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COVID19 AND THE MACROECONOMIC E¤ECTS OF COSTLY DISASTERS

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ABSTRACT

The outbreak of COVID19 has significantly disrupted the economy. This paper attempts to quantify the macroeconomic impact of costly and deadly disasters in recent US history, and to translate these estimates into an analysis of the likely impact of COVID19. A costly disaster series is constructed over the sample 1980:1-2020:04 and the dynamic impact of a disaster shock on economic activity and on uncertainty is studied using a VAR. While past natural disasters are local in nature and come and go quickly, COVID19 is a global, multi-period event. We therefore study the dynamic responses to a sequence of large disaster shocks. Even in a fairly conservative case where COVID19 is a 5-month shock with its magnitude calibrated by the cost of March 2020 Coronavirus relief packages, the shock is forecast to lead to a cumulative loss in industrial production of 20% and in service sector employment of nearly 45% or 64 million jobs over the next 12 months. For each month that a shock of a given magnitude is prolonged from the base case, heightened macro uncertainty persists for another month.

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1 Introduction

Short term fluctuations in a typical economic model are presumed to be driven by random shocks to preferences, factor inputs, productivity, or policies that directly impact the supply or demand of goods and services. While there is some scope for considering fluctuations attributable to shocks driven by natural disasters such as earthquakes and tsunamis, these types of "conventional" disaster shocks are typically assumed to be short-lived, with an initial impact that is local in nature. It is only when these shocks propagate across sectors, states, and countries that the aggregate effects are realized.

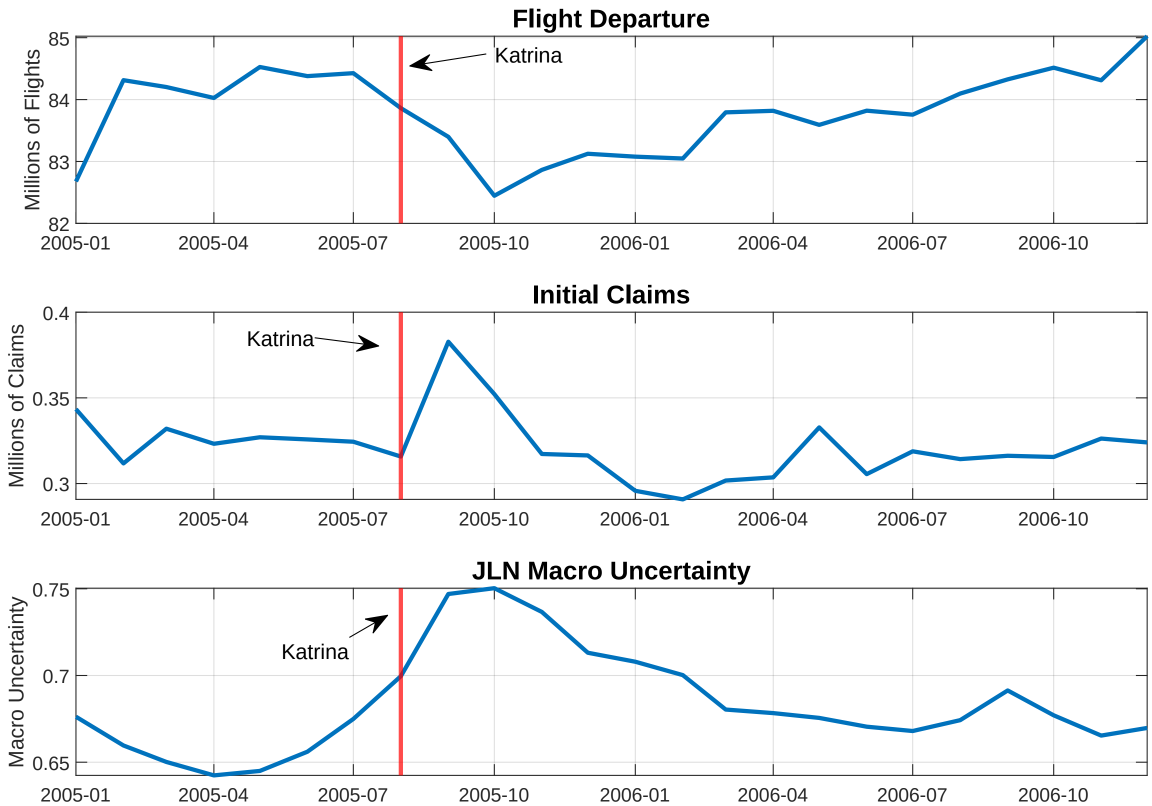
Figure 1 shows the responses of US flight departures, initial claims for unemployment insurance, and macro uncertainty from Jurado, Ludvigson, and Ng (2015) to Hurricane Katrina in 2005:08. The number of flight departures dropped immediately in response to Katrina's landfall and both initial claims and macro uncertainty rose sharply. But the impact on initial claims was highly transitory, while the peak effects on macro uncertainty and flight departures slowly build.

A global pandemic is likewise a natural disaster that functions as an exogenous shock with potentially grave economic consequences. But unlike a conventional natural disaster shock, the Coronavirus (COVID19) shock is a multi-period event that simultaneously disrupts supply, demand, and productivity channels, that is almost perfectly synchronized within and across countries, and that has cataclysmic health, social, and economic implications not just for the foreseeable few weeks after the crisis, but for a long time period.

The ability to design policies to mitigate the economic impact of COVID19 requires reference estimates of the effects of the shock. This paper provides some preliminary estimates of these effects. Our analysis has two ingredients. The first is the construction of a costly disaster (CD) time series from historical data to measure the pecuniary costs of previous disasters. The second is an analysis of the dynamic impact of a costly disaster shock on different measures of economic activity and on a measure of uncertainty. We then design different profiles for the shock to engineer the dynamic effects of a natural disaster interpreted as a large, multi-period, constraint on the ability to produce and consume, as would be characteristic of a pandemic.

We find that the macroeconomic impact of COVID19 is larger than any catastrophic event that has occurred in the past four decades. Although the CD series has short memory, the effects on economic activity are more persistent. Even under a fairly favorable scenario where the shock persists for only five months and where the initial magnitude is calibrated by the cost of Coronavirus relief packages passed in March of 2020, the estimates suggest that there

