What do we know about the future? Uncertainties and Time Series Econometrics

A proxy-SVAR Approach

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Abstract

We analyze macroeconomic and financial uncertainty as underlying determinants of business cycle fluctuations. To do so, we exploit a proxy-SVAR approach that has been used to study the dynamic effects of tax changes but that, to our knowledge, is new to the literature on uncertainty. Instrumenting both macroeconomic and financial uncertainty with an auxiliary VAR specification, we find that positive shocks in either ones have large, signifcant and sizeable negative effects on GDP growth. This holds true regardless of the particular relation one assumes between the two uncertainties. Moreover, we show regime dependence in pre/post-Covid effects[1]. Our results partially align with previous results in the literature on uncertainty identification.[2]

[1]We highly thank our colleagues, and most importantly friends, Simone Trambaiolo and Matteo Carrai for sharing with us their results on regime-dependency: our contribution on pre/post-Covid subsample heavily relies on their beautiful identification of the structural break in the effect of uncertainty on macroeconomic aggregates.

[2]The replication files and detailed data sources can be found in the following Dropbox folder.

Section I: Introduction

This paper sheds light on the causal relation between uncertainty and GDP volatility. In particular, we distinguish between financial and macroeconomic uncertainty and we ask whether exogenous changes in either one have dynamic effects on production. Reduced form SVARs represent a useful framework for the problem since they allow to flexibly study dynamic macro-relations without the need to impose excessive structure.

To show convincing effects we depart from the standard recursive specification of Choleski matrices. Instead, we adopt the framework of Mertens and Ravn (2013), which study the context of tax changes by instrumenting observed variations with narratively identified policy changes. The framework closely resembles a standard static IV approach (Wooldridge (2010), Hansen (2022)), where a relevance and an orthogonality condition must be satisfied to reach local identification. We inherit our instruments from Ludvigson, Ma, and Ng (2021): macroeconomic uncertainty is instrumented by the log difference in the real price of gold; financial uncertainty is instrumented by an index of aggregate stock market return. Two caveats must be made: we do not want nor need to assume that the two instruments are uncorrelated, since our question focuses on their impact on GDP, not on the disentangling of their joint effects; Ludvigson, Ma, and Ng (2021) do not argue these variables are valid instruments, since they reach identification by imposing further structure on the variance-covariance matrix decomposition. To address this concern we will avoid using directly our instruments: instead, we will use their innovations based on a 2-variable auxiliary VAR as suggested by Mertens and Ravn (2013) and Angelini and Fanelli (2019).

In addition to the methodological references of Mertens and Ravn (2013) and Ludvigson, Ma, and Ng (2021) this paper relates to: Angelini and Fanelli (2019) whose contribution is mainly theoretical but also find that macroeconomic and financial uncertainty can be considered "*exogenous drivers of real economic activity*"; Angelini, Bacchiocchi, et al. (2019) which show that uncertainty is regime dependent, i.e. its impact is time-variant, which must be accounted for in its structural identification. We contribute to the literature on three main ways: our approach for local identification is new to the literature on uncertainty and represents an easy and convincing way to establish causal relations; following the contribution of Angelini, Bacchiocchi, et al. (2019) we acknowledge the importance of regime-dependent parameters and thus repeat our analysis on pre/post-Covid subsamples, to look for the possibility of structural breaks; we extend Angelini and Fanelli (2019) in that, while the authors instrument production and test the uncertainties' exogeneity through inference, we directly instrument uncertainty in the hope of convincingly show its effects, switching the focus from a statistically driven perspective to a more economic framework. Our empirical analyses match closely those of Angelini, Cavaliere, and Fanelli (2024), although they follow a different empirical strategy: instead of identifying two valid external variables for uncertainty measures, they instrumented the non-target shock variable, production, to identify its response to a macro and financial uncertainty shock.

We find large and sizeable negative effects of uncertainty shocks on production and GDP growth: in particular, for the whole sample period (November 2007 to December 2022), our estimates imply that a 20% increase in either financial or macroeconomic uncertainty lead to a loss of about -0.2 to -0.6 percentage points in month-on-month GDP growth, when evaluated at the mean of the uncertainties. A 20% change in uncertainty is actually a small change, compared to the huge swings our indexes document. However, we also find considerable evidence in favor of a regime change in the uncertainty-production relation: the pre-Covid period shows no effect of financial uncertainty on macroeconomic outcomes while macroeconomic uncertainty leads to small losses in GDP but with long lasting effects. On the contrary, in the post-Covid period we document huge negative effects due both to financial and macroeconomics uncertainty, which however are reabsorbed in very little time (around one month). F.e., a one standard deviation in macroeconomic uncertainty leads to a -0.10 percentage points loss in GDP during the pre-Covid sample and to a loss of -1.5 percentage points in the post-Covid one; these effects are reabsorbed in eight and two months respectively. For comparison, this means that shocks in the post-Covid era are thirty times larger than in the pre-Covid subsample: a 20% shock, at the mean, in macroeconomic uncertainty leads to a loss of -0.1 percentage points in GDP growth pre-Covid; post-Covid, instead, a 10% shock in macroeconomic uncertainty is sufficient to cause a degrowth of -1.5 percentage points (these computations are based on the case in which macroeconomic uncertainty is more exogenous than financial uncertainty, but are robust to all other specifications). Our results are robust to the ordering of financial and macroeconomic uncertainty, of which we remain agnostic.

The rest of the paper proceeds as follows: Section II presents a brief literature review and its in depth relation with the present work; Section III explains in depth the methodology we adopt; Section IV presents data, their sources and limitations; Section V carries out the analysis, presents its results and shows some robustness checks; Section VI concludes.

Section II: Related Literature

The relationship between uncertainty and economic fluctuations has been widely studied in macroeconomics. A stylized fact is that uncertainty measures increase sharply during economic recessions (Bloom 2014), raising the question of whether uncertainty is an exogenous driver in the business cycle. Some models predict that uncertainty shocks lead to a sharp decline in output, while others argue that uncertainty should instead be considered as an endogenous response to economic fluctuations (for review of theoretical models, see Ludvigson, Ma, and Ng 2021). Several empirical studies have attempted to test whether uncertainty causes economic recessions or is rather a response to them (Ludvigson, Ma, and Ng 2021, Angelini and Fanelli 2019, Carriero, Clark, and Marcellino 2018). However, empirical research is ongoing to estimate the effect of uncertainty on the business cycle and how important it is. In one of the most relevant article on this field, Bloom (2009) builds a parameterized model to simulate a large macro uncertainty shock, and finds evidence that it produces a rapid decline in output, employment, and productivity growth.

The potential problem of reverse causality makes it difficult to identify the effects of uncertainty. The identification of SVARs has been achieved mainly in the literature by exploiting the restrictions provided by economic theory on the relevant parameters, for example by imposing a lower Choleski triangular decomposition on the matrix that maps VAR innovations to structural shocks (Lutz Kilian 2009). These restrictions are often debated, as different authors may impose different questionable structures on the same problem. Alternatively, endogeneity is addressed by exploiting narrative policy shocks (C. D. Romer and D. H. Romer 2010), which, however, are difficult to identify and require a high level of arbitrariness.

