Uncertainty accross volatility regimes: an extension with COVID data

Samuele Borsini (0001083685)
Mario D'Agostino (0001084078)

January 28, 2024

Abstract

This paper addresses three main questions in the empirical literature on uncertainty: is uncertainty exogenous? Is causality between macro and financial uncertainty unidirectional or bidirectional? Do the impacts of uncertainty shocks change in different macroeconomic regimes? We employ a nonrecursive SVAR model that exploits breaks in the volatility of macroeconomic variables that includes the pandemic period and allows for time-varying structural parameters. Results suggest that uncertainty is an exogenous source of decline in the economic activity, unidirectional causality from financial to macroeconomic uncertainty disappears during the COVID period, and the effects of uncertainty shocks amplify during periods of crisis.

1 Introduction

Whether uncertainty is an exogenous driver of the business cycle or an endogenous response to it and how the relationship between uncertainty and real economic activity changes in different macroeconomic conditions are questions that deserve renewed interest after the Great Financial Crisis of 2008 and, more recently, after the COVID-19 pandemic. Nevertheless, there is no unambiguous answer to these questions in the literature.

When it comes to the main findings of the extant literature on the topic, Christiano et al. (2014) find that fluctuations in risk are the most important shock driving the business cycle while Bachmann and Moscarini (2011) explore the hypothesis that the causation runs the opposite way since recessions are times of increased uncertainty and volatility at the micro level. Moreover, the time-varying relation between uncertainty and real economic activity is deeply explored by Arellano et al. (2019) and Basu and Bundick (2017), in moments of high financial stress or constrained conventional monetary policy respectively.

Within the framework of Structural Vector Autoregression (SVAR), the exogeneity/endogeneity issue is empirically explored by Ludvigson et al. (2021) and Carriero et al. (2018) with mixed results. Indeed, the former finds that sharply higher macroeconomic uncertainty in recessions is often an endogenous response to output shocks, while uncertainty about financial markets is a likely source of output fluctuations, but the latter shows that macroeconomic uncertainty can be considered as exogenous and financial uncertainty can at least in part arise as an endogenous response to some macroeconomic developments.

Despite the different methodologies employed by Ludvigson et al. (2021) and Carriero et al. (2018), both the papers do not address completely the issue since the former does not directly address how uncertainty shocks change over time while the latter does not model together the two measures of uncertainty. These shortcomings might be even more relevant if we consider that the time-varying relation between uncertainty and real economic activity can not be disantangled from the exogeneity/endogeneity issue when modelling financial and macro uncertainty together: indeed, if the impact of uncertainty shocks is not constant over time it may be also the case that the direction of causality changes over time. In line with this crucial consideration, Angelini et al. (2019), which is the main reference for this paper, are able to address both the questions simultaneously by employing a nonrecursively identified SVAR model that exploits breaks in the (unconditional) volatility of post-WW2 US macroeconomic variables. Angelini et al. (2019) estimate a small-scale SVAR over the period 1960:M8-2015:M4 with a measure of real economic activity (Y_t, growth rate of real industrial production index), one of macroeconomic uncertainty and one of financial uncertainty (U_{Mt} and U_{Ft} respectively) and identify the shocks of interest with the "identification-through-heteroskedasticity" method with regime-dependent Impulse Response Functions (IRFs) developed by Bacchiocchi and Fanelli (2015) and Bacchiocchi et al. (2018). In particular, they are able to achieve identification by exploiting the differences in the variance-covariance matrix between three volatility regimes: Great Inflation (GI), Great Moderation (GM), Great Recession and Slow Recovery (GR+SR). In doing so, they find that both macro and financial uncertainty are exogenous drivers of the business cycle, with the latter that is able to affect negatively the real economic activity only indirectly through triggering the macroeconomic uncertainty from the Great Moderation onwards, and that, since they allow structural parameters to vary accross different volatility periods, the effects of such uncertainty shocks amplify in periods of economic and financial turmoil.

This paper follows Angelini et al. (2019) in addressing the same questions: is uncertainty exogenous? Is causality between macro and financial uncertainty unidirectional or bidirectional? Do the impacts of uncertainty shocks change in different volatility regimes?

In answering these questions, this paper extends the dataset with the same variables used by Angelini et al. (2019) to the most recent days and exploits the same identification method. In doing so, we have two possibilities: one is to ignore the distortionary effects of the pandemic crisis in 2020 and consider data up to December 2019, the other is to consider COVID-19 and model also data referred to this unparalleled shock. The analysis conducted up to December 2019 allows us to draw the same exact conclusions as Angelini et al. (2019) on the topic and it is briefly reported, as an additional exercise, at the end of this paper [1]. Our main focus is on the analysis that includes also COVID data, which is the main contribution of this paper. In particular, there are two ways in which we can deal with COVID: either we consider COVID observations as outliers belonging to the third volatility regime developed in Angelini et al. (2019) or we add to the game another volatility regime starting indeed from the beginning of the pandemic crisis. We report the results for both specification. We leave however the first as an additional exercise at the end of this paper [2] and we focus on the second one with four volatility regimes which we believe to be the right way to proceed: as a matter of fact, Lenza and Primiceri (2020) sustain that the ad-hoc strategy of dropping COVID observations is inappropriate, in particular for the purpose of forecasting, because it vastly underestimates uncertainty. In addition, we believe that the COVID era, characterized by its degree of instability and indeed uncertainty, has to be treated as a different volatility regime because it has induced also structural changes to be recovered with regime-dependent IRFs.

Consequently, in the main specification of our paper we show that data exhibit 4 volatility regimes with 3 structural breaks, that are exploited to achieve identification for the structural shocks: Great Inflation (1960:M7-1984:M3), Great Moderation (1984:M4-2007:M12), Great Recession and Slow Recovery (2008:M1-2020:M2) and COVID period (2020:M3-2023:M6), where the 3 structural breaks are given by March 1984 for the beginning of the Great Moderation, December 2007 for the beginning of the Great Recession period and February 2020 for the start of the pandemic and post-pandemic era.

[1]The Matlab code with all the comments related to the results up to December 2019 with three regimes is available.
[2]The Matlab code with all the comments related to the results up to June 2023 with three regimes is available.

The findings of our main specification can be summarized as follows. First, macroeconomic uncertainty is exogenous to the business cycle and triggers decline in the real economic activity. The highest drop in the industrial production caused by the macroeconomic uncertainty is indeed observed in the COVID era, followed by the Great Recession and Slow Recovery period, while the lowest during the Great Moderation period. Our result is consistent with Angelini et al. (2019) and Carriero et al. (2018) but not with Ludvigson et al. (2021). Second, as Angelini et al. (2019), we find that financial uncertainty affect real economic activity only indirectly through the macro uncertainty starting from the Great Moderation period. However, we find that this is no longer true in the COVID era where the "one-way" causality from financial to macro uncertainty disappears. Third, the estimated time-varying Impulse Response Functions (IRFs) confirm the idea that structural parameters are not fixed accross different volatility regimes.

In order to achieve these conclusions, we consider three overidentified nonrecursive SVARs: the first featuring endogenous macroeconomic uncertainty and letting both types of uncertainties affect each other, the second in which macro uncertainty does not respond contemporaneously to real activity shocks and does not affect financial uncertainty in all the four volatility regimes (unidirectionality) and the third, which is our proposal supported by the empirical evidence, in which macro uncertainty is still exogenous in all the four regimes but starts to affect also financial uncertainty in the last regime (bidirectionality from the COVID period). All the specifications assume that financial uncertainty does not respond on impact to negative economic shocks, following Angelini et al. (2019) and being supported by the reduced-form evidence associated with the estimated SVAR. As a final step, we plot the IRFs arising from the accepted specification of the model.

The rest of this paper is organized as follows. Section 2 outlines the econometric methodology employed to deal with both regime dependence and the joint identification of uncertainty and real activity shocks, compared to the benchmark case of "indentification-through-heteroskedasticity". Section 3 discusses the data and the empirical results from the estimated SVARs with four volatility regimes, including the plots of the Impulse Response Functions. Section 4 reports the additional analyses performed with three volatility regimes, with and without COVID data. Section 5 concludes.

