Tracking Labor Market Developments during the COVID-19 Pandemic: A Preliminary Assessment

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Adrian Hamins-Puertolas   Christopher Kurz[*]

First draft: April 15, 2020

Abstract

Many traditional official statistics are not suitable for measuring high-frequency developments that evolve over the course of weeks, not months. In this paper, we track the labor market effects of the COVID-19 pandemic with weekly payroll employment series based on microdata from ADP. These data are available essentially in real-time, and allow us to track both aggregate and industry effects. Cumulative losses in paid employment through April 4 are currently estimated at 18 million; just during the two weeks between March 14 and March 28 the U.S. economy lost about 13 million paid jobs. For comparison, during the entire Great Recession less than 9 million private payroll employment jobs were lost. In the current crisis, the most affected sector is leisure and hospitality, which has so far lost or furloughed about 30 percent of employment, or roughly 4 million jobs.

Keywords: labor market, economic measurement, big data.

JEL Classification: J2, J11, C53, C55, C81.

1 Introduction

The COVID-19 pandemic, and the associated social distancing measures, have deeply affected the U.S. labor market. The unprecedented speed of deterioration in labor market conditions calls for higher frequency indicators than are currently available in traditional statistical data such as the BLS Current Employment Statistics (CES) and the Current Population Survey (CPS). And while the weekly initial claims for unemployment insurance collected by the Department of Labor provide information to help understand labor market developments, claims only provide a partial picture because they capture only job destruction and not decreased hiring.[1]

In this paper, we build on our extensive previous work in which we constructed employment measures from the ADP payroll microdata; see Cajner et al. (2018), Cajner et al. (2019a), Cajner et al. (2019b), and Cajner et al. (2020). In particular, we use two measures of employment: i) *active* employment, which corresponds to the number of individuals active in the payroll system regardless of whether they were paid or not in a given pay period; and ii) *paid* employment, which corresponds to the number of individuals issued a paycheck in a given pay period.[2] The distinction between active and paid employment is especially useful in the context of labor market developments during the COVID-19 episode. More precisely, changes in active employment should reflect only (permanent) layoffs, but not (temporary) furloughs. On the other hand, changes in paid employment should capture both layoffs and unpaid furloughs. In other words, our active employment series should be similar in concept to CPS employment, while our paid employment series should be analogous to CES employment.[3] We construct both types of employment series at the weekly frequency, which allows us to track the dynamics of employment losses occurring since the onset of the COVID-19 crisis.

Importantly, in previous work we found that ADP data are reasonably representative of

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[1]Additionally, not all workers that lose a job apply for unemployment insurance and the severe processing delays of initial claims that occurred in the second half of March 2020 imply some further challenges when using initial claims data to infer current labor market conditions.

[2]Active employees include wage earners with no hours in the pay period, workers on unpaid leave, and the like. Paid employees include any wage or salary workers issued regular paychecks during the pay period as well as bonus checks and payroll corrections.

[3]Active employment may also be affected by delays in payroll system maintenance. For example, if workers are permanently separated, some might not be automatically removed from payroll systems. That said, in the previous work cited above we found that ADP active employment is better than paid employment for forecasting CES employment.

U.S. businesses, with a wide range of coverage across business size, industry, and geography. In this respect, ADP data are unique among private sector data sources currently being used to track labor markets during the COVID-19 crisis. Moreover, our main ADP indexes are based on ADP data aggregated with size-by-industry weights derived from the BLS Quarterly Census of Employment and Wages (QCEW), so the data are able to provide a good measure of the U.S. private sector. We also emphasize that our ADP-based employment measures are distinct from those published jointly by ADP and Moody's in the monthly National Employment Report (NER).

We find that, among paycheck-to-paycheck continuing businesses, active employment has cumulatively declined by a bit more than 6 million between February 15 and April 4; recall that this decline captures laid off workers who were removed from the payroll system. On the other hand, paid employment has cumulatively declined by about 18 million during the same period. Most severe job losses were experienced in the second half of March; our estimates suggest that the U.S. economy lost about 13 million jobs between March 15 and March 28. For comparison, during the entire Great Recession (between December 2007 and February 2010) 8.8 million jobs were lost. Our estimates of employment losses are also comparable to those in other recent papers: Brynjolfsson et al. (2020) estimate that about 16 million Americans lost jobs through April 5, while Coibion, Gorodnichenko and Weber (2020) estimate that about 20 million jobs were lost by April 8.

Our estimate of employment losses is based on the sample of PACs that can be longitudinally matched over consecutive pay periods, which implies we do not account for lower business entry and higher business exit. In some preliminary work, we find that reduced entry and elevated exit could potentially increase cumulative employment losses, perhaps by as much as 5 to 10 million.[4]

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[4]Moreover, recently released weekly data on new business applications from the Census Bureau show a sharp decline; see Haltiwanger (2020).

2 Methodology for Constructing Weekly Employment Indexes

The weekly employment data used in this paper come from the company ADP, which processes payrolls for about 20 percent of total U.S. private employment.[5] The microdata are at the level of Payroll Account Controls (PAC), which often correspond to business establishments (but may sometimes correspond to firms) as defined by the Census Bureau and the BLS. Each PAC updates their record at the end of each pay period. The record consists of the date payroll was processed, employment information for the pay period, and many time-invariant PAC characteristics (such as an anonymized PAC identifier, NAICS industry code, zip code, etc.).[6] PAC records include both the number of individuals employed ("active" employees) and the number of individuals issued a paycheck in a given pay period ("paid" employees). Active employees include wage earners with no hours in the pay period, workers on unpaid leave, 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 and payroll corrections.

The data begin in July 1999, but are available at the weekly frequency only since July 2009. As argued in Cajner et al. (2018), ADP payroll data appear to be quite representative of the U.S. economy, though the data somewhat overrepresent the manufacturing sector and large businesses, as compared to the QCEW universe of establishments. 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. In short, we calculate the weighted average growth of employment at PACs appearing in the data for two consecutive weeks. We build a weekly time series of employment for each PAC, estimating employment at the PAC each Saturday. Technically, the employment concept is PAC employment for the pay period that includes the Saturday in question, as we cannot observe within-pay period changes. 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 re-

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[5]Other papers that use ADP data include Cho (2018) and Grigsby, Hurst and Yildirmaz (2019).