Figure 1: Responses to Hurricane Katrina



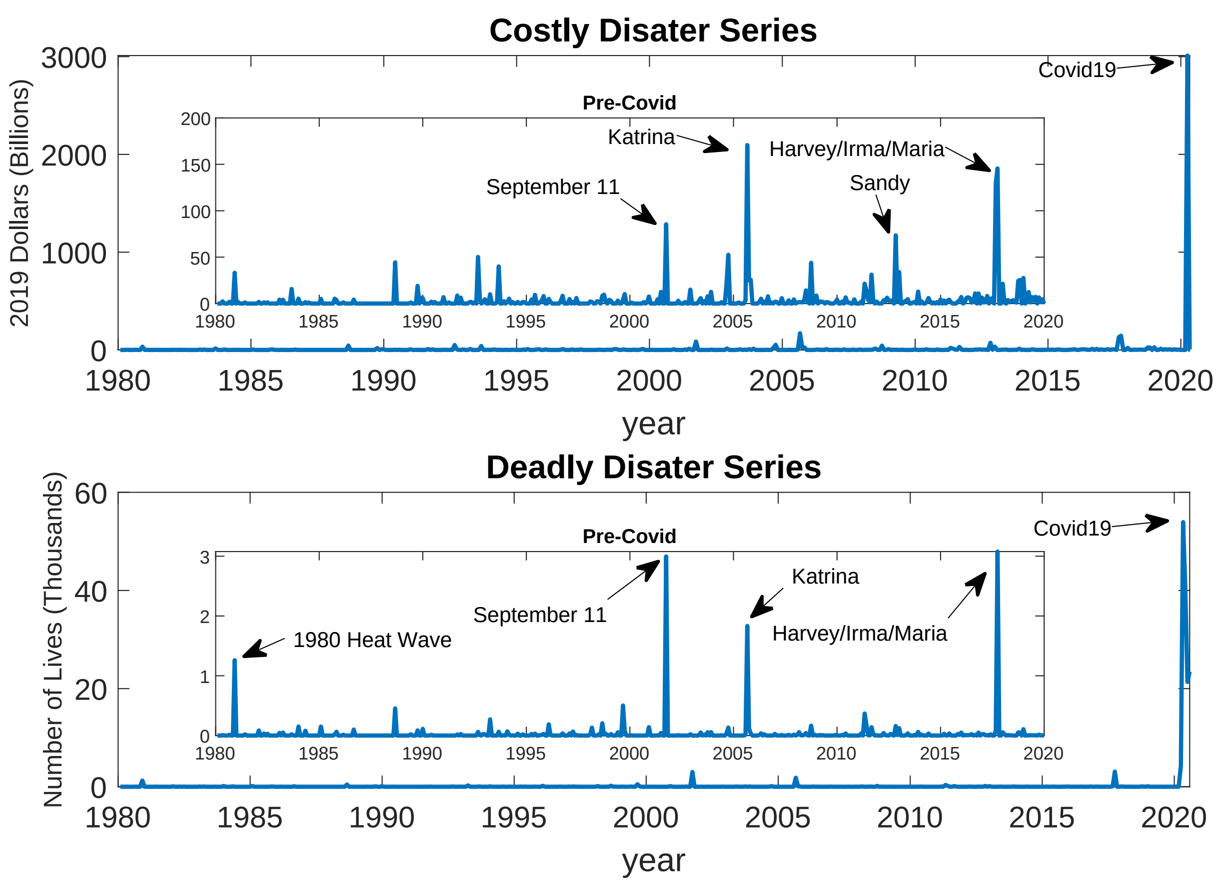
Note: The figure plots number of flight departures in the US, initial claims and JLN macro uncertainty during 2005:01 to 2006:12. The vertical red line indicates the month of Katrina landfall in 2005:08.

will be a peak loss in industrial production of 11.80% and in service sector employment of 5.17% respectively. This translates into a cumulative ten-month loss in industrial production of 20.17%, an employment loss of nearly 45% (or 64 million jobs), and six months of elevated macroeconomic uncertainty. Estimates that allow for nonlinear effects give more pessimistic predictions entailing steeper and longer losses. To the best of our knowledge, this paper is one of the very few time-series analyses of natural disasters on aggregate economic activity, and the first such study of COVID19.

2 Data and Methodology

Our analysis uses monthly data on disasters affecting the U.S. over the last forty years taken from two sources. The first is NOAA, which identifies 258 costly natural events ranging from wildfires, hurricanes, flooding, to earthquakes, droughts, tornadoes, freezes, and winter storms spanning the period 1980:1-2020:04 for $T = 482$ data points, of which 198 months have non-zero cost values.[1] These data, which can be downloaded from `ncdc.noaa.gov/billions/events`, record both the financial cost of each disaster as well as the number of lives lost over the span of each disaster. As explained in Smith and Katz (2013), the total costs reported in NOAA are in billions of 2019 dollars and are based on insurance data from national programs such as flood insurance, property claims, crop insurance, as well as from risk management agencies such as FEMA, USDA, and Army Corps. We take the CPI-adjusted financial cost series as provided by NOAA, and mark the event date using its start date. To obtain the monthly estimate, we sum the costs of all events that occurred in the same month.

Figure 2: Time Series of Disaster Series: 1980:1-2020:04



Note: The figure plots the Costly and Deadly Disaster series. The sample spans 1980:01 to 2020:04.

The second source of data is the Insurance Information Institute (III), which reports the ten costliest catastrophes in the US reported in 2018 dollars. The data, available for download

[1]The number of months with nonzero cost values is less than the number of events because there were many events that occurred in the same month, and we sum them up.

from `www.iii.org/table-archive/2142`, covers property losses only. Thus the cost for the same event reported in the III dataset is lower than that reported in the NOAA dataset. But in agreement with the NOAA data, the III dataset also identifies Hurricane Katrina as the most costly disaster in US history. The III dataset is of interest because it records 9/11 as the fourth most costly catastrophic event, arguably the most relevant historical event for the purpose of this analysis given the large loss of lives involved. But as 9/11 is not a natural disaster, it is absent from the NOAA data. We therefore use the III data to incorporate the event into the NOAA data. To deal with the fact the two data sources define cost differently, we impute the cost of September 11 as follows. We first compute the ratio of cost (in 2018 dollars) of Katrina relative to 9/11 from the III data, which is 1.99. We then divide the cost of Katrina in NOAA data by this ratio to get the insurance-based estimate of 9/11 cost in the same units as those reported in NOAA.

It is more challenging to measure the dollar cost of the COVID19 shock. Ideally, one would measure the total dollar cost of mandatory stay-at-home orders across the United States. Although firm-level insurance against losses attributable to business closures exists, these policies cover only short-term closures due to idiosyncratic incidents such as fire and flooding–they do not cover losses due to pandemics or legally mandatory shut-downs. We therefore instead use the dollar value of the Coronavirus relief packages that were passed by U.S. Congress and signed into law in March 2020 as a crude estimate of the dollar cost of COVID19. These packages total 3.01 trillion dollars, authorized in four separate measures.[2] Because this dollar cost dwarfs any of those associated with previous U.S. natural disasters in our dataset, we forgo including it directly in the CD series due to concerns about the reliability of estimators in the presence of extreme outliers in the data. Instead, we use it as a means of calibrating the size of the COVID19 shock using estimates based on pre-COVID19 data. The nonlinearities implied by outlier shocks are partially addressed in the penultimate section of the paper.

An important limitation of the data needs to be made clear at the outset. With the exception of Hurricane Sandy, the natural disasters in our data have been concentrated in the southern states with FL, GA, or LA having experienced disasters most frequently. However, industrial production is concentrated in the New England area, the Great Lakes area, the mid-West, and the Mid-Atlantic States which have been much less impacted by natural disasters. The data may not be able to establish a clear relation between industrial production and disasters.

[2] Source: https://www.npr.org/2020/05/15/854774681/congress-has-approved-3-trillion-for-coronavirus-relief-so-far-heres-a-breakdown

The packages include 26 billion for testing, 217 billion for state and local governments, 312 billion for public health, 513 billion for all businesses in the form of tax breaks meant to help all businesses, 532 billion for large corporations in the form of loans, 784 billion for individuals, and 871 billions for small businesses in the form of forgivable loans under certain conditions.

The cost measures are based on monetary damages but do not include the value of lives lost, which is another measure of the severity of the disaster. Separately reported in NOAA is the number of deaths associated with each event. Since the number of deaths directly linked to 9/11 is known to be 2,996, we are able to construct a deadly disaster series that tallies the number lives lost for all 259 events considered in the analysis.[3]

Figure 2 plots the resulting *costly disaster* (CD) series, in units of billions of 2019 dollars, and the *deadly disaster* (DD) series, in units of lives lost. There are four prior events in the CD series that stand out: Hurricanes Katrina in 2005, Harvey/Irma/Maria in 2017, Sandy in 2012, and 9/11 in 2001. As a point of reference, the value of CD at these four events are at least four standard deviations away from the mean of the series. In terms of the number of deaths, the sum of the DD series over the sample is 14,221, but three events, namely, Hurricane Harvey/Irma/Maria, 9/11, and Katrina, accounted for nearly two-thirds of the total deaths. Both disaster series are evidently heavy-tailed, and we will return to this point below.[4] Because the size of the increases in both our calibrated COVID19 CD shock and COVID19 deaths dwarfs the previous disasters, the latter are shown in inset on the figure, where the COVID19 values appear on the far right.