2 Econometric Framework

Given the heteroskedastic framework we are working in, we decided to follow Angelini et al. (2019) and assume time-varying VAR coefficients, both for the autoregressive ones Π and for the variance-covariance matrix Σ_u. Therefore:

$$\Pi(t) = \Pi_1 \times \mathbb{I}(t \leq T_{b1}) + \Pi_2 \times \mathbb{I}(T_{b1} < t \leq T_{b2}) + \Pi_3 \times \mathbb{I}(T_{b2} < t \leq T_{b3}) + \Pi_4 \times \mathbb{I}(T_{b3} < t) \tag{1}$$

$$\Sigma_u(t) = \Sigma_{u,1} \times \mathbb{I}(t \leq T_{b1}) + \Sigma_{u,2} \times \mathbb{I}(T_{b1} < t \leq T_{b2}) + \Sigma_{u,3} \times \mathbb{I}(T_{b2} < t \leq T_{b3}) + \Sigma_{u,4} \times \mathbb{I}(T_{b3} < t) \tag{2}$$

where $\mathbb{I}(\cdot)$ is the indicator function. Our SVAR is defined by the structural specification:

$$u_t = \begin{cases} Be_t & 1 < t \leq T_{b1} \\ (B + Q_2)e_t & T_{b1} < t \leq T_{b2} \\ (B + Q_2 + Q_3)e_t & T_{b2} < t \leq T_{b3} \\ (B + Q_2 + Q_3 + Q_4)Be_t & T_{b3} < t \leq T \end{cases} \tag{3}$$

where u_t is the vector of VAR innovations, whereas e_t is the vector of SVAR identified shocks. B is the matrix of on-impact responses in the first period, while each matrix Q_i captures the changes in the structural parameters from the $i-1$-th to the i-th volatility regime. Since $V(e_t) = \mathbb{I}_M$ by definition, then:

$$\begin{aligned}\Sigma_{u,1} &= BB' \\ \Sigma_{u,2} &= (B+Q_2)(B+Q_2)' \\ \Sigma_{u,3} &= (B+Q_2+Q_3)(B+Q_2+Q_3)' \\ \Sigma_{u,4} &= (B+Q_2+Q_3+Q_4)(B+Q_2+Q_3+Q_4)' \end{aligned} \tag{4}$$

The system in Equation 4 provides $r = 2M(M+1)$ identifying restrictions on B, Q_2, Q_3 and Q_4 induced by symmetry, whereas the total number of elements of the RHS matrices is $4M^2$, hence it is necessary to impose at least $2M(M-1)$ additional constraints to achieve identification. We can represent the (linear) identifying restrictions in explicit form by:

$$\psi = G\theta + d$$

where $\psi = (\text{vec}(B)', \text{vec}(Q_2)', \text{vec}(Q_3)', \text{vec}(Q_4)')$, θ is the vector of free parameters, G is the selection matrix and d is the vector containing the known elements. We can also conveniently summarize these restrictions along with the one imposed by the system in Equation 4 as

$$\sigma^+ = g(\theta) \tag{5}$$

where $\sigma^+ = (\text{vech}(\Sigma_{u,1})', \text{vech}(\Sigma_{u,2})', \text{vech}(\Sigma_{u,3})', \text{vech}(\Sigma_{u,4})')$ and $g(\cdot)$ is a nonlinear differentiable vector function. Bacchiocchi and Fanelli (2015) proves that the necessary and sufficient condition for identification is that the Jacobian matrix $J(\theta) = \frac{\partial g(\theta)}{\partial \theta'}$ is regular and full column rank when evaluated in a neighborhood of the true parameter value θ_0.

In this framework, the model generates regime-dependent IRFs. Let $\mathcal{C}_i$ be the companion matrix associated with volatility regime i, then we can retrieve the responses after h period as

$$\text{IRF}_{\bullet,\bullet}(h) = R'\mathcal{C}_i^h R B_i$$

where R is the selection matrix, and:

$$B_i = \begin{cases} B & 1 < t \leq T_{b1} \\ B + Q_2 & T_{b1} < t \leq T_{b2} \\ B + Q_2 + Q_3 & T_{b2} < t \leq T_{b3} \\ B + Q_2 + Q_3 + Q_4 & T_{b3} < t \leq T \end{cases}$$

2.1 Multiplicative approach

Another possible way of modelling breaks in volatility is by the Lanne and Lütkepohl (2008) approach. Instead of using an additive factor to model each change like in Angelini et al. (2019) and as shown above, their structural specification is as $\Sigma_{u,i} = B\Lambda_i B'$, where $\Lambda_1 = \mathbb{I}_M$ and Λ_i is diagonal with elements different from 1. Notice that $B_i = B\Lambda_i^{\frac{1}{2}}$, therefore the j-th columns of all the B_i's will be collinear. Thus, the IRF would not change shape from period to period (keeping constant the companion matrix). Due to this drawback, we will use the above-described method, yet we will compute the IRFs with the multiplicative approach as benchmark.

3 Model Specification and Empirical Results

Applying Angelini et al. (2019) identification method described in the previous section, that exploits the different volatility regimes in the data, we are able to address the main questions of this paper:

is uncertainty exogenous with respect to the business cycle? Is causality between macro and financial uncertainty unidirectional or bidirectional? Does the response of real economic activity to uncertainty vary accross different volatility regimes?

3.1 Data

Our data are monthly and cover the 1960:M7-2023:M6 for a total of 756 observations. The estimated SVAR includes 3 variables: a measure of real economic activity, Y_t, which is the first difference of the log of real industrial production taken from the FRED database (Figure 1), a measure of macroeconomic uncertainty U_{Mt} and a measure of financial uncertainty U_{Ft}, both 1-month-ahead, taken from Jurado et al. (2015) and Ludvigson et al. (2021) (Figure 2) [3].

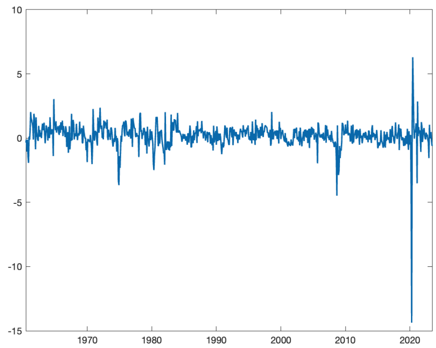

Figure 1: Industrial production index time series

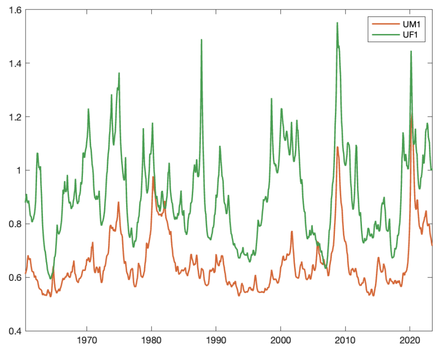

Figure 2: Macroeconomic (orange) and financial (green) uncertainty time series

3.2 Volatility regimes

In order to achieve identification, it is crucial in our specification to identify breaks in the variance-covariance matrix [4]. We estimate a VAR for our vector of variables $W_t = (U_{Mt}, Y_t, U_{Ft})'$ with four lags both recursively and over 10-year and 15-year rolling windows. Figure 3 shows the estimates of the six elements on the variance-covariance matrix Σ_u over the whole sample, where the blue lines are the variances and covariances estimated recursively, the red and yellow lines the estimates with 10-year and 15-year rolling windows respectively. It can be immediately noticed that the impact of COVID is huge: when looking at the variance of the industrial production index in position $(2, 2)$, all the spikes during the 70s and 80s as well as the spike in the period of the Great Financial Crisis seem small when compared to the one observed starting from 2020. This observation instantly allows us to understand the impact of the COVID crisis. Moreover, inspecting all the other estimates, we can notice how the pandemic actually reverses the sign of the the covariance between the macroeconomic uncertainty and the real production index in position $(1, 2)$. Except for the variance of the financial uncertainty in position $(3, 3)$, whose major spike is in the 80s probably because of the process of financial innovation that characterizes US financial markets (see Angelini et al. (2019)), all the variances and covariances estimated display their peaks exactly during the COVID period, as expected.

[3] The two indexes are estimated as the average of the time-varying volatility, as produced by stochastic volatility models, of the forecast error of each series in a large panel of macroeconomic and financial variables, conditional on information available.

[4] We refer to Angelini et al. (2019) and claim that our small-scale VAR is not affected by nonfundamentalness, which implicitly amounts to claim that it does not omit important variables.

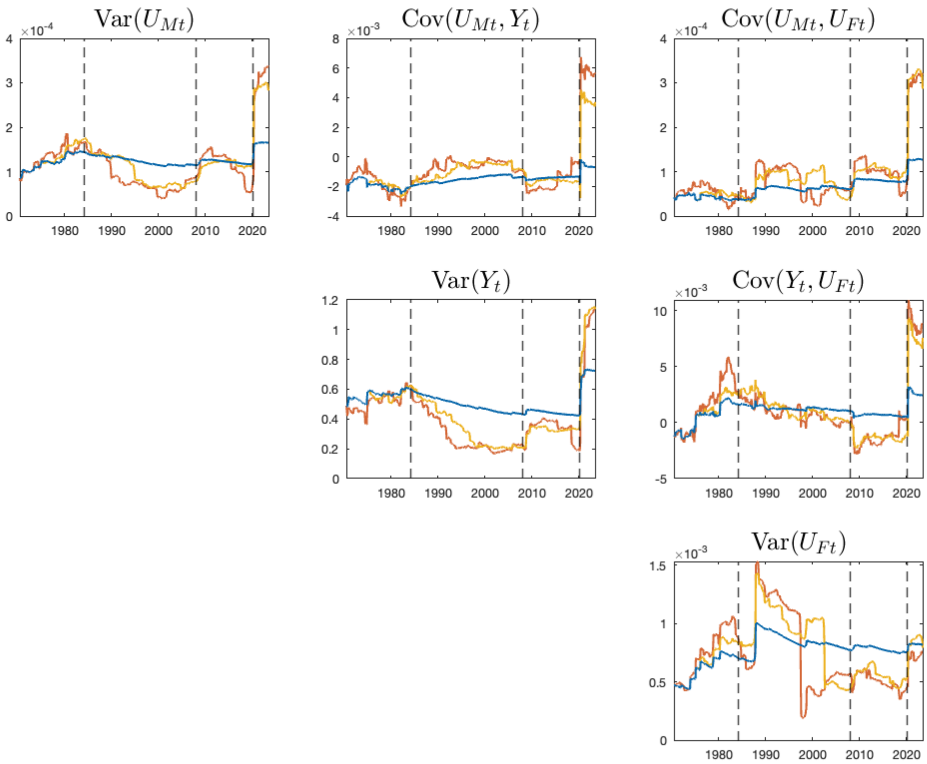

Figure 3: Recursive (blue line), 10-year (red line), and 15-year (yellow line) rolling window estimates of the error covariance matrix of the VAR. Dashed black lines denote the three break dates $T_{b1} =$ 1984:M3, $T_{b2} =$ 2007:M12 and $T_{b3} =$ 2020:M2 that separate the four volatility regimes used to identify the shocks. Overall sample: 1960:M7–2023:M6.

