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The US Labor Market during the Beginning of the Pandemic Recession

ABSTRACT Using weekly administrative payroll data from the largest US payroll processing company, we measure the evolution of the US labor market during the first four months of the global COVID-19 pandemic. After aggregate employment fell by 21 percent through late April, employment rebounded somewhat through late June. The reopening of temporarily shuttered businesses contributed significantly to the employment rebound, particularly for smaller businesses. We show that worker recall has been an important component of recent employment gains for both reopening and continuing businesses. Employment losses have been concentrated disproportionately among lower wage workers; as of late June employment for workers in the lowest wage quintile was still 20 percent lower relative to mid-February levels. As a result, average base wages increased between February and June, though this increase arose entirely through a composition effect. Finally, we document that businesses have cut nominal wages for almost 7 million workers while forgoing regularly scheduled wage increases for many others.

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We use administrative data from Automatic Data Processing, Inc. (ADP)—one of the world's largest providers of cloud-based human resources management solutions—to measure detailed changes in the US labor market during the first few months of the Pandemic Recession.[1] In the current pandemic, data from ADP have many advantages over other data sources. First, ADP processes payroll for about 26 million US workers each month (about 20 percent of total US private employment). As discussed in Cajner and others (2018, 2020) and Grigsby, Hurst, and Yildirmaz (forthcoming), the ADP data are representative of the US workforce along many labor market dimensions. First, the sample sizes are orders of magnitudes larger than most household surveys, which measure individual labor market outcomes at monthly frequencies. Second, the ADP data are available at weekly frequencies. As a result, statistics on the labor market can be observed in almost real time. This facilitates high-frequency analysis such as examining employment responses when states lift closure restrictions on certain industries. Third, the ADP data link to both workers and firms, which permits study of worker recall. The data also include worker and firm characteristics that allow for the estimation of the distributional effects of the recession across demographic group, industry, firm size, and location. Finally, the data include administrative measures of wages that are free from measurement error, facilitating the study of nominal wage adjustments. Collectively, the ADP data allow for a detailed analysis of high-frequency changes in labor market conditions in the first months of the current Pandemic Recession, complementing the data produced by US statistical agencies.

We find that paid US private sector employment declined by 21 percent between mid-February and late April 2020 and then rebounded partially thereafter. As of late June, US employment was still 13 percent below February levels. About 30 percent of the employment decline through mid-April was driven by business shutdowns. However, some of these businesses started coming back during May and June, albeit at a smaller size. About one-third of the increase in US paid employment since the late April trough can be attributed to the reopening of businesses that

1. Importantly, our series are constructed from the ADP micro data and are distinct from the National Employment Report (NER), the monthly employment series published jointly by ADP and Moody's which has the goal of predicting Bureau of Labor Statistics (BLS) employment numbers. The ADP micro data tracked the last recession remarkably well; online appendix figure A1 shows that monthly employment changes using ADP micro data closely match the monthly employment changes reported in the BLS's Current Employment Statistics (CES) survey during the fifteen years prior to the Pandemic Recession.

temporarily closed. Employment declines through April were largest for businesses with fewer than fifty employees, with closures and reopenings playing an even larger role for this size group. We also document that reentering businesses are primarily bringing back their original employees. Finally, we find that despite a staggering 50 percent of all continuing businesses substantively shrinking between February and June, over 10 percent of businesses actually grew during this time period.

Importantly, we also show employment declines were disproportionately concentrated among lower wage workers. Segmenting workers into wage quintiles, we show that more than 35 percent of all workers in the bottom quintile of the wage distribution lost their job—at least temporarily—through mid-April. The comparable number for workers in the top quintile was only 9 percent. Through late June, bottom quintile workers still had employment declines of 20 percent relative to February levels, but many previously nonemployed workers had been recalled to their prior employer. We also find that employment declines were about 4 percentage points larger for women than for men. Very little of the differences across wage groups or gender can be explained by business characteristics such as firm size or industry. Finally, we show that states that reopened earlier had larger employment gains in the reopening sectors.

The massive decline in employment at the lower end of the wage distribution implies meaningful selection effects when interpreting aggregate data. For example, we document that average wages of employed workers rose sharply—by over 6 percent—between February and April, consistent with official data. However, all of this increase is due to the changing composition of the workforce. After controlling for worker fixed effects, worker base wages during the beginning of the recession have been flat. Moreover, we find evidence that businesses were much less likely to increase the wages of their workers and slightly much more likely to cut the wages of their workers during the first four months of the Pandemic Recession. We find that nearly 7 million continuously employed workers received a nominal wage cut between March and June 2020.[2]

2. Our paper complements many recent papers that use a variety of different data sources to track labor market outcomes during the recent recession. A sampling of those papers includes Bartik, Bertrand, Cullen and others (2020), Bartik, Bertrand, Lin and others (2020), Barrero, Bloom, and Davis (2020), Bick and Blandin (2020), Brynjolfsson and others (2020), Chetty and others (2020), Dingel and Neiman (2020), Coibion, Gorodnichenko, and Weber (2020), Kahn, Lange, and Wiczer (2020), and Kurmann, Lalé, and Ta (2020). As discussed above, our ADP data have advantages over the data used in many of these other papers in that they are nationally representative, have large sample sizes, track both employment and

I. Data and Methodology

We use anonymized administrative data provided by ADP. ADP is a large international provider of human resources services including payroll processing, benefits management, tax services, and compliance. ADP has more than 810,000 clients worldwide and now processes payroll for more than 26 million individual workers in the United States per month. The data allow us to produce a variety of metrics to measure high-frequency labor market changes for a large segment of the US workforce. A detailed discussion of the data and all variable definitions can be found in the paper's online appendix.

We use two separate anonymized data sets—one measuring business-level outcomes and another measuring employee-level outcomes—to compute high-frequency labor market changes. The business-level data set reports payroll information during each pay period. Each business's record is updated at the end of every pay period for each ADP client.[3] The record consists of the date payroll was processed, employment information for the pay period, and many time-invariant business characteristics such as North American Industry Classification System (NAICS) industry code. Business records include both the number of paychecks issued in a given pay period ("paid" employees) and the total number of individuals employed ("active" employees). Paid employees include any workers issued regular paychecks during the pay period as well as those issued bonus checks or any other payments. Active employees include paid employees as well as workers with no earnings in the pay period (such as workers on unpaid leave or workers who are temporarily laid off).

The data begin in July 1999 but are available at a weekly frequency only since July 2009. As shown in Cajner and others (2018), ADP payroll data appear to be quite representative of the US economy; the data modestly overrepresent the manufacturing sector and large businesses, but we emphasize that coverage is substantial across the entire industry and size distribution. While some forms of selection into ADP cannot be

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wages, and allow for the joint matching of individual workers to individual businesses. For overlapping questions, our findings are mostly similar to the results in these other papers. When results differ, we discuss further in the text.

3. Note that we use the terms *business* and *firm* throughout the paper to denote ADP clients. Often, entire firms contract with ADP. However, sometimes establishments or units within a firm contract separately. The notion of business in our data is therefore a mix of US Census Bureau notions of an establishment (i.e., a single operating business location) and a firm (i.e., a collection of establishments under unified operational control or ownership).

observed (i.e., certain types of firms choose to contract with ADP), we ensure representativeness in terms of observables by reweighting the data to match Statistics of U.S. Businesses (SUSB) employment shares by firm size and two-digit NAICS industry; a further discussion can be found in the online appendix. For businesses that do not process payroll every week (for example, businesses whose workers are paid biweekly), we create weekly data by assuming the payroll in the missing intermediate period is what is observed in the next period for which the business processes payroll. We then build a weekly time series of employment for each business.[4]

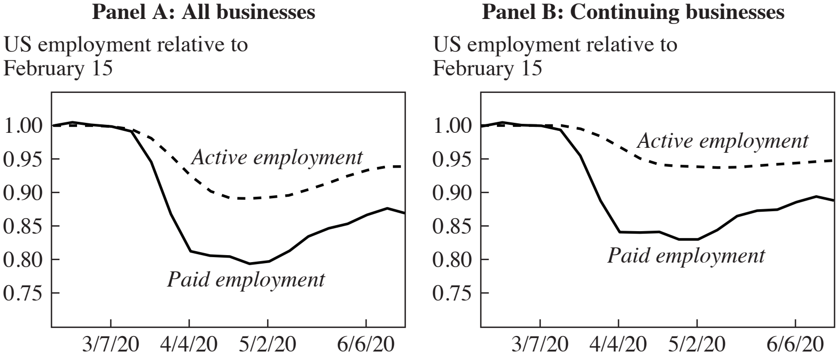
The business-level data report payroll aggregates for each business. For a very large subset of businesses, we also have access to their anonymized de-identified individual-level employee data.[5] That is, we can see detailed anonymized payroll data for individual workers. As with the business data, all identifying characteristics (names, addresses, etc.) are omitted from our research files. Workers are provided an anonymized unique identifier by ADP so that they may be followed over time. We observe various additional demographic characteristics such as the worker's age, gender, tenure at the business, and residential state location. We also can match the workers to their employer. As with the business-level data described above, we can observe the industry and business size of their employer.

The benefits of the employee data relative to the business data described above are threefold. First, we can explore employment trends by worker characteristics such as age, gender, initial wage levels, and worker residence state. This allows us to discuss the distributional effects of the current recession across different types of workers. Second, the individual-level data allow us to measure additional labor market outcomes such as worker wages as well as recall rates of a given worker as businesses start to reopen. Finally, the panel structure of the data permits analysis of individual wage dynamics. In all the work that follows, we will indicate whether we are

4. The methodology we adopt for this paper differs slightly from that used in our previous work with the ADP business-level data (see, for example, Cajner and others 2018, 2020). In particular, in light of the extreme employment changes during the beginning of the Pandemic Recession, in the present work we do not seasonally adjust the data, and we measure employment changes of surviving businesses, closing businesses, and reopening businesses relative to mid-February levels rather than constructing longer-term time series.

5. Unlike the business-level data, the data for our employee sample skew toward employees working in businesses with at least fifty employees. These are the same data used in Grigsby, Hurst, and Yildirmaz (forthcoming). While the data come from employees mostly in businesses with more than fifty employees, there is representation in these data for employees throughout the business size distribution. Again, we weight these data so that they match aggregate employment patterns by industry and firm size from the SUSB.

Figure 1. Aggregate Paid and Active Employment



Source: ADP anonymized payroll records and authors' calculations.

Notes: The solid black line in panel A shows the trend in paid payroll employment for all businesses. The dashed black line in panel A shows the trend in active employment for all businesses. Panel B shows the same patterns for businesses that continually make scheduled payroll payments throughout the entire sample period starting on February 15.

using the business-level data or the employee-level data for our analysis. Unless indicated otherwise, we report weighted results.[6]

II. Employment Changes in the Pandemic Recession

This section presents weekly labor market indexes in the United States compiled from the ADP business-level micro data. Panel A of figure 1 shows our estimated aggregate employment changes spanning the payroll week covering February 15 through late June.[7] Importantly, this panel shows employment changes at both continuing businesses and businesses that have shut down (i.e., those not issuing any paychecks during regularly scheduled pay periods), where shutdowns could reflect either permanent or temporary inactivity. The indexes plot employment levels relative to

6. For all aggregate results, the weighted employment changes found in both data sets are nearly identical during the beginning of the Pandemic Recession.

7. For all figures based on the business-level data, we report two-week trailing moving averages to smooth through volatility that results from offsetting pay frequencies across ADP businesses, the majority of which are biweekly but not all occurring on the same weeks. Also, these results—like all results in the paper—are weighted to match SUSB employment (treating the ADP businesses as firms). In the online appendix, we show results weighting to match Quarterly Census of Employment and Wages employment (treating the ADP businesses as establishments).

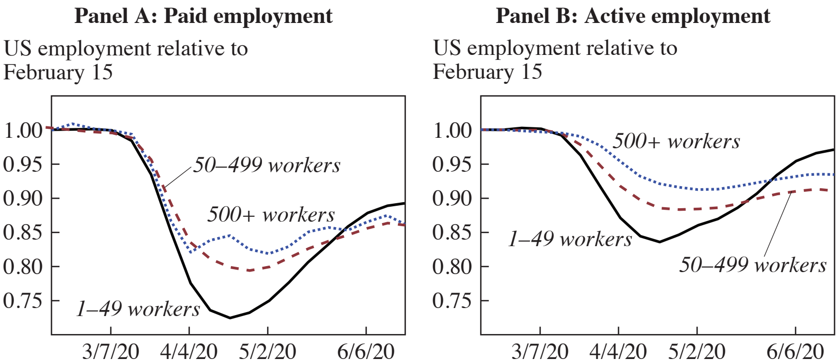
February 15 levels without seasonal adjustment. The figure shows the evolution for paid employees (solid line) and active employees (dashed line). Between mid-February and the labor market trough in late April, paid employment in the United States fell by 20.6 percent, and active employment fell by about 11 percent. The sharper drop in paid employment is to be expected if many businesses initially placed their workers on temporary layoff. Since mid-April, paid employment has increased by 7.4 percentage points through June 20. However, as of late June, paid employment in the United States was still about 13 percent below its level at the start of the recession. Importantly, the bulk of the rebound occurred in May, and the pace of job gains slowed measurably toward the end of June. As we highlight below, the employment increases from mid-April until the end of June are associated with many states starting to reopen their businesses.

The job loss numbers in the ADP data are broadly consistent with employment data published in the BLS's Current Employment Statistics (CES) survey for overlapping weeks. The CES, which measures employment during the week containing the twelfth of the month, estimated private employment declines of 1 million in March and 18.9 million in April, followed by rebounds of 3.7 million in May and 5.4 million in June (not seasonally adjusted). In our measure of total paid employment, focusing on the pay periods corresponding with CES reference weeks, we observe employment declines of about 1.2 million in March and 23.9 million in April followed by rebounds of 3.8 million in May and 5.3 million in June.[8]

Panel B of figure 1 shows employment losses for continuing businesses. We define continuing businesses in a given week as those businesses who have continually made scheduled payroll payments between February 15 and that week. Notice that paid employment for continuing businesses declined by 16.9 percent through late April before rebounding through late June, leaving paid employment 11.2 percent below mid-February levels. The differences between panels A and B highlight the importance of firm closures (which may be temporary) in driving employment declines through late April and the importance of those firms reopening in driving the increase in employment during May and June. Continuing firms accounted for about three-quarters of the employment losses through late

8. These numbers were computed using our estimated employment declines multiplied by total US private sector employment in February 2020. The corresponding numbers for active employment were −0.7 million, −13.1 million, +1.6 million, and +4.4 million for March, April, May, and June, respectively.

Figure 2. Employment Change by Business Size



Source: ADP anonymized payroll records and authors' calculations.

Notes: Panel A shows the trend in payroll employment for each size grouping. Panel B shows the same patterns for active employment.

April. We further explore the importance of business shutdown and reentry to aggregate employment trends in section V.

It is worth mentioning the active employment series shown in figure 1. Recall that active employment measures the number of workers in payroll databases, including those not receiving pay in a given pay period.[9] Active employment among *continuing* businesses actually declined by about 0.5 million jobs between the April and May CES reference periods while other measures showed gains; in other words, businesses in continuous operation trimmed their active employees in the payroll databases, on net, even while aggregate paid employees increased. This pattern hints at important gross employment flows underlying the net numbers we highlight: even while employment has resumed net growth (driven largely by the return of temporarily inactive workers), many businesses were shedding jobs.

Much attention has been given to the preservation of small businesses in the current recession. The roughly $2 trillion stimulus package signed into law on March 27 made special provisions to support small businesses through a large expansion in federal small business loans, and a second tranche of small business loan appropriations was signed on April 24. Figure 2 plots the change in employment by initial business size relative to February 15. The figure shows that businesses with fewer than fifty

9. Importantly, we do not observe active employment of firms not issuing paychecks; that is, active employment is necessarily zero among firms that have shut down.

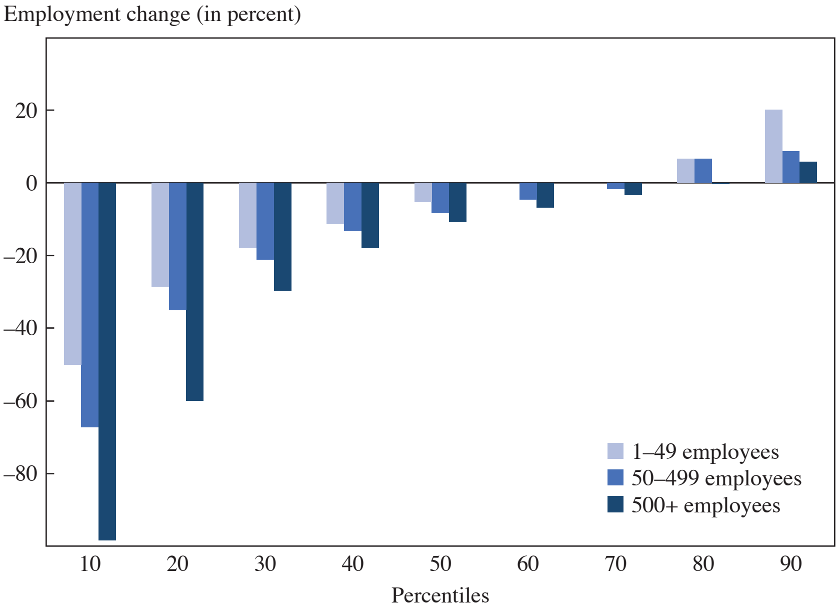
employees reduced both paid employment (panel A) and active employment (panel B) at a faster rate than their larger counterparts throughout March and April. However, businesses of all sizes saw massive employment declines during the first few months of the current recession. Businesses with fewer than fifty employees saw paid employment declines of more than 25 percent through April 18, while those with between fifty and 500 employees and those with more than 500 employees, respectively, saw declines of 15–20 percent during that same time period and reached troughs a week or two later than the smallest businesses.[10] Notably, the growth in paid employment since late April has been much larger for smaller businesses. Between late April and late June, smaller businesses increased employment by 17 percent (of February 15 levels). Businesses with more than fifty employees increased employment by between 4 percent and 7 percent during the same time period. As employment is rebounding, it is the smaller firms that are primarily increasing employment. Again, as we highlight below, much of this differential growth for smaller firms is due to the reopening of smaller firms that temporarily shuttered during the state-imposed shutdowns.

Figure 2 hides interesting heterogeneity across businesses even within size classes. In figure 3, we report the entire distribution of employment changes within and across business size classes, limiting our focus to businesses that survive through this time period (continuers) so we can study a meaningful growth distribution. For each initial employment size class, we report percentiles of employment change between February 15 and June 20, where percentiles are constructed from the employment-weighted business distribution.

