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HETEROGENEOUS LABOR MARKET IMPACTS DURING THE EARLY STAGES OF THE COVID-19 PANDEMIC

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Heterogeneous Labor Market Impacts During the Early Stages of the Covid-19 Pandemic

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Abstract

The Covid-19 pandemic is having profound impacts on labor markets around the world. This paper analyzes the heterogeneous impacts observed during the early stages of the pandemic across different occupations and workers using the latest available labor force survey data from the Current Population Survey, the primary source of labor force statistics for the United States. I show that the early stages of the pandemic had a disproportionately negative impact on employment and hours in lower-paying occupations. The one notable exception are janitors and building cleaners, for whom employment grew strongly between mid-February and mid-March 2020. Workers who were employed in lower-paying occupations in mid-February 2020 are disproportionately less likely to be employed by mid-March 2020 compared to workers who were employed in higher-paying occupations. I also document increased attrition from the sample among workers who were employed in lower-paying occupations in mid-February 2020.

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1 Introduction

The Covid-19 pandemic is having profound impacts on labor markets around the world. Unemployment insurance claims in the United States, for example, have risen to unprecedented levels.[1] While it has become clear that the pandemic has led to dramatic rates of job destruction, it is still less clear how the virus has impacted the labor market outcomes of different types of jobs and different groups of workers.

This paper analyzes the heterogeneous labor market impacts of the early stages of the Covid-19 pandemic across different occupations and workers using the latest available labor force data from the Current Population Survey (CPS), the primary source of labor force statistics for the United States. The data correspond to the second week of March 2020, and hence precedes most of the major lock-down orders issued throughout the U.S. It therefore only captures the very early impacts of the pandemic. The results show, however, that there were already substantial employment declines by mid-March. Understanding the heterogeneity in these early impacts may serve as important guiding information for researchers and policymakers trying to address the more widespread employment effects observed in subsequent weeks.

2 Data and Aggregate Patterns

The analysis is based on monthly data from the Current Population Survey (CPS). The CPS is sponsored jointly by the U.S. Census Bureau and the U.S. Bureau of Labor Statistics (BLS). This analysis relies on the microdata made publicly available by IPUMS (Flood et al., 2018). I restrict the sample to non-institutionalized civilians aged 16 and older.

The reference week for the CPS is normally the 7-day calendar week that includes the 12th of the month. For March 2020, the reference week was March 8–14. It is important to note that the majority of the major lock-down orders and other strict social distancing measures had not yet been implemented at that time throughout the United States. Data from the Department of Labor shows that initial unemployment insurance claims totaled 250,892 in the week ending March 14 – a substantial increase relative to the previous week (25.2 percent), but nowhere near the unprecedented levels that were observed in subsequent weeks (see `https://www.dol.gov/ui/data.pdf`).

[1] See `https://www.dol.gov/ui/data.pdf`.

Hence, the March 2020 CPS data only captures the very early effects of the Covid-19 pandemic.

Panel A of Figure 1 shows aggregate employment rate changes between February and March for each year since 1976. Between mid-February and mid-March of 2020, the employment rate fell by more than 1 percentage point, a very large monthly change by historical standards. Analysts at the BLS have determined that many people who should have been recorded as unemployed in March 2020 due to Covid-related reasons seem to have been recorded as employed but absent from work.[2] In order to (imperfectly) account for this mis-coding, Panel B plots changes in the employment rate when *all* individuals who are absent from work are excluded in all months, therefore only counting individuals who were employed *and at work* during the reference week as employed. Based on this measure, the employment rate declines by more than 2p.p., again a large swing by historical standards. Finally, Panel C plots February-March changes in aggregate hours per capita (i.e. total hours-weighted employment normalized by the total population in each period). This series can be constructed from 1989 onwards. The data shows a decline of nearly 1 weekly hour per capita between February and March 2020, also a substantial monthly change by historical standards.

Figure 2 shows the analogous patterns using 1-year changes (March-to-March of each year). Though the patterns look less dramatic, it should be noted that the employment losses between March 2019 and March 2020, which are almost entirely driven by the 1-month losses between February and March of 2020, are nearly as large as those experienced at an annual frequency during earlier recessions, with the exception of the financial crisis.

The analysis in this paper focuses on heterogeneous impacts across occupations and across workers in different types of occupations.[3] Occupational codes used in the CPS changed in January 2020 (from 2010 to 2018 Census code categories). The changes are relatively minor, but may affect the comparability across detailed occupational categories for periods overlapping the coding system change. When focusing only on changes in 2020, I directly use the codes at the 2018 Census code level – in some cases aggregated to a set of 23 broader occupational categories ("2-digit level"). In order to compare the changes observed in 2020 to the changes observed in 2019, I first crosswalk

[2]See `https://www.bls.gov/cps/employment-situation-covid19-faq-march-2020.pdf`.

[3]See also Alon et al. (2020), who analyze the expected heterogeneous impacts across genders, due to the fact that the pandemic particularly impacts sectors with high female employment shares.

the 2018 Codes to 2010 Codes based on information provided by IPUMS, and then aggregate to the 23 broader occupational categories. At this 2-digit level, no important discontinuities are observed at the time of the coding system change.

