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The U.S. Labor Market during the Beginning of the Pandemic Recession*

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Abstract

Using weekly, anonymized administrative payroll data from the largest U.S. payroll processing company, we measure the evolution of the U.S. labor market during the first three months of the global COVID-19 pandemic. After aggregate employment fell by 21 percent through late-April, we highlight a modest employment rebound through late-May. 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 May employment for workers in the lowest wage quintile was still 30 percent lower relative to mid-February levels. As a result, average base wages increased by over 5 percent between February and May, though this increase arose entirely through a composition effect. Finally, we document that businesses have cut nominal wages for about 10 percent of continuing employees while forgoing regularly scheduled wage increases for others.

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1 Introduction

A novel coronavirus—later named COVID-19—originated in China in December 2019. The virus quickly spread to the rest of the world. The first confirmed case within the U.S. occurred in mid-January. On March 11th, the World Health Organization declared the COVID-19 outbreak a global pandemic. On the same day, the U.S. government banned travel from dozens of European countries. As of mid-June 2020, there were approximately 8.5 million confirmed COVID-19 cases worldwide resulting in roughly 450,000 deaths. Just in the U.S., there were over 2 million confirmed COVID-19 cases resulting in 120,000 deaths.

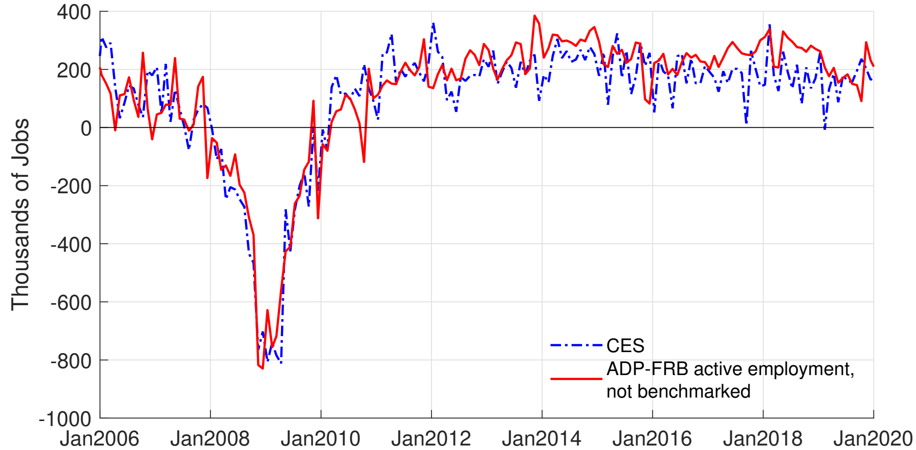
In response to the global pandemic, almost all U.S. states issued stay-at-home orders. On March 19th, California became the first state to set mandatory stay-at-home restrictions to slow the spread of the virus. In doing so, all non-essential services, including dine-in restaurants, bars, health clubs, and clothing stores, were ordered to close. Over the subsequent weeks, most other states put in place similar stay-at-home restrictions and non-essential business closures. In mid-March, the U.S. federal government urged Americans to restrict their domestic travel and to stay at home. Such policies have restricted labor demand by mandating the shuttering of many U.S. businesses. Additionally, the resulting income losses from layoffs and the desire for individuals to avoid exposure have reduced the demand for many goods and services; indeed, the labor market began weakening by early March, before the widespread imposition of stay-at-home orders. Starting in late April, many states started opening non-essential businesses and lifting stay-at-home orders, and the labor market began to improve.

In this paper, 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] ADP data tracked the last recession remarkably well; Figure 1 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.

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. 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. These

[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.

Figure 1: 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.

sample sizes are orders of magnitudes larger than most household surveys, which measure individual labor market outcomes at monthly frequencies. Specifically, the ADP data cover roughly 20 percent of total U.S. private employment, similar to the BLS CES sample size. Second, the ADP data are available at weekly frequencies. As a result, statistics on the health of 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 contain both worker and business characteristics. From our perspective as researchers, the data come anonymized such that no individual business or worker can be identified. However, each worker and business have a consistently defined, anonymized unique identifier so that workers and businesses can be followed over time. 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 high-quality data produced by U.S. statistical agencies.

We find that paid U.S. private sector employment declined by about 21 percent between mid-February and late-April 2020 and then rebounded slightly thereafter. In particular, our weekly data are consistent with the positive BLS employment report for the month of May, which found 3.6 million net added private payroll jobs (not seasonally adjusted) between the April and May reference weeks (which include the 12th of the month).[2] On the eve of that data release, the Bloomberg consensus forecast called for a decline in nonfarm payroll

[2] The seasonally adjusted figure was 3.1 million.

employment of roughly 8 million, resulting in a forecast miss of more than 10 million jobs.[3] In contrast with that forecast, our paid employment data show a gain of 3.7 million jobs over the same period, essentially matching the BLS estimate. Moreover, our weekly data illustrate the timing of the employment trough, which occurred just a week or two after the April CES reference week.

As of late May, U.S. employment is still 15 percent below February levels. About one-fifth of the employment decline through mid-April was driven by business shutdowns. However, some of these businesses started coming back during late-April and May, albeit at a lower 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 during the Pandemic Recession were much larger for businesses with fewer than 50 employees, with closures 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 May, over ten percent of businesses actually grew during this time period.

Importantly, we show employment declines were disproportionately concentrated among lower-wage workers. Segmenting workers into wage quintiles, we find 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 mid-May, bottom quintile workers still had employment declines of 30 percent relative to February levels but some workers have been re-called to their prior employer. We also find that employment declines were about 4 percentage points larger for women relative to 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 employment losses were larger in U.S. states with more per-capita COVID-19 cases and 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 in the United States, consistent with official data.[4] However, all of this increase is due to the changing composition of the workforce. After controlling for worker fixed effects,

[3] Presumably private forecasters based their payroll forecast on surging initial claims for unemployment benefits, but these capture only the layoff margin and miss developments on the hiring margin. As employers have started recalling previously furloughed workers, the hiring margin has a big effect on payroll employment changes.

[4] Average hourly earnings in CES rose roughly 5 percent between February and April.

worker base wages during the beginning of the recession have been flat. Moreover, we find evidence that businesses are less likely to increase the wages of their workers and much more likely to cut the wages of their workers during the first three months of the Pandemic Recession. So far, the extent to which business are cutting worker wages is twice as large as it was during the Great Recession.[5]

The paper is organized as follows. We begin in Section 2 by describing the ADP data and our methodology for measuring changes in labor market activity. In Section 3, we highlight the decline in employment for the aggregate economy during the first three months of this recession. In this section, we also highlight patterns by firm size and industry as well as measure the distribution of firm growth rates during this period. Section 4 documents the distributional effects of the employment declines across workers in various wage quintiles and by gender. Section 5 discusses changes in wages during the beginning of this recession. We explore firm shutdown, firm re-entry, and worker recall in Section 6. In Section 7, we explore cross-state variation in employment changes including employment rebounding as states re-open. Section 8 concludes.

2 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 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.[6] The

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

[6]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.

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 sector; 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 the business processes payroll. We then build a weekly time series of employment for each business.[7]

The business-level data report payroll aggregates for each business. For a very large subset of businesses, we also have access to their anonymized de-identified individual-level employee data.[8] 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

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).

[7]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.

[8]Unlike the business-level data, 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 firm size from the SUSB.

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 wages per worker 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—which includes all businesses but not any worker characteristics—or the employee-level data—which includes workers from most (but not all) businesses but does include worker characteristics. For all aggregate results, the weighted employment changes found within both data sets are nearly identical during the beginning of the Pandemic Recession.

3 Aggregate Labor Market Changes during the Pandemic Recession

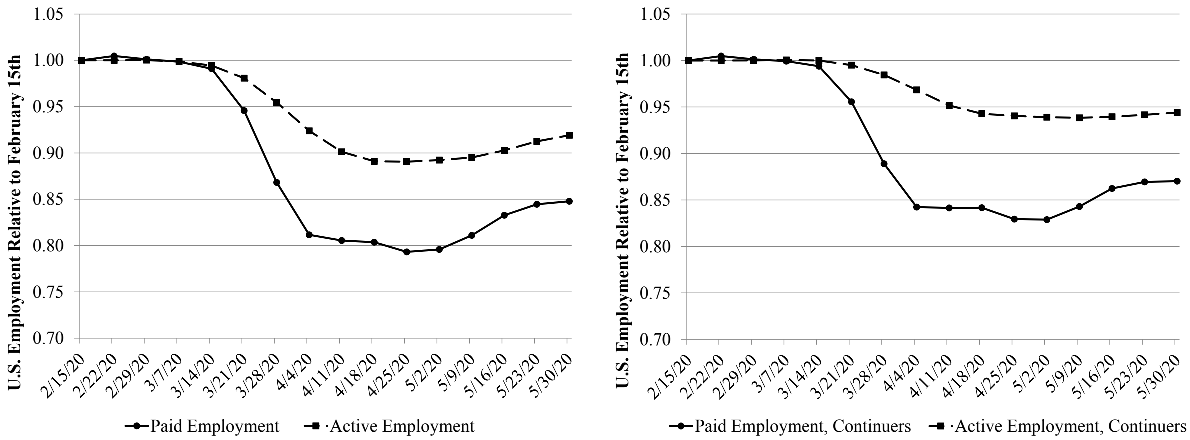
This section presents weekly labor market indices in the United States between February and May of 2020 compiled from the ADP microdata. We focus first on aggregate employment changes and compare those changes to the published monthly BLS CES values. We then turn our attention to business size and industry employment changes.

