INSTITUTO DE ECONOMÍA

DOCUMENTO de TRABAJO

569

2023

Are the Effects of Uncertainty Shocks Big or Small?

Piergiorgio Alessandri, Andrea Gazzani y Alejandro Vicondoa.

www.economia.uc.cl · ISSN (edición impresa) 0716-7334 · ISSN (edición electrónica) 0717-7593

Are the Effects of Uncertainty Shocks Big or Small?*

Piergiorgio Alessandri[†] Andrea Gazzani[‡] Alejandro Vicondoa[§]

April 5, 2023

Abstract

Previous works have reached widely divergent conclusions on the macroeconomic relevance of uncertainty shocks. We show that this disagreement reflects identification problems linked to the use of financial data in low-frequency VAR models. To bypass this difficulty, we identify uncertainty shocks using daily data and use their monthly averages as instruments in VARs. This novel identification approach captures within-month interactions between uncertainty and asset prices, providing a full picture of the pivotal role of financial markets in propagating uncertainty to the real economy. Once these interactions are accounted for, the disagreement disappears: uncertainty shocks have a small but significant impact on economic activity across specifications and identification schemes.

JEL classification: E32; C32; C36

Keywords: uncertainty shocks; financial shocks; structural vector autoregression; high-frequency identification; external instruments

*This paper supersedes works that were previously circulated under the title "Bridge Proxy-SVAR: estimating the macroeconomic effects of shocks identified at high frequency" and "The real effects of uncertainty shocks: a daily identification approach". We are grateful to Evi Pappa, Fabio Canova and Juan Dolado for fruitful discussions and suggestions. We also thank Torben Andersen, Scott Baker, Ambrogio Cesa-Bianchi, Paul Beaudry, Dario Caldara, Danilo Cascaldi-Garcia, Ian Dew-Becker, Maarten Dossche, Michele Piffer, Luca Gambetti, Aeimit Lakdawala, Peter Hansen, Matteo Iacoviello, Francesca Loria, Riccardo Jack Lucchetti, Kurt Lunsford, Michele Piffer, Giorgio Primiceri, Morten Ravn, Juan Rubio-Ramirez, Viktor Todorov, Andreas Tryphonides, Sreko Zimic, and participants at many seminars and conferences for helpful comments and suggestions. Vicondoa acknowledges financial support from ANID Fondecyt Regular Grant 1220513. The views expressed in the paper are those of the authors only and do not involve the responsibility of the Bank of Italy.

[†]Bank of Italy. Email: piergiorgio.alessandrii@bancaditalia.it.

[‡]Bank of Italy. Email: andreagiovanni.gazzani@bancaditalia.it.

[§]Instituto de Economía, Pontificia Universidad Católica de Chile. Email: alejandro.vicondoa@uc.cl

1 Introduction

Isolating the role of uncertainty in the business cycle is challenging because spikes in uncertainty often coincide with a deterioration of the macroeconomic outlook. This problem is particularly apparent when considering the interaction between financial markets and the real economy. High stock market volatility, rising credit spreads and economic slowdowns often materialize together, but researchers disagree on the interpretation of this coincidence, interpreting uncertainty either as an independent source of fluctuations or as an endogenous by-product of the business cycle.

We examine this puzzle using a novel empirical strategy that is specifically designed to identify uncertainty shocks from fluctuations in asset prices. Financial variables incorporate macroeconomic expectations and risk premia that reflect, among other factors, changes in aggregate uncertainty (Baumeister, forth). To isolate the role of aggregate uncertainty, we identify the shocks in a daily VAR, average them to the monthly frequency, and then use this average as an instrument in a monthly VAR model. This procedure delivers consistent estimates of the low-frequency impact of the shocks because, in linear VARs, the causal effect of the sum of daily shocks coincides with the sum of their individual (daily) effects. Furthermore, it allows us to (i) control for changes in expectations at the daily frequency, accounting for the quick response of market investors to macroeconomic news, and (ii) leave the relation between financial and real variables unrestricted at the monthly frequency. In our framework the validity of the restrictions at the monthly frequency can be tested rather than assumed *ex ante*.

The procedure requires the standard invertibility assumption to hold in the daily VAR model. In our application we study its validity empirically, through the Forni and Gambetti (2014) test, and in simulations based on the general equilibrium models of Basu and Bundick (2017), Berger et al. (2019) and Bloom et al. (2018).

After discussing our identification approach , we revisit three influential studies that reach different conclusions on the relation between aggregate uncertainty and the business cycle. We start with Berger et al. (2019) (BDG), who focus specifically on the interaction between uncertainty and asset prices. BDG identify uncertainty shocks as perturbations that explain the largest share of the forecast error variance (FEV) of the expected (option-implied) volatility of the stock market but have no contemporaneous impact on its realized volatility, interpreted as a proxy of changes in macroeconomic fundamentals. We then consider Caldara et al. (2016) (CFGZ), where uncertainty and financial shocks are identified jointly as orthogonal perturbations that maximize respectively the responses of the VXO and the Excess Bond Premium. Finally, we broaden the scope of the analysis by revisiting the work of Baker et al. (2016) (BBD), in which uncertainty is captured by the Economic Policy Uncertainty (EPU) index rather than a financial volatility indicator, and identification relies on more traditional recursive schemes. In all cases we exploit our strategy to impose the identification restrictions on daily rather than monthly data, leaving the responses in the monthly VARs unrestricted. The exercise leads to three conclusions. First, aggregate uncertainty shocks cause a small but statistically significant decline in economic activity in all models. Under a daily identification, the responses are also more robust to the specific assumptions embedded in the identification schemes, such as the ordering of the shocks. Second, the quantitative relevance of the shocks for the business cycle turns out to be similar across specifications: the elasticities of employment and industrial production to aggregate uncertainty are 4% and 10% at the one-year horizon, and uncertainty shocks explain about 5% of the forecast error variance of both variables. Third, capturing the behavior of financial markets is critical to understand the overall transmission mechanism. As other scholars noted, aggregate uncertainty can respond endogenously to changes in financial conditions, but it can also have a strong impact on stock prices, bond spreads and market volatility. Daily models broadly agree on the relevance and relative weight of these two mechanisms, while monthly models disagree and tend to emphasize one of the two at the expense of the other.

Related literature. This paper makes two main contributions to the literature. The first one is a reappraisal of the influence of aggregate uncertainty on the business cycle.[1] Very different views have emerged on the identification of uncertainty shocks and on the implications of such shocks for the real economy (CFGZ, Carriero et al., 2018, Ludvigson et al., 2018, BDG). Our paper shows that temporal aggregation can completely cloud causality in this context, and that capturing the interaction between uncertainty and asset markets is key to estimate the effects of uncertainty on real outcomes. In developing a deeper and more comprehensive view on uncertainty shocks, our work is

[1]See e.g. Fernandez-Villaverde et al. (2011), Jurado et al. (2015), Baker et al. (2016), Basu and Bundick (2017), Arellano et al. (2019). Extensive reviews of the literature can be found in Bloom (2009) and Fernandez-Villaverde and Guerron-Quintana (2020).

inspired by similar efforts carried out by Coibion (2012) and Barnichon et al. (2022) on monetary policy and financial shocks, respectively. Few other works have employed daily or weekly data to identify uncertainty shocks. Ferrara and Guerin (2018) find that a mixed-frequency VAR with weekly and monthly data closely mimics a standard monthly VAR, while Paccagnini and Parla (2021) uncover significant temporal aggregation biases in a similar model estimated with Bayesian methods. Both papers rely on recursive identification schemes at weekly frequency that are unlikely to accurately describe the feedbacks between uncertainty and macroeconomic conditions, or more generally between financial and real variables.[2] Piffer and Podstawski (2018) use variations in gold prices around specific events as external instruments in a VAR, concluding that uncertainty shocks are a major driver of the business cycle. We propose a robust and flexible alternative to event-based identification strategies that allows us to control for a broad range of factors at the daily frequency, delivering far more conservative estimates of the overall impact of uncertainty shocks.

Our second contribution is to show how to exploit high-frequency information to construct proxies that can be used in lower-frequency VAR models. The estimation of dynamic effects based on external information has recently spread in the empirical macroeconomics literature (Stock and Watson, 2012; Mertens and Ravn, 2013). We demonstrate theoretically and through simulations that, as long as the data-generating process is a VAR, averaging the high-frequency proxy to a lower frequency delivers

[2]See e.g. Stock and Watson (2012), Baker and Bloom (2013), Baker et al. (2016), Cascaldi-Garcia and Galvao (2021) and Ludvigson et al. (2018).

consistent estimates of the responses in a broad range of empirical setups and model specifications. The strategy we propose is computationally simple and highly flexible: the shocks obtained from high-frequency data can be employed as external or internal instruments, included in an exogenous block of the VAR, or used in a local projection setup.[3] Hence, it can be used in a broad range of cases where identification restrictions imposed at "low" frequencies could bias the results.[4] Daily VARs have been used to identify, among others, monetary policy shocks (Wright, 2012) and shocks to growth expectations and risk premia (Cieslak and Pang, 2021). We show that researchers can combine daily identification schemes of this type with a lower-frequency estimation of the macroeconomic impact of the shocks, gaining a significant degree of empirical flexibility.

Outline. The remainder of this paper is organized as follows. Section 2 describes our strategy, illustrating its theoretical properties and its performance in Monte Carlo simulations based on VAR and general equilibrium models. Section 3 presents three empirical applications in which we revisit BDG, CFGZ and BBD identifying uncertainty shocks on daily rather than monthly data. Section 4 concludes.

[3]The use of external information in VARs is recently discussed in Miranda Agrippino and Ricco (2018) and Paul (2020). See Plagborg-Moller and Wolf (2021) and Herbst and Johannsen (2021) for a discussion of the relation between VARs and local projections.

[4]The temporal aggregation bias is discussed by Sims (1971), Christiano and Eichenbaum (1987), Marcet (1991), and Marcellino (1999) among others.

2 Identification Approach

We propose a new strategy to exploit high-frequency data (obtained for instance from financial markets) in order to estimate the effects of structural shocks on variables that are only available at lower frequencies (such as economic activity or inflation indicators). Our proposal is motivated by the consideration that the use of high-frequency observations can significantly improve the structural identification of VAR models that combine financial and macroeconomic variables. Macroeconomists routinely use monthly or quarterly series to examine the implications of various structural shocks. However, insofar as investors react quickly to economic news, these shocks are likely to propagate across markets and asset classes in far shorter time intervals. Trading in the US stock market has been highly fluid at least since the early 1980s, with institutional investors generating a cumulative turnover of up to 100 trades per day on thousands of single-label shares (Boehmer and Kelley, 2009). The flow of information associated to these activities implies that in a monthly or quarterly dataset exogenous shocks and endogenous responses might be inextricably mixed, and even theoretically sound identification strategies may fail to disentangle them. We argue that this is a critical lesson for a very broad set of VAR models based on financial data. The simple strategy proposed in this paper can be easily exploited in other contexts where researchers lack external instruments (based e.g. on event-studies) but can apply plausible identification restrictions to high-frequency datasets in which the endogenous feedbacks between variables are less pervasive. After summarizing the logic of our approach below, we prove its general validity in Section 2.2 and provide an analytical example of its application to a stylized VAR model in Section 2.3. Section 2.4 documents the performance of the strategy through Monte Carlo tests based on a range of alternative VAR and DSGE models.

2.1 A three-step Identification strategy

Our strategy to identify uncertainty shocks is a three-step one: I) estimate high-frequency (HF) VAR and apply the appropriate identification strategy; II) aggregate the shocks at the lower frequency (LF) of macroeconomic aggregates through averaging; III) compute the dynamics effects by employing the averaged shocks as an instrument for the LF-VAR. Before explaining those steps in detail, we discuss the omission of macroeconomic aggregates from the HF-VAR.