Starting on the left-hand side of figure 3, the tenth percentile business within every size class saw declines of at least 50 percent, with the largest class (at least 500 employees) seeing a decline of about 98 percent. These are large firms that essentially shut down, keeping only a handful of original employees on payroll. Even the smallest business size class (1–49) saw substantial declines. The facts that small businesses saw even more overall employment declines (as highlighted in figure 2) and employment changes in the bottom decile of continuing firms were smaller for small businesses suggest that most of the total decline in employment for

10. The somewhat jagged variation in employment changes for the larger businesses is an artifact of the heterogeneity of varying payroll frequencies. In our employee-level data, we can control for the pay frequency of a given worker exactly and such small week-to-week variations are smoothed out.

Figure 3. The Distribution of Employment Change by Business Size among Survivors



Source: ADP anonymized payroll records and authors' calculations.
Notes: Shutdown businesses are excluded. Change in employment is measured between February 15 and June 20.

businesses with fewer than fifty employees is due to business closures. Conversely, all business size groups experienced positive growth at the ninetieth percentile. Even during the Pandemic Recession, some firms added net employment.

Between the extremes, we also observe a wide range of businesses whose employment is close to unchanged. Among the smallest size group at least 10 percent of businesses had little employment change (those spanning the sixtieth through the seventieth percentiles). Similarly a large swath of midsize and larger businesses experienced only modest changes (those spanning the sixtieth through the eightieth percentiles saw changes of less than 7 percent). Taken together, figure 3 reveals striking heterogeneity in the experiences of businesses, even within size classes.[11] The

11. We observe qualitatively similar results when focusing on active employment instead of paid employment, though the distribution of changes in all directions is notably narrower.

Table 1. Paid Employment Changes by Industry (in percent)

Industry	*Feb 15–April 25*	*Feb 15–June 20*
Arts, Entertainment and Recreation	–50.7	–31.7
Accommodation and Food Services	–45.4	–26.8
Retail Trade	–28.9	–17.5
Other Services	–25.1	–14.6
Transportation and Warehousing	–21.8	–20.5
Real Estate, Rental and Leasing	–21.0	–16.9
Information Services	–17.7	–11.3
Wholesale Trade	–17.5	–12.8
Administrative and Support	–16.8	–15.5
Health Care and Social Assistance	–16.5	–10.3
Educational Services	–16.2	–18.9
Construction	–13.8	–4.0
Manufacturing	–12.6	–10.4
Professional, Scientific, and Tech Services	–12.1	–8.3
Finance and Insurance	–1.2	–4.9

Source: ADP anonymized payroll records and authors' calculations.

Notes: Total decline (inclusive of shutdowns) in paid employment for all firms in each two-digit NAICS industry. All changes are relative to February 15, 2020. Data from the business-level sample. Weekly data (without two-week moving average).

median surviving small businesses (less than fifty employees) declined 5 percent, while the medium and large business median declines were 8 and 11 percent, respectively.

The results by firm size are not overly surprising in light of the industry results documented next. The industries that were hit hardest in the beginning of the Pandemic Recession also tend to be the industries with the smallest businesses as documented by Hurst and Pugsley (2011). Table 1 shows employment changes by two-digit NAICS industries during two time periods: February 15 to April 25 (the aggregate employment trough, prior to states starting to reopen) and February 15 to June 20 (i.e., the entire period). These results are shown in columns 1 and 2 of the table, respectively. The largest declines in employment were in sectors that require substantive interpersonal interactions. Through late April, paid employment in both the arts, entertainment and recreation and accommodation and food services sectors (i.e., leisure and hospitality) fell by more than 45 percent while employment in retail trade fell by almost 30 percent. The other services industry, which includes many local or neighborhood businesses like laundromats and hair stylists, also experienced declines in employment of 25.1 percent through late April. Despite a boom in emergency care treatment within hospitals, the health care and social assistance industry experienced a 16.5 percent decline in employment through late April. Industries that employ higher-educated workers—like finance and insurance—saw smaller initial employment declines.

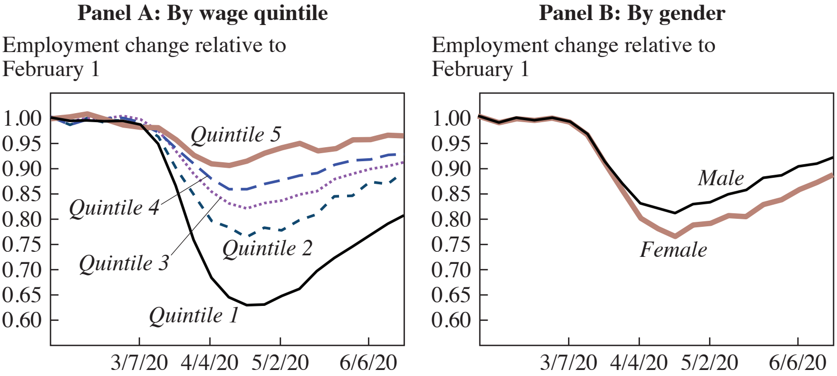
Since bottoming out in late April, most sectors have seen some recovery in employment. Much of the relatively larger increases are in sectors where reopenings have occurred. For example, most states started reopening manufacturing and construction sectors in early May. These sectors saw employment gains of about 20 percent and 70 percent, respectively, of their initial employment losses. Large recoveries are also seen in some of the sectors that experienced the largest initial declines, such as accommodation and food services, retail trade, and other services. Businesses in these three sectors started opening up during May as many states started to lift restrictions on restaurants, retail outlets, and personal service businesses such as barbershops, beauty parlors, and nail salons. Despite states reopening and employment rebounding slightly, employment in these sectors still remains significantly depressed relative to mid-February levels. Notice that, as travel remained depressed and schools remained closed, employment in the transportation and education sectors had not seen the rebound found in retail trade or food services through June 20. Another sector which saw a large rebound is health care and social assistance, which recovered nearly 40 percent of lost employment by the end of June as hospitals and other health providers have attempted to start returning to normal activities.[12]

III. Distributional Effects across Workers

In this section, we document the heterogeneity in job loss across different types of workers using our employee sample. We begin by exploring the labor market outcomes for workers at different points of the base wage distribution at the beginning of the current downturn. We first segment workers by their initial place in the wage distribution. Specifically, we use early February data to define wage quintiles for our analysis based on a worker's administrative base hourly wage. We pool together hourly and salaried workers when making our quintiles. For hourly workers, we use their exact hourly wage. For salaried workers, we assume they work forty hours per week when computing their hourly wage. For weekly (biweekly) salaried individuals, this is just their weekly (biweekly) base administrative

12. In the online appendix, we provide a table of the weekly employment and wage changes by two-digit sector from February through June to facilitate the calibration of various models of the Pandemic Recession.

Figure 4. Employment Changes by Initial Wage Quintile and Gender



Source: ADP anonymized payroll records and authors' calculations.
Notes: Employment declines measured relative to early February. Data for this figure use the employee-level sample.

contracted earnings divided by 40 (80). We hold these thresholds fixed throughout all other weeks of our analysis. The nominal thresholds for the quintiles are $13.50, $16.41, $24.53, and $32.45 per hour.[13]

Panel A of figure 4 shows the employment changes for workers in different wage quintiles relative to early February. As seen from the figure, employment declines in the initial stages of this recession are disproportionately concentrated among lower wage workers. Workers in the bottom quintile of the wage distribution experienced a staggering 37 percent decline in employment between early March and late April. Employment for this group had partially rebounded through late June, but their employment remained depressed by roughly 20 percent relative to mid-February levels. Conversely, employment of workers in the top quintile of the wage distribution declined nearly 10 percent through the end of April. Only about 4 percent of these top earning workers remained out of work through late June. The employment losses during the Pandemic Recession have been disproportionately concentrated among lower wage workers.

13. These cutoffs match well the distribution of wages in the 2019 March Supplement of the Current Population Survey (CPS). Computing hourly wages as annual earnings last year divided by annual hours worked last year, the twentieth, fortieth, sixtieth, and eightieth percentile of hourly wages (measured in nominal dollars per hour) in the 2019 CPS were $12.00, $17.10, $24.00, and $36.10 (authors' calculation).

How much of the larger decline in employment among low-wage workers can be attributed to the industrial composition of the COVID-19 shock? Low-wage workers are more likely to work in restaurants, retail, and leisure services and are also more likely to work in smaller businesses. To assess whether differential exposure to the recession by business characteristics (industry and business size) or worker characteristics (age and location) can explain the differential pattern across either gender or the wage distribution, we further exploit the panel nature of our data and estimate a linear probability model of monthly employment for a given worker at a given firm on wage quintile dummies and detailed controls for industry and business size.[14] Specifically, we measure whether the employee is paid at that firm at the beginning of each given month.

The baseline separation probability between February and March is 6.1 percentage points higher for bottom quintile earners than for top quintile earners. After controlling for only wage quintile fixed effects, bottom quintile earners were 21.5 percentage points less likely to be employed by their February employer in the first two weeks of April relative to top quintile earners, reflecting the patterns in panel A of figure 4. Including industry and firm size fixed effects reduces the gap in excess separation rates between bottom quintile earners and top quintile earners only slightly to 19.1 percentage points. Therefore, a differential firm size and industry mix can explain 12.2 percent (1 − 19.1/21.5) of the gap in job loss between low-wage and high-wage workers during the beginning of this recession, but a substantial gap remains even after accounting for firm size and industrial composition. However, including controls for worker age further reduces the gap in excess separation probabilities between low-wage and high-wage workers to 16.5 percentage points. As highlighted in the online appendix, younger workers were more likely to be displaced during the early part of the recession, and younger workers systematically have lower wages. Overall, we conclude that there is a substantial difference in the behavior of low- and high-wage workers during the early stages of the Pandemic Recession. Only a small part of these differences can be accounted for by differences in industry, business size, and age.

Panel B of figure 4 plots employment changes by gender. Through late April, women experienced a decline in employment that was 4 percentage points larger than men (about 22 percent versus 18 percent). The gap

14. The online appendix discusses the details of this specification as well as plotting the coefficients and standard errors from the regression output.

remained roughly constant through late June. These patterns stand in sharp contrast to prior recessions where men experienced larger job declines. Historically, male-dominated industries such as construction and manufacturing contract the most during recessions. However, as noted above, this recession is hitting a different set of industries, including retail, leisure, and hospitality industries. Can the differential industry declines explain the gender differences in employment losses? In the online appendix, we again exploit the panel nature of our data to assess this question. Less than half a percentage point of the 4–5 percentage point difference can be explained by industry. In other words, even within detailed industries, women are experiencing larger job declines relative to men. The fact that industry or other firm characteristics do not explain the gender difference in employment declines is interesting in its own right. Future research using household level surveys with additional demographic variables can explore whether other facets of the pandemic—such as the increased need for child care—explains some portion of the gender gap in employment losses during this recession.

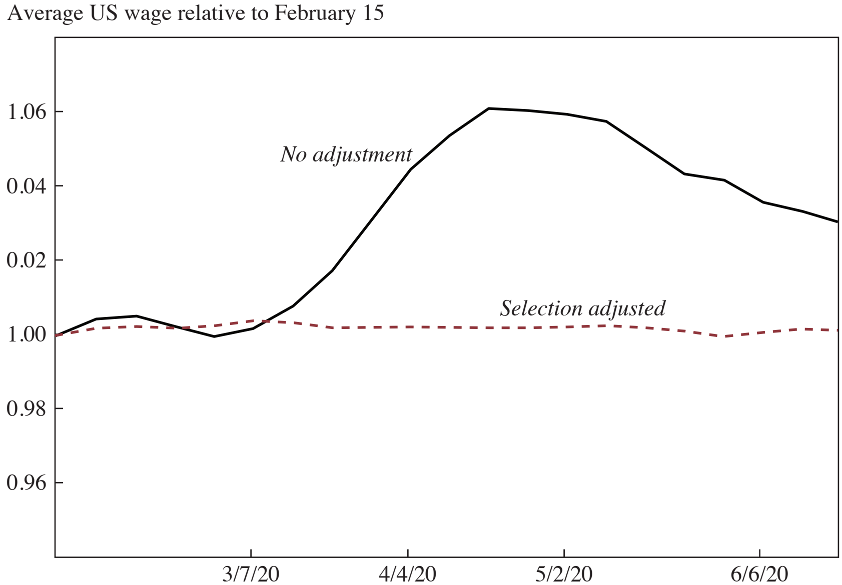
IV. Wage Changes during the Pandemic Recession

Figure 5 shows the trends in wages in the economy during the pandemic recession. The solid line creates a wage index by measuring the mean contract per period wage rate of all working individuals in the economy.[15] Since the start of the recession, observed average wages in the ADP sample grew by nearly 6 percent through mid-May. As highlighted in Solon, Barsky, and Parker (1994), the changing composition of workers over the business cycle can distort measures of wage cyclicality.[16] As seen from panel A of figure 4, workers at the bottom of the wage distribution were much more likely to have employment reductions than those at the top of the wage distribution. From March through the end of April, the sample became more selected toward higher-earning individuals, while the reverse happened thereafter.

15. Contract per period wages are the contracted per hour wage rate for workers paid hourly and the contracted per period weekly or biweekly earnings for salaried workers (depending on pay frequency). The online appendix outlines the wage concept in greater detail.

16. Grigsby (2019) documents that measured growth in average wages has become countercyclical during the last few recessions. He documents that the changing selection of workers during the recent recessions has been responsible for the observed countercyclicality of wages.

Figure 5. Trend in Base Wages, Controlling for Selection



Source: ADP anonymized payroll records and authors' calculations.
Notes: The solid line averages base wages across all employed workers in each period. The dashed line controls for selection by measuring the base wage of a given worker over time.

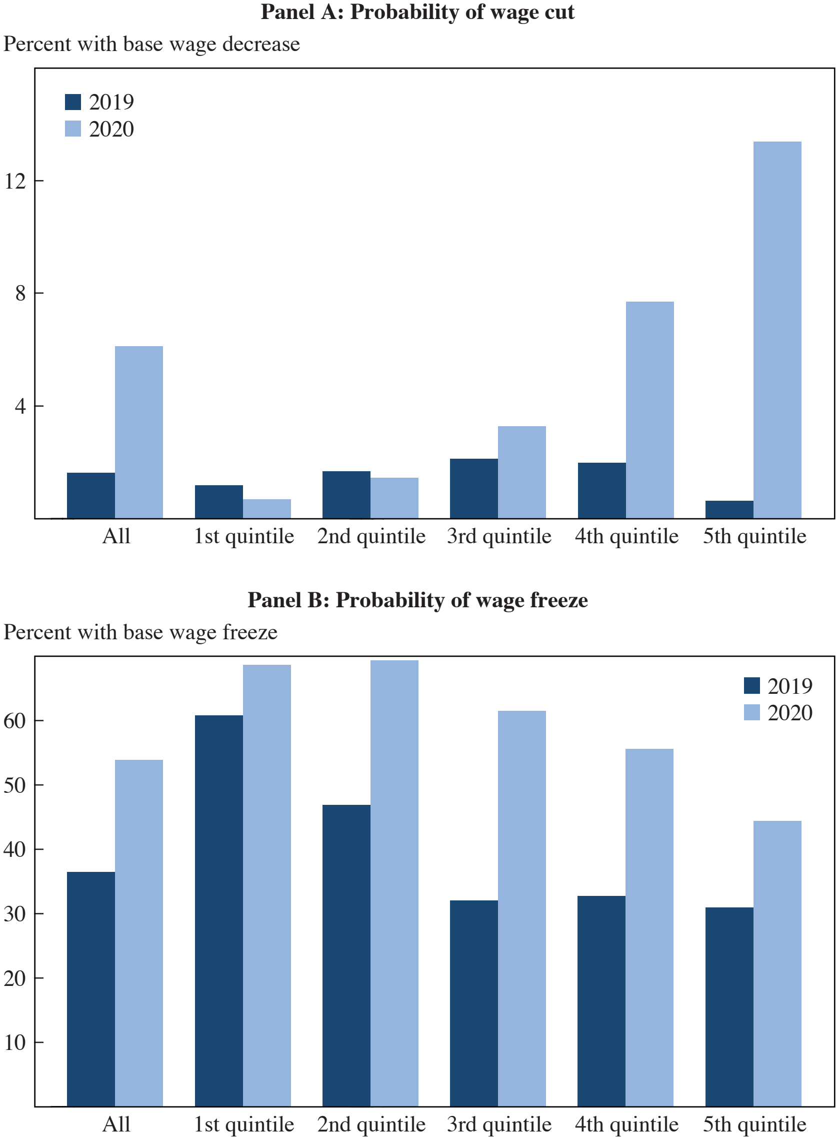
To assess the importance of this selection, we again exploit the panel nature of the ADP data. In particular, we compute individual wage growth for a sample of continuing workers between pay periods t and $t + 1$. By considering individual wage *growth* rather than *levels*, we restrict attention to workers who are in the sample in consecutive periods, thereby purging the wage series of the principal form of selection. We then produce a selection-adjusted wage index by chain-weighting this average wage growth from the reference week ending February 15. The result of adjusting for selection in this way is shown in the dashed line in figure 5. Two things are of note. First, despite the rapid nominal wage growth for the average employed worker (solid line), there is essentially no nominal wage growth for continuing workers during this period (dashed line). In other words, all of the observed aggregate wage growth is due to selection. Second, the selection effects are largest through late April when employment declines were largest. Since late April there has been a decline in aggregate average unadjusted wages as employment has disproportionately increased for lower wage workers. These patterns also reveal themselves within industries. In the online appendix, we present employment, mean base wage, and selection-adjusted wage indexes by two-digit NAICS industry. In every industry, selection-adjusted base wages are much flatter than average wages, with the selection-adjusted wage falling in many industries. The flat composition-adjusted wages in figure 5 suggest that nominal wage growth has actually slowed. Normally, over a period of a few months, nominal wages increase as some workers receive their regularly scheduled wage adjustments, while wage cuts are exceedingly rare.

This was not the case at the beginning of the Pandemic Recession. Figure 6 provides a summary comparison of the employee wage adjustment patterns in 2019 (darker bars) and 2020 (lighter bars). Panel A plots the share of continuously employed workers who receive a base wage cut in our sample. Specifically, it plots the share of workers who were employed with a given firm in both March and June who saw declines in their base per period pay rate between March and June. The first column shows that 6.2 percent of these workers saw wage declines between March and June of 2020. This stands in stark contrast to the patterns for 2019, when just 1.6 percent of workers saw wage cuts between these same months. Base wage cuts are a remarkable feature of the labor market in the Pandemic Recession.

