Causes and Effects of Business Cycles: An Updated Identification Through Heteroskedasticity SVAR Using Uncertainty Data

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Abstract

Building upon the non-recursive identification scheme for uncertainty shocks proposed by Angelini et al. 2019, this paper advances the research on the topic to explore the causal relationship between uncertainty and the business cycle up to most recent observations. The research employs a small-scale structural vector autoregression (SVAR) model, exploiting breaks in the volatility of two uncertainty measures and industrial production growth, using U.S. data from Jurado, Ludvigson, and Ng 2015. The purpose of this analysis is to identify uncertainty as a source of business cycle or an endogenous response to its fluctuations, and to examine the diverse impacts of macroeconomic and financial uncertainty on economic fluctuations across various volatility regimes. Additionally, it investigates the propagation effects of uncertainty shocks during periods of economic, financial, and exogenous turmoil such as the pandemic crisis. While confirming the findings of Angelini et al. 2019, this paper emphasizes the singularity of the COVID-19 recession, which figures as a new volatility regime, shedding light on its unique implications and calling out for other variables to be considered.

Contents

1 Introduction

Understanding the relationship between uncertainty and the business cycle remains a central challenge in macroeconomics. The existing literature consistently finds a negative correlation between uncertainty and the business cycle, but the causal direction of this relationship remains unclear. This ambiguity arises from the wide range of models used to analyze uncertainty, which often diverge in their explanations of the underlying mechanisms. Some studies suggest that uncertainty stems from economic fundamentals, such as productivity shocks, which amplify market frictions and discourage real economic activity. Others emphasize the role of financial shocks, which disrupt the economy through both direct and indirect channels, as occurred during the Great Recession. However, even the possibility of reverse causality could offer insights into this dilemma. This study seeks to bridge these gaps by examining both real and financial uncertainty across key economic regimes, using the most up-to-date information available.

The methodological framework proposed by Angelini et al. 2019 forms the foundation of this analysis, that aims at extending their work to the new events occurred after the upheavals of COVID-19. The framework provides a non-recursively identified Structural Vector Autoregression (SVAR) model, which disentangles the causes and consequences of macroeconomic and financial uncertainty. Unlike traditional recursive SVAR models that rely on restrictive Cholesky decompositions, this approach levers an "identification-through-heteroskedasticity" strategy. By exploiting structural breaks induced by events such as policy shifts, macroeconomic or financial crises, and exogenous event such as the pandemic crises, the model identifies time-varying shocks responses across volatility regimes. This allows for simultaneous on-impact effects between uncertainty and real activity, providing a more nuanced understanding of their interactions.

The central questions this paper addresses are: is uncertainty primarily a source of business cycle fluctuations or a consequence of them? What roles do financial and macroeconomic uncertainty play in economic fluctuations? Are there distinct volatility regimes that shape these dynamics? To answer these questions, the study employs orthogonal measures of macroeconomic and financial uncertainty developed by Jurado, Ludvigson, and Ng 2015, alongside industrial production growth, a real activity proxy. Using monthly U.S. data from 1960 to 2024, four distinct macroeconomic volatility regimes are identified: the Great Inflation (*1960:M7–1984:M3*), the Great Moderation (*1984:M4–2007:M12*), the Great Recession + Slow Recovery (*2008:M1–2020:M2*) and the COVID-19 Recession (*2020:M3-2024:M6*).

The empirical findings confirm key insights from Angelini et al. 2019, while extending the analysis to additional observations from 2015 including COVID-19 recession [1]. First, macroeconomic uncertainty behaves largely as an exogenous driver during recessions, exerting a negative but short-lived impact on real activity. In contrast, business cycle fluctuations exhibit a lagged, more prolonged influence on macroeconomic uncertainty. Second, financial uncertainty is identified as an exogenous impulse, with indirect effects on economic activity, at least until the COVID-19 occurrence, through the amplification effect provided by macroeconomic uncertainty. Consistent with Ludvigson, Ma, and Ng 2021, macroeconomic uncertainty is shown to propagate other shocks, such as financial disruptions or exogenous events like the COVID-19 pandemic. Importantly, economic downturns are found to have negligible lagged effects on financial uncertainty until 2020, when these effects become significant and the exogenous impact of financial

[1] It is worth noting that the contribution of this work are mainly relative to the last two volatility regimes since the analysis by Angelini et al. 2019 spans $1960: M7-2015: M4$.

uncertainty to business cycle turns direct on-impact. Overall, COVID-19 represents a difficult challenge to face. The exogeneity of this event presumably requires the integration of new variables for the study. Nonetheless, the results obtained from this empirical analysis appear satisfactory. In fact, the impact of the pandemic seems to confirm the exogeneity of both forms of uncertainty. On-impact we found that the advent of the pandemic traumatized the financial markets on the one hand and the macroeconomic forecasts regarding unemployment, inflation and GDP on the other. This may have had an immediate impact on the drastic drop in production, which however, due to precautionary measures such as the lockdown, had a lagged effect in turn on financial and macroeconomic uncertainty. In fact, it is not possible to completely exclude the endogeneity of macroeconomic uncertainty to the economic decline of the pandemic.

These results underscore the limitations of recursive SVAR models, as they fail to capture the contemporaneous effects between uncertainty and the business cycle. Moreover, by distinguishing between macroeconomic and financial shocks, this study disentangles their unique contributions to economic dynamics. Ultimately, the findings reveal that both macroeconomic and financial uncertainty act as exogenous drivers of the business cycle, with varying contractionary effects over time, reinforcing the validity of accounting for structural breaks and regime-dependent volatility. Our conclusion are supported by explicit tests for exogeneity, which do not reject models treating macroeconomic uncertainty as endogenous, but show that considering uncertainty as a driver of the business cycle better fits data. Note that this result slightly differs from Angelini et al. 2019, who reject the endogenous macroeconomic uncertainty model at 5% level of significance with respect to a reduced form VAR, but are supported by evidences from Ludvigson, Ma, and Ng 2021. This finding could also be motivated by the introduction of COVID-19 in the analysis.

The work is organized as follows. Section 2 reviews the literature on uncertainty, providing economic explanations that justify our findings. Section 3 outlines the methodological approach adopted, which is based on Angelini et al. 2019. Section 4 presents anecdotal evidence supporting the restrictions for the non-recursive $SVAR$ model, while Section 5 concludes the research by addressing the key economic questions. Specifically, it tests for the endogeneity and exogeneity of macroeconomic uncertainty and explores the dynamic causal effects between variables over time through the representation of impulse response functions (*IRFs*). Finally, Section 6 summarizes the results achieved.

This study is inspired by the methodological framework proposed in Angelini et al. 2019, while emphasizing the novelty introduced by the occurrence of the Covid-19 recession. Particular attention is given to additional observations introduced during the Great Recession and Slow Recovery period, as well as the final regimes of the Covid-19 recession. Despite these extensions, our results remain consistent with those of Angelini et al. 2019, except for differences attributable to the updated data from Jurado, Ludvigson, and Ng 2015.

2 Literature Review

While some unconventional models, such as the Growth Option Theory, propose a positive relationship between uncertainty and the business cycle, the majority of economists widely acknowledge a negative correlation, a view often supported by empirical evidence. However, a more contentious aspect of uncertainty theory lies in the direction of causality within this relationship. This paper aims at addressing this critical and controversial issue, as the assumptions made by models about causality often shape their conclusions.

Specifically, it seeks to answer the following key questions: First, does causality flow from uncertainty to the business cycle, or vice versa? Second, does uncertainty primarily stem from macroeconomic factors, financial factors, or their interaction? Finally, is this relationship time-varying? Hence, to introduce the theoretical framework underlying our work, we start by presenting the three main theories that explain the sign of the correlation and the direction of causality between uncertainty and economic fluctuations. Through the examination of these theories, we briefly present the methodological strategies for identification using *SVAR* that should be avoided when addressing this theoretical question, highlighting their main limitations.

As mentioned above, positive relationship between uncertainty and real economic activity is proposed by Growth Option Theories. This evidence is not frequently supported by the data and that's why those theories represent a subset of the literature. Nevertheless, the interesting contribution they deliver suggests that an increase in risk, with unbounded upside potential, can stimulate investment and hiring. Craine 1989 show that a mean-preserving spread in the price of output increases the expected value of profits, which often leads to a higher demand for capital by firms. Consequently, exogenous risk can lead to an increase in output, creating a procyclical effect of uncertainty. Ludvigson, Ma, and Ng 2021 partially supports this theory, as their findings show that macroeconomic uncertainty shocks increase real activity in the short run, though by a relatively modest amount. However, the idea of uncertainty acting as a potential stimulus to growth is contested by other studies, such as Angelini et al. 2019, which suggest that uncertainty is predominantly countercyclical. This discrepancy presents a challenge for researchers, posing a limitation during the identifying scheme in structural models. Indeed, the need to avoid making a definitive assumption about the effect of uncertainty on the business cycle results in avoiding sign restrictions as an identification strategy.

Another branch of the literature considers uncertainty as a consequence of economic decline. Indeed, during economic downturns, heightened uncertainty among economic agents can emerge as an endogenous response, leading to increased risk aversion and negatively influencing their behavior. For instance, firms and households may engage in riskier behavior when faced with reduced opportunities for safe investments (Bachmann, Moscarini, et al. 2011). Such dynamics can lead to suboptimal financial decisions, resulting in the misallocation of capital. Indeed, according to Ai, Li, and Yang 2015, adverse shocks to agency frictions exacerbate capital misallocation and result in variations of the total factor productivity at the aggregate level. Basically, the economy described here would be characterized by two key factors: widespread risky behavior and a feedback loop in which deteriorating economic conditions generate increasingly unpredictable outcomes. The consequence of this is a reduction in the quality of information and the ability to forecast future events, which typically results in increased uncertainty. Information quality plays a central role in theories that view uncertainty as a consequence of the business cycle. For instance, Van Nieuwerburgh and Veldkamp 2006 provide evidence suggesting that when labor productivity drives negative economic cycles, the data collected tends to be noisy. This noise is further amplified by factors such as lower labor participation rates, as well as decreases in investment and production, all of which contribute to an increase in uncertainty among economic agents. Finally, some other theory suggests that uncertainty can arise also from policies aimed at mitigating economic downturns. These policies can deter investment and heighten economic instability, making stocks more volatile and more correlated, particularly during periods of economic weakness (Pástor and Veronesi 2013).

Nevertheless, the findings of this paper align with the literature that identifies uncertainty as a driver of economic decline. These theories typically conceptualize uncertainty as an exogenous shock to economic fundamentals, which triggers downturns in economic activity. From this perspective, uncertainty directly influences household and firm investment decisions, generating adverse effects on the economy through several channels. For instance, uncertainty may delay investment decisions as firms postpone projects, leading to a reduction in economic activity as pointed out by Pindyck 1986. Additionally, uncertainty can increase the cost of external financing by heightening lender risk aversion (Gilchrist, Sim, and Zakrajšek 2013) or encourage precautionary savings as a risk-hedging mechanism against potential negative shocks (Basu and Bundick 2017), leading to reduction in investment and then to a production decline. According to Bloom et al. 2018, when we consider a dynamic stochastic general equilibrium (*DSGE*) model with heterogeneous firms, sudden changes in technology or innovation can generate uncertainty about the future economic environment, positioning technology as a central driver of uncertainty shocks with tangible economic impacts.

As noted by Ludvigson, Ma, and Ng 2021, these theories gain a new perspective when uncertainty is separated into macroeconomic and financial components, rather than being treated as a single, general one. This consideration is a central points addressed in this paper and represents a significant turning point in Uncertainty Theory. Specifically, while Ludvigson, Ma, and Ng 2021 identifies financial uncertainty as the primary driver of economic downturns, Angelini et al. 2019 highlights macroeconomic uncertainty as an equally important exogenous driver, rather than an endogenous consequence of the business cycle. Consistent with the results of this paper, which serves as the basis for the employed methodological framework, this finding remains valid even in the post-COVID-19 era.

Despite these valuable insights, challenges persist in empirical analyses due to the lack of theoretical consensus. The theories proposed thus far yield divergent predictions, often remaining ambiguous regarding both the direction and magnitude of the relationship between uncertainty and economic activity. As discussed earlier, sign restrictions are not suitable for addressing the issue of causality direction between uncertainty and the business cycle. Unfortunately, this is not the only empirical identification challenge researchers face when implementing a *Structural VAR*. As we will elaborate in the next section, recursive SVAR methods exclude contemporaneous interactions between uncertainty and economic activity, which directly pertains to the question under investigation, making this type of specification unfeasible. Furthermore, the instrumental variable approach presents its own challenges as an identification scheme. External variables often lack credibility, particularly when more than one variable is involved, as argued by Ludvigson, Ma, and Ng 2021. One remaining possibility to address the questions motivating this paper, which also corresponds to the path we followed, is the implementation of a non-recursive identification scheme for uncertainty shocks, which exploits breaks in the volatility of macroeconomic variables.

