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Uncertainty across volatility regimes

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Summary

We propose a nonrecursive identification scheme for uncertainty shocks that
exploits breaks in the volatility of macroeconomic variables and is novel in the
literature on uncertainty. This approach allows us to simultaneously address
two major questions in the empirical literature: Is uncertainty a cause or effect
of decline in economic activity? Does the relationship between uncertainty and
economic activity change across macroeconomic regimes? Results based on a
small-scale vector autoregression with US monthly data suggest that (i) uncer-
tainty is an exogenous source of decline of economic activity, and (ii) the effects
of uncertainty shocks amplify in periods of economic and financial turmoil.

1 | INTRODUCTION

Since the aftermath of the recent global financial crisis (GFC), there has been renewed attention to the role played by
uncertainty as a driver of the business cycle. Three main findings have emerged from the extant literature: First, heightened
uncertainty triggers a contraction in real activity; second, uncertainty tends to be higher during economic recessions;
third, the effects of uncertainty shocks are not constant over time. The first finding is consistent with the theoretical
literature, which shows why uncertainty can have negative macroeconomic effects. The prevailing view is that uncertainty
is recessionary in the presence of real options effects (e.g., Bloom, 2009) or financial frictions (e.g., Christriano, Motto, &
Rostagno, 2014). However, uncertainty appears also to endogenously increase during recessions, as lower economic growth
induces greater dispersion at the micro level and higher aggregate volatility. This second finding is consistent with the
theoretical literature on "endogenous uncertainty," which contends that uncertainty is rather a consequence, not a cause,
of declining economic activity, as, for example, in Van Nieuwerburgh and Veldkamp (2006), Bachmann and Moscarini
(2012), Fajgelbaum, Taschereau-Dumouchel, and Schaal (2017), Gourio (2014), Navarro (2014), and Plante, Richter, and
Throckmorton (2018). The fact that the relationship between uncertainty and real activity may not be constant over time
is consistent with theoretical models that show how the effects of heightened uncertainty can be amplified in extreme
conditions such as high financial stress (e.g., Alfaro, Bloom, & Lin, 2018; Arellano, Bai, & Kehoe, 2018; Gilchrist, Sim,
& Zakrajsek, 2014) or when monetary policy is constrained by the zero lower bound (Basu & Bundick, 2017).

   Whether causality runs from uncertainty to real activity, or from real activity to uncertainty, or in both directions,
and whether this relationship changes under different macroeconomic conditions, are issues that can be investigated
empirically within a structural vector autoregression (SVAR) framework. The first issue requires moving away from recur-
sive identification schemes, which are by construction ill suited to shed light on the reverse causality issue. This topic
has been explicitly analyzed in Ludvigson, Ma, and Ng (2018a) and Carriero, Clark, and Marcellino (2018b), reporting

mixed evidence. The second issue requires moving away from linear SVARs, which would not allow to uncover possibly regime-dependent effects of uncertainty shocks. This concern has been addressed in the recent literature, and evidence that uncertainty shocks have time-varying effects has been provided by, among others, Alessandri and Mumtaz (2018), Caggiano, Castelnuovo, and Groshenny (2014), and Caggiano, Castelnuovo, and Pellegrino (2017). These early attempts of examining causality and time variation of uncertainty shocks have looked at the two issues in isolation. In light of the findings in the literature, however, this seems to be a strong limitation: If the relationship between uncertainty and real activity is indeed time varying (or regime dependent), it may very well be the case that also the direction of causality might change over time—something which a time-invariant SVAR would be unable to uncover.

This paper fills this gap by proposing a nonrecursively identified SVAR model that exploits breaks in the (unconditional) volatility of post-WW2 US macroeconomic variables. Within this framework, we can allow both for on-impact effects of uncertainty on real activity and vice versa, and for regime dependence in these effects. As discussed in Magnusson and Mavroeidis (2014), structural breaks induced by policy shifts and/or the occurrence of financial crises provide exogenous identifying information that can be fruitfully used for inference. The identification strategy we apply extends the standard "identification-through-heteroskedasticity" approach, popularized in the empirical macroeconomic literature by Rigobon (2003), Rigobon and Sack (2003), and Lanne and Lütkepohl (2008), to the case where the structural parameters (on-impact coefficients), and hence the associated impulse response functions (IRFs), may vary across volatility regimes (see Bacchiocchi, Castelnuovo, & Fanelli, 2018; Bacchiocchi & Fanelli, 2015). In this setup, changes in the VAR covariance matrix can be also ascribed to variations in the structural parameters, and identification is achieved by imposing restrictions on the changes that characterize these parameters across volatility regimes. This opens up interesting possibilities for practitioners relative to "standard" SVARs. In general, there are more moment conditions that can be used to identify the shocks jointly with theory-based restrictions, and the method is flexible enough to jointly allow for recursive and nonrecursive structures across volatility regimes, provided a necessary and sufficient rank condition is respected. This is particularly important when addressing the issue of exogeneity/endogeneity of uncertainty, since it endows us with a formal test for exogeneity with the highly desirable property of accounting for potential dependence to macroeconomic (volatility) regimes.

We estimate, as in Ludvigson et al. (2018a), a small-scale SVAR with three variables: a measure of real activity, Y_t; an index of macroeconomic uncertainty, U_{Mt}; and an index of financial uncertainty, U_{Ft}. Real activity is proxied by either industrial production or employment, and the indices of macroeconomic and financial uncertainty are taken from Jurado, Ludvigson, and Ng (2015) and Ludvigson et al. (2018a), respectively.[1] As argued in Ludvigson et al. (2018a), the joint use of macroeconomic and financial uncertainty indices is crucial to correctly uncover the relationship between uncertainty and real activity, since they can display substantially different properties. Data are monthly and span the 1960–2015 sample. Using recursive and rolling-windows estimates of the VAR covariance matrix, we show that two main volatility breaks are consistent with the pattern of data, and can be associated with two important episodes of the US history: One is the onset of the Great Moderation, and the other is the GFC of 2007–2008. This leads to the identification of three broad volatility regimes in the data, which correspond to three well-known macroeconomic regimes: the "Great Inflation" period (1960:M8–1984:M3), the "Great Moderation" period (1984:M4–2007:M12) and the "Great Recession + Slow Recovery" period (2008:M1–2015M4).[2] We then identify shocks by specifying a nonrecursive structural model that exploits the differences in the average level of volatility displayed by macroeconomic variables in the three different subsamples.

Our main findings can be summarized as follows. First, macroeconomic uncertainty can be better described as an exogenous driver of the US business cycle. Macroeconomic uncertainty shocks trigger a decline in US real economic activity, whose magnitude and persistence are estimated to be larger during Great Recession + Slow Recovery period, while the opposite is not supported by the empirical evidence. This finding holds true in all three macroeconomic regimes and is robust to several perturbations of the baseline model, such as the use of alternative measures of real activity and macroeconomic uncertainty, and also controlling for financial stress. Second, from the Great Moderation onwards, the pass-through of financial uncertainty to real economic activity is found to be indirect: Financial uncertainty shocks trigger macroeconomic uncertainty and, via this channel, a contraction in real activity, with effects that amplify after the GFC. Financial uncertainty does not respond to real economic activity shocks nor to macroeconomic uncertainty shocks.

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[1]Other measures of macro uncertainty available in the literature have been proposed by Rossi, Sekhposyan, and Soupre (2016) and Scotti (2016). We use the measure proposed by Jurado et al. (2015) to be consistent with the VAR specification in Ludvigson et al. (2018a); see below. In Carriero, Clark, and Marcellino (2018a) uncertainty and its effects are instead estimated in a single step within the same model.

[2]Given the strong and well-established association between the (average) volatility of most macroeconomic variables and specific macroeconomic regimes of US economic history (e.g.,McConnell & Perez-Quiros, 2000), throughout the paper we use the terms "volatility regime" and "macroeconomic regime" interchangeably.

Third, the estimated impulse responses differ substantially from those coming from a benchmark represented by a SVAR identified with heteroskedasticity along the lines of Lanne and Lütkepohl's (2008) method—that is, by imposing that the autoregressive and the structural parameters are fixed across volatility regimes.

Overall, our findings support the claim that uncertainty, both macro and financial, is an exogenous driver of the business cycle, with contractionary effects on real activity that change over time. While we share the exogeneity of financial uncertainty with other contributions (e.g., Ludvigson et al., 2018a), one key finding of our paper is the exogeneity of macroeconomic uncertainty. We explicitly test this assumption in our structural model, and do not reject it. To this end, we consider two overidentified nonrecursive SVARs, one featuring "endogenous" macroeconomic uncertainty in the three volatility regimes, and a restricted (nested) version in which macroeconomic uncertainty does not respond contemporaneously to real activity shocks in the three volatility regimes. The SVAR with "endogenous" macroeconomic uncertainty (and exogenous financial uncertainty) is rejected at the 5% significance level, whereas the SVAR featuring "exogenous" macroeconomic uncertainty (and exogenous financial uncertainty) is supported by the data. Both specifications implicitly assume that financial uncertainty does not respond on impact to negative economic shocks. It is important to stress that this assumption, which is required to jointly identify economic activity and macro uncertainty shocks, is not arbitrary but is supported by the reduced-form evidence associated with the estimated SVAR, which suggests that financial uncertainty is poorly correlated with real economic activity until the beginning of the Great Recession + Slow Recovery period, and is correlated with macroeconomic uncertainty only starting from the beginning of the 1980s.

The closest papers to ours are Ludvigson et al. (2018a) and Carriero et al. (2018b). Both papers deal with the issue of exogeneity/endogeneity of uncertainty. Similarly to Ludvigson et al. (2018a), our results are consistent with the view that financial uncertainty is exogenous to the business cycle. However, in stark contrast to their findings and in line with Carriero et al. (2018b), we find strong evidence that macroeconomic uncertainty is an exogenous driver of the business cycle.[3]

Ludvigson et al. (2018a) propose a novel set identification strategy in a time-invariant framework that allows the joint identification of uncertainty and real activity shocks, without imposing any restrictions on the contemporaneous relations (see also Ludvigson, Ma, & Ng, 2018b). Their identification strategy uses two types of *shock-based* restrictions. The first is what they label "event constraints," which require that the identified financial uncertainty shocks must be large enough during two major financial disruptions–for example, the 1987 stock market crash and the 2007–09 financial crisis. The second set of constraints are "correlation constraints," which require the use of external instruments to generate additional inequality constraints which narrow the identified set. Using the same VAR specification as ours, they find that only financial uncertainty can be considered exogenous to the business cycle, while macroeconomic uncertainty should be treated as an endogenous response to business cycle fluctuations. They also find that, while financial uncertainty shocks are contractionary shocks, macro uncertainty shocks have positive effects on real activity, in line with "growth options" theories. This major difference on the role of macroeconomic uncertainty can be explained by considering the different identification methods. In Ludvigson et al. (2018a), identification is based on external information, which is used asymmetrically between the two types of shocks: Event constraints are imposed mainly on financial uncertainty shocks. Moreover, relative to their analysis, the flexibility of our SVAR allows us to uncover relevant regime-dependent effects: financial uncertainty becomes a crucial factor for business cycle developments only after the 1980s. This result lines up with Ng and Wright's (2013) argument that financial factors have played a crucial role in driving the US business cycle after the mid-1980s, and is consistent with Caldara, Fuentes-Albero, Gilchrist, and Zakrajšek (2016) and Caldara and Scotti (2018). Interestingly, our nonrecursive SVAR shows that financial uncertainty affects real economic activity mostly indirectly, by fostering greater macroeconomic uncertainty.