3 Heterogeneous Impacts on Employment and Hours

Figure 3 explores how the employment losses observed in aggregate between February and March of 2020 are distributed across occupations. For comparison purposes, changes between February and March of 2019 are also shown. This analysis is at the level of 23 2-digit occupations, which are ranked in the graph from the lowest paying (occupational wage rank 1) to the highest paying (occupational wage rank 23) based on their mean wage in February 2020. The full list of changes by occupation is detailed in Table 1.

Panel A plots changes in employment per capita. A clear pattern emerges: between February and March of 2020, lower paying occupations tended to experience larger employment losses. The fact that such a pattern is not observed in the left panel for 2019 suggests that this pattern is not seasonal. Meanwhile, Panel B plots the changes in average hours worked in each occupation. Average hours decline in most occupations between February and March of 2020, with the only exceptions being some of the highest paid occupations. Once again, this does not appear to be driven by seasonality, given that similar patterns were not observed in 2019.

Figure 4 illustrates the heterogeneous changes in employment and hours across occupations through a series of scatter-plots. Changes for each of the 23 occupations between January and February of 2020 are depicted with blue circles and a solid line of best fit, while changes between February and March of 2020 are depicted with red squares and a dashed line of best fit). Panels A and B confirm the evidence of larger declines in employment in lower-paying occupations. The pattern is particularly strong when individuals who were absent from work are excluded from employment counts in Panel B, indicating a disproportionate increase in the incidence of absences from work in these occupations. Meanwhile, Panels C and D confirm the disproportionate decline in average hours worked in lower paying occupations. Panel D focuses only on average hours among individuals who were at work during the reference week (therefore including only individuals who worked a positive number of hours) and shows that, even among individuals who remain employed and at work, there is still a stronger decline in average hours per worker in lower-paying occupations. Figure 5 compares the February-March 2020 changes to the changes observed across the same two months in 2019, and rules out the possibility that the larger declines observed for low-wage occupations are driven by seasonal patterns.

Table 1 lists the employment and hours changes for each of the 23 occupations between mid-February and mid-March 2020. The occupations with the largest declines in employment were Food Preparation and Serving, and Sales and Related occupations. This shows that the dining and retail sectors were already experiencing employment contractions by mid-March. Meanwhile, Cleaning and Maintenance occupations, in spite of being relatively low paid, were one of the few occupational groups that did not experience a decline. This is consistent with the increased demand for cleaning services as a result of the outbreak. The strongest decline in hours is observed among Arts, Design, Entertainment, Sports and Media occupations. Interestingly, these occupations experienced positive employment growth between February and March of 2020, and hence experienced a contraction along the hours margin rather than the employment margin. Other occupations with important declines in hours include Educational Instruction and Library occupations, as well as Food Preparation and Serving.

Figure 6 plots the changes in employment and hours at a more granular occupational level. Mean wages are computed for each 3-digit occupation, and each occupation is then ranked according to its position in the employment-weighted distribution of occupational wages in February 2020. The figure plots changes in employment and hours per worker for occupations at each percentile of the distribution. The general pattern is consistent with the earlier findings. Panel A shows generally larger employment declines in lower paying occupations. However, there are also some notable exceptions. In particular, the two occupations below the 25th percentile which experience substantial increases in employment are Janitors and Building Cleaners (15th percentile) and Couriers and Messengers (22nd percentile). Going forward, it will be important to determine the extent to which workers in other low paid occupations are able to transition into these growing jobs, at least temporarily. The figure also shows that some high-paid occupations experience relatively strong declines, such as Post-Secondary Teachers (79th percentile).

Meanwhile, Panel B confirms that the reductions in hours per worker are widespread across occupations, with smaller declines generally observed only towards the top of the distribution. The exception observed at the 16th percentile corresponds to Farmers, Ranchers and Other Agricultural Managers, and Other Healthcare Support Workers. Both of these groups experience large increases in average hours per worker. Towards the top of the distribution, the group that experiences a large decline in average hours per worker are Dentists (96th percentile).

Figure 7 turns to an analysis of the underlying individual-level transition patterns.[4] To do this, I take advantage of the rotating nature of the CPS sample: households remain in the sample for four consecutive months, then exit the sample for eight months, and subsequently return for an additional four months. This implies that up to 75% of the sample can be matched from one month to the next (all except those in month-in-sample four or eight, who are scheduled to exit the survey). In practice, the fraction of respondents that can be matched is lower. This is partly due to the fact that the BLS is sometimes unable to contact the corresponding household (i.e. household non-response), and also partly due to the fact that the CPS is an address-based survey and hence, if individuals move to a new residence, they are not followed by the survey.

The BLS has reported that the response rate was about 10 percentage points lower in March 2020 compared to previous months, with individuals in their first or fifth month in sample being particularly affected.[5] For the purposes of understanding transitions between February and March of 2020, the higher non-response rate of individuals in their first or fifth month in sample in March 2020 is not relevant, as they would in any case not have been scheduled to be interviewed in February 2020. Non-response rates, however, also increased for individuals in other months-in-sample. Moreover, it is possible that geographic mobility may have increased for certain groups of workers, which would also limit the ability to track their transitions across these two months.

