COVID-19 and the Macroeconomic Effects of Costly Disasters

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Motivation

- COVID-19 is a disastrous health and economic shock.
- COVID-19 is both a **natural disaster** and a **business cycle** shock.
- Unlike most business cycle shocks, natural disasters are cleanly **exogenous** shocks.
- **This paper**:
  - Models COVID-19 as a natural disaster shock in a dynamic empirical setting to provide preliminary estimates of the short-term economic effects.
  - Construct a **Costly Disaster series (CD) series** and a **Deadly Disaster series (DD) series** from past natural disasters.
  - Analyze effects on IP (industrial production), IC (initial claims), SIE (service industry employment), and SFD (scheduled flight departures).
  - Using estimates of these effects, we **engineer** a disaster shock profile to account for differences with past natural disasters and match our understanding of COVID-19 as a series of big, multi-period shocks.

Data Source 1: NOAA

National Oceanic and Atmospheric Administration (NOAA)

- NOAA provides data on natural disasters from 1980:01 and 2020:04
  - 258 costly natural events ranging from wildfires, hurricanes, flooding, to earthquakes, droughts, tornadoes, freezes, and winter storms.
- $T = 484$, with 198 non-zero values on financial costs of each disaster as well as the number of lives lost over the span of each disaster.
- The total costs in billions of 2019 dollars from insurance data and risk management agencies, e.g., FEMA, USDA, Army Corps.
- Take the CPI-adjusted NOAA cost series, 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.

Data Source 2: Insurance Information Institute (III)

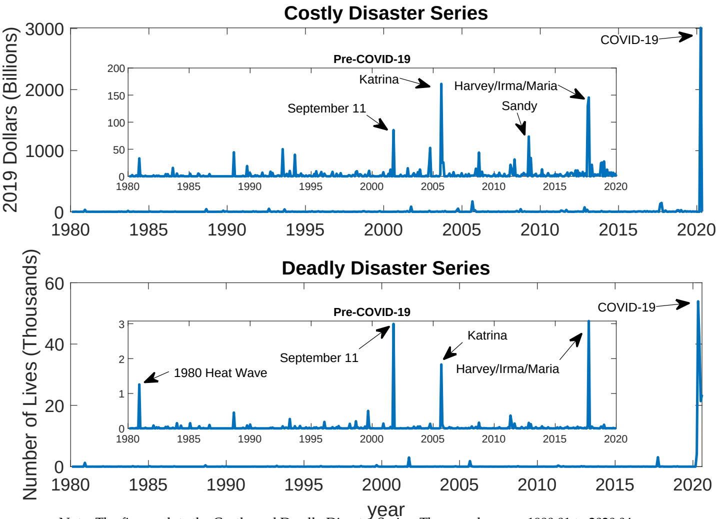
- III reports the ten costliest US catastrophes in 2018 dollars.
  - III includes September 11, 2001 but NOAA does not.
  - III: property losses only, always smaller than NOAA.
- NOAA and III agree Katrina is most costly disaster.
  - Based on Katrina in both datasets, impute 9/11 NOAA value to splice onto costly disaster series (CD).
  - 2966 lives lost in 9/11. Splicing these gives deadly disaster series (DD).

Data Source 3: Coronavirus Relief Packages and APCIA Estimates

More challenging to measure the dollar cost of COVID-19.

- For COVID-19, we use dollar value of the coronavirus relief packages that were passed by the U.S. congress and signed into law in March 2020, in total of 3.01 trillion dollars.
  - It includes 26 billion for testing, 217 billion for state and local governments, 312 billion for public health, 513 billion for all businesses, 532 billion for big corporations, 784 billion for individuals, and 871 billion for small businesses.
- We also consider a more conservative profile based on an estimated cost of business closure provided to us by American Property Casualty Insurance Association, which results in a one-trillion dollar cost during the peak of COVID-19. Covers only estimated losses due to payroll and benefits.

Costly and Deadly Disaster Series



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

Sample for Parameter Estimates

- Because COVID-19 values for *CD* and *DD* dwarf prior disasters, we estimate parameters on pre-COVID data (1980:01-2002:02) due to concerns about reliability of estimators in the presence of extreme outliers.
- But we use the COVID-19 obs. to engineer disaster shock profiles appropriate or COVID-19.