Aware of these limitations, for our analyses we rely on the methods proposed by Mertens and Ravn (2013), who contributed to the recent devolvement in the literature that has proposed to achieve identification through an instrumental variable approach, called proxy-SVAR, by exploiting additional moment conditions provided by *valid* external, or proxy, variables that are not included in the VAR (Stock and Watson 2012, Mertens and Ravn 2013, Stock and Watson 2018). To be valid, external variables must satisfy two main conditions: they must be relevant, correlated with the structural shock of interest, and they must be exogenous, uncorrelated with all other structural shocks.

In addition to addressing the issue of reverse causality, empirical macroeconomic research faces the challenge that there is no objective measure of uncertainty. For our analyses, we rely on Jurado, Ludvigson, and Ng (2015), who provide a new econometric estimate of uncertainty that does not depend on the structure of specific theoretical models, and following the approach of Ludvigson, Ma, and Ng (2021), we distinguish between macroeconomic and financial uncertainty.

Section III: Methodology

Our empirical strategy follows that proposed by Mertens and Ravn (2013). This allows us to depart from the standard recursive approach by identifying through external variables the causal effects of uncertainty shocks. As in Ludvigson, Ma, and Ng (2021) and Angelini and Fanelli (2019), we consider a VAR model with $n = 3$ variables: the index of financial uncertainty (U_{Ft}), the index of macroeconomic uncertainty (U_{Mt}), and the growth rate of industrial production (a_t). Let the $\mathbf{u_t}$ denote the vector of reduced form residuals which are related to the structural shocks by

$$\mathbf{u_t} = \begin{pmatrix} u_{F,t} \\ u_{M,t} \\ u_{a,t} \end{pmatrix} = \begin{pmatrix} \beta_{F,F} & \beta_{F,M} & \beta_{F,a} \\ \beta_{M,F} & \beta_{M,M} & \beta_{M,a} \\ \beta_{a,F} & \beta_{a,M} & \beta_{a,B} \end{pmatrix} \begin{pmatrix} \varepsilon_{F,t} \\ \varepsilon_{M,t} \\ \varepsilon_{a,t} \end{pmatrix} = \mathbf{B}\varepsilon_{\mathbf{t}} \tag{1}$$

Instead of imposing restrictions on the $\mathbf{B}$ matrix, Mertens and Ravn (2013) proposed to exploit additional moment conditions provided by external variables to achieve identification of a subset of k target-shocks. Since we are interested in estimating the response of output to the $k = 2$ shocks of the uncertainty measures, we consider the partition of the $\mathbf{B}$ matrix

$$\underbrace{\begin{pmatrix} u_{F,t} \\ u_{M,t} \\ u_{a,t} \end{pmatrix}}_{u_t} = \underbrace{\begin{pmatrix} \beta_{F,F} & \beta_{F,M} \\ \beta_{M,F} & \beta_{M,M} \\ \beta_{a,F} & \beta_{a,M} \end{pmatrix}}_{B_1} \underbrace{\begin{pmatrix} \varepsilon_{F,t} \\ \varepsilon_{M,t} \end{pmatrix}}_{\varepsilon_{1,t}} + \underbrace{\begin{pmatrix} b_{F,a} \\ b_{M,a} \\ b_{a,a} \end{pmatrix}}_{B_2} \underbrace{\begin{pmatrix} \varepsilon_{a,t} \end{pmatrix}}_{\varepsilon_{2,t}} \tag{2}$$

where ε_1 is the vector that collects uncertainty measures shock, which are our target-shock. Following the notation of Mertens and Ravn (2013), let $\mathbf{m_t}$ be the 2×1 vector containing the external variables and define $\Sigma_{\mathbf{x_{1t}x_{2t}}} = E\left[\mathbf{x_{1t}x_{2t}}\right]$ for any couple of random vectors x_{1t} and x_{2t}. The external variables are *valid* instruments if they met two conditions: they must be relevant, correlated with the structural shock of interest,

$$\Sigma_{\mathbf{m_t}\varepsilon_{\mathbf{1,t}}} = \mathbf{\Phi} \tag{3}$$

where $\mathbf{\Phi}$ is an unknown non-singular 2×2 matrix; and they must be exogenous, uncorrelated with all other structural shocks (in our case only one shock),

$$\Sigma_{\mathbf{m_t}\varepsilon_{a,t}} = \mathbf{0} \tag{4}$$

Equations (4) and (2) imply that

$$\mathbf{\Phi B_1} = \Sigma_{\mathbf{mu'}} \tag{5}$$

Even though the system is of dimension $n \times k(= 3 \times 2)$, Mertens and Ravn (2013) did not impose any arbitrary assumption on the k^2(=4) element of the matrix $\mathbf{\Phi}$. As a result, equation (5) provides $nk - k^2(= 3)$ new restrictions, which can be expressed as

$$\beta_{\mathbf{21}}\beta_{\mathbf{11}}^{\mathbf{-1}} = (\mathbf{\Sigma}_{\mathbf{mu_1'}}^{\mathbf{-1}}\mathbf{\Sigma}_{\mathbf{mu_a'}})' \tag{6}$$

where

$$\beta_{\mathbf{11}} = \begin{pmatrix} \beta_{F,F} & \beta_{F,M} \\ \beta_{M,F} & \beta_{M,M} \end{pmatrix} \quad \text{and} \quad \beta_{\mathbf{12}} = \begin{pmatrix} \beta_{a,F} \\ \beta_{a,M} \end{pmatrix}$$

$\Sigma_{\mathbf{mu_1'}}$ and $\Sigma_{\mathbf{mu_a'}}$ are the partitions of the covariances between the instruments and, respectively, the VAR innovations of the target-shock variables and the VAR innovations of production. $(\mathbf{\Sigma}_{\mathbf{mu_1'}}^{\mathbf{-1}}\mathbf{\Sigma}_{\mathbf{mu_a'}})$ can be interpreted as a two-stage least squares (2SLS) estimator that operates in a regression from u_{at} to $\mathbf{u_{1t}}$, using $\mathbf{m_t}$ as a instrument for $\mathbf{u_{1t}}$. This implies that conditions in equations (4) and (3) state that the external variables are valid instruments as long as $\mathbf{m_t}$ affect u_{at} only though $\mathbf{u_{1t}}$.

