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**Article — Published Version**

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Economic Inquiry

**Provided in Cooperation with:**

John Wiley & Sons

*Suggested Citation:* Herwartz, Helmut; Lange, Alexander (2023) : How certain are we about the role of uncertainty in the economy?, *Economic Inquiry*, ISSN 1465-7295, Wiley, Hoboken, NJ, Vol. 62, Iss. 1, pp. 126-149,  
<https://doi.org/10.1111/ecin.13166>

This Version is available at:

<https://hdl.handle.net/10419/288182>

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## ORIGINAL ARTICLE

# How certain are we about the role of uncertainty in the economy?

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**Funding information**

Deutsche Forschungsgemeinschaft

**Abstract**

While causes and consequences of uncertainty in the US economy have attracted viable interest, the literature still lacks a consensus on several aspects. To name two matters of debate, it remains unclear whether uncertainty shocks are a source or the result of recessions and whether uncertainty shocks have adverse (or even stimulating) effects on the economy. We find that ambiguous results in these regards can be traced back to the selection of an appropriate identification strategy in structural vector autoregressive models. We find that both macroeconomic and financial uncertainty are exogenous to business cycle fluctuations and cause economic slowdowns.

**KEYWORDS**

heteroskedasticity, independent components, model selection, non-Gaussianity, structural vector autoregression, uncertainty shocks

**JEL CLASSIFICATION**

C32, E32, E44, G01

## 1 | INTRODUCTION

Considered as forms of immeasurable or unpredictable risks, changes in economic uncertainty can have far-reaching effects on the economy. Witnessing that uncertainty often drastically increases in periods of economic turmoil, a large strand of literature has advanced the modern understanding of economic uncertainty in many facets (e.g., Baker & Bloom, 2013; Bekaert et al., 2013; Bernanke, 1983; Bloom, 2009, 2014; Caballero & Krishnamurthy, 2008; Christiano et al., 2014; Stock & Watson, 2012). At least two fundamental aspects are a matter of viable debate, however. First, researchers have come to quite different opinions whether heterogeneous forms of uncertainty are exogenous causes or endogenous results of economic slack (e.g., Angelini et al., 2019; Carriero et al., 2018; Ludvigson et al., 2021). Strikingly, the prominent studies of Angelini et al. (2019) and Ludvigson et al. (2021) provide opposite insights into the source of macroeconomic uncertainty although their analysis builds upon almost identical sample information. Second, even if

**Abbreviations:** ABCF, Angelini et al. (2019); AIC, Akaike information criterion; BDBG, Berger et al. (2019); FEVD, forecast error variance decomposition; ICA, independent component analysis; LMN, Ludvigson et al. (2021); MA, moving average; SVAR, structural vector autoregressive; US, United states of America; VAR, vector autoregressive; VIX (VXO), option implied stock market volatility.

**Managing Editor:** Qinglai Meng

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most studies tend to detect adverse impacts of uncertainty on economic activity (e.g., due to the postponing of investment decisions or financial frictions), some recent studies have reported refined results. For example, Ludvigson et al. (2021) find that the direction of the effect of uncertainty on economic activity depends on the former's origin, and conclude that economic activity benefits (suffers) from enhancements of macroeconomic (financial) uncertainty. In contrast, Berger et al. (2019) argue that uncertainty has no effect at all on the real economy, and that previous studies have only found significant effects as a reflection of the strong correlation between notions of uncertainty and realized volatility (i.e., between forms of unpredictable and predictable risks).<sup>1</sup>

A specific concern in the empirical uncertainty literature is the choice of an appropriate strategy to identify structural uncertainty shocks. The issue of causality analysis and the identification of exogenous variations in uncertainty is particularly intricate, since there is no consensus on either the direction or sign of the interaction effects of uncertainty and the real economy that could be exploited for identification. Moreover, it is difficult to separate uncertainty shocks from other dynamics such as news shocks or realized volatility shocks (Baker & Bloom, 2013; Piffer & Podstawski, 2017). Hence, as potential means of identification, easy-to-employ exclusion restrictions most often lack an economic justification and exclude contemporaneous feedbacks by construction. In addition, more sophisticated approaches such as proxy structural vector autoregressives (SVARs) and narrative sign restrictions are subject to two major shortcomings, (i) the external information used for identification is hardly testable and/or (ii) narrative constraints are typically specific for a given small-scale SVAR specification. In particular the latter point bears the risk of excluding important information which leads to estimated shocks that are actually compound signals rather than structural uncertainty shocks.

To address the glaring ambiguities documented in recent studies, the objectives of this work are twofold. First, we provide an unified framework (i) to compare results of some important studies (in particular, Angelini et al., 2019; Ludvigson et al., 2021; Berger et al., 2019, henceforth ABCF, LMN and BDBG, respectively), and (ii) to highlight eventual limitations of the identification strategies used in these studies. Second, we take a stance on the role of alternative means to identify structural relations to obtain divergent results, and employ an alternative flexible and agnostic data-driven identification approach that overcomes several of the limitations of the strategies used in the benchmark studies, and leaves room for the data to object against a priori judgments. This identification method has been suggested by Matteson and Tsay (2017), and relies on the uniqueness of linear combinations of non-Gaussian distributed independent components (Comon, 1994). As such, it fits well into the class of methods of independent component analysis (ICA). As an outcome, structural shocks retrieved from ICA are not only orthogonal (uncorrelated) but independent and thereby inherit an information content that perfectly aligns with considering such shocks as purely exogenous.<sup>2</sup>

Unlike approaching the identification of structural shocks with strong theoretical a priori assumptions, shocks that are identified by statistical methods do not necessarily allow for an economically meaningful interpretation. Hence, data-based identification schemes such as ICA deserve an ex-post modeling step of assigning sound economic labels to identified shocks (see the discussion of “shock-labeling” in Herwartz & Lütkepohl, 2014). Taking a stance on the origins of conflicting results of LMN and ABCF, we argue in this work that the pursued ICA approach to identification can reconcile these evidences as alternative solutions to the shock-labeling problem. While the replication step of our analysis can be seen to add an interesting embedding of the benchmark structural models to the literature, it is not conclusive with regard to opting for a specific structural model approach. Noticing that alternative structural models equivalently align with a given reduced-form model specification, the comparison of alternative structural models is always a complicated endeavor that ultimately requires an analyst to rely on informal criteria such as the “accordance” of structural implications and theoretical underpinnings. To actually opt for a specific structural model approach (and the corresponding causal implications), we consider an augmented sample period that covers the emergence of the 2020 health (or pandemic) crisis. As a particular merit of such an exercise, it is worth noting that the health crisis can be considered as an exceptional event driven by important (uncertainty and activity) shocks for which all models are largely agnostic. As it turns out, both benchmark approaches show a markedly different scope of issuing sizeable shocks to both financial uncertainty and economic activity. For disentangling the effects of (unpredictable) economic uncertainty shocks and surprise information in (partly) predictable realized volatilities, we also augment the sample information provided by benchmark studies. In this case, however, sample augmentation applies to the cross equation dimension when moving from the stylized three variable model of LMN to a five-dimensional specification that includes measures of realized macroeconomic and financial volatility.

After examining the role of uncertainty in the US economy in several directions, our main results are fourfold. First, we find that narrative restrictions combined with external instruments—as proposed by LMN—are hardly sufficient to

disentangle the interaction between uncertainty and the business cycle. Second, extending the sample information to cover the global pandemic crisis reveals that, unlike rival specifications, the LMN model does not issue a sizeable financial uncertainty shock in March 2020. Moreover, in a pseudo-predictive exercise the LMN model is unique in predicting beneficial patterns of economic growth early in 2020 as a result of positive shocks to macroeconomic uncertainties. Third, macroeconomic and financial uncertainty are likely exogenous sources of business cycle fluctuations, and both have significantly contractionary effects on economic activity. Fourth, when uncertainty is proxied by means of an information-rich measure in a vector autoregressive (VAR) model, shocks to uncertainty have much stronger impacts on economic variables than shocks to realized volatility. Our results show no support for the findings of BDBG who argue for a general overestimation of the impact of uncertainty on the economy when measures of realized volatility are omitted. By contrast, we find evidence that the opposite holds, that is, there is a higher risk of underestimating the importance of uncertainty, especially if a relatively weak uncertainty proxy is used.

The next section reviews concisely the macroeconomic uncertainty literature. In Section 3 we discuss approaches to identification, and provide a comprehensive comparison of alternative structural model specifications and their causal implications. Section 4 shows how the extension of the sample period to cover the emergence of the health crisis supports the choice among alternative SVARs which show marked performance differentials in terms of issuing sizeable financial uncertainty shocks early in 2020. Section 5 reconsiders the evidence from the small-scale benchmark VAR in the context of an informationally richer model that includes measures of realized volatility. Section 6 concludes. In a set of online appendices we provide (i) additional details on identification in the benchmark studies of LMN and ABCF (Supporting Information S1: Appendix A), (ii) diagnostic results on covariance breaks and a time-invariant structural model as an alternative to the suggestion of ABCF (Supporting Information S1: Appendix B), (iii) diagnostic evidence on the non-Gaussianity and independence of structural shocks (Supporting Information S1: Appendix C), (iv) robustness analysis (Supporting Information S1: Appendix D), (v) a revisit of the results of BDBG (Supporting Information S1: Appendix E), (vi) first comparative results on the transmission of macroeconomic versus financial uncertainty to the real economy (Supporting Information S1: Appendix F), and (vii) an overview of the data used in the analysis (Supporting Information S1: Appendix G).

## 2 | BRIEF OVERVIEW OF THE MAIN FINDINGS AND OPEN QUESTIONS FROM THE LITERATURE ON ECONOMIC UNCERTAINTY

The first inclusion of uncertainty into economic theory dates back to the seminal work of Frank Knight (*Knightian uncertainty*, Knight, 1921), who separates uncertainty from the concept of risk. While it is possible to calculate risk because there is a known probability distribution over a set of events, this does not hold for uncertainty. Thus, uncertainty can be better characterized as an immeasurable risk, that is, uncertainty has an unknown probability distribution and is typically described in an economic context as the conditional volatility of unpredictable disturbances (see, e.g., Jurado et al., 2015). From this theoretical characterization follows the empirical issue of how to measure uncertainty. Since no objective method exists to quantify uncertainty in general, many alternative proxies have been employed in the relevant literature such as option-implied stock market volatility (e.g., VIX, VXO, Bloom, 2009), cross-sectional dispersions of firm profits (Bachmann et al., 2013) or the appearance of key words in newspaper articles and/or twitter posts (Baker et al., 2016, 2021). Jurado et al. (2015) have recently argued that most of these measures—for example, stock market volatility—can jump remarkably without changes in the uncertainty about economic fundamentals, and cross-sectional dispersion in firm-level profits can fluctuate due to heterogeneity in the cyclicalities of firms' business activities. To overcome these obstacles, Jurado et al. (2015) propose a method to specifically estimate *macroeconomic uncertainty* by aggregating implied forecast errors from a large number of economic time series.<sup>3</sup> By removing all forecastable components from the forecast errors, Jurado et al. (2015) interpret this measure as common variation in the economy-wide lack of predictability that shows much less important uncertainty episodes in comparison with alternative popular uncertainty proxies. However, if an increase in this index emerges, it is typically larger, more persistent and more strongly correlated with real activity than other uncertainty proxies (such events include the energy crisis around 1974, the early-1980s recession and the Great Recession in 2008/2009). In a comparative assessment, Caldara et al. (2016) find that the Jurado et al. (2015) index has the highest predictive content for economic activity among all considered uncertainty proxies, and VARs including this index indicate a maximum impact of uncertainty on the business cycle. LMN adopt the Jurado et al. (2015) approach to a large sample of financial time series for constructing an index of *financial uncertainty*.