Econometric Model I: VAR

- Baseline VAR(6),

$$X_t = \begin{pmatrix} CD_t \\ Y_t \\ U_t \end{pmatrix} = \begin{pmatrix} \text{Costly Disaster} \\ \log\left(\text{Real Activity}\right) \\ \text{Uncertainty} \end{pmatrix}$$

- Reduced-form innovations η_t, structural shocks e_t by

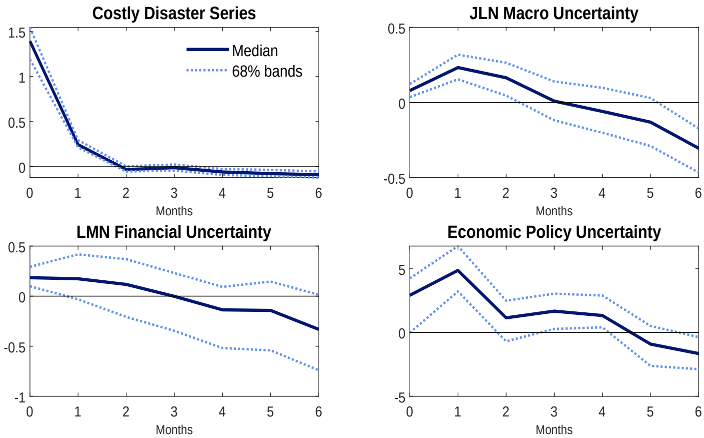
$$\eta_t \quad = \quad Be_t, \quad e_t \sim (0, \Sigma).$$

- Structural moving average representation:

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

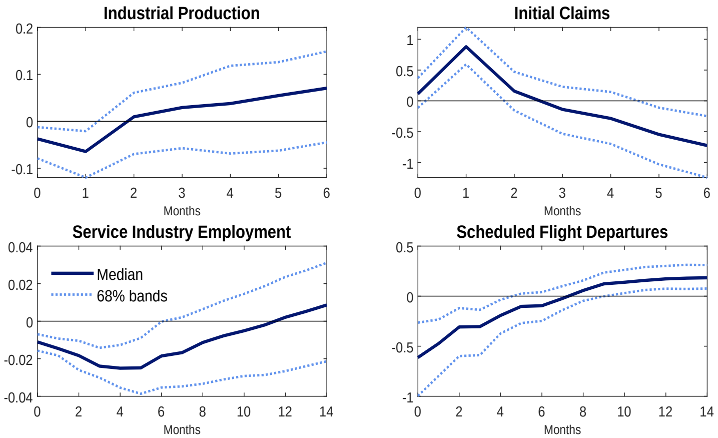
- COV matrix of VAR residuals orthogonalized using a Cholesky decomposition with variables ordered as listed above.
- Interested in dynamic response to **positive** CD shock, or first column of Ψ_h.

Dynamic Response of CD and U



Note: 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.

Dynamic Response of Real Activities



Note: 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.

COVID-19 is a Different Type of Disaster

	Past Disasters	COVID-19
breadth	local, domestic	global, all states
duration	quick punch	end date unclear
deaths	Katrina + 9/11 = 5000+	160,000+ and counting
production	physical capital	cannot produce and consume
social dist.	no such thing	hurts service sector hard

- COVID-19 is not a one-shot shock.
- It is also a BIG shock, compared to past natural disasters.
- Use estimated costs of COVID-19 to calibrate the size of the event.
- Use the duration of ‘stay-at-home’ policies to calibrate duration of the event.

Modeling Multiperiod Shocks

- From moving average representation:

$$X_{t+h} = \Psi_0 e_{t+h} + \Psi_1 e_{t+h-1} + \Psi_2 e_{t+h-2} + \ldots \Psi_h e_t + \Psi_{h+1} e_{t-1},$$

- $\mathbb{X}^t$ collects all information in X at time t and at all lags.
- Example: 2 consecutive one-σ shocks at t and $t-1$. Then the dynamic response of X_{t+h} is:

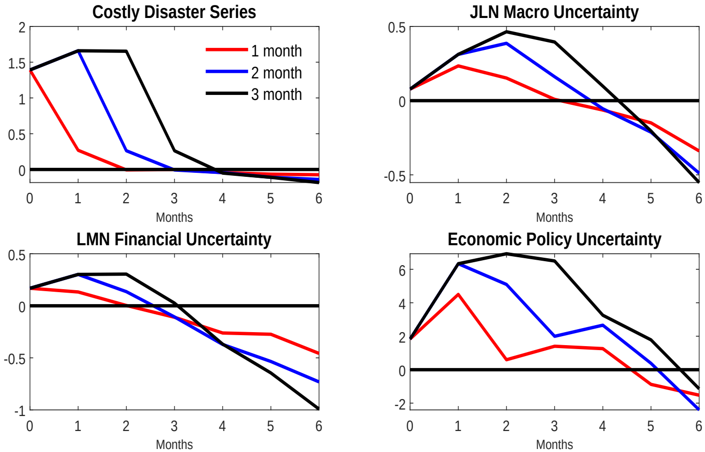
$$\begin{aligned}\mathbb{E}\left[X_{t+h} \middle| e_{1t} = \sigma, e_{1t-1} = \sigma; \mathbb{X}^t\right] - \mathbb{E}\left[X_{t+h} \middle| e_{1t} = 0, e_{1t-1} = 0; \mathbb{X}^t\right] \\ = \Psi_h d_1 + \Psi_{h+1} d_1, \qquad d_j \text{ is the } j\text{-th column of } B\Sigma^{1/2}.\end{aligned}$$

- If the shock at t is of size $.5\sigma$, and the one at $t+1$ is of size 2σ, the desired response matrix is

$$.5\Psi_h d_1 + 2\Psi_{h-1} d_1.$$

- Scaling and summing the Ψ_h coefficients allows us to evaluate the dynamic responses to a multi-period disaster shock at a magnitude deemed appropriate.

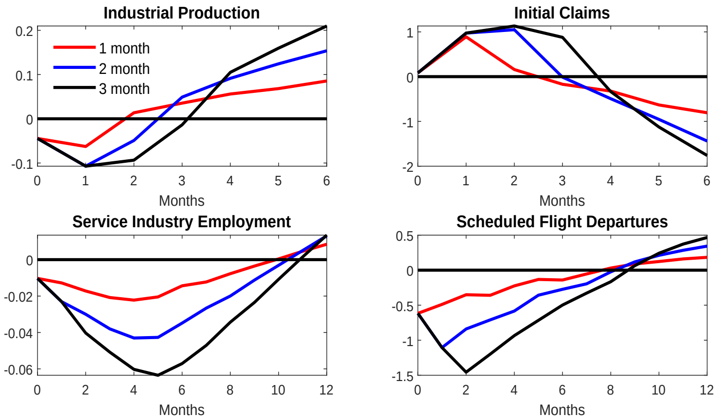
Response of CD and U: Multi-period One σ Shock



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.

Response of Real Activities: Multi-period One σ Shock

- Responses to multiple one σ shocks are larger and more persistent.



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.

COVID-19 Shock Profiles

Now engineer shock profiles to reflect our understanding of the COVID-19 disaster.

- Combine multiperiod event with **large** shocks.
- **Calibration of magnitude of initial COVID shock**. First, note Katrina is 11σ event.
- The CD observation for 2020:03 calibrated from March relief packages is 17.5 times larger than the cost of Katrina => take 192σ (11 times 17.5) as benchmark magnitude of COVID-19.
- Also consider a more conservative profile based on APCIA estimated costs of business closures driven by payroll and benefits obligations alone (nothing for lost revenue or operating expenses).
  - Results in a cost that is 5.9 times larger than that of Katrina, so 65σ is the magnitude of COVID-19 for this case.

COVID-19 Shock Profiles: Duration

- As of July 31, 52.4% GDP earned in states not reopening $=>$ size of July shock $= 0.524 \times (192\sigma)$, or 100σ.