Of course, many workers separated from their job over this time period. Overall, we find that 5.3 percent of all workers in our sample who were employed in March (regardless if they remained employed through June) saw a base wage cut between March and June. Given that total US employment at the beginning of March was 128 million workers, this amounts to approximately 6.8 million workers receiving base wage cuts in addition to the tens of millions more who lost their job.

Of course, firms may choose to forgo scheduled wage increases without actually cutting workers' wages. Studying such wage freezes is made more complicated by the fact that most continuously employed workers only receive one base wage change per year (Grigsby, Hurst, and Yildirmaz forthcoming). However, as highlighted in Grigsby, Hurst, and Yildirmaz (forthcoming), most firms adjust their base wages annually in a given month. For example, some firms always provide annual base wage adjustments in April while others do their adjustments in July. To study wage freezes during the beginning of the Pandemic Recession, we create a sample of firms who made at least 75 percent of their 2019 base wage changes in March, April, May, or June. These are firms for which March through June are their normal base wage adjustment months.

Figure 6. Probability of Base Wage Cuts and Freezes in 2019 and 2020 by Base Wage Quintile



Source: ADP anonymized payroll records and authors' calculations.

Notes: Panel A includes all workers employed with the same firm in both March and June. The sample for panel B consists of workers at firms that usually adjust wages in March–June and restricts the sample to firms that made 75 percent of their annual wage changes for their employees in 2019 during March, April, May, or June.

We plot the probability that workers receive a wage freeze (i.e., zero base wage change) in these firms in panel B of figure 6. Column 1 shows that these firms adjusted the base wages of roughly 64 percent of their continuously employed workers from March through June of 2019 (i.e., kept the wages fixed for 36 percent of their employees). This number is similar to the decadelong average of base wage changes within the firms in the ADP employee sample found in Grigsby, Hurst, and Yildirmaz (forthcoming). Moreover, essentially all base wage changes in 2019 were increases; these firms only decreased the nominal wages of 0.7 percent of their workers during these months of 2019. However, during the same four months in 2020, these same firms froze the wages of 58 percent of their workers. In addition to the millions of base wage cuts observed in March to June, millions of workers have seen zero base wage changes at firms due to make their annual wage adjustment.[17]

The 6.3 percent of workers receiving nominal base wage cuts during the Pandemic Recession is of similar magnitude to the 6 percent found by Grigsby, Hurst, and Yildirmaz (forthcoming) during the Great Recession. However, many firms have yet to make their scheduled wage adjustments in 2020, and it remains to be seen whether such base wage cuts will continue. Similarly, during the Great Recession, over half of workers still received nominal wage increases. So far during the Pandemic Recession, base wages are increasing much less and decreasing slightly more than they did during the Great Recession.

The remaining columns of figure 6 show the probability of a wage cut (panel A) and the probability of a wage freeze (panel B) for workers in different initial wage quintiles. Wage freezes were more common throughout the wage distribution in 2020 relative to 2019. However, while employment losses were concentrated among low-wage workers (figure 4), nominal wage cuts were disproportionately concentrated among higher wage workers. More than three-quarters of all nominal wage cuts were concentrated in workers in the top two deciles of the wage distribution. For this sample, 13.4 percent of all workers in the top wage quintile received a nominal wage reduction between March and June 2020.

17. Nine percent of workers at these firms saw wage cuts between March and June of 2020. The full histogram of base wage changes for these firms in 2019 and 2020 is shown in the online appendix.

Table 2. Decomposition of Employment Growth in Shutdown and Reentering Businesses

Week	*Continuers*	*New entry*	*Ever shut down*	*Shut down and reentered*	*Total*
2/15/2020	0.0	0.0	0.0	0.0	0.0
2/22/2020	0.5	0.1	–0.1	0.0	0.5
2/29/2020	0.1	0.3	–0.3	0.0	0.1
3/07/2020	–0.1	0.5	–0.6	0.0	–0.1
3/14/2020	–0.6	0.6	–1.0	0.1	–0.9
3/21/2020	–4.4	0.7	–1.9	0.1	–5.4
3/28/2020	–10.7	0.8	–3.4	0.1	–13.2
4/04/2020	–15.0	1.0	–4.8	0.1	–18.8
4/11/2020	–15.0	1.1	–5.7	0.2	–19.4
4/18/2020	–14.8	1.2	–6.1	0.2	–19.6
4/25/2020	–15.8	1.2	–6.4	0.5	–20.6
5/02/2020	–15.8	1.3	–6.6	0.8	–20.3
5/09/2020	–14.4	1.5	–6.8	0.9	–18.8
5/16/2020	–12.5	1.6	–6.9	1.2	–16.6
5/23/2020	–11.7	1.8	–7.0	1.6	–15.4
5/30/2020	–11.6	2.0	–7.2	2.1	–14.7
6/06/2020	–10.5	2.2	–7.4	2.4	–13.3
6/13/2020	–9.7	2.3	–7.5	2.6	–12.4
6/20/2020	–10.3	2.3	–7.9	2.7	–13.1

Source: ADP anonymized payroll records and authors' calculations.

Notes: Decomposition of total employment growth into employment contributions from continuously operating firms, newly entering firms, firms that were shut down at some point since February 15, and firms that were shut down but subsequently reentered. Data from the business-level sample. Percentages expressed in terms of February 15 employment.

V. Business Shutdown, Reentry, and Worker Recall

So far, most of our results combine employment changes for businesses that suspend operations (whether temporarily or permanently) and businesses that continue operating. Separating these groups is useful: a primary determinant of the speed of recovery from this crisis may be the extent to which irreversible disinvestments occur. This question has come to the forefront recently as employment has increased. Are business closures permanent? How much of the employment increase has occurred as the result of businesses reopening or firms recalling workers that were temporarily laid off?

Table 2 shows the decomposition of aggregate employment growth into the contributions from continuers (employment at firms that operated continuously since February 15), entry (employment at firms that did not exist in our sample on February 15), shutdown (initial employment at firms that shut down at any point since February 15), and reentry (employment at firms that shut down at some point since February 15 but subsequently reopened). The sum of these four contributions equals total aggregate paid employment growth. To create this table we use our business-level sample and report all contributions as percent of total employment as of February 15. We define a firm as "shutting down" if they issued no paychecks during a week in which we would expect them to have done so (given past pay frequency patterns). We define a firm as "reentering" if it had shut down and started paying its workers again.

On June 20, job losses at firms that operated continuously contributed 10.3 percentage points out of 13.1 percent total employment decline since mid-February (as highlighted in figure 1).[18] As of June 20, 7.9 percent of mid-February employment was shut down at some point and 2.7 percent of (mid-February) employment that was previously shut down had returned by June 20. In other words, one-third of employment in firms that had shut down at some point during the first few months of the pandemic had returned by late June. The difference between shutdown and reentry columns in table 2 measures the employment in firms that have remain closed and the change in employment at reentering firms (the former component accounts for most of the difference). Newly entering firms added 2.3 percent (of February levels) to employment through late June, though we caution against interpreting these figures in terms of genuine new business formation.[19]

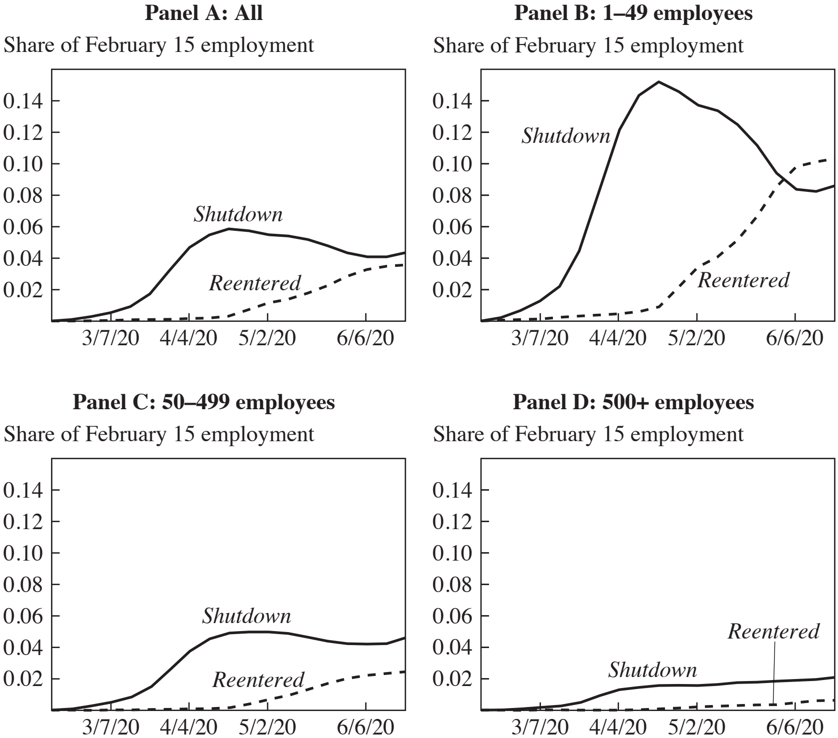
Between April 25 and June 20, aggregate employment increased by 7.5 percentage points (relative to February 15 levels). About three-quarters of that growth (5.5 out of 7.4 percentage points) was due to employment gains in continuing firms, and about one-third (2.2 out of 7.4 percentage points) was due to employment contributions of firms that reopened.[20] The findings suggest that the reopening of temporarily shuttered businesses contributed meaningfully to aggregate employment gains during May and June.

18. The numbers under "Continuers" in table 2 differ slightly from those in panel B of figure 1 due to different normalizations. In figure 1 we normalize the series by employment in *continuing firms* in February 2020 while in this table we normalize the series by total employment across *all* firms in February 2020.

19. Note that entry does not necessarily correspond to new firm formation; it could simply capture existing firms newly contracting with ADP or firms that existed at some point in the past, were closed during February, and later reopened again, for example, seasonal businesses. We do note, however, that Census Bureau data on new business applications with planned wages described by Haltiwanger (2020) indicate that application rates had returned to their 2019 pace by early June.

20. The employment gains from newly entering businesses during May and early June and the employment losses from businesses that newly shuttered in May and early June roughly offset each other.

Figure 7. Employment in Shutdown and Reentered Firms



Source: ADP anonymized payroll records and authors' calculations.

Notes: Solid line indicates the share of February 15 employment at firms that were shut down as of each date; dashed line indicates the share of February 15 employment at firms that had shut down and then reentered. The sample of firms is defined as of mid-February and is followed over time. Shutdown firms are defined as those where no payroll was processed.

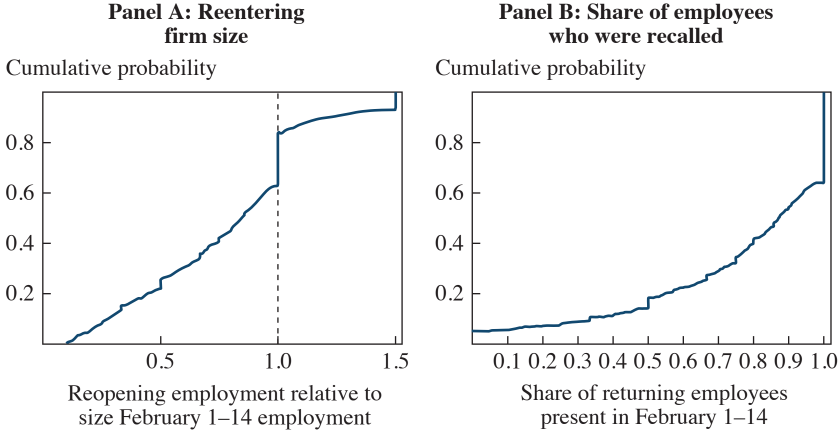
Panel A of figure 7 shows the dynamics of employment at currently shut-down (solid line) and reentered (dashed line) businesses for all businesses during the recession. Specifically, the solid lines in each panel measure the employment lost in currently shutdown firms during each pay period. The dashed line shows the employment gains coming from reentering firms. Panel A shows the employment losses associated with business shutdown for the US economy peaked in late April. Since then, as highlighted in table 2, some of these shuttered firms have reopened, contributing to aggregate employment growth. As of late June, there is still 4 percent of February employment in firms that are still shut down. Notably, however, the decline in shutdown employment from its April peak is smaller in magnitude than the employment generated by reentry (about 2 percentage points versus nearly 4 percentage points), reflecting the fact that shutdowns continued to occur even after mid-April.

In the online appendix, we additionally show that firm shutdown disproportionately affected low wage workers. By the end of April, approximately three times as many bottom quintile workers were in firms that have shut down than were top quintile workers. This partly reflects differences in firm closure by industry: firms in the entertainment and accomodation and food service industries were most likely to shut down in our sample.

The remaining panels in figure 7 show firm shutdown and reentering patterns by business size. Business shutdown was much more prominent among smaller firms, with shutdown firms contributing about 15 percent of the initial employment decline by late April among those businesses with fewer than fifty employees. However, many of these small businesses had reopened through late June. As seen in figure 2, total paid employment in small businesses increased by nearly 17 percentage points (relative to February levels) between mid-April and late June. Employment growth in firms that temporarily shuttered—that is, shuttered and then reopened—contributed about half of the employment gains among businesses with less than fifty employees from mid-April through the end of June. Businesses with 50–499 employees saw lower, but still notable, levels of shutdown, peaking around 5 percent of initial employment. Shutdown has been subdued among the largest firms, though it is noteworthy that the series had not peaked and had continued to gradually increase through late June.

When businesses reenter, they may not hire back all of their preexisting workforce. Figure 8 explores this possibility. Panel A plots the distribution of firm employment at reentry relative to the firm's employment during early February, weighting each firm by its initial size. The figure shows that about 60 percent of returning firms are smaller than they were in the beginning of February. The median reentering firm reopened with 86 percent of its initial employment, while the mean firm only has 78 percent of its initial employment. We present versions of this figure weighting firms by their February employment in the online appendix. That employment-weighted figure shows that returning large firms disproportionately return smaller: the employee-weighted median reentering firm has 65 percent of its February employment. Although firm reentry is contributing to a recovery in overall employment, these reentering firms are operating below their initial capacity. In part, this may be due to firms allowing individuals to return to work in stages in order to minimize social contact in the office.

Figure 8. Employee Recall in Reentering Firms



Source: ADP anonymized payroll records and authors' calculations.

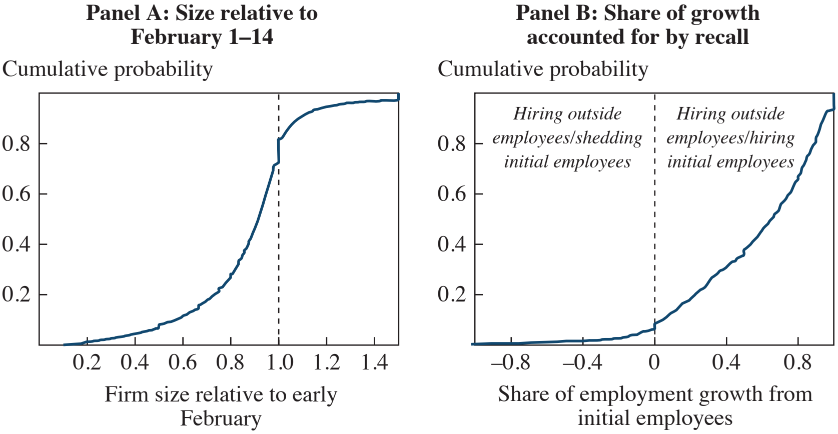
Notes: The sample consists of those firms that existed in early February 2020, temporarily shut down, and then subsequently reopened (i.e., resumed paycheck issuance). Employment measurements are through late June.

Monitoring this subcapacity operation will be important to the overall recovery dynamics.

When businesses return, they can choose to either rehire their prior workforce or seek new employees. Panel B of figure 8 shows the share of returning businesses' workforce that was previously employed with that same business in the first two weeks of February. Such workers represent "recalls." Again, the distribution is weighted by initial business size. In almost half of reentering firms the new workforce comprises at least 90 percent of employees who worked in the firm in early February. Hardly any firms reenter without having their workforce comprising at least half of the workers who were with the firm in early February. The results in this figure suggest that the overwhelming majority of reentering businesses are seeking to avoid costly searching by simply rehiring from their initial workforce. Again, most of these businesses are still well below their initial size, so as the recovery continues they may be able to bring back more of their initial workers.

As we highlight throughout, firm shutdown has not been the only source of employment declines at the beginning of this recession. Continuing employees have also seen enormous employment declines followed by small employment increases over the last few months. As these continuing firms recover, they too face a choice of whether to rehire existing employees

Figure 9. Growth of Continuing Businesses



Source: ADP anonymized payroll records and authors' calculations.

Notes: Panel A plots the distribution of business employment in late June relative to the first two weeks of February. Panel B plots firm-level distribution of the share of firm growth of continuing businesses accounted for by recall of previously employed workers. Firm growth measured between the firm's trough employment after March 11 and late June. *Recall* defined as hiring workers who were employed by the firm in the first two weeks of February. Throughout attention is limited to firms whose trough employment occurred after March 11. In panel B, attention is limited to firms that add at least ten employees.

or seek outside employment. Panel A of figure 9 plots the distribution of the current firm size for firms that contracted during the beginning of the recession but then subsequently started growing again. Specifically, we consider the growth in employment between the week in which a continuing firm has its lowest observed employment (after some contraction) and the final week of our sample (the end of June). We then calculate the firm's current size relative to its size in mid-February. The figure shows that the median growing continuing firm is currently at a size that is 10 percent lower than its mid-February level. Consistent with the patterns in figure 3, roughly 15 percent of these growing firms are now larger than they were in mid-February.

Panel B shows the share of trough-to-peak employment growth for continuing businesses accounted for by recalling previously employed workers. For each growing continuing firm, we calculate the share of this employment growth accounted for by growth in workers who were employed by the firm in the first two weeks of February. Note that this share can be negative if the business continues to shed existing workers while simultaneously hiring new outside workers. Finally, to remove noise from small-growth firms, we consider only continuing firms that grow by at least ten workers from their trough to peak.[21] The figure shows that roughly 90 percent of firms grow at least in part by recalling existing workers. Almost 10 percent of continuing firms hired exclusively from recall.[22] However, the complement of these findings is also interesting. Almost 10 percent of continuing firms are growing from external hires, even as they shed their initial workforce. Even in these uncertain times, there remains some worker churn. The fact that workers are being reallocated among existing business during the Pandemic Recession is consistent with the findings in Barrero, Bloom, and Davis (2020).

