Socio-Economic Impact of the Covid-19 Pandemic in the U.S.

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Abstract

This work proposes a dynamic cascade model to investigate the systemic risk posed by sector-level industries within the U.S. inter-industry network. We then use this model to study the effect of the disruptions presented by Covid-19 on the U.S. economy. We construct a weighted digraph G = (V,E,W) using the industry-by-industry total requirements table for 2018, provided by the Bureau of Economic Analysis (BEA). We impose an initial shock that disrupts the production capacity of one or more industries, and we calculate the propagation of production shortages with a modified Cobb–Douglas production function. For the Covid-19 case, we model the initial shock based on the loss of labor between March and April 2020 as reported by the Bureau of Labor Statistics (BLS). The industries within the network are assigned a resilience that determines the ability of an industry to absorb input losses, such that if the rate of input loss exceeds the resilience, the industry fails, and its outputs go to zero. We observed a critical resilience, such that, below this critical value, the network experienced a catastrophic cascade resulting in total network collapse. Lastly, we model the economic recovery from June 2020 through March 2021 using BLS data.

Objectives

Our objective in this study is to first estimate the systemic risk posed by individual sector level industries. We model the production of each industry via a modified Cobb–Douglas function, where an industry's outputs rely on their productivity, labor input, and industrial inputs from upstream suppliers. The propagation of production shortages is evaluated with a dynamic cascade model, in which the production decreases according to the rate of loss in the inputs over subsequent periods, scaled by the parameters of the Cobb–Douglas function. By comparing the critical resilience from each industry disruption scenario, we estimate the ranking of risk posed by each industry. Using the methodology for single industry shocks, we model the disruption of the Covid-19 pandemic by the observed unemployment spike between March and April 2020. We identify the critical resilience r_c for the Covid-19 shock, above which the network experiences varying levels of reduced production, and below which the network collapses.

Data and the Model

For this study, we use data from the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS). The BEA publishes the Industry-by-Industry Total Requirements Table which we use to build our network. The BLS data provides information on monthly unemployment and productivity levels across each industry, which we incorporate into our study of the impact of Covid-19 on the U.S. economy.

