Dynamic Effects of News Shocks under Uncertainty

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Abstract

This paper bridges two strands of the literature of business cycles driven by agents’ beliefs: news shocks and uncertainty. I propose an estimation and identification procedure that allows investigating the empirical relationship between agents’ responses to future technological improvements and the level of uncertainty in the economy. I show that the economic responses to news shocks change substantially over time, and uncertainty endogenously reacts to it. Macroeconomic uncertainty reduces after a news shock, in response to the increase in the information about the expected future path of the economy. Financial uncertainty initially increases after a news shock, in line with the idea of ‘good uncertainty’. The financial uncertainty rapidly resolves, as the market converges to a consensus about the interpretation of the news. Periods of high financial uncertainty are characterized by higher positive economic effects of news shocks on output, consumption and investment. These results indicate that the continuous updating of agents’ expectations about the current and future economic situation operates as a transmission channel for news shocks.

Keywords: forecasting error variance, stochastic volatility, structural VAR, news shock, uncertainty.

JEL codes: E32, E44.

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1 Introduction

How do economic agents react to new information about future technological improvements? Although much has been done to answer this question, the results are not conclusive. Conventional wisdom is that the expectation of technological progress produces positive economic outcomes, but the empirical research still disagrees on the size and direction of this effect. In this paper, I show that a plausible reason for these differences is that agents react differently over time to news about technology. More importantly, these changes are intrinsically related to the degree of uncertainty about the economy.

'News shocks' – changes in the future total factor productivity (TFP) that are foreseen by the economic agents (Beaudry and Portier, 2006) – characterize one strand of the literature of business cycles driven by agents’ beliefs. The idea is that technological innovations take time to have an impact in the economy. Part of this technological impact is foreseen by the economic agents, who react to it in the present. A new oil discovery is an example of a news shock.

Another strand studies the effect of uncertainty on the economy. Agents form beliefs about the current and future path of the economy, and take consumption and investment decisions based on this (conjectured) path. Unexpected changes on these beliefs make the agents to react accordingly, causing aggregate short-term effects. Uncertainty measures aim at capturing these aggregate changes, and are usually proxied as the volatility of economic variables. The current debate on this literature lies on separating different sources of uncertainty from financial or macroeconomic nature, and if these changes arise exogenously or are endogenous responses to other economic movements.

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Although it will take years to be effectively explored, the expectation of future higher oil production induces the companies to invest now. Arezki, Ramey, and Sheng (2017) explore the news shock properties related to oil discoveries.

Bloom (2009) defines uncertainty as an increase in the volatility of total factor productivity shocks that have a temporary negative effect on output growth.

See, for example, Muntaz and Zanetti (2013), Alessandri and Muntaz (2014), Jurado, Ludvigson, and Ng (2015), Ludvigson, Ma, and Ng (2016), Carriero, Clark, and Marcellino (2018a), Shin and Zhong (2018), Carriero, Clark, and Marcellino (2018b) and Caldara, Scotti, and Zhong (2019).
This paper connects these two strands. If agents receive news about future technological improvements, as a news shock, it is plausible that they will also update their beliefs about the current and future path of the economy. In other words, the level of uncertainty should endogenously respond to exogenous news shocks. While a few recent empirical papers deal with the potential connection between news and uncertainty,\(^5\) this is the first that allow for endogenous responses of uncertainty to news.

I propose an estimation and identification procedure to investigate whether agents change the way they respond to news about future productivity over time, and if this behavior depends on economic uncertainty. Investigating for heterogeneous responses over time means that the news shock identification should allow for nonlinear and time-varying models. Investigating for the interaction between uncertainty and news shocks means that such a model should be flexible enough to capture systemic changes in the economic responses to a news shock based on the level of uncertainty. I employ a stochastic volatility model that treats macroeconomic and financial uncertainties as latent variables, estimated within the model, and allowed to feedback to and from the endogenous variables.

The baseline model builds upon Carriero et al. (2018a), as a nonlinear stochastic volatility Bayesian vector autoregressive (VAR) model for large datasets. With this structure, it is possible to identify first moment shocks, as news shocks, allowing for unrestricted interrelationship between the first and second moments of the data. The estimated volatilities are divided into two components: an idiosyncratic and a common component. The common component is either a latent factor across all macroeconomic variables included in the VAR, or across all financial variables. These common factors are the proxies for macroeconomic and financial uncertainties. The common volatility factors are included in the VAR, contemporaneously affecting the conditional mean of the variables. Finally, the common volatility factors also depend on the lagged variables, creating a complete nonlinear feedback effect between first and second moments of the variables.

I also propose an identification method for news shocks that extends the current

standard procedure for nonlinear and time-varying cases. The identification method is a generalization of the Barsky and Sims (2011) procedure of maximizing the variance decomposition of utilization-adjusted TFP over a predefined forecast period. Instead of assuming a constant variance, the identification procedure proposed here explicitly accounts for potential changes of the total forecast error variance at each point in time. Moreover, I modify the identification strategy such that it takes into account the nonlinear relationship between variables and their volatilities (volatility in mean) through the construction of generalized impulse response functions.

The identification of news shocks period by period allows for a better understanding of the reasons behind the distinct empirical results presented by this literature. On an aggregate level, technological news shocks generate long-term co-movement among GDP, consumption and investment, and it is deflationary in the medium-term. However, there is still an ongoing discussion, both theoretical and empirical, about (i) the extent to which this shock explains business cycles, (ii) how quickly one would observe an effect on productivity, and (iii) the effect on other important macroeconomic variables. For example, there is contradictory empirical evidence about the effect of a news shock on hours worked. While Beaudry and Portier (2006) show that a news shock generates a positive and significant effect on hours (consistent with the results from Christiano, Eichenbaum, and Vigfusson, 2003), Barsky and Sims (2011) present a negative effect of news on hours (in line with the technological shock from Galí, 1999).

In fact, both results can be empirically observed just by changing the time-span of the estimation. Figure 1 presents the deciles of the impulse responses after a news shock identified over different periods in time, with a 20-year rolling window from 1975Q1 to 2012Q3. On average, the effect of a news shock on hours worked is positive in the medium-term, and negative in the long-term. However, depending on the identification period considered, the effect on hours can be positive in the medium-term and converging

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6 As demonstrated by Beaudry and Portier (2006), Barsky and Sims (2011) and Beaudry and Portier (2014).

7 The estimation is conducted as a large Bayesian VAR in levels, with four lags, with the variables described in tables C.1 and C.2 and prior selection following procedure proposed by Gianonne, Lenza, and Primiceri (2015).
to zero, or close to zero in the medium-term and negative in the long-term.

Figure 1 Percentiles of responses to news shocks over different time periods

Note: Impulse responses of a news shock computed over a rolling window of 20 years, with quarterly data ranging from 1975Q1 to 2012Q3. The first window is from 1975Q1 to 1994Q4, while the last one is from 1992Q4 to 2012Q3. Each line corresponds to the deciles of the impulse responses calculated at the posterior mean from the 72 rolling window estimations, while the red line is the median. The shock is normalized to a 1% increase in utilization-adjusted TFP after 20 quarters. The identification follows the Barsky and Sims (2011) methodology, in a large Bayesian VAR consisting of the variables described in tables C.1 and C.2.

While the effect on hours worked changes both quantitatively and qualitatively, there are still differences in the size of the responses of real macroeconomic variables. Figure 1 shows that, on average, a news shock leads to a long-term positive effect on consumption, GDP and investment. However, depending on the time-span considered, this effect may be substantially stronger or converge to zero, with no long-term effects. More broadly, these discrepancies show that the agents react to information about future technological improvements in different ways over time, and raises the question of whether such behavior is random or systemic. The time-varying estimation and identification procedure proposed here allow for a better understanding of this dynamics.
I bring two contributions to the empirical literature on measuring the economic effects of news shocks. First, I evaluate whether the impact of a news shock changes over time and whether the theoretical assumption of positive co-movement holds in different periods. The evidence provided here of heterogeneous responses over time indicates that news shock identifications based on processes with time invariant covariances may not be appropriate.

Second, I show that news shocks interact with uncertainty. The results indicate that there is a close link between the arrival of information about future productivity and how this information is absorbed by the agents. The economic effects led by technology news depend on how agents update their expectations about macroeconomic and financial conditions. After a news shock, macroeconomic uncertainty falls, as news bring more information about the expected future path of the economy. Financial uncertainty initially rises, in line with the idea of a ‘good uncertainty’ effect. This increase in financial uncertainty rapidly resolves, as the market converges to a consensus about the interpretation of the news.

This paper is aligned with literature about the relationship between news shocks and financial markets. Beaudry and Portier (2006) and Barsky and Sims (2011), for example, show how the stock market reacts to news shocks. Kurmann and Otrok (2013), Cascaldi-Garcia (2017) and Kurmann and Sims (2017) debate the effect of a news shock on short and long-term interest rates. Görtz, Tsoukalas, and Zanetti (2016) present the role of news shocks in light of propagation through frictions in financial intermediation. This paper also relates to an extensive literature on stochastic volatility VAR models. Mumtaz and Zanetti (2013), for example, allow for a lagged feedback of the volatilities to the mean. Alessandri and Mumtaz (2014), Shin and Zhong (2018) and Carriero, Clark, and Marcellino (2016a) propose models with a contemporaneous feedback of a common volatility factor to the mean.

The outline of the paper is as follows. I present the underlying model that allows for

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9Cascaldi-Garcia and Galvao (2018) show that high uncertainty increases the likelihood of news shocks, creating a ‘good uncertainty’ effect.
stochastic volatility in mean, the estimation procedure and the estimated latent macro and financial uncertainty measures in Section 2. Section 3 introduces an identification procedure for the news shock that takes into account nonlinear and time-varying models. Section 4 summarizes the results for a news shock and its relations with uncertainty measures. Section 5 concludes this paper.

2 A stochastic volatility in mean model

The empirical model aims at allowing a full interaction between uncertainty and macroeconomic variables so that orthogonal shifters of first and second moments can be identified. The proposed model setup is a large heteroskedastic VAR built upon Carriero et al. (2018a), in which the individual volatilities are a combination of a common uncertainty factor and an idiosyncratic volatility component. I modify its baseline framework to handle variables in levels. The choice of two common factors follows the recent literature on unobserved uncertainty components as a way of separating macroeconomic and financial sources of uncertainty (Jurado et al., 2015 and Carriero et al., 2018a).

The non-observed macroeconomic and financial factors (proxies for macro and financial uncertainties) are included in the conditional mean of the VAR, which allows for a contemporaneous effect on the variables. In addition, the factors are dependent on the lagged variables, permitting a nonlinear feedback of the variables on their volatilities.

2.1 Model description

The model is estimated as a structural nonlinear VAR, with $y_t$ representing a $(n \times 1)$ vector that stacks the $n_m$ macroeconomic endogenous variables $y_{m,t}$ and the $n_f = n - n_m$ financial endogenous variables $y_{f,t}$, in levels, as in $y_t = (y_{m,t}; y_{f,t})$. $g_t$ is a $(2 \times 1)$ vector that stacks the non-observed macroeconomic and financial uncertainty factors, denoted as $g_t = (\ln m_t; \ln f_t)$. Here renamed as ‘Main VAR’ for notation purposes, the model is
represented under the reduced form

\[ y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + B_0 g_t + \ldots + B_l g_{t-l} + v_t, \]

where \( A_i \) are \((n \times n)\) matrices that collect the coefficients of the lags of \( y_t \) from 1 to \( p \), \( B_i \) are \((n \times 2)\) matrices that collect the coefficients of the lags of \( g_t \) from 0 to \( l \). This setup is similar to a VAR-X configuration, where \( g_t \) is modeled as an exogenous component.

The reduced form shocks \( v_t \) are modeled as

\[ v_t = A_0^{-1} \Lambda_t^{1/2} \epsilon_t, \quad \epsilon_t \sim iid \: N(0, I), \]

where \( A_0 \) is a lower \((n \times n)\) triangular matrix with ones in the main diagonal, and \( \Lambda_t \) is the time-varying \((n \times n)\) diagonal matrix that collects the variance of each variable. Each element of \( \Lambda_t \) is composed of an idiosyncratic component and a common uncertainty factor, which may be macroeconomic or financial depending on the chosen variable. The first \( n_m \) variables form the macroeconomic factor measure, while the \( n_f = n - n_m \) variables form the financial factor measure. The elements of \( \Lambda_t \) (in logs) are defined as

\[ \ln \lambda_{j,t} = \begin{cases} 
\beta_{m,j} \ln m_t + \ln h_{j,t} & \text{if } j = 1, \ldots, n_m \\
\beta_{f,j} \ln f_t + \ln h_{j,t} & \text{if } j = n_m + 1, \ldots, n
\end{cases}, \]

where \( \beta_{m,j} \) and \( \beta_{f,j} \) are the individual loadings to the common macroeconomic and financial factors, respectively. For identification purposes, I set \( \beta_{m,1} = 1 \) and \( \beta_{f,n_m+1} = 1 \).