3 Methodology

In the attempt of unraveling the causal relationship between uncertainty and the business cycle, we adopt the methodology proposed by Angelini et al. 2019. Our objective is to test whether the conclusions drawn from their analysis remain valid when applied to an extended sample period, which includes the recent COVID-19 pandemic and its significant impact on the U.S. economy. In Section 3.1, we summarize the econometric approach of Angelini et al. 2019. In Section 3.2, we describe the dataset used in our analysis before proceeding to the model specification.

3.1 Econometric Framework

Our procedure towards the identification and estimation of both uncertainty and real economic activity shocks is drawn from Angelini et al. 2019, expanding the standard framework of Structural VAR analysis to time series that exhibit unconditional volatility breaks, in order to retrieve time-varying dynamic causal effects.

The authors approach is rooted in a long-standing economic literature identifying three historical periods within US macroeconomic time series, associated to two salient events of US economic history: namely, the "Great Moderation" starting from 1984 and the Great Financial Crisis of 2008. Angelini et al. 2019 paper explicitly relies on this assumption, identifying three "volatility regimes" within the period 1960-2015, set off by breaks in unconditional variance observed in the sample. Then, the econometric technique is based on the novel identification-through-heteroskedasticity exposed in Bacchiocchi and Fanelli 2015, which exploits the presence of multiple variance-covariance matrices of VAR innovations to achieve a richer identification for structural analysis and, more importantly, a set of regime-specific structural Impulse Response Functions.

Our contribution to this way of assessing the endogeneity or exogeneity of uncertainty with respect to business cycle lies in applying the methodology of Angelini et al. 2019 to a broader dataset, ranging monthly from *1960:M7* to *2024:M6*. As already anticipated, this alters the duration of the third regime, and requires the addition of a new fourth volatility regime, set out by the economic crisis resulting from the COVID-19 pandemic in March 2020 until the end of the sample.

Formally stated, we consider a system of $M = 3$ variables: $W_t = (U_{Mt}, Y_t, U_{Ft})'$, where U_M and U_F are the macroeconomic and financial uncertainty measures, respectively, and Y_t is a measure of real economic activity. Suppose the vector of independent variables W_t has a reduced-form finite-order autoregressive representation:

$$W_t = c + \Phi_1 W_{t-1} + ... + \Phi_p W_{t-p} + u_t = \Pi W_t + u_t \quad t = 1, 2, ..., T$$

where T is the sample size, p is the finite number of VAR lags, $\Pi = (c, \Phi_1, ...\Phi_p)$ collects the $p+1$ reduced-form autoregressive parameters – including the constant c – in a compact form, and $W_t = (1, W'_{t-1}, W'_{T-2}, ..., W'_{t-p})$ is the vector of $p+1$ explanatory variables of the model. Finally, u_t is the $M \times 1$ vector of VAR innovations, which has $M \times M$ variance-covariance matrix:

$$\Sigma_u = \mathbb{E}[u_t u_t'] = \begin{pmatrix} \sigma^2_M & \sigma_{M,Y} & \sigma_{M,F} \\ & \sigma^2_Y & \sigma_{Y,F} \\ & & \sigma^2_F \end{pmatrix}$$

Now, following Angelini et al. 2019, we acknowledge the presence of three unconditional volatility breaks in the data, namely at $t = T_{B1}$, at $t = T_{B2}$ and at $t = T_{B3}$ such that $1 < T_{B1} < T_{B2} < T_{B3} < T$. This divides the 1960-2024 sample into four volatility regimes: the ”Great Inflation” period (*1960:M7–1984:M3*), the “Great Moderation” period (*1984:M4–2007:M12*), the “Great Recession+Slow Recovery” period (*2008:M1–2020:M2*) and the "Covid-19 Recession" period (*2020:M3-2024:M6*). For each of them, we specify a reduced-form VAR of the type described above, implying that, for the same number of lags and the same variables, the whole time series has a composite vector autoregressive representation of the type:

$$W_t = \Pi W_t + u_t \quad \Sigma_u = \mathbb{E}[u_t u_t'] \qquad t = 1, 2, ..., T$$

Where the VAR reduced form parameters change across volatility regimes:

$$\Pi(t) = \Pi^{(1)} \times \mathbb{1}(t \leq T_{B1}) + \Pi^{(2)} \times \mathbb{1}(T_{B1} < t \leq T_{B2}) + \Pi^{(3)} \times \mathbb{1}(T_{B2} < t \leq T_{B3}) + \Pi^{(4)} \times \mathbb{1}(T_{B3} < t \leq T)$$

As does the variance-covariance matrix of VAR innovations:

$$\Sigma_u(t) = \Sigma_u^{(1)} \times \mathbb{1}(t \leq T_{B1}) + \Sigma_u^{(2)} \times \mathbb{1}(T_{B1} < t \leq T_{B2}) + \Sigma_u^{(3)} \times \mathbb{1}(T_{B2} < t \leq T_{B3}) + \Sigma_u^{(4)} \times \mathbb{1}(T_{B3} < t \leq T)$$

Indeed, a necessary condition for this approach is the presence of unconditional heteroskedasticity in the data, that is $\Sigma_u^{(1)} \neq \Sigma_u^{(2)} \neq \Sigma_u^{(3)} \neq \Sigma_u^{(4)}$. It is also important, but not necessary, that $\Pi^{(1)} \neq \Pi^{(2)} \neq \Pi^{(3)} \neq \Pi^{(4)}$, implying different dynamics shaping the IRFs for each regime. Both conditions may be tested using Chow-type tests.

Moving to the structural analysis, the presence of four variance-covariance matrices of innovations allows to impose a regime-dependent specification of the structural parameters within the same SVAR. Following Bacchiocchi and Fanelli 2015, we adopt a B-model error structure of the type:

$$u_t = \begin{cases} Be_t & t \leq T_{B1} \\ (B + Q_2)e_t & T_{B1} < t \leq T_{B2} \\ (B + Q_2 + Q_3)e_t & T_{B1} < t \leq T_{B3} \\ (B + Q_2 + Q_3 + Q_4)e_t & T_{B1} < t \leq T \end{cases}$$

Where $e_t \sim WN(0_{M\times1}, \mathbb{I}_{M\times M})$ is the vector of zero-mean, unit-variance and serially uncorrelated structural shocks, $e_t = (e_{Mt}, e_{Yt}, e_{Ft})'$, corresponding each to one of the $M = 3$ variables. This structure implies that matrix B outlines the on-impact effect of the structural shocks on the variables in the first regime; the matrices Q_2, Q_3 and Q_4, instead, express the evolution of the structural parameters – and, therefore, of the dynamic causal effects – from one regime to the next. Notably, the task of assessing the reverse-causality between uncertainty and the business cycle requires to adopt a structural specification that also allows for "two-way" on-impact causality between the variables. To this end, the choice of a B-model error structure is most suitable for our research question, aiming at a non-recursive specification for contemporaneous causal effects between the variables. Conversely, other SVAR specifications such as the Choleski structure, would have required a precise stand on the propagation of structural shocks in the system, allowing only one-way causality to run from the most exogenous to the most endogeous variable.

Moving on, our regime-dependent specification implies the following variance decompositions:

$$\begin{aligned}
\Sigma_u^{(1)} &= BB' \\
\Sigma_u^{(2)} &= (B + Q_2)(B + Q_2)' \\
\Sigma_u^{(3)} &= (B + Q_2 + Q_3)(B + Q_2 + Q_3)' \\
\Sigma_u^{(4)} &= (B + Q_2 + Q_3 + Q_4)(B + Q_2 + Q_3 + Q_4)'
\end{aligned}$$

Thus, Bacchiocchi and Fanelli 2015 approach takes advantage of multiple variance-covariance matrices in heteroskedastic time series to allow some of the structural parameters to be time varying. As the unconditional variance changes across regimes, the on-impact transmission of structural shocks described in matrix B will change accordingly, as a result of the addition of the new structural parameters in Q_2, Q_3 and Q_4.

Moving towards the estimation of the SVAR thus described, two identification conditions must be verified. The necessary order condition requires the number structural parameters to be equal or lower to the number of reduced-form parameters: given our system with $M = 3$ variables, the total number of structural parameters is $4M^2 = 36$; the variance decompositions already provide $\frac{4}{2}M(M+1) = 24$ restrictions due to the symmetry of the variance-covariance matrices $\Sigma_u^{(i)}$. It is therefore necessary to impose at least $4M^2 - \frac{4}{2}M(M+1) = \frac{4}{2}M(M-1) = 12$ restrictions, appropriately motivated by economic theory, in order to assure identification.

The necessary and sufficient rank condition requires to define the structural parameters as a function of the reduced form parameters. Let $\Theta = (vec(B)', vec(Q_2)', vec(Q_3)', vec(Q_4)')'$ be the $4M^2 \times 1$ vector of structural parameters; then, the identifying restrictions may be conveniently represented in explicit form as:

$$\Theta = S_B\theta + s_B$$

Where θ is the $\frac{4}{2}M(M+1) \times 1$ vector of "free" elements within the matrices of structural parameters, S_B is a $4M^2 \times \dim(\theta)$ selection matrix and s_B is a $4M^2 \times 1$ vector of known elements. The link between the "free" structural parameters within θ to the unique reduced form parameters can now be summarized as: $\sigma^+ = g(\theta)$, where $\sigma^+ \equiv (vech(\Sigma_u^{(1)})', vech(\Sigma_u^{(2)})', vech(\Sigma_u^{(3)})' vech(\Sigma_u^{(4)})')'$ is the vectorization of the unique elements within the variance-covariance matrices. The necessary and sufficient rank condition requires to compute the Jacobian matrix associated to the function $g(\cdot)$, through the analytical results:

$$J_B(\theta) \equiv \frac{\partial g(\theta)}{\partial \theta'} = 2D_M^+(B \otimes \mathbb{I}_M)S_B$$

Where $D_M^+ \equiv (D_M' D_M)^{-1} D_M'$ is the Moore-Penrose pseudo-inverse of the Duplication matrix (D_M). Then, identification is achieved if and only if the matrix has full column rank: $\text{rank}(J(\theta)) = \dim(\theta)$.

Having verified the identification conditions, we retrieve $\tilde{B} = B(\theta)$, $\tilde{Q}_2 = Q_2(\theta)$, $\tilde{Q}_3 = Q_3(\theta)$ and $\tilde{Q}_4 = Q_4(\theta)$, *i.e.* the counterparts of B, Q_2, Q_3 and Q_4 satisfying the identification conditions. It is possible to proceed to the estimation of the dynamic causal effects, which will be regime-dependent as a consequence of our SVAR specification. Let A_i be the VAR Companion matrix of $i = 1,2,3,4$ reduced-form models; then, the dynamic response of W_t h periods ahead to a one standard deviation structural shock will be represented by the set of structural Impulse Response Functions:

$$IRF_{\bullet,\bullet}(h) \equiv \begin{cases} R(A_1)^h R'B & t \leq T_{B1} \\ R(A_2)^h R'(B+Q_2) & T_{B1} < t \leq T_{B2} \\ R(A_3)^h R'(B+Q_2+Q_3) & T_{B2} < t \leq T_{B3} \\ R(A_4)^h R'(B+Q_2+Q_3+Q_4) & T_{B3} < t \leq T \end{cases}$$

Where R is the selection matrix retrieving the autoregressive parameters from the Companion matrix. Thus, the structural IRFs will outline regime-specific dynamic causal effects that depend on both the structural parameters and the autoregressive reduced-form parameters of each regime. As long as the time series exhibits unconditional heteroskedasticity in a way that allows to divide it into subperiods, this approach allows to achieve a richer SVAR identification in which the structural parameters change over time, within a non-recursive framework.

3.2 Data

In order to focus intensively on the effect of uncertainty on the business cycle, we adopt the small set of three variables adopted in Angelini et al. 2019: a measure of US real economic activity, and two specific measures of uncertainty. The choice of considering two distinct sources of uncertainty allows to model the relation between each of them and economic performance separately, as they may well exhibit different effects on industrial production. The resulting time series are reported monthly, spanning from *1960:M7* to *2024:M6*, for a total sample size of $T = 768$ periods.

