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UNCERTAINTY MATTERS: EVIDENCE FROM A HIGH-FREQUENCY IDENTIFICATION STRATEGY

by Piergiorgio Alessandri*, Andrea Gazzani* and Alejandro Vicondoa+

Abstract

Assessing the role of uncertainty shocks as a driver of business cycle fluctuations is challenging because spikes in uncertainty often coincide with news about economic fundamentals. To tackle this problem, we exploit daily data to identify uncertainty shocks that (i) impact the VXO volatility index, and (ii) are statistically independent from level shocks affecting stock prices. We then use the identified series of uncertainty shocks in a monthly VAR to estimate their macroeconomic effects on the US economy. An exogenous increase in uncertainty depresses economic activity and prices, significantly affecting both labor and capital goods markets. Uncertainty shocks account for about 20% of the cyclical fluctuations in employment and industrial production.

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Keywords: uncertainty shocks, high-frequency identification, SVAR, business cycle.
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1 Introduction[1]

Economic uncertainty has been increasingly identified by both researchers and policymakers as a key source of financial and macroeconomic fluctuations especially after the Global Financial Crisis.[2] However, assessing the role of uncertainty in the business cycle is far from trivial. Uncertainty often rises endogenously in response to a deterioration in economic fundamentals, and many events influence at once agents' expectations and their perception of the riskiness of the economic environment. This fact implies that disentangling first- and second-moment effects is inevitably challenging.

To illustrate the relevance of this challenge, in Figure 1 we plot two principal components calculated using a range of "TFP news" (pc_n - considered in inverted scale) and "uncertainty" shocks (pc_u) available from the literature.[3] Each of the two components explains over 60% of the variability of the underlying shocks. The two components are highly correlated (0.65) and their comovement is particularly striking during the recessions experienced by the US in 2001 and in 2008-2009. This correlation is a clear indication that bad news and uncertainty often come together, and that different models can interpret the same episodes in different ways depending on their specification and identification assumptions.

This paper proposes a new empirical strategy to identify uncertainty shocks and to estimate their macroeconomic impact. The strategy involves two steps. First, we identify the shocks by applying *Independent Component Analysis* (ICA) to the reduced form residuals of a daily VAR model that includes the S&P500 stock price index (sp) and the VXO volatility index (vxo), together with a range of additional financial indicators. We assume that (i) the shocks are statistically independent rather than just orthogonal to one another; (ii) at most one of them is normally distributed; and (iii) first- and second-moment (i.e. price level and uncertainty) shocks have a larger contemporaneous impact respectively on sp and vxo.[4] Thus, our identification assumptions are significantly less restrictive than those employed in previous works: we allow the shocks to affect all variables contemporaneously (i.e. within the same day) and place no restrictions on the sign of any of the responses. Second, we aggregate uncertainty and level shocks to the monthly frequency and use

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[2]Blanchard (2009), Bloom (2009), Fernandez-Villaverde et al. (2011); Christiano et al. (2014), Yellen (2017), Draghi (2018), Bloom et al. (2018).

[3]The TFP news shocks are taken from Beaudry and Portier (2014), who consider thirteen VAR specifications that follow Beaudry and Portier (2006) and Barsky and Sims (2011), while the uncertainty shocks come from Baker et al. (2016), Basu and Bundick (2017), and Berger et al. (2019). Similar results hold if we consider also the news shocks identified directly in Barsky and Sims (2011) and Kurmann and Otrok (2013). However, those series are available only until 2005-2007, respectively.

[4]Statistical independence provides sufficient restrictions to fully identify a VAR structure if at most one of the structural shocks is gaussian: see Gourieroux et al. (2017) and Gourieroux et al. (2018) among others.

them in a monthly VAR model of the US economy.

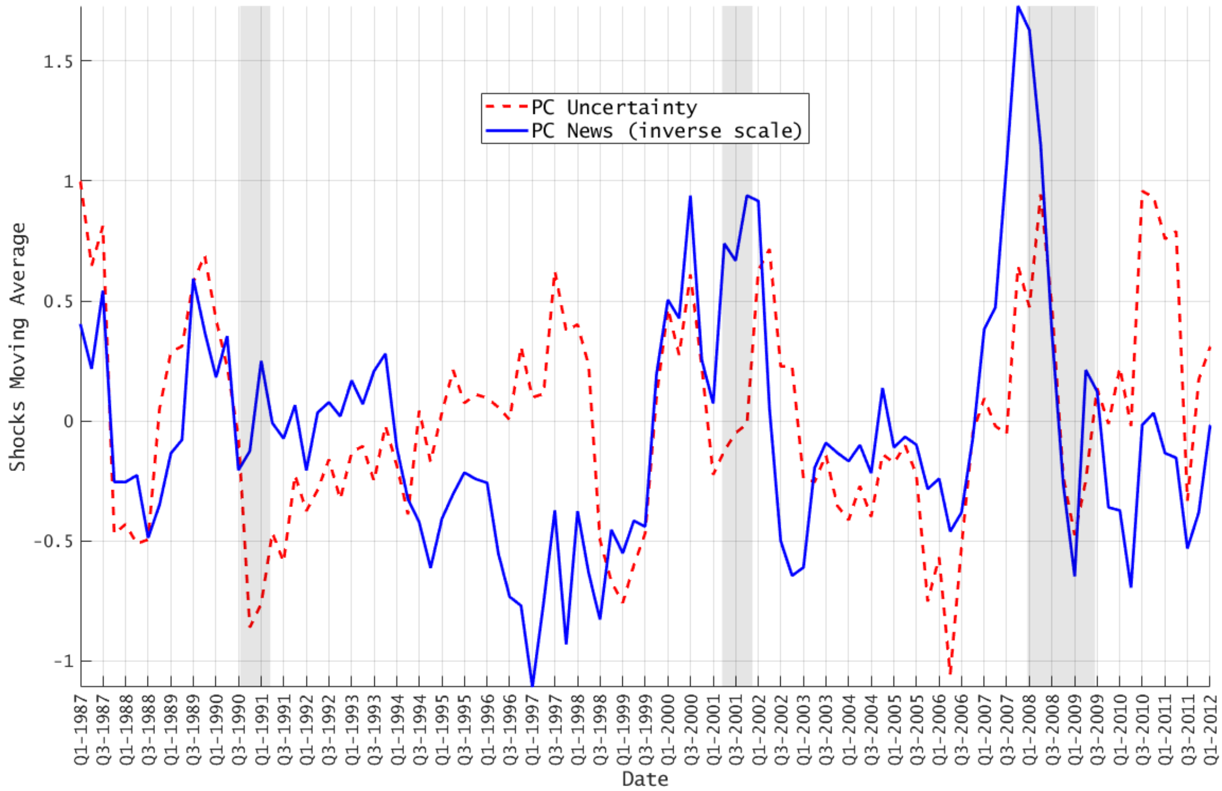

Figure 1: Comparison between news and uncertainty shocks

Principal components of the news shocks estimated by Beaudry and Portier (2014) (PC News) and of the uncertainty shocks estimated by Baker et al. (2016), Basu and Bundick (2017) and Berger et al. (2019) (PC Uncertainty). All principal components are plotted as three-quarters moving averages. PC News is inverted in sign, so a spike stands for negative news shocks. Grey areas represent NBER recessions.

We focus primarily on the analysis of the second-moment shock, which reflects changes in risk and uncertainty. By contrast, the first-moment shocks isolated by the procedure do not have a structural interpretation since they capture a broad range of perturbations – including news on future TFP – that would otherwise confound the estimation of uncertainty shocks. The premise of our work, highlighted in Figure 1, is that controlling for the role of 'news' is necessary in order to assess the effects of uncertainty. The use of high-frequency, non-Gaussian financial data is crucial because it allows us to achieve identification by combining a strong statistical assumption (independence), which is consistent with the definition of structural shocks in theoretical models, with a relatively weak economic assumption (a restriction on the relative magnitude of the responses of sp and vxo). This implies that we can avoid the limitations of other commonly used identification schemes. A crucial benefit of our approach is that it delivers shocks that are unrelated across the entire distribution and not just on average. This feature is useful because, as we show in the empirical analysis, the interaction between news and uncertainty goes well beyond linear correlation: bad trading days are typically characterized by sharp drops in prices and jumps in volatility. This type of tail dependence is completely ignored by identification strategies (such as Cholesky decomposition) that only orthogonalize the residuals of a VAR model.

The uncertainty shocks identified by our method capture the key geopolitical events in our sample period and correlate strongly with firm-level investment decisions, in line with the "wait and see" effect (Bloom, 2009). Furthermore, the method successfully retrieves uncertainty shocks in Monte Carlo tests based on the models by Basu and Bundick (2017), Bloom et al. (2018) and Berger et al. (2019).

Our main result is that uncertainty 'matters'. An exogenous rise in uncertainty causes a contraction in economic activity, and uncertainty shocks account for about 10% to 20% of the fluctuations in employment and industrial production in our sample. Furthermore, the negative responses recorded by wages, hours, and new orders of capital goods suggest that the shocks propagate through both labor and capital goods markets.

The challenges in the identification of uncertainty shocks were first stressed by Stock and Watson (2012). The potential confusion between uncertainty and the release of new information on economic fundamentals is also highlighted by Baker and Bloom (2013), Baker et al. (2016) and Cascaldi-Garcia and Galvao (2016). Several mechanisms can complicate this identification problem. On the one hand, since uncertainty is recessionary, agents might plausibly revise their expectations downwards after a genuine uncertainty shock. On the other hand, negative news could cause an endogenous increase in the agent's uncertainty about the state of the economy. Recessions are times when business practices and relationships break down (Bachmann and Moscarini, 2011 and Fostel and Geanakoplos, 2012) and new, unfamiliar policies are activated (Pastor and Veronesi, 2013 and Bianchi and Melosi, 2017). These difficulties are reflected in the wide range of results documented in the empirical literature, where uncertainty shocks have been alternatively found to be strongly recessionary (Christiano et al., 2014,Piffer and Podstawski, 2018) or entirely irrelevant (Berger et al., 2019). Recent research has highlighted two important complications of this problem. The first one is that uncertainty is not a univocal concept, as agents might experience bouts of both 'good' and 'bad' uncertainty that have radically different implications for their behavior (Segal et al., 2015, Kilic and Shaliastovich, 2019; see also the discussions in Basu and Bundick, 2017 and Bloom et al., 2018). The second one is that the source of the shock may matter: Jurado et al. (2015) argue that financial uncertainty has a negative impact on economic activity, while macroeconomic uncertainty adjusts endogenously to business cycle fluctuations.

In an influential and closely related work, Berger et al. (2019) (BDG henceforth) explicitly tackle the relation between news and uncertainty using data on the S&P500 equity market. Uncertainty shocks are identified as changes in the expected volatility of the price index that are unrelated to the realized volatility of the stock market in a given month, thus isolating uncertainty from a broad range of economic news. BDG find that uncertainty shocks have no significant effect on the economy and that the recessionary effects documented in the literature are caused by a systematic overlap between spikes in volatility and large adverse shocks to the fundamentals of the economy. We also exploit stock and option price data for identification. However, we relax the BDG identification scheme allowing for two-way feedbacks between uncertainty and the observed volatility of the stock market. This generalization relies on two innovations relative to BDG. First, we use daily data that contain richer information on the relationship between economic news and uncertainty compared to monthly or quarterly observations. Second, we look for shocks that are independent and not merely orthogonal, thus imposing restrictions on the higher-order moments of the data. The moment restrictions allow us to achieve identification with minimal assumptions on the impact matrix, and to avoid any confusion between uncertainty and 'tail' shocks to the fundamentals. The daily structural shocks are then aggregated to the monthly frequency and used in a monthly VAR model following Gazzani and Vicondoa (2020). These innovations turn out to be crucial: our identification strategy, which is valid under a broader set of assumptions on the data generating process, allows us to reject the hypothesis that uncertainty shocks do not affect the business cycle.[5]

The remainder of the paper is organized as follows. Section 2 describes our empirical model. Section 3 works through a stylized VAR that only includes stock prices and implied volatility. This application allows us to discuss analytically the role of daily data and the relation between our identification assumptions and those employed by BDG, and highlights the dramatic improvement delivered by moment restrictions relative to recursive identification schemes. Section 4 illustrates the results of the daily VAR, providing a high-frequency, model-based narrative of the main uncertainty shocks that occurred in the US between February 1986 and December 2019. Section 5 contains the main empirical results. Section 6 compares the results with those obtained in previous studies. Section 7 covers the robustness exercises. Section 8 concludes.

2 Identifying the Dynamic Effects of Uncertainty Shocks

Consider a vector of n time series w_t modeled as a causal and covariance-stationary SVAR of lag length p:

$$A(L)w_t = B\varepsilon_t \tag{1}$$

where $A(L)$ is a polynomial lag operator and ε_t is a vector of stochastic innovations that represent the structural shocks in the economy, and B is a $n \times n$ matrix whose coefficients

[5] Gazzani and Vicondoa (2020) show that the data frequency also plays a role in the BDG approach, which yields different results when applied to daily rather than monthly data. The identification restrictions employed in this paper allow us to leave the daily responses of prices, realized volatility and VXO to news and uncertainty shocks completely unrestricted.

determine the contemporaneous impact of ε_t on w_t. We assume that w is sampled at the daily frequency t. More specifically, $w_t = \{sp_t, vxo_t, \Omega_t\}$ where sp_t is the logarithm of the S&P500 stock price index, vxo_t is the (logarithm of) VXO implied volatility index (our baseline proxy of aggregate uncertainty) and Ω_t is a vector of control variables of dimension $n_\Omega \times 1$. We allow for the existence of a set of endogenous variables, collected in the vector y ($n_y \times 1$), which might be affected by the primitive shocks ε_t but cannot be observed on a daily basis. This vector includes the typical variable of interest in macroeconomics, e.g. inflation and economic activity indicators. The vector Ω_t has to be large enough to make the daily VAR informationally sufficient, guaranteeing that the omission of y_t from equation (1) is inconsequential for identification purposes. This assumption is implicit in any VAR analysis and can be tested after the estimation. The daily model can be written more explicitly as follows:

$$A(L)\begin{bmatrix} sp_t \\ vxo_t \\ \Omega_t \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & B_{13} \\ b_{21} & b_{22} & B_{23} \\ B_{31} & B_{32} & B_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_t^e \\ \varepsilon_t^u \\ \varepsilon_t^\Omega \end{bmatrix} \tag{2}$$

The first column of the B matrix, $B_{\bullet 1}$, captures the impact of first-moment shocks that primarily affect the stock price level on any given trading day (ε_t^e). The second column, $B_{\bullet 2}$, capture instead second-moment shocks stemming from changes in the expected volatility of the market over the following month (ε_t^u). A key objective of our analysis consists of estimating $B_{\bullet 1}$ and $B_{\bullet 2}$, disentangling the contribution of price level news and volatility news to the dynamics of the daily data.[6]

Standard identification schemes would assume that some elements of the B matrix are zero or have particular signs that can be derived by some underlying economic theory. However, these strategies are not suitable in this case.Zero restrictions are problematic because of the two-way feedback between stock prices and implied volatility documented in the finance literature. On the one hand, an unexpected drop in equity prices reduces the firms' net worth and increases their leverage, causing equity prices to be more volatile. On the other hand, an increase in volatility reduces the investors' discount factor bringing about a drop in equity prices. These 'leverage' and 'volatility feedback' effects are quantitatively significant for daily S&P500 observations, and they both contribute to the negative conditional correlation between price level and volatility found in the data (see e.g. Carr and Wu, 2017). Hence, a reliable identification strategy should allow prices and volatility to respond to both first-moment and second-moment shocks

Although, in principle, it might be possible to design sign restrictions that are compatible with these mechanisms, in practice, economic theory does not provide clear guidance on how this task could be accomplished. Figure 1 suggests that coming up with workable restrictions

[6]Notice that ε_t^u is a proper structural shock, with a well-defined theoretical interpretation grounded in the uncertainty literature, whereas ε_t^e is a catch-all term that is meant to capture a broad range of changes in the fundamentals of the economy. See BDG for a discussion.

might be impossible: to the extent that bad news and rising uncertainty have qualitatively similar implications for economic agents, one would suspect that the elements of $B_{\bullet 1}$ and $B_{\bullet 2}$ have opposite signs, and this would prevent a separation between ε_t^e and ε_t^u based on sign restrictions.