We will also make use of two additional pieces of information from these two data files. The first is the number of states being affected as reported in III. For example, Katrina directly impacted six states: AL, FL, GA, LA, MS, TN, while the direct impact of 9/11 was local to the city of New York and the D.C. region. The second is the duration of the event. As reported in NOAA, Katrina was a five-day event, Superstorm Sandy was a two-day event, while the 9/11 attack was a one-day event. From 1980 to 2019, the average duration of an event is 40 days and ranges from one day (e.g., 9/11 and 2005 Hurricane Wilma) to one year (e.g., the 2015 Western Drought). These statistics will be helpful in thinking about the size of the COVID19 shock subsequently.

To estimate the macroeconomic impact of a disaster shock, we begin as a baseline with a six-lag, $n = 3$ variable vector autoregression (VAR) in

$$\mathbf{X}_t = \begin{bmatrix} \mathrm{CD}_t \\ Y_t \\ U_t \end{bmatrix} = \begin{bmatrix} \text{Costly Disaster} \\ \text{log (Real Activity)} \\ \text{Uncertainty} \end{bmatrix},$$

where CD is our costly disaster series just described, U is a measure of macroeconomic uncertainty, and Y is one of four measures of real activity that will be discussed below. The long-run

[3] Source: `https://en.wikipedia.org/wiki/Casualties_of_the_September_11_attacks`

[4] We also considered CD scaled by real GDP (in 2019 dollars). The VAR analysis using scaled series delivers quantitatively similar results. It's worth noting that 1992 Hurricane Andrew and 1988 Drought costed more, scaled by 1992 and 1988 real GDP, than 2012 Hurricane Sandy.

trends of all three variables are removed using the methodology in Müller and Watson (2017) before the VAR estimation.[5]

We estimate the VAR using monthly data from 1980:01 to 2020:02, and thus exclude the extremely high value of CD during the COVID19. The reduced form VAR is

$$A(L)X_t = \eta_t.$$

The reduced form innovations η_t are related to mutually uncorrelated structural shocks e_t by

$$\eta_t = Be_t, \quad e_t \sim (0, \Sigma)$$

where Σ is a diagonal matrix with the variance of the shocks, and $\text{diag}(B) = 1$. For identification, B is assumed to be lower triangular. That is, the covariance matrix of VAR residuals is orthogonalized using a Cholesky decomposition with the variables ordered as above. The CD series is ordered first given that the disaster events are, by their very nature, exogenous. The resulting structural VAR (SVAR) has a structural moving average representation taking the form

$$X_t = \Psi_0 e_t + \Psi_1 e_{t-1} + \Psi_2 e_{t-2} + \dots, \tag{1}$$

with the impact effect of shock j on variable j measured by the j-th diagonal entry of Ψ_0, which is also the standard deviation of shock j. The dynamic effects of a one time change in e_t on X_{t+h} are summarized by the Ψ_h matrices which can be estimated directly from the VAR using Bayesian methods under flat priors, or by the method of local projections due to Jorda (2005). The goal of the exercise is to trace out the effect of COVID19 on itself, on economic activity Y over time, and on macroeconomic uncertainty U. This amounts to estimating the first columns of the 3 by 3 matrix Ψ_h at different horizons h.

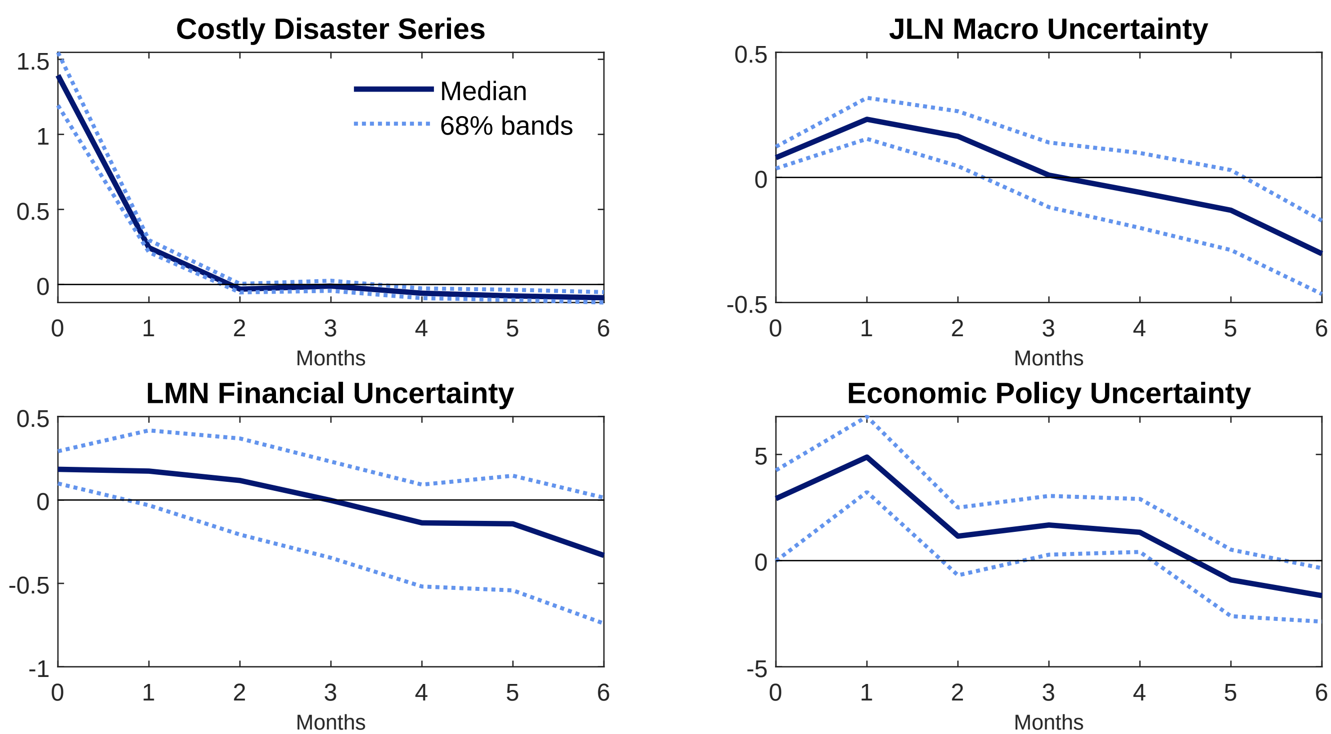
We will consider four monthly measures of real activity Y: industrial production (IP), initial claims for unemployment insurance (IC), number of employees in the service industry (ESI), and scheduled plane departures (SFD). The first three variables are taken from FRED, and the last from the Bureau of Transportation Statistics and is available from 2000 onwards. IP is a common benchmark for economic activity, while unemployment claims are perhaps the most timely measure of the impact on the labor market. In the data, initial claims one month after Katrina (i.e., September 2005) increased by 13.3% compared to its level the previous year. The variable ESI is studied because non-essential activities such as going to restaurants, entertainment, repairs, and maintenance can be put on hold in the event of a disaster, and these are all jobs in the service sector. Disasters tend to disrupt travel due to road and airport closures. Data constraints limit attention to air traffic disruptions, as measured by the number of scheduled flight departures, SFD.

[5] Our results remain robust if we instead include a long-run trend in the VAR estimation.

3 Responses to a One σ One Period Shock

For each measure of Y, we estimate a VAR and compute the response coefficient Ψ_h scaled so that it corresponds to a one standard deviation increase in the innovation to CD. In what follows, the blue line depicts the median response and the dotted lines refer to 68 percent confidence bands. Since the dynamic responses of CD and U to a CD shock are insensitive to the choice of Y and U, we only report these two impulse response functions using the VAR with IP as Y.