The recent review of Bloom (2014) summarizes conveniently the current understanding of the interaction between uncertainty and economic activity. On the one hand, an important literature points out a negative relation between uncertainty and economic activity, and argues that the uncertainty about economic fundamentals originates in the form of exogenous shocks that cause agents to adjust their economic planning. In this regard, two transmission channels can be in place. First, in the framework of the “real options theory,” so-called “wait-and-see effects” summarize that firms face irreversibility of fixed costs in investment (or hiring), and higher uncertainty causes them to exercise their option to wait and postpone investment. An analogous argument applies to the postponing of consumption by households. Second, under risk aversion of economic agents (e.g., investors) exogenous uncertainty shocks can raise financing costs, and so-called “financial friction effects” cause economic slack. On the other hand, it is also conceivable that as a result of enhanced volatility of innovation, exogenous uncertainty shocks could also come with beneficial economic opportunities and, hence, cause economic upswing. In this regard, proponents of growth options arguments mainly argue with firms focusing on projects with a limited downside but high upside potential. For instance, the so-called “Oi–Hartman–Abel effect” highlights the possibility that if firms manage to easily cut or expand their production capacities, they could limit their downside potential during negative outcomes but fully exploit potential profits in the case of favorable innovative outcomes. As a matter of fact, the described cause and effect relations are straightforward to derive under the assumption that uncertainty emerges primarily in the form of (unpredictable) exogenous shocks. This view, however, has been challenged in the literature from two perspectives. On the one hand, it has become an open debate whether uncertainty is exogenous to the business cycle. This is a particular problem when analyzing—for example—the dynamics during the Great Recession. Noticing that measures of uncertainty spike during recessions, a viable debate has emerged if uncertainty is truly the result of exogenous shocks or endogenous. In this debate prominent positions have been taken by Bloom (2009) and Bloom et al. (2018) considering uncertainty as an exogenous source of business cycle fluctuations, and Bachmann et al. (2013) who argue that uncertainty appears to be more an outcome of recessions. Bloom (2014) encounters four reasons why uncertainty might be raised during recessions, namely (i) firms trade less during recessions, which lowers information flows, (ii) forecasting is more intricate during recessions, (iii) economic downturns are usually characterized by more political interventions, and (iv) resources are reallocated during crises. On the other hand, some authors have questioned the adverse role of (unpredictable) uncertainty in macroeconomic performance, and argue that instead (predictable) accelerations in realized volatilities trigger economic downturns (Ambrocio, 2021; Dew-Becker et al., 2021, BDBG). In this context, BDBG point at the key identification problem of separating uncertainty about the future from current economic conditions, and find that previous studies have (implicitly) focused on the responses of economic variables to mixtures of realized and anticipated volatilities.

Although Bloom (2014) has emphasized the dominance of the contractionary mechanisms at least in the short run, empirical results on the impacts of uncertainty on the real economy are diverse. Bloom (2009) finds that increased uncertainty has a negative effect on the real economy on impact and a positive effect after a few months (overshooting). Negative impacts of uncertainty on the economy have also been found by other studies (e.g., ABCF, Caldara et al., 2016; Piffer & Podstawski, 2017). By contrast, BDBG and Schaal (2017) find no indication that uncertainty shocks explain prolonged shifts in output after recessions, and LMN even find expansionary effects from macroeconomic uncertainty to economic activity. Contributing to the debate on the ultimate origin of uncertainty, the structural models of ABCF and LMN hold opposing positions, with the former (latter) arguing in favor of the exogeneity (endogeneity) of macroeconomic uncertainty. After adopting an information rich, high-dimensional VAR model with stochastic volatility Carriero et al. (2018) take an intermediate position, and conclude that macroeconomic uncertainty is exogenous, while financial uncertainty quantified as implied volatility (VXO) “can in part arise as an endogenous response to some macroeconomic developments.” Analyzing the transmission channel of financial frictions, BDBG find that investors have historically paid high premia to hedge against realized volatility but not to hedge against implied volatility.

### 3 | IS UNCERTAINTY AN ENDOGENOUS RESPONSE OR AN EXOGENOUS SOURCE OF BUSINESS CYCLE FLUCTUATIONS?

To investigate whether uncertainty (in particular macroeconomic uncertainty) is an exogenous contributor to business cycle fluctuations or an endogenous response, we consider LMN and ABCF as benchmark studies for our analysis for two reasons. First, LMN have led the debate toward the distinction of alternative sources of uncertainty, that is, their

model allows separating uncertainty that originates from economic fundamentals (macroeconomic uncertainty) and uncertainty that is specific to financial markets (financial uncertainty). Second, a debate has recently developed on their model implications, as ABCF use almost the same data set but come to remarkably different results. In analogy to the SVARs considered in both studies (i.e., LMN and ABCF), the system used in this work consists of three variables, namely:

- $Um_t$ —one-month ahead macroeconomic uncertainty index (i.e., the Jurado et al. (2015) index);
- $ip_t$ —linearly detrended log of U.S. real industrial production; and
- $Uf_t$ —one-month ahead financial uncertainty index.

The uncertainty indices  $Um_t$  and  $Uf_t$  have been constructed from a large set of macroeconomic and financial time series (see Jurado et al., 2015 and LMN for a detailed description) and can be drawn from Sydney C. Ludvigson's website.<sup>4</sup> The industrial production index has been downloaded from the Federal Reserve Bank of St. Louis database. It is worth noting that while LMN include industrial production in log-level form, ABCF rely on log differences. Moreover, LMN estimate a VAR model with six lags, whereas ABCF use four lags. Against this background, we follow ABCF and estimate the reduced-form VAR with four lags as suggested by the AIC. The analyzed time series are displayed in Figure 1.<sup>5</sup>

In this section, we consider the original LMN sample period from 1960:07 to 2015:04 with monthly data comprising  $T = 658$  observations (i.e., observations up to the horizontal blue line in Figure 1). Since the studies of LMN and ABCF rely on different estimation techniques—which might be a potential reason for the competing results—we compare a set of three alternative (or complementary) approaches to SVAR identification. In the following we highlight methodological issues and provide a thorough comparison of the structural insights from the benchmark studies. Regarding the former, we provide (i) a brief outline of the identification problem in structural VARs, (ii) a description of identification based on ICA methods, and (iii) a sketch of the benchmark identification schemes of LMN and ABCF. The comparison of alternative structural models includes the discussion of impulse response functions (IRFs), forecast error variance decompositions (FEVDs) and a critical assessment of the event and correlation constraints suggested by LMN.

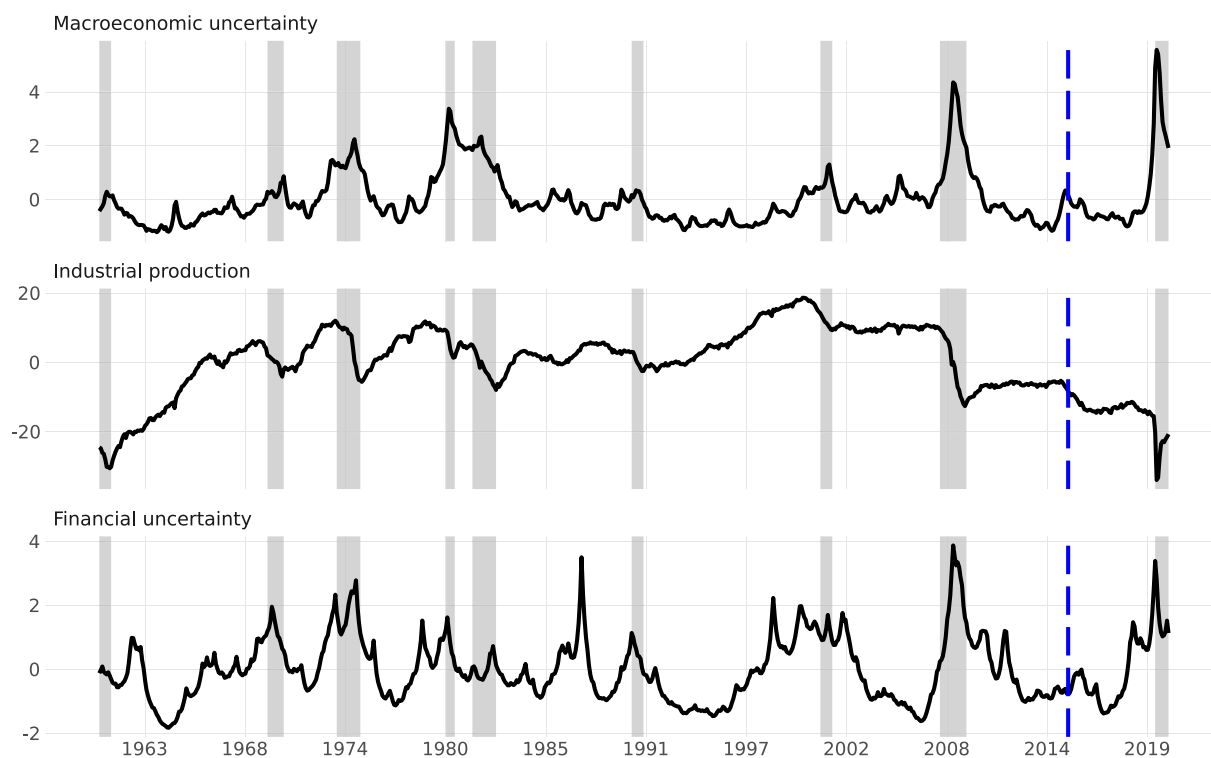


FIGURE 1 Extended trivariate data set of LMN and ABCF. Gray shaded areas correspond to NBER recession dates and vertical blue marks indicate the end of the sample period considered in LMN and ABCF.



### 3.1 | Structural VARs

#### 3.1.1 | A general outline

The econometric model in this analysis is a  $K$ -dimensional VAR of order  $p$ , that is,

$$y_t = v_t + A_1 y_{t-1} + \dots + A_p y_{t-p} + u_t, \quad (1)$$

$$= v_t + A_1 y_{t-1} + \dots + A_p y_{t-p} + B \varepsilon_t, \quad (2)$$

$$\Leftrightarrow A(L)y_t = v_t + B \varepsilon_t, \quad t = 1, \dots, T, \quad (3)$$

with vector-valued deterministic terms  $v_t$  and  $A(L) = (I_K - A_1 L - \dots - A_p L^p)$ , where  $L$  denotes the lag operator, such that for example,  $Ly_t = y_{t-1}$  and  $I_K$  is the  $K \times K$  identity matrix. The model is weakly stationary (causal) by assumption, that is,  $\det A(z) = \det(I_K - \sum_{j=1}^p A_j z^j) \neq 0$  for the roots of the polynomial being  $|z| \leq 1$ . The stochastic model components are commonly characterized from two perspectives, first: zero mean *reduced-form residuals*  $u_t$ ,  $E(u_t) = 0$ , are subject to cross-equation correlation with covariance matrix  $\Sigma_u = BB'$  and second, *structural shocks*  $\varepsilon_t = B^{-1}u_t$  are uncorrelated across equations with  $E(\varepsilon_t) = 0$  and  $\Sigma_\varepsilon = I_K$ . Under the weak stationarity condition,  $y_t$  can be expressed in the form of a Wold moving average (MA) representation, which can be straightforwardly transformed for tracing the dynamic effects of structural shocks on the system variables, that is,

$$y_t = \mu_t + \sum_{i=0}^{\infty} \Phi_i u_{t-i} \quad (4)$$

$$= \mu_t + \sum_{i=0}^{\infty} \Phi_i B \varepsilon_{t-i} = \mu_t + \sum_{i=0}^{\infty} \Theta_i \varepsilon_{t-i}, \quad (5)$$

where  $\mu_t = A(L)^{-1}v_t$ ,  $\Phi_0 = I_K$  and  $\Theta_i = \Phi_i B$ . Specifically, the structural impulse responses obtain sequentially as  $\Theta_i = \sum_{j=1}^i A_j \Theta_{i-j}$  with  $A_j = 0$  for  $j > p$  (see, e.g., Kilian & Lütkepohl, 2017, chap. 2).

While reduced-form residuals can be estimated consistently by means of ordinary least squares or maximum likelihood techniques, the decomposition of the covariance matrix  $\Sigma_u = BB'$  is not unique. For instance, alternative covariance decompositions obtain as

$$\Sigma_u = DD' = DRR'D' = DR(DR)', \quad (6)$$

with  $D$  denoting for example, the lower triangular Choleski factor of  $\Sigma_u$  and  $R$  any rotation matrix ( $R \neq I_K$ ,  $RR' = I_K$ ). Accordingly, the representation  $B = DR$  highlights  $B$  as a specific member from a space of covariance factors, all of which are in line with the reduced-form covariance matrix ( $\Sigma_u = BB'$ ). In parametric form, the matrix  $R = R(\rho)$  could be specified as a product of Givens rotation matrices defined through an associated  $(K(K-1)/2) \times 1$ -dimensional vector of rotation angles  $\rho = (\rho_1, \dots, \rho_{K(K-1)/2})$ . Noting that  $u_t = B \varepsilon_t$ , the structural matrix  $B$  formalizes the instantaneous impacts of the structural shocks on the variables of the system (or their residuals). Hence, it carries informational content for causal relationships within the dynamic system, and a central goal in structural analysis is to identify the matrix  $B$  properly.