0) On the omission of macro-variables from the HF-VAR. The omission of macroeconomic aggregates from the HF-VAR may seem to be problematic at a first glance, as SVARs practitioners are used to incorporate macroeconomic variables into them to address macroeconomic or macro-financial questions. We explain in what follows that, actually, omitting the macro aggregates from the HF-VAR does not constitute a problem *per se*. The ability of any VAR model to identify a shock of interest rests upon the concept of invertibility that has been widely studied in the literature. Invertibility is a very strong, although commonly made, assumption: the structural shock(s) of interest have to be linearly mapped by the reduced form residual obtained by the VAR. Fernandez-Villaverde et al. (2007) formulate the "Poor's man invertibility condition" that needs to be satisfied to allow a VAR analysis to recover the shocks of interest.[5] In the words of Stock and Watson (2018) "under invertibility, a forecaster using a VAR would find no value in augmenting her system with data on the true macroeconomic shocks, were they magically to become available." Forni and Gambetti (2014) put it differently, yet equivalently: "There are no state variables that Granger cause the variables included in the VAR". The VAR should incorporate enough information on the state variables of the underlying structural model as to allow the correct identification of the structural shocks. The presence of macro aggregates among the observables does not automatically yield invertibility. In the same fashion, the omission of these variables does not constitute a violation of invertibility *per se*. On the contrary, in several cases, appending VAR models with asset prices has been proposed as a remedy to achieve invertibility. In the popular case of fiscal foresight, Leeper et al. (2013) argue: "If asset markets are efficient, the information contained in asset prices should coincide with all available information to agents, and adding asset prices to a VAR should help align the information sets of the econometrician and agent." The informational sufficiency of the VAR for a shock of interest (or vice-versa its invertibility with respect to a candidate VAR model) should be investigated case by case. Some authors have used purely financial structural VARs, implicitly relying on the invertibility

[5] In what follows we will use the term invertibility as including also the concepts of partial and approximate invertibility Partial invertibility refers to invertibility holding only for a subset of the shocks driving the system but that may be the only one of interest (in our case, uncertainty shocks). Approximate invertibility means instead that although the VAR residuals may span the structural shock to a certain degree, which may be still sufficient to characterize their dynamic causal effects (Beaudry et al. 2019; Forni et al. 2019).

assumption (Wright, 2012; Cieslak and Pang, 2021).

Empirically, Forni and Gambetti (2014) propose to proxy the state variables of the economy by estimating factors from large macro-financial dataset and perform a Granger causality test for the shocks of interested. Related to our work, Miranda Agrippino and Ricco (2018) suggest to apply the Forni and Gambetti (2014) test to monetary policy surprises that constitute a proxy for monetary policy shocks. The shocks we employ in our empirical applications always pass the Forni and Gambetti (2014) test (see also point II below).In a simulated environment, one can also use general equilibrium models to test whether a VAR estimated on financial data is informationally sufficient and, consequently, the estimated residuals span the structural shock of interest. In our case , simulations based on the leading general equilibrium models of Basu and Bundick (2017), Bloom et al. (2018), and Berger et al. (2019) (see Section 2.4) confirm the validity of the informational sufficiency assumption.

I) Identification of the shocks on high-frequency data. The first step of our strategy consists of recovering the structural shock(s) of interest by applying an appropriate identification strategy to a VAR model estimated on 'high-frequency' (HF) data. We deliberately use the HF label in a loose sense: the label simply indicates a frequency for which the identification restrictions are reasonable. This is often higher than the (monthly or quarterly) frequency of the macroeconomic aggregates for which one intends to estimate impulse-response functions. In the empirical applications of Section 3 we use daily data for the identification step. Higher-frequency observations might be preferable in other contexts, although moving to narrower intra-daily time windows entails a complex trade-off between the exogeneity and the statistical power of the estimated shocks (see Nakamura and Steinsson, 2018). The specification of the VAR must of course allow the identification of the shock of interest.

II) Temporal aggregation of the shocks. The second step consists of computing low-frequency (LF, e.g. monthly or quarterly) averages of the high-frequency shocks obtained in (I). One strength of our approach is its robustness: if the underlying HF data generating process is a VAR, then averaging is the correct temporal aggregation filter for the shocks irrespective of the gap between the two frequencies and the type of variables employed in the analysis (prices, flows, stocks, etc.; see subsections 2.3–2.4). This result on the optimal aggregation filter is also relevant for VARs identified using external information (i.e. proxies), which have recently become very popular in the applied macroeconomics literature (see e.g. Gertler and Karadi, 2015; Ramey and Zubairy, 2018). Our analysis demonstrates that there are indeed good reasons to stick to simple within-period averaging rather than using alternative filters, such as moving averages, large shocks, or shocks that occur at the beginning or the end of each month/quarter (see Section 2.2). The averaged LF shocks are tested as in Forni and Gambetti (2014): in our applications we show that they are orthogonal to past information obtained from large auxiliary data sets.

III) Estimation of the impact of the shocks on low-frequency variables. The third and last step consists of employing the series of LF shocks obtained in (II) as a proxy or instrument to estimate the causal effects on the endogenous variables of interest. The estimation can be carried out using a VAR model or through local projections (Jorda, 2005; Stock and Watson, 2018) . In a VAR setup, the LF shocks can be treated as 'external' or 'internal' instruments. In the first case, if the proxy does not Granger-cause the residuals of the LF-VAR invertibility is not rejected and standard inference applies. Otherwise, inference based on the Proxy-SVAR is not valid, but the relative IRFs can still be estimated by including the proxy and its lags as an exogenous variable in the VAR (Paul, 2020). In the second case, the proxy is included as an additional endogenous variable in the VAR and ordered first in a Cholesky decomposition (see e.g. Plagborg-Møller and Wolf, Forthcoming, Miranda Agrippino and Ricco, 2018 for extensive discussions of advantages and disadvantages of all these alternative methods).

2.2 General Proposition

The strategy described in the previous section is underpinned by a general theoretical result on identification under temporal aggregation. Consider the general structural VAR process given by $A(L)y_t = B\varepsilon_t$, where L is the lag operator and $A(L)$ a lag polynomial of order p. The SVAR corresponds to a multiplicity of reduced-form VAR representations of the form $A(L)y_t = u_t$. Temporal aggregation can be expressed as a two-step filter. First, the data are made observable only once every m periods, which represents the frequency mismatch, via the filter $D(L) = \mathcal{I} + D_1 L + D_2 L^2 + ... + D_{pm-p} L^{pm-p}$. The specification of $D(L)$ has to be such that the elements of $D(L)A(L)$ are powers of L^m, meaning that only the observable data points enter the transformed process. The conditions for the existence of such a filter and the D_i matrices are derived in Marcellino (1999). The second filter, denoted by $W(L)$, depends on the temporal aggregation scheme considered; skip-sampling (or point-in-time sampling) is usually applied to stock variables (e.g. prices) whereas averaging is typically applied to flow variables (e.g. volumes). Our approach rests on the following proposition:

Proposition I. *Let y_t follow an underlying high-frequency (HF) VAR process with structural shocks ε_t and reduced-form innovations u_t, with $t = 1, 2, ...T$; and let y_τ represent the low-frequency (LF) version of the process obtained by applying the filters $D(L)$ and $W(L)$ to y_t,* with $\tau = m, 2m, ..., T$. *A consistent estimate of the contemporaneous impact of ε_t on y_τ can be recovered by projecting the LF residuals u_τ on the averages of the HF shocks that occurred within the LF periods, i.e. $\varepsilon_\tau = \frac{\sum_{t=\tau-m+1}^{\tau} \varepsilon_t}{m}$ for every τ.*

Proof: see Appendix B. ■

Proposition I implies that the causal effects of structural shocks in a low-frequency VAR can be recovered using simple averages of the structural shocks identified using high(er) frequency data. This procedure is appropriate irrespective of how the underlying series are aggregated over time, and hence it can be safely applied to VARs that include stocks, flows, or any combination of the two. This result hinges on the linearity of VAR models, which implies that the sum of the causal effect of the HF shocks ε_t in a given time window

τ is equal to the causal effect of their average ε_T.[6]

Comparison with Mixed-Frequency models. VAR models with mixed frequency data are typically studied using a state-space representation (Schorfheide and Song, 2015) or a stacked VAR approach (Ghysels, 2016). In state-space models low-frequency variables are treated as high-frequency variables with missing observations and recovered with the Kalman filter. While in principle this approach is optimal conditional on employing the right model specification, its performance depends in practice on the model's accuracy in reconstructing the high-frequency dynamics of the low-frequency variables. This procedure can be inaccurate when the frequency mismatch is high and the information on the missing states is scarce. Our identification strategy does not suffer from these shortcomings because it does not require a reconstruction of the full high-frequency dataset. In the stacked VAR approach, a high-frequency variable is decomposed into several low-frequency variables and directly employed in the VAR. This prevents the implementation of more sophisticated identification restrictions, forcing researchers to use recursive identification strategies (as in Ferrara and Guerin, 2018 and Paccagnini and Parla, 2021) that are not generally suited to capturing macro-financial interactions, and particularly unsound in the case of uncertainty shocks (Kilian et al., 2022). Moreover, there is no trivial way to obtain a unique measure of the impact of a high-frequency shock on low-frequency variables (Ghysels, 2016). Our

[6]Although we do not deal explicitly with shocks identified using narrative sources and event studies, our results on temporal aggregation are also relevant for this strand of literature. One implication of our work, for instance, is that the practice of aggregating HF shocks by taking a moving average or a weighted average of within-period observations is inconsistent if the true data-generating process is a HF VAR.

identification strategy can exploit any type of identification restrictions, and it is particularly well-suited to setups with a daily-monthly frequency mismatch and a potentially large set of daily series. As such, it has a strong comparative advantage in a broad range of macro-financial applications that rely on asset price data.

2.3 Illustrative VAR(1) case

Assume that the data generating process is a bivariate VAR(1) at the high frequency t, $Y_t = AY_{t-1} + B\varepsilon_t$, or equivalently:

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^x \\ \varepsilon_t^y \end{bmatrix}, \tag{1}$$

where $[x_t\, y_t]'$ are scalar endogenous variables and $\varepsilon_t = [\varepsilon_t^x\, \varepsilon_t^y]'$ is a vector of structural shocks , with $\mathbb{E}\left[\varepsilon_t \varepsilon_t'\right] = \mathcal{I}_2$.[7] The reduced-form residuals $u_t = B\varepsilon_t$ are correlated, with $\mathbb{E}\left[u_t u_t'\right] = \Sigma_{u_t} = BB'$. Assume further that the goal of the empirical analysis is to identify the effect of the shock ε^y on x, but y is observed in every period $t = 1, 2, .., T$ whereas x is observed every two periods, i.e. in $\tau = 2, 4, ..., T$. This frequency mismatch generates an estimation problem as the SVAR in Eq.(1) is not observable. If the variables are aggregated using end-of-period values, the low-frequency system is defined by $Y_\tau = A^2 Y_{\tau-1} + u_\tau$, where $\mathbb{E}\left[u_\tau u_\tau\right] = \Sigma_{u_\tau} = ABB'A' + BB'$ (see Appendix B). In this model a Cholesky decomposition does not recover the impulse-response functions

[7] We use for simplicity a lower-triangular impact matrix B but the results can be generalized to the case where $b_{12} \neq 0$.

because the DGP is still a VAR(1) but its residual covariance matrix is not diagonal. The same problem arises if the data is aggregated using averages rather than end-of-period values. In other words, temporal aggregation prevents a correct identification of the shocks.[8] Suppose the researcher estimates a (suitably defined and informationally sufficient) VAR at the frequency t, recovering the high-frequency shock ε_t^y or at least a proxy of the shock, $z_t = \varepsilon_t^y + \eta_t$ where $\eta_t \perp \varepsilon_t^y$ represents noise. In Appendix B.5 we demonstrate that, in line with Proposition I, the impact on $x_\mathcal{T}$ of the average within-period shock $\varepsilon_\mathcal{T}^y = \left(\varepsilon_t^y + \varepsilon_{t-1}^y\right)/2$ can be recovered using an average of this proxy, $z_\mathcal{T} = (z_t + z_{t-1})/2$, as an instrument in the low-frequency VAR. Under the standard assumptions of exogeneity and strength of the proxy ($\mathbb{E}\left[z_t \varepsilon_t^x\right] = 0$, $\mathbb{E}\left[z_t \varepsilon_t^y\right] \neq 0$), by regressing $u_\mathcal{T}$ on $z_\mathcal{T}$ the researcher correctly identifies $[0\ b_{22}]'$ up to a scale factor μ and obtains an unbiased estimate of the IRF ratio $0/b_{22}$. This is not the case for alternative aggregation schemes. In particular, aggregations of the high-frequency shocks that rely on moving averages, or on weights based on the number of days left in a month (e.g. Kuttner, 2001; Gertler and Karadi, 2015), are formally inconsistent with an underlying high-frequency VAR structure.