The common macroeconomic factor is part of the volatility of all macroeconomic variables, and the financial factor is part of the volatility of the financial variables. The idiosyncratic component \( \ln h_{j,t} \) follows an AR(1) process of the form

\[ \ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1} + e_{j,t}, \quad j = 1, \ldots, n, \]

where \( e_t = (e_{1,t}, \ldots, e_{n,t})' \) is jointly and independently distributed as \( iid \: N(0, \Phi_e) \), and \( \Phi_e = diag(\phi_1, \ldots, \phi_n) \).
I define the common macroeconomic and financial volatility factors as proxies for macroeconomic and financial uncertainty measures, respectively. These uncertainty measures $g_t = (\ln m_t; \ln f_t)$ also follow a VAR structure, and is referred to as ‘Uncertainty VAR’ for notation purposes. The Uncertainty VAR is modeled as

$$
g_t = D_1 g_{t-1} + ... + D_k g_{t-k} + \delta \Delta y_{t-1} + u_t,
$$

where $D_i$ are $(2 \times 2)$ matrices that collect the coefficients of the lags of the uncertainty factors $g_t$ from 1 to $k$. $\delta$ is a $(2 \times n)$ matrix that collects the coefficients of the lagged variables $y_t$ (in differences). The shocks to the uncertainty factors $u_t = (u_{m,t}; u_{f,t})$ are independent from $\epsilon_t$ and $\epsilon_t$, with mean 0 and full covariance matrix defined as

$$
\Phi_u = \begin{bmatrix}
\phi_{n+1} & \phi_{n+3} \\
\phi_{n+3} & \phi_{n+2}
\end{bmatrix}.
$$

The covariance matrix of the uncertainty measures is purposely constructed as full, to allow for co-movement between macroeconomic and financial uncertainty measures. I adapt the model structure by using lagged $y_t$ variables in differences and not in levels. Carriero et al. (2018a) present a rich discussion on the suitability of this structure for identifying macroeconomic and financial uncertainties, and how this setup relates to the stochastic volatility literature.

The model embeds the assumption that uncertainty measures are affected by feedback from the lagged variables, and that uncertainty measures have a contemporaneous effect on the mean of the variables. It is not possible to have contemporaneous feedback to and from uncertainty simultaneously, for identification reasons. The choice of contemporaneous (and not lagged) feedback from uncertainty to the mean follows the assumption that the economic variables rapidly react to uncertainty shocks, and uncertainty causes short-term economic fluctuations (Bloom, 2009).

This setup imposes the limitation that shocks to the mean of the variables can only influence the level of uncertainty with, at least, one lag. One obvious alternative would be
to assume that uncertainty measures are affected contemporaneously by the variables, and that uncertainty measures have a lagged effect on the mean of the variables. However, under such an assumption, economic variables would only react to uncertainty shocks after one lag. This seems implausible in a quarterly data information set, especially with respect to financial variables such as stock prices.

The non-observed idiosyncratic volatilities $h_{jt}$ are estimated by the standard algorithm proposed by Kim, Shephard, and Chib (1998), using a 10-state mixture of normals approximation from Omori, Chib, Shephard, and Nakajima (2007). The estimation of the non-observed macroeconomic and financial uncertainties is substantially more complex, presenting a multi-variate nonlinear state-space representation. I follow Mumtaz and Theodoridis (2015) and employ a particle Gibbs step to estimate $\ln m_t$ and $\ln f_t$. The particle Gibbs construction is based on Andrieu, Doucet, and Holenstein (2010) and the ancestor sampling improvements proposed by Lindsten, Jordan, and Schön (2014), with 100 particles.

I estimate the full model with $p = 4$ lags, $l = 1$ lag of the macro and financial factors in the Main VAR (equation 1), and $k = 1$ lag of the macro and financial factors in the Uncertainty VAR (equation 5). The full estimation procedure is described in detail in the Appendices.¹⁰

2.2 Data

The dataset comprises both macroeconomic and financial variables in levels. The variables are measured quarterly, which allows the use of macroeconomic variables such as utilization-adjusted TFP (necessary for the news shock identification) and gross domestic product (GDP). For variables which are available at a higher frequency, I construct the time-series by taking the quarterly average. The period is from 1975Q1 to 2012Q3.

The dataset contains 14 macroeconomic variables, namely utilization-adjusted TFP,

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¹⁰Appendix A.1 describes the triangularization procedure for drawing the coefficients in large VARs proposed by Carriero, Clark, and Marcellino (2016b). This procedure is statistically equivalent to a conventional Bayesian stochastic volatility Monte Carlo Markov Chain (MCMC) estimation, but has the advantage of being less computationally intensive. Appendix A.2 presents the steps of the MCMC algorithm. Appendix A.3 describes the particle Gibbs with ancestor sampling.
personal consumption per capita, GDP per capita, private investment per capita, hours
worked, GDP deflator, Federal funds rate, total nonfarm payroll, industrial production
index, help wanted to unemployment ratio, real personal income, real manufacturing
and trade sales, average of hourly earnings (goods producing) and producer price index
(finished goods). These are the macroeconomic variables that are usually considered in
the news shock literature.

The 14 financial variables are the spread between the 10-year yield and the Federal
funds rate, S&P500 stock prices index, S&P dividend yields, excess bond premium, CRSP
excess returns, small-minus-big risk factor, high-minus-low risk factor, momentum, small
stock value spread (R15-R11), and five industry sector-level returns (consumer, manufac-
turing, high technology, health and other). The financial variables mostly matches those
used by Jurado et al. (2015) and Carriero et al. (2018a) to construct their measures of
financial uncertainty.

A full description of the sources and construction of the 28 variables can be found in
Appendix C.

2.3 Latent uncertainty measures

In this Section I present the estimated macro and financial uncertainties from the stochas-
tic volatility in mean model described in Section 2. The (estimated) stochastic volatility
of each variable is composed of a common factor, which can be macroeconomic or financial
depending on the underlying variable, and an idiosyncratic component. The common fac-
tors across the volatilities are the estimations of aggregate macroeconomic and financial
uncertainties.

Figure 2 displays the estimated aggregate macroeconomic uncertainty, and Figure 3
shows the estimated financial uncertainty. The stochastic volatilities of the macroeco-
nomic and financial variables are presented in Appendix D. The economic assumption
that macro and financial uncertainty may be related to each other is captured by the inter-
action between the two uncertainty measures included in the Uncertainty VAR (equation
5) and the full variance-covariance matrix between the two factors (equation 6). Figures
2 and 3 show that some periods in time share high macro and financial uncertainties, but some are marked by either a hike mainly in macro or financial uncertainty. Comparing these series with the recessions identified by the National Bureau of Economic Research (NBER), it is possible to match each recession with a macroeconomic uncertainty hike, a financial uncertainty hike, or both.

Figure 2 Aggregate macroeconomic uncertainty

![Graph showing aggregate macroeconomic uncertainty with shaded areas indicating recession periods.]

*Note:* Macroeconomic uncertainty measured as the common factor on macroeconomic volatilities. The dotted lines define the 68% confidence bands computed with 200 posterior draws. The VAR model includes all variables in Tables C.1 and C.2. Shaded areas are the recession periods calculated by the NBER.

The Great Moderation period (mid-1980s) for example, characterized by a decline in the business cycle volatility of aggregate macroeconomic variables, is captured by a hike in the macroeconomic uncertainty. During the dot-com crisis (1999-2001), which was mainly a speculative financial bubble in the stock market, there is a higher financial uncertainty. The 2008 crisis shows high macro and financial uncertainties.

While the uncertainty measures match crisis periods, they also follow closely the monthly macro and financial uncertainties estimated by Ludvigson et al. (2016), which I take here as a benchmark for comparison purposes. The macroeconomic uncertainty presented in Figure 2 and the 1-month ahead macroeconomic uncertainty from Ludvigson et al. (2016) share a correlation of 0.76 over the period 1975Q1 and 2012Q3,\textsuperscript{11} with 0.77

\textsuperscript{11}I transform the uncertainty measures calculated by Ludvigson et al. (2016) from monthly to quarterly
Figure 3 Aggregate financial uncertainty

*Note:* Financial uncertainty measured as the common factor on financial volatilities. The dotted lines define the 68% confidence bands computed with 200 posterior draws. The VAR model includes all variables in Tables C.1 and C.2. Shaded areas are the recession periods calculated by the NBER.

for both the 3-months ahead and 12-months ahead versions. The correlation of the financial uncertainty presented in Figure 3 and the 1-month ahead financial uncertainty from Ludvigson et al. (2016) is 0.68, with same coefficient when taking into consideration the 3-months, and 0.69 for the 12-months ahead version of the financial uncertainty.

The two series estimated here are also correlated with each other, a direct result of the possibility of transmission of macro-to-financial uncertainty, and vice versa. The correlation coefficient of the two series is 0.37. The uncertainty measures from Ludvigson et al. (2016) present a higher correlation with each other. Considering the 1-month ahead macro and financial uncertainty, the correlation coefficient is 0.53 over the period 1975Q1 and 2012Q3. The correlation coefficients of the 3-months and 12-months ahead uncertainty versions are, respectively, 0.52 and 0.45.

It is important to notice that the estimation procedure for the measures presented here is substantially different from the Ludvigson et al. (2016) methodology. First, Ludvigson et al. (2016) use of the FRED-MD database by averaging across the quarter.

12 McCracken and Ng (2016).
I use quarterly data in levels. Second, Ludvigson et al. (2016) construct uncertainty measures by averaging the conditional volatility of unforecastable components of the future value of the macroeconomic or financial series. Here, I estimate the uncertainty measures with a particle filter, where these uncertainties depend on the (lagged) dependent variables, and the dependent variables can react contemporaneously to the uncertainties (stochastic volatility in mean). Lastly, Ludvigson et al. (2016) and this paper use different variables. While Ludvigson et al. (2016) employ 132 macro series and 147 financial series, I construct the uncertainty measures using only 14 macro and 14 financial series.

3 Identification procedure for news shocks

In this Section I present the strategy for identifying news shocks. This is an innovative identification procedure that takes into account nonlinear and time-varying models, in which the news shock presents different economic responses in each point in time.

3.1 News shocks identification for nonlinear and time-varying models

The identification for the news shock is constructed upon the procedure proposed by Barsky and Sims (2011). This approach is based on the assumption that a technology news shock is the structural shock that best explains the unpredictable movements of utilization-adjusted TFP over a fixed long-term horizon, with the imposition of no effect on impact \((t = 0)\). It is constructed following the maximum forecast error variance approach presented in Uhlig (2005) and Francis, Owyang, Roush, and DiCecio (2014).

The identification procedure presented by Barsky and Sims (2011) is broadly adopted in the news shock literature. However, this identification method is only applicable to time invariant covariance cases. A more flexible identification method is needed to

\[^{13}\text{Please refer to the On-line Appendix of Jurado et al. (2015) for a detailed description of the database employed by the authors.}\]

\[^{14}\text{I follow Barsky and Sims (2011) by fixing the horizon at 40 quarters ahead.}\]

investigate the idea of an underlying transmission mechanism relating the technology news (a shock to the mean of the variables) and the variables’ volatilities.

I start from the model presented in equation 1. Considering a model with a fully exogenous uncertainty measure $g_t$, I rewrite equation 1 as a function of the lag operator $L$, leading to a VAR-X representation of the form

$$y_t = A(L)y_t + B(L)g_t + A_0^{-1}A_1^{1/2} \varepsilon_t,$$

(7)

where $A(L) = A_1 + A_2L^2 + \ldots + A_pL^p$ and $B(L) = B_0 + B_1L + \ldots + B_lL^l$. A moving average representation of this model\(^{16}\) is defined as the infinite polynomial of the lag operator $L$ as $C(L) = C_0 + C_1L + \ldots = [I_n - A(L)]^{-1}$, where $C_0 = I_n$, as

$$y_t = C(L)B(L)g_t + C(L)A_0^{-1}A_1^{1/2} \varepsilon_t.$$ (8)

Suppose that there is a linear mapping of the innovations ($\varepsilon_t$) and the structural shocks ($s_t$) as in

$$\varepsilon_t = P\, s_t,$$

(9)

which implies

$$A_0^{-1}A_1^{1/2}\varepsilon_t = A_0^{-1}A_1^{1/2}P\, s_t.$$ (10)

The innovations $\varepsilon_t$ and the structural shocks $s_t$ are i.i.d. $N(0, I_n)$. To ensure that $E[A_0^{-1}A_1^{1/2} \varepsilon_t \varepsilon_t' A_1^{1/2} A_0^{-1}'] = E[A_0^{-1}A_1^{1/2} P_s s_t' P' \Lambda_1^{1/2} A_1^{1/2} A_0^{-1}'] = \Sigma_t$, it suffices that $PP' = I_n$. $P$ can take the form of any of the infinite alternatives that satisfy this condition. Under this structure, the moving average representation can be rewritten as

$$y_t = C(L)B(L)g_t + C(L)A_0^{-1}A_1^{1/2} P\, s_t,$$

(11)

where $s_t = P^{-1}\varepsilon_t$.