Mertens and Ravn (2013) showed that the identification of $\mathbf{B_1}$ depends on the identification of $\mathbf{S_1}$, a

$k \times k (= 2 \times 2)$ matrix that is associated with structural shocks and VAR innovations through the system (2) rewritten as

$$\mathbf{u}_{1,t} = \eta u_{a,t} + \mathbf{S}_1 \boldsymbol{\varepsilon}_{1,t} \tag{7}$$

$$u_{a,t} = \boldsymbol{\zeta} \mathbf{u}_{1,t} + S_a \varepsilon_{a,t} \tag{8}$$

However, when multiple shocks need to be identified ($k > 1$), the restrictions allow to isolate only $\mathbf{S_1 S_1'}$ and not $\mathbf{S_1}$. To identify the causal effects of shocks on both types of uncertainty, and following Mertens and Ravn (2013), we impose $\mathbf{S_1}$ to be lower triangular, resulting from a Choleski decomposition of $\mathbf{S_1 S_1'}$: at least $1/2k(k-1)(= 1)$ restrictions must be placed on its columns. But how should we order the two measures of uncertainty? The interpretation of the hypothesis on the structure of $\mathbf{S_1}$ comes from equations (7) and (8). Suppose that financial uncertainty is ordered first and impose that $\mathbf{S_1}$ is lower triangular. Then, an exogenous macro uncertainty shock allows the VAR innovations of financial uncertainty u_{Ft} to respond in (7) only via feedback from u_{at}, whose change follows from equation (8). Mertens and Ravn (2013) describes this mechanism as if u_{Ft} were unchanged in terms of *cyclical adjustment*, meaning that it does not respond to a shock in macro uncertainty net of the contemporaneous change in u_{at}. The response of the macro uncertainty to a financial uncertainty shock, instead, operates not only through the feedback of u_{at}, but also through a direct channel running from $\varepsilon_{F,t}$ and u_{Mt}, proportional to the non-zero element off the diagonal in the matrix $\mathbf{S_1}$. This structure, in the end, also alters the dynamics of u_{at}, whose response is of our primary interest.

Other empirical studies that estimated the effect of uncertainty also relied on both the use of external variables and additional restrictions. Angelini and Fanelli (2019) used a partial identification methodology that does not require additional restrictions, but unlike us, their target shock was output, as they aim to directly test whether uncertainty measures are an endogenous response of the business cycle. To identify all shocks and thus obtain the impulse response for output, they imposed an additional restriction on $\mathbf{B}$. In particular, they assumed that $\beta_{FM} = 0$, which they borrowed from Angelini, Bacchiocchi, et al. (2019). Ludvigson, Ma, and Ng (2021) complemented the use of external variables as instruments for uncertainty measures with sign restrictions corresponding to particular identified events (*event constraints*). To estimate the impulse response of output to uncertainty shocks, Angelini, Cavaliere, and Fanelli (2024) instrumented a_t and imposed the same restriction as Angelini, Bacchiocchi, et al. (2019).

Mertens and Ravn (2013) performed their analyses with narrative policy shocks from C. D. Romer and D. H. Romer (2010) as instruments for fiscal liabilities. While these instruments are probably valid, the use of narrative policy shocks has some drawbacks: the fact that the time series are censored implies that they only recovered the effect for the identified events for which the changes in liabilities were considered exogenous. In this aspect, our methodology differs from that of Mertens and Ravn (2013): since there are no narrative shocks identified for our uncertainty measures, we follow the approach of Ludvigson, Ma, and Ng (2021). We instrument financial uncertainty with a stock market return index, as periods of high volatility are associated with a downtrend in the aggregate stock market, and macroeconomic uncertainty with the price of gold, since it has been traditionally used by investors as a safe havens asset (Piffer and Podstawski 2018). Notice that our approach did not require to impose structure on the matrix $\mathbf{\Phi}$: for example, we do not need to assume zero correlation between financial uncertainty shock and the price of gold, and between macro uncertainty shock and the index of stock market return. In that case $\mathbf{S_1}$ would be diagonal and no further restrictions would be necessary. The *raw* time series of the instruments are however not orthogonal to the history of the variables in the main VAR. As suggested by Mertens and Ravn (2013), and by Angelini and Fanelli (2019), in Section V we completed our analyses with an auxiliary regression to obtain the instruments in innovation form.

Section IV: Data

The main analysis is done on the following three variables: the difference in logs of the U.S. monthly production (available at the FRED database); financial and macroeconomic uncertainties as taken from Professor Ludvigson's website, whose methodological construction is described in Jurado, Ludvigson, and Ng (2015) and Ludvigson, Ma, and Ng (2021). We instrument macroeconomic uncertainty with the real log price change of gold (available at the World Bank database) and financial uncertainty with the S&P500 value-weighted stock market index. We are guided to these choices by Ludvigson, Ma, and Ng (2021).

The sample is restricted to the time range from November 2007[3] to the last available date in our sample, specifically December 2022. This choice is aimed at capturing the uncertainties' effects during both the financial crisis and the onset of the Covid pandemic. Figure 1 displays the time series for our production measure (left panel) and the uncertainty measures (right panel). The time series behaves as expected: both at the onset of the 2008 Financial Crisis and the start of the Covid pandemic there is a huge surge in both financial and macroeconomic uncertainty, which correspond to a sharp decline in production (as visible from the negative changes registered in those months). We highlight a stylized fact: the surge in financial uncertainty during the 2008 Crisis is enormous but it corresponds to rather smaller changes in macro uncertainty and production; on the contrary, the Covid shock can be rather interpreted as a macroeconomic shock since the extreme drop in production corresponds to a significant surge in macroeconomic uncertainty. As a sidenote, notice from Figure 1 (right panel) that there is a sizeable surge in uncertainty in correspondence of the first election of President Donald Trump. The right panel suggests what Angelini, Bacchiocchi, et al. (2019) find: uncertainty may be working in regimes and so its impact should be regarded as time-varying.

As regards our instruments, they are plotted in Figure 2. Both these instruments provide a lot of variation

[3]Since we include 11-2007 and 12-2007, the residuals of the VAR with 2 lags perfectly match the period 2008-2022, without missing observations.

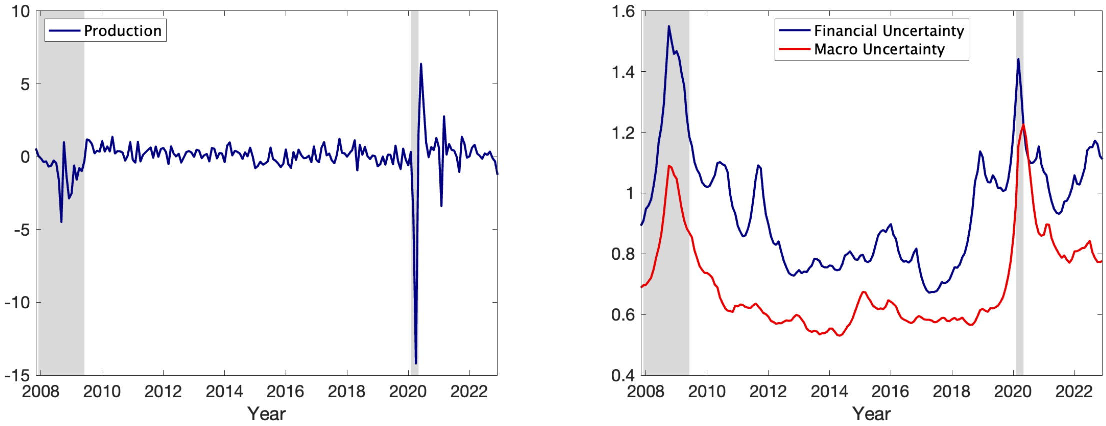

Figure 1: Time Series: Main Variables of Interest

Notes: The figure displays the change in log U.S. production (left panel) and uncertainty measures (right panel) in the 11-2007 to 12-2022 period. Both the depressing effect of the 2008 financial crisis and the recessive effects of the Covid onset are clearly visible. Grey vertical bands indicate economic recessions.

over the sample period since, in a certain sense, they display a higher frequency than the main variables of interest in Figure 1. However, recall our main specification is based on an auxiliary regression as in Angelini and Fanelli (2019). Thus, we will use their innovations, conditional on the values of production, macroeconomic uncertainty and financial uncertainty from $t-1$ to $t-2$.

