Uncertainty and Risk during COVID-19*

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August 9, 2021

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In Caldara et al. (2021), we use a stochastic volatility VAR (SV-VAR) to study the joint conditional distribution of US GDP growth and corporate credit spreads. As discussed in the main paper, we measure uncertainty (the volatility implied by the conditional distributions), and risk (the probability of tail events) of these two variables estimating the model recursively and using quarterly real-time data. We refer to the main paper for details about the estimation and the construction of the conditional distributions.

An SV-VAR can accommodate large fluctuations in economic time series data. However, the COVID-19 pandemic has brought a recession in the United States that was unique both in size and persistence, being the deepest recession since World War II and the shortest in U.S. history. This unique event created some challenges for the ability of the model to produce plausible joint conditional distributions that could be used for real-time assessment of uncertainty and risk.

In this note, we discuss adjustments to our framework aimed at extracting more plausible measures of risk and uncertainty than those that come out from a straight reading of the predictive distributions. This exercise is similar in spirit to the adjustments of the uncertainty measures proposed by Ludvigson et al. (2021) in the latest update of their measures of macroeconomic and financial uncertainty, and to the forecasting framework proposed by Primiceri and Tambalotti (2020).[1] This note showcases the ability of an SV-VAR to construct plausible conditional forecasts operating only through disciplined adjustments of the structural shocks. We did not implement any change to the model and the estimation algorithm. The reason is that, at least so far, using data for 2020 had only a small effect on most of the estimated model coefficients, the exception being a rise in the standard deviation of the residuals in the volatility equation. We found that the model relies on volatility residuals to account for the large drop in Q2 GDP. Thus, within the context of our SV-VAR model, estimation adjustments such as those proposed by Lenza and Primiceri (2020) for estimating linear VARs using data after March 2020 are not essential.

The top panel of Figure 1 plots the predictive distributions for average GDP growth and corporate credit spreads given advanced GDP estimates through 2019:Q4 (the solid black distributions), 2020:Q1 (dashed blue), and 2020:Q2 (dotted red). The three vintages containing these data are from 2020:Q1,

[1]The adjustment implemented by Ludvigson et al. (2021) can be found in the companion site of the paper, where the authors release the monthly updates to their uncertainty measures.

Table 1: Uncertainty and Tail Risks during the COVID-19 Recession

	Macro			Financial		
	UNC	SF	LR	UNC	SF	LR
COVID-19 Recession						
- Baseline						
2019:Q4	1.89	-1.31	6.80	0.30	1.55	2.83
2020:Q1	2.21	-3.48	5.91	0.41	1.89	3.63
2020:Q2	9.97	-27.01	19.34	1.03	1.70	6.24
- Counterfactual						
2020:Q1	3.06	-11.50	1.53	0.69	2.19	5.10
2020:Q2	5.52	0.26	24.55	0.60	1.64	3.96

Note: This table shows uncertainty and risk associated with macroeconomic and financial conditions at the one-year horizon during the the COVID-19 induced recession. The counterfactual is explained in the main text. UNC: uncertainty; SF: expected shortfall; LR: expected longrise.

2020:Q2, and 2020:Q3 and are published on January 30, April 29, and July 30, 2020, respectively. Regarding GDP growth, the model forecasts for median GDP growth over the the first three quarters of 2020 are 2.9 percent, 1.6 percent and negative 2.5 percent, respectively. By comparison, the median forecasts over the same horizon from the Survey of Professional Forecasters (SPF) conducted by the Federal Reserve Bank of Philadelphia are 2 percent, negative 4 percent and 8.4 percent, respectively.[2] When comparing these two sets of numbers, the forecasts from the SV-VAR model based on the 2020:Q2 and 2020:Q3 vintages have two main issues: The timing of the initial COVID shock is off by one quarter—by April 2020 forecasters already knew the shock had hit the economy, while our model sees the shock only at the end of July—and the model does not have the data to see the rebound prompted by the accommodative policies enacted to contain the virus. These two issues imply that the associated measures of risk and uncertainty are also timed incorrectly and likely have implausible magnitudes. As shown in panel (b) of Table 1, uncertainty and risk are still generally low in 2020:Q1 and spike abruptly in 2020:Q2, when the model first sees the collapse in real GDP growth.

To overcome these issues and generate plausible estimates of risk and uncertainty, we construct a

[2]The survey is available on the Federal Reserve Bank of Philadelphia's website at `https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters`. The surveys for 2020:Q1, 2020:Q2, and 2020:Q3 were conducted on February 14, 2020; May 15, 2020; and August 14, 2020 respectively. The timing aligns well with the data we use to estimate the model.