Now, the Barsky and Sims (2011) identification procedure for the news shock relies on

\(^{16}\)See Ocampo and Rodríguez (2012) for a comprehensive description of the moving average representation of VAR-X models.
finding one of the infinite alternatives of $P$ that maximizes the variance decomposition of the utilization-adjusted TFP over a predefined forecast horizon, and has no effect on impact ($t = 0$). It is derived from the assumption that technology is a stochastic process driven by two shocks: a surprise (or unanticipated) technological shock, and an anticipated news shock. The total unexplained variance of utilization-adjusted TFP can be decomposed as

$$\Gamma_{1,1}(k)_{\text{surprise}} + \Gamma_{1,2}(k)_{\text{news}} = 1 \forall h, \quad (12)$$

where $\Gamma_{i,j}(h)$ is the share of the forecast error variance of variable $i$ of the structural shock $j$ at horizon $k$, $i = 1$ refers to utilization-adjusted TFP (where this variable is ordered first in the VAR), $j = 1$ is the unexpected TFP shock, and $j = 2$ is the news shock.

While the $K$-step ahead forecast error in this model is given by

$$y_{t+K} - \mathbb{E}[y_{t+K}] = \sum_{k=0}^{K} (C_k B_k g_{t+k} + C_k A_0^{-1} A_{t+k}^{1/2} P s_{t+K-k}), \quad (13)$$

the share of the forecast error variance of the news shock is

$$\Gamma_{1,2}(K)_{t,\text{news}} = \frac{q_1' \left( \sum_{k=0}^{K} (C_k B_k g_{t+k} + C_k A_0^{-1} A_{t+k}^{1/2} P q_2) (C_k B_k g_{t+k} + C_k A_0^{-1} A_{t+k}^{1/2} P q_2)' \right) q_1}{q_1' \left( \sum_{k=0}^{K} C_k \Sigma_{t+k} C_k' \right) q_1} \cdots = \ldots$$

$$= \frac{\sum_{k=0}^{K} (C_{1,k} B_{1,k} g_{t+k} + C_{1,k} A_0^{-1} A_{t+k}^{1/2} \tau) (C_{1,k} B_{1,k} g_{t+k} + C_{1,k} A_0^{-1} A_{t+k}^{1/2} \tau)'}{\sum_{k=0}^{K} C_{1,k} \Sigma_{t+k} C_{1,k}'}, \quad (14)$$

where $q_1$ is a selection vector with 1 in the position $i = 1$ and zeros elsewhere, $q_2$ is a selection vector with 1 in the position $i = 2$ and zeros elsewhere, and $C_k$ is the matrix of moving average coefficients measured at each point in time until period $k$. The combination of selection vectors with the proper column of $P$ can be written as $\tau$, which is an orthonormal vector that makes $A_0^{-1} A_{t}^{1/2} \tau$ the impact of a news shock over the variables.

One additional complication that arises is that the share of the forecast error variance of the news shock depends on $g_t$, $A_{t}^{1/2}$ and $\Sigma_t$. In other words, the variance decomposition depends on the time $t$ in which it is measured. The news shock is identified by picking $\tau$
that maximizes the share described in equation 14, but the dependence of this share on \( t \) can lead to a different \( \tau \) in each point in time. This characteristic forms the basis of the identification procedure for the news shock proposed here. The news shock is identified by solving the optimization problem

\[
\tau_{t,\text{news}} = \text{argmax} \sum_{k=0}^{K} \Gamma_{1,2}(k)_{t,\text{news}},
\]

subject to

\[
A_0(1,j) = 0, \forall j > 1
\]
\[
\tau_t(1,1) = 0
\]
\[
\tau_t'\tau_t = 1,
\]

where \( K \) is an truncation period, and the restrictions imposed imply that the news shock does not have an effect on impact \((t = 0)\) and that the \( \tau_t \) vector is orthonormal.

In practice, two elements introduce additional nonlinearity to the forecast error described in equation 13: the contemporaneous feedback effect that the uncertainty factors \( g_t \) have on the variables \( y_t \) (because of the stochastic volatility in mean), and the dependence of the time-varying volatility \( \Lambda_t^{1/2} \) on the uncertainty factors \( g_t \). I deal with this nonlinearity by employing a generalized impulse response structure\(^{17}\) in substitution for the forecast error described by equation 13. Since generalized impulse response structures do not depend on the model functional form, this substitution makes the procedure even more broad by allowing the identification of news shocks under different forms of nonlinear and time-varying relationships.

The generalized impulse responses are constructed by creating simulated shocked and baseline paths. The difference between these two paths captures the effect of the desired shock, conditional on a random simulated innovation \( \omega_{j,t} \), where \( j \) identifies the variable. The overall effect of the identified shock is the average of the difference between the baseline and shocked paths across a significant number of random innovations \( \omega_{j,t}^r \).

\(^{17}\)Adapting the procedure proposed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998).
The full identification procedure and steps for the generalized impulse responses are described in Appendix B. To summarize, it is possible to show that, conditional on the draw $r$ of the random innovation $\omega_{j,t}$, on the information set containing all the known history up to time $t$ defined as $Z_t = (y_{t-p}, ..., y_t; g_{t-p}, ..., g_t)$, and on the coefficient matrices $\Pi = [A_i, B_i, D_i, \beta_j, \gamma_j, \delta]$, the generalized impulse response at time $k$ of a generic utilization-adjusted TFP shock is given by

$$GI_{TFP,t}(k, \tau_{TFP}^r, \omega_{j,t}^r, Z_t, \Pi) = E[y_{t+k, TFP}; g_{t+k, TFP} | \tau_{TFP}^r, A_{t+k, TFP}, \omega_{j,t}^r, Z_t, \Pi] - E[y_{t+k, base}; g_{t+k, base} | \Lambda_{t+k, base}, \omega_{j,t}^r, Z_t, \Pi],$$

where $\tau_{TFP}^r$ is a vector with 1 in the first position (where utilization-adjusted TFP is ordered first in the VAR) and zeros elsewhere.

With this setup, it is possible to substitute the TFP impulse responses ($C_1 B_{1,k} g_{t+k} + C_1 A_0^{-1} A_1^{1/2} \tau$) in equation 14 for $GI_{TFP,t}(k, \tau_{TFP}^r, \omega_{j,t}^r, Z_t, \Pi)$, or simply $GI_{TFP,t}(k)$ for notation purposes.

A news shock for a draw $r$ of the random innovation $\omega_{j,t}^r$ can be identified in each period $t$ as

$$\tau_{t, news}^r = \arg \max \sum_{k=0}^K GI_{TFP,t}(k, \tau_{TFP}^r) GI_{TFP,t}(k, \tau)^t \sum_{k=0}^K C_1 \Sigma_{t+k} C_1,$$

subject to

$$A_0^{-1}(1, j) = 0, \quad \forall j > 1,$$

$$\tau(1, 1) = 0,$$

$$\tau' \tau = 1.$$  

After obtaining the identification vector for the news shock $\tau_{t, news}^r$ for the draw $r$ of the random innovations $\omega_{j,t}^r$, it is possible to construct the generalized impulse responses for the news shock at each point in time. Conditional on the draw $r$ of the random innovation $\omega_{j,t}^r$, on the information set $Z_t$, and on the coefficients $\Pi$, the generalized

\footnote{Where $g_t = (\ln m_t; \ln f_t)$.}
impulse response at time $k$ of the technology news shock is given by

$$GI_{t,\text{news}}(k, \tau_{t,\text{news}}, \omega_{j,t}; Z_t, \Pi) = \mathbb{E}[y_{t+k,\text{news}}^r, g_{t+k,\text{news}}^r | \tau_{t,\text{news}}, \Lambda_{t+k,\text{base}}, \omega_{j,t}^r; Z_t, \Pi]$$

$$- \mathbb{E}[y_{t+k,\text{base}}^r, g_{t+k,\text{base}}^r | \Lambda_{t+k,\text{base}}, \omega_{j,t}^r; Z_t, \Pi]. \tag{20}$$

Taking the averages of each path across a sufficiently large number of draws of the random innovations $\omega_{j,t}$, the overall generalized impulse response at time $k$ of a news shock, conditional on the information set at time $t$, is given by

$$GI_{t,\text{news}}(k, \tau_{t,\text{news}}, Z_t, \Pi) = [\bar{y}_{t+k,\text{news}}(k, \tau_{t,\text{news}}, Z_t, \Pi), \bar{g}_{t+k,\text{news}}(k, \tau_{t,\text{news}}, Z_t, \Pi)]$$

$$- [\bar{y}_{t+k,\text{base}}(k, Z_t, \Pi), \bar{g}_{t+k,\text{base}}(k, Z_t, \Pi)]. \tag{21}$$

Note that this identification procedure is a generalization of the standard homoskedastic Barsky and Sims (2011) identification. With a time invariant covariance model and no exogenous variables, the Barsky and Sims (2011) procedure can be nested by the structure presented here. Consider, for example, equation 7. If there are no time-varying volatility or exogenous variables, this equation is reduced to

$$y_t = A(L)y_t + A_0^{-1} \Lambda^{1/2} \epsilon_t, \tag{22}$$

and its moving average representation is simply

$$y_t = C(L) A_0^{-1} \Lambda^{1/2} \epsilon_t. \tag{23}$$

Now, considering the same linear mapping between the innovations ($\epsilon_t$) and the structural shocks ($s_t$) as in equation 9, the share of the forecast error variance of the news shock defined in equation 14 becomes

$$\Gamma_{1,2}(k)_{\text{news}} = \frac{q_1' \left( \sum_{k=0}^{K} (C_k A_0^{-1} \Lambda^{1/2} P q_2) (C_k A_0^{-1} \Lambda^{1/2} P q_2)' \right) q_1}{q_1' \left( \sum_{k=0}^{K} C_k \Sigma C_k' \right) q_1} = \frac{\sum_{k=0}^{K} (C_{1,k} A_0^{-1} \Lambda^{1/2} \tau) (C_{1,k} A_0^{-1} \Lambda^{1/2} \tau)'}{\sum_{k=0}^{K} C_{1,k} \Sigma C_{1,k}'}. \tag{24}$$
and $\Gamma_{1,2}(k)$\textit{news} does not depend on $t$ anymore. The procedure of finding $\tau$ that maximizes the share of the forecast error variance of equation 24 under the same restrictions described in equation 16 is equivalent to the Barsky and Sims (2011) procedure.

4 Dynamic effects of a news shock

In this Section I present the results of a news shock identified under the procedure described in Section 3. I first present the time-varying generalized impulse responses after a news shock and its economic interpretation. Following, I discuss the relation between news shocks and uncertainty. Lastly, I propose a counterfactual to study the transmission effect of news shocks through uncertainty.

4.1 Impulse responses to a news shock

In this Section I present the results of the news shock identification. The economic responses after a news shock are different for every point in time, conditional on the estimated time-varying volatility. Figure 4 shows the effect of a technology news shock over the utilization-adjusted TFP. The shock is normalized to a 1\% increase in utilization-adjusted TFP after 20 quarters.

Figure 4 Effect of news shock on utilization-adjusted TFP

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure4.png}
\caption{Effect of news shock on utilization-adjusted TFP}
\end{figure}

\textit{Note:} Distribution (50\%, 68\% and 95\% percentiles) over time of the median effect of a news shock. Shocks are normalized to a 1\% increase in utilization-adjusted TFP after 20 quarters. The news shock is identified under the procedure proposed in Section 3.1. The generalized impulse responses for each period are the average of 5,000 simulated random innovations, as described in Appendix B.

The identification procedure of the news shock maximizes the variance decomposition
of this variable over a fixed forecast horizon of 40 quarters ahead, imposing a zero effect on impact \( (h = 0) \). This assumption is important to ensure that the identified shock refers to future technological developments, and not to contemporaneous surprise technological changes. Utilization-adjusted TFP goes from zero to a new higher level in the long-term. The economic effects on the other variables included in the information set are a response to this expected path of TFP.

