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COVID-19 restrictions in the US: wage vulnerability by education, race and gender

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ABSTRACT

We study economic vulnerability to the stay-at-home orders and social distancing measures imposed to prevent COVID-19 contagion in the US by education, race, gender, and state. Under 2 months of lockdown plus 10 months of partial functioning we find that, without compensating policies, wage inequality and poverty would increase in the US for all social groups and states. We estimate a national potential increase in inequality of 4.1 Gini points and of 9.7 percentage points for poverty, with uneven increases by race, gender, and education. The restrictions imposed to curb the pandemic produce a double process of divergence: both inequality within and between social groups increase, with education accounting for the largest part of the rise in inequality between groups. Education level differences also impact wage poverty risk more than differences by race or gender, making the low-educated the most vulnerable group, while workers with higher education of any race and gender are less exposed. When measuring the potential percentile rank change, most women with secondary education or higher move up, while most men without higher education suffer downward mobility. Our findings can inform public policy aiming to address the disparities in vulnerability to pandemic-related shocks across different socioeconomic groups.

KEYWORDS

COVID-19; inequality; poverty; mobility; United States

JEL CLASSIFICATION

D33; I32; J31; O51.

1. Introduction


The lockdown and social distancing measures imposed by governments have been vital to control the COVID-19 pandemic around the world, save lives, and avoid the collapse of healthcare systems, but have also had dramatic economic consequences.¹ Thus, the International Monetary Fund calculates a global growth contraction of 3.5% for 2020; the drop in real GDP for advanced economies is estimated to be 4.9% (IMF 2021).

Importantly, the policies required to curb the pandemic are also likely to produce significant distributional changes (Bartik et al. 2020; Bonacini et al., 2021; Furceri et al. 2020; Palomino, Rodríguez, and Sebastian 2020; Kim et al. 2021). One central reason for this distributional impact is that stay-at-home orders and social distancing measures affect the labour

market asymmetrically. While essential occupations like health services, food industry and freight transport have functioned throughout the pandemic, activities like hospitality, accommodation and entertainment have been significantly limited or even shut down. Other activities may continue to be carried out only to the extent that they can be done from home. Employees able to continue to work maintain their earnings, while those who cannot work can only draw on their savings (if any) to get by if there are not compensatory measures by governments. This uneven impact across workers can not only produce significant changes in inequality and poverty at the national level but also affect social groups with different intensity and increase disparities among them. To evaluate these disparities, we estimate the

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¹The public health consequences of stay-at-home orders to curb the spread of COVID-19 in the US have been evaluated in Friedson et al. (2020). Qiu, Chen, and Shi (2020) show that movement restrictions and enforced social distancing did have an effect in stopping the spread of the virus in China's early wave. Comparing a set of countries with different policies, Moosa (2020) finds a relation between the timeliness and strictness of the measures and the containment of the virus spread in the early stages of the pandemic.

 Supplemental data for this article can be accessed [here](#).

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distributional effects of the stay-at-home orders and social distancing restrictions on the wage distribution in the US, and how vulnerability—in terms of wage inequality, poverty and mobility—varies by race, gender, education level and state of residence.²

We are guided by the events and measures observed in the US during the first year of the pandemic to assess the impact of the restrictions implemented to limit the spread of COVID-19. Thus, we assume two months of lockdown plus ten months of partial functioning for the closed occupations, during which they operate at different levels of their total capacity depending on the stage of the pandemic that the economy is in. This scenario is consistent both with the decisions adopted by the Federal and State governments and with the consumers' voluntary change in behaviour to prevent contagion (Goolsbee and Syverson 2021).

We assume a common scenario across states for two important reasons. First, by adopting the same scenario for all states, we can estimate how the productive structure of a given state influences the effects of the pandemic in that territory. While essential and teleworkable occupations can keep functioning during the pandemic, other activities like entertainment are significantly limited or even shut down, so the effects of COVID-19 on inequality and poverty are mainly driven by the productive structure of the territory under consideration. In fact, to better understand the link between the wage distributional changes caused by COVID-19 restrictions and the productive structure of a given economy, we concentrate on the effect of enforced and voluntary social distancing and do not consider indirect effects like shortages in supply chains and reductions in consumption due to income effects. Thus, it is the prevalence of different types of economic activities—essential, closed or teleworkable—that will determine

the potential impact of the restrictions on the labour market as a whole and on the different regions and social groups.

Second, by assuming the same lockdown and social distancing measures, we isolate our results from the economic policies implemented by each state government to cope with the pandemic. As a result, we can directly compare the bare effects of the pandemic across states prior to compensating measures and reveal the vulnerability of each social group. Thus, our results could be used as a benchmark to measure the effectiveness of the policies applied by states, by comparing the effects of the pandemic on inequality and poverty after the policy implementation with our findings. The difference would give us an estimate of the capacity that policy measures implemented by state and federal governments have had to mitigate the effects of the pandemic across different regions and social groups.

Given that the type of occupation a worker has is likely to be connected with personal characteristics like race or education, we can expect an uneven effect of the restrictions due to the pandemic on different social groups. Kim et al. (2021) already show that less-educated Asian Americans are substantially more likely to lose employment than equally educated Whites because of the lockdown (see also, Fairlie, Couch, and Xu 2020; Montenegro et al. 2020). Likewise, Bartik et al. (2020) observe that the negative economic effect of the lockdown is more conspicuous among less-educated workers than among the highly educated. We go beyond these studies to offer a systematic evaluation of the vulnerability of different groups of workers to lockdown and social distancing measures, considering four key individual characteristics: race, gender, education and state of residence. Then, we contrast the relative importance of each of the four dimensions.³

To calculate the changes in wage inequality and poverty, we need first to measure the ability of individuals to work under the pandemic. Our tool

²The effects of stay-at-home orders and social distancing policies on measures of inequality such as the Gini index have been studied for a number of European countries by Palomino, Rodríguez, and Sebastian (2020) and Almeida et al. (2020). Instead, O'Donoghue et al. (2020), Brunori et al. (2020), Li et al. (2020), and Palomino, Rodríguez, and Sebastian (Palomino, et al.,) have focused on the cases of Ireland, Italy, Australia, and Spain, respectively. As far as we are aware, this analysis has not yet been done for the US. (See Stantcheva 2021, for a review of the literature on this topic up to date).

