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THE U.S. LABOR MARKET DURING THE BEGINNING OF THE PANDEMIC RECESSION

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ABSTRACT

Using weekly administrative payroll data from the largest U.S. payroll processing company, we measure the evolution of the U.S. 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 re-opening 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 re-opening 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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A data appendix is available at http://www.nber.org/data-appendix/w27159

Introduction

We use administrative data from ADP—one of the world's largest providers of cloud-based human resources management solutions—to measure detailed changes in the U.S. labor market during the first few months of the Pandemic Recession.[1] In the current pandemic, data from ADP have many advantages over existing data sources. First, ADP processes payroll for about 26 million U.S. workers each month (about 20% of total U.S. private employment). As discussed in Cajner et al. (2018), Cajner et al. (2020) and Grigsby et al. (2019), the ADP data are representative of the U.S. workforce along many labor market dimensions. 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 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 which 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 U.S. statistical agencies.

We find that paid U.S. private sector employment declined by 21 percent between mid-February and late-April 2020 and then rebounded partially thereafter. As of late June, U.S. employment is 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 U.S. paid employment since the late-April trough can be attributed to the re-opening of businesses that temporarily closed. Employment declines through April were largest for businesses with fewer than 50 employees, with closures and re-openings playing an even larger role for this size group. We also document that re-entering businesses are primarily bringing back their original employees. Finally, we find that despite a staggering fifty percent of all continuing businesses substantively shrinking between February and June,

[1] Importantly, our series are constructed from the ADP microdata 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 BLS employment numbers. The ADP microdata tracked the last recession remarkably well; Appendix Figure A1 shows that monthly employment changes using ADP microdata closely match the monthly employment changes reported in the BLS's Current Employment Statistics (CES) survey during the 15 years prior to the Pandemic Recession.

over ten 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 re-called 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 that states that re-opened earlier had larger employment gains in the re-opening 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 six 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 are 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]

Section 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 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

[2] Our paper complements many recent papers which use a variety of different data sources to track labor market outcomes during the recent recession. A sampling of those papers includes: Bartik et al. (2020a), Bartik et al. (2020b) Barrero et al. (2020), Bick and Blandin (2020), Brynjolfsson et al. (2020), Chetty et al. (2020), Dingel and Neiman (2020), Coibion et al. (2020), Kahn et al. (2020) and Kurmann et al. (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 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.

for a large segment of the U.S. 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' 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 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 et al. (2018), ADP payroll data appear to be quite representative of the U.S. 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 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 2-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

[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 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).

[4] The methodology we adopt for this paper differs slightly from that used in our previous work with the ADP business-level data (e.g., Cajner et al. (2018) and Cajner et al. (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 re-opening businesses relative to mid-February levels rather than constructing longer-term time series.

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

Section II. Employment Changes in the Pandemic Recession

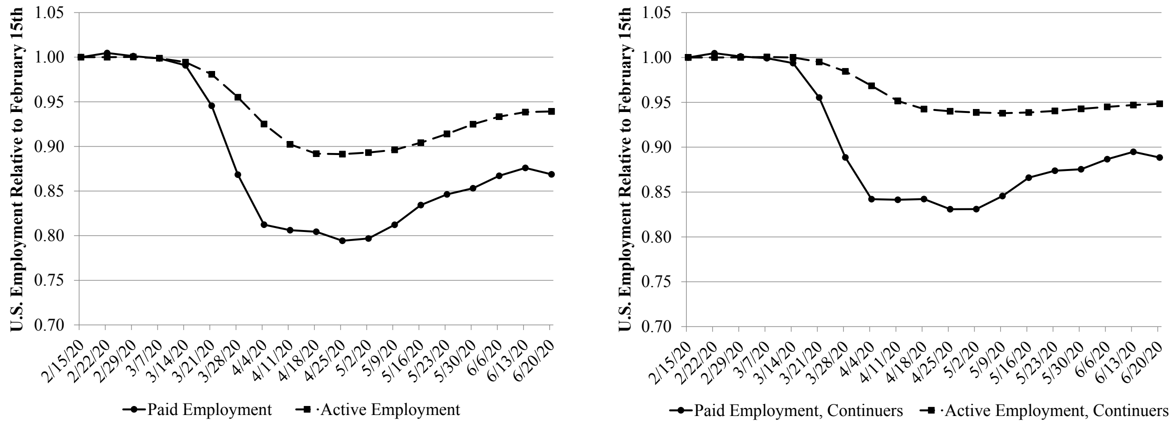
This section presents weekly labor market indices in the United States compiled from the ADP business-level microdata. Panel A of Figure 1 shows our estimated aggregate employment changes spanning the payroll week covering February 15 through late June.[7] Importantly, this panel shows employment changes 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 in-

[5]Unlike the business-level data, the data for our employee sample skew toward 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 they match aggregate employment patterns by industry and firm size from the SUSB.

[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 2-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 the match QCEW employment (treating the ADP businesses as establishments).

Figure 1: Aggregate Paid and Active Employment



Panel A: All Businesses

Panel B: Continuing Businesses

Notes: Figure shows employment changes relative to February 15th within the ADP business-level sample at the weekly frequency using 2-week trailing moving averages. The solid black line with circles in Panel A shows the trend in paid payroll employment for all businesses. The dashed black line with squares in Panel A shows the trend in active employment for all businesses. Panel B shows the same patterns for businesses who continually make scheduled payroll payments throughout the entire sample period starting on February 15th.

dices plot employment levels relative to February 15th levels without seasonal adjustment. The figure shows the evolution for paid employees (solid line, circles) and active employees (dashed line, squares). Between mid-February and the labor market trough in late-April, paid employment in the U.S. 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 20th. However, as of late June, paid employment in the U.S. is 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—or perhaps even stalled—toward the end of June. As we highlight below, the employment increases since mid-April 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 12th of the month, estimated employment declines of 1.0 million in March and 18.9 million in April followed by rebounds of 3.7 million in May and 5.5 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 15th and that week. Notice that paid employment for continuing businesses declined by 16.9 percent through late-April before rebounding through the 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 re-opening in driving the increase in employment during May and June. Continuing firms accounted for about three-quarters of the employment losses through late April. We further explore the importance of business shutdown and re-entry to aggregate employment trends in Section Section V..