3.1 Aggregate Employment

Panel A of Figure 2 shows our estimated aggregate employment changes spanning the payroll week covering February 15 through May 30 using the ADP business-level data.[9] Importantly, this panel shows data inclusive of both employment changes at continuing businesses and among businesses that have shut down (i.e., those not issuing any paychecks during regularly scheduled pay periods), where shutdowns could be either permanent or just temporary inactivity. Panel B separately highlights changes only for continuing businesses. The changes are plotted as percent changes relative to February 15th employment levels without seasonal adjustment. The figure shows the evolution for paid employees (solid line, circles) and active

[9]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 occuring on the same weeks. This makes little difference for quantitative results.

Figure 2: 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. All trends are weighted such that the ADP sample is representative by business size crossed with 2-digit NAICS industry.

employees (dashed line, squares). Between mid-February and the labor market trough in late-April, paid employment in the U.S. fell by roughly 21 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. For the shutdown-inclusive series, the trough in employment losses occurred around April 25th. Since mid-April, paid employment has increased by 5.5 percentage points through the end of May. However, as of late May, paid employment in the U.S. is still about 15 percent below the start of the recession.

Given that U.S. private employment in February of 2020 was 128 million workers (on a non-seasonally adjusted basis), the ADP data suggest that total paid employment in the U.S. fell by about 26.5 million through late April. As of late May, paid employment is still about 19.5 million jobs below its mid-February levels. In other words, about 7 million jobs have come back between late April and late May. As we highlight below, the employment increases are associated with many states starting to reopen their businesses.

It is also worth noting that the job loss numbers in the ADP data are broadly consistent with employment data published in the BLS's Current Employment Statistics Survey (CES) during this period. The CES, which measures employment during the week containing the

12th of the month, estimated employment declines of 1.0 million in March and 18.7 million in April followed by a rebound of 3.6 million in May (on a non-seasonally adjusted basis). 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 24.0 million in April followed by a rebound of 3.7 million in May.[10] That is, ADP data have been reasonably close to CES estimates during recent months. Overall, the total three-month decline in private payroll employment was about 16 million in CES and 21 million in ADP.[11]

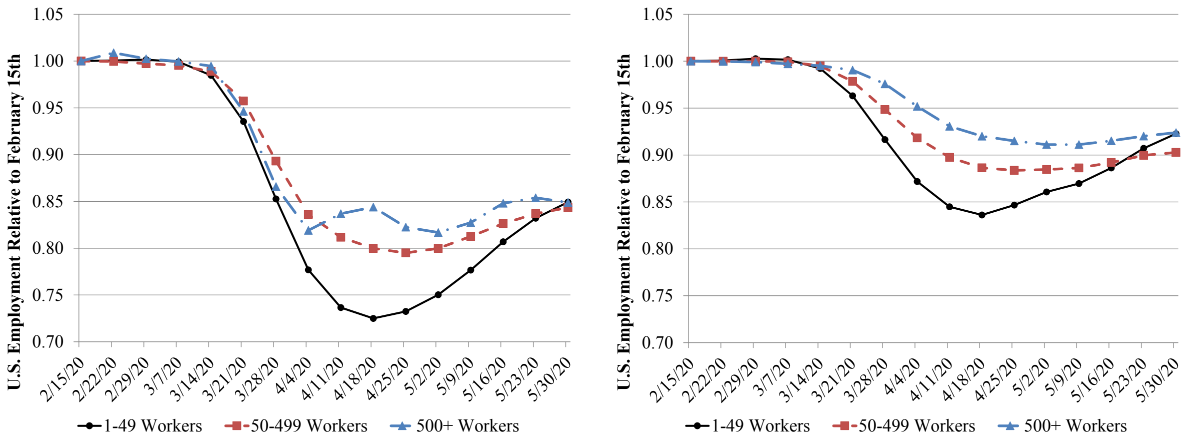
Panel B of Figure 2 shows employment losses for continuing businesses. We define continuing businesses as those businesses who continually make scheduled payroll payments throughout the entire sample period starting in mid-February. Notice that paid employment for continuing businesses declined by about 17 percent through late-April before rebounding slightly through the end of May, leaving paid employment roughly 13 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. Business shutdowns accounted for just under 20 percent of employment losses through late April. We further explore the importance of business shutdown and re-entry to aggregate employment trends in Section 6.

It is also worth briefly mentioning the active employment series shown on Figure 2. Recall that active employment measures the number of workers in payroll databases, including those not receiving pay in a given pay period. Active employment among *continuing* businesses actually declined by about 0.4 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 still shedding jobs.

[10]The corresponding numbers for active employment were -0.7 million, -13.2 million, and +1.5 million for March, April, and May, respectively.

[11]Note that our estimates account for entry (and re-entry) of business into ADP sample, but we make no additional attempt to adjust numbers for estimated business births, whereas CES estimates include such an adjustment. Census Bureau data show that business entry slowed dramatically as the pandemic recession began but did not completely cease; see Haltiwanger (2020). Note also that employment as measured in the Current Population Survey (CPS) adjusted to the CES private employment concept fell by about 23.5 million between the February and May reference weeks.

Figure 3: 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.

3.2 Employment by Business Size and Industry

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. Such focus is not unfounded. Large though it may be, COVID-19 is likely to be a mostly temporary shock to the economy. Therefore, a primary determinant of the speed of recovery from this crisis may be the extent to which irreversible dis-investments occur. Financially-constrained firms, such as small and young businesses, may be forced to close if they are unable to pay their employees in the short run. If this happens, the recovery from this crisis may be far more protracted. Indeed, a JP Morgan study from 2016 found that roughly half of small businesses did not have a large enough cash buffer to support 27 days without revenue.[12]

The changes in employment documented in Figure 2 are broad-based throughout the economy but also exhibit substantial heterogeneity across industries and businesses of differing size. Figure 3 plots the change in employment by initial business size relative to February 15th. The figure shows that businesses with fewer than 50 employees have been reducing both paid employment (Panel A) and active employment (Panel B) at a faster rate than

[12] Accessed from https://www.jpmorganchase.com/corporate/institute/document/jpmc-institute-small-business-report.pdf on April 11, 2020.

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, saw declines of 15-20 percent during that same time period and reached troughs a week or two later than the smallest businesses.[13] Notably, the growth in paid employment since late April has been primarily confined to smaller businesses. Between late April and late May, smaller businesses increased employment by 12 percent (of February 15th levels). Businesses with more than 50 employees increased employment by less than 5 percent during the same time period. As employment is rebounding, it is the smaller firms that are increasing employment. Again, as we highlight below, much of this differential growth for smaller firms is due to the re-opening of smaller firms who temporarily shuttered during the state imposed shutdowns.

The results by firm size are not overly surprising in light of the industry results documented next. The industries that were hit hardest in the beginning of the pandemic recession also tend to be the industries with the smallest businesses as documented by Hurst and Pugsley (2011). Table 1 shows employment changes by two-digit NAICS industries during two time periods: Feb 15-April 25th (the aggregate employment trough, prior to states starting to re-open) and Feb 15 - May 30 (over 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. Another two-digit industries that experienced declines in employment of nearly 30 percent through late-April is"Other Services" which includes many "local" or neighborhood businesses like laundromats and hair stylists. 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 and Professional/Scientific Services—only saw smaller employment declines.[14]

[13]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. In the appendix, we reproduce Figure 3 using the employee level data and show that that jaggedness for the large firms disappears.

[14]Kurmann et al. (2020) use Homebase data, which have strong coverage of "local" small businesses, in a manner similar to our approach: they apply QCEW weights to Homebase establishment-level data (with attached NAICS industry codes) to assess aggregate employment changes. They find employment declines of about 60 percent through mid-April among small businesses in retail trade (NAICS 44-45), education and health services (61-62), leisure and hospitality (71-72), and other services (81). In a similar exercise

Table 1: Paid Employment Changes By 2-Digit Industry

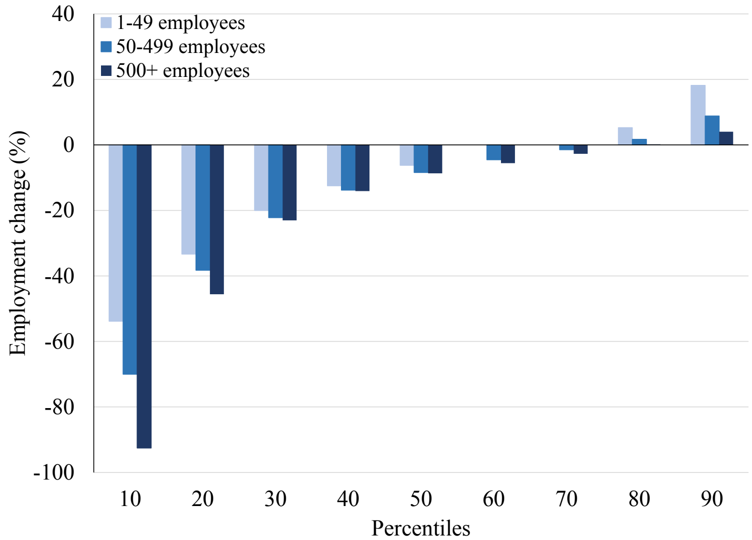
Industry	Feb 15 - April 25	Feb 15 - May 30
Arts, Entertainment and Recreation	-50.7%	-41.5%
Accommodation and Food Services	-45.5%	-34.1%
Retail Trade	-28.7%	-18.5%
Other Services	-25.0%	-17.1%
Transportation and Warehousing	-21.7%	-23.2%
Real Estate, Rental and Leasing	-20.9%	-19.6%
Information Services	-18.2%	-4.0%
Wholesale Trade	-17.6%	-12.3%
Administrative and Support	-17.0%	-17.1%
Educational Services	-16.6%	-17.5%
Health Care and Social Assistance	-16.5%	-8.8%
Construction	-13.5%	-4.5%
Manufacturing	-12.4%	-8.6%
Professional, Scientific, and Tech Services	-12.1%	-9.1%
Finance and Insurance	-1.3%	-0.7%

Notes: Table shows total (i.e., inclusive of shutdowns) decline in paid employment through April 25th, 2020 (column 1) and through May 30rd, 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.