2.4 Monte Carlo Validation

Our strategy raises three related questions. The first one is whether invertibility can hold in HF VAR models that omit by construction low-frequency macroeconomic indicators. This requires the high-frequency variables included in the model to capture all the

[8] See Marcellino (1999) for a more general discussion of the temporal aggregation bias.

relevant structural shocks in the economy, which is not trivial. The second one is whether, subject to the HF VAR being invertible, our three-step strategy delivers better IRF estimates than alternatives approaches. The third one is whether the strategy successfully retrieves uncertainty shocks, which are known to raise particularly delicate identification issues. In the three subsections below we investigate these issues using data generated from a range of alternative VARs as well as widely-known DSGE models.

2.4.1 Invertibility

For the first set of tests we rely on the workhorse macroeconomic model by Smets and Wouters (2007), as extended in Kliem and Uhlig (2016). Our objective is to check whether a VAR based on a set of high-frequency variables allows identification in a standard economic model driven by a realistic combination of structural shocks (technology, labor supply, capital adjustment, wage markup and government spending). We assume that only 4 of the variables featured in the model can be observed or proxied at high frequency: risk-free interest rate, return on physical capital, excess return on equity and stochastic discount factor.[9] In order to assess invertibility we estimate the VAR and compute the R^2 coefficients in regressions where the true structural shocks are projected onto the VAR residuals (Beaudry et al., 2019; Forni et al., 2019).[10] With 5 structural shocks and 4 variables the VAR cannot by construction achieve invertibility for all the shocks. Furthermore, the VAR is only an approximation to the solution of the

[9]Risk free rate, return on capital and excess return on equity are directly observable; stochastic discount factors can be obtained from asset prices under various assumptions on market completeness and segmentation (see e.g. Sandulescu et al., 2021).

[10]We repeat the exercise 1000 times employing samples of 500 observations generated by the model.

DSGE model, which has a VARMA structure. The results in the first column of Table 2 show that, despite these limitations, the VAR is highly invertible with respect to technology (0.95), labor supply (0.77), and capital adjustment shocks (0.96). For comparison, we also report a similar set of statistics for two models that exploit the information contained in all the endogenous variables of the DSGE model. The second column refers to a FAVAR based on 4 factors extracted from all the endogenous variables (a model that includes again less variables than shocks, and is thus structurally informationally deficient like the previous VAR). Invertibility drops for labor supply and wage markup shocks and increases substantially for fiscal shocks. The third column shows instead the results for a FAVAR with 5 variables, which represents the upper bound of what linear VAR models can achieve in this context: all R^2 coefficients lie in this case around 0.95. The exercise shows that, on average, asset prices capture the information on the aggregate shocks in the economy fairly well, implying that financial VARs can be reliably used for identification. However, it also shows that invertibility can vary significantly across shocks. This motivate the analysis in Section 2.4.3, where our strategy is tested using DSGE models with uncertainty shocks.

2.4.2 Comparison with VAR and mixed-frequency models

In this section we use VAR-generated data to compare our strategy to (i) a naive VAR based on low-frequency data only, and (ii) the mixed-frequency models proposed by Schorfheide and Song (2015) and Ghysels (2016). Invertibility holds by construction in these tests (see section 2.4.1); the key question is how the models perform in estimating

IRFs in small samples (see **Annex C.3** for details). In the first test we simulate data using the VAR(1) model of equation 1 under alternative assumptions on sample size, frequency mismatch and temporal aggregation schemes. Our strategy (*HF+LF VAR*) consistently outperforms a VAR based on low-frequency data (*LF VAR*), generating accuracy gains in the estimation of the impulse-responses that range between 20% and 85% (see Table C1). By misestimating the contemporaneous impact of the shock, the LF VAR can generate distortions that spread across variables and over time causing the responses to be biased up to a one-year horizon, as in the example of Section 2. In the second test we employ a four-variable VAR(1) system to compare the HF+LF VAR to the mixed-frequency models proposed by Schorfheide and Song (2015) and Ghysels (2016).[11] The results confirm that the HF+LF VAR is a valid alternative to these models: the HF+LF VAR features a lower Mean Absolute Distance (MAD) between true and estimated IRFs in all the combinations of frequency mismatches and data aggregation schemes considered in the tests (see Table C2). Our strategy is particularly attractive in datasets that combine daily and monthly series, for which mixed-frequency and state-space models are either non-viable or subject to an extremely large estimation uncertainty. With daily data, these models generate MADs that can be up to 10 times larger than those of the HF+LF VAR.

[11] The model must include at least 4 variables in order to have a multivariate (i.e. bivariate) high-frequency block and a multivariate low-frequency block.

2.4.3 DSGE models with uncertainty shocks

The final piece of our validation analysis represents the most direct test of the empirical strategy employed in the next section, and it consists of Monte Carlo tests based on leading DSGE models with aggregate uncertainty shocks (see Appendix C for details). We use the general equilibrium models of Basu and Bundick (2017) (BB), Bloom et al. (2018) ("Really Uncertain Business Cycle", RUBC) and Berger et al. (2019) ("Really Skewed Business Cycle", RSBC), relying throughout on the calibrations originally employed by the authors. The test is designed in the same way in the three cases. We first define a "high-frequency" dataset for each of the DSGE models: this includes alternatively VXO, stock price and interest rate (BB) or realized stock market volatility and VXO index (RSBC and RUBC). The data is monthly in RSCB and quarterly in BB and RUBC. We then aggregate the series into "low-frequency" datasets that are quarterly for RSBC and annual for BB and RUBC. High- and low-frequency variables are defined here purely on the basis of which information is available to the econometrician: we assume that the financial variables included in the models can be observed at both frequencies, whereas the macroeconomic variables are only observed at low frequency.[12] Finally, we compare the performance of HF+LF VARs (where high-frequency financial instruments are used for identification in HF-VAR and then aggregated to estimate its causal effect on variables only available at the lower frequency) to the performance of counterfactual HF

[12]Using a daily high-frequency benchmark would be more appealing, but it would also be problematic because it would require re-calibrating the three DSGE models to the daily frequency. These daily calibrations would be inevitably arbitrary and they could significantly alter the dynamics of the models relative to the original specifications, rendering the Monte Carlo tests less informative.

VARs (where both macro and financial series are assumed to be available at high frequency) in recovering uncertainty shocks in the simulated data. In these comparisons all the models employ identification schemes that are consistent with the underlying DSGE structures: the difference is that the HF+LF VARs identify structural shocks using a smaller set of high-frequency variables. Table 1 displays the correlations between true and estimated shocks in the three models.

The correlations between true and estimated shocks in the HF-VAR are respectively 0.87, 0.88 and 0.98 for RSBC, BB and RUBC. Owing to the nonlinearity of the data-generating processes, even this model faces limitations in recovering the shock series. More importantly, however, the correlations are virtually identical for HF VARs and HF+LF VARs. This implies that the informational content of the financial indicators is sufficient for identification; or, put differently, that the unobservability of the macro series at high frequency is not a first-order problem for the identification of uncertainty shocks in any of the three DSGE models. A comparison between the estimated IRFs reinforces this message (see Figures 1 and 2). The HF+LF VARs accurately track the responses of both financial and real variables, with performances that are comparable to those of the counterfactual HF VARs. The method works well both in the BB model, in which uncertainty has a sizable impact on output, and in the RSBC model, in which it has no impact.

3 Uncertainty, Volatility, and Financial Markets

The debate on the role of uncertainty in the business cycle is open and fluid. Earlier studies documented a strong impact of aggregate uncertainty on investment and output, but recent contributions have cast doubt on those conclusions showing that uncertainty is often an endogenous response to changes in fundamentals rather than an independent source of fluctuations. This ambiguity is particularly evident when considering the interactions between financial markets and the real economy. Recessions in the US typically coincide with spikes in the volatility of the stock market, but researchers are very much at odds on the interpretation of this coincidence. Baker et al. (2016) (BBD) show that policy uncertainty generates volatility in firm-level equity evaluations, a drop in stock prices and a significant decline in economic activity. Caldara et al. (2016) (CFGZ) find that both policy uncertainty and stock market volatility can have an adverse impact on the economy. Ludvigson et al. (2018) point out that 'financial' uncertainty shocks are a specific and quantitatively important source of business cycle fluctuations (see also Carriero et al., 2018). At the other extreme of the spectrum, Berger et al. (2019) (BDG) argue that, once they are properly isolated from concurrent changes in fundamentals, exogenous shifts in the expected volatility of the stock market have no impact on output and employment. In this section we contribute to this debate by combining our approach with the identification schemes proposed by BBD, BDG and CFGZ. In all cases we take the identification schemes as given and simply shift the restrictions from the monthly frequency used in the original papers to the daily frequency. The motivation for this test is straightforward: if investors respond to uncertainty and macroeconomic news on a daily basis, then monthly data may return a partial and potentially misleading picture of the effects of uncertainty on the real economy.

3.1 Berger, Dew-Becker and Giglio (2019)

Berger et al. (2019) (BDG) point out that, since financial market volatility reflects changes in fundamentals as much as uncertainty about the future, a rise in volatility can predict an economic slowdown even if it does not cause it in any way. To solve the problem BDG identify “uncertainty shocks” as innovations to expected volatility that are orthogonal to the realized volatility of the US stock market within a given month (a proxy of market reactions to changes in other macroeconomic fundamentals). BDG employ a VAR model that includes realized volatility (rv), an option-implied volatility measure constructed by the authors (v_1), the Fed Funds rate (ffr), industrial production (ip), and employment (emp). The model is estimated over the period between 1983 and 2014. Following a strategy originally used for TFP news shocks (see e.g. Barsky and Sims, 2011), uncertainty shocks are identified as the linear combination of the reduced-form residuals that maximizes the two-year ahead forecast error variance (FEV) of v_1 but has no contemporaneous effect on rv. The authors find that realized volatility shocks cause a significant decline in economic activity while uncertainty shocks have no effects on the real economy.