#### 3.1.2 | Specific issues in the SVAR uncertainty literature

In the context of economic uncertainties, it is particular challenging to find a suitable identification strategy, since the impact direction of uncertainty shocks on economic variables is ambiguous and it is difficult to distinguish uncertainty shocks from other source signals such as financial shocks or news shocks (Caldara et al., 2016; Piffer & Podstawski, 2017). Nevertheless, the SVAR literature to date has provided several alternative approaches to solve the identification problem. The most popular approach is to rely on recursive identification schemes (e.g., Bachmann

et al., 2013; Bloom, 2009; Scotti, 2016). However, restricting  $\mathbf{B}$  to be a lower triangular matrix has been criticized, since it excludes contemporaneous feedbacks by construction (Baker & Bloom, 2013; Ludvigson et al., 2021). While such feedback patterns might generally originate from realistic behavior, in the present context some “technical” interdependence of observables emerges from certain variables (here  $ip_t$  and  $Um_t$ ) as the first- and second-order moment of one “underlying” process. Moreover, the ordering of the variables in such hierarchical models might be subject to debate, as it is typically unclear whether and which variables are affected by uncertainty shocks immediately and which variables are affected with a time lag (see e.g., Gilchrist et al., 2014).<sup>6</sup> More recent studies rely on instrumental variable estimation to identify uncertainty shocks. For instance, Piffer and Podstawski (2017) suggest using variation in the price of gold around certain events as an instrument.

The issue of finding an appropriate identification approach for uncertainty shocks is crucial, since the economic implications appear to be closely linked to a chosen identification strategy. Given the informality of structural model selection, the decision in favor of a particular identification scheme can benefit from a careful comparison of structural models retrieved from alternative identification schemes. In this regard, the present study not only provides a comparative replication of the results in LMN and ABCF but also extends the set of structural models with outcomes from a further data-based identification approach that could be seen as a natural alternative or complement of the baseline studies. In sum, we consider three distinct identification strategies, that is, (i) economically-motivated narrative event and correlation constraints from the benchmark study of LMN, (ii) identification based on changes in the covariance structure (Rigobon, 2003) in the vein of ABCF, and (iii) ICA-based non-Gaussian shocks as suggested by Matteson and Tsay (2017). Approaching the identification problem by means of ICA is motivated by (i) a minimal number of assumptions required for uniqueness of the structural model, (ii) strong deviations of uncertainty shocks from Gaussianity as documented, for example, in LMN, and (iii) the robust performance of ICA-based identification within a rich variety of SVARs generated from heteroskedastic or non-Gaussian distributed model residuals (Herwartz, Lange, & Maxand, 2022).<sup>7</sup> Overall, these circumstances make principles of ICA particularly well suited to identify uncertainty shocks, and to critically reassess core findings of both benchmark studies.

### 3.1.3 | Identification through the detection of independent components

An important result of Comon (1994) states that the reduced form residuals  $u_t$  in Equation (1) can be uniquely traced back to the underlying shocks  $\varepsilon_t$ , if these are not only orthogonal but independent and at most one of the shocks is (marginally) Gaussian distributed. Hence, under these conditions, the matrix  $\mathbf{B}$  in Equation (3) is uniquely identified. As an intuitive account of the uniqueness of independent non-Gaussian shocks, consider a case of two alternative structural matrices  $\mathbf{B}$  (the true model) and  $\mathbf{D} \neq \mathbf{B}$  that also aligns with the covariance restriction  $\Sigma_u = \mathbf{D}\mathbf{D}'$  (for instance,  $\mathbf{D}$  could be a lower triangular Cholesky factor of  $\Sigma_u$ ). By assumption, the underlying shocks  $\varepsilon_t = \mathbf{B}^{-1}u_t$  are non-Gaussian and independent. Now suppose that an analyst believes in the model implied by  $\mathbf{D}$ . Accordingly, she considers the shocks  $\varepsilon_t^{(D)} = \mathbf{D}^{-1}u_t = \mathbf{D}^{-1}\mathbf{B}\varepsilon_t = \mathbf{F}\varepsilon_t$  as structural. However, since  $\mathbf{F} \neq \mathbf{I}_K$ , the elements in  $\varepsilon_t^{(D)}$  are linear combinations of the true shocks in  $\varepsilon_t$ , and therefore dependent.

Although the assumption of independent shocks appears strong at first sight, principles of ICA are well suited for structural analysis for at least three reasons. First, SVARs aim at tracing movements in the data back to economically interpretable and distinguishable sources that are exogenous to each other. Hence, it is tempting to identify structural shocks that minimize their mutual information content. In other words, minimizing the entire dependency structure among the shocks and not only their linear relationship seems to best fit the notion of exogeneity. While any orthogonalization of jointly Gaussian random variables obtains independent components, the independence assumption of non-Gaussian components is restrictive and applies to exactly one set of orthogonalized model residuals. Second, a fundamental result of information theory is that Gaussian random variables have the largest entropy among all random variables of equal variance (Cover & Thomas, 1991; Papoulis, 1991), that is, they have the least information content, which is in obvious contradiction to the concept of economically meaningful structural shocks. Third, the assumption of non-Gaussianity might be reasonable for economic data to allow, for example, leptokurtic distributions (see, e.g., Chib & Ramamurthy, 2014; Cúrdia et al., 2014, for DSGE models with  $t$ -distributed shocks). In sum, ICA appears to be a natural approach to minimize the mutual information between the structural shocks  $\varepsilon_t$ , and maximize the self-information of the shocks. Complementing these general considerations, the adoption of ICA principles to the detection of specific uncertainty shocks finds specific support in core results of LMN who encounter the non-Gaussianity of their identified uncertainty shocks among the four main results of their study.



Meanwhile the econometric literature has developed a variety of specific ICA-based identification schemes (see, e.g., Lanne et al., 2017; Moneta et al., 2013). In their large scale simulation study Herwartz, Lange, and Maxand (2022) provide guidance for the choice of a most promising identification method in the realistic case that actual data features are heterogeneous and unknown, and economic theory is not sufficiently conclusive to deliver fully convincing external information. With this background and noticing the conflicting theoretical considerations delivered in the benchmark studies of LMN and ABCF, we opt for the flexible and agnostic identification approach of Matteson and Tsay (2017). These authors suggest minimizing a loss statistic that summarizes information from so-called distance covariances (Székely et al., 2007). For the  $K$ -dimensional vector  $\varepsilon_t$ ,  $t = 1, \dots, T$ , the distance covariance  $\mathcal{V}_T^2$  detects dependence between two subsets of the components. Between the  $k$ -th component  $\varepsilon_{tk}$ ,  $k \in \{1, \dots, K\}$  and all other ones  $\varepsilon_{t,k_-}$  with  $k_- = \{1, \dots, K\} \setminus \{k\}$  dependence is measured by the distance between the joint characteristic functions  $\left(\varphi_{\varepsilon_{t,k}, \varepsilon_{t,k_-}}\right)$  and the one under independence (i.e., a product of characteristic functions  $\varphi_{\varepsilon_{t,k}} \varphi_{\varepsilon_{t,k_-}}$ ). Then, a criterion to measure mutual dependence reads as

$$\mathcal{U}_T(\hat{\varepsilon}_{t,1}, \dots, \hat{\varepsilon}_{t,K}) = T \cdot \sum_{k=1}^{K-1} \mathcal{V}_T^2(\hat{\varepsilon}_{t,k}, \hat{\varepsilon}_{t,k_-}). \quad (7)$$

The statistic  $\mathcal{U}_T(\hat{\varepsilon}_{t,1}, \dots, \hat{\varepsilon}_{t,K})$  is minimized to identify samples  $\{\hat{\varepsilon}_t = \mathbf{B}^{-1} \hat{\mathbf{u}}_t\}_{t=1}^T$  with least dependent components, characterizing the estimated matrix  $\hat{\mathbf{B}}$ . Identification through independent components is implemented in the R package *svars* (Lange et al., 2021).

While in lack of consensual economic theory, the agnosticism of ICA appears as a strong merit, a potential obstacle of any data-driven identification technique is that it is by no means clear that the detected independent components in  $\hat{\mathbf{B}}^{-1} \mathbf{u}_t$  obey any sound economic features. Moreover, with  $b_{.,k}$  denoting a column of  $\mathbf{B}$ , it is easy to see that  $\Sigma_u = \mathbf{B}\mathbf{B}' = \sum_{k=1}^K b_{.,k} b_{.,k}'$  such that any matrix  $\mathbf{B}$  is unique only up to column signs and orderings. Since  $\mathbf{u}_t = \sum_k b_{.,k} \varepsilon_{k,t}$  the stochastic origins of reduced form residuals call for a sound economic label to support the causal patterns implied by data-based estimates  $\hat{\mathbf{B}}$  in a theory-conforming manner. Herwartz and Lütkepohl (2014) highlight the important role of shock-labeling that consists of the assignment of a theory-guided interpretation (and ordering) of the columns of initial estimates  $\hat{\mathbf{B}}$  and their signs (i.e., the signs of the shocks).

To establish sign uniqueness, we follow the convention to consider effects of positive shocks, that is, if an intermediate estimate of a diagonal element of  $\mathbf{B}$  is negative, we multiply the respective column with minus one. To link the columns in  $\mathbf{B}$  with economically meaningful shocks, we use two alternative strategies. First, we notice that LMN consider their event and correlation constraints as important features of (macroeconomic and financial) uncertainty shocks and shocks to economic activity. Accordingly, we opt for the particular column permutation of the estimated  $\mathbf{B}$  matrix that maximizes all event and correlation constraints jointly (we refer to these structural estimates with the short-hand notation “DC\_LMN”). Second, we label the shocks regarding the relative size of the diagonal elements in  $\mathbf{B}$  (“DC\_loadings”). Put differently, this column ordering establishes that the effect of the structural shocks on their own target variable is stronger in comparison with cross-variable effects. For instance, financial uncertainty shocks are supposed to have a higher loading on changes of the one-month ahead financial uncertainty index  $Uf_t$  than, for example, on adjustments of industrial production  $ip_t$  (Caldara et al., 2016). It is worth noticing that both devices of column ordering do not necessarily obtain distinct results.

### 3.1.4 | Identification in benchmark studies

Adopting principles of narrative restrictions (Antolín-Díaz & Rubio-Ramírez, 2018; Zeev, 2018) and taking advantage of the literature on so-called proxy SVARs (Stock & Watson, 2012), LMN suggest, respectively, the following six event (E1–E6) and two correlation constraints (C1, C2) for set identification of the structural parameter matrix  $\mathbf{B}$  in Equation (3).<sup>8</sup>

#### 1. Event constraints directly imposed on the structural shocks:

- E1. Financial uncertainty shocks are subject to a large positive shock ( $\varepsilon_{Uf} \geq k_1$ ) in October 1987 (Black Monday).
- E2. The financial uncertainty shock or the macroeconomic uncertainty shock or both in September 2008 (the month of the Lehman collapse) show a large positive value ( $\varepsilon_{Uf} \geq k_2 \vee \varepsilon_{Um} \geq k_3$ ).
- E3. The macroeconomic uncertainty shock in December 1970 should be large ( $\varepsilon_{Um} \geq k_4$ ).

- E4. The sum of the shocks to economic activity from 2007:12 to 2009:06 (corresponding to the Great Recession) is non-positive ( $\sum \varepsilon_{ip} \leq 0$ ).
- E5. Both financial uncertainty and macroeconomic uncertainty shocks are non-negative in October 1979 (Volcker experiment,  $\varepsilon_{Uf} \geq 0 \wedge \varepsilon_{Um} \geq 0$ ).
- E6. Both financial uncertainty and macroeconomic uncertainty shocks are non-negative during the European debt-ceiling crisis in July and August 2011 ( $\varepsilon_{Uf} \geq 0 \wedge \varepsilon_{Um} \geq 0$ ).
2. Correlation constraints motivated from the role of risk premia in asset pricing (e.g., Lintner, 1965; Sharpe, 1964):
- C1. Macroeconomic uncertainty shocks and financial uncertainty shocks are negatively correlated with stock market returns  $S_t$  (i.e.,  $\text{cor}(S_t, \hat{\varepsilon}_{Um}) \leq 0 \wedge \text{cor}(S_t, \hat{\varepsilon}_{Uf}) \leq 0$ ).
- C2. Shocks to financial and macroeconomic uncertainty are positively correlated with gold returns  $G_t$  (i.e.,  $\text{cor}(G_t, \hat{\varepsilon}_{Um}) \geq 0 \wedge \text{cor}(G_t, \hat{\varepsilon}_{Uf}) \geq 0$ ).