Figures 5 and 6 present the economic responses of selected variables after a news shock, identified and calculated for each point in time as generalized impulse responses.\(^{19}\) The graphs in Figure 5 show the median impulse responses in three dimensions: period in time of identification (x-axis), size of impact (y-axis) and the effect \( h \) quarters ahead (each line). Figure 6 presents the distribution (50%, 68% and 95% percentiles) of the impulse responses from Figure 5.

Consumption, GDP and investment react positively to news, growing to a new higher level. The responses of hours worked are positive in the medium-term \( (h = 12) \), and negative in the long-term \( (h = 40) \). There is a deflationary effect in the medium-term after a news shock, as evidenced by the literature.\(^{20}\) This path is consistent with a ‘supply shock’, and the current inflation being the expected present discounted value of future marginal costs (Barsky and Sims, 2011). By employing a covariance-stationary identification procedure, Barsky et al. (2014) point out that the peak of the negative effect on inflation is about 10 quarters after the news shock, similar to the results presented here. The effect on stock prices is positive, as initially indicated by Beaudry and Portier (2006).

Even though the shock is normalized, the economic effects over these variables change substantially over time. The peak effect on GDP is after nine quarters, with a median hike of 1.3%. However, this effect may be as low as 1.1% (5% percentile) or as high as 1.6% (95% percentile) depending on the period in which the news shock is observed. The same is valid for the effect on investment. After nine quarters, the median positive

\(^{19}\) As described in Appendix B. The generalized impulse responses for all the variables included in the VAR can be found in Appendix D.

\(^{20}\) See, for example, Christiano, Ilut, Motto, and Rostagno (2010), Barsky and Sims (2011) and Barsky, Basu, and Lee (2014).
Figure 5 Time-varying effects of news shocks

Note: Median effect of a news shock for each period in time. Shocks are normalized to a 1% increase in utilization-adjusted TFP after 20 quarters. The news shock is identified under the procedure proposed in Section 3.1. The generalized impulse responses for each period are the average of 5,000 simulated random innovations, as described in Appendix B.

effect is of 3.8%, ranging from 3.2% (5% percentile) to 4.9% (95% percentile). In the long-term (h = 40), the positive effect on consumption has a median effect of 0.8%, being as low as 0.7% (5% percentile) or as high as 1%. Stock prices react strongly on impact (h = 0), with a median effect of 6.8%, but ranging from 3.6% (5% percentile) to 13.6% (95% percentile).

Figure 7 presents the effect of a news shock on the (endogenously estimated) uncertainty measures. This effect is captured by the feedback of the mean of the variables to their second moment.\textsuperscript{21} By construction, the impact effect (h = 0) of the news shock on

\textsuperscript{21} Coefficients $\delta$ from equation 5.
Figure 6 Distribution of time-varying effects of news shocks

Note: Distribution (50%, 68% and 95% percentiles) over time of the median effect of a news shock. Shocks are normalized to a 1% increase in utilization-adjusted TFP after 20 quarters. The news shock is identified under the procedure proposed in Section 3.1. The generalized impulse responses for each period are the average of 5,000 simulated random innovations, as described in Appendix B. The uncertainties is zero, as the level of the variables are only allowed to feedback to the uncertainties with one lag. After one period, the effect may be weakened or amplified by the feedback effect of the second moment to the level of the variables (stochastic volatility in mean).\textsuperscript{22}

Macroeconomic uncertainty falls one period after the news shock hits the economy. The median effect over time is a drop of 4.5%, but this can be as low as 1.5% (5% percentile) or as high as 12.1% (95% percentile). This effect rapidly dissipates, being close to zero after three years. The macroeconomic uncertainty is constructed as a factor over the

\textsuperscript{22}Coefficients $B_0$ and $B_1$ from equation 1.
Figure 7 Distribution of time-varying effects of news shocks on uncertainty measures

Note: Distribution (50%, 68% and 95% percentiles) over time of the median effect of a news shock. Shocks are normalized to a 1% increase in utilization-adjusted TFP after 20 quarters. The news shock is identified under the procedure proposed in Section 3.1. The generalized impulse responses for each period are the average of 5,000 simulated random innovations, as described in Appendix B.

 volatility of real macroeconomic variables. This reduction of macroeconomic uncertainty comes from the fact that the news shock brings more information about the expected future path of the economy. Shen (2015) argues that an increase in the information volume better anchors expectations and reduces the volatility of macroeconomic variables. Jaimovich and Rebelo (2009) show that when news shocks change from noisy signals to perfect foresight, volatility becomes smaller. The results presented here confirms empirically these theoretical propositions.

Differently from the macro uncertainty, financial uncertainty increases one period after the news shock. The median effect over time is a hike of 0.4%, but this can be as low as drop of 0.1% (5% percentile) or as high as a hike of 1.5% (95% percentile). the initial hike is explained by the nature of financial uncertainty. This measure is constructed as a factor over the volatility of financial variables, which move quickly than macroeconomic variables. The initial hike is in line with the idea of ‘good uncertainty’. Segal, Shaliastovich, and Yaron (2015) argue that good news are linked to positive growth
opportunities, but the size of this growth effect is unknown. This situation increases the volatility of financial variables, generating the ‘good uncertainty’ effect. Song and Tang (2018) show that when news shocks contradict prior beliefs, uncertainty increase, and this rise is more apparent when news is more accurate. Cascaldi-Garcia and Galvao (2018) also find a positive short-lived effect of news shocks on several measures of financial uncertainty. However, these uncertainty measures are taken as observables from the literature, and not endogenously generated as in the model presented here.

The financial uncertainty rapidly resolves after this initial hike, falling by 0.7% after two quarters (median) and converging back to zero after around three years. The ‘good uncertainty’ effect dissipates as the market converges to a consensus about the interpretation of the news. Importantly, the ‘good uncertainty’ effect is only observed on the financial uncertainty due to the fast evaluation of the news by the financial markets, while macro uncertainty respond in a slower pace based on economic fundamentals.

The results presented here bring two novel features to the news shock literature. First, they show that the effect of a news shock change over time, depending on when the shock is observed. In the conventional linear setup, with fixed variance-covariance, all the impulse responses in Figure 5 would be the same, and the responses in Figure 6 would collapse to a single (median) line. Second, it allows the evaluation of the endogenous effect of a (first moment) news shock on the second moment of the variables, measured by the macro and financial uncertainty proxies.

4.2 News shocks and the relationship to uncertainty

As shown, the economic effects after a news shock differ across time. In this Section I investigate if these differences may be connected to the level of uncertainty of the economy when the shock is observed. For example, is it possible that the economic effects of a news shock is higher or lower in periods of high macro and/or financial uncertainty?

I first evaluate this proposition by calculating the correlation between several uncertainty measures estimated here or taken from the literature and the medium \((h = 12)\) and long-term \((h = 40)\) effects of a news shock on consumption, GDP, investment and
hours worked. Table 1 presents these correlations, while the description and availability of the uncertainty measures can be found in Table C.3 in Appendix C.

Table 1 shows that there is no clear correlation between the responses to a news shock and the level of macroeconomic uncertainty when the shock is observed. However, these responses are (positively) correlated to the level of financial uncertainty. This result is robust to all financial uncertainty measures considered, including the one endogenously estimated here. It implies that when the economy receives a news shock, either positive or negative, its effects will be boosted if this is a period of high financial uncertainty.

Bloom (2009) shows that uncertainty creates an ‘inaction zone’ in investment, due to firms becoming more cautious. With firms close to the investment threshold, small positive volatility shocks generate an investment response, while small negative shocks generate no response. After the initial recessive effect of uncertainty, firms would want to scale up their investment plans to address pent-up demand. The result is a medium-term overshoot in productivity growth. Periods of high uncertainty are also related to a higher potential return on investment, increasing the range of growth options (Segal et al., 2015).

Cascaldi-Garcia and Galvao (2018) suggest that uncertainty shocks anticipate two effects on total factor productivity: a short-term negative reduction on utilization factors, and a medium-term positive effect on the utilization-adjusted productivity. This medium-term positive effect relates to the overshoot in productivity growth idea presented by Bloom (2009). It follows that uncertainty foresees future technology improvements, as a ‘good uncertainty’ effect. From this literature, one would expect a positive relationship between high uncertainty periods and the positive economic outcomes from a higher expected future technology growth, as in a news shock.

It is important to note that the news shocks identified across time are normalized, with the same size. The correlation of the medium and long-term effects presented in Table 1 is a result of the transmission mechanism of the uncertainty measures to the mean of the variables presented in equations 1 and 5. This transmission mechanism makes the news shock stronger in periods of higher financial uncertainty, as suggested by the data.
Table 1 Correlations between news shock economic responses and uncertainty measures

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<td>Investment</td>
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</tbody>
</table>

Note: The Macro uncertainty and Financial uncertainty in **bold** are the measures calculated in this paper, and presented in Figures 2 and 3. Medium-term and long-term responses are calculated 12 and 40 quarters ahead, respectively. The p-values for the test with zero correlation under the null hypothesis are in brackets. The statistic is calculated as $t = \rho_0 \sqrt{\frac{T-2}{1-\rho_0^2}}$. For details on the uncertainty measures and availability, see Table C.3 in Appendix C.
when viewed through the stochastic volatility in mean VAR model.

Figure 8 presents a clearer image of the differences between the effects of a news shock during high and low financial uncertainty periods. The red lines correspond to the average of generalized impulse responses on periods of high financial uncertainty, while the blue lines correspond to the average of generalized impulse responses on periods of low financial uncertainty. I define high financial uncertainty as the periods with the highest 10% of values for financial uncertainty, and low financial uncertainty with the lowest 10% of values.

Figure 8 Distribution of time-varying effects of news shocks in periods of high and low financial uncertainty

Note: Distribution (50% and 68% percentiles) over time of the median effect of a news shock. Shocks are normalized to a 1% increase in utilization-adjusted TFP after 20 quarters. Red and blue lines correspond to the average of generalized impulse responses on periods of high and low financial uncertainty, respectively. High and low financial uncertainty are the periods with the higher and lower 10% values for the financial uncertainty.
The effects of a news shock on consumption, GDP, investment, hours worked and stock prices are higher in periods of high financial uncertainty. The effect on consumption is higher in the high financial uncertainty periods mainly in the long-term. With respect to GDP, the biggest difference between the high and low financial uncertainty periods is in the medium-term. This is a direct result of the economic response of investment, which peaks about two to three years after the news shock occurred. In the long-term, the path of investment in the high financial uncertainty periods converges to the path of the low financial uncertainty period.

The deflationary effect of the news shock is the same no matter if the news shock was observed in a period of high or low financial uncertainty. The stock market is more responsively to news in periods of high financial uncertainty. This implies that positive news may indicate a reversion of the recessionary outcomes of high financial uncertainty, and that negative news may indicate that this situation will be extended for a longer period of time.

4.3 The uncertainty transmission mechanism of news shocks

How important is uncertainty for the effect of news shocks on the economy? Does it depend only on the level of uncertainty at the time of the shock, or is there an uncertainty transmission mechanism that influences the effect of a news shock throughout time? I investigate these questions through a counterfactual: what would happen to a news shock if there was no feedback effect to and from uncertainty. In summary, the idea is to restrict to zero the feedback coefficients \( B_0 \) and \( B_t \) from equation 1 and \( \delta \) from equation 5. Section B.2 in the Appendix provides the full description of the procedure for the counterfactual.

Figure 9 compares the generalized impulse responses of a news shock without feedback to and from uncertainty (counterfactual) with the benchmark model (as in Figure 6) for selected variables. The shock is normalized to have the same utilization-adjusted TFP path in both cases. By construction, macro and financial uncertainty do not respond to a news shock under the counterfactual. Figure D.4 in the Appendix presents the generalized impulse responses for utilization-adjusted TFP, macro and financial uncertainty, with and
without the feedback effect.

Figure 9 Time-varying median effects of news shocks with and without feedback from uncertainty

\[ \text{Figure 9 Time-varying median effects of news shocks with and without feedback from uncertainty} \]

\[ \text{Note: Distribution (50\% and 68\% percentiles) over time of the median effect of a news shock. Shocks are normalized to a 1\% increase in utilization-adjusted TFP after 20 quarters. Red and blue lines correspond to the average of generalized impulse responses of the benchmark and counterfactual models, respectively. The news shock for the counterfactual is identified for each period in time under the procedure proposed in Section B.2. The generalized impulse responses for each period are the average of 5,000 simulated random innovations, as described in Appendix B.} \]

The pattern of the responses from the counterfactual are quite similar to the responses from the benchmark model, in which there is a feedback effect from uncertainty. The model with no feedback seems to present a higher medium-term effect on consumption, and is more deflationary than the benchmark. The main difference between comparing these two alternative views is on impact \((h = 0)\). The effect on impact captures exactly the anticipation of the agents to the expected future increase in utilization-adjusted TFP. Figure 10 presents the distribution over time of the median effects on impact for the
benchmark and counterfactual models.