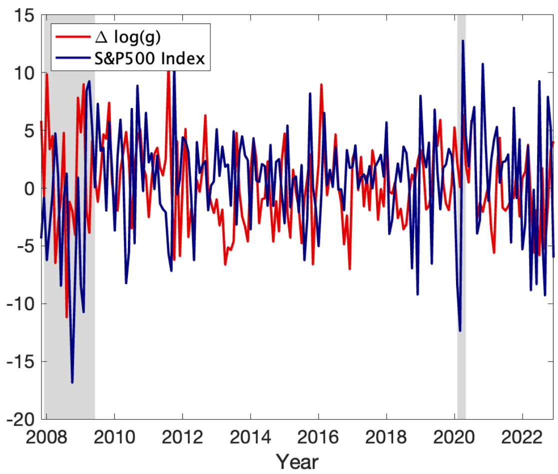

Figure 2: Time Series: Raw Instruments

Notes: The figure displays the time series of our instrumental variables: the change in log price of gold and the S&P 500 Index (properly scaled). The period of interest is from 11-2007 to 12-2022. Grey vertical bands indicate economic recessions.

As consuetudinary, we ran a series of tests on our time series: an Augmented Dicky-Fuller Test (ADF) accepts the hypothesis of non-stationarity for both macroeconomic and financial uncertainty (as one may had conjectured from Figure 1). Instead, we reject the null of a unit-root for the production data (Figure 1), which is to be expected since it is already measured in first difference. As regards our instruments, the ADF rejects for both the hypothesis of a unit root (Figure 2). Although transforming all variables may be tempting, we choose to keep uncertainties in level form since our ultimate goal is to ensure interpretability. Our choice will be reassured in Section V, since our VAR specifications will present residuals for which we can reject both autocorrelation and non-stationarity. All the results for the ADF tests can be found in the appendix, in Table 1.

Section V: Analysis

Main VAR Specification

Although the results in Table 1 point towards a non-stationarity issue, we will use levels for both financial and macroeconomic uncertainty for the sake of interpretation. We ran VARs with up to 12 lags (1 year) to choose the correct specification. Results for the AIC and BIC criteria are reported in Table 2: they both agree upon two lags being the best specification so this will constitute our benchmark.

A simple look at Figure 1 shows that, likely, no trend has to be inserted in the VAR. However, we formally test this through a series of Likelihood Ratio tests (LR). With two lags, we ran three specification: including no trend; including a deterministic linear trend; including a deterministic quadratic trend. Under the H0 of no trend against a linear one we accept the null (LR $= -2859.91$, p-value $= 1.0000$); similarly, when testing the null of a linear trend against a quadratic one we accept the null (LR $= -249.54$, p-value $= 1.0000$). We can thus confidently avoid the inclusion of any trend in our benchmark specification.

Under standard theory for modeling time series dynamics, innovations are expected to follow a Martingale Difference Sequence (MDS):

$$\mathbb{E}[\varepsilon_t|\mathbb{I}_{t-1}] = 0$$

i.e., innovations are mean-independent of the history of the variables. In other words, knowing the full information set $\mathbb{I}_{t-1}$ of the previous period carries no information on the value of the innovations at time t. In itself, this implies uncorrelation in the innovations. Generally speaking, residuals from a VAR model can be interpreted as estimators of the innovations and thus they should also be exhibiting uncorrelation. To check this we ran a Ljung-Box (LB) test on the residuals for up to a year of data (that is 12 data points). We reject the null of autocorrelated residuals for all the three equations in our VAR. Results of the test are reported in the appendix in Table 3. Moreover, we checked for the stationarity of the residuals, rejecting for all the three series of residuals the null of a unit root with an ADF test.

Summing up: our benchmark specification consists in a 3-equation VAR with two lags and no trend, which we regard as being a well-specified model due to the results of the tests above, even though two of the three variables included are non-stationary (as highlighted in Section IV).

Auxiliary VAR Specification

Following Angelini and Fanelli (2019) in using the innovations in the instruments from an auxiliary regression rather then the instruments themselves, we specify a 2-equations VAR where our instruments are regressed on their lags up to period $t-2$ and the values of the three main variables of interest (i.e., macroeconomic uncertainty, financial uncertainty and production). Specifically, we employ as independent variables the first and second lag of the three variables of interest. These follows from a simple reasoning: our instruments may be dependent on the history of production, which would violate the requirements explicitly proposed in Section III. Projecting our instruments on the information set at $t-1$ $\mathbb{I}_{t-1}$ and then using their innovations as new instruments should instead satisfy these requirements, under the additional assumption that the innovations in instruments impact the uncertainties within the month. Notice we do not regress the raw instruments on the value at t of production as, indeed, we do not need the innovations to be uncorrelated with production: if the two uncertainties respond on impact from innovations in the instruments and production responds on impact to structural shocks in the uncertainties, we would have correlation. Nonetheless, we will also report results for the raw instruments, even though our benchmark specification uses their innovations as specified here.

Benchmark Results: Raw Variables and Innovations as Instruments

Figure 3 presents our first results, using the raw instruments rather than their innovations. The left panel presents the effect of a one standard deviation shock in *instrumented* financial uncertainty on production while the right panel presents the results of a one standard deviation shock in *instrumented* macroeconomic uncertainty.