Carriero et al. (2018b) jointly identified real activity and uncertainty shocks by using a novel stochastic volatility approach in the context of VARs that featured measures of macroeconomic and financial uncertainty (one at a time), along with measures of real economic activity. Accordingly, they did not separately identify the effects of macroeconomic and financial sources of uncertainty on economic fluctuations. Their empirical evidence is partly consistent with ours: They also document that macroeconomic uncertainty is broadly exogenous to business cycle fluctuations, while they find that financial uncertainty might, at least in part, arise as an endogenous response to some macroeconomic developments. The identification approach in Carriero et al. (2018b) is based on a stochastic volatility mechanism; hence it is inherently different from our heteroskedasticity-based approach to identification. Our method requires the occurrence of separate variance regimes which must be either known or inferred from the data, and this may possibly affect the inference and

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[3]To save space, a more comprehensive discussion of how our paper is connected to the large empirical literature on the identification of uncertainty shocks can be found in the Technical Supplement (Supporting Information).

identification results if the volatility breaks are misspecified. The stochastic volatility approach in Carriero et al. (2018b) hinges on the specification of an independent stochastic process that governs the changes of the variances over time. This adds flexibility to the model and facilitates identification issues, but also raises computational issues. For instance, the extension of Carriero et al.'s (2018b) approach to the joint modeling of macroeconomic and financial uncertainty, may become computationally demanding. Moreover, our approach allows, without imposing, regime-specific effects of uncertainty shocks, which may uncover important changes in the transmission mechanism over time, as we find for the effects of financial uncertainty.

The paper is organized as follows. Section 2 introduces the identification problem and presents our nonrecursive identification approach. Section 3 discusses the data and the empirical results obtained from the estimated SVAR. Section 4 provides some concluding remarks. Additional technical details and empirical results and robustness checks may be found in an online Technical Supplement (Supporting Information).

2 | ECONOMETRIC FRAMEWORK

In this section we outline our econometric methodology to deal with both regime dependence and the joint identification of uncertainty and real activity shocks. Section 2.1 presents the general setup and discusses the nature of the problem one faces in "standard" SVARs, while Section 2.2 extends the analysis to the "identification-through-heteroskedasticity" method exploited in the paper.

2.1 | Identifying uncertainty and real economic activity shocks under homoskedasticity

Consider the following SVAR:

$$X_t = c + \Phi_1 X_{t-1} + \cdots + \Phi_p X_{t-p} + B e_t = \Pi W_t + B e_t, \ e_t \sim \text{WN}(0_{n \times 1}, I_n), \ t = 1, \ldots, T, \quad (1)$$

where T is the sample length, p is the system lag order, X_t is the $n \times 1$ vector of endogenous variables, c is an $n \times 1$ constant, $\Phi_i, i = 1, \ldots, p$ are $n \times n$ matrices of parameters, $\Pi := (\Phi_1, \ldots, \Phi_p, c), W_t := (X'_{t-1}, \ldots X'_{t-p}, 1)', B$ is an $n \times n$ nonsingular matrix containing what we call "structural parameters," and e_t is the vector of mean zero, (normalized) unit variance and uncorrelated structural shocks. It is assumed that the autoregressive polynomial $\Phi(L) := I_n - \Phi_1 L - \cdots - \Phi_p L^p$ is such that the solutions to $\det(\Phi(z)) = 0$ satisfy $|z| > 1$. Let

$$\eta_t = B e_t \quad (2)$$

be the $n \times 1$ vector of reduced form innovations, with (unconditional) covariance matrix $\Sigma_\eta = BB'$.

Suppose we are interested in the dynamic effects of the structural shocks in e_t. Let A be the VAR companion matrix, $X^c_t := (X'_t, X'_{t-1}, \ldots, X'_{t-p+1})'$ the state vector associated with the VAR companion form, and $R := (I_n, 0_{n \times n}, \ldots, 0_{n \times n})$ a selection matrix such that $X_t = R X^c_t, RR' = I_n$. As is known, the dynamic response of X_{t+h} to shock e_{jt} to the variable X_{jt} is summarized by the (population) IRF:

$$\text{IRF}_j(h) := R(A)^h R' b_j, \ h = 0, 1, 2, \ldots, \ j = 1, \ldots, n, \quad (3)$$

where b_j is the jth column of B; that is, $B := (b_{\bullet j} : b_j : b_{j \bullet})$, and $b_{\bullet j}$ and $b_{j \bullet}$ are the submatrices that contain the columns that precede (if any) and follow (if any) the column b_j, respectively. Absent further restrictions on the coefficients, the IRF in Equation 3 requires that b_j is identified in the sense that it contains independent information relative to the columns in $b_{\bullet j}$ and/or in $b_{j \bullet}$. For $h = 0$, the IRF in Equation 3 is such that, up to possible normalizations of the shocks, the element b_{lj} of the B matrix in Equation 2 captures the instantaneous (on-impact) effect of the jth structural shock on the lth variable of the system.

Consider now our specific case, where $n = 3$. Let Y_t denote a (scalar) measure of real activity, and let U_{Mt} and U_{Ft} be two (scalar) measures of macro and financial uncertainty, respectively, so that $X_t := (U_{Mt}, Y_t, U_{Ft})'$. In the absence of further restrictions, the structural relationship in Equation 2 is given by the following system of equations:

$$\begin{pmatrix} \eta_{Mt} \\ \eta_{Yt} \\ \eta_{Ft} \end{pmatrix}_{\eta_t} = \underbrace{\begin{pmatrix} b_{MM} & b_{MY} & b_{MF} \\ b_{YM} & b_{YY} & b_{YF} \\ b_{FM} & b_{FY} & b_{FF} \end{pmatrix}}_{B} \underbrace{\begin{pmatrix} e_{Mt} \\ e_{Yt} \\ e_{Ft} \end{pmatrix}}_{e_t}, \tag{4}$$

where we conventionally call e_{Mt} "macroeconomic uncertainty shock," e_{Ft} "financial uncertainty shock," and e_{Yt} "real economic activity shock." As is known, at least three restrictions are needed in Equation 4 to identify the shocks in a "Gaussian setup".[4] The covariance matrix $\Sigma_\eta = BB'$ provides $n(n + 1)/2 = 6$ symmetry restrictions to identify the 9 elements of B, leaving 3 elements unidentified. A common solution to this problem is to specify B as a triangular matrix, which provides the 3 zero (identifying) restrictions. The empirical literature on the identification of uncertainty shocks largely relies on the use of recursive SVARs because the interest typically lies on the effect of uncertainty shocks on Y_t, while it is presumed that U_{Mt} (U_{Ft}) responds to shocks to Y_t only with lags. If one imposes an upper (lower) triangular structure on B, or "conventional" zero restrictions, it is not possible to identify simultaneously the parameters of interest b_{YM}, b_{YF}, b_{MY}, and b_{FY}, meaning that "reverse causality" cannot be addressed.

The reverse causality issue and the related identification problem can in principle be tackled by using valid external instruments that permit increasing the number of useful moment conditions other than $\Sigma_\eta = BB'$, without further restricting B; see, for example, Stock and Watson (2012, 2018) and Mertens and Ravn (2013); see also Carriero, Mumtaz, and Theodoridis (2015). Ludvigson et al. (2018a) discuss the peril of such an approach in the uncertainty framework, and improve upon this methodology by arguing that if U_{Mt} and U_{Ft} are potentially endogenous (i.e., they may respond to e_{Yt}), then it is difficult to find credible observable exogenous external instruments for the uncertainty shocks.

While the combined use of external instruments and set identification methods allow us to address the reverse causality issue, it does not help dealing with the problem of possibly regime-dependent effects of uncertainty shocks, which is the issue analyzed next.

2.2 | Using heteroskedasticity to identify uncertainty and real economic activity shocks

In order to jointly address the reverse causality and possible regime-dependent effects of uncertainty shocks, one needs to combine a nonrecursive structure for B with the case where the elements in B may change across macroeconomic regimes with the changes in the unconditional covariance matrix Σ_η, generating regime-dependent IRFs. We solve this problem by exploiting the heteroskedasticity displayed by the reduced-form errors η_t across different macroeconomic regimes that characterize the US business cycle. Our identification methodology is based on the existence of different volatility regimes in the post-WW2 US business cycle—that is, different values that Σ_η may take across subsamples. Allowing for changes in the structural parameters, B represents a major generalization relative to the "standard" identification approach based on heteroskedasticity developed in Rigobon (2003), Lanne and Lütkepohl (2008), and Lanne, Lütkepohl, and Maciejowska (2010); see also Lewis (2018).[5]

Going back to the SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ defined in Equation 1, consider the unconditional covariance matrix Σ_η:

$$\Sigma_\eta = E(\eta_t \eta_t') := \begin{pmatrix} \sigma_M^2 & \sigma_{M,Y} & \sigma_{M,F} \\ & \sigma_Y^2 & \sigma_{Y,F} \\ & & \sigma_F^2 \end{pmatrix}, \tag{5}$$

where $\sigma_{M,Y} = E(\eta_{Mt} \eta_{Yt})$, $\sigma_{M,F} = E(\eta_{Mt} \eta_{Ft})$ and $\sigma_{Y,F} = E(\eta_{Yt} \eta_{Ft})$. For ease of exposition, assume that there are two structural changes in this unconditional error covariance matrix, which correspond to the existence of three distinct volatility regimes.[6] If $t=T_{B_1}$ and $t=T_{B_2}$ denote the dates of the two structural breaks, with $1 < T_{B_1} < T_{B_2} < T$, then the reduced-form VAR in Equation 1 can be generalized to

$$X_t = \Pi(t)W_t + \eta_t, \ \Sigma_\eta(t) := E(\eta_t \eta_t'), \ t = 1, \ldots, T, \tag{6}$$

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[4]It is worth stressing that regardless of the type of identifying restrictions we impose on B, we do not have enough information in this stylized small-scale model to claim that e_{Yt} is a demand or supply shock. In general, e_{Yt} could be a combination of technology, monetary policy, preferences and government expenditures. For this reason, and in line with Ludvigson et al. (2018a), we refer to e_{Yt} as "real activity shock." Likewise, we do not have enough information to disentangle whether uncertainty shocks originate from economic policies and/or technology.

[5]We refer to Lütkepohl (2013), Lütkepohl and Netšunajev (2017), and Kilian and Lütkepohl (2017, chapter 14) for a review of this literature. Chen and Netšunajev (2018) provide an application of such methodology in the context of uncertainty shocks.