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

source departments, according to which job start dates often coincide with the beginning of pay period. The restriction to "continuers" allows us to abstract from changes in the size of ADP's client base. Growth rates are weighted by PAC employment and further weighted for representativeness by size and industry (treating PACs as establishments for weighting purposes). We use QCEW employment counts by establishment size and two-digit NAICS as the target population. Formally, let $w_{j,t}$ be the ratio of QCEW employment in a size-industry cell j to ADP employment in cell j in week t, let $C(j)$ be the set of ADP businesses in cell j, let $e_{i,t}$ be the employment of the i'th business, and let $g_{i,t} = \frac{e_{i,t} - e_{i,t-1}}{e_{i,t-1}}$ be the weekly growth rate of business i.[7] Aggregate growth is estimated as:

$$g_t = \frac{\sum_{j=1}^{J} w_{j,t-1} \sum_{i \in C(j)} e_{i,t-1} g_{i,t}}{\sum_{j=1}^{J} w_{j,t-1} \sum_{i \in C(j)} e_{i,t-1}}. \tag{1}$$

Cumulating the weekly growth rates yields a weekly index level for employment. We benchmark the data annually to QCEW employment levels and use a forward benchmarking projection akin to the CES birth and death model. While we believe benchmarking is important, since the QCEW (when available) represent the most complete and accurate estimate of employment, the raw ADP data align well with official sources even before benchmarking. The top panel of Figure 1 compares the *monthly* change in employment in the unbenchmarked ADP-FRB series to the (QCEW-benchmarked) CES series through February 2020. The series track each other closely, indicating that both are picking up the same underlying signal (i.e., true U.S. payroll growth.) The bottom panel of Figure 1 shows the more recent evolution of monthly estimates, including the sharp declines in March 2020.[8] Note that the ADP-FRB monthly series is calculated as the change in the monthly average level of employment, whereas the CES calculates differences between pay periods including the 12th of the month. As such, the monthly ADP-FRB series is more influenced by the last half of March, which helps explain the larger decline we see in that series.

Returning to the weekly data, the last step is to seasonally adjust the series using the methods of Cleveland and Scott (2007), which combine a fixed coefficient regression with locally

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[7]For weighting, we use March QCEW employment values for each year.

[8]In the bottom panel we use our preferred, benchmarked version of the ADP-FRB series.
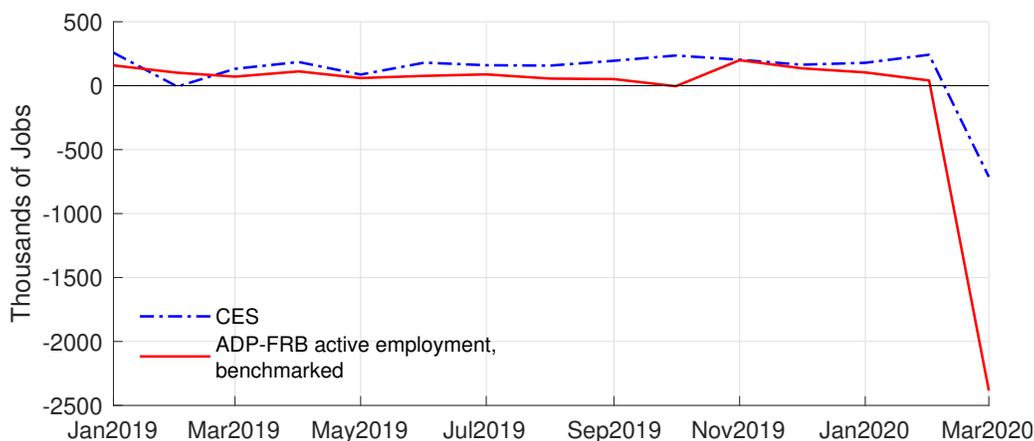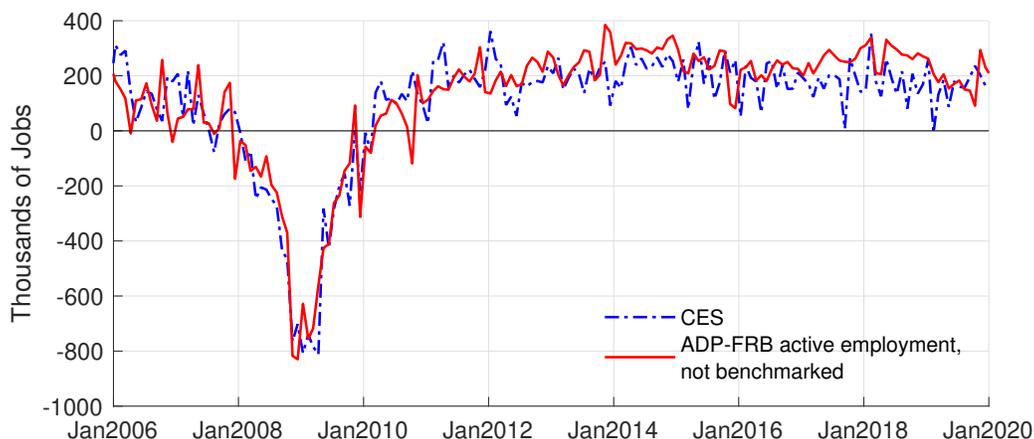
Source: CES, ADP, authors' calculations.

Figure 1: Monthly Change in Private Payroll Employment

weighted regressions on trigonometric functions. Note that the Cleveland and Scott approach was employed by the BLS to seasonally adjust the weekly unemployment claims release.[9]

Since the primary focus of this paper is in weekly data, it is worth noting the distribution of pay frequencies in the ADP data. As of March 2017, 22 percent of PACs 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).

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[9]For the weekly seasonal adjustment, we specifically control for holiday weeks, including Thanksgiving, Memorial Day, Labor Day, New Years, Christmas, and July 4th. We also account for strong employment weeks leading up to holidays and the seasonal employment related to Christmas. Special thanks to Charlie Gilbert for his assistance with seasonal adjustment.

These fractions are not far from what the BLS reports.[10]

3 Measuring Employment Losses during COVID-19 Pandemic

Figure 2 summarizes our main aggregate results by showing cumulative employment changes since February 15 2020, weekly employment changes, and initial claims for unemployment insurance, which serve as a comparison point. As the BLS March employment report indicated, significant payroll employment losses had already occurred in the first half of March (the BLS CES employment numbers refer to the pay period including March 12), and our ADP-FRB employment numbers are consistent with an early March decline. Employment losses then sharply accelerated in the second half of March; our ADP-FRB paid employment number suggests that an additional 13 million jobs were lost between March 15 and March 28. For comparison, during the entire Great Recession (between December 2007 and February 2010) 8.8 million jobs were lost.