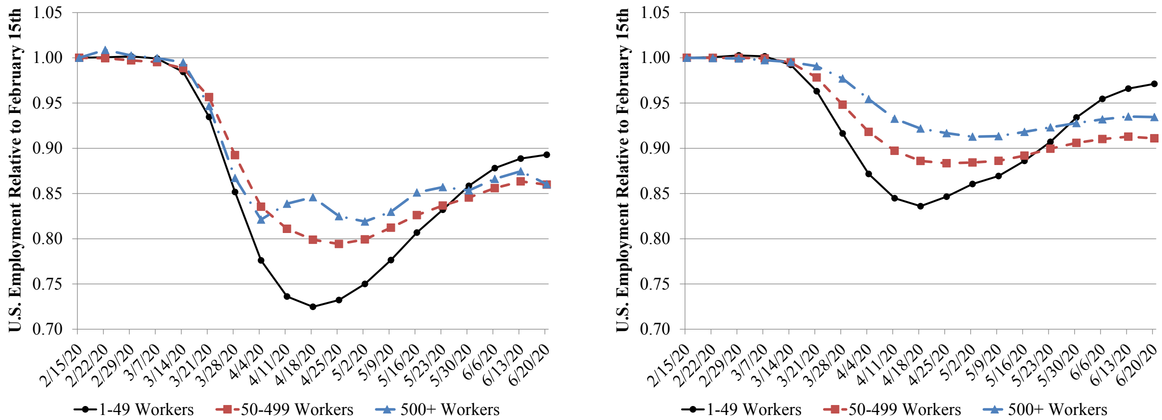
It is worth mentioning the active employment series shown on Figure 1. Recall that active employment measures the number of workers in payroll databases, including those not receiving pay in a given pay period.[9] Active employment among *continuing* businesses actually declined by about 0.5 million jobs during 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 $2 trillion stimulus package signed into law on March 27 makes 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 15th. The figure shows that businesses with fewer than 50 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 50 employees saw paid employment declines of more than 25 percent through April 18, while those with between 50 and 500 employees and those with more than 500 employees, respectively,

[8]Numbers 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.

[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.

Figure 2: Employment Change By Business Size



PANEL A: PAID EMPLOYMENT

PANEL B: ACTIVE EMPLOYMENT

Notes: Figure shows employment changes relative to February 15th within the ADP business-level sample at the weekly frequency with two-week trailing moving averages. Panel A shows the trend in payroll employment for each size grouping. Panel B shows the same patterns for active employment.

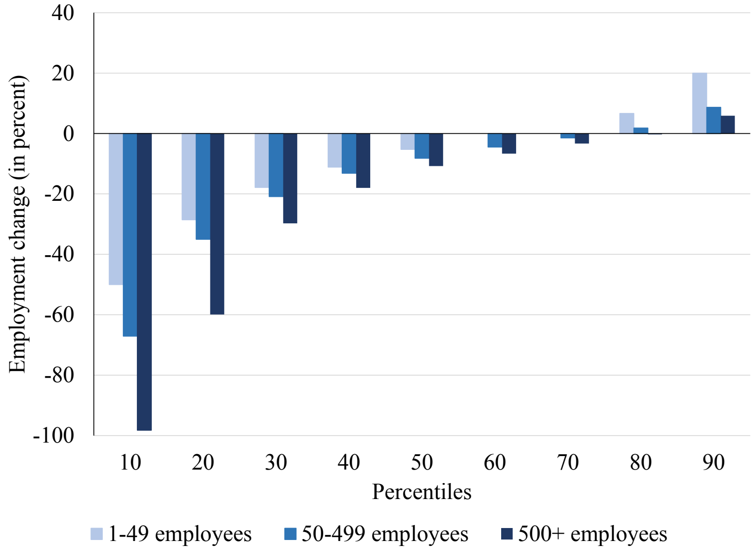
saw declines of 15-20 percent during that same time period and reached troughs a week or two later than the smallest businesses.[10] Notably, the growth in paid employment since late April has been much larger for smaller businesses. Between late April and late June, smaller businesses increased employment by 17 percent (of February 15th levels). Businesses with more than 50 employees increased employment by between 4 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 re-opening 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 20th, where percentiles are constructed from the employment-weighted business distribution.

Starting on the left-hand side of Figure 3, the 10th percentile business within every size class saw declines of at least 50 percent, with the largest class (at least 500 employees) seeing

[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



Notes: Figure shows change in paid employment by initial business size and employment change at each decile of the paid employment-weighted change distribution using the businesses-level sample. Shutdown businesses are excluded. Change in employment is measured between February 15th and June 20th.

a decline of about 98 percent. These are large firms that essentially shut down only keeping a handful of original employees on payroll. Even the smallest business size class (1-49) saw substantial declines. The facts that (1) small business saw even more overall employment declines (as highlighted in Figure 2) and (2) employment changes in the bottom decile of continuing firms were smaller for small businesses suggest that most of the total decline in employment for businesses with fewer than 50 employees is due to business closures. Conversely, all business size groups experienced positive growth at the 90th 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 60th through the 70th percentiles). Similarly a large swath of mid-size and larger businesses experienced only modest changes (those spanning the 60th through the 80th 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 median surviving small (less than 50) business declined 5 percent, while the medium and large median declines were 8 and 11 percent, respectively.

The results by firm size are not overly surprising in light of the industry results docu-

[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.

mented 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-April 25th (the aggregate employment trough, prior to states starting to re-open) and February 15-June 20th (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 the "Arts, Entertainment and Recreation" and "Accommodation and Food Services" sectors (i.e., leisure and hospitality) both 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/Insurance—saw smaller initial employment declines.

Since bottoming in late April, most sectors have seen some recovery in employment. Much of the relatively larger increases are in sectors where re-openings have occurred. For example, most states started re-opening manufacturing and construction sectors in early May. Both of these sectors saw employment gains of about 20 and 70 percent, respectively, of their initial employment losses. Large recoveries are also seen in some of the sectors that saw 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 re-opening and employment rebounding slightly, employment in these sectors still remains significantly depressed relative to mid-February levels. Notice, as travel has still remained depressed and schools remain closed, employment in the transportation and education sectors have not seen the rebound found in retail trade or food services. Another sector which saw a large rebound is health care and social assistance which has recovered nearly 40 percent of lost employment as hospitals and other health providers have attempted to start returning to normal activities.[12]

[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 model of the Pandemic Recession.

Table 1: Paid Employment Changes By 2-Digit Industry (in percent)

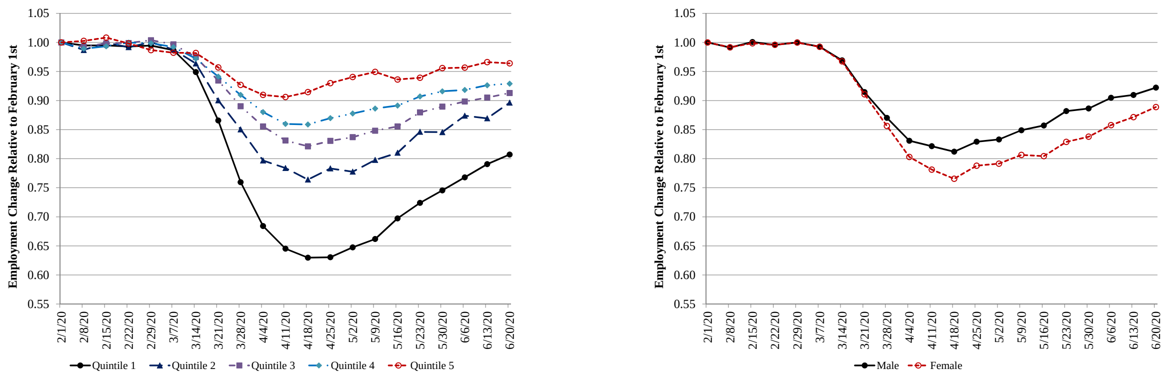
Industry	Feb 15 - April 25	Feb 15 - June 20
Arts, Entertainment and Recreation	-50.7	-31.7
Accommodation and Food Services	-45.4	-26.8
Retail Trade	-28.9	-17.5
Other Services	-25.1	-14.6
Transportation and Warehousing	-21.8	-20.5
Real Estate, Rental and Leasing	-21.0	-16.9
Information Services	-17.7	-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

Notes: Table shows total (i.e., inclusive of shutdowns) decline in paid employment through April 25th, 2020 (column 1) and through June 20th, 2020 (column 2) for all firms in each two-digit NAICS industries. All changes are relative to February 15th, 2020. Data from the business-level sample. Weekly data (without two-week moving average).