The BDG restrictions can be easily exploited within our three-step procedure. Like BDG, we estimate a monthly VAR that includes a constant and four lags of rv, v_1, ffr, ip and emp (all expressed in natural logarithms but for ffr). Following the procedure described in Section 2, we then: (I) estimate a daily VAR including rv and v_1, applying the BDG identification scheme to recover realized and implied volatility shocks (and using an identical horizon, adjusted to the daily frequency, for the forecast error variance maximization); (II) calculate monthly averages of the daily shocks; and (III) use these averages as external instruments for the residuals of the monthly VAR model. The daily model employs the BDG measure for v_1 and the squared daily return on the S&P500 index as a proxy of realized market volatility rv.[13] The relation between v_1 and rv is not affected by the switch to daily observations: in particular, v_1 is a powerful predictor of rv for horizons of up to 6 months (see Table Table A.1 of the Appendix). Two modeling issues are worth commenting on. The first one is informational sufficiency. Although BDG rely on two financial indicators only, we find that the shocks obtained from a bivariate daily VAR based exclusively on rv and v_1 fail the Forni and Gambetti (2014) test. We consequently replace the bivariate specification in step (I) with a richer model that includes a range of daily indicators for bond, equity and commodity markets.[14] The

[13]Our sample starts in 1986 rather than 1983 because the daily v_1 series constructed by BDG, unlike its monthly counterpart, is only available from 1986 onward. This change does not distort the comparison: BDG show indeed that their results also hold for the 1988-2014 period. Squared daily returns (an unbiased but noisy measure of daily market volatility) are not used in the applications of sections 3.2 and 3.3.

[14]The expanded daily VAR includes (in logs) $s\&p500$ price index, Fed Funds rate, BAA corporate bond spread, euro-dollar exchange rate, Economic Policy Uncertainty index, the $s\&p$ Goldman Sachs Commodity Index (GSCI) - gold spot price. If these variables are included in a forecasting regression for rv_t, the R^2 increases from 0.46 to 0.68, see table Table A.1 of the Appendix. The shocks identified in this specification pass the information sufficiency test: see Table Table A.2 of the Appendix.

second issue relates to invertibility. The shocks obtained from high-frequency data can be used indifferently as internal or external instruments in the monthly VAR model (see Section 2): since we find no evidence of Granger-causality running from the shocks to the reduced-form residuals of the monthly VAR, following Paul (2020) and Noh (2018), we employ the shocks as external instruments for the residuals of the rv_t and $v_{1,t}$ equations.

Figure 3 compares the impulse-response obtained from our strategy (*Daily+Monthly VAR*, left column) to those obtained from our replication of the monthly BDG model (*Monthly VAR*, right column). In the monthly setup the contemporaneous response of rv to a v_1 shock is zero by construction. In our model, by contrast, this response is large and positive, suggesting that rv rises significantly during the month in which the shock takes place (see top row of the figure). This result is important because the identification scheme *per se* says nothing about the time interval over which the rv response should be held constant at zero. BDG argue that, since prices respond in opposite directions to positive and negative uncertainty shocks, realized volatility (a function of squared price changes) should not respond to the shock on impact. The question is what 'on impact' means in practice. In financial markets a one-month horizon is likely to capture short- or medium-term adjustments rather than contemporaneous adjustments. Hence, fixing the daily response of rv is more sensible and far less restrictive that fixing its monthly response. Figure 3 shows that the difference matters: once the shock is identified using daily observations, the data reveals a strong within-month response of realized volatility to uncertainty shocks.[15] The rest of Figure 3 shows that switching to a daily identification has first-order implications for the other variables in the system too. The responses of ffr, ip and emp are now consistently negative, and the shock causes a small but statistically significant drop in both industrial production and employment. Unlike the *Monthly VAR*, the *Daily+Monthly VAR* rejects the null hypothesis that a rise in uncertainty has no real economic implications.[16] This rejection reflects both a bias and a variance factor. On the one hand, the point estimates of the ffr, emp and ip responses are negative at all horizons. The change in the sign of the response is particularly visible for ffr, which is instead estimated to rise on impact and remain above zero for over a year (albeit not significantly) in the original setup. On the other hand, the confidence bands are narrower than in the monthly model. This result, however, depends on how the IRFs are bootstrapped. The confidence intervals in figure 3 are based on the recursive homoskedastic bootstrap of Plagborg-Møller and Wolf (Forthcoming), which allows a straightforward computation of forecast error variance decomposition (see below). If this is replaced by a wild or moving-block bootstrap, the IRFs remain significant but the confidence bands become more similar to those of the monthly model (see Appendix

[15] This result is extremely robust to an "agnostic" set-identification procedure: out of 1 million random draws of the impact matrix of the daily VAR, not even one is compatible with rv remaining constant for 21 business days. The persistence of the rv and v_1 responses in figure 3 may appear puzzling at first (efficient stock and option markets should in principle adjust instantaneously to all shocks, uncertainty included), but it is consistent with a large body of empirical evidence. Financial economists have long documented 'momentum' and persistence in asset prices using reduced-form models (Fama and French, 2015, Ehsani and Linnainmaa, 2021); and stock and bond yields often display gradual and persistent responses to monetary policy shocks in structural VAR models (Nakamura and Steinsson, 2018, Miranda-Agrippino and Ricco, 2021). These VAR responses are based on *ex-post* estimates, so they do not necessarily imply the existence of forms of return predictability that could have been exploited in real time.

[16] BDG acknowledge that high-frequency dynamics could invalidate their monthly identification procedure and propose a robustness test on this issue in Section 6.1.3 of the paper: the relation between their test and our results is discussed in Appendix D.1.3.

D.1). Furthermore, narrower bands only appear in the BDG setup: in the applications of sections 3.2 and 3.3 our strategy corrects the point estimates of the responses without affecting the standard errors around them.

We conclude this section with a comment on the implications of our analysis for the overall relevance of uncertainty shocks in the business cycle. The peak responses of emp and ip to an rv shock are respectively twice and thrice the size of those associated to a v_1 shock; as a result, rv shocks explain a significantly larger fraction of the forecast error variance of both employment and industrial production (see figures A.4 and A.5 of the Appendix). Our strategy shows that uncertainty shocks 'matter', but it also corroborates the conclusion that first-moment shocks 'matter more'. As we show in the next subsections, these conclusions emerge clearly in setups that use different identification restrictions and uncertainty proxies.

3.2 Caldara, Fuentes-Albero, Gilchrist and Zakrajsek (2016)

Caldara et al. (2016) (CFGZ) focus on the interactions between uncertainty and credit conditions, proposing an identification strategy that avoids contemporaneous restrictions on asset prices. CFGZ estimate a range of Bayesian VAR(6) models using monthly data for the period January 1975–March 2015. The specifications include 10 variables: industrial production (IPM), private payroll employment (EMPL), real personal consumption expenditures (PCE), PCE deflator (PPCE), the S&P Goldman Sachs (SPGS) Commodity Index, stock market returns (all in log-differences), the 2-year and 10-year Treasury bond yields, the Excess Bond Premium of Gilchrist and Zakrajsek (2012) and an aggregate uncertainty proxy (in logarithms). The estimation relies on a standard Minnesota prior on the reduced-form parameters. To account for the simultaneity between asset prices and uncertainty, CFGZ use the penalty function approach (PFA) developed by Faust (1998) and Uhlig (2005). The authors identify uncertainty (resp. financial) shocks as the linear combination of reduced-form residuals that maximize the response of the uncertainty (resp. financial condition) indicator over a predefined horizon. The identification is implemented sequentially, imposing an orthogonality condition between the two structural shocks. Although the PFA leaves the impact matrix of the VAR unrestricted, its results may depend on which shock is identified first, pretty much as in a recursive identification scheme. CFGZ find indeed that 'financial' uncertainty shocks extracted from the VXO index matter if and only if they are identified first: under the alternative ordering, a rise in uncertainty causes a decline in stock prices with no implications for the real economy. This dichotomy is problematic because there are no economic arguments to favor either of the two orderings.

We revisit this conclusion applying the CFGZ restrictions to daily rather than monthly data. Our monthly VAR is identical to the CFGZ model, except for the fact that we replace EBP (which is not available at daily frequency) with the spread between BAA corporate bond yields and the 10-Year Treasury yield (BAA10Y).[17] The daily VAR is

[17]To ensure that this change does not influence the results, we (i) replicate the monthly analysis of CFGZ using the BAA spread instead of EBP; and (ii) estimate an additional specification where identification is based on the daily BAA spread but EBP is used as a proxy of financial conditions in the monthly VAR. The

estimated using the financial indicators included in the monthly model (VXO, bond spread, SPGS Commodity Index, stock market return, 2- and 10-year Treasury bond yields). We use the CFGZ estimation sample and set the PFA maximization horizon in the daily model to 120 business days to match the 6-month window used by the authors. The estimated shocks pass the information sufficiency test of Forni and Gambetti (2014). Unlike in section 3.1, however, the shocks Granger-cause the residuals of the VAR, so we use them as internal rather than external instruments in the model.

Figure 4 compares the responses to an uncertainty shock obtained using our strategy (*Daily+Monthly VAR*, left column) to those obtained from our replication of the monthly CFGZ model (*Monthly VAR*, right column). To ease the comparison across models and identification orderings, the shocks are normalized to generate a 3% increase in the VXO index in all cases. We focus on the responses of the VXO index, the BAA spread and the key macroeconomic aggregates included in the model (IPM, EMPL, PCEPPCE), referring readers to Appendix D.2 for more details. The figure reports median responses along with 90% credible sets; the IRFs obtained with uncertainty shocks ordered first are shown in red (VXO-BAA case), while those obtained with uncertainty ordered second are in green (BAA-VXO case). A first important result is that using daily data is sufficient to resolve the ambiguity encountered in CFGZ. In the *Monthly VAR* the shock affects credit spreads and economic activity if it is identified first (green bands), but becomes completely irrelevant if not (red bands). In the *Daily+Monthly VAR*, by contrast, it causes a sizable and persistent increase in the spread, a decline in industrial production and

results are reported in Annex D.2.

employment and a fall in prices irrespective of the identification ordering. For most variables the median responses are indeed almost indistinguishable across orderings. The second result is that the behavior of credit spreads is key in explaining the discrepancy between models. Under the BAA-VXO ordering, uncertainty shocks affect VXO only after 'netting out' the impact of financial shocks on both volatility and credit spreads. This seemingly minor restriction has dramatic implications for the monthly identification (which suggests that the spread falls on impact and is unaffected in the longer term, two equally puzzling results) and no impact whatsoever for the daily identification (for which the spread behaves pretty much as under the alternative ordering).[18] Bond markets presumably price uncertainty on a daily rather than a monthly basis, with the bulk of portfolio adjustments taking place within a few days after a shock. The daily model takes into account these endogenous market responses, rendering the estimation robust to the identification sequence. The monthly model, by contrast, interprets the change in spread observed in a given month as a consequence of the shock that is identified first, rendering uncertainty irrelevant in the BAA-VXO case. A third interesting result is the large negative response of the PCE price index. This deflationary effect is far more pronounced than in the original CFGZ model, and it corroborates the idea that uncertainty acts mainly through the demand side of the economy (Leduc and Liu, 2016 and Basu and Bundick, 2017). The *Daily+Monthly VAR* shows that uncertainty and credit shocks have qualitatively similar but quantitatively

[18] The negative initial response of the BAA spread in figure 4 is consistent with CFGZ, who find that EBP also falls after a rise in uncertainty in models where financial shocks are identified first.

different macroeconomic implications (see Appendix D.2). Both cause a rise in spreads and an economic slowdown, but the real economy responses are roughly twice as big after a credit shock: uncertainty shocks only accounts for 2% (4%) of the forecast error variance of IMP (EMPL) in the medium term.