Unlike LMN, ABCF employ a statistical approach to identification, namely, identification through heteroskedasticity which is combined with theoretically motivated exclusion restrictions in a three-state structural model framework (for an explicit outline, see Supporting Information S1: Appendix A.2). The authors motivate two considered break dates  $TB_1$  and  $TB_2$  capturing the beginning of the Great Moderation in March 1984 and of the Great Recession in December 2007, respectively. Similar (or even identical) time instances of (co)variance breaks have been employed in the literature on US monetary policy shocks (Brunnermeier et al., 2019; Herwartz & Plödt, 2016; Lanne & Lütkepohl, 2008; Lütkepohl & Netšunajev, 2017).

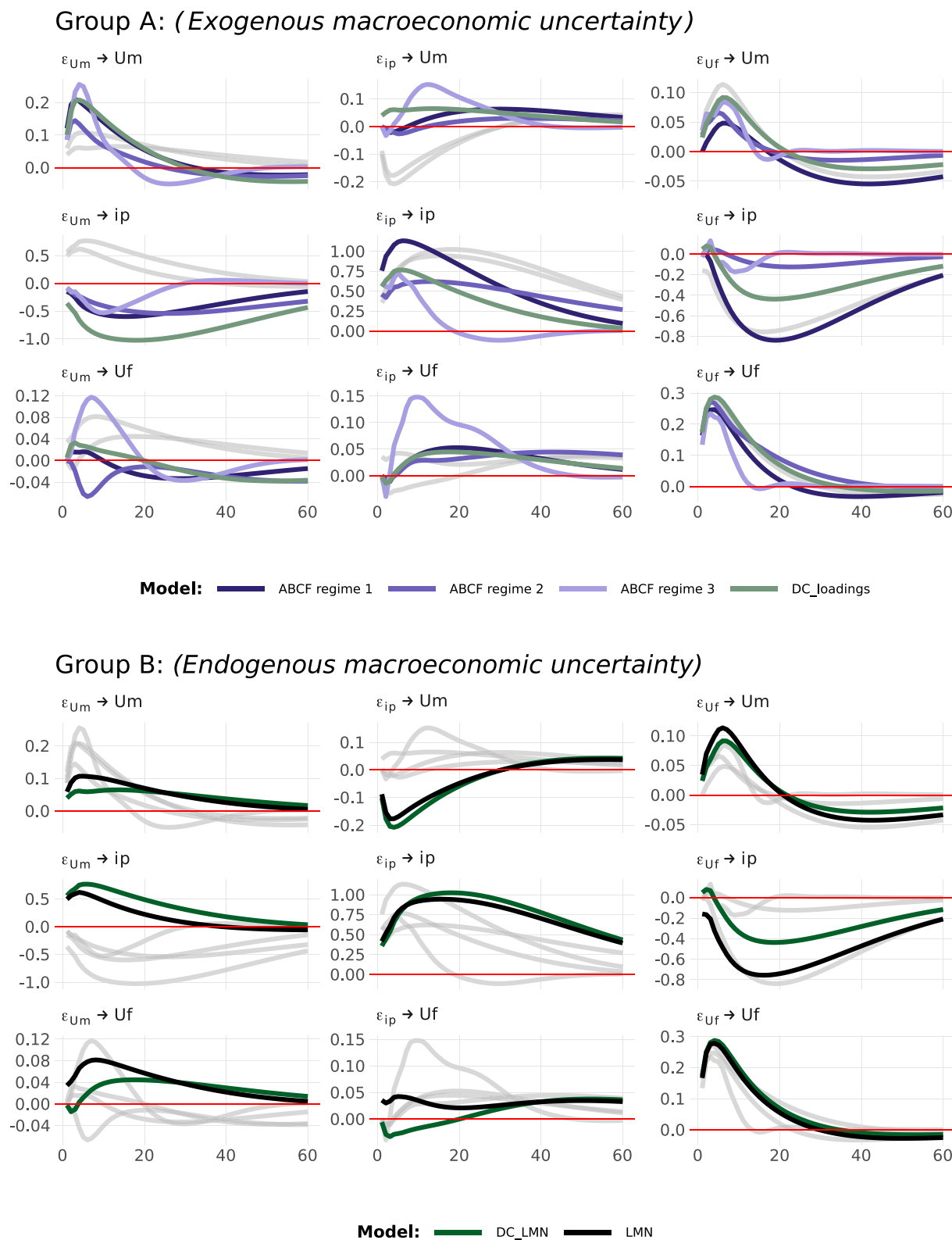
### 3.2 | Evaluating two competing strands in the literature (LMN vs. ABCF)

#### 3.2.1 | Impulse responses and forecast error variance decompositions

Figure 2 shows the estimated IRFs from the ABCF, LMN and DC models. Note that the ABCF model implies specific IRFs for each of the three covariance regimes. ICA-based identification relies crucially on non-Gaussianity and independence of the structural shocks. From diagnostic results documented in Supporting Information S1: Appendix C we conclude that both preconditions are met by the extracted shocks with conventional significance. The two alternative variants of DC models stem from the same estimation, but rely on distinct criteria for column ordering (DC\_LMN vs. DC\_loadings). Given the opposing results of LMN and ABCF, it is unsurprising to see that structural IRFs shown in Figure 2 allow for a classification into two groups: Models associated with the first group—henceforth  $\mathcal{A} = \{\text{ABCF}, \text{DC\_loadings}\}$ —imply exogenous macroeconomic uncertainty and a contractionary effect of macroeconomic uncertainty on economic activity. Models in the second group—henceforth  $\mathcal{B} = \{\text{LMN}, \text{DC\_LMN}\}$ —signify endogenous macroeconomic uncertainty and an expansionary effect of macroeconomic uncertainty on economic activity.<sup>9</sup>

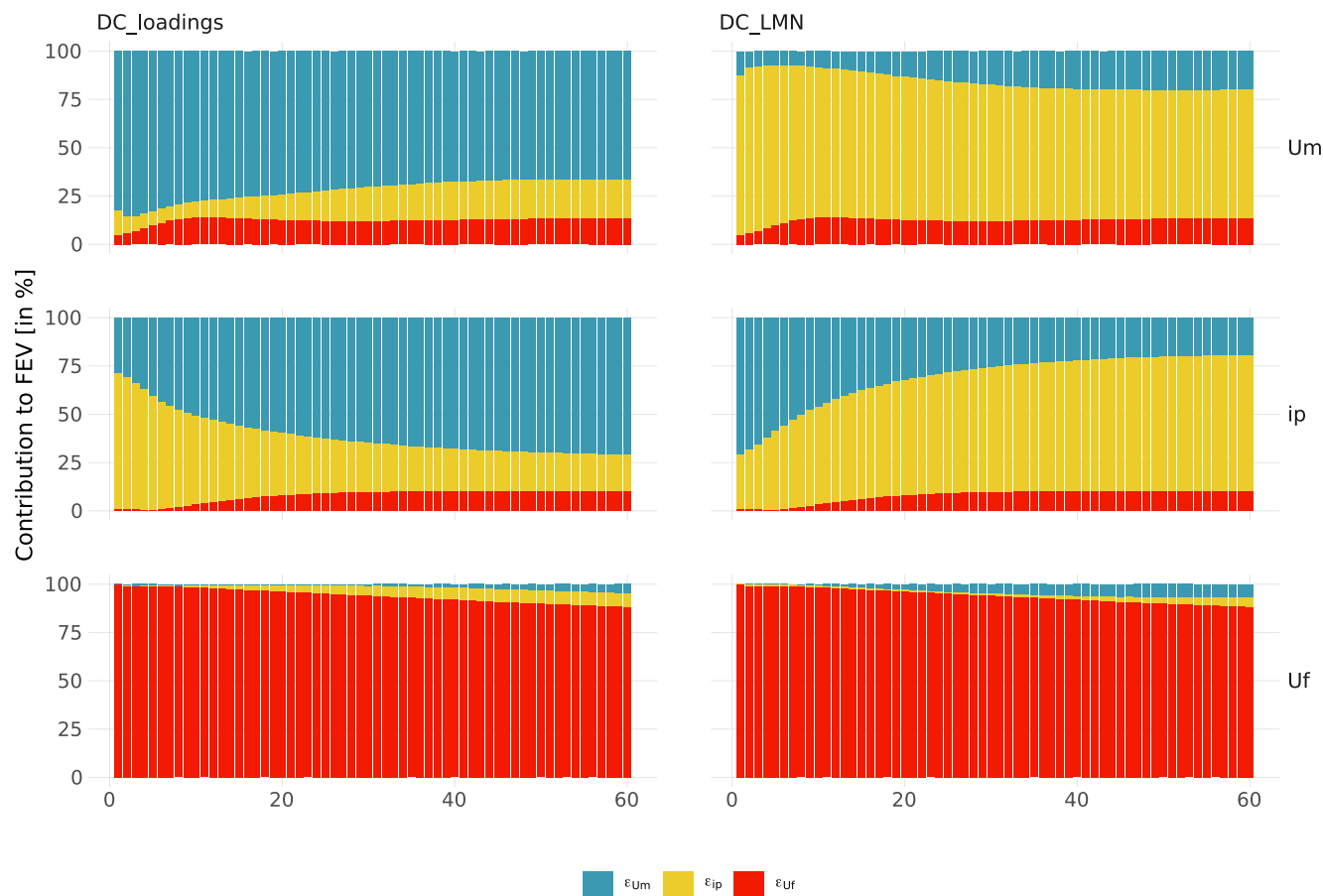
Figure 3 depicts a visual comparison of the implied FEVDs, for the DC\_loadings and the DC\_LMN model as representatives for  $\mathcal{A}$  and  $\mathcal{B}$  models, respectively. The results from DC\_LMN are very similar compared with the findings from LMN, that is, shocks to industrial production  $\varepsilon_{ip,t}$  explain the lion's share of variation in the forecast errors of macroeconomic uncertainty, while shocks to macroeconomic uncertainty  $\varepsilon_{Um,t}$  explain a large fraction of variation in industrial production on impact, which slowly tapers off. By contrast, FEVDs implied by DC\_loadings show only a marginal contribution of production shocks  $\varepsilon_{ip,t}$  to macroeconomic uncertainty. In contrast to LMN and similar to the results of Caldara et al. (2016), macroeconomic uncertainty shocks  $\varepsilon_{Um,t}$  have a relatively small impact on industrial production during the first 6 months but explain about 50% in the variation after 12 months.

Turning to the economic implications, models of group  $\mathcal{B}$  suggest that increases in macroeconomic uncertainty translate immediately into higher economic output. Although arguments from growth option theory connect uncertainty with the potential of expansionary economic dynamics, this finding clearly contradicts well-established theories and empirical findings of wait-and-see effects and precautionary savings at the firm and household level, respectively (Bloom, 2009). By contrast, the results from  $\mathcal{A}$  models coincide with the classical uncertainty theory regarding the direction of the industrial production response. Moreover, the increasing contribution of uncertainty shocks to economic activity over time is plausible, since firms and market participants in the real economy usually incorporate information more sluggishly than, for example, financial market agents and



**FIGURE 2** Comparison of point estimates of IRFs from alternative models. Panels in the upper (lower) part highlight IRFs that imply exogenous (endogenous) macroeconomic uncertainty, that is, group  $\mathcal{A}$  ( $\mathcal{B}$ ) models. IRFs, impulse response functions.

adjustments to exogenous shocks happen rather slowly. Hence, it appears more plausible that the results from the bottom row in Figure 2 and the right-hand side of Figure 3 stem from mislabeled shocks that are characteristic for models of group  $\mathcal{B}$ .

