An empirical evaluation of news and uncertainty shocks as sources of business cycles

by

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Declarations

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This Thesis is submitted to the University of Warwick in support of my application for the degree of Doctor of Philosophy. I declare that this Thesis is the result of my own work and this includes the part in which co-authored paper has been derived as indicated. This Thesis has not been submitted in any previous application for any degree.

Chapter 3 has been circulated as "News and Uncertainty shocks", a paper co-authored by Ana Beatriz Galvão, and presented at the Society for Nonlinear Dynamics and Econometrics Symposium 2016 (SNDE), Paris (France), Royal Economics Society Conference 2017 (RES), Bristol (UK), International Association for Applied Econometrics Conference 2017 (IAAE), Sapporo (Japan), European Economic Association Conference 2017 (EEA), Lisbon (Portugal), LuBraMacro 2017, Porto de Galinhas (Brazil) and Computational and Financial Econometrics Conference 2017 (CFE), London (UK), and as a seminar at Warwick Business School, Economic Modelling and Forecasting brown bag seminar 2015, Coventry (UK), University of Warwick, Macroeconomics workshop 2015, Coventry (UK), University of São Paulo, Ribeirão Preto (Brazil) and University of Valencia, Valencia (Spain). The paper is currently submitted for publication in an academic journal.

Chapter 4 has been circulated as the paper “Amplification Effects of News Shocks Through Uncertainty”, and presented at the Society for Nonlinear Dynamics and Econometrics Symposium 2018 (SNDE), Tokyo (Japan), Royal Economics Society Conference 2018 (RES), Brighton (UK), Uncertainty and Economic Activity: Measurement, Facts and Fiction Conference 2018, Beijing (China) and Inflation Targeting Conference 2018, Rio de Janeiro (Brazil), and as a seminar at University of Warwick, Macroeconomics workshop, Coventry (UK). It was granted the Gerald P. Dwyer prize for the best paper in finance presented by a graduate student at the 26th Symposium of the Society of Nonlinear Dynamics and Econometrics.

Chapter 5 has been circulated as the paper “News Shocks and the Slope of the Term Structure of Interest Rates: Comment”, and presented at the Computational and Financial Econometrics Conference 2015 (CFE), International Association for Applied Econometrics Conference 2016 (IAAE), Milan (Italy) and Brazilian Econometrics Society Conference 2016 (SBE), Foz do Iguaçu (Brazil). It was granted the Young Investigator Training Program (YITP) Research Prize 2016 (International Association for Applied Econometrics) and the Award for Outstanding Contribution to Research 2016-2017 (Warwick Business School). A shorter version of this paper was published as “News Shocks and the Slope of the Term Structure of Interest Rates: Comment” at the *American Economic Review*, 2017, volume 107(10), pages 3243-49 (Cascaldi-Garcia, 2017).

Chapter 6 has been circulated as the paper “Forecast Revisions as Instruments for News Shocks”.

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Abstract

This Thesis contributes to the literature of business cycles driven by agents' beliefs. In Chapter 3, we provide novel empirical evidence linking the effects of technology news shocks to uncertainty shocks. Their correlation implies that when financial uncertainty shocks hit the economy, utilization-adjusted total factor productivity (TFP) increases over the medium-term. This leads to an attenuation of the effects on economic activity from news shocks in the short-term and from uncertainty shocks in the medium-term. Supported by these results, we propose an identification strategy to measure the effects of 'good uncertainty' shocks and disentangle the importance of technological news, good and bad uncertainties, and ambiguity shocks in explaining business cycle variation.

In Chapter 4, I investigate the empirical relationship between agents' responses to future technological changes and the level of uncertainty in the economy. I show that the economic responses to news shocks change substantially over time, and that this dynamic couples with periods of high and low uncertainty. Periods of high uncertainty are characterized by higher positive economic effects of news shocks on output, consumption, investment and real personal income. 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, amplifying its positive outcomes.

Kurmann and Otrok [2013] show that the effects on economic activity from news on future productivity growth are similar to the effects from unexpected changes in the slope of the yield curve. In Chapter 5, I show that these results do not hold in the light of a recent update in the utilization-adjusted TFP series produced by Fernald [2014].

In Chapter 6, I propose a novel method of identifying technological news shocks through instrumental variables based on forecast revisions from the Survey of Professional Forecasters. I construct proxy measures for the slope of the long-run trend of GDP, investment and industrial production, which are strong instruments for recovering the underlying news shock. The procedure has the advantage of relying on information about agents' expectations, instead of the statistical procedures currently used for the news shock identification. By employing a proxy SVAR, I show that news shocks produce substantial effects on impact on GDP and investment. The effects on consumption in the short-run, however, are milder than usually presented by the news shock literature.

Chapter 1

Introduction

What are the main sources of economic fluctuations in the short and long-run? This Thesis explores this question by evaluating the role of anticipated changes in the technology level of the economy, or *news shocks*, on driving business cycles, and its relation to uncertainty.

The idea of business cycles is that economic activity can be decomposed into two parts: a *trend*, which represents the long-run growth of the economy, and the *cycle*, which is the unpredictable fluctuation around the long-run trend. These fluctuations are caused by temporary shocks, such as unexpected technological innovations, higher uncertainty, changes in fiscal policy, oil price variations, and money supply, among others.

The Real Business Cycle theory says[1] that fluctuations are the efficient response to these random exogenous shocks. There are costs associated to fluctuations, which arise from the deep and complex relationship among economic variables and agents. First, heterogeneity across agents makes the effect of recessions hit people unequally. Second, fluctuations may affect the average level of employment and output. Third, 'big shocks' are different from 'small shocks'. For example, the strong recessionary impact of the financial crisis of 2007/08 may have reduced not only the level of the output, but also the potential of the economy, creating permanent negative effects. Understanding the main structural sources of these fluctuations, the economic effects, and the underlying transmission mechanisms are fundamental for the design of stabilization policies.

In this Thesis I focus specifically on business cycles driven by agents' beliefs, namely news and uncertainty shocks. News shocks are formally defined as changes in the future total factor productivity (TFP) that are foreseen by the economic agents.[2] The idea behind a news shock is that technological innovations take time to have an impact on the economy. Part of this technological impact is foreseen by the economic agents, who react to it in the present. If the agents are rational, positive news should generate positive (and permanent) co-movement among GDP, consumption and investment. It follows that the expectation of higher future productivity is capable of generating booms and busts even before effective technological change materializes.

Bloom [2009] formally defines uncertainty shocks as an increase in the volatility of TFP shocks that have a temporary negative effect in output growth. The idea is that, if there is an unexpected hike in the uncertainty level of the economy, firms and consumers will take precautionary actions in the short-run such as reducing investment, consumption and employment. As a result, sudden increases in uncertainty produce short-run negative fluctuations in the economy.

[1] See Stadler [1994] for an extensive review of the real business cycle literature.
[2] Beaudry and Portier [2006].

While the economic effects of news and uncertainty have been vastly explored by the business cycle literature, this is the first research that shows the possible interconnections between them. In Chapter 3, we provide novel empirical evidence linking the empirical effects of technological news shocks to uncertainty shocks. We identify news and a series of uncertainty shocks separately, by maximizing the respective forecasting error variances of productivity and observed uncertainty. Following Barsky and Sims [2011], news shocks maximize the productivity long-run variance (over 10 years) and uncertainty shocks maximize the uncertainty short-run variance (over two quarters, as in Caldara et al., 2016).

After a news shock, it is possible to observe a short-lived hike in financial uncertainty, which is similar to an uncertainty shock. When the financial uncertainty shock is identified, the result on utilization-adjusted TFP is positive in the medium-run, which is similar to the expected path of a news shock. As a result, reconstructed news and uncertainty shocks are positively correlated. If news and financial uncertainty shocks are, indeed, independent drivers of the business cycle, they should not present such a correlation. We propose an identification procedure in which it is possible to separate the news shock from its correlated part with uncertainty ('truly news'), and the uncertainty shock from its correlated part with news ('truly uncertainty').

In Chapter 4, I study the different effects of a news shock over time, amplified by uncertainty mechanisms. While in Chapter 3 proxies of uncertainty measures are taken as observed, in Chapter 4 uncertainty is estimated endogenously from the second moment of the variables. I propose an empirical model and identification procedure to investigate whether economic responses to news about future productivity change 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.

The premise of the model is that uncertainty measures the agents' expectations about current and future economic conditions. It is reasonable to think that these expectations should also be updated when the agents receive news about future productivity. In other words, the level of uncertainty *endogenously* responds to exogenous news shocks. To meet these requirements, I employ a stochastic volatility in mean model that treats macroeconomic and financial uncertainties as latent variables. The baseline model builds upon Carriero et al. [2016a], as a nonlinear stochastic volatility Bayesian vector autoregressive (VAR) model for large datasets.

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 I propose 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. This setup allows the evaluation of whether the impact of a news shock changes in periods of high or low uncertainty, and if the theoretical assumption of positive comovement[3] among macroeconomic variables after a news shock holds.

While Chapters 3 and 4 deal with the relationship between technological news and uncertainty, in Chapter 5, I explore the relationship between news shocks and the slope of the term structure, defined as the spread between the yield on a long-term treasury bond and a short-term bill rate. Kurmann and Otrok [2013] show that reconstructed news shocks and shocks to the slope of the term structure share a correlation of 0.86. Since the economic responses after a slope shock are identical to a news shock, the authors conclude that the uneven effect between the short and long-term rates is the *endogenous* response of the monetary policy to a news shock. I revisit these results in light of an update in the quarterly utilization-adjusted TFP series calculated by Fernald [2014], which is the series that supports the news shock identification in Kurmann and Otrok [2013].

Finally, Chapter 6 is solely dedicated to technological news shocks. I propose a novel identification procedure for news shocks, based on instrumental variables. The idea is to explore the information about agents' expectations to empirically identify the news shock. The application I propose is based on only one assumption: if agents expect a higher future productivity, they should expect a higher future economic growth as well. It follows that positive news about productivity should be (positively) correlated with news about future economic activity.

While news about future TFP is not directly observed, proxies for news about future economic activity can be constructed through forecast revisions. The Survey of Professional Forecasters (SPF) provides quarterly forecasts for a series of economic indicators, up to one year ahead. Three of these series are particularly relevant for technological news: GDP, investment and industrial production. Positive news about

[3] Beaudry and Portier [2006].

future technology should be reflected as a higher future GDP, investment and industrial production. I propose a methodology of measuring revisions about the long-run trend of these variables by calculating differences between updates on forecasts and *nowcasts*. This method allows the construction of a quarterly time series for forecast revisions about future GDP, investment and industrial production. I employ these measures as instruments for the news shock through the external validity procedure introduced by Mertens and Ravn [2013] and Stock and Watson [2012]. This approach identifies structural shocks based on information not contained on the VAR, which are noisy measures of the structural shock.

Chapter 2

Literature review

In this Chapter I present a brief literature review which nests this Thesis. A more detailed review is conducted in each of the four main Chapters (3, 4, 5 and 6).

The main bulk of this Thesis relates to the literature about technological news shock. Although much has been done to answer the question of how do economic agents react to information about future technological improvements,[1] 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. There remains an ongoing discussion about (i) the extent to which the news shock explains business cycles, (ii) how quickly one would observe an effect on productivity, and (iii) the effect on other important macroeconomic variables.

On an aggregate level, the literature on technological news shocks shows that positive news generates long-term co-movement among GDP, consumption and investment, and it is deflationary in the medium-term. These results are demonstrated by Beaudry and Portier [2006], Barsky and Sims [2011] and Beaudry and Portier [2014]. However, the empirical evidence is contradictory about the effects on the labor market. While Beaudry and Portier [2006] show that a news shock generates a positive and significant effect on hours worked (consistent with the results from Christiano et al., 2003), Barsky and Sims [2011] present a negative effect of news on hours (in line with the technological shock from Galí, 1999).

News shocks generate booms and busts based on agents' beliefs, and the literature has already shown the predictive power of expectations on driving business cycles. Miyamoto and Nguyen [2017] argue that the precision of news shocks improves when forecast data is also considered in the information set. Levchenko and Pandalai-Nayar [2018] show that a non-technological expectation shock accounts for a large share of business cycle fluctuations in the short-run. Clements and Galvao [2018] show that data uncertainty influences the impact of expectation shocks on the economy.

This Thesis also relates to the uncertainty literature. Bloom [2009] shows that uncertainty shocks are a source of business cycle fluctuations and have a temporary negative effect on output growth. Bachmann et al. [2013], Jurado et al. [2015], and Baker et al. [2016] provide evidence of the short-run negative effects of uncertainty shocks on economic activity. Ilut and Schneider [2014] describe how ambiguity shocks, that is, changes in Knightian uncertainty, have direct effects on productivity and are an alternative source of business cycle fluctuation. Periods of high uncertainty are related to

[1] See, for example, Beaudry and Portier [2006], Jaimovich and Rebelo [2009], Barsky and Sims [2011], Kurmann and Otrok [2013], Schmitt-Grohe and Uribe [2012], Blanchard et al. [2013], Forni et al. [2014], Beaudry and Portier [2014], Vukotić [2017], Cascaldi-Garcia and Galvao [2017] and Levchenko and Pandalai-Nayar [2018].

a higher potential return on investment, increasing the range of growth options (Segal et al., 2015). While uncertainty reduces the utilization of production factors, it also creates an incentive to substitute less flexible for more flexible capital (Comin, 2000, Bloom, 2009, Cascaldi-Garcia and Galvao, 2017).

A recent advance in the uncertainty literature refers to the separation between macroeconomic and financial uncertainty, the approach also followed by this Thesis. Jurado et al. [2015] and Carriero et al. [2016a], for example, construct latent macro and financial uncertainty measures based on common factors across the volatilities of macro and financial variables. From a methodological perspective, the estimation of these factors 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 [2016] and Carriero et al. [2016c] propose models with a contemporaneous feedback of a common volatility factor to the mean.

This Thesis is also aligned with the literature that explores 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. Harvey [1988], Estrella and Hardouvelis [1991] and Ang and Piazzesi [2003] show that the slope of the term structure carries information that helps to predict macroeconomic activity, and is connected to the transmission of monetary policy. Kurmann and Otrok [2013], Cascaldi-Garcia [2017] and Kurmann and Sims [2017] debate whether the macroeconomic predictability of the slope of the term structure relates to the effect of news shocks. Görtz et al. [2016] present the role of news shocks in light of propagation through frictions in financial intermediation.

From the methodological perspective, this Thesis is linked to the literature that deals with the calculation of proxies for the technology level, and its use for the identification of news shocks. Fernald [2014] calculates such a proxy as a utilization-adjusted TFP series by employing the methodology described by Basu et al. [2006] and Basu et al. [2013]. This series is used by both main empirical identification strategies for news shocks available in the literature: one based on a combination of short and long-run restrictions (Beaudry and Portier, 2006), the other based on explaining the medium-run effects on TFP (Barsky and Sims, 2011).

Finally, this Thesis relates to the business cycle literature that employs exogenous variables as instruments for the identification of structural shocks. Mertens and Ravn [2013] and Stock and Watson [2012] propose an identification method by relying on external validity in a Structural VAR (proxy SVAR). Ramey [2016] and Kilian and

Lütkepohl [2017] present an extensive overview of identification based on extraneous data. The method has been applied to identify monetary policy shocks (Stock and Watson, 2012, Gertler and Karadi, 2015, Miranda-Agrippino and Ricco, 2018), fiscal policy shocks (Mertens and Ravn, 2014, Caldara and Kamps, 2017), uncertainty shocks (Carriero et al., 2015b, Piffer and Podstawski, 2017) and oil supply shocks (Montiel Olea et al., 2016). With respect to news shocks, extraneous data have been applied to news about future fiscal spending (Auerbach and Gorodnichenko, 2012) and for news about future oil supply (Arezki et al., 2017).

Chapter 3

News and uncertainty shocks

3.1 Introduction

News shocks are anticipated shocks that affect the economy in the current period even though it may take some time until they materialize. Jaimovich and Rebelo [2009] explain how news about future total factor productivity affects current output, consumption and investment. Using VARs, Beaudry and Portier [2006] and Barsky and Sims [2011] provide empirical evidence of the effects of technology news shocks on macroeconomic variables. Schmitt-Grohe and Uribe [2012] show that anticipated shocks explain a large share of business cycle fluctuations, but they argue that anticipated shocks on productivity are not very important. Christiano et al. [2014] establish that anticipated risk shocks explain business cycle fluctuations in a model with financial frictions.

Bloom [2009] shows that uncertainty shocks are a source of business cycle fluctuations and have a temporary negative effect on output growth. Bachmann et al. [2013], Jurado et al. [2015], and Baker et al. [2016] provide evidence of the short-run negative effects of uncertainty shocks on economic activity. Ilut and Schneider [2014] describe how ambiguity shocks, that is, changes in Knightian uncertainty, have direct effects on productivity and are an alternative source of business cycle fluctuation.

In this paper, we provide novel empirical evidence linking the empirical effects of technology news shocks to uncertainty shocks. News and uncertainty shocks are identified by maximizing the respective forecasting error variances of productivity and observed uncertainty. Following Barsky and Sims [2011], news shocks maximize the productivity long-run variance (after 10 years) and uncertainty shocks maximize the uncertainty short-run variance (after 2 quarters, as in Caldara et al., 2016). If these shocks are structural from an economic perspective, they should be orthogonal even when separately identified. However, we find that news and financial uncertainty shocks are positively correlated, indicating that the interpretation of its economic responses are inaccurate. It follows that the standard identification assumptions from the literature are unable to properly identify the true news and uncertainty shocks. We test this correlation for a specific group of uncertainty measures, which coincides with the financial uncertainty measures in Ludvigson et al. [2016]. They are measures of quantifiable risk as in Christiano et al. [2014]. In contrast, news and uncertainty shocks are not correlated (or are negatively correlated) if we employ macroeconomic measures of uncertainty as in Ludvigson et al. [2016]. One of these measures includes professional forecaster dispersion, which is associated with ambiguity changes as in Ilut and Schneider [2014].

When financial uncertainty shocks hit the economy, utilization-adjusted total factor productivity increases over the medium run. This leads to an attenuation of the negative impact of increasing uncertainty on economic activity. Financial uncertainty shocks are short lived. In contrast, macroeconomic uncertainty shocks have no effect on utilization-adjusted productivity, so the negative effects of uncertainty shocks are deeper and more persistent. Also, the positive effects of technology news shocks on output, consumption, investment and hours are attenuated over the short run. This is supported by evidence that news shocks are followed by increasing financial uncertainty over the short run.

Supported by these empirical results, we propose a new identification strategy to obtain the impact of 'good uncertainty' shocks and disentangle the importance of news, financial uncertainty and ambiguity shocks in explaining business cycle variation. The strategy requires the identification of 'truly news' shocks, uncorrelated with unexpected changes in financial uncertainty and ambiguity, and of 'truly uncertainty' shocks, uncorrelated with unexpected changes in technology and ambiguity.

Our identification strategy provides evidence of positive and significant responses of output, consumption, investment and hours to technology news shocks, even at short horizons. A recent survey by Beaudry and Portier [2014] indicates that by applying the Barsky and Sims [2011] identification scheme, the response over hours is normally positive, but it is not statistically different from zero over short horizons. By removing the correlation between news and financial uncertainty shocks, we remove the uncertainty attenuation bias and find a positive and significant effect in hours.

Our identification strategy also provides evidence that not all observed uncertainty measures are equal. By working with the correlation between financial uncertainty and news shocks, we are able to measure the impact of 'good uncertainty' shocks, that is, shocks that increase the likelihood of technology news shocks. We show that they explain a larger share of the variation in output over medium-run horizons (2 years), while bad uncertainty shocks play a more important role over short horizons. We also demonstrate that ambiguity shocks have more persistent effects than financial uncertainty shocks, implying that they have a role explaining business cycle variation over long horizons.

Ludvigson et al. [2016] and Carriero et al. [2016a] provide strategies to disentangle the impact of different uncertainty shocks in the macroeconomy. In this paper, we exploit a novel strategy to understand whether different uncertainty measures quantify different types of shocks. The strategy is based on correlations between some uncertainty shock measures and technology news shocks. Our results support a variety of theories that consider the role of uncertainty as a business cycle driver, including 'wait-and-see' effects (Bachmann et al., 2013), confidence effects (Ilut and Schneider, 2014), growth options effects (as suggested in Bloom, 2014) and the possibility of uncertainty traps (Fajgelbaum et al., 2017).

We survey the structural VAR literature on news and uncertainty shocks in Section 3.2, where we also provide the details of our baseline model and analysis of the responses to news and uncertainty shocks. Section 3.3 describes the identification strategy used to disentangle all sources of business cycle variation and our measure 'good uncertainty'. Section 3.3 also presents the empirical results obtained with this new strategy and discusses implications for the DSGE literature on understanding the effects of uncertainty.

3.2 News, uncertainty shocks and the macroeconomy

We start by measuring the impact of news and uncertainty shocks on measures of economic activity. Uncertainty is proxied by a set of financial and macroeconomic uncertainty measures available in the literature. In this section, we provide the details of an identification scheme for both news and uncertainty shocks, and we show that financial uncertainty and news shocks are positively correlated.

3.2.1 Literature review

Barsky and Sims [2011] report that news shocks explain approximately 40% of the variation in output over long horizons (10 years), while Bachmann et al. [2013] provide evidence that 12% of the long-run variation in manufacturing product is explained by shocks to stock market volatility – a popular measure of financial uncertainty. In contrast to the long-run effects of news shocks, the impact of uncertainty shocks typically peaks after one year (Jurado et al., 2015; Baker et al., 2016). Bachmann et al. [2013] report an exception, showing that shocks to a measure of business forecaster dispersion have a persistent impact on manufacturing output, explaining up to 39% of the variation after 5 years. The Bachmann et al. [2013] uncertainty measure is computed using forecaster dispersion from the Business Outlook Survey. In general, uncertainty shocks explain 10% of the long-run variation in economic activity, as suggested by Gilchrist and Zakrajšek [2012], Jurado et al. [2015], Caldara et al. [2016].

Recently, Carriero et al. [2016a] results suggest that macroeconomic uncertainty explains approximately 20% of the variation in economic activity variables, while financial uncertainty explains approximately 10%. The identification scheme in Ludvigson et al. [2016] reverts these results in favor of financial uncertainty shocks. In the literature, macroeconomic uncertainty measures are typically related to the forecasting uncertainty of macroeconomic variables, such as real GDP and the aggregate price level. Financial uncertainty variables are measures of equity markets volatility, that is, of quantified risk.

Bloom [2014] considers professional forecasters' dispersion as a measure of uncertainty, but Ilut and Schneider [2014] employ forecasters' dispersion as a measure of ambiguity. Table 3.1 describes the measures of uncertainty considered and divides them into two groups: financial and macroeconomic uncertainty. Policy uncertainty and business uncertainty, listed in the bottom panel, are not typical macroeconomic uncertainty measures, since they are not computed with respect to variables such as GDP and inflation, but they are illustrative of the macroeconomy beyond financial markets.

3.2.2 Identification procedure and estimation

The news shock is identified following procedure proposed by Barsky and Sims [2011], and is closely related to Francis et al. [2014] and Uhlig [2005]'s maximum forecast error variance approach. The news shock identification finds the shock that best explains future unpredictable movements of utilization-adjusted TFP, which is a proxy for technology. This is equivalent to find the orthogonalization across the innovations that maximizes the forecasting variance of productivity over a predefined period. Moreover, this shock is imposed to be orthogonal to TFPs own innovation, which is the unexpected TFP shock. This restriction guarantees that the news shock has zero effect on utilization-adjusted TFP on impact. It follows that two potential structural shocks are identified: news and unexpected TFP shocks. The full description of the identification scheme is present in Appendix A.1. Following Barsky and Sims [2011] and Kurmann and Otrok [2013], the horizon to maximize the forecasting variance of productivity is set to 10 years ($H = 40$). Because of the large information set included in the VAR model described, we are confident that fundamentalness is not an issue affecting these empirical results, as suggested by Forni et al. [2014].

We employ the same identification procedure for the uncertainty shock, with two caveats. First, following Caldara et al. [2016], uncertainty shocks are identified by maximizing the forecast error variance of uncertainty over two quarters, instead of 10 years for the news shock. Second, there are no restrictions of the contemporaneous effect of the shock on uncertainty. This approach is not very different from the short-run restrictions implied by the Cholesky decomposition, but it has the advantage of clearly stating that uncertainty shocks have typically short-run effects in contrast with the long-run effects of technology news shocks.

Table 3.1: Description of variables

	Name	Description	Source
1	Utilization-adjusted TFP	Utilization-adjusted TFP in log levels. Computed by Fernald [2014].	Fernald's website (Nov/2015)
2	Consumption	Real per capita consumption in log levels. Computed using PCE (nondurable goods + services), price deflator and population.	Fred
3	Investment	Real per capita investment in log levels. Computed using PCE durable goods + gross private domestic investment, price deflator and population.	Fred
4	Output	Real per capita GDP in log levels. Computed using the real GDP (business, nonfarm) and population.	Fred
5	Hours	Per capita hours in log levels. Computed with Total hours in nonfarm business sector and population values.	Fred
6	Prices	Price deflator, computed with the implicit price deflator for nonfarm business sector.	Fred
7	SP500	SP500 stock index in logs levels.	Fred
8	EBP	Excess bond premium as computed by Gilchrist and Zakrajšek [2012].	Gilchrist's website (Mar/2015)
9	FFR	Fed funds rate.	Fred
10	Spread	Difference between the 10-year Treasury rate and the FFR.	Fred
	Financial Uncertainty Measures		
1	Realized Volatility	Realized volatility computed using daily returns using the robust estimator by Rousseeuw and Croux [1993].	CRPS
2	VXO	Option-implied volatility of the SP100 future index. Available from 1986Q1.	CBOE
3 4 5	LMN-fin-1 LMN-fin-3 LMN-fin-12	Financial forecasting uncertainty computed by Ludvigson et al. [2016]. -1 is one-month-ahead, -3 is three-months and -12 is one-year ahead.	Ludvigson's website (Feb/2016)
	Macroeconomic Uncertainty Measures		
1	Policy uncertainty	Economic Policy Uncertainty Index in logs computed by Baker et al. [2016].	Bloom's website (Mar/2016)
2	Business uncertainty	Business forecasters dispersion computed by Bachmann et al. [2013] up to 2011Q4.	AER website
3	SPF disagreement	SPF forecasters dispersion on one-quarter-ahead Q/Q real GDP forecasts computed using the interdecile range.	Philadelphia Fed
4 5 6	LMN-macro-1 LMN-macro-3 LMN-macro-12	Macro forecasting uncertainty computed by Ludvigson et al. [2016]. -1 is one-month-ahead, -3 is three-months and -12 is one-year ahead.	Ludvigson's website (Feb/2016)

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

For both the identification of news and uncertainty shocks, the VAR model is estimated in levels with 5 lags, with the aid of the Minnesota priors (Litterman, 1986) to address the reasonably large number of endogenous variables, and the 'dummy observation prior'. The option for the variables in levels is in line with Barsky and Sims [2011], allowing for the possibility of cointegration among the variables. The estimation of the model and the prior hyper-parameters follow methodology proposed by Bańbura et al. [2010] and Carriero et al. [2015a].[1] with 1,000 posterior draws. Confidence bands for the impulse response graphs are computed using all the draws from the posterior distribution.[2]

Relevant forward-looking variables are included among the endogenous variables.[3] Following the news shock literature (Beaudry and Portier, 2006, Barsky and Sims, 2011), technology-induced productivity changes are measured using the utilization-adjusted total factor productivity computed by Fernald [2014]. The model includes consumption, output, investment and hours as measures of economic activity. Additional endogenous variables are measures of aggregate prices, equities prices (S&P500), the policy rate, and the slope of the yield curve (following the link between news and slope shocks in Kurmann and Otrok, 2013). The VAR model also includes a measure of credit conditions – the excess bond premium, as computed by Gilchrist and Zakrajšek [2012], and a measure of financial uncertainty based on the S&P500 realized volatility. The details of the time series employed are available in Table 3.1. Quarterly data from 1975Q1 to 2012Q3 is employed.

3.2.3 Responses to news shocks

Figure 3.1 shows the responses of economic activity variables (output, consumption, investment, hours), productivity (utilization-adjusted TFP) and uncertainty, as measured by the realized volatility, to news shocks. These results follow the previous literature surveyed in Beaudry and Portier [2014]. News shocks have a positive impact effect on output, consumption and investment, as in Beaudry and Portier [2006] and Barsky and Sims [2011], but the impact effects are not significantly different from zero, as indicated by the 68% confidence bands. In the long run, technology news shocks explain 35% of the variation of the utilization-adjusted TFP, 28% of consumption variation, 22% of output variation and 15% of investment variation.

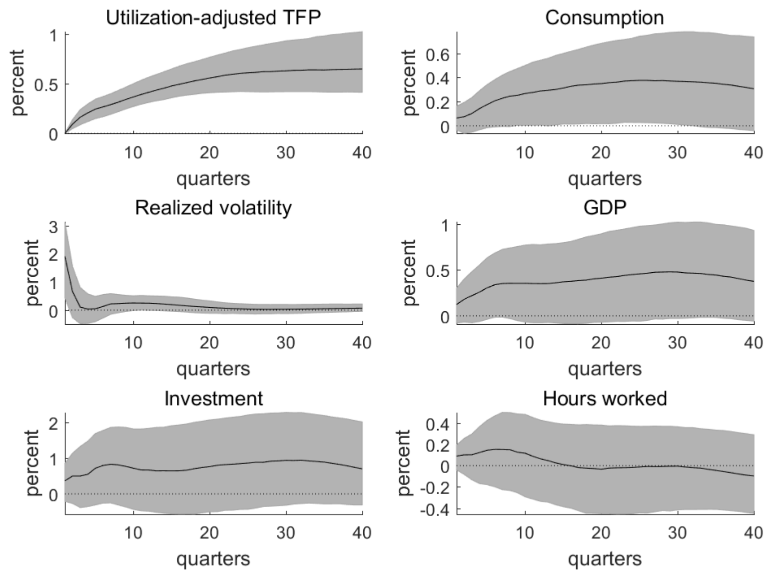
A novel interesting result arises from observing the effect of news shocks on financial uncertainty. News shocks drive a significant increase in uncertainty of approximately

[1]We obtain the overall prior tightness of 0.2 by maximizing the log-likelihood over a discrete grid, as in Carriero et al. [2015a].