Figure 10 Distribution over time of median impact effects of news shocks with and without feedback from uncertainty.

Note: Distribution over time of the median impact effect (h=0) of a news shock. Shocks are normalized to a 1% increase in utilization-adjusted TFP after 20 quarters. Red and blue distributions correspond to the average of generalized impulse responses of the benchmark and counterfactual models, respectively. The solid horizontal lines represent the median effect over time. The news shock for the counterfactual is identified for each period in time under the procedure proposed in Section B.2. The generalized impulse responses for each period are the average of 5,000 simulated random innovations, as described in Appendix B.

The distribution of the median impact effect is wider when there is no feedback to and from uncertainty. It means that, when the agents are not allowed to update their beliefs about macroeconomic and financial conditions, the anticipation effect of a news shock is more scattered over time.

In general, when macro and financial uncertainties are allowed to react to news shocks, the anticipation effects of such news are diminished. This is more evident with respect to investment. While the median anticipation effect of the benchmark model with feedback
to and from uncertainty is of an increase of 0.4%, the counterfactual shows an increase of 1.4%. This result is also evidenced with GDP: increase of 0.2% in the benchmark model, and 0.8% with the counterfactual. There is a difference on the anticipation of consumption as well, but in both cases the effect is not economically relevant (less than 0.1%). The counterfactual also shows a more deflationary effect, and a stronger reaction from the stock markets.

These results are in line with a new stream in the literature on news and uncertainty shocks, which explores the dynamics of uncertainty updating based on the arrival of news. Forni et al. (2017) propose a model in which uncertainty is generated by news about future developments in economic conditions. Uncertainty arises from the fact that these conditions are not perfectly predicted by the economic agents. Berger et al. (2017) define an uncertainty shock as a second-moment news, or changes in the expected future volatility of aggregate stock returns. The authors argue that news about the squared growth rates are changes in the conditional variance, which is equivalent to an uncertainty shock.

In summary, the results from the counterfactual suggest that the arrival of information about future technology makes the economic agents update not only their expectations about future productivity, as in the news shock literature, but also their expectations about macroeconomic and financial conditions, proxies to uncertainty. This process is continuous, with consecutive updates as the effects of this new information materialize. More broadly, the level of uncertainty reacts to information about the state of the economy, and the state of the economy reacts to the level of uncertainty.

5 Conclusion

This paper shows that the economic effects of news on the future increase in technology differ depending on the level of uncertainty of the economy. It contributes to the literature on shocks driven by agents’ beliefs in two ways.

First, I propose an innovative method of checking whether the effects of technology
news shocks change depending on the point in time at which it is identified. By employing this identification strategy, I show that economic responses to a news shock vary quantitatively across time. While the conventional Barsky and Sims (2011) identification is not robust to changes in the estimation period, the results from this paper indicate that processes with time invariant covariances may not be appropriate for a news shock identification. Moreover, the fact that the responses to news shocks vary significantly over time helps to explain why there is still no consensus in the news shock literature about the effects on macroeconomic variables.

The second contribution is new evidence supporting a dynamic relationship between technology news and uncertainty. I propose a nonlinear model that allows a feedback effect between the level of uncertainty and the macroeconomic and financial variables. Macroeconomic uncertainty reduces after a news shock, in response to the increase in the information about the expected future path of the economy. Financial uncertainty initially increases after a news shock, in line with the idea of ‘good uncertainty’. Good news are linked to positive growth opportunities, but the size of this growth effect is unknown (Segal et al., 2015). The financial uncertainty rapidly resolves, as the market converges to a consensus about the interpretation of the news.

The effects of news on consumption, GDP and investment are amplified when the news shock hits the economy in periods of high financial uncertainty. The results from a counterfactual suggest that the size of these effects depends on how expectations about macroeconomic and financial conditions are updated, creating a transmission effect of the news shock through uncertainty. A counterfactual shows that the anticipation effects of a news shock, before the actual change in technology, are smaller when allowing for a feedback to and from uncertainty.

From the perspective of the news shock literature, this evidence implies that neglecting the uncertainty transmission effect leads to the conclusion that the anticipation effects of news shocks are stronger than they really are. From the perspective of the uncertainty

23 See an empirical evaluation in the Introduction Section of this paper.
24 See Beaudry and Portier (2014) for a review of the empirical evidence of news shocks under different assumptions and identification methods.
literature, it raises the question of how the arrival of news, and the realization of its economic effects, influences the way economic agents update their expectations about macroeconomic and financial conditions.
References


A Appendix: Estimation procedure

A.1 Triangular estimation

In this Appendix I describe the triangular estimation procedure proposed by Carriero et al. (2016b). Consider the model presented by the equation 1, but rewriting the reduced form residuals $v_t$ from equation 2 as

$$
\begin{bmatrix}
v_{1,t} \\
v_{2,t} \\
... \\
v_{n,t}
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & ... & 0 \\
0 & 1 & ... & 0 \\
... & ... & ... & 1 \\
0 & 0 & ... & 1
\end{bmatrix}
\begin{bmatrix}
a^{*}_{j,1} \\
a^{*}_{j,2} \\
... \\
a^{*}_{j,n-1}
\end{bmatrix}
\begin{bmatrix}
\lambda_{1,t}^{1/2} & 0 & ... & 0 \\
0 & \lambda_{2,t}^{1/2} & ... & 0 \\
... & ... & ... & 0 \\
0 & 0 & ... & \lambda_{n,t}^{1/2}
\end{bmatrix}
\begin{bmatrix}
\epsilon_{1,t} \\
\epsilon_{2,t} \\
... \\
\epsilon_{n,t}
\end{bmatrix},
$$

(A.1)

where $a^{*}_{j,i}$ are the elements of the matrix $A^{-1}_0$. Under this structure, it is possible to rewrite each equation of the main VAR described in 1 and variable $j$ as

$$
y_{t,j} - (a^{*}_{j,1} \lambda_{1,t}^{1/2} \epsilon_{1,t} + ... + a^{*}_{j,j-1} \lambda_{j-1,t}^{1/2} \epsilon_{j-1,t}) = \sum_{i=1}^{n} \sum_{c=1}^{p} A^{(i)}_{j,c} y_{t,c} + \sum_{c=0}^{l} B_{c,j} g_{t-c} + \lambda_{j,t} \epsilon_{j,t},
$$

(A.2)

where $A^{(i)}_{j,c}$ represents the coefficients of the matrices $A_i$, and $B_{c,j}$ represents the coefficients of the matrices $B_i$. The VAR can be estimated equation-by-equation following this structure by taking into account that, for equation $j$, the left-hand side is known a priori: it is the difference between $y_{t,j}$ and the residuals from the previous $(j-1)$ equations. By rescaling $y_{t,j}$ as

$$
y^{*}_{t,j} = y_{t,j} - (a^{*}_{j,1} \lambda_{1,t}^{1/2} \epsilon_{1,t} + ... + a^{*}_{j,j-1} \lambda_{j-1,t}^{1/2} \epsilon_{j-1,t}),
$$

(A.3)

it is possible to estimate equation A.2 as a standard generalized least squares (GLS) model.
A.2 Steps of the MCMC algorithm

The MCMC algorithm for this estimation follows the steps and notation proposed by Carriero et al. (2018a), which I describe here. The conditional posterior distributions for the draws described in this Section are detailed in Appendix A.5.

**Step 1: Draw of the idiosyncratic volatilities.**

Rescaling $v_t$ as $\tilde{v}_t = A_0 v_t$, combined with the linear factor model for the log-volatilities described by equation 3, it is possible to define the observation equations

\[
\begin{align*}
\ln(\tilde{v}^2_{j,t} + \bar{c}) - \beta_{m,j} \ln m_t &= \ln h_{j,t} + \ln \epsilon^2_{j,t} \quad \text{if } j = 1, \ldots, n_m, \\
\ln(\tilde{v}^2_{j,t} + \bar{c}) - \beta_{f,j} \ln f_t &= \ln h_{j,t} + \ln \epsilon^2_{j,t} \quad \text{if } j = n_m + 1, \ldots, n,
\end{align*}
\]

(A.1)

where $\beta_{m,j}$ and $\beta_{f,j}$ are the loadings drawn from the previous MCMC iteration, $\bar{c}$ is a small constant in order to avoid near-zero values, and $S_{1:T}$ is the states from the 10-state mixture of normals draw from the previous iteration of the MCMC. Since $\epsilon_{j,t}$ is Gaussian with unit variance, it is possible to produce an approximate Gaussian system conditional on $S_{1:T}$.

I first produce a draw for the $j$ states $h_{1:T}$ as

\[
h_{1:T}|\Theta, S_{1:T}, m_{1:T}, f_{1:T}.
\]

(A.2)

using the Kim et al. (1998) algorithm, where $\Theta$ collects the coefficients from the matrices $A_i, B_i, \delta, D_i$, the coefficients in the conditional mean of the idiosyncratic components $\gamma = (\gamma_{j,0}, \gamma_{j,1})$, the elements of the matrix $A_0$, and the elements of the volatility matrices $\Phi_v$ and $\Phi_u$, as in

\[
\Theta = (A_i, B_i, \delta, D_i, \gamma, A_0, \Phi_v, \Phi_u).
\]

(A.3)

**Step 2: Draw of the factor loadings.**

Next, I produce a draw for the factor loadings $\beta_{m,j}$ and $\beta_{f,j}$, as

\[
\beta_{m,j}, \beta_{f,j}|\Theta, h_{1:T}, S_{1:T}, m_{1:T}, f_{1:T}.
\]

(A.4)
The loadings can be drawn through a generalized least squares form, conditional on the draws of \( h_{1:T} \) and \( S_{1:T} \), by transforming the observation equations as

\[
\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \ln h_{j,t} = \begin{cases} 
\beta_{m,j} \ln m_t + \ln \epsilon_{j,t}^2 & \text{if } j = 1, \ldots, n_m \\
\beta_{f,j} \ln f_t + \ln \epsilon_{j,t}^2 & \text{if } j = n_m + 1, \ldots, n 
\end{cases} \quad (A.5)
\]

**Step 3: Draw of the model coefficients and volatilities.**

The posterior coefficients and volatilities collected in \( \Theta \) are drawn as

\[
\Theta | \beta_{m,j}, \beta_{f,j}, h_{1:T}, S_{1:T}, m_{1:T}, f_{1:T}. \quad (A.6)
\]

**Step 4: Draw of the macroeconomic and financial states.**

Next, the macroeconomic and financial states \( m_{1:T} \) and \( f_{1:T} \) are drawn as

\[
m_{1:T}, f_{1:T} | \Theta, \beta_{m,j}, \beta_{f,j}, h_{1:T}, S_{1:T}. \quad (A.7)
\]

by employing the particle Gibbs with ancestor sampling proposed by Andrieu et al. (2010) and Lindsten et al. (2014) described in Appendix A.3.

**Step 5: Draw of the 10-state mixture approximation.**

Finally, I draw the 10-state mixture or normals from Omori et al. (2007) as

\[
S_{1:T} | \Theta, \beta_{m,j}, \beta_{f,j}, h_{1:T}, m_{1:T}, f_{1:T}. \quad (A.8)
\]

### A.3 Particle Gibbs with ancestor sampling

Consider a state space model as in

\[
\ln(\tilde{v}_t^2 + \bar{c}) - \ln h_t = \ln m_t + \ln \epsilon_t^2, \quad \ln \epsilon^2 \sim \chi^2(0, s_T) \quad (A.1)
\]

\[
\ln m_t = D_1 \ln m_{t-1} + \delta_m \Delta y_{t-1} + u_{m,t}, \quad u_t \sim IW(0, \phi) \quad (A.2)
\]
where \( \ln(\tilde{v}^2_t + \bar{c}) \) is a rescaled combination of the residuals from the VAR based on the loadings \( \beta_j \), \( \ln h_t \) is a rescaled combination of the idiosyncratic volatilities \( \ln h_{j,t} \), and \( \ln \epsilon^2_t \) has a variance which is a rescaled combination of the 10-state mixture of states draw \( S_{1:T} \).