Our estimate of job losses between March 15 and March 28 is higher than the sum of initial unemployment insurance claims filed during those two weeks. One likely explanation is that our estimates of employment losses also include reduced hiring, while initial claims predominantly capture job destruction (workers fired or furloughed). Additionally, initial claims lag job losses, some workers never file a claim, and unemployment offices were facing substantial processing delays in the second half of March. We currently see some stabilization of employment losses in the week ending April 4, although it is possible that the estimate for that week will get revised downward when more data become available (revision properties are described in the next subsection).

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[10] See BLS (2019) "Length of pay periods in the Current Employment Statistics survey."
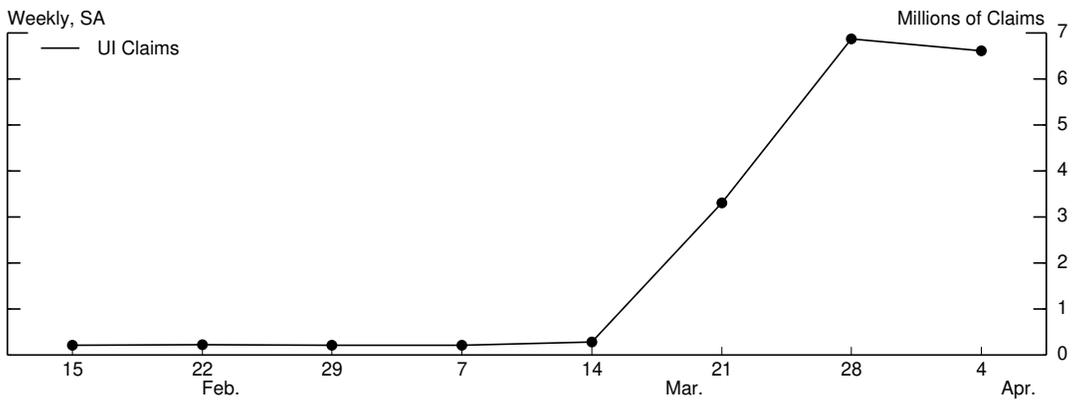
Cumulative Job Loss since 15 Feb 2020
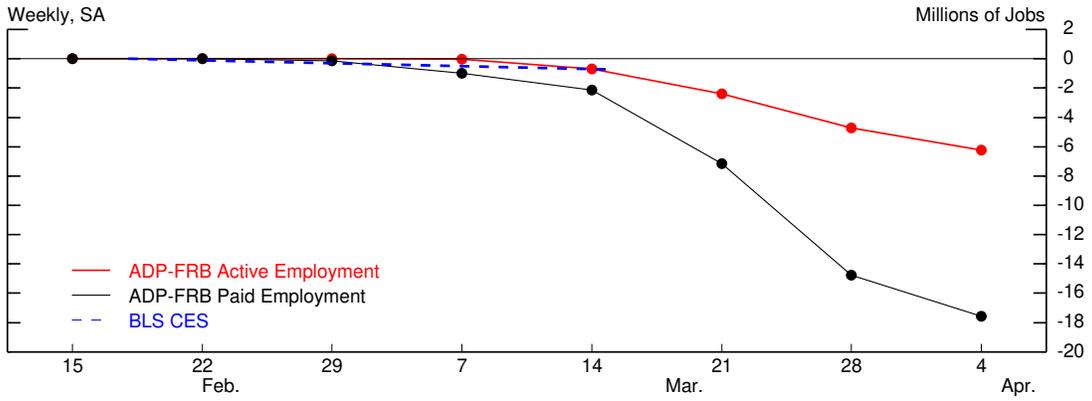
ADP FRB First Differences
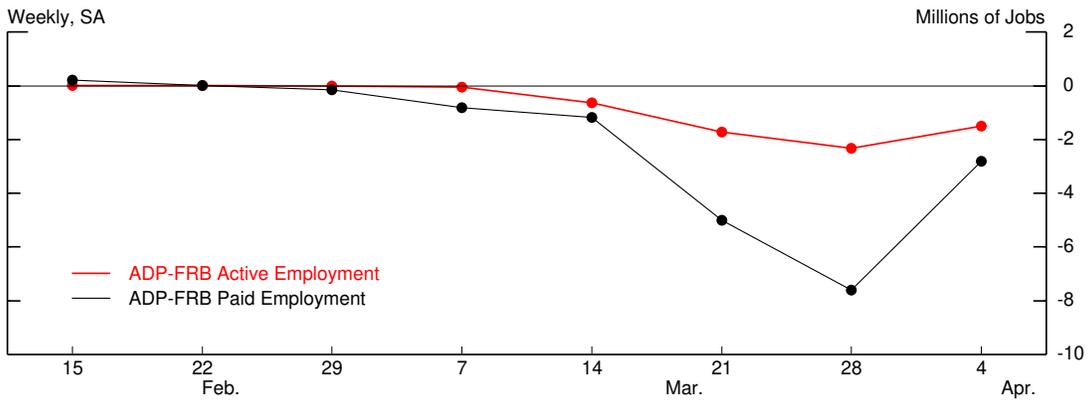
Average Weekly Initial Claims

Note: ADP-FRB figures refer to the pay periods including each Saturday, UI claims refer to the week ending on each Saturday.