³Note that no significant effect of the gender and race dimensions in terms of compliance with social distancing norms has been found in the US (Papageorge et al. 2021). Also, the labour market impact of the stay-at-home orders and capacity restrictions estimated here takes place at the workplace level and is not contingent of individual choices.

for this purpose is the Lockdown Working Ability (LWA) index, which incorporates the occupation's ability to work from home (Dingel and Neiman 2020) and, crucially, adjusts this for workers whose occupation is essential—they are not affected by social distancing regardless of their teleworking capacity—and for those whose occupation is closed so they are unable to work (Palomino, Rodríguez, and Sebastian 2020). We then compute the potential wage loss due to the lockdown and the de-escalation period for all workers and measure the potential changes in wage inequality and poverty in the US by race, gender, education, and state of residence.

We estimate that, based on the economy's productive structure and wage distribution, during the COVID-19 pandemic the Gini index would increase 4.1 Gini points at the national level and also increase in each and every one of the US states (ranging between 2.6 Gini points in District of Columbia and 6.6 in Nevada). When total inequality is decomposed in the within- and the between-groups components (according to individual's education, race, gender, and state), we find that the restrictions imposed to curb the spread of the pandemic would push up both within- and between-groups inequality in the US. More importantly, we find that education accounts for more than 60% of between-groups inequality and is the only social dimension whose weight in the between-groups inequality component increases during the COVID-19 pandemic.

Without compensating measures, the percentage of workers whose labour income would fall below the poverty line also rises at the national level (9.7% points) and in every one of the US states (between 4.7% points in District of Columbia and 18.7 in Nevada). By social groups, exposure to poverty increases (measured by the headcount ratio) is the highest for Asians (men and women) with secondary education or lower, while it is the lowest for Asians (men and women) and Black women with tertiary education. It seems that Asians are in fact affected as two separate groups according to their level of education (Barringer, Takeuchi, and Xenos 1990). When we approximate the relative poverty risk of a population group as the potential change in the poverty of this group relative to the change in overall poverty, we observe that Whites, Asians, women and workers with tertiary education have

a lower-than-average risk. Also, regardless of the gender and race/ethnicity considered, all groups tend to reduce their relative poverty risk as their level of education increases, and differences in relative poverty risk among sexes and races tend to disappear. In fact, differences among college graduate workers are almost inexistent. These findings apply to the US not only at the national level but also within all states. Thus, it seems that, also for poverty, the educational level is the most important of the analysed dimensions in driving the effects of COVID-19 restrictions on the wage distribution of workers.

Finally, by comparing the wage distributions before and after the stay-at-home orders and social distancing measures, we estimate wage mobility as the change in the mean percentile rank of workers from different groups. We find that, in the overall wage distribution rank, women tend to move up, especially those with secondary or higher education, while men from all races tend to move down unless they have higher education. Asians (men and women) would move up only when they are college graduates—otherwise suffer the strongest percentile decrease—while black women move up for all education levels.

For robustness, we replicate the whole analysis (see Appendix F) considering the differences in the closure policies implemented by state governments. For this task, we use the Stringency index across US states calculated by Hatibie et al. (2021) on a daily basis. This index is the arithmetic mean of nine component indicators recording information on the containment and closure policies put in place by states during the pandemic. We find that the results are similar, with just slightly larger increases in inequality and poverty.

Our findings call for public policies intending to alleviate the economic consequences of the COVID-19 restrictions to take these differential effects by social groups into account. This could contribute to maximize the effectiveness of the measures and, crucially, to address the structural vulnerability of the most affected groups in the labour market.

The three main emergency assistance programmes implemented in the US to date—the CARES Act in 27 March 2020, the Consolidated Appropriations Act in 27 December 2020, and the American Rescue Plan Act in 11 March 2021—

provided personal stimulus checks (unrelated to occupation) to all individuals and families below certain income thresholds (\$75,000 if single or married but filed taxes separately, \$112,000 if filed as head of household, and \$150,000 if married and filed a joint tax return), taking into account the number of children and dependents or disabled adults in each household. They also established an enhanced general scheme of benefits to unemployed individuals who submitted a tax return in the US until September 2021.

However, the challenges of inequality and poverty imposed by the COVID-19 pandemic need to be tackled at various levels. Support for workers in the most affected industries and occupations is critical, but our findings also call for occupational and education policies that increase the resilience of the most vulnerable groups in the labour market. If anything, our results show very clearly the extent of existing inequalities in the quality and resilience of jobs accessible to different groups. Policies that expand education and access to quality employment contribute to counteract the rise in poverty and wage inequality caused by the stay-at-home orders and social distancing conditions for the most affected groups, reducing at the same time their vulnerability against potential future economic shocks. Additionally, more equal opportunities for people with different backgrounds and in different regions will help to extend the use of new technologies to groups of disadvantaged workers who otherwise would be left behind, which can increase overall productivity (Marrero and Rodríguez 2013).

In conclusion, in addition to measuring the vulnerability and exposure of each social group to the pandemic related restrictions, and assessing the role of each social dimension (gender, education and race/ethnicity) in that vulnerability, we provide a key benchmark to assess the effect of compensating economic policies across socio-demographic groups. By comparing our labour market effect estimates with future estimates on disposable income –that include government compensating measures–, researchers and policymakers will be able to assess the extent to which counteracting policies have succeeded in cushioning poverty and inequality increases across social groups.

The rest of the paper is structured as follows. In [Section 2](#) we explain the database and its construction. The methodology to measure the ability of the US labour force to work during the pandemic, the wage loss experienced by workers, and the strategy to explore the changes in wage inequality and poverty are explained in [Section 3](#). Then, in [Section 4](#), we explore the changes in the within- and between-groups inequality components, the variations in the relative poverty risk for all social groups and states analysed, and the expected mobility of the US workers. Finally, [Section 5](#) concludes.

