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# COVID-19 restrictions in the US: wage vulnerability by education, race and gender[1]

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## Abstract

We study the wage 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 both wage inequality and poverty increase in the US for all social groups and states. For the whole country, we estimate an 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 spread of 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. We also find that education level differences impact wage poverty risk more than differences by race or gender, making lower-educated groups the most vulnerable while graduates of any race and gender are similarly less exposed. When measuring mobility as the 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.

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**Keywords**: COVID-19; inequality; poverty; mobility; United States.

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## 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.[2] Thus, the International Monetary Fund estimates a global growth contraction of 3.5 percent for 2020, being the drop in real GDP for the advanced economies 4.9 percent (IMF, 2021).

Importantly, the policies necessary to curb the pandemic are estimated to produce also significant distributional changes (Bartik et al., 2020; Bonacini et al., 2020, Furcery et al., 2020; Palomino et al., 2020; Kim et al., 2021). One central reason for this distributional impact is that stay-at-home orders and social distancing measures generate an asymmetric effect on the labor market. While essential occupations like health services, food industry and freight transport keep functioning during the pandemic, activities like restoration, accommodation and entertainment are significantly limited or even shut down. The rest of the activities are carried out, but only if 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 eventual savings to get by if there are not compensatory measures by governments. This uneven impact across workers can not only cause 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 distributional effects of the stay-at-home orders and social distancing restrictions on the wage distribution in the US, and the vulnerability ─in terms of wage inequality, poverty and mobility─ by race, gender, education level and state of residence.[3]

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

[2] The 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 et al. (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.

[3] The 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 et al. (2020) and Almeida et al. (2020). Instead, O'Donoghue et al. (2020), Brunori et al. (2020), and Li et al. (2020) have focused on the cases of Ireland, Italy, and Australia, 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).

their total capacity depending on the stage of the first and second waves 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 concentrate on the effect of enforced and voluntary social distancing and do not consider indirect effects like shortages in the supply chains and reductions in consumption due to income effects to understand better the link between the wage distributional changes caused by COVID-19 restrictions and the productive structure of the economy. During the pandemic, the prevalence of different types of economic activities −essential, closed or teleworkable− will determine the extent at which enforced and voluntary distancing impact in the economy as a whole and the different regions and social groups.

Given that the type of occupation a worker has is likely to be connected to some extent with personal characteristics like race or education, we can also expect an uneven effect of the restrictions due to the pandemic on different social groups. For example, Kim et al. (2021) find that less-educated Asian Americans are substantially more likely to lose employment than equally educated Whites because of the lockdown (see also, Fairlie et al., 2020, and Montenovo 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. To examine which groups of workers suffer the most from the lockdown and social distancing, we consider here four important individual characteristics: race, gender, education and state of residence. In addition, we contrast the relative importance of each of the four dimensions.[4]

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 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 distance regardless of their teleworking capacity─ and for those whose occupation is closed and are unable to work (Palomino et al., 2020). We then compute the potential wage loss due to the lockdown

[4] Note 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 labor 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.

and the de-escalation period for all workers and measure the changes in wage inequality and poverty in the US by race, gender, education and state of residence. For inequality measurement we employ the popular Gini coefficient and the Mean Logarithmic Deviation (MLD), which is the only additively decomposable inequality index (Bourguignon, 1979; Shorrocks, 1980) that has a path-independent decomposition (Foster and Shneyerov, 2000). This properties of the MLD will later help us to decompose overall inequality in the US into the between- and within-groups inequality components, both nationally and by social groups and states. 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 lockdown and social distancing.

We estimate that during the COVID-19 pandemic the Gini index increases 4.1 Gini points at the national level and 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 imply the increase of both within- and between-groups inequality in the US, although their relative contribution remains the same. More importantly, it is observed that, among the four factors under consideration, education accounts for more than 60% of the between-groups inequality component and is the only factor whose weight in the between-groups inequality component increases during the COVID-19 pandemic.

The percentage of workers whose wages are below the poverty line also rises at the national level (9.7 percent points) and in each and every one of the US states (between 4.7 percent points in District of Columbia and 18.7 in Nevada). By social groups, poverty (measured by the headcount ratio) rises the most for Asians (men and women) with secondary education or lower, while it increases the least 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 (Berringer et al., 1990). When we approximate the relative poverty risk of a population group as the 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 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 for the group of graduated workers are almost inexistent. These findings apply to the US not only at the national level but also occur within all states. Thus, it seems that, also for poverty, the educational level is the most important of the analyzed 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) move up only when they are graduated, and otherwise suffer the strongest decrease, while black women move up for all education levels.

Our findings call for public policies to alleviate the economic consequences of the restrictions imposed to curb the spread of the COVID-19 that take these differential effects 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 labor market.

The three emergency assistance programmes implemented in the US so far ─the CARES Act in March 27th 2020, the Consolidated Appropriations Act in December 27th 2020, and the American Rescue Plan Act in March 11th 2021─ have 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 have 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 labor market. If anything, our results show very clearly the extent of existing inequalities in the quality 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 goups, increasing at the same time the resilience 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).

The rest of the paper is structured as follows. In Section 2 we measure the ability of the US labor force to work during the pandemic and estimate the changes in wage inequality and poverty for the US by race, gender, education and state. The changes in the within- and between-groups inequality components for all social groups and states are obtained in Section 3. Next, the variations in the relative poverty risk and mobility of the US workers are analyzed in Sections 4 and 5, respectively. Finally, Section 6 concludes.

## 2. The ability to work under the pandemic and its effects on inequality and poverty

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) (see Appendix A).

Then, following Dingel and Neiman (2020), we have estimated occupational teleworking from the American O*NET (O*NET-SOC 2010) database and then translated it into ACS occupational data (ACS SOC 2018) which includes demographic variables like race and gender along with economic information (e.g., occupation, industry, salary, and education). The ACS sample covers 5% of the US population and for our analysis we have considered only those individuals aged 16-64 who were working in the previous year of 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 in the last year. The final size of our sample is 1,381,501 observations and we use the Census sampling weights for all our calculations.

After identifying essential ($e$) and closed ($c$) occupations, we construct the Lockdown Working Ability (LWA) index (Palomino et al., 2020). First, we divide the population of $N$ workers into three groups according to the occupation $o_i$ of each worker $i \in \{1, 2, \ldots, N\}$. 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 ($o_i = c$), $LWA_i = (1 - C_i)T_i$, 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 extend 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, $T_i \in [0,1]$.

Then, 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 the two-month lockdown in annual terms. If the job of the worker is closed, we need to consider additionally the wage loss due to the partial functioning of her occupation for ten additional months.[5] 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

[5] The lockdown in the US started on March 13th, 2020, and lasted for circa two months in the majority of the 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.

Chetty et al., (2020) and analyzed 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:

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

where $1_c = \begin{cases} 1 & if\ o_i = c \\ 0 & if\ o_i \neq c \end{cases}$ 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.[6]

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.[7] The former is the most widely used inequality index in the literature, while the latter is the only additively decomposable inequality index that has a path-independent decomposition (Foster and Shneyerov, 2000). 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, race, education and state dimensions when constructing the groups. In addition, we compute the change in the headcount poverty index driven by the stay-at-home orders and social distancing

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

[7] The Gini coefficient is defined as:

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

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

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

measures on labor market earnings. We show our main results in Table 1 (see also Table C1 and Figure C1 in appendix C).

The average ability of workers to work during the pandemic (LWA index) varies across US states, but no particular pattern is found by geographical regions.[8] Still, 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).

However, we see clear patterns in the average LWA index for different social groups, showing that the 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 (particularly among Blacks) and for all combinations of race 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 racial group with occupations less able to keep their labor 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 bear the working restrictions of the pandemic (Table 1).

Now, if we look at the LWA index by social groups across states, the patters 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. Among racial groups, Others and Hispanics have the lowest average LWA index in most states (Table C1 in appendix C).

The different capacity to work during the pandemic that workers have will translate in an increase in our measures of inequality. The Gini index increases 4.1 points at the national

[8] Forsythe et al. (2020) also find that the initial impact of the COVID-19 pandemic on labor demand was relatively homogeneous across the U.S. states.

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).[9] By population subgroups, both the Gini coefficient and the MLD show that the increase inequality is greater as we consider groups with lower education levels, and this is consistent in the overall population and also across all racial groups. When we focus on the racial dimension, it stands out that the increase in inequality within the white workers group is markedly lower than in the rest of the racial 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 experimenting a lower increase in inequality than the subgroup of graduate men.

However, more than in inequality changes within different subgroups, one would probably be more interested in the 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 percent points) and in each and every one of the US states (between 4.7 percent points in District of Columbia and 18.7 percent points in Nevada) (see Table 1 and Table D1 in Appendix D). There is a lower average increase in headcount poverty for Whites than for the other races but crossing the race and education dimensions provides a sharper picture. The headcount ratio rises the most for Asians with no more than secondary education (women and men), while it increases 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 (Berringer et al., 1990). By gender, poverty increases are larger for men, especially in the Black and Hispanic racial groups. Overall and across all racial groups, high-educated workers (graduate) are much less likely to go into poverty than all their less educated counterparts, as we will formalize in section 4 using a relative poverty risk measure.

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

## 3. Changes in between- and within-groups inequality

One of our main findings is that overall wage inequality increases in the whole US by 4.1 Gini points and 10.7 MLD points. The size of these values flags the importance of implementing economic policy measures that counteract the expected increase in inequality after the restrictions imposed to prevent the spread of the pandemic. 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).[10] Thus, we observe that in the original distribution between-races inequality represents 4.1% of total inequality, and that when we divide the population by gender instead, between gender inequality is 3.4% of total inequality. Analogously, the between 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) -which averages the effect of all possible combinations of individual characteristics- to the between-groups inequality component, one can obtain the contribution of each dimension to the between component (last module of Table 2).[11] 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.

[10] Formally, the decomposition of the MLD is the following. Let $w = (w^1, \ldots, w^K)$ 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 $\mu_k$ the mean of $w^k$. After grouping workers by their socioeconomic characteristics and states, the MLD index can be exactly decomposed as

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

where $1^n$ is a vector of ones of size $n$. The first component, $T(\mu_1 1^{n_1}, \mu_2 1^{n_2}, \ldots, \mu_K 1^{n_K})$, 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, $\sum_{k=1}^{K} \frac{n_k}{n} T(w^k)$, is the weighted sum of wage inequalities within different groups (within-groups inequality).