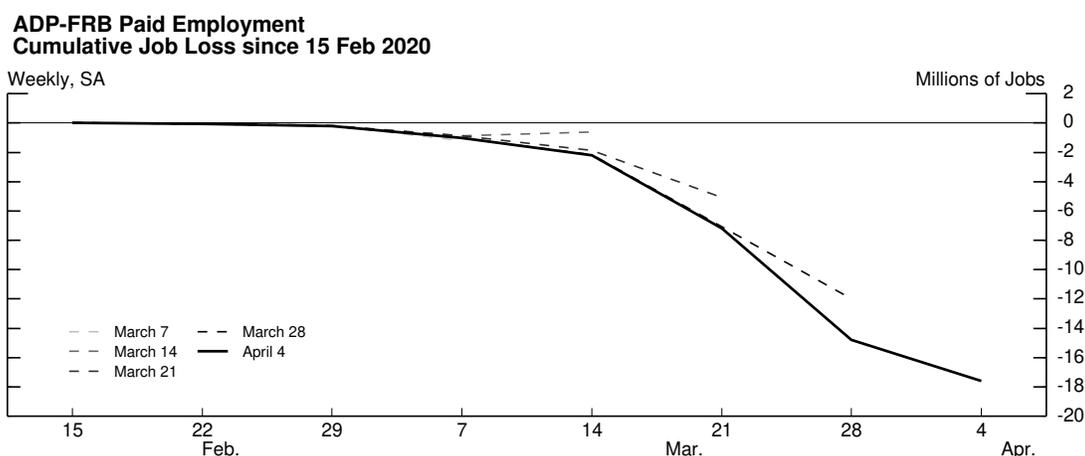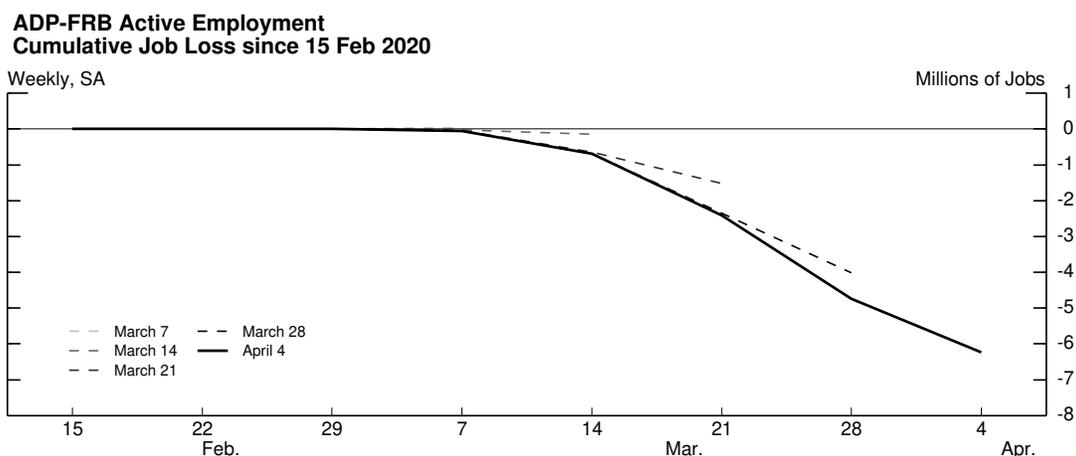*Source:* ADP, authors' calculations.

Figure 2: Labor Market Developments since February 15 2020

3.1 Evolution of Real-Time Estimates

When calculating weekly employment estimates, the most recent observation incorporates data from PACs with weekly pay frequency and approximately half of the PACs with biweekly pay frequency. As additional PACs report payroll, our employment estimates for the more recent weeks revise. Our real time estimation procedure attempts to account for the not-yet-available data from nonreporting PACs by using the historical relationship between the raw "first print" estimate and the final estimate, obtained when data from all PACs have arrived. While this procedure works reasonably well during normal times, the current sharp movements in employment represent additional challenges for the real-time estimation of employment, since the forecasting part of the estimation might work less well than usual.[11]

Figure 3 shows the evolution of real-time estimates for active and paid employment since the beginning of March. These data indicate that initial employment estimates have been generally somewhat too high, revising down when more data became available. That said, after the second read, revisions appear to be relatively small. Thus, it seems likely that the current estimate of employment during the week including April 4 will get revised (most likely downward), but estimates before that week are likely to remain little revised.

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[11]Indeed, our real-time adjustment to the most recent week of data in hand has performed worse during the COVID-19 crisis than at any point since 2005. However, errors in the real-time forecasts do not persist, since the adjustment is replaced by reporting PACs.

ADP-FRB Active Employment
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

ADP-FRB Paid Employment
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

Note: ADP-FRB figures refer to the pay periods including each Saturday.
Source: ADP, authors' calculations.

Figure 3: Real-Time Estimates of Payroll Employment since February 15 2020

3.2 Sector Level Data

Since ADP microdata also contain information about NAICS industry of PACs, we construct estimates of active and paid employment at the "supersector" level.[12] These estimates are presented in Table 1 and Figures 4-7.[13]

In absolute terms, the most notable cumulative drops in paid employment were in leisure and hospitality (almost 4 million); trade, transportation, and utilities (almost 2.5 million); and professional and business services (1.3 million). Large paid employment losses were also

