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# Essentially Unemployed: Potential Implications of the COVID-19 Crisis on Wage Inequality

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# Essentially Unemployed: Potential Implications of the COVID-19 Crisis on Wage Inequality

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**Abstract**

The aim of this paper is to determine how wage inequality is likely to be affected by the current COVID-19 pandemic. I first estimate the impact that social distancing will have on US state-level employment using pre-crisis industry data. I then consider the joint impact of states' unemployment benefit programs and the federal CARES Act on national inequality using representative sampling and Markov-Chain-Monte-Carlo estimations. I find that while wage inequality is likely to improve in the short-run with the added federal subsidy, allowing this support to expire prematurely will result in a worsening of pre-crisis wage inequality.

**Keywords:** Wage inequality, unemployment, COVID-19, Markov-Chain-Monte-Carlo, Gibbs sampling, structuralist method
**JEL Classification:** E24, E27, C15

## Introduction

On March 26, 2020, the US Division of Labor announced it had received over three million claims for unemployment in one week, the largest single increase in history. In response, the federal government passed the CARES act on March 27. A major component of the 2.2 trillion dollar bill is its supplement to state unemployment benefits. All recipients of unemployment payments will receive six hundred dollars per week in addition to the standard weekly benefit. The law went into affect April 5 and is slated to end on July 31.

The historical significance of this crisis is immense. Its occurrence corresponds with the secular phenomenon of rising wealth and income inequality. In his widely circulated work, Piketty (2014) presents compelling evidence to suggest that inequality in the US and western European countries is at its highest level in a century. An important theme throughout Piketty's book is that the dual crises of the Great Depression and WWII were strong leveling forces, which saw a transformation of highly inegalitarian societies to progressive economies with low levels of wealth and income inequality. These post-crisis decades are often referred to as the "golden age" of western capitalism. This period of equality and prosperity did not last, with the degree of inequality steadily increasing from the 1960s onward (Schneider & Tavani, 2016).

The scope of COVID-19's economic fallout is far from being realized. But a question that must begin to be considered is whether this crisis will have a similar leveling effect as that of the Great Depression and WWII, or whether it will in fact exacerbate inequality as is generally thought to have occurred following the 2008 financial crisis and Great Recession (Taylor *et al.* (2017), Meyer & Sullivan (2013), Mendieta-Muñoz *et al.* (2019)). The goal of this paper is to utilize existing employment and wage data on the state and industry level to predict the joint impact of state-level unemployment benefit programs and the CARES Act on weekly wage inequality. The US is very much at the beginning of the COVID-19 crisis at the time this paper is being written, and only time will reveal the accuracy of these forecasts.

The remainder of the paper is broken down into two sections. The first section is an attempt to determine which jobs will likely be preserved as the crisis unfolds, and which will likely be eliminated. After completing this delineation, I use current state-level industry data to estimate the pre-crisis shares of employment that are at risk of elimination. Finally, I compare the distribution of average weekly wages for secure and at-risk types of employment. The second section consists of a simulation exercise using representative sample generation followed by Markov-Chain-Monte-Carlo sampling to estimate the joint impact of the CARES Act and state unemployment programs on national wage inequality in the context of the current crisis. The final section suggests policy prescriptions and concludes.

## 1 Who is essential? Who can work from home?

Among the litany of COVID-related terms that have populated our lexicon in the past few months, two phrases in particular have come to bear incredibly important economic significance: "essential activity" and "able to work from home". If your employment falls into one or both of those categories, your short-term job security is relatively high. If not, it is quite likely that your employment has been suspended or terminated.

The definition of an "essential activity" is slippery at best, and varies significantly between countries and states. This ambiguity will likely increase as more federal, state, and local governments grapple with social distancing in the coming weeks and months. However, it appears that many