Overall, firm shutdown was an important driver of employment losses at the beginning of the Pandemic Recession, and firm reopening is likewise contributing to the labor market recovery. However, reentering firms operate at far below capacity, only hiring back a fraction of their prior workforce. Although both continuing and shutdown firms principally recall their prior employees to spur growth at this stage of the recovery, many continuing firms are also looking toward external labor markets for their hiring.

VI. Employment Gains and State Reopening

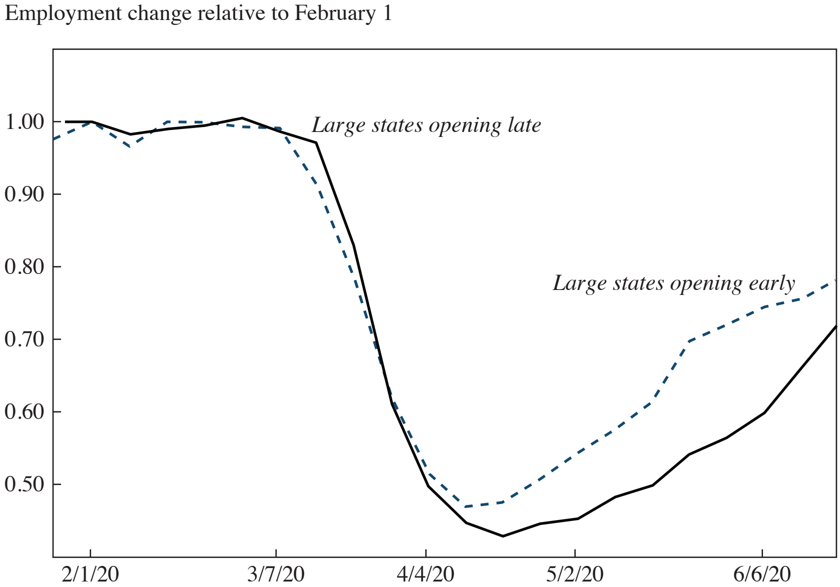
Figure 10 explores the effects of states reopening certain sectors on employment. To facilitate exposition, we create two groups of states—a set of large states that broadly opened in late April or early May and a set of large states that broadly opened in late May and early June.[23] For the set of states opening early we pool data from Florida, Georgia, and Texas. These states opened restaurants and lifted stay-at-home orders between April 24 and May 4. For the set of states opening later we pool data from Illinois, Pennsylvania, Virginia, and Washington. The late-opening states opened restaurants and lifted stay-at-home orders after May 31. Our results focus on one sector where reopening had the most direct effect: the food and accommodation sector (NAICS 72).

21. We present the distribution of these recall shares for firms that grow by at least one or five employees in the online appendix.

22. These findings are broadly consistent with the results in Fujita and Moscarini (2017) showing the importance of employee recall in prior recessions.

23. We focus on large states because there is less noise in employment fluctuations at the state-by-industry level within the ADP data. We use our employee sample for this analysis so that we can measure state of residence. There are small differences in aggregate employment declines by sector between our business sample and our employee sample given the slightly different sampling frames.

Figure 10. State Reopening and Employment: Accommodation and Restaurant Sector



Source: ADP anonymized payroll records and authors' calculations.
Notes: Employment in NAICS Industry 72 (Accommodation and Food Service). Dashed line indicates a set of large states that opened in late April or early May (Florida, Georgia, Texas); solid line indicates a set of large states that opened in late May or early June (Illinois, Pennsylvania, Virginia, Washington). Data come from the ADP employee sample.

The figure shows that employment in restaurants and accommodations fell similarly through mid-April in both state groupings. Starting in late April, employment in this sector within the states opening early increased faster than employment in the states opening later. The state groups start to diverge during the week of April 18, which was a week prior to the Georgia reopening of in-person dining. Given that the state openings were announced in advance, firms started ramping up some employment prior to the actual date of opening. This qualitative pattern is not overly surprising.

The quantitative patterns are, however, noteworthy. First, even in the states that opened early, employment in this sector is still more than 20 percent below February levels as of late June. Opening, per se, does not guarantee employment will fully rebound in this sector. If individuals are concerned about contracting the virus in public places, the demand for these types of services may remain depressed even as these sectors start to reopen. Second, employment in these sectors within states that opened late started to increase even prior to those states reopening. The increase was modest but suggests that demand was increasing (perhaps for take-out meals) even prior to official reopenings. These demand effects could interact with disease trends within the state that could also prompt states to lift stay-at-home orders. Additionally, the expectation of reopening likely resulted in some firms bringing back workers early to prepare for serving customers in person. Researchers seeking to attach a causal quantitative interpretation of employment gains associated with state reopening should do so cautiously. Finally, employment in this sector had almost converged between the two groups of states as of late June. Again, this suggests that once states reopen, employment in previously constrained sectors will rise but demand forces will still prevent employment from returning to prerecession levels.

VII. Conclusion

In this paper, we use high-frequency payroll data from ADP to track the behavior of the labor market in the early part of the Pandemic Recession. The data show an unprecedented collapse in employment from mid-February through late April with employment falling by 21 percent relative to early February levels. As states started to reopen, employment rebounded partially. As of late June, employment was still 13 percent below February levels. The employment declines as of late June were massive relative to past recessions; during the Great Recession employment troughed at 7 percent of prerecessionary levels.

Our results highlight that the employment losses were disproportionately concentrated among smaller firms and lower wage workers. Much of the fiscal stimulus implemented during the early part of the recession was targeted toward these groups. Job losses, in percentage terms, had converged between smaller and larger businesses as of late June (relative to prerecession levels). Many previously shuttered businesses—particularly smaller businesses—reopened during May and June, bringing back laid-off workers. This could be consistent with government stimulus provided through programs like the Paycheck Protection Program (PPP) allowing some smaller businesses to survive the beginning of the recession during the mandated shutdowns. However, further research will be needed to try to causally isolate the effects of PPP on small business employment.

One finding of ours that needs to be monitored going forward is how the Pandemic Recession is affecting wages of workers who did not get displaced. During the first few months of the recession, we have shown that many workers are receiving nominal cuts to their contracted wage while many others are receiving pay freezes. The extent of nominal wage cuts and wage freezes are large relative to nonrecessionary years and are even larger than what was observed in the Great Recession. How broader measures of compensation adjust—including components such as bonuses, performance pay, and fringe benefits—is worth monitoring as the recession continues. Our initial findings suggest that both the employment adjustments and the wage adjustments are large relative to prior recessions.

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Online Appendix: "The U.S. Labor Market during the Beginning of the Pandemic Recession" (Not for Publication)

Appendix A Data Description

We use anonymized administrative data provided by ADP. ADP is a large international provider of human resources services including payroll processing, benefits management, tax services, and compliance. ADP has more than 810,000 clients worldwide and now processes payroll for over 26 million individual workers in the United States per month. The data allow us to produce a variety of metrics to measure high-frequency labor market changes for a large segment of the U.S. workforce.

Subsection I. Business Level Data

We use two separate data sets to measure high-frequency labor market changes. In this section we introduce a business-level data set, while the subsequent section covers a worker-level data set.[24] The business-level data set reports payroll information during each pay period. Each business' record is updated at the end of every pay period. The record consists of the date payroll was processed, employment information for the pay period, and many time-invariant business characteristics such as NAICS industry code.[25] Business records include both the number of individuals employed ("active" employees) and the number of paychecks issued in a given pay period ("paid" employees). Active employees include wage earners with no hours in the pay period, workers on unpaid leave, workers who are temporarily laid-off and the like. Paid employees include any wage or salary workers issued regular paychecks during the pay period as well as those issued bonus checks or any other payments.

[24] When accessing the microdata, we follow a number of procedures to ensure confidentiality. Business names are not present in the data.

[25] Note that we use the term "business" throughout the paper to denote ADP clients. Often, entire businesses contract with ADP. However, sometimes establishments or units within a firm contract separately. The notion of business in our data is therefore a mix of Census Bureau notions of an establishment (i.e., a single operating business location) and a business (i.e., a collection of establishments under unified operational control or ownership).

The data begin in July 1999 but are available at a weekly frequency only since July 2009. As shown in Cajner et al. (2018), ADP payroll data appear to be quite representative of the U.S. economy, though the data modestly overrepresent the manufacturing sector and large businesses (as compared to the SUSB universe of firms). We address these issues by reweighting the data as explained below. The process of transforming the raw data into usable aggregate series is complex, and we refer the interested reader to Cajner et al. (2018) for details of the creation of the ADP-Federal Reserve Board (ADP-FRB) high frequency employment series for additional information. In short, for businesses that do not process payroll every week (for example, businesses whose workers are paid biweekly), we create weekly data by assuming the payroll in the missing intermediate period is what is observed in the next period the business processes payroll. We build a weekly time series of employment for each business, estimating employment at the business each Saturday.[26]

In our baseline analysis we treat ADP payroll units as firms for weighting purposes. As a result, we use 2017 SUSB employment counts by firm size and two-digit NAICS as the target population (2017 is the latest year available). We use six size bins defined by 1-19, 20-49, 50-99, 100-299, 300-499, and 500 or more employees.[27] For the analysis in this paper, we keep the weights fixed throughout the COVID-19 period.[28]

Since the primary focus of this paper is on weekly data, it is worth noting the distribution of pay frequencies in the ADP data. As of March 2017, 22 percent of ADP clients were issuing paychecks weekly, 46 percent biweekly, 21 percent semi-monthly, and 11 percent monthly (in terms of employment, these shares are 23 percent, 55 percent, 18 percent, and 4 percent,

[26]Technically, the employment concept is business employment for the pay period that includes the Saturday in question, as we cannot observe changes within pay period. Lacking any information on events within a pay period, we assume that businesses adjust their employment discretely at the beginning of each pay period and that employment is constant within the pay period. This assumption is consistent with the typical practice of human resource departments, according to which job start dates often coincide with the beginning of pay periods. It is also analogous to the CES methodology, which asks for employment for the pay period including the 12th of the month.

[27]We also conducted all reported exercises using a weighting scheme with one additional bin at 1000+ employees. This makes only modest differences for the results (and only affects firms in the "large" size category): at most, total employment for large firms differs by less than 2 percent of February 15 employment, with most weeks (including the trough week and the most recent week) differing by less than 1 percent. For overall (all-sizes) employment, the trough and most recent weeks differ by less than 0.5 percent. The employment series become more volatile under the 7-bin weighting scheme, however, so we prefer the 6-bin scheme.

[28]Formally, let w_j be the ratio of SUSB employment in a size-industry cell j to employment from ADP data in cell j, where SUSB employment are from 2017 (the latest year available) and ADP employment are fixed in the week ending February 15 for weighting purposes. Then weighted employment for any firm i in cell j is given by $w_j e_{i,j,t}$, where e is firm employment. We calculate aggregate employment declines based on the change in total weighted employment. Exercises using percentile changes calculate firm-level growth rates then evaluate percentiles on the full employment-weighted distribution where employment is SUSB-weighted employment.

respectively). These fractions are not far from what the BLS reports.[29]

Finally, it is worth noting that we only measure employment declines once we observe a business's regularly scheduled payroll. This can mean that there is some lag in our measurement. For example, suppose a business pays all of its workers biweekly. We will observe the business's payroll in week t and then again in week $t+2$. Suppose the business lets 20 percent of its workers go in week $t+1$. We would not be able to infer this paid employment decline until week $t+4$, since those workers worked some in the $t+2$ pay period. Given that the payroll would be missing in $t+4$, we attribute the job loss occurring in $t+2$. All of this is to say that our measurement may, at times, be shifted a week or two relative to when a hire or separation took place. This is part of our motivation for focusing on the pay period employment concept, discussed above.

Subsection II. Worker Level Data

The business-level data reports payroll aggregates for each business. For a very large subset of businesses, we also have access to their anonymized de-identified individual-level employee data.[30] That is, we can see detailed anonymized payroll data for individual workers. As with the business data, all identifying characteristics (names, addresses, etc.) are omitted from our research files. Workers are provided an anonymized unique identifier by ADP so that workers may be followed over time. We observe various additional demographic characteristics such as the worker's age, gender, tenure at the business and residential state location. We also can match the workers to their employer. As with the business-level data described above, we can observe the industry and business size of their employers.

The benefits of the employee data relative to the business data described above are three-fold. First, we can explore employment trends by worker characteristics such as age, gender, and initial wage levels. This allows us to discuss the distributional effects of the current recession across different types of workers. Second, the individual-level data allow us to measure additional labor market outcomes such as wages per worker as well as recall rates of a given worker as businesses start to re-open. Finally, the individual level data allows us to measure the state where a worker livers allowing us to compute high frequency local labor market measures as the economy recovers.[31]

[29] See BLS (2019) "Length of pay periods in the Current Employment Statistics survey."

[30] The data for our employee sample skew towards employees working in businesses with at least 50 employees. This is the same data used in Grigsby et al. (2019). While the data come from employees mostly in businesses with more than 50 employees, there is representation in this data for employees throughout the business size distribution. Again, we weight these data so that it matches aggregate employment patterns by industry and business size.

[31] The business level data set tracks the location of the firm. However, for larger firms, this is often the location of the headquarters and not the local establishment.

The individual-level data allows us to observe the worker's contractually obligated pay rate as well as their gross earnings during the pay period. For hourly workers, the per-period contract pay rate is simply the worker's base hourly wage. For salaried workers, the per-period contract rate constitutes the pay that the worker is contractually obligated to receive each pay period (e.g., weekly, biweekly, or monthly). For workers who are paid hourly, we also have administrative records of how many hours they worked during the pay period. For workers who are salaried, the hours are almost always set to 40 hours per week for full-time workers and some fraction of 40 hours per week for part-time workers. For example, workers who are half-time are usually set to 20 hours per week. As a result, the hours for salaried workers are more indicative of full-time status than actual hours worked.

When reporting hours, employment, and wage statistics using the employee-level sample, we also weight the data to ensure that it is representative of the U.S. population by 2-digit industry and business size. To create the weights for this part of our analysis, we use data from the U.S. Census' 2017 release of the Statistics of US Businesses. Specifically, we weight the ADP data so that it matches the share of businesses by 2-digit NAICS industry and business size. As highlighted in Grigsby et al. (2019) the weighted employee-level data is representative of the U.S. labor market on many dimensions.

To construct employment indices, we exploit the high-frequency nature of the ADP data. To facilitate our measurement using the employee data, we limit our attention to workers paid weekly or biweekly for these analyses to avoid time aggregation issues. These account for about 80 percent of all employees in our employee sample. Unsurprisingly, this is nearly identical to the share of weekly and biweekly employees in the business-level sample described above.[32] Biweekly workers are generally paid either on every even week (e.g. the 4th, 6th, and 8th week of the year) or on every odd week. We designate biweekly workers to be "even biweekly" workers if their regularly scheduled paychecks are disbursed on even weeks, or "odd biweekly" workers if their regularly scheduled paychecks are disbursed on odd weeks. We then sum all paychecks—earnings and hours—in a two-week period to the nearest subsequent even week for even biweekly workers, and the nearest subsequent odd week for odd biweekly workers. We additionally sum all paychecks in a given week for all weekly workers. The result of this is an individual-by-week panel. We then produce separate indices for weekly, biweekly-even, and biweekly-odd employees and then combine the indices into an aggregate employment index. We use these indices when computing employment changes by worker characteristics (age, sex, worker location, and wage percentile). We compute hours and wage indices similarly. However, the panel nature of our data allows us to make indices for

[32] Our preliminary evidence suggests that workers paid semi-monthly look nearly identical to those paid bi-weekly.

hours worked and wages following a given worker over time. This allows us to control for the changing selection of the workforce at the aggregate level over this period. To account for most of our data sample is paid bi-weekly, we lag the employment measure from the employee sample by two-weeks. For example, the payroll week of February 15th measures employees who worked during the week of February 1st.

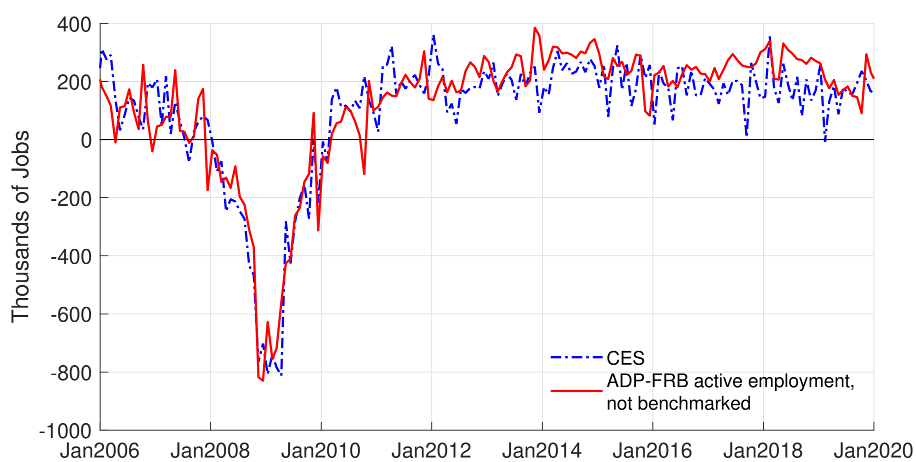
Appendix B Additional Results

In this section, we show various other results from our analysis. We start by documenting gross job creation and job destruction rates from our employee sample. Next we show trends in hours worked for continuing workers. We then explore patterns by age. We also highlight trends in employment by business size using our employee data where we can control for the timing of pay-check receipt exactly. We then discuss our regressions explaining differences in employment changes by wage quintile and gender. Finally, we conclude with additional results associated with firm closures, firm openings and worker recall.

Subsection I. Historical Comparison of ADP Data to BLS CES

ADP data tracked the last recession remarkably well; Appendix Figure A1 compares the *monthly* change in employment in the unbenchmarked ADP-FRB series (constructed by Cajner et al. (2018)) to the Bureau of Labor Statistics (BLS) Current Employment Statistics (CES) series from January 2006 through February 2020. The two series pick up the same underlying signal—aggregate U.S. payroll growth.

Figure A1: Historical Monthly Change in Private Payroll Employment: ADP-FRB and CES



Notes: Source CES, ADP, and Cajner et al. (2018). CES data benchmarked to the QCEW.