[6]This is the case we will deal with in our empirical . Our analysis, however, can be easily generalized to the case in which there are m structural breaks in the unconditional error covariance matrix, corresponding to $m + 1$ volatility regimes in the data. The inferential issues that arise when the break dates are misspecified is a topic that has not yet been explicitly analyzed in the identification-through-heteroskedasticity literature, and is the subject of future research. Podstawski and Velinov (2018) have extended the identification approach we present and apply in this paper to the case in which VAR parameters switch endogenously across volatility regimes.

where $W_t := (X'_{t-1}, \ldots, X'_{t-p}, 1)'$ contains lagged regressors and a constant, $\Pi(t)$ is the matrix of associated slope (autoregressive) coefficients given by

$$\Pi(t) := \Pi_1 \times \mathbb{1}\left(t \leq T_{B_1}\right) + \Pi_2 \times \mathbb{1}\left(T_{B_1} < t \leq T_{B_2}\right) + \Pi_3 \times \mathbb{1}\left(t > T_{B_2}\right), \tag{7}$$

and, finally, the error covariance matrix $\Sigma_\eta(t)$ is given by

$$\Sigma_\eta(t) := \Sigma_{\eta,1} \times \mathbb{1}\left(t \leq T_{B_1}\right) + \Sigma_{\eta,2} \times \mathbb{1}\left(T_{B_1} < t \leq T_{B_2}\right) + \Sigma_{\eta,3} \times \mathbb{1}\left(t > T_{B_2}\right), \tag{8}$$

where $\mathbb{1}(\cdot)$ is the indicator function. Key to our identification approach is that $\Sigma_{\eta,1} \neq \Sigma_{\eta,2} \neq \Sigma_{\eta,3}$. Important for our analysis, note that the specification in Equations 6–8 covers the case in which also the slope (autoregressive) parameters vary across volatility regimes ($\Pi_1 \neq \Pi_2 \neq \Pi_3$).

We assume that the system described by Equations 6–8 is subject to a set of regularity assumptions (Assumptions 1–3 in the Technical Supplement), which allow standard inference. Given the existence of three volatility regimes, the SVAR is defined by the structural specification:

$$\begin{array}{ll} \eta_t = Be_t & 1 \leq t \leq T_{B_1} \\ \eta_t = (B + Q_2)\, e_t & T_{B_1} < t \leq T_{B_2} \\ \eta_t = (B + Q_2 + Q_3)\, e_t & T_{B_2} < t \leq T, \end{array} \tag{9}$$

where B, Q_2, and Q_3 are 3×3 matrices containing structural parameters and $e_t := (e_{Mt}, e_{Yt}, e_{Ft})'$ is the vector of structural shocks such that $E(e_t) = 0_{3 \times 1}$ and with normalized covariance matrix $E(e_t e_t') := I_3$.[7] As before, we call e_{Mt} "macroeconomic uncertainty shock," e_{Ft} "financial uncertainty shock," and e_{Yt} "shock to real activity." In Equation 9 B is the nonsingular matrix that governs the structural contemporaneous relationships (on-impact responses) between the variables and the shocks in the first volatility regime. The matrix Q_2 captures the changes in the structural parameters, if any, from the first to the second volatility regime; hence the nonsingular matrix $(B + Q_2)$ captures the structural contemporaneous relationship (on-impact responses) between the variables and the shocks in the second volatility regime. The matrix Q_3 captures the change in the structural parameters, if any, from the second to the third volatility regime; hence the nonsingular matrix $(B + Q_2 + Q_3)$ captures the structural relationship (on-impact responses) between the variables and the shocks in the third volatility regime.

Equation 9 leads to the system of second-order moment conditions

$$\Sigma_{\eta,1} = BB', \tag{10}$$

$$\Sigma_{\eta,2} = (B + Q_2)(B + Q_2)', \tag{11}$$

$$\Sigma_{\eta,3} = (B + Q_2 + Q_3)(B + Q_2 + Q_3)', \tag{12}$$

which link the reduced form to the structural parameters. Equations 10–12 provide $r = \frac{3}{2}n(n+1)$ identifying restrictions on B, Q_2, and Q_3 induced by symmetry. The total number of elements in B, Q_2, and Q_3 is $3n^2$; hence it is necessary to impose at least $3n^2 - r$ additional constraints to achieve identification. These $3n^2 - r$ identifying constraints are provided by economic reasoning about the way the on-impact coefficients may change across regimes, which means that the suggested identification approach combines both data properties (i.e., the heteroskedasticity provided by the data) and theoretical considerations reflected in the specification of the structure of the matrices B, $(B + Q_2)$ and $(B + Q_2 + Q_3)$. Let ψ be the vector defined as $\psi := (\text{vec}(B)', \text{vec}(Q_2)', \text{vec}(Q_3)')'$. The set of theory-based linear identifying restrictions on B, Q_2 and Q_3 can be represented compactly in explicit form by

$$\psi = G\theta + d, \tag{13}$$

where θ is the vector containing the "free" elements in B, Q_2, and Q_3, G is a known $3n^2 \times \dim(\theta)$ selection matrix of full column rank, $d := (d'_B, d'_{Q_2}, d'_{Q_3})'$ is an $3n^2 \times 1$ vector containing known elements.[8] The moment conditions in Equations 10–12 along with the constraints in Equation 13 can be conveniently summarized in the expression

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[7]An alternative and equivalent parametrization of the SVAR in Equation 9 is discussed in the Technical Supplement, and is based on the assumptions that the structural shocks have a diagonal matrix covariance matrix that changes across volatility regimes; that is, $E(e_{i,t} e'_{i,t}) := \Lambda_i := \text{diag}(\lambda_{i,1}, \ldots, \lambda_{i,n})$, where $e_{i,t}$ is the vector of structural shocks at time t in the regime volatility i, and $\lambda_{i,j}$ is the variance of the structural shock to variable j in the volatility regime i. The IRFs presented and discussed in Equation 15 below can be "scaled" accordingly. To keep exposition as simple as possible, in the paper we refer, without loss of generality, to the parametrization of the SVAR in Equation 9.

[8]Other than accounting for (possibly) nonhomogeneous restrictions (meaning that the vector d can be nonzero), Equation 13 allows for cross-regime constraints—that is, simultaneous restrictions that involve the elements of the matrices B, Q_2 and Q_3 like, for example, $b_{12} + q_{2,12} = 0$ or $b_{12} + q_{2,12} + q_{2,12} = 1$, where b_{12}, $q_{2,12}$ and $q_{3,12}$ are the $(1,2)$ elements of B, Q_2, and Q_3, respectively.

$$\sigma^+ = g(\theta), \tag{14}$$

where $\sigma^+ := (\text{vech}(\Sigma_{\eta,1})', \text{vech}(\Sigma_{\eta,2})', \text{vech}(\Sigma_{\eta,3})')'$ is $r \times 1$, and $g(\cdot)$ is a nonlinear (differentiable) vector function (see Bacchiocchi & Fanelli, 2015, for details). It turns out that the necessary and sufficient rank condition for identification is that the Jacobian matrix $J(\theta) := \frac{\partial g(\theta)}{\partial \theta'}$ be regular and of full column rank when evaluated in a neighborhood of the true parameter value θ_0. The necessary order condition is $\dim(\theta) \leq r$. The Jacobian $J(\theta)$ can be derived analytically or evaluated numerically. Thus, in order to identify the shocks, it is necessary that the restrictions in Equations 10–13 satisfy also the necessary and sufficient rank condition.

We denote by $\tilde{B} = B(\theta)$, $\tilde{Q}_2 = Q_2(\theta)$ and $\tilde{Q}_3 = Q_3(\theta)$ the counterparts of B, Q_2, and Q_3 which fulfill the identification conditions. Interestingly, $\tilde{B}$ (first regime), $(\tilde{B}+\tilde{Q}_2)$ (second regime), and $(\tilde{B}+\tilde{Q}_2+\tilde{Q}_3)$ (third regime) may be either triangular or "full" depending on the specification at hand; therefore reverse causality phenomena can in principle be modeled. Notably, in this setup overidentified SVARs—that is, those for which $\dim(\theta) < r$—can be tested against the data.

The SVAR thus identified generates regime-dependent IRFs. Let A_i, $i = 1, 2, 3$, be the reduced-form companion matrices associated with the system in Equation 6. The dynamic response of X_{t+h} to a one-standard-deviation shock in variable j at time t is summarized by the (population) IRFs:

$$\text{IRF}_j(h) := \begin{cases} R'(A_1)^h R\tilde{b}_j & t \leq T_{B_1} \\ R'(A_2)^h R(\tilde{b}_j + \tilde{q}_{2j}) & T_{B_1} < t \leq T_{B_2} \\ R'(A_3)^h R(\tilde{b}_j + \tilde{q}_{2j} + \tilde{q}_{3j}) & t > T_{B_2} \end{cases} \quad \begin{aligned} h &= 0, 1, \ldots, h_{\max} \\ j &= M, Y, F, \end{aligned} \tag{15}$$

where R is the selection matrix introduced in Section 2.1, $\tilde{b}_j$ is the jth column of the matrix $\tilde{B}$, $\tilde{b}_j + \tilde{q}_{2j}$ is the jth column of the matrix $\tilde{B} + \tilde{Q}_2$, $\tilde{b}_j + \tilde{q}_{2j} + \tilde{q}_{3j}$ is the jth column of the matrix $\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3$, respectively, and $h_{\max}$ is the largest horizon considered. Even in the special case in which the slope (autoregressive) coefficients do not vary across volatility regimes—that is, when $A_1 = A_2 = A_3$ (meaning that $\Pi_1 = \Pi_2 = \Pi_3$ in Equation 7)—the IRFs in Equation 15 change across volatility regimes because of the changes in the on-impact response coefficients.

3 | MODEL SPECIFICATION AND EMPIRICAL RESULTS

In this section, we apply the SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ presented in Equation 1 and discussed in the previous section to address our two main research questions: (i) Does the response of Y_t to shocks to (U_{Mt}, U_{Ft}) vary across macroeconomic regimes? (ii) Are U_{Mt} and U_{Ft} exogenous sources of fluctuations in Y_t, or do U_{Mt} and U_{Ft} respond endogenously to shocks in Y_t? In Section 3.1 we present the data and in Section 3.2 we provide evidence for the existence of three broad volatility regimes. In Section 3.3 we specify and discuss the baseline nonrecursive SVAR and in Section 3.4 we test for exogenous uncertainty and analyze the resultant IRFs.

3.1 | Data

Our VAR includes three variables—$U_{Mt}(f)$, $U_{Ft}(f)$, and Y_t—where Y_t is a measure of real economic activity, $U_{Mt}(f)$ is a measure of f-period-ahead macroeconomic uncertainty, and $U_{Ft}(f)$ is a measure of f-period-ahead financial uncertainty, where $f = 1$ (1 month) or $f = 12$ (1 year). Our measure of real economic activity is the growth rate of the log of real industrial production, denoted by Δip_t. The real industrial production index is taken from the FRED database. The measure of financial uncertainty is taken from Ludvigson et al. (2018a), while the index of macroeconomic uncertainty is taken from Jurado et al. (2015).[9] The data are monthly and cover the period 1960:M8–2015:M4 for a total of $T = 653$ observations. As discussed in Ludvigson et al. (2018a), jointly modeling financial and macroeconomic uncertainty is key to obtain a correct understanding of the relationship between uncertainty and the business cycle.

