The Distributional Short-Term Impact of the COVID-19 Crisis on Wages in the United States

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Preliminary draft – some results are subject to change as real-time data are used

Abstract

This paper uses BLS employment and wage data to study the early distributional impact of the COVID-19 crisis on wages in the United States. It answers whether wages of lower-wage workers were hurt more than others', and to what extent? We find that the COVID-19 outbreak exacerbates existing inequalities. Weekly wages of workers at the bottom quintile decreased by 5% on average between mid-February and mid-March. The average decrease for higher quintiles was less than 1%. We find that workers aged 16–24 were hit much harder than older workers. Hispanic workers were also hurt more than other racial groups. Their wages decreased by 0.4–0.5 percentage points more than other workers'. Wages of female workers decreased by 0.2 percentage points more than of male workers.

Keywords: Income inequality, COVID-19, Growth incidence curves

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1 Introduction

The COVID-19 outbreak led to an unprecedented abrupt shock to many countries, with the United States becoming the epicenter of the pandemic in late March 2020. With more than a million COVID-19 cases, and hundreds of millions of people in lockdown, the economic impact of the pandemic is massive and expected to become even greater in the near future.

Among the early outcomes of the "Great Lockdown" that followed the outbreak of the pandemic were the shutdown of many businesses and large-scale layoffs of workers. By the week ending April 18, millions of US workers have filed initial unemployment claims, bringing the insured unemployment rate in the US to 12.4% (Department of Labor, 2020). The labor market impact of the lockdown is worst for jobs that cannot be performed remotely and are not considered essential. Such jobs are also generally lower-paid (Adams-Prassl et al., 2020). Early evidence of the impact on unemployment suggests that it rises faster for women and "people of color" (Adams-Prassl et al., 2020; Kalev, 2020).

This paper presents evidence for the distributional impact of the COVID-19 crisis on wages. In particular, it answers whether, indeed, wages of lower-wage workers decreased more than others' and to what extent? It also clarifies the magnitude of the effect – what share of the labor force was substantially impacted? This paper also addresses gender- and race-specific impact. It answers whether wages of female workers were hurt more than of male workers, and how the impact on wages depended on race.

To answer these questions one would have to compare wages of employees just before the coronavirus pandemic outbreak in the US, to their wages at a later time. Yet, reliable large-scale real-time tracking of individual wages is challenging. Administrative data cannot be used in real-time. Surveys, such as the Current Population Survey (CPS), report earnings on a quarterly or annual basis. Several ad-hoc surveys have been conducted in the US and elsewhere (Bartik et al., 2020a; Adams-Prassl et al., 2020), but their scale is limited and samples potentially non-representative. They may also more informative on employment, but less so on wages. This paper uses wage and employment data from the monthly establishment survey of the Bureau of Labor Statistics (BLS, see Bureau of Labor Statistics (2020a)). These data represent about 130 million private sector workers, divided into industry sectors.

Combining employment and wage data we create synthetic panels for private sector workers, from which we estimate non-anonymous growth incidence curves (NAGICs, see Bourguignon (2011)). NAGICs quantify the average wage growth rates of individuals occupying a specific wage rank at the beginning of a given period, but not necessarily the same rank by the end of the period. Thus, constructing a NAGIC for US workers for a period that spans from just before the outbreak of the pandemic in the US and a later point in time would quantify its impact on wages at different points along the wage distribution.

NAGICs for weekly wages between February 2020 and March 2020 show that the bottom 20% of employees lost 5% of their wages on average. The rest, *i.e.* top 80%, lost less than 1% on average by mid-March. For comparison, between January 2020 and February 2020, all quintiles, including the bottom, gained about 0.6% of their wages on average.

We find no evidence for a significant change on hourly wages between mid-February 2020 to mid-March 2020 for workers employed in both months. Thus, the major reduction of weekly wages among workers at the bottom quintile is due to lay offs and reductions in working hours. It is not, at least by mid-March, due to decreased hourly wages.

Combining the panels with CPS data on the composition of industry sectors by age, gender, and race, we study the impact of the COVID-19 outbreak on the wages of different subgroups. We find that the reduction in weekly wages following the COVID-19 outbreak was more pronounced among women than among men. Wages of female workers decreased by 0.2 percentage points more than of male workers. The decrease in wages was also more pronounced among younger workers, aged 16–24, than among older workers.

The decrease in weekly wages was particularly pronounced among Hispanic workers. The average reduction in weekly wages between mid-February 2020 and mid-March 2020 was greater by 0.4 percentage points among Hispanic workers than among all workers, and by 0.5 percentage points within the bottom quintile. All subgroups considered (young, female, male, White, Black, Asian, and Hispanic workers) suffered from an average reduction of 4.8%–6% in weekly wages between mid-February 2020 and mid-March 2020 within the bottom quintile.

The primary contribution of this paper is empirical. It provides new information on hourly and weekly wage losses among workers along the wage distribution following the COVID-19 outbreak. It also enables identifying the differential impact on wages by race and by gender. It joins the growing literature on labor market impact of the COVID-19 outbreak (Alon et al., 2020; Adams-Prassl et al., 2020; Bartik et al., 2020a,b; Brunori et al., 2020), focusing mainly on employment and the reaction of firms so far. It also joins the growing literature on how inequalities contribute to unequal health outcomes during the outbreak (Ahmed et al., 2020; Glover et al., 2020; van Dorn, Cooney and Sabin, 2020).

From a methodological perspective the paper contributes to the labor and inequality literatures on short-run distributional changes, especially such that take into account panel data (Kopczuk, Saez and Song, 2010; Bourguignon, 2011; Piketty, Saez and Zucman, 2018; Berman, 2019). Usually such research relies on large scale surveys, tax data or social security data, which cannot be used in real-time. This paper presents a way to use a reliable existing data source that is published on a monthly basis, the BLS establishment survey, to study short-run distributional changes. This would allow to easily expand the analysis done here in the following months. We also hope that this work will stimulate similar work in other countries with similar data sources.

The paper is organized as follows. Section 2 lays out necessary background on growth incidence curves, which serve as the primary tool for our analysis. Section 3 describes the data we use. Section 4 presents the main results, on the distributional impact on wages, and Section 5 presents the impact on wages by age, gender, and race. We conclude in Section 6.