The graph clearly shows us that it is possible to detect 4 volatility regimes; as in Angelini et al. (2019) the big changes in volatility are in correspondence of the beginning of the Great Moderation and Great Recession period, to which we need to add the major shift observed with the beginning of the pandemic. In Figure 3 the dashed vertical lines are the 3 break dates, which are $T_{b1} = 1984{:}M3$, $T_{b2} = 2007{:}M12$, $T_{b3} = 2020{:}M2$, that allow us to identify the 4 volatility regimes for our identification strategy: Great Inflation (1960:M7–1984:M3, $T = 281$), Great Moderation (1984:M4–2007:M12, $T = 285$), Great Recession and Slow Recovery (2008:M1–2020:M2, $T = 146$) and COVID period (2020:M3-2023:M6, $T = 40$). Of course, we must exercise a certain degree of caution when it comes to the last volatility period given its nature and the limited number of observations available up to now.

In addition to the information provided by Figure 3, Table 1 reports the Maximum Likelihood estimates of the variance-covariance matrix for the VAR estimated on the overall sample as well as the estimates of the 4 variance-covariance matrices for the different volatility periods. To provide evidence in support of the detected volatility regimes we perform two different LR-type Chow tests: first, we test the null H_0

$$H_0 : \Theta_1 = \Theta_2 = \Theta_3 = \Theta_4 = \Theta,$$

where $\Theta_i = (\Pi_i; \Sigma_{u,i})$, $i = 1, 2, 3, 4$. We reject the null H_0 at 1% significance level. Second, we test the null H_0'

$$H_0' : \Sigma_{u,1} = \Sigma_{u,2} = \Sigma_{u,3} = \Sigma_{u,4} = \Sigma_u$$

under the maintained restriction that the autoregressive parameters are constant accross volatility regimes $\Pi_1 = \Pi_2 = \Pi_3 = \Pi_4 = \Pi$. We again reject the null H_0' at the 1% significance level.

Overall our analysis supports the claim that the relationship between uncertainty and real economic activity has changed over time. The four volatility regimes associated with recognizable historical events can then allow us to achieve identification for the structural shocks in our SVAR specification.

3.3 Nonrecursive SVAR specification

After defining the vector of structural shocks $e_t = (e_{UM,t}, e_{Y,t}, e_{UF,t})'$, where we call e_{UMt} a macroeconomic uncertainty shock, e_{Yt} a real economic activity shock and e_{UFt} a financial uncertainty shock, it is possible to discuss the main specification of $\tilde{B}(\theta)$, $\tilde{Q}_2(\theta)$, $\tilde{Q}_3(\theta)$, $\tilde{Q}_4(\theta)$ from the matrices defined in Equation 4 after having imposed restrictions.

Framing our identification approach within Rothenberg (1971), in order to satisfy the necessary order condition, we need that the number of free structural parameters p does not exceed the number of reduced form parameters r that can be recovered from the data. In particular, given the mapping as the one presented in Equation 5, our specification displays 24 reduced-form parameters (6 free elements in each of the 4 variance-covariance matrices) and 36 structural parameters (9 elements in B, as well as in the Q_i matrices capturing the change from one volatility regime to another). Consequently, we need at least 12 restrictions l to be placed between B, Q_2, Q_3 and Q_4 as to have exact identification. Nevertheless, in line with Angelini et al. (2019), we impose more than 12 restrictions in each of the 3 specifications of the structural model described below such that, since we have an overidentified model, we are able to test the $r - p$ additional restrictions on the reduced-form parameters.

Additionally, the restrictions placed in the matrices B, Q_2, Q_3 and Q_4 must satisfy the necessary and sufficient rank condition, that is the Jacobian matrix, defined in Section 2, must be regular and full column rank. Consequently, following Bacchiocchi and Fanelli (2015), we are able to achieve identification if:

$$rank\big(J(\theta)\big) = p \tag{6}$$

Overall period: 1960:M7–2023:M6 ($T = 752$)

$$\hat{\Sigma}_u = \begin{bmatrix} 1.65e-04^{***} & -0.001^{*} & 1.27e-04^{***} \\ & 0.723^{***} & 0.002^{***} \\ & & 0.001^{***} \end{bmatrix} \qquad \hat{\rho}_u = \begin{bmatrix} 1 & -0.063^{*} & 0.345^{***} \\ & 1 & 0.099^{***} \\ & & 1 \end{bmatrix}$$

GI: 1960:M7–1984:M3 ($T = 281$)

$$\hat{\Sigma}_{u,1} = \begin{bmatrix} 1.44e-04^{***} & -0.002^{***} & 3.75e-05^{**} \\ & 0.601^{***} & 0.002 \\ & & 0.001^{***} \end{bmatrix} \qquad \hat{\rho}_{u,1} = \begin{bmatrix} 1 & -0.213^{***} & 0.118^{**} \\ & 1 & 0.078 \\ & & 1 \end{bmatrix}$$

GM: 1984:M4–2007:M12 ($T = 285$)

$$\hat{\Sigma}_{u,2} = \begin{bmatrix} 8.12e-05^{***} & -0.001^{***} & 8.31e-05^{***} \\ & 0.216^{***} & 4.50e-04 \\ & & 0.001^{***} \end{bmatrix} \qquad \hat{\rho}_{u,2} = \begin{bmatrix} 1 & -0.16^{***} & 0.323^{***} \\ & 1 & 0.034 \\ & & 1 \end{bmatrix}$$

GR+SR: 2008:M1–2020:M2 ($T = 146$)

$$\hat{\Sigma}_{u,3} = \begin{bmatrix} 1.21e-04^{***} & -0.001^{*} & 1.35e-04^{***} \\ & 0.331^{***} & -0.001 \\ & & 0.001^{***} \end{bmatrix} \qquad \hat{\rho}_{u,3} = \begin{bmatrix} 1 & -0.155^{*} & 0.513^{***} \\ & 1 & -0.053 \\ & & 1 \end{bmatrix}$$

Covid: 2020:M3–2023:M6 ($T = 40$)

$$\hat{\Sigma}_{u,4} = \begin{bmatrix} 0.001^{***} & 0.011^{**} & 0.001^{***} \\ & 1.725^{***} & 0.011^{*} \\ & & 0.001^{***} \end{bmatrix} \qquad \hat{\rho}_{u,4} = \begin{bmatrix} 1 & 0.344^{**} & 0.702^{***} \\ & 1 & 0.282^{*} \\ & & 1 \end{bmatrix}$$

$H_0 : LR_T = 831.47$ [0.000] (no breaks in all VAR coefficients)

$H_0' : LR_T = 436.31$ [0.000] (no breaks in VAR covariance matrix)

Asterisks indicates the pvalue of the significance test: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Estimated reduced-form VAR covariance and correlation matrices and Chow-type tests for structural breaks.

In detail, we consider three specifications, that allow us to test whether macro uncertainty is endogenous/exogenous and whether it exists the "one-way" causality channel from financial to macro uncertainty.

First, we specify our baseline specification, in which we define the following matrices (the 0s represent the restricted elements) for the 3 volatility regimes in common with Angelini et al. (2019):

$$\underset{\tilde{B}}{\begin{pmatrix} b_{MM} & b_{MY} & 0 \\ b_{YM} & b_{YY} & 0 \\ 0 & 0 & b_{FF} \end{pmatrix}};\ \underset{\tilde{Q_2}}{\begin{pmatrix} q_{2,MM} & 0 & q_{2,MF} \\ q_{2,YM} & q_{2,YY} & 0 \\ q_{2,FM} & 0 & q_{2,FF} \end{pmatrix}};\ \underset{\tilde{Q_3}}{\begin{pmatrix} 0 & 0 & q_{3,MF} \\ q_{3,YM} & q_{3,YY} & q_{3,YF} \\ 0 & 0 & q_{3,FF} \end{pmatrix}} \tag{7}$$

and the following matrix Q_4 for the additional COVID volatility period:

$$\underset{\tilde{Q_4}}{\begin{pmatrix} q_{4,MM} & q_{4,MY} & 0 \\ q_{4,YM} & q_{4,YY} & q_{4,YF} \\ q_{4,FM} & 0 & 0 \end{pmatrix}} \tag{8}$$

The above specification of the matrices $\tilde{B}$ (Great Inflation period), $\tilde{Q_2}$ (from Great Inflation to Great Moderation period) and $\tilde{Q_3}$ (from Great Moderation to Great Recession and Slow Recovery period) in Equation 7 follows Angelini et al. (2019). Indeed, even if our third volatility period ends now at February 2020 with the most updated data, we recall that the parameters in the Q_i matrices capture the changes, if any, of the on-impact response coefficients when moving from one regime to another.