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[12]Our ADP supersector definitions correspond to the broad supersector divisions reported in CES releases.
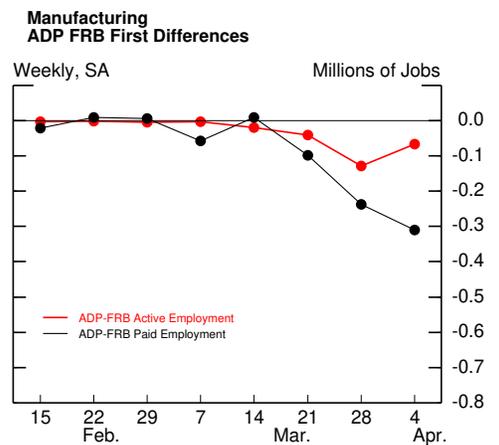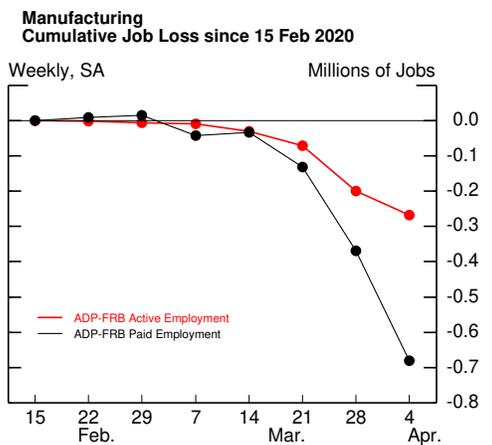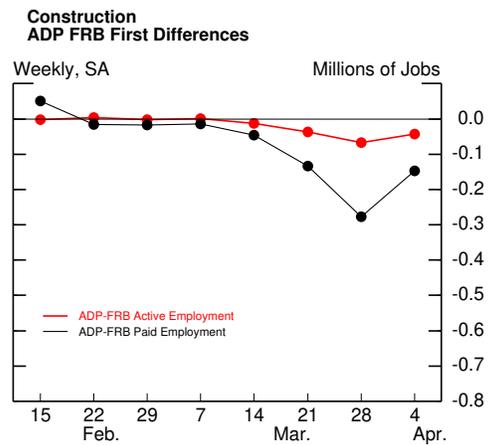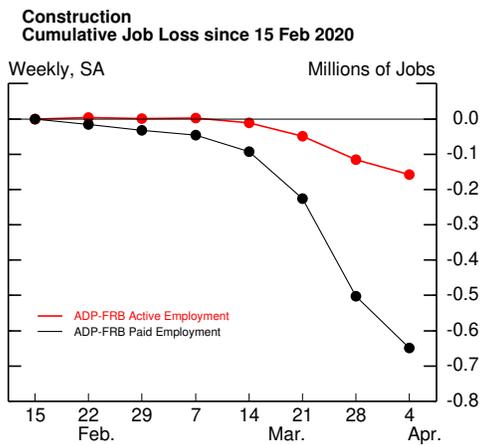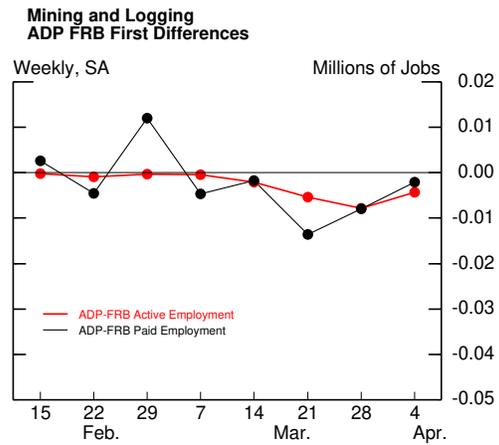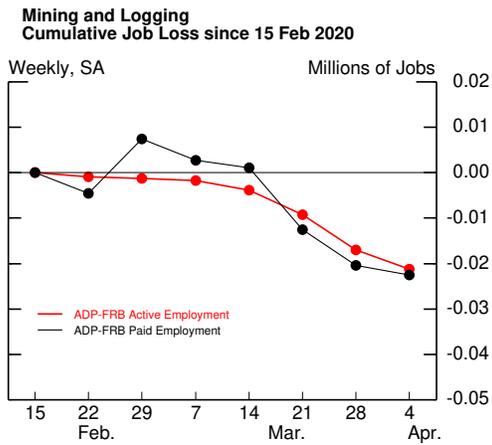
[13]Note that supersector estimates do not necessarily add up to topline estimates, since the topline estimate is constructed independently by using aggregated data only.

	Percent change in employment		Ability to telework
	Active emp	Paid emp	(share, in percent)
Mining and logging	-2.9	-2.9	ND
Construction	-2.2	-9.3	17.2
Manufacturing	-2.1	-5.5	30.3
Trade, transportation, and utilities	-4.1	-9.4	15.8
Information Services	-2.6	-4.7	53.3
Financial Services	-1.3	-1.9	57.4
Professional and Business Services	-2.4	-6.6	53.4
Education and Health Services	+0.7	-4.5	25.9
Leisure and Hospitality	-10.5	-30.5	8.8
Other Services	-2.7	-9.9	27.7

Table 1: Cumulative Employment Changes and Ability to Telework

recorded in education and health (1 million); manufacturing (0.7 million); and construction (0.65 million). In relative terms, the largest employment losses were in leisure and hospitality (30.5 percent), other services (9.9 percent), trade, transportation, and utilities (9.4 percent), and construction (9.3 percent). Table 1 also reports general ability to telework as estimated by the BLS.[14] It appears that the largest employment losses occurred in sectors with low general ability to telework.

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[14]See, https://www.bls.gov/news.release/pdf/flex2.pdf. For similar estimates, see also Dingel and Neiman (2020).

Mining and Logging
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

Mining and Logging
ADP FRB First Differences

Weekly, SA   Millions of Jobs

Construction
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

Construction
ADP FRB First Differences

Weekly, SA   Millions of Jobs

Manufacturing
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

Manufacturing
ADP FRB First Differences

Weekly, SA   Millions of Jobs

Note: The most recent week of the sector series is not corrected for incomplete reporting of biweekly, semimonthly, and monthly payers.
Source: ADP, authors' calculations.

Figure 4: Sector Payroll Employment since February 15 2020
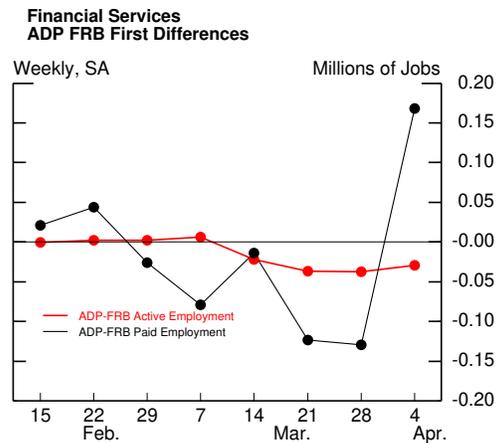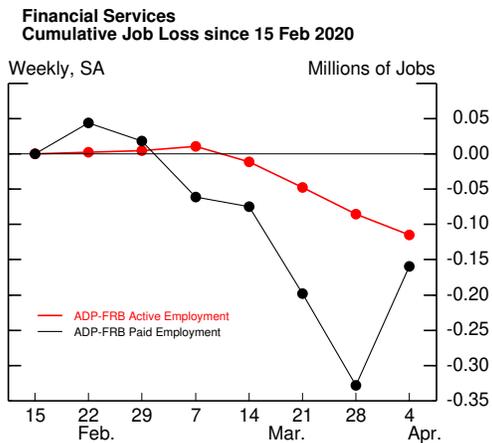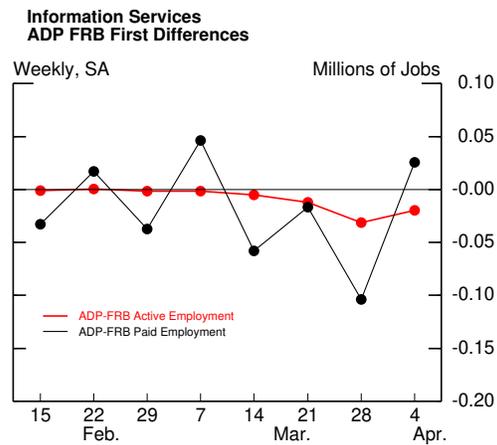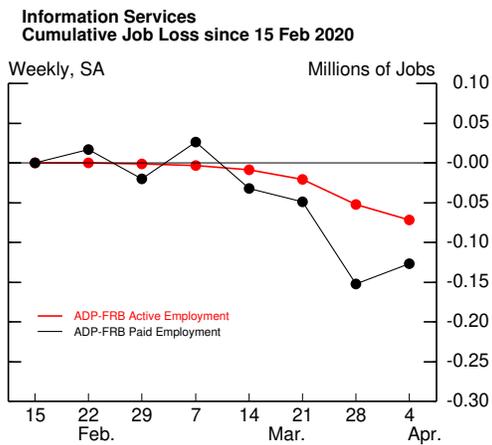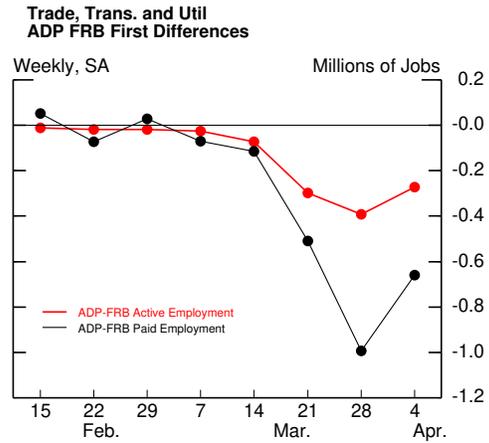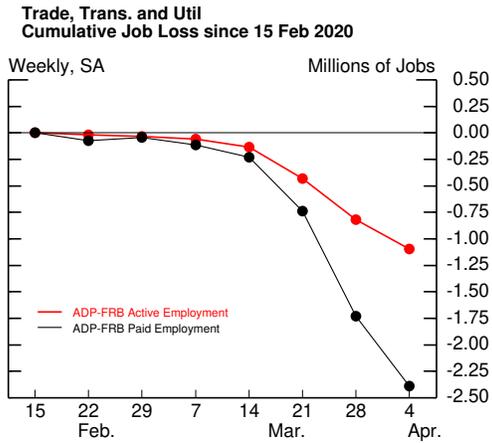
Trade, Trans. and Util
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