In order to circumvent these limitations, we resort to an identification strategy that exploits the moments of the distribution of ε_t and places only minimal restrictions on the impact matrix B. We assume that: *(i)* the structural shocks are statistically independent; (ii) at most one of them is normally distributed; and (iii) ε_t^u (ε_t^e) has a larger impact on vxo_t (sp_t). Assumption (i) cannot be tested, but it is consistent with theoretical models and with the general notion of exogenous shocks. Assumption (ii) may or may not be valid depending on the application, and it is plausible for our daily financial data (see Section 3). Gourieroux et al. (2017) and Gourieroux et al. (2018) show that, under assumptions (i) and (ii), the identification problem of VAR and VARMA models can be solved by exploiting higher-order moments of the distribution of the residuals (over and above their covariance matrix). We exploit this general result by using independent component analysis (ICA) to search for the unique B matrix that yields the most independent shocks $\left\{\varepsilon_t^e, \varepsilon_t^u\right\}$. In essence, ICA amounts to searching for a B matrix that maximizes the non-gaussianity of the shocks.

Our implementation of ICA is discussed in detail in Appendix C; here, we exploit the results by Keweloh (2020) to illustrate ICA within the more common generalized methods of moments (GMM) framework. ICA can be expressed as a computationally efficient GMM estimator of the impact matrix based on the standard covariance condition (eq.3) and on two conditions based on higher-order moments. (eq.4-5), here analytically represented by coskewness. Coupled with the standard normalization $b_{11} = 1$ and $b_{22} = 1$, these restrictions guarantee that the columns $B_{\bullet 1}$ and $B_{\bullet 2}$ are globally identified.

$$\mathbb{E}\left[\varepsilon_t^u \varepsilon_t^e\right] = 0 \tag{3}$$

$$\mathbb{E}\left[\varepsilon_t^u \left(\varepsilon_t^e\right)^2\right] = 0 \tag{4}$$

$$\mathbb{E}\left[\left(\varepsilon_t^u\right)^2 \varepsilon_t^e\right] = 0 \tag{5}$$

To obtain an economic interpretation for the (uniquely identified) components, we resort to assumption (iii). In particular, we assume that ε_t^u and ε_t^e are the two components that exert their maximum contemporaneous impact on, respectively, vxo_t and sp_t:

$$
\begin{aligned}
|b_{11}| &> |b_{1i}| \ \forall i \neq 1 \\
|b_{22}| &> |b_{2i}| \ \forall i \neq 2
\end{aligned} \tag{6}
$$

Assumption (6) implies that vxo_t (sp_t) is relatively more sensitive to second-moment (first-moment) shocks: in particular, it requires the daily innovation to the uncertainty proxy vxo_t to be predominantly driven by genuine uncertainty shocks.[7] This setup allows all variables in the system – including vxo_t and sp_t – to respond contemporaneously to the two shocks of interest. As such, it can easily accommodate the presence of leverage and volatility feedback effects, as well as the more complex interactions between first and second moments discussed in Section 1.

Since we are interested in examining the impact of the daily shocks $\{\varepsilon_t^u, \varepsilon_t^e\}$ on a set of macroeconomic variables y_τ that are available only at a lower frequency τ (e.g. monthly), the calculation of the impulse responses requires temporal aggregation of the shocks. Following Gazzani and Vicondoa (2020), the aggregated shocks are calculated as monthly averages:

$$
\begin{aligned}
\varepsilon_\tau^u &= \frac{\sum_{t=1}^m \varepsilon_t^u}{m} \\
\varepsilon_\tau^e &= \frac{\sum_{t=1}^m \varepsilon_t^e}{m}
\end{aligned} \tag{7}
$$

where m is the number of trading days within each calendar month.[8]

To compute the response of y_τ to the two shocks of interest, we use a monthly VAR where the y_τ vector is modeled along with monthly averages of the daily stock price and uncertainty series used in the daily model:

$$
\tilde{A}(L) \begin{bmatrix} y_\tau \\ vxo_\tau \\ sp_\tau \end{bmatrix} = \begin{bmatrix} u_\tau^y \\ u_\tau^u \\ u_\tau^e \end{bmatrix} \tag{8}
$$

where $\tilde{A}(L)$ contains the autoregressive structure of the monthly VAR and u_τ denotes the monthly reduced-form residuals. As usual, the mapping between residuals and shocks is determined by some unknown impact matrix $\tilde{B}$ such that $u_\tau = \tilde{B}\varepsilon_\tau$. Identification is achieved by using the shocks $\{\varepsilon_\tau^u, \varepsilon_\tau^e\}$ as (internal or external) instruments for the VAR residuals. The instruments allow us to identify the first two columns of the $\tilde{B}$ matrix that are our object of

[7]We do not use directly magnitude restrictions because they are unappealing and unfeasible in our case. First, imposing directly the magnitude restrictions exclusively on sp and vxo would not allow us to separate first-moment and uncertainty shocks from other innovations hitting the daily VAR system (e.g. monetary policy shocks). Second, imposing magnitude restrictions on our large VAR system is computationally unfeasible.

[8]Within-month averaging recovers the correct impact effects of $\{\varepsilon^x, \varepsilon^e\}$ on y under a general VAR structure – see Gazzani and Vicondoa (2020).

interest. The dynamic responses of the economy are computed using the matrix $\tilde{A}(L)$ through a VARX where the shocks are exogenous variables in the VARs. Since the two shocks $\{\varepsilon^u_\tau, \varepsilon^e_\tau\}$ are uncorrelated by construction if the daily VAR includes a sufficient number of lags, the inference can be conducted separately for each shock.

3 Bivariate VAR

This section illustrates the logic of our empirical strategy through a stylized bivariate VAR model that only includes stock prices and implied volatility. First, we demonstrate the role of high-frequency data in our identification strategy (Section 3.1). Second,we discuss the relationship between our approach and the one pursued in BDG (Section 3.2). Finally, we compare the performance of moment and recursive restrictions in identifying uncertainty shocks in our sample (Section 3.3).

3.1 The Role of High-Frequency Data

Consider a stylized version of the VAR model in equation (2). For simplicity, we set the lag length to $p = 1$ and omit the additional control variables Ω_t, so that the system only includes vxo_t and sp_t:

$$\begin{bmatrix} vxo_t \\ sp_t \end{bmatrix} = \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} vxo_{t-1} \\ sp_{t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon^u_t \\ \varepsilon^e_t \end{bmatrix} \tag{9}$$

The reduced-form residuals are linked to the structural shocks by the relation $u_t = B\varepsilon_t$. As in the previous discussion, we use the subscripts t and τ to denote high and low frequency, respectively. We further assume for analytical tractability that the sampling ratio between τ and t (i.e. the frequency mismatch m) is equal to 2. The temporal aggregation has two problematic implications. First, it alters the covariance matrix of the residuals. This implies that identification restrictions that are valid at high frequency can turn out to be invalid at low(er) frequencies. Second, it washes away information on the higher moments of the data. Thus, identification restrictions that exploit co-skewness and other forms of tail dependence in the data may simply not be viable at low frequencies. We discuss these points in turn below.

The influence of temporal aggregation on the residual covariance matrix can be examined by aggregating eq.(9) to the lower frequency τ. Aggregation is obtained by applying the filter $D(L) = I + AL$ to the original process, where A is the autoregressive matrix of the high-frequency VAR and L is the lag operator. Intuitively, the filter $D(L)$ makes the data observable only once every m periods t. For the case with $m = 2$, the process at frequency τ is given by:

$$\begin{bmatrix} vxo_\tau \\ sp_\tau \end{bmatrix} = \begin{bmatrix} a_{11}^2 + a_{12}a_{21} & a_{11}a_{12} + a_{12}a_{22} \\ a_{11}a_{21} + a_{21}a_{22} & a_{12}a_{21} + a_{22}^2 \end{bmatrix} \begin{bmatrix} vxo_{\tau-1} \\ sp_{\tau-1} \end{bmatrix} + \begin{bmatrix} u_\tau^{vxo} \\ u_\tau^{sp} \end{bmatrix} \tag{10}$$

$$\begin{bmatrix} u_\tau^{vxo} \\ u_\tau^{sp} \end{bmatrix} = \begin{bmatrix} b_{11} + L\left(a_{11}b_{11} + a_{12}b_{21}\right) & b_{21} + L\left(a_{11}b_{12} + a_{12}b_{22}\right) \\ b_{12} + L\left(a_{11}b_{21} + a_{12}b_{22}\right) & b_{22} + L\left(a_{21}b_{12} + a_{22}b_{22}\right) \end{bmatrix} \begin{bmatrix} \varepsilon_t^u \\ \varepsilon_t^e \end{bmatrix} \tag{11}$$

The impact matrix in eq.(11) is clearly different from the original B matrix. A diagonal B matrix, for instance, does not necessarily lead to a diagonal $(I + AL)\,B$ matrix. This means that even if sp and vxo index were accurately described by a recursive system at the daily frequency (which, as we argue in Section 1, is extremely unlikely), the recursive structure would most probably break down at the monthly or quarterly frequency. More generally, plausible restrictions at the HF might not hold at the LF, and the contemporaneous responses estimated using a LF-VAR will typically differ from those obtained from a Bridge-Proxy SVAR where identification is achieved at HF. This problem is particularly relevant when dealing with financial variables, as financial markets quickly absorb and propagate most economic perturbations.

The influence of temporal aggregation on the higher moments of the data-generating process stems directly from the Central Limit Theorem. The probability density function of a sum of N random variables converges monotonically over N to the Gaussian p.d.f. in terms of relative entropy (Barron, 1986). This result implies that temporal aggregation of the data dramatically increases the entropy (Gaussianity) of the residuals of a VAR model. Define $\Upsilon\,(u)$ as the the number of random variables that linearly determine the reduced-form residuals u. Then $\Upsilon\,(u_t) = n$ and $\Upsilon\,(u_\tau) = nm$, and for $m \geq 1$ we can immediately conclude that $\Upsilon\,(u_\tau) \geq \Upsilon\,(u_t)$. In other words, the low-frequency residuals u_τ are inevitably more Gaussian than the original high-frequency residuals u_t. When m and n are large (as in our empirical specification, where $m = 22$ is the average number of business days within a month and the baseline VAR includes $n = 10$ variables), the difference becomes quantitatively important. This loss of information plays a critical role in our case. The daily series display rich forms of statistical interdependence. It is precisely this interdependence that allows ICA to identify a unique set of structural shocks without imposing stringent theoretical restrictions on the impact matrix. As we show in the next section, this route is not viable with Gaussian monthly or quarterly samples.[9]

[9] Ferrara and Guerin (2018) is a related work that tackles the temporal aggregation bias by resorting to mixed-frequency models (MIDAS regressions or stacked VARs), but rely on a recursive identification scheme that does not resolve the endogeneity between first and second moments. We show instead that the linkages between stock prices and VXO are a key obstacle in the identification of uncertainty shocks. Although temporal aggregation exacerbates

3.2 Restricting the Relation between Prices and Expected Volatility

Our empirical setup bears a clear resemblance to BDG: in both cases level and uncertainty shocks (or equivalently first- and second-moment shocks) are identified using stock prices and implied volatility, the assumption being that actual uncertainty shocks should be orthogonal to changes in several economic fundamentals that directly hit equity prices. However, there is a key difference in how this idea is implemented. BDG capture price-level news using the realized volatility of the stock market, defined as the squared return $rv_t = (\Delta sp_t)^2$, and identify uncertainty shocks as innovations to the option-implied volatility vxo_t that are orthogonal to the innovations to rv_t. This orthogonalization guarantees that ε_t^u captures changes in expected volatility that are separated from changes in current volatility driven by news on fundamentals. However, identification relies on the key assumption that rv_t does not respond contemporaneously to ε_t^u: uncertainty must have no impact on the current volatility of the stock market. In Appendix B we prove that our identification assumptions generalize those used by BDG removing this restriction. In particular, we show that the VAR system in equation (9) is consistent with a stylized equity price model in which stock prices follow a random-walk process with stochastic volatility. Price and volatility innovations are driven by the two structural shocks ε_t^e and ε_t^e, while rv_t includes by construction the squares and the cross-product of the two shocks. The model suggests that there are economically interesting cases where the system is not recursive and ε_t^u has a contemporaneous impact on rv_t, leading to a failure of the BDG assumption. In particular, this happens when (i) the 'volatility feedback' effect is active ($b_{12} < 0$ in equation 2) and (ii) the distribution of ε_t^u is skewed, implying that ε_t^u and $(\varepsilon_t^u)^2$ are not orthogonal. Our strategy is not subject to this limitation. By restricting directly the moments of the joint distribution of the shocks, we ensure that ε_t^u is orthogonal to both ε_t^e and $(\varepsilon_t^e)^2$ without taking *a priori* a strong stance on the impact matrix. Our approach separates ε_t^u from both price level and realized volatility shocks, and is thus consistent with the BDG argument but, crucially, it allows us to achieve this separation without preventing either sp_t or rv_t from responding contemporaneously to ε_t^u.

Since our identification strategy is novel, before moving to the empirical analysis we test its performance in a Montecarlo setup using three leading general equilibrium models with uncertainty shocks: Basu and Bundick (2017) (BB), the 'really uncertain business cycle' model of Bloom et al. (2018) (RUBC) and the 'really skewed business cycle' model of Berger et al. (2019) (RSBC).[10] A summary of the results is reported in Table 1. ICA successfully retrieves the actual

this identification challenges, this problem is also pervasive in daily data, which implies that recursive restrictions are problematic irrespective of the sampling frequency. This motivates our approach, where identification is obtained at high frequency through a more flexible identification strategy - ICA - and the shocks are subsequently used to construct external instruments for a lower-frequency VAR model.

[10] We follow BDG and we run this exercise by running our VAR identification on data drawn from the ergodic distribution of the variables in the models. The shocks in these models are Gaussian (the only exception being the

structural shocks in all models. Its precision is high in absolute terms, with correlations between true and estimated shocks above 90%. It is also higher than that achieved by the BDG recursive identification strategy, which in the three models under consideration delivers correlations of 0.94, 0.98 and 0.87 (see BDG Section 6.1). These results imply that, although the BDG restrictions approximately hold in these models, our strategy is also reliable in cases where the timing restriction is not satisfied (due to the double feedback mechanism previously described) and/or the shocks are not symmetrically distributed.

Model	BB	RUBC	RSBC
Correlation	0.98	0.98	0.91

Table 1: Montecarlo performances of ICA in leading models of uncertainty
BB, RUBC, RSBC denote the general equilibrium models of Basu and Bundick (2017), Bloom et al. (2018) and Berger et al. (2019). For each model, the table reports the correlation between actual uncertainty shocks and the uncertainty shocks identified by Independent Component Analysis.