[11] The Shapley value decomposition is the only decomposition method that solves the tension between marginality and additivity (Chantreuil and Trannoy, 2013). See also, Shorrocks (2013) and Rodríguez (2004).

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

| | | LWA | | | | | Δ Gini | | | | | Δ MLD | | | | | Δ Headcount ratio | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Race | Gender | Education | | | | | Education | | | | | Education | | | | | Education | | | | |
| | | Primary | Secondary | Post-Secondary | Graduate | Total | Primary | Secondary | Post-Secondary | Graduate | Total | Primary | Secondary | Post-Secondary | Graduate | Total | Primary | Secondary | Post-Secondary | Graduate | Total |
| Asian | Female | 0.32 | 0.39 | 0.58 | 0.82 | 0.68 | 8.3 | 7.5 | 5.9 | 2.1 | 4.2 | 13.5 | 12.5 | 12.5 | 5.9 | 12.3 | 19.1 | 20.5 | 12.8 | 4.2 | 9.2 |
| | Male | 0.28 | 0.34 | 0.47 | 0.80 | 0.63 | 6.8 | 6.4 | 5.6 | 2.2 | 4.0 | 12.1 | 10.9 | 11.3 | 5.7 | 11.5 | 19.4 | 20.4 | 14.2 | 4.4 | 9.5 |
| | Total | 0.30 | 0.36 | 0.52 | 0.81 | 0.65 | 7.5 | 6.9 | 5.6 | 2.1 | 4.0 | 13.1 | 11.8 | 11.7 | 5.7 | 11.9 | 19.3 | 20.5 | 13.5 | 4.3 | 9.4 |
| Black | Female | 0.44 | 0.52 | 0.63 | 0.82 | 0.64 | 6.6 | 5.2 | 4.5 | 2.1 | 4.4 | 14.6 | 10.3 | 9.0 | 4.5 | 10.4 | 9.0 | 11.5 | 9.7 | 4.2 | 8.5 |
| | Male | 0.30 | 0.32 | 0.43 | 0.70 | 0.45 | 5.0 | 4.9 | 4.9 | 3.3 | 5.1 | 11.3 | 9.4 | 9.8 | 7.0 | 11.1 | 13.7 | 15.6 | 13.5 | 7.8 | 13.0 |
| | Total | 0.37 | 0.41 | 0.54 | 0.77 | 0.55 | 5.5 | 4.8 | 4.4 | 2.5 | 4.6 | 12.7 | 9.5 | 9.1 | 5.4 | 10.5 | 11.4 | 13.7 | 11.4 | 5.7 | 10.6 |
| Hispanic | Female | 0.34 | 0.45 | 0.61 | 0.78 | 0.57 | 6.3 | 6.9 | 5.2 | 2.3 | 5.7 | 9.7 | 11.9 | 10.5 | 6.0 | 12.4 | 15.0 | 13.7 | 10.7 | 5.5 | 10.9 |
| | Male | 0.35 | 0.35 | 0.46 | 0.72 | 0.44 | 3.7 | 4.8 | 4.9 | 3.2 | 4.9 | 6.1 | 8.3 | 9.8 | 7.2 | 9.8 | 16.7 | 16.2 | 13.1 | 6.7 | 13.8 |
| | Total | 0.35 | 0.40 | 0.53 | 0.75 | 0.50 | 4.8 | 5.4 | 4.7 | 2.6 | 5.0 | 8.4 | 9.9 | 9.9 | 6.4 | 10.9 | 16.1 | 15.2 | 11.9 | 6.1 | 12.5 |
| Other | Female | 0.33 | 0.44 | 0.58 | 0.77 | 0.55 | 6.1 | 6.8 | 5.7 | 2.8 | 5.9 | 9.8 | 12.2 | 11.4 | 6.8 | 13.0 | 15.3 | 14.6 | 10.8 | 6.4 | 11.4 |
| | Male | 0.34 | 0.35 | 0.44 | 0.69 | 0.43 | 4.4 | 5.2 | 5.3 | 3.4 | 5.3 | 7.1 | 9.2 | 10.1 | 7.9 | 10.5 | 17.3 | 16.5 | 14.4 | 6.9 | 14.4 |
| | Total | 0.34 | 0.39 | 0.51 | 0.73 | 0.48 | 5.1 | 5.6 | 5.2 | 3.0 | 5.4 | 8.8 | 10.4 | 10.5 | 7.2 | 11.5 | 16.6 | 15.7 | 12.6 | 6.6 | 13.1 |
| White | Female | 0.37 | 0.52 | 0.65 | 0.81 | 0.68 | 6.1 | 5.6 | 4.6 | 2.0 | 3.9 | 14.7 | 11.1 | 10.2 | 5.2 | 10.3 | 11.0 | 12.6 | 9.6 | 4.6 | 8.1 |
| | Male | 0.32 | 0.37 | 0.48 | 0.75 | 0.54 | 3.7 | 3.8 | 4.1 | 2.4 | 3.9 | 10.3 | 7.7 | 8.8 | 5.9 | 9.7 | 10.9 | 12.1 | 10.5 | 4.7 | 8.8 |
| | Total | 0.34 | 0.43 | 0.56 | 0.78 | 0.61 | 4.5 | 4.1 | 3.9 | 2.1 | 3.6 | 12.8 | 9.1 | 9.1 | 5.4 | 9.8 | 11.0 | 12.3 | 10.1 | 4.7 | 8.4 |
| Total | Female | 0.36 | 0.50 | 0.63 | 0.81 | 0.65 | 6.4 | 5.9 | 4.8 | 2.1 | 4.3 | 12.2 | 11.3 | 10.3 | 5.3 | 10.6 | 13.3 | 13.1 | 10.0 | 4.7 | 8.8 |
| | Male | 0.33 | 0.35 | 0.47 | 0.75 | 0.52 | 4.1 | 4.3 | 4.4 | 2.5 | 4.3 | 8.6 | 8.5 | 9.4 | 6.3 | 11.2 | 14.8 | 13.9 | 11.7 | 5.2 | 10.4 |
| | Total | 0.34 | 0.41 | 0.55 | 0.78 | 0.58 | 5.0 | 4.6 | 4.2 | 2.2 | 4.1 | 10.7 | 9.6 | 9.5 | 5.6 | 10.7 | 14.2 | 13.5 | 10.8 | 4.9 | 9.7 |

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

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, education is the only factor whose contribution increases (in 4.9 percentage points), explaining now even a greater share of the between component (68.3%). The contribution of race 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.

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

| | | **Original Distribution** | **Share (%)** | **After COVID-19 Distribution** | **Share (%)** | **Change** | **Change in Share** |
|---|---|---|---|---|---|---|---|
| **Inequality (MLD)** | **Total** | 0.470 | | 0.576 | | 0.107 | |
| **Race** | **Within** | 0.450 | 95.9 | 0.553 | 96.0 | 0.103 | 0.08 |
| | **Between** | 0.019 | 4.1 | 0.023 | 4.0 | 0.004 | -0.08 |
| **Gender** | **Within** | 0.454 | 96.6 | 0.562 | 97.6 | 0.109 | 0.95 |
| | **Between** | 0.016 | 3.4 | 0.014 | 2.4 | -0.002 | -0.95 |
| **Education** | **Within** | 0.393 | 83.7 | 0.475 | 82.5 | 0.082 | -1.21 |
| | **Between** | 0.077 | 16.3 | 0.101 | 17.5 | 0.024 | 1.21 |
| **State** | **Within** | 0.460 | 98.0 | 0.565 | 98.1 | 0.105 | 0.06 |
| | **Between** | 0.009 | 2.0 | 0.011 | 1.9 | 0.002 | -0.06 |
| **All groups** | **Within** | 0.359 | 76.4 | 0.440 | 76.4 | 0.082 | -0.01 |
| | **Between** | 0.111 | 23.6 | 0.136 | 23.6 | 0.025 | 0.01 |
| **Contribution to the** | **Race** | 0.014 | 12.2 | 0.016 | 11.8 | 0.002 | -0.40 |
| **between component** | **Gender** | 0.018 | 16.7 | 0.017 | 12.7 | -0.001 | -4.00 |
| **(Shapley Value)** | **Education** | 0.070 | 63.4 | 0.093 | 68.3 | 0.023 | 4.90 |
| | **State** | 0.008 | 7.7 | 0.009 | 7.2 | 0.001 | -0.50 |

## 4. 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.

Let $w = (w^1, \ldots, w^K)$ 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

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

where $z$ is the relative poverty line, $\frac{\mathrm{n_k}}{\mathrm{n}}$ is the population share of group k, and $\mathrm{H_k(z)}$ is the headcount ratio for group k. Therefore, the poverty share of group $k$ is $\left[\frac{\mathrm{n_k}}{\mathrm{n}} \mathrm{H_k(z)}\right] / \mathrm{H(z)}$.

In addition, we know that the pandemic increases poverty in all groups, although this increase is uneven across them (recall Section 2). As a result, there is a penalty (premium) in terms of poverty for those workers with the most disadvantageous (advantageous) characteristics. To calculate this penalty, we propose the relative poverty risk which for group $k$ is the change in the poverty of this group over the change in total poverty:

$$R_k = \frac{\Delta H_k}{\Delta H}, \tag{3}$$

where the operator $\Delta$ 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 $\mathrm{R_k} > 1$ the increase in poverty for group $k$ is bigger than the increase in poverty for the whole population and, therefore, there is a larger risk for the workers of this group than for the mean worker of becoming poor after the COVID-19 pandemic restrictions. On the contrary, if $\mathrm{R_k} < 1$ the members of group $k$ will have a lower probability of becoming poor than the average worker. Our results are presented in Table 3 and the robustness checks by regions are shown in Table E1 and Figure E1 (see Appendix E).

The poverty shares across groups (column 3 in Table 3) are uneven and strongly determined by their population shares (column 1 in Table 3). Thus, for example, we find (column 2 in Table 3) that 49% ($\mathrm{H_k}$ = 0.488) of workers with primary or no education are poor, while this percentage is only 14% ($\mathrm{H_k}$ = 0.142) for graduated workers. However, the poverty share of the former group ─which represents a smaller share in the population─ is lower than the poverty share of the latter, and a similar pattern is observed for race and gender. If we now focus on the initial poverty level, it is observed that this variable 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).