Much of the literature (Angelini and Fanelli 2019, Angelini, Bacchiocchi, et al. 2019) assumes financial uncertainty to be more exogenous than macroeoconomic uncertainty. However, we prefer not to take a stand on the matter: as in Mertens and Ravn (2013), we remain agnostic of the joint relation between our two instrumented variables. In other words, we will always report IRFs both for the case of financial uncertainty being more exogenous than macroeconomic one and viceversa. As one may notice from Figure 3 our choice pays in that the dynamics are very similar across both specification: our results do not in fact rely on the particular joint relationship between uncertainties. We estimate that a one standard deviation positive shock in financial uncertainty actually has a positive on impact effect on production, resulting in 0.4 percentage points growth regardless of the ordering. This positive effect turns negative at the second month leading to a de-growth of *circa* -0.2 to -0.6 percentage points. The effect fades out after the 3^{rd} month. Shocks in macroeconomic uncertainty have a similar dynamics (Figure 3, right panel): they have no on impact effect but they appear to have negative impacts sooner (-0.4 to -0.6 percentage points at the 1^{st} month), which also fade out at the 2^{nd} to 3^{rd} month. Although, one can think of positive on impact effects of shocks to financial uncertainty (for example large public

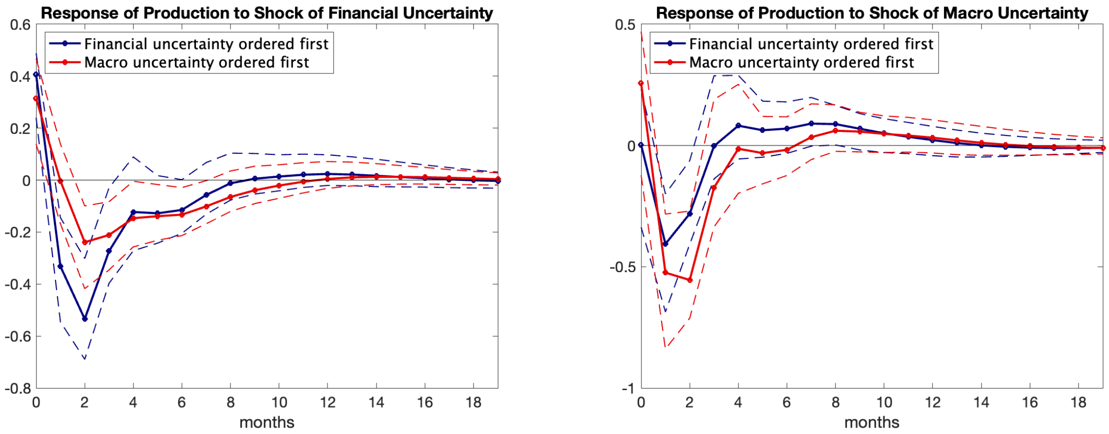

Figure 3: Production IRFs for Raw Instrumented Shocks

Notes: The figure displays the estimated IRFs, when instrumenting macroeconomic and financial uncertainty with the raw, untransformed instruments. We report the response of production to a shock of financial uncertainty (left panel) and the response of production to a shock of macroeconomic uncertainty (right panel). Confidence bands come from a Wild Bootstrap at the 90% level, 5000 replications (details about our bootstrap methodology can be found in the appendix).

investment plans following recessionary times, such as the Financial Crisis or the Covid pandemic, may be contemporaneously increasing financial uncertainty, if unexpected, and raising production) we regard this as a side effect of employing raw instruments. Recall we instrument financial uncertainty with the level of the S&P 500 Index which is for sure somewhat correlated and responsive to macroeconomic aggregates and, arguably, with exogenous macroeconomic shocks. This is a potential confounding effect.

Figure 4 reports our benchmark specification: we instrument uncertainty shocks with the innovations of a 2-variable auxiliary VAR model specified above in the paper. We reckon this adds an *exogeneity* level to the analysis, ruling out weird confounding behaviour that affected our results in Figure 3. Indeed, with respect to Figure 3, in Figure 4 we can rule out positive on impact effect of shocks in instrumented uncertainties. The general dynamics is however similar: a one standard deviation shock in financial uncertainty (left panel) leads to -0.2 to -0.5 percentage point decrease in GDP growth after a month, while the effect fades out after the 3^{rd} month; similarly, a one standard deviation shock in macroeconomic uncertainty (right panel) reduces production growth of about -0.5 percentage points after one month, with the effect fading out from the 3^{rd} month. This being our preferred specification we reckon that, at least to our sample period, both macroeconomic and financial uncertainty have similar-sized effects on production, which are the most significant after a month and very short lived, generally disappearing before the 4^{th} month. Our results match a dynamic similar to Angelini and Fanelli (2019) but, we have to highlight, with a much faster fading out of the negative effects. These effects may look small at first but they are instead large and significant. In particular, we find that when evaluated at the mean a 20% rise in either financial or macroeconomic uncertainty leads to -0.2 to -0.5 percentage point loss in GDP growth. Consider Figure 1 (right panel): periods of high uncertainty distress show much more than 20%

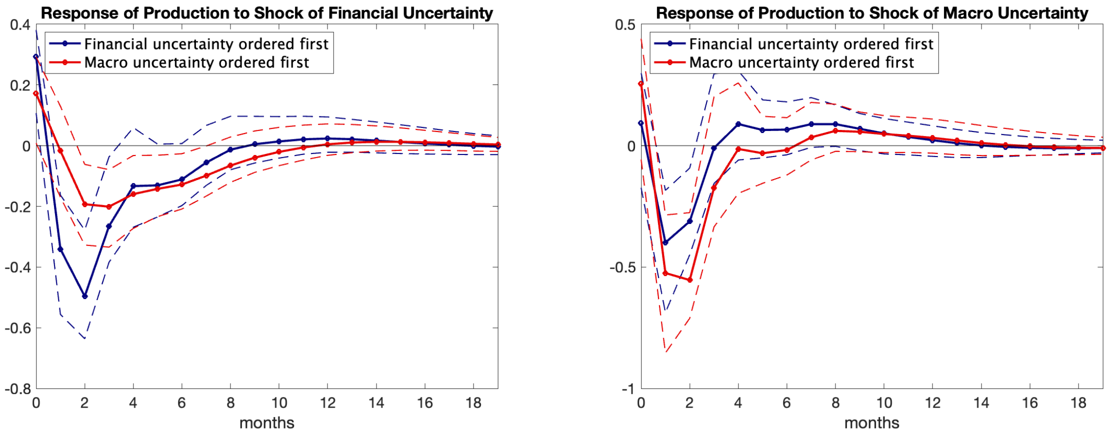

Figure 4: Production IRFs for Innovations as Instruments

Notes: The figure displays the estimated IRFs, when instrumenting macroeconomic and financial uncertainty with the innovations from the auxiliary VAR specified in Section V. We report the response of production to a shock of financial uncertainty (left panel) and the response of production to a shock of macroeconomic uncertainty (right panel). Confidence bands come from a Wild Bootstrap at the 90% level, 5000 replications (details about our bootstrap methodology can be found in the appendix).

changes, leading to huge growth effects. We report all other IRFs of interest for this main specification in the appendix, Figure 7.

Covid19 Sub-sample: Regime Dependence?

Following ongoing research from our colleagues Trambaiolo and Carrai (2025)[4], we are interested in analysing the changes in regime-dependency. In particular, they identified a structural break in the relationship between uncertainty and production at December 31st 2019, understandably. Consequently, we split the sample in two subsamples: from January 1st 2008 to December 31st 2019 (Figure 5); from January 1st 2020 to December 31st 2022 (Figure 6).