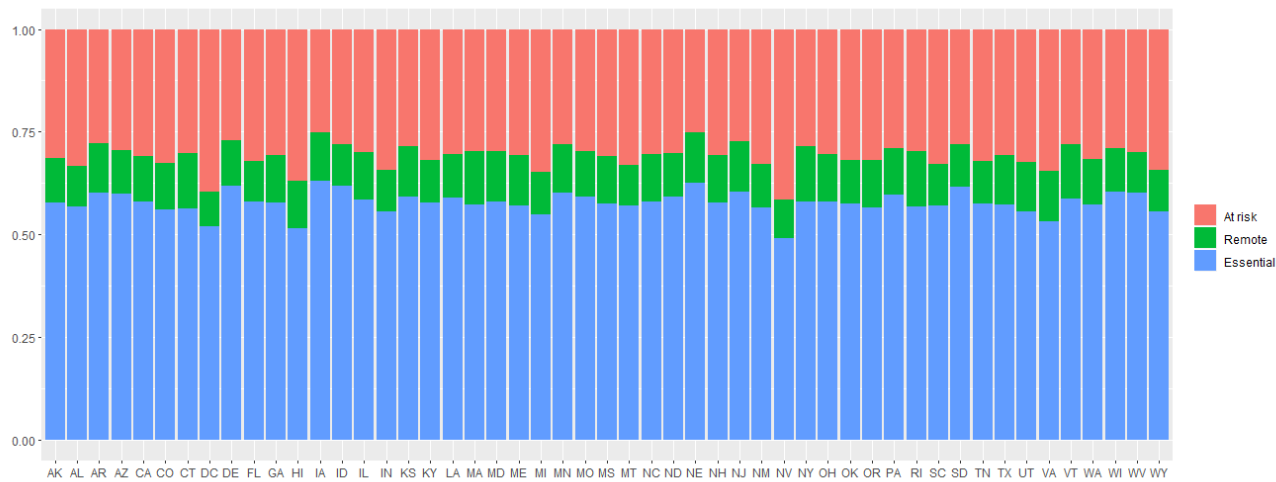


Figure 1: Employment share breakdown

US states have elected a "follow the leader" approach by adopting policies from states that were earliest to implement stay-at-home orders. Governor Andrew Cuomo of New York, the hardest hit US state up to this point, signed the "New York State on PAUSE" executive order on March 22nd, which suspended all economic activity except 'essential businesses and entities'. A list of industries and activities considered "essential" is supplied with the order (see governor.ny.gov).

The Quarterly Census of Employment & Wages (QCEW) provides industry employment and wage data on a quarterly and annual basis for all US states. The most recent complete annual data set is 2018. The industries are broken down in to 2, 3, 4, 5, and 6-digit NAICS classification. However, missing data becomes a pervasive issue beyond the 3-digit level. Using the 3-digit industry list, I proceed in classifying each as "essential" or "non-essential" based on the New York executive order. From the set of industries classified as "non-essential", I determine whether the industry is capable of transitioning to remote operations. If so, this industry is classified as "remote". See Table 1 (Appx. A) for results.

Figure 1 displays the employment shares of essential, remote and at-risk (non-essential-non-remote) industries across states. A few interesting observations can be made. First, states whose economies rely heavily on tourism such as Hawaii, Nevada, and Wyoming, tend to have high shares of at-risk employment. This comes as no surprise, as tourism, entertainment, and recreation activities require personal interactions that are neither essential nor (at least in most cases) capable of being done remotely. Second, states with large essential industries generally have a lower at-risk share (agriculture: Iowa, Idaho, Nebraska; finance: Delaware; oil and natural gas: North Dakota, South Dakota). The implications of these state-level risk disparities will be explored further in the following section.

There is undoubtedly inaccuracies in my method for classification. For example, I designate "Educational services" as a non-essential, non-remote industry. While this may be true for public primary and secondary schools, which in most cases have been closed, many colleges and universities have moved courses and administration entirely online, and hence many in the industry are working remotely. Furthermore, there is clearly a significant degree of labor hording occurring; many salaried employees such as teachers are being kept on payroll with the hope that schools will reopen within a period of time. While these jobs have been effectively eliminated in the short-term, these individuals may technically still be "employed". A second complication is the possibility of labor transfers. While most industries have seen a dramatic decline in output, certain activities have seen an increase in demand generated by the crisis.[1] With this shift in economic focus, it is likely some newly unemployed workers will be reabsorbed rather than simply displaced. Nevertheless, in the short-run these saving graces are likely the exception, not the rule, as the record level of jobless claims of the previous weeks can attest.

Although the process is surely messier than the distinction in Table 1 suggests, at the end of the day it is those whose employment fall into the category of at-risk that will bear the brunt of COVID-19 unemployment, while those in essential or remote-capable positions – henceforth "safe" – will be disproportionately spared.[2] The question I turn to in the the remainder of the paper is how this great division will impact wage inequality in the weeks and months to come.

## 2 Simulating the impact on wage inequality

If all workers, regardless of industry and state, were paid the same weekly wage prior to the crisis, then a process of mass elimination of jobs would necessarily increase inequality as the wages of unemployed workers went to zero. There are two complications to this: 1) workers are not paid the same across industry and state, and 2) with some form of unemployment benefit program existing in every US state as well as the federal CARES Act, an individual's weekly income does not fall to zero when she becomes unemployed. I will address these two complications in the order they were introduced.