2 Growth incidence curves

The main tool we will use to quantify and characterize the impact of the COVID-19 outbreak on wages is non-anonymous growth incidence curves (NAGICs). The concept of growth incidence curves (GICs) is central in studies of poverty and inequality. It is a useful tool for illustrating how income (or expenditure, or wealth) grows (or degrows) over a time period along the income distribution. GICs quantify the average income growth at each income rank in the distribution. Yet, it matters how the ranks are defined and how incomes are compared, and there are two main types of GICs – anonymous and non-anonymous.

Anonymous GICs (Ravallion and Chen, 2003) quantify the growth of the average income in the same income fractile over a time period. They ignore the identity of individuals within fractiles. In general, GICs are upward sloping, *i.e.* low for the bottom of the distribution and higher at the top, when inequality is increasing and vice versa. They are insensitive to mobility between income ranks.

Non-anonymous GICs (Grimm, 2007; van Kerm, 2009; Bourguignon, 2011) quantify the average income growth of individuals occupying a specific income rank at the beginning of a given period, but not necessarily the same income rank by the end of the period. They can be downward (upward) sloping depending on whether poorer individuals experience higher (lower) average growth rates than richer individuals. The NAGIC and the GIC thus differ through the former incorporating personal income mobility. They coincide when no reranking occurs between the initial and terminal dates.

While NAGICs are seemingly more informative of the individual experience of income changes, they require panel data, which are more difficult to obtain, and are more sensitive to measurement error than anonymous GICs. It is possible to overcome data limitations and create approximate NAGICs using quasi-NAGICs. In quasi-NAGICs individual incomes are not followed over time. Instead, the population is divided into groups and the average income within each group is followed over time. Mobility within each group is ignored. For example, Lakner and Milanovic (2016) apply this to the global income distribution in which the identity of a particular country-decile is preserved, ignoring changes in the identity of individuals within each country-decile.

We use a similar approach by dividing workers into industry sectors. This is done as follows: For two points in time, A and B (say two surveys, like February and March), each sector $s = 1, 2, \ldots, S$ is characterized by the respective numbers of employed workers in the sector – n_s^A, n_s^B – and their respective average wages (hourly or weekly) – w_s^A, w_s^B. We create a panel of length $N = \sum_{i=1}^{S} \max\left\{n_i^A, n_i^B\right\}$ for the wages of the entire population of workers at times A and B. The wages of each worker are set to either w_s^X (X being the point in time and s being the industry sector of that worker) or 0, if the wages of n_s^X workers were already set to w_s^X. This allows taking into account layoffs. If in all sectors $n_s^B < n_s^A$, as expected in a major crisis, then there will be workers whose wages at time A were set to w_s^A, but at time B to 0, which represent laid-off workers.

This approximate panel now allows estimating NAGICs.[1] We will consider two cases, one which considers employees in February that may have been laid off by mid-March. The other will only include workers that stayed employed by mid-March (thus the panel will exclude workers with zero wages in March).

3 Data

Ideally, to quantify and characterize the distributional impact of the coronavirus pandemic on wages, one would have to compare wages of employees just before its outbreak, to their wages at a later time. Yet, large-scale real-time tracking of individual wages is practically impossible. Administrative data cannot be used in real-time. Surveys such as the Current Population Survey (CPS) only report earnings data in a quarterly or annual basis. Several ad-hoc surveys exist, in the US (Adams-Prassl et al., 2020; Bartik et al., 2020a) and elsewhere (Adams-Prassl et al., 2020), but their scale is limited, and their focus is on employment rather than on wages.

We use wage and employment data from the establishment survey published monthly by the BLS (Bureau of Labor Statistics, 2020a). Each month the BLS surveys US businesses on employment, hours, and earnings of employees. The data represent about 130 million workers, excluding about 30 million government workers, agricultural workers, self-employed workers whose businesses are unincorporated, unpaid family workers, and private household workers.

The BLS data are not individual data, and are given by industry sector. Specifically, the available real-time (*i.e.* monthly) data represent 14 broad sectors: Mining and logging, Construction, Durable goods, Nondurable goods, Wholesale trade, Retail trade, Transportation and warehousing, Utilities, Information, Financial activities, Professional and business services, Education and health services, Leisure and hospitality, and Other services. We use the number of employees in each sector, and the average hourly and weekly wages in each sector. In addition, we use the CPS data for 2019

[1] Such synthetic panels will not capture some potential systematic effects. For example, if within sectors better-paid employees were more or less likely to be laid off than lower-paid employees, the analysis results would be biased. Nevertheless, the analysis provides a benchmark for the impact on wages given the specified assumptions. As more data is obtained in time, more accurate picture could be drawn. Furthermore, at this point in time, it is crucial to inform policy and the public discussion with the best possible analysis given the existing data.

to account for the share of employees in each sector by age, gender, and race (Bureau of Labor Statistics, 2020b). We therefore assume these shares remain stable by March 2020.

For clarity and simplicity, we refer by the name of the month (*e.g.* February 2020) to the data released for the specific month, although these data represent the pay period that includes the 12th of each month (usually the week that includes that day every month, see Bureau of Labor Statistics (2020a) Employment Situation Technical Note for more details). Thus, it is more accurate to treat the monthly data as representing the mid-point of each month. The February survey represents the situation just before the COVID-19 outbreak in the US. The March survey represents the initial impact of the evolving crisis.

4 Impact on wages along the wage distribution

First, we study the impact of the coronavirus pandemic outbreak on wages along the wage distribution using non-anonymous growth incidence curves. These will present the average change in wages along the distribution: for each quintile we estimate the average relative change in wages between mid-February and mid-March for individuals that occupied this quintile in mid-February, *i.e.* just before the outbreak.[2]

Specifically, since following individual wages is not possible, we construct quasi-NAGICs (see Section 2). We use the number of employees and the weekly and hourly wages of employees in 14 different industry sectors.[3] By following the number of employees in each sector over time, layoffs are taken into account, as explained in Section 2. We assume the same wage for all workers within each sector,[4] and that workers do not move between sectors during the time period in question. Specifically, we assume that laid-off employees were not re-employed in another sector. These are

[2]All the changes in wages we refer to are "democratic", *i.e.* we consider the average relative change in wages within each wage rank, rather than the change in average wage within each wage rank, which is more sensitive to the right tail of the distribution (Chenery et al., 1974; Saez and Zucman, 2019). The difference between the two can be substantial, in general. In this case, since we only consider short periods of time, in which the distribution does not change substantially, the difference between the two types of growth rate is small (see Appendix A).

[3]For non-seasonally adjusted data it is possible to use a finer division to 32 sectors. Yet, the differences between the resulting NAGICs with 14 or 32 sectors are very small (see Appendix B), and we would like to compare the non-seasonally adjusted data to the seasonally adjusted data in a consistent manner.