3.3 Empirical Illustration

This section employs the bivariate VAR discussed in the previous subsections to illustrate the comparison between recursive and ICA-based identifications. The VAR is estimated alternatively on daily or monthly data for the S&P500 stock price index (sp_t) and the VXO volatility index (vxo_t) over the period 1986m2-2019m12. Both variables are used in logarithms. Following the Akaike information criterion, the number of lags is set to 10 and 3, respectively, for the daily and monthly model. Not surprisingly, sp and vxo display a strong negative correlation at both the monthly and the daily frequency, with correlation coefficients of, respectively, -0.76 and -0.72. This immediately points to the perils of using a recursive identification scheme irrespective of the sampling frequency. Appendix E shows that the role of uncertainty shocks during the GFC is indeed reversed under alternative recursive schemes both at daily and monthly frequency.[11]

When applied to the residuals of the VAR models, ICA recovers two distinct shocks in the daily but not in the monthly dataset: in the latter case, temporal aggregation (and the associated loss of information) prevents a clear separation between first- and second-moment shocks. This result is entirely consistent with Figure 1. Furthermore, the daily ICA identification is sharply at odds with the Cholesky decomposition. The estimated off-diagonal elements of the impact matrix

skewed productivity shock in RSBC); however, the mispecification associated to the discrepancy between SS and VAR representations introduces a degree of non-normality, and this turns out to be sufficient for ICA to work. In separate tests, we find that - unsurprisingly - ICA is also accurate when the structural shocks are drawn directly from non-Gaussian distributions (e.g. Beta and Bernoulli)

[11] Similar conclusions are drawn by analyzing the mutual information contained in first-moment and uncertainty shocks. Table A.2 included in Appendix A summarizes the differences between Cholesky and ICA in terms of the mutual information contained in the estimated shocks. The table confirms that there are forms of dependence between stock prices and VXO that survive the Cholesky orthogonalization, whereas ICA succeeds in breaking down that dependence.

are -0.38 and -0.50, implying that 'leverage' and 'volatility feedback' effects coexist in the data: a positive price shock $\varepsilon_t^e > 0$ reduces vxo_t on impact, while a positive volatility shock $\varepsilon_t^u > 0$ causes a decline in sp_t. Finally, the exercise shows how ICA exploits the high-order moments of the distribution to break the interdependence among news and uncertainty. To illustrate this point, we study the joint distribution of residuals, Cholesky and ICA-based shocks using local-linear regressions and cluster analysis.

Figure 2 shows scatterplots of the data with local-linear regressions that allow the relation between sp_t and vxo_t to change smoothly across the distribution. The VAR residuals display the usual negative relation between price and volatility (panel a). A Cholesky factorization transforms this relation rather than removing it from the data: the 'shocks' are still correlated, and the sign of the correlation changes across the distribution (panel b).[12]

The ICA shocks, by contrast, are orthogonal across the entire distribution (panel c). Figure 3 shows a partition of shocks and residuals into separate clusters. Following the AIC criterion, we estimate 5 clusters and let mean and variance change across clusters; in each panel of the figure, the legend reports the within-cluster correlation coefficients, their p-values (in brackets) and the share of observations assigned to the clusters. Panel (a) confirms that the residuals are negatively and significantly correlated, albeit to different degrees. The negative correlation is still dominant among the Cholesky shocks, where it involves 77% of the observations (panel b). ICA entirely removes the correlation among the shocks in three out of the five clusters (panel c). It also reduces drastically the magnitude of the correlation coefficients, that are bounded between -0.04 and 0.26. Taken together, Figures 2 and 3 confirm that ICA yields a credible separation between structural (and hence exogenous and independent) first- and second-moment shocks.

[12] Away from the boundaries, the standard negative correlation dominates in the 'bad news' region $\varepsilon_t^e < 0$ while a strong positive correlation shows up in the 'good news'. This switch might be compatible with the occurrence of "good uncertainty" after a positive news shocks (Cascaldi-Garcia, 2017) region $\varepsilon_t^e > 0$. Irrespective of the interpretation, it is symptomatic of a failure of the Cholesky factorization to isolate authentic structural shocks.

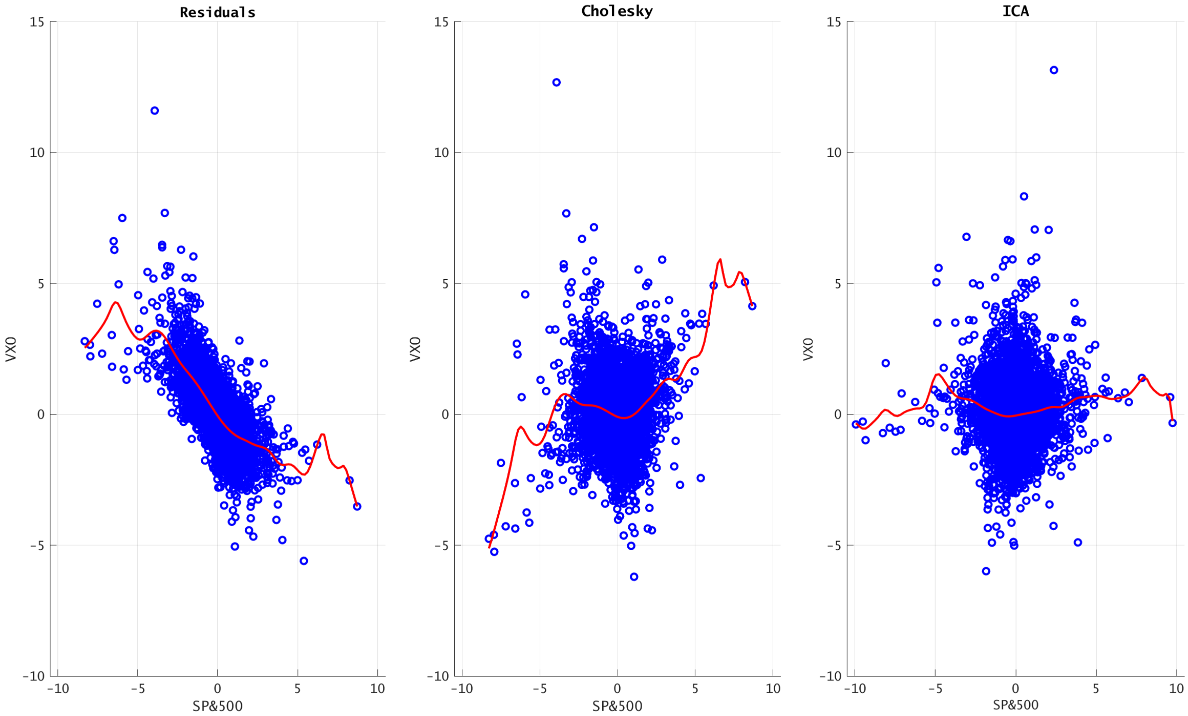

Figure 2: Local linear regression

The left panel shows a scatterplot of the residuals from a bivariate daily VAR model that includes the S&P500 stock price index and the VXO volatility index. The middle panel shows scatter and regression lines for the S&P and VXO shocks identified through a Cholesky orthogonalization, ordering VXO first. The right panel shows scatter and regression lines for the shocks obtained through Independent Component Analysis. The estimation period is 1986-2019, and the VAR includes 10 lags.

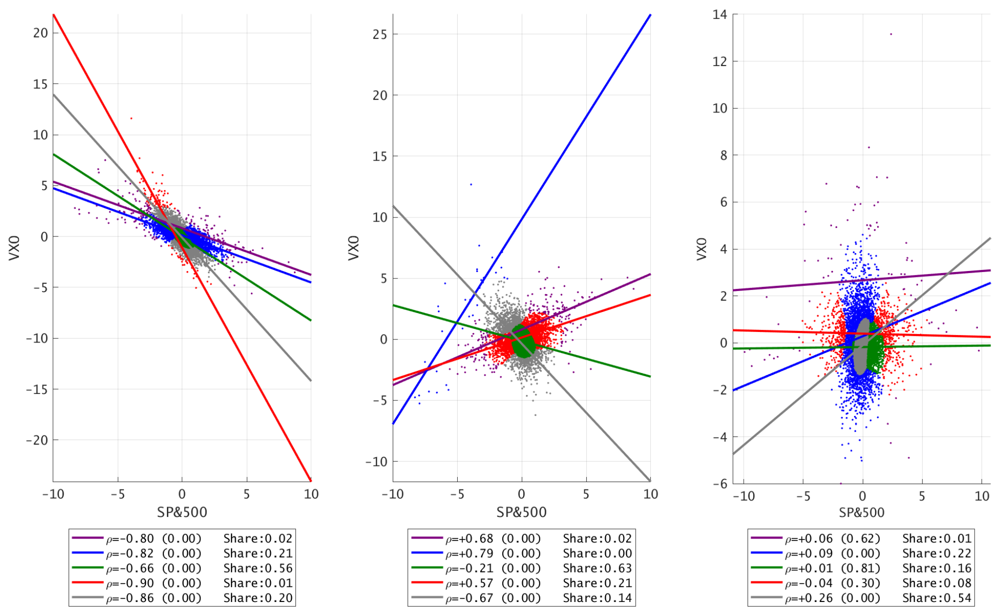

Figure 3: Shock correlation across clusters

The figure displays with different colors the identified cluster for the residuals (left panel), Cholesky shocks (middle panel), and ICA shocks (right panel) together with regression lines of each of the clusters.

4 A New Series of Uncertainty Shocks

The first step of our analysis consists of estimating a daily VAR model with ten daily series, mainly from the US financial markets, that span from January 1^{st} 1986 to December 31^{st} 2019. The variables included in the daily VAR are sp, vxo, *Brent Oil Prices, Gold Price Index, Euro-dollar FX, Dollar-pound FX, 3m Treasury Bills, 1y Treasury Rate, 5y Term Premium 10y Term Premium.* Our analysis focuses on vxo as a proxy of aggregate uncertainty (as commonly done in the literature: e.g. Bloom, 2009; Basu and Bundick 2017; and BDG) and sp as a proxy of first-moment (see e.g. Cheung and Ng, 1998; Beaudry and Portier, 2014; Dison and Theodoridis, 2017 among others). The model is estimated using all variables in log-levels except for the interest rates.[13] Our baseline includes 10 lags, but nearly identical results are obtained with 22 or 1 lags. The null hypothesis of normally-distributed residuals is rejected for all residuals at the 10% significance level (or lower) by both the Jarque-Bera and Kolmogorov-Smirnov statistics, confirming the feasibility of ICA. ICA isolates by construction 10 components, one for each variable included in the system, which are not just uncorrelated but (nearly) independent.

To obtain an economic interpretation for the shocks, we match each variable to the component that explains most of its variance on impact. Following our identifying assumption based on magnitude restrictions (see Section 2), uncertainty shocks are the component that has the maximum impact on vxo, whereas the first-moment shocks correspond to the component that has the largest impact on sp . Importantly, we only attach a structural interpretation to the uncertainty shock ε^u. This shock represents a change in the second (or higher) moments of the equity market, allowing an impact feedback on sp that is independent to the first-moment shock ε^e. In other words, ε^u captures a change in the implied volatility of stock returns (an uncertainty shocks) controlling for a range of confounding factors that affect sp on the same day through a first-moment effect. By contrast, the first-moment shock is by construction a catch-all term without a structural interpretation: it captures all the events that affect investor expectations on a given trading day. Thus, it includes for instance news on TFP, macroeconomic surprises associated to new data releases or policy announcements. It follows that this is not a "news" shock: it does not refer exclusively to TFP, and it reflects observed changes in fundamentals as well as news on future fundamentals.

A crucial feature of ICA is that, unlike a Cholesky factorization, it does not prevent ε^e from affecting vxo on impact or ε^u from affecting sp contemporaneously. It merely ensures that we can separately trace the impact (on both vxo and sp) of innovations that (i) affect predominantly one of the two variables, and (ii) are independent of one another. The identified coefficients of

[13] All series are provided by Datastream. Since most financial variables feature heteroskedasticity, ARCH or GARCH models would presumably provide a more accurate description of the data-generating process. However, the OLS estimation of the linear VAR is consistent and the identification of the shocks (which is the only objective of the exercise) only depends on the point estimates of the coefficients.

the impact matrix that link sp and vxo, reported in Table 2, are consistent with the preliminary evidence presented in Section 3.3. The elements on the main diagonal come from a normalization, as in a standard Cholesky factorization. The non-zero off-diagonal elements confirm that even at the daily frequency first-moment and uncertainty shocks affect simultaneously both vxo and sp, providing further evidence against recursive identification schemes. The direction of this influence is consistent with the economic intuition: positive first-moment shocks that raise the sp cause a simultaneous decline in vxo, while uncertainty shocks cause a drop in stock prices.

Figure 4 displays the monthly averages of the estimated daily shocks, which are used as instruments in the monthly VAR model (see Section 5). The outburst of the Great Recession corresponds to sizable adverse first-moment shocks, while large uncertainty shocks hit the economy later on, particularly in 2015. In Section 6.1 we explore more in detail the main first- and second-moment shocks. The top panel focuses on negative first-moment shocks (ε_t^e) and the bottom panel on positive second-moment shocks (ε_t^u).

	ε_t^e	ε_t^u
u_t^{sp}	1	-0.5
u_t^{vxo}	-0.34	1

Table 2: Impact matrix from the daily VAR

The table reports the impact matrix identified by ICA and magnitude restrictions in a VAR model that includes 15 financial time series as stock prices, gold and oil prices, credit spreads, VXO, and other uncertainty proxies. The VAR has 10 lags and the estimation sample runs from January 1st, 1986 to December 31st, 2019.

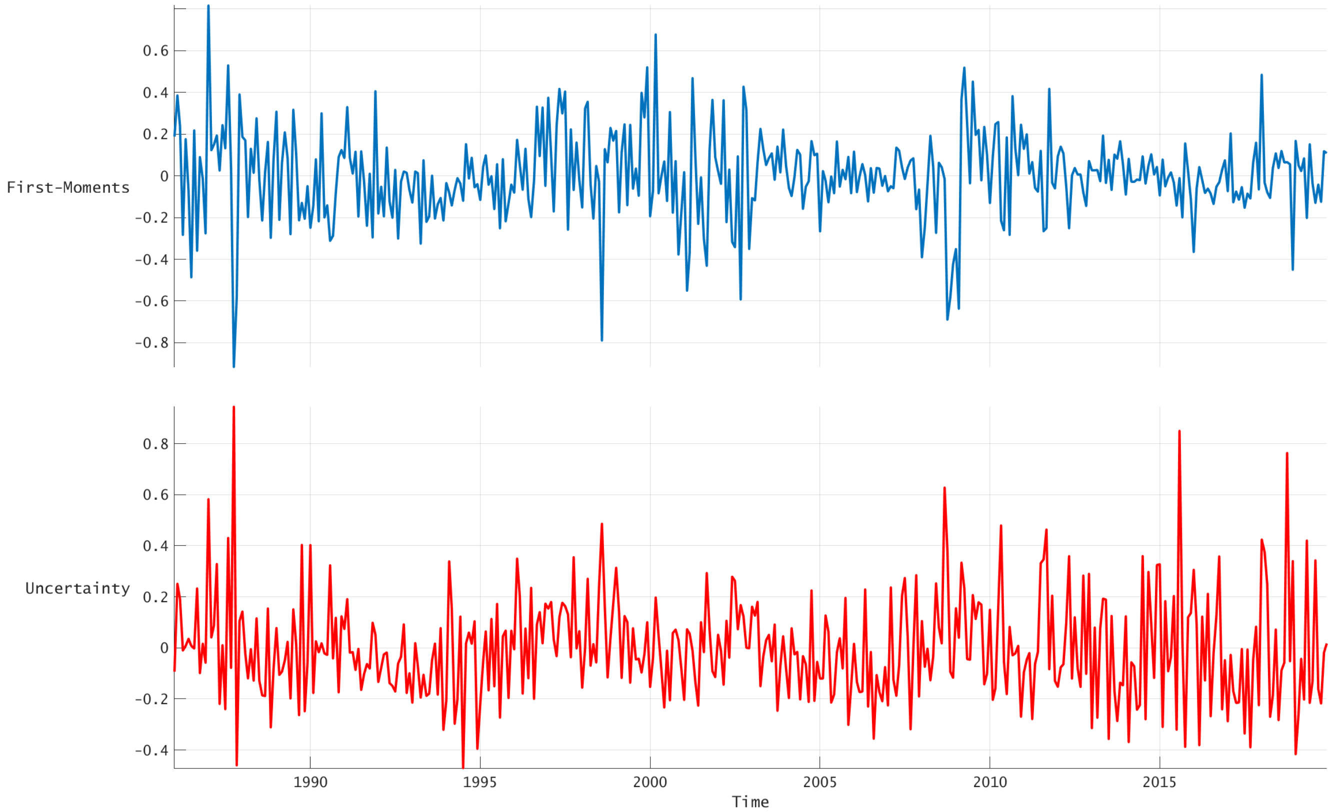

Figure 4: Level (first-moment) and uncertainty (second-moment) shocks as monthly averages. *The plots show monthly averages of daily shocks obtained by applying ICA and magnitude restrictions to the residuals of a VAR model that includes 15 financial time series as stock prices, gold and oil prices, credit spreads, VXO and other uncertainty proxies. The VAR has 10 lags and the estimation sample runs from January 1st, 1986 to December 31st, 2019.*
.