Figure 3: Dynamic Response of CD and U to a σ Shock



Note: The figure plots the dynamic responses to a positive one-standard deviation CD shock. The posterior distributions of all VAR parameters are estimated using Bayesian estimation with flat priors and the 68% confidence bands are reported in dotted lines. The sample spans 1980:01 to 2020:02.

The top left panel of Figure 3 is based on the measure of macro uncertainty in Jurado, Ludvigson, and Ng (2015) (JLN). It shows that the impact of a one-standard deviation positive CD shock on itself dies out after two months, suggesting that the CD is a short-memory process that does not have the autoregressive structure typically found in SVARs for analyzing supply and demand shocks. The top right panel of Figure 3 shows that JLN uncertainty rises following a positive CD shock, and that the heightened uncertainty persists for three months. The bottom panel replaces the JLN measure of macro uncertainty by the measure of financial uncertainty developed in Ludvigson, Ma, and Ng (2019) (LMN). A CD shock raises financial uncertainty for one month but quickly becomes statistically insignificant. The bottom right panel uses the measure of policy uncertainty (EPU) in Baker, Bloom, and Davis (2016). A costly disaster shock increases policy uncertainty for about three months, similar to the duration of the impact on JLN uncertainty. In both cases, uncertainty is highest one month after the shock. These results suggest that short-lived disasters have statistically significant adverse effects on uncertainty that persist even after the shock subsides.

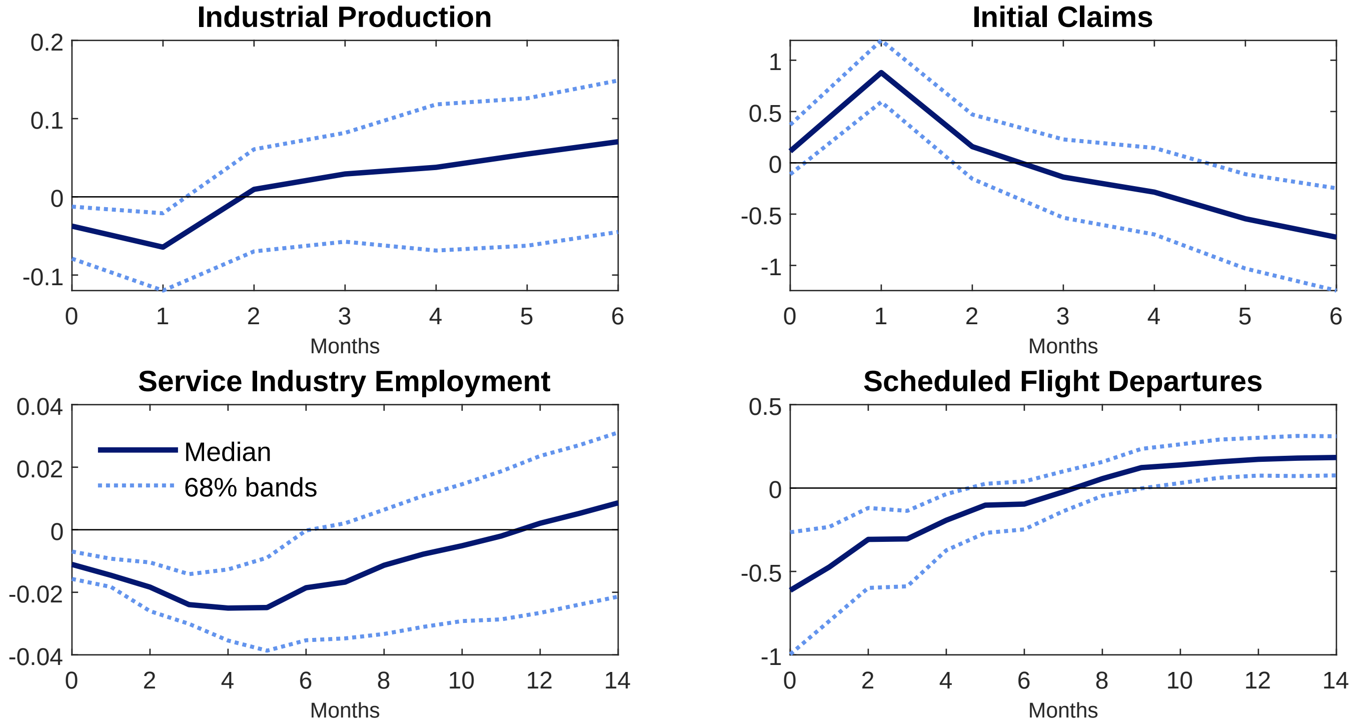
Next, we consider the effect of a one standard deviation CD shock on four measures of Y, all using JLN macro uncertainty in the VAR. The left top panel of Figure 4 shows that monthly IP immediately drops by 0.05% on impact but becomes statistically insignificant after two months. As seen from Figure 3, two months is also the duration needed for the CD series to return to zero. There is, however, some evidence of a strong rebound in the economy but the effect is not statistically well determined. The small estimated effect of CD on IP may be attributable to the fact that natural disasters have not had much direct impact on regions of the U.S. where the bulk of industrial production takes place. The top right panel shows that a CD shock triggers a statistically significant rise in unemployment claims IC for about two months with a statistically significant decline in claims (i.e. a rebound in employment) thereafter.

The bottom left panel of Figure 4 shows that a CD shock leads to an immediate and statistically significant drop in the number of employed workers in the service industry, ESI. Unlike results using IP and IC as Y, the ESI response is more persistent, with the effect bottoming out at about 4 months. It is worth noting that ESI is a national measure of service employment and may mask the higher impact in some regions. The bottom right panel shows that a CD shock forces an immediate and persistent decline in the number of scheduled flights, SFD. Of all the measures of real activity, the impact effect of a CD shock on SFD is not only the largest, but also the most sustained. Though recovery follows right after the shock, the process is slow, taking up to six months for the effect to become statistically insignificant.

Taken together, this baseline estimation using pre-COVID19 data suggests that a one-period, one-standard-deviation increase in CD will have statistically significant adverse effects on real economic activity. Though there are variations in how long the impact will last, for all four real activity measures considered, the effects of the one period shock will die out within a year.

COVID19 differs from historical disasters in several dimensions. The initial impact of the historical disasters had been local in terms of both the geographical area and population affected. In fact, never in the 30 years of data was there a disaster that involved more than one of the five largest states in the country simultaneously. The historical disasters were also

Figure 4: Dynamic Response of Real Activities to a σ Shock



Note: The figure plots the dynamic responses to a positive one-standard deviation CD shock. The posterior distributions of all VAR parameters are estimated using Bayesian estimation with flat priors and the 68% confidence bands are reported in dotted lines. The sample spans 1980:01 to 2020:02.

short-lived, and with the exception of a drought that lasted over a year, they have an average duration of only one month. Even with 9/11, the North American airspace was closed for a few days while Amtrak stopped service for two days, but activity resumed by September 14, albeit gradually.

The same cannot be said of COVID19. COVID19 is a global pandemic and the effects traverse across states and countries. In April 2020, 91% of the world population live in countries with restricted travel.[6] By contrast, the most disastrous events in our CD disaster series in terms of loss of life were Katrina and 9/11, but the number of deaths due to COVID19 far exceeds the deaths due to Katrina and 9/11 combined. Moreover, five months into the pandemic, the crisis had yet to reach its peak, and there is a good deal of uncertainty as to whether normalcy will return by the end of 2020. Social distancing was not imposed in past disasters, and Gascon (2020) documents that the consequence of social distancing may be particularly harsh for those employed in the service sector. Past disasters created destruction in physical capital,

[6]Source: https://www.pewresearch.org/fact-tank/2020/04/01/more-than-nine-in-ten-people-worldwide-live-in-countries-with-travel-restrictions-amid-covid-19/

while COVID19 creates no such damage. Instead, the labor force is constrained from working efficiently, and resources are diverted to unanticipated uses. Finally, as mentioned above, industrial production was not severely impacted by past natural disasters. Taken together, these considerations suggest that the dynamic effects of CD need to be altered to reflect shock profiles commensurate with our understanding of COVID19, which means shocks that last longer than one period, and much larger than one standard deviation.