The fraction of workers in each occupation that can be matched across the February and the March 2020 CPS samples is plotted in Panel A of Figure 7. For comparison purposes, the figure also plots the match rate across the January and February 2020 CPS samples. The data shows a clear decline in the match rate across all occupations. However, the decline is particularly strong among workers who were in lower paying occupations. This disproportionate increase in attrition among workers from lower-paying occupations may reflect a higher likelihood of moving to a new address and/or a higher non-response rate, both of which may be driven by

[4] See also Forsythe (2020).

[5] See `https://www.bls.gov/cps/employment-situation-covid19-faq-march-2020.pdf`.

employment-related shocks that we are not able to capture directly.

Panel B shows the fraction of matched individuals who are observed in non-employment in month $t + 1$, according to their occupation in t. The downward slope of both the solid and the dashed lines is driven by the fact that workers from lower-paid occupations are generally more likely to switch to non-employment. However, the stronger slope of the dashed line – corresponding to transitions between February and March 2020 – indicates that the likelihood of transitioning to non-employment increased disproportionately among workers in lower-paying occupations. For workers in Food Preparation and Serving, for example, the monthly probability of switching out of employment increased from 5.4% between January and February to 11.7% between February and March.

Finally, Panels C and D track changes in hours worked during the reference week among matched individuals. Panel C shows a substantial decline in hours among workers who start off in lower-paying occupations. This is due to a combination of switches to non-employment (as illustrated in Panel B), increased job absences, and reductions in hours. Panel D focuses on workers who remain employed and at work (with a positive number of hours) across the two months. Even among this group, we observe disproportionate declines in hours worked among workers who start off in lower paying occupations.

4 Conclusions

This paper shows that the early stages of the Covid-19 pandemic had a disproportionately negative impact on employment and hours in lower-paying occupations, with individuals who were initially employed in such occupations experiencing higher rates of job separations and larger reductions in hours of work as compared to individuals initially employed in higher-paying occupations. These asymmetric effects may reflect heterogeneities in the extent to which occupations can be performed remotely (see Brynjolfsson et al., 2020; Dingel & Neiman, 2020; Saltiel, 2020), as well as more pronounced demand decreases in certain sectors (Food Preparation and Serving occupations, for example, experience strong declines in both employment and average hours per worker).

There are, however, some low-paying occupations, such as janitors and building cleaners, that have experienced strong employment growth. Going forward, it will be important to understand the extent to which occupational mobility can enable workers to mitigate the impact of Covid-related occupational-level shocks. It may be the case that not enough time had passed by mid-March for workers to identify which occupations are growing, but one might also worry that barriers to occupational mobility, such as those identified by Cortes & Gallipoli (2017), may be preventing workers from moving.

Overall, the main conclusion of the analysis presented here is that there is clear evidence that the initial impacts of the pandemic were very asymmetric across workers in high- vs low-paying occupations, an important fact for policymakers to take into account.

Although the employment and hours effects documented here are large by historical standards, it is important to note that they only capture the very early impacts of the pandemic, as the data collection preceded most of the major lock-down and social distancing measures implemented in the U.S.