Moreover, additional guidance on how restrictions can be placed, including the novelty of Q_4 in Equation 8, are inferred from the Table 1, from which we can highlight 3 crucial considerations. First, the negative and significant correlation between macroeconomic uncertainty and real industrial production becomes actually positive (34%) during the last volatility period. Second, the correlation between financial uncertainty and real economic activity turns negative only during the Great Recession period, and then becomes again positive in the COVID regime. Third, the correlation between macroeconomic and financial uncertainty increases substantially accross the four volatility regimes up to the point in which they are very highly correlated during COVID (12%, 32%, 51% and 70%, respectively).

Consequently, in the matrix $\tilde{B}$ for the Great Inflation period restrictions are imposed such that, given heavily regulated financial markets, financial uncertainty reacts neither to a macro uncertainty shock ($b_{FM} = 0$) nor to a real economic activity shock ($b_{FY} = 0$). Likewise, financial uncertainty is assumed not to have on-impact effect on macro uncertainty by setting $b_{MF} = 0$. The structural parameters b_{MY} and b_{FY} in the second column are then crucial for the endogeneity/exogeneity issue: letting b_{MY} free allows to have a say on the endogeneity of the macroeconomic uncertainty based on the significance of the parameter and to test the second and third specifications in which this parameter, together with $q_{4,MY}$, is restricted to 0; on the other hand, b_{FY} is set equal to 0, meaning that we assume that financial uncertainty can react only with lags to a real economic activity shock. This same restriction is placed in all the other matrices, including the new Q_4.

In the matrix Q_2 for the transition from the Great Inflation to the Great Moderation period, consistently with the observation in Table 1, both $q_{2,MF}$ and $q_{2,FM}$ are left free in order to understand whether the increased correlation can be ascribed to a macro or to a financial uncertainty shock. Indeed, these two parameters are crucial because they allow to understand, as in Angelini et al. (2019), the direction of causality between the two types of uncertainty.

In the matrix Q_3 for the transition from the Great Moderation to the Great Recession and Slow Recovery period, the roles of financial and macro uncertainty exhibited in the Great Inflation period are actually inverted. While it is reasonable to assume that the impact of macro uncertainty to financial uncertainty has not changed with respect to the previous macroeconomic regime ($q_{3,FM}$), both $q_{3,MF}$ and $q_{3,YF}$ in the third column are left unrestricted, consistently with the evidence in Table 1.

Lastly, we report the restrictions placed in Q_4. Overall, the impacts of each shock to real economic activity as well as the impacts of macro uncertainty to each variable are left unrestricted. Since the evidence in Table 1 points out a change in the sign of the correlation between macroeconomic uncertainty and real economic activity, given the nature of the shock COVID to the economy, we leave unrestricted both $q_{4,YM}$ and $q_{4,MY}$ in this specification. This is done to infer whether this change in correlation between U_{Mt} and Y_t observed during COVID relatively to all the other volatility regimes can be ascribed to real economic activity or macro uncertainty shocks, or to both types of shocks. Moreover, $q_{4,MY}$ is an another crucial parameter, together with b_{MY}, in understanding whether macro uncertainty is exogenous or endogenous. Contrarily to the Great Recession and Slow Recovery period that was actually a financial crisis, we leave unrestricted $q_{4,FM}$, i.e. the impact of macro uncertainty shock onto financial uncertainty, but not $q_{4,MF}$, i.e. the impact of financial uncertainty shock onto macro uncertainty: we strongly believe that the net increase in the correlation between macro and financial uncertainty can be ascribed to a macro uncertainty shock rather than a financial uncertainty shock during the COVID period. The parameter $q_{4,FM}$ is another crucial element, as $q_{2,FM}$, in order to understand the direction of causality between the two types of uncertainty. As a final remark, we recall that also $q_{4,FY}$ is restricted to be equal to 0, as in B, Q_2 and Q_3: financial uncertainty reacts to a real economic activity shock only with lags.

In this first specification of the structural model, defined in Equation 7 and Equation 8, the number of restrictions l is 14, leaving us with $p = 22$ structural parameters to be recovered from $r = 24$ reduced-form parameters. Hence, we have $r - p = 24 - 22 = 2$ overidentification restrictions that are testable. As Angelini et al. (2019), the specified structural model features possibly endogenous uncertainty, since it allows the structural parameters b_{MY} and $q_{4,MY}$ to be nonzero. Hence testing $b_{MY} = q_{4,MY} = 0$ amounts to testing for exogeneity of macroeconomic uncertainty.

Our testing procedure compares the specification of Equation 7 and Equation 8 with two restricted versions.

The first restricted version features 4 additional restrictions related to the hypothesis of exogenous macro uncertainty and the hypothesis that macro uncertainty does not trigger financial uncertainty. Jointly the other 4 restrictions are:

$$b_{MY} = q_{4,MY} = 0 \tag{9}$$

that allow for the exogeneity of the macro uncertainty, restricting both the parameters in the GI and COVID period and

$$q_{2,FM} = q_{4,FM} = 0 \tag{10}$$

that allow for the "one-way" causality from financial to macro uncertainty, restricting both the parameters in the GM and COVID period. Overall, this second specification of our structural model, given by Equation 7, Equation 8, Equation 9 and Equation 10, features 6 testable overidentification restrictions.

The second restricted version features 3 additional restrictions related to the same hypotheses: our guess is that after COVID the "one-way causality" from financial to macro uncertainty found by Angelini et al. (2019) does not hold anymore, while we continue to mantain the hypothesis that macro uncertainty is exogenous. Jointly the 3 supplementary restrictions are:

$$b_{MY} = q_{4,MY} = 0 \tag{11}$$

that again allow for the exogeneity of the macro uncertainty, restricting both the parameters in the GI and COVID period and

$$q_{2,FM} = 0 \tag{12}$$

that allows for the "one-way" causality from financial to macro uncertainty, restricting only in the GM period but keeping unrestricted $q_{4,FM}$, that represents the change during the COVID period of the impact of a macro uncertainty shock onto financial uncertainty. Overall, this third specification of our structural model, given by Equation 7, Equation 8, Equation 11 and Equation 12, features 5 overidentification restrictions, again testable.

In all the specifications described the necessary and sufficient rank condition, evaluating the rank of the Jacobian matrix as in Equation 6 and checking that it is indeed full, is satisfied.

3.4 Reverse causality/exogeneity

Defining as in Equation 3 B, on-impact responses during the Great Inflation period, $B_2 = B + Q_2$, on-impact responses during the Great Moderation period, $B_3 = B + Q_2 + Q_3$, on-impact responses during the Great Recession and Slow Recovery period, and $B_4 = B + Q_2 + Q_3 + Q_4$, on-impact responses during the COVID period, Table 2 reports the results for all the three specification of our structural model.

The upper panel of Table 2 shows the results for the first specification defined in Equation 7 and Equation 8: in this structural model macro uncertainty is endogenous, since both b_{MY} (during the GI period) and $q_{4,MY}$ (during the COVID period) are left free, and bidirectional causality between macro and financial uncertainty from the Great Moderation onwards is allowed, given that we leave $q_{2,MF}$ and $q_{2,FM}$ (during the GM period), $q_{3,MF}$ (during the GR+SR period) and $q_{4,FM}$ (during the COVID period) unrestricted. The LR test for the 2 overidentification restrictions featured by the model display a p-value equal to 0.0279, hence the model is not supported by the data at 5% significance level. Our result is consistent with what is obtained by Angelini et al. (2019), despite the additional COVID data presented by our analysis. Exactly as Angelini et al. (2019), the parameter b_{MY}, which captures the on-impact response of macroeconomic uncertainty to real economic activity shocks and the parameter $q_{2,FM}$, which captures on-impact response of financial uncertainty to macro uncertainty shocks, both in the first 3 volatility regimes, are not statistically significant. On the other hand, the additional parameters $q_{4,MY}$ and $q_{4,FM}$ are significant.

The middle panel of Table 2 shows the results for the second specification defined in Equation 7 and Equation 8 with the additional 4 restrictions provided by Equation 9 and Equation 10. As Angelini et al. (2019) we now impose exogeneity of the macro uncertainty and unidirectional causality from financial to macro uncertainty. This model is accepted in Angelini et al. (2019) with data up to 2015. Nevertheless, given the additional COVID period in our analysis, we are not able to do the same. Indeed, the LR test for the 6 overidentification restrictions featured by the model display a p-value equal to 0.0006, hence the model is not supported by the data at 1% significance level.