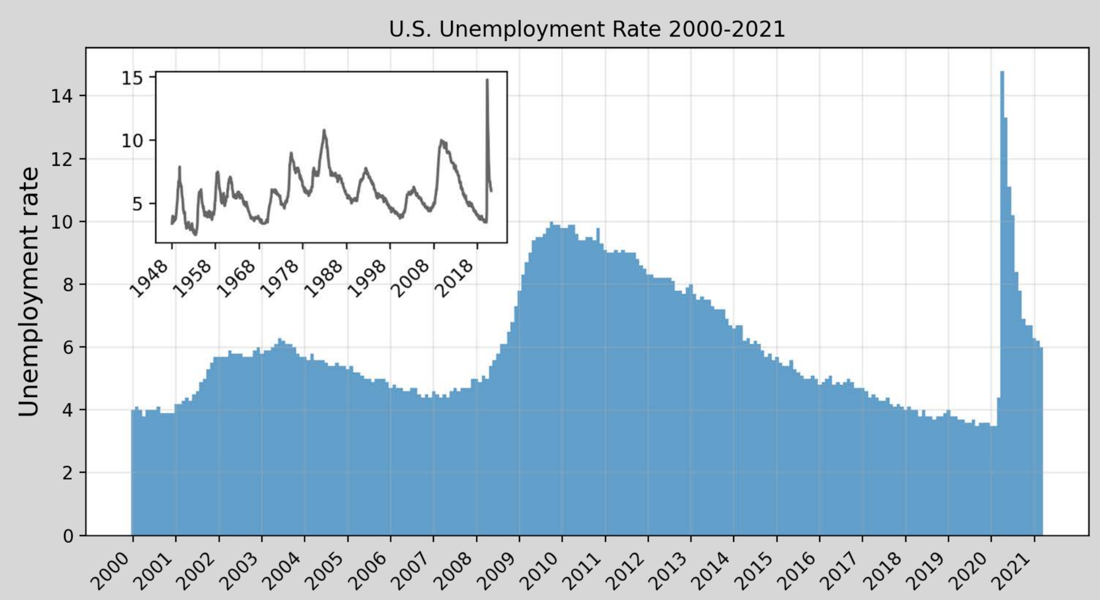

Fig 1: Graph of the U.S unemployment rate from 2000 to 2021. Peak unemployment of approximately 14% March-April 2020.

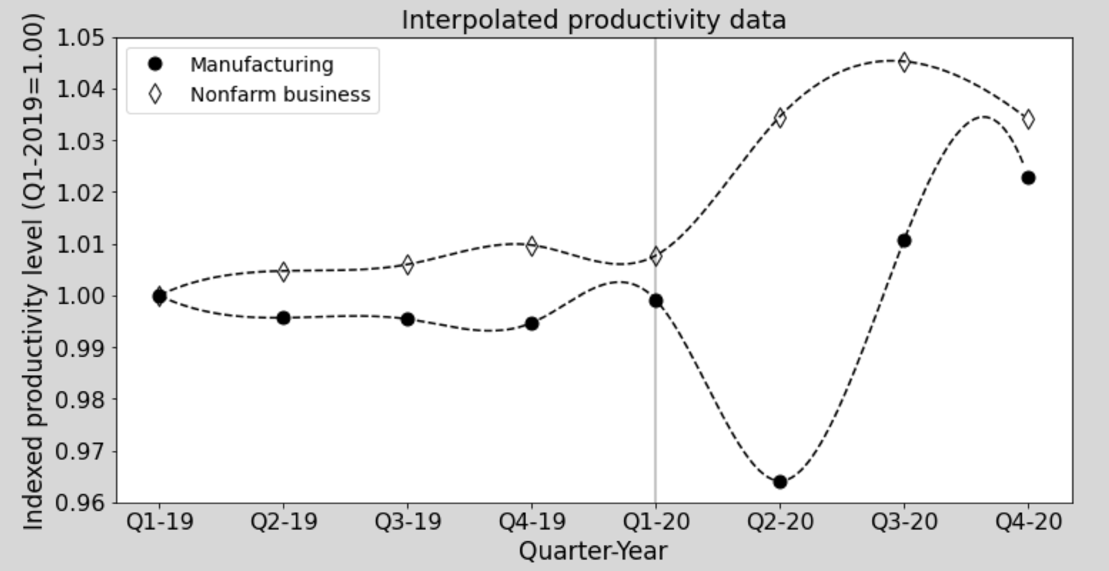

Fig 2: Interpolated quarterly productivity levels in Manufacturing and Non-Farm business sectors. Onset of Covid-19 shock indicated by vertical dashed line.