As a proxy for real economic activity, we consider a widely used index of business cycle fluctuations: the US industrial production growth (percent) rate, denoted by Y_t[2]. We manipulated the original index into log-differential to reduce its volatility and achieve stationarity, as observable in Figure 6. Still, as reported in Figure **??**, the variable exhibits severe negative spikes corresponding to disruptive events such as the Great Recession of 2007-2008, and, even more, the Covid-19 pandemic in 2020.

The two uncertainty variables are taken from Jurado, Ludvigson, and Ng 2015, which constructs these indices as an aggregate of multiple estimated uncertainty measures[3]. Stated briefly, Jurado, Ludvigson, and Ng 2015 consider a set $Y_t^C = (y_1^C t, ..., y_{N^C}^C)'$ of time series concerning a specific category C, for instance aggregate real economy or financial markets. For each of these variables, they consider the following statistics:

$$U_{j,t}^C(h) = \sqrt{\mathbb{E}\left[\left(y_{j,t+h}^C - \mathbb{E}[y_{j,t+h}^C|\mathscr{I}_t]\right)^2 | \mathscr{I}_t\right]}$$

Which expresses the conditional volatility of its forecast error, based on a stochastic volatility model. This value essentially captures how unpredictable the variable will be h periods in the future, conditional on all information $\mathscr{I}_t$ available at a time t. Finally, the general uncertainty measure U_C will result from the aggregation of all individual uncertainty series in the category, as in:

$$U_t^C(h) = \text{plim}_{N_C \to \infty} \frac{1}{N_C} \sum_{j=1}^{N_C} U_{jt}^C(h)$$

In our analysis, we consider *macro* and *financial* uncertainty, denoted by U_M and U_F respectively. Each of them is available for monthly, quarterly and yearly time horizons, that is for $f = \{1, 3, 12\}$. The main specification used throughout the paper will be based on the monthly uncertainty, but the resulting IRFs also include the yearly index. Basic descriptive analysis summarized in the Appendix, in Figures 5 and 7, highlights that all uncertainty measures exhibit high serial correlation and non-stationarity. Nonetheless, following Angelini et al. 2019, we will not apply any manipulation, aiming at the estimation of their direct dynamic causal effect on real economic activity. The representation of the time series of macro and financial uncertainty expressed in standardized units is available in Figure 1.

[2]The total index – reported in levels – is available on the FRED database: `https://fred.stlouisfed.org/series/INDPRO`

[3]The series are freely available on Sidney Ludvigson website: `https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes`

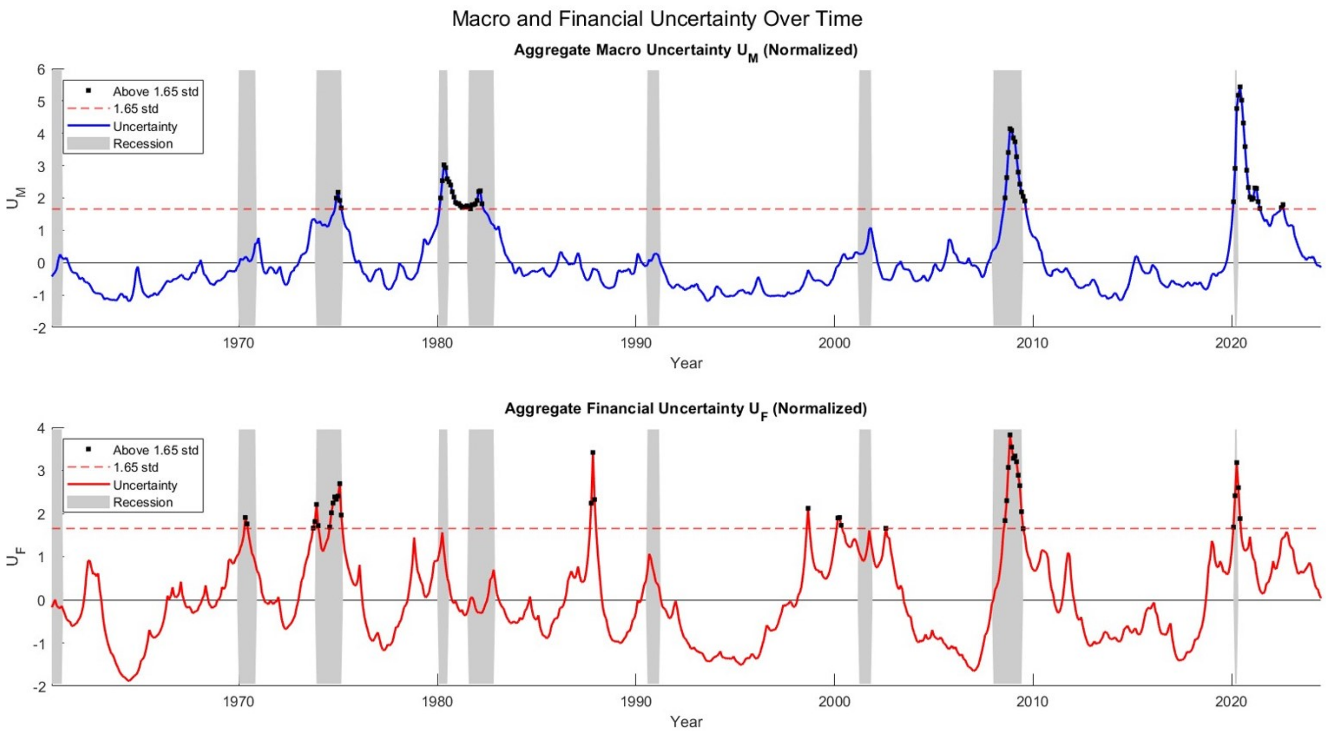

Figure 1: Time series of macro uncertainty and financial uncertainty expressed in standardized units that span the period 1960 : 07 to 2024 : 06. Shaded areas correspond to $NBER$ recession dates. The horizontal line corresponds to 1.65 standard deviations above the unconditional mean of each series (which has been normalized to zero);the black dots are months when uncertainty is at least 1.65 standard deviations above the mean.

4 Model Specification

In this section, we outline the empirical methodology used to address the core questions of this study: the heterogeneity across volatility regimes and the direction of causality between real economic activity and uncertainty. Building upon the framework of Angelini et al. 2019, we first confirm their evidences to justify the borrowing of their restrictions for overlapping periods of the analysis, and secondly we propose a new set of structural specifications for the additional volatility regime rising from the extension of the dataset. Section 4.1 provides evidence for the existence of four distinct volatility regimes; section 4.2 outlines the baseline non-recursive SVAR model under two different sets of restrictions.

4.1 Empirical Evidence for Volatility Breaks

Using the small-scale system $W_t = (U_{Mt}, Y_t, U_{Ft})'$, we apply the identification strategy proposed by Angelini et al. 2019, which relies on breaks in the unconditional volatility of the variables. We present evidences of the time variation by assuming information sufficiency of uncertainty variables in two steps. We first implement recursive and rolling window estimates of residual variances and covariances (Figure 2) then we perform Chow-type tests for structural breaks (bottom line of Table 1). This procedure highlights *TB1 = 1984:M3*, *TB2 = 2007:M12*, and *TB3 = 2020:M2* as break dates. Even if those dates are exogenously set, differently from what done in Ludvigson, Ma, and Ng 2021, they perfectly align with the recession dates identified by *NBER* (Economic Research n.d.) and with Angelini et al. 2019 for the overlapping periods.

To begin, we estimate the baseline VAR model for $W_t = (U_{Mt}, Y_t, U_{Ft})'$ with four lags ($p = 4$), consistent with Angelini et al. 2019. As a remark, it is important to note that potential within-regime heteroskedasticity may reduce the efficiency of our estimates but does not undermine the identification strategy. Figure 2 presents three estimation approaches: recursive estimation (blue line), a 10-year rolling window (red line), and a 15-year rolling window (orange line). The diagonal plots display the error term variances for each variable in the VAR, while the off-diagonal plots show the covariances between the error terms for each pair of variables. The dashed black lines mark the three identified break dates.

Just graphically it is possible to confirms the time-varying volatility in the unconditional variance of the residuals for each variable. For example, Y_t (panel (2,2) in Figure 2) exhibits four distinct volatility regimes. Starting from higher volatility levels during the 1970s and 1980s it recorded a marked decline from the mid-1980s to 2007 when the financial crisis occurred. The subsequent stabilization is been followed by dramatic surge during the 2020 COVID-19 crisis, that is precisely the contribution of this work. It is noteworthy that the unconditional variance of macroeconomic uncertainty (U_{Mt}) follows a similar pattern to economic activity (Y_t) across the four regimes (panel (1,1) in Figure 2). In contrast, financial uncertainty (U_{Ft}) displays a distinct pattern, characterized by a steady increase up to the 1990s, likely driven by financial innovation in U.S. markets, and negligible responses to the pandemic crises compared to its macroeconomic counterpart.

Figure 2 broadly confirms the presence of four distinct volatility regimes over the sample period from August 1960 (1960:$M$7) to July 2020 (2020:$M$6). The first regime corresponds to the so-called Great Inflation period (1960:$M$7–1984:$M$3), characterized by persistent macroeconomic instability, with a total duration of $T = 280$ months. During the 1980s, likely due to shifts in monetary policy, the U.S. economy transitioned into the Great Moderation period (1984:$M$4–2007:$M$12), a phase of reduced volatility lasting $T = 285$ months. The onset of the Global Financial Crisis in 2008 marked the beginning of the next volatility regime, referred to as the Great Recession and Slow Recovery (2008:$M$1–2020:$M$2), with $T = 88$ months.

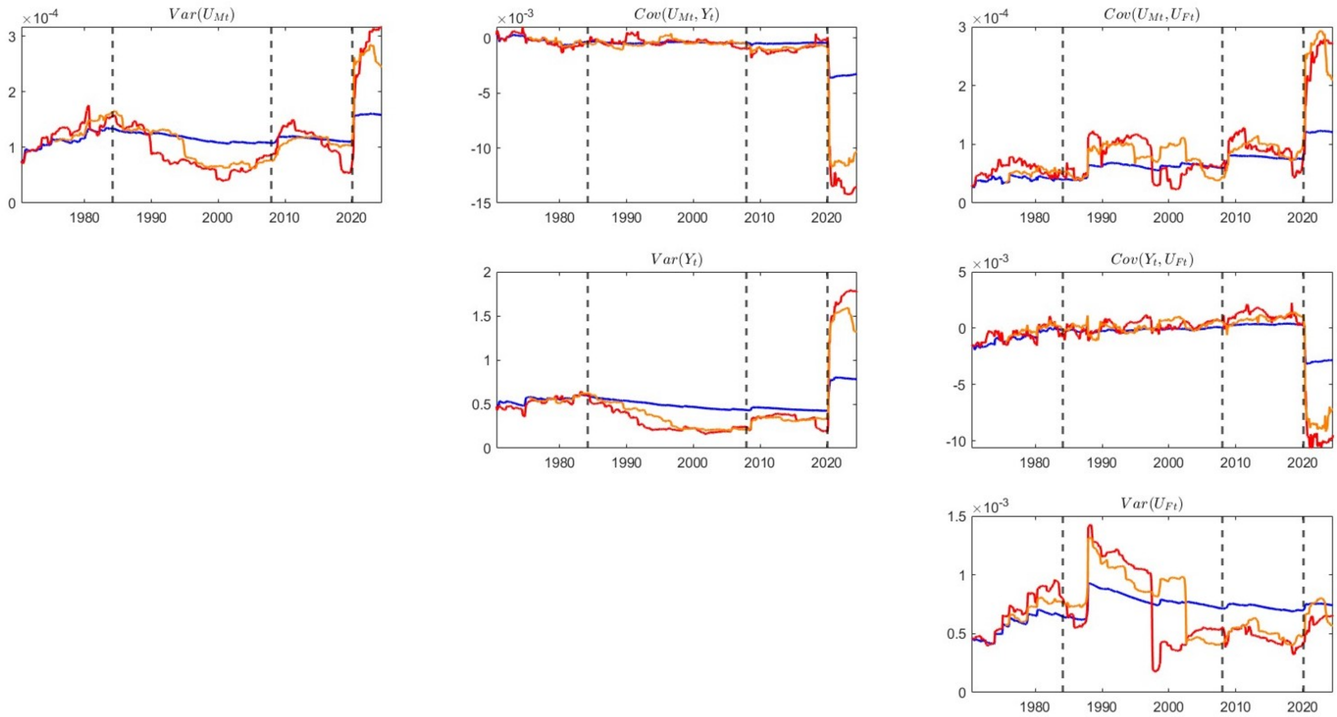

Figure 2: Recursive (blue line), 10-year (red line), and 15-year (orange line) rolling window estimates of the error covariance matrix of the VAR. Dashed black lines denote the three break dates $TB1 = 1984 : M3$, $TB2 = 2007 : M12$, $TB3 = 2020 : M3$.