I have constructed three binary categorizations that can be applied to all industries: essential, remote, and safe. Figure 2 displays the densities of average weekly wage distributions for each of these categorizations. Income data generally follows a log-normal distribution, which is the case in Figure 2 as well. However, it appears that the wage distribution of non-essential and non-remote employment are more severely right skewed than essential and remote, respectively. This discrepancy is even more apparent when comparing at-risk and secure wage distributions. Risk of job loss (and therefore loss of income) appears to be disproportionately born by those employed at the lower end of the income distribution. This implies that the impact of COVID-19 job displacement will likely exacerbate inequality beyond simply eliminating certain jobs while preserving others; the jobs it will eliminate are those that were already disproportionately clustered at the low end of the income distribution.

As mentioned in the previous section, it is generally not the case that an individual that becomes unemployed sees her income fall to zero. If she qualifies, a portion of her previous income will be paid to her in the form of unemployment benefits for a certain period of time. The quantity and length of time of unemployment assistance, as well as whether an individual qualifies at all, depends on many factors including in which state the worker resides. In the current COVID-19 crisis, the CARES Act supplements state unemployment benefits with an additional six hundred dollars per week until July 31. Thus, the income of unemployed works in the short term will be the combination of state-level benefits plus the government subsidy.

[1] Activities such as health care, food and grocery delivery, shipping services, online retain, grocery chains, and medical equipment manufacturing have all seen a rise in demand.

[2] At least in the short-run


Figure 2: Pre-crisis weekly average earnings densities by state-level industry

## Gibbs Sampling Methodology

To simulate the impact of COVID-19 displacement on inequality, I perform the following. I first calculate the share of national employment for each state-level industry. I then construct a representative national sample by drawing 6000000 observations without replacement from the national employment share distribution. This set of simulated individuals is thus representative of the US employment structure. To assign a wage to each representative worker, I draw from a log-normal distribution with a log-mean equal to that of their respective state-level industry and a log-standard deviation equal to 0.79.[3]

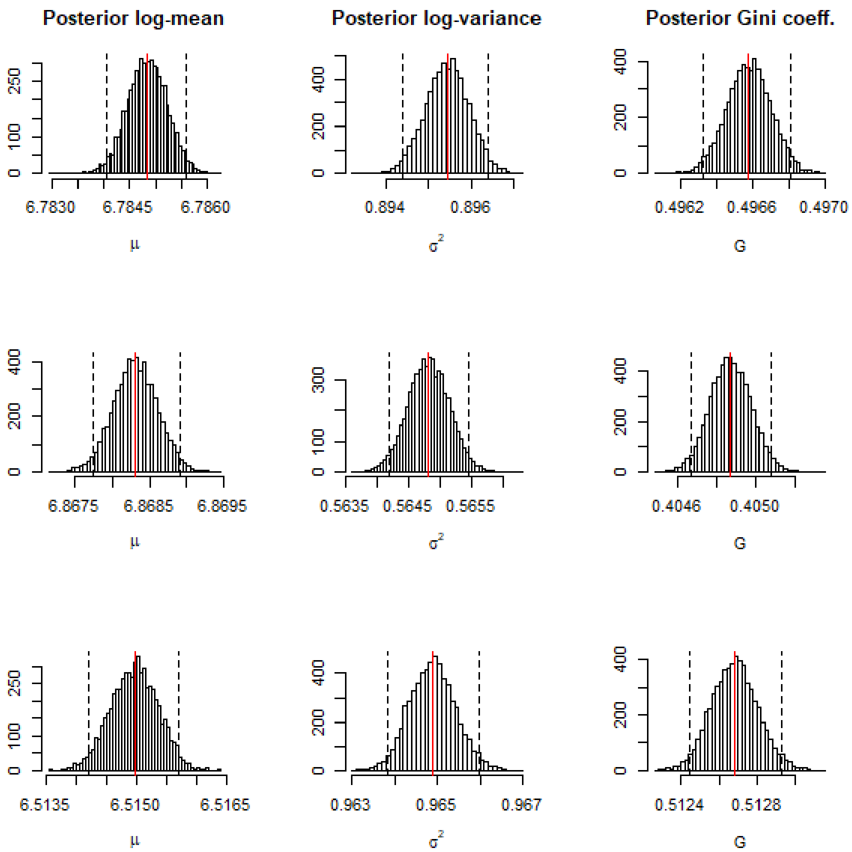


Figure 3: Posterior estimates for $\mu$ $\sigma^2$, and $G$ under three scenarios: pre-COVID (top row), under CARES act (middle row), and without CARES act (bottom row). Dashed lines indicate 95 percent confidence interval, red line indicates maximum likelihood estimate.