U.S. Inter-Industry Network

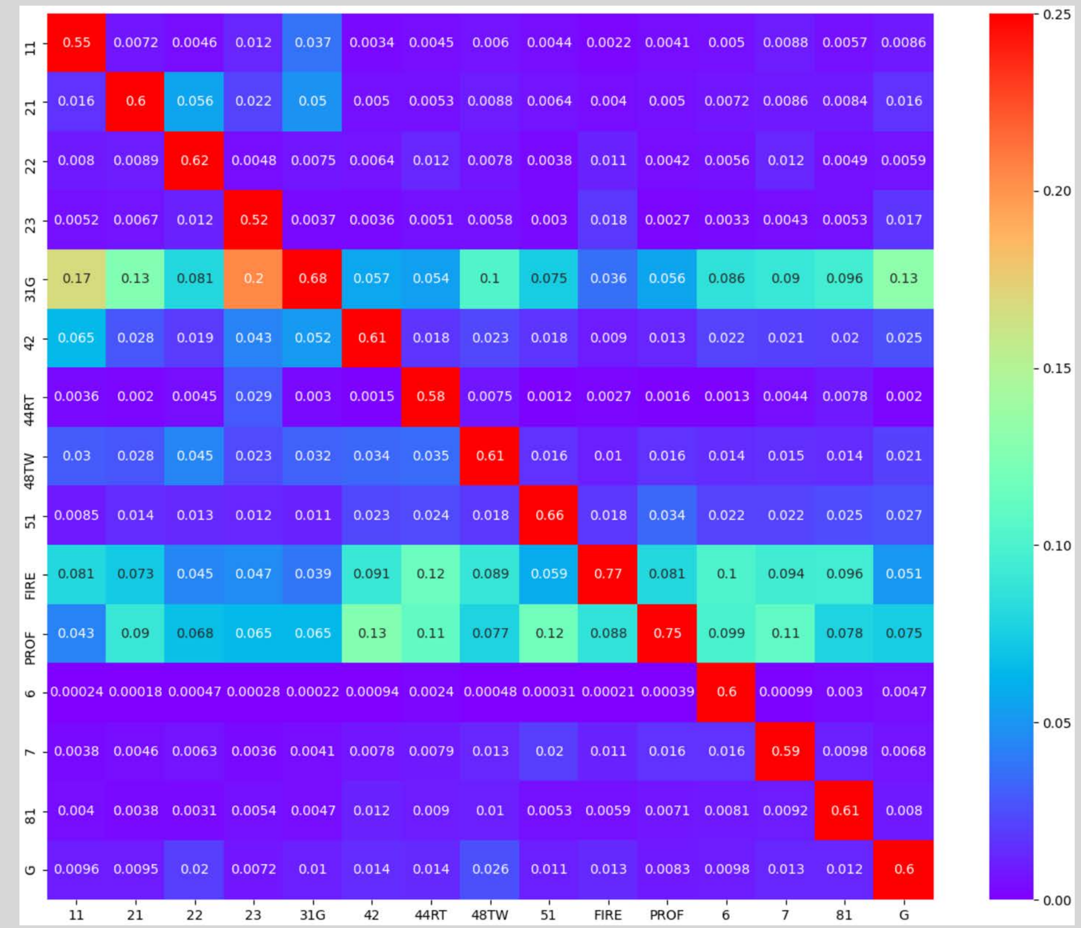

Fig 3: Visualization of the U.S. inter-industry network. Each cell is represented by its weight in the column sum (Total Input) in which it is located. Diagonal entries (self-input) carry the largest weight.

Model

The basis of the model is the modified Cobb-Douglas Equation below, where the output of each industry, Y_i, is given by that industries productivity A_i, labor input L_i, and their intermediate inputs from other industries x_{ij}, which are the given by the total-requirements table in Fig 3.

$$Y_i = A_i L_i^{\alpha} \sum_j (x_{ij})^{\gamma}$$

The exponents α and γ are the elasticities of labor and input respectively, and are commonly set to 0.3 and 0.7 for the U.S. economy.

An initial labor shock has the following effect:

$$Y_i^1 = (S_i)^{\alpha} \times Y_i^0 \text{ ; where } S_i = {L_i^1}/{L_i^0}$$

Where the superscript on Y_i denotes the time period t.

The damage due to loss in input is spread in the subsequent time periods as:

$$Y_i^{t+1} = (p_i^t)^{\gamma} \times Y_i^t \text{ ; where } p_i^t = \frac{\sum_j x_{ij}^t}{\sum_j x_{ij}^{t-1}}$$

If $p_i^t > r$, the industry resilience level, then the industry i fails and its outputs go to 0.