[4]This assumption matters greatly to the wage distribution, of course, but not to the NAGICs. NAGICs quantify the income growth of average wages, and are therefore less sensitive to the shape of the distribution within each sub-group of the population. See Appendix C for more details.

assumptions imposed by the limitations of the available data. Yet, in practice, since only short time periods are considered, they only have a small impact on the estimated NAGICs.

The procedure described results in a synthetic panel of all nonfarm private sector employees, each of which is characterized by her wages at two different points in time. The NAGICs are easily produced from these panels (Bourguignon, 2011). Fig. 1 presents NAGICs for February–March. It shows that hourly and weekly wages of lower-paid workers were hurt more than of better-paid workers. Lower-paid workers were more likely to see their wages and working hours decrease and to be laid off.

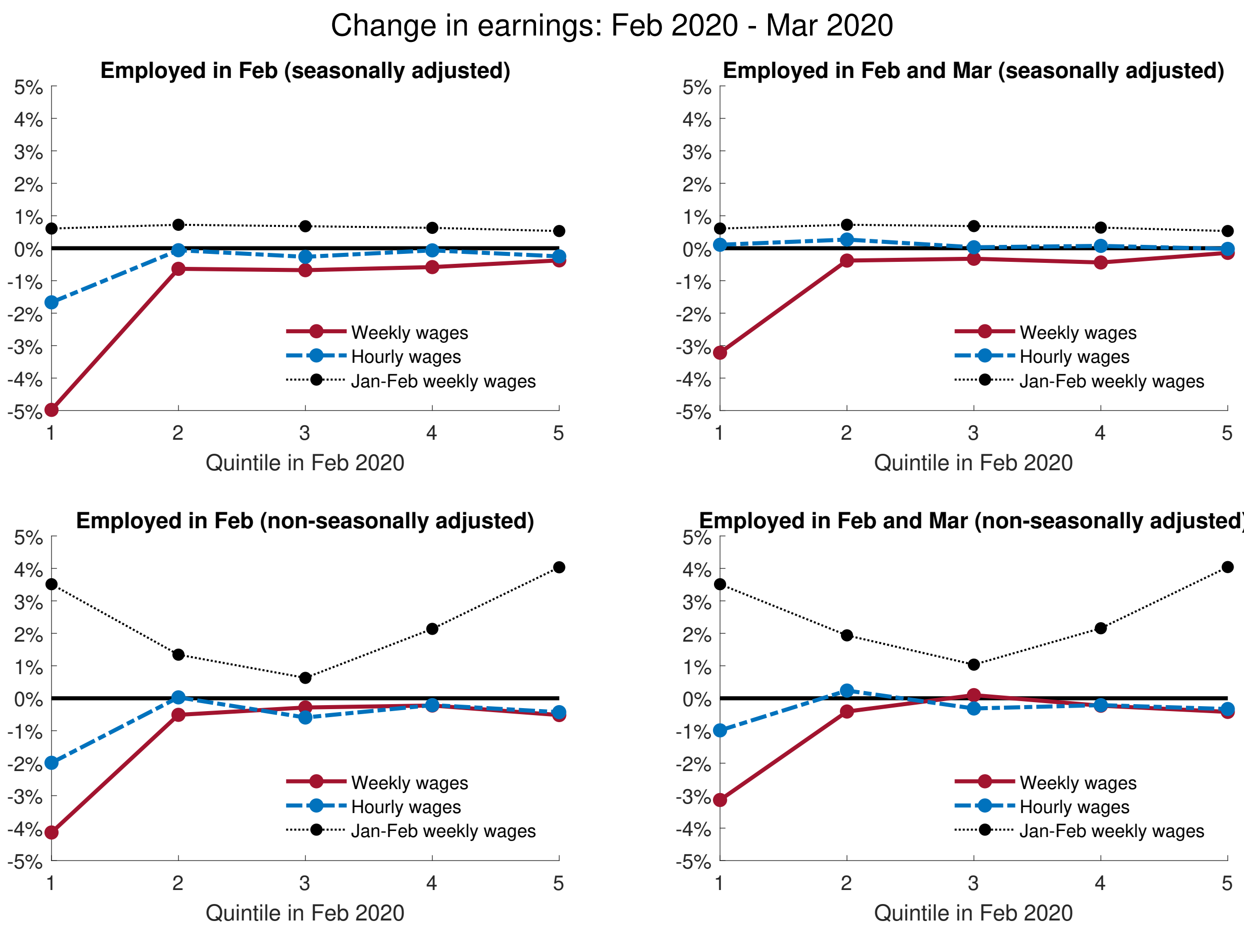

Figure 1: Non-anonymous growth incidence curves for US private sector workers between February 2020 and March 2020. Left) Conditional on being employed in February (but not necessarily in March); Right) Conditional on being employed in February and in March. For reference, the thin dotted black curves show the non-anonymous growth incidence curves for weekly wages in the period January 2020 to February 2020. The two top panels are based on seasonally adjusted data. The two bottom panels are based on non-seasonally adjusted data.

All wage ranks were negatively impacted, but to a small extent outside the bottom quintile. The

NAGICs are also quite flat above the bottom quintile. Taking the January–February NAGIC as a reference, the COVID-19 impact is even more pronounced – the typical monthly change in weekly wages tends to be positive, and rather flat. Not only that between February and March the change is lower than this reference, it is significantly below 0, and especially low for workers at the bottom quintile.

The top-right panel in Fig. 1 suggests that hourly wages did not change for workers who were still employed in March across the wage distribution. This takes into account seasonality. Non-seasonally adjusted hourly wages show a decrease of about 1% for the bottom 20% of workers. This is mainly due to a decrease in hourly wages among leisure and hospitality workers. The rest of the hourly wages NAGIC and the other NAGICs remain qualitatively unchanged if non-seasonally adjusted wages are considered. In all specifications weekly wages were down by 5%–3% on average for workers at the bottom quintile. Thus, the substantial decrease in weekly wages is a combination of fewer working hours and layoffs (inline with the findings of Bartik et al. (2020a)). By mid-March hourly wages were essentially still unaffected by the pandemic outbreak.

5 Impact on wages by age, gender, and race

When producing the NAGICs, we created synthetic panels of employees. Employees were characterized by their wages (determined by their industry sector) at two different points in time, such as mid-February and mid-March. This panel can be augmented by combining it with data on the share of workers of different genders, age groups, and races in each sector (Bureau of Labor Statistics, 2020b). This allows addressing questions of gender-, age-, and race-specific impact, *e.g.* whether wages of female workers were hurt more than males', or whether employees of a certain race were impacted more than of other races.