Using the representative national sample, I then perform Gibbs sampling estimation of the first and second moments of weekly income distribution, assuming log-normal likelihood and a noninformative prior. I run the Gibbs sampler for 10000 iterations, eliminating the first 2000 observations as "burn in". Trace plots are displayed in Figure 6 (Appx. C). The Gini coefficient ($G$) of the posterior can be calculated using the maximum likelihood estimate for the second moment ($\sigma$):

$$G = \mathrm{erf}(\sigma/2) \tag{1}$$

[3]The first moment of state-industry wage distribution is known, but the second moment and distribution type is unknown. Given that wage income at the aggregate level tends to be log-normally distributed (Schneider & Scharfenaker, 2019), I assume that industry-level wage follows a similar distribution. For the second moment parameter, I select a value that corresponds to the 2018 estimate of the Gini coefficient for US income inequality.

I repeat this process three times. First, all wages are drawn from their respective state-industry wage distributions. In the second iteration, those whose employment is deemed "safe" draw from their respective industry distributions, while those "at-risk" are assigned unemployment benefits determined by their respective state policy[4] *plus six hundred* from the CARES Act. The third iteration is identical to the second, except it removes the CARES Act subsidy. These three outcomes represent the "pre-COVID", "CARES Act" and "post-CARES Act" states of inequality, respectively. Comparisons between these scenarios allow for counter-factual analysis to possibly inform policy.

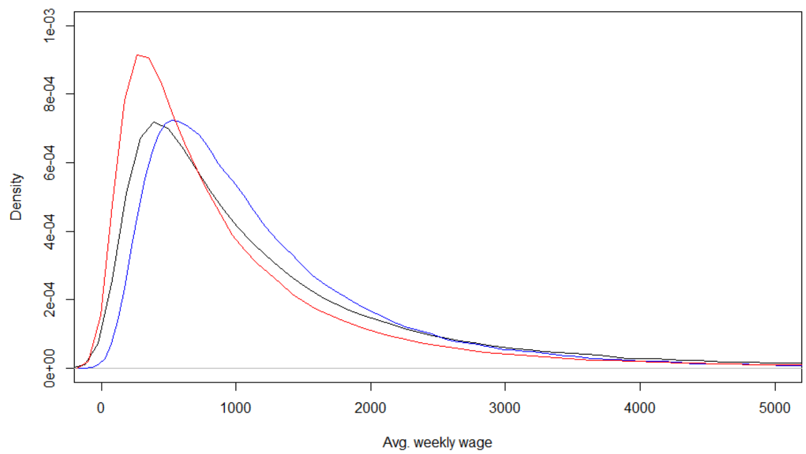


Figure 4: Estimated posterior wage distributions: pre-COVID (black), under CARES act (blue), and without CARES act (red).

Estimated parameters are presented in Figure 3 and posterior income distributions are shown in Figure 4. The results of the pre-COVID simulation (see Fig. 3, row I) suggests a pre-crisis Gini coefficient of approximately 0.497, which is consistent with current estimates for the US provided by the US Census Bureau. Mean income is estimated at approximately \$885 dollars, which is again consistent with other 2018 estimates. Under the CARES Act (see Fig. 3, row II), the simulation estimates a mean weekly income to approximately \$960, and a Gini coefficient of approximately 0.404. Finally, estimations of the crisis impact *without* the CARES Cct (see Fig. 3, row III) show a marked fall in weekly income from pre-crisis levels to approximately \$675 and a rise in the Gini coefficient to approximately 0.513.

## 3 Policy Implications & Conclusion

This statistical exercise is in many ways a gross oversimplification of the crisis at hand. The economic impacts of COVID-19 will be severe and lasting. Economic contraction and insufficient demand will likely displace workers to a greater extent than temporary shutdown orders. Indeed, these forms of job loss will likely be invariably more painful and difficult to address. Nevertheless,

[4] see Table 3 (Appx. B)

the true nature of the crisis at hand is not yet known, and accurate estimates of the "second wave" of economic impact is difficult to estimate. This paper simply aims to understand the following: which forms of employment are currently displaced due to social distancing measures, and how the interaction of this displacement with current state and federal policies impact the national income distribution?