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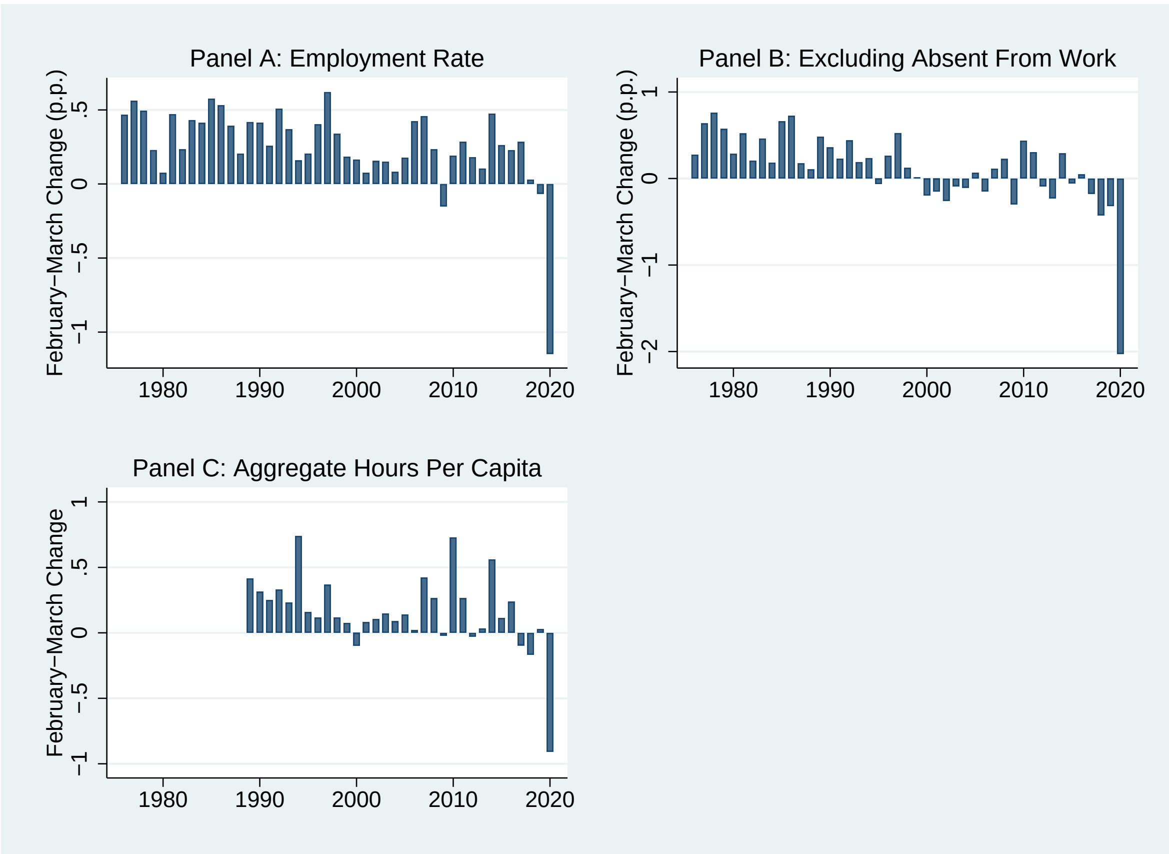
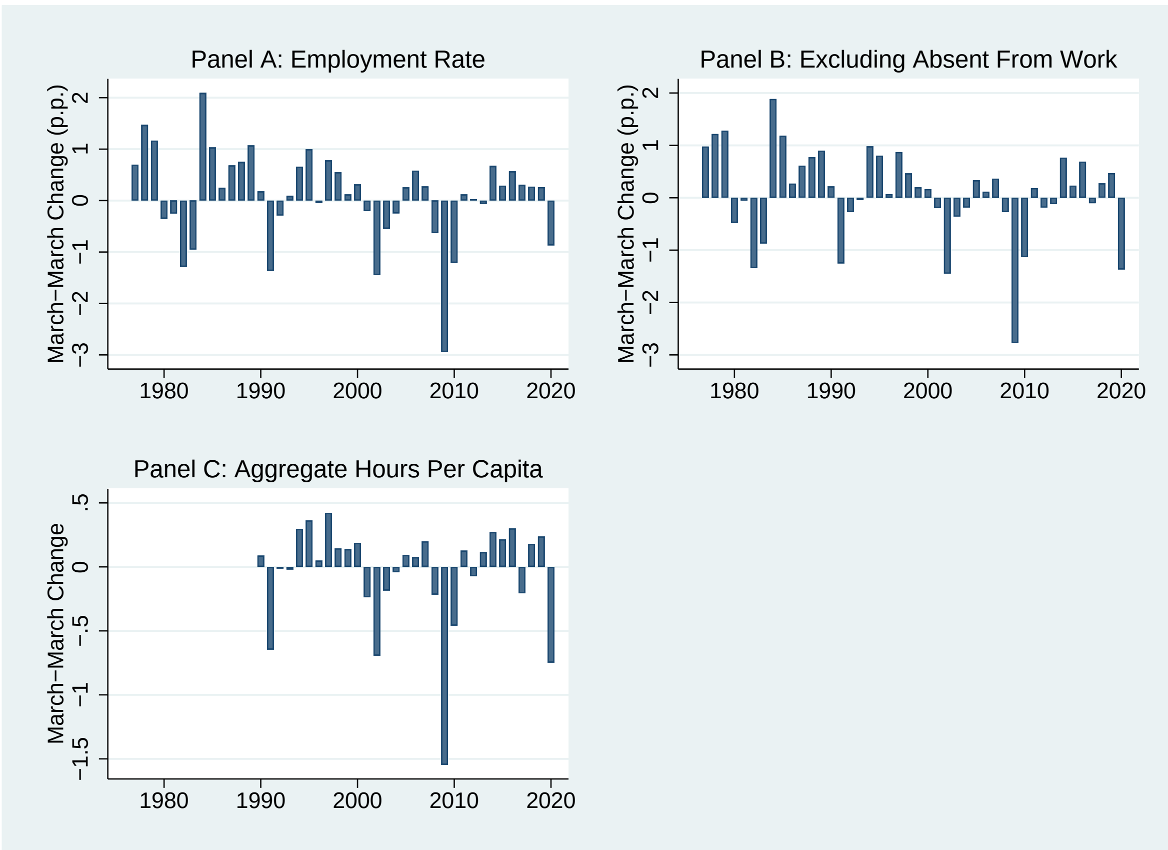
Figure 1: Aggregate Monthly Changes, February-March of Each Year