Table A1: Aggregate Employment Patterns under Two Weighting Schemes

	SUSB	QCEW
Total paid employment change, February 15 to April 25	-20.6%	-22.5%
Share of decline contributed by business closure	0.18	0.27
Total paid employment gain, April 25 to June 20	7.4%	10.3%

Notes: Table shows aggregate employment patterns as implied by two different weighting schemes. The SUSB column reports the main results of the paper, which rely on firm-based weights from the Census Bureau's 2017 Statistics of U.S. Businesses. The QCEW column reports alternative results treating ADP business units as establishments and weights from the March 2019 BLS Quarterly Census of Employment and Wages. All figures expressed as percents of February 15 employment.

Subsection II. The Importance of Weights

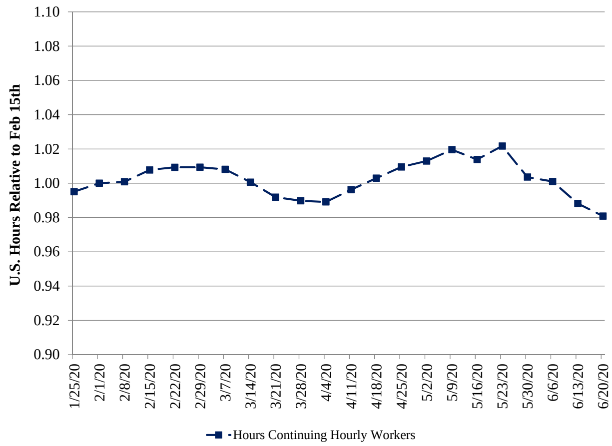
The aggregate numbers shown in Section Section II. are based on the ADP sample with SUSB weights to ensure representativeness in terms of industry and firm size. As noted in our data description, however, some business units in ADP may be more akin to establishments (i.e., single operating locations that may be part of a larger firm) than to firms. An alternative approach to mapping ADP data to the U.S. business universe would be to treat ADP business units as establishments and then apply establishment-based weights; indeed, some previous work with ADP data takes this approach (e.g., Cajner et al. (2020)). Appendix Table A1 compares aggregate employment patterns under SUSB weights (i.e., those used in our main results in Section Section II.) and QCEW weights (i.e., those that treat ADP businesses as establishments rather than firms). Aggregate series based on QCEW weights show a somewhat larger decline (and rebound) in aggregate employment; the reason is that establishment-based weights have more activity in smaller units than do firm-based weights, and as we documented above, smaller ADP businesses have seen a deeper decline (and stronger rebound) in employment than have larger businesses.[33] Moreover, the QCEW weighting scheme produces a stronger post-trough rebound in total employment, again consistent with the stronger rebound observed among smaller ADP units that have larger weights in QCEW. As a result, the two weighting schemes suggest a similar total decline from February 15 through June 20.

Subsection III. Hours Worked For Continuing Workers

Appendix Figure A2 shows the decline in hours of continuing hourly workers during the beginning of the recession using the ADP employee sample. We create an index of hours

[33] The result that weights matter in our data differs from Chetty et al. (2020) who find that the private sector data samples they work with track relevant national benchmarks without reweighting.

Figure A2: Hours Worked Index for Continuing Hourly Workers



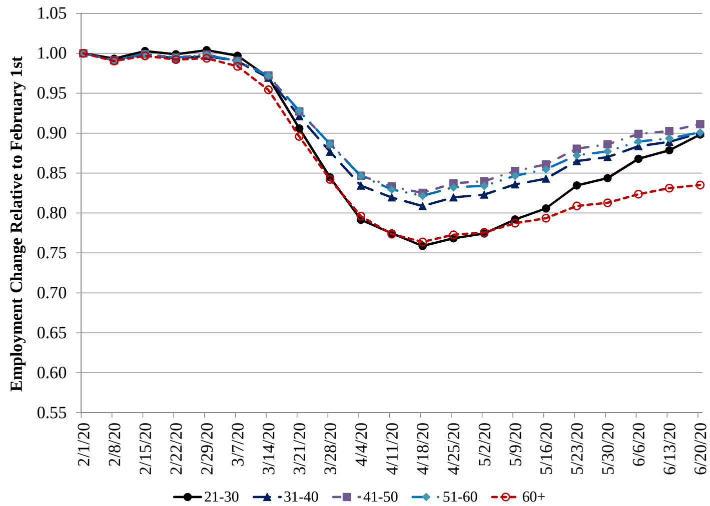
Notes: Figure shows the change in hours worked for hourly workers who remain continuously employed between pay periods. We create a chain weighted index of the hours changes. The index is relative to hours worked during the week of February 15th. The data come from the employee sample and are weighted such that the sample is representative by business size crossed with 2-digit NAICS industry.

of continuing hourly workers relative to February 15th. There has been little adjustment of hours worked for hourly workers throughout the recession. Essentially all of the employment adjustment has occurred on the extensive margin of labor supply.

Subsection IV. Employment Declines By Age

Appendix Figure A3 plots paid employment changes by age bin using our employee sample. Employment changes are relative to February 15th. The figure shows an inverted-U between age and employment declines through late April. The youngest workers—those between the ages of 21 and 30—and the oldest workers—those 60+—saw the largest employment declines in the first two months of the recession. Young workers, however, have seen their employment recover more sharply than any other group betweeen late April and late June. All age groups from 21-60 years old have employment which is approximately 10 percentage points below their February levels, while workers over 60 had employment that is 15 percentage points below February as of the end of June.

Figure A3: Employment Changes by Age



Notes: Figure shows paid employment declines by different age ranges. All changes relative to February 15th, 2020. Employee sample is used for this analysis. Data are weighted so that the sample matches aggregate employment shares by 2-digit industry cross business size.

Subsection V. Controlling for Industry in Explaining Different Employment Declines Across Demographic Groups

To assess whether differential exposure to the recession by business characteristics (industry and business size) or worker characteristics (age and location) can explain the differential pattern across either gender or the wage distribution, we exploit the panel nature of our data and estimate the following linear probability model with OLS:

$$E_{ijt} = \alpha_{q(i)t} + \beta_t X_{ijt} + \epsilon_{ijt} \tag{A1}$$

where E_{ijt} is an indicator equal to one if worker i is employed by firm j in the first two weeks of month t, and $q(i)$ is the base wage quintile of worker i as of the first two weeks of February. The quintile-by-month fixed effect $\alpha_{q(i)t}$ captures the employment probability of quintile q workers in month t. We include observable business- and worker-level controls X_{ijt} in some regressions, and allow the relationship between X_{ijt} and employment probabilities to differ in each month.

Our sample for this regression is the set of workers, paid either weekly or biweekly, who are ever employed by an ADP firm from February-May. Because of this, the estimated coefficients may be interpreted as capturing workers' differential separation probabilities, adjusted by the probability of returning to employment after a job loss. As with the analysis in Figure 4 of the main text, we define the quintiles in early March based on the aggregate wage distribution within the ADP sample and hold the quintile boundaries fixed when sorting workers into the quintiles during early February.

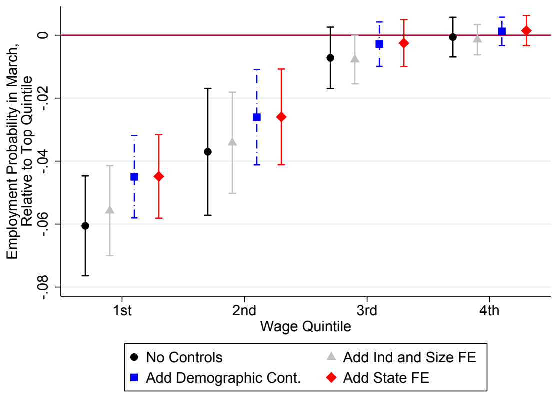
We control for worker i's wage quintile at the beginning of the period to allow the baseline separation rate to differ for workers in different quintiles q. Our variable of interest is how the employment probabilities of each quintile change during the beginning of the recession. This is captured by the coefficients α_{qt}. We then ask how these α_{qt} coefficients change as we include various business and worker controls, X_{ijt}.

Appendix Figure A4 plots the α_{qt} coefficients across various specifications of equation (A1). Panel A shows the estimated coefficients for March – the baseline separation probabilities – while Panels B and C show the employment probabilities in April and May. The black points (circles) show our estimates including no additional X_{ijt} controls, along with a 95% confidence interval using standard errors clustered at the 3-digit NAICS-by-firm size level. We omit the coefficient from quintile 5 (the top wage quintile). As a result, all coefficients should be interpreted as the employment declines in quintile q relative to the decline of quintile 5. The baseline separation probability between February and March is approximately 6 percentage points higher for bottom quintile earners than that of top quintile earners. After controlling for wage quintile fixed effects, bottom quintile earners were 21.5 percentage points less likely to be employed in April than were top quintile earners, reflecting the patterns in Figure 4. In May, bottom quintile workers were 37.2 percentage points less likely to be employed than top quintile workers.[34] The employment probabilities rise monotonically throughout the base wage distribution.

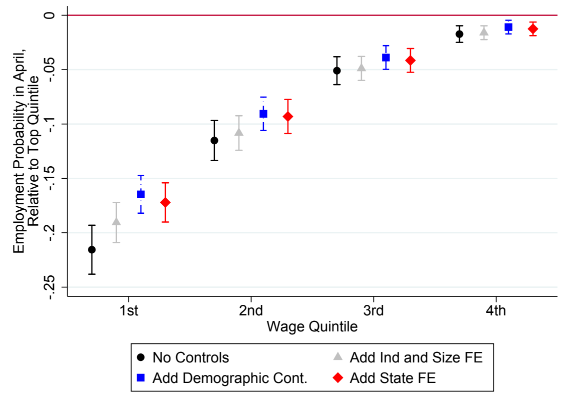
Recent research by Mongey et al. (2020) suggests that low-income workers tend to work in "social" sectors and the large decline observed in these sectors will result in job loss concentrated among lower wage workers. The gray points (triangles) explore this hypothesis by introducing firm size and 2-digit NAICS industry fixed effects as additional regressors. Including industry fixed effects reduces the gap in excess separation rates between bottom quintile earners and top quintile earners in April and May only slightly to 19.1 and 33.1 percent, respectively. Therefore, a differential size and industry mix can explain 12.2% (April) and 11.0% (May) of the gap in job loss between low-wage and high-wage workers during the beginning of this recession, but a substantial gap remains even after accounting for industrial composition. The explanatory power is primarily embedded in the industry fixed effects

[34] The results in Table A4 are not directly comparable to those in Figure 4 given that we are focusing on a balanced panel of businesses. Some of the additional employment decline we highlight in Figure 4 is due to business shutdown.

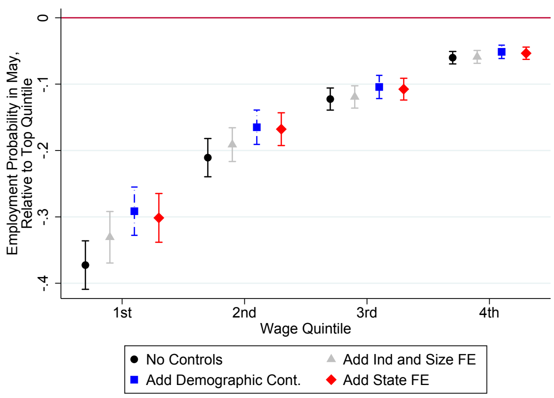
Figure A4: Probability of Employment by Wage Quintile and Sex, Conditional on Observables



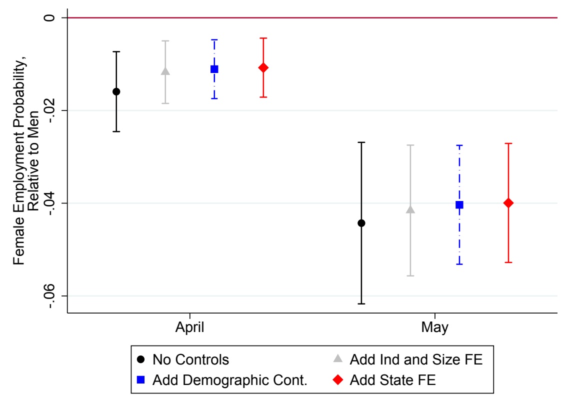
Panel A: March Employment by Wage Quintiles



Panel B: April Employment by Wage Quintiles



Panel C: May Employment by Wage Quintiles



Panel D: Female Employment

Notes: Figure plots estimated employment probabilities by wage quintile (Panels A-C) and sex (Panel D) conditional on observable characteristics. Panels A-C plots the estimated α_{qt} from equation (A1) for March, April and May, respectively. The omitted category is top quintile workers. Base wages defined according to the distribution of wages in the first two weeks of February. Panel D plots the γ_t for April and May, as estimated from equation (A2), and shows the employment probability of women relative to men. The black lines (circles) show estimates with no controls. The gray lines (triangles) control for firm size and 2-digit NAICS industry fixed effects. The blue lines (squares) add controls for age and (for Panels A-C) sex. The read lines (diamonds) also control for state of residence. Error bars report 95% confidence interval using standard errors clustered at the 3-digit NAICS cross firm size level.

The blue dashed points (squares) additionally include fixed effects for worker demographics; namely, 5-year age bins and gender. This reduces the gap in excess separation probabilities between low-wage and high-wage workers to 16.4 (April) and 29.1 (May) percent. As seen below, younger workers and women were more likely to be displaced, and younger workers systematically have lower wages. This additional reduction in excess separations suggests that the differential age and industry composition of low-wage workers can jointly explain between one-fifth and one-quarter of the gap between low- and high-wage worker employment behavior during the early stages of the Pandemic Recession. Finally, the column with the red markers (diamonds) include state fixed effects. Doing so reinflates the gap between top and bottom quintile workers to 17.2 (April) and 30.1 (May) percent, suggesting that low-wage workers are disproportionately in states which do not have large employment declines.

Finally, we repeat the exercise by sex, estimating the following linear probability model:

$$E_{ijt} = \gamma_t \cdot Female_i + \theta_t X_{ijt} + \eta_{ijt}. \tag{A2}$$

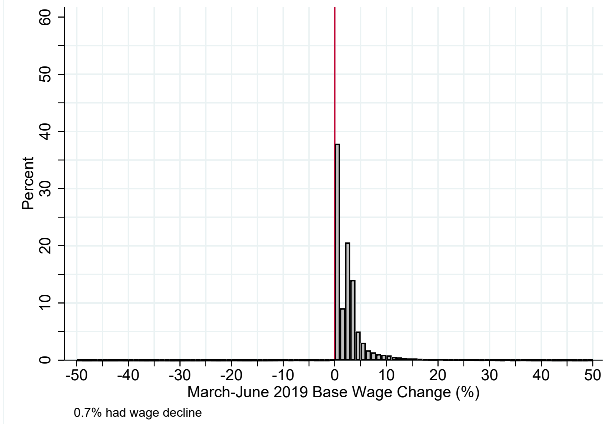
Here, γ_t represents the employment probability of women relative to men in month t, after controlling for observables X_{ijt}. These γ_t are plotted in Panel D of Appendix Figure A4. The figure shows that including controls for industry, firm size, age, or location do not meaningfully affect the result that women were less likely to be employed in April and May than men.

Subsection VI. Additional Results on Nominal Wage Adjustments

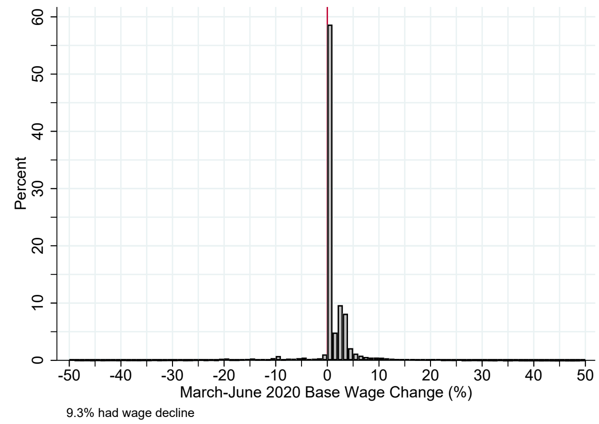
Appendix Figure A5 shows the histogram of wage changes for workers in firms that historically provide annual wage changes to their employees in March - June. Specifically, the sample includes any worker in a firm that did at least 75 percent of their 2019 base wage adjustments between March and June. Panel A shows the unconditional distribution of wage changes in 2019 while Panel B shows unconditional distribution of wage changes in 2020. Panels C and D show the corresponding distributions conditional on a wage change occurring. As seen in the main text, almost 60 percent of workers received a nominal wage change in these firms during 2019 while only 40 percent of workers got a wage change in these firms during the same months in 2020. About one-fifth of the wage changes in 2020, conditional on a wage change occurring, were negative (Panel D).