To explain how the panel is augmented, let us consider the case of female workers as an example. Suppose there are n_s^A employees in sector s, at time A, of which a share ρ_s are female employees, we randomly choose $\rho_s \cdot n_s^A$ employees, which then correspond to female employees in this sector. Repeating this for all sectors, we create a division of the population of employees to female and male, enabling the calculation of the average change in wages among female employees only and among male employees only. The random assignment means that each assignment will result in a slightly different average rate of change in wages. In each case we produced 1000 random assignments and consider the distribution of results to account for statistical significance. The uncertainty in these results is only due to the random assignment. It would not take into account potential biases which the data cannot account for, such as a preference to lay off women compared to men in some sectors, or vice versa. We also note that this method ignores the observation that within sectors there is a wage gap between men and women, white and non-white workers, *etc.*. Yet, the test presented in Appendix C demonstrates that taking into account a distribution of wages rather than average wages does not have a large impact on the results.

This procedure was separately performed in each case, considering female and male workers, young workers (*i.e.* workers aged 16–24) and then four different racial groups: White, Black or African American, Asian, and Hispanic or Latino. The results are presented in Fig. 2. It shows that between January 2020 and February 2020 all groups enjoyed an average increase in wages of about 0.6%. The increase was slightly milder among women and among Asian Americans, but only in about 0.04 percentage points.

Between February 2020 and March 2020 the picture is strikingly different. First, all groups suffered from an average decrease in wages of about 1.4%. However, women, Black, and particularly young workers and Hispanic workers suffered from significantly higher decreases. The decrease was slightly lower for White, although only mildly.

Focusing on workers at the bottom quintile in February, which, as Fig. 1 shows, were hurt much more than others, the picture remains largely unchanged. All subgroups suffered from large decreases to their weekly wages. Again, Hispanic workers seem to have been hit more than other groups, with an average reduction of 5.5% in their weekly wages. Weekly wages of young workers at the bottom quintile decreased by almost 6%. Unlike the picture for the entire population of workers, Asian workers in the bottom quintile experienced relatively large decrease in wages. Hourly wages show very similar patterns (see Appendix D).

The differences between racial groups reflect the composition of different industry sectors. The leisure and hospitality sector, which was hurt more than any other sector between February and March, has a large share of Hispanic workers (24%), but only a small share of Asian workers (6.9%).

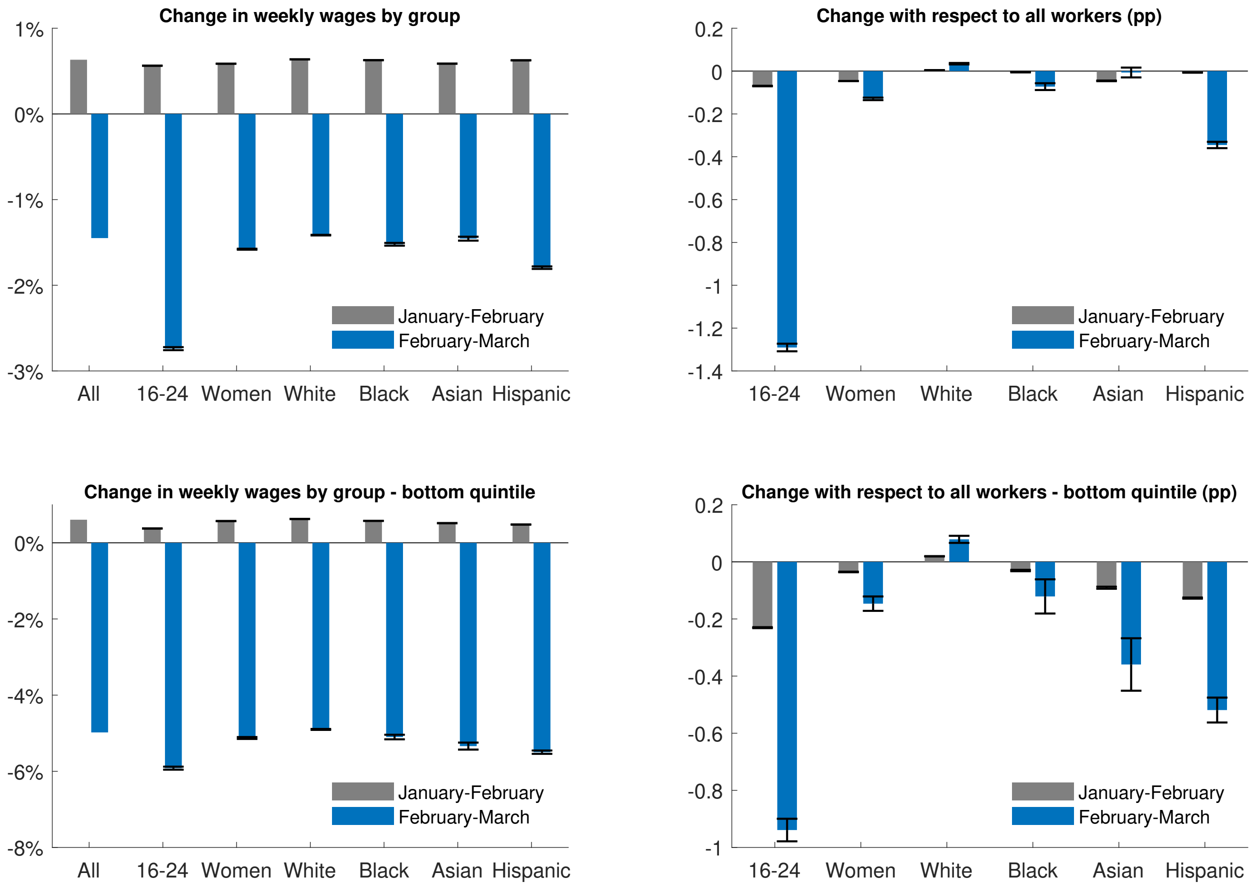

Figure 2: Average relative change in weekly wages among different groups. Top left) The average relative change in wages in each group (all workers, young workers, women, Black, Asian, and Hispanic) for the periods January 2020 – February 2020 (gray), and February 2020 – March 2020 (blue); Top right) The difference between the average relative change in wages in each group and the change among all workers (in percentage points) for the periods January 2020 – February 2020 (gray), and February 2020 – March 2020 (blue); Bottom left and right) Similar to top but within the bottom quintile of the wage distribution. The error bars represent 95% confidence bounds for the estimates produced through the random assignments, as explained above.