3.2 | Volatility breaks

Two crucial features of our VAR are that the identification approach requires breaks in the unconditional volatility of the data, and that a small-scale system like ours is not affected by nonfundamentalness, which implicitly amounts to claim that it does not omit important variables. Our major hypothesis is that the relationship between uncertainty and

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[9]The Technical Supplement discusses at length how the two proxies of uncertainty have been constructed.
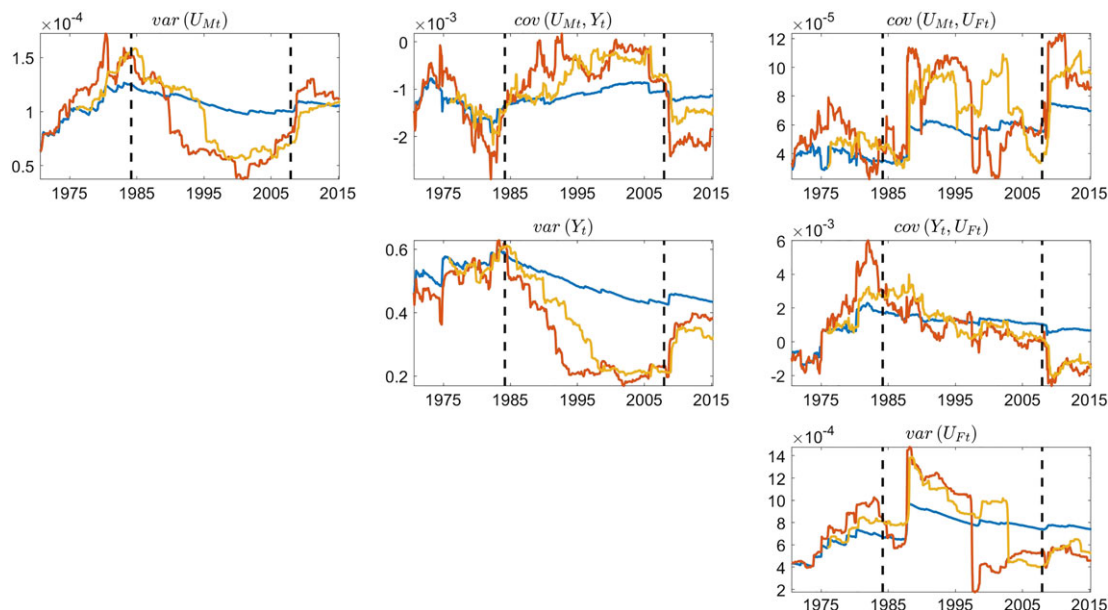
FIGURE 1 Recursive (blue line), 10-year (red line), and 15-year (yellow line) rolling window estimates of the error covariance matrix of the VAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth). Dashed black lines denote the two break dates $T_{B_1} = 1984{:}M3$ and $T_{B_2} = 2007{:}M12$ that separate the three volatility regimes used to identify the shocks. Overall sample: 1960:M8–2015:M4 [Colour figure can be viewed at wileyonlinelibrary.com]

real activity vary across the main macroeconomic regimes of post-WW2 US business cycle because of changes in the unconditional variance of Y_t. To provide evidence in favor of volatility breaks, we proceed in two steps. First, we provide suggestive evidence of time variation by looking at recursive and rolling windows estimates of the residual variances and covariances in our baseline VAR. Second, we formally test for the existence of two structural breaks using Chow-type tests, with possible break dates identified in the previous step. Next, we deal with potential nonfundamentalness of our VAR by testing for its "informational sufficiency" using the procedure by Forni and Gambetti (2014) and factors extracted from McCracken and Ng's (2015) large set of macroeconomic and financial variables. The detailed investigation of this last issue, sketched in the Technical Supplement, is important in light of the small dimension of $X_t := (U_{Mt}, Y_t, U_{Ft})'$ because nonfundamentalness is best seen as an informational deficiency problem. The empirical analysis shows that we do not reject the informational sufficiency of $X_t := (U_{Mt}, Y_t, U_{Ft})'$, meaning that we can correctly estimate the effects of uncertainty shocks through IRFs.

We start by estimating our baseline VAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ with four lags ($p = 4$) both recursively and over 10- and 15-year rolling windows. Estimates of the six elements of the unconditional VAR error covariance matrix Σ_η are plotted in Figure 1. The graphs on the diagonal report the estimated variances, while the off-diagonal terms report the estimated covariances for the recursive (blue line), the 10-year (red line) and 15-year (yellow line) rolling windows VARs. The graph in position $(2, 2)$ reports the unconditional variance of the residuals of the second equation of our VAR, the one associated with Y_t; that is, Σ_Y^2 in Σ_η in Equation 5. The graph clearly shows that the average volatility level is time varying, being higher during the 1970s and 1980s, declining from the mid-1980s until the end of 2007, and then increasing again after the financial crisis of 2007–08 before stabilizing. All the remaining graphs in Figure 1 broadly confirm the presence of three volatility regimes. As expected, the two main changes in volatility occur in correspondence of the beginning of the Great Moderation and Great Recession periods, respectively. The two dashed vertical lines correspond to the possible break dates; that is, $T_{B_1} = 1984{:}M3$ and $T_{B_2} = 2007{:}M12$. These two break dates would partition the whole sample period 1960:M8–2015:M4 into three different subsamples: the Great Inflation period (1960:M8–1984:M3, $T = 280$), the Great Moderation period (1984:M4–2007:M12, $T = 285$), and the Great Recession + Slow Recovery period (2008:M1–2015:M4, $T = 88$).[10] It is worth noting, however, that while the unconditional variance associated with the proxy of macroeconomic uncertainty roughly follows the same volatility pattern as the unconditional volatility of Y_t (position $(1, 1)$ in Figure 1),

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[10]As concerns the third volatility regime, according to the US National Bureau of Economic Research the Great Recession began in December 2007 and ended in June 2009, thus extending over 19 months. Thus we treat $T_{B_2} = 2007{:}M12$ as the date in which the Great Moderation ends. Considering three distinct volatility regimes does not necessarily rule out the possibility that the VAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ might display unconditional (or possibly

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

Overall period: 1960:M8–2015:M4 ($T = 653$)

log-likelihood = 2871.6
N_{DH} = 645.281[0.000]
AR_5 = 19.216[0.997]

$$\hat{\Sigma}_\eta = \begin{pmatrix} 1.05e-04^* & -0.011^* & 6.94e-05^* \\ & 0.433^* & 6.80e-04 \\ & & 7.39e-04^* \end{pmatrix}, \qquad \hat{\rho}_\eta = \begin{pmatrix} 1 & -0.167^* & 0.249^* \\ & 1 & 0.038 \\ & & 1 \end{pmatrix}$$

GI: 1960:M8–1984:M3 ($T = 280$)

log-likelihood = 1170.5
N_{DH} = 111.242[0.000]
AR_5 = 35.521[0.843]

$$\hat{\Sigma}_{\eta,1} = \begin{pmatrix} 1.25e-04^* & -0.001^* & -3.49e-05^* \\ & 0.587^* & 0.002 \\ & & 6.72e-04^* \end{pmatrix}, \qquad \hat{\rho}_{\eta,1} = \begin{pmatrix} 1 & -0.157^* & 0.120^* \\ & 1 & 0.086 \\ & & 1 \end{pmatrix}$$

GM: 1984:M4–2007:M12 ($T = 285$)

log-likelihood = 1399.9
N_{DH} = 317.978[0.000]
AR_5 = 51.729[0.228]

$$\hat{\Sigma}_{\eta,2} = \begin{pmatrix} 7.18e-05^* & -5.58e-04^* & 7.62e-05^* \\ & 0.221^* & 4.24e-04 \\ & & 7.84e-05^* \end{pmatrix}, \qquad \hat{\rho}_{\eta,2} = \begin{pmatrix} 1 & -0.140^* & 0.321^* \\ & 1 & 0.032 \\ & & 1 \end{pmatrix}$$

GR+SR: 2008:M1–2015:M4 ($T = 88$)

log-likelihood = 428.1
N_{DH} = 108.785[0.000]
AR_5 = 79.523[0.001]

$$\hat{\Sigma}_{\eta,3} = \begin{pmatrix} 8.51e-05^* & -0.001^* & 7.90e-05^* \\ & 0.378^* & -0.001 \\ & & 4.62e-04^* \end{pmatrix}, \qquad \hat{\rho}_{\eta,3} = \begin{pmatrix} 1 & -0.214^* & 0.398^* \\ & 1 & -0.089 \\ & & 1 \end{pmatrix}$$

$H_0 : \text{LR}_T = 253.99[0.000]$ (no breaks in all VAR coefficients)
$H_0' : \text{LR}_T = 96.061[0.000]$ (no breaks in VAR covariance matrix)
$H_0'' : \text{F}_T = 4.221[0.000]$ (homoskedasticity in VAR residuals with regime-dependent autoregressive parameters)

Note. Results are based on a VAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ (with four lags) with $Y_t = \Delta ip_t$ (industrial production growth). Top panel: estimates on the whole sample. Second, third, and fourth panels: estimates on partial samples. Bottom panel: LR Chow-type tests for the null H_0 in Equation 16 and the null H_0' in Equation 17, and F-type test for the null H_0'' of vector homoskedasticity in the VAR residuals with regime-dependent autoregressive parameters. Asterisks (*) denote statistical significance at the 10% confidence level. N_{DH} is the Doornik–Hansen multivariate test for Gaussian disturbances. AR_5 is an LM-type test for the absence of residual autocorrelation against the alternative of autocorrelated VAR disturbance up to 5 lags. *p*-values in brackets. GI, Great Inflation; GM, Great Moderation; GR+SR, Great Recession + Slow Recovery.

the unconditional variance associated with the proxy of financial uncertainty increases until the beginning of the 1990s, probably because of the process of financial innovation that characterizes US financial markets (position (3, 3) in Figure 1). Interestingly, these differences in volatility patterns provide identification information in our approach.

The evidence reported in Figure 1 is broadly consistent with the information conveyed in Table 1.[11] The second column of Table 1 summarizes the ordinary least squares (OLS)-based estimates of the VAR covariance matrix Σ_η on the whole sample—that is, under the null hypothesis that there are no volatility regimes in the data ($H_0' : \Sigma_{\eta,1} = \Sigma_{\eta,2} = \Sigma_{\eta,3}$), and then separately on the three volatility subperiods.[12] As already shown in Figure 1, these results confirm that unconditional variances and covariances have changed over time. Table 1 also summarizes some diagnostic statistics associated with the estimated models, which suggest that VAR residuals tend to be not Gaussian but not serially correlated within regimes. The nonnormality of VAR disturbances is detected, as expected, on the overall sample period but also within macroeconomic regimes and is fully consistent with the analysis in Cúrdia, Del Negro, and Greenwald (2014), for example. We remark that the possible presence of within-regime heteroskedasticity (conditional or unconditional), while affecting the full efficiency of our estimates, does not represent a major obstacle to the identification strategy presented below.