5 Macroeconomic Effects of Uncertainty Shocks

To quantify the macroeconomic effects of uncertainty shocks, we estimate a monthly VAR using US data for the period 1992:2-2019:12. The system includes the S&P500 Stock Price index*(sp), the VXO volatility index (vxo), Industrial Production, Employment, Hours, Wage, New Orders Capital Goods, Capacity Utilization,* and the *1-year Treasury Bond Yield*. The monthly model provides a direct link to the existing literature, which is predominantly based on monthly data, and allows us to identify the macroeconomic effects of uncertainty shocks (plus the effects of the first-moment shocks for the sake of comparison). We include variables that capture different dimensions of the labor market (i.e. extensive vs. intensive margins), as well as capacity utilization and new orders, in order to shed more light on the channels through which uncertainty propagates in the economy. All variables are in log-levels except for interest rate and capacity utilization (that are included in percentage points) and hours (a level based on weekly averages). Following the standard information criteria, we set the number of lags to 3.

In order to identify uncertainty and first-moment shocks, we use monthly averages of daily first-moment and uncertainty shocks as an internal instrument in the monthly VAR (see Section

2).[14] We test the possibility of using the proxy as external instruments but a Granger causality test of the proxies on the residuals rejects this approach (see Paul, forth and Noh, 2018).[15] While we employ several specifications that yield comparable results, our favorite specification follows Paul (forth) by employing the monthly first-moment and uncertainty shocks in an exogenous block that features three lags as the endogenous one. Since the aggregated uncertainty and first-moment shocks are unpredictable, we impose that both shocks are not affected by lags of the other variables to achieve a more efficient estimation. As we show in the Appendix, results are robust to relaxing this assumption.

The responses to a one-standard deviation uncertainty shock and to a first-moment shock are depicted in Figure 5: to facilitate the comparison we consider a positive uncertainty shock (red lines) and a negative first-moment shock (blue lines). First, we note that these shocks affect strongly both vxo and sp: the recursive restrictions often used in the literature (at monthly or even lower frequencies) can be rejected based on our high-frequency and non-recursive identification assumptions. Second, uncertainty shocks are recessionary, leading to a persistent fall in industrial production, consumer prices, labor market outcomes, and investment decisions. Finally, the IRFs generated by the two shocks are qualitatively similar for most variables. This result implies that (at least within the information set we consider) sign restrictions would have no chance of separating the two shocks. It also supports theoretical mechanisms that create a strong structural link between first and second moments, such as ambiguity aversion (see Section 1). The main differences are that, compared to first-moment shocks, uncertainty shocks have a larger effect on the vxo and a somewhat delayed impact on the other variables in the system.

The estimated monthly VAR can be used to quantify the contribution of uncertainty and first-moment shocks to the US business cycle. Figure 6 displays the Forecast Error Variance Decomposition (FEVD) of all the variables to the two shocks. Uncertainty shocks explain a significant fraction of most of the variables in the system. In particular, they account for around 20% and 10% of the cyclical fluctuations in industrial production and prices, respectively. Uncertainty affects both labor and capital markets, explaining nearly 20% of the variance of employment and 10% of the variance of new orders of capital goods. These estimates suggest that, although uncertainty is an important driver of the US business cycle, its role has been often overestimated in the literature (see, for example, Christiano et al., 2014 and Piffer and Podstawski, 2018). The discrepancy between our results and those obtained in earlier studies is likely attributable to our stricter definition of uncertainty shocks, and in particular to the sharp

[14] Gazzani and Vicondoa (2020) show that averaging is the correct filter to compute the monthly IRFs.

[15] The Proxy-SVAR, or external instrument approach, is valid only under the partial invertibility of the shocks of interest. This property implies that the shocks can be expressed as a linear combination of contemporaneous reduced-form residuals. We find instead that the shocks are correlated with future residuals and thus, employing them as internal instruments, we fix this temporal dependence issue that compromises the estimation of the dynamic effects of the shocks. The Granger causality test are reported in Tables E.1 in the Appendix.

separation between first- and second-moment shocks enforced by our identification strategy. First-moment shocks explain between 30% and 40% of the variability of employment and industrial production in our model: given the strong correlation between prices and volatility, identification strategies that do not isolate these shocks could seriously overestimate the role of uncertainty.

However, our estimates also reject the extreme conclusion by BDG that uncertainty plays no role in the business cycle. This divergence is particularly interesting because our exercise follows a similar logic to BDG but relies on different assumptions regarding the relation between prices and implied volatility in the stock market (see Section 9). Our high-frequency identification strategy allows us to relax an assumption that plays a critical role in BDG, namely that uncertainty does not affect the realized volatility of the market in a given day or month. Our findings suggest that this assumption is unduly restrictive and that the recessionary effects of uncertainty shows up clearly as long as the link between prices and volatility is left unrestricted.

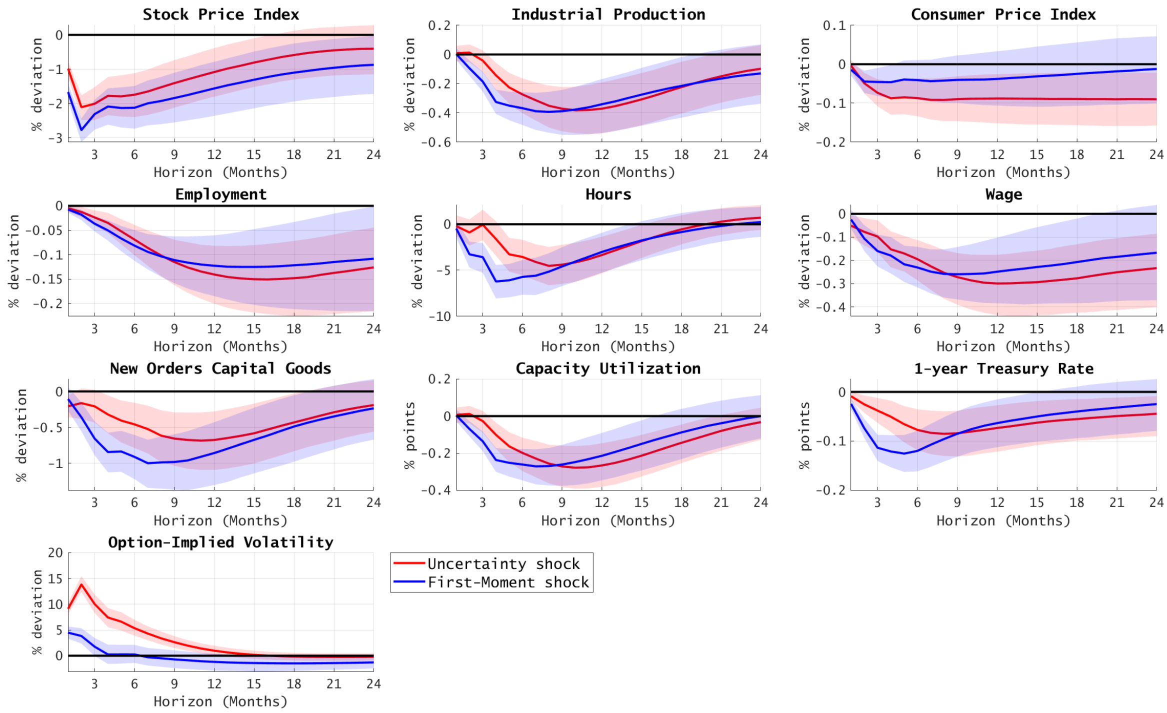

Figure 5: Impulse Responses

IRFs to uncertainty (red) and level (blue) shocks. The VAR is estimated on monthly data and includes 3 lags (AIC). The effects on the variables in the system are computed using the daily shocks, aggregated as monthly averages, in an exogenous block (VARX). Shaded areas correspond to 90% bootstrapped confidence bands from 1000 replications.

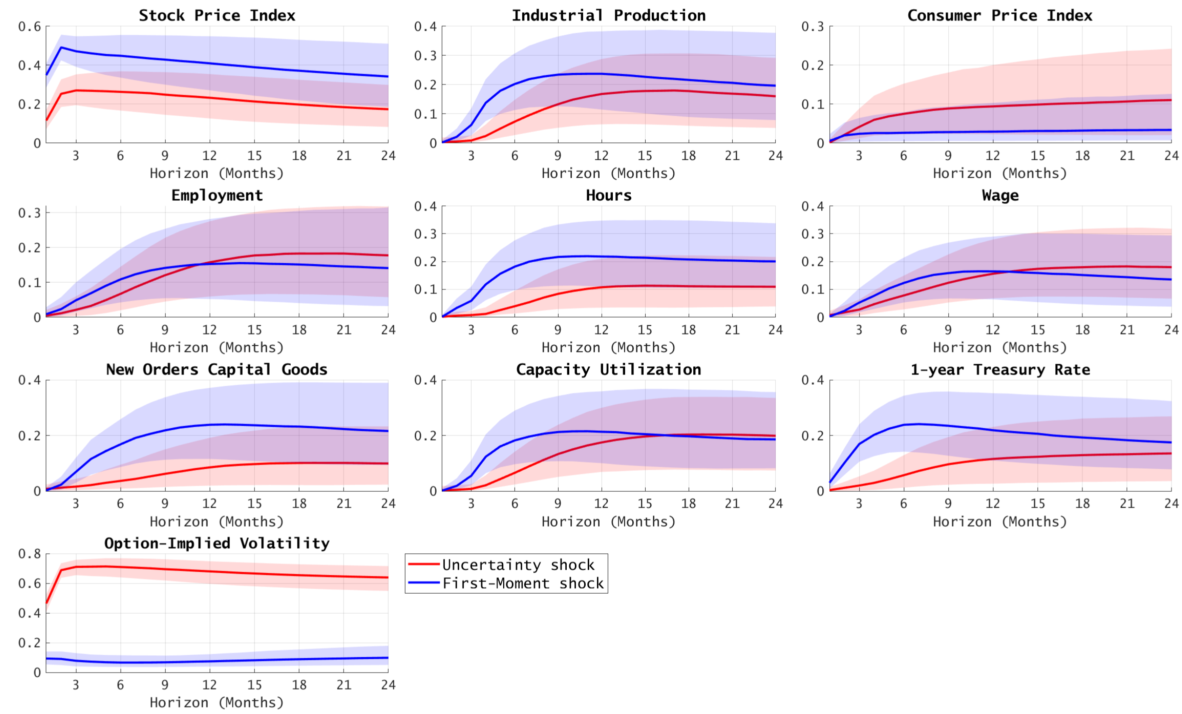

Figure 6: Forecast Error Variance Decomposition

FEV contribution of uncertainty (red) and level (blue) shocks. The VAR is estimated on monthly data and includes 3 lags (AIC). The effects on the variables in the system are computed using the daily shocks, aggregated as monthly averages, in an exogenous block (VARX). Shaded areas correspond to 90% bootstrapped confidence bands from 1000 replications.

6 Ex-post validation of the identification strategy

In this section we validate the procedure from a broader economic perspective. We follow three complementary routes. First, we provide a narrative account of the trading days that were associated with the largest shocks in our sample. Second, we relate the shocks to various alternative estimates available from the literature. Third, we exploit the dataset of Bloom et al. (2016) to study the impact of uncertainty shocks on the sales, investment, and R&D expenditure of a large panel of US firms. All tests support the conclusion that the separation between level and uncertainty shocks obtained through ICA is intuitively plausible and consistent.

6.1 Narrative validation

Do the estimated shocks map into economically plausible changes in uncertainty? Table 3 displays the largest negative first-moment shocks and the largest positive second-moment shocks. In all the cases, the shocks map with important events in the US and worldwide.[16] We explore more in detail these events with three exercises.

The first one is to examine all dates that were characterized by large second-moment shocks

[16]Most of these events are included in the Stock Market Jumps database. https://stockmarketjumps.com/ contains a more detailed description of these events.

Date	ε^n	ε^u	Event
			Largest (negative) first-moment shocks
October 19, 1987	-14.2	16.5	Dow Jones falls 22.6% due to panic-driven trading. The drop exceeds the one in October 28th 1929 (12.8%). Explanations mentioned by analysts: inflation fears, increasing interest rates, and conflict with Iran.
October 26, 1987	-9.9	-0.4	Dow Jones plunges -8.04% in Heavy Trading; Bond Prices Surge, and Dollar Falls Against the Mark. A Japanese official said the day before that japanese government foresaw the yen raising further against the dollar.
December 1, 2008	**-9.5**	-0.3	Declines in financial indicators accelerated after JP Morgan Chase CEO James Dimon said on CNBC that home prices could fall 20% from already depressed levels. Dow Jones fell 196.33 points (2.2%), lead mainly by the manufacturing and financial components.
November 20, 2008	-8.3	-0.7	S&P registered a 52% fall from its peak, returning to 1997 levels. In the search for safer securities, Treasury Bond prices are on their highest levels in more than 35 years. Crude-oil futures are in their lowest levels in 3.5 years (below $50). Part of the problem is attributed to the Treasury Department's recent decision not to buy the troubled mortgaged-backed debt it onced planned to purchase.
September 29, 2008	-8.1	2.0	Bailout plan rejected, forcing new scramble to solve the crisis. The House of Representatives defeated the White House's historic $700 billion financial-rescue package. Concerns that the US faces a strong recession if the legislation isn't revived.
			Largest (positive) second-moment shocks
October 19, 1987	-14.2	16.5	Dow Jones falls 22.6% due to panic-driven trading. The drop exceeds the one in October 28th 1929 (12.8%). Explanations mentioned by analysts: inflation fears, increasing interest rates, and conflict with Iran.
February 5, 2018	2.4	**13.2**	Dow Jones drops more than 1,100 points (largest single-day point decline ever). Investors comment about "borderline panic-type selling".
February 27, 2007	0.5	8.3	Very sudden market drop on a heavy trading day. There was a delay in the mechanism that calculates the averages, exaggerating the drop. Spooked by a selloff of Chinese shares.
September 9, 2016	1.2	7.1	(1) North Korea conducts its fifth nuclear test at the Punggye-ri Nuclear Test Site, at the time its largest ever test at 10 kilotons. (2) Asian Markets Fall After North Korea Nuclear Test (3) Oil prices fell on a stronger dollar and skepticism that a large drop in US inventories last week marks the beginning of a trend. (4) US government bonds weakened, increased speculation that the Federal Reserve could raise interest rates this month.
August 10, 2017	2.0	7.0	(1) Dow Jones falls 205 points as North Korea tensions persist. (2) A gauge of US business prices fell in July for the first time in 11 months, suggesting nagging downward pressure on inflation. Analysts expected the index to rise. (3) Escalating war of words between US and North Korea drove investors into haven investments.