II. Data

For our analysis, we use the most up-to-date wave of the American Community Survey (ACS 2019, released in 2020). The 2019 ACS sample covers 5% of the US population and it is provided by IPUMS USA, the U.S. Census Data for Social, Economic, and Health Research. In addition to an exceptional coverage, this database provides rich information about personal characteristics like race and ethnicity, gender and state of residence, along with detailed socio-economic information (occupation, industry, salary, work status, and education).

The US Census Bureau categories for race/ethnicity that we use are defined in the following way: ‘White’ includes white individuals that are non-Hispanic; ‘Hispanic’ is composed by white individuals that also define themselves as from Hispanic origin; ‘Black’ is defined as black African or African American; ‘Asian’ are respondents having origins in any of the original peoples of the Far East, Southeast Asia, or the Indian subcontinent; and, finally, in ‘Other race’ we aggregate American Indian or Alaska Native, Hawaiian and other pacific Islanders, or respondents who choose to provide two or more races.

Education is classified as follows: ‘Primary Education’ includes individuals whose highest educational level is refers to nursery school, kindergarten, grades 1–11, or grade 12 with no diploma; ‘Secondary Education’ is refers to completed Secondary education and includes those with regular high school with diploma or has

fulfilled the General Education Development or alternative equivalent credential; 'Post-secondary Education' applies to those with one or more years of college but with no diploma or associate's degree; and 'Graduate Education' refers to bachelor's degree, master's degree, doctoral degree or a professional degree following one of these accreditations.⁴

To evaluate the working ability of employees during the lockdown and social distancing, we need first to identify which occupations are essential and which occupations are partially or totally closed to contain the spread of COVID-19. Based on the decisions made by the Cybersecurity and Infrastructure Security Agency (CISA) of the US about essential critical infrastructure workers, we have defined the essential and closed occupations using the occupation and industry codes of the American Community Survey (ACS). Then, following Dingel and Neiman (2020), we have estimated occupational teleworking from the American O*NET (O*NET-SOC 2010) database and then have translated it into the 2019 ACS occupational data.⁵ As a result, we have information on essentiality, closure and teleworking to be merged with the 2019 ACS sample for a matrix of 530 occupations x 271 industries (see Appendix A for detailed description of our database construction).

Our sample includes the individuals between 16 and 64 who were working in the year preceding the survey. We drop from the sample workers with zero wages, residents of institutional group quarters (prisons and psychiatric institutions), unpaid family workers, and individuals that still attend the school and work less than 20 hours per week or less than 13 weeks per year. All calculations are weighted by the Census sampling weight being the final size of our sample 1,381,501 observations.

III. Methodology

In this section we describe how we calculate the ability of individuals to work throughout the pandemic. Based on this ability and the wage

information reported at the ACS, we compute the wage loss experienced by workers and estimate the potential effects on inequality, poverty, and rank mobility in the US across states and social groups.

The ability to work during the pandemic

After identifying which occupations are essential (e) and closed (c) based on CISA, and calculating the teleworking index, we construct the Lockdown Working Ability (LWA) index (Palomino, Rodríguez, and Sebastian 2020). First, we divide the population of N workers into three groups according to the occupation o_i of each worker $i \in \{1, 2, \dots, N\}$. If the worker has an essential occupation ($o_i = e$), we compute the index as $LWA_i = E_i + (1 - E_i)T_i$, where $E_i \in (0, 1]$ is the essentiality score given to the occupation of the individual (see Table A2 in Appendix A) and $T_i \in [0, 1]$ is the value of her index of teleworking (see Table A4 in Appendix A). Note that for partially essential occupations ($0 < E_i < 1$), workers can work during lockdown only to the extent that their occupation is essential E_i and that their non-essential tasks $(1 - E_i)$ are teleworkable. If the occupation of the worker is closed ($o_i = c$), then $LWA_i = (1 - C_i)T_i$, where $C_i \in (0, 1]$ is the close score given to the closed job of the employee (see Table A3 in Appendix A). Fully closed occupations ($C_i = 1$) cannot work at all, while in partially closed occupations ($0 < C_i < 1$), the non-closed share of the occupation $(1 - C_i)$ can work to the extent that is teleworkable. Finally, if the individual has an occupation that is neither essential nor closed, the value of her LWA_i index is equal to the value of her index of teleworking, $T_i \in [0, 1]$.

The wage loss experienced during the pandemic

We calculate the wage loss (wl) experienced by every worker during the lockdown (2 months) as $wl_{it} = w_{it-1} \cdot \frac{2}{12} \cdot (1 - LWA_i)$ where w_{it-1} is the annual wage of individual i in period $t - 1$ (before the lockdown) and $\frac{2}{12}$ represents the duration of

⁴Note that our categorization of race/ethnicity is based on the ACS race categorization but detaching from the broad White race category those individuals identifying as Hispanic, and aggregating some of the original race categories as described above. Thus, it is a complete classification of the survey sample and the aggregation of the shares in our race/ethnicity variable adds up to 1.

⁵The occupation code in the 2019 ACS survey is the 2018 Census Code (ACS SOC 2018 code).

the two-month lockdown in annual terms. If an employee's workplace is closed or subject to capacity restrictions, we need to additionally consider the wage loss due to the partial functioning of her occupation for ten additional months.⁶ Following the events observed in the US we consider that the partial functioning of closed occupations evolved during the de-escalation period according to two consecutive waves. After the lockdown, the first wave of the virus decreased until its minimum in mid-September 2020. Later, the second wave began, and after reaching its maximum in mid-January 2021 it started decreasing gradually over the rest of 2021. This pattern is also consistent in a stylized way with the high-frequency data collected on consumption for closed sectors (entertainment and hospitality) reported by Chetty et al. (2020) and analysed also by Dong et al. (2021). We represent this evolution over time and formalize it mathematically in Appendix B.