The first important finding is that those employment positions most likely at risk of displacement on average receive lower weekly compensation than those that are either deemed "essential" or are capable of being performed remotely. This suggests that a negative income shock that disproportionately impacts these "at risk" workers is likely to exacerbate inequality. I test this hypothesis using Gibbs sampling method and compare outcomes of displacement under different regimes. The first regime, which most closely reflects the current reality, is the situation where current state unemployment benefits are supplemented by the federal government via the CARES Act. The counter-factual scenario is one in which state-level unemployment programs remain intact, but the federal subsidy is eliminated. While as of now this scenario remains hypothetical, it closely resembles the situation that will occur once the CARES Act expires July 31, should the crisis persist and no additional bill be passed.

I find evidence to suggest that the CARES Act is effective in preventing exacerbation of the already high level of inequality. The subsidy appears to sufficiently bolster the income of displaced workers such that inequality actually declines, and average income rises. However, when left to the care of their respective state unemployment programs, inequality increases and average income falls below pre-crisis levels. If crisis conditions persist into the fall, a situation that appears all but certain, failure by federal and state governments to pass legislation improving and expanding benefits to displaced workers will result in a sharp decline an aveage income, standard of living, and effective demand, and is likely to further exacerbate the already historically-high level of inequality.

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# Appendix

## A NAICS 3-digit Classification

| | Industry | Essential | Remote |
|---|---|---|---|
| 1 | NAICS 111 Crop production | 1 | 0 |
| 2 | NAICS 112 Animal production and aquaculture | 1 | 0 |
| 3 | NAICS 113 Forestry and logging | 0 | 0 |
| 4 | NAICS 114 Fishing, hunting and trapping | 0 | 0 |
| 5 | NAICS 115 Agriculture and forestry support activities | 1 | 0 |
| 6 | NAICS 211 Oil and gas extraction | 0 | 0 |
| 7 | NAICS 212 Mining, except oil and gas | 0 | 0 |
| 8 | NAICS 213 Support activities for mining | 0 | 0 |
| 9 | NAICS 221 Utilities | 1 | 0 |
| 10 | NAICS 236 Construction of buildings | 0 | 0 |
| 11 | NAICS 237 Heavy and civil engineering construction | 1 | 0 |
| 12 | NAICS 238 Specialty trade contractors | 1 | 0 |
| 13 | NAICS 311 Food manufacturing | 1 | 0 |
| 14 | NAICS 312 Beverage and tobacco product manufacturing | 1 | 0 |
| 15 | NAICS 313 Textile mills | 0 | 0 |
| 16 | NAICS 314 Textile product mills | 0 | 0 |
| 17 | NAICS 315 Apparel manufacturing | 0 | 0 |
| 18 | NAICS 316 Leather and allied product manufacturing | 0 | 0 |
| 19 | NAICS 321 Wood product manufacturing | 0 | 0 |
| 20 | NAICS 322 Paper manufacturing | 1 | 0 |
| 21 | NAICS 323 Printing and related support activities | 1 | 0 |
| 22 | NAICS 324 Petroleum and coal products manufacturing | 1 | 0 |
| 23 | NAICS 325 Chemical manufacturing | 1 | 0 |
| 24 | NAICS 326 Plastics and rubber products manufacturing | 0 | 0 |
| 25 | NAICS 327 Nonmetallic mineral product manufacturing | 0 | 0 |
| 26 | NAICS 331 Primary metal manufacturing | 0 | 0 |
| 27 | NAICS 332 Fabricated metal product manufacturing | 0 | 0 |
| 28 | NAICS 333 Machinery manufacturing | 1 | 0 |
| 29 | NAICS 334 Computer and electronic product manufacturing | 1 | 0 |
| 30 | NAICS 335 Electrical equipment and appliance mfg. | 1 | 0 |
| 31 | NAICS 336 Transportation equipment manufacturing | 0 | 0 |
| 32 | NAICS 337 Furniture and related product manufacturing | 0 | 0 |
| 33 | NAICS 339 Miscellaneous manufacturing | 0 | 0 |
| 34 | NAICS 423 Merchant wholesalers, durable goods | 1 | 0 |
| 35 | NAICS 424 Merchant wholesalers, nondurable goods | 1 | 0 |
| 36 | NAICS 425 Electronic markets and agents and brokers | 1 | 0 |
| 37 | NAICS 441 Motor vehicle and parts dealers | 1 | 0 |
| 38 | NAICS 442 Furniture and home furnishings stores | 0 | 0 |
| 39 | NAICS 443 Electronics and appliance stores | 1 | 0 |
| 40 | NAICS 444 Building material and garden supply stores | 1 | 0 |
| 41 | NAICS 445 Food and beverage stores | 1 | 0 |
| 42 | NAICS 446 Health and personal care stores | 1 | 0 |
| 43 | NAICS 447 Gasoline stations | 1 | 0 |
| 44 | NAICS 448 Clothing and clothing accessories stores | 0 | 0 |
| 45 | NAICS 451 Sports, hobby, music instrument, book stores | 0 | 0 |