Trade, Trans. and Util
ADP FRB First Differences

Weekly, SA   Millions of Jobs

Information Services
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

Information Services
ADP FRB First Differences

Weekly, SA   Millions of Jobs

Financial Services
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

Financial Services
ADP FRB First Differences

Weekly, SA   Millions of Jobs

Note: The most recent week of the sector series is not corrected for incomplete reporting of biweekly, semimonthly, and monthly payers.
Source: ADP, authors' calculations.

Figure 5: Sector Payroll Employment since February 15 2020 (continued)
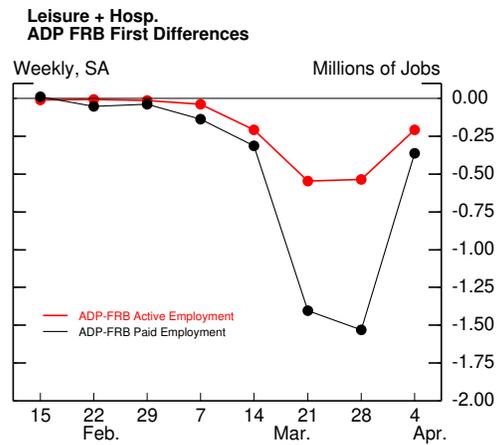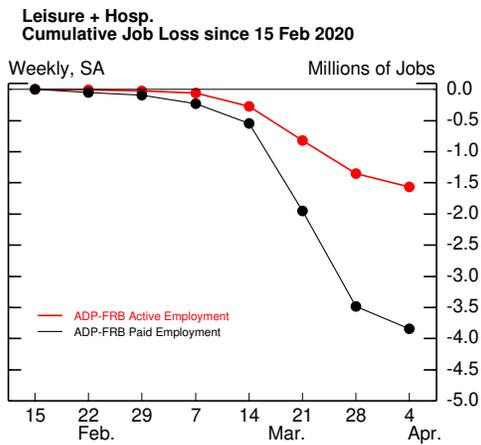
Prof. & Bus. Services
Cumulative Job Loss since 15 Feb 2020

Prof. & Bus. Services
ADP FRB First Differences

Edu. & Health
Cumulative Job Loss since 15 Feb 2020

Edu. & Health
ADP FRB First Differences

Leisure + Hosp.
Cumulative Job Loss since 15 Feb 2020

Leisure + Hosp.
ADP FRB First Differences
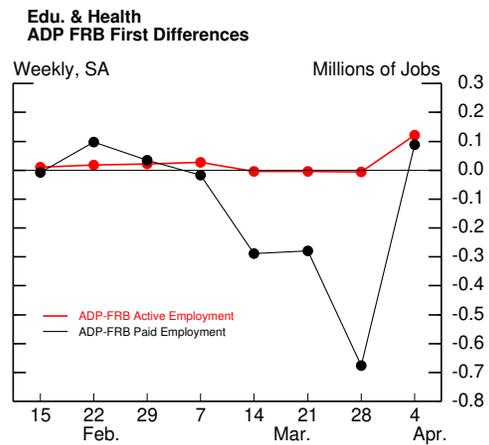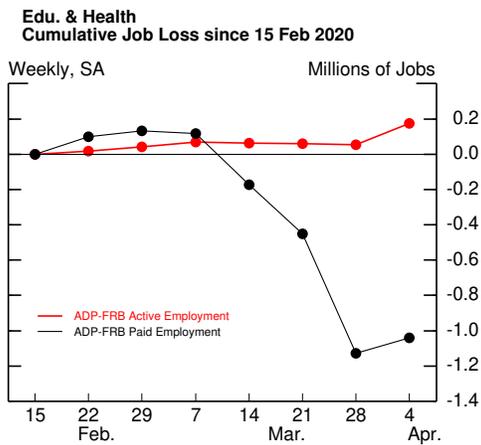
Note: The most recent week of the sector series is not corrected for incomplete reporting of biweekly, semimonthly, and monthly payers.
Source: ADP, authors' calculations.

Figure 6: Sector Payroll Employment since February 15 2020 (continued)

13

Other Services
Cumulative Job Loss since 15 Feb 2020

Weekly, SA   Millions of Jobs

ADP-FRB Active Employment
ADP-FRB Paid Employment

15   22   29   7   14   21   28   4
Feb.   Mar.   Apr.