For this scenario of two months of lockdown and ten months of de-escalation in two waves, the equation that we estimate is the following:

$$w_{it} = w_{it-1} \left[\frac{2}{12} \cdot (1 - LWA_i) + 1_c \cdot C_i \cdot \frac{1}{12} \cdot \left(\int_2^6 a^{m-2} dm + 0.8 \int_6^{12} b^{|10-m|} dm \right) \right] \quad (1)$$

where $1_c = \begin{cases} 1 & \text{if } o_i = c \\ 0 & \text{if } o_i \neq c \end{cases}$ and the ratio $\frac{1}{12}$ in the second summand is a normalization term to transform monthly data into annual data. The index m defines the month under consideration, and the variable a represents the exponential decrease of closure in the de-escalation between the 2nd and 6th months, counting from the onset of the lockdown, so that the functioning of closed occupations reaches 80% of full capacity (20%

closure) in the 6th month. The term b is obtained to represent a second wave with four months of exponential increase in closure (up to 80% of closure in the 10th month) and two months of exponential decrease, down to 40% of closure in the 12th month.⁷

For robustness, we replicated the analysis substituting the above-described evolution of partial functioning at the national level by the evolution of the Stringency index (Hatibie et al. 2021) in each state. This index records daily information on containment and closure policies at the state level (see Appendix F). We found that the results considering differences in containment and closure policies by states were similar to our main specification. Differences across socio-economic groups had the same pattern and overall estimated increases in inequality and poverty were comparable and only slightly higher than our main estimates (see Tables F2-F4).

Changes in inequality, poverty and expected mobility

By calculating the wage loss for all workers using the LWA, we can compute the change in our metrics of inequality and poverty comparing the wage distributions before and under the restrictions due to the pandemic.

We apply two indices of income inequality, the Gini coefficient and the MLD.⁸ The former is the most widely used inequality index in the literature, while the latter is the only additively decomposable inequality index (Bourguignon 1979; Shorrocks 1980) that has a path-independent decomposition

⁶The lockdown in the US started on March 13th, 2020 and lasted for circa two months in the majority of US States. By considering ten months for the de-escalation period, we simulate the economic consequences of the COVID-19 restrictions for a full year, which allows a year-to-year comparison of the pre- and post-pandemic wage distribution.

⁷The values of a and b to model these levels of closure are, respectively, 0.67 and 0.71 (see Appendix B).

⁸The Gini coefficient is defined as:

$$G(w) = \frac{1}{2N^2\mu} \sum_N^{i=1} \sum_N^{j=1} |w_i - w_j|,$$

where w represents the wage distribution, w_i is the salary of individual i , and μ is the mean wage of the economy. Meanwhile, the MLD is:

$$MLD(w) = \frac{1}{N} \sum_N^{i=1} \ln\left(\frac{\mu}{w_i}\right).$$

(Foster and Shneyerov 2000).⁹ This property will help us decompose overall inequality in the US into the between- and within-groups inequality components in the next section, taking into account the gender, ethno-racial, education and state dimensions when constructing the groups.

We measure changes in poverty by computing the variation in the headcount poverty index—the percentage of workers whose income falls below the poverty line—caused by the stay-at-home orders and social distancing measures. Taking advantage of the additive decomposability of the headcount ratio, we explore this question across the different socio-demographic groups.

Let $w = (w^1, \dots, w^K)$ be a partition of the wage distribution into K mutually and exclusive groups, being n_k the population size associated with the group w^k , where $n = \sum_{k=1}^K n_k$. Then, we know that the headcount ratio (H) can be written as:

$$H(z) = \sum_{k=1}^K \frac{n_k}{n} H_k(z) \quad (2)$$

where z is the relative poverty line, $\frac{n_k}{n}$ is the population share of group k , and $H_k(z)$ is the headcount ratio for group k . The ‘poverty share’—or relative contribution to overall poverty—of group k is then

$$\left[\frac{n_k}{n} H_k(z) \right] / H(z) \quad (3)$$

We can then compute the increase in the poverty of group k as

$$\Delta H_k = H_{kt} - H_{kt-1}, \quad (4)$$

where H_{kt} is the headcount ratio estimated after the pandemic restrictions and associated wage loss and H_{kt-1} is the pre-pandemic headcount ratio.

By comparing the poverty increase of a certain group k with the overall increase across the population, we can evaluate the poverty risk associated with being a member of that socio-economic group. To calculate this poverty risk (penalty or premium) for group k , we compute the change in the poverty of this group over the change in total poverty:

$$R_k = \frac{\Delta H_k}{\Delta H} \quad (5)$$

where the operator Δ indicates the change of the variable under consideration.

By setting up the change in total poverty as our reference, the measure of relative poverty risk has a straightforward interpretation. If $R_k > 1$ the increase in poverty for group k is larger than the increase in poverty for the whole population and, therefore, there is a greater risk of becoming poor after the COVID-19 pandemic restrictions for workers of this group than for the mean worker. On the contrary, if $R_k < 1$ the members of group k will have a lower probability of becoming poor than the average worker.

Finally, we focus on the relative position of workers of different socio-economic groups in the wage distribution and measure the expected rank mobility as the change in the mean percentile rank of the different social groups analysed.

By comparing the pre- and post-restrictions wage distributions, we can measure the expected rank mobility of group k as the change in its mean percentile rank:

⁹Formally, the decomposition of the MLD is the following. Let $w = (w^1, \dots, w^K)$ be a partition of the wage distribution into K groups, being n_k the population size associated with the wage distribution w^k , where $n = \sum_{k=1}^K n_k$, and μ_k the mean of w^k . After grouping workers by their socioeconomic characteristics and states, the MLD index can be exactly decomposed as

$$MLD(w) = MLD(\mu_1 1^{n_1}, \mu_2 1^{n_2}, \dots, \mu_K 1^{n_K}) + \sum_{k=1}^K \frac{n_k}{n} MLD(w^k),$$

where 1^n is a vector of ones of size n . The first component, $MLD(\mu_1 1^{n_1}, \mu_2 1^{n_2}, \dots, \mu_K 1^{n_K})$, is the between-groups inequality component which captures the level of wage inequality that would arise if each worker in a group enjoys the mean wage of the group. The second component, $\sum_{k=1}^K \frac{n_k}{n} MLD(w^k)$, is the weighted sum of wage inequalities within different groups (within-groups inequality).