[2]As the VAR parameters change, the signs of the identified shocks might flip because the identification is based on the forecast error variance. To ensure a positive news shock, we check whether the response of total factor productivity is positive after 40 quarters. If the response is negative, all computed responses are multiplied by (-1). In the case of uncertainty shocks, we simply check whether the shock has a positive impact on the uncertainty measure and multiply the responses by (-1) if they are negative.

[3]The presence of forward-looking economic variables, such as stock prices, is a necessary condition for the proper identification of a news shock (Beaudry and Portier, 2006).

Figure 3.1: Responses to news shocks in the baseline VAR model



Note: Shaded areas are 68% confidence bands computed with 1,000 posterior draws. The baseline identification scheme for news shocks is described in section 3.2.2, and appendix A.1. The VAR model includes all variables in the first panel of Table 3.1 + realized volatility.

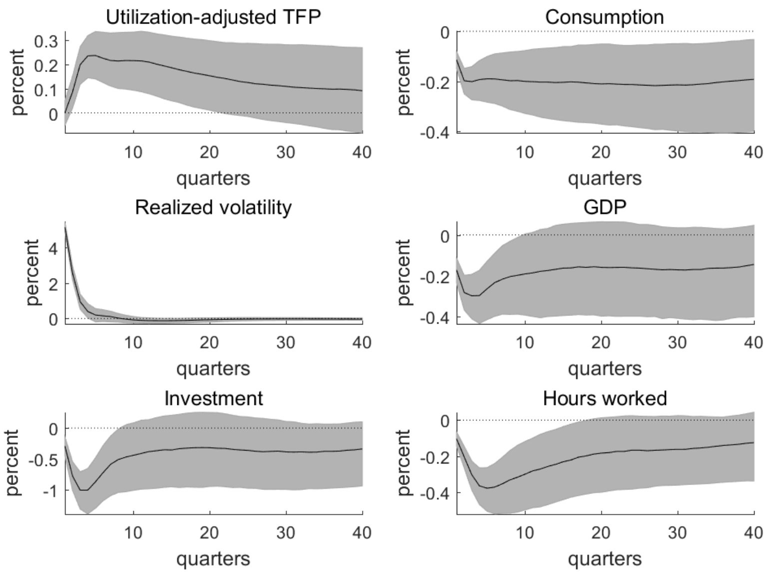
1.9 p.p., albeit a short-lived effect that is near zero after one year. Although the positive effect of news shocks on uncertainty is new in this aggregate context, these results are not surprising, since Bloom [2009] finds a positive correlation between stock market volatility and cross-sectional standard deviation of industry TFP growth. Matsumoto et al. [2011] show that news shocks are positively related to equity prices and equity volatility. An increase in stock market volatility arises from the delayed adjustment of prices by firms following a news shock, but this effect tends to vanish over time so the effects are short lived.

Görtz et al. [2016] show that news shocks have negative effects on the excess bond premium (EBP). The baseline VAR specification includes EBP as endogenous variable and confirms their results, although, in this paper, we treat EBP as a variable that should be kept in the information set, but the main aim is to make inference on how uncertainty responds to news shocks.

3.2.4 Responses to uncertainty shocks

Table 3.1 describes a list of 11 uncertainty measures considered in the literature. We apply the uncertainty shock identification scheme described in section 3.2.2 by including one uncertainty measure at a time in a VAR model with the 10 variables described in the top panel of Table 3.1. These exercises allow us to check whether the responses of economic activity and technology to uncertainty shocks are robust to how uncertainty is measured. Responses for each uncertainty measure listed in Table 3.1 are in the Appendix A.2, Figures A.2.1 to A.2.11. The main differences are between financial and macroeconomic uncertainty measures. As a consequence, Figure 3.2 presents the responses for our baseline financial uncertainty variable – realized volatility – and Figure 3.3 shows the responses when uncertainty is measured by Ludvigson et al. [2016] 3-month-ahead macroeconomic volatility.

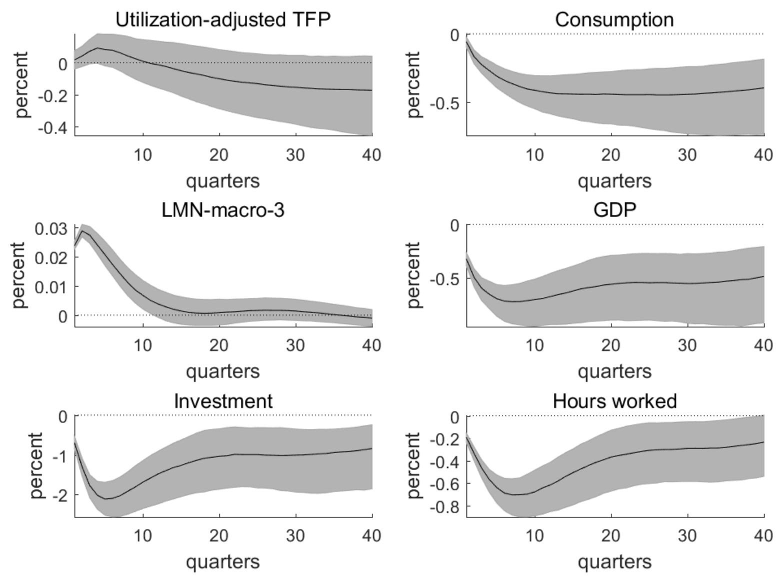
Figure 3.2: Responses to financial uncertainty (realized volatility) shocks in the baseline VAR model



Note: Shaded areas are 68% confidence bands computed with 1,000 posterior draws. The baseline identification scheme for uncertainty shocks is described in section 3.2.2. The VAR model includes all variables in the first panel of Table 3.1 + realized volatility.

As in Bachmann et al. [2013], Jurado et al. [2015], Baker et al. [2016] and Caldara et al. [2016], uncertainty shocks have significant negative effects on economic ac-

Figure 3.3: Responses to macroeconomic uncertainty (LMN-macro-3) shocks in the baseline VAR model



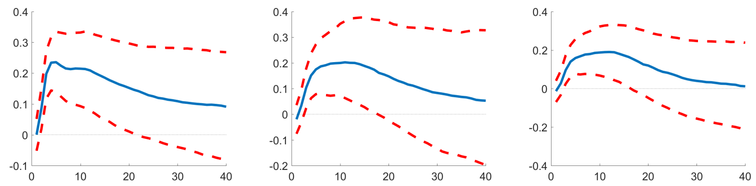
Note: See notes to Figure 3.2. The VAR model includes all variables in the first panel of Table 3.1 + macroeconomic uncertainty (LMN-macro-3).

tivity variables. The responses to macroeconomic uncertainty shocks (Figure 3.3) are stronger and more persistent than the responses to financial uncertainty (Figure 3.2). Surprisingly, financial uncertainty shocks have positive effects on technology (utilization-adjusted TFP), while macroeconomic uncertainty shocks have no significant effects on technology changes. The effect of financial uncertainty on technology peaks at 5 quarters, but it is persistent, dying out only over the long run.

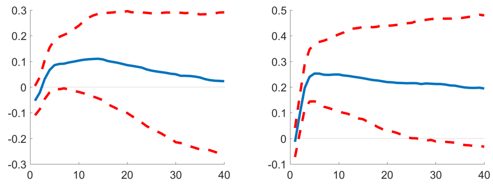
These differences in the effects of macro and financial uncertainty on technology hold even if the proxy for financial and macroeconomic uncertainty is changed. Figure 3.4 presents the effect of a financial uncertainty shock on utilization-adjusted TFP for all the five measures of financial uncertainty considered here, and Figure 3.5 considers the six measures of macroeconomic uncertainty. The negative effects of financial uncertainty on economic activity have been attenuated by the positive effects of financial uncertainty on productivity by comparing responses in Figures 3.2 and 3.4 with the macroeconomic uncertainty effects in Figures 3.3 and 3.5.

The persistent positive effect of financial uncertainty shocks on technology might be seen as counterintuitive. Bloom et al. [2014] and Bloom [2014] note that uncertainty

Figure 3.4: Responses of utilization-adjusted TFP to different measures of financial uncertainty shocks in the baseline model



(a) Realized volatility (b) LMN-fin-1 (c) LMN-fin-3



(d) LMN-fin-12 (e) VXO

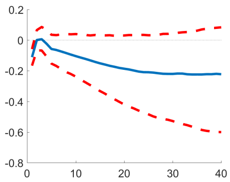
Note: See Table 3.1 for description of uncertainty measures. Dotted lines are 68% confidence bands computed with 1,000 posterior draws. These responses are computed for one financial uncertainty variable at a time in a VAR that also includes the 10 variables in the top panel of Table 3.1. Identification scheme as described in section 3.2.2.

makes productive firms less aggressive in expanding and unproductive firms less aggressive in contracting. This reallocation of production factors after an uncertainty shock should reduce total productivity.

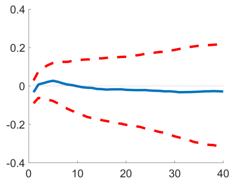
We shed a light on this puzzle by examining the responses of non-adjusted TFP to uncertainty shocks. They allow us to evaluate the impact of utilization adjustment, that is, the removal of productivity changes due to factor utilization, on these results. Figure 3.6 provides the impulse responses of TFP to financial uncertainty shocks, and Figure 3.7 shows similar results for macroeconomic uncertainty shocks. The results are now consistent with Bloom et al. [2014] and Bloom [2014], since both types of uncertainty shocks have short-lived negative effects on productivity. This implies that responses of productivity to uncertainty shocks reflect a combination of two effects: a short-lived negative effect driven by a reduction of factor utilization and a positive medium-horizon effect generated by technology improvements.

This novel medium-run effect of financial uncertainty shocks to technology changes might be the result of firms reaction to the new economic environment. After the initial negative effect, firms seek to become more productive to reduce the impact of possible similar future shocks. The notion of an adaptation period recalls Comin [2000], who

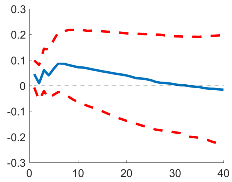
Figure 3.5: Responses of utilization-adjusted TFP to different measures of macroeconomic uncertainty shocks in the baseline model



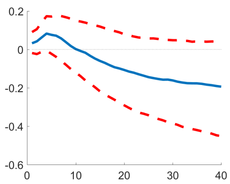
(a) Policy uncertainty



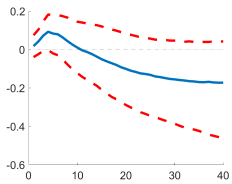
(b) Business uncertainty



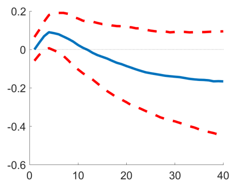
(c) SPF disagreement



(d) LMN-macro-1



(e) LMN-macro-3



(f) LMN-macro-12

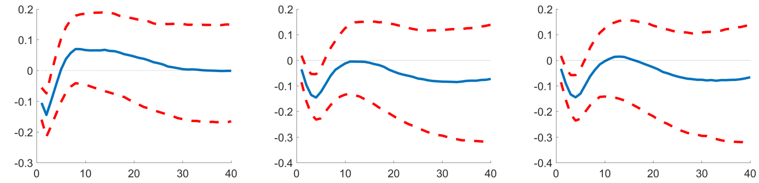
Note: See notes to Figure 3.4. These responses are computed for one macroeconomic uncertainty variable at a time in a VAR that also includes the 10 variables in the top panel of Table 3.1. Identification scheme as described in section 3.2.2.

focus on the impact of uncertainty on the productivity of specialized capital. The initial negative impact of uncertainty shocks induces firms to substitute old technologies (inflexible and obsolete in an uncertain business environment) for more flexible ones, generating a positive shift in TFP. Bloom et al. [2014] also provide support for these 'good uncertainty' medium-run effects. Uncertainty delays firms' investment projects, affecting expansion decisions and hiring of new employees. However, when uncertainty recedes, firms re-evaluate their suspended investment plans in order to attend to the constrained demand. Bloom et al. [2014] argue that after the uncertainty period vanishes, firms increase hiring and investment, which can lead to increasing productivity.

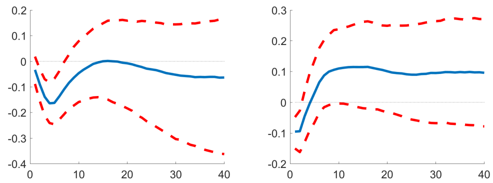
3.2.5 Correlation between news and uncertainty shocks

Our empirical results so far suggest that financial uncertainty shocks generate a positive medium-run effect on technology that resembles the effects of a news shock. Financial uncertainty and news shocks only differ in the long-run, as uncertainty shock effects die out, whereas news shocks persist. This section investigates the correlation between news and uncertainty shocks, which is measured by employing the set of uncertainty measures in Table 3.1. We recover the news and uncertainty structural shocks for the 1975-2012

Figure 3.6: Responses of non-adjusted TFP to different measures of financial uncertainty shocks in the baseline model



(a) Realized volatility (b) LMN-fin-1 (c) LMN-fin-3



(d) LMN-fin-12 (e) VXO

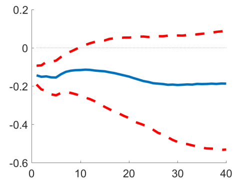
Note: See notes to Figure 3.4. These responses are computed for one financial uncertainty variable at a time in a VAR that also includes the 10 variables in the top panel of Table 3.1. The difference between these results and Figure 3.4 is that here TFP is not adjusted for utilization. Identification scheme as described in section 3.2.2.

period using the identification schemes discussed in section 3.2.2. We then calculate the correlations between news and each measure of uncertainty shocks. These values are presented in Table 3.2 and include the results of a test of the null hypothesis that the correlation is equal to zero.

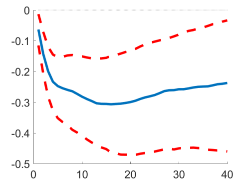
The main result from Table 3.2 is that there is a positive and significant correlation between news and financial uncertainty shocks, which indicates that these are not structural shocks. The correlation is stronger if financial uncertainty is proxied by the VXO (0.59), although this might be the effect of the shorter period for which this series is available (since 1986). The correlation decreases with the forecasting horizon employed by Ludvigson et al. [2016] in the computation of uncertainty measures. In contrast, the correlations between news and macroeconomic uncertainty shocks are either zero in the case of professional forecaster dispersion measures or negative in the case of macroeconomic forecasting uncertainty measures.

The fact that news and financial uncertainty shocks are positively correlated indicates that these identified shocks are not structural. It reinforces our previous results that uncertainty shocks may have positive medium run effects on productivity and economic activity measures. They also imply that the positive effects of technology news

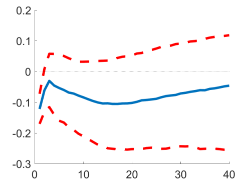
Figure 3.7: Responses of non-adjusted TFP to different measures of macroeconomic uncertainty shocks in the baseline model



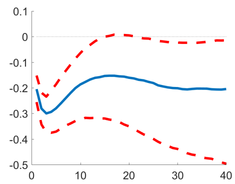
(a) Policy uncertainty



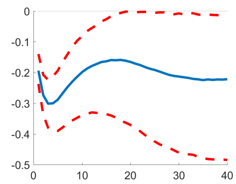
(b) Business uncertainty



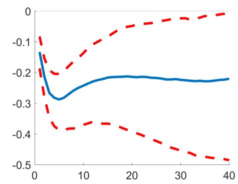
(c) SPF disagreement



(d) LMN-macro-1



(e) LMN-macro-3



(f) LMN-macro-12

Note: See notes to Figure 3.4. These responses are computed for one macroeconomic uncertainty variable at a time in a VAR that also includes the 10 variables in the top panel of Table 3.1. The difference between these results and Figure 3.5 is that here TFP is not adjusted for utilization. Identification scheme as described in section 3.2.2.

shocks may be attenuated by the fact that news shocks tend to increase financial uncertainty over the short run.

We see this novel interesting result as motivation for our new identification scheme discussed in the next section.

3.3 Disentangling uncertainty and news as sources of business cycle fluctuation

Our previous results suggest that the positive effects of news shocks on economic activity are attenuated by rising financial uncertainty at the time of the shock. Likewise, the negative effects of financial uncertainty shocks on economic activity are attenuated by increasing productivity over the medium run as a result of the improving likelihood of technology news shocks from the increase in financial uncertainty. In this section, we identify both news and uncertainty shocks in the same model such that we are able to measure their relevance in explaining business cycle variation, while also considering that macroeconomic uncertainty, as measured by professional forecaster disagreement,

Table 3.2: Correlation between news and uncertainty shocks for different uncertainty measures

	Correlation	
Financial uncertainty		
Realized volatility	0.43	[0.000]
LMN-fin-1	0.49	[0.000]
LMN-fin-3	0.36	[0.000]
LMN-fin-12	0.34	[0.000]
VXO	0.59	[0.000]
Macro uncertainty		
Policy uncertainty	-0.22	[0.008]
Business uncertainty	0.05	[0.553]
SPF disagreement	0.02	[0.811]
LMN-macro-1	-0.37	[0.000]
LMN-macro-3	-0.28	[0.000]
LMN-macro-12	-0.21	[0.011]

Note: The p-values for the test with zero correlation under the null hypothesis are in brackets. The statistic is calculated as $t = \rho_0 \sqrt{\frac{T-2}{1-\rho_0^2}}$. *These results are based on a VAR model with the 10 variables in the first panel of Table 3.1 + one measure of uncertainty at time, as indicated. For details on data and availability, see Table 3.1.*

is also a source of business cycle fluctuation.

3.3.1 Identification of news, financial and ambiguity shocks

In this section, we describe our two identification schemes: the 'truly news' and the 'truly uncertainty'. In both cases, we use a VAR model with the 10 variables in the top panel of Table 3.1 plus two measures of uncertainty. We include realized volatility as the measure of financial uncertainty and SPF disagreement as the measure of macroeconomic uncertainty. We choose SPF disagreement as the measure of macroeconomic uncertainty because it is uncorrelated with news shocks (as discussed in section 3.2) and measures changes in Knightian uncertainty (Ilut and Schneider, 2014).[4] At the end of this section, we check the robustness of this choice using business uncertainty, as computed by Bachmann et al. [2013], instead of SPF disagreement as a measure of macroeconomic uncertainty.

The main advantage of considering two identification schemes is that together they allow us to measure the impact of 'good uncertainty' shocks in explaining business

[4]For an alternative measure of ambiguity obtained by exploiting the SPF, see Rossi et al. [2016].

cycle variation. We call 'good uncertainty' shocks the unexpected changes in financial uncertainty that are correlated with news shocks. These are 'good uncertainty' shocks because they typically improve technology in the medium run.

The identification of the 'truly news' shock can be understood as a sequential identification of the maximization of the variance decomposition (Section 3.2.2), conditional on the orthogonality with respect to the previous identified shocks. The first identified shock is the unexpected TFP shock, which is TFP's own innovation. The second shock is the financial uncertainty shock, which is the orthogonalization that brings the maximum of the variance decomposition of the financial uncertainty measure over two quarters ahead, *conditional on being orthogonal to the unexpected TFP shock*. The third shock is the ambiguity shock, which is the orthogonalization that brings the maximum of the variance decomposition of the ambiguity measure over two quarters ahead, *conditional on being orthogonal to the unexpected TFP and financial uncertainty shocks*. Finally, the fourth shock is the 'truly news' shock, which is the orthogonalization that brings the maximum of the variance decomposition of productivity over 40 quarters ahead, *conditional on being orthogonal to the unexpected TFP, financial uncertainty and ambiguity shocks*. It follows that all four shocks constructed under the 'truly news' identification are orthogonal and structural.

The 'truly news' identification scheme implies that both uncertainty and ambiguity shocks are able to affect the technology news shock and that financial uncertainty shock have an impact on ambiguity. This is motivated by the fact that ambiguity increases during periods of high volatility (Bachmann et al., 2013; Ilut and Schneider, 2014) and that the likelihood of news shocks may increase during periods of high volatility (Bloom, 2009).

The 'truly news' identification scheme is built sequentially by imposing orthogonality between the news identification vector γ_2^{news} and those obtained for identification of the financial γ_3^{finunc} and ambiguity γ_4^{amb} shocks. The 'truly news' identification scheme is based on a four-step procedure. In the first step, the procedure for the identification of the unexpected TFP and news shocks, described in Appendix A, is applied to obtain γ_2^{news} (and γ_1^{unexp}). Then, the financial uncertainty identification vector γ_3^{finunc} is obtained by maximizing the variance decomposition of financial uncertainty up to horizon 2. The third step obtains γ_4^{amb} by maximizing the variance decomposition of the SPF disagreement up to horizon 2. The fourth and last step imposes the orthogonality between the news shock, the financial uncertainty shock and the ambiguity shock. This is achieved by employing a QR decomposition[5] over the four γ vectors such that we ob-

[5]The QR decomposition is an application of the Gram-Schmidt orthonormalization procedure. In our

tain γ_2^{news*}, $\gamma_3^{finunc*}$ and γ_4^{amb*} from the orthonormal, 'Q part' of the decomposition. As γ_2^{news*} is ordered last in the QR decomposition, this identification scheme removes the part of the news shock that is correlated with both financial uncertainty and ambiguity.

The 'truly uncertainty' identification scheme is similar to the 'truly news', but it implies a different ordering in the orthonormalization. In the case of the 'truly uncertainty' scheme, the news shock vector is ordered first in the orthogonalization structure, so we extract the news shock effect from both the ambiguity and financial uncertainty shocks. The 'truly uncertainty' identification scheme implies that news shocks are not affected by both uncertainty shocks and that the financial uncertainty shock is affected by news shocks. Although this identification has less support in the literature than the previous one, it helps us to show that the ordering assumptions between news and financial uncertainty shocks have a crucial impact on the empirical evidence based on structural VARs.

By computing both identification schemes, we are able to measure the impact of 'good uncertainty' on business cycles. The impact of 'good uncertainty' shocks is measured by the differences between the 'truly uncertainty' and the 'truly news' identification strategies on the variation explained by financial uncertainty shocks. The intuition is that under the 'truly news' identification, we measure the impact of 'bad uncertainty', which is mainly a short-run phenomenon, since raising uncertainty does not affect the arrival of technological changes in this case. Based on the 'truly uncertainty' identification, financial uncertainty shocks have an impact on the arrival of news about future technological changes.

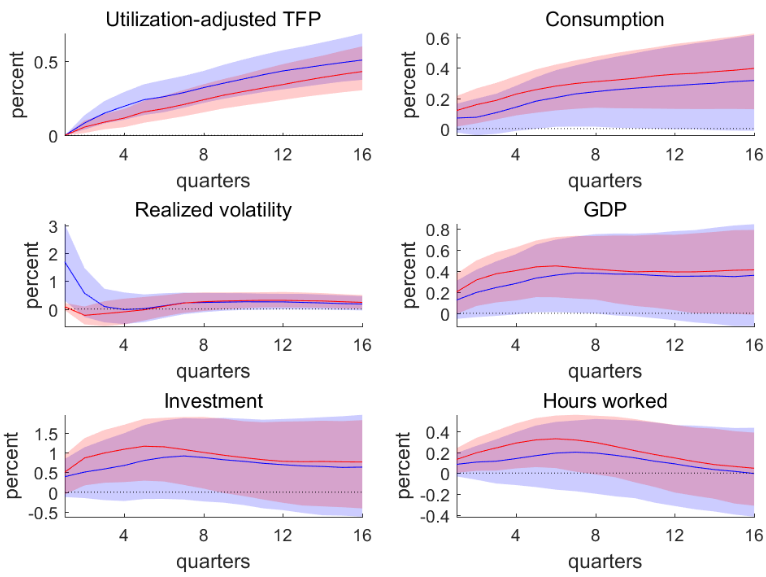
3.3.2 Responses to 'truly' news and uncertainty shocks

Figures 3.8, 3.9 and 3.10 show the responses to news, financial uncertainty and ambiguity shocks, respectively. We present the results for both the 'truly news' and 'truly uncertainty' identification schemes, and 68% confidence bands are included.

Figure 3.8 clearly shows that news shocks have larger effects on economic activity variables (consumption, investment, hours and output) if we assume that news shocks are orthogonal to uncertainty and ambiguity shocks as in the case of the 'truly news' identification scheme. The difference between the red and blue lines is a measure of the attenuation effect of increasing uncertainty with the arrival of technology news.

application, the first vector (orthonormal by construction) remains unchanged. The second is computed by subtracting its projection over the first one. The third is obtained by subtracting its projection over the first two. Finally, the fourth vector is computing by subtracting its projecting over the previous three vectors.

Figure 3.8: Responses to news shocks with the 'truly news' (red lines) and the 'truly uncertainty' (blue lines) identification schemes

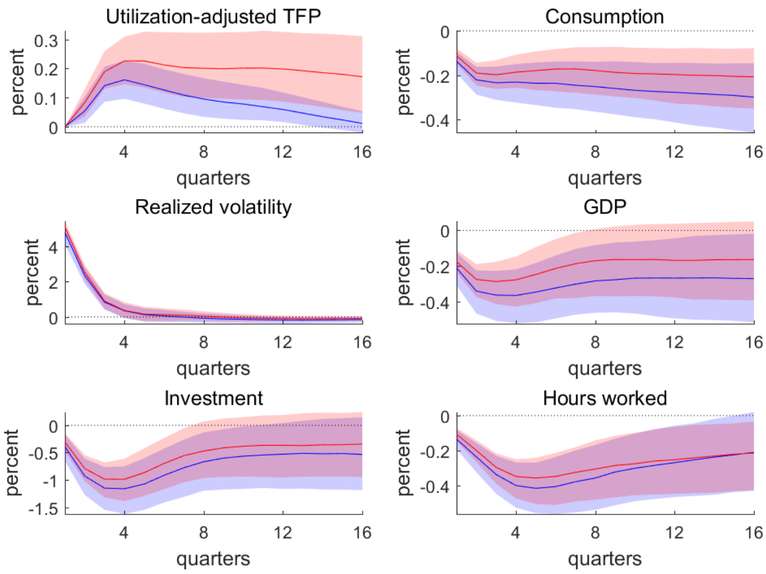


Note: Shaded areas are 68% confidence bands computed with 1,000 posterior draws. The 'truly news' and 'truly uncertainty' identification schemes are described in section 3.3.1. The VAR model includes all 10 variables in the first panel of Table 3.1 + realized volatility + business uncertainty.

Interestingly, the 'truly news' identification scheme recovers responses that show that hours, consumption and investment move together with output, including responses that are significantly different from zero (based on the 68% bands) at the time of the impact of the news shock. This comovement is suggested by Beaudry and Portier [2006], but it is normally not observed when news shocks are identified by maximizing the forecasting variance, as in Barsky and Sims [2011] and this paper.

Figure 3.9 indicates that financial uncertainty shocks have a relatively muted negative effects on the economic activity variables under the 'truly news' identification scheme. This is mainly explained by the medium-run positive effects on technological changes, measured by the utilization-adjusted TFP changes. The difference between the red ('truly news') and the blue ('truly uncertainty') responses is our measure of the impact of 'good uncertainty' shocks. In the case of output, the response is -0.4% after four quarters but only -0.3% if we allow for good uncertainty effects. This difference, although small, persists over various time horizons.

Figure 3.9: Responses to financial uncertainty shocks with the 'truly news' (red lines) and the 'truly uncertainty' (blue lines) identification schemes



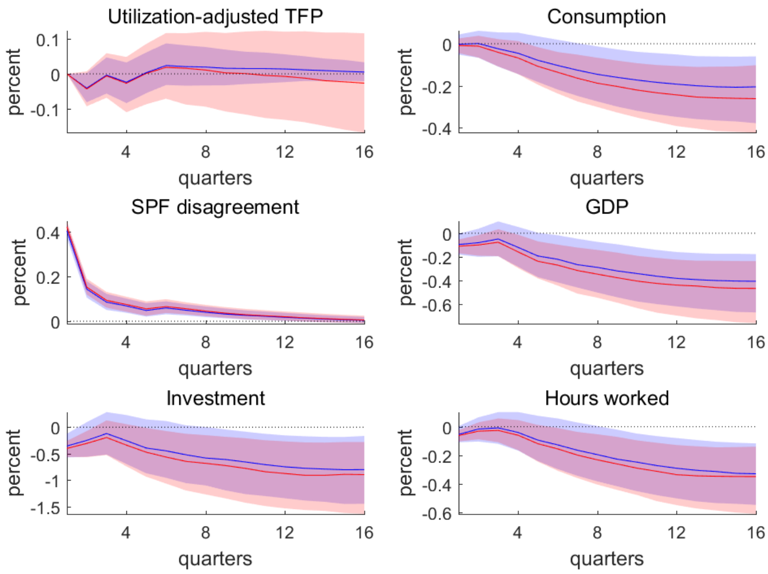
Note: See notes to Figure 3.8.

Our previous results suggest that ambiguity shocks, measured using SPF disagreement, are not correlated with news shocks and have no impact on utilization-adjusted TFP. As a consequence, it is no surprise that Figure 3.10 suggests very small differences between identification schemes. It is interesting to note that economic activity variables' responses to ambiguity shocks are typically not significantly different from zero (using 68% bands) over short horizons but are significantly negative for horizons longer than a year. This suggests that responses to ambiguity shocks are less immediate than responses to financial uncertainty.