Table 3: Largest adverse first- and second-moment shocks identified through Independent Component Analysis in the daily VAR model.

($e^{vxo} > 5\sigma$) combined with non-negative first-moment shocks ($e^{sp} > 0$), which should capture cases where uncertainty rose, but market expectations remained stable or improved. Of the nine dates isolated by this procedure, five occurred in the period 2016-2019: February 5th, 2018 (strong decline in stock prices due to "borderline panic-type selling"); September 9th, 2016 (skepticism that a large drop in US inventories implies lower growth); August 10th 2017 (escalating war of words between the US and North Korea); May 7th, 2019 (increased likelihood that the US was going to increase tariffs on Chinese goods soon); and August 17th, 2017 (escalating war of words between the US and North Korea).

In the second exercise we extract the dates characterized by an adverse combination of large first- and second-moment shocks ($e^{vxo} > 3\sigma, sp < -3\sigma$). This occurs six times in 40 years: August 8th, 2011 (when Standard & Poor's downgraded the US); September 17th, 2001 (the day when trading resumed after the 9/11 market shutdown); October 27th, 1997 (when the market collapsed because of the Asian crisis); October 13th, 1989 (fear of repeating the 1987 crisis increased); January 8th 1988 (volatile trading week with takeovers of US companies by overseas concerns); and October 19th, 1987 (stock market crash). Since these events arguably represent a genuine combination of adverse first- and second-moment shocks, the results of the identification seem plausible.

In the third and final exercise, we extract all dates between 2007 and 2009 that were characterized by significant first- *and/or* second-moment shocks of either sign ($|e^i| > 3\sigma, i = vxo, sp$). The GFC is obviously punctuated by adverse shocks of both types, with a prevalence of 'bad news'. Interesting differences emerge between the policy interventions that took place during this period. Many of the interventions carried out by the Fed in the early stages of the GFC lowered the VXO index without affecting stock prices.However, the submission of the first draft of the \$700bn bailout plan to Congress on September 18th, 2008 had the opposite effect. There are also policy interventions that reduce both stock prices and volatility: this is the case, for example, of the announcement of the Commercial Paper Funding Facility and the increases in deposit insurance (October 7th, 2008), or the deployment of the Capital Purchase Program (December 18th, 2008) Markets might have learned at once that the crisis was worse than expected and that the authorities were strongly determined to avoid a meltdown of the financial sector. The negative price impact might also be caused by the recourse to public purchases of senior preferred stock (a common ingredient in the cases listed above), which created dilution risk for private stakeholders. Interestingly, the Fed's purchase of MBS from the GSEs (announced on November 26th, 2008 and started on December 30th, 2008), which do not raise dilution concerns, are associated with positive stock price shocks.

VARIABLES	(1) pc^n	(2) pc^n_{BS}	(3) pc^u
ε^e	0.59***	0.70***	-0.44***
	(0.072)	(0.051)	(0.064)
ε^u	-0.22**	-0.32***	0.55***
	(0.095)	(0.062)	(0.072)
Constant	0.10	0.07	0.01
	(0.078)	(0.055)	(0.067)
Observations	78	107	112
R-squared	0.48	0.68	0.51

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regression of standardized principal components from the news shocks literature (pc^n) and the uncertainty shock literature (pc^u) on the news and uncertainty shocks obtained from the daily VAR model (ε^e_t, ε^x_t). pc^n_{BS} is the principal component for news shocks computed employing only the estimates in Barsky and Sims (2011) .

6.2 Relation with Existing News and Uncertainty Shock Estimates

To better illustrate the relationship between our work and the literature, we estimate a set of simple OLS regressions where the principal components of news and uncertainty shocks identified in previous works (pc^n, pc^u, see Section 1) are regressed on our news and uncertainty shocks (ε^e_t, ε^x_t). The results are summarized in Table 4.

Each of the two shocks has a strong positive correlation with the corresponding principal component, confirming that our news and uncertainty shock estimates are qualitatively in line with the existing evidence. Furthermore, the first-moment shock ε^e_t loads negatively on pc^u and the second-moment shock ε^x_t loads negatively on pc^n. Our reading of these results is that the principal components contain both news and uncertainty shocks and that this confusion stems from (some combination of) three factors: (a) an identification strategy that focuses on only one of the two shocks instead of estimating them jointly; (b) a temporal aggregation bias associated to the use of low-frequency data; (c) identification assumptions that do not fully capture the two-way interactions between first and second moments.

6.3 The Effects of Uncertainty on US Firms

Our analysis shows that uncertainty shocks have a significant influence on wages and employment levels. In this section we study their impact on firms using the firm-level dataset of Bloom et al. (2016), available from the authors' websites. This dataset contains quarterly data on sales and investment for 3799 firms in the US and covers the period 1996:Q2-2013:Q1. Bloom et al. (2016) consider firm level information from Compustat, excluding firms that belong to the utilities and financial sectors and firms that declare negative assets, sales, or stockholder's equity. While investment is measured as firms' capital investment rate (capital expenditures per existing unit), R&D is proxied by R&D expenditures. Following Bloom et al. (2016), we measure sales and investment in growth rates, as the change of this variable relative to the previous year divided by the average of the two years. These growth rates approximate the log-change for small groups, are symmetric around zero, and accommodate entry and exit with bounded values of plus and minus two. In order to estimate the effects of uncertainty shocks on firm decisions, we estimate the following equation:

$$x_{i,t} = \alpha_i + B(L)x_{i,t-1} + \gamma_0 \varepsilon_t^u + \gamma(L)\varepsilon_t^u + bt + \epsilon_{i,t} \tag{12}$$

where $x_{i,t}$ denotes the change in the variable of interest (sales, investment, or R&D) and ε_t^u denotes the uncertainty shock identified in the previous sections aggregated to the quarterly frequency. $B(L)$ and $\gamma(L)$ are two polynomial functions in the lag operator L. Table 5 displays the estimated coefficients for the different specifications.[17]

Uncertainty shocks cause a significant decline in investment, sales, and $R\&D$ growth. A one standard deviation uncertainty shock induces on impact a decline in investment of around 1.3 percentage points , a fall in sales of 5 percent, and a decline in $R\&D$ growth of 6 percentage points. The estimated coefficients are robust to including lags of the dependent variable in the specification. The muted response of $R\&D$ expenditures relative to investments and sales is consistent with Bloom et al. (2016), who show that R&D is influenced by long-run uncertainty rather than the short-run uncertainty captured by the VXO index.[18]

[17]This framework does not require GMM because the shocks employed as regressors are exogenous and not serially correlated.

[18]The VXO captures implied volatility over a 30-day horizon. Bloom et al. (2016) employ the spread between the six-month and one-month option implied volatility index as a proxy for long-term uncertainty and find that this variable is the most important driver for $R\&D$.

VARIABLES	(1) Investment	(2) Investment	(3) Sales	(4) Sales	(5) R&D	(6) R&D
Y_{t-1}		0.2676***		0.5794***		-0.6337***
		(0.009)		(0.038)		(0.023)
Y_{t-2}		0.0835***		0.0720		-0.5706***
		(0.006)		(0.052)		(0.026)
Y_{t-3}		0.0240***		0.0475*		-0.5501***
		(0.006)		(0.026)		(0.027)
Y_{t-4}		0.0424***		0.1789***		0.2903***
		(0.011)		(0.050)		(0.025)
ε_t^u	-0.0202***	-0.0130***	-0.1278***	-0.0447***	-0.0132	-0.0566***
	(0.002)	(0.002)	(0.017)	(0.009)	(0.016)	(0.016)
ε_{t-1}^u	-0.0134***	-0.0069***	-0.0925***	-0.0063	0.0055	-0.0262***
	(0.002)	(0.002)	(0.013)	(0.009)	(0.011)	(0.008)
ε_{t-2}^u	-0.0105***	-0.0035**	-0.0712***	0.0266***	0.0196*	0.0103
	(0.001)	(0.002)	(0.012)	(0.010)	(0.010)	(0.008)
ε_{t-3}^u	-0.0091***	-0.0046**	-0.0549***	0.0078	0.0041	0.0114
	(0.002)	(0.002)	(0.015)	(0.010)	(0.013)	(0.013)
ε_{t-4}^u	-0.0061***	-0.0001	-0.0668***	0.0160**	-0.0080	-0.0004
	(0.002)	(0.002)	(0.014)	(0.008)	(0.015)	(0.011)
trend	-0.0007***	-0.0003***	0.0184***	0.0017***	-0.0001	-0.0006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.1054***	0.0611***	4.9031***	0.6738***	0.2425***	0.0866***
	(0.003)	(0.003)	(0.057)	(0.061)	(0.039)	(0.011)
Observations	80,799	78,699	81,785	81,660	57,659	53,998
# of firms	3,625	3,625	3,650	3,650	2,558	2,558
R-squared	0.3434	0.4219	0.9522	0.9838	0.0786	0.8014
Firm FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES

Table 5: Estimated Effects of Uncertainty Shocks on Firms' Decisions
Note. Estimated results using OLS of equation (12). Y_{t-i} denotes the lagged value of the dependent variable of each specification for the period $(t-i)$ and Ushock$_t$ denotes the estimated uncertainty shock aggregated to the quarterly frequency. All the specifications consider clustered standard errors at 3-digit industry level.
$***p<0.01, **p<0.05, *p<0.1$.

7 Sensitivity Analysis

This section describes the robustness exercises performed over our baseline specification of daily and monthly VAR models (the corresponding results are included in Appendix D). First, we obtain nearly identical shocks (0.99 correlation) if we use 1 or 30 lags in the daily VAR (versus 10 in our baseline). Second, we use 12 lags in the monthly VAR obtaining consistent conclusions from our exercise (versus 3 in the baseline). Third, we estimate the effect of uncertainty shocks employing a hybrid VAR (internal instrument) and Proxy-SVAR (external instrument) and obtain similar results to the baseline VARX. Fourth, results are unchanged if we extend the monthly sample back to 1986 by excluding capacity utilization and new capital orders from the monthly

VAR. Overall, our main conclusions are thus robust to several alternative specifications to the baseline model.

8 Conclusions

Uncertainty has recently come to the fore as an important driver of the economy. However, identifying genuine uncertainty shocks is notoriously challenging, and no consensus has emerged yet on the quantitative relevance of these shocks for the business cycle.

We start by showing that this identification problem originates from a systematic overlap between changes in uncertainty and the arrival of news on economic fundamentals. Bad news and uncertainty spikes often come together, and different models can lead to opposite conclusions as to which of these factors played a key role during the recessions experienced by the US in the last three decades. We then offer both a methodological and an empirical contribution to the debate. We propose a new identification strategy that is specifically designed to disentangle second-moment (uncertainty) shocks from level shocks that affect financial markets. By applying Independent Component Analysis (ICA) to the residuals of a daily VAR model, we identify the shocks as fluctuations in the VXO volatility index that are statistically independent of changes in the S&P500 equity price index. ICA imposes restrictions on the higher moments of the distribution of the VAR residuals. This strategy allows us to (i) avoid both timing and sign restrictions, and (ii) recover structural shocks that are unrelated throughout the distribution and not just around the mean. In order to assess the macroeconomic implications of uncertainty shocks, we compute monthly averages of the estimated daily shocks and use them as instruments in a Proxy-SVAR model of the US economy.

Our main result is that uncertainty matters. Uncertainty shocks cause a decline in output and prices that is both economically sizable and statistically significant: the shocks account for about 10% and 20% of the fluctuations in employment and industrial production in our sample. Wages, worked hours and new orders of capital goods all drop following a rise in uncertainty, suggesting that the shocks propagate through both labor and capital markets. We conclude that, although identification issues have often caused its role to be overestimated in previous studies, uncertainty remains a quantitatively important driver of the US business cycle.

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A Additional Results

		Cholesky, sp (vxo) first		ICA	
		ε^e	ε^u	ε^e	ε^u
Monthly data:	sp	1	0 (-0.76)	n.a	n.a
	vxo	-0.76 (0)	1	n.a	n.a
Daily data:	sp	1	0 (-0.73)	1	-0.5
	vxo	-0.73 (0)	1	-0.38	1

Table A.1: Impact matrices across frequency and identification strategy

The matrices show the contemporaneous responses of the S&P500 stock price index (SP) and the VXO volatility index (VXO) to price and volatility shocks $\{\varepsilon^e, \varepsilon^u\}$ in bivariate VAR models that employ alternative data and identification strategies. Top and bottom half of the table are based respectively on monthly and daily observations. The identification schemes are Cholesky with SP ordered first, Cholesky with VXO ordered first, and Independent Component Analysis (ICA). The sample is 1/1/1986–31/12/2019.

Dependence	VAR residuals	Cholesky shocks	ICA shocks
Daily	100	19.83	4.69

Table A.2: Dependence between shocks

Estimated dependence index between the VAR residuals, Cholesky shocks, and ICA shocks at the monthly and daily frequency. The dependence is measured by the mutual information contained in pairs, and it is normalized by the value taken for the daily VAR residuals.

Uncertainty shocks ε^e				Uncertainty shocks ε^u			
Lagged shocks	F	p-value	# obs	Lagged shocks	F	p-value	# obs
1 lags	4.9	0	330	1 lags	330	2.51	0.01
2 lags	1.75	0.07	329	2 lags	329	0.45	0.92
3 lags	0.53	0.87	328	3 lags	328	0.44	0.93
4 lags	0.22	0.99	327	4 lags	327	2.17	0.02
5 lags	0.28	0.99	326	5 lags	326	0.78	0.65
6 lags	0.94	0.49	325	6 lags	325	0.72	0.71
7 lags	0.51	0.88	324	7 lags	324	1.2	0.29
8 lags	1.31	0.22	323	8 lags	323	1.05	0.4
9 lags	0.87	0.56	322	9 lags	322	0.46	0.92
10 lags	0.75	0.68	321	10 lags	321	1.66	0.09
11 lags	2.69	0	320	11 lags	320	0.68	0.74
12 lags	0.82	0.61	319	12 lags	319	0.35	0.97

Table A.3: Granger Causality Test

Regression of the VAR residuals on lagged shocks (Granger causality test). Sample 1992:m2-2019:m11.

VARIABLES	(1) ε^u_τ	(2) ε^x_τ
$\varepsilon^u_{\tau-1}$	-0.10*	
	(0.057)	
L.factor1	0.06*	-0.06*
	(0.036)	(0.037)
L.factor2	-0.04	0.01
	(0.044)	(0.045)
L.factor3	-0.03	0.04
	(0.059)	(0.061)
L.factor4	-0.04	-0.08
	(0.073)	(0.077)
L.factor5	-0.03	-0.13*
	(0.070)	(0.071)
L.factor6	0.08	0.10
	(0.063)	(0.066)
L.factor7	-0.02	-0.01
	(0.059)	(0.064)
$\varepsilon^x_{\tau-1}$		0.02
		(0.064)
Constant	-0.00	0.01
	(0.013)	(0.014)
Observations	331	331
R-squared	0.03	0.03
Adjusted R-squared	0.0110	0.00804
F test	0.172	0.225

Table A.4: Invertibility test

Regression of the monthly shocks on lagged factors from FRED-MD database. Sample: 1986-2019.