Section 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 the workers work 40 hours per week when computing their hourly wage. For weekly (biweekly) salaried individuals, this is just their weekly (biweekly) base administrative 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 13.5, 16.41, 24.53 and 32.45 dollars

Figure 4: Employment Changes By Initial Wage Quintile and Gender



Panel A: By Wage Quintile

Panel B: By Gender

Notes: Figure shows changes in employment through the beginning of the Pandemic Recession by initial wage quintile (Panel A) and by gender (Panel B). Employment declines measured relative to early February. Data for this figure use the employee sample.

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 has partially rebounded through late-June, but their employment still remains depressed by 20 percent relative to mid-February levels. Conversely, employment of workers in the top quintile of the wage distribution declined 10 percent through the end of April. Only about 4 percent of these top earning workers remain out of work through late June. The employment losses during the Pandemic Recession are disproportionately concentrated among lower wage workers.

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

[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 20th, 40th, 60th, and 80th percentile of hourly wages (measured in nominal dollars per hour) in the 2019 CPS were 12.0, 17.1, 24.0, and 36.1 (author's calculation).

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 percent. 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 amount 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 (22 percent vs 18 percent). The gap has 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 contracted 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 appendix, we again exploit the panel nature of our data to assess this question. Less than 0.5 percentage points of the 4 to 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

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

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 childcare—explains some portion of the gender gap in employment losses during this recession.

Section IV. Wage Changes during the Pandemic Recession

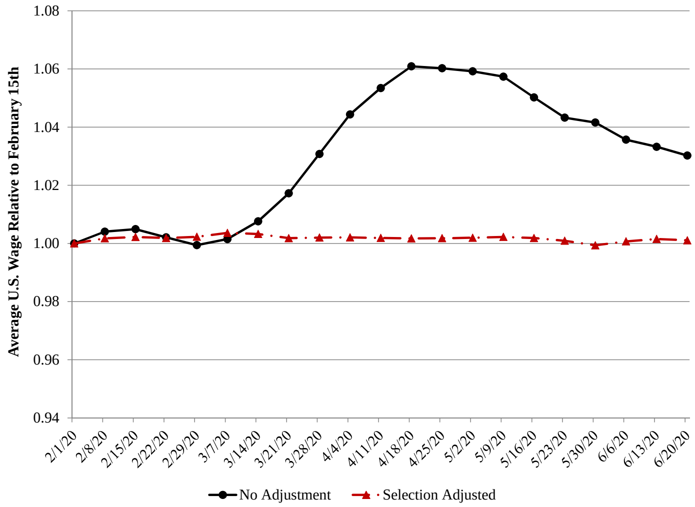
Figure 5 shows the trends in wages in the economy during the pandemic recession. The solid line creates a wage index by measuring the mean contract per-period wage rate of all working individuals in the economy.[15] Since the start of the recession, observed average wages in the ADP sample grew by nearly 6 percent through mid-May. As highlighted in Solon et al. (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 towards higher-earning individuals, while the reverse happened thereafter.

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

[15] Contract per-period wages are the contracted per hour wage rate for workers paid hourly and the contracted per-period weekly or bi-weekly 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



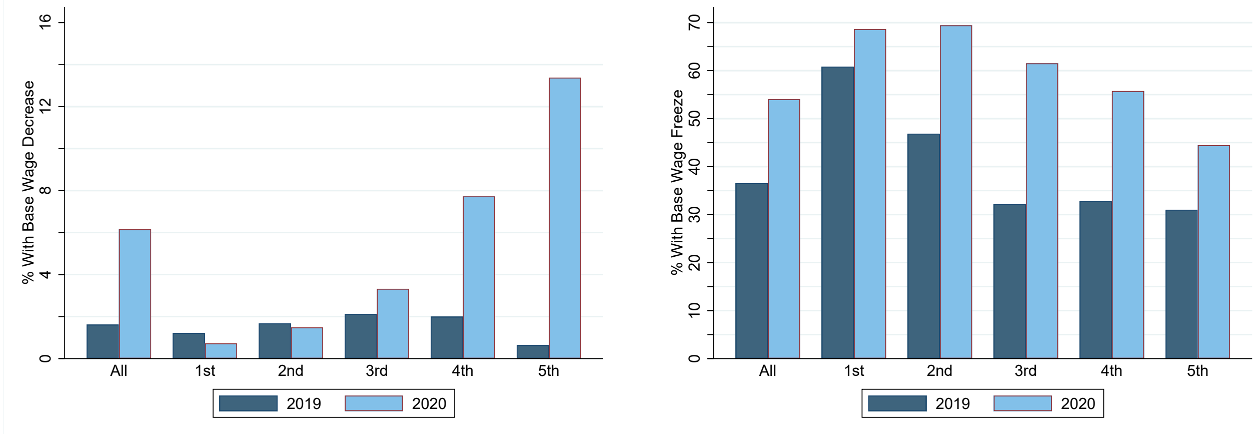
Notes: Figure shows trends in weekly wages during the beginning of the Pandemic Recession. The solid line (circles) averages base wages across all employed workers in each period. The dashed line (triangles) controls for selection by measuring the base wage of a given worker over time.

appendix, we present employment, mean base wage, and selection-adjusted wage indices by 2-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 few month period, 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 of Figure 6 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% of job-stayers saw wage declines between March and June of 2020. This stands in stark contrast to the patterns for 2019, when just 1.6% 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% of all workers in our sample who were employed in March (regardless if they

Figure 6: Probability of Base Wage Cut and Freeze in 2019 and 2020 by Base Wage Quintile
Sample: Workers at Firms that Usually Adjust Wages in March - June



Panel A: Probability of Wage Cut Panel B: Probability of Wage Freeze

Notes: Figure shows the probability of a wage cut (Panel A) and the probability of a wage freeze (Panel B) for different wage quintiles. Panel A includes all workers employed with the same firm in both March and June. Panel B restricts the sample to firms that made 75 percent of their annual wage changes for their employees in 2019 during March, April, May and June.

remained employed through June) saw a base wage cut between March and June. Given that total U.S. employment at the beginning of March was 129 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 and remain out of work.

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. However, as highlighted in Grigsby et al. (2019), 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 did at least 75 percent of their 2019 base wage changes in March, April, May and June. These are firms for which March-June are their normal base wage adjustment months.