3.3.3 Explaining business cycle variation

Table 3.3 presents the variance decomposition of economic activity variables (output, consumption, investment and hours) explained by three shocks (news, financial uncertainty and ambiguity) based on three identification schemes (baseline, 'truly news', 'truly uncertainty'). In the baseline identification scheme described in section 3.2.2, the shocks are identified separately. The values are computed at the posterior mean for horizons after zero quarters (at impact) and eight quarters (two years), 16 quarters (four years)

Figure 3.10: Responses to ambiguity shocks with the ‘truly news’ (red lines) and the ‘truly uncertainty’ (blue lines) identification schemes



Note: See notes to Figure 3.8.

and 40 quarters (10 years).

There are two main results from Table 3.3. First, the identification scheme has a limited impact on the importance of ambiguity in explaining business cycle variation. Over long horizons, ambiguity explains 13% of output variation, 8% of consumption variation, and 8% of investment variation.

Second, the relative importance of news and financial uncertainty shocks depends on whether we are able to assume that technology news shocks are orthogonal to financial uncertainty. If that is the case, then technology news shocks explain a large share of the variance in the long run: 29% of output variation, 45% of consumption variation and 21% of investment variation. However, if we let news shocks to have a contemporaneous impact on financial uncertainty, then the shares of the variation explained by news shocks decrease and are similar to the baseline results. The shares of variation explained by financial uncertainty shocks are larger based on the ‘truly uncertainty’ identification scheme.

We explain these results using the notion of ‘good uncertainty’ shock. A ‘good uncertainty’ shock is the one that raises the likelihood of technology news shocks. Based

Table 3.3: Variance decomposition of output, consumption, investment and hours to news, financial uncertainty and ambiguity shocks

(a) Output

h	News Shocks			Financial Uncertainty			Good Unc	SPF Disagreement		
	Base-line	Truly News	Truly Unc.	Base-line	Truly News	Truly Unc.		Base-line	Truly News	Truly Unc.
0	5.7	12.4	5.7	5.2	5.2	13.1	7.9	2.4	2.1	0.9
8	14.2	24.6	14.2	5.8	5.8	18.9	13.1	6.2	5.5	2.8
16	14.0	29.9	14.0	3.8	3.8	14.7	10.9	12.9	12.1	8.1
40	19.9	28.1	19.9	3.4	3.4	16.6	13.2	14.6	13.6	8.7

(b) Consumption

h	News Shocks			Financial Uncertainty			Good Unc	SPF Disagreement		
	Base-line	Truly News	Truly Unc.	Base-line	Truly News	Truly Unc.		Base-line	Truly News	Truly Unc.
0	5.1	13.8	5.1	6.8	6.8	15.5	8.7	0.2	0.1	0.1
8	13.8	27.8	13.8	9.6	9.6	25.8	16.2	4.5	3.6	1.5
16	19.3	33.9	19.3	8.6	8.6	27.4	18.8	10.1	8.7	4.5
40	26.4	45.4	26.9	8.5	8.5	31.3	22.8	9.3	7.8	3.4

(c) Investment

h	News Shocks			Financial Uncertainty			Good Unc	SPF Disagreement		
	Base-line	Truly News	Truly Unc.	Base-line	Truly News	Truly Unc.		Base-line	Truly News	Truly Unc.
0	6.8	11.0	6.8	2.3	2.3	8.4	6.1	4.5	4.2	2.1
8	10.6	21.0	10.6	7.4	7.4	19.7	12.3	4.2	3.5	1.6
16	9.3	15.7	9.3	4.4	4.4	13.2	8.8	7.8	4.1	4.6
40	14.0	21.4	14.0	3.6	3.6	14.2	10.6	9.0	8.2	5.1

(d) Hours

h	News Shocks			Financial Uncertainty			Good Unc	SPF Disagreement		
	Base-line	Truly News	Truly Unc.	Base-line	Truly News	Truly Unc.		Base-line	Truly News	Truly Unc.
0	5.4	11.7	5.4	4.6	4.6	11.9	7.3	2.7	1.6	0.6
8	7.0	19.5	7.0	13.0	12.9	26.8	13.9	4.0	2.5	1.1
16	4.6	12.0	4.6	9.1	9.1	18.5	9.4	9.8	7.7	5.7
40	2.6	6.9	2.6	6.7	6.7	12.7	6.0	11.1	9.0	7.3

Note: The baseline identification scheme is described in section 3.2.2, and the 'truly news' and 'truly uncertainty' schemes in section 3.3.1. In all cases, the VAR model includes all 10 variables in the first panel of Table 3.1 + realized volatility + SPF disagreement.

on the computation in Table 3.3 using both identification schemes, a good uncertainty shock explains a large share of variation at the two-year horizon. In the case of output variation at the two-year horizon, 5.8% is explained by 'bad uncertainty' shocks, 13.1% by 'good uncertainty' shocks and 5% by ambiguity shocks.

As a consequence, we provide evidence that not all uncertainty shocks are equal. An increase in equity market volatility may improve technology and productivity after one year if it is followed by a higher likelihood of technology news shocks. The proportion of variation in output due to this 'good uncertainty' is actually larger than the negative effects of typical uncertainty shocks, including ambiguity shocks.

3.3.4 Robustness check

The results in section 3.2.5 suggest that news shocks are not correlated with the business uncertainty measure computed by Bachmann et al. [2013]. Although business uncertainty may not be a good measure of ambiguity, it is based on a forecasters' dispersion measure as the SPF disagreement. We recomputed all results in Table 3.3 using business uncertainty as a proxy for 'ambiguity'. The results presented in Table 3.4 suggest that the relative importance of news, good and bad uncertainty shocks are similar to the model using SPF disagreement. However, shocks to business uncertainty explain a larger share of business cycle variation than shocks to SPF disagreement. Over longer horizons, business uncertainty explains 34% of output variation, 12% of consumption variation, and 50% of investment variation. These results are consistent with Bachmann et al. [2013], but they suggest that not all uncertainty measures are equal in the sense of measuring the same economic concept.

3.3.5 Discussion

Employing an unexpected correlation between technology news shocks and different measures of uncertainty shocks, we are able to provide evidence that not all uncertainty shocks are equal in their impact on the macroeconomy. The consensus is that we normally expect negative short-run effects from uncertainty shocks (Leduc and Liu, 2016), so our results are novel and unexpected. Bloom [2014] argues, however, that many mechanisms might explain the impact of uncertainty shocks in the economy, so our novel evidence that different uncertainty measures deliver shocks with different effects on the economy is consistent with this view.

Typical uncertainty-driven business cycle theories (Bloom et al., 2014) are based on the idea that uncertainty reduces investment because when uncertainty is high, the

Table 3.4: Variance decomposition of output, consumption, investment and hours to news, financial uncertainty and business uncertainty shocks

(a) Output

h	News Shocks			Financial Uncertainty			Good Unc	Business Uncertainty		
	Baseline	Truly News	Truly Unc.	Baseline	Truly News	Truly Unc.		Baseline	Truly News	Truly Unc.
0	7.6	17.4	7.6	5.4	5.4	14.7	9.3	2.8	2.0	2.4
8	13.5	28.3	13.5	6.2	6.3	19.4	13.1	17.5	15.6	17.2
16	13.3	25.8	13.3	3.9	3.9	14.4	10.5	28.4	26.7	28.7
40	16.1	28.9	16.1	2.8	2.8	13.3	10.5	34.0	32.5	34.8

(b) Consumption

h	News Shocks			Financial Uncertainty			Good Unc	Business Uncertainty		
	Baseline	Truly News	Truly Unc.	Baseline	Truly News	Truly Unc.		Baseline	Truly News	Truly Unc.
0	5.3	14.5	5.3	7.2	7.2	16.2	9.0	0.4	0.1	0.2
8	13.0	20.6	13.0	9.8	9.8	25.4	15.6	6.9	5.4	6.5
16	18.0	37.0	18.0	8.1	8.2	25.5	17.3	12.3	10.5	12.1
40	23.4	44.8	23.4	7.4	7.4	27.1	19.7	12.2	10.6	12.3

(c) Investment

h	News Shocks			Financial Uncertainty			Good Unc	Business Uncertainty		
	Baseline	Truly News	Truly Unc.	Baseline	Truly News	Truly Unc.		Baseline	Truly News	Truly Unc.
0	9.8	17.7	9.8	2.1	2.1	9.3	7.2	4.1	3.5	4.1
8	9.2	22.6	9.2	7.5	7.5	19.0	11.5	29.2	26.8	28.6
16	7.2	16.6	7.2	4.1	4.1	11.6	7.5	42.6	40.8	42.6
40	7.6	16.2	7.6	2.9	2.9	9.4	6.5	51.5	49.8	51.9

(d) Hours

h	News Shocks			Financial Uncertainty			Good Unc	Business Uncertainty		
	Baseline	Truly News	Truly Unc.	Baseline	Truly News	Truly Unc.		Baseline	Truly News	Truly Unc.
0	8.2	16.8	8.2	4.1	4.0	12.5	8.5	0.1	0.0	0.1
8	6.9	22.4	6.9	14.0	14.0	28.3	14.3	11.2	9.4	10.5
16	4.6	15.8	4.6	10.1	10.0	19.9	9.9	21.7	19.9	21.0
40	2.5	9.1	2.5	7.0	6.9	12.6	5.7	30.9	29.4	30.3

Note: See notes to Table 3.3. The VAR model includes all 10 variables in the first panel of Table 3.1 + realized volatility + business uncertainty.

price of the wait-and-see option is higher. Business cycle theories that focus on risk as a cause of business cycles (Christiano et al., 2014) employ financial constraints to explain how uncertainty affects growth. In both cases, we expect short-run negative effects from increased uncertainty, which is compatible with our results for financial uncertainty shocks.

The evidence that uncertainty may have a positive effect on productivity is related to the idea that uncertainty increases the size of the potential return on an investment, that is, uncertainty increases the range of growth options. Segal et al. [2015] employ a long-run risk consumption-based asset pricing model to disentangle the impact of good and bad uncertainty from that of positive and negative innovations on consumption growth. Although both measures of uncertainty have an impact on asset pricing within their model, they do not attempt to measure the relative impact of good and bad uncertainty on business cycle variation. Our results suggest that good uncertainty is more important at medium-term horizons (two years) and that bad financial uncertainty is typically a short-run phenomenon.

Our results support ambiguity (Ilut and Schneider, 2014) as a cause of business cycles in addition to the effects of financial uncertainty. They also support the idea that professional forecaster dispersion measures confidence rather than uncertainty. The impacts of ambiguity shocks are more long lasting than those of typical uncertainty shocks. Our results based on two measures of ambiguity (SPF and business survey dispersion) differ from those of Rossi et al. [2016], who find no economic effects from shocks to disagreement when employing a novel decomposition based on SPF forecasts.

Our results suggest that the business cycle variation explained by macroeconomic uncertainty shocks (Tables 3.3 and 3.4) is normally higher than that explained by financial uncertainty, in particularly over long horizons. As a consequence, our results support Carriero et al. [2016a] on the relative importance of macroeconomic over financial uncertainty in explaining business cycle variation rather than Ludvigson et al. [2016]. However, we agree with Ludvigson et al. [2016] that to measure the impact of uncertainty on business cycles, we have to remove variation that is correlated with macroeconomic shocks. In this paper, we show that the relevant variation is related to news about future technological changes.

When macroeconomic uncertainty shocks are measured by the Bachmann et al. [2013] uncertainty measure, we find long-lasting negative effects on output, consumption, investment and hours, even though we consider many other sources of shocks, including technology news shocks. A possible explanation is that the business uncertainty measure is able to identify the periods in which the economy enters an uncertainty trap, as in the theory proposed by Fajgelbaum et al. [2017].

3.4 Conclusion

Financial uncertainty and news shocks are correlated when standard identification assumptions are employed. It follows that the standard procedures fail to identify the true structural shocks. The implication is that responses of economic activity to news and uncertainty shocks include attenuation bias. In the case of news shocks, attenuation bias plays a role in the short run and implies that positive effects are lower than they would be if news shocks were assumed to be orthogonal to financial uncertainty shocks. For financial uncertainty shocks, the attenuation bias plays a role in the medium run, and it is characterized by an increase in utilization-adjusted total factor productivity. The bias implies that the negative effects of uncertainty shocks are not as deep or persistent as they could have been.

Based on our identification strategy to disentangle the effects of difference sources of business cycle variation, we find that in the long run, technology news shocks explain 30% of output growth variation, 'good uncertainty' and ambiguity shocks explain 13% each, and bad uncertainty explains 4%. In general, our novel empirical evidence support the development of theories that focus on anticipated shocks (Jaimovich and Rebelo, 2009), confidence (Ilut and Schneider, 2014) and uncertainty (Bloom et al., 2014; Fajgelbaum et al., 2017) as sources of business cycles.

Chapter 4

Amplification effects of news shocks through uncertainty

4.1 Introduction

How do economic agents react to new information about future technological improvements? Although much has been done by the literature on business cycles driven by agents' beliefs to answer this question,[1] 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.

The idea behind business cycles driven by 'news shocks' – changes in the future total factor productivity (TFP) that are foreseen by the economic agents (Beaudry and Portier, 2006) – 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.[2]

On an aggregate level, the literature on technological news shocks shows that positive news generates long-term co-movement among GDP, consumption and investment, and it is deflationary in the medium-term.[3] 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 et al., 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 4.1 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

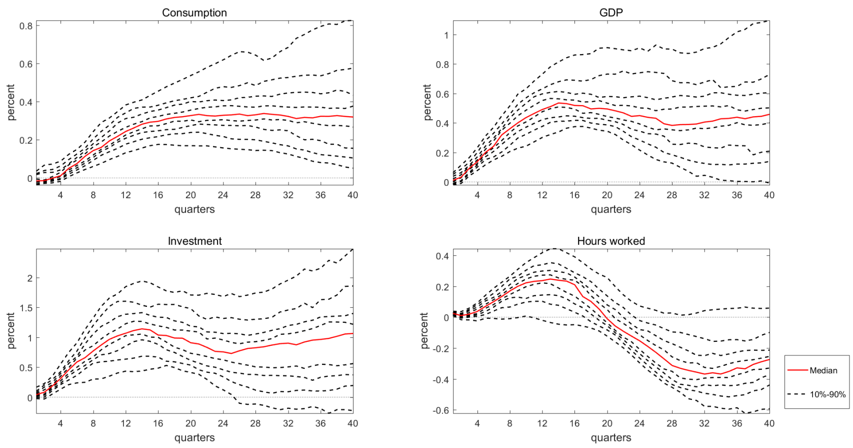
[1] See, for example, Beaudry and Portier [2006], Jaimovich and Rebelo [2009], Barsky and Sims [2011], Kurmann and Otrok [2013], Schmitt-Grohe and Uribe [2012], Blanchard et al. [2013], Forni et al. [2014], Beaudry and Portier [2014], Vukotić [2017], Cascaldi-Garcia and Galvao [2017] and Levchenko and Pandalai-Nayar [2018].

[2] Although it will take years to be effectively explored, the expectation of future higher oil production induces the companies to invest now. Arezki et al. [2017] explore the news shock properties related to oil discoveries.

[3] As demonstrated by Beaudry and Portier [2006], Barsky and Sims [2011] and Beaudry and Portier [2014].

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 to zero, or zero in the medium-term and negative in the long-term.

Figure 4.1: 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 71 rolling window estimations, while the red line is the median. The identification follows the Barsky and Sims [2011] methodology, in a large Bayesian VAR consisting of the variables described in tables B.2 and B.3.

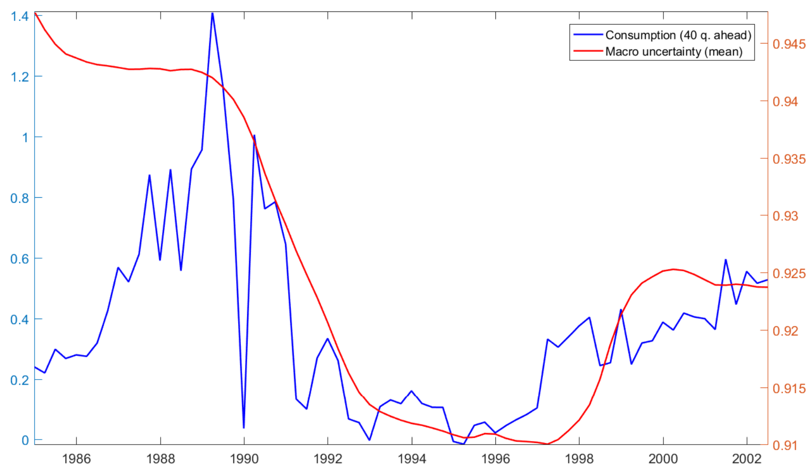
While the effect on hours worked changes both quantitatively and qualitatively, there are still differences in the size of the responses of real macroeconomic variables. Figure 4.1 shows that, on average, a news shock leads to a long-term positive effect on consumption, GDP and investment. However, depending on the time-span considered, this effect may be substantially stronger or converge to zero, with no long-term effects.

The economic effects of a news shock are far from robust to time changes. 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. This question can be addressed by studying how the economic agents acquire information about future productivity, for example through the financial market.

Shen [2015] argues that agents are more responsive to information when signals are sufficiently precise. Uncertainty plays a role in how information is assimilated by the agents: information can be interpreted in different ways in periods of high or low uncertainty, indicating a potential amplifying effect of news shocks through an uncertainty transmission channel.

The rolling window identification exercise supports this relationship between news about future productivity and uncertainty. Figure 4.2 presents the long-term effects of a news shock on consumption identified in a 20-year rolling window, and compares it with a measure of macroeconomic uncertainty.[4] There is a clear period of high long-term effects until 2001, followed by a period of low long-term effects, increasing again after 2007. This behavior is systematic, and matches with periods of high and low macroeconomic uncertainty.

Figure 4.2: Long-term effects of a news shock on consumption and macroeconomic uncertainty



Note: In red: Mean of a macroeconomic uncertainty measure calculated by Ludvigson et al. [2016]. In blue: Long-term effects of a news shock on consumption. Long-term defined as 40 quarters ahead of the news shock. The news shock is 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. The x-axis shows the mid-point of the window. The identification follows the Barsky and Sims [2011] methodology, in a large Bayesian VAR consisting of the variables described in tables B.2 and B.3.

In this paper, I propose a model and identification procedure to investigate whether agents change the way they respond to news about future productivity over

[4] Macroeconomic uncertainty measure calculated by Ludvigson et al. [2016].

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.

The premise of the model is that uncertainty measures the agents' expectations about current and future economic conditions. It is reasonable to think that these expectations should also be updated when the agents receive news about future higher productivity. In other words, the level of uncertainty *endogenously* responds to exogenous news shocks. To meet these requirements, I employ a stochastic volatility model that treats macroeconomic and financial uncertainties as latent variables.

The baseline model builds upon Carriero et al. [2016a], 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.

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[5] holds in different

[5]Beaudry and Portier [2006].

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. This information is interpreted in different ways in periods of high or low uncertainty, influencing the impact of the news. The positive economic effects led by technology news are systematically higher in periods of high uncertainty, depending on the initial degree of uncertainty (level effect) and on how agents update their expectations about macroeconomic and financial conditions (transmission effect).

These results are consistent with Bloom [2009]'s interpretation of an overshooting of productivity in the medium-term after a period of high uncertainty. Productivity grows as firms address their pent-up demand for investments, and substitute less flexible for more flexible capital (Comin, 2000). Cascaldi-Garcia and Galvao [2017] show that high uncertainty increases the likelihood of news shocks, creating a 'good uncertainty' effect.

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 et al. [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 [2016] and Carriero et al. [2016c] 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 stochastic volatility in mean and the estimation procedure in Section 4.2. Section 4.3 introduces an identification procedure for the news shock that takes into account nonlinear and time-varying models, and a procedure for identifying uncertainty shocks. Section 4.4 presents the estimated latent macro and financial uncertainty measures. Section 4.5 summarizes the results for a news shock and its relations with uncertainty measures, while Section 4.6 describes the results of macroeconomic and uncertainty shocks. Section 4.7 concludes this paper.

4.2 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. [2016a], 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., 2016a).

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.

4.2.1 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 (2×1) 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

$$y_t = \mathbf{A}_1 y_{t-1} + ... + \mathbf{A}_p y_{t-p} + \mathbf{B}_0 g_t + ... + \mathbf{B}_l g_{t-l} + v_t, \tag{4.1}$$

where $\mathbf{A}_i$ are $(n \times n)$ matrices that collect the coefficients of the lags of y_t from 1 to p, $\mathbf{B}_i$ 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

$$v_t = \mathbf{A}_0^{-1} \mathbf{\Lambda}_t^{1/2} \epsilon_t, \quad \epsilon_t \sim iid\, N(0, I), \tag{4.2}$$

where $\mathbf{A}_0$ is a lower $(n \times n)$ triangular matrix with ones in the main diagonal, and $\mathbf{\Lambda}_t$ is the time-varying $(n \times n)$ diagonal matrix that collects the variance of each variable. Each element of $\mathbf{\Lambda}_t$ 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 $\mathbf{\Lambda}_t$ (in logs) are defined as

$$\ln \lambda_{j,t} = \begin{cases} \beta_{m,j} \ln m_t + \ln h_{j,t} & \text{if } j = 1, ..., n_m \\ \beta_{f,j} \ln f_t + \ln h_{j,t} & \text{if } j = n_m + 1, ..., n \end{cases}, \tag{4.3}$$

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

$$\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1} + e_{j,t}, \quad j = 1, ..., n, \tag{4.4}$$

where $e_t = (e_{1,t}, ..., e_{n,t})'$ is jointly and independently distributed as *iid* $N(0, \mathbf{\Phi_e})$, and $\Phi_e = diag(\phi_1, ..., \phi_n)$.

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

$$g_t = \mathbf{D}_1 g_{t-1} + ... + \mathbf{D}_k g_{t-k} + \delta \Delta y_{t-1} + u_t, \tag{4.5}$$

where $\mathbf{D}_i$ are (2×2) matrices that collect the coefficients of the lags of the uncertainty factors g_t from 1 to k. δ 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 e_t and ϵ_t, with mean 0 and full covariance matrix defined as

$$\Phi_u = \begin{bmatrix} \phi_{n+1} & \phi_{n+3} \\ \phi_{n+3} & \phi_{n+2} \end{bmatrix}. \tag{4.6}$$

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. [2016a] 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 $h_{j,t}$ are estimated by the standard algorithm proposed by Kim et al. [1998], using a 10-state mixture of normals approximation from Omori et al. [2007]. The estimation of the non-observed macroeconomic and financial uncertainties is substantially more complex, presenting a multi-variate non-linear 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 et al. [2010] and the ancestor sampling improvements proposed by Lindsten et al. [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 4.1), and $k = 1$ lag of the macro and financial factors in the Uncertainty VAR (equation 4.5). The full estimation procedure is described in detail in the Appendices.[6]

4.2.2 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

[6]Appendix B.1 describes the triangularization procedure for drawing the coefficients in large VARs proposed by Carriero et al. [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 B.2 presents the steps of the MCMC algorithm. Appendix B.3 describes the particle Gibbs with ancestor sampling.

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, 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, manufacturing, high technology, health and other). The financial variables mostly matches those used by Jurado et al. [2015] and Carriero et al. [2016a] to construct their measures of financial uncertainty.

A full description of the sources and construction of the 28 variables can be found in Appendix B.7.

4.3 Identification procedure for news and uncertainty shocks

In this Section I present the strategy for identifying news and uncertainty shocks. These procedures can be considered as two separate computation methods, one time-varying and the other is time-invariant. The first is an innovative identification procedure for news shocks that takes into account nonlinear and time-varying models, in which the news shock presents different economic responses in each point in time. The second is a standard generalized impulse response procedure for macroeconomic and financial uncertainty shocks. Since the latent macro and financial factors have time invariant covariances, the identification procedure is also invariant over time.

4.3.1 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,[7] 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 et al. [2014].

The identification procedure presented by Barsky and Sims [2011] is broadly adopted in the news shock literature.[8] However, this identification method is only applicable to time invariant covariance cases. A more flexible identification method is needed to 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 4.1. Considering a model with a fully exogenous uncertainty measure g_t, I rewrite equation 4.1 as a function of the lag operator L, leading to a VAR-X representation of the form

$$y_t = \mathbf{A}(L)y_t + \mathbf{B}(L)g_t + \mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\epsilon_t, \tag{4.7}$$

where $\mathbf{A}(L) = \mathbf{A}_1 L + \mathbf{A}_2 L^2 + ... + \mathbf{A}_p L^p$ and $\mathbf{B}(L) = \mathbf{B}_0 + \mathbf{B}_1 L + ... + \mathbf{B}_l L^l$. A moving average representation of this model[9] is defined as the infinite polynomial of the lag operator L as $\mathbf{C}(L) = \mathbf{C}_0 + \mathbf{C}_1 L + ... = [\mathbf{I}_n - \mathbf{A}(L)]^{-1}$, where $\mathbf{C}_0 = \mathbf{I}_n$, as

$$y_t = \mathbf{C}(L)\mathbf{B}(L)g_t + \mathbf{C}(L)\mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\epsilon_t. \tag{4.8}$$

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

$$\epsilon_t = \mathbf{P}s_t, \tag{4.9}$$

which implies

$$\mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\epsilon_t = \mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\mathbf{P}s_t. \tag{4.10}$$

The innovations ϵ_t and the structural shocks s_t are i.i.d. $N(0, \mathbf{I}_n)$. To ensure that $\mathbb{E}[\mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\epsilon_t\epsilon_t^{'}\mathbf{\Lambda}_t^{1/2'}\mathbf{A}_0^{-1'}] = \mathbb{E}[\mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\mathbf{P}s_t s_t^{'}\mathbf{P}'\mathbf{\Lambda}_t^{1/2'}\mathbf{A}_0^{-1'}] = \mathbf{\Sigma}_t$, it suffices that $\mathbf{P}\mathbf{P}' = \mathbf{I}_n$. $\mathbf{P}$ 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

$$y_t = \mathbf{C}(L)\mathbf{B}(L)g_t + \mathbf{C}(L)\mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\mathbf{P}s_t, \tag{4.11}$$

[7] I follow Barsky and Sims [2011] by fixing the horizon at 40 quarters ahead.

[8] For example, Coibion and Gorodnichenko [2012], Kurmann and Otrok [2013], Forni et al. [2014], Ben Zeev and Khan [2015], Görtz et al. [2016] and Cascaldi-Garcia and Galvao [2017]. See Beaudry and Portier [2014] for an extensive discussion about identification methods for news shocks.

[9] See Ocampo and Rodríguez [2012] for a comprehensive description of the moving average representation of VAR-X models.

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

Now, the Barsky and Sims [2011] identification procedure for the news shock relies on finding one of the infinite alternatives of $\mathbf{P}$ 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

$$\Gamma_{1,1}(k)_{surprise} + \Gamma_{1,2}(k)_{news} = 1 \forall h, \tag{4.12}$$

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

$$y_{t+K} - \mathbb{E}[y_{t+K}] = \sum_{k=0}^{K} (\mathbf{C}_k \mathbf{B}_k g_{t+k} + \mathbf{C}_k \mathbf{A}_0^{-1} \mathbf{\Lambda}_{t+k}^{1/2} \mathbf{P} s_{t+K-k}), \tag{4.13}$$

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

$$\begin{aligned}\Gamma_{1,2}(K)_{t,news} =& \frac{q_1' \left(\sum_{k=0}^{K} (\mathbf{C}_k \mathbf{B}_k g_{t+k} + \mathbf{C}_k \mathbf{A}_0^{-1} \mathbf{\Lambda}_{t+k}^{1/2} \mathbf{P} q_2)(\mathbf{C}_k \mathbf{B}_k g_{t+k} + \mathbf{C}_k \mathbf{A}_0^{-1} \mathbf{\Lambda}_{t+k}^{1/2} \mathbf{P} q_2)' \right) q_1}{q_1' \left(\sum_{k=0}^{K} \mathbf{C}_k \mathbf{\Sigma}_{t+k} \mathbf{C}_k' \right) q_1} = \dots \\ =& \frac{\sum_{k=0}^{K} (\mathbf{C}_{1,k} \mathbf{B}_{1,k} g_{t+k} + \mathbf{C}_{1,k} \mathbf{A}_0^{-1} \mathbf{\Lambda}_{t+k}^{1/2} \tau)(\mathbf{C}_{1,k} \mathbf{B}_{1,k} g_{t+k} + \mathbf{C}_{1,k} \mathbf{A}_0^{-1} \mathbf{\Lambda}_{t+k}^{1/2} \tau)'}{\sum_{k=0}^{K} \mathbf{C}_{1,k} \mathbf{\Sigma}_{t+k} \mathbf{C}_{1,k}'},\end{aligned} \tag{4.14}$$

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 $\mathbf{C}_k$ 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 $\mathbf{P}$ can be written as τ, which is an orthonormal vector that makes $\mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\tau$ 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, $\mathbf{\Lambda}_t^{1/2}$ and $\mathbf{\Sigma}_t$. In other words, the variance decomposition depends on the time t in which it is measured. The news shock is identified by picking τ that maximizes the share described in equation 4.14, but the dependence of this share on t can lead to a different τ 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

$$\tau_t^{news} = argmax \sum_{k=0}^{K} \Gamma_{1,2}(k)_{t,news}, \tag{4.15}$$

subject to

$$\begin{aligned} &\mathbf{A}_0(1,j) = 0, \forall j > 1 \\ &\tau_t(1,1) = 0 \\ &\tau_t^{'}\tau_t = 1, \end{aligned} \tag{4.16}$$

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 τ_t vector is orthonormal.

In practice, two elements introduce additional nonlinearity to the forecast error described in equation 4.13: 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 $\mathbf{\Lambda}_t^{1/2}$ on the uncertainty factors g_t. I deal with this nonlinearity by employing a generalized impulse response structure[10] in substitution for the forecast error described by equation 4.13. 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 $\omega_{j,t}^r$.

The full identification procedure and steps for the generalized impulse responses are described in Appendix B.6. To summarize, it is possible to show that, conditional on the draw r of the random innovation $\omega_{j,t}^r$, on the information set containing all the known history up to time t defined as $\mathbf{Z}_t = (y_{t-p}, ..., y_t; g_{t-p}, ..., g_t)$,[11] and on the coefficient matrices $\mathbf{\Pi} = [\mathbf{A}_i, \mathbf{B}_i, \mathbf{D}_i, \beta_j, \gamma_j, \delta]$, the generalized impulse response at time

[10]Adapting the procedure proposed by Koop et al. [1996] and Pesaran and Shin [1998].