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 30 and 60 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. Again, business in these three sectors started opening up during May as many states started to lift restrictions on restaurants, retail outlets, and personal service

limiting the ADP data to these same sectors and business units with fewer than 50 employees, we find a total employment decline through mid-April of between 35 and 40 percent using either SUSB (firm) employment weights or QCEW (establishment) employment weights. The shallower decline in ADP data could reflect differences in coverage within industries (i.e., the Homebase coverage of "local" businesses may select narrow industries harder hit by social distancing) or across business sizes within this small size group; in this respect, Homebase provides a detailed view of potentially highly vulnerable small businesses. Additionally, Homebase employment is based primarily on hourly wage earners, whereas ADP data include all paid employees. However, such differences should be kept in mind when attempting to extrapolate Homebase data to make inferences about either the aggregate economy or the health of small businesses in general.

Figure 4: 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 May 30th.

businesses such as barbershops, beauty parlors and nail salons. Despite states re-opening and employment rebounding slightly, employment in these sectors still remain significantly depressed relative to mid-February levels. Notice, as travel has still remained depressed and schools still 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 almost half of lost employment as hospitals and other health providers started returning to normal activities.

3.3 The Distribution of Business Size Changes During the Pandemic Recession

Figure 3 hides interesting heterogeneity across businesses even within size classes. In Figure 4 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 May 30th, where percentiles are constructed from the employment-weighted business distribution.

Starting on the left-hand side of Figure 4, the 10th percentile business within every size class saw declines of at least 50 percent, with the largest class (at least 500 employees) seeing a decline of more than 90 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 fact that (1) small business saw even more overall employment declines (as highlighted in Figure 3) and (2) that employment changes in the bottom decile of continuing firms was 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—a point we will return to below. 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 5 percent). Taken together, Figure 4 reveals striking heterogeneity in the experiences of businesses, even within size classes.[15] The median surviving small (less than 50) business declined 6 percent, while the medium and large median declines were 9 and 11 percent, respectively.

In the Appendix, we additionally decompose aggregate employment changes into a job creation and job destruction rate, respectively. The job creation rate holds steady around 4 percent from the beginning of February through even the depths of the crisis in mid April. Although employment declined hugely in aggregate, many workers still found new jobs. This has also been found in survey data by Barrero et al. (2020). The relatively strong job creation numbers imply that weekly job destruction rates spiked to an unprecedented 14 percent at the end of March and beginning of April, before slowly receding to the baseline level of around 4 percent by the end of May. Job creation rates have picked up in May, reflecting employee recall and other new hires. This pattern – a sharp job destruction rate spike followed by a prolonged period of relatively muted job creation and continued job reallocation – is common to most modern U.S. recessions. This recession differs in the speed and magnitude of the job destruction spike.

3.4 The Importance of Weights

The aggregate numbers shown on Figure 2 are based on the ADP sample with SUSB weights to ensure representativeness in terms of industry and firm size. As noted above, however, some business units in ADP may be more akin to establishments (i.e., single operating loca-

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

Table 2: Aggregate Employment Patterns under Two Weighting Schemes

	SUSB	QCEW
Total paid employment change, February 15 to April 25	-20.7%	-22.5%
Share of decline contributed by business closure	0.18	0.26
Total paid employment gain, April 25 to May 30	5.5%	7.4%

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.

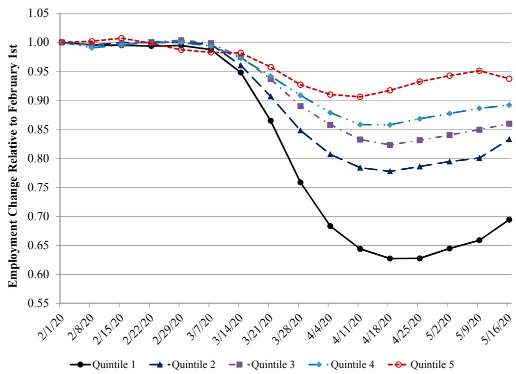
tions that may be part of a larger firm) than to firms. An alternative approach to mapping ADP data to the U.S. business universe would be to treat ADP business units as establishments and then apply establishment-based weights; indeed, some previous work with ADP data takes this approach (e.g., Cajner et al. (2020)). Table 2 compares aggregate employment patterns under SUSB weights (i.e., those used in our main results) 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.[16] It is worth noting, though, that both weighting procedures have current U.S. payroll down about 15 percent in late-May relative to mid-February levels.

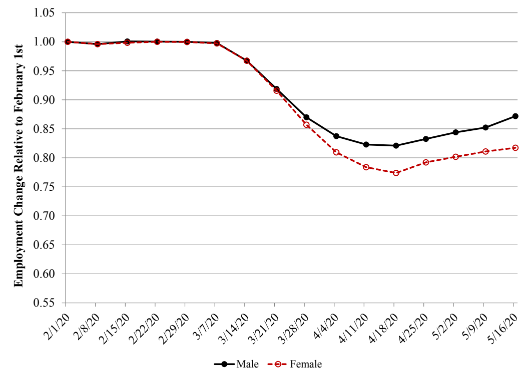
4 Distributional Effects across Workers

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 earnings divided

[16]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 5: 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. All data are weighted such that the sample matches aggregate employment by 2-digit NAICS cross business size.

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 per hour.[17]

Panel A of Figure 5 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 only rebounded modestly. By mid-May, employment for workers in the bottom quintile was still depressed by 30 percent. Conversely, employment of workers in the top quintile of the wage distribution declined 10 percent through the end of April. Only about 5 percent of these top earning workers remain out of work through mid-May. 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

[17]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).

(industry and business size) or worker characteristics (age and location) can explain the differential pattern across either gender or the wage distribution, we further exploit the panel nature of our data and estimate a linear probability model of monthly employment for a given worker at a given firm on wage quintile dummies and detailed controls for industry and business size.[18] Specifically, we measure whether the employee is paid at that firm at the beginning of each given month. Given our data, we are able to measure transitions from February to March, March to April, and April to May.

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 5. 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, 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 5 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 grown slightly after the trough to 5 percentage points through mid-May. 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 harder 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

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

industry. In other words, even within detailed industries, women are experiencing larger job declines relative to men. For example, within the manufacturing industry, men and women, respectively, experienced a 14 and 17 percent employment decline through mid-May. Similar patterns were found in most industries. The fact that industry or other firm characteristics do not explain the gender difference in employment declines is interesting in its own right. Future research using household level surveys with additional demographic variables can explore whether other facets of the Pandemic – such as the increased need for childcare – explains some portion of the gender gap in employment losses during this recession.

5 Wage Changes during the Pandemic Recession

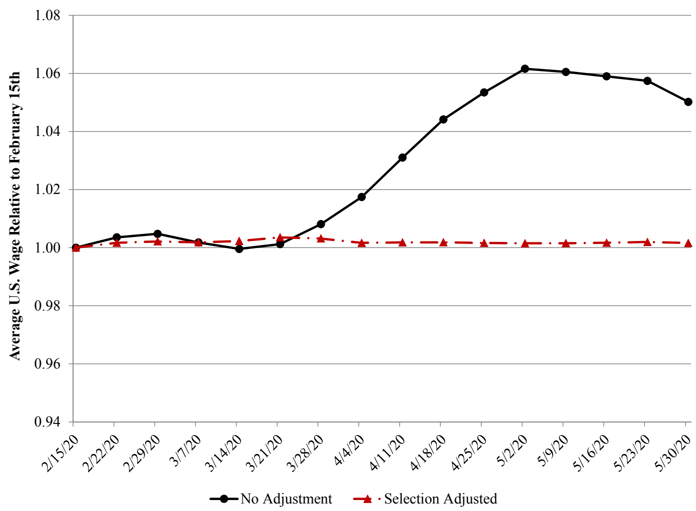
Figure 6 shows the trends in wages in the economy during the pandemic recession. The solid line creates a wage index by measuring the mean base wage of all working individuals in the economy. Since the start of the recession, observed average base wages in the ADP sample grew by nearly 6 percent through mid-May. As highlighted in Solon et al. (1994), the changing composition of workers over the business cycle can distort measures of the cyclically of wages.[19] As seen from Panel A of Figure 5, 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. Throughout this period, the sample is becoming more selected towards higher-earning individuals.

To assess the importance of this selection, we again exploit the panel nature of the ADP data. In particular, we compute base wage growth for a sample of continuing workers. 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 aggregate wage growth adjusting for selection is shown in the dashed line in Figure 6.[20] Three 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

[19] Recently, 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.

[20] See Grigsby et al. (2019) for a full discussion of base wage measurement in the ADP employee sample. Briefly, base wages for hourly workers is the contracted hourly wage. Base wages for salaried workers is contractually obligated earnings per pay-period (i.e., the workers contracted annual base salary divided by the number of pay periods during the year). We measure individual changes separately for hourly and salaried workers and then create an index combining the two.