**Step 1:** Draw of \( \phi \) from the IW distribution.

Compute the error between \( \ln m_t \) from the previous iteration \((i - 1)\) and the predicted \( \ln m_t \), as in

\[
    u_{m,t} = \ln m_{t}^{i-1} - (D_1 \ln m_{t-1}^{i-1} + \delta_m \Delta y_{t-1}) .
\]

(A.3)

Draw \( \tilde{\phi} \) as following

\[
    \phi \sim IW \left( d_\phi \phi + \sum_{t=1}^{T} u^2_{m,t}, d_\phi + T \right) .
\]

(A.4)

**Step 2:** Compute importance weights for \( t = 1 \).

Define a matrix \( X_m(N, T) \), which collects the \( N \) particles. Define the first observation of the \( N \)th particle as the first observation of \( m_{t}^{i-1} \), and zero for the other particles, as in

\[
    X_m(N, 1) = \ln m_{t}^{i-1}(1, 1), \quad X_m(1 : (N - 1), 1) = 0.
\]

(A.5)

Compute \( \ln \epsilon^2_{1,(j)} \) for each of the \( j = 1 : N \) particles, as in

\[
    \ln \epsilon^2_{1,(j)} = (\ln(\tilde{v}^2_1 + \bar{c}) - \ln h_1) - X_m(j, 1).
\]

(A.6)

Compute importance weights by comparing the variance of the \( N \) particles and the \( S_{1:T} \) state draw, as in

\[
    w(j, 1) = \exp \left( \frac{1}{2} \left( \frac{\ln \epsilon^2_{1,(j)}}{S_{1:T}(1)} \right)^2 \right) ,
\]

(A.7)

and normalizing

\[
    w(j, 1) = \frac{w(j, 1)}{\sum_{j=1}^{N} w(j, 1)} .
\]

(A.8)

**Step 3:** Compute importance weights for \( t = 2 : T \).
Compute $N$ predicted $m_t$ based on the previous particles, as in

$$\ln \hat{m}(j, t) = (D_1 X_m(j, t - 1) + \delta \Delta y_{t-1}). \quad (A.9)$$

Draw an index vector $\text{ind}(N)$ that samples the particles from $P(\text{ind}(j) = j) \propto w(1 : j, t - 1)$, and ranging on the interval $[1, N]$ – these are the ancestor indexes. This index will point out which particles will be collected in the current $t$-step for the $N - 1$ first particles. Store the particles as in

$$X_n(j, t) = \ln \hat{m}(\text{ind}(j), t) + \tilde{\phi}^{1/2} \ast \text{randn}(1, 1), \quad (A.10)$$

and set the $N$th particle as the previous iteration $(i - 1)$ value for $m_t$

$$X_m(N, t) = \ln m_t^{i-1}(1, t). \quad (A.11)$$

Compute $\ln \epsilon_{1}^{2(j)}$ for each of the $j = 1 : N$ particles as before, following

$$\ln \epsilon_{1}^{2(j)} = (\ln(\tilde{\epsilon}_t^2 + \tilde{c}) - \ln h_t) - X_m(j, t), \quad (A.12)$$

the importance weights as

$$w(j, t) = \exp \left( -\frac{1}{2} \left( \ln \epsilon_{1}^{2(j)} \right)^2 \frac{1}{S_{1:T}(t)} \right), \quad (A.13)$$

and normalizing

$$w(j, t) = \frac{w(j, t)}{\sum_{j=1}^{N} w(j, t)}. \quad (A.14)$$

The last part of this step is defining the $N$th ancestor index. In a conventional Particle Gibbs, this is done by simply assigning $\text{ind}(N) = N$, ensuring that $m_t^{i-1}(1, t)$ from the previous iteration is one of the particles. With the ancestor sampling, a new value for $\text{ind}(N)$ is sampled to artificially assign a history to this partial path, by connecting
\( m_t^{i-1}(1, t) \) to one of the particles. Formally, this sample is done by computing

\[
w_{\text{ind}}(j, t) = w(j, t - 1) \ast \exp \left( -\frac{1}{2} \frac{\left( m_t^{i-1}(1, t) - \tilde{m}(j, t) \right)^2}{\phi} \right), \tag{A.15}\]

normalizing

\[
w_{\text{ind}}(j, t) = \frac{w_{\text{ind}}(j, t)}{\sum_{j=1}^{N} w_{\text{ind}}(j, t)}, \tag{A.16}\]

and drawing \( \text{ind}(N) \) from \( P(\text{ind}(N) = j) \propto w_{\text{ind}}(j, t) \). Finally, store the ancestor indexes in a matrix \( a(N, T) \) as \( a(1 : N, t) = \text{ind}(1 : N) \).

**Step 4:** Compute the final filtered \( m_t^i \).

Rearrange \( X_m(j, t) \) in order to generate the trajectories of the \( N \) particles based on the ancestor indexes stored in \( a(N, T) \) following the last ordering \( a(j, T) \). Draw an indicator \( J \) from \( P(J = j) \propto w(j, 1 : T) \), and set \( \ln m_t^i = X_m(J, 1 : T) \).

### A.4 State-space representation

The model described by equations 1 and 5 can be combined and rewritten in a state-space representation. This transformation makes it easier to check the stationarity of the system and to compute impulse responses.

Consider a model in which the macroeconomic and financial factors only depend on their previous values (\( D_i \) lag order is \( k = 1 \)) and on \( \Delta y_{t-1} \). Equation 5 becomes

\[
g_t = D_1 g_{t-1} + \delta \Delta y_{t-1} + u_t, \tag{A.1}\]

or simply

\[
g_t = D_1 g_{t-1} + \delta y_{t-1} - \delta y_{t-2} + u_t. \tag{A.2}\]

Consider now that the main VAR (equation 1) has lag order of \( y_t \) of \( p, l = 1 \) lag of the macro and financial factors \( g_t \), and \( v_t = A_0^{-1} \Lambda_1^{1/2} \epsilon_t \). Rewrite equation 1 as

\[
y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + B_0 g_t + B_1 g_{t-1} + A_0^{-1} \Lambda_1^{1/2} \epsilon_t, \tag{A.3}\]
substituting \( g_t \) from equation A.2 in equation A.3, results in

\[
y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + B_0 (D_1 g_{t-1} + \delta y_{t-1} - \delta y_{t-2} + u_t) + \ldots \\
\ldots + B_1 g_{t-1} + A_0^{-1} \Lambda_t^{1/2} \epsilon_t,
\]

which can be rearranged as

\[
y_t = (A_1 + B_0 \delta) y_{t-1} + (A_2 - B_0 \delta) y_{t-2} + \ldots + A_p y_{t-p} + \ldots \\
\ldots + (B_1 + B_0 D_1) g_{t-1} + B_0 u_t + A_0^{-1} \Lambda_t^{1/2} \epsilon_t.
\]

Now, this equation can be conveniently written in a state-space form as in

\[
\begin{bmatrix}
  y_t \\
  y_{t-1} \\
  \ldots \\
  y_{t-p} \\
  g_t
\end{bmatrix}
= \begin{bmatrix}
  F_1 & F_2 & \ldots & F_3 & F_4 \\
  I_n & 0 & \ldots & 0 & 0 \\
  \ldots & \ldots & \ldots & \ldots & \ldots \\
  0 & 0 & \ldots & I_n & 0 \\
  \delta & -\delta & \ldots & 0 & D_1
\end{bmatrix}
\begin{bmatrix}
  y_{t-1} \\
  y_{t-2} \\
  \ldots \\
  y_{t-p-1} \\
  g_{t-1}
\end{bmatrix}
+ \begin{bmatrix}
  A_0^{-1} \Lambda_t^{1/2} & 0 & \ldots & 0 & B_0 \\
  0 & 0 & 0 & 0 & 0 \\
  \ldots & \ldots & \ldots & \ldots & \ldots \\
  0 & 0 & 0 & 0 & 0 \\
  0 & 0 & 0 & 0 & I_2
\end{bmatrix}
\begin{bmatrix}
  \epsilon_t \\
  u_t
\end{bmatrix},
\]

where

\[
F_1 = (A_1 + B_0 \delta), \\
F_2 = (A_2 - B_0 \delta), \\
F_3 = A_p, \\
F_4 = (B_1 + B_0 D_1).
\]

The matrix \( \Lambda_t \) takes the form

\[
\Lambda_t = \begin{bmatrix}
  \lambda_{1,t} & 0 & \ldots & 0 \\
  0 & \lambda_{2,t} & \ldots & 0 \\
  0 & 0 & \ldots & \lambda_{n,t}
\end{bmatrix},
\]

(A.8)
where each of its coefficients are a combination of an idiosyncratic shock $h_{j,t}$ and either a macroeconomic factor $m_t$ or a financial factor $f_t$, as in

$$
\lambda_{j,t} = \begin{cases} 
    m_t^{\beta_{m,j}} h_{j,t} & \text{if } j = 1, \ldots, n_m \\
    f_t^{\beta_{f,j}} h_{j,t} & \text{if } j = n_m + 1, \ldots, n 
\end{cases},
$$

(A.9)

where the log of the idiosyncratic shocks $\ln h_{j,t}$ follow an AR(1) process as in

$$
\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1} + e_{j,t}, \quad j = 1, \ldots, n.
$$

(A.10)

### A.5 Priors and conditional posteriors

Here I present the prior and conditional posterior distributions for the parameters and coefficients for the MCMC steps explained in Appendix A.2. I follow the proposed priors and notation from Carriero et al. (2018a), with priors defined as

$$
\text{vec}(A_i; B_i) \sim N(\text{vec}(\mu_A), \Omega_A), \quad i = 1, \ldots, p,
$$

(A.1)

$$
a_j \sim N(\mu_{a,j}, \Omega_{a,j}), \quad j = 2, \ldots, n,
$$

(A.2)

$$
\beta_j \sim N(\mu_{\beta}, \Omega_{\beta}), \quad j = 2, \ldots, n_m, n_{m+2}, \ldots, n,
$$

(A.3)

$$
\gamma_j \sim N(\mu_{\gamma}, \Omega_{\gamma}), \quad j = 1, \ldots, n,
$$

(A.4)

$$
\delta \sim N(\mu_{\delta}, \Omega_{\delta}),
$$

(A.5)

$$
\phi_j \sim \text{IG}(d_{\phi,\phi}, d_{\phi}), \quad j = 1, \ldots, n,
$$

(A.6)

$$
\Phi_u \sim \text{IW}(d_{\Phi_u}, d_{\Phi_u}).
$$

(A.7)

Under these priors, the posterior conditional distributions follow

$$
\text{vec}(A_i; B_i) | A_0, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} \sim N(\text{vec}(\mu_A), \Omega_A), \quad i = 1, \ldots, p,
$$

(A.8)
\[
a_j | \mathbf{A}_i, \mathbf{B}_i, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} \sim N(\mu_{a,j}, \Omega_{a,j}), \quad j = 2, ..., n,
\]
(\text{A.9})

\[
1 \beta_j | \mathbf{A}_i, \mathbf{A}_0, \mathbf{B}_i, \gamma, \Phi, \beta, m_{1:T}, f_{1:T}, S_{1:T}, y_{1:T} \sim N(\mu_\beta, \Omega_\beta), \quad j = 2, ..., n_m, n_{m+2}, ..., n,
\]
(\text{A.10})

\[
\gamma_j | \mathbf{A}_i, \mathbf{A}_0, \mathbf{B}_i, \Phi, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} \sim N(\mu_\gamma, \Omega_\gamma), \quad j = 1, ..., n,
\]
(\text{A.11})

\[
\delta | \mathbf{A}_i, \mathbf{A}_0, \mathbf{B}_i, \Phi, \gamma, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} \sim N(\mu_\delta, \Omega_\delta),
\]
(\text{A.12})

\[
\phi_j | \mathbf{A}_i, \mathbf{A}_0, \mathbf{B}_i, \gamma, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} \sim IG(d_\phi, d_\phi), \quad j = 1, ..., n,
\]
(\text{A.13})

\[
\Phi_u | \mathbf{A}_i, \mathbf{A}_0, \mathbf{B}_i, \gamma, \beta, \delta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} \sim IW(d_\Phi, d_\Phi).
\]
(\text{A.14})

The posterior \( \bar{\mu}_A \) is drawn equation-by-equation through the triangularization method described in Section A.1. The posteriors \( \bar{\mu}_{a,j}, \bar{\mu}_\delta \) and \( \bar{\mu}_\gamma \) follow the results from the standard linear regression model. The factor loadings \( \beta \) are drawn following a GLS-based form depending on the mixture states drawn for the volatilities, as in Carriero et al. (2018a).

With regard to the priors, I adopt a Minnesota-type structure for the VAR coefficients in \( \mathbf{A}_i \). This model contains stationary and non-stationary variables, so the prior coefficients of the stationary variables are set to 0, while the prior coefficients of the non-stationary variables are set to 1. The variance-covariance matrix \( \Omega_A \) is diagonal, with standard Minnesota shrinkage form, as in

\[
\Omega_A = var[A_{ij}^{ij}] = \begin{cases} 
\left( \frac{\theta_2}{\bar{\tau}} \right)^2, & \text{if } i = j, \\
\left( \frac{\theta_1 \theta_2 \sigma_i}{\bar{\tau} \sigma_j} \right)^2, & \text{if } i = j, \\
(\theta_0 \sigma_i)^2, & \text{if intercept or } g_t,
\end{cases}
\]
(A.15)

where \( l \) is the lag. The overall prior tightness \( \theta_1 \) is set here as 0.05, the cross-shrinkage parameter \( \theta_2 \) is set to 0.5 and the intercept shrinkage parameter \( \theta_0 \) is set to 5,000. I follow Carriero et al. (2018a) by also setting a prior variance for the uncertainty factors \( \ln m_t \) and \( \ln f_t \) equal to the intercept. The variance parameters \( \sigma_t \) come from the residual variances of an \( AR(p) \) process for each variable.
The prior means and variances for the remainder of the coefficients are presented in Table A.1.