When 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, to have primary or no education increases the most the probability of becoming poor after the stay-at-home orders and social distancing measures (in comparison with the average worker): 47%. On the other hand, relative poverty risk is the lowest for those workers with tertiary education, being their probability of becoming poor half the one of the average worker.

**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 | $n_k/N$ | $H_k$ | $[(n_k/N)\cdot H_k]/H$ | $\Delta H_k$ | $R_k = \Delta H_k/\Delta H$ |
| Race | **Asian** | 0.063 | 0.233 | 0.052 | 0.094 | 0.971 |
| | **Black** | 0.127 | 0.355 | 0.159 | 0.106 | 1.097 |
| | **Hispanic** | 0.118 | 0.352 | 0.147 | 0.125 | 1.297 |
| | **Other** | 0.087 | 0.362 | 0.111 | 0.131 | 1.353 |
| | **White** | 0.605 | 0.247 | 0.530 | 0.084 | 0.874 |
| **Total** | | 1.000 | 0.282 | 1.000 | 0.096 | 1.000 |
| **Gender** | **Female** | 0.480 | 0.343 | 0.584 | 0.088 | 0.912 |
| | **Male** | 0.520 | 0.226 | 0.416 | 0.104 | 1.081 |
| **Total** | | 1.000 | 0.282 | 1.000 | 0.096 | 1.000 |
| **Education** | **Primary** | 0.081 | 0.488 | 0.141 | 0.142 | 1.470 |
| | **Secondary** | 0.249 | 0.375 | 0.332 | 0.135 | 1.403 |
| | **Post-Secondary** | 0.308 | 0.317 | 0.346 | 0.108 | 1.122 |
| | **Graduate** | 0.361 | 0.142 | 0.181 | 0.049 | 0.511 |
| **Total** | | 1.000 | 0.282 | 1.000 | 0.096 | 1.000 |

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 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 graduated 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).

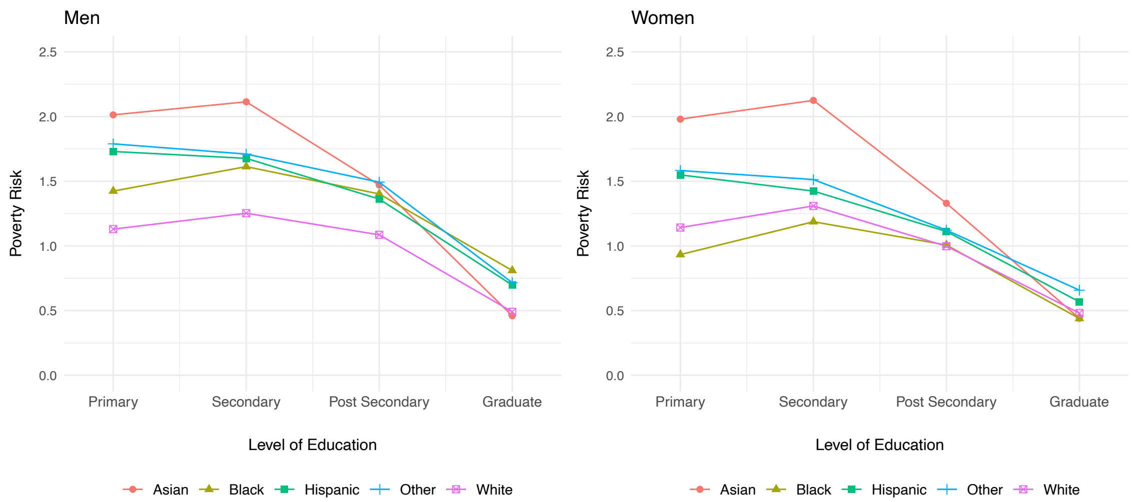
## 5. Rank mobility in the wage distribution

The absolute changes in labor income derived of the restrictions imposed to prevent the spread of the pandemic imply higher levels of inequality and poverty. However, these changes in wages also alter the relative position that workers have in the wage distribution. 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:

$$\Delta\overline{r_k} = \frac{1}{n_k}\sum_{i=1}^{n_k}[r_i(t) - r_i(t-1)], \quad (4)$$

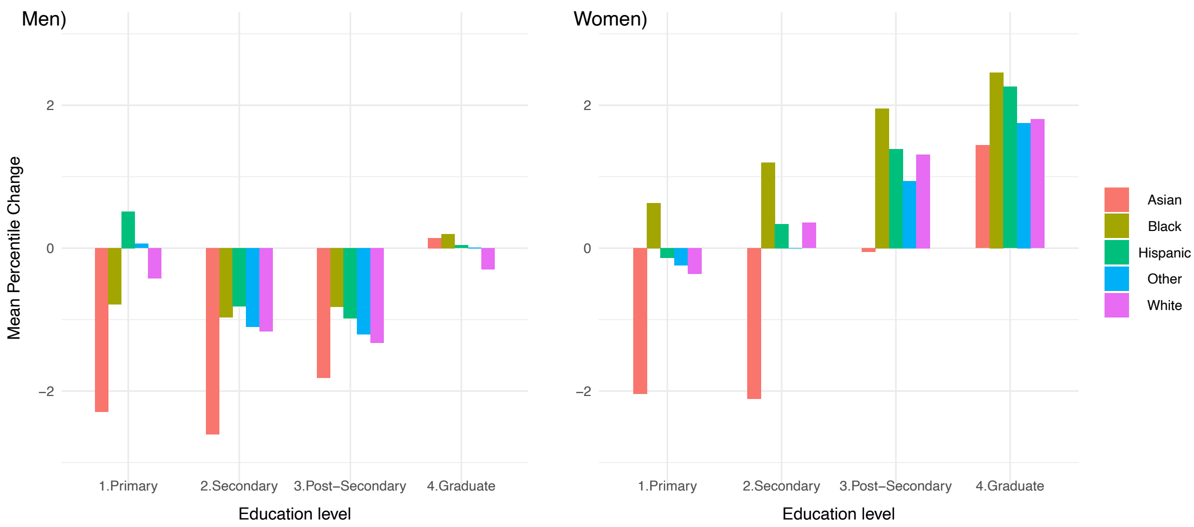
where $r_i(t-1)$ represents the pre-pandemic percentile rank of worker $i$ in the global wage distribution and $r_i(t)$ is the rank of that individual in the wage distribution after being imposed the restrictions to curb the propagation of the pandemic.

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




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, educated 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 labor 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.

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




## 6. 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 are causing on the wage distribution in the United States overall and, crucially, for different sociodemographic groups based on gender, race and education.

Our results reveal a sizeable 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 of the 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 increase in poverty 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 poverty than Hispanics, Blacks and Other races.

Our findings also reveal that a cross-dimensional perspective can help to better recognize the social groups most impacted by 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 have 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.

Finally, interventions to expand 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 can contribute to inform better targeted policies aiming to counteract the negative effects of the COVID-19 restrictions and to increase the resilience of the economy to similar shocks in the future.

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**Appendix A: The matrices of essentiality, closure and teleworking.**

Our classification of occupations and industries is based on the Cibersecurity and Infrastructure Security Agency (CISA) from the U.S. Department of Homeland Security, which during the pandemic developed a guidance of "Essential Critical Infrastructure Workforce", identifying sectors that should continue working based on its essentiality. The CISA guidance has been revised and updated during the pandemic. In our study we use the first version in order to capture the guidance issued for the initial lockdown, which we model. The guidance was not mandatory and each US state was free to use it or not. Despite that not all states have fully followed the CISA reference, we apply it generally for two main reasons. First, we want to consider the same stay-at-home orders and social distancing conditions for all states to make homogenous comparisons among them. Second, we want to isolate the economic effects of the restrictions due to the pandemic from particular decisions adopted by the state governments. In this manner, we can evaluate how the productive structure of a given state influences the economic effect of the pandemic on its levels of inequality and poverty.[12]

By applying CISA we identify which critical infrastructures (2018 Census Code and 2018 NAICS code, 4 digits) and essential workforces (2018 ACS code, 4 digits) are essential. This is a crucial point as we need to translate the CISA information into IPUMS industry and occupation codes (at the 4-digit level). CISA identifies 18 critical infrastructures and lists the number of essential workforces related to each sector. Using this information, we match each CISA category to industry (271 sectors at the 4-digit level) and occupation (530 occupations at the 4-digit level). The results are shown in Table A1 which for simplicity are presented at the 3-digit level: 21 sectors and 12 occupations. Thus, for example, the "Retail trade" industry (3-digit level) actually refers to the following industries at the 4-digit level: "Supermarkets and Grocery", "Pharmacies and Drug store", "Gasoline stations", "Florists", "Automobile dealers", "Electronic stores", "Clothing stores", "Gift, novelty, and souvenir stores" and "Jewellery, luggage, and leather goods stores".[13] Based on the CISA guidance, we first construct the matrix of essentiality (Table A2), then the matrix of closure (Table A3) and finally the matrix of teleworking (Table A4).

[12] At the early stage, Forsythe et al. (2020) find that the labor market collapsed at the same time across the U.S. irrespective of the state-level policies imposed.

[13] The disaggregated results at the 4-digit level are available in the online appendix of the paper.

The matrix of essentiality

To assign the essentiality score at the 4-digit level (271 industries and 530 occupations), we adopt the following procedure. First, if a given industry or occupation is referred by CISA, it receives a value of 1 (completely essential). For example, in the "Agriculture, Forestry, Fishing, and Hunting, and Mining" sector all industries are essential so that they receive a value of 1. Second, if CISA does not include any specific reference to a given industry or occupation but it is deduced that it is needed for the essential infrastructure, then we assign it a value of partial essentiality (the more critical is the industry or occupation, the higher the assigned value). For example, the 'florists' from the Retail Trade Industry: While CISA does not make any specific reference to them, this activity has been maintained to some extent to support hospitality and charity. Based on this criterion, we assign the following values of partial essentiality to the supportive industries and occupations: 0.8 to "Construction"; 0.7 to "Administrative and support and waste management services"; 0.5 to "Manufacturing"; and 0.2 to "Retail Trade" and "Wholesale trade". Finally, for the rest of cases, the industry or occupation is considered as non-essential and receives a value equal to 0.