Figure 6: Trend in Base Wages, Controlling for Selection

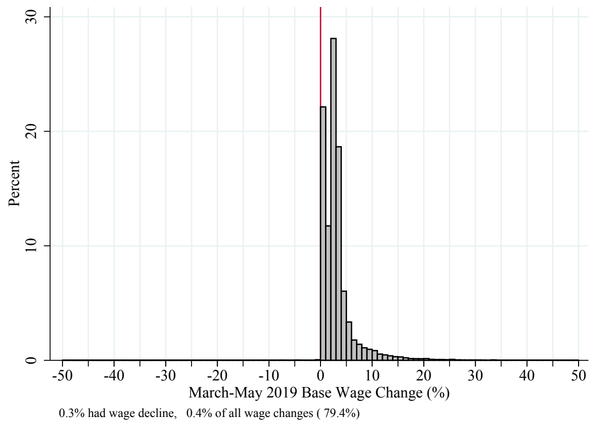


Notes: Figure shows trends in weekly wages during the beginning of the Pandemic Recession. The solid line (circles) averages base wages across all employed workers in each period. The dashed line (triangles) controls for selection by measuring the base wage of a given worker over time. All data are weighted so that the ADP primary sample matches aggregate employment shares by 2-digit industry cross business size.

to selection. Second, the selection effects are largest through late April when employment declines were largest. Finally, since late April there has been a slight decline in aggregate average unadjusted wages as aggregate employment has increased. The decline in unadjusted aggregate wages since late April is quite small given that relative employment increases for low wage workers has been relatively muted (as see in Panel A of Figure 5).

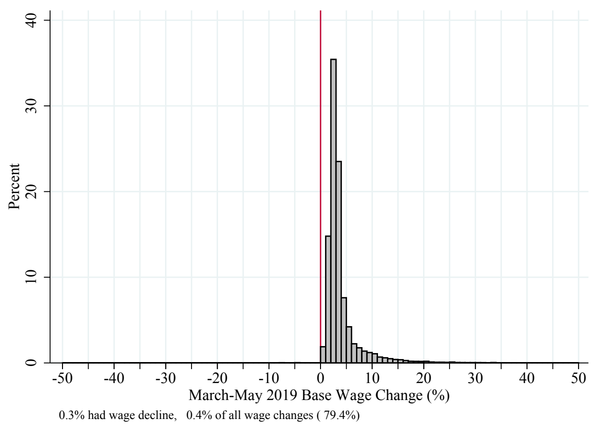
The flat composition-adjusted base wages in Figure 6 suggest that nominal base wage growth has actually slowed. Normally, over a few month period, nominal base wages increase as some workers see their regularly scheduled wage increases. As highlighted in Grigsby et al. (2019), most continuously employed workers only receive one base wage change per year and 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 see how base wage dynamics are playing out during the beginning of the Pandemic Recession, we create a sample of firms who did at least 75 percent of their employee base wage changes in March, April and May of 2019. These are firms for which March, April and May are their normal base wage adjustment months. This sample includes roughly ten percent of the businesses in the ADP sample who continuously employed workers during

Figure 7: Distribution of Base Wage Changes for Continuing Workers Over Time
Sample: Workers at Firms that Usually Adjust Wages in March - May

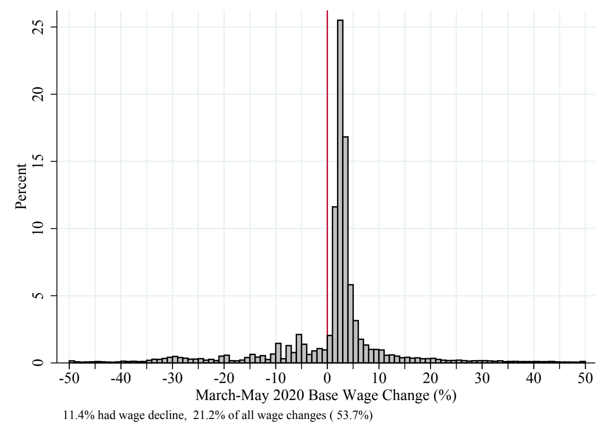


Panel A: 2019 (Unconditional)

Panel B: 2020 (Unconditional)



Panel C: 2019 (Conditional)



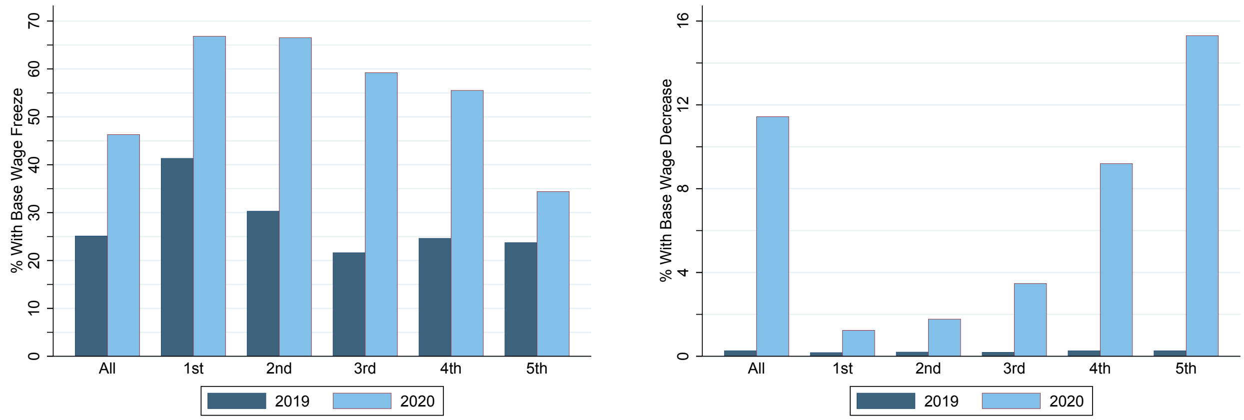
Panel D: 2020 (Conditional)

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 and May. Panel A and B show the unconditional wage changes for workers in those during the months of March, April and May 2019 and March, April and May 2020, respectively. Panels C and D show the corresponding distributions conditional on a non-zero wage change. The data we show here are the unweighted distribution of wage changes and come from the employee sample.

all of 2019 and the first half of 2020. Figure 7 plots the distribution of monthly base wage changes for employees in these firms for March, April and May 2019 (Panels A and C) and for March, April and May 2020 (Panels B and D). Panels A and B show the unconditional wage changes and Panels C and D show the distribution conditional on a wage change occurring.

The differences in the base wage change distribution for these firms between 2019 and 2020 are stark. During 2019, these firms increased the base wages of nearly 80 percent of

Figure 8: 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 - May



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

Notes: Figure shows the probability of a wage freeze (Panel A) and probability of a wage cut (Panel B) for different wage quintiles. Sample is restricted to firms that made 75 percent of their annual wage changes for their employees in 2019 during March, April and May. The data we show here are the unweighted distribution of wage changes and come from the employee sample.

their continuously employed workers during March, April and May of that year. This number is slightly higher than the decade-long average of base wage changes within the firms in the ADP employee sample found in Grigsby et al. (2019) and reflects the overall strength of the US labor market in 2019.[21] Moreover, essentially all base wage changes were increases; these firms only decreased the nominal wages of 0.3% of their workers during these months of 2019. However, during the same three months in 2020, these firms adjusted the wages of only 53.7% of their workers. Of the 53.7% workers who received wage changes, 11.4% received nominal base wage cuts: over a fifth of all base wage changes were cuts. The distributions of base wage changes – conditional on a base wage change occurring – shown in Panels C and D highlight the amount of wage cuts during the early part of the Pandemic Recession. There are slightly large spikes at round numbers indicating that some firms are cutting the base wages of their employees by 5, 10, or 20 percent.[22]

Figure 8 shows the probability of a wage freeze (Panel A) and the probability of a wage cut (Panel B) for workers in different initial wage quintiles for the set of firms that usually adjust their wages in March-May. The darker bar show the patterns for 2019 while the lighter bars show the patterns for 2020. Wage freezes were more common throughout the

[21] Between 2008 and 2016, 63% of continuously-employed job-stayers in the ADP sample saw year-over-year base wage increases.

[22] These results focus on a worker's base wage. As highlighted in Grigsby et al. (2019), firms can adjust the compensation of their workers in other ways by altering bonuses and benefits. Given that such forms of compensation accrue at lower frequencies, we leave an analysis of such adjustments to future research.

wage distribution in 2020; wage freezes were the least likely in 2020 for high wage workers. However, while employment losses were concentrated among low wage workers (Figure 5), nominal wage cuts were disproportionately concentrated among higher wage workers. Over three quarter of all nominal wage cuts were concentrated in workers in the top two deciles of the wage distribution.

Overall, the 11.4% of workers receiving nominal base wage cuts in this sample during the Pandemic Recession is roughly twice the 6% found by Grigsby et al. (2019) during the Great Recession. 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 much more than they did during the Great Recession. As this recession continues to evolve, it will be interesting to further monitor wage dynamics.

6 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, particularly given the concerns that an economic recovery may be sluggish if many businesses exit permanently rather than just shrinking or shutting down temporarily. This question has come to the forefront recently as employment has increased. 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 3 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 (employment at firms that shut down at any point since February 15), and reentry (employment at firm that shut down at some point since February 15 but are now open). The sum of these four contributions total aggregate employment growth. To create this table we use our business-level sample and report all employment changes as percent difference from February 15th levels. Formally, 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 a firm that has shut down starts paying their workers again.

At the end of May, employment at firms that operated continuously was 12.4 percent lower than in mid-February (as highlighted in Figure 2). 7.4 of employment as of May 30th was in firms that shutdown since mid-February, of which 2.6 percent of employment returned by the end of May. In other words, one-third of employment in firms that have shutdown at some point during the first few months of the pandemic has returned by late May. The

Table 3: 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	0.0	-0.9
3/21/2020	-4.4	0.7	-1.9	0.1	-5.4
3/28/2020	-10.7	0.8	-3.4	0.0	-13.2
4/04/2020	-15.0	1.0	-4.8	0.0	-18.8
4/11/2020	-15.0	1.1	-5.7	0.1	-19.5
4/18/2020	-14.9	1.2	-6.1	0.2	-19.6
4/25/2020	-16.1	1.2	-6.4	0.6	-20.7
5/02/2020	-16.2	1.3	-6.6	1.0	-20.4
5/09/2020	-14.8	1.5	-6.8	1.3	-18.9
5/16/2020	-13.0	1.6	-6.9	1.6	-16.7
5/23/2020	-12.4	1.8	-7.1	2.1	-15.5
5/30/2020	-12.4	2.0	-7.4	2.6	-15.2

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.

difference between shutdown and re-entry columns in Table 3 measures the employment in firms that have remain closed. Newly entering firms added 2 percent (of February levels) to employment through the end of May, though we caution against interpreting these figures in terms of genuine new business formation.[23]

Between April 25th and May 30th, aggregate employment increased by 5.5 percentage points (relative to February 15th levels). About two-thirds of that growth (3.7 out of the 5.5 percentage points) was due to employment gains in continuing firms. The remaining one third of employment growth during May (2.0 out of 5.5 percentage points) was due to employment increases in firms that re-opened.[24] The findings suggest that the re-opening of temporarily shuttered businesses is contributing meaningfully to aggregate employment gains during May 2020.