Table A.1 Mean and variance priors

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Variance</th>
<th>Degree of freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_j$</td>
<td>0</td>
<td>10</td>
<td>-</td>
</tr>
<tr>
<td>$(\gamma_{i,0}, \gamma_{i,1})$</td>
<td>$(\ln \sigma_i^2, 0)$</td>
<td>$(2, 0.4^2)$</td>
<td>-</td>
</tr>
<tr>
<td>$\beta_j$, for $j = 2, \ldots, m_n$, and $j = m_n + 2, \ldots n$</td>
<td>1</td>
<td>0.4</td>
<td>-</td>
</tr>
<tr>
<td>$D_i$</td>
<td>0.8, for first own lag, 0 otherwise</td>
<td>0.2</td>
<td>-</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0</td>
<td>0.1^2</td>
<td>-</td>
</tr>
<tr>
<td>$\phi_j$</td>
<td>0.03</td>
<td></td>
<td>10</td>
</tr>
<tr>
<td>$\Phi_u$</td>
<td>0.01$I_n$</td>
<td>10</td>
<td>-</td>
</tr>
<tr>
<td>$\ln m_0$ and $\ln f_0$</td>
<td>0</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\ln h_{i,0}$</td>
<td>$\ln \sigma_i^2$</td>
<td>2</td>
<td>-</td>
</tr>
</tbody>
</table>

There is discussion in the literature on the impact of the prior on the components $a_j$ of matrix $A_0$. The model may be dependent on the ordering of the variables, along with the priors imposed on $a_j$. This is an issue primarily in using this model for forecasting purposes. I address these questions by following Carriero et al. (2018a) and Cogley and Sargent (2005) and imposing a prior fairly uninformative for $a_j$, with mean of 0 and variances of 10. In addition, the identification procedure of maximizing the variance decomposition over a predefined forecast period is order-invariant, avoiding the problem of choosing the wrong order of variables.

Finally, the dependence of the uncertainty factors on lagged values of $y_t$ creates an (indirect) extra dependency of current values of $y_t$ to lagged values not captured by the main VAR. This dependency is clearly noticed when the main VAR is rewritten in a state-space model, as in equation A.6, where the coefficients $\delta$ are also part of $F_1$ and $F_2$. I follow strategy similar to Mumtaz and Theodoridis (2015) by imposing additional shrinkage to the variance of $\delta$, which I set to $\left(\frac{\theta^2}{\tau^2}\right)$.
B Appendix: Generalized impulse responses procedure

In this Appendix I present the procedure of estimating the generalized impulse responses for the news shock and the uncertainty shocks.

Due to the non-linearity that the time-varying volatilities bring to the model, the feedback effect that the variables cause to the volatility through the uncertainty factors, and the feedback of the uncertainty factors on the mean of the variables, it is not possible to employ a conventional impulse response setting in this case. The strategy here is to use an adaptation of the procedure proposed by Koop et al. (1996) and Pesaran and Shin (1998), taking into account that the shocks \( v_t = A_0^{-1} \Lambda_t^{1/2} \epsilon_t \) are orthogonal by construction.

The idea is to create two distinct forecast paths for the variables \( y_t \), a baseline and a shocked containing the shock of interest (namely, \( \tau_j \)). The generalized impulse responses are the difference between these two paths. To accomplish this, it is necessary to construct a set of random shocks \( \omega_{j,t} \) over the forecast period that mimic the behavior of \( \epsilon_t \). The generalized impulse response (GI) of a \( r \) set of randomly drawn \( \omega_{j,t} \) is given by

\[
GI_r(k, \tau_j, \omega_{j,t}^r, Z_t, \Pi) = E[y_{t+k}^r|\tau_j, \omega_{j,t}^r, Z_t, \Pi] - E[y_{t+k}^r|\omega_{j,t}^r, Z_t, \Pi], \quad (B.1)
\]

where \( k \) is the forecast point in time, \( Z_t \) is the information set containing all the known history up to time \( t \) defined as \( Z_t = (y_{t-p}, ..., y_t; g_{t-p}, ..., g_t) \).\(^{25}\) \( \Pi \) collects the coefficient matrices as \( \Pi = [A_i, B_i, D_i, \beta_j, \gamma_j, \delta] \), \( E[y_{t+k}^r|\tau_j, \omega_{j,t}^r, Z_t] \) is the shocked path of \( y_t \) and \( E[y_{t+k}^r|\omega_{j,t}^r, Z_t] \) is the baseline path of the baseline path of \( y_t \).

Repeat the procedure of equation B.1 \( R \) times, and take the averages over \( R \) of these paths. Koop et al. (1996) show that as \( R \rightarrow \infty \), by the Law of Large Numbers these averages will converge the conditional expectations \( E[y_{t+k}|\tau_j, Z_t, \Pi] \) and \( E[y_{t+k}|Z_t, \Pi] \),

\(^{25}\)Where \( g_t = (\ln m_t; \ln f_t) \).
and the generalized impulse response can be constructed as

\[ GI(k, \tau_j, Z_t, \Pi) = E[y_{t+k}|\tau_j, Z_t, \Pi] - E[y_{t+k}|Z_t, \Pi]. \]  

(B.2)

### B.1 Generalized impulse responses for a news shock

For the news shock case, I start with the state-space procedure presented in equations A.6 and A.9 (Appendix A.4). The news shock is identified as the orthogonalization of the shocks on the mean of the variables that maximize the variance decomposition of one objective variable over a predefined forecast period. It follows that the identification relies on an orthogonalization of the innovations \( \epsilon_t \). By construction, \( \epsilon_t \) is independent from the idiosyncratic innovations \( e_{j,t} \) and the uncertainty innovations \( u_{m,t} \) and \( u_{f,t} \). Since I am only interested in \( \epsilon_t \) for the news shock identification, I set \( e_{j,t} = 0 \), \( u_{m,t} = 0 \) and \( u_{f,t} = 0 \) in this procedure.

With this simplification, it is possible to rewrite equations A.6 and A.9, respectively, as

\[
\begin{bmatrix}
y_t \\
y_{t-1} \\
\vdots \\
y_{t-p} \\
g_t
\end{bmatrix} =
\begin{bmatrix}
F_1 & F_2 & \cdots & F_3 & F_4 \\
I_n & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & I_n & 0 \\
\delta & -\delta & \cdots & 0 & D_1
\end{bmatrix}
\begin{bmatrix}
y_t-1 \\
y_{t-2} \\
\vdots \\
y_{t-p-1} \\
g_{t-1}
\end{bmatrix}
+ \begin{bmatrix}
A_0^{-1} \Lambda_t^{1/2} & 0 & \cdots & 0 & B_0
\end{bmatrix}
\begin{bmatrix}
\epsilon_t
\end{bmatrix},
\]

(B.3)

and

\[
\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1}, \quad j = 1, \ldots, n.
\]

(B.4)

Now that the model has only a single set of innovations \( \epsilon_t \), the generalized impulse responses for the news shock can be constructed with the following steps. The identification of the news shock is dependent on the total variance, and the variance changes over time, so the following procedure is executed at each point in time. This allows the
construction of a time-varying identification, with different impulse responses at every point in the time span considered.

**Step 1: Construct a baseline path.**

Considering one draw $r$ of the random innovations $\omega_{j,t}^r$ and $K$ being the forecast period, construct by simulation a baseline path from $t + 1$ to $t + K$ for the idiosyncratic innovations $\ln h_{j,t}^r$ using equation B.4, and for $y_{t,\text{base}}^r$, $g_{t,\text{base}}^r$ and $\Lambda_{t,\text{base}}^r$ using equation B.3.

**Step 2: Construct a shocked path for a utilization-adjusted TFP shock.**

Take the same draw $r$ from Step 1, and the idiosyncratic innovations $\ln h_{j,t}^r$. For $t + 1$, construct a one standard deviation shock on utilization-adjusted TFP by adding to $\omega_{j,t+1}^r$ the shock $\tau_{TFP}^r$, which is a vector with 1 in the first position (where utilization-adjusted TFP ordered first in the VAR) and zeros elsewhere. Construct by simulation a TFP shocked path from $t + 1$ to $t + K$ for $y_{TFP,t}^r$, $g_{TFP,t}^r$ and $\Lambda_{TFP,t}^r$ using equation B.3.

**Step 3: Construct the impulse responses for a TFP shock.**

Following equation B.1, construct the impulse responses for a utilization-adjusted TFP shock as the differences between the shocked and the baseline paths for the draw $r$ as

$$GI_{TFP,t}^r(k, \tau_{TFP}^r, \omega_{j,t}^r, Z_t, \Pi) = \mathbb{E}[y_{t+k,TFP}^r, g_{t+k,TFP}^r | \tau_{TFP}^r, \Lambda_{t+k,TFP}^r, \omega_{j,t}^r, Z_t, \Pi] - \mathbb{E}[y_{t+k,\text{base}}^r, g_{t+k,\text{base}}^r | \Lambda_{t+k,\text{base}}^r, \omega_{j,t}^r, Z_t, \Pi].$$

(B.5)

**Step 4: Identify the news shock.**

Identify the news shock for the draw $r$ as the orthogonalization on $\epsilon_t$ that maximizes the variance decomposition of utilization-adjusted TFP over a predefined $K$ forecast period.\footnote{Where $g_{t,\text{base}} = (\ln m_{t,\text{base}}; \ln f_{t,\text{base}})$.} The idea of identifying the news shock for every $r$ draw is in line with the discussion about the difference between structural and model identification from Fry and Pagan (2011). Every $r$ draw is a realization of a different model among infinite alternative models, leading to unique identification of the news shock. The best approximation of

\footnote{Where $g_{t,TFP} = (\ln m_{t,TFP}; \ln f_{t,TFP})$.}

\footnote{For this paper, I follow Barsky and Sims (2011) and set $K = 40$ quarters ahead.}
the structural identification will be the average across all \( r \) impulse responses after the news shock is properly identified for each different model.

Following the identification procedure proposed in Section 3.1, the news shock \( \tau_{t,\text{news}}^r \) can be identified as

\[
\tau_{t,\text{news}}^r = \arg \max \frac{\sum_{k=0}^{K} GI_{t,TFP}^r(k, \tau_{TFP}^r, \omega_{j,t}^r, Z_t, \Pi, \tau) GI_{t,TFP}^r(k, \tau_{TFP}^r, \omega_{j,t}^r, Z_t, \Pi, \tau)^r}{\sum_{k=0}^{K} B_1 A^{-1} A^{1/2}_{t+k,TFP} (A^{-1} A^{1/2}_{t+k,TFP})' B_1'}.
\]

(B.6)

subject to

\[
A^{-1}(1, j) = 0, \quad \forall j > 1,
\]

\[
\tau(1, 1) = 0,
\]

\[
\tau^r \tau = 1,
\]

where \( B_1 \) is the line correspondent to the utilization-adjusted TFP coefficients in the state-space representation described in equation A.6 (Appendix A.4).

**Step 5: Construct a shocked path for the news shock.**

Take the same draw \( r \) from Step 1, and the idiosyncratic innovations \( \ln h_{j,t}^r \). For \( t + 1 \), construct a TFP news shock by adding the shock \( \tau_{t,\text{news}}^r \) to \( \omega_{j,t}^r \). Construct by simulation a news shocked path from \( t + 1 \) to \( t + K \) for \( y_{t,\text{news}}^r, g_{t,\text{news}}^r \) and \( \Lambda_{t,\text{news}}^r \) using equation B.3.

**Step 6: Construct the impulse responses for the news shock.**

Following equation B.1, construct the impulse responses for the news shock as the differences between the shocked news path and the baseline path from Step 1 for the draw \( r \) as

\[
GI_{t,\text{news}}^r(k, \tau_{t,\text{news}}^r, \omega_{j,t}^r, Z_t, \Pi) = \mathbb{E}[y_{t+k,\text{news}}^r, g_{t+k,\text{news}}^r | \tau_{t,\text{news}}^r, \Lambda_{t+k,\text{news}}^r, \omega_{j,t}^r, Z_t, \Pi] - \mathbb{E}[y_{t+k,\text{base}}^r, g_{t+k,\text{base}}^r | \Lambda_{t+k,\text{base}}^r, \omega_{j,t}^r, Z_t, \Pi].
\]

(B.8)

**Step 7: Construct the average impulse responses for the news shock.**

Repeat Steps 1 to 6 for \( R \) number of times and form the averages of the shocked news.