4 Effects of Prolonged Shocks

This section addresses the problem that COVID19 is not a one-shot shock. Ideally, the duration of the shock is the life of the virus which is not only unobservable, but potentially endogenous. To the extent that a COVID19 shock can be thought of as an economic shock that constrains consumers and producers from conducting economic activities, we use the expected duration of the 'stay-at-home' policy as the government's expected duration of the shock.

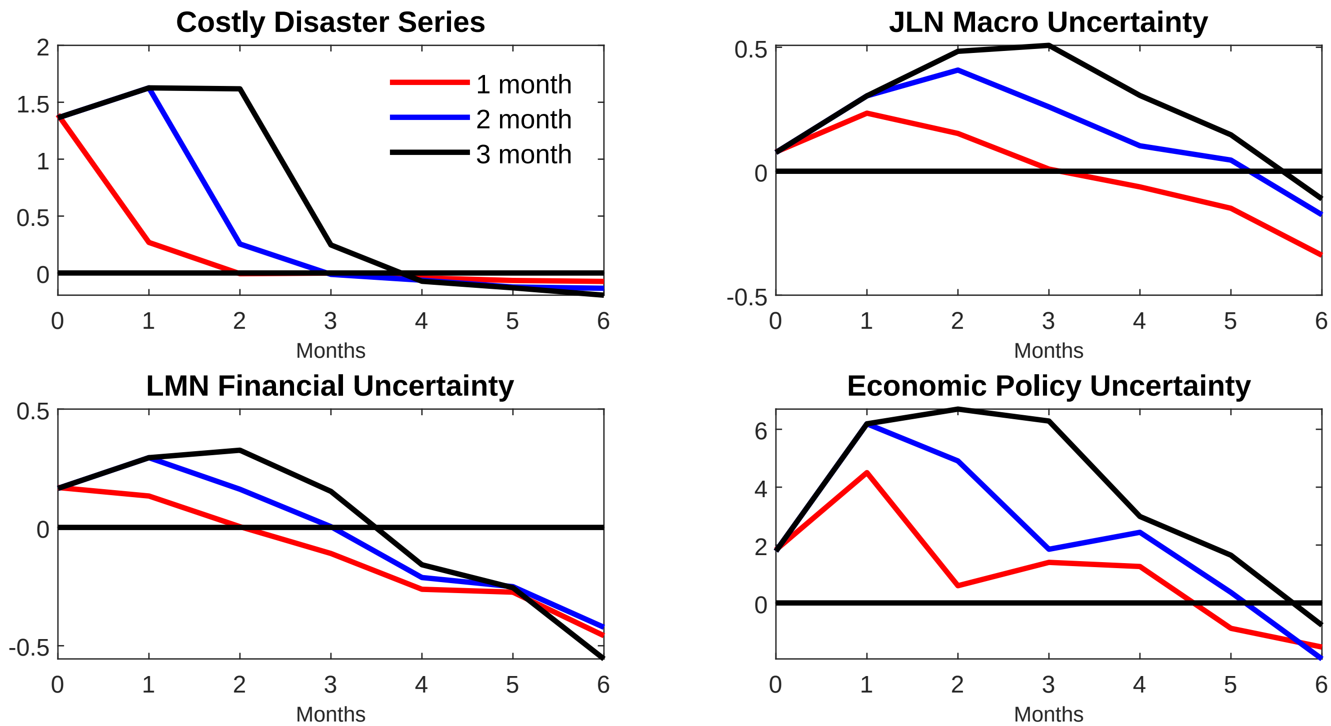
Let $\mathbb{X}^t$ collect all information in X at time t and at all lags. From the moving-average representation of the SVAR given in (1), we see that if there are two consecutive shocks of one standard deviation, the dynamic response of X_{t+h} is

$$\mathbb{E}\Big[X_{t+h}\Big|e_{1t}=\sigma, e_{1t-1}=\sigma;\mathbb{X}^t\Big]-\mathbb{E}\Big[X_{t+h}\Big|e_{1t}=0, e_{1t-1}=0;\mathbb{X}^t\Big]=\Psi_h+\Psi_{h+1}.$$

If the shock in t is of size $.5\sigma$, and the one at $t+1$ is of size 2σ, the desired response matrix is $.5\Psi_h+2\Psi_{h-1}$. Scaling and summing the Ψ_h coefficients allows us to evaluate all the dynamic responses to each of the shocks at a magnitude deemed appropriate. The idea is akin to the one used in Box and Tiao (1975) to study the effect of interventions on a response variable in the presence of different dependent noise structure, or the innovational outlier model studied in Fox (1972). We are only interested in the effect of a disaster shock now interpreted as a constraint on economic activity and so only need to estimate the first column of Ψ_h for $h=1,...H$.

Figure 5 reports the response of CD and U, similar to Figure 3, except that there are now consecutive one-standard deviation shocks. To avoid clutter, the confidence bands are not plotted as their significance can be inferred from Figure 3. The red line is the same as the one period shock reported in Figure 3 and serves as a benchmark. Evidently, the CD series now requires three months to die out after a two-period shock, and four months after a three-period shock. The effects on all measures of uncertainty become larger and more persistent. Taking the JLN measure as an example, U peaks after three months instead of one, and is four times larger.

Figure 5: Dynamic Response of CD and U to Multi-period one σ Shock



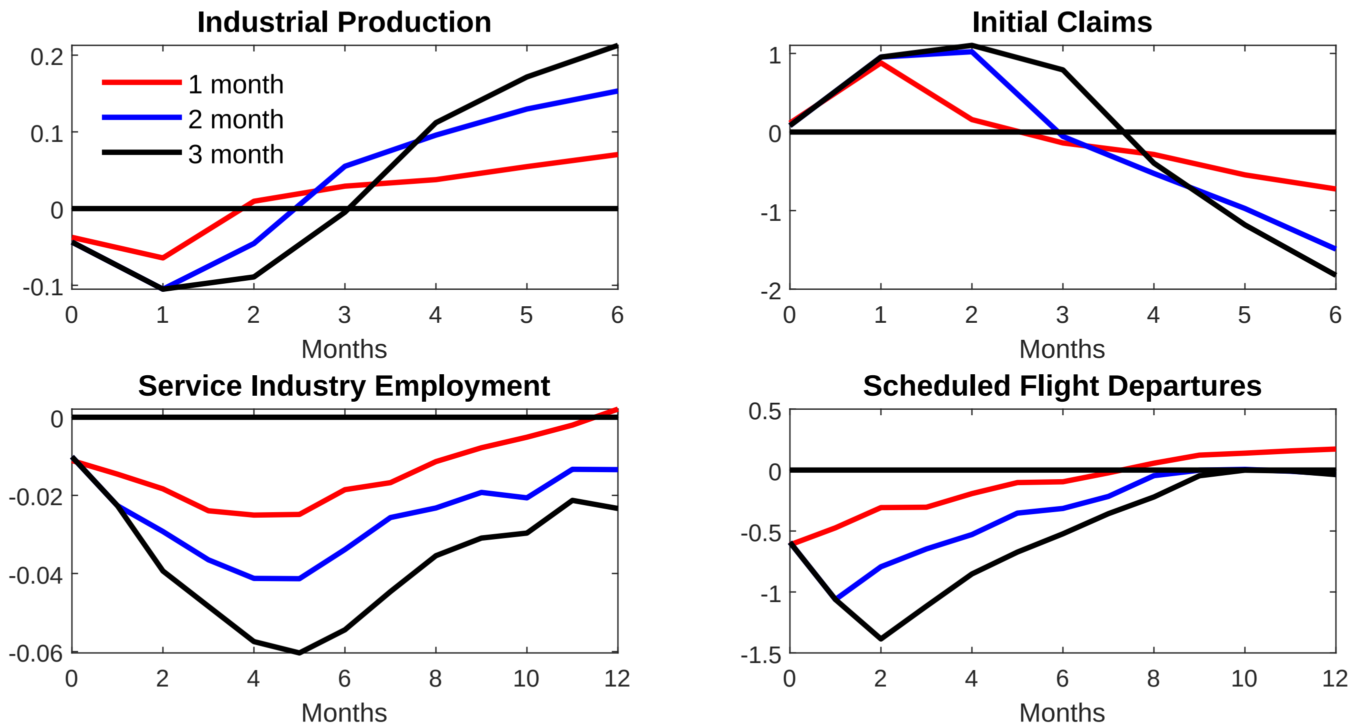
Note: The figure plots the dynamic responses to multi-period consecutive positive one-standard deviation CD shocks. The sample spans 1980:01 to 2020:02.