Finally, the lower panel of Table 2 shows the results for the third specification defined in Equation 7 and Equation 8 with the additional 3 restrictions provided by Equation 11 and Equation 12. The idea behind these additional restrictions arises from deeper considerations on the COVID crisis: as we know and can be confirmed also from Figure 1 and Figure 2, the peculiarity of the bulk of the pandemic crisis, that makes it different from any other crisis ever experienced in the world from the 1st Industrial Revolution, was represented by the forced closure of any economic activity except essentials. Nevertheless, we believe that this aspect does not prevent us to consider the macro uncertainty always an exogenous driver of the cycle. Moreover, we believe that the COVID period has actually introduced bidirectionality in the relation between the two sources of uncertainty: the unprecedented nature of the crisis led to uncertainties about the duration, severity, and economic repercussions during the

$$\hat{B} = \begin{bmatrix} 0.012^{***} & -1.76e-04 & 0 \\ -0.1538 & 0.7596^{***} & 0 \\ 0 & 0 & 0.0265^{***} \end{bmatrix} \qquad \hat{B}+\hat{Q}_2 = \begin{bmatrix} 0.0077^{***} & -1.76e-04 & 0.0046^{***} \\ -0.0763 & 0.458^{***} & 0 \\ -0.0059 & 0 & 0.028^{***} \end{bmatrix}$$

$$\hat{B}+\hat{Q}_2+\hat{Q}_3 = \begin{bmatrix} 0.0077^{***} & -1.76e-04 & 0.0078^{***} \\ -0.0654 & 0.5698^{***} & -0.0479 \\ -0.0059 & 0 & 0.0231^{***} \end{bmatrix} \qquad \hat{B}+\hat{Q}_2+\hat{Q}_3+\hat{Q}_4 = \begin{bmatrix} 0.0191^{***} & 0.0146^{***} & 0.0078^{***} \\ -0.4485 & 0.9366^{**} & 0.804^{**} \\ 0.0175^{***} & 0 & 0.0231^{***} \end{bmatrix}$$

Model with "endogenous" macroeconomic uncertainty: 2 overidentification restrictions: $\mathrm{LR}_T = 7.1579$ [0.0279]

$$\hat{B} = \begin{bmatrix} 0.012^{***} & 0 & 0 \\ -0.165^{***} & 0.7573^{***} & 0 \\ 0 & 0 & 0.0265^{***} \end{bmatrix} \qquad \hat{B}+\hat{Q}_2 = \begin{bmatrix} 0.0089^{***} & 0 & 0.003^{***} \\ -0.0874^{***} & 0.4566^{***} & 0 \\ 0 & 0 & 0.0286^{***} \end{bmatrix}$$

$$\hat{B}+\hat{Q}_2+\hat{Q}_3 = \begin{bmatrix} 0.0089^{***} & 0 & 0.0066^{***} \\ -0.0805^{*} & 0.5683^{***} & -0.0377 \\ 0 & 0 & 0.0251^{***} \end{bmatrix} \qquad \hat{B}+\hat{Q}_2+\hat{Q}_3+\hat{Q}_4 = \begin{bmatrix} 0.0207^{***} & 0 & 0.0066^{***} \\ 0.3103 & 1.2308^{***} & 0.1881 \\ 0 & 0 & 0.0251^{***} \end{bmatrix}$$

Model with "exogenous" macroeconomic uncertainty: 6 overidentification restrictions: $\mathrm{LR}_T = 23.758$ [0.0006]

$$\hat{B} = \begin{bmatrix} 0.012^{***} & 0 & 0 \\ -0.165^{***} & 0.7573^{***} & 0 \\ 0 & 0 & 0.0265^{***} \end{bmatrix} \qquad \hat{B}+\hat{Q}_2 = \begin{bmatrix} 0.0088^{***} & 0 & 0.003^{***} \\ -0.0873^{***} & 0.4566^{***} & 0 \\ 0 & 0 & 0.0286^{***} \end{bmatrix}$$

$$\hat{B}+\hat{Q}_2+\hat{Q}_3 = \begin{bmatrix} 0.0088^{***} & 0 & 0.0056^{***} \\ -0.0805^{*} & 0.5683^{***} & -0.0301 \\ 0 & 0 & 0.0241^{***} \end{bmatrix} \qquad \hat{B}+\hat{Q}_2+\hat{Q}_3+\hat{Q}_4 = \begin{bmatrix} 0.0246^{***} & 0 & 0.0056^{***} \\ 0.4231^{**} & 1.2308^{***} & 0.1706 \\ 0.0151^{***} & 0 & 0.0241^{***} \end{bmatrix}$$

Model with "exogenous" macroeconomic uncertainty: 5 overidentification restrictions: $\mathrm{LR}_T = 9.583$ [0.0879]

Asterisks indicates the pvalue of the significance test: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 2: SVAR estimation with four volatility regimes

pandemic and to doubts on how the economies would recover from the shock during the immediate post-pandemic period, causing financial markets to react as a consequence. Indeed, the LR test for the 5 overidentification restrictions featured by our proposal of the structural model display a p-value equal to 0.0879: consequently, our proposed structural model is supported by the empirical evidence.

Given the uniqueness of the COVID crisis, we believe that our results are perfectly in line with Angelini et al. (2019). Indeed, we find that macroeconomic uncertainty is exogenous despite the COVID shock and that financial uncertainty is a driver of the business cycle, not a reaction to it. However, according to our identification scheme, as again Angelini et al. (2019), financial uncertainty affects the business cycle indirectly by triggering greater macroeconomic uncertainty on-impact up to the end of the Great Recession and Slow Recovery period. This unidirectional causality from financial to macro uncertainty then no longer holds with the confounding pandemic and post-pandemic dynamics, that suggest actually a bidirectional causality between the two types of uncertainty. Still, this particular result can be ascribed to the COVID crisis only: as a matter of fact, when performing the analysis up to December 2019 with 3 volatility regimes (results in Section 4 and in the Appendix), we detect unidirectionality from financial to macro.

3.5 IRFs

In this section we show the plots of the regime-dependent IRFs over a horizon of $h_{max} = 60$ months from the accepted specification of the structural model proposed in Equation 7, Equation 8, Equation 11 and Equation 12, whose estimates are reported in the lower panel of Table 2. The identification approach adopted by Angelini et al. (2019), following Bacchiocchi and Fanelli (2015) and Bacchiocchi et al. (2018), shown in Section 2, indeed allows for different on-impact responses in each volatility regime. This novelty with respect to Lanne and Lütkepohl (2008) approach, also described in Section

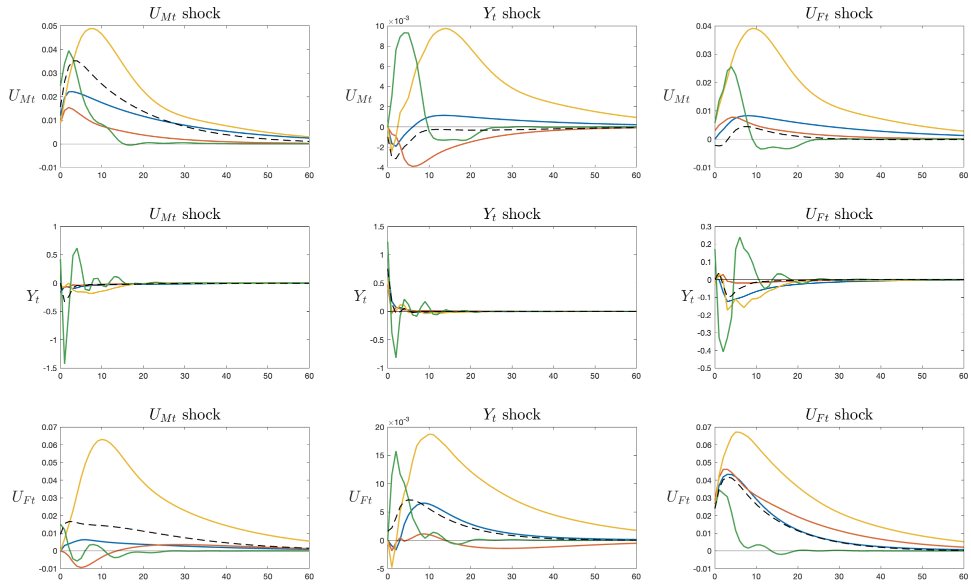

Figure 4: IRFs obtained from the baseline nonrecursive SVAR that constitutes our proposal. $U_{Mt}$and U_{Ft} refer to the 1-month ($f = 1$) uncertainty horizon. The blue line refers to the first volatility regime (Great Inflation, 1960:M7–1984:M3); the red line refers to the second volatility regime (Great Moderation, 1984:M4–2007:M12); the yellow line refers to the third volatility regime (Great Recession + Slow Recovery, 2008:M1–2020:M2); the green line refers to the fourth volatility regime (COVID, 2020:M3-2023:M6). Dashed black lines plot the IRFs obtained with Lanne and Lutkepohl approach, estimated on the whole sample, 1960:M7–2023:M6. Responses are measured with respect to one standard deviation changes in structural shocks.