[11]Where $g_t = (\ln m_t; \ln f_t)$.

k of a generic utilization-adjusted TFP shock is given by

$$\begin{aligned} GI^r_{TFP,t}(k, \tau^r_{TFP}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}) = \mathbb{E}[y^r_{t+k,TFP}, g^r_{t+k,TFP} | \tau^r_{TFP}, \mathbf{\Lambda}^r_{t+k,TFP}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}] \\ - \mathbb{E}[y^r_{t+k,base}, g^r_{t+k,base} | \mathbf{\Lambda}^r_{t+k,base}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}], \end{aligned} \tag{4.17}$$

where τ^r_{TFP} 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 ($\mathbf{C}_{1,k}\mathbf{B}_{1,k}g_{t+k} + \mathbf{C}_{1,k}\mathbf{A}_0^{-1}\mathbf{\Lambda}^{1/2}_{t+k}\tau$) in equation 4.14 for $GI^r_{TFP,t}(k, \tau^r_{TFP}, \omega^r_{j,t}, \mathbf{Z}_t, , \mathbf{\Pi})$, or simply $GI^r_{TFP,t}(k)$ for notation purposes.

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

$$\tau^r_{t,news} = \arg\max \frac{\sum_{k=0}^{K} GI^r_{TFP,t}(k,\tau) GI^r_{TFP,t}(k,\tau)'}{\sum_{k=0}^{K} \mathbf{C}_1 \mathbf{\Sigma}_{t+k} \mathbf{C}_1'}, \tag{4.18}$$

subject to

$$\begin{aligned} &\mathbf{A}_0^{-1}(1,j) = 0, \quad \forall j > 1, \\ &\tau(1,1) = 0, \\ &\tau'\tau = 1. \end{aligned} \tag{4.19}$$

After obtaining the identification vector for the news shock $\tau^r_{t,news}$ for the draw r of the random innovations $\omega^r_{j,t}$, 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 $\omega^r_{j,t}$, on the information set $\mathbf{Z}_t$, and on the coefficients $\mathbf{\Pi}$, the generalized impulse response at time k of the technology news shock is given by

$$\begin{aligned} GI^r_{t,news}(k, \tau^r_{t,news}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}) = \mathbb{E}[y^r_{t+k,news}, g^r_{t+k,news} | \tau^r_{t,news}, \mathbf{\Lambda}^r_{t+k,news}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}] \\ - \mathbb{E}[y^r_{t+k,base}, g^r_{t+k,base} | \mathbf{\Lambda}^r_{t+k,base}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}]. \end{aligned} \tag{4.20}$$

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

$$\begin{aligned} GI_{t,news}(k, \tau_{t,news}, \mathbf{Z}_t, \mathbf{\Pi}) = & [\bar{y}_{t+k,news}(k, \tau_{t,news}, \mathbf{Z}_t, \mathbf{\Pi}), \bar{g}_{t+k,news}(k, \tau_{t,news}, \mathbf{Z}_t, \mathbf{\Pi})] \\ & - [\bar{y}_{t+k,base}(k, \mathbf{Z}_t, \mathbf{\Pi}), \bar{g}_{t+k,base}(k, \mathbf{Z}_t, \mathbf{\Pi})]. \end{aligned} \tag{4.21}$$

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 4.7. If there are no time-varying volatility or exogenous variables, this equation is reduced to

$$y_t = \mathbf{A}(L)y_t + \mathbf{A}_0^{-1}\mathbf{\Lambda}^{1/2}\epsilon_t, \tag{4.22}$$

and its moving average representation is simply

$$y_t = \mathbf{C}(L)\mathbf{A}_0^{-1}\mathbf{\Lambda}^{1/2}\epsilon_t. \tag{4.23}$$

Now, considering the same linear mapping between the innovations (ϵ_t) and the structural shocks (s_t) as in equation 4.9, the share of the forecast error variance of the news shock defined in equation 4.14 becomes

$$\begin{aligned} \Gamma_{1,2}(k)_{news} = & \frac{q_1' \left(\sum_{k=0}^{K} (\mathbf{C}_k \mathbf{A}_0^{-1} \mathbf{\Lambda}^{1/2} \mathbf{P} q_2)(\mathbf{C}_k \mathbf{A}_0^{-1} \mathbf{\Lambda}^{1/2} \mathbf{P} q_2)' \right) q_1}{q_1' \left(\sum_{k=0}^{K} \mathbf{C}_k \mathbf{\Sigma} \mathbf{C}_k' \right) q_1} = ... \\ = & \frac{\sum_{k=0}^{K} (\mathbf{C}_{1,k} \mathbf{A}_0^{-1} \mathbf{\Lambda}^{1/2} \tau)(\mathbf{C}_{1,k} \mathbf{A}_0^{-1} \mathbf{\Lambda}^{1/2} \tau)'}{\sum_{k=0}^{K} \mathbf{C}_{1,k} \mathbf{\Sigma} \mathbf{C}_{1,k}'} \end{aligned} \tag{4.24}$$

and $\Gamma_{1,2}(k)_{news}$ does not depend on t anymore. The procedure of finding τ that maximizes the share of the forecast error variance of equation 4.24 under the same restrictions described in equation 4.16 is equivalent to the Barsky and Sims [2011] procedure.

4.3.2 Measuring the uncertainty transmission effect

In this section I present two counterfactuals to evaluate the relation between news shocks and the level of uncertainty. The different effects of the news shock over time may come from three sources of nonlinear transmission channels:

(i) the time-varying volatility ($\mathbf{\Lambda}_t$ in equation 4.2);

(ii) the contemporaneous reaction of the variables to the uncertainty level (coefficients $\mathbf{B}_i$ in equation 4.1); or

(iii) the lagged reaction of uncertainty to the variables (coefficients δ in equation 4.5).

The first counterfactual relates to the time-varying volatility (i), and its purpose is to check whether the initial uncertainty condition matters for the effect of the news shock. Since the time-varying volatility is a linear (positive) function of the uncertainty measures, higher uncertainty increases the size of the shock, creating a direct level effect. One way to measure the level effect of uncertainty on the transmission of the news shock is to fix the uncertainty level across time. I fix the macroeconomic and financial uncertainties to their means, and compare it to the identification with time-varying uncertainty. In this procedure I still allow for the transmission channels (ii) and (iii) of reaction of the variables to (and from) uncertainty. The procedure consists of calculating the difference between the (baseline) generalized impulse responses from the time-varying procedure described by equation 4.21, and an artificial generalized impulse response in which the initial condition is changed. Since the only difference between this counterfactual and the baseline is the level of uncertainty (and, consequently, the size of the shock), this counterfactual isolates the level effect of uncertainty to the news shock.

Formally, define the artificial information set containing all the known history up to time t and the means of the macro and financial uncertainties as $\mathbf{Z}_t^* = (y_{t-p}, ..., y_t; \overline{g})$, where $\overline{g} = (\frac{1}{T}\sum_{t=1}^{T} \ln m_t; \frac{1}{T}\sum_{t=1}^{T} \ln f_t)$. Following the steps described in section 4.3.1, the artificial generalized impulse responses with fixed initial uncertainty conditions can be constructed as

$$\begin{aligned} GI^*_{t,news}(k, \tau^*_{t,news}, \mathbf{Z}^*_t, \mathbf{\Pi}) = {} & \mathbb{E}[y_{t+k}, g_{t+k} | \tau^*_{t,news}, \mathbf{\Lambda}^*_{t+k,news}, \mathbf{Z}^*_t, \mathbf{\Pi}] \\ & - \mathbb{E}[y_{t+k}, g_{t+k} | \mathbf{\Lambda}^*_{t+k}, \mathbf{Z}^*_t, \mathbf{\Pi}]. \end{aligned} \tag{4.25}$$

The final effect of the initial uncertainty condition on the news shock can be calculated as the difference between the generalized impulse responses from equation 4.21 and from equation 4.25, as in

$$GI_{t,level} = GI_{t,news}(k, \tau_{t,news}, \mathbf{Z}_t, \mathbf{\Pi}) - GI^*_{t,news}(k, \tau^*_{t,news}, \mathbf{Z}^*_t, \mathbf{\Pi}). \tag{4.26}$$

The second counterfactual aims to check whether there is a nonlinear feedback between uncertainty and the news shock. It involves shutting down the transmission channels (ii) and (iii) of the contemporaneous feedback of uncertainty to the mean of the variables and the lagged feedback effect of the variables to uncertainty. The transmission effect (i) of time-varying volatility is still on, which means that higher uncertainty increases the size of the shock both on the baseline and on this counterfactual. It follows that the only difference between the baseline and this counterfactual is the transmission (to and from) uncertainty, so calculating the difference between the generalized impulse responses isolates the transmission effect.

Recalling the Main and Uncertainty VARs (equations 4.1 and 4.5), the contemporaneous feedback of uncertainty to the mean of the variables is captured by the coefficients $\mathbf{B}_i$ in equation 4.1, and the lagged feedback effect of the variables to uncertainty by the coefficients δ in equation 4.5. Shutting down the nonlinear feedback (to and from) uncertainty means restricting to zero the coefficient matrices $\mathbf{B}_i$ and δ. Following these restrictions, the Main and Uncertainty VARs would be respectively written as

$$y_t = \mathbf{A}_1 y_{t-1} + ... + \mathbf{A}_p y_{t-p} + v_t, \tag{4.27}$$

and

$$g_t = \mathbf{D}_1 g_{t-1} + ... + \mathbf{D}_k g_{t-k} + u_t. \tag{4.28}$$

The procedure for the second counterfactual consists of calculating the difference between the generalized impulse responses from the time-varying procedure described by equation 4.21, and an artificial generalized impulse response in which the coefficients matrices $\mathbf{B}_i$ and δ are restricted to zero. Formally, define a restricted set of coefficients as $\mathbf{\Pi}^\dagger = [\mathbf{A}_i, \mathbf{B}_i = \mathbf{0}, \mathbf{D}_i, \beta_j, \gamma_j, \delta = \mathbf{0}]$. Following the steps described in section 4.3.1, the artificial generalized impulse responses with no uncertainty feedback can be constructed as

$$\begin{aligned} GI^\dagger_{t,news}(k, \tau^\dagger_{t,news}, \mathbf{Z}_t, \mathbf{\Pi}^\dagger) = {} & \mathbb{E}[y_{t+k}, g_{t+k} | \tau^\dagger_{t,news}, \mathbf{\Lambda}^\dagger_{t+k,news}, \mathbf{Z}_t, \mathbf{\Pi}^\dagger] \\ & - \mathbb{E}[y_{t+k}, g_{t+k} | \mathbf{\Lambda}^\dagger_{t+k}, \mathbf{Z}_t, \mathbf{\Pi}^\dagger]. \end{aligned} \tag{4.29}$$

The final effect of the transmission (to and from) uncertainty on the news shock can be calculated as the difference between the generalized impulse responses from equation 4.21 and from equation 4.29, as in

$$GI_{t,feedback} = GI_{t,news}(k, \tau_{t,news}, \mathbf{Z}_t, \mathbf{\Pi}) - GI^\dagger_{t,news}(k, \tau^\dagger_{t,news}, \mathbf{Z}_t, \mathbf{\Pi}^\dagger). \tag{4.30}$$

4.3.3 Identification procedure for macroeconomic and financial uncertainty shocks

The uncertainty shocks are modeled as a shock to the common uncertainty factors that compose the volatilities of each variable. Since these factors are also included in the Main VAR, the uncertainty shock can affect both the mean and the variance of the variables of interest y_t.

In this model, there are two uncertainty factors (macro and financial), which share a full variance-covariance matrix defined as

$$\mathbf{\Phi}_u = \begin{bmatrix} \phi_{n+1} & \phi_{n+3} \\ \phi_{n+3} & \phi_{n+2} \end{bmatrix}. \tag{4.31}$$

This setup demands imposing an orthogonalization structure to achieve the structural macro and financial shocks. Employing a Cholesky structure leads to two possible orthogonalizations: macro uncertainty ordered first with financial uncertainty ordered last, and the inverse.

As a benchmark, I define financial variables as "fast" variables, while macro variables are "slow" variables. It means that financial uncertainty can react contemporaneously to macroeconomic uncertainty shocks, but macroeconomic uncertainty can only react to financial uncertainty shocks with one lag. This ordering is equivalent to modeling macro uncertainty first and financial uncertainty last in the Cholesky identification structure.

In contrast to the news shock, the variance-covariance matrix of the uncertainties does not change across time. I identify both shocks at the last observation T, so the information set here is $\mathbf{Z}_T = (y_{T-p}, ..., y_T; g_{T-p}, ..., g_T)$.[12]

The full identification procedure is described in Appendix B.6, but the general idea is to produce a baseline and a shocked path for y_t, g_t and $\mathbf{\Lambda}_t$ based on each of the uncertainty shocks (macro and financial). The shocks are identified as

$$\begin{aligned} \tau^r_{macro} &= \tilde{\mathbf{\Phi}}_u * q_i^{macro}, \\ \tau^r_{fin} &= \tilde{\mathbf{\Phi}}_u * q_i^{fin}, \end{aligned} \tag{4.32}$$

where $\tilde{\mathbf{\Phi}}_u$ is the lower triangular Cholesky decomposition of $\mathbf{\Phi}_u$, r is the index of the set of randomly drawn $\omega^r_{j,t}$ innovations, q_i^{macro} is a 2×1 vector with 1 in the first position and zero in the second, and q_i^{fin} is a 2×1 vector with zero in the first position and 1 in

[12] Where $g_T = (\ln m_T; \ln f_T)$.

the second. For $T+1$, I construct a one standard deviation shock on macro uncertainty by substituting $(u_{m,t}, u_{f,t})'$ in equation B.33 for τ^r_{macro}. I then construct by simulation a macro shocked path from $T+1$ to $T+K$ for $y^r_{t,macro}$, $g^r_{t,macro}$ and $\mathbf{\Lambda}^r_{t,macro}$ using equation B.33. I repeat the process for the financial uncertainty by using τ^r_{fin} to construct paths for $y^r_{t,fin}$, $g^r_{t,fin}$ and $\mathbf{\Lambda}^r_{t,fin}$.

By employing the generalized impulse response structure described in Appendix B.6, the final economic effect of the uncertainty shock is measured as

$$\begin{aligned} GI_{macro}(k, \tau_{macro}, \mathbf{Z}_T, \mathbf{\Pi}) &= \mathbb{E}[y_{T+k}, g_{T+k} | \tau_{macro}, \mathbf{\Lambda}_{T+k,macro}, \mathbf{Z}_T, \mathbf{\Pi}] \\ &\quad - \mathbb{E}[y_{T+k}, g_{T+k} | \mathbf{\Lambda}_{T+k}, \mathbf{Z}_T, \mathbf{\Pi}], \\ GI_{fin}(k, \tau_{fin}, \mathbf{Z}_T, \mathbf{\Pi}) &= \mathbb{E}[y_{T+k}, g_{T+k} | \tau_{fin}, \mathbf{\Lambda}_{T+k,fin}, \mathbf{Z}_T, \mathbf{\Pi}] \\ &\quad - \mathbb{E}[y_{T+k}, g_{T+k} | \mathbf{\Lambda}_{T+k}, \mathbf{Z}_T, \mathbf{\Pi}]. \end{aligned} \tag{4.33}$$

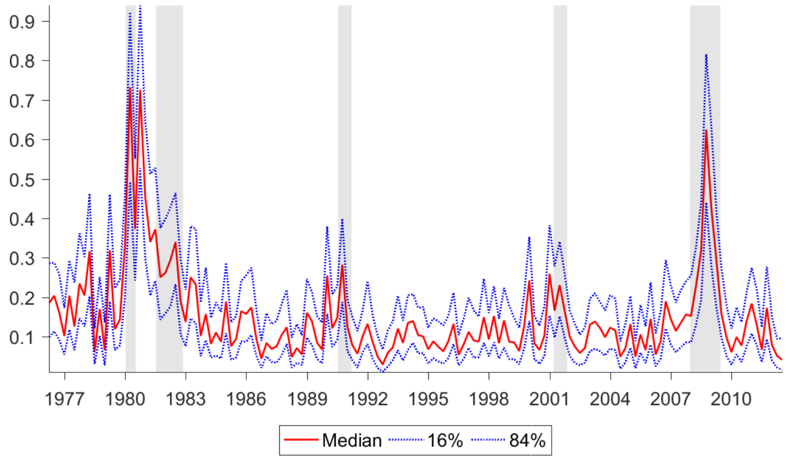
4.4 Latent uncertainty measures

In this Section I present the estimated macro and financial uncertainties from the stochastic volatility in mean model presented in Section 4.2. 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 factors across the volatilities are the estimations of aggregate macroeconomic and financial uncertainties.

Figure 4.3 displays the estimated aggregate macroeconomic uncertainty, and Figure 4.4 shows the estimated financial uncertainty. The stochastic volatilities of the macroeconomic and financial variables are presented in Appendix B.8. The economic assumption that macro and financial uncertainty may be related to each other is captured by the interaction between the two uncertainty measures included in the Uncertainty VAR (equation 4.5) and the full variance-covariance matrix between the two factors (equation 4.6). Figures 4.3 and 4.4 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.

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

Figure 4.3: Aggregate macroeconomic uncertainty



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 B.2 and B.3. Shaded areas are the recession periods calculated by the NBER.

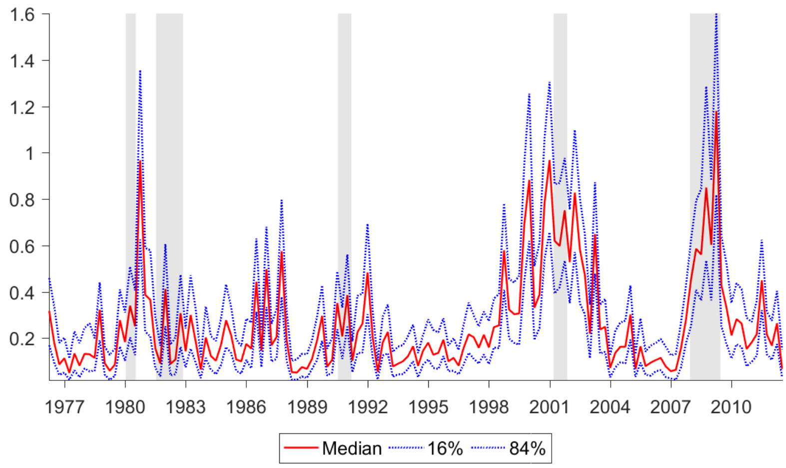
uncertainty. The 2008 crisis shows high macro and financial uncertainties.

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 4.3 and the 1-month ahead macroeconomic uncertainty from Ludvigson et al. [2016] share a correlation of 0.76 over the period 1975Q1 and 2012Q3,[13] with 0.77 for both the 3-months ahead and 12-months ahead versions. The correlation of the financial uncertainty presented in Figure 4.4 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 or 12-months ahead versions 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 0.36. 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

[13] I transform the uncertainty measures calculated by Ludvigson et al. [2016] from monthly to quarterly by averaging across the quarter.

Figure 4.4: 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 B.2 and B.3. Shaded areas are the recession periods calculated by the NBER.

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[14] with stationary monthly data, while 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,[15] I construct the uncertainty measures using only 14 macro and 14 financial series.

[14]McCracken and Ng [2016].

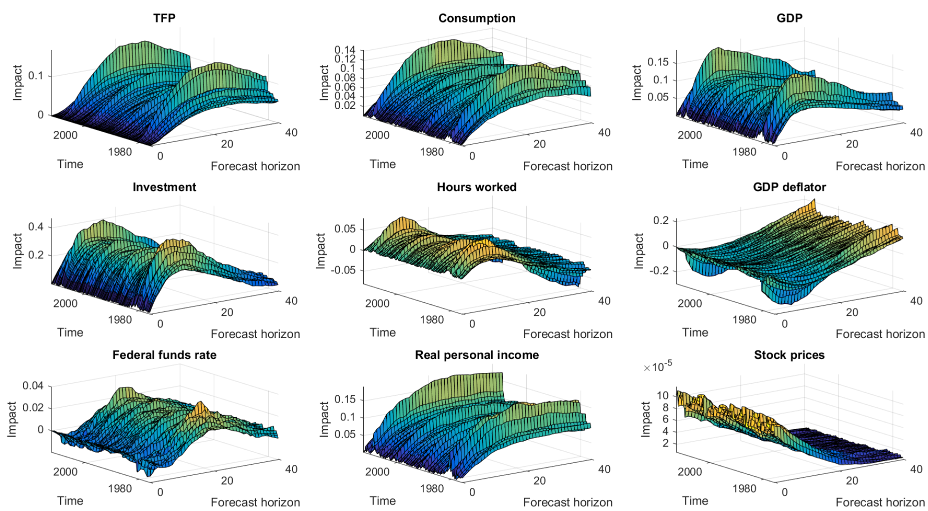
[15]Please refer to the On-line Appendix of Jurado et al. [2015] for a detailed description of the database employed by the authors.

4.5 Time-varying impulse responses to a news shock

In this Section I present the results of the news shock identification. For every point in time the news shock economic responses are different, conditional on the estimated time-varying volatility. This procedure makes it possible to understand the different effects of a news shock on periods of high and low macro and financial uncertainty.

Figures 4.5 and 4.6 present the economic responses of selected variables after a news shock, identified and calculated for each point in time as generalized impulse responses.[16] The graphs in Figure 4.5 show 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 4.6 presents these same impulse responses "sliced" at selected forecast horizons.

Figure 4.5: Time-varying effects of news shocks

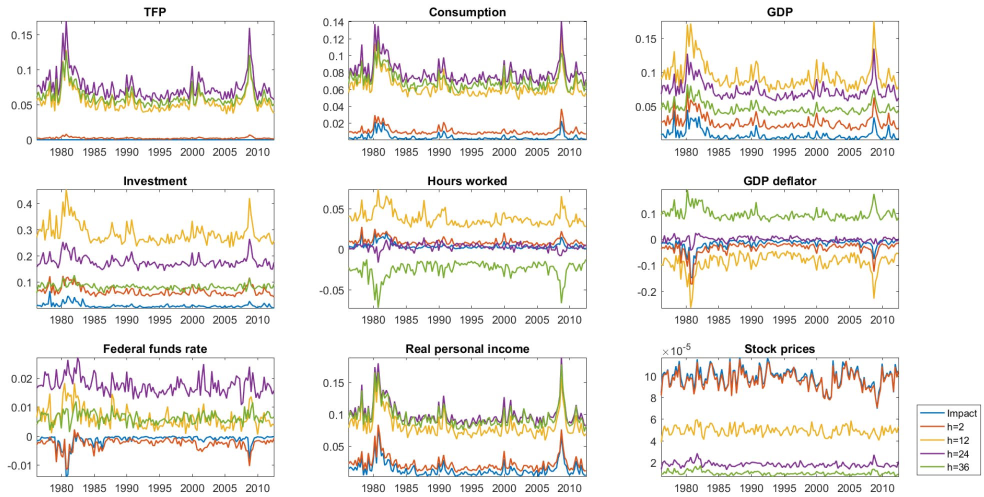


Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.1. The generalized impulse responses for each period are the average of 1,000 simulated random innovations, as described in Appendix B.6.

The top-left graph of Figure 4.6 shows the effect of a technology news shock over the utilization-adjusted TFP. 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 graph provides evidence for how

[16] As described in Appendix B.6. The generalized impulse responses for all the variables included in the VAR can be found in Appendix B.10.

Figure 4.6: Time-varying effects of news shocks over different forecast horizons



Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.1. The generalized impulse responses for each period are the average of 1,000 simulated random innovations, as described in Appendix B.6. Each line corresponds to the effect of the news shock h-quarters ahead from the point in time, as "slices" of the graphs from Figure 4.5.

different the effects of a news shock can be over time when a time-varying volatility is taken into account. The long-term effect of a news shock identified in the period 1980-1983 or during the 2008 crisis is about twice the effect in more stable periods, as for example, the early 1990s.

These differences over time are also found in the impulse responses for consumption, GDP, investment and real personal income. The positive effect of a news shock on consumption and personal income peaks after about 12 quarters. This new higher level of consumption and real personal income is sustained in the long-term, while GDP and investment peak at about 12 quarters and decay in the long-term. Nevertheless, the positive effects on consumption, personal income, GDP and investment are more intense during periods in which the effect of a news shock on utilization-adjusted TFP is stronger.

The responses of hours worked are positive in the medium-term ($h = 12$), and negative in the long-term ($h = 36$). These effects are substantially more intense in periods of higher volatility (early 1980s and 2008). There is a deflationary effect in the medium-term after a news shock, as evidenced by the literature.[17] 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. Figure 4.6 shows that, after 12 quarters, there is indeed a deflationary effect, but this is much more intense in periods of high volatility.

The effect on stock prices is positive, as initially indicated by Beaudry and Portier [2006]. These effects peak on impact ($h = 0$) and converge to zero in the long-term. It is worth noting, however, that the effect on stock prices is largely unrelated to the size of the effect of the news shock on utilization-adjusted TFP. The positive news about future technology is interpreted by the stock market in similar way across time, with positive effects on impact.

4.5.1 News shocks and the relationship to uncertainty

As shown, the effects of a news shock are substantially different across time. In this Section I investigate if these differences come from a potential connection between technology news shocks and uncertainty.

Bloom [2009] shows that uncertainty[18] 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. The idea is that, 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 [2017] suggest that uncertainty shocks generate 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.

I first evaluate this proposition by calculating the correlation between a series of

[17] See, for example, Christiano et al. [2010], Barsky and Sims [2011] and Barsky et al. [2014].

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

uncertainty measures and the medium ($h = 12$) and long-term ($h = 36$) effects of a news shock on utilization-adjusted TFP, consumption and GDP. Tables 4.1 and 4.2 present these correlations, while the description and availability of the uncertainty measures can be found in Table B.4 in Appendix B.7.

Table 4.1: Correlations between medium-term news shock economic responses and uncertainty measures

	Medium-term					
	TFP		Consumption		GDP	
Macro uncertainty measures						
Macro uncertainty	0.96	[0.000]	0.92	[0.000]	0.93	[0.000]
LMN-macro-1	0.79	[0.000]	0.73	[0.000]	0.76	[0.000]
LMN-macro-3	0.80	[0.000]	0.74	[0.000]	0.77	[0.000]
LMN-macro-12	0.80	[0.000]	0.74	[0.000]	0.78	[0.000]
Policy uncertainty	0.01	[0.949]	-0.02	[0.772]	0.02	[0.860]
Business uncertainty	-0.01	[0.936]	-0.02	[0.791]	-0.08	[0.373]
SPF disagreement	0.53	[0.000]	0.50	[0.000]	0.55	[0.000]
Financial uncertainty measures						
Financial uncertainty	0.52	[0.000]	0.27	[0.000]	0.39	[0.000]
LMN-fin-1	0.45	[0.000]	0.32	[0.000]	0.39	[0.000]
LMN-fin-3	0.45	[0.000]	0.31	[0.000]	0.39	[0.000]
LMN-fin-12	0.45	[0.000]	0.30	[0.000]	0.39	[0.000]
Realized volatility	0.47	[0.000]	0.39	[0.000]	0.43	[0.000]
VXO	0.65	[0.000]	0.49	[0.000]	0.64	[0.000]

*Note: The Macro uncertainty and Financial uncertainty in **bold** are the measures calculated in this paper, and presented in Figures 4.3 and 4.4. Medium-term responses are calculated 12 quarters ahead. 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 B.4 in Appendix B.7.*

Tables 4.1 and 4.2 show that the responses to a news shock are (positively) correlated with both macro and financial uncertainties. Generally speaking, the correlation is higher with macroeconomic uncertainty measures, and is higher in the medium-term than in the long-term. There is a high correlation with the aggregated macroeconomic uncertainty estimated here and with the macro uncertainties from Ludvigson et al. [2016].[19] The correlation is also positive and significant with the disagreement measure from the Survey of Professional Forecasters (SPF), ranging from 0.50 to 0.55 in the medium-term,

[19] Between 0.78 and 0.96 in the medium-term across TFP, consumption and GDP, and between 0.68 and 0.95 in the long-term.