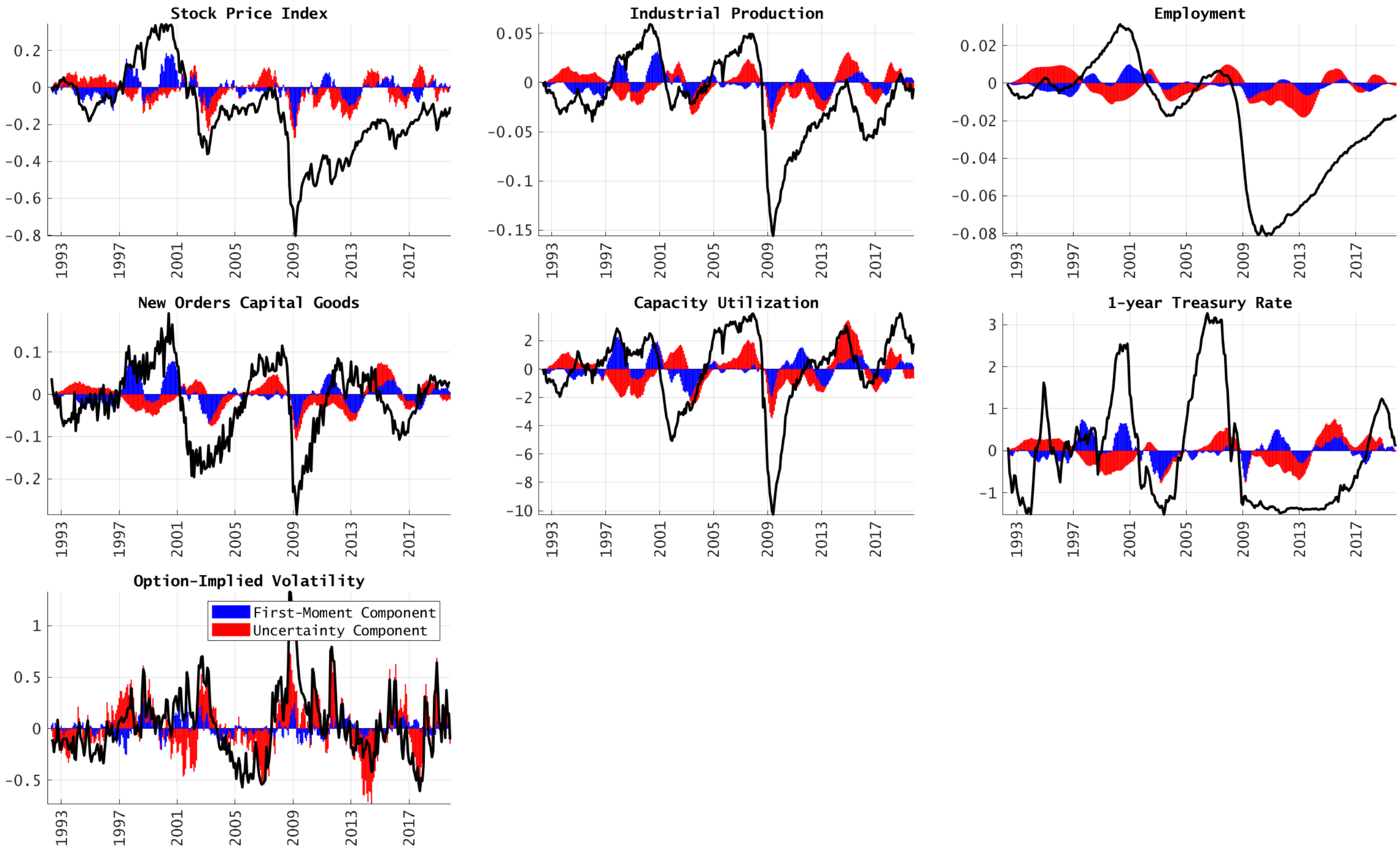

Figure A.1: Historical Decomposition
Historical Decomposition from the baseline VARX.

B Relation with Berger, Dew-Becker and Giglio (2019) (2019)

Berger et al. (2019) (2019, BDG) study uncertainty shocks using an identification strategy that, like the one proposed in this paper, exploits equity prices and implied volatility as proxies of news and uncertainty on the economic outlook. The key difference between the two approaches lies in the identification assumptions: BDG restrict the relationship between realized and implied stock market volatility, while we also place restrictions on higher-order moments (e.g. third- and fourth-moments) of the price and implied volatility series. In this Appendix we illustrate analytically the relationship between the two approaches using a stylized asset pricing model. The analysis shows that our approach is more general. BDG require uncertainty shocks to be symmetrically distributed and/or to have no contemporaneous impact on stock prices: if these assumptions do not hold the BDG restrictions fail, and their failure can cause an underestimation of the role of uncertainty in driving the business cycle. By contrast, our strategy remains valid irrespective of the distribution of these shock because it does not restrict the response of prices and realized volatility to uncertainty shocks.

Assume that the log-stock price sp_t follows a random walk with time-varying volatility σ_t: [1B]

$$
\begin{aligned}
s_t &= s_{t-1} + \sigma_{t-1}\epsilon_t \\
\sigma_t^2 &= \alpha + \rho\sigma_{t-1}^2 + v_t
\end{aligned}
\tag{B.1}
$$

Assume further that the reduced-form innovations capture two distinct structural shocks, which represent respectively news on the fundamentals of the economy (ε_t^e) and uncertainty, i.e. news on future volatility (ε_t^u):

$$
\begin{bmatrix} \epsilon_t \\ v_t \end{bmatrix} = \begin{bmatrix} 1 & \beta \\ \theta & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^e \\ \varepsilon_t^u \end{bmatrix}
\tag{B.2}
$$

Under the assumptions above, the realized volatility of the stock market in period t, defined as in BDG as the squared within-period return, includes the squares and the cross-product of the two structural shocks:

$$
rv_t \equiv (\Delta s_t)^2 = \sigma_{t-1}^2 \left[(\varepsilon_t^e)^2 + \beta^2(\varepsilon_t^u)^2 + 2\beta\varepsilon_t^e\varepsilon_t^u \right]
\tag{B.3}
$$

The S&P500 and VXO indices employed in our empirical analysis represent proxies of s_t and σ_t, while the squared stock return rv_t plays an important role in BDG (see below). Notice

[1B] BDG use this set-up to study the implications of their identification strategy: see in particular equation A.3 and A.4 in the Appendix to the paper. The time interval t can be a day or a month: The frequency of the data is clearly important from an empirical perspective (our identification restrictions require non-gaussian observations, and are thus best suited to daily data), but it is not relevant for the derivations below.

that the diagonal elements of the impact matrix in (B.2) are normalized to unity, whereas the off-diagonal elements are left unrestricted. These coefficients capture two interactions between prices and volatility that are well-known in the finance literature. The first one is the 'volatility feedback' effect, by which a rise in volatility can reduce the investors' discount factor, causing *ceteris paribus* a drop in equity prices (β<0). The second one is the 'leverage effect': an unexpected drop in prices reduces the net worth of the firms, increasing their leverage and thus rendering their equity more volatile going forward (θ<0). Both mechanisms contribute to the strong negative correlation between prices and volatility that is well-documented in the literature. The difference among them, however, is crucial for our purposes. The leverage effect is a confounding factor: it causes endogenous fluctuations of the VXO in response to economic news that should be filtered out by the identification restrictions. The volatility feedback effect, by contrast, is a key link in the transmission mechanism: it captures the first and most obvious implication of an exogenous rise in uncertainty, namely a drop in stock prices.

The system (B.1)-(B.3) can be written as a VAR as follows:

$$\begin{bmatrix} r_t \\ rv_t \\ \sigma_t^2 \end{bmatrix} = C + \Gamma \begin{bmatrix} r_{t-1} \\ rv_{t-1} \\ \sigma_{t-1}^2 \end{bmatrix} + \Sigma_{t-1} \begin{bmatrix} 1 & 0 & \beta \\ 0 & 1 & 0 \\ \theta & \gamma & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^e \\ \varepsilon_t^{rv} \\ \varepsilon_t^u \end{bmatrix} + \sigma_{t-1}^2 \begin{bmatrix} 0 \\ u_t \\ 0 \end{bmatrix} \tag{B.4}$$

where $\varepsilon_t^{rv} \equiv \left(\varepsilon_t^e\right)^2$, $u_t \equiv \beta^2(\varepsilon_t^u)^2 + 2\beta\varepsilon_t^e\varepsilon_t^u$, and C, Γ, Σ_{t-1} are known matrices of fixed or predetermined parameters. In this formulation the innovation to rv_t is split into two components: a realized volatility shock given by the squared price level news (ε_t^{rv}), and an additional term that depends on both level and volatility news (u_t). Equation (B.4) also shows that the vxo can in principle respond to both price and squared price shocks, which implies that both must be expunged from the data in order to identify the actual uncertainty shock ε_t^u. The question is thus which identification scheme is most effective in achieving this objective.[2B]

B.1 Restricting the impact matrix

BDG assume that rv_t does not respond on impact to ε_t^e . Equation (B.4) shows that the impact matrix is lower-triangular for ε_t^{rv} and ε_t^u, which is consistent with this assumption. However, it also shows that another condition is necessary for the assumption to hold: u_t must be orthogonal to ε_t^u . This condition can be written as follows:

[2B] Note that ε_t^e and ε_t^{rv} may or may not be orthogonal. If ε_t^e has a symmetric distribution they are, and the system in equation (B.4) includes three genuine fundamental shocks. If not, it is a "tall" system that includes more observables than shocks. We find that adding rv_t to our baseline specification does not affect the result; BDG also show that adding s_t to a model that includes rv makes little difference. Both results are consistent with the presence of price jumps causing a strong correlation between ε_t^e and ε_t^{rv}.

$$E(u_t\varepsilon_t^u) = \beta^2 E(\varepsilon_t^u)^3 + 2\beta\mathbb{E}\left[\varepsilon_t^e\left(\varepsilon_t^u\right)^2\right] = \beta^2\mathbb{E}\left(\varepsilon_t^u\right)^3 = 0 \tag{B.5}$$

(the second term in the summation is zero under the maintained assumption that the structural shocks are statistically independent). Equation (B.5) clarifies that orthogonality holds as long as (i) there is no volatility feedback effect ($\beta = 0$) and/or ε_t^u is symmetrically distributed $\left(\mathbb{E}\left(\varepsilon_t^u\right)^3 = 0\right)$. Neither condition is trivial. The asset pricing literature provides ample evidence of strong volatility feedback effects, particularly for the S&P500 index (Carr and Wu, 2017). The distribution of ε_t^u is unobservable and its symmetry cannot be taken for granted. Asset pricing models typically include discrete "volatility jumps" to account for the non-gaussian features of the data. Intuitively, large spikes in uncertainty could be generated by wars and financial or political crises; the geopolitical risk shocks of Iacoviello and Caldara (2018), for instance, have a skewness coefficient of 2.3.[3B]

The example also clarifies the implications of a failure of the BDG assumptions. If equation (B.5) does not hold, ε_t^u has a contemporaneous impact on rv_t that is wrongly neglected by the identification strategy. The BDG model interprets the correlation between realized volatility and vxo residuals exclusively as an endogenous response of vxo to $(\varepsilon_t^e)^2$, ignoring the causal mechanism that operates in the opposite direction and distorting the estimation of ε_t^u. The direction of the bias depends on the skewness of the shock: if $\mathbb{E}\left[\left(\varepsilon_t^u\right)^3\right] > 0$ the correlation is positive and uncertainty shocks are unduly downplayed by the identification restrictions.

B.2 Restricting the correlation and co-skewness of ε_t^e and ε_t^u

By placing restrictions directly on the higher moments of ε_t^e and ε_t^u we can achieve identification without relying on the BDG assumption or restricting the impact matrix in any way. When applied to a bivariate VAR in (s_t, σ_t), the moment restrictions impose three conditions on the underlying structural shocks: $\mathbb{E}\left[\varepsilon_t^e\varepsilon_t^u\right] = 0$, $\mathbb{E}\left[\left(\varepsilon_t^e\right)^2\varepsilon_t^u\right] = 0$, $\mathbb{E}\left[\varepsilon_t^e\left(\varepsilon_t^u\right)^2\right] = 0$. These conditions guarantee that ε_t^u is orthogonal not just to the price level shock ε_t^e but also to the realized volatility shock $(\varepsilon_t^e)^2$. This separation is achieved without taking a stance on the distribution of the shocks or the impact matrix, where β and γ are left unrestricted. The third restriction lacks a theoretical justification, but it is innocuous: if the shocks are truly structural they should be statistically independent, so imposing $\mathbb{E}\left[\varepsilon_t^e\left(\varepsilon_t^u\right)^2\right] = 0$ can do not harm. In principle, one could also use the realized volatility series and apply the moment restrictions to a bivariate VAR in (rv_t, σ_t) or to a trivariate VAR in (s_t, rv_t, σ_t). In practice, though, this is not a good idea. If s_t is replaced by rv_t the moment restrictions are imposed on

[3B]We estimate the shock using a VAR that includes Gilchrist and Zakrajsek (2012) bond spread, unemployment rate, CPI and 1-year and 10-Y Tbill rates along with the along with the GPR index. The GPR is ordered first, as in Iacoviello & Caldara (2018).

$\left\{\left(\varepsilon_t^e\right)^2, \left(\varepsilon_t^e\right)^4, \varepsilon_t^u, \left(\varepsilon_t^u\right)^2\right\}$, while the relation between ε_t^e and ε_t^u is left unrestricted. This relation is strong and negative in the data, whereas fourth-moment effects are unlikely to be important, so the change weakens identification. If rv_t is added to s_t the system is subject to 6 additional moment restrictions, but most of them (i.e. those where $\left(\varepsilon_t^e\right)^2$ is replaced by ε_t^{rv}) are redundant. Robustness checks confirm that adding realized volatility to the daily and monthly VARs has no impact on the estimation of the shocks and the impulse-response functions.

C Independent Component Analysis

C.1 Setup and Estimation

Let $\boldsymbol{\varepsilon} = \left\{\varepsilon^1, ..., \varepsilon^n\right\}$ be n independent and identically distributed random variables, defined over the supports $\{S_1, ..., S_n\}$, respectively. Assume that at most one of the shocks is normally distributed and that we observe over time only a linear combination of them:

$$u_t = B\boldsymbol{\varepsilon_t} \tag{C.1}$$

In a VAR framework, $\boldsymbol{\varepsilon_t}$ are the stochastic innovations that drive the system, $\boldsymbol{u}_t$ are the reduced form residuals, and the impact matrix B is unknown. Due to the assumed independence and non-gaussianity, higher moments of the distribution of the data can be used to identify B, rather than resorting to timing assumptions or restrictions derived by the economic theory. Independence means that the product of the marginal distributions is equal to the joint distribution of $\boldsymbol{\varepsilon}$ as shown in eq.(C.2); in other words, no mutual information is contained in $\boldsymbol{\varepsilon}$ and no additional information on $f\left(\varepsilon^i\right)$ can be drawn by observing $f\left(\boldsymbol{\varepsilon}\right)$.

$$\int_{S_1} \cdots \int_{S_n} f\left(\boldsymbol{\varepsilon}\right) = \int_{S_1} f\left(\varepsilon^1\right) d \cdots \int_{S_n} f\left(\varepsilon^1\right) \tag{C.2}$$

The deviations of the product of marginals distribution from the joint one can be expressed by the Kullback–Leibler divergence (*KLIC*)

$$KLIC = \int_{S_1} \cdots \int_{S_n} f\left(\boldsymbol{\varepsilon}\right) log \frac{f\left(\boldsymbol{\varepsilon}\right)}{f\left(\varepsilon^1\right) \cdots f\left(\varepsilon^n\right)} d\varepsilon^1 \cdots d\varepsilon^n$$

While the final objective would be the minimization of such divergence, the direct computation of *KLIC* is not straightforward as it requires to approximate a n dimensional joint distribution. On the other hand, the Central Limit Theorem tells us that u, being a linear combination of the original $\boldsymbol{\varepsilon}$, are "more gaussian" than the original $\boldsymbol{\varepsilon}$. Exploiting entropy theory (which goes beyond this discussion), ICA maximizes the non-gaussianity of the components (negentropy), thus recovering the underlying structural innovations. Our implementation of

ICA relies on the *FastICA* and Icasso packages developed in Hyvarinen (1999) and Himberg et al. (2004), but the GMM estimation proposed in Keweloh (2020) yields very similar results.