3.3 Baker, Bloom and Davis (2016)

Baker et al. (2016) (BBD) introduced a new and now widely used Economic Policy Uncertainty (EPU) indicator based on the frequency of newspaper articles referring to uncertainty and policy-related topics. To study the role of uncertainty in the business cycle, BBD resort *inter alia* to VAR models where uncertainty shocks are identified through a Cholesky decomposition. This setup is interesting for two reasons. The first one is that the EPU index has an obvious high-frequency component (news come at all times) but, unlike the uncertainty proxies used in sections 3.1 and 3.2, it does not rely on financial data. The second one is that, in sharp contrast to BDG, the results point in this case to a sizable influence of uncertainty on the real economy. By revisiting the BBD analysis we can thus test our strategy using a news-based rather than a volatility-based uncertainty indicator, and check to what extent the divergence between BBD and BDG depends on distortions associated to the monthly identification schemes used in the two papers. The baseline specification employs monthly U.S. data from January 1985 to December 2014, including three lags of (in this order) the EPU index, the log of the S&P500 index, the federal funds rate, log employment (EMP) and log industrial production (IP). Since the EPU index is available on a daily basis, the results can be easily reassessed following the same logic of the previous subsections. To do so we estimate an informationally sufficient daily VAR model using EPU, S&P500, Fed Funds rate, 2, 5 and 10-year Treasury Bill yields and the GSCI commodity price index. The estimation sample is 1985-2014. Following BBD, we then identify uncertainty shocks using two alternative Cholesky orderings. In the baseline case EPU is ordered first, so that uncertainty shocks are not orthogonalized with respect to the shocks that hit interest rates and stock prices in the same day or month. In the alternative setup EPU is ordered third, after the S&P500 price index and the fed funds rate.

The responses are shown in figure 5. The HF+LF VAR method estimates for both real and financial variables responses that are virtually identical in the two Cholesky orderings. A 1σ EPU shock leads to a fall in the policy rate and a contraction in IP and EMP of 0.2% and 0.1% respectively. This is not the case for the monthly VAR, where the impact of the shock on IP and EMP is roughly halved under the more restrictive ordering (EPU third) compared to the one that gives more prominence to uncertainty (EPU first). The change in the stock price response is particularly striking: equity valuations fall by 2% if EPU is ordered first, but they actually rise in the medium term if EPU is ordered third (after the stock price index itself). Qualitatively similar but even stronger quantitative implications arise from the FEVD decomposition. Uncertainty shocks consistently explain about 4% of the FEV for both IP and EMP in the HF+LF VAR model, whereas in the monthly VAR these shares range between 5% and 15%.

3.4 The real impact of uncertainty shocks: a summary

The macroeconomic implications of aggregate uncertainty shocks have proved to be hard to pin down and highly variable across samples, models, and identification strategies. Our work points to an important factor behind these conflicts: the ambiguity is largely caused by daily interactions between news, stock returns, bond spreads, and market volatility that seriously complicate identification in VAR models based on monthly or quarterly data. In Figure 6 we make this point more explicit by bringing together the results obtained in the previous subsections in our re-examination of Berger et al. (2019) (BDG), Caldara et al. (2016) (CFGZ) and Baker et al. (2016)(BBD). Figure 6 shows the estimated impact of uncertainty shocks on industrial production (left panel) and employment (right panel) at the 12-month horizon. We focus on the BDG and CFGZ models, in which uncertainty is captured using an implied stock market volatility indicator (respectively v_1 and the VXO index), and compute ratios between the cumulated responses of industrial production and employment and the cumulative change in v_1 or VXO (i.e. a measure of the elasticity of economic activity to expected volatility after a positive uncertainty shock). If the shocks are identified using monthly data the responses vary substantially across models: the elasticities range between zero and 20% for industrial production and between zero and 6% for employment. By contrast, daily identification schemes deliver elasticities that are virtually identical across models, with central estimates around 8% and 5% for the two variables. The figure shows that temporal aggregation can affect the monthly VARs in either direction: the impact of uncertainty is underestimated in models that restrict tightly the financial response to the shock (BDG, CFGZ EBP-VXO), and overestimated in models that underplay the endogeneity of uncertainty to financial conditions (CFGZ VXO-EBP). Once the bias is removed, the estimates become more similar and statistically more distinguishable from zero.[19]

Figure 7 provides an analogous model comparison based on 12-month-ahead forecast error variances (FEVs). Since this metric does not require a normalization of the shocks, we can include in the comparison the BBD model, in which uncertainty is captured by the EPU index rather than implied stock market volatility. FEVs also have the advantage of providing more information on the overall relevance of the shocks for the business cycle. The impact of switching to daily identification schemes is again clearly visible: monthly VARs deliver central estimates that range between zero and 15-17%, whereas daily schemes generate central estimates that are concentrated in a narrow 2-5% range (with the only exception of BDG, for which the figure is higher but also more uncertain). A striking result in 7 is the high level of confidence with which the monthly BDG and CFGZ EBP-VXO setups rule out any influence of uncertainty on economic activity, generating FEV distributions that lie almost entirely on the zero line. Uncertainty shocks become irrelevant when the responses of stock market volatility and bond spreads are cut off, shutting down the financial side of the transmission mechanism.

In summary, daily data allows a reassessment of the real impact of uncertainty shocks

[19]The higher significance generally results from a downward shift in the distribution of the coefficients. The BDG case also shows an improvement in accuracy, but this is not robust to alternative bootstrap methods (see section 3.1).

that is at once sharper, robust to the identifying assumptions within a given model, and surprisingly similar across models. The correlation between the uncertainty shocks estimated in the models we examine is indeed significantly higher if the shock is identified using daily rather than monthly observations (see Appendix F). In the Appendix F we also illustrate the convergence across models by comparing the volatility-based uncertainty shock estimates obtained from the BDG and CFGZ models in 2001 and around the global financial crisis of 2008. Under a daily identification, the models agree that the largest increase in uncertainty of 2001 occurred in September. With a monthly identification, by contrast, they suggest that an equally large shock (CFGZ) or an even larger one (BDG) took place in October. In the case of the global financial crisis, all estimates point to large rises in uncertainty in September and October 2008, around the bankruptcy of Lehman Brothers. What changes is the magnitude of the shocks, which is stable under a daily identification (at about 4 standard deviations) but changes across models and over time under a monthly identification (ranging between 2 and 6 standard deviations).

4 Conclusions

How strong is the influence of aggregate uncertainty on the real economy? Past research has given very different answers to this question, alternatively characterizing uncertainty as a key driver or an endogenous by-product of the business cycle. In this paper we revisit the question using a new strategy that consists of three steps: we identify uncertainty shocks using daily observations on stock prices, bond yields, implied volatility and/or text-based policy uncertainty indicators, we aggregate the shocks to the monthly frequency, and we use the aggregated shock series as instruments in monthly VAR models of the US economy. This procedure is motivated by a simple consideration: if financial markets react to macroeconomic news and changes in risk on a continuous basis, then using monthly or quarterly data may by construction prevent a correct separation between exogenous shocks and endogenous responses. As long as the economy is described by a VAR at a (suitably defined) 'high' frequency, the problem can be bypassed by identifying the shock of interest at that frequency and then using a low-frequency average of the shock to estimate the impulse-response functions. We show that this approach delivers consistent and unbiased estimates of the responses in a broad range of data-generating processes, including general equilibrium models with uncertainty shocks, and that it is a flexible and robust alternative to mixed frequency methods.

Our empirical analysis shows that daily data delivers a different and more coherent picture of the relation between uncertainty and economic activity. When combined with the identification schemes of Baker et al. (2016), Caldara et al. (2016), and Berger et al. (2019), our strategy reveals that the impact of uncertainty shocks on economic activity is (i) negative and significant in all cases, (ii) fairly small relative to the impact of more traditional drivers of the business cycle, and (iii) very similar across specifications and identification strategies. Accounting for the within-month interactions between uncertainty, stock prices and bond yields is crucial in order to capture the transmission mechanism. Uncertainty can cause large daily swings in asset prices but it can also respond endogenously to financial shocks, and separating these mechanisms is virtually impossible in a monthly dataset.

Future work on the effects of uncertainty should start from the premise that financial markets are a key link in the transmission mechanism, and that using daily or higher-frequency observations is necessary to separate the correlations in the data into exogenous shocks and endogenous responses. More generally, researchers can resort to the approach proposed in this paper in cases where imposing identification restrictions on low-frequency data is problematic and high-frequency data, obtained for instance from financial markets or textual sources, can be used to isolate the shocks of interest.

References

Arellano, C., Y. Bai, and P. J. Kehoe (2019): "Financial Frictions and Fluctuations in Volatility," *Journal of Political Economy*, 127, 2049–2103.

Baker, S. R. and N. Bloom (2013): "Does Uncertainty Reduce Growth? Using Disasters as Natural Experiments," Working Paper 19475, National Bureau of Economic Research.

Baker, S. R., N. Bloom, and S. J. Davis (2016): "Measuring Economic Policy Uncertainty," *The Quarterly Journal of Economics*, 131, 1593–1636.

Barnichon, R., C. Matthes, and A. Ziegenbein (2022): "Are the Effects of Financial Market Disruptions Big or Small?" *The Review of Economics and Statistics*, 104, 557–570.

Barsky, R. B. and E. R. Sims (2011): "News shocks and business cycles," *Journal of Monetary Economics*, 58, 273–289.

Basu, S. and B. Bundick (2017): "Uncertainty Shocks in a Model of Effective Demand," *Econometrica*, 85, 937–958.

Baumeister, C. (forth): "Measuring Market Expectations," in *Handbook of Market Expectations*, ed. by J. B. Taylor and H. Uhlig, Elsevier, vol. 2 of *Handbook of Macroeconomics*, 71–162.

Beaudry, P., P. FÃšve, A. Guay, and F. Portier (2019): "When is nonfundamentalness in SVARs a real problem?" *Review of Economic Dynamics*, 34, 221–243.

Berger, D., I. Dew-Becker, and S. Giglio (2019): "Uncertainty Shocks as Second-Moment News Shocks," *The Review of Economic Studies*.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77, 623–685.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018): "Really Uncertain Business Cycles," *Econometrica*, 86, 1031–1065.

Boehmer, E. and E. K. Kelley (2009): "Institutional Investors and the Informational Efficiency of Prices," *The Review of Financial Studies*, 22, 3563–3594.

Caldara, D., C. Fuentes-Albero, S. Gilchrist, and E. Zakrajšek (2016): "The macroeconomic impact of financial and uncertainty shocks," *European Economic Review*, 88, 185–207.

Carriero, A., T. E. Clark, and M. Marcellino (2018): "Measuring Uncertainty and Its Impact on the Economy," *The Review of Economics and Statistics*, 100, 799–815.

Cascaldi-Garcia, D. and A. B. Galvao (2021): "News and Uncertainty Shocks," *Journal of Money, Credit and Banking*, 53, 779–811.

Christiano, L. J. and M. Eichenbaum (1987): "Temporal aggregation and structural inference in macroeconomics," *Carnegie-Rochester Conference Series on Public Policy*, 26, 63 – 130.

Cieslak, A. and H. Pang (2021): "Common shocks in stocks and bonds," *Journal of Financial Economics*, 142, 880–904.

Coibion, O. (2012): "Are the effects of monetary policy shocks big or small?" *American Economic Journal: Macroeconomics*, 4, 1–32.

Ehsani, S. and J. T. Linnainmaa (2021): "Factor momentum and the momentum factor," *The Journal of Finance*, 77, 1877–1919.