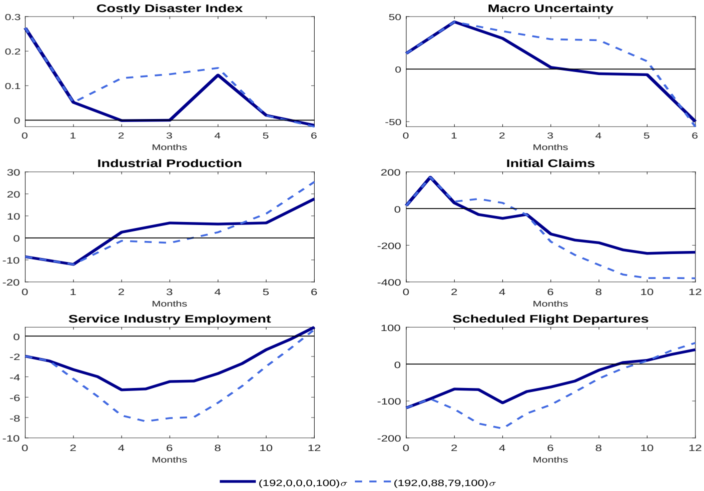
State-level Reopening Summary Statistics

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 (NYT). "Reopening" states include all those where every major sector has reopened or is in the process of reopening, albeit possibly under restrictions such as social distancing; these are categorized as "reopened" or "reopening" by the NYT. "Not reopening" includes all states that are assigned to one of the following NYT categories: "regional opening," "shutdown," "pausing," and "reversing." The state-level 2019 GDP estimates are obtained from Bureau of Economic Analysis.

- Baseline 5-MO profile $(192, 0, 0, 0, 100)\sigma$; relief packages designed to cover lagged effects of initial shock and expire in July.
- Alternative profile $(192, 0, 88, 79, 100)\sigma$; based on the fraction states not reopening weighted by GDP contributions from May to July.

Dynamic Effects of COVID-19 Shock Profiles



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

Max Negative and Cumulative Effects of COVID-19 Shock Profiles

Shock Profiles	Industrial Prod.	Initial Claims	Service Emp.	Flights
	Calibration based on Relief Packages			
$(192,0,0,0,100)\sigma$ *max*	−12.04%	171.12%	−5.28%	−118.63%
Cumulative Losses	−20.58%	217.78%	−39.07%	−653.16%
$(192,0,88,79,100)\sigma$ *max*	−12.04%	171.12%	−8.37%	−174.61%
Cumulative Losses	−24.15%	308.82%	−62.37%	−1040.70%
	Calibration based on APCIA insurance cost			
$(65,0,0,0,34)\sigma$ *max*	−4.07%	57.93%	−1.79%	−40.16%
Cumulative Losses	−6.97%	73.73%	−13.23%	−221.12%
$(65,0,30,27,34)\sigma$ *max*	−4.07%	57.93%	−2.83%	−59.11%
Cumulative Losses	−8.17%	104.55%	−21.11%	−352.33%

Rows labeled *max* show the maximum negative dynamic response from VAR $X_t = (CD_t, Y_t, U_{Mt})'$ for different shock profiles. "Cumulative loss'is the sum of all negative (positive for IC) responses within 12 months. The sample spans 1980:01 to 2020:02.

Modeling Nonlinearities

- A linear model may under-estimate the effect of large shocks. Allow coefficients to be different for severe disasters.

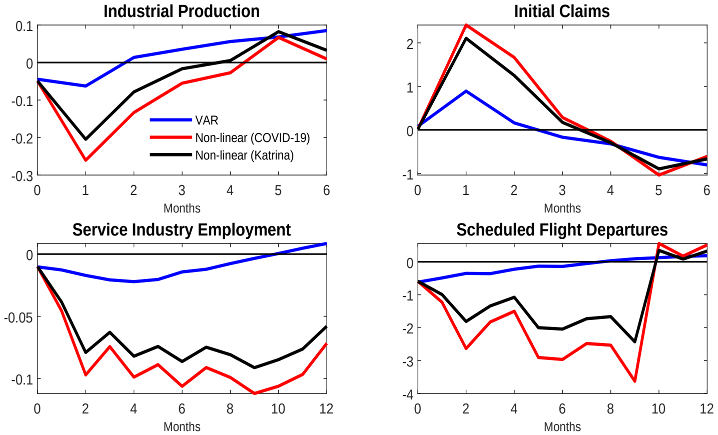
$$X_{it+h} = \alpha_0 + \beta^h(L)'X_{t-1}(L) + S_{t-1}\left(\delta_0^h + \delta_1^{h'}X_{t-1}\right) + \varepsilon_{it+h},$$