It is worth discussing in more detail our concept of nominal wage changes used in the above figure and in Section Section IV. of the main text. The ADP data measures many forms of worker compensation. We focus on measures of a worker's contract – or base – wage. A worker's base wage is their contracted hourly wage (if the worker is paid hourly) or their contracted earnings per pay period (if the worker is paid salary). Specifically, a salaried worker's base earnings per pay period is their contracted annual salary divided by the number of pay-periods per year. For example, for salaried workers that are paid bi-weekly, it is their contracted base annual salary divided by 26. The notion of base wage

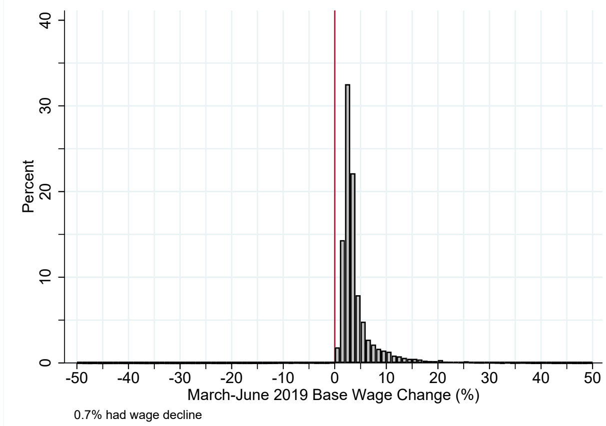
Figure A5: Distribution of Base Wage Changes for Continuing Workers Over Time
Sample: Workers at Firms that Usually Adjust Wages in March - June



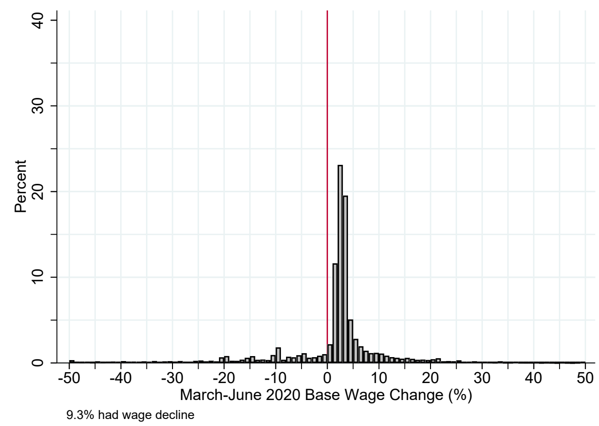
Panel A: 2019 (Unconditional)



Panel B: 2020 (Unconditional)



Panel C: 2019 (Conditional)

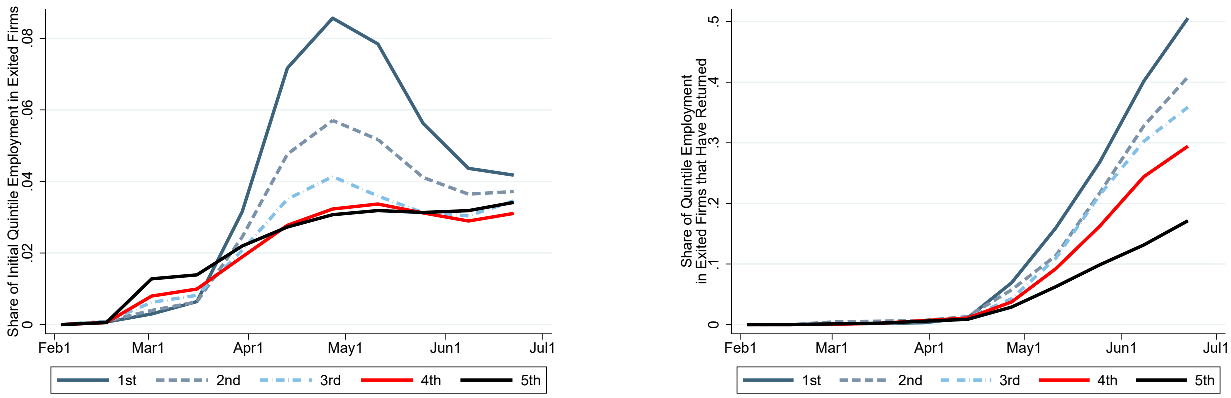


Panel D: 2020 (Conditional)

Notes: Figure shows distribution of base wage change for continuously employed workers. Sample is restricted to firms that made 75 percent of their annual wage changes for their employees in 2019 during March, April, May and June. Panel A and B show the unconditional wage changes for workers in those firms between March and June 2019 and between March and June 2020, respectively. Panels C and D show the corresponding distributions conditional on a non-zero wage change. The data we show here are the weighted distribution of wage changes and come from the employee sample.

is distinct from a workers gross earnings. A worker's gross earnings can include variation in hours worked (for workers paid hourly) as well as other forms of compensation including overtime premiums, bonuses, commissions and performance pay. As highlighted in Grigsby et al. (2019), over 95% of compensation for the median worker comes from base earnings.

Figure A6: Firm Shutdown and Re-Entry by Employee Wage Quintile



Panel A: Employment Lost Through Firm Shutdown

Panel B: Share of Shutdown Employment Re-called by Re-Entry

Notes: Figure plots the share of employment lost to firm shutdown (Panel A) and subsequently recalled through firm re-entry (Panel B) by worker base wage quintile. Data from our employee sample.

Subsection VII. Additional Results on Firm Shutdown, Firm-Rentry, and Worker Recall

In this section we detail additional results on firm shutdown and re-entry. Throughout this section, as in the main text, we restrict attention to businesses that existed in the ADP data as of the first two weeks of February. Appendix Table A2 reports business closures and re-opening by 2-digit NAICS industry using the business-level data. This is the analog of Table 2 in the main text but broken down by industry instead of the aggregate economy. Column 1 presents the share of February employment that was employed in a business in that industry that closed at any point during our sample period (through June 20). Sectors that were hit particularly hard, such as Accommodation and Food Services and Arts, Entertainment and Recreation had a large number of employees in businesses that closed at some point during the early period of the Pandemic Recession.

Column 2 shows the share of employment lost to business closure by industry that has returned by the end of June, as businesses re-opened. Some sectors have seen sharp rebounds from business re-opening. For instance, 38.8% of the employment lost to closure in the Accommodation and Food Services has returned as of the end of June. In contrast, just 6.7% of the employment lost to closure in Mining sector has returned, in part due to the confluence of pandemic-related shutdowns and a collapse in oil and gas prices.

As a result of these industry differences, business closure has disproportionately affected workers at different points in the wage distribution. Appendix Figure A6 shows the time series of the share of February employment lost to business closure by base wage quintile

Table A2: Employment Lost and Recovered through Firm Shutdown and Re-Entry, by 2-digit NAICS Industry

2-digit NAICS Industry	Share of Feb Employment in Firms that Exited by June 20	Share of Exited Employment that has Re-entered by June 20
72: Food/Accomodation	14.8	38.8
81: Other Services	14.3	48.1
71: Arts/Entertainment	12.5	32.2
21: Mining	6.8	6.7
23: Construction	6.6	39.9
51: Information	6.4	18.9
11: Agriculture	6.2	39.5
62: Health Care	6.0	42.8
44-45: Retail Trade	6.0	34.7
61: Education	5.9	31.5
42: Wholesale Trade	5.2	24.8
48-49: Transportation/Warehousing	4.9	11.9
53: Real Estate	4.4	27.2
54: Professional Services	4.3	28.8
56: Admin/Support Services	4.2	15.7
31-33: Manufacturing	3.6	27.4
55: Management of Companies	3.1	7.0
52: Finance/Insurance	2.4	15.9
22: Utilities	0.8	18.2

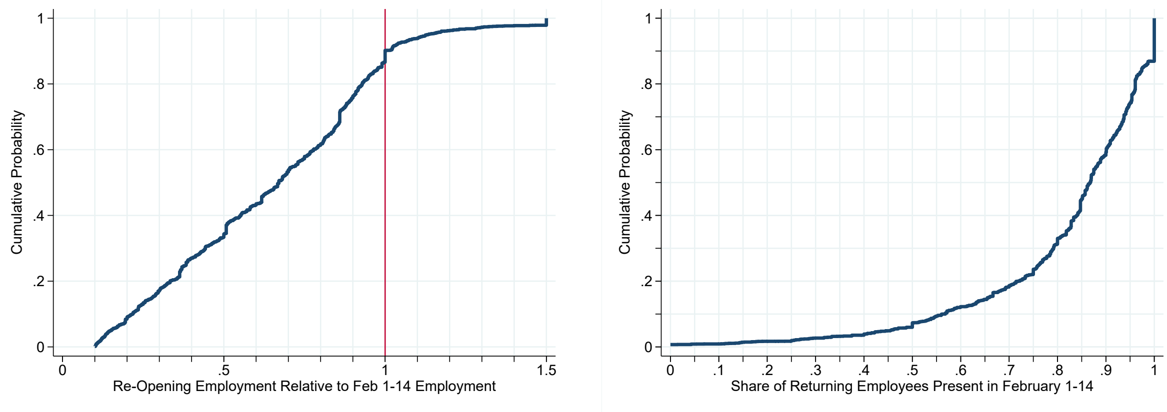
Notes: Table plots the employment losses and gains from shutdown and re-entry by 2-digit NAICS industry. Column (1) shows the share of February 15 employment in firms that ever close through June 20. Column (2) shows the share of this lost employment that has been recovered through re-entry by the end of May.

using our employee sample. As in the main text, we define wage quintile cutoffs as of the first two weeks of February. The solid dark blue plots the patterns for the bottom quintile of workers. This line in Panel A shows that over 8% of February's bottom quintile workers were in firms that had closed by the end of April.[35] By contrast, only 3% of February's top quintile workers were in firms that exited by the end of June.

Panel B reports the share of the employment lost to firm shutdown that had returned. Although bottom quintile workers were most affected by exit, they have also recovered over 50% of the employment lost to shutdown. This is roughly triple the 17% of recovered employment in the top quintile. This in large part reflects the re-opening of bars, restaurants, retail, and construction businesses as states have begun to open up. These industries tend to

[35] These figures were produced using ADP's employee-level sample, which is underweight small firms. As a result, the estimated total losses from business closure are less in this table than those reported in the main text.

Figure A7: Employee Recall in Re-Entering Firms, Firms Weighted by February Employment



Panel A: Re-Entering Firm Size

Panel B: Share of Employees Who Were Recalled

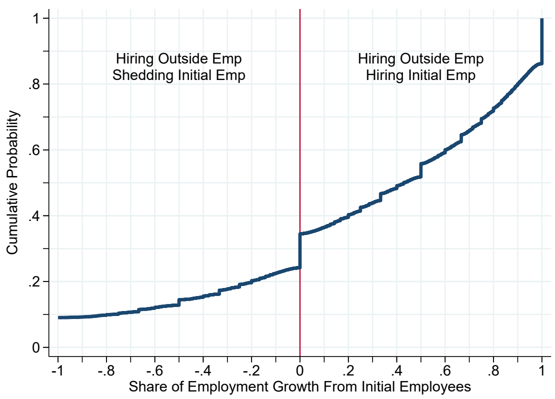
Notes: Figure shows the *employment weighted* CDF of re-entering business size (Panel A) and share of initial business employees recalled (Panel B). The sample of firms is those firms that existed in early February 2020 and that temporarily shut down. Temporary shutdowns are those firms that shut down and then subsequently reopened (i.e., resumed paycheck issuance). Employment measurements are through late June. All trends weighted by firms' February employment, and are reweighted to be representative of the SUSB industry $\times$ firm size mix.

employ many low wage workers. As a result, their closure and re-opening disproportionately affect low wage workers.

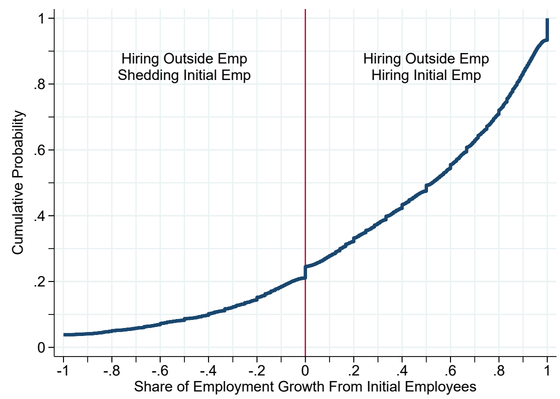
Appendix Figure A7 plots the distribution of re-entering firm size (Panel A) and the share of employees at re-entering firms which had been previously employed by that firm (Panel B), weighting distributions by firms' February employment. The corresponding figures in the main text were firm weighted as opposed to employee weighted. We see that the re-entering firm of the median worker had 59% of their February employment, while nearly every firm re-entered smaller than their initial size after employment weighting. As in the main text, the vast majority of re-entering firms hire back almost entirely workers who had previously been employed by the firm.

Finally, Appendix Figure A8 reproduces Figure 9 in the main text, but looking at continuing firms that increase employment from their trough by at least 1 (Panel A) or 5 (Panel B) employees. That is, it plots the share of employment growth from continuing firms' troughs through the end of June that is accounted for by employees who were previously employed by the firm. In the main text, we restrict our analysis to firms that increase employment from their trough by at least 10 employees. As seen in this appendix figure, our results are not sensitive to this cutoff.

Figure A8: Share of Continuing Firm Trough-to-Peak Employment Growth Accounted for by Recalling Previously Employed Individuals, alternative firm growth cutoffs



Panel A: Growth of at least 1 Employee



Panel B: Growth of at least 5 Employees

Notes: Figure plots the firm-level distribution of the share of firm growth accounted for by recall of previously employed workers in firms that continually paid workers from the first two weeks of February through the end of June. Firm growth measured between the firm's trough employment after March 11 and the end of June. Recall defined as hiring workers who were employed by the firm in the first two weeks of February. Panel A restricts attention to firms which add at least 1 employee, while Panel B restricts attention to firms that add at least 5 employees.

Subsection VIII. Employment Declines and The Ability to Work at Home

There has been a lot of discussion about the ability of a worker to be able to work from home as a form of insurance against job loss during the current pandemic driven recession. For example, Dingel and Neiman (2020) and Mongey et al. (2020) both create measures of a worker's ability to work at home using detailed occupation-level task data. Dingel and Neiman (2020) provide measures of workers' ability to work at home at the level of 3-digit NAICS industry.[36] Their measure ranges from zero to 1 with a larger number implying that more workers in that industry can work at home. Appendix Figure A9 shows a scatter plot using the industry data between the Dingel-Neiman "stay at home" measure and the decline in paid employment in that 3-digit industry through late April (Panel A) and mid June (panel B) using our ADP employee sample. As always, all changes are relative to mid February employment levels. As seen from both panels of the figure, there are a few 3-digit industries that saw employment increases since mid February including non-store retailers, which include online retailers (NAICS 454) and delivery services (NAICS 492).

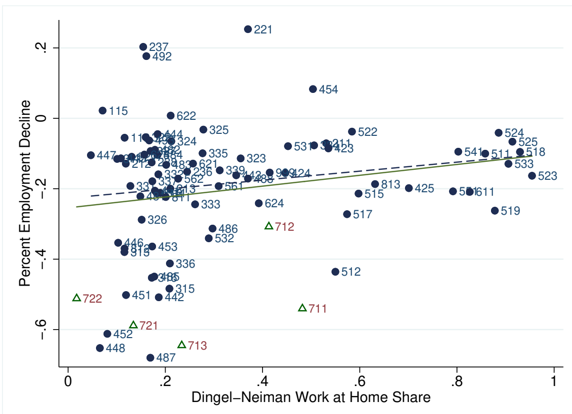
[36] Dingel and Neiman (2020) provide multiple measures for their work at home index. We use their "teleworkable_emp" measure. The patterns in Figure A9 are similar regardless of their measure used.

Appendix Figure A9 highlights a slight positive relationship between industry-level employment declines and the ability to work at home over both periods. The solid line in Panel A is a fitted regression line with a slope coefficient of 0.15, a standard error of 0.08, and an adjusted R-squared of 0.03. The dashed line is a fitted regression line excluding the leisure and hospitality industries. The figure shows that the industries that saw the largest employment declines through late April were, on average, industries where workers are not able to do their tasks at home. These industries are in the bottom left quadrant of the figure. However, there are also many industries where workers were not able to do their tasks at home that saw only modest employment declines (the upper left quadrant of the figure). Additionally, outside of the industries with the lowest work at home measures (work at home share greater than 0.3), there was very little relationship between the ability to work at home and industry employment declines. Even the industries where most workers can work at home had employment declines of 15 percent on average between early March and late April. In Panel B, we show the relationship to work at home and employment declines through mid-June. The fitted regression line is slightly smaller at 0.094 but is no longer statistically significant at standard levels (standard error = 0.71). It should be noted that 3-digit industry variation may be too crude a measure to pick up the importance of the ability to work at home in explaining employment declines. The ability to work at home is an occupation-level variable as opposed to an industry-level variable. However, the patterns in Appendix Figure A9 suggest that the ability to work at home is not the primary factor explaining cross-industry variation in employment declines.

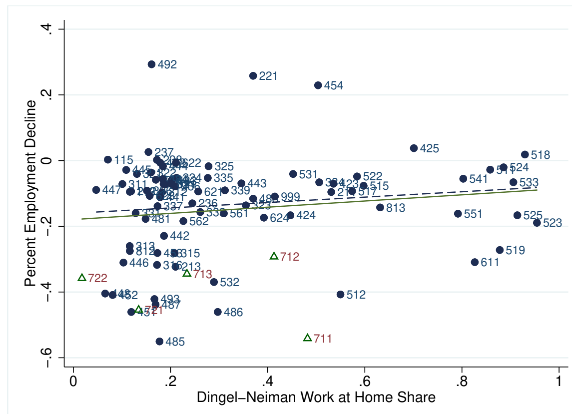
Appendix C Industry Time Series Data

The next set of tables show employment changes and selection adjusted wage changes by week for various industries during the Pandemic Recession. The employment numbers come from our firm level sample and the selection adjusted wage numbers come from the employee sample. For the selection adjusted wage numbers, we track the wages of the same worker in a given industry from week t to $t+1$ and create a chain-weighted index for each industry. See the main text for additional details. The data can be used to calibrate models with multiple sectors during the pandemic. We do not attempt to seasonally adjust these patterns; as a result, some industries, such as agriculture and construction, exhibit large seasonal employment swings.

Figure A9: Relationship Between Dingel-Neiman Work at Home Measure and Actual Paid Employment Declines, 3 Digit NAICS Industry Variation



Panel A: Employment Declines Through Late-April



Panel B: Employment Declines Through Mid-June

Notes: Figure shows the variation in the Dingel-Neiman "Work at Home" index and the decline in paid employment at the three-digit NAICS level through late April (Panel A) and mid June (Panel B) using our employee sample. The leisure and hospitality industries are designated with diamond while all other industries are denoted with circles. The solid line is a fitted regression line across all industries. The dashed line is a fitted regression line through the industries excluding the leisure and hospitality industries. The slopes of the two regression lines are 0.15 (standard error = 0.08) and 0.13 (standard error = 0.08), respectively in Panel A and 0.09 (standard error = 0.07) and 0.08 (standard error = 0.07) in Panel B. Industry points are labeled with their NAICS industry code.