This is the last regime partially overlapping with the findings of Angelini et al. 2019. Finally, the COVID-19 Recession (2020:$M$3–2024:$M$6), with $T = 53$ months, represents the most recent volatility regime, capturing the dramatic economic disruptions triggered by the pandemic. The fall in industrial production observed in 2020, during March and April, caused the residuals to reach exceptional levels. While the residuals of macroeconomic uncertainty exhibit significant positive variations, following the trend in the industrial production residuals, financial volatility remains almost unaffected, as shown in he diagonal panels of figure 2. Furthermore, during the COVID-19 period, the covariance between uncertainties increases significantly, and the sharp decline in production results in a marked reduction in the correlation between Y_t and the uncertainty measures.

Chow-type tests reported in Table 1 confirm these anecdotal evidences by testing structural breaks in the VAR error covariance matrix at $TB_1 = 1984 : M3$, $TB_2 = 2007 : M12$, and $TB_3 = 2020 : M2$ according to two different approaches:

- The joint null hypothesis of no structural breaks in all VAR coefficients (H_0).

$$H_0 : \begin{pmatrix} \Pi_1 \\ \Sigma_{\eta,1} \end{pmatrix} = \begin{pmatrix} \Pi_2 \\ \Sigma_{\eta,2} \end{pmatrix} = \begin{pmatrix} \Pi_3 \\ \Sigma_{\eta,3} \end{pmatrix} = \begin{pmatrix} \Pi \\ \Sigma \end{pmatrix}$$

- The joint null hypothesis of no structural breaks in structural parameters under the restriction of constant slope coefficients $\Pi_1 = \Pi_2 = \Pi_3 = \Pi$.

$$H_0' : \left(\Sigma_{\eta,1}\right) = \left(\Sigma_{\eta,2}\right) = \left(\Sigma_{\eta,3}\right) = \left(\Sigma\right)$$

Homoskedasticity is strongly rejected in both cases, confirming that results by Angelini et al. 2019 can be extended further in time.

Period	**Covariance $\hat{\Sigma}_u$**	**Correlation $\hat{\rho}_u$**	**Log-likelihood**
Overall (T = 768): 1960:M7–2024:M6	$\begin{bmatrix} 1.58e{-}04^* & -0.0033^* & 1.20e{-}04^* \\ & 0.7812^* & -0.0028^* \\ & & 7.40e{-}04^* \end{bmatrix}$	$\begin{bmatrix} 1 & -0.295^* & 0.352^* \\ & 1 & -0.118^* \\ & & 1 \end{bmatrix}$	3025.4
GI (T = 280): 1960:M7–1984:M3	$\begin{bmatrix} 1.33e{-}04^* & -3.25e{-}04 & 3.91e{-}05^* \\ & 0.5938^* & -1.57e{-}04 \\ & & 6.41e{-}04^* \end{bmatrix}$	$\begin{bmatrix} 1 & -0.037 & 0.134^* \\ & 1 & -0.008 \\ & & 1 \end{bmatrix}$	1162.5
GM (T = 285): 1984:M4–2007:M12	$\begin{bmatrix} 7.91e{-}05^* & -5.93e{-}04^* & 8.13e{-}05^* \\ & 0.2199^* & 4.92e{-}04 \\ & & 7.65e{-}04^* \end{bmatrix}$	$\begin{bmatrix} 1 & -0.142^* & 0.331^* \\ & 1 & 0.038 \\ & & 1 \end{bmatrix}$	1391.6
GR+SR (T = 146): 2008:M1–2020:M2	$\begin{bmatrix} 1.04e{-}04^* & -5.55e{-}04 & 1.17e{-}04^* \\ & 0.3253^* & 8.07e{-}04 \\ & & 5.19e{-}04^* \end{bmatrix}$	$\begin{bmatrix} 1 & -0.095 & 0.504^* \\ & 1 & 0.062 \\ & & 1 \end{bmatrix}$	705.03
Covid-19 (T = 53): 2020:M3–2024:M6	$\begin{bmatrix} 4.73e{-}04^* & -0.0261^* & 3.69e{-}05^* \\ & 2.6144^* & -0.0211^* \\ & & 6.75e{-}04^* \end{bmatrix}$	$\begin{bmatrix} 1 & -0.743^* & 0.652^* \\ & 1 & -0.502^* \\ & & 1 \end{bmatrix}$	181.2
Tests	H_0: No breaks in all VAR coefficients: LR = 1203634.8[0.000] H_0': No breaks in VAR covariance matrix: LR = 560.2[0.000]		

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

Empirical evidences reported in Figure 2 are broadly consistent with the information conveyed in the residual correlation matrices (Table 1). Results aligning with Angelini et al. 2019 in three empirical facts up to 2020:M3, that is the break for the last observed volatility regime (Covid-19 Recession). First, we identify a significant fluctuation in the negative correlation between residuals associated with macroeconomic uncertainty and industrial production growth [4]. Second, we estimated a lack of significant correlation between residuals associated with financial uncertainty and real economic activity, implying an indirect effect of financial uncertainty on industrial production through the macroeconomic propagation effect. And finally, we report a gradual increase in the correlation between macroeconomic and financial uncertainty. Results achieved across the first three volatility regimes suggest that the relationship between the business cycle and macroeconomic uncertainty strengthens over time, with varying intensities across subsamples. This statement holds true even for the regime characterizing the COVID-19 Recession. Indeed, from Table 1 we can start to appreciate novelties introduced by this work. Indeed, the correlations between variables after the occurrence of COVID-19 exhibit extremely high values that we hypothesize are influenced by both the reduced number of observations and potential confounding factors rising from the inclusion of upheavals in the production [5]. Furthermore, it is essential to recognize that, even if we assume informational sufficiency as in Angelini et al. 2019, during a pandemic crisis uncertainty may originate from factors beyond macroeconomic and financial domains. Uncertainty related to public health and healthcare-related issues could be relevant regressors to include in this analysis. We nonetheless prefer to stick as much as possible to their set up, in order to replicate and extend the analysis using the same set of regressors and information.

Even if correlations reported in Table 1 do not establish causality, they indicate evolving relationships that will inform the structural specification presented in the following section, while confirming the existence of four broad volatility regimes.

4.2 Non-recursive SVAR Specification

In order to proceed to the application of the Bacchiocchi and Fanelli 2015 SVAR, it is necessary to provide enough restrictions to fulfill the necessary order condition for identification[6]. As anticipated in the theoretical section, the matrices B, Q_2, Q_3, and Q_4 include a total number of $4M^2 = 36$ elements, which must be subject to at least $\frac{4}{2}M(M-1) = 12$ restrictions. This, in turn, leaves space for a maximum of $\frac{4}{2}M(M+1) = 24$ free structural parameters, to be estimated.

Our leading hypotheses will be, on one hand, appropriately motivated by theory and, on the other, grounded on our reduced-form results showing the time-varying relation between uncertainty and business cycle across the macroeconomic regimes in our sample. Indeed, as our work is based on the approach of Angelini et al. 2019, we explicitly refer to the economic reasoning provided by the authors in drawing the causal relations between the variables. Namely, we will replicate their identifying restrictions on $\tilde{B} = B(\theta)$, $\tilde{Q}_2 = Q_2(\theta)$, $\tilde{Q}_3 = Q_3(\theta)$ in order to assure consistency in our results, while providing similar arguments also for the new

[4] it is worth noting that in Angelini et al. 2019 they report a constant increase in the negative correlation that reach a peak in after the financial crises. We probably differ from this result due to the 5 years extension of the third regime that can have reduced the negative correlation between U_M and Y_t

[5] Especially in the April of 2020 production dropped significantly. A dummy variable could be included to account for this unique period correcting residuals

[6] As for the necessary and sufficient rank condition, we rely on the numerical evaluation of the Jacobian, which is available on Matlab replication code.

Covid-19 period at our disposal.

The structural specification will be based on two alternative non-recursive models, that allow to compare the two confronting answers to our research question. The first model shapes macroeconomic uncertainty as an endogenous factor, which responds to business cycle fluctuations and, in turn, amplifies them as in a relation of reverse-causality. Conversely, the second model treats macroeconomic uncertainty as an exogenous driver of business cycle, describing a unidirectional causal effect from uncertainty to real economic activity. In both models, nonetheless, financial uncertainty is considered an exogenous agent of business cycle.

The structural model with endogenous uncertainty is specified through 14 identifying restrictions, thus leaving 22 free structural parameters to be estimated. Hence, the model is overidentified and may be tested through standard Maximum Likelihood inference, in order to establish whether our SVAR specification is a better fit for the data with respect to the four reduced-form models. The structural matrices are arranged as follows:

$$
\begin{aligned}
&\textbf{\textit{Great Inflation:}}\\
&\tilde{B} := \begin{pmatrix} b_{MM} & b_{MY} & 0 \\ b_{YM} & b_{YY} & 0 \\ 0 & 0 & b_{FF} \end{pmatrix}\\
&\textbf{\textit{Great Moderation:}}\\
&\tilde{B} + \tilde{Q}_2 := \begin{pmatrix} b_{MM} + q_{2,MM} & b_{MY} & q_{2,MF} \\ b_{YM} + q_{2,YM} & b_{YY} + q_{2,YY} & 0 \\ q_{2,FM} & 0 & b_{FF} + q_{2,FF} \end{pmatrix}\\
&\textbf{\textit{Great Recession + Slow Recovery:}}\\
&\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3 := \begin{pmatrix} b_{MM} + q_{2,MM} & b_{MY} & q_{2,MF} + q_{3,MF} \\ b_{YM} + q_{2,YM} + q_{3,YM} & b_{YY} + q_{2,YY} + q_{3,YY} & q_{3,YF} \\ q_{2,FM} & 0 & b_{FF} + q_{2,FF} + q_{3,FF} \end{pmatrix}\\
&\textbf{\textit{Covid-19 Recession:}}\\
&\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3 + \tilde{Q}_4 := \begin{pmatrix} b_{MM} + q_{2,MM} + q_{4,MM} & b_{MY} & q_{2,MF} + q_{3,MF} + q_{4,MF} \\ b_{YM} + q_{2,YM} + q_{3,YM} + q_{4,YM} & b_{YY} + q_{2,YY} + q_{3,YY} + q_{4,YY} & q_{3,YF} + q_{4,YF} \\ q_{2,FM} & 0 & b_{FF} + q_{2,FF} + q_{3,FF} + q_{4,FF} \end{pmatrix}
\end{aligned}
\tag{1}
$$

As anticipated, with respect to matrices $\tilde{B}$, $\tilde{Q}_2$, $\tilde{Q}_3$, we explicitly adopted the same specification as Angelini et al. 2019. Namely, the specification of the matrix $\tilde{B}$ relies on the hypothesis that heavily regulated financial markets before the 1980s limited the responsiveness of financial markets to non-financial dynamics and macroeconomic variables to financial uncertainty. During the *Great Inflation* period, financial uncertainty does not respond on impact to real activity (true for all subperiods) or macro uncertainty shocks, nor does real activity to financial uncertainty shocks, although lagged effects are possible. Financial uncertainty is also assumed not to have a contemporaneous effect on macroeconomic uncertainty. The *Great Moderation* regime, instead, exhibits higher correlation between financial and macroeconomic uncertainty, which may be investigated through new on-impact effects introduced by matrix by $\tilde{Q}_2$: the non-zero parameters $q_{2,FM}$ and $q_{2,MF}$ allow reciprocal causal effects between financial and macroeconomic uncertainty. Moreover, in the volatility regime associated to the decade after the *Great Recession*, the matrix structure $\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3$ extends the bi-directional causality, allowing financial uncertainty shocks to directly affect real economic activity and indirectly impact it through macroeconomic uncertainty. The parameters $q_{3,YF}$ and $q_{3,MF}$ capture these dynamics relative to changes after Great Recession break occurrence.