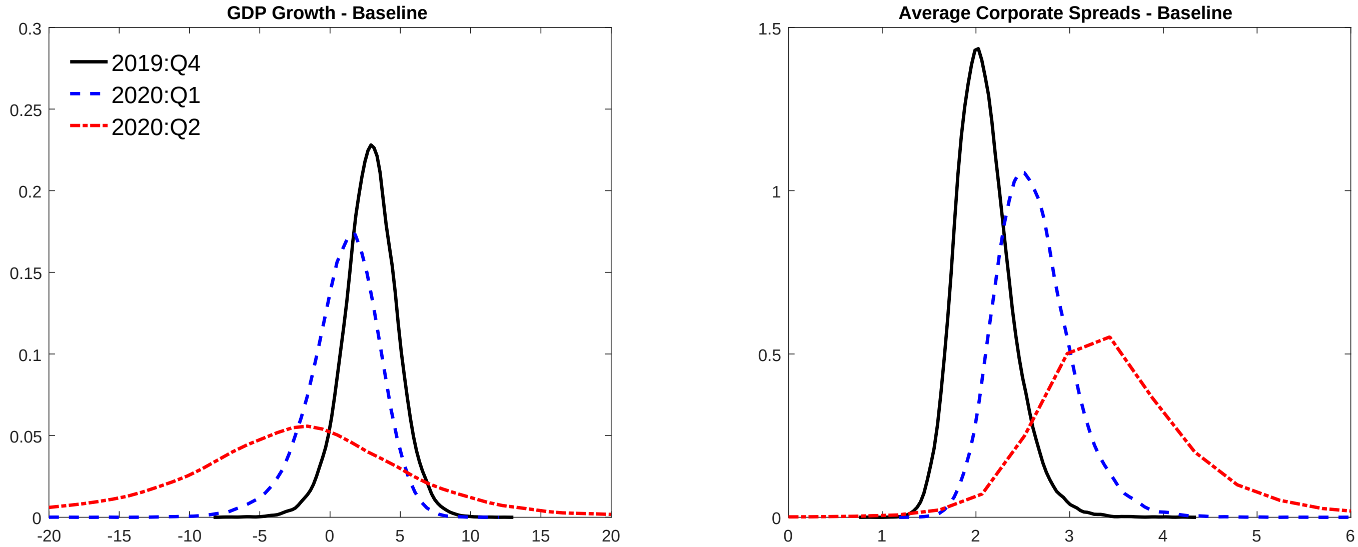
counterfactual proceeding in two steps. First, for the 2020:Q1 and 2020:Q2 forecasts, we tilt the forecast implied by the model to match the one-year ahead median forecast for GDP growth from the SPF. We engineer the tilting through a one-off main business cycle shock hitting in period one of the forecast horizon for both forecasts. With this simple tilting, the model generates forecasts for one-year corporate credit spreads that is within 30 basis points and 50 basis points of the corresponding median forecast from the SPF, respectively.[3] Second, only for 2020:Q2, we keep just the main business cycle and main financial shocks active. The model parses the enormous Q2 decline in GDP growth as signalling a big exogenous spike in volatility, a spike that cannot be attributed to the business and financial cycle correlations captured by the main shocks. The persistence in volatility built into the model propagates this spike for several quarters, generating an implausibly large and persistent increase in volatility. By turning these excess volatility shocks off in Q2, we lower the amount of uncertainty and risk in 2020:Q2 and do not allow volatility (and, consequently, uncertainty and risk) to propagate through the forecast horizon. We found this judgement call to be plausible, given the amount of virus-specific information (from the imposition and lift-off of health and social-distancing policies, news about vaccine development, etc.) that reduced uncertainty and risk over this particular horizon but that the model could not see.[4]

The bottom panel of Figure 1 plots the predictive distributions associated with the counterfactual experiment discussed in the previous paragraph, and the last two lines of Table 1 report the associated measures of risk and uncertainty. By construction, the GDP growth distributions marked as 2020:Q1 and 2020:Q2 (dashed blue and dotted red lines, respectively) are centered around the SPF median forecast. Thus, the model quantifies risk and uncertainty around this forecast. In 2020:Q1, macroeconomic uncertainty is 3.06, almost 40 percent larger than the baseline reading of 2.21, while in 2020:Q2 it is 5.52, about half of the baseline number of 9.98. Comparing these estimates with those at the one-year horizon during the GFC—documented in the main paper—reveals that macro uncertainty increased