Table 4.2: Correlations between long-term news shock economic responses and uncertainty measures

	Long-term TFP		Consumption		GDP	
Macro uncertainty measures						
Macro uncertainty	0.95	[0.000]	0.87	[0.000]	0.85	[0.000]
LMN-macro-1	0.76	[0.000]	0.67	[0.000]	0.67	[0.000]
LMN-macro-3	0.77	[0.000]	0.68	[0.000]	0.68	[0.000]
LMN-macro-12	0.76	[0.000]	0.69	[0.000]	0.68	[0.000]
Policy uncertainty	0.00	[0.973]	-0.03	[0.750]	0.03	[0.757]
Business uncertainty	-0.02	[0.831]	-0.10	[0.231]	-0.08	[0.355]
SPF disagreement	0.51	[0.000]	0.48	[0.000]	0.46	[0.000]
Financial uncertainty measures						
Financial uncertainty	0.45	[0.000]	0.28	[0.000]	0.27	[0.001]
LMN-fin-1	0.41	[0.000]	0.29	[0.000]	0.28	[0.001]
LMN-fin-3	0.40	[0.000]	0.29	[0.000]	0.28	[0.001]
LMN-fin-12	0.40	[0.000]	0.29	[0.000]	0.26	[0.001]
Realized volatility	0.44	[0.000]	0.34	[0.000]	0.35	[0.000]
VXO	0.60	[0.000]	0.52	[0.000]	0.48	[0.000]

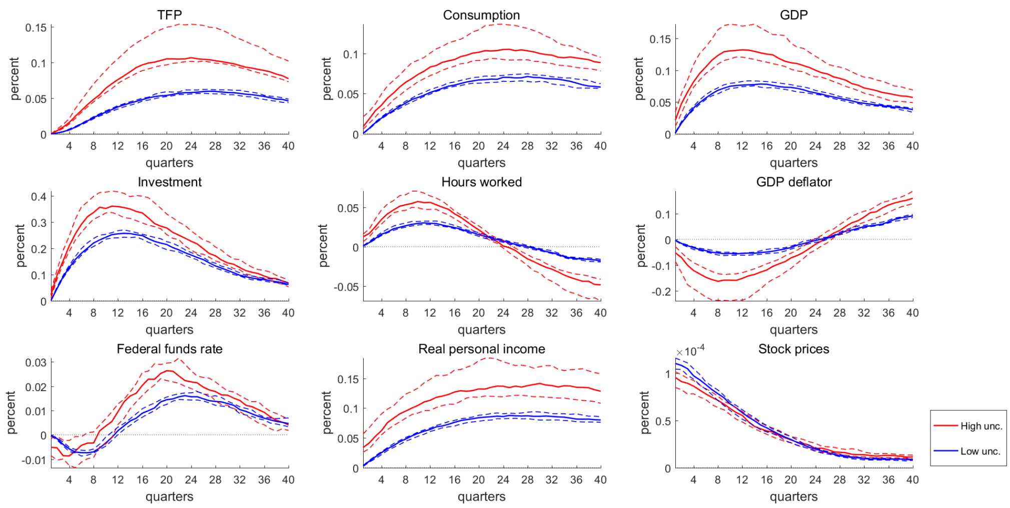
Note: The Macro uncertainty and Financial uncertainty in ***bold*** *are the measures calculated in this paper, and presented in Figures 4.3 and 4.4. Long-term responses are calculated 40 quarters ahead. The p-values for the test with zero correlation under the null hypothesis are in brackets. The statistic is calculated as* $t = \rho_0\sqrt{\frac{T-2}{1-\rho_0^2}}$. *For details on the uncertainty measures and availability, see Table B.4 in Appendix B.7.*

and from 0.46 to 0.51 in the long-term. There is no correlation of the responses with the policy uncertainty calculated by Baker et al. [2016] and with the business uncertainty from Bachmann et al. [2013]. Although smaller, all the correlations between financial uncertainties and the effects on utilization-adjusted TFP, consumption and GDP are statistically significant.

It is important to note that the news shocks identified across time are normalized to one standard deviation. Since the time-varying volatility is a linear function of the uncertainty level, the size of the shock increases in periods of high uncertainty. The high correlation of the medium and long-term effects presented in Tables 4.1 and 4.2 is a result of the transmission mechanism of the uncertainty measures to the mean of the variables presented in equations 4.1 and 4.5. This transmission mechanism makes the news shock stronger in periods of higher macroeconomic and financial uncertainty, as suggested by the data when viewed through the stochastic volatility in mean VAR model.

Figure 4.7 presents a clearer image of the differences between the effects of a news shock during high and low macroeconomic uncertainty periods. The red lines correspond to the average of generalized impulse responses on periods of high uncertainty, while the blue lines correspond to the average of generalized impulse responses on periods of low uncertainty. I define high uncertainty as the periods with the highest 10% of values for macroeconomic uncertainty, and low uncertainty with the lowest 10% of values.

Figure 4.7: Impulse responses to news shocks in periods of high and low macro uncertainty



Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.1. Red and blue lines correspond to the average of generalized impulse responses on periods of high and low uncertainty, respectively. High and low uncertainty are the periods with the higher and lower 10% values for the macroeconomic uncertainty, respectively. Each impulse response is evaluated at the posterior mean. Dashed lines correspond to 68% distribution of the impulse responses in the high and low periods.

In the high uncertainty period, the positive effects of a news shock on utilization-adjusted TFP, consumption, investment and real personal income are substantially higher. The path of utilization-adjusted TFP (top-left graph of Figure 4.7) is flatter in the low uncertainty period, while it has a positive peak about 20 quarters ahead in the high uncertainty period. Cascaldi-Garcia and Galvao [2017] show that, after an uncertainty shock, utilization-adjusted TFP rises in the medium-term, converging to zero in the long-term. This hump-shaped path of utilization-adjusted TFP observed in the high uncertainty period is in line with the view that uncertainty predicts a medium-term positive effect on technology.

The positive effect on consumption is higher in the high macroeconomic uncertainty period over the entire forecast horizon of 40 quarters, following same pattern as real personal income. With respect to GDP, the biggest difference between the high and low uncertainty periods is in the medium-term. This divergence 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 uncertainty period converges to the path of the low uncertainty period.

The deflationary effect of the news shock is more pronounced in the high macroeconomic uncertainty period. In the low uncertainty period the response of the GDP deflator is flatter, and close to zero. The effect of the news shock on the hours worked is positive in the medium-term and negative in the long-term under the high uncertainty period, while it is closer to zero under the low uncertainty period. There is no perceptible difference between the responses of the stock prices in the high or low uncertainty macroeconomic periods. It is positive on impact, converging to zero in the long-term in both cases.

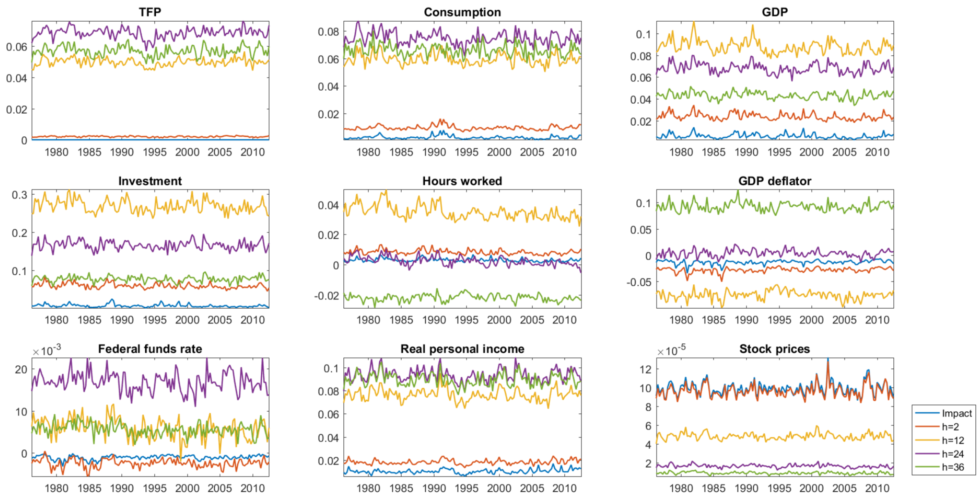
In summary, these results provide evidence that news shocks have quantitatively different effects in periods of high and low uncertainty. In periods of high uncertainty the positive effects of news shocks are boosted, in line with the notion of a transmission mechanism of technology news through uncertainty.

4.5.2 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 by providing two counterfactuals: what would happen to a news shock (i) if uncertainty would remain unchanged across time, or (ii) if there was no feedback effect from uncertainty. Section 4.3.2 provides the full description of the procedure for these two counterfactuals.

The first counterfactual checks if the initial uncertainty condition matters for the effect of the news shock. Figure 4.8 presents the impulse responses of a news shock identified with a fixed uncertainty. Differently from Figure 4.6, the effects of the news shock do not change over time when the initial uncertainty condition is fixed. Figure 4.9 outlines the importance of the initial uncertainty condition, by showing the differences between the impulse responses with time-varying uncertainty and with fixed uncertainty. This is constructed by taking the responses from Figure 4.6 and subtracting the responses from Figure 4.8. The effects of a news shock are more substantial in periods of high uncertainty, confirming the level effect that the initial uncertainty condition generates in the responses to a news shock.

Figure 4.8: Time-varying effects of news shocks over different forecast horizons with fixed uncertainty

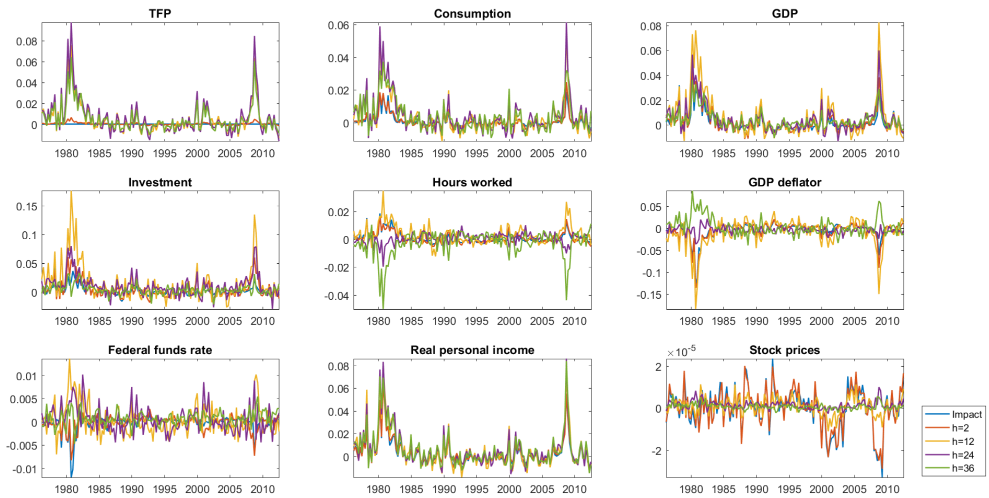


Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.2. The generalized impulse responses for each period are the average of 1,000 simulated random innovations, as described in Appendix B.6. Each line corresponds to the effect of the news shock h-quarters ahead from the point in time.

The second counterfactual checks if there is nonlinear feedback between uncertainty and the news shock. Figure 4.10 presents the generalized impulse responses of a news shock without feedback effect from uncertainty. The pattern of these responses is quite similar to the responses from the full model, in which there is a feedback effect from uncertainty (Figure 4.6). However, these effects differ in magnitude. Figure 4.11 depicts the differences between the impulse responses with and without feedback from uncertainty. This is constructed by taking the responses of Figure 4.6 and subtracting the responses from Figure 4.10.

Overall, the presence of an uncertainty feedback creates a positive bias in the effect of a news shock on consumption, GDP and investment. This can be easily observed by averaging these time-varying impulse responses, as in Figure 4.12. This Figure

Figure 4.9: Differences between responses to a news shock computed with time-varying uncertainty and with fixed uncertainty



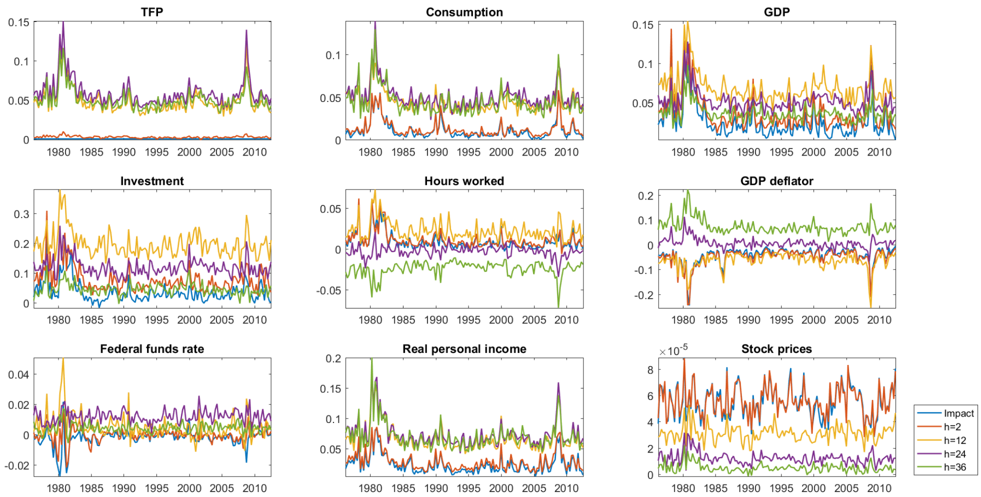
Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.2. The generalized impulse responses for each period are the average of 1,000 simulated random innovations, as described in Appendix B.6. Each line corresponds to the effect of the news shock h-quarters ahead from the point in time.

summarizes the nonlinear feedback effect of uncertainty over the news shock. On average, the feedback effect generates a positive medium-term effect on utilization-adjusted TFP, investment and GDP. Interestingly, the positive bias on investment peaks after about 10 quarters, a period in which there is still no positive bias on utilization-adjusted TFP. This is evidence that investment is anticipating future expected productivity, in line with the findings of Beaudry and Portier [2006]. In the long-term, this positive bias on utilization-adjusted TFP, investment and GDP tends to die out. With regard to consumption and real personal income, there is a positive bias that tends to persist in the long-term.

In summary, the counterfactuals presented here indicate that uncertainty and news shocks are linked through two mechanisms: an initial condition effect and a transmission effect. The initial condition effect means that, if the initial level of uncertainty in the economy is high, the effects of the news shock will also be high. This evidence is in line with the 'good uncertainty' shock literature, described before.

The transmission effect is more complex. The empirical results from the second counterfactual show that when macro and financial uncertainties are allowed to react

Figure 4.10: Time-varying effects of news shocks over different forecast horizons with no feedback effect from uncertainty



Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.2. The generalized impulse responses for each period are the average of 1,000 simulated random innovations, as described in Appendix B.6. Each line corresponds to the effect of the news shock h-quarters ahead from the point in time.

to news shocks, the positive effects of such news are amplified. 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 second 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.

Figure 4.11: Differences between responses to a news shock computed with and without feedback effect from uncertainty

Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.2. The generalized impulse responses for each period are the average of 1,000 simulated random innovations, as described in Appendix B.6. Each line corresponds to the effect of the news shock h-quarters ahead from the point in time.

4.6 Responses to macroeconomic and financial uncertainty shocks

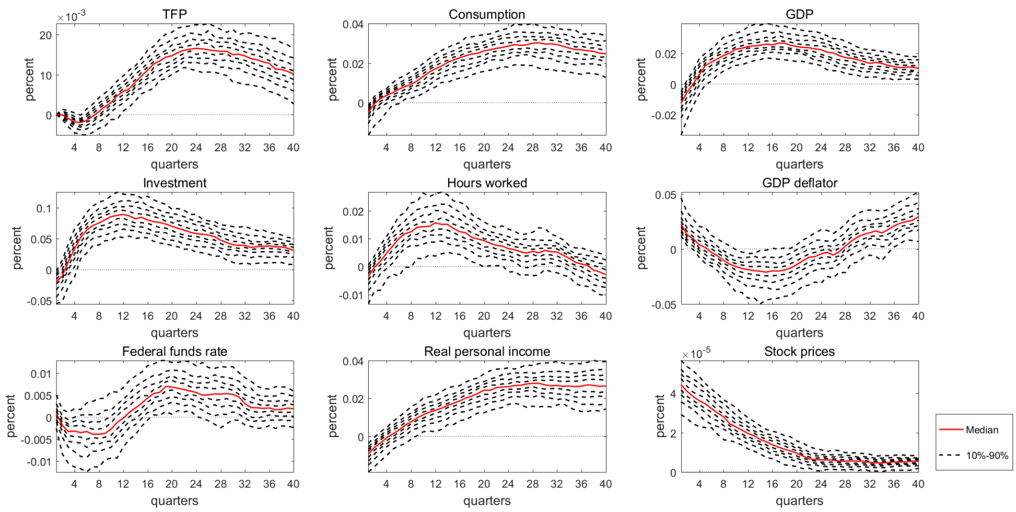
In this Section I present generalized impulse responses of macroeconomic and financial uncertainty shocks.[20] These responses help to better understand the link between uncertainty and news shocks. The uncertainty shocks are disturbances to the common macroeconomic and uncertainty volatility factors, or a second-moment shock to the variables. The benchmark results presented here consider the macro uncertainty as the first orthogonalization position, and the financial uncertainty as the last.[21]

Figure 4.13 shows the generalized impulse responses of a financial uncertainty shock for selected variables. The full generalized impulse responses can be found in Appendix B.10. The most interesting result here is the effect on utilization-adjusted TFP. After the financial uncertainty shock, utilization-adjusted TFP increases in the

[20] Appendix B.6 presents the procedure of identification of the macro and financial uncertainty shocks and the calculation of the generalized impulse responses.

[21] The alternative impulse responses considering the inverted ordering (first financial and second macro uncertainty) are presented in Appendix B.9.

Figure 4.12: Percentiles of the differences between responses to a news shock computed with and without feedback effect from uncertainty



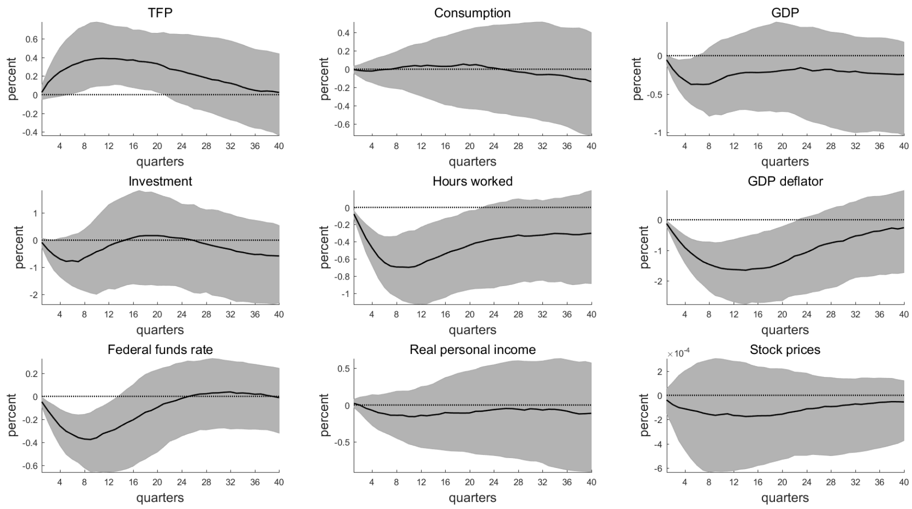
Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.2. Each line corresponds to the deciles of the differences between the news shock impulse responses with and without feedback effect from uncertainty, identified in each point in time and calculated at the posterior mean. The red line is the median.

medium-term, starting from a zero effect on impact ($t = 0$), and converging to zero in the long-term. This path resembles the expected result of a news shock on this variable. This result is in line with Cascaldi-Garcia and Galvao [2017], who show that a financial uncertainty shock foresees a medium-term positive hike in utilization-adjusted TFP.[22]

The similarity of the responses on utilization-adjusted TFP presented here and in Cascaldi-Garcia and Galvao [2017] are noteworthy, in the sense that the identification method for the financial shock is substantially different. While Cascaldi-Garcia and Galvao [2017] identify the financial uncertainty shock as the orthogonalization that maximizes the variance decomposition of an observable *proxy* of financial uncertainty in the short-term, here the financial uncertainty shock is a second moment shock to a latent estimated financial uncertainty measure from a stochastic volatility process. Nevertheless, the impact of financial uncertainty on technology follows the evidence from Cascaldi-Garcia and Galvao [2017].

[22]It is also robust to the alternative identification with financial uncertainty ordered first, as presented in Figure B.9.3 in Appendix B.9.

Figure 4.13: Impulse responses to a financial uncertainty shock



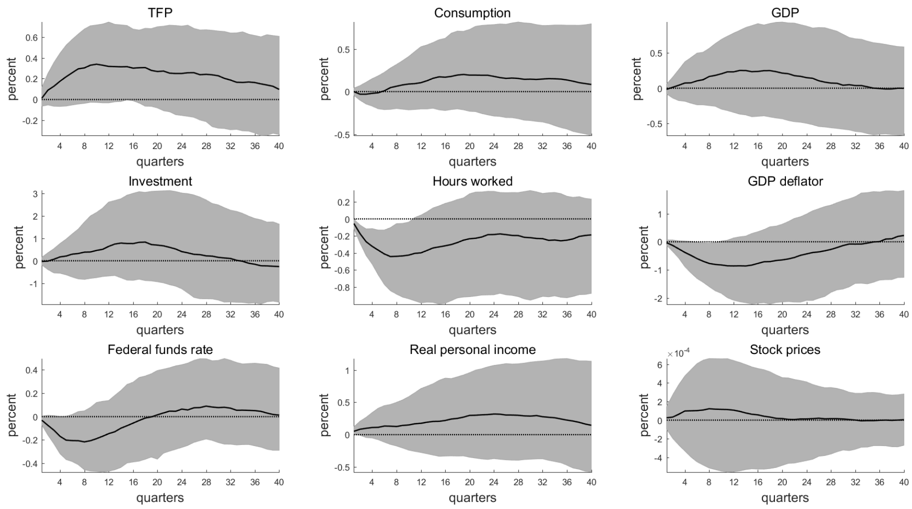
Note: The uncertainty shocks are identified through Cholesky decomposition with macroeconomic uncertainty ordered first, and financial uncertainty ordered last, as described in Section 4.3.3. The generalized impulse responses of the uncertainty shock are the average of 1,000 simulated random innovations, as described in Appendix B.6. The shaded areas define the 68% confidence bands computed with 200 posterior draws.

The effect of the financial shock on other variables is distinct from the utilization-adjusted TFP. There is no significant effect on consumption. GDP falls after the shock, driven by a reduction on investment. Both GDP and investment paths converge to zero in the medium-term, confirming the short-lived characteristic of uncertainty shocks. There is a deflationary effect, and the Federal funds rate goes down to counteract the recessionary impact.

Figure 4.14 presents the generalized impulse responses of a macroeconomic uncertainty shock on selected variables. The full generalized impulse responses can be found in Appendix B.10. Although smaller, the effect on utilization-adjusted TFP is similar to that observed in the financial uncertainty shock, with a medium-term positive effect.[23] The effect on consumption, GDP and investment are virtually zero. There is a negative impact on hours worked, and a deflationary effect in the medium-term.

[23] Similar results can be found in the alternative identification with financial uncertainty ordered first, as presented in Figure B.9.4 in Appendix B.9.

Figure 4.14: Impulse responses to a macroeconomic uncertainty shock



Note: The uncertainty shocks are identified through Cholesky decomposition with macroeconomic uncertainty ordered first, and financial uncertainty ordered last, as described in Section 4.3.3. The generalized impulse responses of the uncertainty shock are the average of 1,000 simulated random innovations, as described in Appendix B.6. The shaded areas define the 68% confidence bands computed with 200 posterior draws.

4.7 Conclusion

This paper shows that the positive 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,[24] 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.[25]

[24] See an empirical evaluation in the Introduction Section of this paper.

[25] See Beaudry and Portier [2014] for a review of the empirical evidence of news shocks under different

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. The effects of news on consumption, GDP, investment and real personal income are amplified when the news shock hits the economy in periods of high uncertainty. The results from two counterfactuals suggest that the size of these effects depends on the initial degree of uncertainty (initial condition effect) and on how expectations about macroeconomic and financial conditions are updated (transmission effect).

The initial condition effect is in line with the idea of a 'good uncertainty' shock, that is, high uncertainty increases the likelihood of news shocks (Cascaldi-Garcia and Galvao, 2017). Periods of high uncertainty are related to a higher potential return on investment, increasing the range of growth options (Segal et al., 2015). While uncertainty reduces the utilization of production factors, it also creates an incentive to substitute less flexible for more flexible capital (Comin, 2000, Bloom, 2009, Cascaldi-Garcia and Galvao, 2017).

The transmission effect relates to how uncertainty is updated with the arrival of positive technological news (Forni et al., 2017, Berger et al., 2017). The second counterfactual shows that the positive effects of a news shock are even higher 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 positive effects of news shocks are weaker than they really are. From the perspective of the uncertainty 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.

assumptions and identification methods.

Chapter 5

News shocks and the slope of the term structure of interest rates: Comment

The economic findings of Beaudry and Portier [2006] contributed to the literature on business cycles driven by agents' beliefs with the empirical identification of the 'news shock' – changes in the future total factor productivity (TFP) that are foreseen by the economic agents. The idea behind the news shock is that future technological improvements (free from utilization factors) take time until they have an impact on the economy. From a rational expectations perspective, the agents can foresee this technological impact (to some extent) and react to it now.

Kurmann and Otrok [2013] provide an important result concerning the relationship between a news shock and other economic shocks. They report a correlation of 0.86 between a news shock and the shock to the slope of the term structure, defined as the spread between the yield on a long-term treasury bond and a short-term bill rate. As emphasized by Kurmann and Otrok [2013], it is known from the finance and business cycle literatures that the slope of the term structure (i) carries information that helps to predict macroeconomic activity[1] and (ii) relates to the transmission of monetary policy.

Adopting a procedure of identification of structural shocks by maximizing the forecast error variance of a target variable,[2] Kurmann and Otrok [2013] show that the link between monetary policy transmission and economic activity is the relation between news shocks and the slope of the term structure. A positive slope shock foresees smooth future growth in consumption and utilization-adjusted TFP, accompanied by a drop in inflation. Interestingly, this is also the predicted behavior of a news shock as in Beaudry and Portier [2006]. The increase in the slope comes from a stronger response to the policy rate than the long rate, with the Federal Funds rate falling more than inflation. Since the economic responses after a slope shock are identical to a news shock, the authors conclude that the uneven effect between the short and long-term rates is the *endogenous* response of the monetary policy to a news shock.

As a result, both slope and news shocks are supposedly measuring the same economic effect. The authors also confirm these similarities by showing that news shocks explain more than half of the movements in the slope. This comment presents evidence that this relationship between news and slope of the term structure diminishes substantially after an update in the utilization-adjusted TFP series employed by Kurmann and Otrok [2013]. The correlation between news and slope shocks falls to 0.14 and the impulse responses of these shocks are fundamentally different.

The identification of the news shock in Kurmann and Otrok [2013] relies on the

[1] See Harvey [1988], Estrella and Hardouvelis [1991], Ang and Piazzesi [2003] and Kurmann and Otrok [2013].

[2] As in Faust [1998] Uhlig [2005] and Barsky and Sims [2011].

quarterly utilization-adjusted TFP series calculated by Fernald [2014]. Beaudry and Portier [2006] emphasize that when considering the identification of a news shock it is very important to control for utilization factors, capturing as closely as possible the effects of a technological change. Therefore, measures of raw TFP are not suitable to identify news shocks because their unexpected changes may be related to variations in the utilization of factors instead of technology changes.

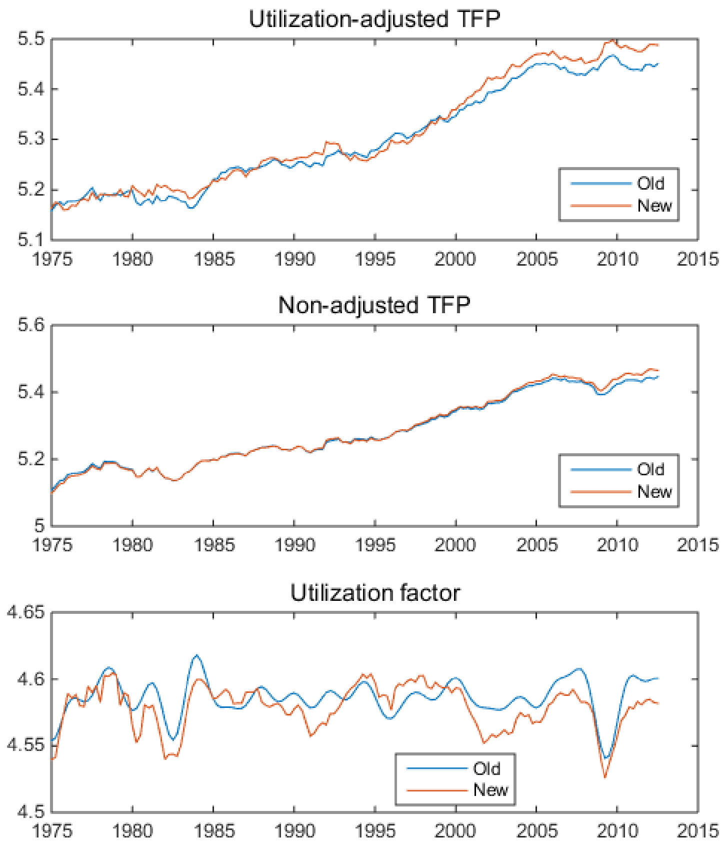
Fernald [2014] applies growth-accounting methods for imputation of capital and labor controlling for heterogeneity and adjustments for variations in factor utilization (including non-technological factors, such as the intensity margin for the workweek of capital and labor effort). Initially employed by Beaudry and Portier [2006], it became a common practice in the news shock literature to use this series for identification purposes.[3]

The utilization-adjusted TFP series is constantly updated by the author, and went through severe revisions in 2014. The main changes include the parameter estimates on utilization (from the Basu et al., 2006 methodology to Basu et al., 2013) and the imputation of hours per worker. The result of this update is a substantial change in the utilization factor and, consequently, in the utilization-adjusted TFP. A simple graph comparison (Figure 5.1) of the new and old series shows that the non-adjusted TFP is very similar before and after the update of the utilization parameters. However, the utilization factor is substantially different. Here I revisit Kurmann and Otrok [2013] in light of these changes.

The structure of this comment is as follows. In Section 5.1, I show that the Kurmann and Otrok [2013] results are sensitive to updates in the utilization-adjusted TFP series from Fernald [2014] by replicating these results with a new version of the series. Section 5.2 is a robustness check, showing that an alternative model, comprising different information set, time span and slope measure is also sensitive to the update in the utilization-adjusted TFP series. In Section 5.3, I show that a slope shock produces a positive impact on the utilization factor, indicating that the relation of slope and TFP found in Kurmann and Otrok [2013] can be some remaining effect of utilization. Section 5.4 concludes the discussion.

[3] See, for example, Barsky and Sims, 2011, Barsky et al., 2014, Forni et al., 2014 and Beaudry and Portier, 2014.

Figure 5.1: Old and new Fernald [2014] TFP series decomposed by utilization factor



Calculation from the series available at Federal Reserve Bank of San Francisco (new utilization-adjusted TFP – Nov/2015 vintage) and from Beaudry and Portier [2014] database (old utilization-adjusted TFP – Nov/2012 vintage).