To verify formally the hypothesis that there are two main structural breaks in the VAR error covariance matrix at the dates $T_{B_1} = 198:4M3$ and $T_{B_2} = 2007:M12$, we compute a set of Chow-type tests and misspecification-type tests. We first test whether the joint null hypothesis of absence of structural breaks in all VAR coefficients

$$H_0 : \begin{pmatrix} \Pi_1 \\ \Sigma_{\eta,1} \end{pmatrix} = \begin{pmatrix} \Pi_2 \\ \Sigma_{\eta,2} \end{pmatrix} = \begin{pmatrix} \Pi_3 \\ \Sigma_{\eta,3} \end{pmatrix} = \begin{pmatrix} \Pi \\ \Sigma_\eta \end{pmatrix} \tag{16}$$

conditional) heteroskedastic disturbances within regimes, other than across them. This is clearly seen from the graphs in Figure 1 but, as discussed below, does not represent a major obstacle to the implementation of our identification approach.

[11] Admittedly, the evidence in Figure 1 could also support a time-varying specification. We refer to Mumtaz and Theodoridis (2016) and Carriero et al. (2018a, 2018b) for different views on how time-varying specifications can be fruitfully exploited to address empirically the role of uncertainty. As already stressed, crucial to our identification approach is the existence of broad volatility regimes in the data.

[12] The OLS estimates in Table 1 correspond to maximum likelihood estimates generated by maximizing Gaussian densities within each of the considered samples. In the Technical Supplement, we also discuss a classical minimum distance (CMD) estimation approach that does not require any distributional assumption. We prefer to stick to Gaussian maximum likelihood estimation of our SVAR to be as close as possible to the more familiar identification-through-heteroskedasticity approach put forth by Lanne and Lütkepohl (2008) in the context of SVARs.

is rejected and, conditional on the rejection of H_0, we test the null hypothesis of absence of volatility regimes

$$H_0' : \Sigma_{\eta,1} = \Sigma_{\eta,2} = \Sigma_{\eta,3} \tag{17}$$

under the maintained restriction: $\Pi_1 = \Pi_2 = \Pi_3 = \Pi$ on slope coefficients. Results are summarized in the bottom panel of Table 1, which reports the likelihood ratio (LR) tests for hypotheses H_0 and H_0', respectively. Both H_0 and H_0' are strongly rejected by the data. As a final check, we investigate to what extent the detected regime dependence in the residual covariance matrix can be ascribed to the regime dependence that characterizes the autoregressive parameters. To do so, we estimate the VAR in Equation 6 by allowing the autoregressive parameters to change as in Equation 7 with $T_{B_1} = $ 1984:M3 and $T_{B_2} = $ 2007:M12, keeping the covariance matrix Σ_η constant. In the model thus estimated we perform a test for the null hypothesis of (unconditional) homoskedasticity in the residuals (H_0''), which is reported in the lower panel of Table 1. Results show that the hypothesis of homoskedasticity is strongly rejected by the data. This evidence confirms that the changes that characterize the unconditional covariance matrix Σ_η cannot be solely ascribed to the changes in the autoregressive parameters. Overall, our results are consistent with Aastveit, Carriero, Clark, and Marcellino (2017), who, using a wide range of econometric techniques, provide substantial evidence against the stability of common VARs in the period since the Great Recession.

Other than documenting the existence of three broad volatility regimes in the data, Table 1 provides some rough evidence concerning the changing nature of the relationships between our proxies of uncertainty, U_{Mt} and U_{Ft}, and real economic activity, Y_t. Although it is not possible to infer any causality direction from the correlations in Table 1, the data clearly point towards changing relationships. The information provided by the correlations in Table 1 will be used to inform the structural specification in the next section.

Overall, the estimated reduced-form system for $X_t := (U_{Mt}, Y_t, U_{Ft})'$ provides a reasonable fit to the data and is "informational sufficient." We consider it a statistically satisfactory reduced-form representation of the nonrecursive SVAR specified next.

3.3 | Nonrecursive SVAR specification

In this section we discuss the specification of the matrices of structural parameters $\tilde{B} = B(\theta)$, $\tilde{Q}_2 = Q_2(\theta)$ and $\tilde{Q}_3 = Q_3(\theta)$ in Equation 9. The vector of structural shocks is $e_t := (e_{Mt}, e_{Yt}, e_{Ft})'$, and we call conventionally e_{Mt} "macroeconomic uncertainty shock," e_{Ft} "financial uncertainty shock", and e_{Yt} "real activity shock"; see the discussion in Section 2.

To inform the structural specification, valuable indications may be inferred from the VAR residuals correlation matrices sketched in Table 1. Three main empirical facts emerge from this table. First, the negative correlation between (the residuals associated with) macroeconomic uncertainty and industrial production growth increases by about 50%, from −14% to −21%, when moving from the Great Moderation to the Great Recession + Slow Recovery period. This reduced-form evidence is consistent with the structural analysis in Caggiano, Castelnuovo, and Pellegrino (2017) and Plante et al. (2018), for example. Second, the correlation between (the residuals associated with) financial uncertainty and industrial production growth turns negative only in the Great Recession + Slow Recovery period (3.8%, 3.2%, and −8.9%, respectively) and is not significant. Third, the correlation between (the residuals associated with) macroeconomic and financial uncertainty increases substantially across the three volatility regimes (12%, 32%, and almost 40%, respectively), suggesting that the two sources of uncertainty developed in a relatively independent way during the Great Inflation period, and started to be much more correlated thereafter, when periods of financial turmoil had become more prominent. These three empirical facts suggest that the (negative) relationship between macroeconomic uncertainty and real economic activity is likely regime dependent and intensifies after the GFC. On the other hand, the channel that connects financial uncertainty and real economic activity appears to be indirect: Since financial uncertainty is virtually uncorrelated with real activity, its effects on the business cycle, if any, might work only via its correlation with macroeconomic uncertainty. This latter correlation is almost irrelevant in the first subsample, and increases only after the mid-1980s.

Based on these considerations, we formulate our hypotheses on the structural parameters. The three volatility regimes detected in the previous section provide us with $r = 3/2(n)(n + 1) = 18$ moment conditions. In the absence of restrictions, B, Q_2 and Q_3 contain $3n^2 = 27$ elements; hence it is necessary to place at least $3n^2 - r = 9$ parameter constraints on these matrices in order to achieve identification. These restrictions, which can be represented compactly as in Equation 13, must satisfy the necessary and sufficient identification rank condition discussed in Section 2.2; that is, the Jacobian matrix associated with the function in Equation 14 must be regular and full column rank. We consider a total of 11 identifying restrictions (which lead to $11 - 9 = 2$ overidentification restrictions) and the following matrices $\tilde{B}$, $\tilde{B}+\tilde{Q}_2$, and $\tilde{B}+\tilde{Q}_2+\tilde{Q}_3$:

Great Inflation:

$$\tilde{B} := \begin{pmatrix} b_{MM} & b_{MY} & 0 \\ b_{YM} & b_{YY} & 0 \\ 0 & 0 & b_{FF} \end{pmatrix};$$

Great Moderation:

$$\tilde{B} + \tilde{Q}_2 := \begin{pmatrix} b_{MM} + q_{2,MM} & b_{MY} & q_{2,MF} \\ b_{YM} + q_{2,YM} & b_{YY} + q_{2,YY} & 0 \\ q_{2,FM} & 0 & b_{FF} + q_{2,FF} \end{pmatrix};$$

Great Recession + Slow Recovery:

$$\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3 := \begin{pmatrix} b_{MM} + q_{2,MM} & b_{MY} & q_{2,MF} + q_{3,MF} \\ b_{YM} + q_{2,YM} + q_{3,YM} & b_{YY} + q_{2,YY} + q_{3,YY} & q_{3,YF} \\ q_{2,FM} & 0 & b_{FF} + q_{2,FF} + q_{3,FF} \end{pmatrix};$$

(18)

so that the vector of structural parameters θ contains 16 nonzero elements (dim(θ)=16).

The specification of the matrix $\tilde{B}$ (Great Inflation) in Equation 18 is based on one crucial hypothesis. Inspired by Ng and Wright (2013) and the previously mentioned reduced-form evidence in Table 1, we maintain that heavily regulated financial markets before the 1980s slowed down the response of financial markets to nonfinancial dynamics on the one hand, and the response of macroeconomic variables to the uncertainty generated by financial markets on the other. Thus financial uncertainty is assumed not to respond on-impact to real activity shocks ($b_{FY} = 0$) nor to macro uncertainty shocks ($b_{FM} = 0$), and real activity is assumed not to respond on-impact to financial uncertainty shocks ($b_{YF} = 0$), though lagged responses are not ruled out and depend on the estimated dynamics. Likewise, it is also assumed that financial uncertainty does not exert contemporaneous effects on macroeconomic uncertainty ($b_{MF} = 0$). Overall, according to the $\tilde{B}$ matrix in Equation 18, macroeconomic uncertainty can be potentially endogenous, depending on the significance of the parameter b_{MY}, whereas financial uncertainty is treated as a variable that can react only with lags.

Moving to the second volatility regime (Great Moderation), the nonrecursive structure of the matrix $\tilde{B} + \tilde{Q}_2$ in Equation 18 is still consistent with the idea that macroeconomic uncertainty shocks may affect real economic activity instantaneously through the parameter $b_{YM} + q_{2,YM}$ ($q_{2,YM}$ captures the change of impact relative to the Great Inflation) and, in turn, real activity shocks may affect macro uncertainty through the parameter $b_{MY} + q_{2,MY}$ (again, $q_{2,MY}$ captures the change relative to the Great Inflation). Unlike the Great Inflation period, however, we now admit that causation among the two sources of uncertainty may run both ways through the parameters $q_{2,FM}$ (position (3,1)) and $q_{2,MF}$ (position (1, 3)), respectively. This is done to infer whether the increased correlation between U_{Mt} and U_{Ft} observed during the Great Moderation relative to the Great Inflation can be ascribed to financial or macro uncertainty shocks, or to both types of shocks. For instance, with $q_{2,FM} = 0$ and $q_{2,MF} \neq 0 (q_{2,MF} > 0)$ in Equation 18, we might conclude that causality runs from financial uncertainty shocks to macroeconomic uncertainty alone.

Finally, the causality relationships entailed by the structure of the matrix $\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3$ (Great Recession + Slow Recovery) in Equation 18 is similar to that of the Great Moderation, the main difference being that we now allow financial uncertainty shocks to affect real economic activity both directly (through the parameter $q_{3,YF}$) and indirectly through its effect on macroeconomic uncertainty (through the parameter $q_{2,MF} + q_{3,MF}$ where, recall, $q_{3,MF}$ captures the possible change of effect relative to the Great Moderation).