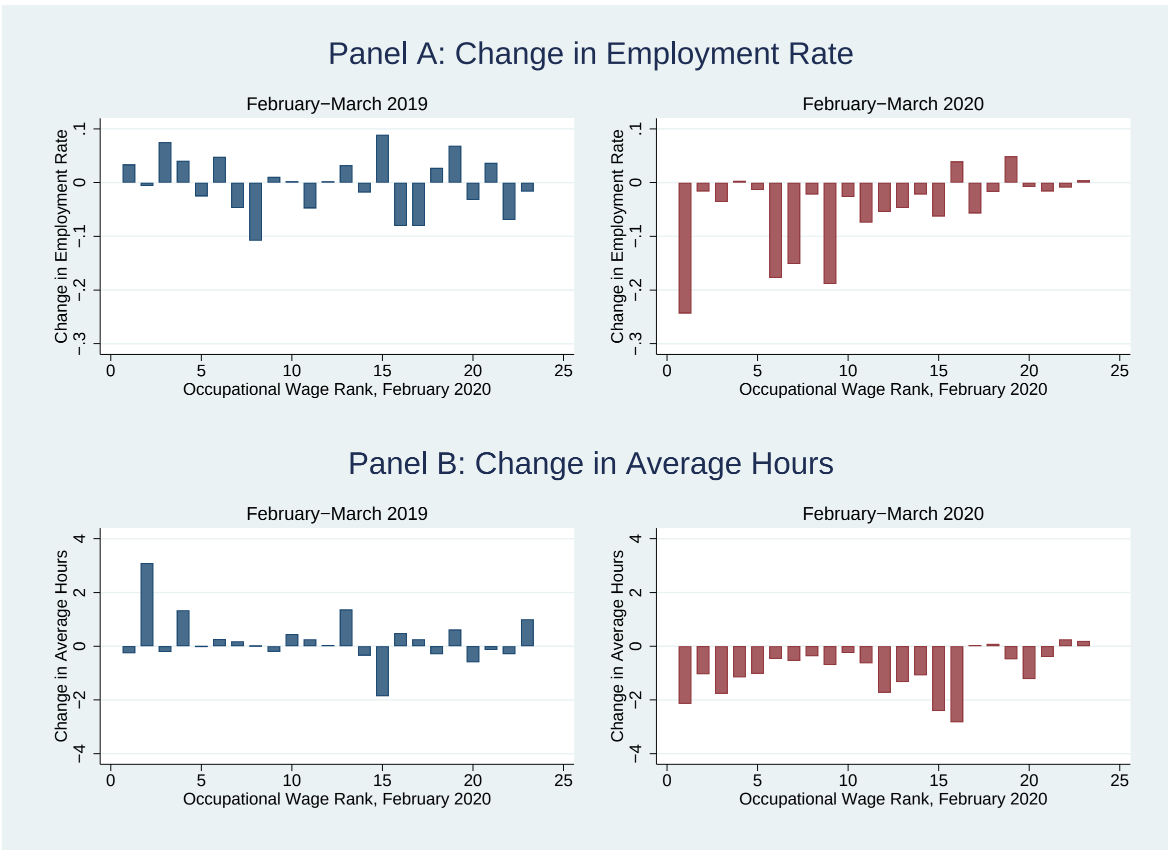
Note: The figure plots the monthly change between February and March of each year based on monthly CPS data from IPUMS. The employment rate in Panel B excludes individuals who are recorded as employed but absent from work. Panel C computes changes in hours-weighted employment normalized by the total population in each period.

Figure 2: Aggregate Annual Changes, March-March of each year



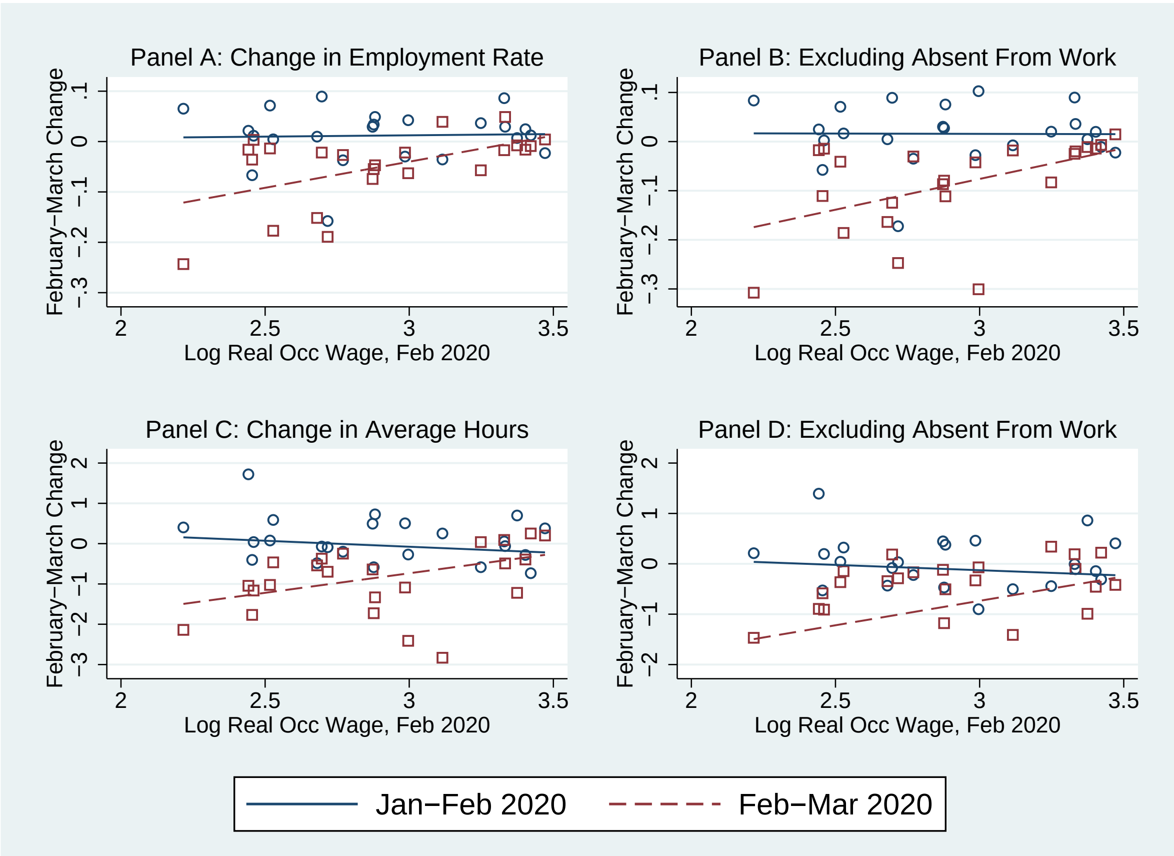
Note: The figure plots the 12-month change as of March of each year based on monthly CPS data from IPUMS. The employment rate in Panel B excludes individuals who are recorded as employed but absent from work. Panel C computes changes in hours-weighted employment normalized by the total population in each period.