In total, we find that 56 industries are completely essential, 88 industries are partially essential and the remain 127 industries are non-essential. The same assignment procedure is applied to the list of occupations. As a result, we find that 141 occupations are completely essential, 74 are partially essential and the rest (315) of occupations are non-essential.

Once we have assigned the essentiality score to each industry and occupation, we build the $M_{industries}\ x\ N_{occupations}$ matrix of essentiality. For this task we use the following mechanism:

$$E_{mn} = \begin{cases} E_m \times E_n & if\ E_m \neq 1 \\ 1 & if\ E_m = 1 \end{cases} \tag{A1}$$

According to the above expression if the essentiality of the industry is completed ($\mathrm{E_m} = 1$), the score given to the cell $m\,x\,n$ of the essentiality matrix ($E_{mn}$) is 1. However, if the essentiality of the industry is partial or null ($\mathrm{E_m} \neq 1$), the method in [A1] assigns the result of multiplying $E_m$ by $E_n$ to the cell $E_{mn}$. Hence, the industry-occupation combination is non-essential ($E_{mn} = 0$) when either the industry is not essential ($\mathrm{E_m} = 0$) or the occupation is not essential ($\mathrm{E_n} = 0$).

**Table A1:** Correspondences between CISA and industry and occupations codes.

| CISA Category | Industry | Occupation |
|---|---|---|
| CHEMICAL | Mining, Quarrying, and Oil and Gas Extraction | Construction and Extraction Occupations |
| | Manufacturing | Production Occupations |
| | Professional, Scientific, and Technical Services | Computer, Engineering, and Science Occupations |
| COMMERCIAL FACILITIES | Accommodation and Food Services | Education, Legal, Community Service, Arts, and Media Occupations |
| | | Farming, Fishing, and Forestry Occupations |
| | Arts, Entertainment, and Recreation | Sales and Related Occupations |
| | | Production Occupations |
| | Retail Trade | Service Occupations |
| COMMUNICATIONS AND INFORMATION TECHNOLOGY | Information | Installation, Maintenance, and Repair Occupations |
| | Professional, Scientific, and Technical Services | Computer, Engineering, and Science Occupations |
| CRITICAL MANUFACTURING | Mining, Quarrying, and Oil and Gas Extraction | Construction and Extraction Occupations |
| | | Transportation and Material Moving Occupations |
| | Manufacturing | |
| DEFENSE INDUSTRIAL BASE | Military | Transportation and Material Moving Occupations |
| EDUCATION | Educational Services | Education, Legal, Community Service, Arts, and Media Occupations |
| | Professional, Scientific, and Technical Services | |
| ENERGY | Mining, Quarrying, and Oil and Gas Extraction | Construction and Extraction Occupations |
| | Utilities | |
| | Wholesale Trade | Installation, Maintenance, and Repair Occupations |
| | Construction | |
| FINANCIAL SERVICES | Finance and Insurance | Management, Business, and Financial Occupations |
| | Real Estate and Rental and Leasing | |
| FOOD AND AGRICULTURE | Accommodation and Food Services | Farming, Fishing, and Forestry Occupations |
| | Agriculture, Forestry, Fishing, and Hunting | Production Occupations |
| | Professional, Scientific, and Technical Services | Sales and Related Occupations |
| | Manufacturing | |
| | Retail Trade | Service Occupations |
| | Wholesale Trade | |
| HAZARDOUS MATERIALS | Administrative and support and waste management services | Office and Administrative Support Occupations |
| | Mining, Quarrying, and Oil and Gas Extraction | Construction and Extraction Occupations |
| HEALTHCARE / PUBLIC HEALTH | Health Care and Social Assistance | Healthcare Practitioners and Technical Occupations |
| | Professional, Scientific, and Technical Services | Service Occupations |
| | Administrative and support and waste management services | Office and Administrative Support Occupations |
| HYGIENE PRODUCTS AND SERVICES | Health Care and Social Assistance | Healthcare Practitioners and Technical Occupations |
| | Retail Trade | Service Occupations |
| | | Sales and Related Occupations |

| | | |
|---|---|---|
| LAW ENFORCEMENT, PUBLIC SAFETY, AND OTHER FIRST RESPONDERS | Professional, Scientific, and Technical Services | Education, Legal, Community Service, Arts, and Media Occupations |
| | Management of companies and enterprises | Management, Business, and Financial Occupations |
| | Military | Transportation and Material Moving Occupations |
| OTHER COMMUNITY- OR GOVERNMENT-BASED OPERATIONS AND ESSENTIAL FUNCTIONS | Administrative and support and waste management services | Office and Administrative Support Occupations |
| | Management of companies and enterprises | Education, Legal, Community Service, Arts, and Media Occupations |
| | | Management, Business, and Financial Occupations |
| PUBLIC WORKS AND INFRASTRUCTURE SUPPORT SERVICES | Public Administration | Service Occupations |
| | Construction | |
| | Military | |
| RESIDENTIAL/SHELTER FACILITIES, HOUSING AND REAL ESTATE, AND RELATED SERVICES | Health Care and Social Assistance | Healthcare Practitioners and Technical Occupations |
| | Other Services, Except Public Administration | |
| | Accommodation and Food Services | Management, Business, and Financial Occupations |
| | Management of companies and enterprises | |
| TRANSPORTATION AND LOGISTICS | Transportation and Warehousing | Transportation and Material Moving Occupations |
| | Construction | |
| WATER AND WASTEWATER | Utilities | Installation, Maintenance, and Repair Occupations |
| | | Transportation and Material Moving Occupations |

By using this method, we compute the value of 143,630 cells (271 industries times 530 occupations) with the following distribution: 30.210 cells receive the highest value of essentiality; 18,920 cells receive a score of partial essentiality, and 94,500 cells represent non-essential combinations. In total, after matching the value of these cells with the ACS database, 508,148 observations have a job with some degree of essentiality, being the essentiality average 0.309.

## The matrix of closure

The matrix of closure is built following two stages. First, for any $m\ x\ n$ combination of the matrix that has a positive essentiality score ($E_{mn} > 0$), its score of closure is 0 ($C_{mn} = 0$). That is, the $m\ x\ n$ combination cannot be closed if it is considered to be part of a critical infrastructure. Second, for all non-essential $m\ x\ n$ combinations, the score of closure is 1 ($C_m = 1$) if the industry was closed during the pandemic. For example, "Arts, Entertainments and Recreation", "Accommodation and Food Services", "Wholesale trade" and "Retail Trade".[14] In sum, out of 143,630 cells, 113,150 cells are classified as non-closed activities (78.7% of the total) while 30,480 cells are considered to be closed (21.3%). In total, 271,643 observations have a job with some degree of closure, being the closure average 0.181.

<u>The matrix of teleworking</u>

Following Dingel and Neiman (2020), we estimate occupational teleworking by making use of the teleworking information acquired from some key attributes of occupations in the American O*NET database. Then, we use the latest 2019 wave of ACS (2020 release) to obtain occupational teleworking information for the US occupational categories. In total, 601,710 observations have a job that is neither essential nor closed, with an average teleworking equal to 0.430.

[14] Note that the scores in Table A3 are averages at the 3-digit level and, for this reason, there are scores of closure between 0 and 1.

**Table A2.** Matrix of essentiality.

| | Accommodation and Food Services | Administrative and support and waste management services | Agriculture, Forestry, Fishing, and Hunting | Arts, Entertainment and Recreation | Construction | Educational Services | Finance and Insurance | Health Care and Social Assistance | Information | Management of companies and enterprises | Manufacturing | Military | Mining, Quarrying, and Oil and Gas Extraction | Other Services, Except Public Administration | Professional, Scientific, and Technical Services | Public Administration | Real Estate | Retail Trade | Transportation and Warehousing | Utilities | Wholesale Trade | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Computer, Engineering, and Science Occupations** | 0.000 | 0.098 | 1.000 | 0.000 | 0.028 | 0.000 | 0.019 | 0.996 | 0.399 | 0.000 | 0.306 | 1.000 | 0.323 | 0.023 | 0.125 | 0.568 | 0.000 | 0.131 | 0.023 | 1.000 | 0.010 | 0.262 |
| **Construction and Extraction Occupations** | 0.000 | 0.508 | 1.000 | 0.000 | 0.543 | 0.000 | 0.389 | 0.997 | 0.289 | 0.000 | 0.275 | 1.000 | 0.492 | 0.032 | 0.067 | 0.656 | 0.000 | 0.058 | 0.277 | 1.000 | 0.047 | 0.517 |
| **Education, Legal, Community Service, Arts, and Media Occupations** | 0.000 | 0.251 | 1.000 | 0.000 | 0.183 | 0.000 | 0.290 | 0.636 | 0.036 | 0.000 | 0.209 | 1.000 | 0.375 | 0.003 | 0.629 | 0.678 | 0.000 | 0.086 | 0.286 | 1.000 | 0.023 | 0.185 |
| **Farming, Fishing, and Forestry Occupations** | 0.000 | 0.172 | 1.000 | 0.000 | 0.389 | 0.000 | - | 1.000 | - | 0.000 | 0.354 | - | 0.533 | 0.000 | 0.585 | 0.093 | 0.000 | 0.047 | 0.200 | 1.000 | 0.191 | 0.898 |
| **Healthcare Practitioners and Technical Occupations** | 0.000 | 0.609 | 1.000 | 0.000 | 0.800 | 0.000 | 0.496 | 0.998 | 0.074 | 0.000 | 0.776 | 1.000 | 0.800 | 0.006 | 0.855 | 0.488 | 0.000 | 0.854 | 0.500 | 1.000 | 0.123 | 0.913 |
| **Installation, Maintenance, and Repair Occupations** | 0.000 | 0.374 | 1.000 | 0.000 | 0.224 | 0.000 | 0.287 | 0.989 | 0.761 | 0.000 | 0.162 | 1.000 | 0.528 | 0.006 | 0.073 | 0.833 | 0.000 | 0.060 | 0.372 | 1.000 | 0.010 | 0.270 |
| **Management, Business, and Financial Occupations** | 0.000 | 0.101 | 1.000 | 0.000 | 0.015 | 0.000 | 0.051 | 0.940 | 0.310 | 0.000 | 0.207 | 1.000 | 0.049 | 0.050 | 0.103 | 0.696 | 0.000 | 0.125 | 0.016 | 1.000 | 0.005 | 0.214 |
| **Office and Administrative Support Occupations** | 0.000 | 0.067 | 1.000 | 0.000 | 0.002 | 0.000 | 0.077 | 0.985 | 0.304 | 0.000 | 0.126 | 1.000 | 0.003 | 0.069 | 0.308 | 0.727 | 0.000 | 0.194 | 0.097 | 1.000 | 0.001 | 0.303 |
| **Production Occupations** | 0.000 | 0.261 | 1.000 | 0.000 | 0.276 | 0.000 | 0.048 | 0.995 | 0.130 | 0.000 | 0.184 | 1.000 | 0.188 | 0.289 | 0.094 | 0.713 | 0.000 | 0.369 | 0.087 | 1.000 | 0.039 | 0.242 |
| **Sales and Related Occupations** | 0.000 | 0.047 | 1.000 | 0.000 | 0.002 | 0.000 | 0.001 | 0.980 | 0.364 | 0.000 | 0.145 | 1.000 | 0.000 | 0.157 | 0.054 | 0.696 | 0.000 | 0.206 | 0.013 | 1.000 | 0.000 | 0.142 |
| **Service Occupations** | 0.000 | 0.169 | 1.000 | 0.000 | 0.124 | 0.000 | 0.158 | 0.924 | 0.037 | 0.000 | 0.149 | 1.000 | 0.224 | 0.045 | 0.695 | 0.910 | 0.000 | 0.470 | 0.099 | 1.000 | 0.023 | 0.363 |
| **Transportation and Material Moving Occupations** | 0.000 | 0.469 | 1.000 | 0.000 | 0.297 | 0.000 | 0.099 | 0.964 | 0.213 | 0.000 | 0.083 | 1.000 | 0.236 | 0.125 | 0.086 | 0.746 | 0.000 | 0.313 | 0.164 | 1.000 | 0.029 | 0.219 |
| **Total** | 0.000 | 0.185 | 1.000 | 0.000 | 0.353 | 0.000 | 0.061 | 0.936 | 0.288 | 0.000 | 0.192 | 1.000 | 0.298 | 0.057 | 0.241 | 0.747 | 0.000 | 0.246 | 0.139 | 1.000 | 0.012 | 0.309 |