[23]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.

[24]The employment gains from newly entering businesses during May and the employment losses from businesses that newly shuttered in May roughly offset.

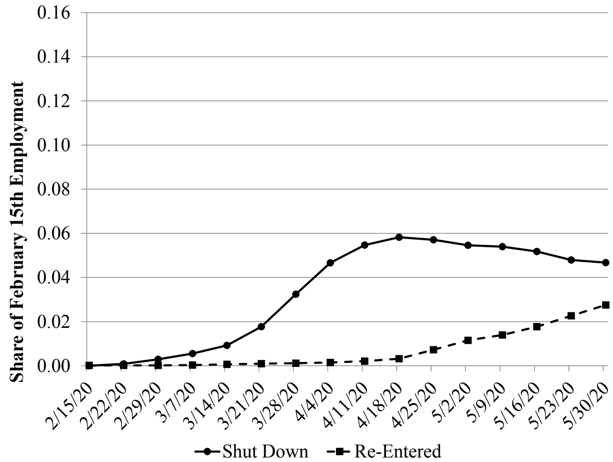
Panel A of Figure 9 shows the dynamics of employment at currently *shut down* (solid line) and *re-entered* (dashed line) businesses during the early parts of the Pandemic Recession for all businesses. The solid lines in each panel measure the employment lost in currently shutdown firms during each pay period while the dashed line shows the employment gains coming from re-entering firms. Employment in currently shutdown firms is just the difference between columns 4 (Ever Shutdown) and 5 (Shutdown Re-Entry) in Table 3. Panel A shows the employment losses associated with business shutdown for the US economy peaked in late-April. Since then, as highlighted in Table 3, some of these shuttered firms have re-opened contributing to aggregate employment growth. 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 9 show firm shutdown and re-entering patterns by business size. Business shutdown was much more prominent among smaller firms, with shutdown firms contributing more than 15 percent of the initial employment decline by late April among those businesses with fewer than 50 employees. However, many of these small businesses have re-opened in the last 6 weeks. As seen in Figure 3, total employment in small businesses increased by nearly 13 percentage points (relative to February levels) between mid April and late May. Employment growth in firms that temporarily shuttered—i.e., shuttered and then reopened—contributed to over 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 peaked and continues to gradually increase through late May.[25]

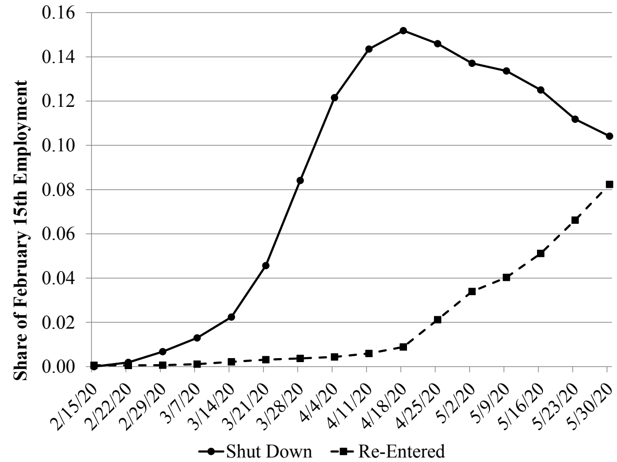
When businesses re-enter, they may not hire back all of their pre-existing workforce. Figure 10 explores this possibility. Panel A plots the distribution of firm employment at re-entry relative to the firm's employment during early February, weighting each firm by their initial size. The figure shows that almost every returning firm re-enters smaller than they were in the beginning of February. The median re-entering firm re-opened with roughly a quarter of their initial employment, while the mean firm only has 40% of its initial em-

[25]The weighting issues discussed above are highly relevant for the results in Panel A of this figure. While the individual size categories in panels B, C, and D are little affected, a switch to QCEW weightings, which significantly increases the weight of smaller business units, would shift the solid line in panel A up significantly such that it peaks around 10 percent instead of 6 percent. This highlights the importance of careful attention to weighting when working with non-representative samples.

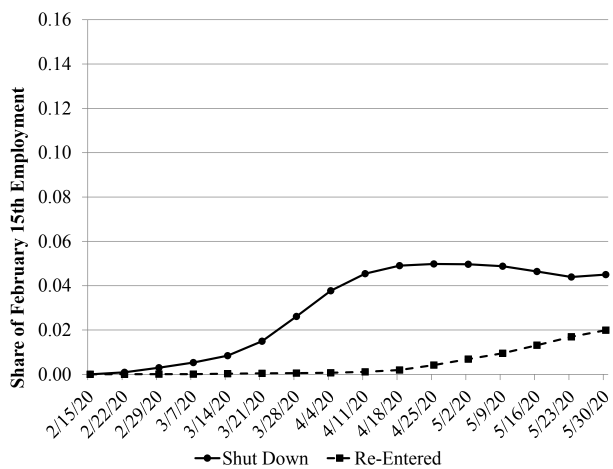
Figure 9: Employment in Shutdown and Re-Entering Firms



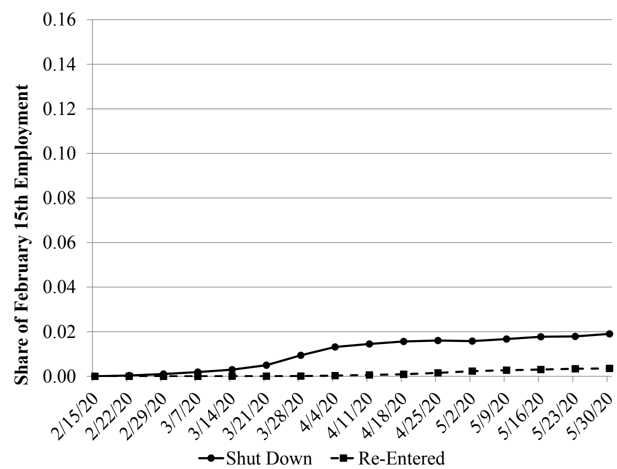
Panel A: All



Panel B: 1-49 Emps



Panel C: 50-499 Emps



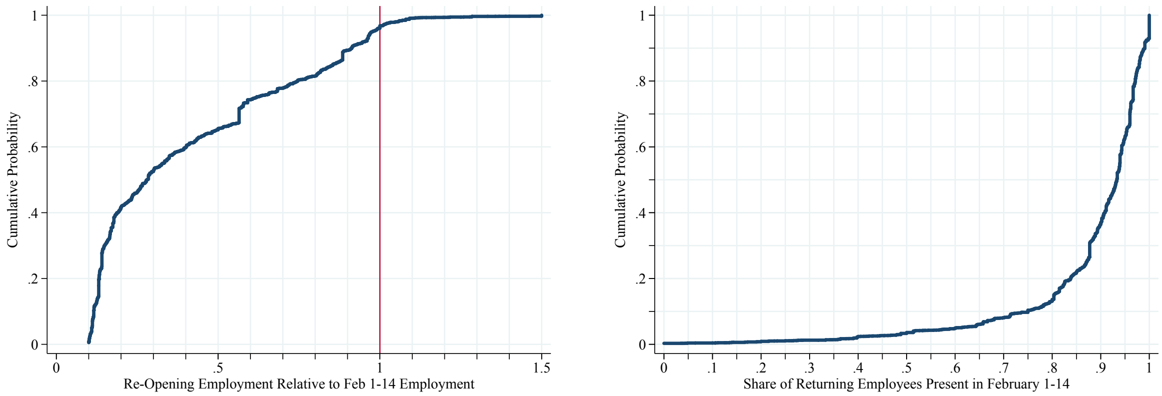
Panel D: 500+ Emps

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. The aggregate statistics are weighted such that the ADP sample is representative by business size crossed with 2-digit NAICS industry.

ployment. Although firm re-entry is contributing to a recovery in overall employment, these re-entering firms are operating far 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

Figure 10: Employee Recall in Re-Entering Firms



Panel A: Re-Entering Firm Size

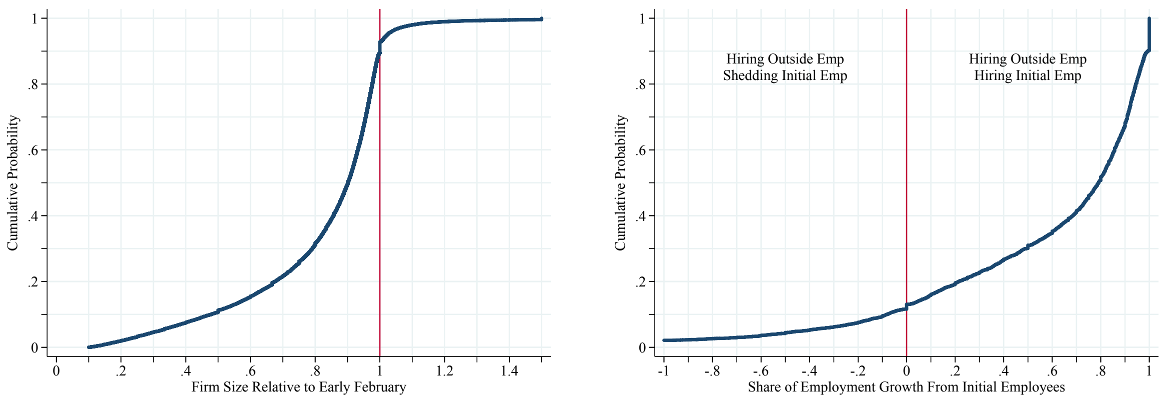
Panel B: Share of Employees Who Were Recalled

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 May. All trends are unweighted.

new employees. Panel B of Figure 10 shows the share of returning businesses' workforce that was previously employed with that same business in the first two weeks of February. Such workers represent "recalls." Again, the distribution is weighted by initial business size. Seventy percent of re-entering firms (employee weighted) have their new workforce comprised of at 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 11 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 May. We then calculate the firm's current size

Figure 11: 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 May 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 the end of May. 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.