The contribution of this work lies in the specification of matrix $\tilde{Q}_4$, which covers the changes in structural parameters occurring from March 2020 onward. In the choice of the identifying restrictions, we considered the complex features of Covid-19 outbreak, which indeed was an unexpected event and, more importantly, unrelated to economic dynamics such as uncertainty and the business cycle. Hence, our approach is to allow any contemporaneous interplay between the three variables considered, while preserving the greater economic framework applied in Angelini et al. 2019. This solution is furthermore supported by reduced-form evidence in Table 1, showing a sharp increase in both volatility and correlation which has to be disentangled through a structural analysis. Thus, we impose a lagged dynamic effect of real economic activity on financial uncertainty through $q_{4,FY} = 0$, while the restrictions $q_{4,MY} = 0$ and $q_{4,FM} = 0$ assure a time-invariant effect from real economic activity to macroeconomic uncertainty on one hand, and to financial uncertainty on the other. The remaining 6 elements of matrix $\tilde{Q}_4$ are left unrestricted: (*i*) $q_{4,MM}$, $q_{4,YY}$ and $q_{4,FF}$ account for the increased variance of all three variables considered; (*ii*) $q_{4,YM}$ and $q_{4,YF}$ allow industrial production to react instantaneously to both macroeconomic and financial uncertainty, given the unpredictable and sudden escalation of COVID-19 pandemic; (*iii*) $q_{4,MF}$ include the on-impact effect of financial uncertainty, magnifying the instantaneous reaction of macroeconomic uncertainty.

A separate argument is required for the restrictions $q_{4,MY} = 0$ and $q_{4,FY} = 0$, included in this set-up. Indeed, an additional alternative hypothesis could have been tested, based on the assumption that the COVID-19 crisis initially impacted industrial production, driven by exogenous factors such as public health and safety concerns, and only subsequently affected economic uncertainty as a consequence. However, despite conducting various tests, we find that the data reject this hypothesis. Specifically, allowing $q_{4,MY} \neq 0$ results in a failure of the rank condition, while setting $q_{4,FY} \neq 0$ leads to the rejection of the model compared to a standard reduced-form one, based on the likelihood ratio test.

The alternative structural model considers both sources of uncertainty as exogenous. Its specification is equivalent to the matrices in Equation 1, with two additional restrictions: $b_{MY} = 0$, representing the exogeneity of macroeconomic uncertainty with respect to real economic activity; $q_{2,FM} = 0$, implying one-way causality from financial to macroeconomic uncertainty. Notably, this model offers a higher number of overidentifying restrictions, which allows to compare the two alternative structural specification through Maximum Likelihood inference.

5 Empirical Results

This section presents the core findings of our analysis, derived from the most recent dataset available. In the previous section, we demonstrated how the relationship between uncertainty and economic activity varies across macroeconomic regimes, providing a rationale for the structural specifications employed. Here, imposing the already discussed non-recursive SVAR specifications, we address the remaining key research question: is uncertainty a cause or a consequence of economic downturns, and do macroeconomic and financial uncertainty interact differently with the business cycle? Subsection 5.1 focuses on the estimated structural parameters derived from the non-recursive SVAR framework, while Section 5.2 explores and comments on the Impulse Response Functions (IRFs) from the model, assuming uncertainty as an exogenous driver of economic fluctuations.

It is important to note that the analysis was conducted using $p = 4$, aligning with the approach of Angelini et al. 2019. This choice ensures comparability of results over overlapping periods while also capturing new insights from our extended analysis. However, as indicated by the partial autocorrelation functions shown in Figures 6, 5, and 7 in the appendix, three lags would have been enough. Hence, to verify robustness, we extended the analysis to models with up to nine lags, finding that our conclusions remain consistent across these specifications.

5.1 Endogeneity vs. Exogeneity

Table 2 presents the final estimates of the structural parameters for the four discussed regimes. These estimates guide the identification of the instantaneous relationships between the three variables of interest and structural shocks. While the analysis primarily focuses on the coefficients b_{MY} and $q_{2,FM}$ (as outlined in Section 4.2), the full set of relationships is discussed alongside the corresponding Impulse Response Functions (IRFs). Particular attention is also given to medium and long-run causal effects, motivated by economic theory and literature reviewed in Section 2, with a focus on the novelties introduced by the COVID-19 pandemic.

The upper panel of Table 2 examines a framework with endogenous macroeconomic uncertainty ($b_{MY} \neq 0$) and bidirectional causality between the two sources of economic uncertainty ($q_{2,FM} \neq 0$ and $q_{2,MF} \neq 0$). The likelihood ratio (LR) test for the four overidentification restrictions yields a value of 5.06, with a p-value of 0.075, indicating that the model cannot be rejected at the 5% significance level. This result aligns with Ludvigson, Ma, and Ng 2021, who document an endogenous, negative, and persistent impact of macroeconomic uncertainty on real economic activity, coupled with a positive but less pronounced effect of U_M on Y, partially supporting the Option Growth Theory. In this framework the significant coefficient for the negative impact of business cycle on macroeconomic uncertainty supports the endogeneity hypothesis,

Model for Endogenous Uncertainty											
$\hat{B}$ 1960:$M7$–1984:$M3$			$\hat{B}+\hat{Q}_2$ 1984:$M4$–2007:$M12$			$\hat{B}+\hat{Q}_2+\hat{Q}_3$ 2008:$M1$–2020:$M2$			$\hat{B}+\hat{Q}_2+\hat{Q}_3+\hat{Q}_4$ 2020:$M2$–2024:$M6$		
0.0114 (0.0005)	−0.0016 (0.0006)	0	0.0074 (0.0009)	−0.0016 (0.0006)	−0.0047 (0.0012)	0.0074 (0.0009)	−0.0016 (0.0006)	−0.0069 (0.0015)	0.0208 (0.0031)	−0.0016 (0.0006)	−0.0062 (0.0053)
0.0802 (0.0623)	0.7664 (0.0331)	0	0.0225 (0.0351)	0.4684 (0.0196)	0	0.0399 (0.0488)	0.5688 (0.0336)	−0.0104 (0.0617)	−1.1017 (0.2152)	1.1636 (0.1098)	0.2158 (0.3205)
0	0	0.0253 (0.0011)	0.0219 (0.0021)	0	0.0169 (0.0034)	0.0219 (0.0021)	0	0.0064 (0.0041)	0.0219 (0.0021)	0	0.0140 (0.0057)
Test			2 overidentifying restrictions: LR = $5.0635_{\chi^2(\text{df}=2)}$[0.075]								
Model for Exogenous Uncertainty											
$\hat{B}$ 1960:$M7$–1984:$M3$			$\hat{B}+\hat{Q}_2$ 1984:$M4$–2007:$M12$			$\hat{B}+\hat{Q}_2+\hat{Q}_3$ 2008:$M1$–2020:$M2$			$\hat{B}+\hat{Q}_2+\hat{Q}_3+\hat{Q}_4$ 2020:$M2$–2024:$M6$		
0.0115 (0.0005)	0	0	0.0085 (0.0003)	0	0.0030 (0.0005)	0.0085 (0.0003)	0	0.0051 (0.0008)	0.0165 (0.0016)	0	0.0142 (0.0027)
−0.0282 (0.0460)	0.7701 (0.0326)	0	−0.0784 (0.0280)	0.4626 (0.0194)	0	−0.0809 (0.0452)	0.5631 (0.0330)	0.0354 (0.0471)	−0.8868 (0.1720)	1.0818 (0.1051)	−0.8110 (0.2084)
0	0	0.0253 (0.0011)	0	0	0.0277 (0.0012)	0	0	0.0228 (0.0013)	0	0	0.0260 (0.0026)
Test			4 overidentifying restrictions: LR = $5.9606_{\chi^2(\text{df}=4)}$[0.2021]								

Table 2: Estimated structural parameters based on the non recursive SVAR specification. The estimates in the lower panel are based on the additional restrictions on coefficients b_{MY} and $q_{2,FY}$. Hessian-based standard errors are reported in parentheses.

but the bidirectional causality between the two uncertainty sources is not confirmed. Notably, financial uncertainty indirectly affects real economic activity before COVID-19, primarily through its immediate negative effect on macroeconomic uncertainty. This mechanism exacerbates the impact of uncertainty on industrial production, echoing Angelini et al. 2019, which highlights the unidirectional pass-through from financial to macroeconomic uncertainty. During the COVID-19 pandemic, new dynamics emerge. Macroeconomic uncertainty significantly intensifies its negative effect on the business cycle, and financial uncertainty looses its indirect impact on production fluctuations. The unprecedented magnitude of the macroeconomic uncertainty effect underscores the role of adverse economic conditions in amplifying downturns. As Ludvigson, Ma, and Ng 2021 argue, macroeconomic uncertainty can substantially amplify shocks, such as healthcare crises, leading to more severe economic contractions.

The lower panel of Table 2 explores the macroeconomic uncertainty exogeneity framework, based on Angelini et al. 2019. This "exogenous macro uncertainty model" incorporates two additional restrictions (see Section 4.2). The LR test strongly supports this model, with a statistic of 5.96 and a p-value of 0.2021. Consistent with Angelini et al. 2019, macroeconomic uncertainty is identified as an exogenous driver of the business cycle, with causality between the two uncertainty sources running from financial to macroeconomic uncertainty, as constrained by $q_{i,FM}\ \forall\ i = [1,4]$. Before the pandemic, financial uncertainty indirectly influences the business cycle by positively triggering macroeconomic uncertainty. Following the pandemic, on-impact responses of variables to structural shocks intensify. Production becomes more sensitive to both the direct effects of macroeconomic and financial uncertainty and the indirect effects of financial uncertainty via macroeconomic uncertainty. Overall, the lower panel supports the notion of both financial and macroeconomic uncertainty as drivers of economic fluctuations. Macroeconomic uncertainty, in particular, acts as a propagation mechanism that exacerbates downturns. The significance of all estimated structural shocks in the matrix $\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3 + \tilde{Q}_4$ highlights the profound impact of exogenous events, such as the pandemic crisis, on the economy.

Given the reasonable fit of both models, the exogenous macro uncertainty model is adopted for the $IRFs$ analysis. This decision is supported by an LR test comparing the two models, yielding a statistic of 0.8971 and a p-value of 0.63, indicating its better fit to data. These findings corroborate the results of Angelini et al. 2019 and Carriero, Clark, and Marcellino 2018, emphasizing the exogeneity of macroeconomic uncertainty. Nonetheless, consistent with Ludvigson, Ma, and Ng 2021, evidence from the upper panel suggests that macroeconomic uncertainty may also have an endogenous relationship with the business cycle especially during COVID-19. As a final check, note that the endogenous macroeconomic uncertainty model is rejected if the last regime is not included in the analysis as in Angelini et al. 2019.

5.2 Impulse Response Functions ($IRFs$)

We now use Impulse Response Functions to better understand the dynamic causal effects and propagation mechanisms of shocks over a 60-period horizon (5 years). The identified set of dynamic responses is estimated using regime-specific *SVAR* models across the four macroeconomic volatility regimes, as described in Section 3.1. To implement the *IRFs* and their associated bootstrap confidence intervals, we used specifications tailored for the "exogenous uncertainty model," whose estimates are summarized in the lower panel of Table 2. The *IRFs* in Figure 3 depict the responses of each variable in the *SVAR* to a one-standard-deviation *increase* in each structural shock. In this figure, all *IRFs* for the four regimes are jointly displayed at the 1-month

($f = 1$) uncertainty horizon. Figure 4 pertains to COVID-19, while all the other *IRFs* for each volatility regime are stored separately in the Appendix. For these single-regime dynamic causal effects representations, *IRFs* and the associated 90% bootstrap confidence intervals are shaded in blue for the short-term ($f = 1$) and in red for the long-term ($f = 12$) uncertainty horizons. Due to the similarity between the effects of the two time horizons we prefer to comment on the effects of uncertainty in the short-term, namely when $f = 1$.