Figure 6 reports the dynamic responses of the four measures of Y to the multi-period shock of one standard deviation each period. The red lines are identical to the ones plotted in Figure 4 for a single period shock. For IP, the adverse effects are prolonged but are not significantly magnified. For IC, the maximum increase is the same in the multi-period shock as it is for a single period, presumably because initial claims can only be filed once, and the losses are front loaded, and always occurs one month after the shock. However, multi-period shocks slow the time to recovery from two months to four. For ESI and SPD, there is a clear amplification effect due to consecutive shocks. At the worst of times, employment loss in the service sector is tripled that due to a one-shot shock, and the series is not back to control for well over three quarters. Similarly, instead of an immediate recovery, multi-period shocks reduce scheduled flight departures by two more months before a slow recovery begins.

5 Results for Multiperiod Multi-σ Shocks

We now engineer the shock profile to better reflect our understanding of the COVID19 disaster. For this, we consider dynamic responses to multi-period large shocks. To get a sense of the

Figure 6: Dynamic Response of Real Activities to Multiperiod one σ Shock



Note: The figure plots the dynamic responses to multi-period consecutive positive one-standard deviation CD shocks. The sample spans 1980:01 to 2020:02

magnitude of COVID19, note that by the end of March 2020, 10 million Americans had made initial unemployment insurance claims, which is a 900% increase compared to February 2020, comparable in magnitude to that during the Great Depression. Furthermore, as of August 2020, COVID19 has already resulted in 159,000 deaths in the US, which has more fatalities than the Korean War (92,134) and has exceeded the number of deaths due to the Vietnam War (153,303).[7]

Our baseline profile of COVID19 is based on the fact that Hurricane Katrina was a 11σ shock and CD series in 2020:03 based on the March relief package is 17.5 times larger than the cost of Katrina. Therefore, we take 192σ as the benchmark magnitude of COVID19. We also consider a more conservative profile based on an estimated insurance cost of business closure provided to us by American Property Casualty Insurance Association, which results in one-trillion dollar insurance cost.[8] This translates into a cost of COVID19 that is 5.9 times larger

[7]Source: `https://en.wikipedia.org/wiki/United_States_military_casualties_of_war`.

[8]These estimates were calculated by the American Property Casualty Insurance Association (APCIA), in the framework of looking at Business Interruption type of coverages (which do not normally cover pandemics). So they do not directly reflect assumptions about total revenue and/or total operating expenses, which would result in larger numbers. According to APCIA, the main component driving these estimates are payroll and

than that of Katrina, and therefore we take 65σ as the magnitude of COVID19 for this case.

As for the duration, we calibrate the shock profiles by using the fraction of states that are listed as "not reopening" weighted by their GDP contributions. Table 1 reports the fraction of GDP (2019:Q4) earned in states that are categorized as reopened/reopening versus those that are not. As of July 31, 52.4% of 2019:Q4 GDP was earned in states that are not reopening. Some of these states are pausing or reversing previous reopening plans because of the surge of new COVID19 positive cases in late June and early July. Therefore, we first calibrate the size of shock in July to be 52.4% of the size of shock in March (192σ) or 100σ shock. If we assume that the shock was zero in the interim months, then the five-month shock profile from March 2020 to July 2020, is a (192,0,0,0,100) standard deviation shock profile.

Table 1. State-level Reopening Summary Statistics

Snapshot	Fraction of 2019 Q4 GDP Earned in States	
	Reopening	Not Reopening
As of April 30	12.30%	87.70%
As of May 31	53.90%	46.10%
As of June 30	59.03%	40.97%
As of July 31	47.56%	52.44%

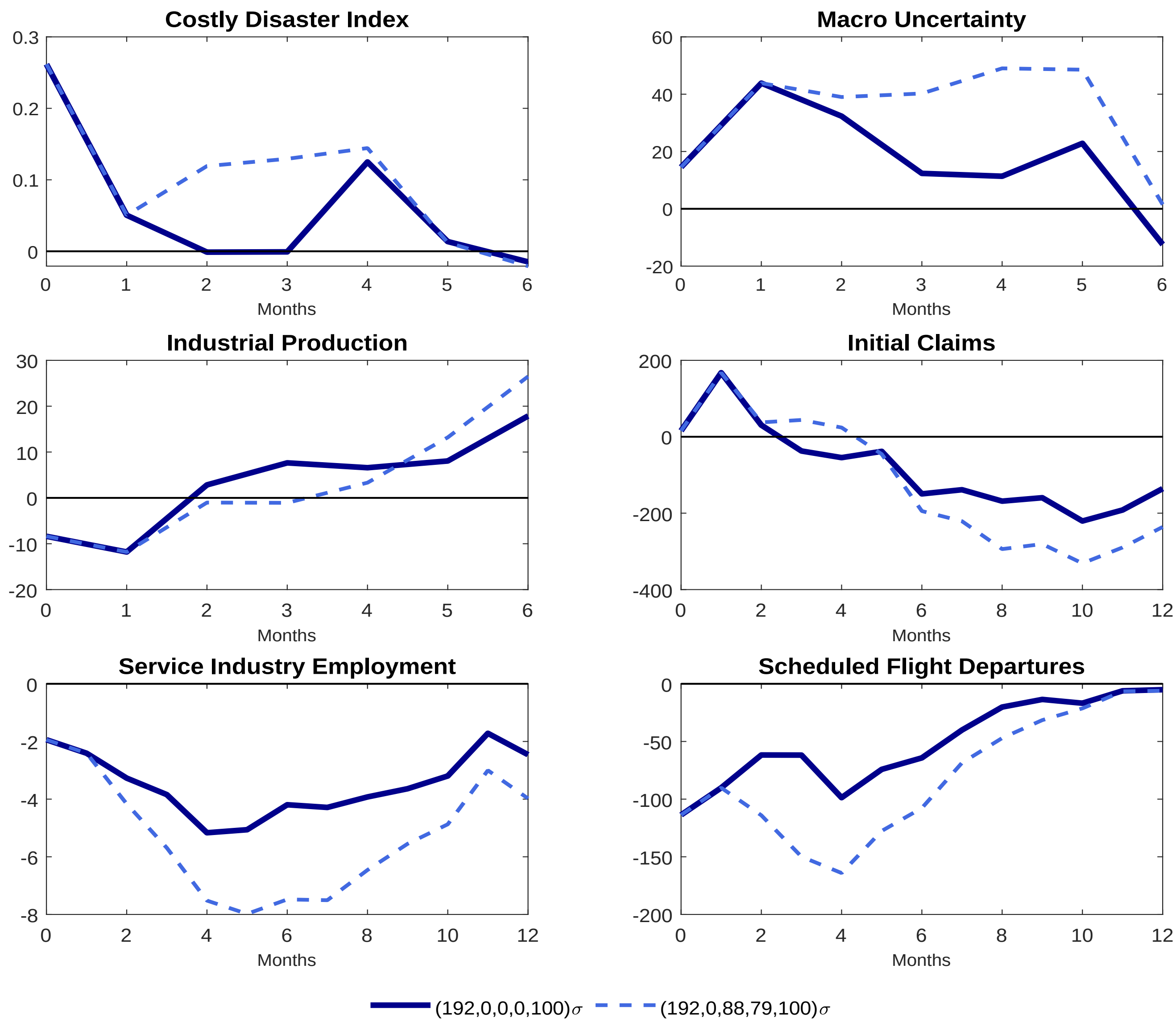
Note: This table report the fraction of 2019 real GDP earned in states that are "reopening" and "not reopening". The source of the data is from the New York Times (link: https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html). "Reopening" states include all those that are either "reopening" or "reopened." "Not reopening" includes all states that are assigned to one of the following categories: "regional opening," "shutdown," "pausing," and "reversing." The state-level 2019 GDP estimates are obtained from Bureau of Economic Analysis.