- $S_t = \frac{\exp(-\gamma DD_t)}{1+\exp(-\gamma DD_t)}$ is a logistic function in the number of deaths normalized to be mean zero and variance one.
- Estimate $\beta^h(L)$ and δ_0^h and δ_1^h by method of local projections: Jorda (2005)
- Estimate parameters on pre-COVID data. Use $\gamma = 0.25$ which down-weights extreme observations, but not to such a degree that we can't distinguish e.g., Katrina and COVID-19.
- Dynamic IRF:

$$\hat{\beta}^h(L)P_1 + S_{DDj}\hat{\delta}_1 P_1,$$

P_1 is the first column of lower triangular Cholesky factor of cov(ε). S_{DDj} = the value commensurate with Katrina DD or avg. monthly COVID-19 deaths March-July 2020.

Responses to One-σ Shocks: Nonlinear Model



This figure plots the dynamic responses to a positive one-standard deviation CD shock from the nonlinear model. The red lines show the dynamic responses using the COVID-19 calibrated value for S_t, which corresponds to DD = 40,000 average monthly deaths. The black lines use the value for S_t when DD is equal to the number of deaths in the month of Hurricane Katrina. The blue line reports dynamic responses estimated by the linear VAR. The dynamic responses for the nonlinear model are estimated via local projection. The sample spans 1980:01 to 2020:02.

Max Neg & Cumulative Effects of COVID-19: Nonlinear Model

Shock Profiles	Industrial Prod.	Initial Claims	Service Emp.	Flights
	Calibration based on Relief Pacakage			
(192,0,0,0,100)σ *max*	-50.02%	462.69%	-31.80%	-742.59%
Cumulative Losses	-142.67%	887.03%	-286.09%	-4479.70%
(192,0,88,79,100)σ *max*	-50.02%	462.69%	-49.84%	-1105.80%
Cumulative Losses	-251.52%	1582.50%	-445.16%	-7380.10%
	Calibration based on APCIA insurance cost			
(65,0,0,0,34)σ *max*	-16.93%	156.64%	-10.76%	-251.40%
Cumulative Losses	-48.30%	300.30%	-96.86%	-1513.20%
(65,0,30,27,34)σ *max*	-16.93%	156.64%	-16.87%	-374.36%
Cumulative Losses	-85.15%	535.75%	-150.71%	-2498.50%

Rows labeled *max* show the maximum negative dynamic response from nonlinear model for $X_t = (CD_t, Y_t, U_{Mt})'$ for different shock profiles, using COVID-19 calibrated value for S_t corresponding to DD = 40,000 average monthly deaths. "Cumulative loss" is the sum of all negative (positive for IC) responses within 12 months from the nonlinear model under the same calibration. The sample spans 1980:01 to 2020:02.

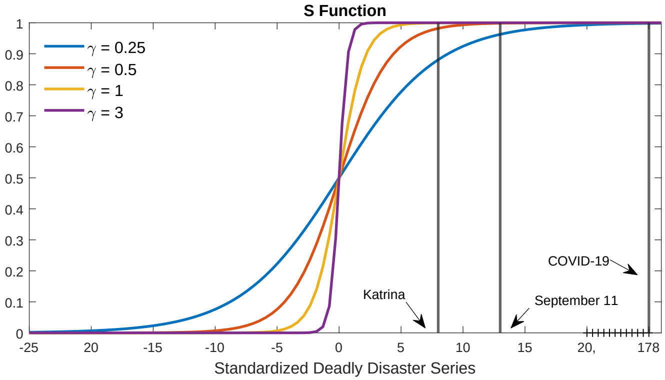
Conclusions and Caveats

- **From data on costly disasters in the U.S. over 40 years**, we provide preliminary estimates of the macroeconomic impact of COVID-19 **over the next 12 months**.
- A conservative scenario implies: 12% monthly drop in IP, cumulative losses exceeding 55 millions jobs in service industry, sustained reductions in air traffic, and heightened macro uncertainty for several months. A nonlinear model is more pessimistic.
- **Caveats**:
  - **COVID-19 is different from past disasters** in many ways, e.g., disasters in history have not led to big disruptions in IP.
  - Really hard to know what shock profile along the lines we calibrated will ultimately transpire.
  - **Longer horizon results not well determined**; hence our focus on next 12 months.
  - **CD series may be heavy-tailed**. It is fair to question standard Bayesian sampling procedures or frequentist asymptotic inference.