**Table A3.** Matrix of closure.

| Closure Matrix | Accommodation and Food Services | Administrative and support and waste management services | Agriculture, Forestry, Fishing, and Hunting | Arts, Entertainment, and Recreation | Construction | Educational Services | Finance and Insurance | Health Care and Social Assistance | Information | Management of companies and enterprises | Manufacturing | Military | Mining, Quarrying, and Oil and Gas Extraction | Other Services, Except Public Administration | Professional, Scientific, and Technical Services | Public Administration | Real Estate | Retail Trade | Transportation and Warehousing | Utilities | Wholesale Trade | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Computer, Engineering, and Science Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.146 | 0.000 | 0.000 | 0.000 | 0.350 | 0.463 | 0.000 | 0.487 | 0.033 |
| Construction and Extraction Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.124 | 0.000 | 0.000 | 0.000 | 0.503 | 0.156 | 0.000 | 0.369 | 0.014 |
| Education, Legal, Community Service, Arts, and Media Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.411 | 0.000 | 0.000 | 0.000 | 0.699 | 0.210 | 0.000 | 0.624 | 0.069 |
| Farming, Fishing, and Forestry Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.446 | 0.000 | 0.000 | 0.000 | 0.720 | 0.300 | 0.000 | 0.017 | 0.017 |
| Healthcare Practitioners and Technical Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.404 | 0.000 | 0.000 | 0.000 | 0.052 | 0.000 | 0.000 | 0.361 | 0.007 |
| Installation, Maintenance, and Repair Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.014 | 0.000 | 0.000 | 0.000 | 0.805 | 0.128 | 0.000 | 0.725 | 0.154 |
| Management, Business, and Financial Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.129 | 0.000 | 0.000 | 0.000 | 0.576 | 0.469 | 0.000 | 0.456 | 0.126 |
| Office and Administrative Support Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.312 | 0.000 | 0.000 | 0.000 | 0.529 | 0.306 | 0.000 | 0.501 | 0.149 |
| Production Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.029 | 0.000 | 0.000 | 0.000 | 0.470 | 0.348 | 0.000 | 0.465 | 0.059 |
| Sales and Related Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.256 | 0.000 | 0.000 | 0.000 | 0.590 | 0.433 | 0.000 | 0.476 | 0.441 |
| Service Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.868 | 0.000 | 0.000 | 0.000 | 0.392 | 0.392 | 0.000 | 0.366 | 0.424 |
| Transportation and Material Moving Occupations | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.502 | 0.000 | 0.000 | 0.000 | 0.504 | 0.172 | 0.000 | 0.339 | 0.236 |
| Total | 1.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.407 | 0.000 | 0.000 | 0.000 | 0.543 | 0.247 | 0.000 | 0.455 | 0.181 |

**Table A4.** Matrix of teleworking.

| Teleworkable Matrix | Accommodation and Food Services | Administrative and support and waste management services | Agriculture, Forestry, Fishing, and Hunting | Arts, Entertainment, and Recreation | Construction | Educational Services | Finance and Insurance | Health Care and Social Assistance | Information | Management of companies and enterprises | Manufacturing | Military | Mining, Quarrying, and Oil and Gas Extraction | Other Services, Except Public Administration | Professional, Scientific, and Technical Services | Public Administration | Real Estate | Retail Trade | Transportation and Warehousing | Utilities | Wholesale Trade | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Computer, Engineering, and Science Occupations | 0.851 | 0.830 | 0.424 | 0.746 | 0.800 | 0.871 | 0.976 | 0.905 | 0.858 | 0.877 | 0.536 | 0.751 | 0.571 | 0.796 | 0.879 | 0.729 | 0.872 | 0.902 | 0.792 | 0.584 | 0.803 | 0.783 |
| Construction and Extraction Occupations | 0.000 | 0.008 | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.019 | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.004 | 0.001 | 0.004 | 0.002 | 0.001 |
| Education, Legal, Community Service, Arts, and Media Occupations | 0.831 | 0.807 | 0.955 | 0.641 | 0.930 | 0.968 | 0.756 | 0.568 | 0.725 | 0.803 | 0.931 | 0.755 | 0.932 | 0.847 | 0.855 | 0.612 | 0.839 | 0.897 | 0.836 | 0.911 | 0.916 | 0.861 |
| Farming, Fishing, and Forestry Occupations | 0.000 | 0.000 | 0.013 | 0.017 | 0.000 | 0.011 | 0.038 | 0.000 | 0.010 | 0.059 | 0.050 | 0.084 | 0.009 | 0.000 | 0.000 | 0.009 | 0.038 | 0.001 | 0.836 | 0.911 | 0.916 | 0.013 |
| Healthcare Practitioners and Technical Occupations | 0.037 | 0.135 | 0.000 | 0.127 | 0.061 | 0.275 | 0.084 | 0.051 | 0.422 | 0.121 | 0.060 | 0.027 | 0.067 | 0.061 | 0.061 | 0.047 | 0.057 | 0.003 | 0.040 | 0.057 | 0.028 | 0.059 |
| Installation, Maintenance, and Repair Occupations | 0.042 | 0.001 | 0.000 | 0.132 | 0.000 | 0.001 | 0.000 | 0.000 | 0.001 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.002 | 0.002 | 0.030 | 0.001 | 0.000 | 0.010 | 0.007 |
| Management, Business, and Financial Occupations | 0.309 | 0.935 | 0.175 | 0.866 | 0.542 | 0.802 | 0.846 | 0.946 | 0.956 | 0.960 | 0.894 | 0.961 | 0.944 | 0.904 | 0.953 | 0.889 | 0.973 | 0.966 | 0.944 | 0.929 | 0.954 | 0.839 |
| Office and Administrative Support Occupations | 0.478 | 0.737 | 0.838 | 0.656 | 0.892 | 0.842 | 0.609 | 0.679 | 0.598 | 0.818 | 0.602 | 0.802 | 0.776 | 0.795 | 0.805 | 0.755 | 0.824 | 0.654 | 0.446 | 0.702 | 0.708 | 0.681 |
| Production Occupations | 0.002 | 0.008 | 0.000 | 0.017 | 0.011 | 0.016 | 0.020 | 0.087 | 0.106 | 0.000 | 0.010 | 0.012 | 0.001 | 0.041 | 0.023 | 0.008 | 0.012 | 0.021 | 0.008 | 0.001 | 0.014 | 0.013 |
| Sales and Related Occupations | 0.044 | 0.609 | 0.769 | 0.196 | 0.895 | 0.356 | 0.958 | 0.625 | 0.552 | 0.736 | 0.879 | 0.310 | 0.937 | 0.711 | 0.748 | 0.505 | 0.523 | 0.015 | 0.728 | 0.874 | 0.953 | 0.325 |
| Service Occupations | 0.053 | 0.122 | 0.042 | 0.189 | 0.058 | 0.211 | 0.510 | 0.114 | 0.300 | 0.180 | 0.071 | 0.092 | 0.107 | 0.113 | 0.109 | 0.048 | 0.052 | 0.090 | 0.162 | 0.205 | 0.084 | 0.100 |
| Transportation and Material Moving Occupations | 0.012 | 0.033 | 0.004 | 0.020 | 0.012 | 0.015 | 0.049 | 0.065 | 0.044 | 0.054 | 0.017 | 0.046 | 0.009 | 0.014 | 0.047 | 0.078 | 0.029 | 0.076 | 0.027 | 0.033 | 0.033 | 0.037 |
| Total | 0.012 | 0.033 | 0.004 | 0.020 | 0.012 | 0.015 | 0.049 | 0.065 | 0.044 | 0.054 | 0.017 | 0.046 | 0.009 | 0.014 | 0.047 | 0.078 | 0.029 | 0.076 | 0.027 | 0.033 | 0.033 | 0.430 |

**Appendix B: Modelling the individual capacity to work under the stay-at-home orders and social distancing measures.**

The Lockdown Working Ability (LWA) index (Palomino et al., 2020) is the following:

$$LWA_i = \begin{cases} E_i + (1 - E_i)T_i & o_i = e \\ (1 - C_i)T_i & o_i = c \\ T_i & o_i \neq e, c \end{cases},$$