Table 1. Working ability and inequality and poverty effects in the US by race, gender and education.

Race/ Ethnicity	Gender	LWA										Δ Gini (bp)										Δ MLD (bp)										Δ Headcount ratio (bp)																																																																																																																																																																																																																																																																																																																																																																																																																																																				
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Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary	Secondary Secondary	Post- Secondary	Primary

Note: All changes in the Gini coefficient, MLD index and Headcount ratio are in basic points (bp) and calculated by comparing each indicator after 2 two months of lockdown plus 10 months of partial closure with their pre-pandemic value. Bootstrapped standard errors are in parenthesis.

$$\Delta \overline{r}_k = \frac{1}{n_k} \sum_{i=1}^{n_k} [r_i(t) - r_i(t-1)] \quad (6)$$

where $r_i(t-1)$ represents the pre-pandemic percentile rank of worker i in the global wage distribution and $r_i(t)$ is the rank of that individual in the wage distribution after being imposed the restrictions to curb the propagation of the pandemic.

IV. Results

After applying our methodology to the 2019 ACS database, we present in [Table 1](#) the LWA index by social groups (see also [Table C1](#) and [Figure C1](#) in [appendix C](#) for results at the state-level). The average ability of employees to work during the pandemic varies across US states, but no particular pattern is found by geographical regions.¹⁰ However, we see clear patterns in the average LWA index for different socio-demographic groups, showing that access to jobs resilient to the pandemic shock is largely unequal. First, the relationship between the LWA index and the educational level attained by workers is positive and monotonic: the more educated the worker, the higher her capacity to work during the pandemic ([Table 1](#)). Second, women show a higher capacity to work under lockdown and social distancing than men for all races and ethnicities considered (particularly among Blacks) and for all combinations of race/ethnicity and education (except for Hispanics and ‘Other Race’ when their level of education is the lowest). Third, Asians reach both the largest and the smallest values of the LWA index, depending on their educational level: when we focus on workers with primary or no education, Asians are the ethno-racial group with occupations less able to keep their labour activity under the pandemic, while the opposite happens when we consider graduate Asians. They are, in fact, the group of workers occupationally best prepared to cope with the working restrictions of the pandemic ([Table 1](#)).

Now, if we look at the LWA index by social groups across states, the patterns are similar to those found at the national level. The monotonic positive

relationship between the average value of the LWA index and the educational level of workers is observed in all states except Idaho and Vermont. Women show – like they did at the national level – a higher LWA index than men in all states without exception. And, among ethno-racial groups, Others and Hispanics have the lowest average LWA index in most states ([Table C1](#) in [appendix C](#)).

Inequality and poverty changes

The uneven capacity to work during the pandemic that workers have will translate into an increase in our measures of inequality. In absence of any compensating measure, the Gini index increases 4.1 points at the national level, and between 2.6 points (District of Columbia) and 6.6 points (Nevada) at the state level. According to the MLD, inequality increases 10.7 points at the national level and between 7.9 points (Nebraska) and 12.9 points (Nevada) at the state level (see [Table 1](#) and [Table D1](#) in [Appendix D](#)).¹¹ By population subgroups, both the Gini coefficient and the MLD show a greater inequality increase at the groups with lower education levels, both in the overall population and within all ethno-racial groups. Considering the race and ethnicity dimension, it stands out that the increase in inequality within the white workers group is markedly lower than in the rest of the groups. Looking at the gender differences, inequality increases more among women than among men at the lower level of education overall and across all races. The opposite happens at the higher levels of education, with the subgroup of graduate women experiencing a lower increase in inequality than the subgroup of graduate men.

We then look at the potential changes on poverty that occur for the whole of the workforce and for each of the social subgroups considered after the restrictions. The percentage of workers with wages that would fall below the poverty line (60% of the median wage) rises at the national level (9.7% points) and in each and every one of the US states (between 4.7% points in District of Columbia and 18.7% points in Nevada) (see [Table 1](#) and [Table D1](#)

¹⁰Forsythe et al. (2020) also find that the initial impact of the COVID-19 pandemic on labour demand was relatively homogeneous across the U.S. states. Nonetheless, we observe that the LWA index is lower in states with a low score of essentiality and a large score of closure, such as Nevada, Florida and Hawaii, while it is higher in states with large scores of teleworking like the District of Columbia, Massachusetts and Maryland (see [Figure C1](#) and [Table C1](#) in [appendix C](#)).

¹¹Because the MLD index is more sensitive to small wages than the Gini coefficient, our results for this index can be slightly different.

in Appendix D). In general, there is a lower average increase in headcount poverty for Whites than for the other ethno-racial groups, but crossing the race and education dimensions provides a sharper picture and reveals stark differences in the vulnerability to the labour market shock. The headcount ratio would rise the most for Asians with no more than secondary education (women and men), while it would increase the least for Black women and Asians with tertiary education (women and men). It thus seems that for poverty increases, Asians are two completely different groups depending on their attained level of education (Barringer, Takeuchi, and Xenos 1990). By gender, estimated poverty increases are larger for men, especially in the Black and Hispanic racial groups. Overall and across all racial groups, higher-educated workers (graduate) are much less likely to fall into poverty than all their less educated counterparts, as we will formalize in section 4.3 using a relative poverty risk measure.

Changes in between- and within-groups inequality

The overall potential inequality increases at the national level (4.1 Gini points and 10.7 MLD points at the national level) flag the importance of

implementing economic policy actions that counteract the distributional effect of the pandemic restrictions. However, to design the most accurate policy measures it is fundamental to find insights about which are the socioeconomic characteristics underlying the observed changes.