Other Services
ADP FRB First Differences

Weekly, SA   Millions of Jobs

ADP-FRB Active Employment
ADP-FRB Paid Employment

15   22   29   7   14   21   28   4
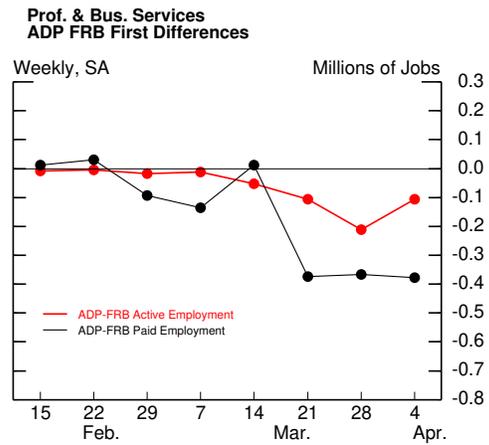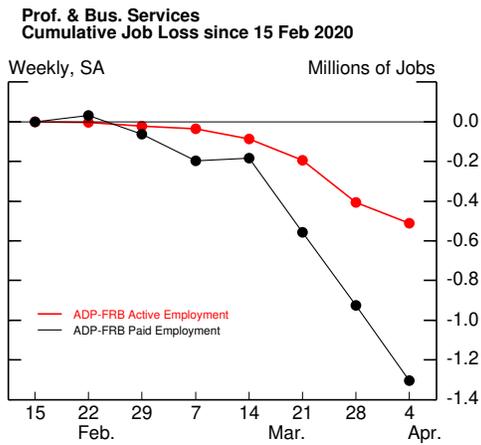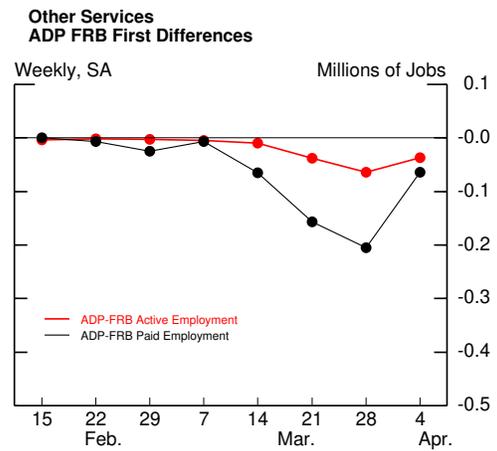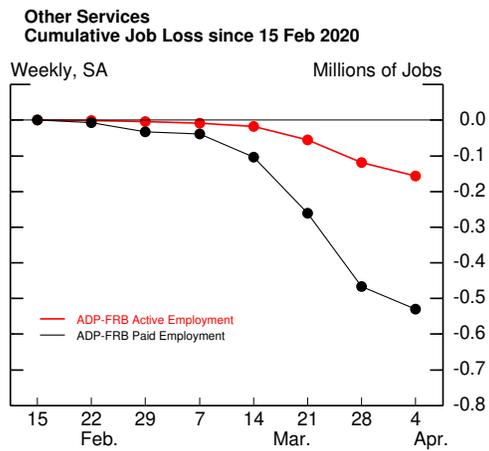Feb.   Mar.   Apr.

Note: The most recent week of the sector series is not corrected for incomplete reporting of biweekly, semimonthly, and monthly payers.
Source: ADP, authors' calculations.

Figure 7: Sector Payroll Employment since February 15 2020 (continued)

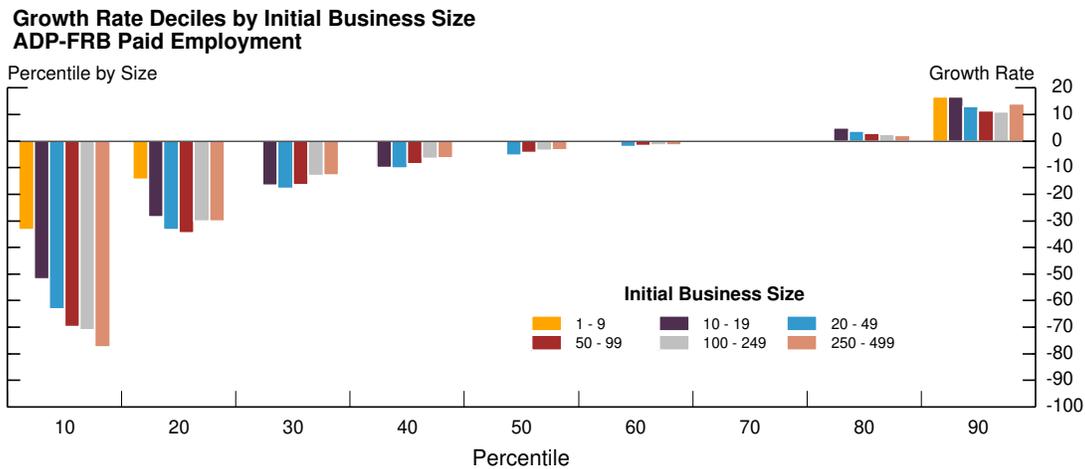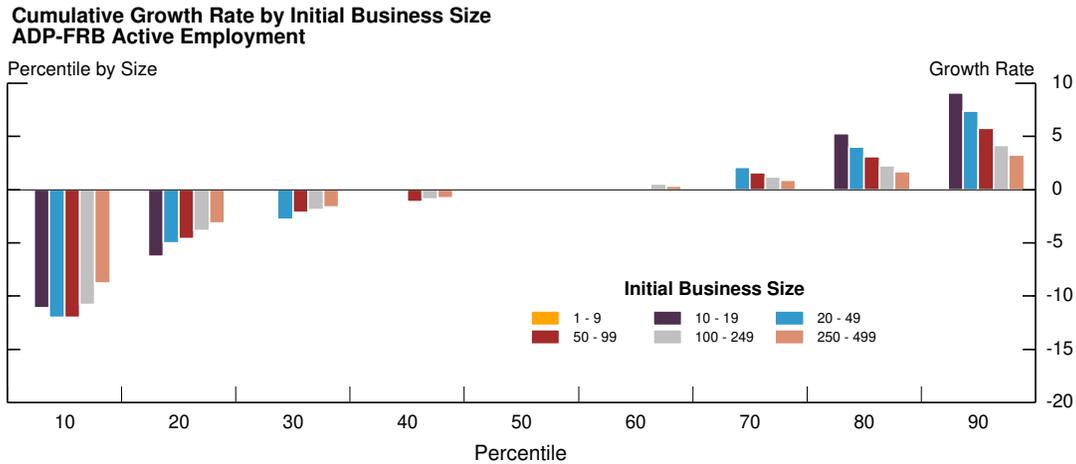## 3.3 The Distribution of Employment Change among Small Businesses