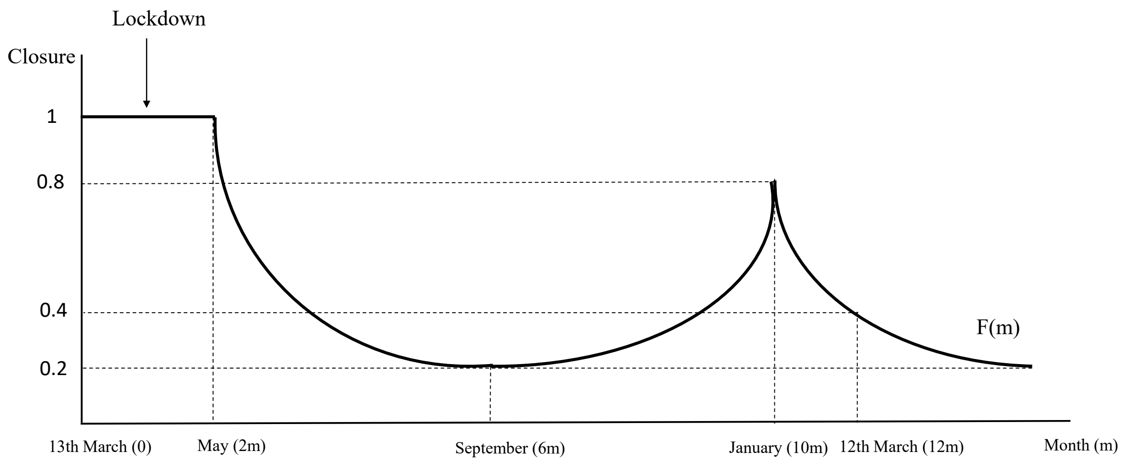
for all $i \in \{1, 2, \dots, n\}$, where $e$ and $c$ represent an occupation that is essential and closed, respectively. By using this index, we calculate the wage loss ($wl$) experienced by every individual during the lockdown:

$$wl_{it} = w_{it-1} \cdot DL \cdot (1 - LWA_i)$$

where $w_{it-1}$ is the annual wage of individual $i$ in period $t-1$ (before the stay-at-home orders) and $DL$ represents the duration of the lockdown in annual terms, i.e., $DL = \frac{2}{12}$.

However, if the individual has a closed occupation, we need to additionally consider the wage loss due to the imposed partial functioning of their occupation for ten additional months. The relevant scenario is represented in Figure B1.

**Figure B1.** The evolution of a closed occupation during the pandemic.




Formally, the evolution of the pandemic for a closed occupation can be represented by the following exponential function:

$$F(m) = \begin{cases} 1 & 0 < m \leq 2 \\ a^{m-2} & 2 < m \leq 6 \\ 0.8 \cdot b^{|10-m|} & 6 < m \leq 12 \end{cases},$$

where $m$ defines the month under consideration, $a = 0.67$ and $b = 0.71$. The values given to the variables $a$ and $b$ are those implied by the function represented in Figure B1. In this respect, note that $F(m)$ should start in 1 at the beginning of the third month (after the lockdown), and then decrease exponentially –between the 2nd and 6th month– until the functioning of closed occupations reaches 80% of full capacity (20% closure). After the sixth month, a second wave of the pandemic interrupts the economy which provokes an increasing difficulty of functioning for individuals with closed occupations. The increasing effects of the shrink in demand (caused by the fear to contagion) and the measures implemented by authorities are assumed to last for four months (at this point the partial functioning of closed occupations is only 20%, 80% closure). Later, the functioning of closed occupations recovers exponentially for at least the next two months for which the level of closure is 40%.

This evolution implies that the wage loss experienced by those individuals with a closed occupation according to the simulated scenario described in Figure B1 is:

$$wl_{it} = w_{it-1}\frac{1}{12}\int_0^{12} F(m)dm$$

where the ratio $\frac{1}{12}$ is a normalization term to transform monthly data into annual data. Now, if we decompose the wage loss in the above expression, we have:

$$wl_{it} = w_{it-1}\frac{1}{12}\left[\int_0^2 1\cdot dm + \int_2^6 a^{m-2}\,dm + \int_6^{12} 0.8\cdot b^{|10-m|}\,dm\right].$$

And solving the integrals, we arrive to the following expression:

$$wl_{it} \approx w_{it-1}\frac{1}{12}\left[2 + \frac{1}{lna}(a^4 - 1) + 0.8\cdot\frac{1}{lnb}(b^4 + b^2 - 2)\right].$$

Hence, the wage loss for each worker with a closed occupation is approximately:

$$wl_{it} \approx w_{it-1}\cdot\ 0.5745366.$$

Note that for any worker, the general formula of the wage loss is the following:

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

where $1_c = \begin{cases} 1 & if\ o_i = c \\ 0 & if\ o_i \neq c \end{cases}.$

## Appendix C: The Lockdown Working Ability (LWA) Index in the US.

In this Appendix we show the decomposition of the LWA index by levels of essentiality, closure, and teleworking across the US states. In addition, we present the values of this index by states and social groups according to people's race, gender and education.