Fama, E. F. and K. R. French (2015): "Dissecting Anomalies with a Five-Factor Model," *The Review of Financial Studies*, 29, 69–103.

Faust, J. (1998): "The robustness of identified VAR conclusions about money," *Carnegie-Rochester Conference Series on Public Policy*, 49, 207 – 244.

Fernandez-Villaverde, J., P. Guerron-Quintana, J. F. Rubio-Ramirez, and M. Uribe (2011): "Risk Matters: The Real Effects of Volatility Shocks," *American Economic Review*, 101, 2530–2561.

Fernandez-Villaverde, J. and P. A. Guerron-Quintana (2020): "Uncertainty shocks and business cycle research," *Review of Economic Dynamics*, 37, 118–146.

Fernandez-Villaverde, J., J. F. Rubio-Ramirez, T. J. Sargent, and M. W. Watson (2007): "ABCs (and Ds) of Understanding VARs," *American Economic Review*, 97, 1021–1026.

Ferrara, L. and P. Guerin (2018): "What are the macroeconomic effects of high-frequency uncertainty shocks?" *Journal of Applied Econometrics*, 33, 662–679.

Forni, M. and L. Gambetti (2014): "Sufficient information in structural VARs," *Journal of Monetary Economics*, 66, 124–136.

Forni, M., L. Gambetti, and L. Sala (2019): "Structural VARs and noninvertible macroeconomic models," *Journal of Applied Econometrics*, 34, 221–246.

Gertler, M. and P. Karadi (2015): "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7, 44–76.

Ghysels, E. (2016): "Macroeconomics and the reality of mixed frequency data," *Journal of Econometrics*, 193, 294–314, the Econometric Analysis of Mixed Frequency Data Sampling.

Gilchrist, S. and E. Zakrajsek (2012): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102, 1692–1720.

Herbst, E. and B. K. Johannsen (2021): "Bias in Local Projections," .

Jorda, O. (2005): "Estimation and Inference of Impulse Responses by Local Projections," *American Economic Review*, 95, 161–182.

Jurado, K., S. C. Ludvigson, and S. Ng (2015): "Measuring Uncertainty," *American Economic Review*, 105, 1177–1216.

Kilian, L., M. Plante, and A. W. Richter (2022): "Macroeconomic Responses to Uncertainty Shocks: The Perils of Recursive Orderings," .

Kliem, M. and H. Uhlig (2016): "Bayesian estimation of a dynamic stochastic general equilibrium model with asset prices," *Quantitative Economics*, 7, 257–287.

Kuttner, K. (2001): "Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market," *Journal of Monetary Economics*, 47, 523–544.

Leduc, S. and Z. Liu (2016): "Uncertainty shocks are aggregate demand shocks," *Journal of Monetary Economics*, 82, 20–35.

LEEPER, E. M., T. B. WALKER, AND S.-C. S. YANG (2013): "Fiscal Foresight and Information Flows," *Econometrica*, 81, 1115–1145.

LUDVIGSON, S. C., S. MA, AND S. NG (2018): "Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?" .

MARCELLINO, M. (1999): "Some Consequences of Temporal Aggregation in Empirical Analysis," *Journal of Business Economic Statistics*, 17, 129–136.

MARCET, A. (1991): "Temporal Aggregation of Economic Time Series," in *Rational Expectations Econometrics*, ed. by L. P. Hansen, T. J. Sargent, J. Heaton, A. Marcet, and W. Roberds, Westview Press Boulder, chap. 10, 237–282.

MERTENS, K. AND M. O. RAVN (2013): "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States," *American Economic Review*, 103, 1212–47.

MIRANDA AGRIPPINO, S. AND G. RICCO (2018): "(A Note on the) Identification with External Instruments in Structural VARs under Partial Invertibility," .

MIRANDA-AGRIPPINO, S. AND G. RICCO (2021): "The Transmission of Monetary Policy Shocks," *American Economic Journal: Macroeconomics*, 13, 74–107.

NAKAMURA, E. AND J. STEINSSON (2018): "High-Frequency Identification of Monetary Non-Neutrality: The Information Effect*," *The Quarterly Journal of Economics*, 133, 1283–1330.

NOH, E. (2018): "Impulse-response analysis with proxy variables," *Mimeo*.

PACCAGNINI, A. AND F. PARLA (2021): "Identifying high-frequency shocks with Bayesian mixed-frequency VARs," Working paper.

PAUL, P. (2020): "The Time-Varying Effect of Monetary Policy on Asset Prices," *The Review of Economics and Statistics*, 102, 690–704.

PIFFER, M. AND M. PODSTAWSKI (2018): "Identifying Uncertainty Shocks Using the Price of Gold," *Economic Journal*, 128, 3266–3284.

PLAGBORG-MOLLER, M. AND C. K. WOLF (2021): "Local Projections and VARs Estimate the Same Impulse Responses," *Econometrica*, 89, 955–980.

PLAGBORG-MØLLER, M. AND C. K. WOLF (Forthcoming): "Instrumental Variable Identification of Dynamic Variance Decompositions," *Journal of Political Economy*, matlab code suite and data (GitHub).

RAMEY, V. A. AND S. ZUBAIRY (2018): "Government Spending Multipliers in Good Times and in Bad: Evidence from US Historical Data," *Journal of Political Economy*, 126, 850–901.

SANDULESCU, M., F. TROJANI, AND A. VEDOLIN (2021): "Model-Free International Stochastic Discount Factors," *The Journal of Finance*, 76, 935–976.

Schorfheide, F. and D. Song (2015): "Real-Time Forecasting With a Mixed-Frequency VAR," *Journal of Business & Economic Statistics*, 33, 366–380.

Sims, C. (1971): "Discrete Approximations to Continuous Time Distributed Lags in Econometrics," *Econometrica*, 39, 545–563.

Smets, F. and R. Wouters (2007): "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," *American Economic Review*, 97, 586–606.

Stock, J. and M. Watson (2012): "Disentangling the Channels of the 2007-2009 Recession," *Brookings Papers on Economic Activity*, Spring, 81–135.

Stock, J. H. and M. W. Watson (2018): "Identification and Estimation of Dynamic Causal Effects in Macroeconomics Using External Instruments," *The Economic Journal*, 128, 917–948.

Uhlig, H. (2005): "What are the effects of monetary policy on output? Results from an agnostic identification procedure," *Journal of Monetary Economics*, 52, 381 – 419.

Wright, J. H. (2012): "What does Monetary Policy do to Long-term Interest Rates at the Zero Lower Bound?*," *The Economic Journal*, 122, F447–F466.

Correlation coefficients			
	BB	RSBC	RUBC
HF+LF VAR	0.88	0.87	0.98
Counterfactual HF VAR	0.88	0.87	0.98

Table 1: Recovering uncertainty shocks in DSGE models

Correlations between true and estimated uncertainty shocks in Monte Carlo tests based on the general equilibrium models of Basu and Bundick, 2017 (BB), Berger et al., 2019 (RSBC) and Bloom et al., 2018 (RUBC). The HF+LF VAR exploits a combination of high- and low-frequency data through an IV step. The Counterfactual HF VAR assumes all variables in the models to be available at all frequencies.

	Financial VAR - 4 variables	Full-information benchmarks	
		FAVAR 4-variables	FAVAR 5-variables
Technology	0.95 [0.91;0.97]	0.90 [0.30;0.97]	0.95 [0.91;0.98]
Labor supply	0.77 [0.71;0.83]	0.62 [0.01;0.94]	0.95 [0.69;0.98]
Capital adjustment	0.96 [0.92;0.98]	0.93 [0.75;0.98]	0.95 [0.92;0.98]
Wage markup	0.62 [0.54;0.67]	0.33 [0.03;0.91]	0.94 [0.20;0.98]
Government expenditures	0.24 [0.15;0.33]	0.91 [0.61;0.98]	0.95 [0.91;0.98]

Table 2: Invertibility of the structural shocks in Kliem and Uhlig (2016)

Invertibility of the shocks in Monte Carlo tests based on the general equilibrium models of Kliem and Uhlig (2016)-Smets and Wouters (2007). The (median) R^2 are obtained from a regression of the actual shocks on the residuals from a VAR estimated on asset prices only (Financial VAR) or on the residuals from a FAVAR that includes all available information (full-information benchmarks). Squared brackets contain 99% confidence intervals.

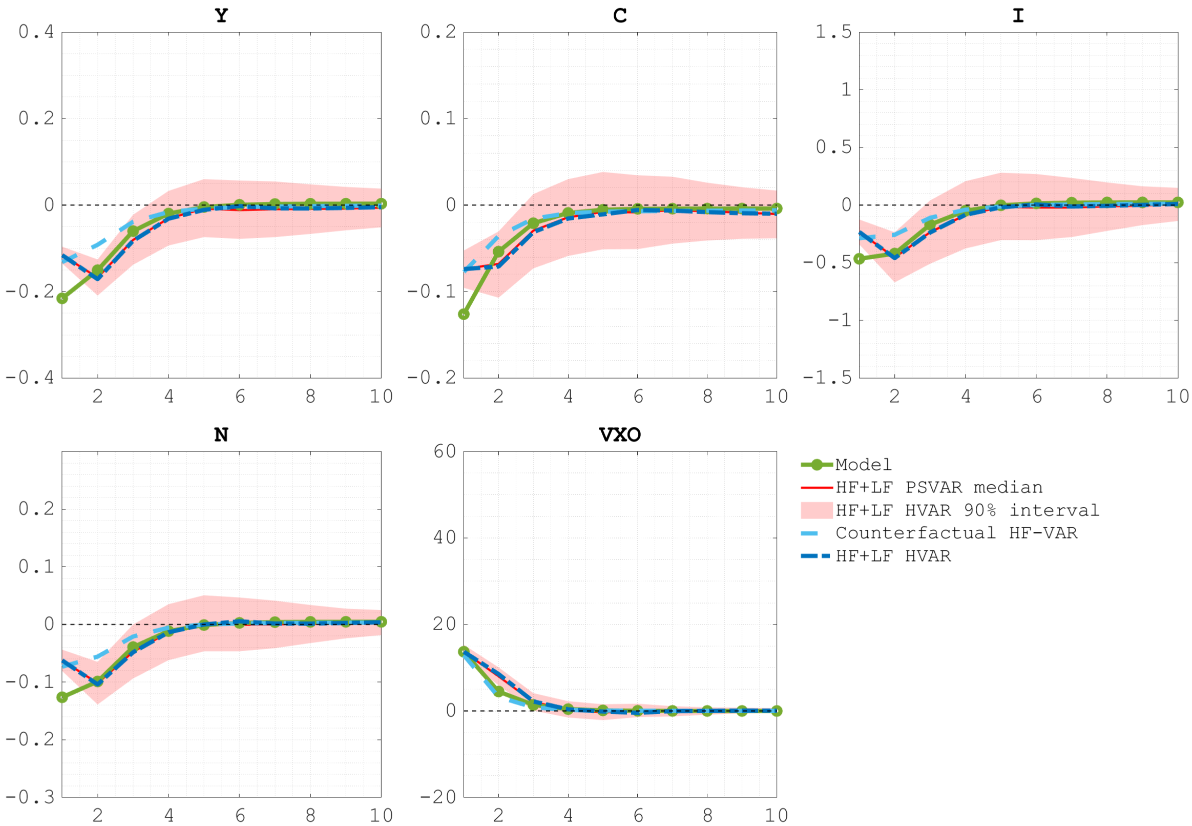

Figure 1: True and estimated IRFs in the BB model

IRFs to an uncertainty shock computed using simulated data from Basu and Bundick (2017) Model. The green continuous line denotes the theoretical IRFs from the model. Dashed light-blue line denotes the IRFs computed using the VAR specification of BB. HF+LF HVAR(PSVAR) denote the IRFs computed using our proposed approach where the aggregated shock is used as in internal (external) instruments for the shock of interest. 90% confidence intervals are computed using Bootstrap based on the HVAR.