6 Conclusion

The outbreak of COVID-19 in the United States had a large impact on workers. Our results illustrate a major negative impact on wages by mid-March that was concentrated at the bottom quintile of workers. This impact is a combination of massive layoffs and a reduction in working hours, affecting mostly lower-paid workers.

Our analysis shows that the reduction in weekly wages following the COVID-19 outbreak was more pronounced among women than among men. Wages of female workers decreased by 0.2 percentage points more than of male workers. The decrease in weekly wages was also pronounced among young workers (aged 16–24), and Hispanic workers.

The paper documents what might be only the tip of iceberg. The mid-April data is likely to be bleak, "with many workers expecting to lose their jobs over the next months." (Adams-Prassl et al., 2020). The results call for continuous monitoring of the impact on employment and wages, which can inform policy trying to mitigate the negative impact of the lockdown on those hurt the most.

Clearly, the economy will reopen during the next few months and many people will be re-hired or employed on other businesses and sectors. Wages will clearly start increasing. Yet, it is still unclear when this will happen, and how quick, if at all, the recovery will be, especially for those hit hardest during the past couple of months.

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A Average change in wages and change of average wages

The change in wages among different groups can be quantified in various ways. The most common way is by the relative change in average wages. This is similar to how income growth is measured. A major advantage of using this measure is that it does not require information on how wages are distributed within a certain group. Only averages are needed. Another common way to quantify the change in wages is by averaging over the individual relative changes in wages. For each individual in a certain group a growth rate is estimated, and then the change in wages of that group is the average across all individual growth rates. The advantage of this approach is that it gives the same weight to each individual in the group, rather than to each dollar earned by a member of the group as in the previous approach.

The differences between two approach have been thoroughly discussed in the literature (Chenery et al., 1974; Atkinson, 1975; Adamou and Peters, 2016; Saez and Zucman, 2019). In the context of domestic product growth, the former approach is the standard way in which GDP growth is quantified. The latter is sometimes referred to as "People's growth" (Saez and Zucman, 2019). Since we aim to quantify as best as possible the experience of individual change in wages, the results in Fig. 1 and Fig. 2 are quantified using the average growth rate. However, the differences between the two approaches in the context of this analysis are very small. This is illustrated in Fig. 3. It shows the approximate NAGICs as in Fig. 1, but using the growth of average wages in each quintile rather than the average growth rate.

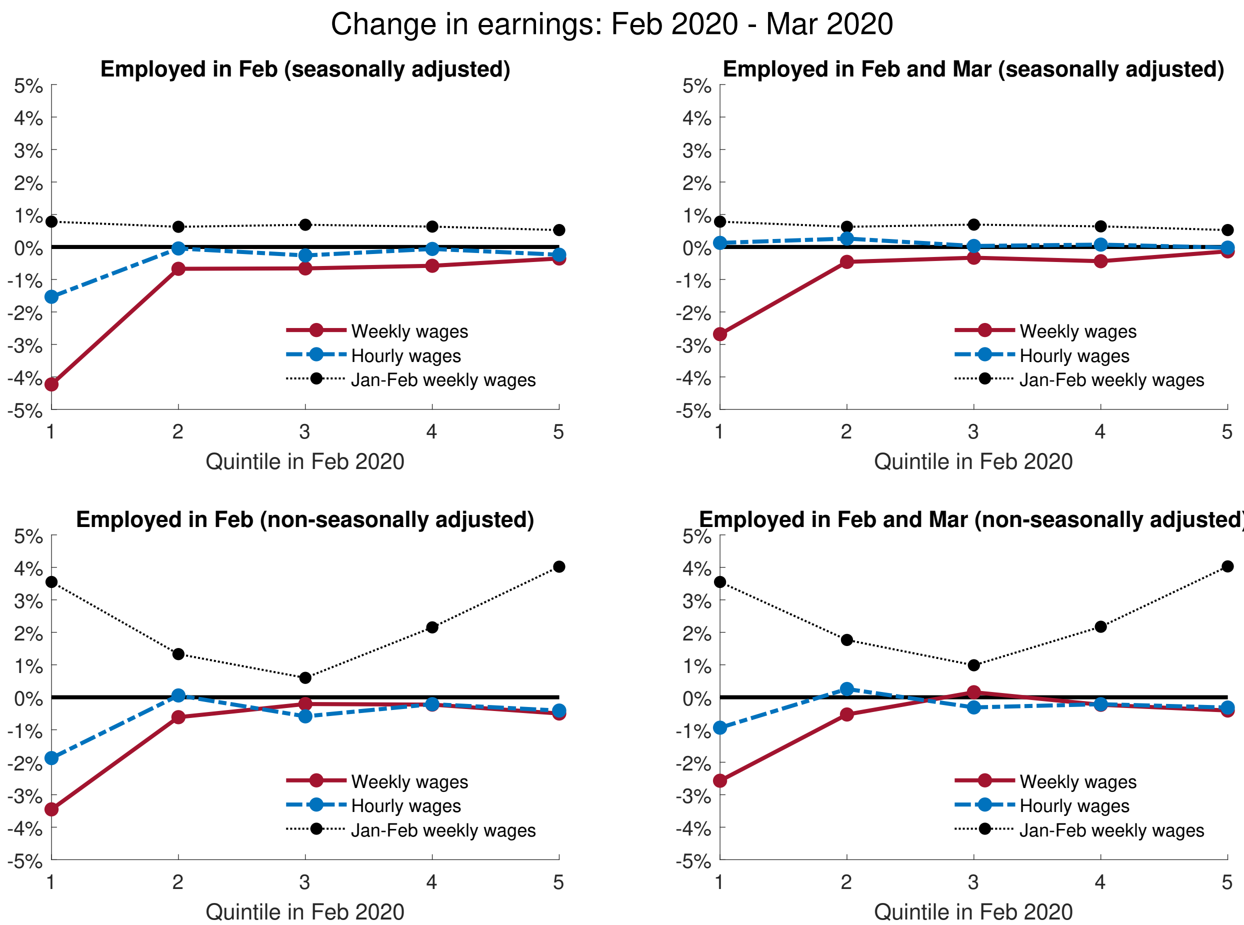

Figure 3: Non-anonymous growth incidence curves for US private sector workers between February 2020 and March 2020. Left) Conditional on being employed in February (but not necessarily in March); Right) Conditional on being employed in February and in March. For reference, the thin dotted black curves show the non-anonymous growth incidence curves for weekly wages in the period January 2020 to February 2020. The change in wages in each quintile is quantified by the relative change in average wages for each quintile, and not the average relative change in wages, used in Fig. 1.