**Figure C1.** Average essentiality, closure, teleworking and LWA index in the US by states.

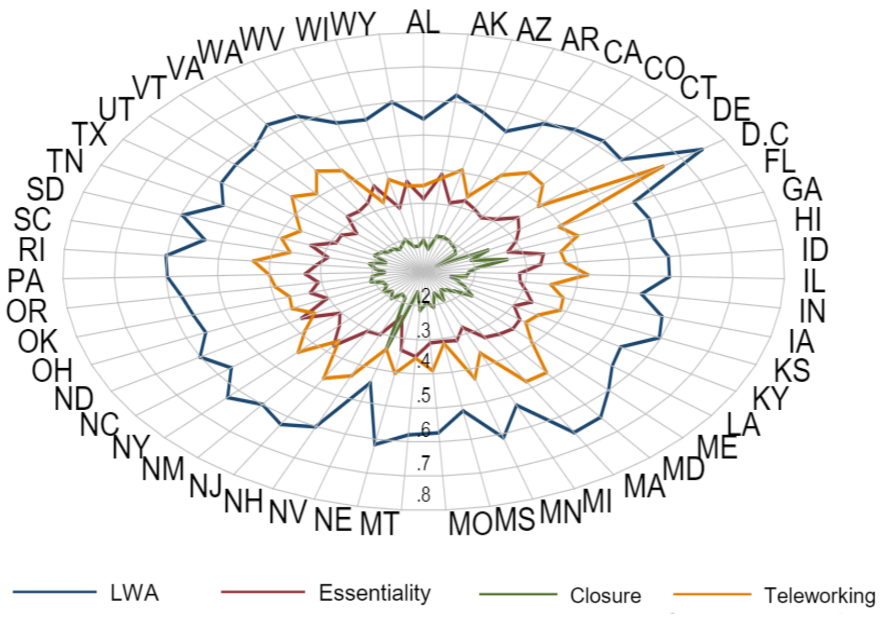


**Table C1.** The LWA index by gender, race, education and state of residence.

| State | Total | Sex | | Race | | | | | Education | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Male | Female | Asian | Black | Hispanic | Other | White | Primary | Secondary | Post-Secondary | Graduate |
| Alabama (AL) | 0.547 | 0.475 | 0.622 | 0.619 | 0.472 | 0.439 | 0.500 | 0.583 | 0.336 | 0.384 | 0.527 | 0.783 |
| Alaska (AK) | 0.620 | 0.545 | 0.712 | 0.544 | 0.836 | 0.549 | 0.525 | 0.595 | 0.357 | 0.507 | 0.638 | 0.748 |
| Arizona (AZ) | 0.579 | 0.520 | 0.646 | 0.666 | 0.585 | 0.500 | 0.512 | 0.625 | 0.344 | 0.435 | 0.573 | 0.776 |
| Arkansas (AR) | 0.540 | 0.455 | 0.629 | 0.551 | 0.520 | 0.449 | 0.421 | 0.559 | 0.386 | 0.412 | 0.539 | 0.747 |
| California (CA) | 0.591 | 0.545 | 0.645 | 0.673 | 0.599 | 0.511 | 0.491 | 0.656 | 0.378 | 0.424 | 0.551 | 0.783 |
| Colorado (CO) | 0.609 | 0.562 | 0.662 | 0.619 | 0.581 | 0.497 | 0.530 | 0.643 | 0.328 | 0.424 | 0.549 | 0.776 |
| Connecticut (CT) | 0.618 | 0.557 | 0.682 | 0.712 | 0.583 | 0.476 | 0.450 | 0.659 | 0.339 | 0.452 | 0.558 | 0.789 |
| Delaware (DE) | 0.605 | 0.530 | 0.681 | 0.722 | 0.602 | 0.526 | 0.404 | 0.620 | 0.330 | 0.474 | 0.573 | 0.785 |
| District of Columbia (D.C) | 0.748 | 0.730 | 0.765 | 0.654 | 0.550 | 0.501 | 0.485 | 0.611 | 0.327 | 0.469 | 0.580 | 0.856 |
| Florida (FL) | 0.556 | 0.494 | 0.622 | 0.596 | 0.550 | 0.505 | 0.487 | 0.588 | 0.339 | 0.414 | 0.542 | 0.746 |
| Georgia (GA) | 0.564 | 0.494 | 0.637 | 0.601 | 0.526 | 0.452 | 0.447 | 0.609 | 0.321 | 0.392 | 0.536 | 0.771 |
| Hawaii (HI) | 0.556 | 0.528 | 0.587 | 0.775 | 0.648 | 0.786 | 0.605 | 0.838 | 0.294 | 0.409 | 0.531 | 0.740 |
| Idaho (ID) | 0.577 | 0.517 | 0.647 | 0.594 | 0.720 | 0.495 | 0.496 | 0.591 | 0.431 | 0.429 | 0.553 | 0.787 |
| Illinois (IL) | 0.577 | 0.507 | 0.652 | 0.696 | 0.540 | 0.449 | 0.425 | 0.617 | 0.285 | 0.384 | 0.527 | 0.776 |
| Indiana (IN) | 0.528 | 0.444 | 0.618 | 0.592 | 0.518 | 0.423 | 0.389 | 0.540 | 0.257 | 0.364 | 0.523 | 0.771 |
| Iowa (IA) | 0.581 | 0.496 | 0.670 | 0.620 | 0.478 | 0.469 | 0.491 | 0.594 | 0.403 | 0.406 | 0.550 | 0.787 |
| Kansas (KS) | 0.596 | 0.533 | 0.666 | 0.631 | 0.483 | 0.459 | 0.487 | 0.626 | 0.371 | 0.430 | 0.572 | 0.786 |
| Kentucky (KY) | 0.542 | 0.453 | 0.633 | 0.643 | 0.456 | 0.454 | 0.406 | 0.555 | 0.301 | 0.377 | 0.541 | 0.762 |
| Louisiana (LA) | 0.559 | 0.472 | 0.648 | 0.561 | 0.518 | 0.455 | 0.522 | 0.588 | 0.360 | 0.444 | 0.544 | 0.771 |
| Maine (ME) | 0.600 | 0.524 | 0.674 | 0.485 | 0.718 | 0.526 | 0.556 | 0.602 | 0.352 | 0.461 | 0.561 | 0.779 |
| Maryland (MD) | 0.648 | 0.584 | 0.712 | 0.696 | 0.644 | 0.541 | 0.478 | 0.680 | 0.347 | 0.452 | 0.594 | 0.827 |
| Massachusetts (MA) | 0.655 | 0.596 | 0.716 | 0.714 | 0.635 | 0.523 | 0.497 | 0.679 | 0.358 | 0.461 | 0.580 | 0.808 |
| Michigan (MI) | 0.531 | 0.452 | 0.617 | 0.626 | 0.449 | 0.464 | 0.445 | 0.549 | 0.275 | 0.345 | 0.507 | 0.749 |
| Minnesota (MN) | 0.611 | 0.534 | 0.695 | 0.623 | 0.564 | 0.470 | 0.517 | 0.625 | 0.362 | 0.425 | 0.563 | 0.783 |
| Mississippi (MS) | 0.515 | 0.427 | 0.603 | 0.505 | 0.459 | 0.307 | 0.436 | 0.562 | 0.320 | 0.359 | 0.507 | 0.772 |
| Missouri (MO) | 0.574 | 0.493 | 0.658 | 0.681 | 0.548 | 0.516 | 0.475 | 0.580 | 0.319 | 0.409 | 0.547 | 0.783 |
| Montana (MT) | 0.580 | 0.530 | 0.635 | 0.840 | 0.266 | 0.601 | 0.541 | 0.583 | 0.368 | 0.437 | 0.552 | 0.749 |
| Nebraska (NE) | 0.616 | 0.539 | 0.701 | 0.643 | 0.604 | 0.484 | 0.469 | 0.637 | 0.404 | 0.462 | 0.565 | 0.799 |
| Nevada (NV) | 0.442 | 0.391 | 0.501 | 0.428 | 0.452 | 0.349 | 0.333 | 0.516 | 0.240 | 0.297 | 0.466 | 0.673 |
| New Hampshire (NH) | 0.601 | 0.523 | 0.684 | 0.585 | 0.606 | 0.540 | 0.436 | 0.608 | 0.389 | 0.414 | 0.531 | 0.796 |
| New Jersey (NJ) | 0.626 | 0.572 | 0.686 | 0.748 | 0.607 | 0.505 | 0.456 | 0.666 | 0.342 | 0.443 | 0.568 | 0.792 |
| New Mexico (NM) | 0.599 | 0.535 | 0.668 | 0.721 | 0.586 | 0.549 | 0.559 | 0.667 | 0.383 | 0.447 | 0.599 | 0.808 |
| New York (NY) | 0.630 | 0.556 | 0.706 | 0.628 | 0.642 | 0.571 | 0.525 | 0.657 | 0.411 | 0.474 | 0.584 | 0.778 |
| North Carolina (NC) | 0.568 | 0.500 | 0.638 | 0.641 | 0.512 | 0.468 | 0.432 | 0.606 | 0.320 | 0.379 | 0.537 | 0.781 |
| North Dakota (ND) | 0.601 | 0.513 | 0.700 | 0.555 | 0.504 | 0.580 | 0.507 | 0.615 | 0.398 | 0.470 | 0.540 | 0.818 |
| Ohio (OH) | 0.559 | 0.477 | 0.646 | 0.657 | 0.518 | 0.439 | 0.463 | 0.570 | 0.298 | 0.383 | 0.547 | 0.777 |
| Oklahoma (OK) | 0.565 | 0.500 | 0.636 | 0.593 | 0.581 | 0.429 | 0.521 | 0.589 | 0.310 | 0.436 | 0.571 | 0.778 |
| Oregon (OR) | 0.576 | 0.516 | 0.640 | 0.577 | 0.570 | 0.503 | 0.494 | 0.594 | 0.368 | 0.411 | 0.539 | 0.760 |
| Pennsylvania (PA) | 0.598 | 0.517 | 0.683 | 0.638 | 0.584 | 0.527 | 0.485 | 0.608 | 0.340 | 0.428 | 0.573 | 0.793 |
| Rhode Island (RI) | 0.602 | 0.516 | 0.693 | 0.684 | 0.603 | 0.507 | 0.446 | 0.627 | 0.298 | 0.446 | 0.583 | 0.776 |
| South Carolina (SC) | 0.535 | 0.456 | 0.615 | 0.467 | 0.463 | 0.438 | 0.453 | 0.576 | 0.313 | 0.363 | 0.520 | 0.753 |
| South Dakota (SD) | 0.597 | 0.514 | 0.683 | 0.452 | 0.614 | 0.505 | 0.641 | 0.598 | 0.385 | 0.442 | 0.585 | 0.774 |
| Tennessee (TN) | 0.535 | 0.451 | 0.623 | 0.588 | 0.484 | 0.414 | 0.431 | 0.556 | 0.316 | 0.364 | 0.516 | 0.754 |
| Texas (TX) | 0.570 | 0.513 | 0.637 | 0.683 | 0.557 | 0.503 | 0.479 | 0.628 | 0.332 | 0.425 | 0.553 | 0.784 |
| Utah (UT) | 0.580 | 0.544 | 0.624 | 0.613 | 0.445 | 0.424 | 0.435 | 0.615 | 0.287 | 0.429 | 0.561 | 0.767 |
| Vermont (VT) | 0.588 | 0.523 | 0.655 | 0.454 | 0.731 | 0.490 | 0.615 | 0.588 | 0.425 | 0.417 | 0.540 | 0.755 |
| Virginia (VA) | 0.626 | 0.564 | 0.691 | 0.714 | 0.574 | 0.530 | 0.486 | 0.655 | 0.315 | 0.424 | 0.570 | 0.817 |
| Washington (WA) | 0.617 | 0.574 | 0.668 | 0.551 | 0.611 | 0.598 | 0.635 | 0.626 | 0.427 | 0.437 | 0.577 | 0.788 |
| West Virginia (WV) | 0.566 | 0.480 | 0.662 | 0.619 | 0.475 | 0.662 | 0.592 | 0.568 | 0.308 | 0.447 | 0.565 | 0.797 |
| Wisconsin (WI) | 0.558 | 0.465 | 0.655 | 0.569 | 0.519 | 0.464 | 0.454 | 0.571 | 0.319 | 0.372 | 0.531 | 0.771 |
| Wyoming (WY) | 0.600 | 0.526 | 0.685 | 0.581 | 0.693 | 0.521 | 0.439 | 0.617 | 0.407 | 0.487 | 0.592 | 0.773 |
| **USA** | 0.582 | 0.516 | 0.653 | 0.654 | 0.550 | 0.501 | 0.485 | 0.611 | 0.343 | 0.414 | 0.550 | 0.779 |

## Appendix D: Changes in inequality and poverty in the US by states of residence.

In this Appendix we show the changes in inequality and poverty according to the Gini coefficient, MLD, and Headcount ratio by regions and population subgroups.