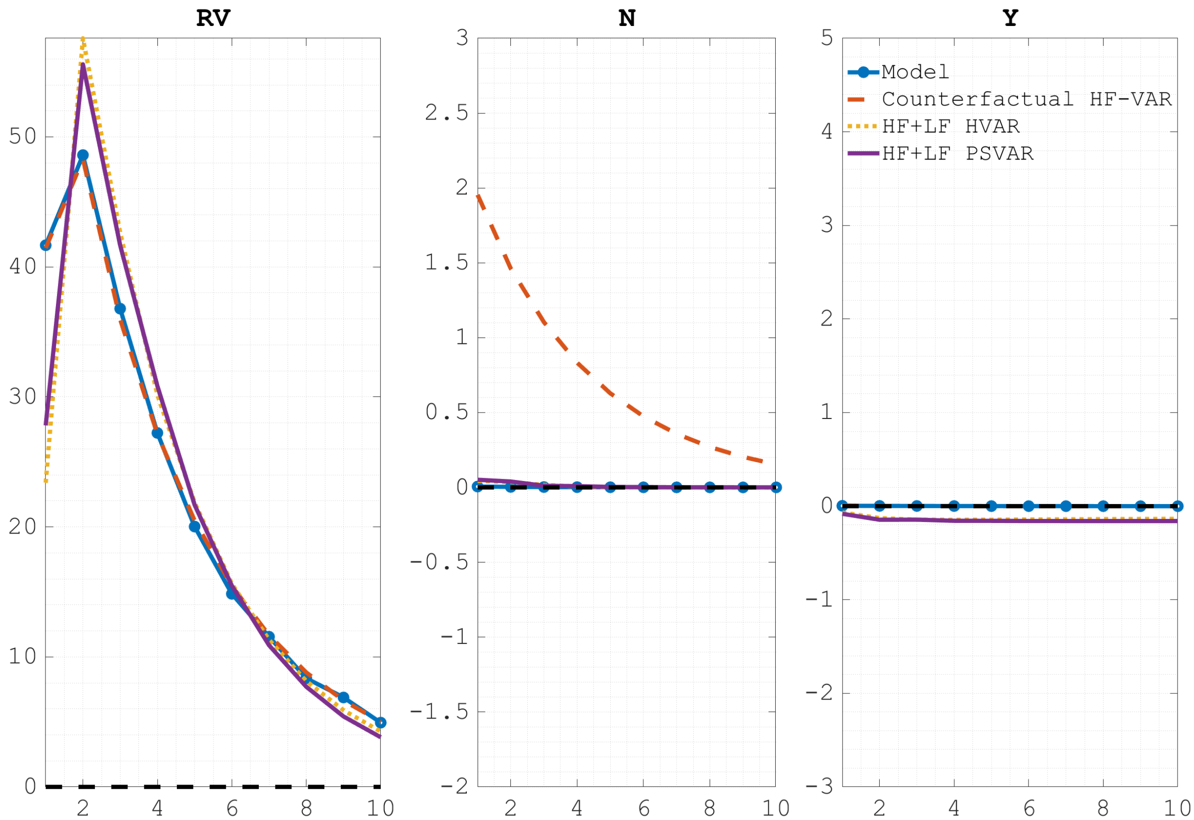

Figure 2: True and estimated IRFs in the RSBC model

IRFs to an uncertainty shock computed using simulated data from Berger et al., 2019 *Model. The continuous blue line with dots denotes the theoretical IRFs from the model. Dashed red line denotes the IRFs computed using the VAR specification of BDG. HF+LF HVAR(PSVAR) denote the IRFs computed using our proposed approach where the aggregated shock is used as in internal (external) instruments for the shock of interest.*

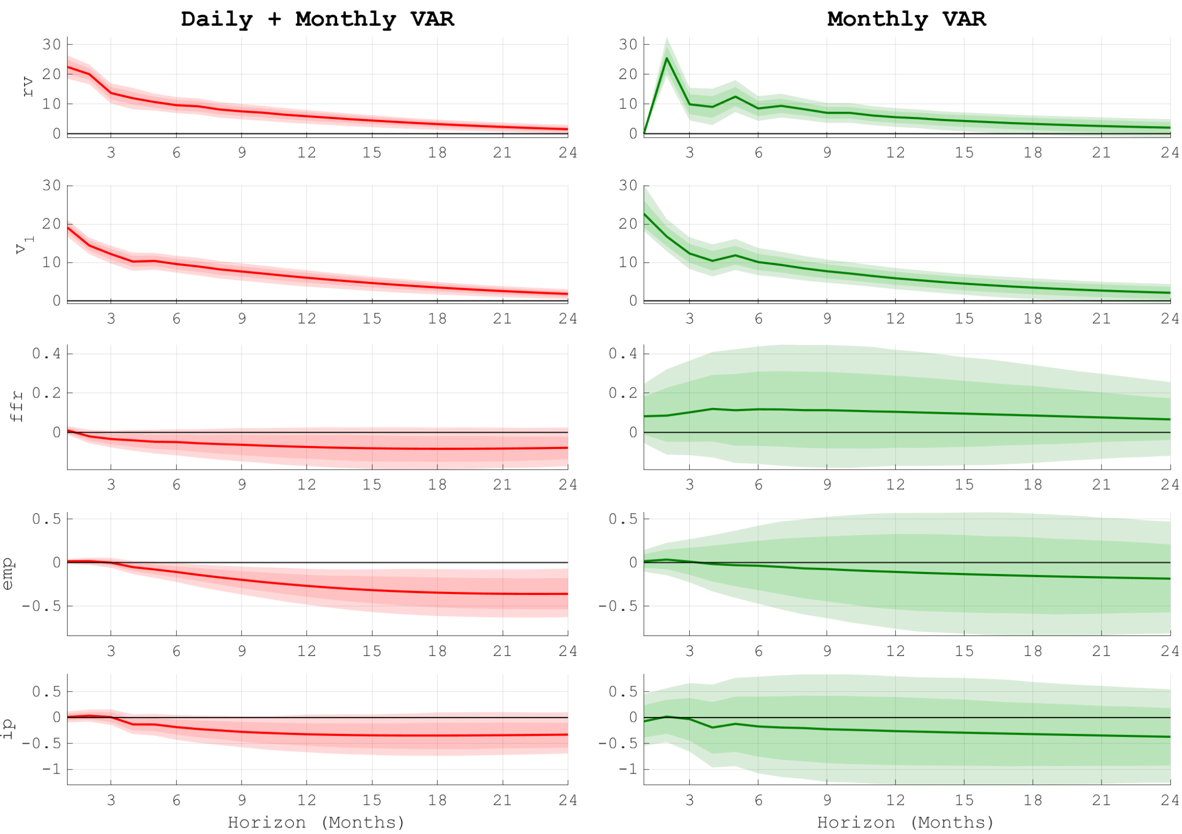

Figure 3: Daily versus monthly identification in BDG

Impact of uncertainty shocks under the identification strategy of Berger et al., 2019. The shocks are identified as innovations to the option-implied expected volatility of the stock market ($[v_1]$) that are orthogonal to the realized market volatility (rv). In the Daily+Monthly VAR (left column) the shock is identified imposing the restrictions on daily data, averaged to the monthly frequency, and then used as an external instrument in the monthly VAR model. In the Monthly VAR (right column) the restrictions are imposed directly on monthly data as in BDG. The estimation sample is January 1983-December 2014. The variables included in the VAR are: realized volatility (rv), option implied volatility (v_1), Fed Funds rate (ffr), employment (emp) and industrial production (ip). Each plot reports the point estimates with 68% and 90% confidence bands computed using 1,000 bootstrap replications as in Plagborg-Møller and Wolf (Forthcoming).

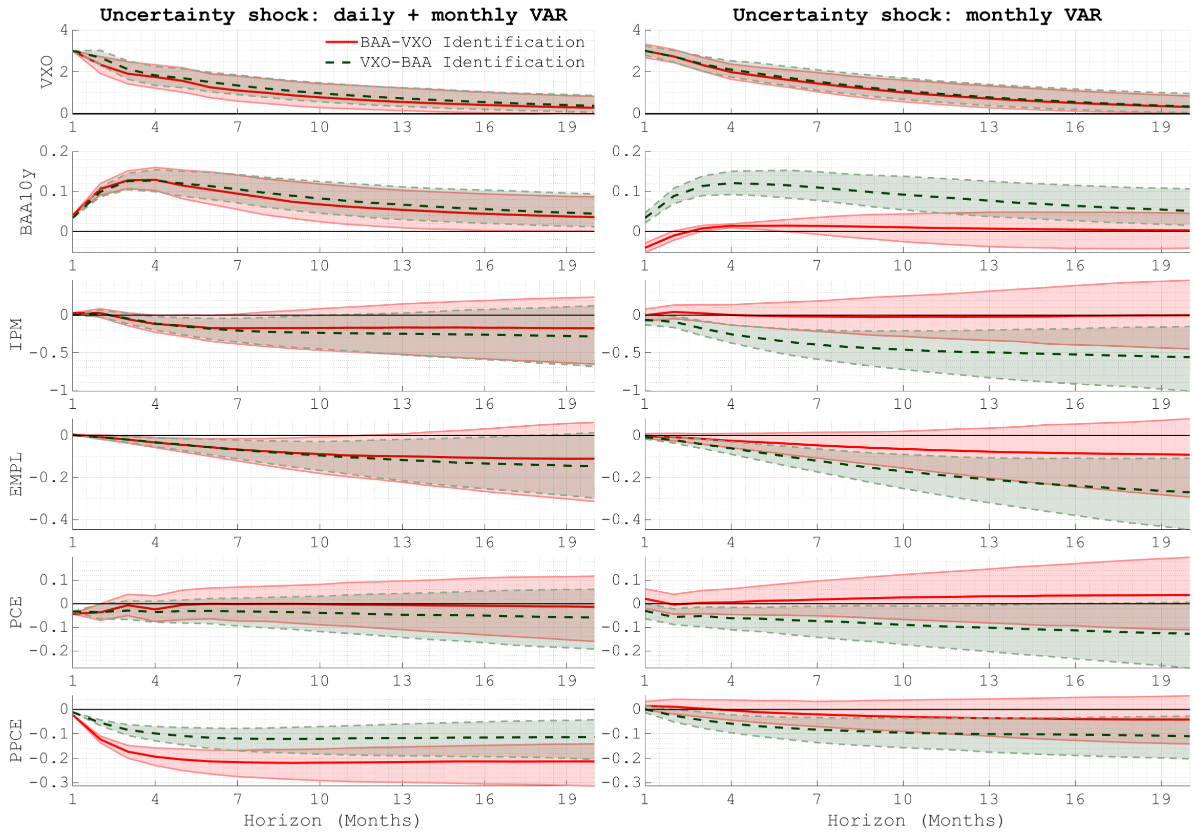

Figure 4: Daily versus monthly identification in CFGZ

Impact of an uncertainty shock under the identification restrictions of Caldara et al. (2016). All IRFs are based on the CFGZ Penalty Function Approach (PFA). In the Daily+Monthly VAR model (left column) the shock is identified imposing the restrictions on daily data, averaged to the monthly frequency and introduced as an additional variable in the monthly VAR model. In the Monthly VAR model (right column) the restrictions are imposed directly on monthly data as in CFGZ. Green and red areas correspond to the responses estimated ordering the ucertainty shock before and after the financial shock in the penalty function maximization. The variables plotted are: VXO index, the spread between US BAA Corporate Yield and the 10Y US Treasury yield (BAA10Y), industrial production (IPM), private payroll employment (EMPL), real personal consumption expenditures (PCE) and PCE deflator (PPCE) .Each plot reports the median response with a 90% Bayesian credible sets.