Single-Industry Shock

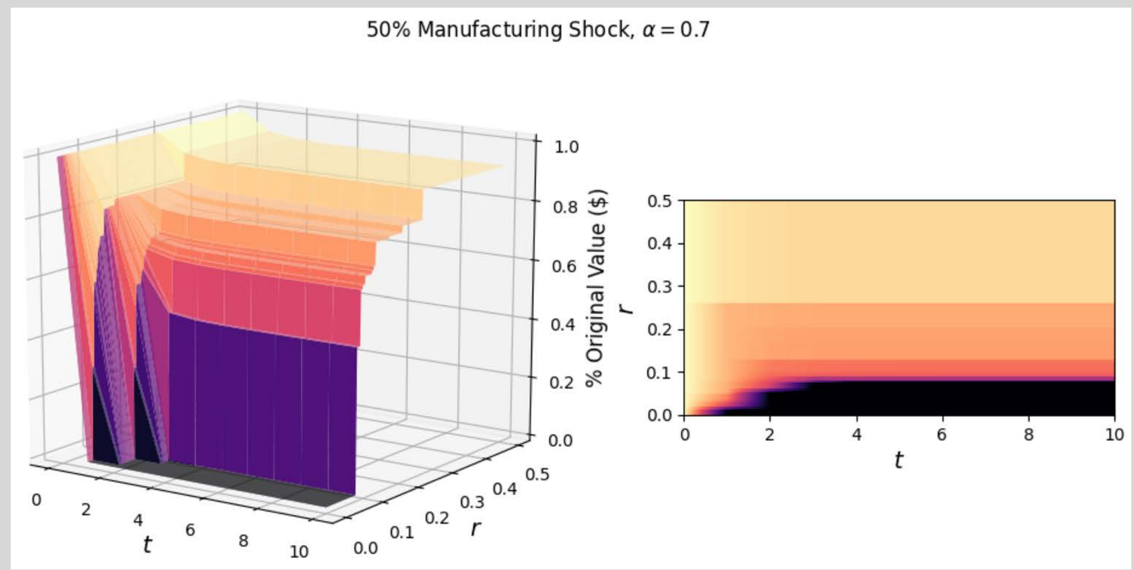

Figure 4: The surface (left) shows the response of the network to a general 50% manufacturing shock for $t \in [0, 10]$ and $r \in [0, 0.5]$. On the right is the projection of the surface in the r-t plane. The critical resilience of the network due to this shock is $r_c = 0.080$. The elasticities of labor and industrial inputs (α, γ) are 0.7 and 0.3, respectively.