A large shock shifts up the dynamic responses relative to a one-standard-deviation shock presented in Figure 4, while a multi-period shock shifts the dynamic responses to the right as shown in Figure 6. It is of interest to ask how the dynamic responses would change if the disruption is spread over more periods. Figure 7 plots the dynamic responses of a $(192,0,0,0,100)\sigma$ shock profile in dark blue. Plotted next in dotted blue is a five-month $(192,0,88,79,100)\sigma$ shock profile. This alternative profile is based on the fraction states that were not reopening weighted by their GDP contributions from May to July.

The picture that emerges from Figure 7 is that cumulative losses are primarily determined by the total magnitude of the shock rather than the magnitude in any one period. But the

benefits.

Figure 7: Dynamic Response to Two Shock Profiles



Note: The figure plots the dynamic responses to different disaster shock profiles. The sample spans 1980:01 to 2020:02

longer the duration holding the shock size each period fixed, the larger are the losses and the slower the recovery. The losses for ESI and SFD are particularly steep and persistent.

We report in Table 2 the maximum response in a 12-month period, where the location of the maximum can be inferred from Figure 6. Table 2 also reports the cumulative loss over the months with negative responses.[9] These maximum and cumulative losses are reported for four different shock profiles. The first two shock profiles, (192,0,0,0,100)σ and (192,0,88,79,100)σ, have initial magnitudes that are calibrated based on the Coronavirus relief package passed in March 2020. The next two shock profiles, (65,0,0,0,34)σ and (65,0,30,27,34)σ, have initial magnitudes that are calibrated based on the APCIA insurance cost. Then the size of the subsequent shocks are calibrated based on the fraction of states that are not reopening, as defined above.

Table 2: Maximum Negative Response to Disaster Shock: Linear Model

Shock Profiles	Industrial Production	Initial Claims	Service Employment	Flights
	Calibration based on Relief Pacakage			
(192,0,0,0,100)σ	−11.80%	167.56%	−5.17%	−113.72%
Cumulative Losses	−20.17%	213.62%	−45.11%	−666.33%
(192,0,88,79,100)σ	−11.80%	167.56%	−7.98%	−164.09%
Cumulative Losses	−22.28%	288.80%	−68.55%	−1048.1%
	Calibration based on APCIA insurance cost			
(65,0,0,0,34)σ	−3.99%	56.73%	−1.75%	−38.50%
Cumulative Losses	−6.83%	72.32%	−15.27%	−225.58%
(65,0,30,27,34)σ	−3.99%	56.73%	−2.70%	−55.55%
Cumulative Losses	−7.54%	97.77%	−23.21%	−354.83%

Note: This table shows maximum negative dynamic response of real activity from VAR $\mathbf{X}_t = (CD_t, Y_t, U_{Mt})'$ for different shock profiles. The size of the positive CD shock is indicated in the first column. The "cumulative loss" is the sum of all negative (positive for IC) responses within 12 months. The sample spans 1980:01 to 2020:02.

Table 2 shows that our first shock profile (192,0,0,0,100)σ will lead to a maximum drop in industrial production of 11.80% occurring after one month, a 5.17% maximum loss in service sector employment (over 7 million jobs) occurring after four months, and a 113.72% reduction in scheduled flights after two months. The reduction in ESI is not trivial because over 75% of workers (or over 140 million) are employed in the service sector. The implied cumulative reduction of 45.11%, or loss of nearly 64 million service sector jobs before the onset of recovery is staggering. These numbers reach a cumulative reduction of 69%, or a loss of 98 million service

[9] The cumulative responses could be overestimated because the response can be statistically zero at lags much earlier than the point estimate of the response crosses the zero line.

jobs, for the (192,0,88,79,100)σ profile.

6 Nonlinearities

While there were 259 disasters in our data, most of these were small. A linear model may underestimate the effect of large shocks. We therefore consider a model that allows the coefficients to be different for large disasters. Let S_t be an observable variable. We estimate a series of single equation regressions, one for each h, to obtain the dynamic response at lag $h \geq 1$:[10]

$$Y_{t+h} = \alpha_0 + \beta^h(L)' X_{t-1}(L) + S_{t-1}\left(\delta_0^h + \delta_1^{h'} X_{t-1}\right) + e_{t+h}, \tag{2}$$

where $S_t = \frac{\exp(-\gamma \text{DD}_t)}{1+\exp(-\gamma \text{DD}_t)}$ is a logistic function in the number of deaths in our deadly disaster series, DD, normalized to be mean zero and variance one.