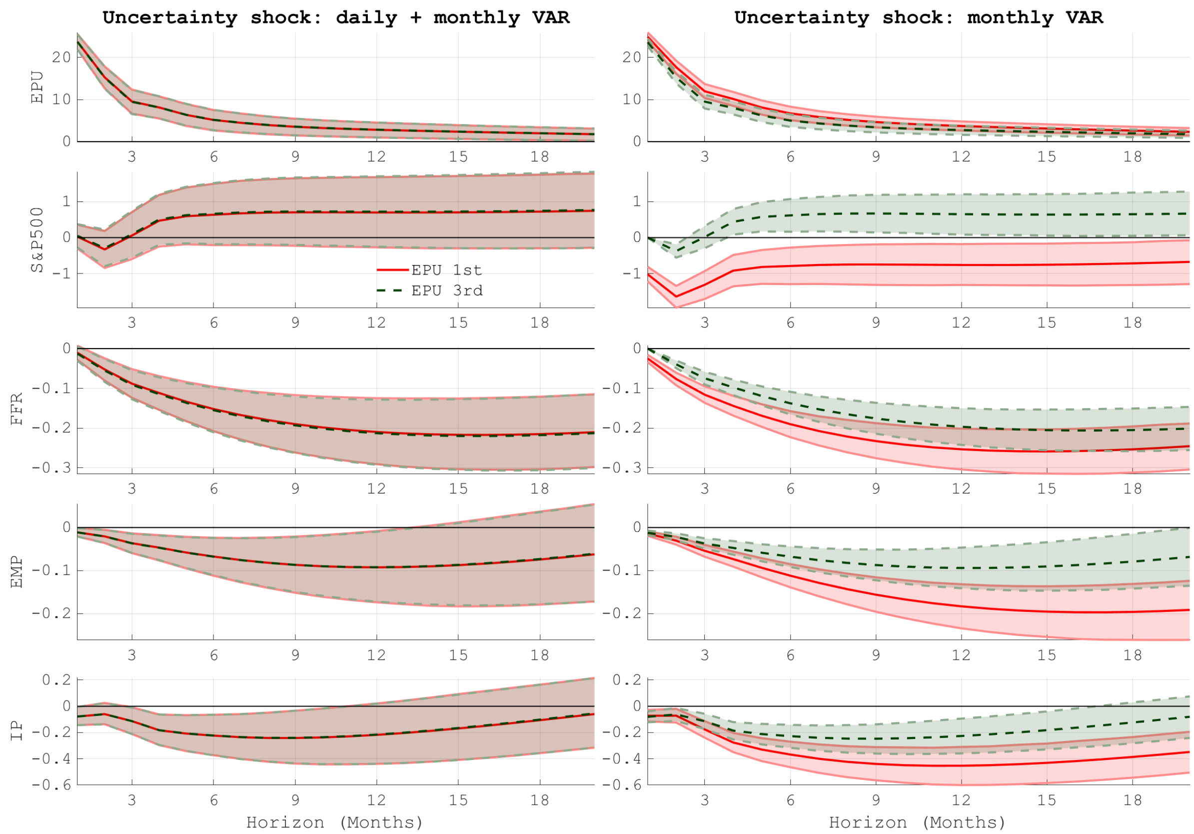

Figure 5: Daily versus monthly identification in BBD

Impact of an uncertainty shock under the identification restrictions of Baker et al. (2016). All IRFs are computed using a recursive identification strategy where EPU is ordered first (red) or third (green, after S&P500 and Fed Funds rate). In the Daily+Monthly VAR model (left column) the shock is identified imposing the restrictions on daily data, averaged to the monthly frequency, and used as an external instrument in the monthly VAR model. In the Monthly VAR model (right column) the restrictions are imposed directly on monthly data as in BBD. The monthly VAR includes the following variables: the Economic Policy Uncertainty Index (EPU), the S&P500 index, the Federal Funds rate (FFR), employment (EMP), and industrial production (IP). Green and red areas correspond to the responses estimated ordering EPU first or third (after S&P500 and FFR) for the recursive identification. Each plot reports the point estimates with a 90% confidence intervals computed using 1,000 bootstrap replications as in Plagborg-Møller and Wolf (Forthcoming).

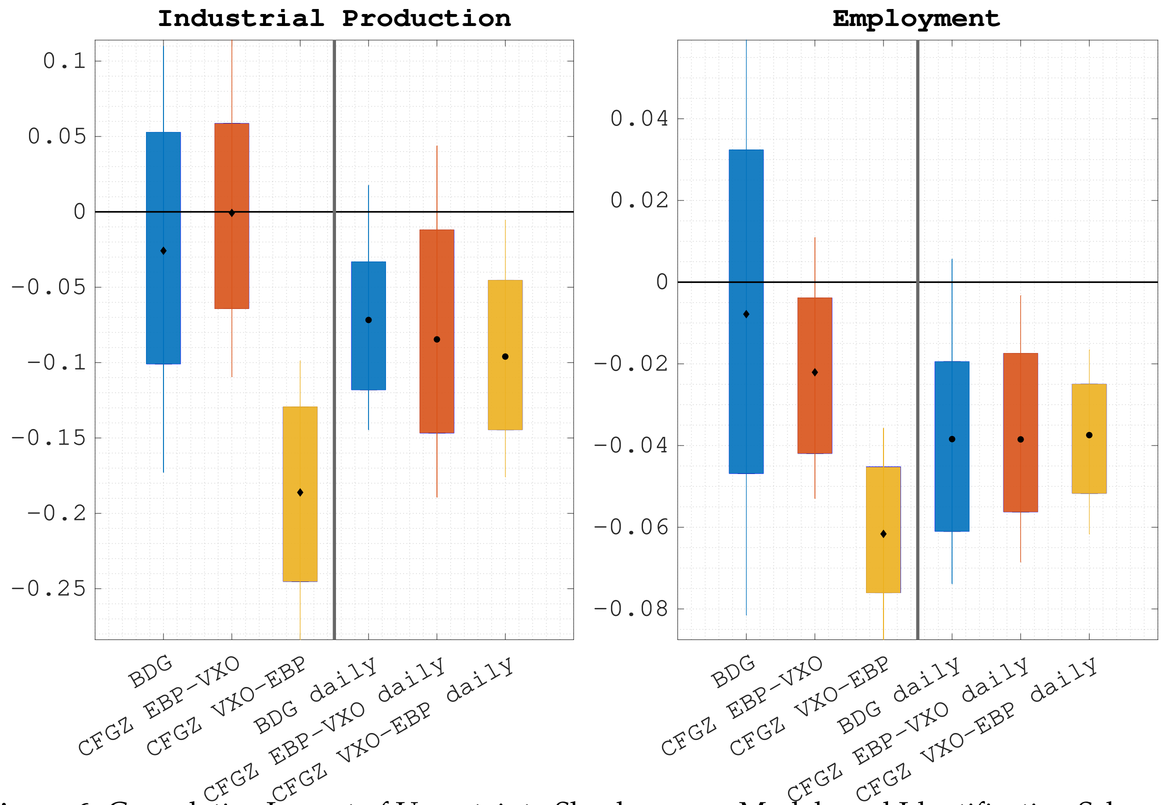

Figure 6: Cumulative Impact of Uncertainty Shocks across Models and Identification Schemes

1-year ahead cumulative responses of industrial production and employment to an uncertainty shock. For each variable the plots compare the monthly LF VAR models (BDG, CFGZ EBP-VXO, CFGZ VXO-EBP) to the corresponding HF+LF VAR models in which identification is based on daily data (denoted by the 'daily' suffix). All IRFs are scaled by the implied volatility responses to ensure comparability across models. The boxplots show bias-corrected central estimates with 68% and 90% bootstrapped confidence intervals (BDG) or credible sets (CFGZ).

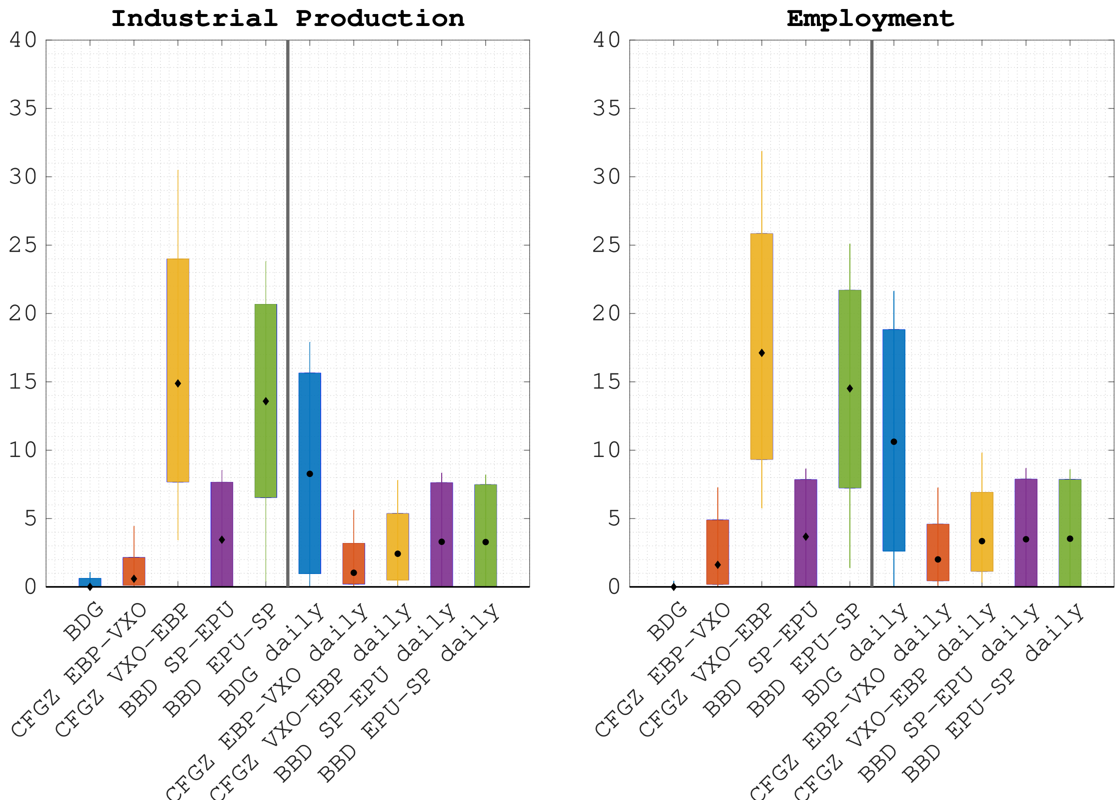

Figure 7: FEV Contribution of Uncertainty Shocks across models and identification schemes

Shares of the 1-year ahead FEVs of industrial production and employment explained by uncertainty shocks. For each variable the plots compare the monthly LF VAR models (BDG, CFGZ, BBD) to the corresponding HF+LF VAR models in which identification is based on daily data (denoted by the 'daily' suffix). CFGZ and BBD are examined under two identification schemes in which uncertainty (resp. VXO or EPU) is ordered before or after financial conditions (resp. EBP or stock prices, SP). The boxplots show bias-corrected central estimates with 68% and 90% bootstrapped confidence intervals (BDG, BBD) or credible sets (CFGZ).