2, can be fully appreciated in Figure 4. In Figure 4 the first column reports the responses of all the variables to a macro uncertainty shock, the second column the responses to an industrial production shock and the third column to a financial uncertainty shock. Distinguishing between separate periods, the blue IRFs refer to the Great Inflation period, the red IRFs to the Great Moderation period, the yellow IRFs to the Great Recession + Slow Recovery period and the green IRFs to the COVID period. Different IRFs do not represent only differences in the structural parameters but also in the autoregressive coefficients. As Angelini et al. (2019) show in their technical supplement, ignoring variations in the autoregressive parameters may lead one to wrongly estimate the dynamic causal effects of uncertainty shocks. Lastly, in Figure 4 the dashed black lines represents the IRFs obtained by estimating the SVAR with Lanne and Lütkepohl (2008) method and regime-invariant autoregressive coefficients, that serves as benchmark.

From Figure 4 it is immediately possible to notice that the structural parameters do change in different volatility regimes. Considering, as Lanne and Lütkepohl (2008), constant IRFs would mean not being able to capture the heterogeneity of responses that actually takes place. For example, although uncertainty shocks lead to a drop in the industrial production in all four macroeconomic regimes, the magnitude of the drop, the persistence of the response and the number of periods after which the negative peak is reached vary across regimes. Overall, Figure 4 allows us to answer our third research question without doubts: the impact of uncertainty shocks changes qualitatively and quantitatively accross different volatility regimes.

Figure 5, Figure 6, Figure 7 and Figure 8 plot the IRFs for each volatility regime with 90%

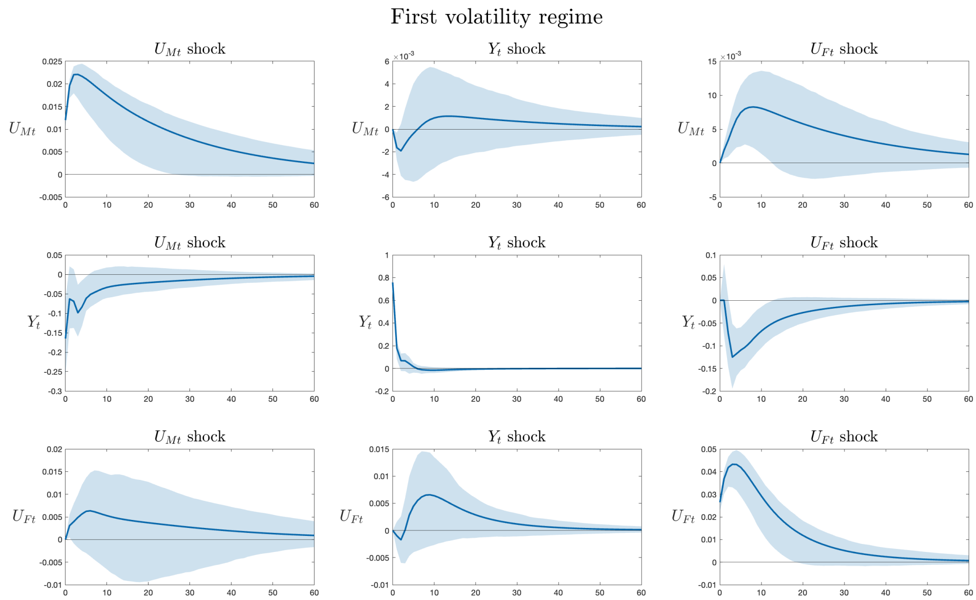

Figure 5: IRFs obtained in the first volatility regime (Great Inflation, 1960:M7–1984:M3) from the baseline nonrecursive SVAR that constitutes our proposal. The blue lines refer to the 1-month ($f = 1$) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands. Responses are measured with respect to one standard deviation changes in structural shocks

bootstrap confidence bands (obtained resampling nonparametrically within each volatility regime following the bootstrap-after-bootstrap method), that allow us to make a detailed comment of the responses in each period.[5] We are going to focus on three main considerations: first, what is the impact of uncertainty shocks (both macro and financial) onto the real industrial production; second, what is the impact of real industrial production on uncertainty; third, what is the relation between the two types of uncertainty.

Figure 5 plots the IRFs of the 1st volatility regime. The graph shows that during the Great Inflation period (1960:M7–1984:M3) a one-standard deviation shock in macro uncertainty U_{Mt} leads to a decline in Y_t which is statistically significant for a large number of months. The highest drop of industrial production is on-impact and it is equal to -0.1650 percentage points. The impact of financial uncertainty U_{Ft} instead is more lagged: the biggest drop in Y_t takes place after 3 months and it is equal to -0.1252 percentage points. This result is in line with the idea that financial uncertainty affects real economic activity only after triggering macro uncertainty: indeed, only the effect of financial uncertainty onto macro uncertainty is significant during the GI period. Lastly, the fact that the responses of the two types of uncertainty to a one-standard deviation shock of Y_t are never significant over the 60-months horizon support the view that uncertainty act as a driver rather than a consequence of the business cycle.

Figure 6 plots the IRFs of the 2nd volatility regime. The graph now shows that also during the Great Moderation period (1984:M4–2007:M12) a one-standard deviation shock in U_{Mt} leads to a decline in Y_t which is statistically significant for a large number of months. As in the GI period, the highest drop of industrial production is on-impact but it is lower with respect to the first volatility regime since it is equal to -0.0873 percentage points. Again, the effect of a shock in U_{Ft} is delayed and reaches its peak only around 8 months. This result is consistent with the idea of unidirectional

[5]All the IRFs plotted in this Section consider only macroeconomic and financial uncertainty 1-month-ahead.

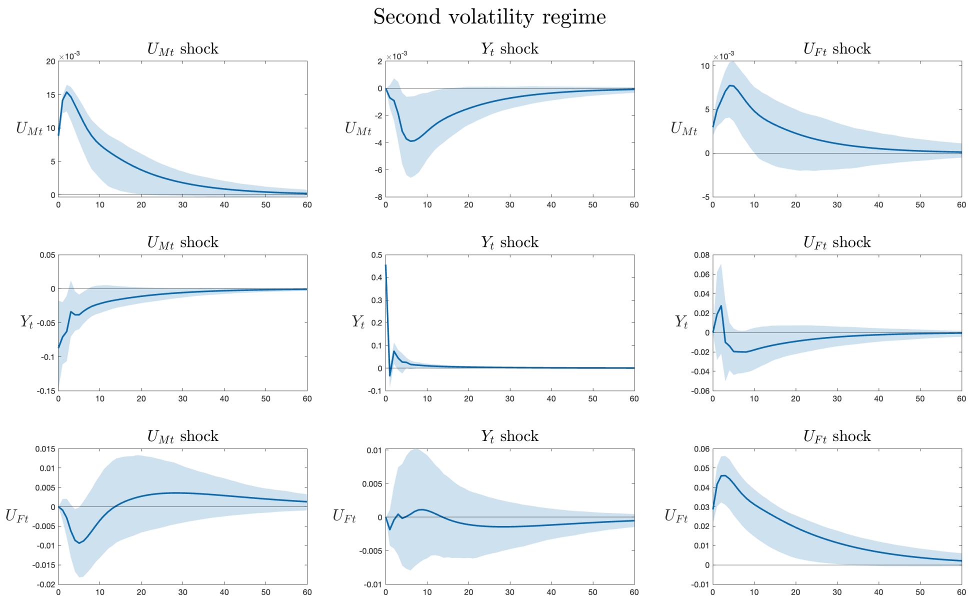

Figure 6: IRFs obtained in the second volatility regime (Great Moderation, 1984:M4–2007:M12) from the baseline nonrecursive SVAR that constitutes our proposal. The blue lines refer to the 1-month ($f = 1$) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands. Responses are measured with respect to one standard deviation changes in structural shocks

causality between uncertainties, endorsed in addition by the fact that only macro uncertainty reacts significantly to a financial uncertainty shock while the response of financial uncertainty to a macro uncertainty shock is never significant. Lastly, the result of exogeneity of uncertainty is once more corroborated by the fact that neither financial nor macro uncertainty react significantly to a one-standard deviation shock in Y_t.

Figure 7 plots the IRFs of the 3rd volatility regime. During the Great Recession + Slow Recovery period (2008:M1–2020:M2) the response of Y_t to a macro uncertainty shock is more persistent and higher in magnitude with respect to the previous volatility regimes: indeed now the peak is, after 7 months and not on-impact, equal to -0.1832 percentage points. As expected, also the effect of financial uncertainty is higher in this macroeconomic regime: indeed, even if the impact of a one-standard deviation shock in U_{Ft} leads to more jagged responses in Y_t, the biggest drop is, after 3 months, equal to -0.1732 percentage points. Again, neither financial nor macro uncertainty react significantly to a one-standard deviation shock in Y_t signalling the exogeneity of the uncertainty measures with respect to the business cycle.