Table 1: NAICS 3-digit industry classification

| | Industry | Essential | Remote |
|---|---|---|---|
| 46 | NAICS 452 General merchandise stores | 0 | 0 |
| 47 | NAICS 453 Miscellaneous store retailers | 0 | 0 |
| 48 | NAICS 454 Nonstore retailers | 0 | 0 |
| 49 | NAICS 481 Air transportation | 1 | 0 |
| 50 | NAICS 482 Rail transportation | 1 | 0 |
| 51 | NAICS 483 Water transportation | 1 | 0 |
| 52 | NAICS 484 Truck transportation | 1 | 0 |
| 53 | NAICS 485 Transit and ground passenger transportation | 1 | 0 |
| 54 | NAICS 486 Pipeline transportation | 1 | 0 |
| 55 | NAICS 487 Scenic and sightseeing transportation | 0 | 0 |
| 56 | NAICS 488 Support activities for transportation | 1 | 0 |
| 57 | NAICS 491 Postal service | 1 | 0 |
| 58 | NAICS 492 Couriers and messengers | 0 | 0 |
| 59 | NAICS 493 Warehousing and storage | 1 | 0 |
| 60 | NAICS 511 Publishing industries, except internet | 1 | 0 |
| 61 | NAICS 512 Motion picture and sound recording industries | 0 | 0 |
| 62 | NAICS 515 Broadcasting, except internet | 1 | 0 |
| 63 | NAICS 517 Telecommunications | 1 | 0 |
| 64 | NAICS 518 Data processing, hosting and related services | 1 | 0 |
| 65 | NAICS 519 Other information services | 1 | 0 |
| 66 | NAICS 521 Monetary authorities - central bank | 1 | 0 |
| 67 | NAICS 522 Credit intermediation and related activities | 1 | 0 |
| 68 | NAICS 523 Securities, commodity contracts, investments | 1 | 0 |
| 69 | NAICS 524 Insurance carriers and related activities | 1 | 0 |
| 70 | NAICS 525 Funds, trusts, and other financial vehicles | 1 | 0 |
| 71 | NAICS 531 Real estate | 0 | 1 |
| 72 | NAICS 532 Rental and leasing services | 1 | 0 |
| 73 | NAICS 533 Lessors of nonfinancial intangible assets | 0 | 0 |
| 74 | NAICS 541 Professional and technical services | 0 | 0 |
| 75 | NAICS 551 Management of companies and enterprises | 0 | 1 |
| 76 | NAICS 561 Administrative and support services | 1 | 0 |
| 77 | NAICS 562 Waste management and remediation services | 1 | 0 |
| 78 | NAICS 611 Educational services | 0 | 1 |
| 79 | NAICS 621 Ambulatory health care services | 1 | 0 |
| 80 | NAICS 622 Hospitals | 1 | 0 |
| 81 | NAICS 623 Nursing and residential care facilities | 1 | 0 |
| 82 | NAICS 624 Social assistance | 1 | 0 |
| 83 | NAICS 711 Performing arts and spectator sports | 0 | 0 |
| 84 | NAICS 712 Museums, historical sites, zoos, and parks | 0 | 0 |
| 85 | NAICS 713 Amusements, gambling, and recreation | 0 | 0 |
| 86 | NAICS 721 Accommodation | 0 | 0 |
| 87 | NAICS 722 Food services and drinking places | 0 | 0 |
| 88 | NAICS 811 Repair and maintenance | 1 | 0 |
| 89 | NAICS 812 Personal and laundry services | 1 | 0 |
| 90 | NAICS 813 Membership associations and organizations | 0 | 0 |
| 91 | NAICS 814 Private households | 0 | 0 |
| 92 | NAICS 999 Unclassified | 0 | 0 |

Table 2: NAICS 3-digit industry classification (continued)

