022**
	(0.013)	(0.012)	(0.009)	(0.009)	(0.011)	(0.010)
Female*married	-0.035**	-0.021	0.003	0.002	0.032**	0.018
	(0.017)	(0.016)	(0.013)	(0.013)	(0.015)	(0.014)
Children	0.030***	0.026**	-0.010	-0.011	-0.020**	-0.015
	(0.012)	(0.011)	(0.008)	(0.009)	(0.010)	(0.010)
Female*children	-0.044***	-0.036**	0.023*	0.023*	0.021	0.013
	(0.017)	(0.016)	(0.012)	(0.012)	(0.014)	(0.013)
Rural	0.025**	0.018	-0.010	-0.012	-0.015*	-0.006
	(0.011)	(0.011)	(0.008)	(0.008)	(0.009)	(0.009)
Less than HS diploma	-0.232***	-0.121***	0.021	0.017	0.211***	0.104***
	(0.021)	(0.023)	(0.015)	(0.017)	(0.019)	(0.020)
HS diploma	-0.200***	-0.111***	0.012	0.013	0.188***	0.098***
	(0.012)	(0.015)	(0.009)	(0.011)	(0.010)	(0.012)
Some college	-0.154***	-0.086***	0.011	0.016	0.143***	0.070***
	(0.012)	(0.014)	(0.009)	(0.011)	(0.009)	(0.011)
College degree	-0.053***	-0.042***	-0.012	-0.001	0.065***	0.043***
	(0.011)	(0.012)	(0.008)	(0.009)	(0.008)	(0.009)
Industry and occupation fixed effects	No	Yes	No	Yes	No	Yes
Mean of dependent variable	0.687	0.687	0.124	0.124	0.19	0.19
R-squared	0.063	0.225	0.011	0.078	0.065	0.225

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. N=17,880. All regressions were weighted using the final basic CPS person weight from February and include state fixed effects (not shown). Dependent variables represent individual worker labor-market transitions from February to April. Omitted categories are as follows: for age dummies: "Age 21-30"; for race dummies: "White"; for education categories: "Advanced degree."