B Sensitivity to resolution of industry sectors

The approximate NAGICs presented above rely on a division of workers into sectors. At this early stage the BLS seasonally adjusted establishment data are only available at a rather coarse resolution, and are based on 14 industry sectors: Mining and logging, Construction, Durable goods, Nondurable goods, Wholesale trade, Retail trade, Transportation and warehousing, Utilities, Information, Financial activities, Professional and business services, Education and health services, Leisure and hospitality, and Other services. The non-seasonally adjusted data are available at a slightly finer resolution, with some of the 14 sectors broken down into sub-sectors. The finer resolution allows dividing all workers into 32 sectors. Finer even finer resolution – into 185 sectors – is available for January 2020 to February.

Clearly, the finer the division into sectors, the more accurate the resulting NAGICs are, since we rely on the sector average wage being representative of the workers in this sector. Since the seasonally adjusted data provide more relevant information for the interpretation of the NAGICs, we use the division to 14 sectors as a baseline. To demonstrate that this rather coarse division does not create a large impact on the resulting NAGICs, we compare the non-seasonally adjusted NAGICs based on a division to 14 sectors to a similar analysis in which workers are divided into 32 sectors and into 185. These results are presented in Fig. 5 and in Fig. **??**. Indeed the differences between the all types of NAGICs for the three resolutions (14, 32, and 185 sectors) are small and do not change any of the main results described above.

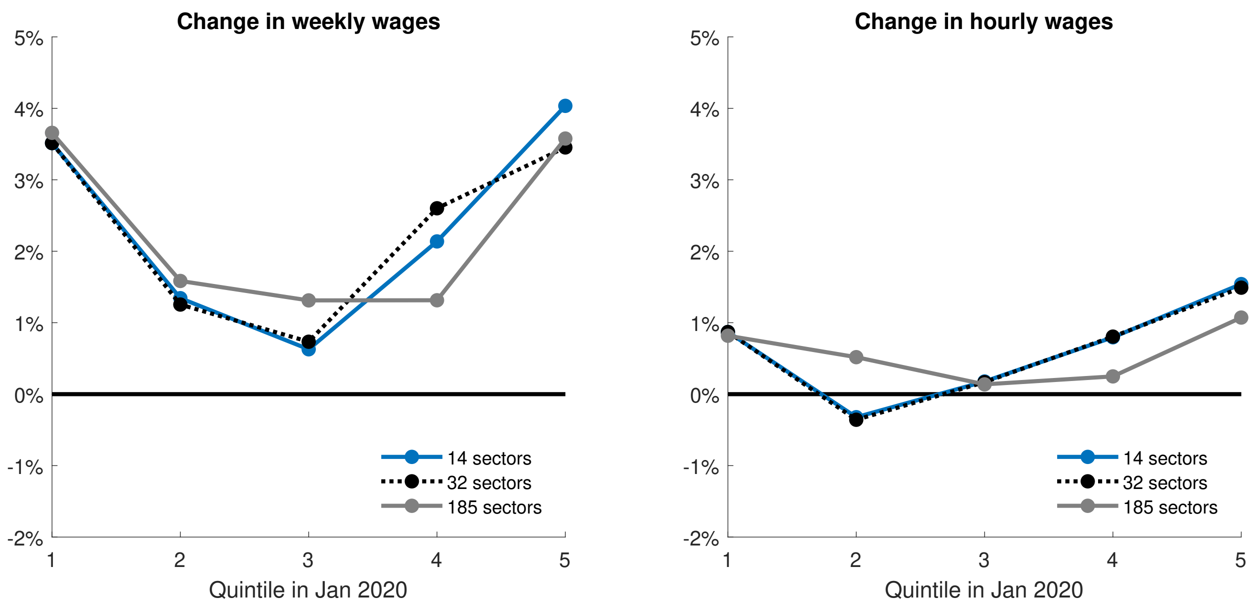

Figure 4: Non-anonymous growth incidence curves for US private sector workers between January 2020 and February 2020 by sector resolution. Left) For weekly wages, conditional on being employed in January (but not necessarily in February); Right) For hourly wages, conditional on being employed in January (but not necessarily in February). All panels are based on non-seasonally adjusted data.