Appendix

Logistic Transformation of Deadly Disaster Series

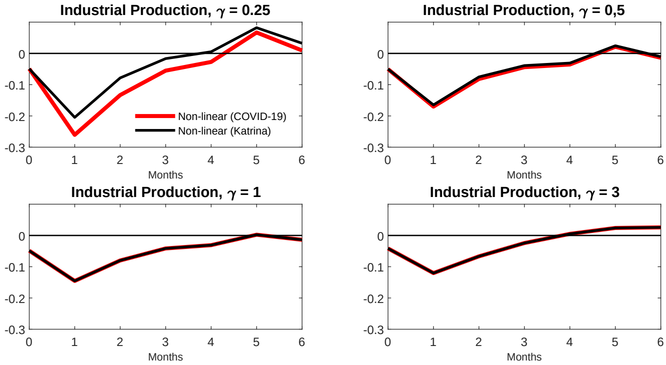
Figure: **Logistic Transformation of Deadly Disaster Series**



The figure plots the function S over standardized DD series under different values of γ. The vertical lines indicate the values of standardized DD from Katrina, September 11, and COVID-19 calibrated value corresponding to 40,000 average monthly deaths.

Sensitivity Checks: Non-linear Model

Figure: **Dynamic Response from Non-linear Model, Sensitivity Checks**



The figure plots the dynamic responses to a positive one-standard deviation CD shock from the non-linear model with different values of γ specified in the subtitle. The red line is the dynamic responses using COVID-19 calibrated value for S corresponding to DD = 40,000 average monthly deaths and the black line uses value of DD series from Katrina. The dynamic responses for the non-linear model are estimated via local projection. The sample spans 1980:01 to 2020:02.

GDP and Unemployment Rate Forecast

- Step 1: Estimate the VAR(6) with variables $\mathbf{X}' =(CD, \log(\text{Service Employment}), \text{Um})$ from 1980:Q1 to 2020:Q1.
- Step 2: Compute the forecasted values from VAR $\hat{\mathbf{X}}$ to 2021:Q1 using the VAR parameters calculated in step 1

$$\hat{\mathbf{X}}_{t+h}= \sum_{j=1}^{6} \hat{\mathbf{A}}_j \mathbf{X}_{t-j}$$

- Step 3: Regress real GDP growth (or unemployment Rate) on $\mathbf{X}$ and SPF median forecast Z_t of GDP growth (or unemployment rate) from 1980:Q1 to 2020:Q1.

$$y_t = a + \mathbf{fi}_X \mathbf{X}_t + \beta_Z Z_t + \eta_t$$

  where y_t is either real GDP growth or unemployment rate.

- Step 4: Calculate forecasted values for GDP_{t+h} growth using the regression coefficients estimated from step 3 and forecasted value $\hat{\mathbf{X}}_{t+h}$ and SPF median forecasts Z_{t+h}.

$$\hat{y}_{t+h} = \hat{a} + \hat{\mathbf{fi}}_X \hat{\mathbf{X}}_{t+h} + \hat{\beta}_Z Z_{t+h}$$

GDP and Unemployment Rate Forecast

GDP Growth and Unemployment Rate Forecasts

	2020Q2	2020Q3	2020Q4	2021Q1
Real GDP Growth (without SPF)	−24.84%	6.01%	2.98%	0.30%
Real GDP Growth (with SPF)	−28.89%	14.23%	4.44%	2.14%
Unemployment Rate (without SPF)	16.42%	13.78%	9.08%	2.88%
Unemployment Rate (with SPF)	17.19%	12.97%	11.34%	9.33%

Note: This table reports the real GDP and unemployment rate forecasts using the VAR model forecasts and SPF forecasts. GMM 95% confidence intervals are reported in parenthesis. Real GDP growth is annualized.