**Table D1.** Changes in inequality and poverty in the US by states.

| State | Gini Index | | | MLD Index | | | Poverty Headcount Index | | |
|---|---|---|---|---|---|---|---|---|---|
| | Original | After | Δ | Original | After | Δ | Original | After | Δ |
| Alabama (AL) | 0.456 | 0.496 | 4.0 | 0.449 | 0.551 | 10.2 | 0.297 | 0.382 | 8.5 |
| Alaska (AK) | 0.432 | 0.467 | 3.5 | 0.427 | 0.519 | 9.2 | 0.302 | 0.375 | 7.3 |
| Arizona (AZ) | 0.459 | 0.502 | 4.3 | 0.442 | 0.548 | 10.5 | 0.271 | 0.373 | 10.2 |
| Arkansas (AR) | 0.455 | 0.484 | 3.0 | 0.430 | 0.511 | 8.1 | 0.256 | 0.361 | 10.5 |
| California (CA) | 0.497 | 0.539 | 4.2 | 0.500 | 0.614 | 11.5 | 0.267 | 0.371 | 10.5 |
| Colorado (CO) | 0.465 | 0.506 | 4.1 | 0.457 | 0.565 | 10.8 | 0.285 | 0.377 | 9.1 |
| Connecticut (CT) | 0.504 | 0.543 | 3.9 | 0.529 | 0.646 | 11.7 | 0.306 | 0.387 | 8.1 |
| Delaware (DE) | 0.455 | 0.494 | 3.8 | 0.446 | 0.549 | 10.2 | 0.263 | 0.344 | 8.1 |
| District of Colu (D.C) | 0.438 | 0.464 | 2.6 | 0.435 | 0.516 | 8.1 | 0.294 | 0.340 | 4.7 |
| Florida (FL) | 0.472 | 0.521 | 4.9 | 0.445 | 0.561 | 11.7 | 0.282 | 0.389 | 10.8 |
| Georgia (GA) | 0.475 | 0.515 | 4.1 | 0.466 | 0.572 | 10.6 | 0.272 | 0.368 | 9.6 |
| Hawaii (HI) | 0.414 | 0.474 | 5.9 | 0.373 | 0.488 | 11.6 | 0.277 | 0.402 | 12.5 |
| Idaho (ID) | 0.464 | 0.504 | 4.0 | 0.482 | 0.582 | 10.0 | 0.273 | 0.374 | 10.1 |
| Illinois (IL) | 0.475 | 0.516 | 4.1 | 0.467 | 0.573 | 10.5 | 0.267 | 0.362 | 9.5 |
| Indiana (IN) | 0.449 | 0.490 | 4.1 | 0.430 | 0.528 | 9.8 | 0.271 | 0.362 | 9.1 |
| Iowa (IA) | 0.433 | 0.470 | 3.7 | 0.399 | 0.484 | 8.5 | 0.278 | 0.361 | 8.2 |
| Kansas (KS) | 0.447 | 0.484 | 3.7 | 0.420 | 0.512 | 9.1 | 0.281 | 0.365 | 8.3 |
| Kentucky (KY) | 0.450 | 0.490 | 4.0 | 0.437 | 0.535 | 9.8 | 0.296 | 0.382 | 8.7 |
| Louisiana (LA) | 0.466 | 0.506 | 3.9 | 0.465 | 0.570 | 10.5 | 0.308 | 0.396 | 8.8 |
| Maine (ME) | 0.438 | 0.478 | 3.9 | 0.415 | 0.512 | 9.7 | 0.270 | 0.352 | 8.2 |
| Maryland (MD) | 0.455 | 0.494 | 3.9 | 0.449 | 0.555 | 10.6 | 0.286 | 0.369 | 8.3 |
| Massachusetts (MA) | 0.471 | 0.506 | 3.6 | 0.464 | 0.561 | 9.7 | 0.275 | 0.357 | 8.2 |
| Michigan (MI) | 0.470 | 0.508 | 3.8 | 0.471 | 0.575 | 10.4 | 0.294 | 0.375 | 8.2 |
| Minnesota (MN) | 0.445 | 0.482 | 3.7 | 0.418 | 0.506 | 8.8 | 0.274 | 0.357 | 8.3 |
| Mississippi (MS) | 0.461 | 0.501 | 4.0 | 0.450 | 0.553 | 10.4 | 0.269 | 0.371 | 10.1 |
| Missouri (MO) | 0.450 | 0.491 | 4.1 | 0.425 | 0.526 | 10.0 | 0.285 | 0.373 | 8.8 |
| Montana (MT) | 0.461 | 0.499 | 3.8 | 0.463 | 0.566 | 10.4 | 0.307 | 0.386 | 7.9 |
| Nebraska (NE) | 0.421 | 0.457 | 3.5 | 0.371 | 0.451 | 7.9 | 0.261 | 0.344 | 8.3 |
| Nevada (NV) | 0.452 | 0.518 | 6.6 | 0.424 | 0.553 | 12.9 | 0.257 | 0.444 | 18.7 |
| New Hampshire (NH) | 0.444 | 0.485 | 4.0 | 0.426 | 0.529 | 10.3 | 0.274 | 0.365 | 9.1 |
| New Jersey (NJ) | 0.491 | 0.528 | 3.7 | 0.496 | 0.600 | 10.4 | 0.295 | 0.384 | 8.9 |
| New Mexico (NM) | 0.463 | 0.504 | 4.1 | 0.452 | 0.560 | 10.7 | 0.286 | 0.377 | 9.0 |
| New York (NY) | 0.495 | 0.532 | 3.7 | 0.501 | 0.602 | 10.1 | 0.291 | 0.375 | 8.4 |
| North Carolina (NC) | 0.471 | 0.512 | 4.1 | 0.464 | 0.571 | 10.8 | 0.276 | 0.364 | 8.8 |
| North Dakota (ND) | 0.439 | 0.475 | 3.6 | 0.404 | 0.492 | 8.8 | 0.268 | 0.355 | 8.7 |
| Ohio (OH) | 0.454 | 0.494 | 3.9 | 0.442 | 0.541 | 9.9 | 0.284 | 0.371 | 8.7 |
| Oklahoma (OK) | 0.460 | 0.501 | 4.1 | 0.445 | 0.549 | 10.4 | 0.282 | 0.374 | 9.2 |
| Oregon (OR) | 0.457 | 0.498 | 4.0 | 0.438 | 0.540 | 10.1 | 0.281 | 0.377 | 9.6 |
| Pennsylvania (PA) | 0.459 | 0.499 | 4.0 | 0.448 | 0.550 | 10.2 | 0.270 | 0.359 | 8.9 |
| Rhode Island (RI) | 0.434 | 0.477 | 4.3 | 0.405 | 0.505 | 10.0 | 0.255 | 0.354 | 9.9 |
| South Carolina (SC) | 0.455 | 0.499 | 4.3 | 0.440 | 0.547 | 10.6 | 0.282 | 0.380 | 9.8 |
| South Dakota (SD) | 0.422 | 0.461 | 3.9 | 0.384 | 0.473 | 8.9 | 0.266 | 0.346 | 7.9 |
| Tennessee (TN) | 0.466 | 0.509 | 4.2 | 0.451 | 0.556 | 10.5 | 0.274 | 0.375 | 10.0 |
| Texas (TX) | 0.478 | 0.519 | 4.0 | 0.472 | 0.580 | 10.8 | 0.292 | 0.384 | 9.2 |
| Utah (UT) | 0.481 | 0.521 | 4.0 | 0.495 | 0.596 | 10.2 | 0.291 | 0.381 | 9.1 |
| Vermont (VT) | 0.419 | 0.460 | 4.2 | 0.391 | 0.483 | 9.1 | 0.267 | 0.371 | 10.4 |
| Virginia (VA) | 0.473 | 0.512 | 3.9 | 0.472 | 0.581 | 10.9 | 0.296 | 0.368 | 7.2 |
| Washington (WA) | 0.466 | 0.507 | 4.1 | 0.454 | 0.559 | 10.4 | 0.280 | 0.371 | 9.1 |
| West Virginia (WV) | 0.443 | 0.482 | 3.9 | 0.419 | 0.522 | 10.4 | 0.261 | 0.354 | 9.4 |
| Wisconsin (WI) | 0.430 | 0.469 | 4.0 | 0.393 | 0.485 | 9.2 | 0.264 | 0.353 | 8.9 |
| Wyoming (WY) | 0.439 | 0.467 | 2.8 | 0.425 | 0.507 | 8.2 | 0.280 | 0.357 | 7.7 |
| **USA** | 0.476 | 0.517 | 4.1 | 0.470 | 0.576 | 10.7 | 0.282 | 0.379 | 9.6 |

Note: All changes are in basic points.

## Appendix E: Poverty risk across regions.

In this Appendix we check the robustness of the poverty risk values found for the population subgroups by regions (West, Mid-West, South, and North-East).

**Table E1.** Poverty risk by race, gender, education and region of residence.

| | | Primary | | Secondary | | Post-Secondary | | Graduate | |
|---|---|---|---|---|---|---|---|---|---|
| | | Male | Female | Male | Female | Male | Female | Male | Female |
| West | Asian | 1.811 | 1.900 | 1.798 | 2.090 | 1.320 | 1.187 | 0.450 | 0.459 |
| | Black | 1.456 | 0.860 | 1.555 | 1.291 | 1.292 | 0.966 | 0.666 | 0.401 |
| | Hispanic | 1.577 | 1.562 | 1.647 | 1.467 | 1.347 | 1.021 | 0.669 | 0.475 |
| | Other | 1.740 | 1.615 | 1.641 | 1.614 | 1.451 | 1.077 | 0.637 | 0.603 |
| | White | 1.040 | 1.278 | 1.174 | 1.346 | 1.003 | 1.001 | 0.426 | 0.470 |
| Midwest | Asian | 1.866 | 2.389 | 2.145 | 1.867 | 1.771 | 0.964 | 0.475 | 0.374 |
| | Black | 1.684 | 0.990 | 1.690 | 1.167 | 1.560 | 1.028 | 0.751 | 0.483 |
| | Hispanic | 1.746 | 1.606 | 1.845 | 1.515 | 1.427 | 1.193 | 0.569 | 0.491 |
| | Other | 1.777 | 2.009 | 1.693 | 1.622 | 1.373 | 1.185 | 0.650 | 0.671 |
| | White | 1.155 | 1.012 | 1.303 | 1.348 | 1.113 | 1.015 | 0.571 | 0.496 |
| South | Asian | 2.238 | 2.260 | 2.286 | 2.063 | 1.574 | 1.703 | 0.475 | 0.419 |
| | Black | 1.325 | 1.001 | 1.564 | 1.219 | 1.386 | 1.028 | 0.751 | 0.422 |
| | Hispanic | 1.651 | 1.412 | 1.518 | 1.239 | 1.253 | 1.072 | 0.569 | 0.612 |
| | Other | 1.500 | 1.399 | 1.560 | 1.209 | 1.404 | 1.064 | 0.650 | 0.570 |
| | White | 1.145 | 1.211 | 1.250 | 1.274 | 1.108 | 0.986 | 0.571 | 0.488 |
| Northeast | Asian | 2.155 | 1.500 | 2.570 | 2.250 | 1.365 | 1.284 | 0.487 | 0.418 |
| | Black | 1.586 | 0.682 | 1.814 | 1.084 | 1.392 | 0.919 | 0.768 | 0.501 |
| | Hispanic | 2.296 | 1.519 | 1.901 | 1.622 | 1.427 | 1.277 | 0.645 | 0.609 |
| | Other | 2.320 | 1.245 | 1.987 | 1.498 | 1.660 | 1.156 | 0.757 | 0.880 |
| | White | 1.210 | 1.113 | 1.363 | 1.395 | 1.162 | 1.042 | 0.503 | 0.490 |
| USA | Asian | 2.013 | 1.980 | 2.114 | 2.125 | 1.471 | 1.330 | 0.460 | 0.440 |
| | Black | 1.424 | 0.933 | 1.613 | 1.187 | 1.402 | 1.007 | 0.810 | 0.439 |
| | Hispanic | 1.730 | 1.549 | 1.677 | 1.424 | 1.362 | 1.112 | 0.698 | 0.568 |
| | Other | 1.789 | 1.583 | 1.710 | 1.513 | 1.493 | 1.122 | 0.716 | 0.658 |
| | White | 1.130 | 1.142 | 1.253 | 1.309 | 1.086 | 0.998 | 0.491 | 0.481 |

**Figure E1.** Essentiality, closure, teleworking and LWA index in the US by regions.