Single Industry Shock Profiles

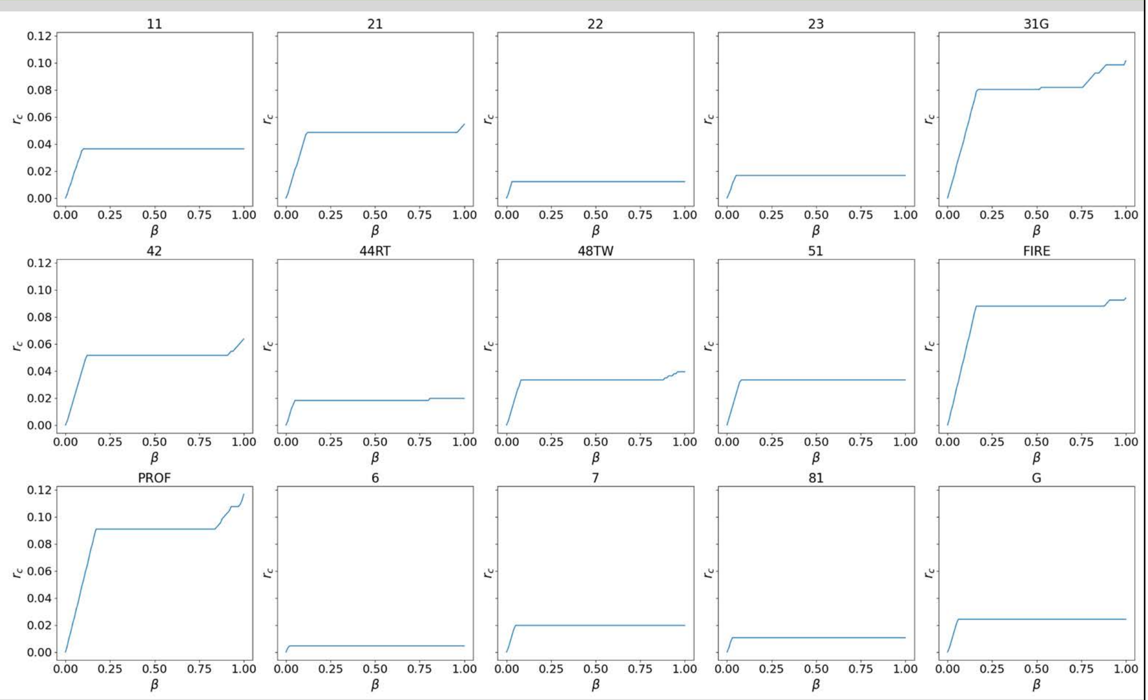

Figure 5: Plots of r_c vs. β for single industry shocks of magnitude β, with $\beta = 1$ being a total loss. The shocked industry is given in the subplot title. The elasticity of the input is set to $1 - \alpha = 0.3$ for all plots.

Covid-19 Shock

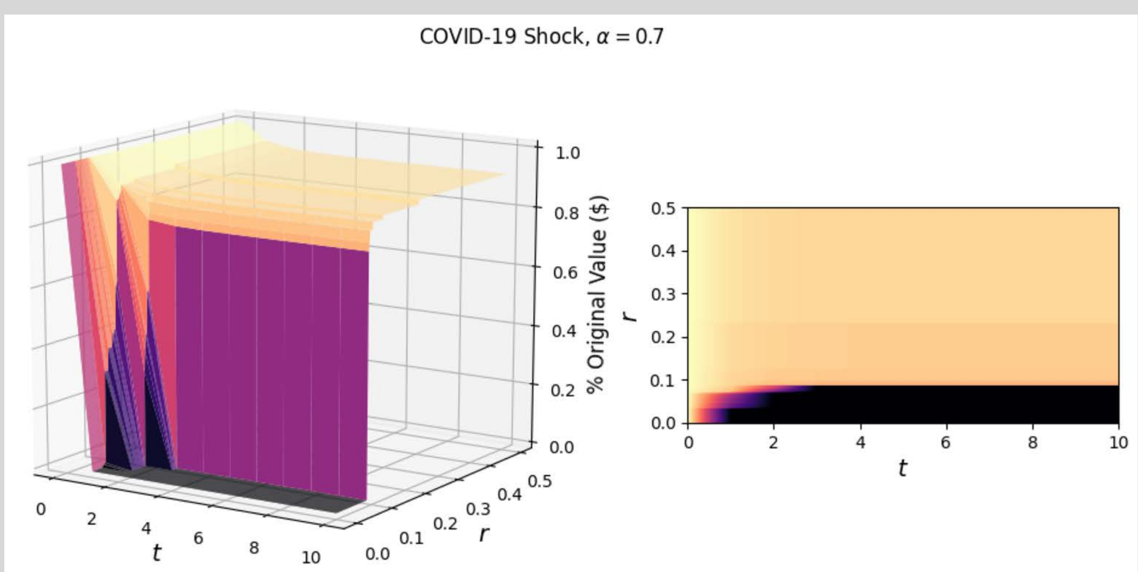

Figure 6: The surface above shows the response of the network to the Covid-19 shock. The resiliency axis, r, shows a total network collapse for values of $r \le r_c$, where the critical resilience $r_c = 0.088$.