Finally, Figure 8 plots the IRFs of the 4th volatility regime. The graph shows that during the COVID period (2020:M3-2023:M6) the impact of a macro uncertainty shock onto Y_t is huge: the peak is reached after 1 month and it is equal to -1.4265 percentage points. This is not the only noticeable difference with respect to the previous three volatility regimes: indeed, despite being the highest drop registered among all the periods, in the COVID period the IRFs becomes positive and slightly significant immediately after a couple of months and then becomes statistically not significant. This reversion of sign has never occurred in the previous three regimes, in which, consistently with Angelini et al. (2019), we can state that the both macroeconomic and financial uncertainty shocks seem to lead to a permanent drop in industrial growth because the dynamics of Y_t does not overshoot its trend significantly after recovering. The difference spotted during the COVID period seems reasonable

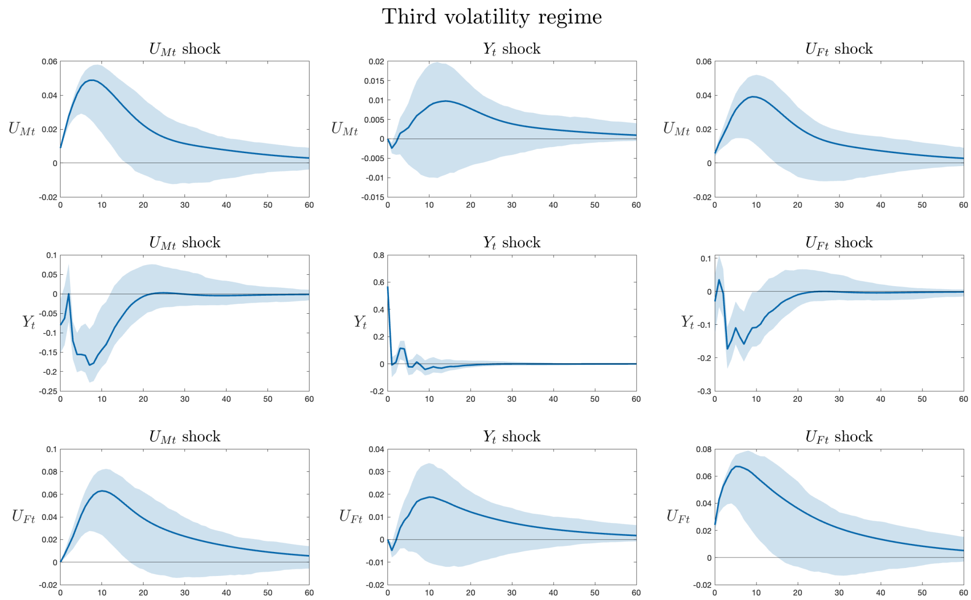

Figure 7: IRFs obtained in the third volatility regime (Great Recession + Slow Recovery, 2008:M1–2020:M2) from the baseline nonrecursive SVAR that constitutes our proposal. The blue lines refer to the 1-month ($f = 1$) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands. Responses are measured with respect to one standard deviation changes in structural shocks

because of the different dynamics carried by this exceptional historical event. In addition, while financial uncertainty does not exert a significant impact on Y_t as in the GM and differently from the GR, again the two measures of uncertainty do no react significantly to real economic activity shocks at any lag, other than on-impact when it comes to the financial uncertainty measure. This result confirms our hypothesis that, despite the developments of COVID crisis, uncertainty can still be considered an exogenous driver of the business cycle. Lastly, we can notice that while macro uncertainty reacts significantly to a financial uncertainty shock for the first 10 months, also financial uncertainty reacts significantly on-impact to a macro uncertainty shock (to then become not significant). However, as a final remark of our analysis, we again stress the fact that our results related to the last volatility regime must be taken with caution given the limited number of observations available.

Overall, we can recall the four main comments stemming from the analysis of the IRFs of each macroeconomic regime, beside the fact that structural parameters' estimates are different accross periods: first, the negative and significant impact of macroeconomic uncertainty reaches its peak during the COVID period, followed by the Great Recession period; however the COVID period represents an exception since it is the only volatility regime in which the drop seems not permanent; second, financial uncertainty has a lagged negative impact on real industrial production index in all the four volatility regimes; third, both financial and macro uncertainty do not react to a Y_t shock in all the four volatility regimes, enhancing the result of exogeneity; fourth, in the last volatility period the "one-way" causality from financial to macro uncertainty seems not to hold differently from the previous periods.

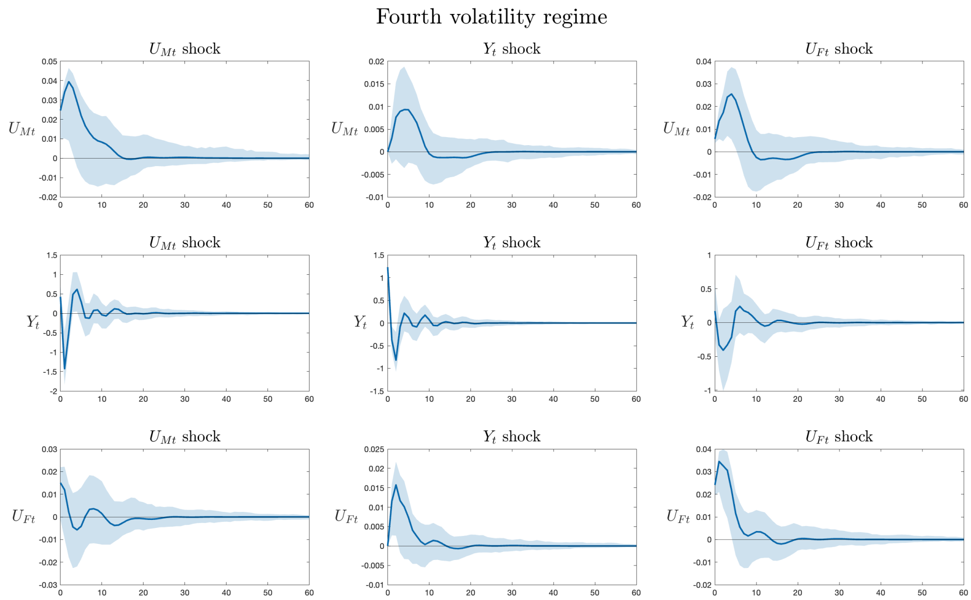

Figure 8: IRFs obtained in the fourth volatility regime (COVID, 2020:M3-2023:M6) from the baseline nonrecursive SVAR that constitutes our proposal. The blue lines refer to the 1-month ($f = 1$) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands. Responses are measured with respect to one standard deviation changes in structural shocks

4 Alternative analyses

As a final exercise in this paper, we report the results for the two additional ways in which the analysis could have been conducted: the first is by ignoring COVID data and truncating the sample up to December 2019, the second is to consider COVID data (and consequently the whole sample up to 2023:M6) but do not recognise COVID as a separate volatility regime with respect to the others.

4.1 Three volatility regimes without COVID

Following Angelini et al. (2019), we partition the whole sample period into the same exact three different sub-samples: the Great Inflation period (1960:M7–1984:M3, $T = 281$), the Great Moderation period (1984:M4–2007:M12, $T = 285$), and the Great Recession + Slow Recovery period (2008:M1–2019:M12, $T = 144$), where we simply enlarge the last volatility period with the most updated data up to December 2019 without considering the COVID shock. Again, we consider two models: the first, reported in the upper panel of Table 3 in the Appendix relies on the same identification scheme used in the first specification of Angelini et al. (2019) and presented in equation Equation 7 with endogenous macro uncertainty (b_{MY} different from 0) and letting macro uncertainty affect financial uncertainty ($q_{2,FM}$ different from 0); the second, reported in the lower panel of Table 3, adds to the identification scheme of Equation 7 the restrictions of exogenous macro uncertainty ($b_{MY} = 0$) and "one-way" causality between financial and macro uncertainty ($q_{2,FM} = 0$). As shown in Table 3, we retrieve the same results of Angelini et al. (2019): the first specification that features 2 overidentification restrictions is rejected at 5% significance level (p-value equal to 0.0279) while the second with 4 overidentification restrictions is accepted by the data (p-value equal to 0.0983). Consequently, we are able to confirm all the results shown by Angelini et al. (2019). Nevertheless, we believe that when updating the dataset it is not correct to ignore completely the COVID era if not because of the criticisms brought by the very few observations of the last volatility regime up to today.

4.2 Three volatility regimes with COVID

Another possibility is then represented by considering three volatility regimes (the same as Angelini et al. (2019) with the same exact restrictions presented in Equation 7) but including in the third regime also observations for the COVID crisis, that are immediately recognizable as outliers from Figure 2 and, especially, Figure 1. In this particular exercise, whose results are presented in Table 4 in the Appendix, we reject not only the model with endogenous macro uncertainty and bidirectionality between financial and macro uncertainty but also the model in which macro uncertainty is exogenous and there is "one-way" causality from financial to macro uncertainty (p-value equal to 0). We impute these results to the dynamics brought in by COVID observations; however, we find these results very unreliable and we strongly believe that, when dealing with observations starting from 2020, COVID has to be treated as a separate volatility regime.