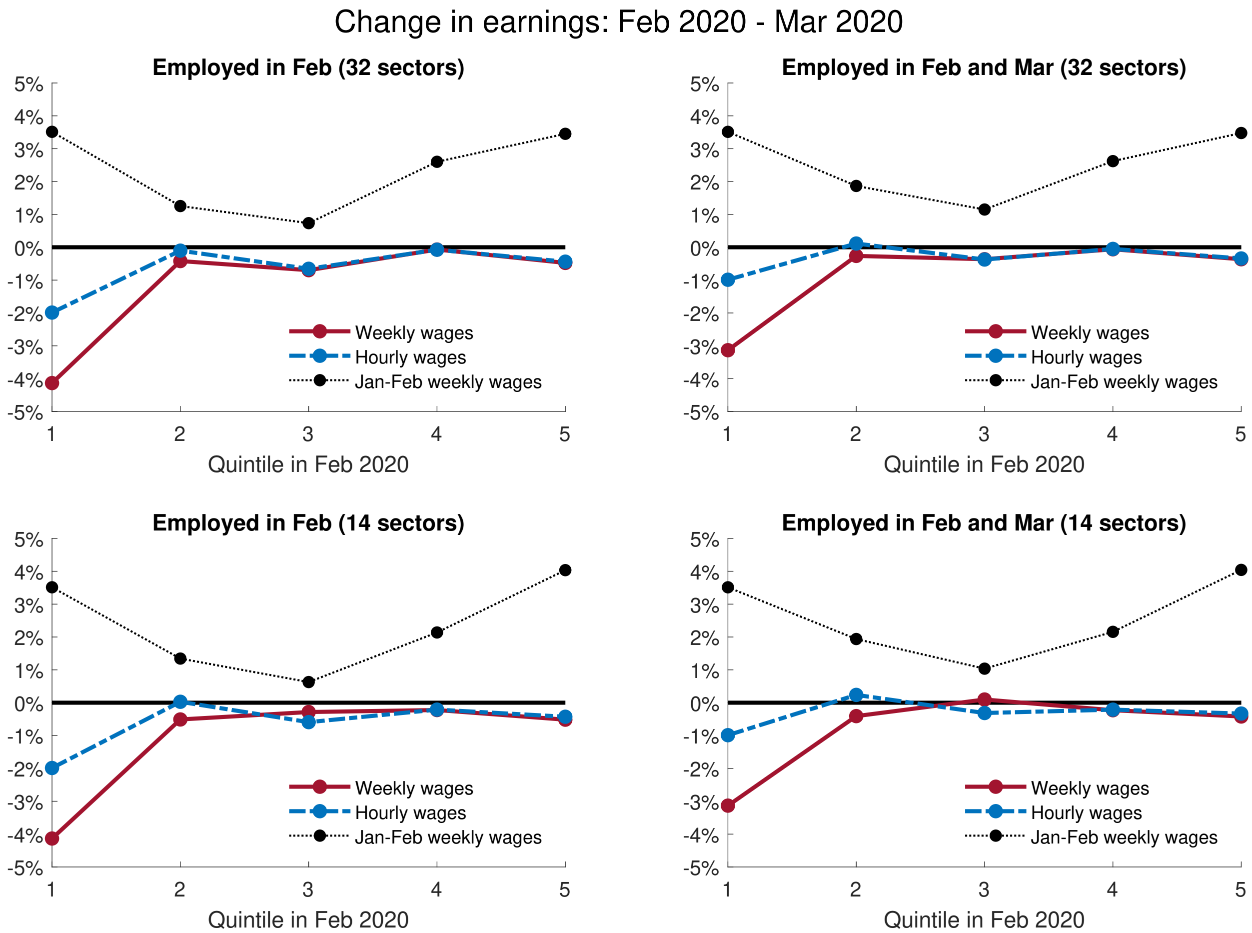

Figure 5: Non-anonymous growth incidence curves for US private sector workers between February 2020 and March 2020. Left) Conditional on being employed in February (but not necessarily in March); Right) Conditional on being employed in February and in March. For reference, the thin dotted black curves show the non-anonymous growth incidence curves for weekly wages in the period January 2020 to February 2020. All panels are based on non-seasonally adjusted data. The top panels are based on a division to 32 sectors (Mining and logging, Construction, Wood products, Nonmetallic mineral products, Primary metals, Fabricated metal products, Machinery, Computer and electronic products, Electrical equipment and appliances, Transportation equipment, Furniture and related products, Miscellaneous durable goods manufacturing, Food manufacturing, Textile mills, Textile product mills, Apparel, Paper and paper products, Printing and related support activities, Petroleum and coal products, Chemicals, Plastics and rubber products, Miscellaneous nondurable goods manufacturing, Wholesale trade, Retail trade, Transportation and warehousing, Utilities, Information, Financial activities, Professional and business services, Education and health services, Leisure and hospitality, Other services). The bottom panels are based on a division to 14 industry sectors (Mining and logging, Construction, Durable goods, Nondurable goods, Wholesale trade, Retail trade, Transportation and warehousing, Utilities, Information, Financial activities, Professional and business services, Education and health services, Leisure and hospitality, and Other services).

C The impact of using sector-average wages

The main limitation of the quasi-NAGIC approach is that the wage of each worker in the synthetic panel is taken to be the average wage in the sector to which she belongs. This is a limitation since wages differ dramatically within sectors. High-rank employees in some companies, whose wages are among the highest in the entire labor force, might be grouped together with employees that are earning the minimum wage. Nevertheless, since we are interested in average changes in wages, and not in the shape of the wage distribution, this limitation may not have a big impact on the estimated NAGICs, and the sector-average wages may still be indicative of the wages of most workers in the sector.

To test this we simulate a distribution of wages within each sector. Within each sector we assume the wage distribution is lognormal, a rather standard assumption,[5] and assume the same degree of inequality within each sector. We simulate the distribution within each sector independently in each month, so we can no longer consider the synthetic panel – the correlation between wages at the two months will no longer represent the realistic correlation, which is close to 1 (Kopczuk, Saez and Song, 2010). Thus, we use anonymous GICs. We compare the GICs produced by the panel approach, using sector-average wages, and the GICs produced when simulating a realistic wage distribution. Since each randomly-generated simulation yields a slightly different GIC, we consider the average of 1000 simulations, noting that in all cases described below the variation between GICs at different realizations was small.

Figure 6 presents the comparison considering weekly wages using the same data used for Fig. 1. It shows that for the period January–February the sector-average and the simulated anonymous GICs are indistinguishable. The differences for the period February–March are noticeable, however, they do not suggest any of the conclusions discussed above is invalid. We also note that the sensitivity of these results to the degree of inequality assumed in the simulated GICs is small within the realistic domain of Gini coefficients, between 0.3 and 0.5. While the simulated GICs may represent better reality than the sector-average based GICs, we remind the reader that the main analysis aims to provide NAGICs, which are more informative on the individual experience of wage changes than

[5] See Pinkovskiy and Sala-i-Martin (2009). Also Bénabou (2000) argued that "the lognormal is a good approximation of empirical income distributions, leads to tractable results, and allows for an unambiguous definition of inequality."

anonymous GICs.