5.1 Revisiting Kurmann and Otrok [2013] with a new TFP series

I start evaluating the connection between news and slope shocks from Kurmann and Otrok [2013] with the new utilization-adjusted TFP series. This first exercise consists of estimating exactly the same model as Kurmann and Otrok [2013] for news and slope shocks, but considering the updated utilization-adjusted TFP series from Fernald [2014]. I employ the code made available by the authors, with the same variables and time period.

With the original database, the correlation coefficient between the recovered news and slope shocks is 0.86 (Kurmann and Otrok, 2013). This result is substantially distinct when I employ the new updated utilization-adjusted TFP series:[4] The correlation between news and slope shocks, now, is only 0.14. This drop in the correlation is also robust to different vintages of utilization-adjusted TFP series.[5] For example, employing the vintage of May/2013, the correlation is 0.82; considering the vintage of May/2014, the correlation falls to 0.38; finally, with the vintage of May/2015, the correlation decreases to 0.18.

The economic responses of slope and news shocks are also notably different, as shown in Figures 5.2 and 5.3. Figure 5.2 provides the impulse response functions of the slope shock, with the solid lines representing the model with the new utilization-adjusted TFP series. The dashed lines represent the model with the old utilization-adjusted TFP series (as in Kurmann and Otrok, 2013). With the old series, the path of the impulse response on the utilization-adjusted TFP resembles a news shock, with zero effect on impact and smoothly converging to a new higher level (top-right graph from Figure 5.2). However, with the updated utilization-adjusted TFP series there is a positive and statistically significant effect on impact ($t = 0$). The slope shock is now capturing the positive effect of technological growth, and not an anticipated slow smooth diffusion of technology (as in a news shock).

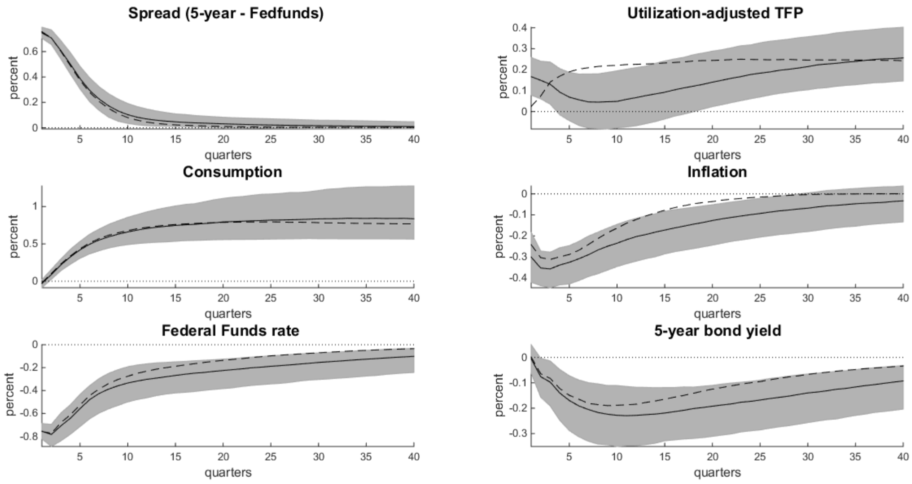
The similarities between the impulse responses after a slope shock with a news shock are the basis of the argument that variations in the slope are the endogenous monetary response to future technological changes. The implications of the slope shock on monetary policy from Kurmann and Otrok [2013] still holds under the updated utilization-adjusted TFP series, but not as a response to a news shock. First, after a slope shock, inflation falls less than the Federal Funds rate, reducing the real short rate, and showing an active expansionary monetary policy. Second, variations in the slope are a result of the drop in the short-run interest rate, since the effect on the long-run (five-year bond yield) is essentially zero. Finally, large slopes predict future economic growth (e.g., an expansion in consumption, as in Harvey, 1988), although the effect on utilization-adjusted TFP is now significant on impact.

Figure 5.3 provides the impulse response functions after a news shock. Again, the solid lines refer to the updated utilization-adjusted TFP series and the dashed lines to the old version. In order to match Kurmann and Otrok [2013], in which a news shock

[4]TFP series downloaded in November/2015 from the Federal Reserve Bank of San Francisco (http://www.frbsf.org/economic-research/economists/john-fernald/).

[5]John Fernald, via email correspondence in March 2016, has kindly provided utilization-adjusted TFP vintages from 2013 to 2015.

Figure 5.2: Comparing responses to a slope shock with the new and old versions of the utilization-adjusted TFP under the Kurmann and Otrok [2013] model



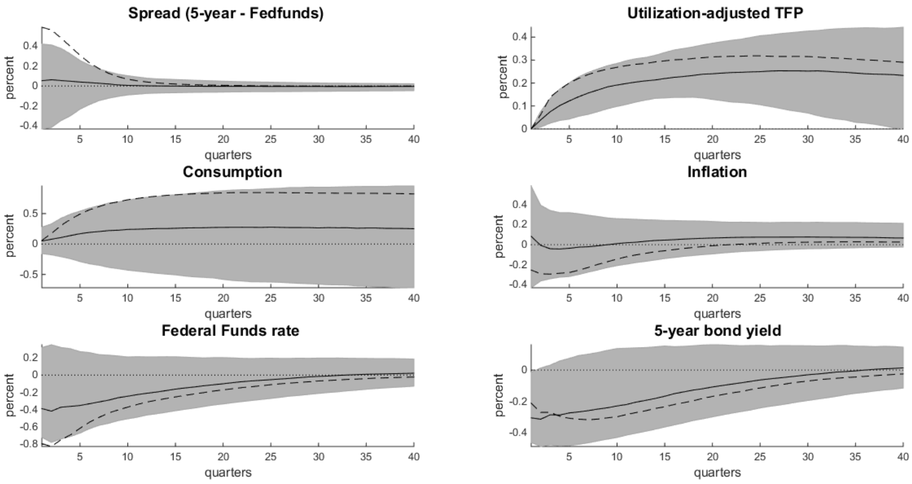
The solid line is the median effect with the revised utilization-adjusted TFP series, and the dashed is with the old utilization-adjusted TFP series. The grey area corresponds to the 16%-84% coverage bands of the model considering the new utilization-adjusted TFP series.

raises the slope of the term structure, the short rate has to decrease faster than the long rate. Here, however, the impact of a news shock on the short and long rate are very similar. As a result, the effect over the slope is nearly zero and not significant. This pattern is different from Kurmann and Otrok [2013] but resembles the DSGE results produced by Kurmann and Otrok [2011].[6]

The empirical results from Kurmann and Otrok [2013] also show that news shocks account for more than 50% of the unpredictable movements of the slope of the term structure. When adopting the new updated utilization-adjusted TFP series this share falls to 20%, and the lower coverage band is close to zero (Figure C.1.1 in Appendix C.1). In summary, the updates performed in the methodology of adjusting TFP for utilization changed the behavior of both news and slope shocks, but particularly the news shock. The result is that news and slope shocks are no longer as strongly correlated as in Kurmann and Otrok [2013].

[6]Adopting estimated DSGE models, the authors show that after a news shock the drop in the short and long rate are about the same.

Figure 5.3: Comparing responses to a news shock with the new and old versions of the utilization-adjusted TFP under the Kurmann and Otrok [2013] model



The solid line is the median effect with the revised utilization-adjusted TFP series, and the dashed is with the old utilization-adjusted TFP series. The grey area corresponds to the 16%-84% coverage bands of the model considering the new utilization-adjusted TFP series.

5.2 Robustness check with a different information set

In Section 5.1, I show that the strong relation between news shocks and the slope of the term structure as presented by Kurmann and Otrok [2013] is no longer valid. Two tests are necessary in order to certify that the update in the TFP series is the only cause of the zero correlation between news and slope shocks. First, alternative models with the old utilization-adjusted TFP series should be able to reproduce the high correlation between news and slope shocks. Second, this correlation must disappear when substituting the old utilization-adjusted TFP series for the new updated version.

I propose here an alternative VAR model[7] incorporating additional financial variables, with relevant forward-looking information that helps to identify the news shock.[8] Since variations in the slope are supposedly responses to news shocks, these new financial variables should also contribute to the identification of the slope shock. This alternative

[7]Bayesian Vector Autoregressive Model estimated with Minnesota Priors (Litterman, 1986) as suggested by Bańbura et al. [2010] and Carriero et al. [2015a].

[8]The presence of forward-looking economic variables, such as consumption and stock prices, is a necessary condition for the proper identification of a news shock (Beaudry and Portier, 2006).

model differs from Kurmann and Otrok [2013] in the variables considered,[9] the time span[10] and the measure of the slope of the term structure.[11] The identification of the news and slope shocks follows the maximization of the forecast error variance of the utilization-adjusted TFP and of the slope, respectively.

Employing the old utilization-adjusted TFP series in the alternative VAR model, the recovered news and slope shocks produce a correlation between them of 0.48, statistically significant at the 1% level. This correlation is lower than the 0.86 of Kurmann and Otrok [2013], the reason being the different time span. In Kurmann and Otrok [2013] the data covers 1959:I to 2005:I and the correlation between news and slope shocks is not as strong as 0.86 throughout the entire series. Adopting an 80 quarter moving window, I show in Figure 5.4 that the correlation is above 0.86 until the first quarter of 2000, falling sharply afterwards. In fact, considering the final sub-sample between 1985:II and 2005:I, the correlation coefficient only accounts for 0.55. In the alternative VAR model the time span is more up-to-date (from 1975:I to 2007:IV), concentrating the period where the correlation between news and slope shocks is lower.[12]

Furthermore, when employing the new updated utilization-adjusted TFP series, the correlation between the recovered news and slope shocks identified under this model is -0.33. The news shock explains only 7% (impact) to 9% (long-run) of the unpredicted movements of the slope of the term structure. In Kurmann and Otrok [2013], the impulse responses after a news and a slope shock are quite similar, which is not the case here (Figure 5.5 for the news shock and Figure 5.6 for the slope shock). Notably, there is no effect on utilization-adjusted TFP after a slope shock under this alternative VAR model. It follows that the positive effect of a slope shock on utilization-adjusted TFP

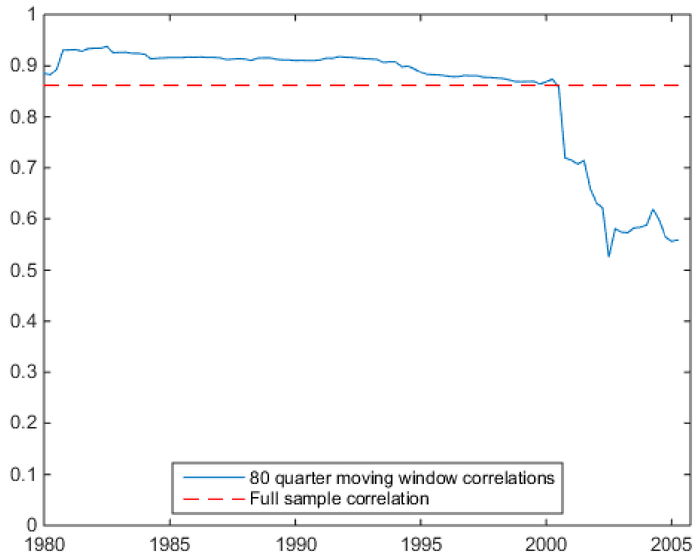
[9]The model consists of a measure of the log of utilization-adjusted total factor productivity (TFP), log of (real) personal consumption expenditures (PCE), excess bond premium (EBP) – calculated by Gilchrist and Zakrajšek [2012] –, a measure of realized volatility (RVOL), log of industrial production, log of private (nonfarm) payroll employment, log of the PCE price deflator, value-weighted total stock market (log) return, effective nominal Federal Funds rate and the slope of the term structure (defined here as the difference between the 10-year Treasury yield and the effective nominal Federal Funds rate). All the variables are US data and, except for utilization-adjusted TFP, transformed from monthly to quarterly as the mean of the period.

[10]Considering the period from 1975:I to 2007:IV, while Kurmann and Otrok [2013] is from 1959:I to 2005:I. I use data only up to 2007:IV to avoid the effect of the zero lower bound in the identification of the slope shock. I would like to thank Christopher Otrok and André Kurmann for raising the zero lower bound issue.

[11]I measure the slope of the term structure as the spread between the 10-year Treasury yield and the effective nominal Federal Funds rate, while Kurmann and Otrok [2013] considers the difference between the 60-month Fama-Bliss unsmoothed zero-coupon yield from the CRSP government bonds files and the Federal Funds rate.

[12]I also evaluated the correlation of the alternative VAR model with the old utilization-adjusted TFP series considering an 80 quarter moving window. The results show that the correlation of 0.48 is quite robust over the series, and can be seen in Figure C.1.2 in the Appendix.

Figure 5.4: Correlations between news and slope shocks on an 80 quarter moving window from Kurmann and Otrok [2013]



Calculation of correlations between the recovered news and slope shocks over an 80 quarter moving window under the original identification of Kurmann and Otrok [2013]. The correlation over the full sample is 0.86. The date in the horizontal axis corresponds to the final observation of the 80 quarter moving window.

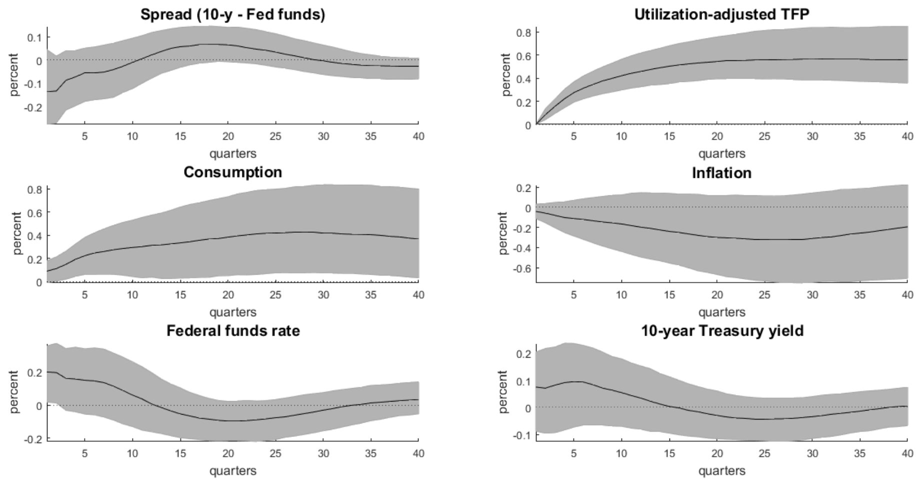
produced by the Kurmann and Otrok [2013] method fades away when the information set is widened with financial variables (Figure 5.6).

As in Section 5.1, there is no evidence from this alternative VAR model of a relationship between news shocks and the slope of the term structure after the update in the utilization-adjusted TFP series.

5.3 Effect of a slope shock on the utilization factor

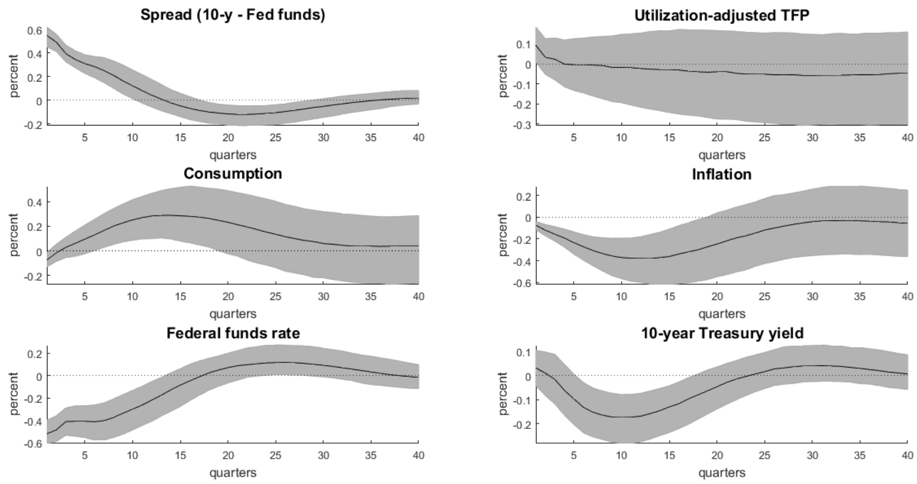
Fernald [2014] argues that the update in the TFP series was caused by a modification in the adjustment for changes in factor utilization from the methodology of Basu et al. [2006] to the one adopted in Basu et al. [2013]. Hence, it is reasonable to consider that the new utilization-adjusted TFP series is a more accurate measure of the unobserved changes in technology. In this Section I check if the relation between news and slope shocks using the older version of the utilization-adjusted TFP series comes from some remaining utilization factor.

Figure 5.5: Impulse responses to a news shock under an alternative VAR model augmented by financial variables



The grey area corresponds to the 16%-84% coverage bands of the model after 1000 replications and considering the new TFP series. The 10-year Treasury yield impulse response is a combination of the Federal Funds rate and the spread.

Figure 5.6: Impulse responses to a slope shock under an alternative VAR model augmented by financial variables



The grey area corresponds to the 16%-84% coverage bands of the model after 1000 replications and considering the new TFP series. The 10-year Treasury yield impulse response is a combination of the Federal Funds rate and the spread.

A statistically significant effect of a slope shock on utilization would be a good indicator that a share of these factors was still included in the old series. Here I conduct a test to verify this effect by evaluating the impact of a slope shock on the utilization factor under the same alternative VAR model of Section 5.2.[13]

Figure 5.7 produces the impulse responses of the slope shock in the alternative VAR model with the utilization factor. There is a positive and significant effect on the utilization factor and on the non-adjusted TFP in the medium-run, starting from zero on impact ($t = 0$). The path of the non-adjusted TFP response is very similar to the utilization factor. Since the utilization factor is part of the total TFP, this implies that most of the effect of a slope shock observed is due to a higher utilization and not to a positive change in the non-utilization part of the TFP (a *proxy* for technology change).

From a macroeconomic perspective, the slope shock is predicting future economic activity (higher industrial production and employment), which justifies the positive effect in the utilization. However, in the long-run the responses of a slope shock on macroeconomic variables converge to zero, and the utilization factor also follows this pattern. This transitory effect in the long-run of both utilization factor and non-adjusted TFP makes the slope shock remarkably different from a news shock.

While future research on this topic is desirable, these preliminary findings indicate that the positive effect of a slope shock on TFP is driven by the utilization factor and might cause the positive correlation between news and slope shocks presented in Kurmann and Otrok [2013].

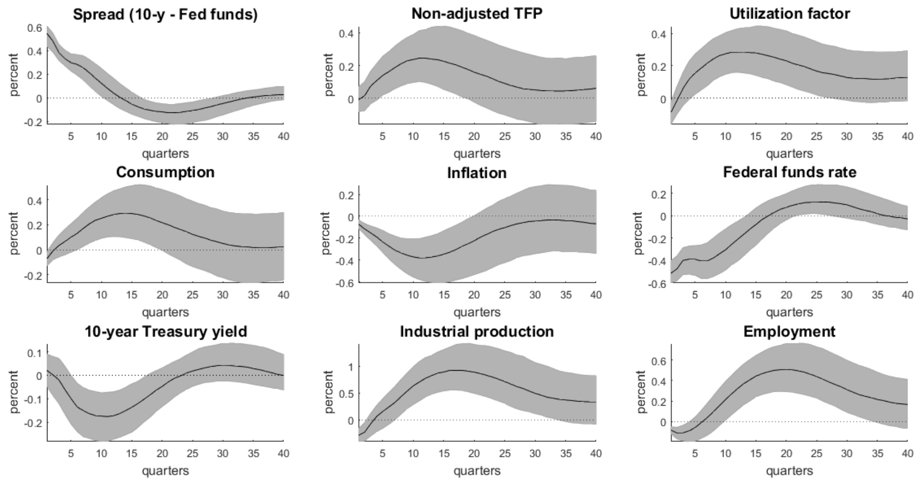
5.4 Conclusion

In this comment I provide evidence that the methodology of extracting the utilization factor from TFP influences the correlation between news and slope shocks, and how economic variables respond to a news shock. The identification of a news shock depends on properly controlling for utilization factors, and the revision of the utilization-adjusted TFP series has a substantial impact on this. Without the adjustment, the response in TFP after a productivity shock may be due to changes in factor utilization, and not in the technology itself. Potentially, important results from the news shock literature that rely on the utilization-adjusted TFP series from Fernald [2014] may also be affected by this revision.

After the update of the utilization-adjusted TFP series, the correlation between

[13] I replace the updated utilization adjusted TFP series for the non-adjusted TFP series and the utilization factor.

Figure 5.7: Impulse responses to a slope shock under an alternative VAR model augmented by financial variables and the utilization factor



The grey area corresponds to the 16%-84% coverage bands of the model after 1000 replications and considering the new TFP series. The 10-year Treasury yield impulse response is a combination of the Federal Funds rate and the spread.

news and slope shocks diminishes and the implications of a news shock become substantially different from Kurmann and Otrok [2013]. The main reason for the positive effect of a news shock on the slope in Kurmann and Otrok [2013] is the endogenous response of monetary policy, driven through the fall of the Federal Funds rate in a larger level than the long-term yield. However, with the new updated utilization-adjusted TFP series the effect of a news shock on inflation is zero, and the drop in the Federal Funds rate is not statistically significant (Figure 5.3), invalidating the 'active monetary policy' channel of a news shock on the slope. As a result, it is no longer possible to conclude that systematic monetary policy is a channel of linking macroeconomic news shocks and term structure dynamics, as initially proposed by Kurmann and Otrok [2013].

Chapter 6

Forecast revisions as instruments for news shocks

6.1 Introduction

The literature on technological news shocks argues that the macroeconomy react to positive expectations about future productivity. The results so far show that positive news generates comovement among GDP, consumption and investment, and is deflationary in the medium-run.[1] However, there remains an ongoing discussion (both theoretical and empirical) on (i) how important is this shock on explaining business cycles, (ii) how 'fast' should one observe an effect on productivity, and (iii) what is the effect on other important macroeconomic variables, such as hours worked.[2]

These questions arise from the fact that the literature is still debating how to properly identify a news shock. Measuring the effect of news about future productivity is a difficult task. First, because identifying a news shock implies separating TFP shocks into unexpected and expected parts. Second, the effect of technological changes on productivity is not directly observed, and its proxies may be subject to measurement errors or substantial revisions.[3] And third, the news information may be 'noisy', which would make a news shock identification infeasible (Blanchard et al., 2013).

In practice, there are two empirical identification strategies for news shocks available in the literature: one based on a combination of short and long-run restrictions (Beaudry and Portier, 2006), and another based on explaining the medium-run effects on TFP (Barsky and Sims, 2011). The Beaudry and Portier [2006] methodology is successful in generating positive comovement among macroeconomic variables. The measure of utilization-adjusted TFP only reacts to a news shock in the medium-run, as it would be expected with an anticipation of future news. However, this identification relies on very strong assumptions about the order of integration of the variables or its cointegrating relationships.[4]

Barsky and Sims [2011] (BS, henceforth) approach is a partial identification strategy and is less restrictive than Beaudry and Portier [2006], relying on the assumption that a limited number of shocks generate movements in utilization-adjusted TFP. The idea is to find the orthogonalization that best explains the TFP's forecast error variance over a finite horizon, and that has no effect on TFP on impact. The economic effects of a news shock employing this method differ from the results presented by Beaudry

[1]See, for example, Beaudry and Portier [2006] and Barsky and Sims [2011].

[2]See Beaudry and Portier [2014] for a comprehensive survey about the challenges of identifying a technological news shock.

[3]See Cascaldi-Garcia [2017] and Kurmann and Sims [2017] for a discussion about the effects of utilization-adjusted TFP updates on news shocks.

[4]Barsky and Sims [2011] present a discussion about the issues of employing long-run restrictions while identifying news shocks.

and Portier [2006]. There is less evidence of a positive comovement on impact, and the effect on hours is either negative or virtually zero.[5] In addition, utilization-adjusted TFP reacts almost immediately after impact, which raises the argument of how much economic variables are anticipating or, rather, tracking TFP growth.

This paper follows a third path. The idea is to identify technological news shocks in a Structural VAR by relying on external validity (proxy SVAR). The use of exogenous variables as instruments for the structural shock of interest is a recent burgeoning literature in business cycles.[6] It has been applied to identify monetary policy shocks (Stock and Watson, 2012, Gertler and Karadi, 2015, Miranda-Agrippino and Ricco, 2018), fiscal policy shocks (Mertens and Ravn, 2014, Caldara and Kamps, 2017), uncertainty shocks (Carriero et al., 2015b, Piffer and Podstawski, 2017) and oil supply shocks (Montiel Olea et al., 2016). With respect to news shocks, extraneous data have been applied to news about future fiscal spending (Auerbach and Gorodnichenko, 2012) and for news about future oil supply (Arezki et al., 2017).

This paper contributes to the literature by empirically identifying technological news shocks based on information about agents' expectations. The application I propose here is based on only one assumption: if agents expect a higher future productivity, they should expect a higher future economic growth as well. It follows that positive news about productivity should be (positively) correlated with news about future economic activity.

While news about future TFP is not directly observed, proxies for news about future economic activity can be constructed through forecast revisions. The Survey of Professional Forecasters (SPF) provides quarterly forecasts for a series of economic indicators, up to one year ahead. Three of these series are particularly relevant for technological news: GDP, investment and industrial production. Positive news about future technology should be reflected as a higher future GDP, investment and industrial production. I propose a methodology of measuring revisions about the long-run trend of these variables by calculating differences between updates on forecasts and *nowcasts*. This method allows the construction of a quarterly time series for forecast revisions about future GDP, investment and industrial production.

I employ the external validity procedure introduced by Mertens and Ravn [2013]

[5] See, for example, Barsky and Sims [2011], Kurmann and Otrok [2013] and Barsky et al. [2014]. Cascaldi-Garcia and Galvao [2017] recover a positive comovement among GDP, consumption, investment and hours worked by employing the BS approach in an identification strategy that imposes orthogonality between news and uncertainty shocks.

[6] See Ramey [2016] and Kilian and Lütkepohl [2017] for an overview of identification based on extraneous data.

and Stock and Watson [2012] to the news shock case. This approach identifies structural shocks based on information not contained on the VAR, namely instruments, which are noisy measures of the structural shock. The idea is to jointly use the constructed series of forecast revisions about future GDP, investment and industrial production as instruments that potentially provide identification of the news shock. The procedure consists of regressing the instruments against the residuals of a reduced-form VAR, and using this information to infer the contemporaneous impact of a news shock on the macroeconomic variables.

While the strategy of identifying a technological news shock through instruments based on expectations is innovative, the literature has already shown the predictive power of expectations on driving business cycles. Miyamoto and Nguyen [2017] argue that the precision of news shocks improves when forecast data is also considered in the information set. Levchenko and Pandalai-Nayar [2018] show that a non-technological expectation shock accounts for a large share of business cycle fluctuations in the short-run. Clements and Galvao [2018] show that data uncertainty influences the impact of expectation shocks on the economy. They find, however, that expectation shocks are not correlated with technological news shocks.

In summary, this paper contributes to the news shock literature with new evidence about the importance of technological news on driving business cycles. The proposed identification procedure relies on more pragmatic assumptions by bridging agents' expectations on future technology with observed revisions on economic forecasts. As such, a news shock constructed with instrumental variables can be more realistic in representing its economic effects than when identified with the current statistical methods found in the literature.

The outline of the paper is as follows. I show the relevance of forecast revisions for measuring technological news shocks in Section 6.2. Section 6.3 presents the identification procedure of the news shocks with instrumental variables (proxy SVAR) and the discussion about the exogeneity of the proposed measures. Section 6.4 summarizes the results of the identified news shock with instrumental variables. Section 6.5 concludes this paper.

6.2 Relevance of forecast revisions for measuring news

The process of identifying the effect of news about the future outcome of economic variables is not simple. The alternative I propose, here, is to look at professional forecast surveys, and measure the change in its forecasts from one period to another. But how informative are these forecasts for the news shock driving the long-run growth of the economy? I answer this question by presenting a simple model with three sources of exogenous shocks, as in Levchenko and Pandalai-Nayar [2018]: surprise technological shocks, technological news shocks and transitory non-technological shocks.

As largely explored by the business cycle literature,[7] productivity changes (e.g., technological shocks) are the predominant source of output fluctuations in the long-run. While permanent technology changes determine the long-run *trend* of output, other sources of shocks (e.g., preferences, tax rates, monetary policy) explain movements in the short-run around this trend.

Suppose real output (in logs) follows a process with a deterministic trend, as in

$$\log y_t = \beta t + \epsilon_{k,t}, \tag{6.1}$$

where β is the slope of the long-run trend and $\epsilon_{k,t}$ captures the short-run non-technological shocks that temporarily deviate $\log y_t$ from its long-run trend, following a process

$$\epsilon_{k,t} = \epsilon_{k,t-1} + \varrho_t. \tag{6.2}$$

Taking the differences of $\log y_t$ leads to

$$\Delta \log y_t = \beta + \Delta\epsilon_{k,t}. \tag{6.3}$$

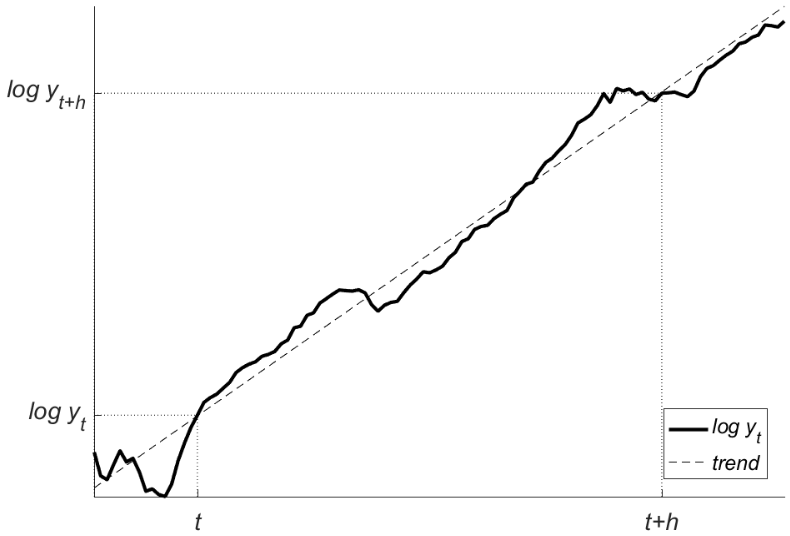
Figure 6.1 presents a possible generic path of real output, in which the dashed line is the time trend estimated by regressing $\log y_t$ on t.