Table A3: Cumulative Changes in Employment, Mean Wages, and Selection-Adjusted Wages, relative to week ending February 8, by 2-digit NAICS (Table 1)

	11: Agriculture			21: Mining			23: Construction		
Week	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage
Feb 1	-2.1	0.1	-0.5	-14.6	0.1	-0.1	1.1	-0.1	10.9
Feb 8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Feb 15	4.2	-0.1	0.1	-3.5	-0.1	0.2	0.1	-0.0	0.1
Feb 22	5.3	0.0	0.2	-2.0	0.0	0.1	1.7	-0.2	0.1
Feb 29	7.9	-0.7	0.2	-9.8	-0.7	0.1	-0.6	-0.1	0.1
Mar 7	7.4	-0.6	0.4	1.0	-0.6	0.4	0.8	0.1	0.3
Mar 14	6.1	-0.1	0.5	-2.6	-0.1	0.7	-0.9	0.2	0.4
Mar 21	5.1	0.6	0.4	-20.2	0.6	0.8	-3.5	0.5	0.3
Mar 28	0.1	1.3	0.6	-29.0	1.3	0.5	-9.6	2.6	0.2
Apr 4	0.1	1.0	0.7	-25.8	1.0	0.1	-12.7	3.2	0.2
Apr 11	0.4	1.2	0.8	-18.8	1.2	-0.6	-14.8	3.5	0.3
Apr 18	5.0	1.9	0.9	-20.3	1.9	-1.2	-14.2	4.1	0.3
Apr 25	5.4	2.9	0.9	-32.3	2.9	-1.8	-13.6	4.2	0.3
May 2	7.6	3.0	1.0	-33.4	3.0	-2.3	-13.0	4.2	0.4
May 9	6.5	4.4	0.9	-32.3	4.4	-2.5	-9.4	4.3	0.6
May 16	10.9	4.8	0.9	-24.6	4.8	-3.4	-5.6	4.4	0.7
May 23	10.2	6.4	1.2	-24.0	6.4	-3.8	-5.8	4.0	0.7
May 30	10.5	7.1	1.2	-23.0	7.1	-4.3	-3.9	3.8	0.7
Jun 6	12.0	6.9	1.2	-23.4	6.9	-4.3	-2.6	3.7	0.8
Jun 13	12.1	6.7	1.5	-23.6	6.7	-4.1	-2.2	3.9	0.9
Jun 20	8.5	6.9	1.5	-26.5	6.9	-4.0	-3.9	2.4	1.0

Table A4: Cumulative Changes in Employment, Mean Wages, and Selection-Adjusted Wages, relative to week ending February 8, by 2-digit NAICS (Table 2)

	31-33: Manufacturing			42: Wholesale Trade			44-45: Retail Trade		
Week	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage
Feb 1	-0.3	-0.2	-4.4	0.4	-0.2	-5.0	0.2	0.3	-0.5
Feb 8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Feb 15	-2.8	0.5	0.1	0.3	0.5	0.1	-4.3	0.8	0.1
Feb 22	-0.1	1.3	0.1	0.5	1.3	0.2	-4.7	0.8	0.2
Feb 29	-1.8	0.8	0.1	-2.0	0.8	0.0	-6.1	0.8	0.3
Mar 7	-3.1	0.3	0.2	-1.2	0.3	-0.0	-0.6	0.6	0.2
Mar 14	-1.6	0.9	0.3	-4.1	0.9	0.1	-6.4	0.8	0.3
Mar 21	-4.4	1.4	0.1	-9.1	1.4	0.0	-13.0	0.8	0.3
Mar 28	-13.6	1.6	-0.1	-11.1	1.6	-0.2	-22.4	1.9	0.5
Apr 4	-16.4	1.8	0.0	-15.1	1.8	-0.4	-27.9	2.4	0.6
Apr 11	-13.0	2.8	0.1	-14.7	2.8	-0.4	-26.7	4.6	0.7
Apr 18	-14.1	4.0	0.0	-13.1	4.0	-0.7	-27.5	5.6	0.7
Apr 25	-15.0	3.6	-0.1	-17.2	3.6	-0.9	-32.0	7.7	0.8
May 2	-11.5	2.7	-0.1	-15.9	2.7	-1.2	-30.8	8.9	0.7
May 9	-12.3	3.0	-0.0	-12.1	3.0	-1.1	-26.6	8.8	0.7
May 16	-12.0	3.6	-0.1	-12.0	3.6	-1.1	-20.3	8.6	0.7
May 23	-11.8	3.8	-0.2	-9.8	3.8	-1.3	-23.5	6.4	0.6
May 30	-11.1	3.2	-0.4	-11.5	3.2	-1.5	-20.2	5.2	0.6
Jun 6	-7.1	3.1	-0.6	-9.8	3.1	-1.6	-19.7	5.6	0.6
Jun 13	-8.9	3.5	-0.4	-9.9	3.5	-1.4	-15.1	5.2	0.7
Jun 20	-12.9	3.4	-0.4	-12.6	3.4	-1.3	-21.0	4.3	0.8

Table A5: Cumulative Changes in Employment, Mean Wages, and Selection-Adjusted Wages, relative to week ending February 8, by 2-digit NAICS (Table 3)

	48-49: Transportation/Warehousing			51: Information			52: Finance/Insurance		
Week	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage
Feb 1	8.6	0.5	-3.4	-3.6	0.5	-0.4	6.7	0.4	-5.3
Feb 8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Feb 15	11.3	3.8	0.0	1.9	3.8	0.9	5.3	0.5	0.5
Feb 22	8.1	2.7	0.1	3.2	2.7	0.9	9.5	1.2	0.0
Feb 29	10.5	1.5	-0.1	-6.7	1.5	-0.4	10.7	0.6	0.0
Mar 7	11.8	0.4	0.1	14.9	0.4	-0.8	3.3	0.0	0.2
Mar 14	3.6	-1.0	0.1	-5.3	-1.0	0.5	5.8	1.1	0.3
Mar 21	4.7	0.5	0.2	-6.8	0.5	0.6	-6.3	2.1	-0.2
Mar 28	-6.0	5.2	0.1	-18.8	5.2	0.2	-11.8	3.3	-0.2
Apr 4	-6.6	11.8	0.3	-11.3	11.8	0.2	-3.7	3.7	-0.1
Apr 11	-7.8	14.0	0.6	-9.6	14.0	0.6	9.8	2.8	-0.5
Apr 18	-16.1	16.0	0.5	-17.8	16.0	0.6	2.6	3.2	-0.9
Apr 25	-12.9	21.1	0.4	-16.1	21.1	-0.4	4.1	3.2	-1.0
May 2	-12.4	14.8	0.5	-18.7	14.8	-0.6	4.0	3.4	-1.1
May 9	-15.0	17.5	0.5	-17.7	17.5	-0.4	9.9	3.7	-1.1
May 16	-15.2	15.3	0.6	5.2	15.3	-0.4	9.3	4.0	-1.2
May 23	-14.2	17.4	0.6	-13.3	17.4	-0.4	7.8	4.1	-1.3
May 30	-14.4	14.1	0.6	-2.1	14.1	-0.7	5.4	3.8	-1.9
Jun 6	-12.2	11.1	0.7	-12.0	11.1	-1.4	9.0	3.3	-2.4
Jun 13	-16.0	4.5	0.6	-6.4	4.5	-1.3	-2.6	3.5	-2.1
Jun 20	-11.5	4.7	0.7	-9.6	4.7	-0.8	0.2	3.6	-1.7

Table A6: Cumulative Changes in Employment, Mean Wages, and Selection-Adjusted Wages, relative to week ending February 8, by 2-digit NAICS (Table 4)

	53: Real Estate			54: Professional Services			55: Management of Companies		
Week	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage
Feb 1	-1.5	0.1	-0.1	-2.9	0.1	-3.6	-2.8	0.1	-0.1
Feb 8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Feb 15	-2.9	0.1	0.2	-0.2	0.1	0.1	-11.2	0.4	0.1
Feb 22	-7.9	0.3	0.3	2.5	0.3	0.3	-10.1	0.2	0.1
Feb 29	-9.8	0.3	0.1	-2.0	0.3	0.2	-15.9	-0.2	0.2
Mar 7	-4.0	-0.0	0.2	-0.9	-0.0	0.0	-10.8	-0.5	0.3
Mar 14	-7.6	0.3	0.4	-2.7	0.3	0.1	-0.2	0.4	0.5
Mar 21	-13.3	-0.3	0.5	-4.8	-0.3	-0.1	-1.9	1.9	0.4
Mar 28	-27.9	0.0	0.3	-11.3	0.0	-0.4	-25.8	3.3	-0.4
Apr 4	-25.5	1.1	0.3	-8.3	1.1	-0.6	-17.5	4.2	-0.3
Apr 11	-22.9	1.9	0.5	-7.9	1.9	-0.6	-24.9	6.3	-0.1
Apr 18	-22.8	2.7	0.5	-9.2	2.7	-0.6	-11.3	8.2	-0.2
Apr 25	-23.3	2.9	0.6	-12.2	2.9	-0.6	-10.2	8.0	-0.6
May 2	-21.3	2.7	0.7	-11.2	2.7	-0.7	-9.0	7.8	-0.7
May 9	-21.2	2.4	0.8	-6.9	2.4	-1.1	-11.0	7.9	-0.9
May 16	-18.6	2.4	0.8	-7.7	2.4	-0.9	-13.4	7.8	-1.0
May 23	-21.6	2.9	0.7	-7.0	2.9	-0.7	-11.7	7.3	-1.2
May 30	-21.6	2.6	0.6	-7.9	2.6	-1.2	-10.1	7.5	-1.2
Jun 6	-22.9	1.1	0.6	-4.7	1.1	-1.9	-12.8	7.6	-1.2
Jun 13	-19.4	1.1	0.7	-7.3	1.1	-1.8	-11.6	7.6	-1.1
Jun 20	-19.3	0.5	0.9	-8.5	0.5	-1.5	-13.7	7.9	-1.0

Table A7: Cumulative Changes in Employment, Mean Wages, and Selection-Adjusted Wages, relative to week ending February 8, by 2-digit NAICS (Table 5)

	56: Admin/Support Services			61: Education			62: Healthcare		
Week	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage
Feb 1	3.0	0.1	-0.6	-11.0	0.1	-0.0	-1.9	0.6	-0.6
Feb 8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Feb 15	5.6	-0.2	0.2	-8.7	-0.2	-0.1	0.1	0.1	0.1
Feb 22	2.4	0.4	0.3	1.9	0.4	-0.1	-0.9	0.4	0.2
Feb 29	4.5	0.7	0.2	-5.4	0.7	0.0	-3.5	0.4	0.2
Mar 7	3.0	-0.0	0.2	5.7	-0.0	0.2	-0.7	0.0	0.3
Mar 14	3.2	1.0	0.3	-9.0	1.0	0.2	-3.6	0.1	0.5
Mar 21	-5.1	0.5	0.3	-16.7	0.5	0.1	-8.4	0.5	0.5
Mar 28	-11.2	1.3	0.3	-23.2	1.3	-0.9	-15.3	0.6	0.5
Apr 4	-16.1	3.2	0.3	-21.2	3.2	-0.9	-15.8	1.8	0.6
Apr 11	-11.2	2.8	0.1	-24.0	2.8	-1.7	-13.4	2.4	0.8
Apr 18	-15.9	3.3	0.2	-18.3	3.3	-1.8	-13.5	2.7	0.8
Apr 25	-12.2	4.8	0.3	-23.5	4.8	-1.9	-16.5	3.1	1.0
May 2	-12.2	5.1	0.4	-16.7	5.1	-1.8	-14.4	3.3	1.1
May 9	-11.7	5.3	0.2	-22.8	5.3	-1.9	-14.5	3.2	1.3
May 16	-12.3	5.7	0.2	-21.1	5.7	-1.8	-11.3	3.0	1.3
May 23	-10.6	6.8	0.4	-29.2	6.8	-1.8	-10.8	3.1	1.3
May 30	-12.2	9.3	0.4	-23.6	9.3	-2.2	-8.1	2.9	1.4
Jun 6	-7.5	11.3	0.1	-29.8	11.3	-2.2	-10.0	2.8	1.3
Jun 13	-9.2	11.2	0.2	-22.2	11.2	-1.9	-8.8	2.4	1.4
Jun 20	-10.7	10.9	0.4	-25.9	10.9	-1.9	-10.2	2.5	1.5

Table A8: Cumulative Changes in Employment, Mean Wages, and Selection-Adjusted Wages, relative to week ending February 8, by 2-digit NAICS (Table 6)

	71: Arts/Recreation			72: Food/Accommodation			81: Other Services		
Week	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage	# Emp.	Base Wage	Selection-Adj. Wage
Feb 1	6.0	-0.0	-2.5	5.7	-0.0	-1.2	-0.4	-0.3	-0.1
Feb 8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Feb 15	9.7	0.7	0.1	-0.2	0.7	0.2	-1.3	0.0	0.4
Feb 22	10.1	-0.1	0.2	3.5	-0.1	0.2	1.2	0.3	0.3
Feb 29	13.3	-0.2	0.3	3.3	-0.2	0.4	-0.4	0.4	0.3
Mar 7	3.7	-0.4	0.2	-2.2	-0.4	0.5	-0.6	0.2	0.4
Mar 14	4.9	-0.1	0.2	-5.1	-0.1	0.7	-3.1	0.2	0.6
Mar 21	-8.7	1.4	0.4	-19.1	1.4	0.6	-9.7	0.5	0.6
Mar 28	-24.2	3.0	0.2	-31.5	3.0	0.4	-19.7	2.3	0.6
Apr 4	-36.0	5.3	-0.4	-39.0	5.3	0.2	-24.4	4.8	0.6
Apr 11	-41.9	8.3	-0.7	-42.4	8.3	0.2	-28.0	6.7	0.5
Apr 18	-48.1	9.3	-1.0	-45.7	9.3	0.5	-25.7	8.5	0.4
Apr 25	-45.9	10.7	-1.2	-45.6	10.7	0.7	-26.0	8.2	0.6
May 2	-43.6	10.6	-1.1	-43.9	10.6	0.8	-26.1	8.1	0.6
May 9	-41.1	10.4	-1.1	-40.3	10.4	1.0	-24.0	7.6	0.7
May 16	-40.7	9.5	-1.0	-37.0	9.5	1.0	-20.7	7.6	0.8
May 23	-39.2	9.0	-1.3	-35.1	9.0	1.0	-21.5	6.3	0.8
May 30	-34.9	7.4	-0.9	-33.6	7.4	1.1	-17.9	4.8	0.5
Jun 6	-33.0	6.1	-0.7	-30.5	6.1	1.1	-17.1	4.1	0.5
Jun 13	-26.1	4.2	-0.5	-27.4	4.2	1.1	-16.2	4.4	0.7
Jun 20	-25.1	3.7	-1.3	-26.9	3.7	1.1	-15.7	4.6	0.9

Note: Comments and discussion cover two papers presented at the Session 1 of Summer 2020 BPEA conference on labor markets and consumer spending.

Comments and Discussion

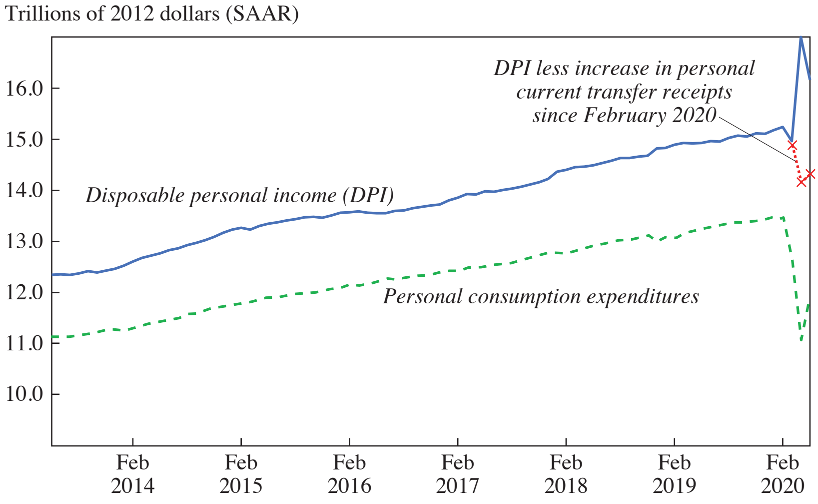
COMMENT BY

JONATHAN A. PARKER Following the identification of a novel form of coronavirus in China at the end of 2019, COVID-19 has spread rapidly around the world causing death and economic destruction. On March 13, 2020, with hundreds of new cases identified each day (soon to be thousands), the United States declared a national emergency. In response both to the spreading virus and to government-ordered partial shutdowns, significant swaths of the US economy simply stopped during much of April. As the spread of the virus was slowed in the late spring and early summer, the reductions in economic activity have been partially reversing. These two excellent papers present some of the first broad-based, quantitative measurement of the massive disruption and partial rebound of employment and consumer spending during the first few months of this pandemic recession. They should be a good guide for what is happening now at the end of July, as new cases currently number in the tens of thousands.

In this discussion, I will first briefly describe how aggregate consumption and income have reacted during these first few months that followed COVID-19 reaching the United States, and then compare these measures to the average consumption and income responses documented in each of the two papers. But the main contributions of these papers lie in the careful analysis of the heterogeneous impact of the pandemic using high-quality, large microeconomic data sets.[1] So, second, I will emphasize what I take as the two main lessons from the combination of the papers. During this initial period of the pandemic, the economic collapse is almost entirely due to the

1. Both papers treat the related literature well, and I choose not to use my space comparing these papers to other rapid-response analyses of the economic effects of COVID-19 using micro data.

Figure 1. Real Personal Disposable Income and Personal Consumption Expenditures



Sources: Bureau of Economic Analysis and authors' calculations.

pandemic directly. That is, whether one defines the shutdown of some sectors of the economy "demand" (e.g., people do not want to consume certain goods) or "supply" (e.g., certain firms cannot produce), the key point is that the papers show that the collapse in consumption is not due to, or amplified by, current income losses, and that the declines in employment are not due to, or amplified by, current low income or liquidity. The other lesson is that this lack of observable propagation through incomes and reduced demand is significantly due to the large policy response. These lessons apply only to these first few months. The pandemic is continuing, and I expect that this recession will slowly turn from a pandemic shutdown into a more typical recession and exhibit the usual economic propagation of recessions through demand channels.

Since these lessons lean more heavily on the consumption results, in the last part of my discussion, I will highlight a few other interesting findings about the decline in employment, and conclude with a few thoughts about real-time analysis by academic economists and economic policy going forward.

Figure 1 shows the disruption that this caused the economy as documented in aggregated statistics. Aggregate personal consumption expenditures (the dashed line) fall by about 6 percent from February to March and then decline precipitously from March to April by 12.2 percent, reaching a level not seen since about seven years earlier. Both to emphasize how rapid and large this decline is, and because I hope never to have the opportunity to write a sentence like this again, let me note that this implies that real personal consumption expenditures declined by 79.1 percent at an annual rate between March and April 2020. Consumption subsequently rebounded in June, rising by 8.1 percent to roughly 11 percent below its February level.