The *FastICA* algorithm consists of the following steps:

1. An orthogonalization is applied to the reduced form residual to impose no correlation (principal components analysis). The principal components are rotated so to solve the following optimization problem

$$\max_{B} J(B)$$

$$J(B) \approx \{\mathbb{E}\left[G(B\varepsilon)\right] - \mathbb{E}\left[G(v)\right]\}^2$$

$$s.t. \mathbb{E}\left[B\varepsilon\right] = 1$$

   where B is the impact matrix of the shocks (demixing matrix in the ICA jargon), and $G(x)$ is the contrast function that we select as $a_1^{-1} logcosh\left(a_1 x\right)$ with a_1 a fine tuning parameter, whose derivative is given by $g_1(u) = tanh(a_1 u)$, $J(.)$ measures the deviation from gaussianity ($G\left(v\right)$ is the contrast function under the normal distribution of all the components). The optimization problem is solved via a fixed-point procedure based on adaptive neural algorithms

2. *Icasso* was developed to enhance the robustness of FastICA, which is known to be sensitive to initial conditions while taking into account the statistical uncertainty of the estimated components. It consists of:

   (a) running*FastICA* H times, changing the initial conditions and bootstrapping the data;

   (b) clustering the resulting $H * n$ estimated components according to their mutual similarities. Icasso uses the absolute value of the linear correlation coefficient between the independent components as a measure of similarity and applies the agglomerative hierarchical clustering with average-linkage selection.

   (c) The final estimates of the independent components, i.e. the shocks, are the centrotype of the cluster: they have the minimum sum of distances to other points in the cluster

C.2 Diagnostics

An essential diagnostic of the stability and statistical difference among the components is displayed in Figure C.1. Of particular relevance is the marked separation between the VXO and the SP500 components, which corroborates the validity of our identification assumptions.

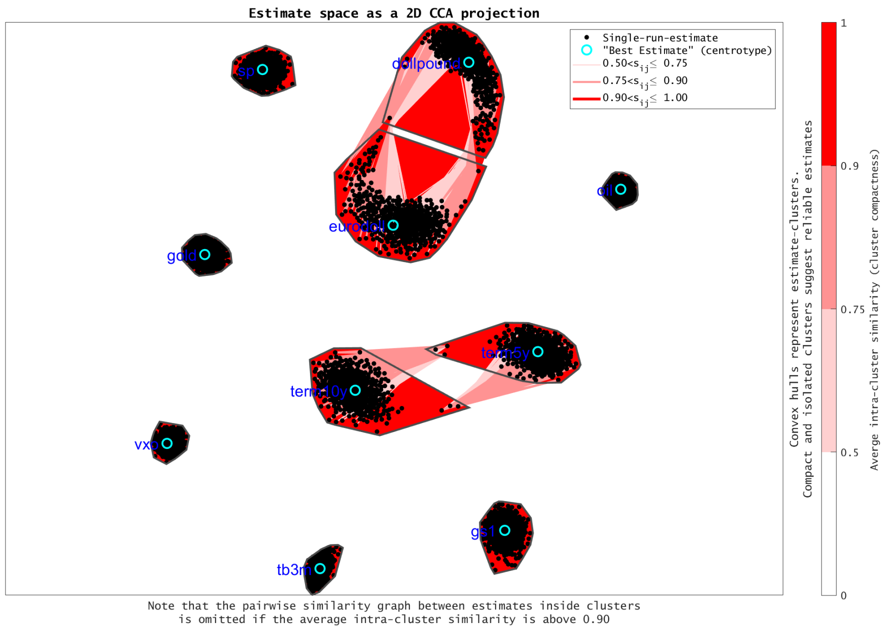

Figure C.1: Similarity graph of the estimated components.
Similarity is evaluated by means of clustering, displayed by the grey sets. The robustness and stastical reliability of the estimates are increasing with the compactness of the clusters, displayed by the red intensity. VXO and SP500 are extremely robust.

D Sensitivity Analysis

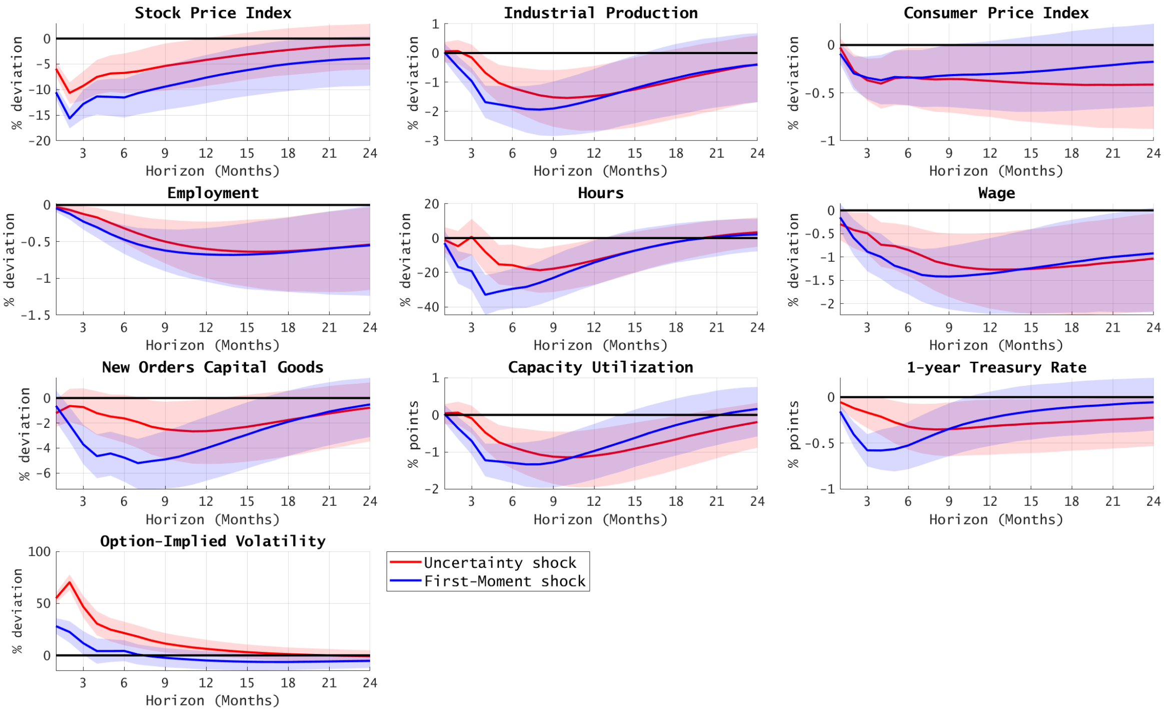

Figure D.1: Impulse Responses - Hybrid VAR (internal instruments identification)

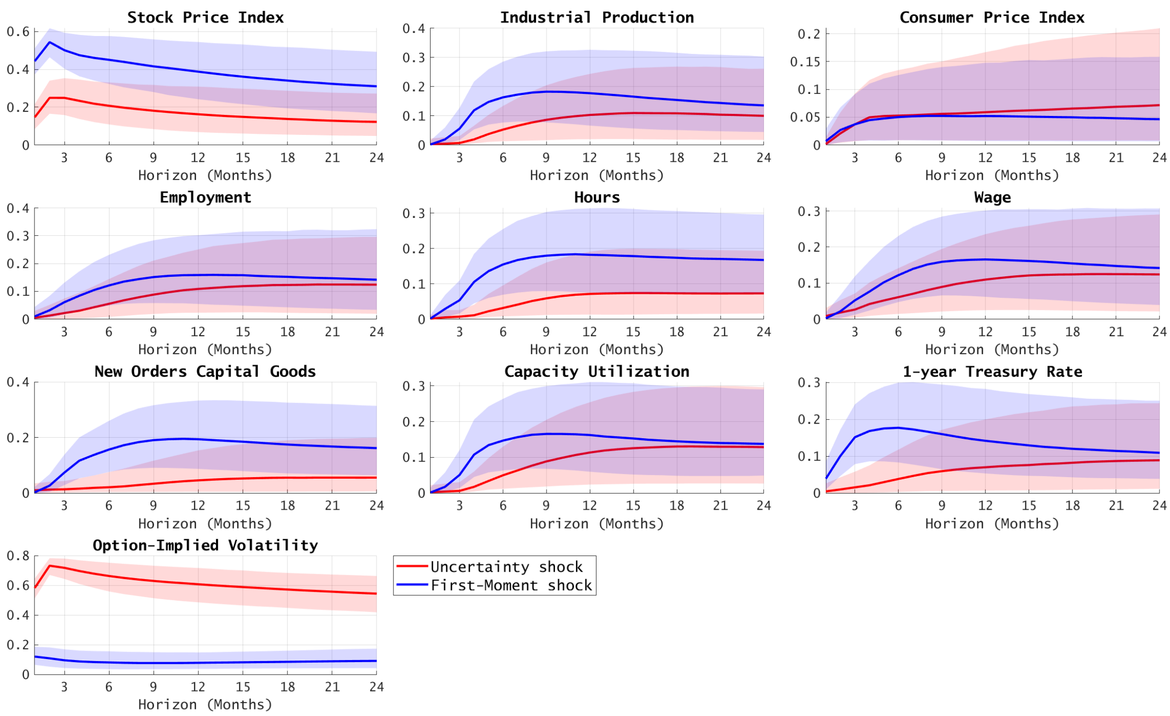

Figure D.2: Forecast Error Variance Decomposition - Hybrid VAR (internal instruments identification)