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 of 36 percent of their employees). This number is similar to the decade-long average of base wage changes within the firms in the ADP employee sample found in Grigsby et al. (2019). Moreover, essentially all base wage changes in 2019 were increases; these firms only decreased the nominal wages of 0.7% of their workers during these months of 2019. However, during the same four months in 2020, these same firms froze the wages of 58% of their workers. In addition to the millions of base wage cuts observed in the last four months, millions of workers have seen zero base wage changes at firms due to make their annual wage adjustment.[17]

The 6.3% of workers receiving nominal base wage cuts during the Pandemic Recession is of similar magnitude to the 6% found by Grigsby et al. (2019) 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 shows 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. Over 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.

Section V. Business Shutdown, Re-Entry 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 dis-investments 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 re-opening 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

[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 are shown in the online appendix.

Table 2: Decomposition of Employment Growth in Shutdown and Re-Entering Businesses

Week	Continuers	New Entry	Ever Shutdown	Shutdown Re-entry	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

Notes: Table shows decomposition of total employment growth into employment contributions from continuously operating firms, newly entering firms, firms that were shutdown at some point since February 15, and firms who used to be shutdown but subsequently re-entered. Data from the business-level sample. Percentages expressed in terms of February 15 employment.

at firms that shut down at some point since February 15 but are now open). 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 15th. We define a firm as "shutting down" if they issue no paychecks during a week in which we would expect them to do so (given past pay frequency patterns). We define a firm as "re-entering" if it has shut down and starts paying its workers again.

On June 20th, job losses at firms that operated continuously contributed 10.3 percentage point out of 13.1 percent total employment decline since mid-February (as highlighted in Figure 1).[18] As of June 20th, 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 returned by June 20th. In other words, one-third of employment in firms that have ever

[18]The numbers in column 1 of 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.

shutdown at some point during the first few months of the pandemic has returned by late June. The difference between shutdown and re-entry columns in Table 2 measures the employment in firms that have remain closed and the change in employment at re-entering firms (the former component accounts for most of the difference). Newly entering firms added 2.3 percent (of February levels) to employment through the late June, though we caution against interpreting these figures in terms of genuine new business formation.[19]

Between April 25th and June 20th, aggregate employment increased by 7.5 percentage points (relative to February 15th 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 re-opened.[20] The findings suggest that the re-opening of temporarily shuttered businesses contributed meaningfully to aggregate employment gains during May and June.

Panel A of Figure 7 shows the dynamics of employment at currently *shut down* (solid line) and *re-entered* (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 re-entering 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 re-opened contributing to aggregate employment growth. As of late June, there is still 4 percent of February employment in firms that are still shutdown. 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.

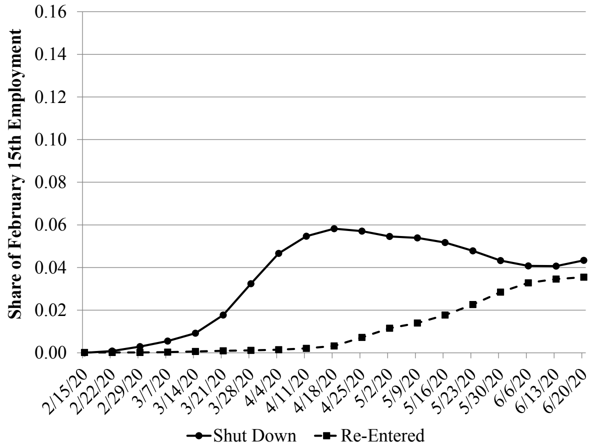
In the Appendix, we additionally show that firm shutdown disproportionately affected low wage workers. By the end of April, approximately three times as many bottom quintile workers were in firms that have shut down than were top quintile workers. This partly reflects differences in firm closure by industry: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

The remaining panels in Figure 7 show firm shutdown and re-entering 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

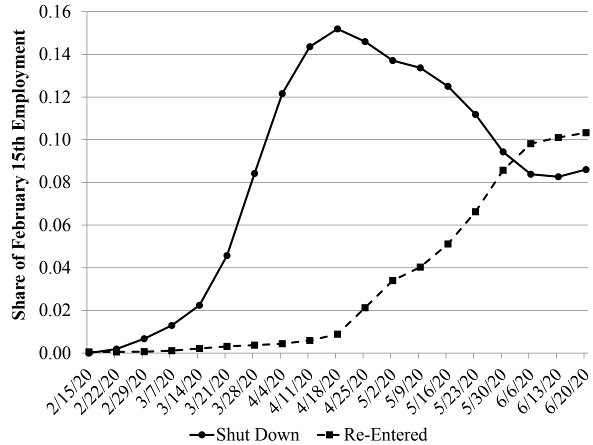
[19]Note that entry does not necessarily correspond to new firm formation; it could simply capture existing firms newly contracting with ADP or firms that existed at some point in the past, were closed during February, and later re-opened again, e.g. seasonal businesses. We do note, however, that Census Bureau data on new business applications with planned wages described by Haltiwanger (2020) indicate that application rates 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.

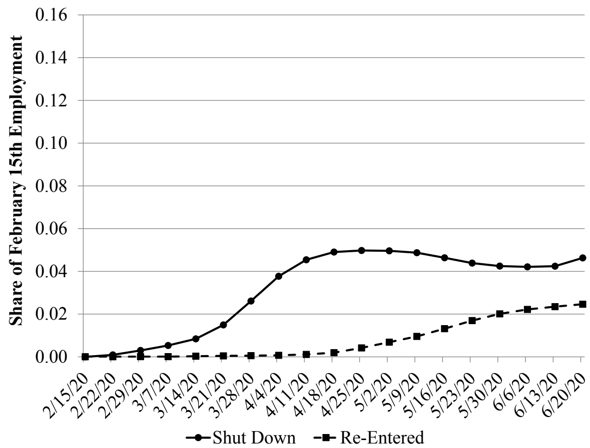
Figure 7: Employment in Shutdown and Re-Entering Firms