Overall, the SVAR based on the specification in Equation 18 is identified in the sense that it satisfies the rank condition discussed in Section 2.2, and gives rise to $r - $ dim(θ) =2 (testable) overidentification restrictions. Financial uncertainty is given the "passive" role of merely amplifying the shocks before the 1980s, while the role of financial markets and the uncertainty stemming from them are brought back to the center stage of business cycle after the mid-1980s.[13] Notably, the specified structural model features possibly endogenous uncertainty, since it allows the structural parameter b_{MY} to be nonzero. Hence testing $b_{MY} = 0$ amounts to testing for exogeneity of macroeconomic uncertainty.

Our testing procedure compares the specification in Equation 18 with a restricted version that features two additional hypotheses about the pass-through from uncertainty to real economic activity: One is the hypothesis of "exogenous" macroeconomic uncertainty, $b_{MY} = 0$, and the other is the hypothesis that macroeconomic uncertainty shocks do not trigger financial uncertainty, $q_{2,FM} = 0$, so that their structural relationship is unidirectional. Jointly, the two restrictions

$$\begin{aligned} b_{MY} = 0 & \quad \text{"exogenous" macro uncertainty} \\ q_{2,FM} = 0 & \quad \text{"one-way" causality from financial to macro uncertainty} \end{aligned}$$

(19)

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[13]Our choice is also supported by institutional facts, in particular the changes in the norms regulating financial markets that occurred in the early 1980s, such as the Depository Institutions Deregulation and Monetary Control Act in 1980, particularly the termination of regulation Q and the Garn–St. Germain Act of 1982, which granted easier access to financial liquidity to households and firms only from the mid-1980s onwards.

imply, when imposed in Equation 18, an overidentified system that features $r - \dim(\theta) = 4$ (testable) overidentification restrictions.

3.4 | On-impact and dynamic causal effects

The nonrecursive SVAR specified in Equation 18 is based on the idea that the changes in the covariance matrices $\Sigma_{\eta,1} \neq \Sigma_{\eta,2} \neq \Sigma_{\eta,3}$ associated with the break dates $T_{B_1} = 1984\text{:M3}$ and $T_{B_2} = 2007\text{:M12}$ are explained by the occurrence of breaks in the structural parameters. As already observed in Section 2.2, the main difference between our approach and Lanne and Lütkepohl's (2008) approach is that in the latter the autoregressive parameters in Equation 7 are kept constant, and the changes in the unconditional covariance matrix in the three volatility regimes are modeled by the simultaneous diagonalization

$$\Sigma_{\eta,1} = BB' \quad , \quad \Sigma_{\eta,2} = B\Lambda_2 B' \quad , \quad \Sigma_{\eta,3} = B\Lambda_3 B, \tag{20}$$

where the elements of B are fixed, and $\Lambda_2 \neq \Lambda_3 \neq I_n$ are two diagonal matrices with positive elements on the diagonal which satisfy a set of identification conditions discussed in detail in Lanne et al. (2010). Equation 20 gives rise to dynamic causal effects that are invariant to volatility regimes. Hence, before moving to the estimation of our structural model, it seems natural to test to what extent the specification in Equation 20 is supported/rejected by the data. The model in Equation 20 entails an overidentified system that incorporates three (testable) restrictions (indeed there are $r = 18$ reduced-form covariance parameters and $9 + 6 = 15$ distinct elements in B, Λ_2, and Λ_3). The likelihood ratio test for the overidentification restrictions implied by the specification in Equation 20 is equal to 10.11 with an associated p-value of 0.0176; hence the model is rejected at the 5% level of significance. We interpret this result as supportive of the fact that the on-impact coefficients of SVARs in the uncertainty framework can possibly change across major macroeconomic regimes of the US economic history. In the analysis that follows, in order to highlight the importance of regime-dependent coefficients, the IRFs implied by the SVAR in Equation 20 will serve as a comparative benchmark against our model.

The nonrecursive SVAR specified in Equation 18 is estimated on the period 1960:M8–2015:M4 by imposing the three volatility regimes associated with the two break dates $T_{B_1} = 1984\text{:M3}$ and $T_{B_2} = 2007\text{:M12}$. The (quasi-)maximum likelihood estimates of the structural parameters θ that enter the matrices $\tilde{B}$, $\tilde{B} + \tilde{Q}_2$, and $\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3$ are reported, for $f = 1$ (1-month uncertainty), in Table 2, along with analytic and bootstrap standard errors.[14] The upper panel of Table 2 refers to the specification in Equation 18, while the lower panel refers to the same model estimated under the two additional restrictions in Equation 19. The estimated structural parameters $\hat{\theta}$ in Table 2 correspond to the on-impact responses featured by our IRFs.

We first discuss the reverse causality/exogeneity issue; then we analyze the dynamic causal effects implied by the estimated IRFs.

3.4.1 | Reverse causality/exogeneity

The estimates in the two panels of Table 2 deliver an answer to our first research question—that is, whether macroeconomic uncertainty is an exogenous source of economic fluctuations or an endogenous response to it, or both. We first analyze the model in the upper panel of Table 2, which allows for "endogenous" macroeconomic uncertainty ($b_{MY} \neq 0$) and bidirectional causality between macroeconomic and financial uncertainty from the Great Moderation onwards ($q_{2,FM} \neq 0$, $q_{2,MF} \neq 0$, $q_{3,MF} \neq 0$). The LR test for the two overidentification restrictions featured by this model is equal to 7.35 and has a p-value of 0.025; hence the model is not supported by the data at the 5% level of significance.

The parameter b_{MY}, which captures the on-impact response of macroeconomic uncertainty to real economic activity shocks in the three volatility regimes, is not statistically significant. The hypothesis of "exogenous" macroeconomic

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[14]Bootstrap standard errors are computed using Kilian (1998)'s bootstrap-after-bootstrap method, keeping the break dates $T_{B_1} = 1984\text{:M3}$ and $T_{B_2} = 2007\text{:M12}$ fixed and resampling (nonparametrically) separately within each volatility regime. This method is also used to compute 90% bootstrap confidence bands for the IRFs that follow. Brüggemann, Jentsch, and Trenkler (2016) have shown that estimation uncertainty in IRFs produced by SVARs may increase dramatically in the presence of conditional heteroskedasticity compared to an i.i.d. setup, depending especially on the persistence characterizing the underlying conditional heteroskedasticity processes. In our setup, the occurrence of conditional heteroskedasticity within the three volatility regimes is an issue that cannot be ruled out a priori, given the diagnostic tests in Table 1. Brüggemann et al. have also shown that the residual-based moving block bootstrap results in asymptotically valid inference (see also ; Kilian & Lütkepohl, 2017, chapter 12). Since available simulation results suggest that the performance of different bootstrap methods is often hardly distinguishable in finite samples, Brüggemann et al. recommend that practitioners should be aware of the fact that reported impulse response intervals may understate the actual estimation uncertainty in the presence of conditional heteroskedasticity. With this in mind, and in the absence of a detailed quantification of the extent of conditional heteroskedasticity in our SVAR (which is beyond the scopes of this paper), we interpret all reported bootstrap confidence bands for IRFs with caution.

TABLE 2 Estimated structural parameters

GI: 1960:M8–1984:M3	GM: 1984:M4–2007:M12	GR+SR: 2008:M1–2015:M4

SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$

$$\hat{B} := \begin{pmatrix} \underset{(0.0005)}{\underset{(0.0007)^*}{0.0112}} & \underset{(0.0029)}{\underset{(0.0055)^*}{0.0003}} & 0 \\ \underset{(0.1969)}{\underset{(0.1989)^*}{-0.1377}} & \underset{(0.0466)}{\underset{(0.0633)^*}{0.7540}} & 0 \\ 0 & 0 & \underset{(0.0011)}{\underset{(0.0018)^*}{0.0259}} \end{pmatrix}, \quad \hat{B}+\hat{Q}_2 := \begin{pmatrix} \underset{(0.0009)}{\underset{(0.0010)^*}{0.0075}} & \underset{(0.0029)}{\underset{(0.0055)^*}{0.0003}} & \underset{(0.0016)}{\underset{(0.0015)^*}{0.0040}} \\ \underset{(0.1634)}{\underset{(0.1767)^*}{-0.0907}} & \underset{(0.0360)}{\underset{(0.0616)^*}{0.4613}} & 0 \\ \underset{(0.0056)}{\underset{(0.0029)^*}{-0.0047}} & 0 & \underset{(0.0015)}{\underset{(0.0040)^*}{0.0276}} \end{pmatrix}, \quad \hat{B}+\hat{Q}_2+\hat{Q}_3 := \begin{pmatrix} \underset{(0.0009)}{\underset{(0.0010)^*}{0.0075}} & \underset{(0.0029)}{\underset{(0.0055)^*}{0.0003}} & \underset{(0.0021)}{\underset{(0.0023)^*}{0.0054}} \\ \underset{(0.2130)}{\underset{(0.1967)^*}{-0.1225}} & \underset{(0.0637)}{\underset{(0.1100)^*}{0.5967}} & \underset{(0.0766)}{\underset{(0.1286)^*}{-0.0839}} \\ \underset{(0.0056)}{\underset{(0.0029)^*}{-0.0047}} & 0 & \underset{(0.0020)}{\underset{(0.0030)^*}{0.0210}} \end{pmatrix}$$

Model with "endogenous" macroeconomic uncertainty: 2 overidentification restrictions: $LR_T = 7.3506_{\chi^2(\mathrm{df}=2)}[0.0253]$

SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$

$$\hat{B} := \begin{pmatrix} \underset{(0.0005)}{\underset{(0.0006)^*}{0.0112}} & 0 & 0 \\ \underset{(0.0455)}{\underset{(0.0595)^*}{-0.1203}} & \underset{(0.0320)}{\underset{(0.0438)^*}{0.7569}} & 0 \\ 0 & 0 & \underset{(0.0011)}{\underset{(0.0017)^*}{0.0259}} \end{pmatrix}, \quad \hat{B}+\hat{Q}_2 := \begin{pmatrix} \underset{(0.0003)}{\underset{(0.0004)^*}{0.0081}} & 0 & \underset{(0.0005)}{\underset{(0.0005)^*}{0.0028}} \\ \underset{(0.0280)}{\underset{(0.0408)^*}{-0.0757}} & \underset{(0.0194)}{\underset{(0.0244)^*}{0.4641}} & 0 \\ 0 & 0 & \underset{(0.0012)}{\underset{(0.0036)^*}{0.0280}} \end{pmatrix}, \quad \hat{B}+\hat{Q}_2+\hat{Q}_3 := \begin{pmatrix} \underset{(0.0003)}{\underset{(0.0004)^*}{0.0081}} & 0 & \underset{(0.0009)}{\underset{(0.0031)^*}{0.0037}} \\ \underset{(0.0617)}{\underset{(0.0810)^*}{-0.1150}} & \underset{(0.0453)}{\underset{(0.0844)^*}{0.6006}} & \underset{(0.0653)}{\underset{(0.1123)^*}{-0.0552}} \\ 0 & 0 & \underset{(0.0016)}{\underset{(0.0024)^*}{0.0215}} \end{pmatrix}$$