Figure 3: Occupational Employment and Hours Changes, Monthly Changes



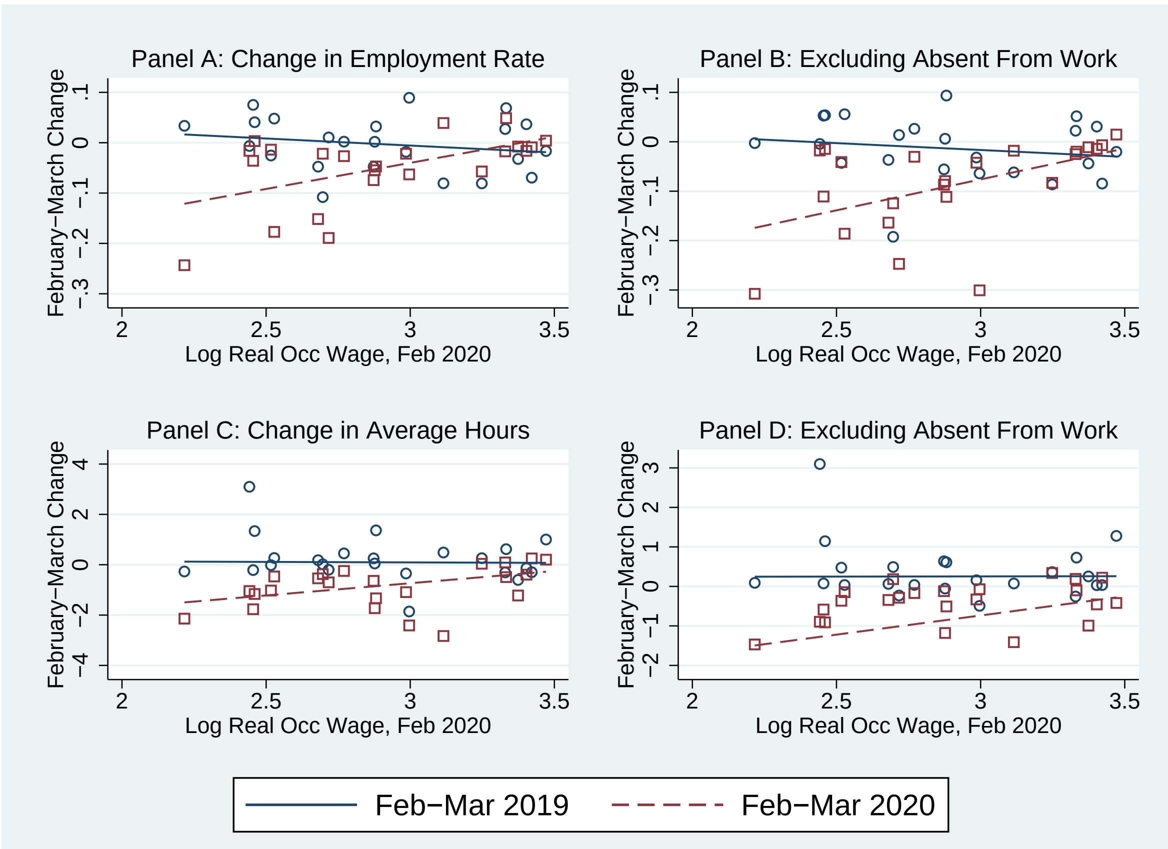
Note: The figure plots the monthly change between February and March of each year for 23 2-digit occupations based on monthly CPS data from IPUMS. Occupations are ranked from the lowest paying (occupational wage rank 1) to the highest paying (occupational wage rank 23) based on their mean wage in February 2020. The full list of changes for each 2-digit occupation is detailed in Table 1.