Aftermath and Recovery

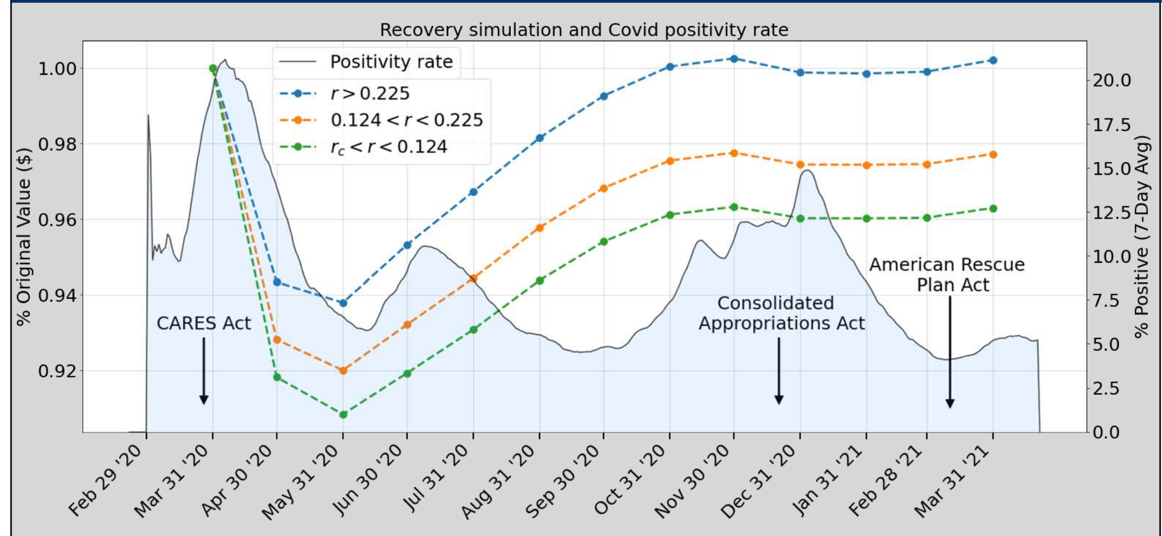

Figure 7: Comparison of the network response (dashed lines, left vertical axis) with the Covid-19 positivity rates in the U.S. (solid line, right vertical axis). The network response is shown as dashed lines for various regions of r and is indexed relative to March 2020 output levels. Dates of signing of CARES Act, Consolidated Appropriations Act, and American Rescue Plan Act included.

Discussion and Conclusion

In this work, we developed a dynamic cascade model to explore the response of the U.S. inter-industry network to various shocks in production capacity, including single industry disruptions and the reduction in economic output due to the Covid-19 pandemic. Our model makes two primary assumptions, the first being that the resilience and elasticity of labor and input are constant across all industries. The model does allow for these parameters to be tuned for individual industries, provided that one has a method to estimate these parameters in each industry.

For single industry shocks, we find that the stability of the network varies with the shock magnitudes and with the industry receiving the initial shock. By ranking the stability levels across all shock magnitudes for each industry, we identify the industries that present the most considerable risk of initiating a catastrophic cascade: Professional Services (PROF), Finance, Insurance, and Real Estate (FIRE), and Manufacturing (31G).

The Covid-19 shock causes an approximately 9% reduction in the network output after three time periods, for regions of $r > r_c$ in which no industries fail. For comparison, the U.S. GDP fell at an annualized rate of 31.7% in the second quarter of 2020 as reported by the BEA, which corresponds to a 9% quarterly reduction.

We find that between March 2020 and March 2021 there is a sharp initial reduction in the economic output followed by a gradual recovery, reaching the initial pre-Covid economic output levels.

This result is in agreement with the BEA estimate that the U.S. GDP is up 1.5% over the same period (March 2020 to March 2021). Our result is robust, with a variation of less than 1% for a $\pm$10% change in the elasticity parameters. The recovery was supported by $5 trillion in cumulative government stimulus, an adaptation to work-from-home policies where possible, and the rapid development of highly effective mRNA vaccines as well as their increasing availability.

References:

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