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 4, roughly 10 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.[26] The figure shows that 65% of firms grow at least in part by recalling existing workers. Almost 10% of continuing firms hired exclusively from recall.[27] However, the complement of these findings is also interesting. Almost 35% of continuing firms are growing from external hires, even as they shed their initial workforce. Even in these uncertain times, there remains some

[26] We present the distribution of these recall shares for firms that grow by at least 1 or 5 employees in the appendix.

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

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. Next, we show how employment declines and growth have correlated with state COVID-19 exposure and re-opening timing.

7 Employment Gains and State Re-Openings

The spread of COVID-19 has not been uniform across the country. The virus is transferred through interpersonal interaction; as a result, urban areas have generally seen more aggressive spreads of the virus. There were over 300,000 confirmed cases and over 22,000 deaths in New York as of April 28th, compared with 46,000 cases and 1,800 deaths in California. Meanwhile, states also differ broadly in their policy directives to combat the virus. California encouraged social distancing measures as early as March 11 while travelers continued to congregate on Florida's beaches. Indeed, research shows that the change in travel behavior of individuals, scraped from cell phone location data, has been heterogeneous across the country.[28]

These differences have manifested themselves somewhat in the labor market as well. Panel A of Figure 12 plots the relationship between cumulative state COVID-19 cases per 100,000 residents through early June against state total employment declines as of late April.[29] Employment declines are relative to mid-February. As seen from Panel A, there is a strong relationship between the exposure to COVID-19 and employment declines. While employment fell in all states, the employment declines were largest in those states that had more disease exposure.

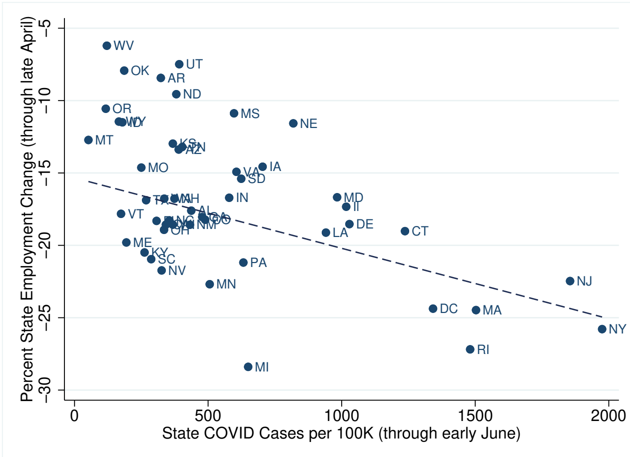
Panel B of the figure explores the effects of states re-opening certain sectors on employment. To facilitate exposition, we create two groups of states - a set of large states that broadly opened in late April or early May and a set of large states that broadly opened in late May and early June.[30] For the first set of states opening early we pool together data

[28]See https://www.nytimes.com/interactive/2020/03/23/opinion/coronavirus-economy-recession.html, accessed April 11, 2020.

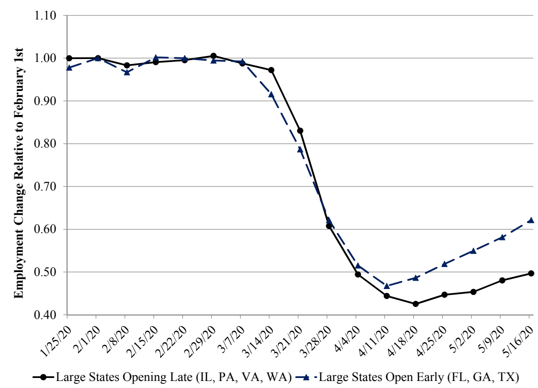
[29]We use the state COVID-19 state per capita cases from the June 9th New York Times database.

[30]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 12: State Variation in Employment Declines



Panel A: Per Capita COVID-19 Cases Exposure vs. State Emp Decline



Panel B: Food/Accommodation Employment Decline Cross State Variation

Notes: Panel A plots state employment declines between mid February and late April in our employee sample against cumulative COVID-19 cases (per 100,000 residents) through early June. Hawaii and Alaska are excluded. Panel B 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). Employment changes are relative to mid February. COVID-19 cases come from the NYTimes Dashboard on June 9th. We use our employee sample for this analysis. Data are weighted to be representative of the aggregate industry-size distribution.

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 at home orders after May 31st.

Panel B plots employment in the Food and Accommodation Sector (NAICS 72) within both groups of states. The figure shows that employment in this sector 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 patterns is not overly surprising. The quantitative patterns are, however, noteworthy. First, even in the states that opened early, employment in this sector is still 40 percent below February levels as of mid-May. 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 slightly 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.[31]

8 Conclusion

In this paper, we use high-frequency payroll data from ADP to track the behavior of the labor market in early parts of the Pandemic Recession. The data have several advantages over commonly employed labor market indicators. First, the data are large and of high quality, coming from administrative reports of paychecks for around 26 million individuals. Second, the data come at a weekly frequency with essentially no lag. Third, they provide information on employment and wage information, as well as characteristics of both workers and businesses. Fourth, they track individual workers and businesses through time, allowing for a complete study of the characteristics of workers and businesses during the beginning of the pandemic.

The data show an unprecedented collapse in employment from mid-February through late April with some slight rebound through late-May. We highlight that the employment losses were much larger for lower wage workers and were larger for women relative to men. We show that while most businesses contracted employment during the early part of the recession, roughly 10 percent of firms added employees. About 20 percent of aggregate employment declines through April were due to firms shuttering. However, many of these firms stated re-opening in May albeit at a much smaller size. Both re-entering firms and

[31]The patterns of employment gains that we document associated with states re-opening is at odds with the results in Chetty et al. (2020) which finds no differential employment effects across states after they re-open. There is large week-to-week employment variation at the state-by-sector level within the ADP data stemming from small sample coverage. That concern motivated us to focus on employment changes within large states and the large restaurant sector where sample sizes were much larger. The employment data used in Chetty et al. (2020) come from the companies Homebase and Earnin which have much smaller coverage - both with respect to the number of employees in their samples and with respect to the types of industries covered - than does the ADP data. As a result, attenuation bias is likely even more severe in these databases when doing high frequency time series analysis at the state-industry level.

continuing firms are adding employment by recalling temporarily displaced workers. Despite the re-openings, employment still remains substantially below mid-February levels. Finally, we document that firms are cutting the wages of their workers as well as forgoing normal pay increases. Collectively, our results present a relatively complete picture of the U.S. labor market during the first three months of this recession.

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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.

Appendix A.1 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, the subsequent section covers a worker-level data set.[32] 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.[33] 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.

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

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

[33]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 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.[34]

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). For the analysis in this paper, we keep the weights fixed throughout the COVID-19 period. [35]

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, respectively). These fractions are not far from what the BLS reports.[36]

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

[34]Technically, the employment concept is business employment for the pay period that includes the Saturday in question, as we cannot observe change 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.

[35]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.

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

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.

Appendix A.2 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.[37] That is, we can see detailed anonymized payroll data for individual workers. As with the business data, all identifying characteristics (names, addresses, etc.) are omitted from our research files. Workers are provided an anonymized unique identifier by ADP so that workers may be followed over time. We observe various additional demographic characteristics such as the worker's age, gender, tenure at the business and residential state location. We also can match the workers to their employer. As with the business-level data described above, we can observe the industry and business size of their employers.

The benefits of the employee data relative to the business data described above are three-fold. First, we can explore employment trends by worker characteristics such as age, gender, and initial wage levels. This allows us to discuss the distributional effects of the current recession across different types of workers. Second, the individual-level data allow us to measure additional labor market outcomes such as wages per worker as well as recall rates of a given worker as businesses start to re-open. Finally, the individual level data allows us to measure the state where a worker livers allowing us to compute high frequency local labor market measures as the economy recovers.[38]

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

[37] 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.

[38] 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.

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.[39] 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 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.

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

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.