While estimating the time trend and its slope demand a sufficiently large number of observations, an approximate measure for the slope ($\tilde{\beta}$) can be obtained with just two points. In the example of Figure 6.1, where $t + h$ is the long-run, it suffices to calculate

$$\begin{aligned} \tilde{\beta} &= \frac{\log y_{t+h} - \log y_t}{(t+h) - t} \\ \tilde{\beta} &= \frac{\log y_{t+h} - \log y_t}{h}. \end{aligned} \tag{6.4}$$

[7] See Stadler [1994] for an extensive review of the real business cycle literature.

Figure 6.1: Long-run output level and trend



By substituting $\log y_t$ and $\log y_{t+h}$, it leads to

$$
\begin{aligned}
\tilde{\beta} &= \frac{\beta(t+h) + \epsilon_{k,t+i} - (\beta t + \epsilon_{k,t})}{h} \\
\tilde{\beta} &= \beta + \frac{(\epsilon_{k,t+h} - \epsilon_{k,t})}{h}.
\end{aligned}
\tag{6.5}
$$

The approximate measure of the slope $\tilde{\beta}$ is defined as the slope of long-run trend plus the short-run deviations around the trend $(\epsilon_{k,t+h} - \epsilon_{k,t})$. By keeping h fixed, equation 6.4 is proportional to

$$\tilde{\beta} \propto \log y_{t+h} - \log y_t. \tag{6.6}$$

It follows that the difference between the two observables $(\log y_{t+h} - \log y_t)$ is proportional to a noisy measure of the slope of long-run trend of output.

Suppose an economy in which its output y_t is described by a technology measure A_t and a generic production function $f(K_t/L_t)$, where K_t/L_t is the ratio between capital and labor, as in

$$y_t = A_t f(K_t/L_t), \tag{6.7}$$

or in logs

$$\log y_t = \log A_t + \log f(K_t/L_t), \tag{6.8}$$

and taking the differences

$$\Delta \log y_t = \Delta \log A_t + \Delta \log f(K_t/L_t). \tag{6.9}$$

As in Smets and Wouters [2007], I assume, here, that technology is the main driver of the long-run growth. If non-technological shocks cause the output to deviate from its long-run trend, technological shocks should produce permanent changes in the trend itself. By linking with equation 6.3, this is equivalent to say that changes in technology define the slope of the long-run trend, as in $\Delta \log A_t = \beta$, and changes in the production factors define the temporary deviations of the trend, as in $\Delta \log f(K_t/L_t) = \Delta\epsilon_{k,t}$.

A positive permanent technological shock should increase output growth, which is equivalent to making the time trend in Figure 6.1 steeper. Similarly, negative technological shocks should make the same curve more flat. It follows that the *slope* of a long-run time trend of output should be informative about the technology level of this economy, and changes in this slope should be informative about changes in technology (technological shocks).

Following the news shock literature, technology is characterized as a stochastic process driven by two shocks. The first ($\epsilon_{surprise,t}$) is a surprise technological shock, which changes the level of technology on impact and generates a temporary effect on the economy. The second ($\epsilon_{news,t-h}$) is the news shock, which is observed h periods ahead and produces no change in technology when observed, but creates a permanent long-run effect on the economy. In such an economy, long-run changes in output are only driven by news shocks observed one period ahead of the effective change in technology. In a univariate context it is not feasible to separate $\epsilon_{surprise,t}$ and $\epsilon_{news,t-h}$.

Say, for example, that technology follows a process as

$$\log A_t = \beta + \log A_{t-1} + \epsilon_{surprise,t} + \epsilon_{news,t-h}, \tag{6.10}$$

where the news shock that changes the level of technology in time t is observed in $t-h$.

It follows that the news shock observed today, $\epsilon_{news,t}$, will change the level of technology in $t+h$, as in

$$\log A_{t+h} = \beta + \log A_{t+h-1} + \epsilon_{surprise,t+h} + \epsilon_{news,t}, \tag{6.11}$$

or

$$\log A_{t+h} = (h+1)\beta + \log A_{t-1} + \sum_{i=0}^{h} \epsilon_{surprise,t+i} + \sum_{i=0}^{h} \epsilon_{news,t-i}. \tag{6.12}$$

The long-run difference ($\log A_{t+h} - \log A_t$) is then defined by

$$\log A_{t+h} - \log A_t = h\beta + \sum_{i=1}^{h} \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i}. \tag{6.13}$$

Since the long-run difference ($\log f(K_{t+h}/L_{t+h}) - \log f(K_t/L_t)$) is

$$\log f(K_{t+h}/L_{t+h}) - \log f(K_t/L_t) = \epsilon_{k,t+h} - \epsilon_{k,t}, \tag{6.14}$$

it follows that the long-run difference ($\log y_{t+h} - \log y_t$) is defined as

$$\log y_{t+h} - \log y_t = h\beta + \sum_{i=1}^{h} \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i} + (\epsilon_{k,t+h} - \epsilon_{k,t}). \tag{6.15}$$

By substituting equation 6.15 into equation 6.4, the noisy measure $\tilde{\beta}$ will be

$$\tilde{\beta} = \beta + \frac{1}{h}\left(\sum_{i=1}^{h} \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i} + (\epsilon_{k,t+h} - \epsilon_{k,t})\right). \tag{6.16}$$

Now, suppose that there is a professional forecaster that continuously forecasts the output $\log y_t$ for the current period (*nowcast*) and for up to h periods ahead. If this agent is rational, this measure should bring information about the future level of technology and, consequently, about the news shock in t ($\epsilon_{news,t}$).

Define the forecast of current period t based on information up to $t-1$ as $\log y_{t|t-1}$.[8] The forecast for the next period, $t+1$, is then defined as $\log y_{t+1|t-1}$. In period $t-1$, this professional forecaster only has information up to that period. The forecast of the slope of the long-run trend of output in $t-1$, as defined in equation 6.16, will be

$$\tilde{\beta}_{|t-1} = \beta + \frac{1}{h}\left(\sum_{i=1}^{h-1} \epsilon_{news,t-i}\right). \tag{6.17}$$

In the next period t, the professional updates her forecasts for $\log y_t$ and $\log y_{t+h}$ with the new information that arrived between $t-1$ and t. The forecast of the slope of the long-run trend of output in t (equation 6.16) will be

$$\tilde{\beta}_{|t} = \beta + \frac{1}{h}\left(\sum_{i=0}^{h-1} \epsilon_{news,t-i} - \epsilon_{k,t}\right). \tag{6.18}$$

[8] I follow the definitions and similar notation as described in Clements [2015].

Now, the only difference between the forecast of the long-run trend evaluated at time $t-1$ and the one evaluated at time t is the new information about technology acquired by the professional forecaster between these periods and the short-run transitory shock $\epsilon_{k,t}$. This new information can be recovered by calculating the difference between the two forecasts for the slope of the long-run trend of output, as in

$$\Delta_{\tilde{\beta}} = \tilde{\beta}_{|t} - \tilde{\beta}_{|t-1}. \tag{6.19}$$

Substituting equations 6.17 and 6.18, this measure becomes

$$\Delta_{\tilde{\beta}} = \left(\beta + \frac{1}{h}\left(\sum_{i=0}^{h-1} \epsilon_{news,t-i} - \epsilon_{k,t}\right)\right) - \left(\beta + \frac{1}{h}\left(\sum_{i=1}^{h-1} \epsilon_{news,t-i}\right)\right) \tag{6.20}$$

leading to

$$\Delta_{\tilde{\beta}} = \frac{1}{h}(\epsilon_{news,t} - \epsilon_{k,t}), \tag{6.21}$$

which is proportional to

$$\Delta_{\tilde{\beta}} \propto \epsilon_{news,t} - \epsilon_{k,t}. \tag{6.22}$$

It follows that a measure of the difference between forecasts of the slope of the long-run trend of output should be a noisy measure of the news shock $\epsilon_{news,t}$, observed today, but that will change the level of technology only in $t+h$. By employing the slope measure as in equation 6.6, the differences between forecasts of the slope of the long-run trend of output can be computed as

$$\Delta_{\tilde{\beta}} \propto (\log y_{t+h|t} - \log y_{t|t}) - (\log y_{t+h|t-1} - \log y_{t|t-1}). \tag{6.23}$$

6.3 Instrumental variable procedure for identifying news shocks

The idea, here, is to employ the methodology of calculating the forecast revisions about the slope of the long-run trend presented in the previous section to construct instruments to identify a technological news shock. A news shock has the capacity of generating booms and busts based on agents' expectations about future technological improvements (Beaudry and Portier, 2006). The evidence shows that positive news about future utilization-adjusted TFP increases consumption, GDP and investment in the medium and long-run.[9]

It follows that an increase in expected future productivity should also be translated into higher expected future GDP, investment and industrial production. In other words, a news shock should be positively correlated with forecast revisions about future GDP, investment and industrial production. While a news shock is not directly observed and relies on different identification procedures, one could use the methodology presented in the previous section to measure forecast revisions about these variables. Under certain assumptions (discussed below), these measures can be used as external validity instruments for the identification of a news shock.

The proposed instruments are slope forecast revisions about the log of the future level of real GDP, of the log of nonresidential fixed investment and of the log of industrial production, in the US, from the Survey of Professional Forecasters (Federal Reserve Bank of Philadelphia). This survey provides forecasts for several economic variables from t to $t+5$ quarters ahead, starting from 1968:Q4 for GDP and industrial production, and from 1981:Q3 for investment. I construct the instruments ($\mathbf{Z}_t$) as a series of forecast revisions of the slope of the long-run trend as in equation 6.23, following

$$\mathbf{Z}_t = (\mathbf{x}_{t+4|t} - \mathbf{x}_{t|t}) - (\mathbf{x}_{t+4|t-1} - \mathbf{x}_{t|t-1}), \tag{6.24}$$

where $\mathbf{Z}_t$ is a matrix collecting the three instruments (GDP, investment and industrial production forecast revisions).

Figure 6.2 shows the three measures constructed here. These series present similar patterns and are highly correlated (Table 6.1); however, the forecast revision about future investment is more volatile than the forecast revisions about future GDP and future industrial production. The most pronounced negative revisions match the recession periods identified by the National Bureau of Research Institute (NBER).

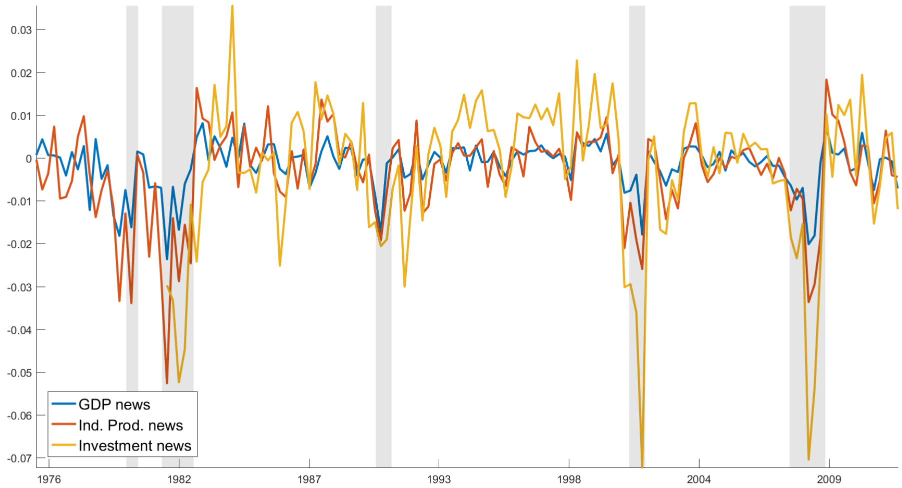
6.3.1 Proxy SVAR and identification procedure

To see how these instruments can be used to identify a news shock, I start with a standard reduced-form VAR. Consider a model with $\mathbf{y}_t$ as a $(n \times t)$ matrix that stacks the n endogenous variables (in levels), in which utilization-adjusted TFP is ordered first. Its reduced-form structure can be modeled as

$$\mathbf{y}_t = \mathbf{A}_1 \mathbf{y}_{t-1} + ... + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{u}_t, \tag{6.25}$$

[9]See, for example, Beaudry and Portier [2006], Barsky and Sims [2011], Cascaldi-Garcia and Galvao [2017], among others.

Figure 6.2: Forecast revisions about future GDP, investment and industrial production



Note: Forecast revisions constructed from expectations about future GDP, future investment and future industrial production, collected from the Survey of Professional Forecasters (SPF), following the procedure described in Section 6.2. Data for GDP and industrial production are displayed from 1976:Q1 to 2012:Q3, and for investment from 1981:Q3 to 2012:Q3. Shaded areas are the recession periods calculated by the NBER.

Table 6.1: Correlations between forecast revisions about future GDP, investment and industrial production

	Real GDP revisions	Ind. prod. revisions	Investment revisions
Real GDP revisions	1.00	0.86	0.77
Ind. prod. revisions	0.86	1.00	0.73
Investment revisions	0.77	0.73	1.00

Note: Correlations between forecast revisions constructed from expectations about future GDP, future investment and future industrial production, collected from the Survey of Professional Forecasters (SPF), following the procedure described in Section 6.2. Correlations calculated from 1981:Q3 to 2012:Q3.

where $\mathbf{A}_i$ are $(n \times n)$ matrices that collect the coefficients of the lags of $\mathbf{y}_t$ from 1 to p. Its moving average representation is written as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \tag{6.26}$$

If there is a linear mapping of the innovations ($\mathbf{u}_t$) and the structural shocks ($\mathbf{s}_t$), this moving average representation can be rewritten as

$$\mathbf{u}_t = \mathbf{A}_0 \mathbf{s}_t \tag{6.27}$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \tag{6.28}$$

where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{A}_0$, $\mathbf{s}_t = \mathbf{A}_0^{-1}\mathbf{u}_t$, and $\mathbf{A}_0$ is the $(n \times n)$ impact matrix that makes

$$\mathbb{E}[\mathbf{u}_t \mathbf{u}_t'] = \mathbb{E}[\mathbf{A}_0 \mathbf{A}_0'] = \underset{n \times n}{\mathbf{\Sigma}}. \tag{6.29}$$

Consider, now, the case in which only one shock is economically identified, say a *news shock*. If the news shock is the first shock of $\mathbf{s}_t$ (namely $s_{news,t}$), it means that obtaining the first column of $\mathbf{A}_0$ (namely $\mathbf{\Lambda}_1$) suffices to identify $s_{news,t}$. The identification of this column is where the instruments $\mathbf{Z}_t$ can be employed.

Following Mertens and Ravn [2013], Stock and Watson [2012] and Gertler and Karadi [2015], let $\mathbf{Z}_t$ be a $(t \times k)$ matrix of proxies correlated to the $(1 \times t)$ structural shock $s_{news,t}$, and $\mathbf{s}_{2,t}$ a $(n - 1 \times t)$ matrix that collects all $(n - 1)$ shocks other than the news shock. The proxies can be used as instruments to identify the news shock if they satisfy three conditions:

$$\begin{aligned} &(i) \quad \mathbb{E}[z_t s_{news,t}'] = \underset{1\times 1}{\phi} \quad \text{(relevance)}, \\ &(ii) \quad \mathbb{E}[z_t \mathbf{s}_{2,t}'] = \underset{1\times(n-1)}{\mathbf{0}} \quad \text{(exogeneity)}, \end{aligned} \tag{6.30}$$

where z_t is a $(t \times 1)$ vector constructed as $z_t = (\mathbf{P}s_{news,t}')'$, and $\mathbf{P}$ is the $(t \times t)$ projection matrix that generates fitted values of $s_{news,t}$ from k instruments present in $\mathbf{Z}_t$, as in $\mathbf{P} = \mathbf{Z}_t(\mathbf{Z}_t'\mathbf{Z}_t)^{(-1)}\mathbf{Z}_t'$.

Condition (i) states that the instruments in $\mathbf{Z}_t$ and the news shock $s_{news,t}$ are correlated. Since $\mathbb{E}[s_{news,t}] = 0$, ϕ represents the (unknown) covariance between z_t (combination of the instruments in $\mathbf{Z}_t$) and the structural news shock $s_{news,t}$. There is no *a priori* assumption about the relationship between the instruments and the structural shock, and the covariance ϕ would be determined by the parameters of the instruments as a function of the news shock. Section 6.2 presents the argument for the relevance of the proposed instruments on recovering the news shock. Condition (ii) states that the instruments in $\mathbf{Z}_t$ are not correlated with other structural shocks. I test this condition in subsection 6.3.3. Conditions (i) and (ii) already ensure that the instruments in $\mathbf{Z}_t$

are correlated with the innovations $\mathbf{u}_t$, because they are correlated with $s_{news,t}$.

Partitioning $\mathbf{A}_0$ as

$$\mathbf{A}_0 = \begin{bmatrix} \underset{n\times 1}{\mathbf{\Lambda}_1} & \underset{n\times(n-1)}{\mathbf{\Lambda}_2} \end{bmatrix}, \quad \mathbf{\Lambda}_1 = \begin{bmatrix} \underset{1\times 1}{\lambda_{11}} \\ \underset{(n-1)\times 1}{\boldsymbol{\lambda}_{21}'} \end{bmatrix}, \quad \mathbf{\Lambda}_2 = \begin{bmatrix} \underset{1\times(n-1)}{\boldsymbol{\lambda}_{12}} \\ \underset{(n-1)\times(n-1)}{\boldsymbol{\lambda}_{22}} \end{bmatrix}, \tag{6.31}$$

it follows from conditions (i) and (ii) that

$$\phi\mathbf{\Lambda}_1^{'} = \underset{1\times n}{\mathbb{E}[z_t\mathbf{u}_t']}. \tag{6.32}$$

By partitioning $\mathbb{E}[z_t\mathbf{u}_t']$ as

$$\mathbb{E}[z_t\mathbf{u}_t'] = \begin{bmatrix} \underset{1\times 1}{\mathbb{E}[z_t u_{1,t}']} & \underset{1\times(n-1)}{\mathbb{E}[z_t\mathbf{u}_{2,t}']} \end{bmatrix}, \tag{6.33}$$

where $\mathbf{u}_{2,t}$ collects all $(n-1)$ innovations other than the first $(u_{1,t})$, it is possible to rewrite equation 6.32 as

$$\frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}} = \left(\mathbb{E}[z_t u_{1,t}']^{-1}\mathbb{E}[z_t\mathbf{u}_{2,t}']\right)'. \tag{6.34}$$

In practice, $\mathbb{E}[z_t u_{1,t}']^{-1}\mathbb{E}[z_t\mathbf{u}_{2,t}']$ can be obtained by a two-stage least squares estimator (2SLS) by first regressing $u_{1,t}$ on $\mathbf{Z}_t$ and producing the fitted value $\hat{u}_{1,t}$, and then regressing $\mathbf{u}_{2,t}$ on $\hat{u}_{1,t}$, as in

$$\mathbf{u}_{2,t} = \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\hat{u}_{1,t} + \xi_t, \tag{6.35}$$

and $\hat{u}_{1,t}$ and ξ_t are orthogonal if condition (ii) holds. By partitioning the reduced form variance-covariance matrix as in

$$\mathbf{\Sigma} = \begin{bmatrix} \Sigma_{11} & \mathbf{\Sigma}_{12} \\ \mathbf{\Sigma}_{21} & \mathbf{\Sigma}_{22} \end{bmatrix}, \tag{6.36}$$

$\boldsymbol{\lambda}_{21}$ and λ_{11} can be identified by applying the restrictions from equation 6.29 following the closed form solution[10]

$$\lambda_{11}^2 = \Sigma_{11} - \boldsymbol{\lambda}_{12}\boldsymbol{\lambda}_{12}', \tag{6.37}$$

[10]As demonstrated by Mertens and Ravn [2013] and Gertler and Karadi [2015].

where

$$
\begin{aligned}
\boldsymbol{\lambda}_{12}\boldsymbol{\lambda}_{12}' &= \left(\boldsymbol{\Sigma}_{21} - \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\Sigma_{11}\right)' \mathbf{Q}^{-1}\left(\boldsymbol{\Sigma}_{21} - \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\Sigma_{11}\right), \\
\mathbf{Q} &= \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\Sigma_{11}\frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}' - \left(\boldsymbol{\Sigma}_{21}\frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}' + \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\boldsymbol{\Sigma}_{21}'\right) + \boldsymbol{\Sigma}_{22}.
\end{aligned}
\tag{6.38}
$$

Now, if $\mathbf{Z}_t$ is the set of instruments constructed based on SPF forecast revisions, the structural news shock $s_{news,t}$ can be recovered by the method described above. Mertens and Ravn [2013] point out that for the case of a single shock the restrictions described in equation 6.34 are sufficient for identification up to sign convention.

The full procedure of the proxy SVAR can be summarized with the following steps:

1. Estimate the reduced-form VAR;
2. Estimate $\mathbb{E}[z_t u_{1,t}']^{-1}\mathbb{E}[z_t \mathbf{u}_{2,t}']$ by the 2SLS regression of the VAR residuals on $\mathbf{Z}_t$;
3. Find the impact effects of a news shock by imposing the restrictions in equation 6.34.

6.3.2 Information set and Bayesian VAR estimation

As a common practice in the literature,[11] I identify the news shock by employing the utilization-adjusted TFP series constructed by Fernald [2014], representing a proxy of the technological level of the US economy. In order to properly extract the signal of the news shock, separating it from the contemporaneous movement on TFP, the information set should include a number of forward-looking variables, such as stock prices and consumption.

The dataset comprises macroeconomic variables in levels, measured quarterly, from 1975:Q1 to 2012:Q3. It contains 11 variables, namely utilization-adjusted TFP, personal consumption per capita, GDP per capita, private investment per capita, hours worked, GDP deflator, S&P500 stock prices index, excess bond premium (calculated by Gilchrist and Zakrajšek, 2012), financial uncertainty (calculated by Ludvigson et al., 2016), Federal funds rate and the spread between the 10-year yield and the Federal funds rate. A full description of the sources and construction of the 11 variables can be found in Table D.1 in the Appendix.

[11] See, for example, Beaudry and Portier [2006], Barsky and Sims [2011], Kurmann and Otrok [2013], Cascaldi-Garcia and Galvao [2017], among others.

I estimate the model under a Bayesian VAR (BVAR) approach, and the identification of the shocks is carried out with a standard two-stage least squares method. While the strategy of Bayesian estimation and classical instrumental variables identification is also employed by Caldara and Kamps [2017], it is worth to note that fully Bayesian proxy-SVAR approaches are available in the literature.[12] The BVAR model is estimated in levels with five lags. The option for the variables in levels is in line with Barsky and Sims [2011], allowing for the possibility of cointegration among the variables. I employ the Minnesota priors (Litterman, 1986) to address the reasonably large number of endogenous variables, and the 'dummy observation prior'. The estimation of the model and the prior hyper-parameters follow methodology proposed by Gianonne et al. [2015], with 20,000 posterior draws. I compute the confidence bands for the impulse response graphs using 1,000 out of the 20,000 total draws from the posterior distribution.[13]

6.3.3 Exogeneity of the instruments

I show in Section 6.2 that a noisy signal for the news shock can be extracted from the measures of forecast revisions about the future output. I employ measures of forecast revisions about future GDP, industrial production and investment, which should be the variables from the supply side most influenced by technological changes. However, the model presented in Section 6.2 takes the assumption that only news shocks drive the long-run trend of the economy.

There are two problems with this assumption. First, other economic shocks may have a long-run impact on the economy. Non-technological shocks $\epsilon_{k,t}$ can cause an effect on the cycle, which would be misunderstood as a change in the long-run trend. If this is the case, forecast revisions about future GDP, industrial production and investment may also be a response to these other shocks, violating condition (*ii*) of exogeneity. This would be particularly true for other types of news, such as news about tax, government spending or oil prices. Second, the measures of news can only be feasibly constructed up to five quarters ahead due to data availability from the SPF. One may argue that five quarters is not sufficient to properly separate long-run effects from the effects of short-run shocks.

Following Piffer and Podstawski [2017], I test the exogeneity of the instruments by examining the relation between the forecast revisions about GDP, industrial production and investment and several economic shocks identified in the literature. As in Caldara

[12]See, for example, Caldara and Herbst [2016] and Arias et al. [2018].

[13]To ensure a positive news shock, I check whether the response of stock prices is positive on impact. If the response is negative, all computed responses are multiplied by (-1).

and Kamps [2017], I consider, here, six different economic shocks: news about tax shocks, news about government defense spending, oil price shocks, monetary policy shocks, tax shocks and technological shocks.[14]

The measure for news about tax shocks is the proxy calculated by Leeper et al. [2013], and is available from 1953:Q1 to 2006:Q3. News about government defense spending is calculated as the nominal present value of Ramey [2011] defense news variable divided by the nominal GDP of the previous quarter, as calculated by Caldara and Kamps [2017], and available from 1950:Q1 to 2006:Q3. Oil price shocks are the net oil increase (3 years) calculated by Caldara and Kamps [2017] based on Hamilton [2003], available from 1950:Q1 to 2006:Q3. Monetary policy shocks are the quarterly sum of the monthly Romer and Romer [2004] variable extended by Barakchian and Crowe [2013], available from 1969:Q1 to 2006:Q3. Tax shocks are the Mertens and Ravn [2011] unanticipated tax series, available from 1950:Q1 to 2006:Q3.

Finally, a technological news shock (and, consequently, its instruments) should be orthogonal to contemporaneous technological shocks. The idea, here, is that technology is an exogenous variable that is driven by only two shocks: the news shock and the surprise technological shock, as in equation 6.10. While a news shock is observed h periods ahead and does not change technology when observed, the surprise technological shock is the only shock capable of changing technology contemporaneously. I proxy the surprise technological shock by the contemporaneous innovation on the utilization-adjusted TFP series of the estimated BVAR (described in detail in subsection 6.3.2).

For each of the three measures in $\mathbf{Z}_t = [z_t^{gdp}, z_t^{ip}, z_t^{inv}]$, I estimate the model

$$z_t^i = \mu_0 + \mu_{1,j} d_{j,t} + \upsilon_{j,t}, \tag{6.39}$$

where i indicates if the instrument is forecast revisions about GDP, industrial production or investment, and $d_{j,t}$ represents each of the structural shocks. A statistically significant $\mu_{1,j}$ indicates the failure of exogeneity of the instrument with respect to the structural shock. The results for the exogeneity tests are summarized in Table 6.2.

The exogeneity tests show that the instrument measures proposed here are also correlated with shocks other than technological news, failing to fulfill condition (ii). In other words, the SPF forecast revisions are also reacting to a variety of structural changes in the economy. This is somewhat expected, as equation 6.21 shows that the slope measure can be contaminated by other non-technological shocks. This is partic-

[14] Apart from the technological shocks, all other economic shocks are downloaded from the Caldara and Kamps [2017] database. Technology shocks are proxied by the mean of the utilization-adjusted TFP residuals across 1,000 posterior draws (as described in subsection 6.3.2).

Table 6.2: Exogeneity tests for the forecast revisions about GDP, industrial production and investment

1. Forecast revision about GDP

Shock	Source	μ_1	P-value	Obs
News about tax	Leeper et al. [2013]	-4.97	0.29	123
News about govt. spending	Ramey [2011]	-15.20	0.70	123
Oil price	Hamilton [2003]	-0.15	0.06	123
Monetary policy	Romer and Romer [2004]	2.54	0.00	123
Tax	Mertens and Ravn [2011]	-1.31	0.67	123
Technology	First residual from the BVAR	0.79	0.27	123

2. Forecast revision about industrial production

Shock	Source	μ_1	P-value	Obs
News about tax	Leeper et al. [2013]	-14.8	0.11	123
News about govt. spending	Ramey [2011]	-68.63	0.37	123
Oil price	Hamilton [2003]	-0.26	0.09	123
Monetary policy	Romer and Romer [2004]	6.02	0.00	123
Tax	Mertens and Ravn [2011]	-1.58	0.79	123
Technology	First residual from the BVAR	0.23	0.87	123

3. Forecast revision about investment

Shock	Source	μ_1	P-value	Obs
News about tax	Leeper et al. [2013]	3.39	0.58	101
News about govt. spending	Ramey [2011]	21.09	0.62	101
Oil price	Hamilton [2003]	-0.04	0.66	101
Monetary policy	Romer and Romer [2004]	5.91	0.00	101
Tax	Mertens and Ravn [2011]	-2.45	0.47	101
Technology	First residual from the BVAR	0.99	0.21	101

Note: Coefficient μ_1 estimated from individual regressions of the forecast revisions about GDP, about industrial production or about investment against the structural shocks. Data for the regressions involving forecast revisions about GDP or about industrial production range from 1976:Q1 to 2006:Q3, while regressions for forecast revisions about investment range from 1981:Q4 to 2006:Q3 due to SPF data availability. Technology shocks are proxied by the mean of the utilization-adjusted TFP residuals across 1,000 posterior draws (as described in Section 6.3.2). All shocks divided by 10^3 for presentation reasons.

ularly more evident for monetary policy shocks in which the regression coefficient is statistically significant at a 1% level for all three instruments. The series of forecast revisions about GDP is also correlated with oil prices, while forecast revisions about industrial production relates to oil prices and news about tax. The measure forecast revisions about investment only correlates with monetary policy.