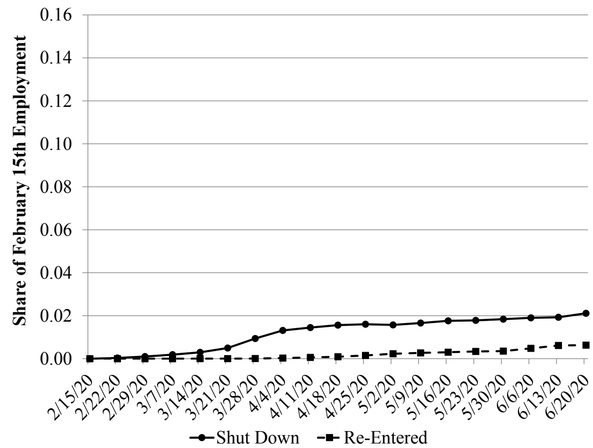
Panel A: All



Panel B: 1-49 Emps



Panel C: 50-499 Emps

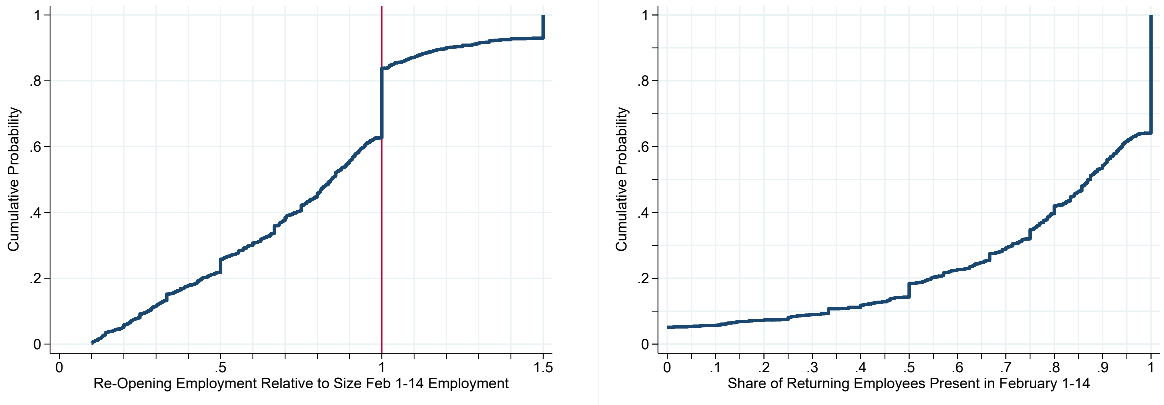


Panel D: 500+ Emps

Notes: Figure shows the share of February 15th employment at firms that were shut down as of each date (solid line), and the share of February 15 employment at firms that had shut down and then re-entered (dashed line). The sample of firms is defined as of mid-February and are followed over time. We define shut downs to be where a firm processes no payroll.

businesses with fewer than 50 employees. However, many of these small businesses have re-opened 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—i.e., shuttered and then reopened—contributed about half of the employment gains in among businesses with less than 50 employments since mid-April. Businesses with 50 to 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 has not

Figure 8: Employee Recall in Re-Entering Firms



Panel A: Re-Entering Firm Size

Panel B: Share of Employees Who Were Recalled

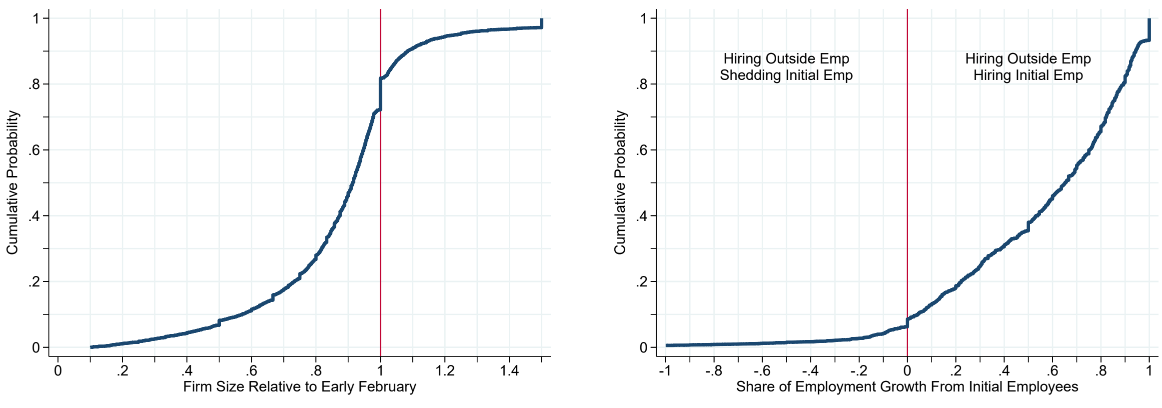
Notes: Figure shows the firm weighted CDF of re-entering business size (Panel A) and share of initial business employees recalled (Panel B). The sample of firms is those firms that existed in early February 2020 and that temporarily shut down. Temporary shutdowns are those firms that shut down and then subsequently reopened (i.e., resumed paycheck issuance). Employment measurements are through late June.

peaked and continues to gradually increase through late June.

When businesses re-enter, they may not hire back all of their pre-existing workforce. Figure 8 explores this possibility. Panel A plots the distribution of firm employment at re-entry relative to the firm's employment during early February, weighting each firm by their initial size. The figure shows that about 60% of returning firms are smaller than they were in the beginning of February. The median re-entering firm re-opened with 86% of their initial employment, while the mean firm only has 78% of its initial employment. We present versions of this figure weighting firms by their February employment in the Appendix. That employment weighted figure shows that returning large firms disproportionately return smaller: the employee-weighted median re-entering firm has 65% of its February employment. Although firm re-entry is contributing to a recovery in overall employment, these re-entering 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. Monitoring this sub-capacity operation will be important to the overall recovery dynamics.

When businesses return, they can choose to either re-hire 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 this figure is weighted by initial business size. Almost half of re-entering firms have their new workforce comprised of at

Figure 9: Growth of Continuing Businesses



Panel A: Size Relative to February 1-14

Panel B: Share of Growth Accounted for by Recall

Notes: Figure shows how continuing businesses have grown through the early stages of recovery. 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 we restrict attention to firms whose trough employment occurred after March 11. In Panel B, we limit attention to firms which add at least 10 employees.

least 90% employees who worked in the firm in early February. Hardly any firms re-enter without having their workforce comprised of at least half workers who were with the firm in early February. The results in this figure suggest that the overwhelming majority of re-entering businesses are seeking to avoid costly search 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 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 their size in mid-February. The figure shows that median growing continuing firm is currently at a size that is ten percent lower than their 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 10 workers from their trough to peak.[21] The figure shows that 90% of firms grow at least in part by recalling existing workers. Almost 10% of continuing firms hired exclusively from recall.[22] However, the complement of these findings is also interesting. Almost 10% 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 et al. (2020).

Overall, firm shutdown was an important driver of employment losses at the beginning of the Pandemic recession, and firm re-opening is likewise contributing to the labor market recovery. However, re-entering 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.

Section VI. Employment Gains and State Re-Openings

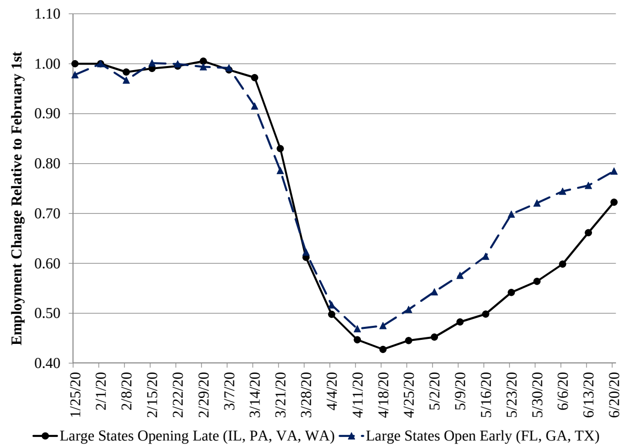
Figure 10 explores the effects of states re-opening certain sectors on employment. To facilitate exposition, we create two groups of states - a set of large states that broadly opened in late April or early May and a set of large states that broadly opened in late May and early June.[23] For the first set of states opening early we pool together data from Florida, Georgia and Texas. These states opened restaurants and lifted stay at home orders between April 24th and May 4th. For the second set of states opening later we pool together data from Illinois, Pennsylvania, Virginia and Washington. The late states opened restaurants and lifted stay

[21] We present the distribution of these recall shares for firms that grow by at least 1 or 5 employees in the 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 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/Restaurant Sector



Notes: Figure plots employment in NAICS Industry 72 (Accommodation and Food Service) in a set of large states that opened in late April/early May (FL, GA, TX) (dashed line) vs a set of large states that opened in late May/early June (IL, PA, VA, WA) (solid line). Data come from the ADP employee sample.

at home orders after May 31st. Our results focus on one sector where reopening had the most direct effect: the Food and Accommodation sector (NAICS 72).