Figure 4: Employment and Hours Changes by Occupation, 2020



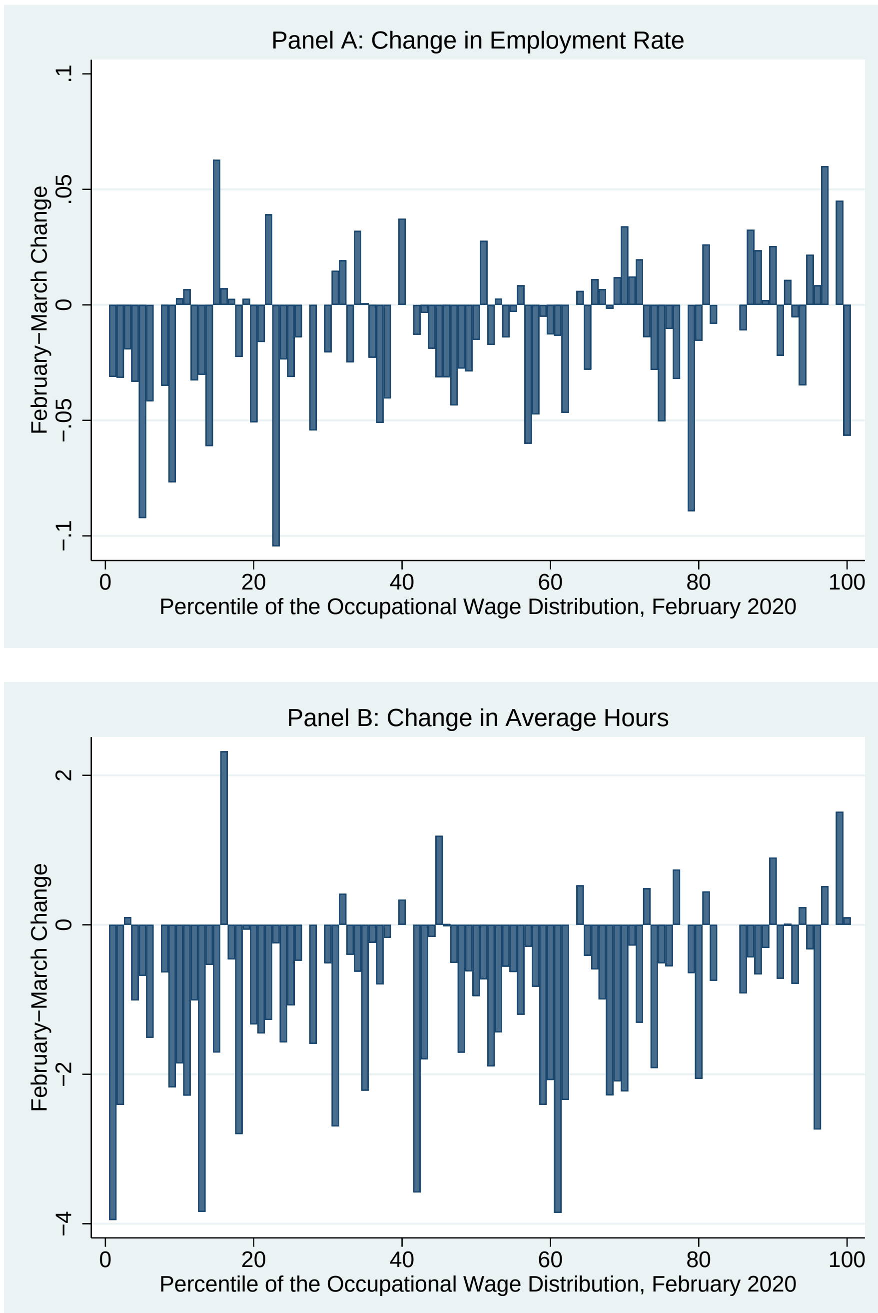
Note: The figure plots the monthly change for 23 2-digit occupations based on monthly CPS data from IPUMS, with blue circles corresponding to the changes between January and February of 2020, and red squares corresponding to the changes between February and March of 2020. Panel B plots changes in employment excluding individuals who were absent from work during the reference week. Panels C and D plot changes in average hours per worker, with Panel D excluding individuals who were absent from work during the reference week. The lines of best fit in Panels C and D are employment-weighted. The full list of changes for each 2-digit occupation is detailed in Table 1.

Figure 5: Employment and Hours Changes by Occupation, February to March of 2019 vs 2020