Figure 5 shows unexpectedly no significant effects for shocks in financial uncertainty on GDP growth (left panel): we are only able to find a small negative change of -0.05 percentage points after one month and only with respect to the case in which financial uncertainty is considered more exogenous than macroeconomic uncertainty (as is the case in Angelini and Fanelli 2019). On the contrary, shocks in macroeconomic uncertainty (Figure 5, right panel) have sizeable and long lasting effects on production. A one standard deviation shock in macroeconomic uncertainty leads to a -0.10 to -0.15 percentage points loss in GDP growth, which is reabsorbed only after eight months. These effects are both better behaved and much smaller than those we find in the overall sample, plotted in Figure 4. For comparison, this means that a 20% change in macroeconomic uncertainty, when evaluated at the mean, leads to a loss of

[4]They use rolling window estimates and Chow-type tests, following Angelini, Bacchiocchi, et al. (2019) to show that a structural break in the uncertainty regime happens in December 2019.

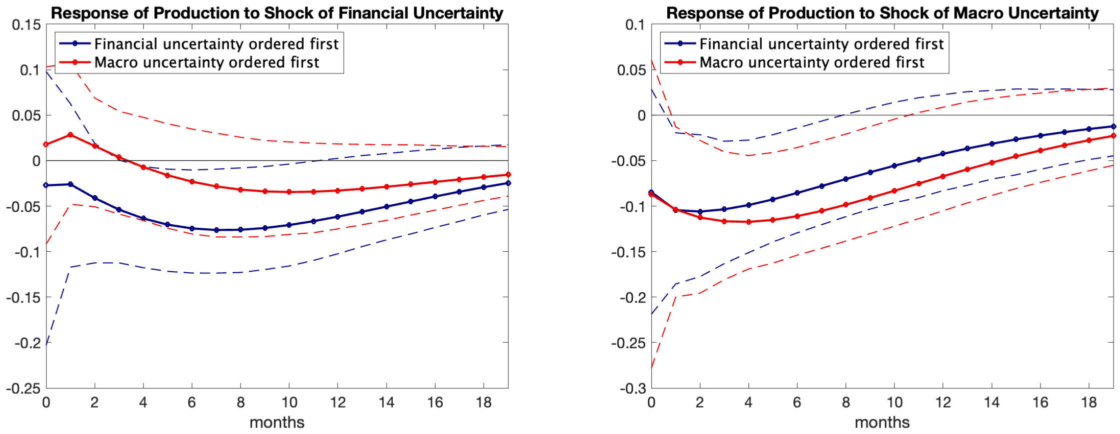

Figure 5: Production IRFs for Financial and Macro uncertainty shocks, Jan 2008 - Dec 2019

Notes: The figure displays the estimated IRFs for production, following a structural shock in financial uncertainty (left panel) and macroeconomic uncertainty (right panel). The subsample is January 1^{st} 2008 to December 31^{st} 2019. Confidence bands come from a Wild Bootstrap at the 90% level, 5000 replications (details about our bootstrap methodology can be found in the appendix).

-0.10 to -0.15 percentage points in GDP growth.

Understandably, post-Covid IRFs imply instead huge effects on GDP growth that, however, disappear in far less time. Figure 6 imply that one standard shocks in either financial (left panel) or macroeconomic (right panel) uncertainty lead to losses from -0.5 to -1.5 percentage points in GDP growth. These shocks are nonetheless reabsorbed in two to three months. Unlike before, this means that a shock to either financial or macroeocnomic uncertainty of 10%, at the subperiod mean, has an impact of -0.5 to -1.5 percentage points of growth. In other words, shocks in the post-Covid subsample have at least effects ten times larger. None of the IRFs in Figure 6 are significant which means that we can only draw clues on the structural behaviour of aggregates in the aftermath of the Covid pandemic. However, one obvious caveat applies: we only have 24 available observations for this subsample which is definitely a low number when trying to identify time series relations.

We draw two main conclusions from Figures 5 and 6, one historical and one theoretical:

1. From an historical point of view, pre-Covid IRFs are consistent with the interpretation of a slow recovery, in which macroeconomic aggregates fluctuate little and the effect of uncertainty is lessened, perhaps, by the liquidity trap which the U.S. economy faced after the huge monetary policy implementations of the first post-Crisis years. Uncertainty may be transmitted with difficulty if monetary policy is actively stabilizing financial markets: despite the huge swings observable in Figure 1 (right panel), these could not be transmitted to the real economy in a period in which bank regulation is on the rise and the Federal Reserve System's balance sheet is exploding due to

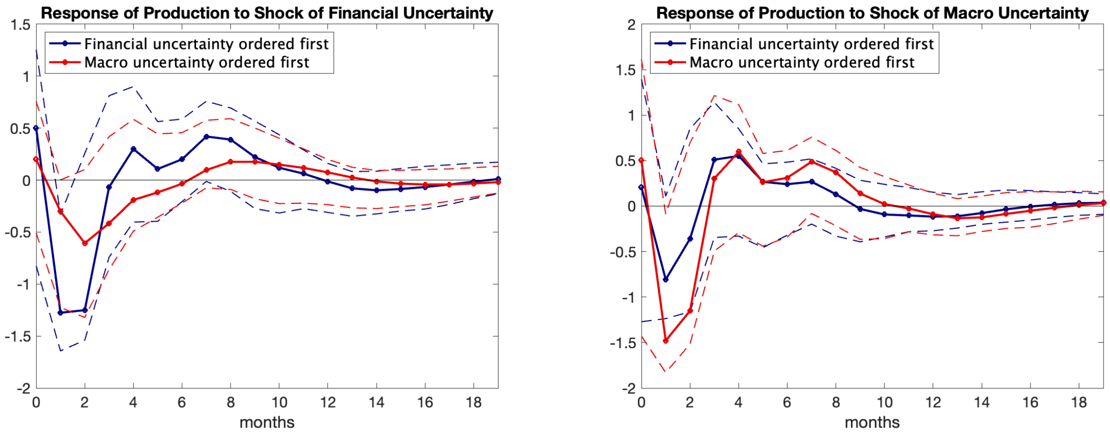

Figure 6: Production IRFs for Financial and Macro uncertainty shocks, Jan 2020 - Dec 2022

Notes: The figure displays the estimated IRFs for production, following a structural shock in financial uncertainty (left panel) and macroeconomic uncertainty (right panel). The subsample is January 1^{st} 2020 to December 31^{st} 2022. Confidence bands come from a Wild Bootstrap at the 90% level, 5000 replications (details about our bootstrap methodology can be found in the appendix).

its stabilizing interventions. At the same time, a simple story about post-Covid comes to mind: the pandemic constituted such a huge swing in both financial and macroeconomic uncertainty that one can understand how our IRFs can show such high negative effects. Moreover, the need to slow down the epidemic lead to personal restrictions to, f.e., travel: these leave limited scope for a stabilisation policy of the post-2008 type. At the same time, the intermitting need for lockdowns *et similia* could lead to significant swings in production: as soon as people can start working and consuming again, the effects of lockdowns (which are obviously considerable a source of uncertainty) would be rapidly reabsorbed.