Appendix B.1 Job Creation and Job Destruction

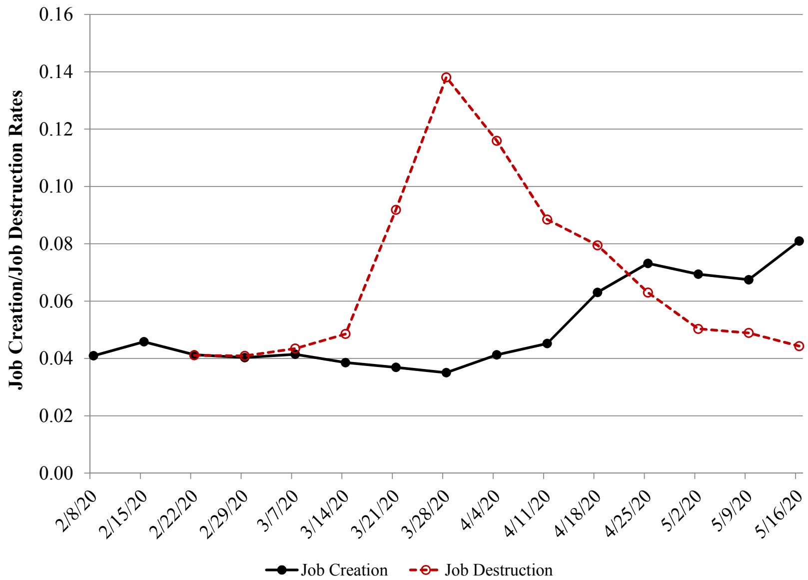
Figure A1 plots the job creation rate (solid black line) and job destruction rate (red dashed line) separately. Job creation rate in week t is defined as the share of workers in the ADP data in t who were not in the data in period $t-1$ (for weekly) or $t-2$ (for biweekly). One can see that the job creation rate held steady at around 4% even through the worst of the crisis, before growing to almost 8% as workers were recalled and the economy reopened in May.

The job destruction rate in period t is defined to be the share of workers in the ADP data in period $t-1$ (for weekly workers) or $t-2$ (for biweekly workers) who are not working for the same employer in period t. We cannot report accurate job destruction rates at the end of the sample because all workers leave the sample in our final week. The job destruction rate was around 4% in early February, roughly in line with the job creation rate, reflecting the relatively stable job growth in the economy at the time. The job destruction rate slowly rose through the end of February, before spiking to 14% at the end of March. Since that peak, the job destruction rate has remained elevated but steadily declining. In most recent periods, the job destruction rate is almost back to the 4% observed in early February. This pattern – a sharp impulse of job destruction followed by a prolonged period of slow job creation – is a feature that has been observed in most prior US recessions. Where this recession differs is the speed and magnitude of the job destruction impulse, as well as the rapid recall of previously employed workers.

Appendix B.2 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 of continuing hourly workers relative to February 15th. There has been little adjustment of

Figure A1: Job Creation and Job Destruction Rates



Notes: The weekly job creation and destruction rates in the ADP data. Job creation in t defined as the share of ADP workers in t who were not present in period $t-1$ (weekly workers) or $t-2$ (biweekly). Job destruction in t defined as the share of ADP workers in $t-1$ (weekly) or $t-2$ (biweekly) who are not present in period t. All numbers weighted to be representative of the firm size $\times$ 2-digit NAICS industry mix in the SUSB.

hours worked for hourly workers throughout the recession. All of the employment adjustment has occurred on the extensive margin of labor supply.

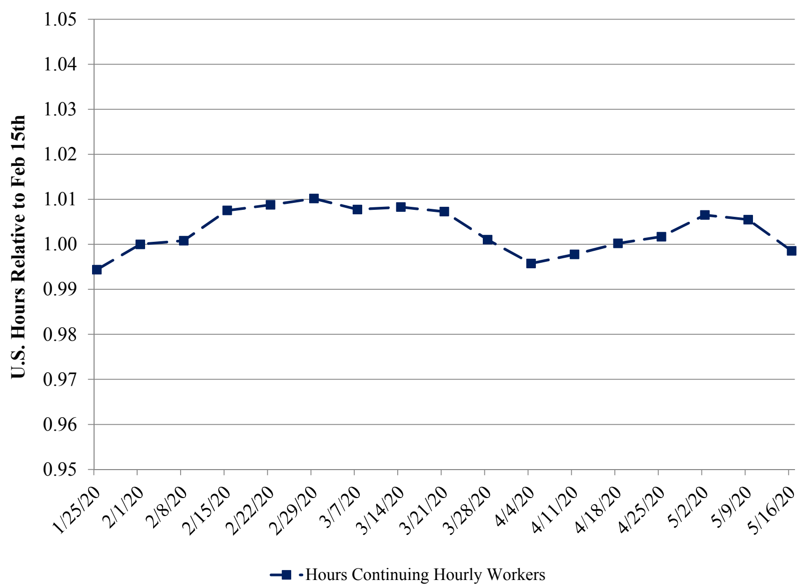
Appendix B.3 Employment Declines By Age

Appendix Figure A3 plots 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. The youngest workers—those between the ages of 21 and 30—and the oldest workers—those 60+—saw the largest employment declines.

Appendix B.4 Employment Declines by Business Size, Employee Sample

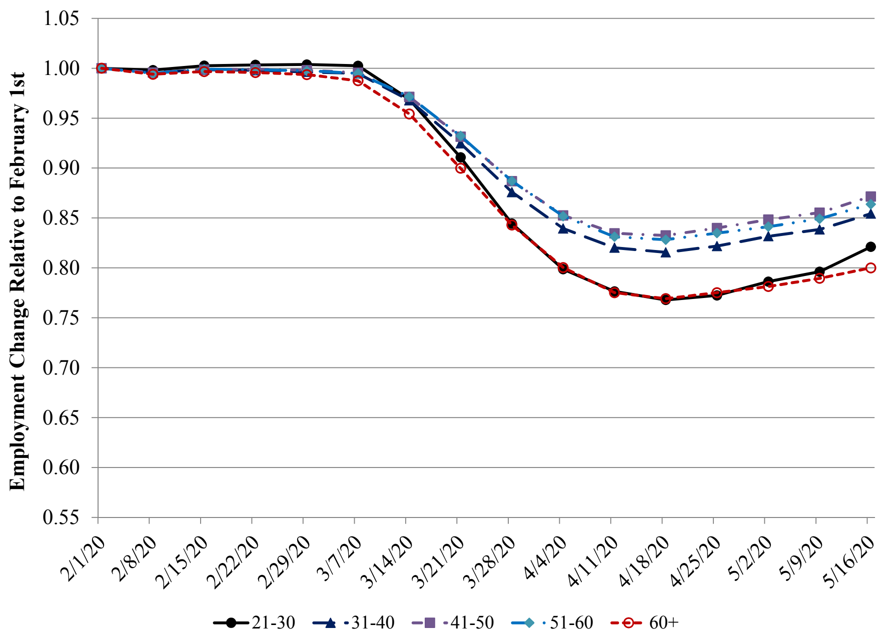
Appendix Figure A4 shows the analog of Figure 3 from the main text using the ADP employee-sample as opposed to the ADP business-sample. One of the benefits of the ADP

Figure A2: Employment and Hours using Employee Data



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.

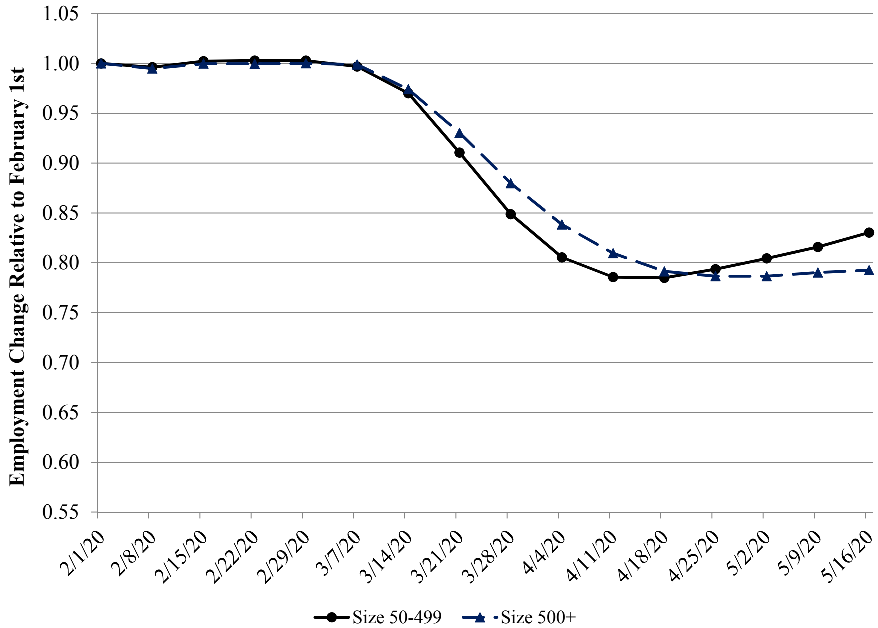
Figure A3: Employment Changes by Age



Notes: Figure shows 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.

employee-sample is that it allows us to measure pay-frequency exactly. A given large firms have many workers paid monthly, bi-weekly, semi-monthly, and weekly. Such variation in pay-periods within a firm can cause a jagged employment growth series. The employee sample allows us to smooth out such variation. The patterns between Appendix A4 using the employee sample and Figure 3 of the main text using the business sample are very similar for mid and larger size firms except the patterns are smoother within the employee sample. The employee-sample under weights smaller firms; the business level sample provide a more reliable measure of employment changes for firms with less than 50 employees and, as a result, are omitted from this figure.

Figure A4: Employment Changes by Firm Size



Notes: Figure shows employment declines by firm size using employee sample. All changes relative to mid February 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.

Appendix B.5 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 5 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.

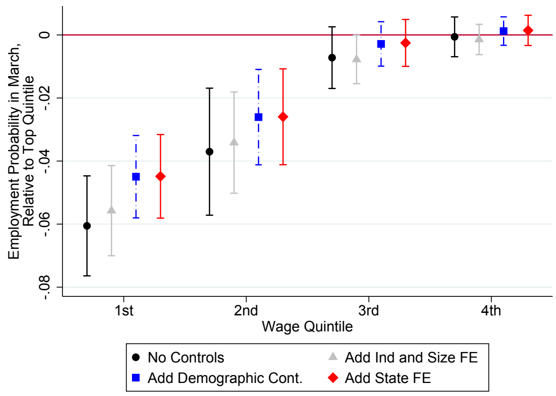
We control for worker i's wage quintile at the beginning of the period to allow the baseline separation rate to differ for workers in different quintiles q. Our variable of interest is how the employment probabilities of each quintile change during the beginning of the recession. This is captured by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

Figure A5 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 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 relative employment declines in quintiles relative to 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 5. In May, bottom quintile workers were 37.2 percentage points less likely to be employed than top quintile workers.[40] The employment probabilities rise monotonically throughout the base wage distribution.