# B Unemployment benefits

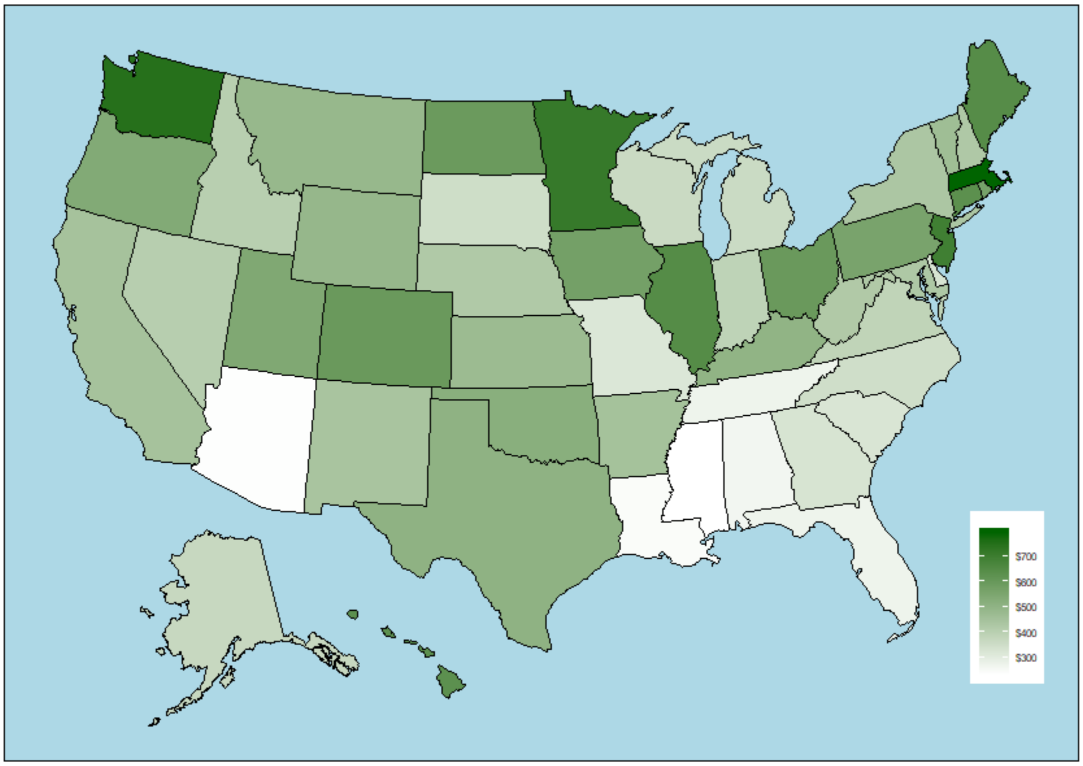


Figure 5: Maximum weekly unemployment benefits by state

| | State | Max. Weekly Benefit ($) | Rate |
|---|---|---|---|
| 1 | Alaska | 370 | 0.50 |
| 2 | Alabama | 265 | 0.50 |
| 3 | Arkansas | 451 | 0.50 |
| 4 | Arizona | 240 | 0.50 |
| 5 | California | 450 | 0.50 |
| 6 | Colorado | 597 | 0.55 |
| 7 | Connecticut | 631 | 0.50 |
| 8 | Dist of Columbia | 425 | 0.50 |
| 9 | Delaware | 330 | 0.50 |
| 10 | Florida | 275 | 0.50 |
| 11 | Georgia | 330 | 0.62 |
| 12 | Hawaii | 630 | 0.62 |
| 13 | Iowa | 573 | 0.59 |
| 14 | Idaho | 405 | 0.50 |
| 15 | Illinois | 648 | 0.47 |
| 16 | Indiana | 390 | 0.47 |
| 17 | Kansas | 474 | 0.50 |
| 18 | Kentucky | 502 | 0.50 |
| 19 | Louisiana | 247 | 0.50 |
| 20 | Massachusetts | 795 | 0.50 |
| 21 | Maryland | 430 | 0.50 |
| 22 | Maine | 646 | 0.50 |
| 23 | Michigan | 362 | 0.50 |
| 24 | Minnesota | 717 | 0.50 |
| 25 | Missouri | 320 | 0.50 |
| 26 | Mississippi | 235 | 0.50 |
| 27 | Montana | 487 | 0.50 |
| 28 | North Carolina | 350 | 0.50 |
| 29 | North Dakota | 595 | 0.50 |
| 30 | Nebraska | 426 | 0.50 |
| 31 | New Hampshire | 427 | 0.50 |
| 32 | New Jersey | 696 | 0.60 |
| 33 | New Mexico | 442 | 0.54 |
| 34 | Nevada | 407 | 0.50 |
| 35 | New York | 435 | 0.50 |
| 36 | Ohio | 598 | 0.50 |
| 37 | Oklahoma | 520 | 0.50 |
| 38 | Oregon | 538 | 0.50 |
| 39 | Pennsylvania | 561 | 0.50 |
| 40 | Rhode Island | 566 | 0.50 |
| 41 | South Carolina | 326 | 0.50 |
| 42 | South Dakota | 352 | 0.50 |
| 43 | Tennessee | 275 | 0.50 |
| 44 | Texas | 507 | 0.50 |
| 45 | Utah | 543 | 0.50 |
| 46 | Virginia | 387 | 0.50 |
| 47 | Vermont | 466 | 0.58 |
| 48 | Washington | 749 | 0.50 |
| 49 | Wisconsin | 363 | 0.40 |
| 50 | West Virginia | 424 | 0.50 |
| 51 | Wyoming | 489 | 0.52 |