As shown in Figure 3, the responses of variables to a standard deviation shock are regime-specific, confirming the importance of the time-variant methodology employed. The *IRFs* vary significantly across regimes in both magnitude and persistence. Starting with industrial production growth, as displayed in the middle row of Figure 3, we observe notable stationarity in the dynamics of responses within our small-scale structural system. Regardless of the shock triggering this variable or its intensity, the return to the steady-state is rapid. This contrasts sharply with macroeconomic and financial uncertainty. As inferred from the upper row of Figure 3, the Great Recession and the COVID-19 Recession triggered significantly higher macroeconomic uncertainty than other regimes. During these periods, structural shocks induced more complex and intense dynamics. A striking result, as discussed later regarding COVID-19, is the inversion of the response of macroeconomic uncertainty to an industrial production shock. It is plausible to assume that the sharp economic downturn, marked by a negative peak in April 2020, heightened forecastability to such an extent that even an increase in production penalized macroeconomic uncertainty. Regarding the responses of financial uncertainty to structural shocks, shown in the lower row of the panel in Figure 4, we find that financial uncertainty exhibited distinct dynamics, particularly during the Great Recession regime. This is not surprising since this crisis stemmed from a financial downturn. An interesting feature of financial structural shocks triggering the business cycle can be drawn from the joint analysis of Table 2 and the *IRFs*,

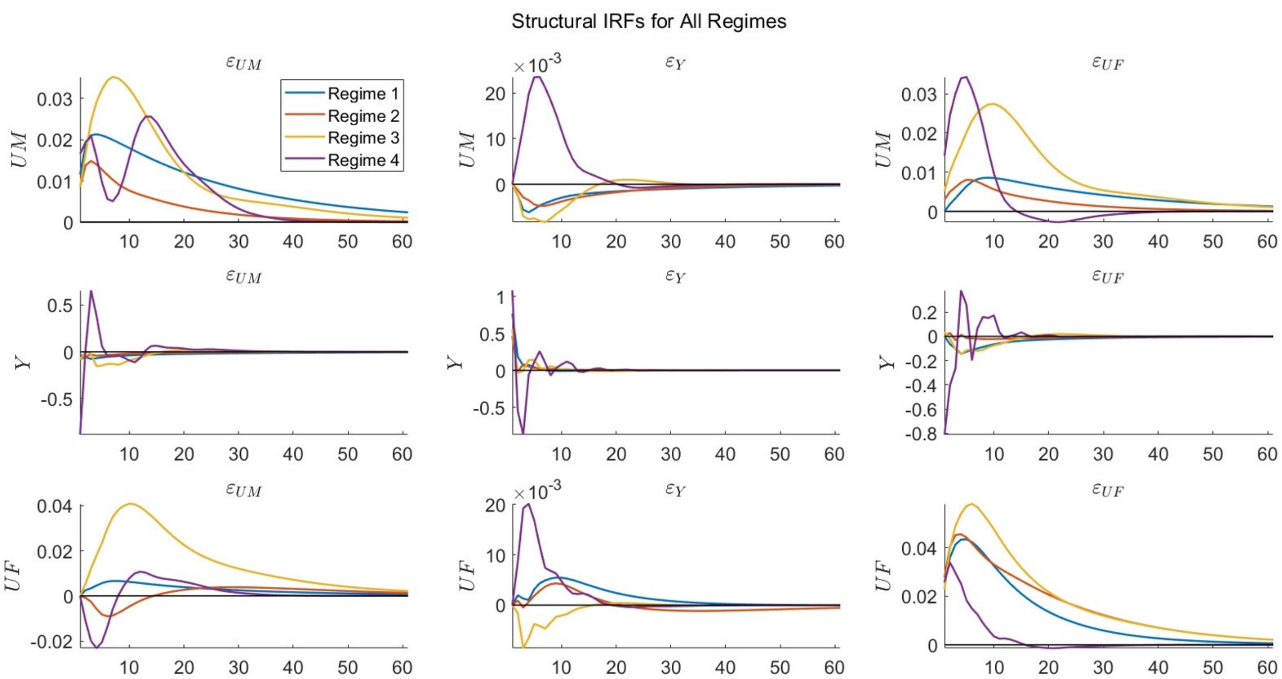

Figure 3: IRFs obtained from the baseline non-recursive $SVAR$ for $X_t := (UM_t, Y_t, UF_t)'$. UM_t and UF_t refer to the 1-month ($f = 1$) uncertainty horizon. The blue line refers to the first volatility regime (Great Inflation, 1960:$M$7–1984:$M$3); the red line refers to the second volatility regime (Great Moderation, 1984:$M$4–2007:$M$12); the yellow line refers to the third volatility regime (Great Recession + Slow Recovery, 2008:$M$1–2020:$M$2); and the purple line refers to the fourth volatility regime (COVID-19 recession, 2020:$M$3–2024:$M$6). Responses are measured with respect to one-standard-deviation changes in structural shocks.

respectively for on-impact and lagged effects. Specifically, while no significant effects are evident in the direct impact on the business cycle (as explained in Section 5.1), the post-Great Recession period saw a dramatic increase in the impact and persistence of financial uncertainty on macroeconomic variables. As shown in the bottom line of Figure 3, macroeconomic uncertainty exacerbated financial uncertainty more persistently over time. During COVID-19, this feature was reversed, but the dynamics in Figure 4 indicate the non-significance of this result. Finally, it is worth noting that after the Great Recession, the impact of adverse events triggered by financial structural shocks heightened financial uncertainty, but the magnitude of this effect was smallest during COVID-19. This could possibly be attributed to government policies that alleviated financial uncertainty or the fact that, during COVID-19, uncertainty, despite some on-impact effects, was mitigated because it was not the primary source of instability.

Following this general discussion on the *IRFs* across various volatility regimes, we adopted the approach of Angelini et al. 2019, plotting the *IRFs* of each regime with the corresponding 90% bootstrap confidence intervals (that can be analyzed in the Appendix at Section 6). This part of the analysis, though largely consistent with the baseline reference paper, identified slightly different significances during the '80s and '90s dynamics. These differences could be attributed to the methodology employed for constructing the bootstrap confidence bands. We used an i.i.d. bootstrap approach, preferred over a normal one due to the residuals not being normally distributed. Nonetheless, the normal approach leads to the same conclusions regarding on-impact effects as the authors. Another factor, as highlighted in Section 3.2 on Data, is the update performed by Jurado, Ludvigson, and Ng 2015 on time series uncertainty data.

5.3 COVID-19 Upheavals

Our work builds upon Angelini et al. 2019, extending their findings by incorporating updated observations for the Slow Recovery regime and the disruptions caused by COVID-19. Up to 2020, as discussed earlier, we observed similar patterns, including time-varying effects of structural shocks and minor differences in the asymmetrical responses between uncertainty and industrial production growth. The key contribution of this analysis lies in examining the dynamics of the COVID-19 Recession.

The COVID-19 pandemic brought unprecedented levels of macroeconomic and financial uncertainty, both of which acted as distinct yet significant drivers of the economic downturn. Initially, these uncertainties were exogenous, as the health crisis disrupted economic activity and destabilized markets, reducing predictability. However, the sharp decline in production triggered lagged endogenous effects, creating a feedback loop that exacerbated uncertainty and that, for the first time according to our study, turned the lag respond of financial uncertainty to business cycle significant. Indeed, on one hand macroeconomic uncertainty arose from disruptions in production, demand, and labor markets, and on the other financial uncertainty stemmed from market volatility, credit risks, and liquidity pressures. However, over time, these uncertainties were amplified by the downturn. To clarify this point note that on impact, *macroeconomic uncertainty* surged due to the sudden inability to forecast key variables during a fatal event such as a pandemic crises. Global lockdowns caused supply chain breakdowns, labor market instability, and a rapid shift to remote work. Over time, these factors reduced productivity and altered consumption patterns, with households prioritizing essential goods over discretionary spending. Although governments and central banks implemented large-scale fiscal and monetary interventions to stabilize economies, these measures introduced long-term concerns about debt sustainability and inflation. Additionally, recurring outbreaks and the unpredictability of new variants complicated recovery efforts, intensifying macroeconomic instability over time. Similarly, *financial uncertainty* began as an exogenous shock, leading to immediate effects such as increased market volatility and tighter credit conditions. Businesses and households faced liquidity shortages due to declining revenues and ongoing expenses, prompting central banks to implement monetary stimulus. Over time, financial uncertainty escalated, driven by rising credit risks, widening credit spreads, and global financial instability. Interconnected financial systems transmitted shocks internationally, while emerging markets faced additional pressures, including currency fluctuations and capital outflows.

A noteworthy feature of the COVID-19 crisis lies in the unprecedented dynamics exhibited by macroeconomic uncertainty. As shown in panels (1,2) of Figure 4, the impact of industrial production on macroeconomic uncertainty increased significantly over time, inverting the typical patterns observed in other regimes. Furthermore, production disruptions triggered financial uncertainty with a lag, further amplifying overall uncertainty. These dynamics underscore the unique nature of the COVID-19 crisis, which stands in stark contrast to financially or economically driven recessions. Unlike traditional crises, the pandemic constituted an exogenous health shock, where increased production paradoxically heightened economic uncertainty due to greater unpredictability in forecasts. Given these complexities, analyzing the pandemic within a structural VAR framework likely requires incorporating additional elements beyond economic uncertainty. These elements may play a critical role in fully understanding the dynamics of the COVID-19 crisis and should be considered to effectively control variable responses to structural shocks.

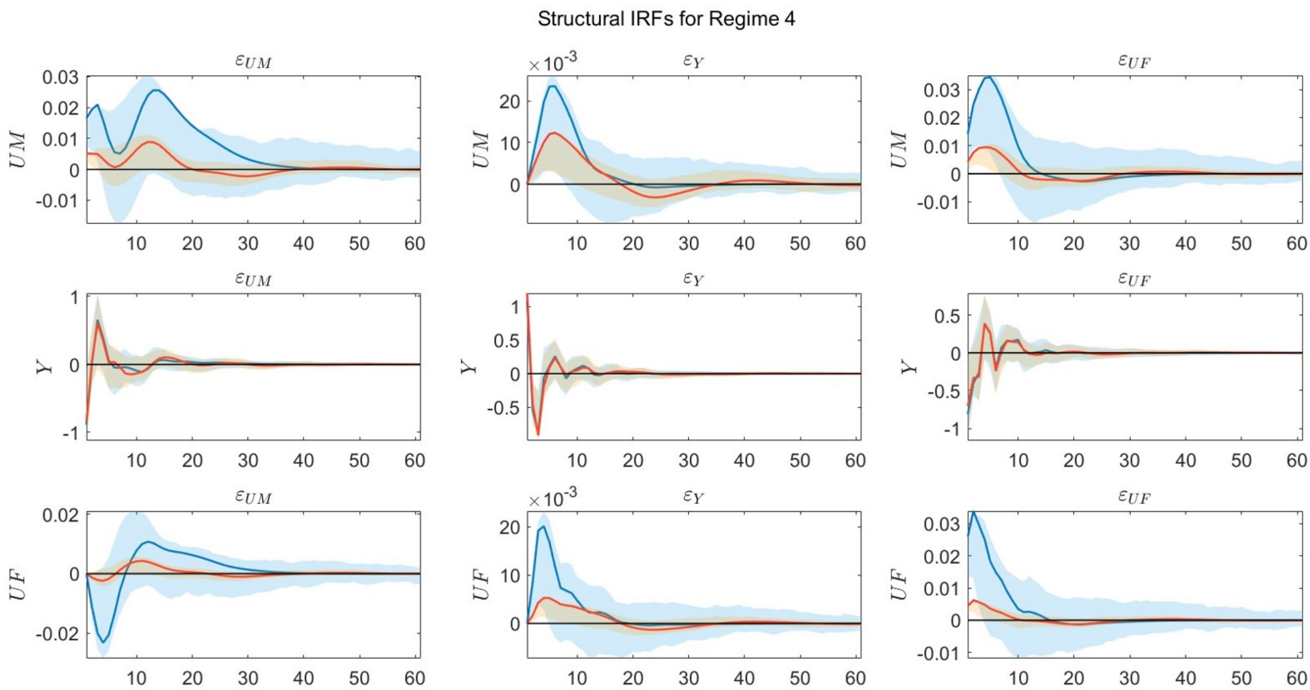

Figure 4: IRFs obtained in the fourth volatility regime (Covid-19 Recession, 1920 : $M2$–2024 : $M7$) from the baseline non-recursive SVAR for $X_t = (UM_t, Y_t, UF_t)'$. The blue lines refer to the 1-month (f = 1) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands; the red lines refer to the 1-year (f = 12) uncertainty horizon and red shaded areas denote the associated 90% bootstrap confidence bands. Responses are measured with respect to one standard deviation changes in structural shocks.

6 Concluding Remarks

Building on the framework proposed by Angelini et al. 2019, this study validates and extends their findings by incorporating a new volatility regime stemming from the COVID-19 pandemic. The analysis employs a non-recursive structural VAR (SVAR) based on the "identification-through-heteroskedasticity" approach, addressing three key questions about uncertainty: whether it primarily acts as a driver of business cycle fluctuations or as an endogenous response to them, whether different types of uncertainty have distinct effects, and whether the real effects of uncertainty shocks vary over time under changing macroeconomic conditions.