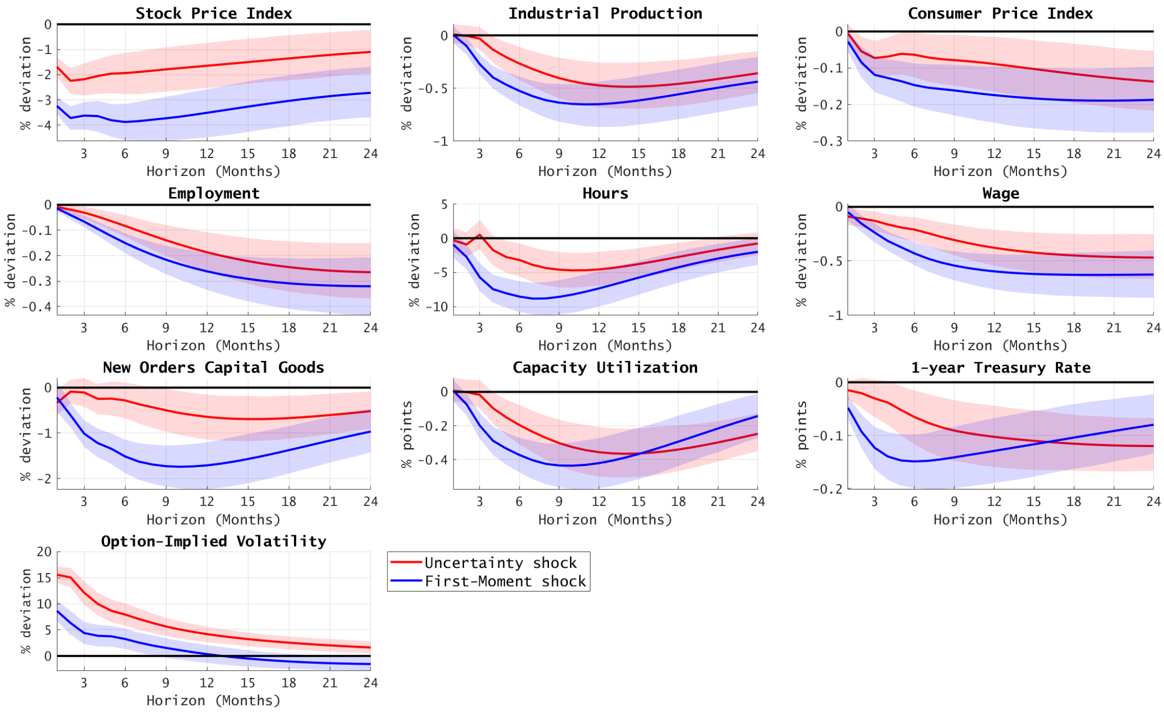

Figure D.3: Impulse Responses - Proxy SVAR

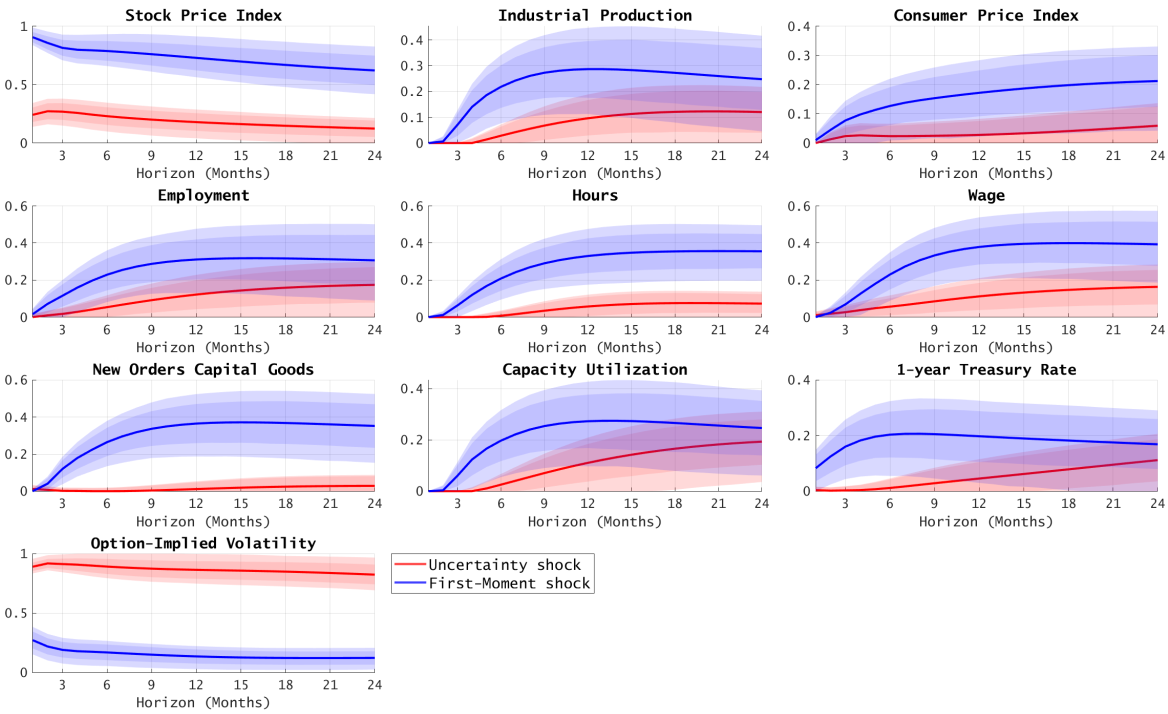

Figure D.4: Forecast Error Variance Decomposition - Proxy SVAR

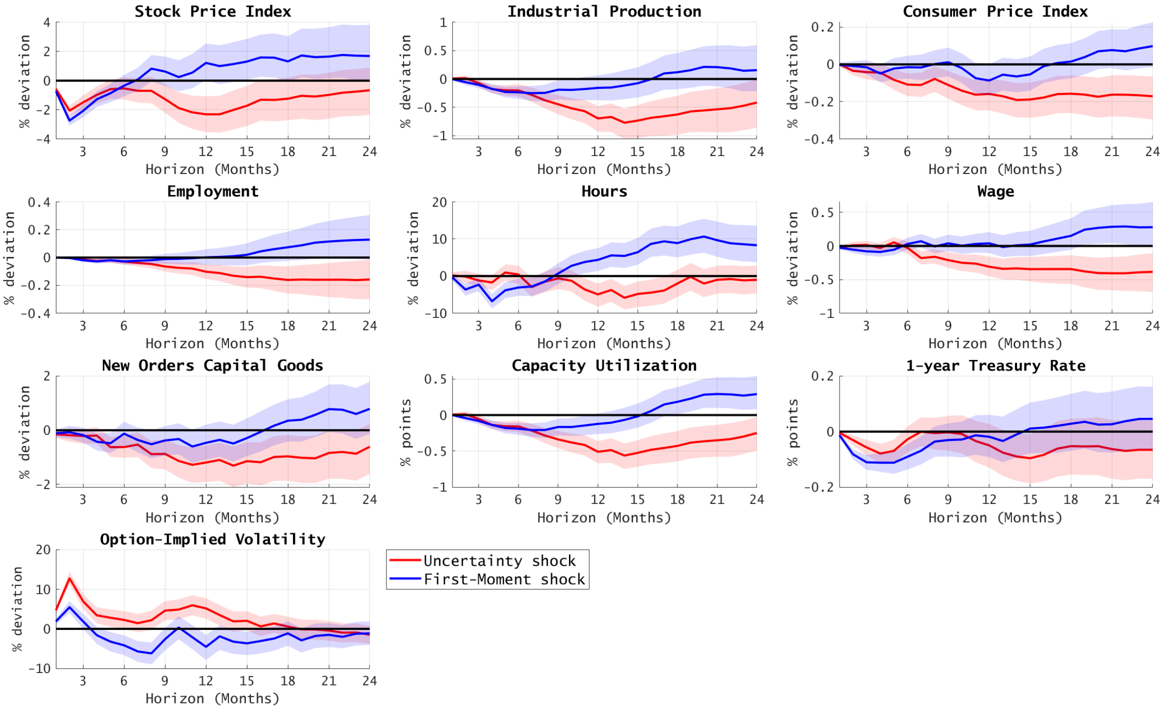

Figure D.5: Impulse Responses - VARX with 12 lags

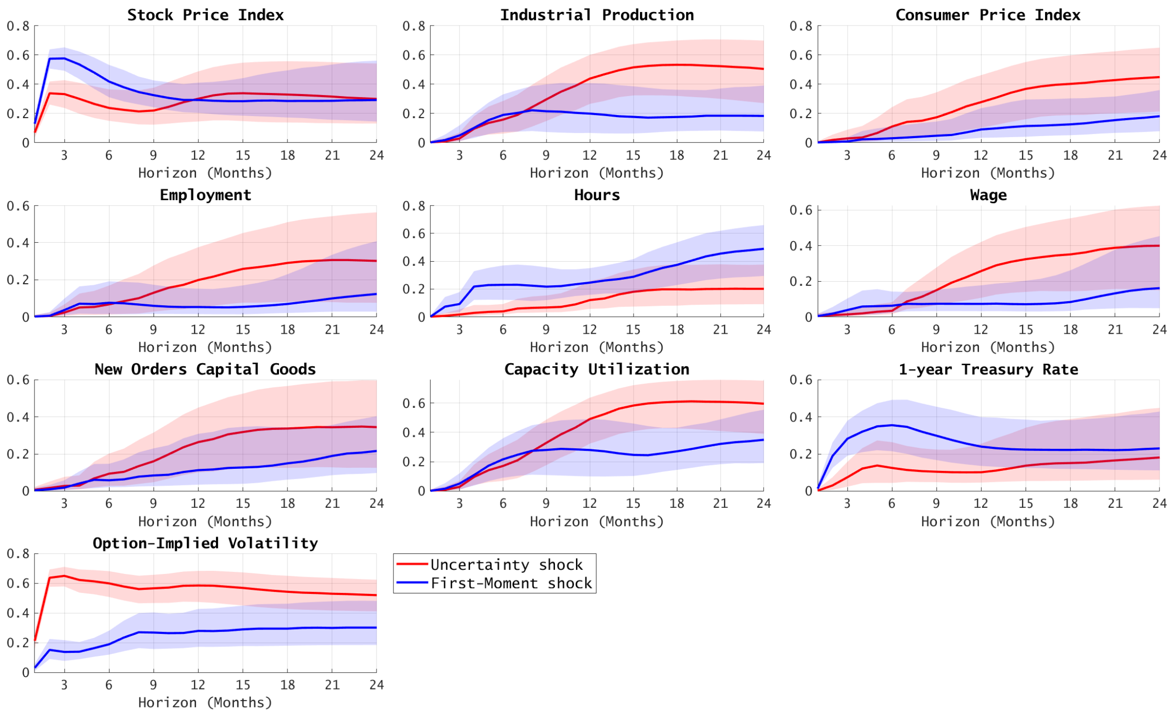

Figure D.6: Forecast Error Variance Decomposition - VARX 12 lags

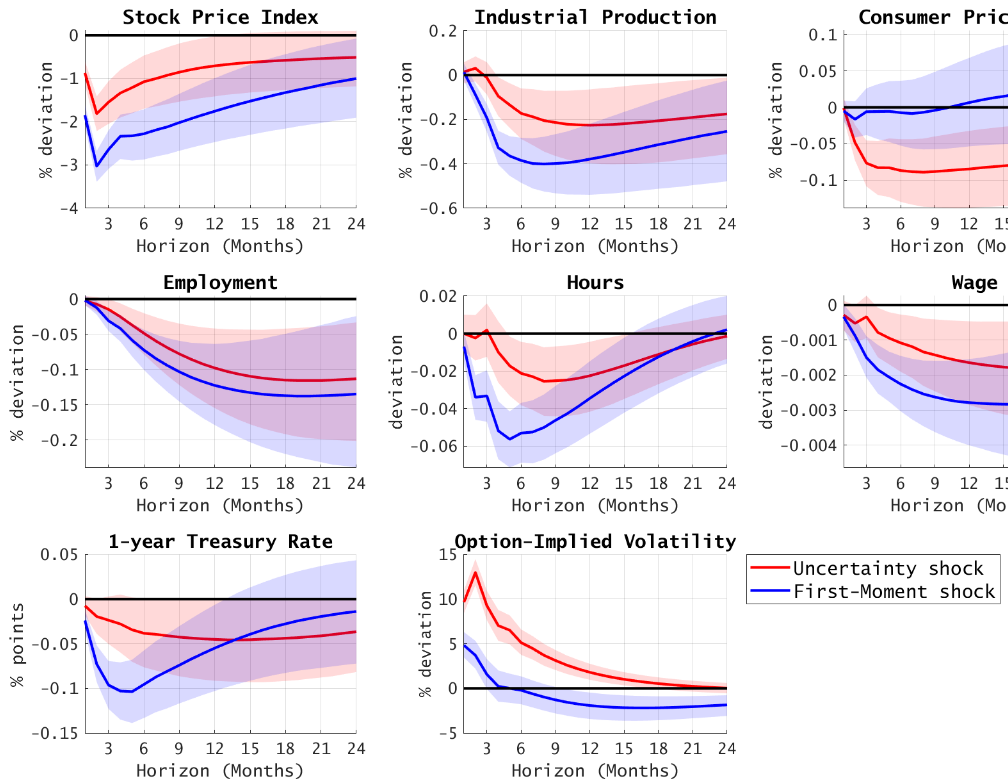

Figure D.7: Impulse Responses - VARX smaller Specification

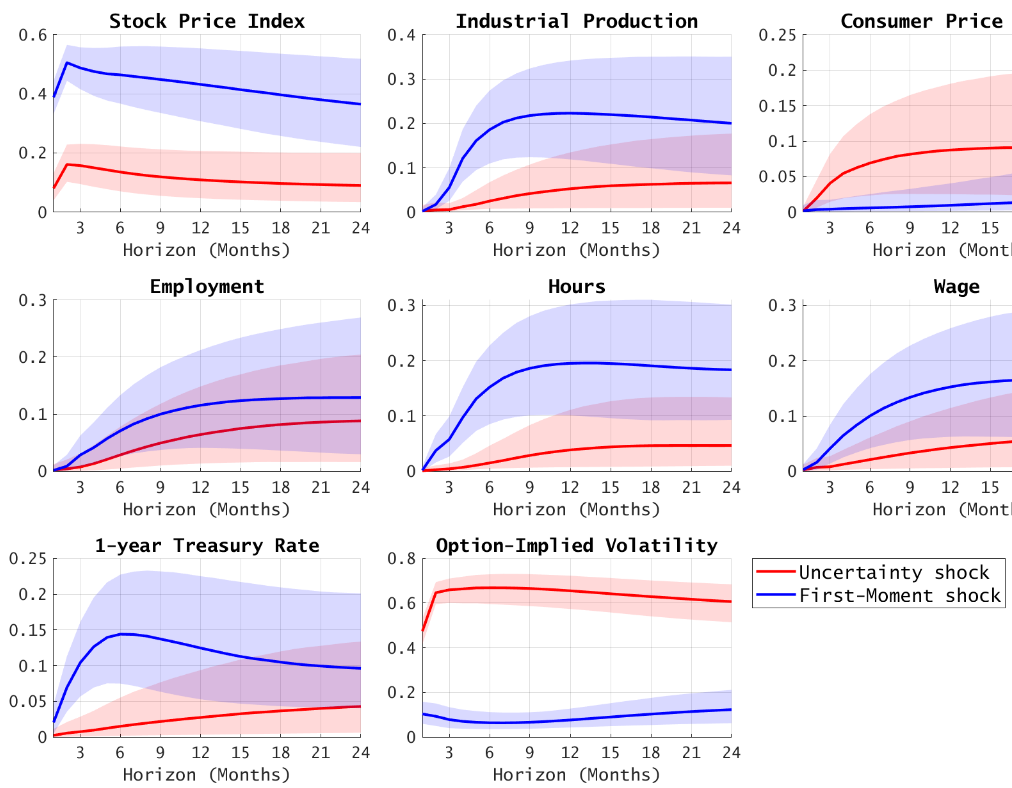

Figure D.8: Forecast Error Variance Decomposition - VARX smaller specification

E Bivariate VAR Evidence

Figure E.1 displays the shocks estimated by applying two alternative orderings (sp - vxo and vxo - sp) to the two samples (monthly and daily). We focus on the Global Financial Crisis only (GFC) for brevity. In the monthly model, the interpretation of the shocks ('news' versus 'uncertainty') is almost entirely determined by the ordering. Using daily data mitigates the problem, but does not solve it: the differences across orderings are still striking, for instance, around October 2008 and in the Spring of 2009. The impact matrices estimated in each of the four cases are reported in the left column of Table A.1. The negative response of VXO (SP) to shocks that hit SP (VXO) confirms the interlinkage between first- and second-moment perturbations. However, the fact that the responses are entirely dependent on the ordering of the variables, which is arbitrary, prevents any conclusion on how the transmission works.

We compare the results from ICA when applied at daily versus monthly data. With monthly data, the estimated response of vxo to sp innovations is very close to zero, as in the recursive identification where VXO is ordered first (left column - Table A.1). However, the diagnostics show that the observations are 'too Gaussian' for ICA to deliver a reliable solution (the stability index is 0.68, see Appendix B). With daily data, this limitation is removed (the stability index reaches 0.97, close to the theoretical maximum of 1) and the estimates differ significantly from those obtained with the recursive schemes: VXO responds to a positive 1% SP shock (i.e. a positive update on the fundamentals) with a -0.38% drop, while SP responds to a 1% VXO shock (i.e. a rise in uncertainty) with a -0.5% drop.

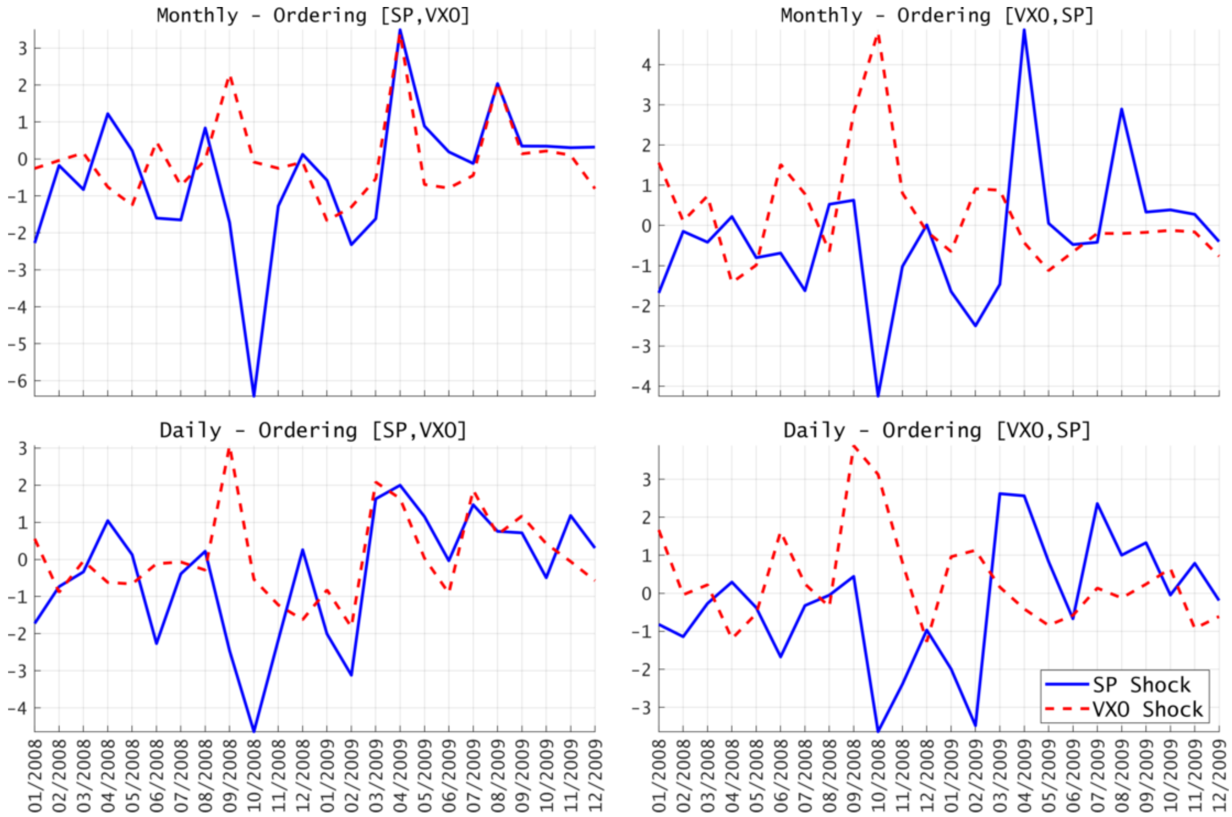

Figure E.1: Alternative estimates of first- and second-moment shocks during the Global Financial Crisis. *The top row shows estimates obtained from monthly data and Cholesky decomposition where either the stock price (left column) or the VOX index (right column) are ordered first. The bottom row replicates the analysis using daily data.*

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