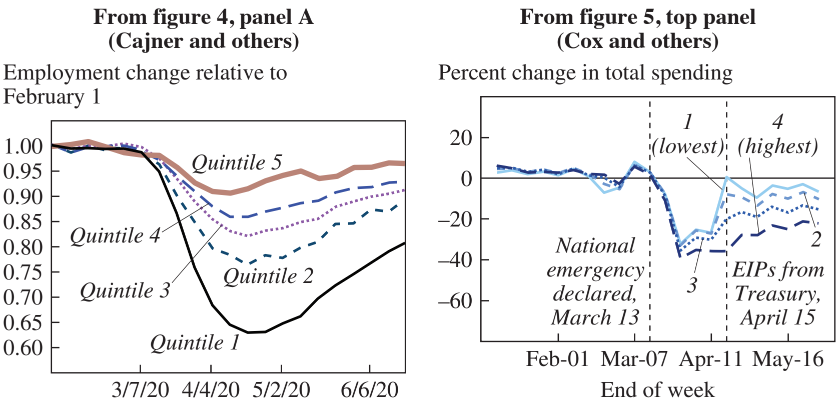
These numbers are broadly consistent with the patterns shown in Cox and colleagues mapped into monthly averages, with two exceptions. First, the high-frequency nature of the paper's data—a significant contribution of the paper—shows some evidence for a spike in spending that occurs before the shutdown, possibly as people stock up ahead of expected increases in infection rates, store closures, and shelter-in-place orders.[2] Second, the paper documents a larger decline in consumption from February to March and a smaller decline from March to April than in the Bureau of Economic Analysis (BEA) data. In favor of the results in Cox and colleagues is that the month-to-month timing of consumption expenditures in official statistics is not particularly reliable. A major source of the data, for example, is a survey of retail establishments about sales volumes in which establishments can choose different time horizons over which to report sales amounts, overlapping horizons that must then be unpacked by the BEA to create monthly data. On the other hand, the Chase data capture only Chase customers and omit certain types of consumer spending. Using account-level data requires that one infer whether an outflow is consumption, saving, or debt payment from the observed counterparty. Paper checks do not have readily observable counterparties, nor do electronic funds transfers (EFTs) in this paper. One might also be concerned that the pandemic changed the means of payment for different types of consumption.[3]

Figure 1 further shows that disposable personal income (solid line) falls slightly in March and then *rises* by 13.6 percent in April before falling back down slightly in June. The personal savings rate—the difference between the two series as a percent of disposable income—rose to more than 30 percent in April, a number consistent with the unprecedented use of the word *unprecedented* during this pandemic.

2. See also Baker and others (2020).

3. That said, cash withdrawals are measured in consumption both before and after the pandemic, so that switches in the composition of spending between cash and cards should only affect the allocation of spending to categories (Cox and colleagues, figure 4).

Figure 2. Consumption and Income by Ex Ante Income Level



Sources: ADP anonymized payroll records and authors' calculations (left); JPMorgan Chase Institute (right).

However, the increase in disposable personal income looks like good news, and nothing like the labor market disruptions documented by Cajner and colleagues. The reason for this discrepancy is that government transfers increased by \$231 billion from March to April (\$2.8 trillion at an annual rate!) mostly due to the disbursement of economic relief payments. The final line (solid with *x*'s) on figure 1 removes the increase in current transfer receipts since February from the disposable personal income series and shows that income less these transfers declined by 2.3 percent in March and then 4.9 percent in April before slightly rebounding by 1 percent in May.

These declines in income are large for one-month movements, but are still slightly lower than one might infer from Cajner and colleagues. The most likely cause of this discrepancy is the difference in populations. The BEA data include government workers and retirees for example, whose regular incomes, as best we know, experienced less of an impact early in the pandemic. This highlights a difference not just between the aggregate data and the population studied by Cajner and colleagues, but also between the populations studied by the two papers. That said, I will now pretend the papers cover the same people and measure what we want them to measure, two assumptions that appear reasonable given the size of the pandemic shock and the point I want to emphasize.

Figure 2 simply reproduces the two figures in the two papers that show changes over time by quintiles or quartiles of the ex ante income distribution. The figure on the left, from Cajner and colleagues, shows that there are dramatically larger declines in employment for ex ante lower income workers. The figure on the right, from Cox and colleagues, shows that there are not larger declines in spending for ex ante lower income workers. The implication: *the initial aggregate collapse of consumption during these months was driven by the unwillingness or inability of people to consume rather than by declines in income.*

The second main point: the most important reason that low-income (harder hit) households have not on average had to cut consumption on average by more than high-income households appears to be the increase in government transfers (economic relief payments, automatic stabilizers, and extended UI benefits). While this point is suggested by figure 1, Cox and colleagues show two important pieces of evidence in favor of this conclusion. First, consumer spending jumps up significantly at exactly the same time that most of the Economic Relief Payments—a major part of the policy response—were disbursed. Second, the paper shows that low-income households maintained substantial liquidity during these first few months despite significant income losses.

Let me note one caveat about the evidence for these conclusions. As shown in the left panel of figure 2, Cajner and colleagues show that employment has rebounded more strongly for ex ante low-income workers (although it remains below its prepandemic level). Further, the paper also shows that wage cuts are more common among high-income workers. Thus, my reading may be exaggerating somewhat the differences in income losses by ex ante income level. If there were only small differences in income, then we would expect little difference in spending responses across income levels and be less confident in the conclusion that income losses in general were not substantially holding back the economy.

My juxtaposition of the results of the two papers in figure 2 can be complemented by a similar comparison of the set of results in the two papers by industry. The pandemic shut down certain industries, and both papers nicely document how this has caused quite different income losses across workers. Yet again, we see little differences in consumption of households who work in different industries.

This conclusion implies that for the first few months of the pandemic in the United States, the goal of policy should have been insurance rather than stimulus. And policy largely met this insurance need. Policy surely also contributed to the lack of economic damage from a collapse in spending, but it did not stimulate the economy beyond this point, which I think is appropriate. When from a public health perspective (and so a welfare perspective), it is optimal to shut down some sectors of the economy, then there is a reduced multiplier from government transfers and income support. In the typical recession, stimulus tends to raise purchases the most for the goods for which demand fell the most. So stimulus tends to generate spending that leads to hiring or maintaining employment for the workers most affected by the recession, who then tend to turn around and maintain consumption instead of cutting it. This is the Keynesian multiplier. However, when some employers are shuttered for health reasons, no stimulus is spent there, so any increase in demand and in resultant incomes go to those workers and industries who are already the least affected.

Further, unlike in a typical recession, when a sector of the economy is temporarily shut down, everyone in that sector with the same skills is out of work at the same time. While some workers can gain employment by moving across industries, if the shutdown is temporary, there is little benefit to having people searching for work which requires employers to on-board and train people whose skills are a poor match for the job at hand. Instead, as emphasized by Guerrieri and others (2020), fiscal targeted transfers are an important part of optimal policy as pandemic insurance. Only once the pandemic is past and as the economy reopens, to the extent that we are in a recession or a slow recovery, then more traditional demand stimulus may be beneficial.

There are also many more fascinating details in each paper, but I only have space to discuss two and will focus on Cajner and colleagues, which I have focused slightly less on up to now.

First, data on average wages show that they have risen substantially in the crisis so far, a point that has received a fair bit of attention. One can only measure wages for employed workers. Cajner and colleagues show that the average wage rises precisely because, as I focused on above, low-wage workers disproportionately lost their jobs. The paper shows that in fact, wages for continuing workers are on average unchanged through these first few months of the recession. The paper also shows that this constant average wage masks lots of different wage changes, and indeed a substantial share of workers have experienced wage reductions.[4] This finding sheds light on the theoretical factors that may constrain wage reductions in typical recessions. In particular, menu costs models predict that wages are more flexible in response to large shocks. Further, in such models, aggregate wage adjustment is slowed by strategic complementarities

4. For example, most senior faculty at MIT experienced a (temporary, we hope) wage cut for 2020, a first as far as I know.

and non-simultaneous adjustments. Both modelling ingredients thus predict that wages are more flexible in response to large and simultaneous economic shocks to firms, which is what this early evidence appears to show.

Second, the pandemic has had significantly different impacts on workers by gender. Cajner and colleagues show a much larger decline in the employment of women than men. Further, this difference is largely unrelated to the fact that women and men tend to work in different industries and at different sized firms. As such, in addition to the unequal burden of childcare and housework as the pandemic has shuttered schools, women may experience longer-lasting and more serious consequences from the labor market shutdown (Alon and others 2020).

Before concluding, I wanted to both praise and make a few suggestions for the conduct of research in this new world in which academic economists work with private-sector companies and conduct nearly real-time analysis, sometimes now directly for high-quality journals like the BPEA. Real-time analysis used to be purely the purview of newspapers, Gallup-type survey firms, and economists in bank research departments that had access to data and produced analyses for clients. And these organizations do still tend to produce analyses of important economic events first.[5] These early analyses partly lay out key questions and partly set narratives that persist in our understanding of events. The involvement of academics in this process is a boon. We can expand the resources available for these analyses, and also add a set of skills and knowledge—about theory, causation, and economic behavior—that can improve these analyses.

But these benefits should also involve some changes in how we operate. First, our usual strengths—the added value of academics—is about getting things right, at the cost of being slow. We are often trusted because we are correct, which involves being diligent, careful, and taking our time. We have to protect that trust, which means being clear that rapid analysis of firm data is not the same product as established research based on painstaking analysis. To be clear, I praise both papers in this regard. Each is extremely careful to delineate its strengths and to clearly state caveats.

Second, we have to be careful ourselves not to take early narratives (like my main conclusions in this discussion) as final truths. As an example, the latest Commerce Department estimate is that the homeownership rate

5. Bank of America, for example, produced an analysis of the spending caused by the economic relief payments on April 22, within days of the first payments being distributed; Michelle Meyer and Anna Zhou, "COVID-19 and the Consumer: Data through April 16," Bank of America Data Analytics.

rose by more than 3 percent between the first and second quarters of 2020. The pandemic has played havoc with the collection of lots of economic data, and I will go out on a limb and say that this large an increase in homeownership is very, very unlikely. Another example is that it has taken academics many years and many papers to overturn the early media consensus that the subprime crisis caused the financial crisis. And we are still—more than a decade later—parsing the relative roles of lending standards, low interest rates, and optimistic beliefs in the housing bubble, which is great. We, and many of the first contributors, have a dogged persistence to refine early findings and get to the truth. But early findings are more persistent the farther one looks from the core researchers. So, to again try to be clear, I have no reason to doubt the results in these papers, but we as a field need to avoid first-impressions bias, and I look forward to updating and refining my understanding from future analyses of the data from more companies and from traditional representative surveys.

To conclude let me return to interpreting the main lessons of these papers. The dramatic aggregate declines in employment and consumption appear to be due to choices rather than responses to low incomes or liquidity. The income declines represent a combination of responses to the pandemic: government policies, motivated by a desire to stop or at least slow the spread of the disease, and human behaviors that incorporate the additional motivation of self-preservation.[6] The effects of the income declines on consumption appear, in the data so far, to have been largely mitigated by fiscal insurance policies.

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6. My reading of the literature so far is that, given the individual responses that already occur in response to the disease, there are few medium-term economic costs of government policies that shut down economic activity, at least on average outcomes, and there are substantial benefits in terms of health and lives saved from the disease (Andersen and others 2020; Correia, Luck, and Verner 2020).

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GENERAL DISCUSSION Adriana Kugler appreciated Cox and coauthors' simulation to estimate changes in income from stimulus policy, and she considered the possibility that Cajner and coauthors could employ a similar simulation to estimate the effects of Paycheck Protection Program (PPP) payments for firms. She postulated that PPP payments could help explain the trajectory of firm size and the nature of employment rebounds being primarily recall-driven (as opposed to being driven by new hires). She proposed that researchers explore the timing differentials that occurred in the implementation of the stimulus to verify this idea.

Kugler also commented on the breakdown of employment changes by gender in Cajner and coauthors' presentation, wondering if perhaps the idiosyncratic effects of the pandemic within individual sectors have been responsible for job losses being concentrated against women. She raised the possibility that using three-digit industry codes, as opposed to two-digit or one-digit codes, could be useful in answering this question.

Lastly, Kugler turned back to Cox and coauthors' paper, suggesting the potential for this study to focus more strongly on differences in pandemic unemployment assistance and relief transfers by state. Kugler proposed a more in-depth exploration of how individual states differed in their program implementation timing, worker composition, welfare infrastructure, and welfare qualification criteria and how those differences drove the results of the paper. Kugler concluded by urging both groups of authors to detail more explicitly the effects of the Coronavirus Aid, Relief, and Economic Security (CARES) Act and general government policy on their respective analyses.

Olivier Blanchard reiterated the finding from Cox and coauthors that saving has increased at the top of the income distribution during the pandemic, noting that he found it particularly striking. He asked the authors and discussant if they had any general predictions for the consumption behavior of the rich in the future.

Hilary Hoynes commended the authors of both papers for examining how their respective analyses found different results for different groups and for articulating important levels of heterogeneity in the trends they observed. She raised the possibility that certain individuals were left out of the samples in each study, a problem she believed was particularly concerning for Cox and coauthors. She questioned if economically disadvantaged Americans, who are disproportionately likely to lack the bank accounts necessary to be included in the JPMorgan Chase data, were properly represented in the study. Similarly, Hoynes pointed out that the lowest income quartile in the study was limited to those with $12,000 or more, again raising the possibility that the sample did not accurately represent the most vulnerable Americans. She echoed discussant Jonathan Parker's comment that cautioned against drawing strong conclusions based on this issue and promoted the papers to be presented later in another conference session (Han and coauthors and Bitler and coauthors) for their results that focused on the poorest Americans.

David Wilcox continued along a similar line of thought. He asked if Cox and coauthors had any information regarding indicators of financial distress for the households in their sample, such as potential delinquencies on rent or a mortgage. He cautioned against concluding that relief measures had succeeded in staving off financial distress in the absence of measures of these indicators to confirm such a conclusion. Wilcox also noted that communities of color have been disproportionately harmed by COVID-19 and asked if it would be possible to examine the data along racial and ethnic lines to draw out additional insights.

Daron Acemoglu suggested to Cox and coauthors that they could use a shift-share composition analysis to explain the differences in their results across income groups. He noted that certain types of consumption would decline more than others because of social distancing (among other pandemic-related factors) and that those types of consumption are not homogeneously distributed across income brackets. Acemoglu proposed that understanding how the composition of different income groups' consumption was affected by the pandemic will be important for understanding changes in savings and consumption as the economy turns toward recovery.

Claudia Sahm was unable to comment directly due to technical difficulties, but moderator James Stock summarized from a comment she posted via the teleconference platform. According to Stock, Sahm said she strongly disagreed with a sentiment expressed by Jonathan Parker urging moderation in the responses of economists, and she exhorted the conference to take action with respect to solving the pressing crises of the pandemic.

Wendy Edelberg said she agreed with Sahm that economists had an imperative to act and also agreed with Parker in cautioning against drawing conclusions too quickly. Turning to her central point, she argued that if one looked at how much consumption by low-income workers changed relative to high-income worker consumption, one might be led to believe that consumption in low-income households was not particularly affected by changes in income. She noted that such a conclusion would upend standard conceptions of marginal propensities to consume and how they differ among the rich and the poor. However, she pointed out that such an understanding would largely require ignoring the actual levels to which low-income consumption fell. Edelberg asked whether, by looking at how much consumption fell for low-income individuals, economists could gain new understandings of marginal propensities to consume among the poor. She concluded by noting that such lessons could have implications for the design of future stimulus policies and for determining whether or not stimulus payments to low-income individuals would largely be spent or saved.

Alessandro Rebucci asked if it was possible to determine the extent to which the pandemic differently affected the markets for goods and for services. He noted that services have been affected more than goods. He continued by commenting on the importance of understanding what has driven saving behavior in the pandemic, and he asked if increases in saving have been more due to precautionary saving in response to increased uncertainty or to declines in nonessential and conspicuous consumption, like vacation spending, due to the lockdowns and travel restrictions. He argued that understanding these drivers is important to form expectations about the recovery and also for policy design.

Ryan Decker, a coauthor on the Cajner paper, represented his colleagues in answering questions. He first noted, in relation to Sahm's comment and the related discussion, that while there has been pressure to release results quickly, he felt confident in his team's ability to work with ADP data. To illustrate this point, he noted that they have released papers using those data going back to 2018 and have other forthcoming papers that have been subject to rigorous academic scrutiny. He credited Wilcox for helping guide the research team to using the ADP data set.

In response to questions about the PPP, Decker said that his team's paper did not specifically examine that initiative. He pointed toward work that David Autor, Crane, and colleagues were presenting the same day at an

Automatic Data Processing, Inc., conference, examining PPP and analyzing how small and large businesses had different experiences with the program.

Lastly, Decker responded to an earlier comment about industry coverage, affirming that his data set was comprehensive across industries, and said that his team's findings about employment differences by gender held true even within detailed industries.

Peter Ganong, a coauthor on the Cox paper, fielded questions for his research team. He directed attention to a figure from his presentation, a bar plot showing changes in debit card spending, income without transfers, and income with transfers ("Estimated changes in income and spending," on figure 13 of his team's presentation).

First, Ganong answered questions regarding the representativeness of the sample in his study, noting that it was comprised of bank account data, and that roughly 95 percent of Americans have bank accounts.[1] He commented that this obviously left out some Americans, particularly low-income ones. Additionally, he affirmed the point raised by Hilary Hoynes, that individuals had to have at least $12,000 in labor income to be included in the sample. As a result, if, prior to the COVID-19 pandemic, an individual earned less than $1,000 per month, they would not be represented in the study sample. Ganong elaborated, stating that the lowest quartile of individuals in the study had annual post-tax labor incomes between $12,000 and $24,000, so while many low-income individuals were represented in the study, those with the lowest incomes were not.

Second, Ganong turned to questions regarding how his study calculated income changes, and what assumptions he and his team made regarding the receipt of unemployment insurance and stimulus. Briefly, he noted that while not all stimulus checks had gone out at that time (referring to economic impact payments), enough had for that fact not to be a large source of uncertainty. What was more important, Ganong said, was the fact that some states have been slower than others in processing unemployment insurance claims and in issuing unemployment insurance payments. He noted that their study does not assume that everyone left unemployed in the pandemic has received unemployment insurance but instead uses information from the Department of Labor to infer the fraction of unemployed Americans receiving unemployment insurance. He stated this was roughly 50 percent in April and 75 percent in May.

1. Economic Inclusion, "FDIC Survey of Household Use of Banking and Financial Services," 2019, https://economicinclusion.gov/surveys/.

Finally, Ganong turned to questions regarding heterogeneity in the team's sample. Noting that the average consumption in the lowest quartile of the sample remained *approximately* constant, this did not mean that every individual in this quartile had constant consumption but rather that some people increased their consumption and some people decreased their consumption. He then concluded briefly in response to Wilcox's earlier point, saying that the JPMorgan Chase Institute is engaged in studies regarding mortgage delinquency and that while those considerations were not in his team's line of research, they would be addressed by others soon.