Model with "exogenous" macroeconomic uncertainty: 4 overidentification restrictions specified in Equation 19: $LR_T = 8.0268_{\chi^2(\mathrm{df}=4)}[0.0906]$

Note. Estimated structural parameters based on the nonrecursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth), specified in Equation 18. The estimates in the lower panel are based on the additional restrictions in Equation 19. "LR_T" are likelihood-ratio tests for the overidentification restrictions. Hessian-based standard errors are in parentheses; bootstrap standard errors are denoted by asterisks (see footnote 15 for details); GI, Great Inflation; GM, Great Moderation; GR+SR, Great Recession + Slow Recovery.

uncertainty is largely supported by the data as the LR test for $b_{MY} = 0$ is equal to 0.056 and has a *p*-value of 0.94. The estimated parameter $q_{2,FM}$ proves to be not strongly significant, confirming our intuition that since the 1980s the pass-through between the two sources of uncertainty is unidirectional: from financial uncertainty shocks to macroeconomic uncertainty. The estimated structural model in the lower panel of Table 2 incorporates these two additional restrictions (see Equation 19). In this case, the LR test for the four overidentification restrictions featured by the SVAR is equal to 8.03 with an associated *p*-value of 0.091, which does not lead us to reject the model at the 5% significance level. An LR test for the structural model in the lower panel against the one in the upper panel of Table 2 is equal to 0.672 and has a *p*-value equal to 0.713. Overall, our empirical evidence supports the specification in Equations 18–19.[15]

It could be argued that macroeconomic and financial uncertainty are treated asymmetrically in our model. Indeed, although the reduced-form evidence speaks loudly about the role of financial uncertainty, the nonresponse of financial uncertainty to real economic activity shocks has been imposed in the structural specification. To address this issue, we reestimate the SVARs in Equations 18–19 by inverting the positions of $U_{M,t}$ and $U_{F,t}$ in the vector X_t. This leads to a radical change in the role played by the two sources of uncertainty in the system and the way they transmit to the business cycle. In this case, the LR test for the overidentification restrictions is equal to 28.47 with a *p*-value of 0.00, which strongly rejects the model. We interpret this evidence as fully consistent with the pass-through of financial and macroeconomic uncertainty to real economic activity hypothesized in our baseline model. In particular, the data seem to support the fact that in the Great Moderation and Great Recession + Slow Recovery periods financial uncertainty shocks foster greater uncertainty about future economic growth.

These findings on reverse causality allow us to make direct contact with Ludvigson et al. (2018a), the closest paper to ours in this respect. In line with their results, our analysis is consistent with the view that financial uncertainty is a driver of the business cycle, not a reaction to it. According to our identification scheme, however, financial uncertainty affects the business cycle indirectly by triggering greater macroeconomic uncertainty on-impact. Instead we find remarkable differences from Ludvigson et al. (2018a) when we look at the behavior of macroeconomic uncertainty: while they report that macroeconomic uncertainty shocks could be characterized as an endogenous response to business cycle fluctuations

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[15]As a referee has pointed out, the increase in *p*-value that characterizes the two LR tests can also be explained by the fact that the latter can be less powerful than the former due to the increased number of restrictions being tested. In the robustness section of the Technical Supplement, we show that all *p*-values associated with the LR tests discussed in this section increase dramatically once we replace (ceteris paribus) the measure of macroeconomic uncertainty, U_{Mt}, with an alternative one obtained by "purging" U_{Mt} from a subset of financial variables, denoted by U_{Mt}^p. Our choice of using U_{Mt} and not directly U_{Mt}^p in the estimation of our baseline SVAR is motivated by the idea of using the same information set as Ludvigson et al. (2018a) to facilitate comparison.

and have positive effects on real activity, we find that macroeconomic uncertainty is exogenous to the business cycle and has a negative on-impact effect on real activity. Ludvigson et al. (2018a) base their conclusions on a novel methodology that combines the external instruments approach with the mechanics of set identification (see also ; Ludvigson et al., 2018b). The endogeneity of macroeconomic uncertainty they document might reflect the "asymmetric" characterization of financial and macroeconomic uncertainty shocks implicit in their approach—that is, the fact that the "event constraints" are imposed mainly on financial uncertainty. Our analysis unveils important time variation (regime dependency) in the dynamic responses to uncertainty shocks, which could further explain the differences between their results and ours.

Our empirical evidence fully lines up with Carriero et al. (2018b) as concerns the exogeneity of macroeconomic uncertainty. Carriero et al. (2018b) identify the shocks by a novel stochastic volatility approach based on nonrecursive SVARs that include measures of macroeconomic and financial uncertainty, one at a time. In their model the on-impact coefficients are constant but an independent stochastic process drives the volatility of the system and facilitates the identification of the shocks compared to our regime-dependent method. The extension of their approach to jointly modelling macroeconomic and financial uncertainty is computationally demanding, and this fact probably explains why they do not separately identify the effects of macroeconomic and financial sources of uncertainty on economic fluctuations, and why in their analysis financial uncertainty is not "as exogenous" as we find in our setup.

3.4.2 | IRFs

The implied IRFs are computed as in Equation 15 by replacing A_1, A_2 and A_3 and $\tilde{B}$, $\tilde{B} + \tilde{Q}_2$ and $\tilde{B} + \tilde{Q}_2 + \tilde{Q}_3$ with their estimates, and are plotted in Figures 2 –5 over a horizon of $h_{\max} = 60$ periods (5 years). Figure 2 plots the IRFs obtained on the three volatility regimes for $f = 1$ (1-month uncertainty). Figures 3 –5 plot the IRFs separately for each regime, disentangling the case $f = 1$ (1-month uncertainty) from the case $f = 12$ (1-year uncertainty).[16] All plots show responses to one standard deviation changes in e_{jt}, $j = M, Y, F$, in the direction that leads to an increase in its own variable X_{it}, $i = M, Y, F$, where $X_{Mt} = U_{Mt}$, $X_{Yt} = Y_t$ and $X_{Ft} = U_{Ft}$, respectively. This normalization allows us to directly compare the responses of real economic activity in the three volatility regimes.

In Figure 2 (which can be fully appreciated in color), the blue IRFs refer to the Great Inflation period, the red IRFs to the Great Moderation period, and the yellow IRFs to the Great Recession + Slow Recovery period. The first row reports the response of macroeconomic uncertainty to the three structural shocks, the second row reports the response of industrial production, and the third row reports the response of financial uncertainty. In this case, confidence bands have not been reported, to ease reading.[17] In order to compare results with a benchmark, Figure 2 also plots the IRFs generated by the SVAR identified by Lanne and Lütkepohl's (2008) method, discussed at the beginning of this section—that is, the structural model based on the specification in Equation 20 and regime-invariant autoregressive coefficients.

The graphs in Figure 2 suggest four main comments. First, there is evidence of substantial time variation in the impulse responses: The estimated IRFs differ quantitatively and qualitatively across the three volatility regimes. Although uncertainty shocks curb industrial production growth in all three macroeconomic regimes, the persistence of the response and the number of periods after which the negative peak is reached vary across regimes. Second, the effects of macroeconomic uncertainty shocks on all variables are larger and more persistent in the Great Recession + Slow Recovery period. In particular, macroeconomic uncertainty seems to have played a sizable role in persistently driving down economic activity during this period. Third, while real economic activity reacts negatively and persistently to uncertainty shocks, uncertainty reacts only mildly to real activity shocks, if anything. Fourth, there exist differences, as expected, between the IRFs estimated with our nonrecursive SVAR and the IRFs produced by keeping the structural parameters fixed.

Overall, combined with the reduced-form evidence in Section 3.2, Figures 2 –5 provide a positive answer to our second research question: The short-run relationship between uncertainty and real economic activity changes qualitatively and quantitatively across macroeconomic regimes. A researcher who ignores the regime-dependent nature of uncertainty shocks is likely to estimate compounded effects, which hide the different dynamics displayed in the data.

The estimated IRFs can also be framed in a recent debate on the role of uncertainty during the zero lower bound. According to Plante et al. (2018), during the zero lower bound, which roughly coincides with the Great Recession +

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[16]To save space, a detailed comment of the IRFs in Figures 3 –5 can be found in the Technical Supplement.