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 states start to to diverge during the week of April 18th which was a week prior to the Georgia re-opening 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 over 20 percent below February levels as of late-June. Opening, per se, does not guarantee employment will fully rebound in these sectors. 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 re-open. Second, employment in these sectors within states that opened late started to increase even prior to those states re-opening. The increase was modest but suggests that demand was increasing (perhaps for takeout meals) even prior to official re-openings. 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 re-opening likely resulted in some firms bringing back workers early to prepare for serving in person customers. Researchers seeking to attach a causal quantitative interpretation of employment gains associated with state reopening should do so cautiously. Finally, employment in this sector has 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 pre-recession levels.

Section VII. Conclusion

In this paper, we use high-frequency payroll data from ADP to track the behavior of the labor market in early part of the Pandemic Recession. The data show an unprecedented collapse in employment from mid-February through late April with employment falling by a 21 percent relative to early February levels. As states started to reopen, employment rebounded partially. As of late June, employment is still 13 percent below February levels. The employment declines as of late June are massive relative to past recessions; during the Great Recession employment troughed at 7 percent of pre-recessionary levels. Despite the rebound, not only is the U.S. currently experiencing the worst employment losses since the Great Depression, but the pace of job gains has slowed measurably.

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 towards these groups. Job losses, in percentage terms, have converged between smaller and larger businesses as of late June (relative to pre-recession levels). Many previously shuttered businesses—particularly smaller businesses—have re-opened 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 non-recessionary 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 threefold. 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.

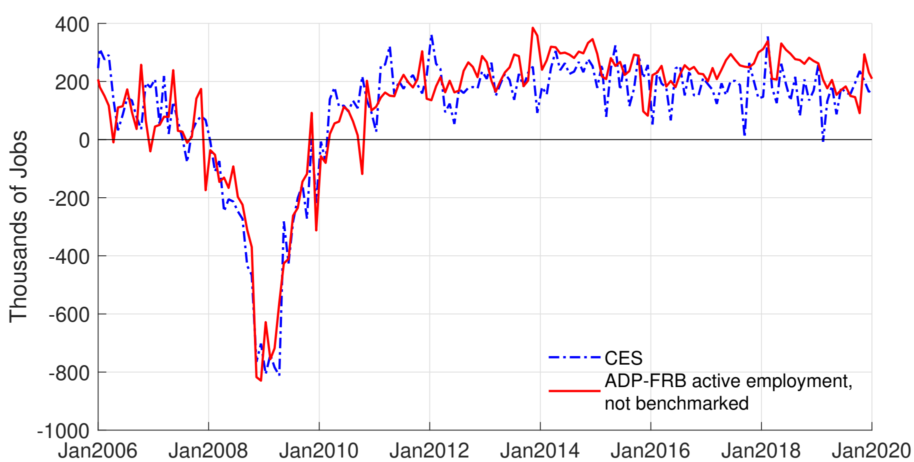
Appendix B Additional Results

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

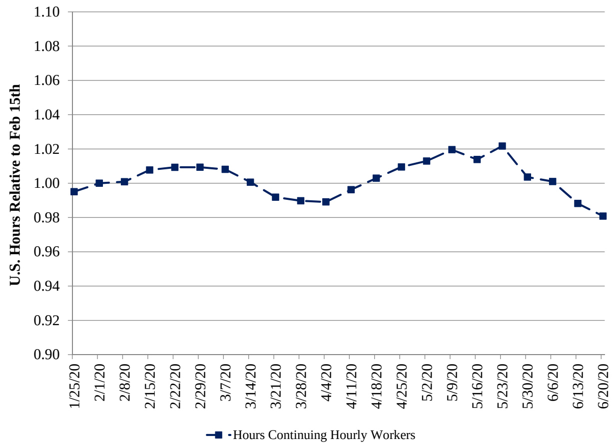
The aggregate numbers shown in Section Section II. are based on the ADP sample with SUSB weights to ensure representativeness in terms of industry and firm size. As noted in our data description, however, some business units in ADP may be more akin to establishments (i.e., single operating locations 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



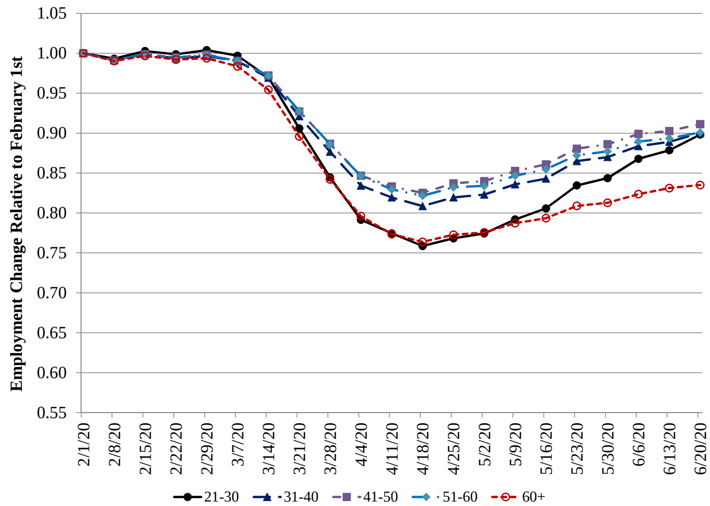
Notes: Figure shows the change in hours worked for hourly workers who remain continuously employed between pay periods. We create a chain weighted index of the hours changes. The index is relative to hours worked during the week of February 15th. The data come from the employee sample and are weighted 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.

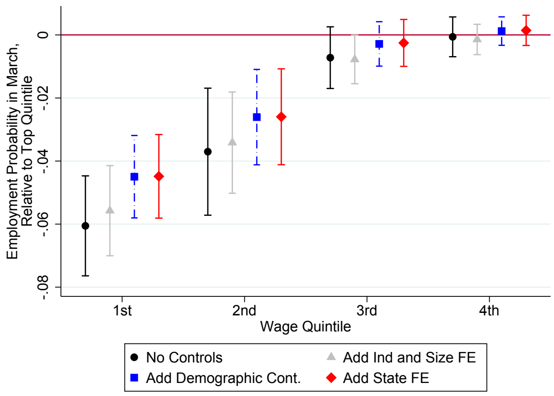
We control for worker i's wage quintile at the beginning of the period to allow the baseline separation rate to differ for workers in different quintiles q. Our variable of interest is how the employment probabilities of each quintile change during the beginning of the recession. This is captured by 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.