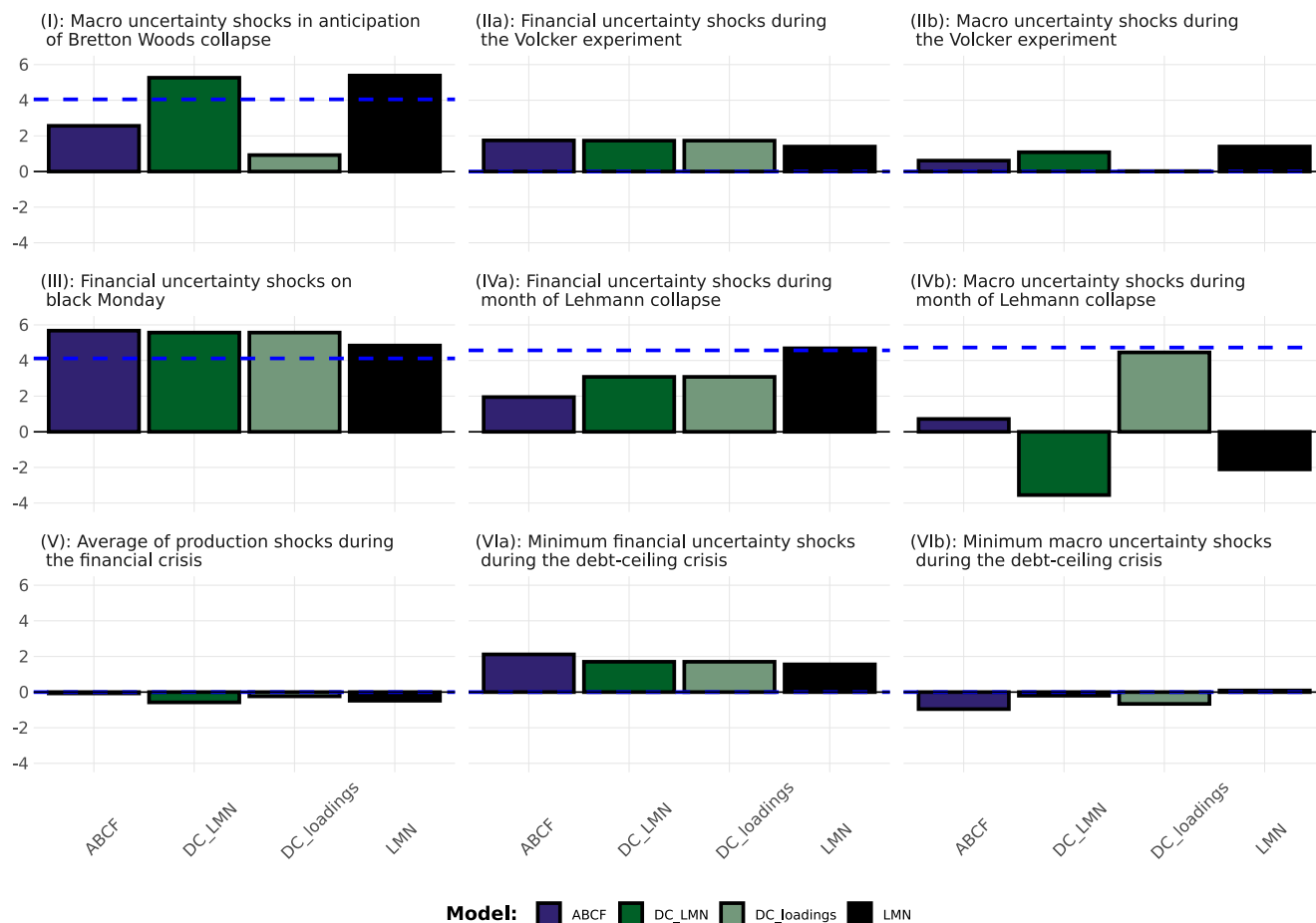


**FIGURE 3** FEVDs obtained from  $\hat{B}_{DC\_loadings}$  (left-hand side column) and  $\hat{B}_{DC\_LMN}$  (right-hand side). FEVD, forecast error variance decomposition.

### 3.2.2 | Event and correlation constraints

Since the event and correlation constraints of LMN are all well founded and in line with economic theory, it seems natural to argue that source signals from structural models should match these constraints to some extent. Unlike the LMN approach, all remaining models are completely agnostic with respect to the inequality restrictions E1–E6 applying to individual shocks. Hence, it is interesting to observe from the shocks displayed in Figure 4 that estimates retrieved from the models of group  $\mathcal{A}$  are also mostly in line with the event constraints. Noteworthy exceptions are the macroeconomic uncertainty shock obtained from the DC\_loadings model prior to the Bretton Woods collapse (panel (I)) and the financial uncertainty shocks from the ABCF model during the Lehmann bankruptcy (panel (IVa)). Moreover, except the LMN specification, all models show at least one negative macroeconomic uncertainty shock during the European debt-ceiling crisis (panel (VIb)). In fact, the estimation results of these models suggest that financial markets were the main source of uncertainty to hit the US economy during the European debt crisis, which seems plausible given that the negative impact on the real economy during this period was mainly confined to European economies.

The most surprising result, however, is seen in panel (IVb). The LMN model as well as DC\_LMN issue a large negative macroeconomic uncertainty shock in September 2008, that is, these models imply a sizable reduction of macroeconomic uncertainty in this month. While this finding appears to be at odds with common opinions on the time of the Lehmann collapse, it is within the space of possible solutions spanned by the event constraints, since E2 is formulated such that only one of the two uncertainty shocks has to be large and positive. By contrast, LMN find that macroeconomic uncertainty peaks in the month after the Lehmann collapse, that is, October 2008. It is worth to recall that benchmark VARs of LMN (and ABCF) comprise one-month ahead uncertainty indices of JLN. Results remain (largely) robust when using the respective 3- and 12-months ahead indices (see Supporting Information S1: Appendix D.2 for details).



**FIGURE 4** Comparison of the magnitudes of the structural shocks during event periods, obtained by  $\hat{B}_{\cdot, \cdot} \in \{ABCF, DC\_LMN, DC\_loadings, LMN\}$ . Blue dashed horizontal lines indicate the threshold parameters  $(k_1, k_2, k_3, k_4)$  from the event constraints E1–E3. The threshold parameters  $k_1, k_2, k_3$  and  $k_4$  are determined as the 75<sup>th</sup> percentile of a shock evaluated at the specific dates, that is, accepted uncertainty shocks are required to exceed 75% of all model-implied shocks in terms of magnitude.

From evaluating the correlation constraints (C1–C2) displayed in Table 1, three aspects are worth highlighting. First, it is apparent that all models with the exception of the ABCF specification fulfill both correlation constraints unconditionally. Second, the correlation of gold returns with both uncertainty shocks is extremely weak (i.e., smaller than 0.02 in absolute value) across all models including LMN. Third, taking the potential of changing structural patterns into account, it is tempting to check whether C1 and C2 uniformly apply to the subsamples identified by ABCF. Interestingly, subsample specific correlations between uncertainty shocks and gold returns are all negative during the subsample beginning with the Great Recession, that is,  $t > TB2$  (where two out of four correlations are non-zero with 5% significance). In particular, the correlation between macroeconomic uncertainty shocks and gold returns is sizable (i.e., between  $-0.057$  and  $-0.224$ ) such that the change in the direction of correlation raises concerns about the adequacy of the correlation constraint C2.

### 3.2.3 | Comparative evidence from the benchmark sample in a nutshell

To summarize, the question of whether uncertainty is endogenous or exogenous is closely related to the question of which SVAR specification (LMN vs. ABCF) better captures the dynamics in the considered system. As it turns out, after retrieving shocks with weakest mutual dependence (DC models) the ICA-approach qualifies as an interesting device to ultimately trace the distinct findings of LMN and ABCF back to alternative solutions of the shock-labeling problem. While structural shocks from the ABCF model show the weakest correspondence with the event and correlation constraints among all candidate models, shocks obtained from the DC models are in line with the constraints for both shock-labeling approaches, with DC\_LMN showing a (slight) lead by construction. Hence, the event and correlations



TABLE 1 Correlation between stock market returns ( $S_t$ ) and structural shocks and gold price returns ( $G_t$ ) and structural shocks for the sample 1960:07–2015:04.

	$\text{cor}(S_t, \hat{\varepsilon}_{Um})$	$\text{cor}(G_t, \hat{\varepsilon}_{Um})$	$\text{cor}(S_t, \hat{\varepsilon}_{Uf})$	$\text{cor}(G_t, \hat{\varepsilon}_{Uf})$
LMN	−0.062	0.018	−0.162	0.011
<TB1	<b>0.052</b>	0.012	−0.121	0.0018
>TB1, <TB2	−0.201	0.072	−0.148	0.021
>TB2	−0.088	<b>−0.093</b>	−0.299	<b>−0.058</b>
ABCF	−0.001	0.010	−0.162	<b>−0.005</b>
<TB1	−0.043	0.048	−0.115	<b>−0.003</b>
>TB1, <TB2	−0.044	0.035	−0.184	0.032
>TB2	<b>0.233</b>	<b>−0.219</b>	−0.229	<b>−0.001</b>
DC_loadings	−0.006	0.004	−0.176	0.015
<TB1	−0.062	0.049	−0.087	0.007
>TB1, <TB2	<b>0.036</b>	<b>−0.005</b>	−0.191	0.036
>TB2	<b>0.088</b>	<b>−0.224</b>	−0.362	<b>−0.026</b>
DC_LMN	−0.027	0.015	−0.176	0.015
<TB1	<b>0.078</b>	0.003	−0.087	0.007
>TB1, <TB2	−0.164	0.067	−0.191	0.036
>TB2	−0.036	<b>−0.057</b>	−0.362	<b>−0.026</b>

Note: Violations of the correlation constraints of LMN are marked in boldface. Alternative column orderings of the structural parameter matrix imply that macroeconomic uncertainty shocks  $\hat{\varepsilon}_{Um}$  (economic activity shocks  $\hat{\varepsilon}_{ip}$ ) of the DC\_LMN model are labeled as economic activity shocks  $\hat{\varepsilon}_{ip}$  (macroeconomic uncertainty shocks  $\hat{\varepsilon}_{Um}$ ) in the DC\_loadings model. Both labeling procedures obtain identical financial uncertainty shocks  $\hat{\varepsilon}_{Uf}$ .

constraints might lack sufficient informational content to elicit a particular structural model. Moreover, the model suggested by LMN has some economic implications that seem to be more difficult to align with consensual economic theory. Hence, the results from the DC model are better in line with economic theory when the columns in the structural parameter matrix  $B$  are ordered according to the loadings on particular variables instead of maximizing the accordance with the LMN constraints.

#### 4 | THE HEALTH CRISIS—EVIDENCE FROM AN EXTENDED SAMPLE

Alternative structural models in Equation (3) and the implied *latent* structural shocks are equivalently in line with the reduced-form model comprising residuals  $u_t$  that can be *estimated consistently* from the data. As a result, the comparison of alternative structural models is a complicated endeavor that is ultimately subject to a priori beliefs, and requires an analyst to rely on informal criteria such as the “accordance” of structural implications and theoretical underpinnings. In the present context a further difficulty of comparing alternative models to obtain sound structural shocks that align with the event constraints E1–E6 is that the LMN model has an advantage by construction, while all other models are agnostic about single shocks. Therefore, it is a tempting exercise to expand the benchmark sample period with more recent data that include the emergence of the 2020 health (or pandemic) crisis, and analyze the structural implications of alternative models for this period. As a particular merit of such an exercise, it is worth noting that the health crisis can be considered as an exceptional event driven by important (uncertainty and activity) shocks for which all models are largely agnostic. Specifically, we proceed with a sample of  $T = 726$  observations covering the period from 1960:07 to 2020:12. Leaving the reduced-form model order unchanged, we estimate the structural models for the extended sample period. After detecting shocks with weakest dependence from the extended sample of reduced form residuals, both alternative criteria for column permutations of the structural parameter matrix  $B$  (DC\_LMN and DC\_loadings) obtain the same column ordering. Henceforth, we refer to this structural estimation result as DC\_loadings, and follow three lines of reasoning to assess alternative structural specifications in this section. First, after

estimating the structural parameters from the extended sample we compare model-implied structural shocks during the global SARS-CoV-2 outbreak in early 2020. Second, we suggest a novel approach in the SVAR literature and compare the alternative structural models in terms of their ability to “predict” the sharp slowdown of economic activity that occurred early in 2020. For this purpose, we combine the structural parameter estimates retrieved from the benchmark sample period (until April 2015) with structural shock estimates derived from the extended sample (including observations until December 2020). Third, we evaluate the robustness of core structural insights retrieved from the structural models after sample extension.

#### 4.1 | The global health crisis as a further event

Economists have some (likely consensual) beliefs about the events characterizing the global pandemic. First, it is reasonable to assume that a large spike in macroeconomic uncertainty occurred in March 2020 when Western Europe and the US started to shut down their economies to prevent the virus from spreading. Second, there should also be increased financial uncertainty in March 2020 when the stock markets crashed globally. Third, March and April 2020 should be characterized by negative production shocks.