The unique properties of the MLD index allow us to undertake this enterprise by computing the changes in the shares of inequality between and within groups (Bourguignon 1979; Shorrocks 1980) when considering race, gender, education and state of residence (Table 2). Thus, we observe that, pre-pandemic, differences by ethno-racial groups represent 4.1% of total inequality. When we divide the population by gender instead, between-gender inequality was 3.4% of total inequality. Analogously, the between-groups inequality component is 16.3% when splitting by levels of education and 2.0% when splitting by state. Overall, when dividing the population by finer groups considering all possible combinations of the four dimensions, 23.6% of total pre-pandemic inequality is associated with inequality between these different groups, while 76.4% occurs within them. Additionally, by applying the Shapley value (Shapley 1953) to the between-groups inequality component, one can obtain the contribution of each dimension to the between compo-

Table 2. Within- and between-groups inequality in the US.

		Original Distribution	Share (%)	After COVID-19 Distribution	Share (%)	Change	Change in share
Ineq (MLD)	Total	0.470 (0.0006)		0.576 (0.0008)		0.107 (0.0002)	
Races	Within	0.450 (0.0008)	95.9 (0.0017)	0.553 (0.0008)	96.0 (0.0015)	0.103 (0.0002)	0.08 (0.0005)
	Between	0.019 (0.0002)	4.1 (0.0004)	0.023 (0.0002)	4.0 (0.0004)	0.004 (0.0000)	−0.083 (0.0001)
Gender	Within	0.454 (0.0009)	96.6 (0.0020)	0.562 (0.0011)	97.6 (0.0020)	0.109 (0.0003)	0.947 (0.0004)
	Between	0.016 (0.0001)	3.4 (0.0004)	0.014 (0.0001)	2.4 (0.0003)	−0.002 (0.0000)	−0.947 (0.0001)
Education	Within	0.393 (0.0008)	83.7 (0.0017)	0.475 (0.0009)	82.5 (0.0016)	0.082 (0.0003)	−1.211 (0.0006)
	Between	0.077 (0.0004)	16.3 (0.0008)	0.101 (0.0004)	17.5 (0.0008)	0.024 (0.0001)	1.211 (0.0002)
State	Within	0.460 (0.0010)	98.0 (0.0021)	0.565 (0.0011)	98.1 (0.0019)	0.105 (0.0003)	0.058 (0.0005)
	Between	0.009 (0.0001)	2.0 (0.0003)	0.011 (0.0001)	1.9 (0.0003)	0.002 (0.0000)	−0.058 (0.0000)
All groups	Within	0.359 (0.0007)	76.4 (0.0015)	0.440 (0.0008)	76.4 (0.0014)	0.082 (0.0003)	−0.009 (0.0001)
	Between	0.111 (0.0003)	23.6 (0.0008)	0.136 (0.0004)	23.6 (0.0008)	0.025 (0.0005)	0.009 (0.0003)
Contribution to the between component (Shapley Value)	Race	0.014	12.2	0.016	11.8	0.002	−0.400
	Gender	0.018	16.7	0.017	12.7	−0.001	−4.000
	Education	0.070	63.4	0.093	68.3	0.023	4.900
	State	0.008	7.7	0.009	7.2	0.001	−0.500

Note: Bootstrapped standard errors in parenthesis.

nent (see last module of Table 2).¹² We can see that education is by far the highest contributor (63.4% of the between-group inequality), followed by race, gender and state of residence.

While the pandemic certainly increases wage inequality as measured by the MLD index from 0.47 to 0.58, the relative distribution of inequality in the between- and within-group components when considering the four factors remains unchanged: the share of the between component is still 23.6%. However, the contribution of each of the factors to between-group inequality does change, revealing that, after accounting for the effects of the pandemic, the contribution of the education factor increases (in 4.9 percentage points), explaining now even a greater share of the between component (68.3%). The contribution of race/ethnicity and state of residence decreases only slightly, while there is a significant reduction (4.0 percentage points) in the contribution of gender. In other words, the stay-at-home orders and

social distancing measures widen the average differences in wage between groups of people with different educational levels, while it decreases the average differences in wage by gender.

The relative poverty risk of being the member of a particular social group

The changes in poverty shown in Table 1 also suggest that the measures necessary to fight the COVID-19 pandemic have an asymmetric effect on the risk of becoming poor across social groups. Taking advantage of the additive decomposability of the headcount ratio, we explore here this question in detail.

We know that the pandemic increases poverty in all groups, although this increase is uneven across them (recall Section 4.1.). As a result, there is a penalty (premium) in terms of poverty for those workers with the most disadvantageous

Table 3. Relative poverty risk in the US by race, gender and education.

		Population Share	Initial Poverty	Poverty Share	Poverty Change	Relative Poverty Risk
k		n(k)/N	H(k)	[n(k)/N*H(k)]/H	$\Delta H(k)$	$\Delta H(k)/\Delta H$
Race/Ethnicity	Asian	0.063 (0.0002)	0.233 (0.0018)	0.052 (0.0004)	0.094 (0.0014)	0.971 (0.0145)
	Black	0.127 (0.0004)	0.355 (0.0016)	0.159 (0.0008)	0.106 (0.0014)	1.097 (0.0125)
	Hispanic	0.118 (0.0003)	0.352 (0.0014)	0.147 (0.0007)	0.125 (0.0010)	1.297 (0.0104)
	Other	0.087 (0.0003)	0.362 (0.0018)	0.111 (0.0007)	0.131 (0.0013)	1.353 (0.0128)
	White	0.605 (0.0005)	0.247 (0.0005)	0.530 (0.0012)	0.084 (0.0003)	0.874 (0.0030)
	Total	1.0	0.282 (0.0005)	1.000	0.096 (0.0004)	1.0
Gender	Female	0.480 (0.0004)	0.3 (0.0008)	0.584 (0.0009)	0.088 (0.0004)	0.912 (0.0043)
	Male	0.520 (0.0004)	0.226 (0.0006)	0.416 (0.0009)	0.104 (0.0004)	1.081 (0.0040)
	Total	1.0	0.282 (0.0005)	1.0	0.096 (0.0004)	1.0
Education	Primary	0.081 (0.0003)	0.488 (0.0021)	0.141 (0.0007)	0.142 (0.0014)	1.470 (0.0123)
	Secondary	0.249 (0.0005)	0.375 (0.0009)	0.332 (0.0010)	0.135 (0.0008)	1.403 (0.0061)
	Post-Secondary	0.308 (0.0005)	0.317 (0.0010)	0.346 (0.0011)	0.108 (0.0006)	1.122 (0.0056)
	Graduate	0.361 (0.0006)	0.142 (0.0005)	0.181 (0.0008)	0.049 (0.0004)	0.511 (0.0043)
	Total	1.0	0.282 (0.0005)	1.0	0.096 (0.0004)	1.0

Note: Bootstrapped standard errors in parenthesis.