\(^{29}\) Where \( g_{t,\text{news}} = (\ln m_{t,\text{news}}; \ln f_{t,\text{news}}) \).
and baseline paths across all $R$ draws of $\omega_{j,t}$ as

$$
\bar{y}_{t+k,\text{news}}(k, \tau_{t,\text{news}}, Z_t, \Pi) = \frac{1}{R} \sum_{r=1}^{R} y^r_{t+k,\text{news}}(\tau^r_{t,\text{news}}, \Lambda^r_{t+k,\text{news}}, \omega^r_{j,t}, Z_t, \Pi),
$$

$$
\bar{g}_{t+k,\text{news}}(k, \tau_{t,\text{news}}, Z_t, \Pi) = \frac{1}{R} \sum_{r=1}^{R} g^r_{t+k,\text{news}}(\tau^r_{t,\text{news}}, \Lambda^r_{t+k,\text{news}}, \omega^r_{j,t}, Z_t, \Pi),
$$

$$
\bar{y}_{t+k,\text{base}}(k; Z_t, \Pi) = \frac{1}{R} \sum_{r=1}^{R} y^r_{t+k,\text{base}}(\Lambda^r_{t+k,\text{base}}, \omega^r_{j,t}, Z_t, \Pi),
$$

$$
\bar{g}_{t+k,\text{base}}(k; Z_t, \Pi) = \frac{1}{R} \sum_{r=1}^{R} g^r_{t+k,\text{base}}(\Lambda^r_{t+k,\text{base}}, \omega^r_{j,t}, Z_t, \Pi).
$$

Lastly, construct the final generalized impulse responses for the news shock as the differences between these averages, as in

$$
GI_{t,\text{news}}(k, \tau_{t,\text{news}}, Z_t, \Pi) = [\bar{y}_{t+k,\text{news}}(k, \tau_{t,\text{news}}, Z_t, \Pi), \bar{g}_{t+k,\text{news}}(k, \tau_{t,\text{news}}, Z_t, \Pi)]
- [\bar{y}_{t+k,\text{base}}(k; Z_t, \Pi), \bar{g}_{t+k,\text{base}}(k; Z_t, \Pi)].
$$

After testing different $R$ sizes, I set $R = 5,000$ for this paper. Changing from $R = 1,000$ to $R = 5,000$ did not present any noticeable difference, so $R = 5,000$ is sufficiently large to achieve the difference between conditional expectations expressed in equation B.2.

### B.2 Measuring the uncertainty transmission effect

The nonlinear model proposed here is flexible enough to investigate whether the effects of news about future productivity depend on the level of uncertainty in the economy. First moment shocks can influence (and be influenced by) the level of uncertainty through two nonlinear feedback devices: a contemporaneous feedback of uncertainty to the mean of the variables, and the lagged feedback effect of the variables to uncertainty. These devices allow expectations on macro and financial conditions to be updated based on the arrival of information about future technology developments. If this update is negligible, or is just noise around the news shock effect, the impulse responses of a news shock under this identification should be similar to the traditional covariance-stationary procedure.
I propose here a counterfactual to evaluate the relation between news shocks and the level of uncertainty. The purpose of the counterfactual is to check whether there is a transmission effect of the news shock through uncertainty. It involves shutting down the contemporaneous feedback of uncertainty to the mean of the variables, and the lagged feedback effect of the variables to uncertainty. Recalling the Main and Uncertainty VARs (equations 1 and 5), the contemporaneous feedback of uncertainty to the mean of the variables is captured by the coefficients $B_i$ in equation 1, and the lagged feedback effect of the variables to uncertainty by the coefficients $\delta$ in equation 5. Shutting down the nonlinear feedback (to and from) uncertainty means restricting to zero the coefficient matrices $B_i$ and $\delta$. Following these restrictions, the Main and Uncertainty VARs would be respectively written as

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + v_t; \quad (B.11)$$

and

$$g_t = D_1 g_{t-1} + ... + D_k g_{t-k} + u_t. \quad (B.12)$$

The procedure for the counterfactual consists of identifying the news shock and calculating the generalized impulse responses from the time-varying procedure described by equation 21 in which the coefficients matrices $B_i$ and $\delta$ are restricted to zero. Formally, define a restricted set of coefficients as $\Pi^\dagger = [A_i, B_i = 0, D_i, \beta_j, \gamma_j, \delta = 0]$. Following the steps described in section 3.1, the artificial generalized impulse responses with no uncertainty feedback can be constructed as

$$G\textit{I}_{t,\text{news}}^\dagger(k, \tau_{t,\text{news}}, Z_t, \Pi^\dagger) = E[y_{t+k}, g_{t+k} | \tau_{t,\text{news}}, A_{t+k,\text{news}}^\dagger, Z_t, \Pi^\dagger] - E[y_{t+k}, g_{t+k} | A_{t+k}^\dagger, Z_t, \Pi^\dagger]. \quad (B.13)$$
### Appendix: Data description

Table C.1 Description of macroeconomic variables

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>2 Consumption</td>
<td>Real per capita consumption in log levels. Computed using PCE (nondurable goods + services), price deflator and population.</td>
<td>Fred</td>
</tr>
<tr>
<td>3 Output</td>
<td>Real per capita GDP in log levels. Computed using the real GDP (business, nonfarm) and population.</td>
<td>Fred</td>
</tr>
<tr>
<td>4 Investment</td>
<td>Real per capita investment in log levels. Computed using PCE durable goods + gross private domestic investment, price deflator and population.</td>
<td>Fred</td>
</tr>
<tr>
<td>5 Hours</td>
<td>Per capita hours in log levels. Computed with Total hours in nonfarm business sector and population values.</td>
<td>Fred</td>
</tr>
<tr>
<td>6 Prices</td>
<td>Price deflator, computed with the implicit price deflator for nonfarm business sector.</td>
<td>Fred</td>
</tr>
<tr>
<td>7 FFR</td>
<td>Fed funds rate.</td>
<td>Fred</td>
</tr>
<tr>
<td>8 Payroll</td>
<td>Total nonfarm payroll: All employees in log levels.</td>
<td>Fred</td>
</tr>
<tr>
<td>9 IP</td>
<td>Industrial production index in log levels.</td>
<td>Fred</td>
</tr>
<tr>
<td>10 Help to unemp.</td>
<td>Help wanted to unemployment ratio.</td>
<td>Fred</td>
</tr>
<tr>
<td>11 Pers. income</td>
<td>Real personal income in log levels.</td>
<td>Fred</td>
</tr>
<tr>
<td>12 M&amp;T sales</td>
<td>Real manufacturing and trad sales in log levels.</td>
<td>Fred</td>
</tr>
<tr>
<td>13 Earnings</td>
<td>Average of hourly earnings (goods producing) in log levels.</td>
<td>Fred</td>
</tr>
<tr>
<td>14 PPI</td>
<td>Producer price index (finished goods) in log levels.</td>
<td>Fred</td>
</tr>
</tbody>
</table>

Note: All for the 1975Q1-2012Q3 period. Monthly series converted to quarterly by averaging over the quarter.
<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Spread</td>
<td>Difference between the 10-year Treasury rate and the FFR.</td>
<td>Fred</td>
</tr>
<tr>
<td>2 S&amp;P500</td>
<td>S&amp;P500 stock index in logs levels.</td>
<td>Fred</td>
</tr>
<tr>
<td>3 S&amp;P dividend yield</td>
<td>S&amp;P dividend yield, in log and annualized.</td>
<td>Fred</td>
</tr>
<tr>
<td>4 EBP</td>
<td>Excess bond premium as computed by Gilchrist and Zakrajšek (2012).</td>
<td>Gilchrist’s website (Mar/2015)</td>
</tr>
<tr>
<td>5 Excess returns</td>
<td>CRSP excess returns, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>6 SMB</td>
<td>Small minus big risk factor, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>7 HML</td>
<td>High minus low risk factor, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>8 Momentum</td>
<td>Momentum, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>9 R15-R11</td>
<td>Small stock value spread, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>10 Ind. 1</td>
<td>Consumer industry sector-level return, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>11 Ind. 2</td>
<td>Manufacturing industry sector-level return, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>12 Ind. 3</td>
<td>High technology industry sector-level return, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>13 Ind. 4</td>
<td>Health industry sector-level return, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
<tr>
<td>14 Ind. 5</td>
<td>Other industries sector-level return, in log and annualized.</td>
<td>French’s website (Jul/2016)</td>
</tr>
</tbody>
</table>

Note: All for the 1975Q1-2012Q3. Monthly series converted to quarterly by averaging over the quarter.
Table C.3 Macroeconomic and financial uncertainties

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Financial Uncertainty Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Realized</td>
<td>Realized volatility computed using daily returns using the robust estimator by Rousseeuw and Croux (1993).</td>
<td>CRPS</td>
</tr>
<tr>
<td>Volatility</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 VXO</td>
<td>Option-implied volatility of the SP100 future index. Available from 1986Q1.</td>
<td>CBOE</td>
</tr>
<tr>
<td>3 LMN-fin-1</td>
<td>Financial forecasting uncertainty computed by Ludvigson et al. (2016). -1 is one-month-ahead, -3 is three-months and -12 is one-year ahead.</td>
<td>Ludvigson’s website (Feb/2016)</td>
</tr>
<tr>
<td>4 LMN-fin-3</td>
<td>Ludvigson et al. (2016). -1 is one-month-ahead, -3 is three-months and -12 is one-year ahead.</td>
<td></td>
</tr>
<tr>
<td>5 LMN-fin-12</td>
<td>three-months and -12 is one-year ahead.</td>
<td></td>
</tr>
<tr>
<td><strong>Macroeconomic Uncertainty Measures</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Policy</td>
<td>Economic Policy Uncertainty Index in logs computed by Baker, Bloom, and Davis (2016).</td>
<td>Bloom’s website (Mar/2016)</td>
</tr>
<tr>
<td>uncertainty</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 Business</td>
<td>Business forecasters dispersion computed by Bachmann, Elstner, and Sims (2013) up to 2011Q4.</td>
<td>AER website</td>
</tr>
<tr>
<td>uncertainty</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 SPF</td>
<td>SPF forecasters dispersion on one-quarter-ahead Q/Q real GDP forecasts computed using the interdecile range.</td>
<td>Philadelphia Fed</td>
</tr>
<tr>
<td>disagreement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4 LMN-macro-1</td>
<td>Macro forecasting uncertainty computed by Ludvigson et al. (2016). -1 is one-month-ahead, -3 is three-months and -12 is one-year ahead.</td>
<td>Ludvigson’s website (Feb/2016)</td>
</tr>
<tr>
<td>5 LMN-macro-3</td>
<td>and -12 is one-year ahead.</td>
<td></td>
</tr>
<tr>
<td>6 LMN-macro-12</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: All for the 1975Q1-2012Q3 period except when noted. Monthly series converted to quarterly by averaging over the quarter.
D  Appendix: Additional graphs

Figure D.1 Volatilities of macroeconomic variables

Note: The estimated volatilities of macroeconomic variables are composed of an idiosyncratic component and the common macroeconomic volatility factor weighted by a loading $\beta_{m,j}$. The dotted lines define the 68% confidence bands computed with 200 posterior draws. The macroeconomic variables are described in Table C.1.

Figure D.2 Volatilities of financial variables

Note: The estimated volatilities of financial variables are composed of an idiosyncratic component and the common financial volatility factor weighted by a loading $\beta_{f,j}$. The dotted lines define the 68% confidence bands computed with 200 posterior draws. The financial variables are described in Table C.2.
Figure D.3 Distribution of time-varying effects of news shocks (all variables)

Note: Distribution (50%, 68% and 95% percentiles) over time of the median effect of a news shock. Shocks are normalized to a 1% increase in utilization-adjusted TFP after 20 quarters. The news shock is identified under the procedure proposed in Section 3.1. The generalized impulse responses for each period are the average of 5,000 simulated random innovations, as described in Appendix B.
Figure D.4 Distribution of time-varying effects of news shocks over different forecast horizons with no feedback effect from uncertainty

Note: Distribution (50% and 68% percentiles) over time of the median effect of a news shock. Shocks are normalized to a 1% increase in utilization-adjusted TFP after 20 quarters. Red and blue lines correspond to the average of generalized impulse responses of the benchmark and counterfactual models, respectively. The news shock for the counterfactual is identified for each period in time under the procedure proposed in Section B.2. The generalized impulse responses for each period are the average of 5,000 simulated random innovations, as described in Appendix B.