Figure 5 shows the model-implied structural shocks during the 2020 health crisis. Overall, the shocks obtained by the ABCF and DC\_loadings model appear most reasonable, since they entail large positive financial uncertainty shocks in March 2020. Given the unprecedented and strong stock market devaluations beginning in early March 2020, a large positive shock seems to be a plausible structural model outcome. By contrast, the LMN model implies the occurrence of a negligible financial uncertainty shock that only mildly exceeds zero.

#### 4.2 | Scattergun predictions

As a further tool for structural model comparison we next turn to specific prediction exercises that are largely inspired by the conditional forecast scenarios of Baumeister and Kilian (2014), to which we refer as “scattergun predictions.” Assume that the standard assumptions regarding conditional forecast scenarios of Baumeister and Kilian (2014) apply and a structural model at hand provides an accurate approximation of the true underlying time-invariant responses of variables to fundamental shocks. Accordingly, “scenarios” of (future) structural shocks should be mapped to the observable variables in terms of the structural MA representation in Equation (5).

The objective of the scattergun predictions is to feed supposedly informative scenarios of future health crisis shocks into the structural MA representations of alternative SVARs (LMN, ABCF, DC\_loadings), which are conditional on information from the benchmark sample period. As shocks of interest, we take the estimated macroeconomic uncertainty, financial uncertainty and economic activity shocks that obtain from alternative SVARs fitted to the extended

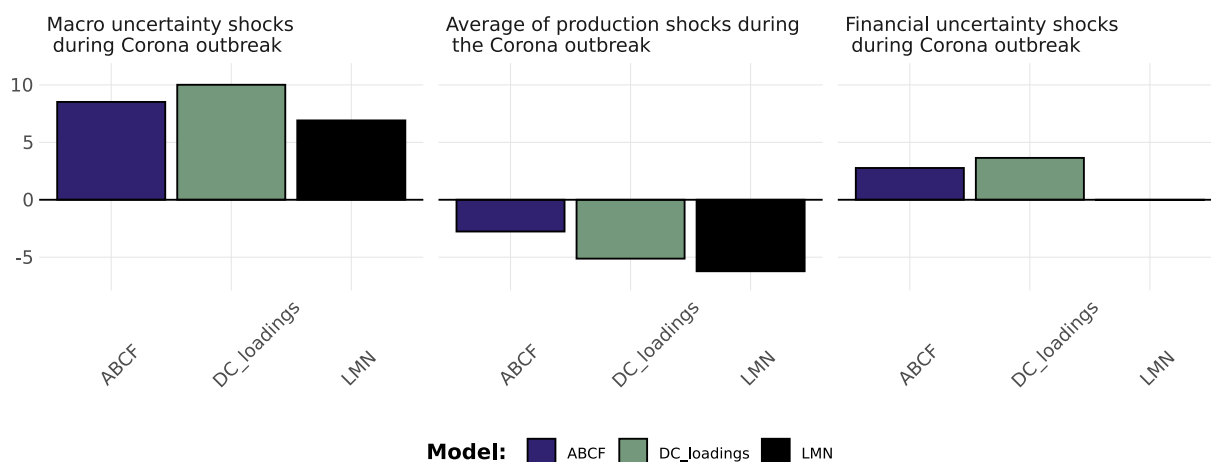


FIGURE 5 Comparison of the magnitudes of the structural shocks during the Covid outbreak, obtained by  $\hat{B}_\cdot \in \{\text{ABCF}, \text{DC\_loadings}, \text{LMN}\}$ . Conditional on the extended sample, the DC\_LMN and DC\_loadings criteria obtain identical column orderings for the structural parameter matrix.

sample for the period from January 2020 to August 2020, that is, model-specific estimates of  $\varepsilon_t$ ,  $t \in [2020:01, 2020:08]$ . Hence, the combination of structural estimates conditioning on the benchmark sample and future shocks enables a comparison of model-specific industrial production forecasts and actual realizations in the first half of 2020.<sup>10</sup> Evidently, if all considered structural models approximate the true dynamics with sufficient accuracy, inserting shocks from alternative specifications should result in similar predictive outcomes.

The results in Figure 6 reveal clear distinctions among the predictive performances of the alternative structural models. The red line in each panel shows a baseline forecast obtained from the reduced-form VAR (see Equation 1) by setting all shocks after December 2019 to their zero expectation. Hence, these baseline forecasts are obtained without using any additional (future) information about the approaching health crisis. Unsurprisingly, the VAR predictions fail to signal the sharp decline in industrial production in March and April 2020. However, adding the (model-specific) responses of (model-specific) health crisis shocks to the forecasts leads to non-trivial estimates of industrial production in 2020. For instance, conditioning on the structural transmission patterns of the ABCF and DC\_loadings model yields largely realistic approximations of the observed economic slowdown. Especially, using the structural shocks from DC\_loadings results in a remarkably close approximation of the actual response of industrial production. By contrast, matching future information (regardless from which model) with the structural MA representation of the LMN model yields a rather weak predictive performance, which signals improvements of industrial production (at least) in the short run for all displayed scenarios. This finding can be explained by noting that all models reveal a large macroeconomic uncertainty shock in March 2020 (see Figure 5), and LMN estimates of the structural MA representation in Equation (5) imply a positive response of industrial production to a positive macroeconomic uncertainty shock (see also the IRFs in Figure 2). An open question for now is how the scattergun predictions of the LMN model fit to the obtained structural shocks from Figure 5. We next address this issue by evaluating structural IRFs conditional on sample information up to December 2020.

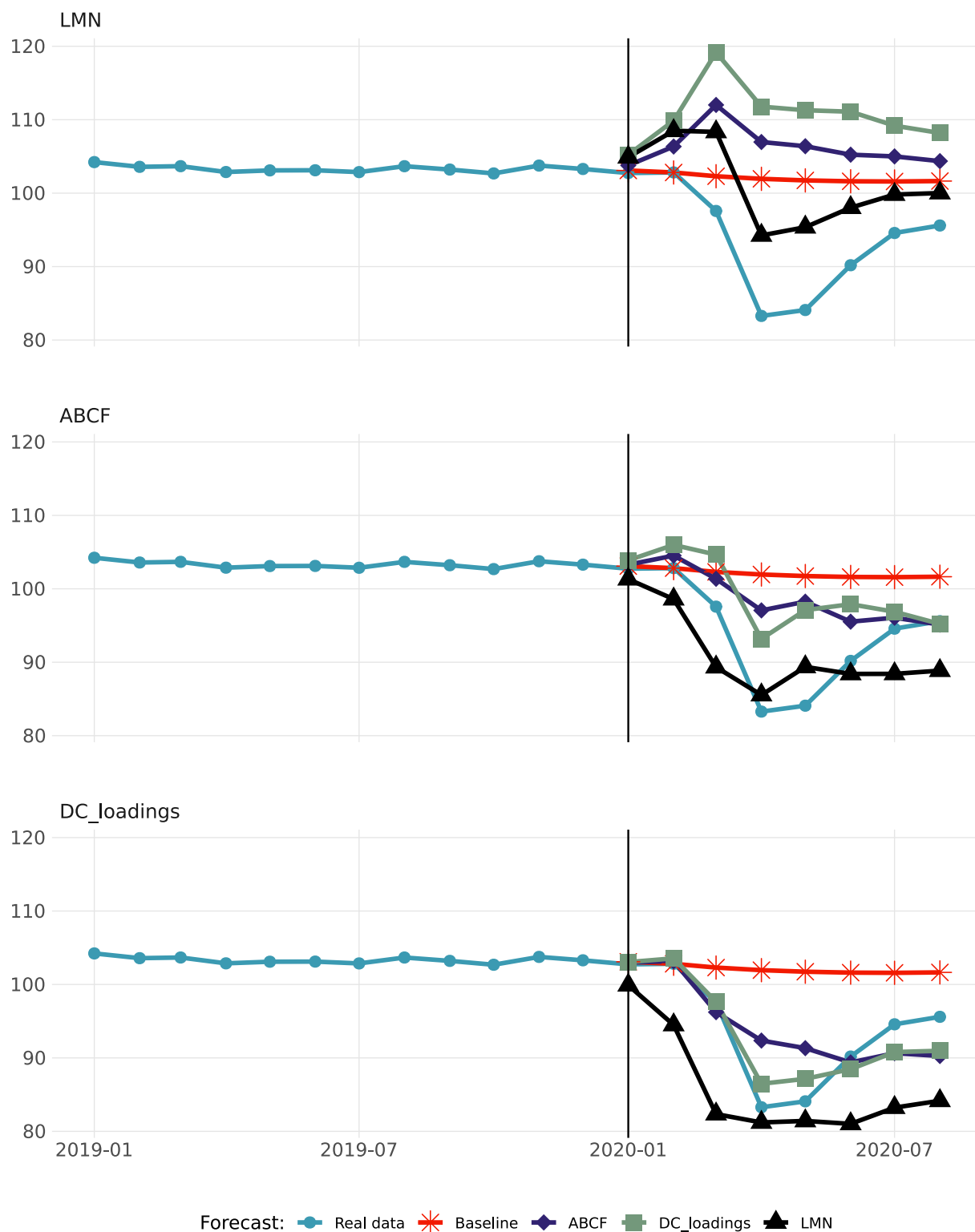
### 4.3 | Robustness of the LMN model in an extended sample

Turning to the structural IRFs conditional on the entire available sample until December 2020, we find remarkable results. While the economic implications from the group  $\mathcal{A}$  models remain largely robust for the extended sample, some of the key results from the LMN approach are subject to considerable changes. In particular, IRFs displayed in Figure 7 show that (i) there is no longer a significantly positive response of industrial production to an increase in macroeconomic uncertainty, and (ii) there is no longer a significantly negative response of macroeconomic uncertainty to an economic activity shock. Hence, it appears that the economic implications of the LMN model approach those of the  $\mathcal{A}$  models, that is, macroeconomic uncertainty is exogenous to the business cycle and adversely affects economic activity.<sup>11</sup>

For the robustness analysis visualized in Figure 7 the health crisis event information has been used somehow *passively* for purposes of structural modeling. As an alternative exercise, one might consider the information from the global pandemic more *actively* to provide an additional event constraint subject to particular large uncertainty shocks in the vein of LMN. It is worth to notice that adding informative constraints to the LMN model by setting the threshold for macroeconomic and financial uncertainty shocks at the 75<sup>th</sup> percentile in March 2020 (both thresholds are about 2.8) leads to an empty solution set. While one could interpret this finding to indicate that the data do not support the extended set of event constraints (E1–E6 & two health crisis constraints), it is interesting to observe that the alternative models (ABCF and DC\_loadings) are largely in line with both narratives of large macroeconomic and financial uncertainty shocks in March 2020 as well as with E1–E6 (to the extent explained above).

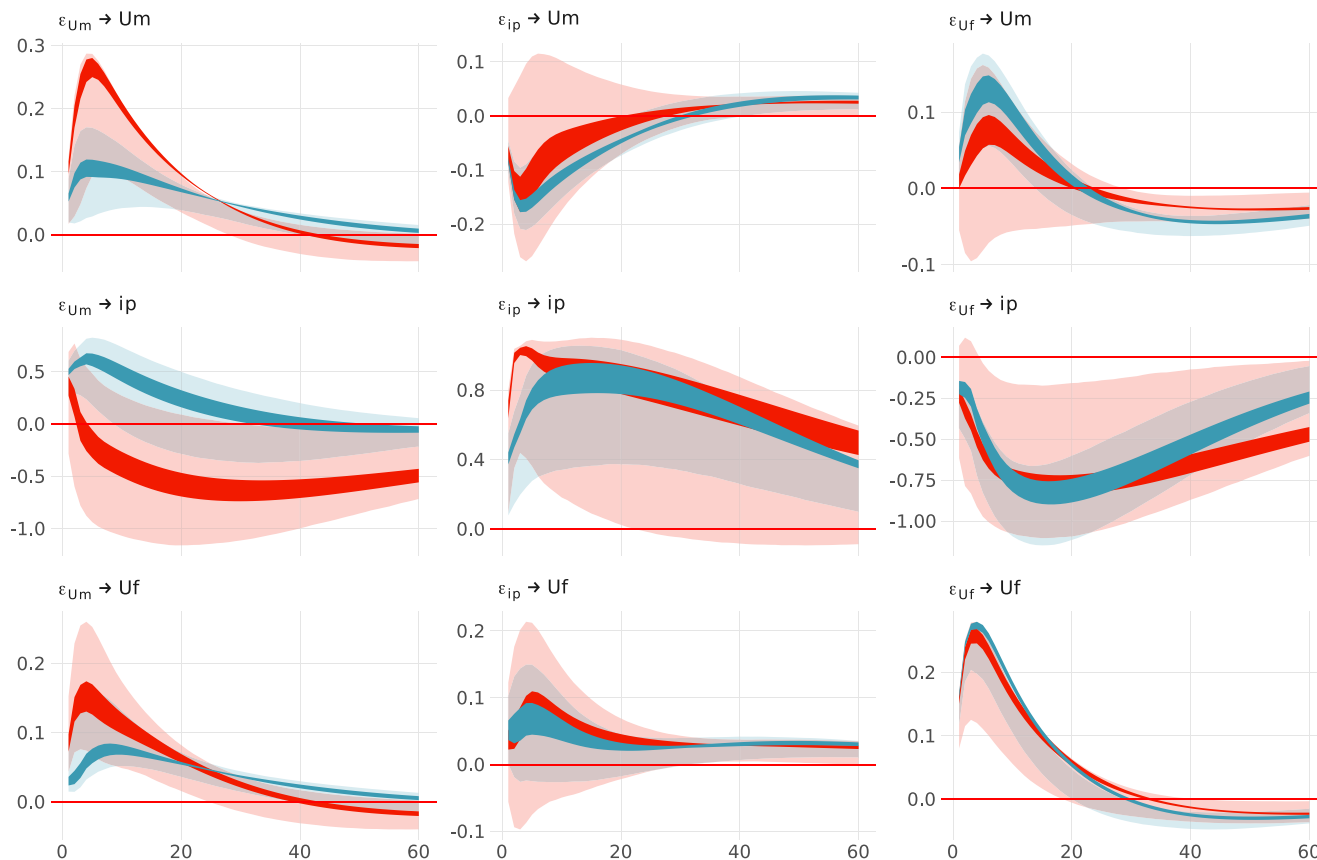
### 4.4 | Evidence from an extended sample in a nutshell