¹²The Shapley value averages the effect of all possible combinations of individual characteristics by each dimension. It is the only decomposition method that solves the tension between marginality and additivity (Chantreuil and Trannoy 2013). See also, Shorrocks (2013) and Rodríguez (2004).

(advantageous) characteristics (see the methodology section). Our results are presented in Table 3 and the robustness checks by regions are shown in Table E1 and Figure E1 (see Appendix E).

First, we find that the initial poverty level (column 2 in Table 3) is a good predictor of the posterior change in poverty (column 4 in Table 3) for race (correlation: 0.87) and education (correlation: 0.96), but not for gender because female workers show greater initial poverty than their male counterparts but a lower change in poverty (correlation: -1.00). Second, the poverty shares, which can be interpreted as the contribution to the overall poverty of each group (column 3 in Table 3), are uneven and to a great extent determined by each group's population share (column 1 in Table 3). Thus, we find that 49% ($H_k = 0.488$) of workers with primary or no education are poor, while this percentage is only 14% ($H_k = 0.142$) for graduate workers (column 2 in Table 3). However, the poverty share of the former group is higher than its own population share, while the opposite happens with the poverty share of the latter group, and a similar pattern is observed for race and gender.

Third, if we use expression (3) to calculate the poverty penalty that the restrictions cause on the workers with disadvantageous characteristics, we observe that Whites and Asians have the lowest relative poverty risk ($R_k < 1$), while Blacks and above all Hispanics and other races present the highest ($R_k > 1$). By education levels, the relationship is negative and monotonic: the higher the

education level, the lower the relative poverty risk. Thus, prior to any palliating measure, to have primary or no education implies the greatest differential (in comparison with the average worker) in the probability of becoming poor after the stay-at-home orders and social distancing: 47% (relative poverty risk is 1.47). On the other hand, this differential risk is the lowest for those workers with tertiary education, being their probability of becoming poor half the one of the average worker (relative poverty risk is 0.51).

The range of the gaps in relative poverty risk found by education levels seems to indicate that education is the most important characteristic explaining the economic impact of the restrictions on poverty and having a higher educational attainment has a buffering effect on the probability of becoming poor. This is more evident when we cross the four dimensions under consideration. First, regardless of sex and race (Figure 1), and of region (Figure E1 in Appendix E), all population groups tend to reduce their relative poverty risk as their education level increases. Second, the differences in relative poverty risk among sexes and races tend to disappear at the national (Figure 1) and regional (Figure E1 in Appendix E) levels when education is higher. In fact, differences in relative poverty risk for the group of graduate workers are almost inexistent, not only for the whole of the US but also for each of the four US regions (West, Mid-West, South, and North-East).

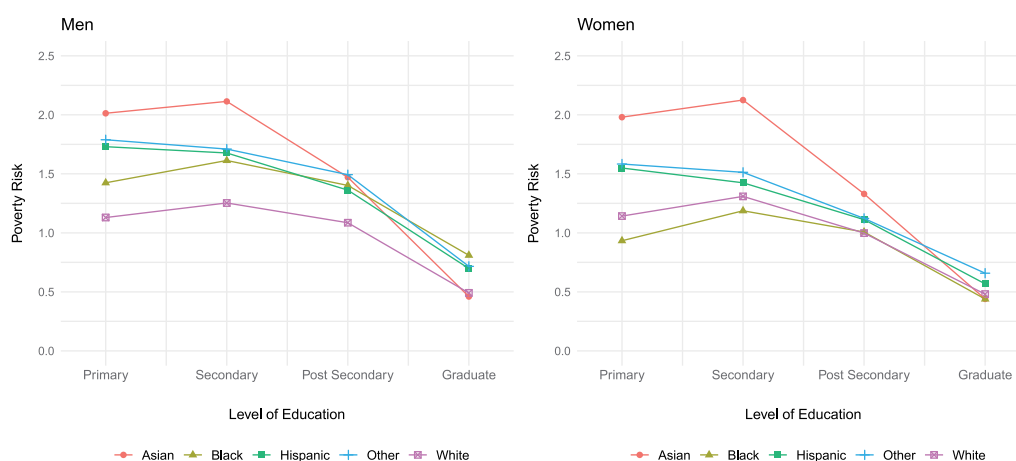


Figure 1. Relative poverty risk in the US by race, gender and education.

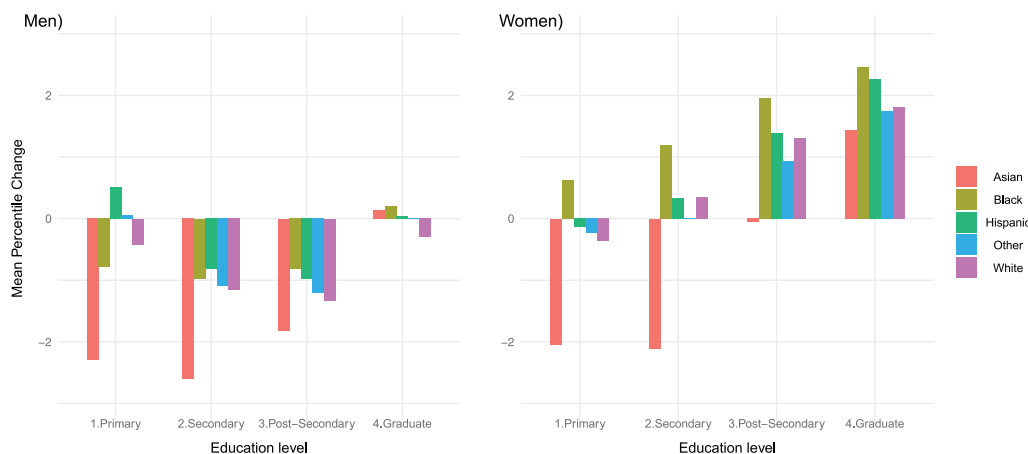


Figure 2. Ranking mobility in the US by race, gender and education.