2. From a theoretical standpoint, we claim we find regime dependence in the uncertainties-production relation: just by looking at Figures 4, 5 and 6 one can see how much of our main results are driven by the post-Covid nuances. This has a stark consequence, highlighted by Angelini, Bacchiocchi, et al. (2019): researchers should not estimate IRFs and structural relations for uncertainty-production over such long periods of time without taking into consideration the changes in structural parameters that may have happened meanwhile. This unfortunately poses a problem of inference: as in our case, the need to distinguish between the pre/post-Covid relations drains the number of available observations, making it almost impossible to reject the hypothesis that any of the coefficients is significantly different from zero, even when performing Bootstrap inference. Since looking at figures is at most indicative, we report in the appendix the identified structural matrices for the pre/post-Covid period, in order to clearly show the regime change: for reference, Tables 4, 5, 6 and 7.

Section VI: Conclusions

The present paper examines the effects of exogenous shocks in financial and macroeconomic uncertainty on GDP growth, during the 2008 Crisis and on-wards period. We employ a methodology novel to the literature on uncertainty identification: in particular we adopt Mertens and Ravn (2013)'s proxy-SVAR approach as we reckon it is a simple and convincing way to establish causality. Moreover we adapt their framework to the study on uncertainty, making use of two external instruments for the uncertainties, which we inherit from Ludvigson, Ma, and Ng (2021). We instrument financial uncertainty with the level of S&P 500 Index and macroeconomic uncertainty with the change in the log real price of gold. These instruments cannot be regarded as fully exogenous, so we use their innovations resulting from an auxiliary VAR rather than their raw levels, as suggested by Mertens and Ravn (2013) and implemented in a different framework by Angelini and Fanelli (2019). We find that a meager 20% change in either type of uncertainty, leads to a de-growth of *circa* -0.2 to -0.5 percentage points month on month, with the effect usually being reabsorbed within a quarter. This relation holds regardless of the joint relation we assume between financial and macroeconomic uncertainty.

Our second finding regards the evidence of regime dependence in the response of production to uncertainty shocks. When splitting the sample between a pre-Covid and a post-Covid subsamples we find two completely different relations between uncertainties and GDP growth. In the pre-Covid subsample only macroeconomic shocks have a significant effect, which remains quite small but surprisingly long lasting: a 20% shock, at the mean, in macroeconomic uncertainty leads to -0.1 percentage points loss in GDP growth, with the effect fading out in eight months. On the contrary, we find in the post-Covid sample evidence of huge effects of both shocks in financial and macroeconomic uncertainty which, however, are always fading away in at most a quarter: a 10% shock in macroeconomic uncertainty leads to a -1.5 percentage points loss in GDP growth, but the effect fades out in two months. The key takeaway is that we document post-Covid shocks being from ten to thirty times more impactful than pre-Covid ones. A simple look at the IRFs and at the estimated matrices shows that our results in the whole sample are largely driven by the post-Covid data, even though it represents only a rather small part of the observations. We provide a historical review of these two subperiods consistent with the observed heterogeneity in uncertainty effects.

We advise future research to closely evaluate breaks in structural parameters, as defined by Angelini, Bacchiocchi, et al. (2019). Our contribution, yet employing a novel estimation method, is mostly interested in evaluating the effects of uncertainty. We do not reckon our instruments perfectly satisfy the exogeneity constraint. Thus, we think future research should follow two ways: first, concentrate on finding valid and convincing instruments in the uncertainty setting, similar to the work done by C. D. Romer and D. H. Romer (2010) for tax shocks; second, establish a consensus of regime breaks in structural parameters, so that findings are not driven by the averaging out of different structural relations.

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Section VII: Appendix

Methodological Note: the Wild Bootstrap

We inherit our bootstrap methodology from Mertens and Ravn (2013), which follow Gonçalves and L. Kilian (2004). This type of bootstrap was first proposed by Wu (1986) but this exposition follows closely Hansen (2022). This procedure carries two huge advantages: first, it is heteroskedastic consistent, which means we can avoid worrying about the variance form of our variables; second, it is designed so that it satisfies the mean-independence restriction specified in Section V. Indeed, given a general VAR model of the form:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \varepsilon_t$$

we require that the innovations follow a Martingale Difference Sequence, which amounts to assuming

$$\mathbb{E}[\varepsilon_t | \mathbb{I}_{t-1}] = 0$$

a mean-restriction of which standard nonparametric bootstrap does not make use (and thus ends up not satisfying). Wild bootstrap draws are generated by the following equation:

$$Y_t^b = \hat{\alpha} + \hat{\beta}_1 Y_{t-1}^b + \hat{\beta}_2 Y_{t-2}^b + \hat{\varepsilon}_t \xi_t \tag{9}$$

where $\hat{\alpha}$, $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimated regressive parameters, $\hat{\varepsilon}_t$ are the VAR residuals and ξ_t are IID random variables with 0 mean and standardised variance, which satisfy $\mathbb{P}[\xi_t = 1] = \mathbb{P}[\xi_t = 0] = \frac{1}{2}$. Throughout the analysis we employ 90% confidence bands, with 5000 replications.

Additional Figures & Tables: Complementary Material

Variable	**Stationarity**	**p-value**
Financial Uncertainty Measure	Non-stationary	0.710
Macroeconomic Uncertainty Measure	Non-stationary	0.642
U.S. Monthly Production, $\Delta \log$	Stationary	0.001
Monthly Real Gold Price, $\Delta \log$	Stationary	0.001
S&P 500, scaled by 100	Stationary	0.001

Table 1: Augmented Dickey-Fuller (ADF) Test Results

Lag	**AIC**	**BIC**
1	-923.17	-884.73
2	**-1214.80**	**-1147.51**
3	-1201.27	-1105.15
4	-1194.61	-1069.65
5	-1186.07	-1032.29
6	-1173.63	-991.00
7	-1157.28	-945.82
8	-1155.47	-915.17
9	-1137.90	-868.78
10	-1128.80	-830.83
11	-1134.19	-807.38
12	-1151.39	-795.75

Table 2: AIC and BIC for Different Lags (Optimal Lag Highlighted)

Variable	**Autocorrelation**	**p-value**
Financial Uncertainty Measure	No autocorrelation	0.804
Macroeconomic Uncertainty Measure	No autocorrelation	0.587
U.S. Monthly Production, $\Delta \log$	No autocorrelation	0.443