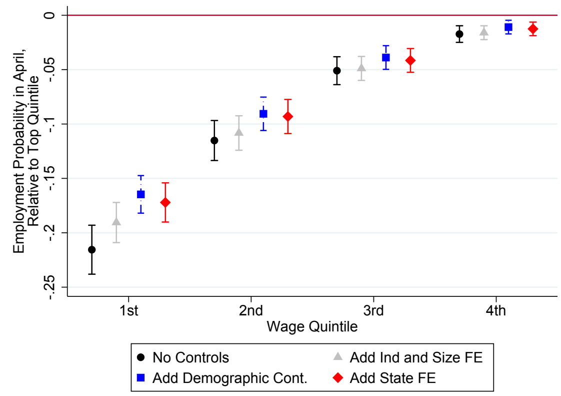
Recent research by Mongey et al. (2020) suggests that low-income workers tend to work in "social" sectors and the large decline observed in these sectors will result in job loss concentrated among lower wage workers. The gray points (triangles) explore this hypothesis by introducing firm size and 2-digit 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.

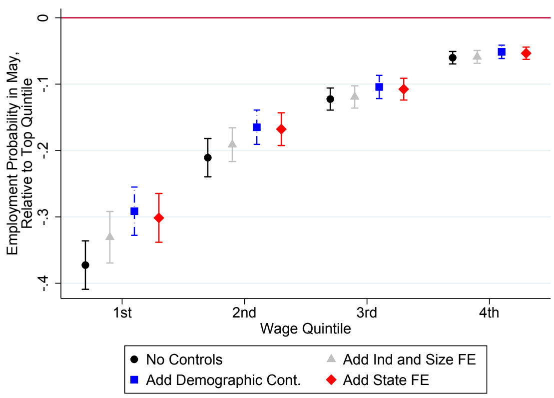
Figure A4: Probability of Employment by Wage Quintile and Sex, Conditional on Observables



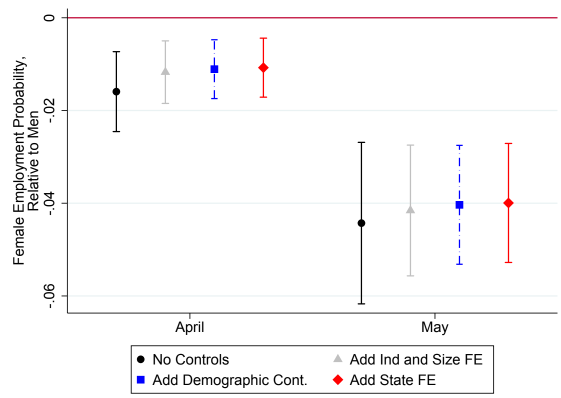
Panel A: March Employment by Wage Quintiles



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:

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

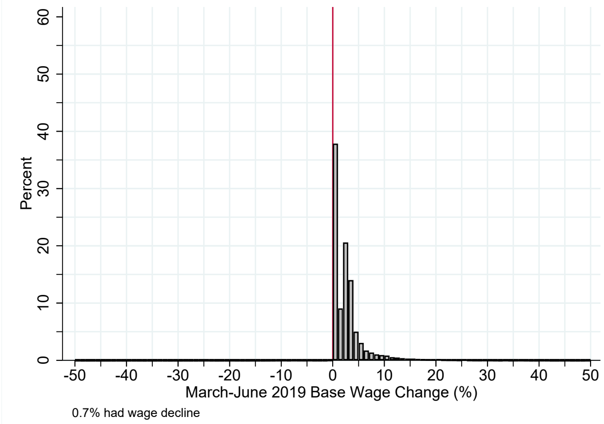
Here, γ_t represents the employment probability of women relative to men in month t, after controlling for observables X_{ijt}. These γ_t are plotted in Panel D of Appendix Figure A4. The figure shows that including controls for industry, firm size, age, or location do not meaningfully affect the result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

Subsection VI. Additional Results on Nominal Wage Adjustments

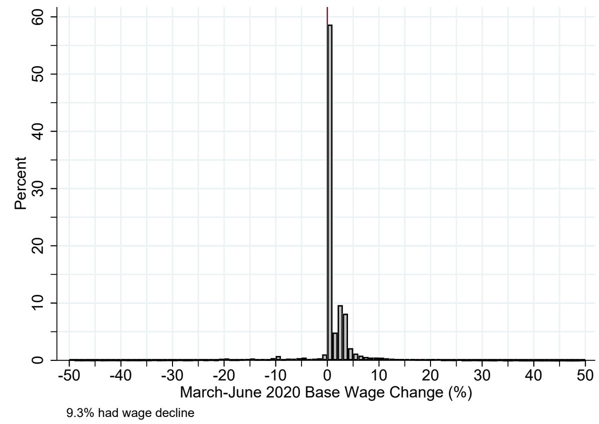
Appendix Figure A5 shows the histogram of wage changes for workers in firms that historically provide annual wage changes to their employees in March - June. Specifically, the sample includes any worker in a firm that did at least 75 percent of their 2019 base wage adjustments between March and June. 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

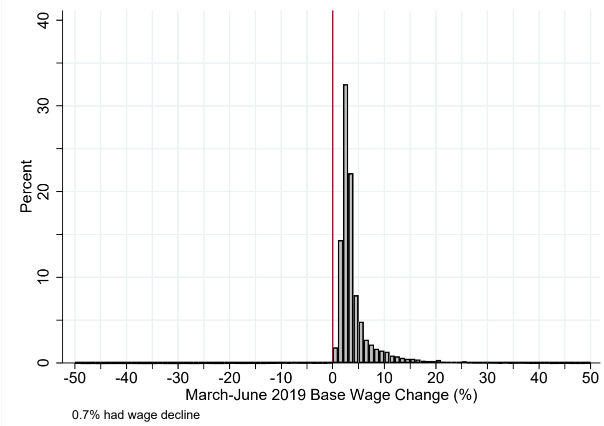
Figure A5: Distribution of Base Wage Changes for Continuing Workers Over Time
Sample: Workers at Firms that Usually Adjust Wages in March - June



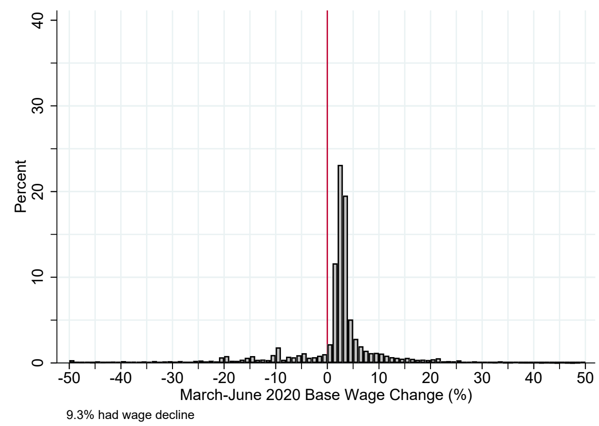
Panel A: 2019 (Unconditional)



Panel B: 2020 (Unconditional)



Panel C: 2019 (Conditional)