Rank mobility in the wage distribution

The absolute changes in labour income derived of the restrictions imposed to prevent the spread of the pandemic can produce higher levels of inequality and poverty, as we have seen. Moreover, these changes in wages also alter the relative position that workers have in the wage distribution and, therefore, can prompt relative mobility. As said in Section 2, we measure mobility for each group as the average percentile (rank) shift that workers belonging to each socio-economic group endure.

The changes in rank for the different groups present quite distinct patterns (see Figure 2). We consistently find that women tend to move up in the percentile rank, especially those with higher educational levels. In fact, women for all races move up if they are in the graduate group, and women from all races, except Asian, increase their average group rank as long as they have secondary or post-secondary education. Men, on the other hand, see their mean group rank go down for all races if they are less than graduates, with the exception of Hispanic and Others with primary education, which have a slight increase. Even if they are graduates, men from all races can on average only maintain their relative status among workers. The gender

divides of the restrictions on the labour market seems to reshuffle women up in the wage rank distribution, especially educated women of any race and black women of any educational level. This at the expense of non-educated men in general and, more strongly, of Asian non-graduate men.

The fact that the occupational structure of educated women makes them have more favourable estimates of relative mobility than their male counterparts should not make us oblivious of a broader assessment of the differential gender effect of the pandemic. Even though women occupations may be on average more suited to keep functioning during pandemic restrictions, the distribution of tasks in couples within households has made women bear even a higher burden of childcare than their male counterparts (Lyttelton, Zang, and Musick 2020).¹³

V. Conclusions

This paper has presented a detailed picture of the uneven effects that the lockdown and social distancing measures implemented to prevent the propagation of the COVID-19 pandemic can produce on the wage distribution in the United States overall and, crucially, how it varies for

¹³It has also been highlighted that women's labour market participation fell sharply during the pandemic (Ewing-Nelson 2021), but a close look at both genders' participation shows that the decrease was just as steep in male workers. Thus, participation went down 2.1 p.p. for men and 1.8 p.p. for women comparing May 2021 with January 2020 and, even at the lowest point in the series (comparing April 2020 with May 2021), the decrease was 3.1 for men and 2.9 p.p. for women. See series of labour force participation at BLS from the CPS at <https://beta.bls.gov/dataViewer/view/timeseries/LNS11300025> (for men) and <https://beta.bls.gov/dataViewer/view/timeseries/LNS11300026> (for women).

different sociodemographic groups based on gender, race and ethnicity and education. Note that, because our estimates are based on the structural labour market determinants of wage changes during the pandemic (occupation, industry, wage distribution and economic restrictions), they represent a raw clear estimation of the vulnerability of each socioeconomic group to the pandemic shock, independent and prior to government compensating measures.

Our results reveal a sizable increase in wage inequality (4.1 Gini points) and poverty (9.7 percentage points) at the national level, with inequality and poverty increasing in all US states. We find that, although wages losses occur across the board, there are major disparities in the impact on workers from different sociodemographic groups, being the differences in the education level the main factor associated to between-groups inequality and to disparities in relative poverty risk. When we look at differences by gender, we find that women tend to have occupations with higher capacity to keep working under the restrictions imposed during the pandemic than men and, on average, their vulnerability to poverty increases is lower and they tend to move up in the wage distribution rank. Across races, White and Asian workers suffer on average a smaller increase in potential poverty than Hispanics, Blacks and other races.

These findings also reveal that a cross-dimensional perspective can help to better recognize the social groups most economically exposed to the stay-at-home orders and social distancing measures. We find that differences in poverty risk by race or gender converge at higher educational levels and are minimal for graduates. Additionally, differences by gender within a given race are substantial only for Blacks, where women have a significantly lower poverty risk than men at all educational levels except graduate. Finally, the Asian group presents a particularly striking divide. The small relative poverty risk for Asians as a whole masks the fact that the subgroup of less educated Asians is significantly more exposed to poverty increases and downward mobility after the restrictions than any other race with equivalent qualifications.

The contention measures taken to control the spread of the COVID-19 pandemic have saved many lives in the US and elsewhere, preventing the collapse of the healthcare system and, possibly, of the whole economy. Still, the economic impact of the stay-at-home orders and social distancing measures has been enormous and its burden unevenly distributed. Thus far, the emergency assistance programmes implemented in the US have provided generalized stimulus checks and unemployment schemes, but these benefits could be better targeted if some of the differential effects found here are considered. Thus, implemented policies may have not weighted appropriately the unequal impact across industries and occupations of the restrictions applied to curb the spread of COVID-19, which could call for longer schemes for most affected industries, where the vulnerable groups we identify here are more heavily represented. Also, the progressivity of the stimulus checks put in place may have been insufficient (for example, single individuals making less than \$75,000 receive the same payment) since we estimate large increases in wage inequality and poverty not only at the national level but also within all the states.

Our wage poverty, inequality and mobility estimates provide a useful benchmark for future research assessment of the effectiveness across social groups of these compensating policies against the pandemic economic shock, by comparing prospective disposable income metrics with our labour market structural results.

Finally, our results also pin education as a key dimension in determining the vulnerability of workers to the pandemic shock. In the long term, our results suggest that interventions expanding education and access to shock-resilient employment could be put in place, not only to palliate the differential vulnerability to poverty and wage inequality found here, but also to provide more equal opportunities for people in different regions and with different sociodemographic backgrounds.

In sum, we believe that the results found here provide a clear description of the stark disparities in vulnerability to COVID-19 restrictions of different socioeconomic and ethno-racial groups and,

importantly, can contribute to assess implemented policies aiming to counteract the negative effects of the COVID-19 restrictions across states and social groups. By identifying the most vulnerable social groups they can also inform additional compensating policies and long-term measures aimed to increase the resilience of the economy to similar shocks in the future.

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