A comparative analysis of alternative structural models is complicated by the fact the reduced form model equally aligns with a multitude of structural specifications. In this regard, a sample extension could provide useful information on model performance in scenarios that have been left unrestricted in the process of structural model building. The health crisis in 2020 is a prime example indicating the limited scope of the LMN model for understanding additional events that are not part of the original information set. Unlike alternative models, it fails to issue sizeable financial uncertainty shocks in March 2020 and model implied scattergun predictions signify profiles of economic growth to occur early in 2020. Moreover, as more observations are incorporated for model estimation, the economic interpretation of the LMN



**FIGURE 6** Scattergun forecasts of industrial production for the global health crisis. The vertical lines represent the beginning of the forecast periods.

model approaches the implications of the ABCF model. Hence, narrative event and correlation constraints have only a limited potential to unravel (effects of) economic uncertainty in a structural manner. Overall, we find more support for the ABCF interpretation that both macroeconomic uncertainty and financial uncertainty are exogenous and that an increase of macroeconomic uncertainty triggers economic slowdown.



**FIGURE 7** Comparison of IRFs obtained from the LMN model conditional on the sample periods 1960:07–2015:04 (blue) and 1960:07–2020:12 (red). The solid ribbons report the identified set of IRFs and the shaded area the 90% bootstrap confidence bands based on the procedure described in LMN. IRFs, impulse response functions.

## 5 | ARE SHOCKS TO UNCERTAINTY OR SHOCKS TO REALIZED VOLATILITY CONTRACTIONARY FOR THE ECONOMY?

A critical discourse has recently emerged on whether economic contractions are falsely attributed to uncertainty shocks, when in fact economic agents respond to accelerations of realized volatility (BDBG; Dew-Becker et al., 2021). Accordingly, BDBG call for a critical reassessment and a careful distinction between current volatility and uncertainty about the future. While increases in the former can be soundly associated with economic slack, the latter lack effects on real economic activity. To differentiate the effects of uncertainty and realized volatility within an informationally augmented VAR, the structural analysis in this Section relies exclusively on the ICA approach to identification for two reasons. First, it is interesting to see that the detection of independent components yields remarkably robust structural results across sample sizes in the benchmark three-dimensional VAR, in terms of both narrative constraints and alignment with economic theory. Second, while adopting ICA-based identification within higher-dimensional systems appears straightforward (see, e.g., Herwartz, Maxand, & Rohloff, 2022), generalizing the benchmark identification approaches of LMN and ABCF toward higher-dimensional VARs is more complicated and likely requires further external information in the form of additional narratives and exclusion restrictions, respectively.

BDBG argue that when modeling the impacts of uncertainty shocks on economic variables by including an uncertainty proxy (in their case implied volatility) without accounting for realized volatility, it becomes likely to estimate a compound signal about expected future volatility that covers an adaptive realized volatility part and an anticipated implied volatility part. In this regard, expectations of economic agents about future volatility are usually considered to be positively correlated with realized volatility, that is, high volatility today predicts high volatility in the future. However, in the framework of structural VAR models, researchers typically aim to isolate the effect of the forward-looking component of implied volatility which should be orthogonal to current realized volatility. BDBG show that by including both option-implied volatility as uncertainty proxy and realized volatility into a VAR model, the identified



uncertainty shocks have no significant impact on economic variables, while realized volatility shocks adversely affect economic activity. In this regard, Supporting Information S1: Appendix E provides a replication of their main empirical results and a respective robustness analysis.

In this section, we conduct a structural analysis for an informational augmentation of the benchmark VAR of LMN. Specifically, we add two additional variables, that is, an index for realized macroeconomic volatility and a measure of realized financial volatility. To construct these variables, we follow Jurado et al. (2015) and first estimate the realized squared forecast errors from the McCracken and Ng (2016) data set by means of factor-augmented regressions. Similar to Dew-Becker et al. (2021), we take the first principal component of the squared residuals for each month to obtain an index of realized macroeconomic volatility.<sup>12</sup> To estimate realized financial volatility, we follow BDBG and take for each month the sum over all daily squared returns of the S&P500. We estimate the five-dimensional SVAR for the extended sample period (1960:07–2020:12) by means of the DC approach with a column ordering of the structural parameter matrix that maximizes the sum of the estimated loadings along the diagonal. Next, we discuss the structural results (IRFs and FEVDs) from the informationally augmented model, and subsequently reconsider the event and correlation constraints of LMN within this framework.

## 5.1 | IRFs and FEVDs from an augmented VAR

Figure 8 shows estimated structural IRFs obtained from the five-dimensional SVAR. Despite the inclusion of realized volatility measures into the model, both macroeconomic and financial uncertainty shocks still reduce economic output. Moreover, neither realized macroeconomic nor financial volatility shocks exert significant impacts on industrial production (see also the replication in Supporting Information S1: Appendix E).<sup>13</sup> We find that the conflicting outcomes can be traced back to the choice of the uncertainty proxy, that is, option-implied volatility indices as used by BDBG are much weaker instruments for general uncertainty than the indices of LMN. More specifically, the LMN index contains option-implied volatility measures in addition to a variety of other financial indicators and is therefore more informative. Hence, the structural shocks retrieved from option-implied volatility are better characterized as a very specific

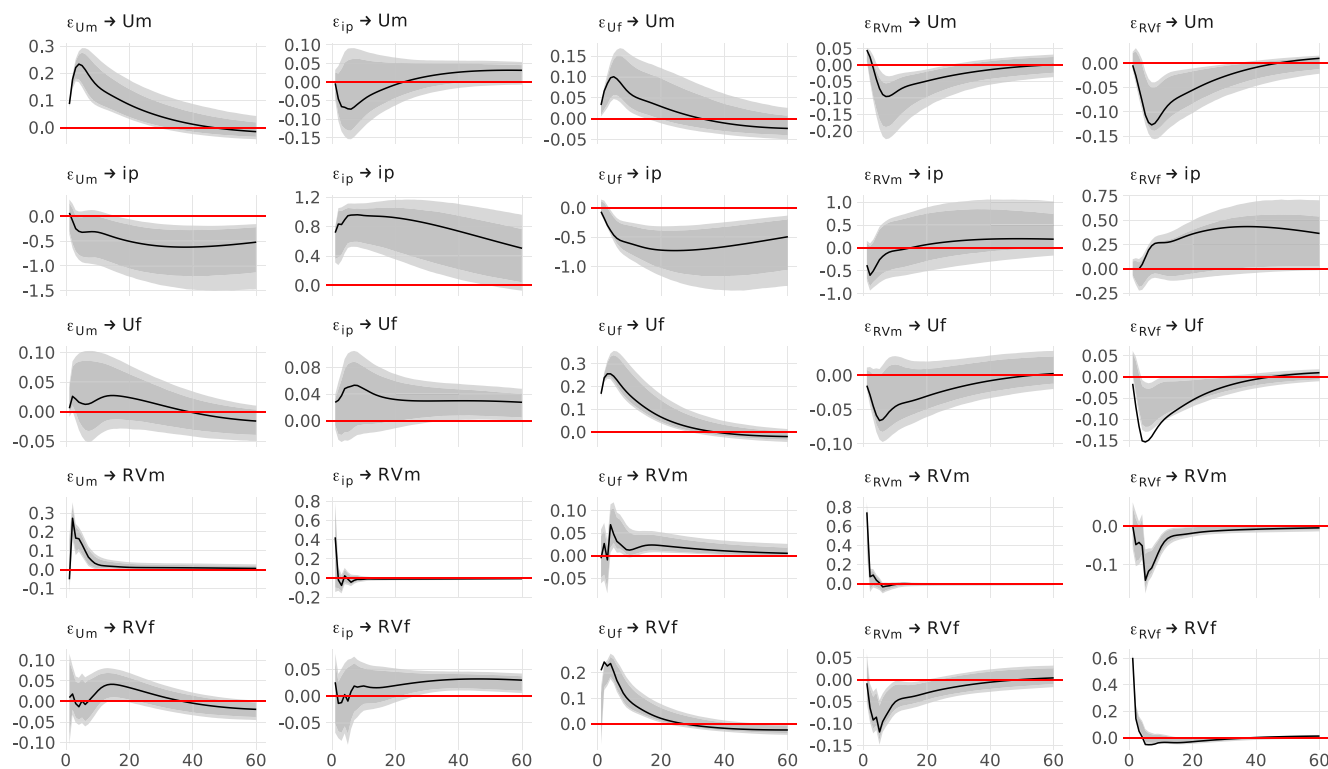


FIGURE 8 IRFs obtained from the DC model jointly with 68% (90%) confidence bands obtained by means of a wild bootstrap. IRFs, impulse response functions.

type of uncertainty, for example, stock market uncertainty, which appears to exert a weaker impact on the business cycle compared with broader notions of financial or macroeconomic uncertainty.

Regarding the potential origins of realized volatility, the IRFs in Figure 8 show that positive shocks for both types of uncertainty also shift the corresponding realized volatility index sharply upward, which does not hold vice versa. In addition, the FEVDs depicted in Table 2 reveal that uncertainty shocks have a larger explanatory content for the variation in realized volatility in comparison with the reverse direction. For instance, financial uncertainty shocks explain about twice as much variation in the forecast errors of realized financial volatility than vice versa. Although both types of uncertainty are not exogenous to their realized counterparts, we conclude that higher realized volatility can be better characterized as an effect rather than a cause of increased uncertainty.

## 5.2 | Uncertainty shocks versus surprise information in realized volatility

We consider again the LMN events and the recent health crisis to describe uncertainty and realized volatility shocks as displayed in Figure 9. To fully capture the dynamics during periods of economic turbulence, we not only look at the exact dates of LMN but also consider the shocks occurring around these dates.

The overall picture regarding a correct specification of the constraints as uncertainty events is ambiguous. For instance, while the three-dimensional as well as the five-dimensional model imply a financial uncertainty shock on the Black Monday in October 1987 of about five standard deviations (see Figure 4), the event in December 1970 seems to be better characterized as a shock to realized macroeconomic volatility rather than a macroeconomic uncertainty shock. Moreover, a large fraction of the macroeconomic uncertainty shock in March 2020 from the three-dimensional model (see Figure 5) must actually be attributed to realized macroeconomic volatility. The event of the European debt-ceiling crisis (E6) is difficult to evaluate, since the crisis evolved over a long time span covering about 2 years (2010–2012). However, the economic downturns in Europe were not transmitted to the US, and spillovers of turmoil were limited to financial markets. The shock sizes displayed in Figure 9 support the narrative of no occurrences of large shocks neither to macroeconomic uncertainty nor realized macroeconomic volatility. By contrast, but in line with E6 of LMN, we detect a sequence of larger financial uncertainty shocks in mid-2011 with the two largest shocks occurring in July and August 2011. Nevertheless, the largest single shock of size three standard deviations during the debt-ceiling crisis is a realized volatility shock that occurred in August 2011, the month featuring the largest loss of the S&P 500 in 2011 and 2012.