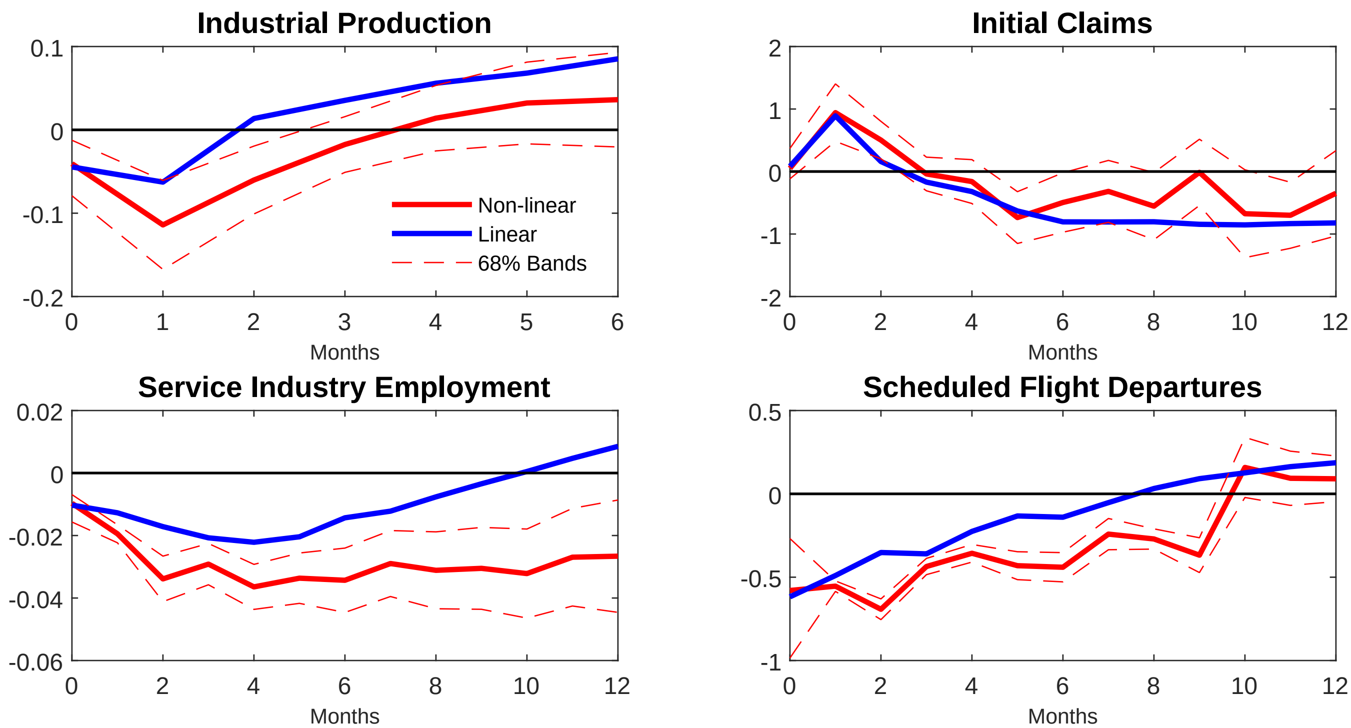
Figure 8 plots the dynamic responses to a one-period, one standard deviation shock constructed from the non-linear model. For IP and IC, the responses of the non-linear model (in red) are similar to the linear model (in blue). Both responses peak almost immediately after the shock. For SFD, the negative responses are larger and more persistent. The ESI losses are larger than those in the linear model, but even in the non-linear model, the effects are statistically insignificant after one year.

Table 3 summarizes the maximum and cumulative responses based on the non-linear model.[11] Compared to estimates from linear model reported in Table 2, the maximum impact of the disaster shock is larger for all measures of activity, and particularly so when the shock extends more than one period. The first profile of (192,0,0,0,100)σ shock now leads to a maximum one-month reduction in IP of 16.38%, a 165% reduction of scheduled flights, and service employment loss in month eight of 10.38% which is roughly 14 million jobs. The cumulative losses are much larger than the linear scenario, generating a 27% cumulative drop in IP and a 100% drop in service sector employment, or 142 million jobs lost. For the (192,0,88,79,100)σ profile, the numbers are even larger: the cumulative losses for service sector employment are 153%, or 217 million jobs lost. This more pessimistic scenario may have seemed inconceivable at the beginning of the year, but between March to July 2020, there were already 55 million unemployment insurance claims in the US.

[10] This procedure has been called the "local projection" method by Jorda (2005).

[11] The estimated CD shock for Katrina from the regression of CD series on the RHS variables in equation (2) is 11.4σ above its mean. Therefore, we continue to take 192σ as the benchmark magnitude of COVID19 for the nonlinear model.

Figure 8: Dynamic Response of Real Activities to a σ Shock: Non-linear Model



Note: The figure plots the dynamic responses to a positive one-standard deviation CD shock from the non-linear model. The posterior distributions of all parameters are estimated using Bayesian estimation with flat priors and the 68% confidence bands are reported in dotted lines. The sample spans 1980:01 to 2020:02.

Table 3: Maximum Negative Response to Disaster Shock: Non-linear Model

Shock Profiles	Industrial Production	Initial Claims	Service Employment	Flights
	Calibration based on Relief Pacakage			
(192,0,0,0,100)σ	-16.38%	190.12%	-10.38%	-165.10%
Cumulative Losses	-26.69%	291.15%	-99.56%	-1365.70%
(192,0,88,79,100)σ	-16.38%	190.12%	-16.21%	-254.33%
Cumulative Losses	-43.02%	483.61%	-152.91%	-2213.70%
	Calibration based on APCIA insurance cost			
(65,0,0,0,34)σ	-5.54%	64.36%	-3.51%	-55.89%
Cumulative Losses	-9.04%	98.57%	-33.70%	-462.33%
(65,0,30,27,34)σ	-5.54%	64.36%	-5.49%	-86.10%
Cumulative Losses	-14.57%	163.72%	-51.77%	-740.42%

Note: This table shows maximum negative dynamic response of real activity from the nonlinear local projection of $\mathbf{X}_t = (CD_t, Y_t, U_{Mt})'$ for different shock profiles. The size of the positive CD shock is indicated in the first column. The "cumulative loss" is the sum of all negative (positive for IC) responses within 12 months. The sample spans 1980:01 to 2020:02.

7 Conclusion

Based on the monthly data on costly disasters affecting the U.S. over the last forty years, we provide some preliminary estimates of the macroeconomic impact of COVID19 over the next 12 months. We find that even in a fairly conservative scenario without nonlinearities, large multiple-period shocks like COVID19 can create a 11.80% monthly drop in IP, a cumulative losses of more than 60 millions jobs in service industry, sustained reductions in air traffic, while macroeconomic uncertainty lingers for up to six months. The non-linear model suggests even more pessimistic outcomes.

There are, of course, caveats to the analysis. First, COVID19 is different from past disasters in many ways, and the historical data may well over- or under-estimate the effects. As mentioned above, the disasters in history have not led to serious disruptions in industrial production. The relatively small loses found for IP must be interpreted in this light. Second, we have focused the dynamic responses under one year because the longer horizon results are not very well determined. This could be a consequence of the short-memory nature of disaster shocks. Furthermore, to the extent that the CD series is heavy-tailed, it is fair to question whether standard Bayesian sampling procedures or frequentist asymptotic inference based on normal errors are appropriate. Nonetheless, the different profiles all suggest steep declines in economic activities, and the longer the duration of the shock, the larger the cumulative losses.

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Appendix

Table A1. List of States that are reopened or reopening

Snapshot	
As of April 30 (10 States)	AK, CO, GA, MN, MS, MT, OK, SC, SD, TN
As of May 31 (38 States)	AL, AK,AZ,AR,CO,CT,DC,FL,GA,HI,ID,IN IA,KS,KY,LA,MD,MA,MN,MS,MO,MT,NV NH,NC,ND,OH,OK,RI,SC,SD,TX,UT,VT,VA WV,WI,WY
As of June 30 (37 States)	AL, AK, CO,CT,DC,FL,GA,HI,IN, IA,KS, KY ME,MD,MA,MN,MS,MO,MT,NE,NH,NJ,NY ND,OH,OK,PA,RI,SC,SD,TN,UT,VT,VA,WV WI,WY
As of July 31 (29 States)	AK,DC,GA,HI,IL,IA,KS,KY,ME,MD,MA,MN MO,MT,NE,NH,NY, ND,OH,OK,PA,RI,SD,TN UT,VT,VA,WV,WI

Note: This table lists the states that were reopened or reopening. The source of the data is from the New York Times (link: https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html). "Reopening states" include all states that are either "reopening" or "reopened" as of the date specified in the first column.

Table A2. Glossary

	Reopened/Reopening
Reopened	States have reopened every major sector, though businesses are almost universally under restrictions, such as allowing fewer customers, requiring workers and customers to wear masks, and enforcing social distancing.
Reopening	States are reopening in stages, allowing some sectors to open ahead of others.
	Not Reopened/Reopening
Regional Reopening	Governors are allowing regions that meet criteria for slowing the outbreak to open ahead of others. The hardest-hit areas remain under stricter lockdowns
Pausing	Sates have reopened some sectors, but paused or delayed plans to reopen further after seeing a rise in coronavirus cases.
Reversing	Some states have moved to close certain sectors statewide or in certain counties after seeing a surge in cases.
Shutdown	States remain on lockdown, with shutdown orders firmly in place.