Table 3: Unemployment benefits by state

## C Trace Plots

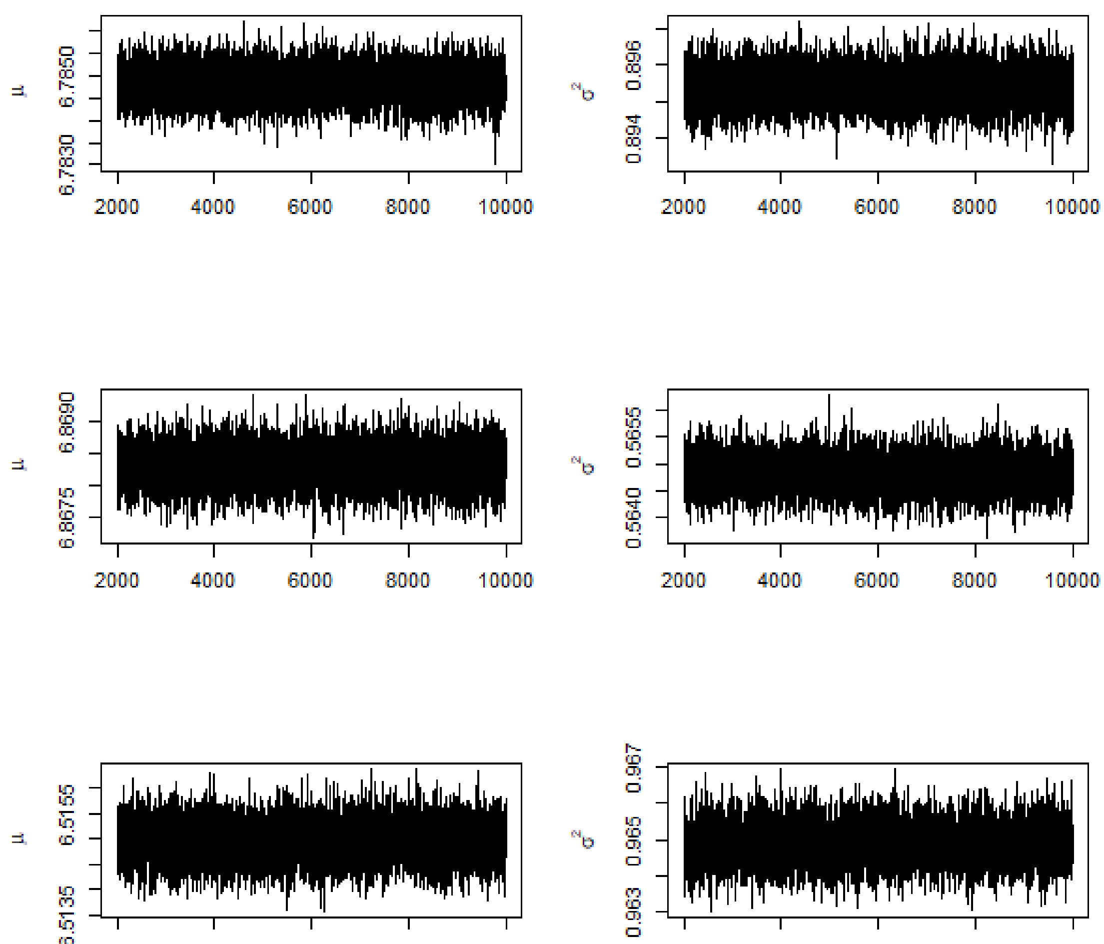


Figure 6: Trace plots for $\mu$ and $\sigma^2$ under three scenarios: pre-COVID (top row), under CARES act (middle row), and without CARES act (bottom row).