We find that the occurrence of a large realized volatility shock that exceeds the threshold of two standard deviations often corresponds to the peak of a certain crisis, for example, the Black Monday, the European debt-ceiling crisis or the recent health crisis. In the following month, financial markets and the real economy usually recover from the turbulence, which fits into the notion that realized volatility is not the cause but the outcome of uncertainty and economic distress. By contrast, sizable uncertainty shocks tend to occur prior to the actual event. For instance, prior to the stock

TABLE 2 FEVDs of uncertainty and realized volatility indices.

FEVD of $U_m$						FEVD of $U_f$				
Horizon	$\varepsilon_{U_m} \rightarrow$	$\varepsilon_{ip} \rightarrow$	$\varepsilon_{U_f} \rightarrow$	$\varepsilon_{RV_m} \rightarrow$	$\varepsilon_{RV_f} \rightarrow$	$\varepsilon_{U_m} \rightarrow$	$\varepsilon_{ip} \rightarrow$	$\varepsilon_{U_f} \rightarrow$	$\varepsilon_{RV_m} \rightarrow$	$\varepsilon_{RV_f} \rightarrow$
1	78.2	4.2	10.9	5.3	1.3	0.8	1.8	90.7	1.1	5.6
6	67.4	6.0	11.6	5.0	10.0	0.4	2.4	74.1	3.4	19.7
12	59.0	5.5	10.2	9.2	16.1	0.6	3.4	69.3	4.0	22.8
$\infty$	55.4	6.8	9.6	11.1	17.1	1.6	7.3	62.9	4.8	23.3
FEVD of $RV_m$						FEVD of $RV_f$				
1	9.3	22.0	0.1	68.2	0.3	0.1	0.2	20.9	0.8	78.0
6	16.4	19.5	0.9	59.0	4.1	0.1	0.2	39.1	6.0	54.6
12	16.6	18.8	1.1	56.6	6.9	0.5	0.4	42.3	7.8	49.0
$\infty$	16.7	18.5	2.0	55.3	7.5	2.7	4.3	39.9	8.6	44.5

Note: The left-hand (right-hand) side depicts macroeconomic (financial) measures.

Abbreviation: FEVD, forecast error variance decomposition.



**FIGURE 9** Comparison of sign and magnitude of estimated structural shocks obtained by the DC model around the special events from LMN. Negative shocks are indicated by red bars and positive shocks by blue bars. For the sake of orientation, the horizontal dotted lines show the size of a two standard deviation shock.

market crash in September 2008, uncertainty shocks are markedly positive, while considerably negative shocks to realized financial volatility fail to accentuate the August 2008 collapse of mortgage companies Fannie Mae and Freddie Mac as an important trigger of an uncertain posture in the US economy. Pointing in a similar direction, large positive financial and macroeconomic uncertainty shocks already occurred in January and February 2020, when there were almost no reported cases of Covid 19 in the US. However, some market participants could have anticipated future turmoil, when the Chinese government began sealing off the city of Wuhan on January 23, 2020, and a global spreading of the virus became more likely.

Evaluating the correlation constraints of LMN, results in Table 3 show that while financial uncertainty shocks are contemporaneously and serially negatively correlated with stock market returns, realized financial volatility shocks are serially positively correlated with S&P500 returns. This finding aligns with the conclusion that enhanced financial uncertainty seems to lead to realized financial turbulence. By contrast, the occurrence of large realized financial volatility shocks could signal spikes in market sell offs, after which markets tend to recover. The dependence between gold returns and the alternative structural shocks is weak across lags.

## 6 | CONCLUSIONS

Although the role of economic uncertainties has recently attracted a huge research interest, the literature still lacks consensus regarding several important aspects, that is, (i) whether or not uncertainty is a source or an effect of business cycle fluctuations, (ii) the impact direction of uncertainty shocks on economic activity, and (iii) the separation of uncertainty shocks from (second-order moment) news shocks or realized volatility shocks. In this work, we have addressed these issues by evaluating alternative SVAR models used in the uncertainty literature and a new method based on independent component analysis. Opposite views held about causal effects of uncertainty on economic activities can be reconciled in the form of alternative solutions to the economic labeling of shocks retrieved from the data in the form of independent components. The identification of underlying shocks as independent non-Gaussian

**TABLE 3** Correlation between stock market returns ( $S_t$ ) and structural shocks and gold price returns ( $G_t$ ) and structural shocks for the sample 1960:07–2020:12.

$\text{cor}(S_t, \hat{\varepsilon}_{t-h})$					$\text{cor}(G_t, \hat{\varepsilon}_{t-h})$			
lag $h$	$\varepsilon_{Um,t-h}$	$\varepsilon_{Uf,t-h}$	$\varepsilon_{RVm,t-h}$	$\varepsilon_{RVf,t-h}$	$\varepsilon_{Um,t-h}$	$\varepsilon_{Uf,t-h}$	$\varepsilon_{RVm,t-h}$	$\varepsilon_{RVf,t-h}$
0	0.02	−0.19	−0.01	−0.2	0.01	0.02	0	0.02
1	−0.04	−0.18	0.09	0.11	−0.03	−0.02	0.03	−0.02
2	−0.01	−0.08	0.06	0.17	−0.02	−0.01	−0.01	−0.01
3	0.02	−0.05	0.06	0.09	−0.07	0.02	0	0.01

*Note:* The table shows the results for stock market and gold returns in month  $t$  and the structural shocks in month  $t - h$ , that is, the first row  $h = 0$  represents the correlation constraint in LMN.

components recovers economically and historically plausible shocks for both, the sample period considered in benchmark studies (Angelini et al., 2019; Ludvigson et al., 2021) and a sample extended up to December 2020 to include the onset of the pandemic crisis and the emergence of economically uncertain states. Moreover, the independent component approach allows for a straightforward generalization of the existing three-dimensional benchmark models toward higher-dimensional SVARs to address the ultimate role of uncertainty shocks or realized volatilities in shaping economic activity (Berger et al., 2019).

We provide four main novel insights into the interaction between uncertainties and the real economy. First, we find that macroeconomic as well as financial uncertainty are exogenous sources of business cycle fluctuations. Second, both types of uncertainty have adverse effects on the economy. These two findings are clearly at odds with results of Ludvigson et al. (2021) but align with the results of Angelini et al. (2019). The conflicting positions in the literature are due to the relatively weak identifying power of the narrative event and correlation constraints suggested by Ludvigson et al. (2021) for set identification. In particular, the model of LMN does not issue large financial uncertainty shocks in March 2020, and in a pseudo-predictive exercise the LMN model is unique in obtaining unreliable projections of economic growth early in 2020 as a consequence of positive shocks to macroeconomic uncertainty. Third, omitting measures of realized volatility does not lead to an overestimation of the effects of uncertainty shocks. In fact, we find that shocks to realized volatility are much less important for economic variables than previously thought, a result that is seemingly at odds with evidence provided by Berger et al. (2019). However, the contradictory results in this regard can be well explained by the circumstance that unlike Ludvigson et al. (2021) and Angelini et al. (2019), Berger et al. (2019) employ a relatively weak proxy for uncertainty (VIX). Hence, SVARs including such uncertainty assessments should be subject to cautious structural analysis and careful interpretation of implied “uncertainty shocks.”

In Supporting Information S1: Appendix F, we already provide in a comparative manner some insights into the transmission of macroeconomic versus financial uncertainties to the economy. From these exercises it appears that both macroeconomic and financial uncertainty are transmitted into the economy through a tightening of financial conditions, but mainly macroeconomic uncertainty causes firms and households to postpone investment and consumption. While this evidence highlights that not only uncertainty emanating from the financial system can pose a threat to the economy, but also uncertainty originating from the real economy, we leave a systematic comparison of relevant transmission channels of financial and macroeconomic uncertainties to economic slack as an interesting issue for future research. Owing to institutional heterogeneities in goods and financial markets, however, the speed of information processing might give an interesting direction of research when it comes to a deeper analysis of relevant transmission channels.

## ACKNOWLEDGMENTS

We gratefully acknowledge helpful comments from three anonymous reviewers, and from participants of research seminars at the Universidad de Chile, Santiago, and the University of Cologne. We also acknowledge gratefully financial support by the Deutsche Forschungsgemeinschaft (BE 5381/1-2, HE 2188/8-2).

Open Access funding enabled and organized by Projekt DEAL.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available at <https://doi.org/10.3886/E188341V1> (Herwartz & Lange, 2023).

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## ENDNOTES

- <sup>1</sup> Risk is often measured as conditional volatility of returns (e.g., by means of generalized autoregressive conditional heteroskedasticity [GARCH] models; Bollerslev, 1986), which is distinct to the definition of uncertainty. However, uncertainty can be one source of time-varying risk.
- <sup>2</sup> Several ICA-based identification schemes have been suggested in the econometric literature on SVAR identification (see, e.g., Matteson & Tsay, 2017; Moneta et al., 2013; Lanne et al., 2017). Kilian and Lütkepohl (2017) provide a textbook treatment of alternative branches of identification in SVARs with an embedding of data-based identification schemes such as ICA-based approaches. Herwartz, Lange, and Maxand (2022) provide a large scale simulation study of alternative identification techniques applying under heterogeneous data generating processes. These authors conclude that the identification approach suggested by Matteson and Tsay (2017) performs remarkably robust and is particularly helpful if an analyst lacks trustworthy information on the actual data generating process. See Section 3.1.3 for more details.
- <sup>3</sup> Jurado et al. (2015) do not use realized forecast errors but estimate the implied volatility component of each realized volatility process by means of stochastic volatility models such that their measure is independent of first-order moment dynamics.
- <sup>4</sup> <https://www.sydneyludvigson.com>. For a systematic overview of all data and data sources see Supporting Information S1: Appendix G.
- <sup>5</sup> As a matter of fact, a small-scale VAR might suffer from nonfundamentality (omitted variables) such that it is not suitable to extract truly structural shocks. Testing the hypothesis of fundamentality explicitly, ABCF do not find evidence in favor of informational deficiencies of the three-dimensional VAR in this respect (see the technical supplement No. 6 of ABCF for details).
- <sup>6</sup> For the present system of variables, the economically admissible model of LMN is clearly at-odds with a recursive model structure (see also the replication of their results as displayed in Figure 7).
- <sup>7</sup> Herwartz, Lange, and Maxand (2022) provide simulation-based evidence on the performance of several alternative identification techniques and stress their (relative) advantages and drawbacks conditional on a broad selection of potential data generating processes. As a particular finding, identification via independent components as applied in this study is more robust with respect to alternative distributional frameworks (including heteroskedastic processes) as long as the innovations are non-Gaussian. Hence the approach suggested by Matteson and Tsay (2017) might be a prime device for data-based identification, if an analyst lacks sufficiently specific knowledge about the true model of data generation.
- <sup>8</sup> For further details on structural model implementation under event and correlation constraints see Supporting Information S1: Appendix A.1.
- <sup>9</sup> The JLN index of macroeconomic uncertainty is also built from financial indicators. The results shown in Figure 2 remain robust if macroeconomic uncertainty is constructed only from real economic data (see Supporting Information S1: Appendix D.1 for details).
- <sup>10</sup> Unlike the forecast scenarios of Baumeister and Kilian (2014), the suggested scattergun predictions do not process hypothetical scenarios or rely on historical shocks, but rather retrieve the realistic scenarios of interest from the structural analysis of an extended sample. For purposes of valid scenario analysis we build implicitly upon the assumption of superexogeneity in the spirit of Engle et al. (1983).
- <sup>11</sup> For a robustness check with the original model specification of LMN see Supporting Information S1: Appendix D.3. IRFs from the remaining models conditional on the extended sample are available from the authors upon request.
- <sup>12</sup> We use code from the replication files of Jurado et al. (2015).
- <sup>13</sup> Note that realized volatility shocks cannot be directly interpreted as structural shocks in an economic sense, since there are multiple sources of realized volatility (Berger et al., 2019). However, for the sake of simplicity, we frame all shocks in the system as structural in this work. Moreover, the findings are robust to replacing realized financial volatility by the first principal component from the squared forecast residuals of the 148 financial time series from the data set of Ludvigson and Ng (2007).

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

**How to cite this article:** Herwartz, H. & Lange, A. (2024) How certain are we about the role of uncertainty in the economy? *Economic Inquiry*, 62(1), 126–149. Available from: <https://doi.org/10.1111/ecin.13166>