Our findings first confirm the conclusions of Angelini et al. 2019, while expanding the time horizon to include the COVID-19 regime. We identify significant differences in the impact and propagation of uncertainty shocks across four major macroeconomic regimes. Macroeconomic uncertainty emerges as an exogenous and direct driver of economic downturns, contributing to its countercyclical behavior in the short run. Similarly, financial uncertainty shocks indirectly influence economic fluctuations through their immediate effects on macroeconomic uncertainty. Notably, the data does not support any on-impact effects of macroeconomic uncertainty on financial uncertainty. For the overlapping periods analyzed in Angelini et al. 2019, our results indicate that the best-fitting model supports the exogeneity of macroeconomic uncertainty in driving the business cycle. However, we cannot entirely rule out its endogeneity, partially aligning with the hypothesis of Ludvigson, Ma, and Ng 2021. Furthermore, the impulse response functions (IRFs) reveal that uncertainty shocks exhibit short-lived on-impact effects on the business cycle, while economic downturns have lagged and significant effects only on macroeconomic uncertainty.

The additional analysis on the COVID-19 crisis highlights unique features in both the magnitude and direction of variables responses to structural shocks. Uncertainty initially triggers the economic downturn; however, the pandemic subsequently causes a surge in both macroeconomic and financial uncertainty, making also the lagged response of financial uncertainty significant. Overall, these findings support theoretical models that treat uncertainty, both macroeconomic and financial, as exogenous drivers of economic fluctuations, capable of independently triggering deep recessions. At the same time, our results also acknowledge some endogenous lagged effects. Moreover, to better understand the COVID-19 recession impact on macroeconomy, we propose incorporating additional variables to capture the unique characteristics of this unprecedented shock. A promising avenue could involve uncertainty measures that account for health-related factors, such as COVID-19 Health Policy Uncertainty (HPU).

References

Ai, Hengjie, Kai Li, and Fang Yang (2015). "Financial intermediation and capital misallocation". In: *Unpublished manuscript, University of Minnesota*.

Angelini, Giovanni et al. (2019). "Uncertainty across volatility regimes". In: *Journal of Applied Econometrics* 34.3, pp. 437–455.

Bacchiocchi, Emanuele and Luca Fanelli (2015). "Identification in Structural Vector Autoregressive models with structural changes, with an application to US monetary policy". In: *Oxford bulletin of economics and statistics* 77.6, pp. 761–779.

Bachmann, Rüdiger, Giuseppe Moscarini, et al. (2011). "Business cycles and endogenous uncertainty". In: *2011 Meeting Papers*. Vol. 36. Society for Economic Dynamics, pp. 82–99.

Basu, Susanto and Brent Bundick (2017). "Uncertainty shocks in a model of effective demand". In: *Econometrica* 85.3, pp. 937–958.

Bloom, Nicholas et al. (2018). "Really uncertain business cycles". In: *Econometrica* 86.3, pp. 1031–1065.

Carriero, Andrea, Todd E Clark, and Massimiliano Marcellino (2018). "Measuring uncertainty and its impact on the economy". In: *Review of Economics and Statistics* 100.5, pp. 799–815.

Craine, Roger (1989). "Risky business: the allocation of capital". In: *Journal of monetary economics* 23.2, pp. 201–218.

Economic Research, National Bureau of (n.d.). *Business Cycle Dating*. URL: `https://www.nber.org/research/business-cycle-dating` (visited on 01/22/2025).

Gilchrist, Simon, Jae W Sim, and Egon Zakrajšek (2013). "Misallocation and financial market frictions: Some direct evidence from the dispersion in borrowing costs". In: *Review of Economic Dynamics* 16.1, pp. 159–176.

Jurado, Kyle, Sydney C Ludvigson, and Serena Ng (2015). "Measuring uncertainty". In: *American Economic Review* 105.3, pp. 1177–1216.

Ludvigson, Sydney C, Sai Ma, and Serena Ng (2021). "Uncertainty and business cycles: exogenous impulse or endogenous response?" In: *American Economic Journal: Macroeconomics* 13.4, pp. 369–410.

Pástor, L'uboš and Pietro Veronesi (2013). "Political uncertainty and risk premia". In: *Journal of financial Economics* 110.3, pp. 520–545.

Pindyck, Robert S (1986). *Irreversible investment, capacity choice, and the value of the firm*.

Van Nieuwerburgh, Stijn and Laura Veldkamp (2006). "Learning asymmetries in real business cycles". In: *Journal of monetary Economics* 53.4, pp. 753–772.

TIME SERIES AND SERIAL CORRELATION

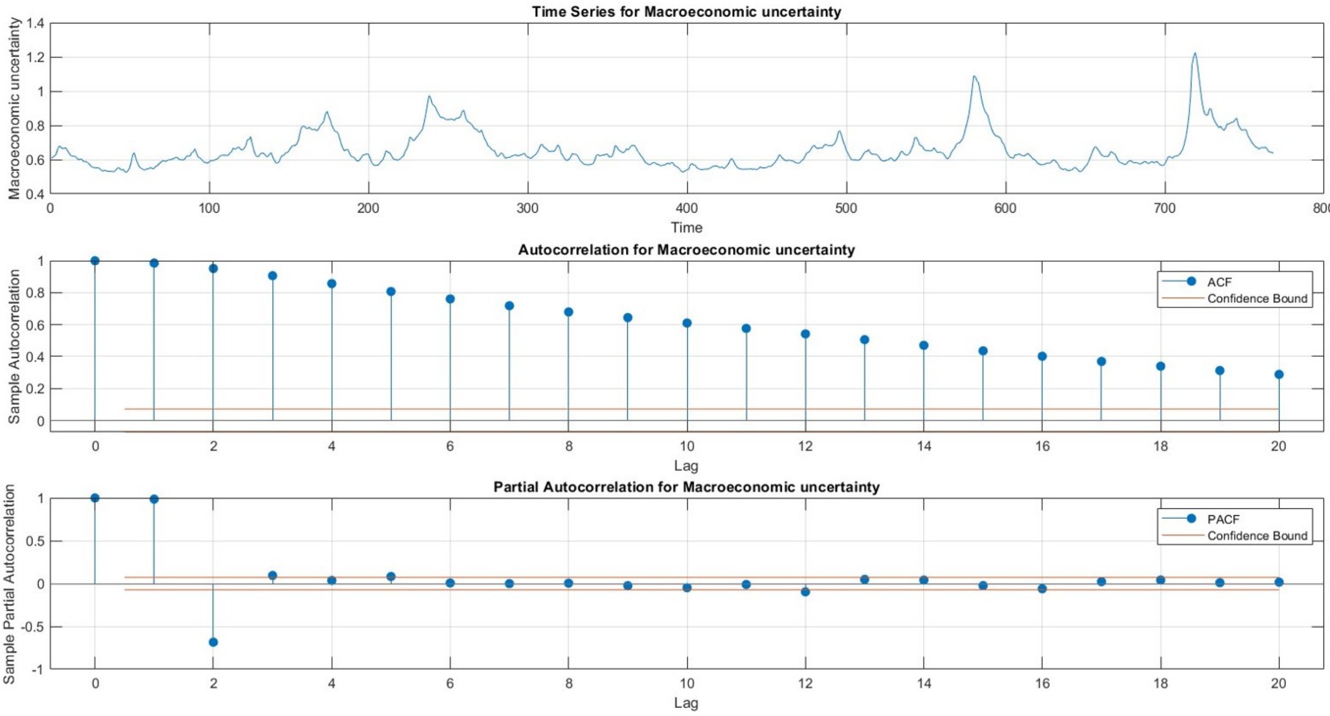

Figure 5: The *Upper panel* presents the Macroeconomic uncertainty (U_M) time series. Dickey-Fuller test fails to be rejected (p-value = 0.4850). The *Middle panel* displays the gradual decline in the autocorrelation function and in the *Lower panel* it is plotted the Partial autocorrelation function, that suggests the inclusion of three lags in the VAR model.

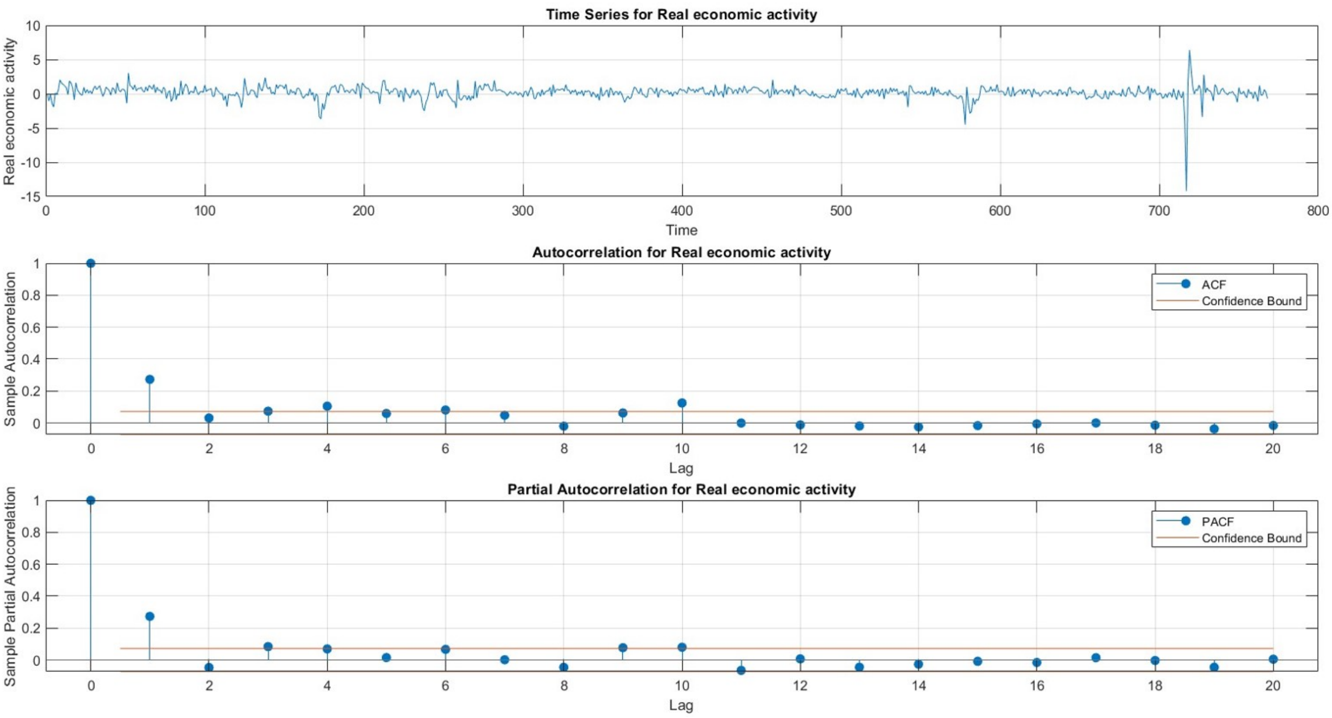

Figure 6: The *Upper panel* presents the Real economic activity growth (Δipt) time series. As this time series is integrated of order one, the Dickey-Fuller test is reject (p-value = 0.001). The *Middle panel* displays the rapid decline in the autocorrelation function and in the *Lower panel* it is plotted the Partial autocorrelation function, that suggests the inclusion of three/four lags in the VAR model. A notable observation is the exceptional drop in industrial production during the COVID-19 recession, with the negative peak occurring in April 2020.