Small businesses (typically defined as those with fewer than 500 employees) have been a particular focus of policymakers, but they are especially difficult to study due to data limitations. We next use the ADP microdata to characterize the distribution of employment changes among small businesses as the U.S. entered the COVID-19 crisis. A particular advantage of the ADP data, as we note elsewhere, is the ability to distinguish between "active" employees (i.e., employees existing on payroll records, regardless of whether they received pay in a given pay period) and "paid" employees (i.e., employees who received pay in a given pay period). The difference between these measures may shed some light on the permanence of employment contractions—complete removal of employees from payroll records may reflect permanent job destruction, while a decline in paid employment could reflect both permanent and temporary layoffs.

ADP data afford a rich characterization of the distribution of employment changes among small business units, both in terms of active and paid employees.[15] Figure 8 reports the distribution of cumulative employment changes from February 15 through March 28 among ADP businesses operating in both periods[16]. For each initial employment size class (defined based on active employment), we report percentiles of employment change. The top panel corresponds to changes in active employment, while the bottom panel refers to changes in paid employment. The figure reveals striking patterns.

We focus first on active employment, which shows markedly smaller declines than paid employment. Among the smallest initial size class (1-9 employees), every decile shows zero cumulative change in active employment; this may be due to "integer problems" (i.e., for very small business units, even a single employee layoff reflects a substantial change in productive capacity), or it may reflect selection issues in which businesses of this size that come under stress must exit entirely rather than shedding employment (in which case they do not appear

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[15]Here we again emphasize that ADP payroll units may not map directly to either firm or establishment concepts used in official data; in this section; we treat payroll units as "small businesses" with the usual caveat that some of them may actually be small establishments of larger firms.

[16]For this figure, we use raw data without seasonal adjustment for simplicity. Moreover, the calculations for this figure are performed directly on the microdata, without additional weighting and index machinery used elsewhere in this paper.

Cumulative Growth Rate by Initial Business Size
ADP-FRB Active Employment

Growth Rate Deciles by Initial Business Size
ADP-FRB Paid Employment

Figure 8: Distribution of Cumulative Employment Changes from February 15 to March 28

in these calculations).

Within the next initial size class (10-19 employees), however, the 10th percentile business saw an active employment decline of more than 10 percent over this period, though the 90th percentile business saw gains of almost 10 percent. Roughly speaking, aside from the smallest (1-9) size category, absolute employment changes in either direction were smallest among the largest businesses; the interdecile range for the largest size class (250-499) is about 12 percentage points, while the range for the 10-19 class was more than 19 percentage points. It is also striking that many businesses saw substantial employment gains over this period, even though the figure is limited to businesses traditionally thought of as "small" (i.e., fewer than 500 em-

ployees). The median business in every size class saw zero change in active employment, with positive gains among many above-median businesses.

We next turn to the bottom panel of Figure 8, which illustrates the employment change distribution in terms of *paid* employment. Here was see substantially larger moves. The 10th percentile business within every size class saw declines of at least 30 percent, with the largest class shown (250-499) seeing a decline of almost 80 percent. Even the smallest business size class (1-9) saw substantial declines among many businesses. This panel also reveals extremely wide dispersion in outcomes; the interdecile range of paid employment changes varies from 50 percentage points among the smallest businesses to over 90 percentage points for the 250-499 size class. Of course, "integer problems" may be playing a role among the smallest businesses.

Interestingly, Bartik et al. (2020) (using rich Homebase data on small business hourly employment and hours) find that declines in hours worked between January and late March are driven almost entirely by business shutdowns (i.e., zero hours worked in a week) and hours reductions among retained employees, with minimal contribution from layoffs of hourly employees.[17] Figure 8 is not markedly inconsistent with this while adding considerable color. The *median* small business shows little movement in either active or paid employment between mid-February and late March, suggesting minimal layoffs among surviving businesses. But underlying this median result is considerable distributional variation: a bit less than half of surviving businesses experienced nontrivial employment declines, and a few businesses experienced dramatic declines approaching 80 percent. On the other hand, some businesses have experienced sizable employment gains. That being said, some tension remains between the results of Bartik et al. (2020) and our results from ADP data in this section and elsewhere in the paper. Generally speaking, in other sections we have documented substantial declines in both paid and active employment among continuing businesses, and Figure 8 shows that the half of businesses showing declines in active employment saw declines that are larger in magnitude than the gains among the roughly half of businesses that saw gains; and for paid employment, declines are seen up to the 60th percentile of small businesses. In other words, ADP data do suggest substantial layoffs among continuing businesses. A possible reason for this discrep-

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[17]Homebase data track "local" types of businesses with concentration in retail and leisure and hospitality industries; see Bartik et al. (2020) for details.

ancy is that Bartik et al. (2020) observe business shutdowns when zero hourly employees clock in; it is likely that some businesses are staying "open" with at least a few salaried employees, so they count as continuing businesses in ADP data despite registering no hourly employment.

Taken together, the various insights from Figure 8 reveal striking heterogeneity in the experiences of small businesses as the U.S. entered the COVID-19 crisis. The relatively muted moves in active employment (relative to paid employment) might, one would hope, suggest that many businesses do not see their layoffs as permanent (though it may also reflect record-keeping inattentiveness), while the extreme declines in paid employment among more than half of small businesses leave ample room for concern about the state of the small business economy.

4 Conclusion

In the coming months, the BLS's monthly labor reports will capture both the depth and breadth of the current employment losses. Unfortunately, the speed of the recent declines makes it necessary to turn to nontraditional data, which can provide some higher-frequency insight about events as they unfold. The responsiveness of policymakers over the past few weeks has been, in part, engendered by an understanding of how rapidly the COVID-19 pandemic has afflicted the economy. A broad spectrum of timely and high-frequency economic information has facilitated this understanding.

Looking forward, in addition to the monthly and weekly employment indexes, we are currently generating a set of diffusion indexes, measures of entry and exit, size and industry class measures, and an employment index solely comprised of individuals with weekly paychecks. This corpus of labor data will not only further our understanding of the rapid deterioration of the employment situation, but will provide evidence of timing and magnitude of the eventual rebound in the labor market.

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