[17]Recall that the reduced-form analysis in Section 3.2 shows that there are significant differences between all VAR coefficients (autoregressive parameters and covariance matrices) across the three volatility regimes. Accordingly, the three IRFs in each graph of Figure 2 read as transformations of parameters that have been established to be statistically different in their population values.
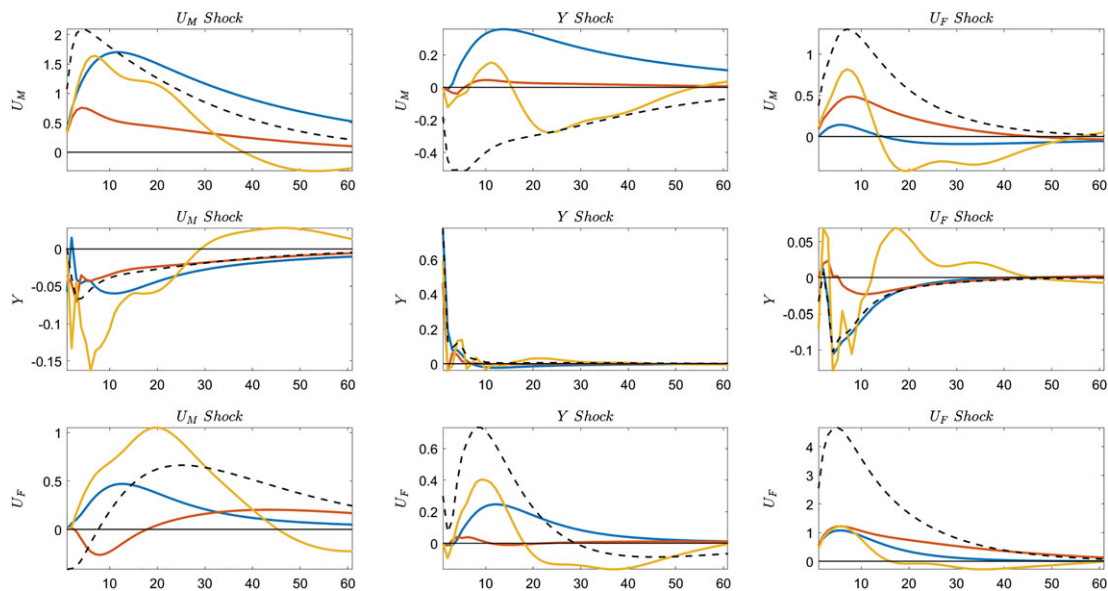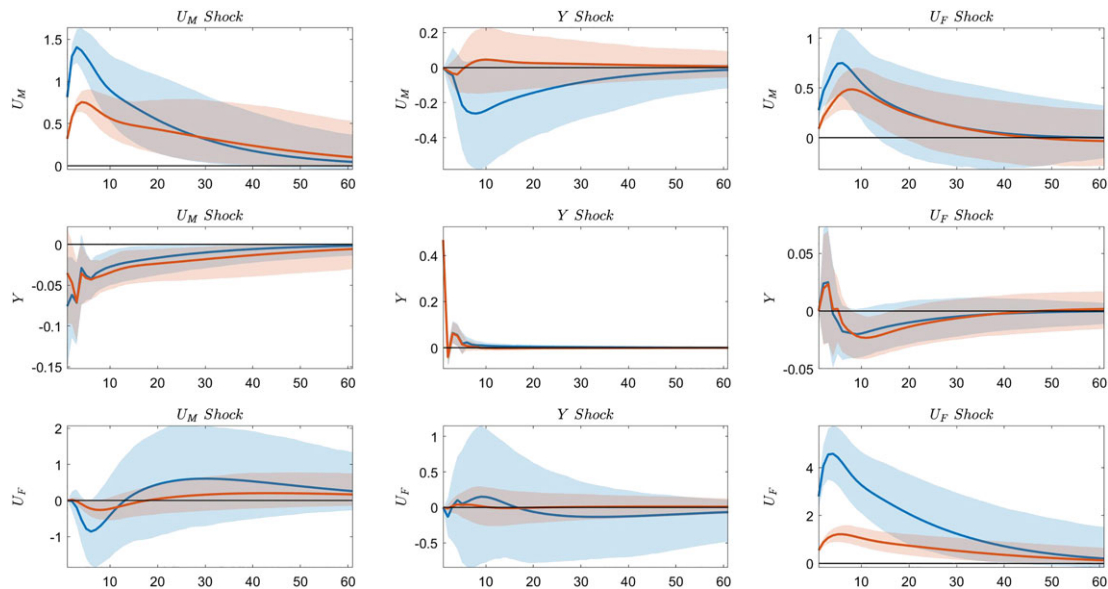
FIGURE 2 IRFs obtained from the baseline nonrecursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in Equations 18–19. U_{Mt} and U_{Ft} refer to the 1-month ($f = 1$) uncertainty horizon. The blue line refers to the first volatility regime (Great Inflation, 1960:M8–1984:M3); the red line refers to the second volatility regime (Great Moderation, 1984:M4–2007:M12); the yellow line refers to the third volatility regime (Great Recession + Slow Recovery, 2008:M1–2015:M4). Dashed black lines plot the IRFs obtained with the SVAR in Equation 20, estimated on the whole sample, 1960:M8–2015:M4. Responses are measured with respect to one standard deviation changes in structural shocks [Colour figure can be viewed at wileyonlinelibrary.com]
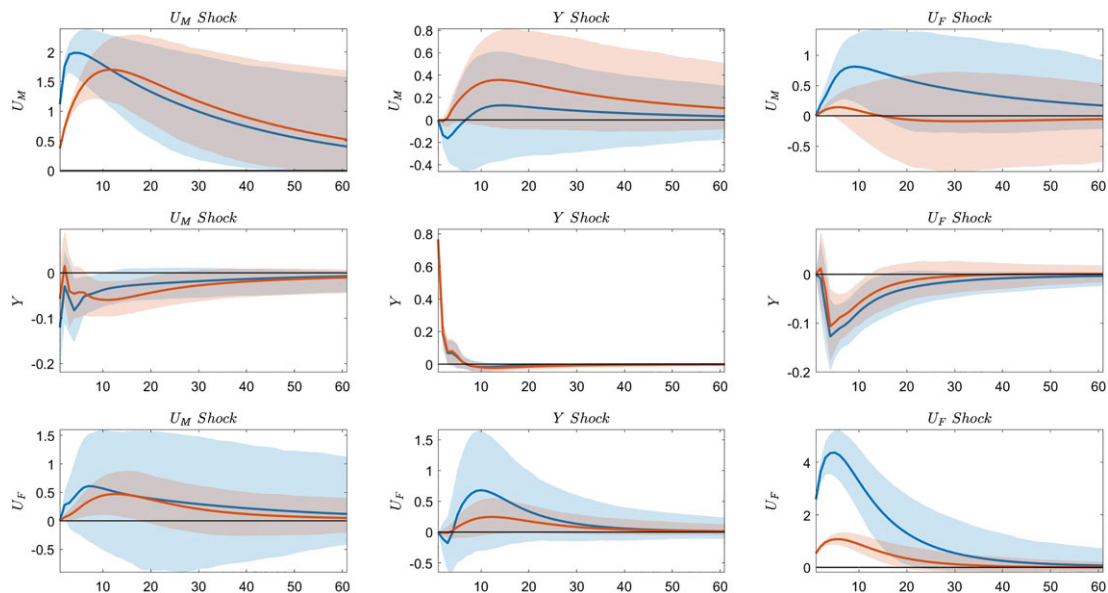
FIGURE 3 IRFs obtained in the first volatility regime (Great Inflation, 1960:M8–1984:M3) from the baseline nonrecursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta ip_t$ (industrial production growth) specified in Equations 18–19. The blue lines refer to the 1-month ($f = 1$) uncertainty 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 [Colour figure can be viewed at wileyonlinelibrary.com]

Slow Recovery period, macroeconomic variables were more responsive to negative shocks hitting the economy because of the inability of the Fed to use conventional instruments to stabilize the economy, inducing a general increase in the uncertainty surrounding future growth. The IRFs in Figures 4 and 5 show that there is indeed a difference in the response of uncertainty to real economic shocks when moving from the Great Moderation to the Great Recession + Slow Recovery period. However, while this effect helps to explain why the correlation between uncertainty and real economic activity

FIGURE 4 IRFs obtained in the second volatility regime (Great Moderation, 1984:M4–2007:M12) from the baseline nonrecursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta i p_t$ (industrial production growth) specified in Equations 18–19. 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 [Colour figure can be viewed at wileyonlinelibrary.com]
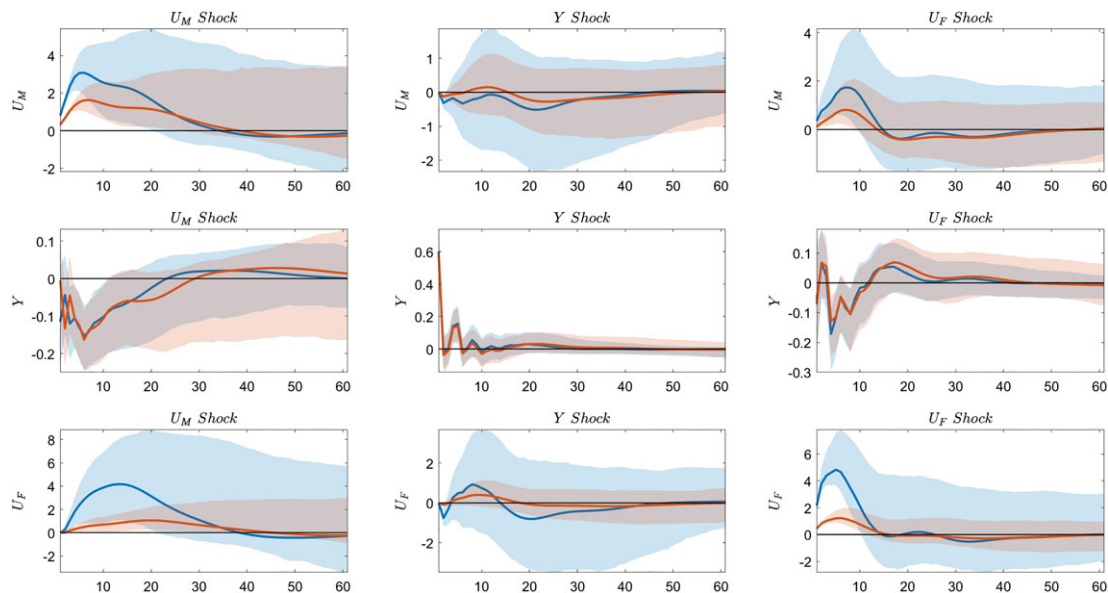
FIGURE 5 IRFs obtained in the third volatility regime (Great Recession + Slow recovery, 200:8M1–2015:M4) from the baseline nonrecursive SVAR for $X_t := (U_{Mt}, Y_t, U_{Ft})'$, $Y_t = \Delta i p_t$ (industrial production growth) specified in Equations 18–19. The blue lines refer to the 1-month ($f = 1$) 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 [Colour figure can be viewed at wileyonlinelibrary.com]

increases after the GFC (see the correlations in Table 1), it is not sufficient to claim that uncertainty is an endogenous (causal) response to real economic activity shocks because, according to our analysis, the response is at most lagged one period, but is not instantaneous.

Finally, the estimated IRFs also line up with several contributions in the literature that highlight how uncertainty shocks have had larger effects after the GFC. This can be due to large financial frictions, as in Alfaro et al. (2018), Caggiano, Castelnuovo, Delrio, and Robinson (2017), and Gilchrist et al. (2014), or to the presence of the zero lower bound, as in

Caggiano, Castelnuovo, and Pellegrino (2017) and Basu and Bundick (2017). They also support theoretical and empirical research that highlights how uncertainty shocks might have time-varying effects that depend on different macroeconomic conditions, such as the level of financial frictions (Alessandri and Mumtaz, 2018; Alfaro et al., 2018; Gilchrist et al., 2014), the stance of the business cycle (Cacciatore & Ravenna, 2016; Caggiano et al., 2014), or the stance of monetary policy (Basu & Bundick, 2017; Caggiano, Castelnuovo, & Pellegrino, 2017).

4 | CONCLUDING REMARKS

This paper has addressed two controversial issues that characterize the empirical literature on uncertainty: whether time variation in uncertainty should be considered as an exogenous driver of the business cycle or, rather, an endogenous response to it; and whether the real effects of uncertainty shocks have changed over time with the changes in macroeconomic conditions. The two issues have been analyzed simultaneously with a small-scale nonrecursive SVAR estimated on US post-WW2 data, by resorting to an "identification-through-heteroskedasticity" approach, which is novel in the literature on uncertainty. Unlike other existing identification approaches, our framework allows us to jointly estimate regime-dependent effects of uncertainty shocks, and is general enough to account for reverse causality—that is, to allow for a contemporaneous response of both real activity to uncertainty shocks and of uncertainty to real activity shocks.

Empirical results suggest that there are important differences in the impact and propagation mechanism of uncertainty shocks across the three main macroeconomic regimes that characterize the US business cycle, and that uncertainty, both macro and financial, is better approximated as an exogenous source of economic decline rather than an endogenous response to it. We find that macroeconomic uncertainty shocks have always had a contractionary impact on real activity, but that these effects have become larger since the GFC. In turn, after the 1980s, financial uncertainty shocks affect real economic activity by fostering greater macroeconomic uncertainty.

Overall, our findings support the theoretical models where uncertainty is treated as an exogenous driver of economic fluctuations, as in Bloom (2009) and Basu and Bundick (2017), for example, and the empirical specifications where uncertainty enters recursive SVARs. In this respect, our analysis is partially consistent with the evidence reported in Ludvigson et al. (2018a) and is not at odds with Carriero et al. (2018b).

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