5 Conclusions

Our paper enters into the controversial debate that characterizes the empirical literature on uncertainty. Indeed, we addressed whether macro uncertainty is an exogenous driver of the business cycle rather than an endogenous answer to it; whether there exists bidirectional or unidirectional causality between financial and macro uncertainty; and whether the impact of an uncertainty shock has different effect on real economic activity in different macroeconomic regimes. In answering these questions we employ, as Angelini et al. (2019), the novel "identification-through-heteroskedasticity" approach with regime-dependent IRFs that combine both data properties (i.e., the heteroskedasticity provided by the data) and theoretical considerations reflected in the specification of the structure of the matrices of structural parameters. We apply our small-scale nonrecursive SVAR structure on US monthly data from 1970:M7 to 2023:M6 that includes COVID observations.

In the main specification of the paper, we are able to distinguish among four volatility regimes, that are Great Inflation (1960:M7-1984:M3), Great Moderation (1984:M4-2007:M12), Great Recession and Slow Recovery (2008:M1-2020:M2) and COVID period (2020:M3-2023:M6). Empirical results suggest that uncertainty, both macro and financial, are exogenous with respect to the business cycle, and that the impact of an uncertainty shock differ qualitatively and quantitatively accross the 4 macroeconomic regimes. In particular, we find that macroeconomic uncertainty has a greater contractionary impact on real economic activity during the Great Recession and, especially, during the COVID period. Moreover, we find that the causal relation between financial and macro uncertainty is unidirectional up to the GR period. In the COVID period, however, also financial uncertainty is affected by macro uncertainty.

As additional exercise, we provide results also for two other possibilities: one is considering data up to December 2019, without including COVID, divided in three volatility regimes, in which we confirm all the results of Angelini et al. (2019); the other is considering data up to June 2023, including COVID, divided in only three volatility regimes, in which we are not able to say neither that macroeconomic uncertainty is exogenous nor that there is unidirectional causality from financial to macro uncertainty. Overall, we strongly believe however that we can not ignore COVID when dealing with uncertainty and that COVID era belongs to a different volatility regime.

Lastly, we remark that our paper needs further attention in the future in order to address the main issue of having very few observation available in the last and most recent volatility regime. Overall, however, up to this moment our findings are perfectly in line with Angelini et al. (2019) and support the empirical and theoretical specifications where uncertainty is treated as an exogenous driver of economic fluctuations.

Bibliography

Angelini, G., Bacchiocchi, E., Caggiano, G., & Fanelli, L. (2019). Uncertainty across volatility regimes. *Journal of Applied Econometrics*, *34*(3), 437–455. https://doi.org/https://doi.org/10.1002/jae.2672

Arellano, C., Bai, Y., & Kehoe, P. J. (2019). Financial Frictions and Fluctuations in Volatility. *Journal of Political Economy*, *127*(5), 2049–2103. https://doi.org/10.1086/701792

Bacchiocchi, E., Castelnuovo, E., & Fanelli, L. (2018). Gimme A Break! Identification And Estimation Of The Macroeconomic Effects Of Monetary Policy Shocks In The United States. *Macroeconomic Dynamics*, *22*(6), 1613–1651. https://ideas.repec.org/a/cup/macdyn/v22y2018i06p1613-1651_00.html

Bacchiocchi, E., & Fanelli, L. (2015). Identification in Structural Vector Autoregressive Models with Structural Changes, with an Application to US Monetary Policy. *Oxford Bulletin of Economics and Statistics*, *77*(6), 761–779.

Bachmann, R., & Moscarini, G. (2011). Business Cycles and Endogenous Uncertainty. (36). https://ideas.repec.org/p/red/sed011/36.html

Basu, S., & Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica*, *85*(3), 937–958. Retrieved January 18, 2024, from http://www.jstor.org/stable/44955145

Carriero, A., Clark, T. E., & Marcellino, M. (2018). Endogenous Uncertainty. (1805). https://doi.org/10.26509/frbc-wp-201805

Christiano, L. J., Motto, R., & Rostagno, M. (2014). Risk shocks. *American Economic Review*, *104*(1), 27–65. https://doi.org/10.1257/aer.104.1.27

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. *American Economic Review*, *105*(3), 1177–1216. https://doi.org/10.1257/aer.20131193

Lanne, M., & Lütkepohl, H. (2008). Identifying monetary policy shocks via changes in volatility. *Journal of Money, Credit and Banking*, *40*(6), 1131–1149. Retrieved January 24, 2024, from http://www.jstor.org/stable/25096299

Lenza, M., & Primiceri, G. E. (2020). How to estimate a var after march 2020. (27771). https://doi.org/10.3386/w27771

Ludvigson, S. C., Ma, S., & Ng, S. (2021). Uncertainty and business cycles: Exogenous impulse or endogenous response? *American Economic Journal: Macroeconomics*, *13*(4), 369–410. https://doi.org/10.1257/mac.20190171

Rothenberg, T. J. (1971). Identification in parametric models. *Econometrica*, *39*(3), 577–91. https://EconPapers.repec.org/RePEc:ecm:emetrp:v:39:y:1971:i:3:p:577-91

Appendix

$$\hat{B} = \begin{bmatrix} 0.0119^{***} & 0.0012 & 0 \\ -0.2376 & 0.7377^{***} & 0 \\ 0 & 0 & 0.0265^{***} \end{bmatrix} \qquad \hat{B} + \hat{Q}_2 = \begin{bmatrix} 0.0081^{***} & 0.0012 & 0.0038^{***} \\ -0.1464 & 0.4406^{***} & 0 \\ -0.0031 & 0 & 0.0284^{***} \end{bmatrix}$$

$$\hat{B} + \hat{Q}_2 + \hat{Q}_3 = \begin{bmatrix} 0.0081^{***} & 0.0012 & 0.0061^{***} \\ -0.1888 & 0.5367^{***} & -0.0684 \\ -0.0031 & 0 & 0.0235^{***} \end{bmatrix}$$

Model with "endogenous" macroeconomic uncertainty: 2 overidentification restrictions: $\text{LR}_T = 7.1579$ [0.0279]

$$\hat{B} = \begin{bmatrix} 0.012^{***} & 0 & 0 \\ -0.165^{***} & 0.7573^{***} & 0 \\ 0 & 0 & 0.0265^{***} \end{bmatrix} \qquad \hat{B} + \hat{Q}_2 = \begin{bmatrix} 0.0087^{***} & 0 & 0.003^{***} \\ -0.0854^{***} & 0.4566^{***} & 0 \\ 0 & 0 & 0.0286^{***} \end{bmatrix}$$

$$\hat{B} + \hat{Q}_2 + \hat{Q}_3 = \begin{bmatrix} 0.0087^{***} & 0 & 0.005^{***} \\ -0.1209^{***} & 0.5578^{***} & -0.0433 \\ 0 & 0 & 0.0237^{***} \end{bmatrix}$$

Model with "exogenous" macroeconomic uncertainty: 4 overidentification restrictions: $\text{LR}_T = 7.8223$ [0.0983]

Asterisks indicates the pvalue of the significance test: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 3: SVAR estimation up to 2019

$$\hat{B} = \begin{bmatrix} 0.0119^{***} & -0.0016^{***} & 0 \\ -0.0611 & 0.7726^{***} & 0 \\ 0 & 0 & 0.0265^{***} \end{bmatrix} \qquad \hat{B} + \hat{Q}_2 = \begin{bmatrix} 0.005^{***} & -0.0016^{***} & -0.0073^{***} \\ 0.0163 & 0.464^{***} & 0 \\ 0.0276^{***} & 0 & 0.0076^{*} \end{bmatrix}$$

$$\hat{B} + \hat{Q}_2 + \hat{Q}_3 = \begin{bmatrix} 0.005^{***} & -0.0016^{***} & 0.0161^{***} \\ 0.1384^{*} & 1.0079^{***} & 0.2675^{***} \\ 0.0276^{***} & 0 & 0.0107^{***} \end{bmatrix}$$

Model with "endogenous" macroeconomic uncertainty: 2 overidentification restrictions: $\text{LR}_T = 7.1579$ [0.0279]

$$\hat{B} = \begin{bmatrix} 0.012^{***} & 0 & 0 \\ -0.165^{***} & 0.7573^{***} & 0 \\ 0 & 0 & 0.0265^{***} \end{bmatrix} \qquad \hat{B} + \hat{Q}_2 = \begin{bmatrix} 0.0107^{***} & 0 & 0.003^{***} \\ -0.1055^{***} & 0.4566^{***} & 0 \\ 0 & 0 & 0.0286^{***} \end{bmatrix}$$

$$\hat{B} + \hat{Q}_2 + \hat{Q}_3 = \begin{bmatrix} 0.0107^{***} & 0 & 0.0105^{***} \\ 0.0604 & 1.0247^{***} & 0.2256^{***} \\ 0 & 0 & 0.0296^{***} \end{bmatrix}$$

Model with "exogenous" macroeconomic uncertainty: 4 overidentification restrictions: $\text{LR}_T = 53.6734$ [0.0000]

Asterisks indicates the pvalue of the significance test: $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table 4: SVAR estimation up to 2023