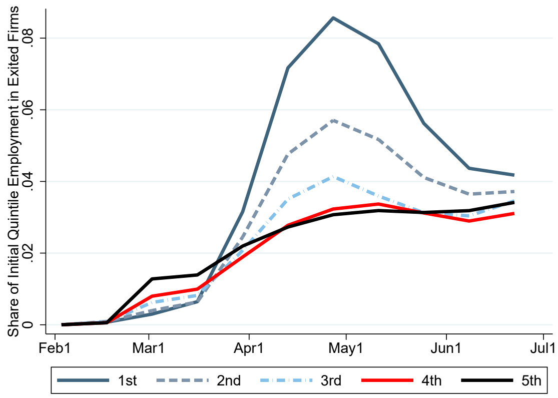


Panel D: 2020 (Conditional)

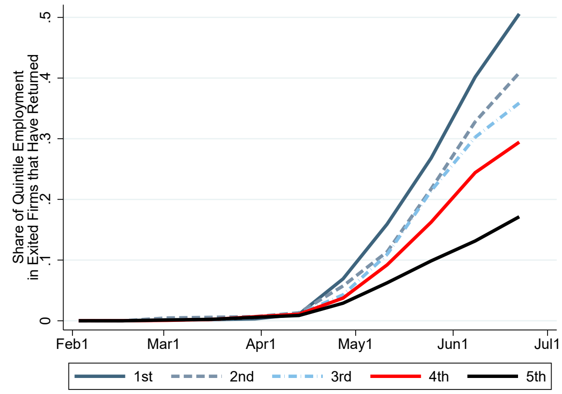
Notes: Figure shows distribution of base wage change for continuously employed workers. Sample is restricted to firms that made 75 percent of their annual wage changes for their employees in 2019 during March, April, May and June. Panel A and B show the unconditional wage changes for workers in those 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

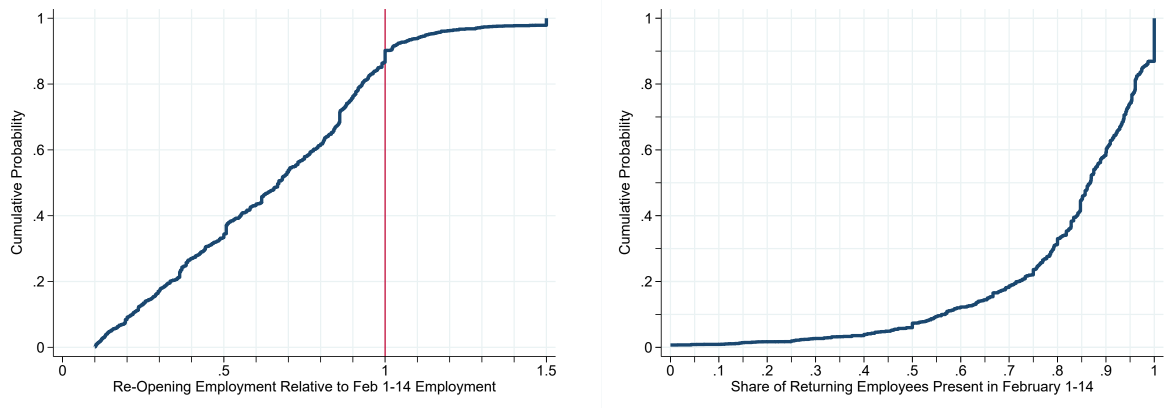
Notes: Table plots the employment losses and gains from shutdown and re-entry by 2-digit NAICS industry. Column (1) shows the share of February 15 employment in firms that ever close through June 20. Column (2) shows the share of this lost employment that has been recovered through re-entry by the end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

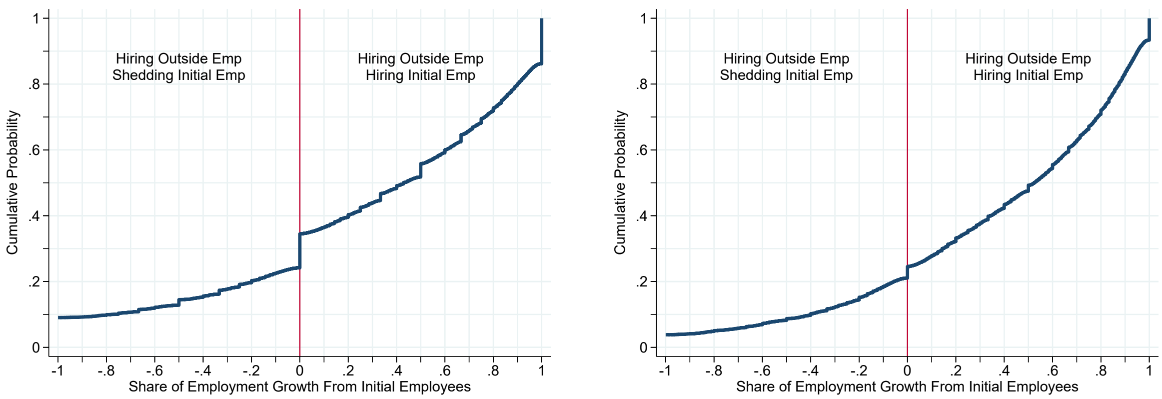
Notes: Figure shows the *employment weighted* CDF of re-entering business size (Panel A) and share of initial business employees recalled (Panel B). The sample of firms is those firms that existed in early February 2020 and that temporarily shut down. Temporary shutdowns are those firms that shut down 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).

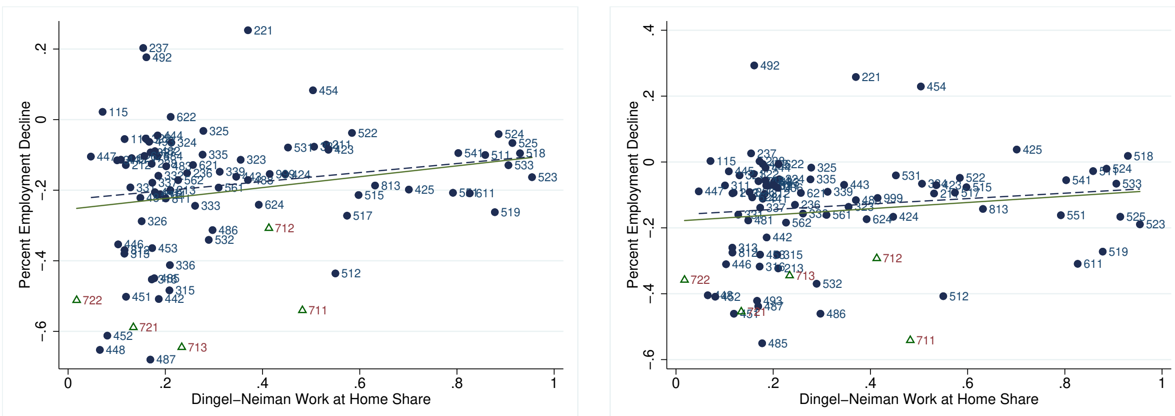
[36] Dingel and Neiman (2020) provide multiple measures for their work at home index. We use their "teleworkable_emp" measure. The patterns in Figure A9 are similar regardless of their measure used.

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