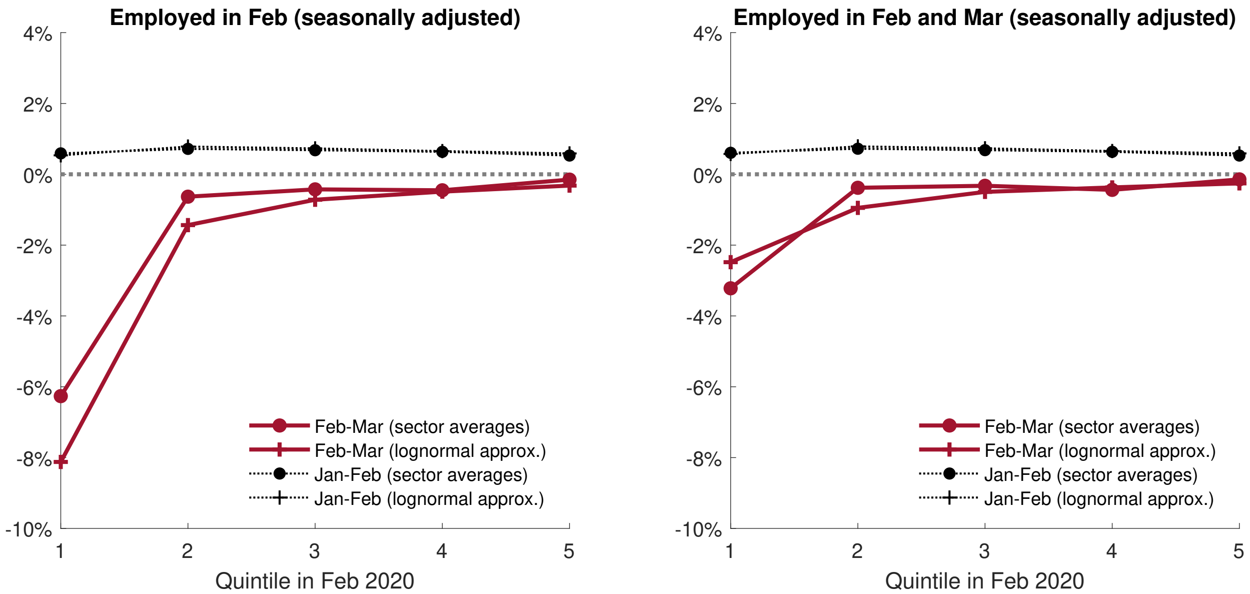

Figure 6: Anonymous growth incidence curves for US private sector workers between February 2020 and March 2020. Left) Conditional on being employed in February (but not necessarily in March); Right) Conditional on being employed in February and in March. For reference, the thin dotted black curves show the anonymous growth incidence curves for weekly wages in the period January 2020 to February 2020. The circles refer to the sector-average GICs and the crosses to the simulated GICs.

D Impact on hourly wages by age, gender, and race

Figure 7 shows the impact on hourly wages by age, gender, and race, similarly to the results shown in Fig. 2 for weekly wages. It shows a similar pattern. Between January 2020 and February 2020 all groups enjoyed an average increase in wages of about 0.25%. The increase was slightly milder among women and among young workers (aged 16–24). Between February 2020 and March 2020 all groups suffered from an average decrease in wages of about 0.5%. Once again, the reduction in wages among women, Black, and particularly young workers, and Hispanic workers was significantly higher than for other groups. The decrease was slightly lower for White workers.

Focusing on workers at the bottom quintile in February, all subgroups suffered from large decreases to their hourly wages. Hispanic and Asian workers seem to have been hit more than other groups, with an average reduction of 1.8% in their hourly wages.

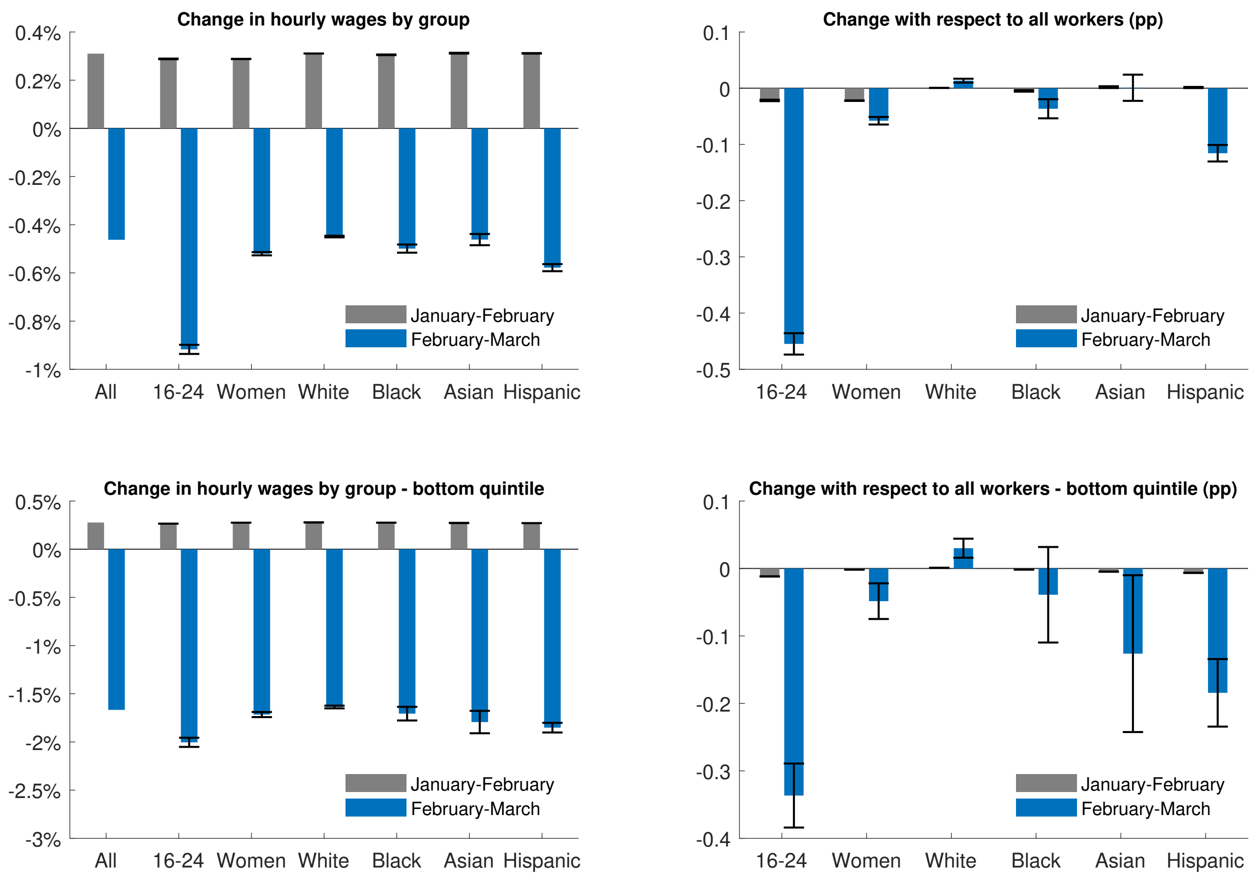

Figure 7: Average relative change in hourly wages among different groups. Top left) The average relative change in wages in each group (all workers, young workers, women, Black, Asian, and Hispanic) for the periods January 2020 – February 2020 (gray), and February 2020 – March 2020 (blue); Top right) The difference between the average relative change in wages in each group and the change among all workers (in percentage points) for the periods January 2020 – February 2020 (gray), and February 2020 – March 2020 (blue); Bottom left and right) Similar to top but within the bottom quintile of the wage distribution. The error bars represent 95% confidence bounds for the estimates produced through random assignments, as explained in Section 5.