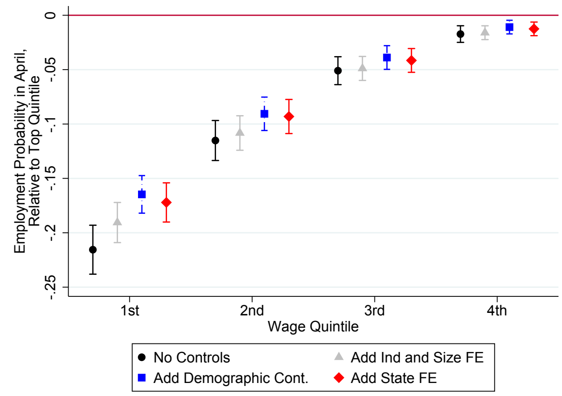
Recent research by Mongey et al. (2020) suggests that low-income workers tend to work in "social" sectors and the large decline observed in these sectors will result in job loss concentrated among lower wage workers. The gray points explore this hypothesis by introducing firm size and 2-digit NAICS industry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

[40] The results in Table A5 are not directly comparable to those in Figure 5 given that we are focusing on a balanced panel of businesses. Some of the additional employment decline we highlight in Figure 5 is due to business shutdown.

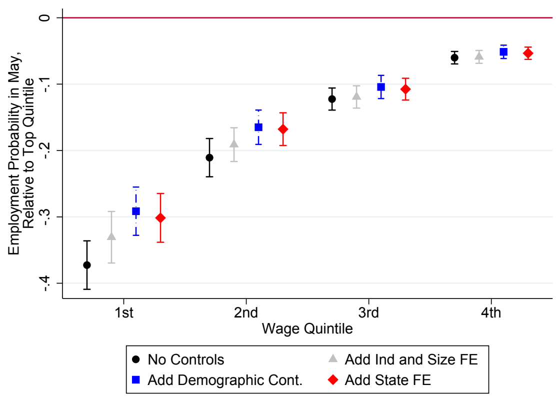
Figure A5: Probability of Employment by Wage Quintile and Sex, Conditional on Observables



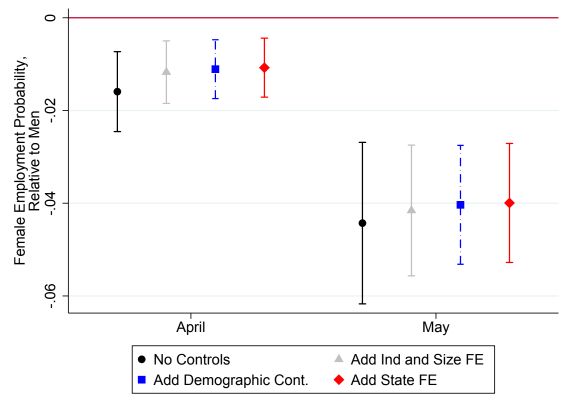
Panel A: March Employment by Wage Quintiles



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 show estimates with no controls. The gray lines control for firm size and 2-digit NAICS industry fixed effects. The blue lines add controls for age and (for Panels A-C) sex. Error bars report 95% confidence interval using standard errors clustered at the 3-digit NAICS cross firm size level.

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

The blue dashed points 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, column the red marker includes 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. Indeed, Michigan, New York, New Jersey, and Massachusetts tend to have higher wages, on average, than other large states with smaller employment declines such as Arizona and North Carolina.

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

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

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 Figure A5. 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 were men.

Appendix B.6 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 firms that existed in the ADP data as of the first two weeks of February. We collapse to firm employment in each two-week period in order to minimize the impact of heterogeneous worker pay frequencies. A firm is then said to have shut down if it cuts at least 90% of its February employment. A firm has re-entered if it previously exited and subsequently has at least 10% of its February employment. Throughout this section we use ADP's employee-level panel.

Table A1 reports business closures and re-opening by 2-digit NAICS industry. Column 1 presents the share of February employment that was employed in a firm that closed at any point during our sample period. Sectors that were hit particularly hard, such as Arts, Entertainment and Recreation, and Accommodation and Food Services, had a large number of business closures.

Table A1: Employment Lost and Recovered through Firm Shutdown and Re-Entry, by 2-digit NAICS Industry

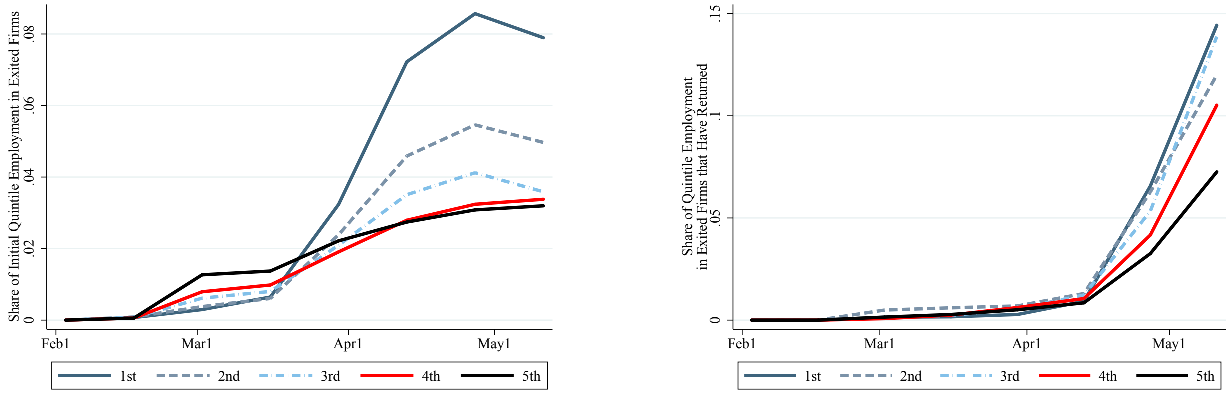
Industry	% of Feb Employment in Firms that Shut down (1)	% of Shutdown Employment that has Returned (2)
Arts, Entertainment and Recreation	19.6	3.5
Accommodation and Food Services	12.2	8.1
Other Services	5.3	21.7
Information	4.4	47.2
Retail Trade	4.4	4.4
Construction	2.9	11.0
Manufacturing	2.5	8.0
Educational Services	2.0	7.9
Transportation and Warehousing	1.5	12.1
Admin/Support and Waste Management Services	1.2	14.5
Real Estate Rental and Leasing	1.1	3.7
Professional, Scientific and Technical Services	1.0	18.7
Wholesale Trade	0.9	28.9
Finance and Insurance	0.6	1.7
Health Care and Social Assistance	0.6	23.6
Management of Companies and Enterprises	0.4	65.0
Mining, Quarrying, and Oil/Gas Extraction	0.1	100.0
Utilities	0.1	100.0

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 1-14 employment in firms that ever close through the end of May. Column (2) shows the share of this lost employment that has been recovered through re-entry by the end of May.

Column 2 shows the share of employment lost to business closure that has returned by the end of May, as businesses began to re-open. Some sectors have seen sharp rebounds from business re-opening. For instance, 47% of the employment lost to closure in the Information sector has returned as of the end of May. In contrast, just 3.5% of the employment lost to closure in Arts, Entertainment and Recreation has returned.

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

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.

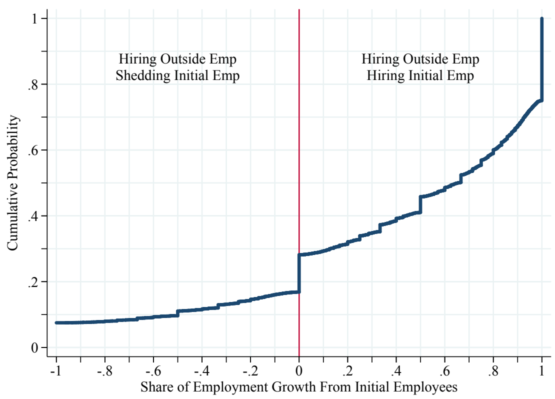
April.[41] By contrast, only 3% of February's top quintile workers were in firms that exited by mid-May.

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 almost 15% of the employment lost to shutdown. This is roughly double the 7% 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 employ many low wage workers. As a result, their closure and re-opening disproportionately affect low wage workers.

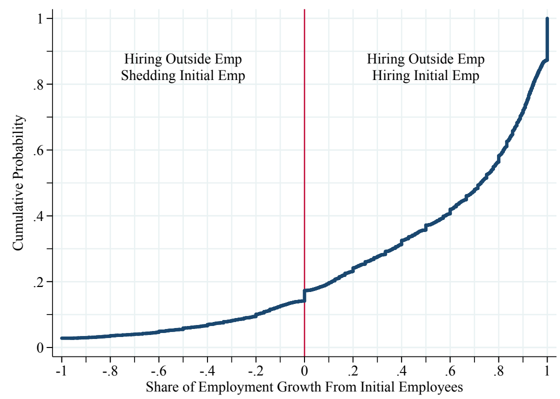
Finally, Figure A7 reproduces Figure 11 in the main text, but looking at continuing firms that increase employment from their trough by at least 1 (Panel A) or 5 (Panel B) employees. That is, it plots the share of employment growth from continuing firms' troughs through the end of May that is accounted for by employees who were previously employed by the firm.

[41]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 section than those reported in the main text.

Figure A7: 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 May. Firm growth measured between the firm's trough employment after March 11 and the end of May. 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.