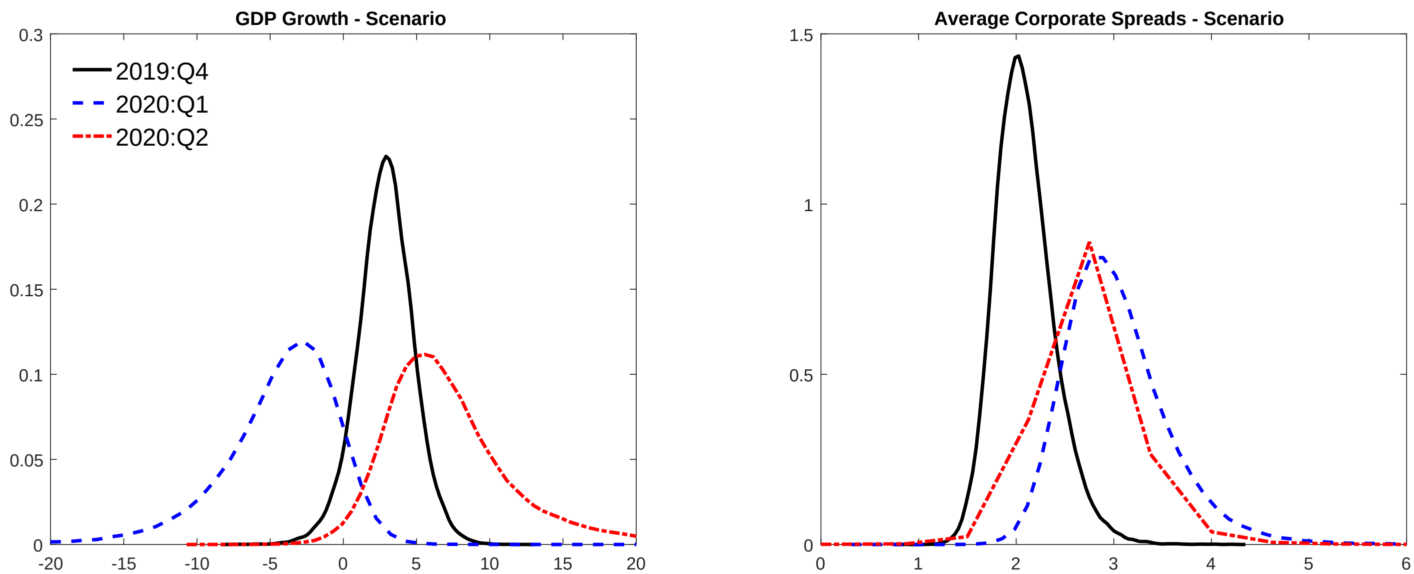
[3] We decided to keep the experiment simple by using only the main business cycle shock. The use of the main financial shock to match the SPF forecast for spreads would only marginally refine the resulting measures of risk and uncertainty.

[4] We had to make this adjustment to track uncertainty and risk during the COVID-19 recession because of the extreme magnitude and speed of how developments materialized. A similar adjustment could be applied to other episodes but would lead to modest refinements in our measures, including for the Global Financial Crisis (GFC), as events in 2008-09 developed less abruptly and were, on a quarterly basis, way less extreme.

Figure 1: Predictive Distributions around the COVID Recession



(a) Baseline distributions



(b) Counterfactual distributions

Note: The two panels plot four-quarter-ahead predictive distributions of average GDP growth and corporate credit spreads. The black distributions are computed using the real-time data vintage through 2019:Q4, the blue dashed distributions using real-time data through 2020Q1 and the red dash-dotted distributions using real-time data through 2020:Q2. In panel (a), we plot the baseline predictive distributions, while in panel (b), for 2020:Q1 and 2020:Q2, we plot counterfactual distributions. See main text for additional details.

much more during the COVID recession, although it remained below the heights of the 1970s. Financial uncertainty largely follows a similar pattern and, according to our estimates, remained well below the peak recorded during the GFC.

The counterfactual estimates of risk are also very different than in the baseline. Under the counterfactual distributions, downside macroeconomic risk is extremely high in 2020:Q1 and collapses in 2020:Q2, whereas upside risk is low in 2020:Q1 and extremely large in 2020:Q2. A similar patter, albeit less extreme, applies to financial risk—downside risk (measured by the longrise) is higher in 2020:Q1 than in 2020:Q2. In contrast, baseline estimates characterize a very different time profile of risk, with downside risk peaking in 2020:Q2.

We view this counterfactual exercise as providing a plausible contour for the evolution of uncertainty and risk during the COVID recession, showing the interplay between the two sets of measures. Our counterfactual highlights that, in the first phase of the recession—captured by the estimates based on 2020:Q1 data released in April—uncertainty was high as the distribution of possible outcomes was assigning positive probability to extreme negative realizations of GDP growth while assigning very low probability to positive realizations. This characterization aligns well with the uncertainty about the depth and persistence of the recession in the early spring months of 2020. During the second phase of the recession—captured by the estimates based on 2020:Q2 data released in July—uncertainty was also high, but for the opposite reason: high probability of extreme positive realizations and low probability of negative ones. This contour aligns well with the fact that, by July, the trough of the 2020 recession had been reached, and the debate had shifted to quantifying the size and speed of the rebound.

References

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