Table 3: Ljung-Box Test Results

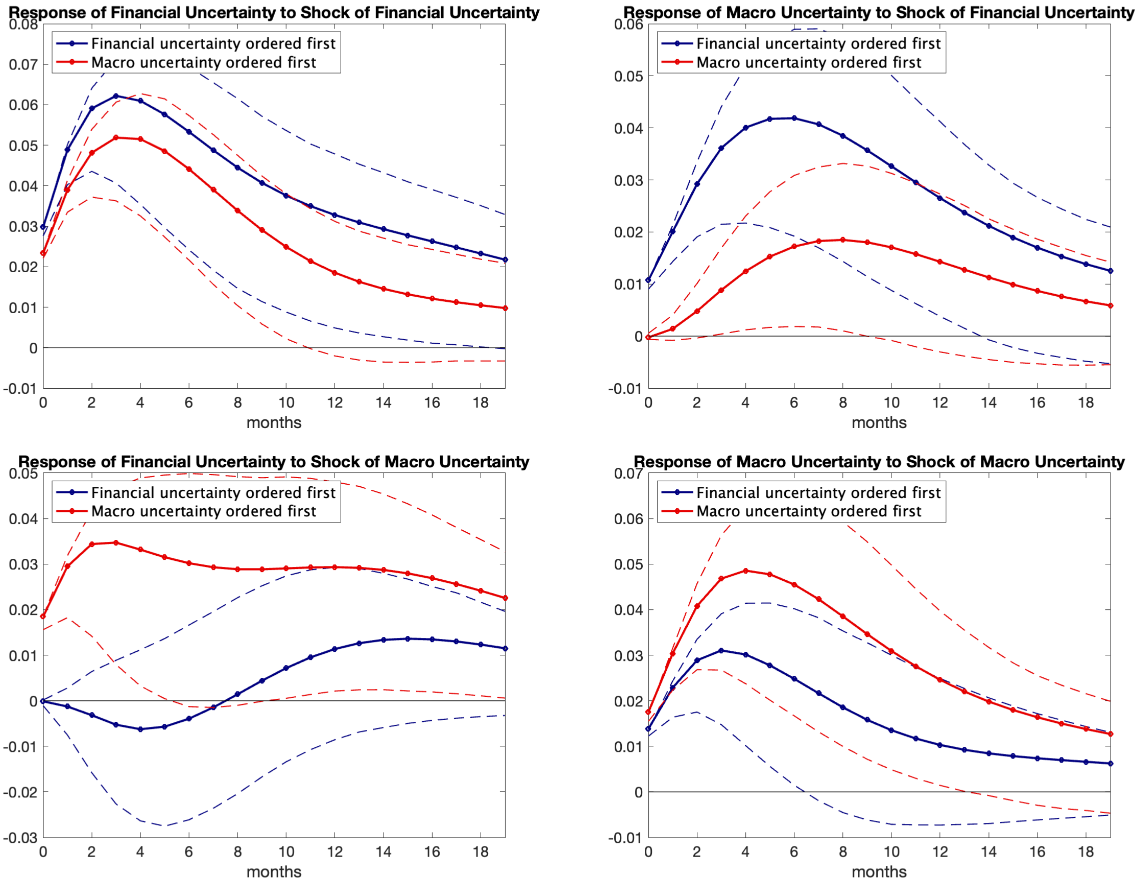

Figure 7: Responses of Uncertainties to Shocks in Uncertainties

Notes: The figure displays the estimated IRFs for all uncertainties and combination of shocks, when instrumenting uncertainties with the innovations from the auxiliary VAR. Confidence bands come from a Wild Bootstrap at the 90% level, 5000 replications.

Financial Uncertainty 1st

$$\hat{\mathbf{B}}_{\mathbf{1}} = \begin{pmatrix} 0.0298 & -0.0001 \\ 0.0107 & 0.0138 \\ 0.2927 & 0.0919 \end{pmatrix}$$

Macro Uncertainty 1st

$$\hat{\mathbf{B}}_{\mathbf{1}} = \begin{pmatrix} 0.0233 & 0.0185 \\ -0.0002 & 0.0175 \\ 0.1713 & 0.2545 \end{pmatrix}$$

Notes: Estimate of the matrix $\mathbf{B_1}$, obtained by instrumenting macroeconomic and financial uncertainty with the innovations from the auxiliary VAR specified in Section V. The left matrix shows the on-impact responses when financial uncertainty is ordered first, while the right matrix shows the responses when macroeconomic uncertainty is ordered first.

Table 4: $\hat{\mathbf{B}}_{\mathbf{1}}$ for Innovations as Instruments

Financial Uncertainty 1st

$$\hat{\mathbf{B}}_{\mathbf{1}} = \begin{pmatrix} 0.0294 & -0.0000 \\ 0.0106 & 0.0139 \\ 0.4061 & 0.0027 \end{pmatrix}$$

Macro Uncertainty 1st

$$\hat{\mathbf{B}}_{\mathbf{1}} = \begin{pmatrix} 0.0229 & 0.0185 \\ -0.0005 & 0.0175 \\ 0.3143 & 0.2573 \end{pmatrix}$$

Notes: Estimate of the matrix $\mathbf{B_1}$, obtained by instrumenting macroeconomic and financial uncertainty with raw external variables. The left matrix shows the on-impact responses when financial uncertainty is ordered first, while the right matrix shows the responses when macroeconomic uncertainty is ordered first.

Table 5: $\hat{\mathbf{B}}_{\mathbf{1}}$ for Raw Instrumented Shocks

Financial Uncertainty 1st

$$\hat{\mathbf{B}}_{\mathbf{1}} = \begin{pmatrix} 0.0236 & -0.0000 \\ 0.0051 & 0.0092 \\ -0.0272 & -0.0847 \end{pmatrix}$$

Macro Uncertainty 1st

$$\hat{\mathbf{B}}_{\mathbf{1}} = \begin{pmatrix} 0.0206 & 0.0116 \\ -0.0000 & 0.0105 \\ 0.0177 & -0.0871 \end{pmatrix}$$

Notes: Estimate of the matrix $\mathbf{B_1}$, obtained by instrumenting macroeconomic and financial uncertainty with the innovations from the auxiliary VAR specified in Section V. The left matrix shows the on-impact responses when financial uncertainty is ordered first, while the right matrix shows the responses when macroeconomic uncertainty is ordered first.

Table 6: $\hat{\mathbf{B}}_{\mathbf{1}}$ Jan 2008 - Dec 2009

Financial Uncertainty 1st

$$\hat{\mathbf{B}}_{\mathbf{1}} = \begin{pmatrix} 0.0400 & 0.0004 \\ 0.0233 & 0.0222 \\ 0.5030 & 0.2058 \end{pmatrix}$$

Macro Uncertainty 1st

$$\hat{\mathbf{B}}_{\mathbf{1}} = \begin{pmatrix} 0.0274 & 0.0292 \\ 0.0001 & 0.0321 \\ 0.1995 & 0.5055 \end{pmatrix}$$

Notes: Estimate of the matrix $\mathbf{B_1}$, obtained by instrumenting macroeconomic and financial uncertainty with the innovations from the auxiliary VAR specified in Section V. The left matrix shows the on-impact responses when financial uncertainty is ordered first, while the right matrix shows the responses when macroeconomic uncertainty is ordered first.

Table 7: $\hat{\mathbf{B}}_{\mathbf{1}}$, Jan 2020 - Dec 2022