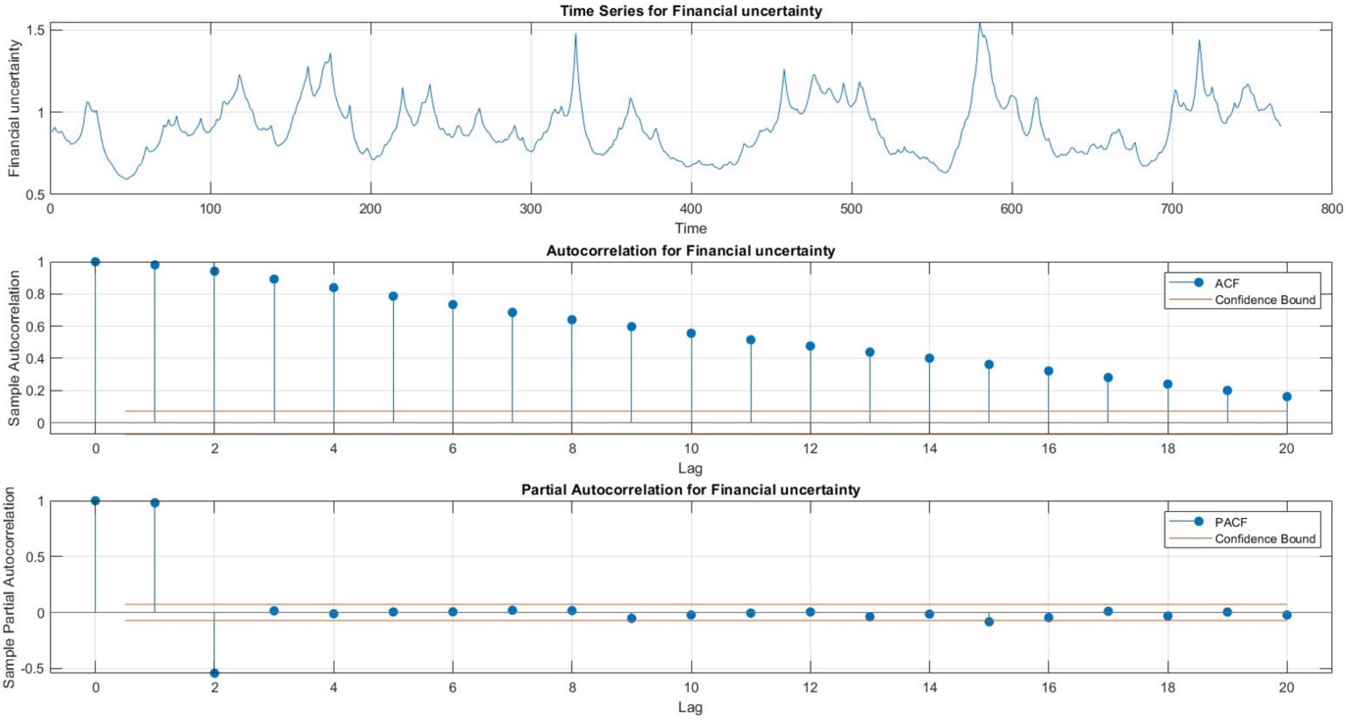

Figure 7: The *Upper panel* presents the Financial uncertainty (U_F) time series. Dickey-Fuller test fails to be rejected (p-value = 0.5347). The *Middle panel* displays the gradual decline in the autocorrelation function suggesting strong dependency over time and in the *Lower panel* it is plotted the Partial autocorrelation function, that suggests the inclusion of two lags in the VAR model.

IRFs

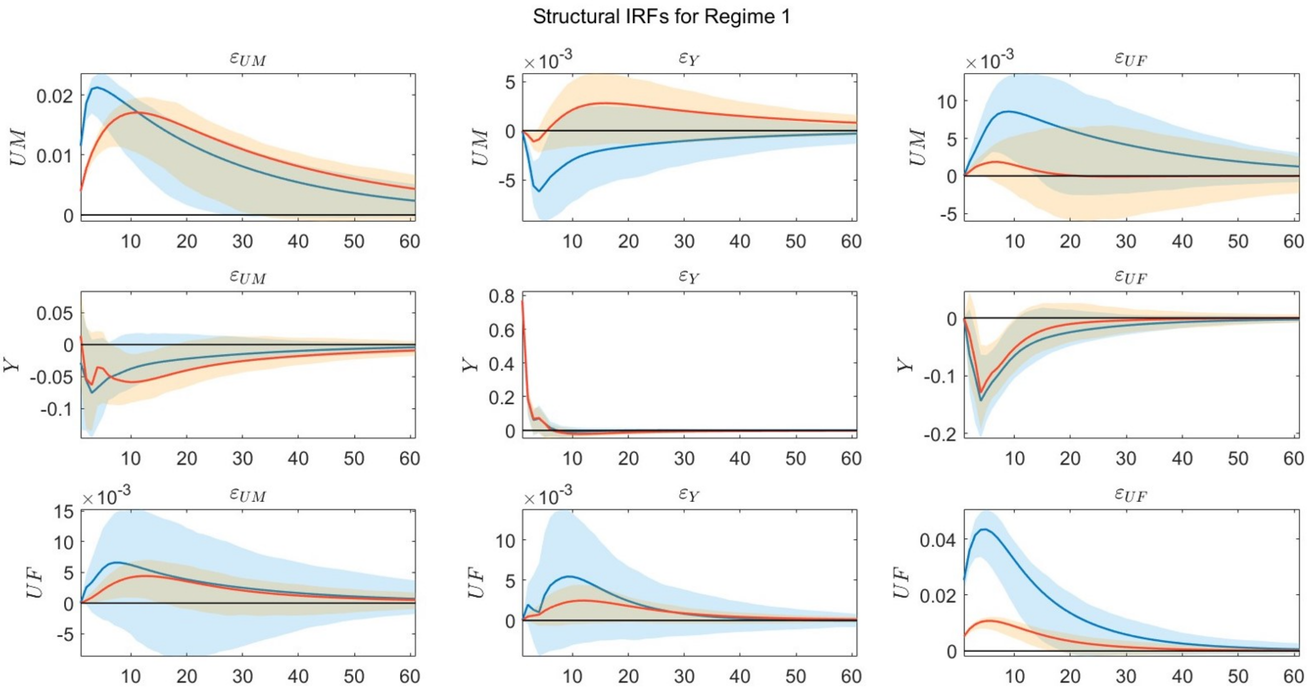

Figure 8: IRFs obtained in the first volatility regime (Great Inflation, $1960:M7$–$1984:M3$) from the baseline non-recursive SVAR for $X_t = (UM_t, Y_t, UF_t)'$. The blue lines refer to the 1-month (f = 1) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands; the red lines refer to the 1-year (f = 12) uncertainty horizon and red shaded areas denote the associated 90% bootstrap confidence bands. Responses are measured with respect to one standard deviation changes in structural shocks.

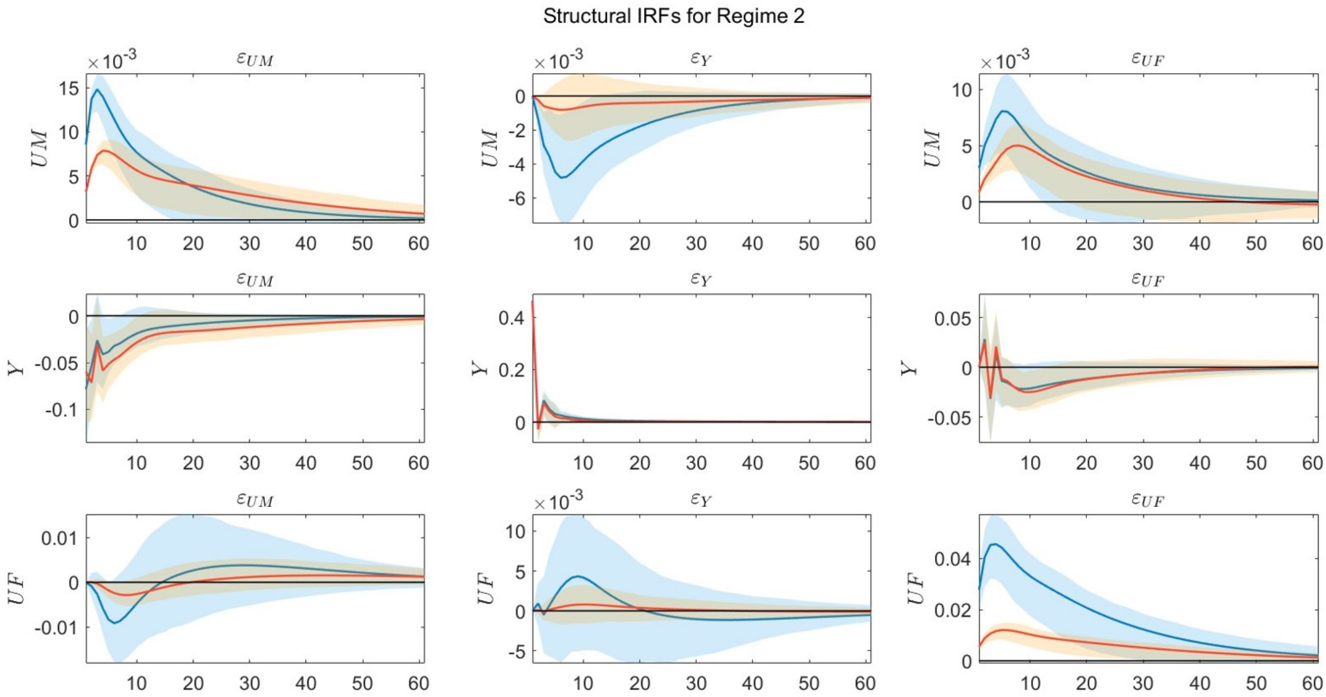

Figure 9: IRFs obtained in the second volatility regime (Great Moderation, 1984 : $M$4–2007 : $M$12) from the baseline non-recursive SVAR for $X_t = (UM_t, Y_t, UF_t)'$.The blue lines refer to the 1-month (f = 1) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands; the red lines refer to the 1-year (f = 12) uncertainty horizon and red shaded areas denote the associated 90% bootstrap confidence bands. Responses are measured with respect to one standard deviation changes in structural shocks.

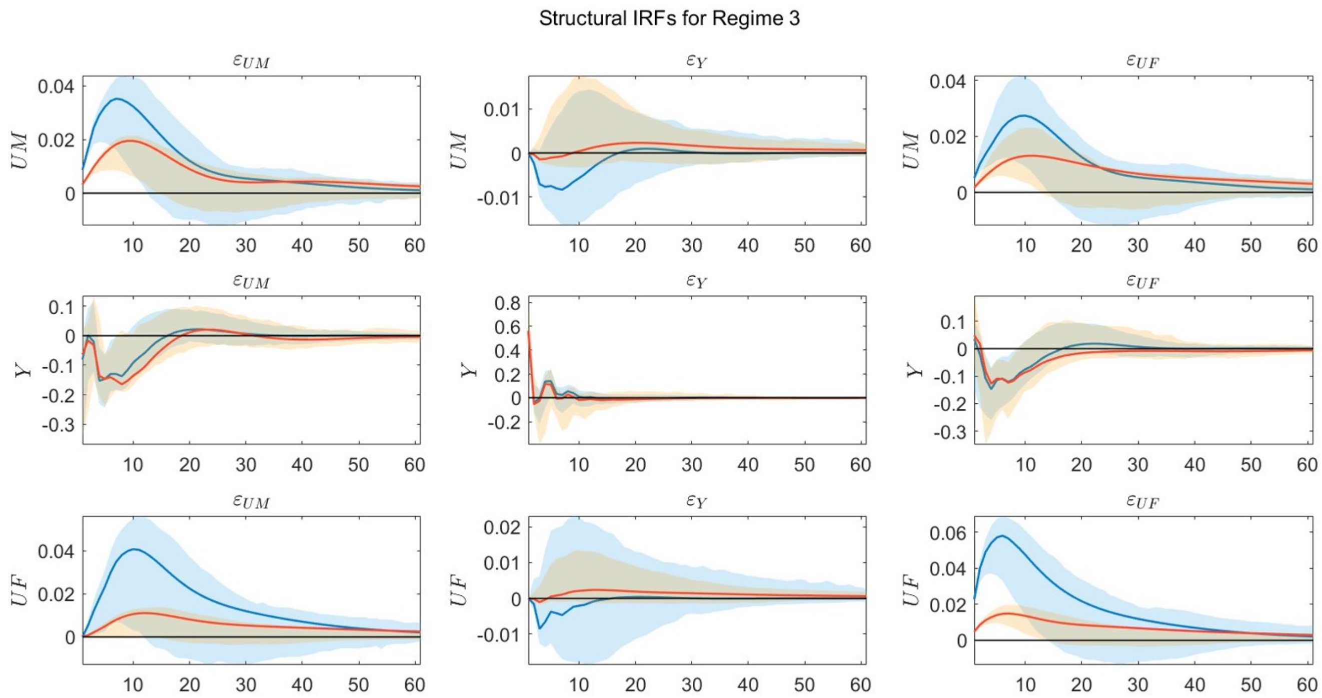

Figure 10: IRFs obtained in the second volatility regime (Great Recession and Slow Recovery, 2008 : $M$1–2020 : $M$2) from the baseline non-recursive SVAR for $X_t = (UM_t, Y_t, UF_t)'$. The blue lines refer to the 1-month (f = 1) uncertainty horizon and blue shaded areas denote the associated 90% bootstrap confidence bands; the red lines refer to the 1-year (f = 12) uncertainty horizon and red shaded areas denote the associated 90% bootstrap confidence bands. Responses are measured with respect to one standard deviation changes in structural shocks.