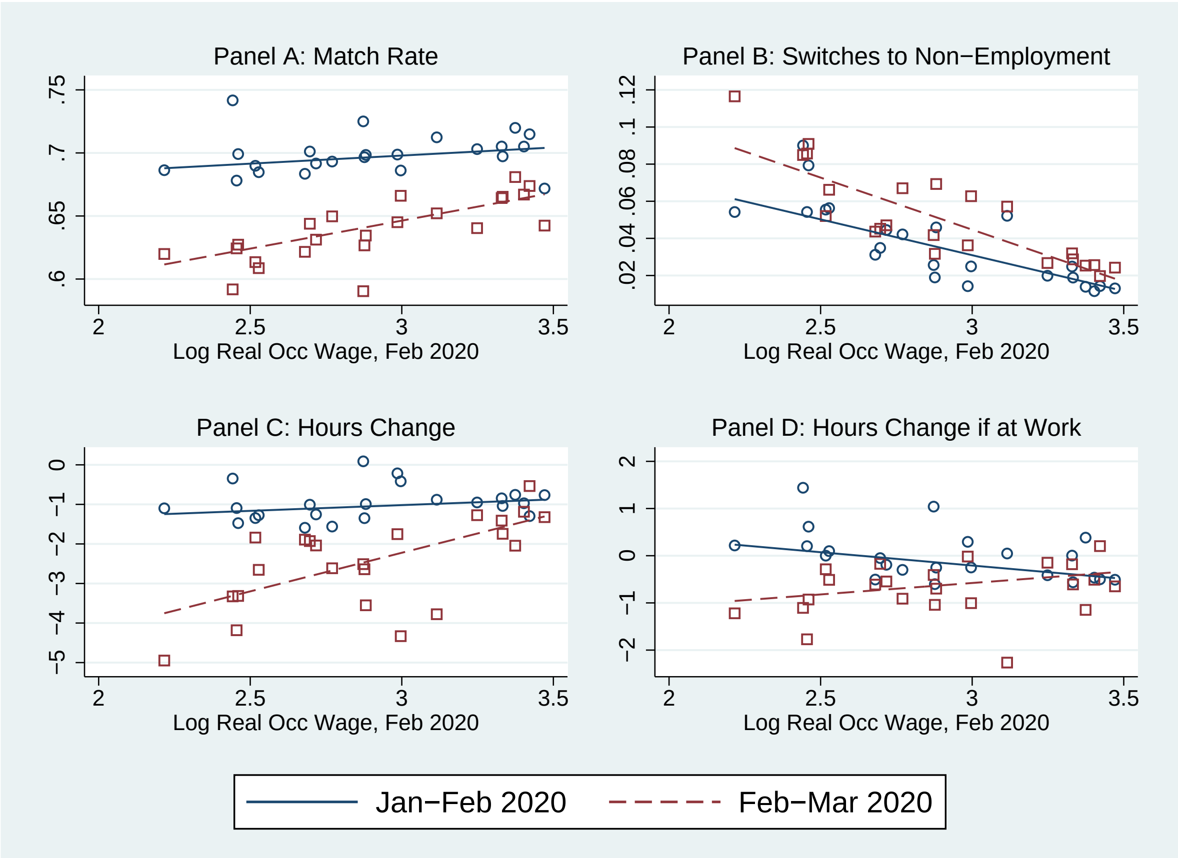
Note: The figure plots the monthly change for 23 2-digit occupations based on monthly CPS data from IPUMS, with blue circles corresponding to the changes between February and March of 2019, and red squares corresponding to the changes between February and March of 2020. Panel B plots changes in employment excluding individuals who were absent from work during the reference week. Panels C and D plot changes in average hours per worker, with Panel D excluding individuals who were absent from work during the reference week. The lines of best fit in Panels C and D are employment-weighted. The full list of changes for each 2-digit occupation is detailed in Table 1.

Figure 6: Changes in Employment and Average Hours by 3-Digit Occupation, February to March 2020



Note: The figure plots the monthly change between February and March of 2020 for occupations at each percentile of the occupational wage distribution in February 2020 based on monthly CPS data from IPUMS.

Figure 7: Individual-Level Match Rates, Transition Patterns and Hours Changes, by Initial Occupation



Note: Panel A plots the fraction of individuals in each occupation that can be matched across consecutive monthly surveys. Panel B plots the fraction of individuals in each occupation that transition out of employment (as a fraction of all individuals in that occupation in the base month that can be matched across surveys). Panel C plots the average change in hours worked among individuals in each occupation in the base month. Panel D plots the average change in hours worked among individuals in each occupation who remain employed and work a positive number of hours in the reference week in both survey months. The lines of best fit in all panels are employment-weighted. Analysis based on monthly CPS data from IPUMS.

Table 1: Changes in Employment and Average Hours per Worker by Occupation

Occupation	Wage Rank (1=lowest)	Log Real Wage (Feb 2020)	Δ Emp/Pop Feb-Mar 2020	Δ Hrs/Worker Feb-Mar 2020
Food Preparation and Serving Related	1	2.22	-0.243	-2.14
Farming, Fishing, and Forestry	2	2.44	-0.016	-1.04
Personal Care and Service	3	2.46	-0.036	-1.77
Building, Grounds Cleaning, Maintenance	4	2.46	0.003	-1.16
Healthcare Support	5	2.52	-0.014	-1.02
Material Moving	6	2.53	-0.177	-0.46
Production	7	2.68	-0.152	-0.54
Office and Administrative Support	8	2.70	-0.022	-0.37
Sales and Related	9	2.72	-0.189	-0.70
Transportation	10	2.77	-0.027	-0.25
Protective Service	11	2.87	-0.074	-0.64
Installation, Maintenance, and Repair	12	2.88	-0.055	-1.73
Construction and Extraction	13	2.88	-0.047	-1.33
Community and Social Service	14	2.99	-0.022	-1.09
Educational Instruction, and Library	15	3.00	-0.063	-2.41
Arts, Design, Entertainment, Sports, Media	16	3.12	0.039	-2.83
Healthcare Practitioners and Technical	17	3.25	-0.057	0.04
Business and Financial Operations	18	3.33	-0.017	0.09
Management	19	3.33	0.049	-0.49
Life, Physical, and Social Science	20	3.37	-0.008	-1.22
Architecture and Engineering	21	3.40	-0.016	-0.39
Computer and Mathematical	22	3.42	-0.009	0.25
Legal	23	3.47	0.004	0.20

Note: Analysis based on monthly CPS data from IPUMS.