In light of this evidence, I employ an agnostic approach of filtering the instruments out of the effects of all these structural shocks, collected by the matrix $\mathbf{d}_t$, and by the first reduced-form residual from the BVAR ($u_{1,t}$), as a proxy for surprise technological shocks. I also filter the instruments out of the effects of an economic activity factor to ensure that the forecast revision measures proposed only carry information acquired in time t. I proxy the economic activity by the first factor of the real activity dataset calculated by Stock and Watson [2016].[15]

I construct a measure $\tilde{\mathbf{Z}}_t$ as the residual from projecting $\mathbf{Z}_t$ on $\mathbf{d}_t$, on $u_{1,t}$ and on five lags of the Stock and Watson [2016] economic activity factor F_t, as in

$$\mathbf{Z}_t = \mu_1 \mathbf{d}_t + \mu_2 u_{1,t} + \mathbf{M}(\mathbf{L}) F_t + \tilde{\mathbf{Z}}_t, \tag{6.40}$$

and use $\tilde{\mathbf{Z}}_t$ as the instruments for the news shock instead. The surprise technological shock is different for every draw from the posterior distribution due to parameter uncertainty. I perform this filtering step for every draw, which ensures the orthogonality of the news shock and the surprise technological shock. Figure 6.3 presents the three instruments after the filtering process, as the mean over 1,000 posterior draws.

6.4 Results

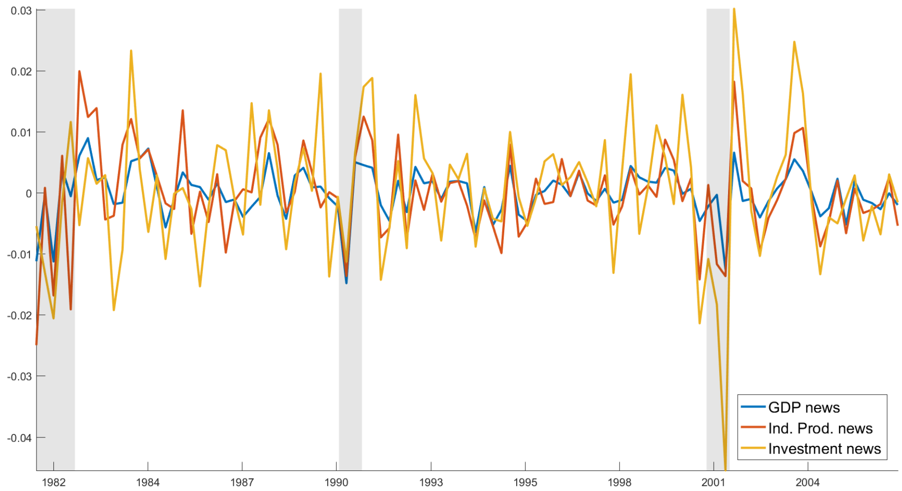
In this section I present the results for a news shock identified using the instruments and the procedure described in Section 6.3. I first provide the results of a medium-scale Bayesian VAR with 11 variables, testing the strength of the instruments and presenting the impulse responses of the identified news shock. Subsequently, I compare the results from the Bayesian VAR with the results from the most standard identification procedure in the news shock literature, based on the maximization of the variance decomposition (BS). Finally, I provide a robustness check by identifying the news shock in a simple three-variables VAR model, showing that the instruments are able to recover the news shock even in a small-scale VAR.

6.4.1 Strength of the instruments

Following Gertler and Karadi [2015] and Piffer and Podstawski [2017], I first test how strong the three proposed instruments are for identifying the news shock. The instruments are said to be strong if they are relevant on recovering the news shock (equation

[15]The dataset and replication files are available at Mark Watson's website.

Figure 6.3: Forecast revisions about future GDP, investment and industrial production (after filtering)



Note: Forecast revisions constructed from expectations about future GDP, future investment and future industrial production, collected from the Survey of Professional Forecasters (SPF), following the procedure described in Section 6.2. Each variable is the residual of a projection over external structural shocks and on five lags of an economic activity factor, as described in subsection 6.3.3. Time period from 1981:Q4 to 2006:Q3 due to data availability. Shaded areas are the recession periods calculated by the NBER.

6.30); or, how strongly correlated they are with the structural shock. The structural shock is not directly observed, but this is a linear combination of the reduced form innovations $\mathbf{u}_t$ from equation 6.25. It follows that, if the instruments are correlated with the structural shock, they should also be correlated with $\mathbf{u}_t$.

The idea of the test is to take each of the reduced-form innovations $u_{i,t}$ from $\mathbf{u}_t$ and regress them against the filtered instruments $\tilde{\mathbf{Z}}_t = [\tilde{z}_t^{gdp}, \tilde{z}_t^{ip}, \tilde{z}_t^{inv}]$, as in

$$u_{i,t} = \alpha + \theta_i \tilde{\mathbf{Z}}_t + \eta_i, \quad i = 2, ..., n, \tag{6.41}$$

where θ_i collects the three coefficients for the instruments. The first innovation $u_{1,t}$ is not considered here because it is orthogonal to the filtered instruments by construction, as $u_{1,t}$ is the proxy for the surprise technological shock (equation 6.40). I test if the three coefficients in θ_i are (jointly) significantly different from zero. If that is the case, the instruments sufficiently correlate with the reduced-form innovations.

Table 6.3 presents the results for the instrument relevance tests. The instruments are jointly significant in explaining the innovations for GDP, investment, stock prices and the Federal funds rate. The predictive power of the instruments over these variables is also relevant, varying between 8% and 14%.

Table 6.3: Instrument relevance tests

Innovation variable	F-stat	P-value	R^2
Consumption	0.45	0.72	0.01
GDP	3.26	0.02	0.09
Investment	2.63	0.05	0.08
Hours worked	0.69	0.56	0.02
GDP deflator	0.23	0.88	0.01
Stock prices	5.44	0.00	0.14
EBP	0.90	0.44	0.03
Financial uncertainty	0.96	0.41	0.03
Federal funds rate	2.65	0.05	0.08
Spread (10y - Fed funds)	0.06	0.98	0.00

Note: F-statistics calculated by testing if the coefficients of the (filtered) instruments forecast revisions about GDP, about industrial production and about investment are (jointly) significant in explaining the residuals from the VAR corresponding to each variable in the first column, as in equation 6.41. The residuals are calculated as the median across 1,000 posterior draws (as described in subsection 6.3.2). Time period is from 1981:Q4 to 2006:Q3 due to data availability (101 observations). The VAR model includes all variables in Table D.1 in the Appendix.

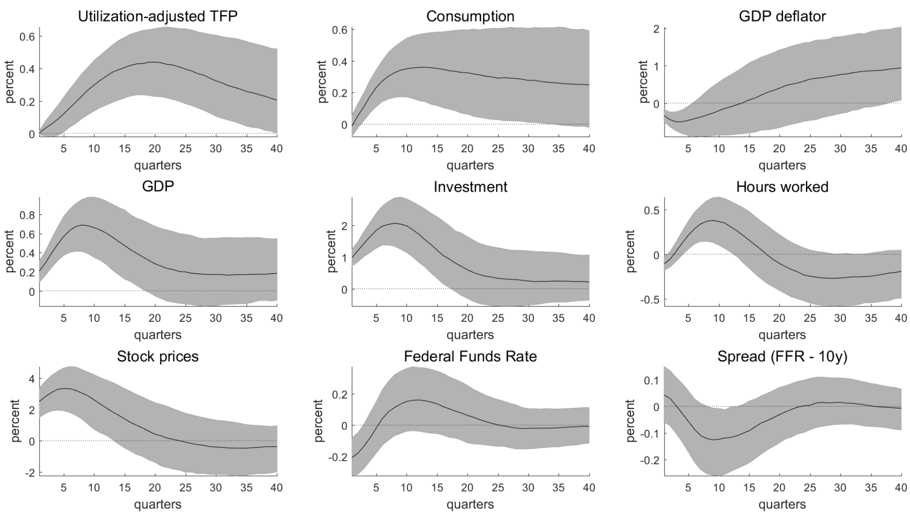
The strong relation of the instruments and stock prices is a positive indication of the connection between the instruments and the news shock. Beaudry and Portier [2006] show that permanent changes in productivity growth are preceded by stock market booms, indicating that agents foresee information about future technological opportunities. The relation with the Federal funds rate remains strong even after filtering the instruments by the monetary policy shocks. This result is in line with the stream of news shock literature that discusses the effectiveness of the monetary policy on reacting to news shocks.[16] Finally, the real macro variables GDP and investment should respond to supply shocks such as technological improvements, as it is the case of a news shock.

[16] See, for example, Kurmann and Otrok [2013], Cascaldi-Garcia [2017] and Gambetti et al. [2017].

6.4.2 Economic responses to a news shock identified with instrumental variables

Figure 6.4 presents the impulse responses after a news shock identified with instrumental variables for selected variables of the BVAR. The gray area defines the 68% confidence bands computed with 1,000 posterior draws, and incorporates the parameter uncertainty on the instruments.[17] The full impulse responses can be found in Figure D.3.1 in the Appendix.

Figure 6.4: Impulse responses to a news shock under an instrumental variable approach



Note: Impulse responses for selected variables of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975Q1 to 2012Q3. The gray area defines the 68% confidence bands computed with 1,000 posterior draws. The VAR model includes all variables in Table D.1 in the Appendix.

The first important result from Figure 6.4 is the effect of the identified shock on the variable utilization-adjusted TFP. This variable is a proxy for the technology level of the economy. Considering that technology is exogenous, a shock that changes the utilization-adjusted TFP should be a technological shock. Here, the effect of the identified shock is zero on impact by construction, from the orthogonality between the instruments and the surprise technological shock (equation 6.40). This imposition is equivalent to the short-run restriction employed both by Beaudry and Portier [2006] and

[17]For every posterior draw, the instruments are filtered taking into consideration the new residual $u_{1,t}$ (as described by equation 6.40). The resulting filtered instruments are then used for the identification on that specific draw. It follows that there are also 1,000 draws for the instruments.

Barsky and Sims [2011]. After around five quarters, utilization-adjusted TFP becomes significantly positive, reaching its highest level after around 20 quarters. In the long-run the effect diminishes, but remains positive.

This path is in line with the expected path of a news shock from the literature (Beaudry and Portier, 2014). A news shock is a change in the technology level that happens in the future, but the economic agents can foresee and react to it today. Indeed, it is possible to notice from the path of the other macroeconomic variables that there is a positive and significant reaction on impact. GDP jumps around 0.2% on impact, driven mainly by the strong effect on investment (about 1% on impact). The effect on stock prices is positive of around 2.5% on impact, showing a strong reaction to the news about the future technology. The effect converges back to zero in the medium-run, consistent with the efficiency of the stock market.

The effect on consumption is zero on impact, showing a milder initial anticipation from the consumers to the news shock than what it is usually found in the literature. However, the effect grows to a new higher level faster than the effect on utilization-adjusted TFP. While utilization-adjusted only reaches its peak after around 20 quarters, consumption reaches its maximum effect earlier, after around 12 quarters. This difference in timing shows that consumption is anticipating, rather than tracking, the technological improvements over time.

The effect of the news shock is deflationary, mainly in the short-run. This path is consistent with the current inflation being the expected present discounted value of future marginal costs (Barsky and Sims, 2011). The drop in GDP deflator is also in line with the idea of a 'supply shock', ruling out the possibility that the identified shock is capturing pressures from the demand side. The Federal funds rate falls by about 0.2 p.p, while the effect on the slope of the term structure is essentially zero. This result is consistent with the mild effects on the spread of the term structure after a news shock presented by Cascaldi-Garcia [2017].

The variable hours worked falls around 0.1% on impact, but the coverage bands do not rule out a zero effect. The response quickly becomes positive, reaching a peak of almost 0.4% after two years. There is a debate on the literature about what is the expected effect of a news shock on hours worked. Beaudry and Portier [2006] show that a news shock generates a positive and significant effect on hours (consistent with the results from Christiano et al., 2003), while Barsky and Sims [2011] present a negative effect of news on hours (in line with the technological shock from Galí, 1999). The positive results in the medium-run presented here support the economic intuition that the substitution effect from the higher future productivity is higher than the income effect, in line with Beaudry and Portier [2006].

The relevance of the news shock identified with instrumental variables on driving business cycles can be asserted from the variance decomposition of the macroeconomic variables. Table 6.4 presents the variance decomposition after a news shock for selected variables. Figure D.3.2 in the Appendix presents the variance decomposition graphs for all variables included in the BVAR.

Table 6.4: Variance decomposition of a news shock identified with instrumental variables

h	TFP	Output	Consumption	Investment	Stock prices
0	0.0	12.1	1.9	28.2	21.8
8	14.3	37.2	21.0	46.9	29.7
16	35.4	34.6	23.5	41.0	25.1
24	41.1	31.7	25.2	37.6	23.7
36	41.2	30.7	25.9	35.7	24.9

Note: Variance decomposition of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975Q1 to 2012Q3. h denotes the forecast horizon. The VAR model includes all variables in Table D.1.

The news shock explains about 41.2% of the unpredictable movements of utilization-adjusted TFP in the long-run. After two years, the news shock only explains 14.3%, reaching 35.4% after four years. This dynamic is in line with the idea of a steady increase in the technology level, with its highest effects in the long-run.

GDP, investment and stock prices react to such news instantaneously. The news shock explains 12.1% of the unpredictable movements of GDP on impact, 28.2% of investment and 21.8% of stock prices. The explanation power on impact for consumption is only 1.9%. In business cycle frequencies, however, the explanation power is substantial for all these variables: 30.7% of GDP in the long-run, 25.9% of consumption, 35.7% of investment and 24.9% of stock prices.

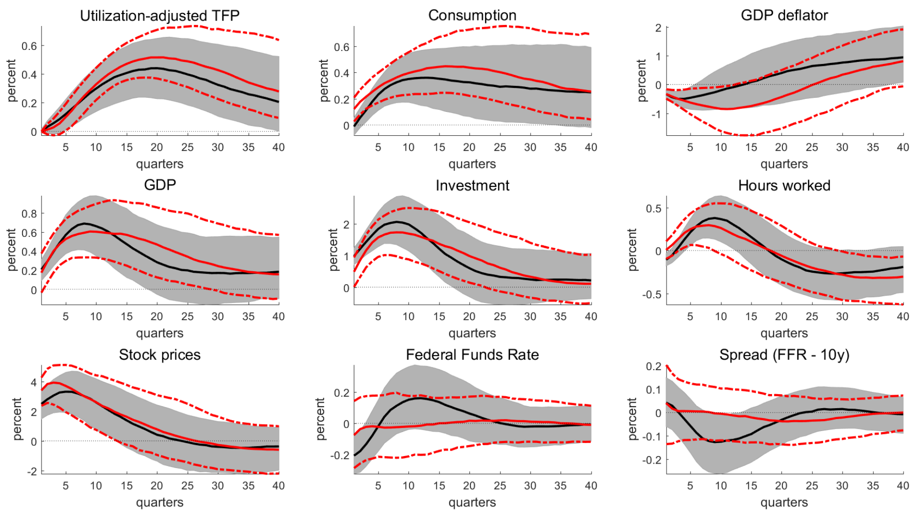
6.4.3 Instrumental variables *versus* maximization of variance decomposition

In this subsection I compare the strategy of identifying news shocks with instrumental variables based on forecast revisions to the most common approach of maximizing the variance decomposition proposed by Barsky and Sims [2011].

The idea of the BS identification for news shocks is to find the orthogonalization among the innovations that best explains unpredictable movements of utilization-adjusted TFP over a predefined forecast horizon, conditional on being orthogonal to surprise changes on the same variable. The procedure was built upon Faust [1998], and has been employed by several papers in the news shock literature.[18] The full identification procedure is described in Appendix D.1.

I compare the results from the identification with instrumental variables by employing the same database, period and BVAR estimation described in subsection 6.3.2, but identifying the news shock as in BS. Figure 6.5 compares the impulse response functions of selected variables for the identification based on maximizing the variance decomposition (BS approach, in red) and for the instrumental variables approach (black). The full impulse response functions for the BS approach can be found in Figure D.3.3 in the Appendix.

Figure 6.5: Impulse responses to a news shock identified with the Barsky and Sims [2011] (red) and instrumental variables (black) approaches



Note: Impulse responses for selected variables of a news shock computed by employing the identification procedure of maximizing the variance decomposition (red) described in Appendix D.1, and by employing the instrumental variables approach (black), with quarterly data ranging from 1975Q1 to 2012Q3. The dotted red lines define the 68% confidence bands for the BS approach, the gray area the confidence bands for the instrumental variables approach, all computed with 1,000 posterior draws. The VAR model includes all variables in Table D.1 in the Appendix.

First, by comparing the impulse responses it is possible to notice that both identification procedures present the same qualitative results. However, the coverage bands

[18] See, for example, Kurmann and Otrok [2013], Beaudry and Portier [2014], Cascaldi-Garcia and Galvao [2017], Levchenko and Pandalai-Nayar [2018], Clements and Galvao [2018], among others.

of the identification using the BS approach are substantially wider than when using the instrumental variables, particularly in the short-run.[19] The economic effects on utilization-adjusted TFP and on consumption are more intense using the BS approach through all forecast horizons. The effect on impact on GDP is basically the same when using either of the procedures, but the coverage bands of the BS approach rule out a zero effect. Investment rises more using the instrumental variable; also, the BS coverage bands also do not rule out a zero effect. The effect on the GDP deflator is deflationary on impact for both methods, but it lasts longer when the BS approach is employed.

One extra point to be highlighted is the effect on hours worked. The effect on impact is essentially zero for both approaches. In the medium-run, the instrumental variables approach presents a significantly positive effect, while BS coverage bands are quite close to zero. The instrumental variables approach gives stronger support to the view of positive comovement among GDP, consumption and hours worked, predicted by Beaudry and Portier [2006].

Finally, I compare the reconstructed historical path of the news shock from the instrumental variables approach and from the BS approach, presented in Figure 6.6. The path of both shocks is very similar, with the news shock from instrumental variables tracking the movements of the news shock from the BS approach. The series with the instrumental variables is somewhat less volatile, with a standard deviation of 0.60 in comparison to the 0.71 of the BS series. The two series share a correlation of 0.74 which, together with the similarity of the impulse responses, confirms the power of the instrumental variables on recovering the news shock.

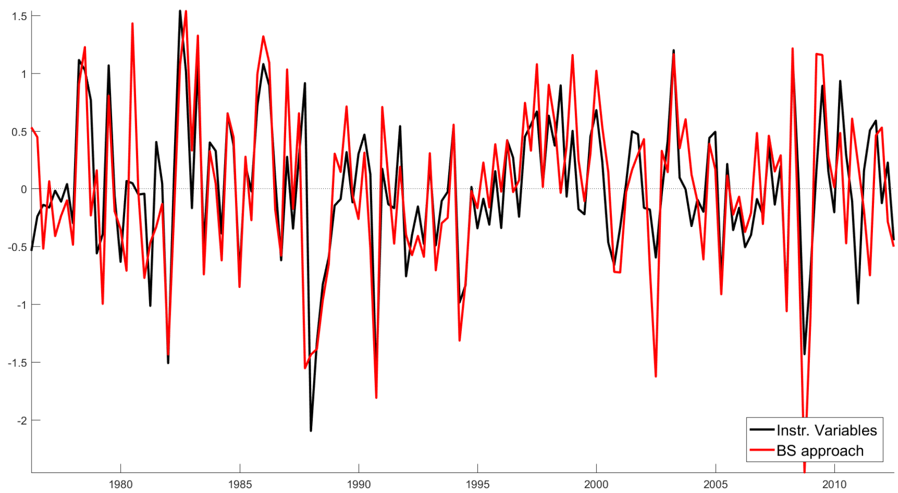
6.4.4 Robustness check in a three-variables VAR model

In this subsection I perform a robustness check by identifying the news shock with instrumental variables in a simple three-variables VAR. I follow the strategy employed by Beaudry and Portier [2014] of estimating a model with utilization-adjusted TFP, stock prices, and a third variable which can be consumer confidence (measured by the Michigan Consumer Survey), investment, hours worked or consumption.[20] The models are estimated with four lags, as vector error correction models (VECM) with two cointegration relations. Figure 6.7 presents the impulse responses for each model, with confidence, investment, hours worked and consumption as the third variable.

[19] I employ the same posterior draws for each procedure, and identify the news shock both with instrumental variables and with the BS approach for every draw.

[20] The Michigan Consumer Survey series is available at the Beaudry and Portier [2014] database. The series for utilization-adjusted TFP, stock prices, investment, hours worked and consumption are

Figure 6.6: Reconstructed news shock identified with the Barsky and Sims [2011] and instrumental variables approaches



Note: News shock computed by employing the identification procedure of maximizing the variance decomposition (red) described in Appendix D.1, and by employing the instrumental variables approach (black), with quarterly data ranging from 1975Q1 to 2012Q3. The series are the median across 1,000 posterior draws. The VAR model includes all variables in Table D.1 in the Appendix.

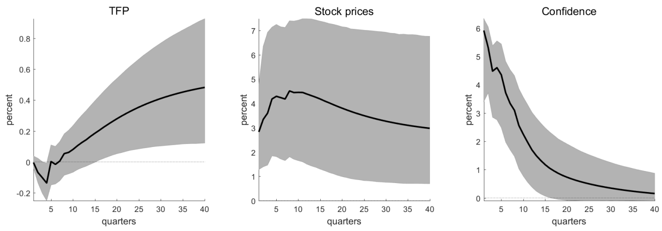
As before, the effect of the news shock identified with instrumental variables on utilization-adjusted TFP is zero on impact. In the long-run utilization-adjusted TFP grows to a new higher level, regardless of which of the four models is considered. The effect on utilization-adjusted TFP only becomes positive around 10 quarters after the shock, in line with the idea of a future change in technology that is anticipated by the economic agents.

The effect on stock prices is positive and significant on impact for all four models. However, the size of the impact and the path over time is quite distinct depending on which variable is chosen as the third in the system. The path of stock prices seems to converge back to zero in the long-run in the models for consumption and for hours worked, but there is no clear reversion for the other two models. These results indicate that the identification of the news shock is considerably sensitive to model specification.

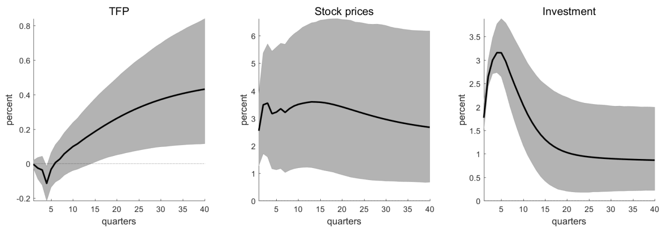
The measure of consumer confidence jumps on impact with the news shock, converging back to zero in the long-run. Investment shows a positive effect on impact,

constructed as described in Table D.1 in the Appendix.

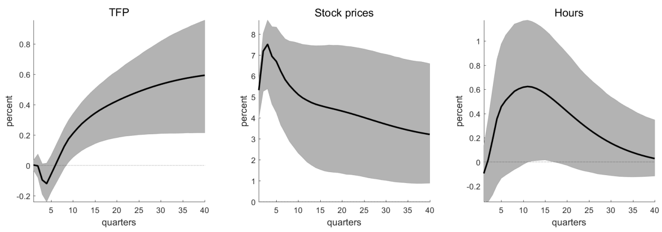
Figure 6.7: Impulse responses for a news shock identified with instrumental variables in a three-variables model



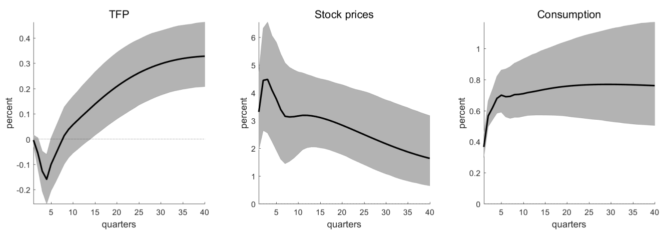
(a) TFP, Stock prices and Confidence



(b) TFP, Stock prices and Investment



(c) TFP, Stock prices and Hours worked



(d) TFP, Stock prices and Consumption

Note: Impulse responses for a news shock computed by employing the instrumental variables approach in a model with three variables, with quarterly data ranging from 1975Q1 to 2012Q3. The gray area defines the 68% confidence bands computed with Bayesian simulated distribution by Monte-Carlo integration with 10,000 draws. The models are estimated with four lags, as vector error correction model (VECM) with two cointegration relations.

achieving its highest effect after around six quarters, and converging to a new higher level in the long-run. The effect on hours worked is zero on impact, with a positive effect in the medium-run, and reverting back to zero in the long-run. The effect on consumption is positive on impact, and continues to grow until it reaches a new higher level in the long-run.

In summary, the results from Figure 6.7 provide qualitative evidence of the power of the instrumental variables on recovering the theoretical economic effects of a technological news shock, even in a small-scale VAR.

6.5 Conclusion

This paper shows that forecast revisions carry valuable information about the future path of the technology level, and can be used as instruments to identify news shocks. It contributes to the news shock literature by highlighting new evidence concerning the economic effects of news shocks through a novel identification method, which relies more on information about agents' expectations than on the implementation of assumptions through statistical procedures (such as long-run restrictions or maximization of the variance decomposition).

If technology is the main driver of the economy in business cycle frequencies, forecast revisions about the long-run of output should also be linked to news about technology. I propose proxy measures for the slope of the long-run trend of GDP, investment and industrial production, based on forecast revisions from the SPF. These variables are strong instruments for recovering the underlying technological news shock.

The news shock identified with instruments produces the theoretical comovement between the real macroeconomic variables, as initially proposed by Beaudry and Portier [2006], and is qualitatively similar to the Barsky and Sims [2011] identification. Investment and, consequently, GDP react instantly after the news shock, anticipating the future technological improvement. Consumption, however, shows less strong evidence of anticipation. There is no effect on impact, growing to a new higher level in the long-run. In business cycle frequencies, the news shock explains about 41% of unpredictable movements of TFP, 31% of GDP, 26% of consumption and 36% of investment.

Chapter 7

Conclusion

Overall, this Thesis expands our knowledge about how the economy reacts to changes in agents' expectations. The contributions presented here bring new quantitative evidence of the capability of technological news shocks on driving business cycles, which can be a baseline for future empirical research. It shows that news about future productivity is confounded with expectations about economic conditions, opening a new venture of research by bridging technological news and economic uncertainty. It provides novel methodological techniques to measure the economic effects of news which are yet to be explored by the business cycle literature. In what follows, I summarize the specific contributions of each of the four main Chapters of this Thesis.

In Chapter 3, we explore the relationship between technological news shocks and unexpected changes in the level of uncertainty of the economy. This provides two main contributions linking the news and uncertainty shock literatures. First, employing the maximum forecast error variance identification as proposed by Barsky and Sims [2011], we show that news and uncertainty shocks are positively correlated. The correlation between news and uncertainty shocks is somewhat striking, because of the distinct nature of these two shocks: while a news shock has a long-run pro-cyclical effect on economic variables, the uncertainty is basically short-lived and counter-cyclical. The effects of news and uncertainty shocks on utilization-adjusted TFP and on the uncertainty measure are quite similar. A news shock generates a hike on impact in the realized volatility in the short-term that disappears after around four quarters. After an uncertainty shock, the utilization-adjusted TFP goes from zero to a positive and significant higher level, reaching its peak at around five quarters. The second main contribution is a novel identification method to obtain orthogonal news and uncertainty shocks – the proposed 'truly news' and 'truly uncertainty' shocks. The 'truly news' shock, free from the correlation with uncertainty, produces positive comovement among consumption, stock prices, employment and industrial production, as the real business cycle literature suggests. The 'truly uncertainty' shock, free from the positive effect of news, produces more intense recessionary effects. While uncertainty shocks explain 5% of output growth variation, this share rises to 15% when the 'truly uncertainty' shock is identified.

In Chapter 4, I study the transmission mechanism of technological news shocks through uncertainty. This contributes to the business cycle literature in two ways. First, I propose an innovative method of checking whether the effects of a news shock 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. The second contribution is new evidence supporting a dynamic relationship between technological news and uncertainty. The effects of news on consumption, GDP, investment and real personal income are amplified when the news shock hits the economy in periods of high uncertainty. The results also suggest that the size of these effects depends on the initial degree of uncertainty (initial condition effect) and on how expectations about macroeconomic and financial conditions are updated (transmission effect). From the perspective of the news shock literature, it implies that neglecting the uncertainty transmission effect leads to the conclusion that the positive effects of news shocks are weaker than they really are. From the perspective of the uncertainty 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.

In Chapter 5, I explore the relationship between news shocks and the slope of the term structure presented by Kurmann and Otrok [2013]. By revisiting the results with an updated version of the utilization-adjusted TFP series, the correlation between news and slope shocks diminishes and the implications of a news shock become substantially different from Kurmann and Otrok [2013]. The main reason for the positive effect of a news shock on the slope in Kurmann and Otrok [2013] is the endogenous response of monetary policy, driven through the fall of the Federal Funds rate in a larger level than the long-term yield. However, with the new updated utilization-adjusted TFP series the effect of a news shock on inflation is zero, and the drop in the Federal Funds rate is not statistically significant.

Finally, in Chapter 6, I propose a new identification procedure for news shocks based on information contained in agents' expectations. I employ the proxy SVAR procedure to the news shock case. The proposed instruments are constructed from forecast revisions for GDP, industrial production and investment. I show that these forecast revisions carry valuable information about the future path of the technology level, allowing for the identification of technological news shocks. This contributes to the news shock literature by confirming the theoretical comovement among the real macroeconomic variables, as initially proposed by Beaudry and Portier [2006] through an alternative identification procedure. The results are also qualitatively similar to those produced with the Barsky and Sims [2011] identification, which became the standard procedure in this literature. Investment and, consequently, GDP react instantly after the news shock, anticipating the future technological improvement. Consumption, however, shows less strong evidence of anticipation.

While this Thesis contributes by bringing new findings to the news and uncertainty literatures, many questions remain unanswered. The reaction of the monetary policy to news shocks, for example, remains unclear. The time-varying effects of the news shock and its relation to the uncertainty level of the economy presented in this Thesis suggest that the monetary authority should adjust its policies accordingly. Another issue of interest is to evaluate whether a news shock produces similar economic effects in different economies, other than the US. This analysis demands the construction of comparable proxies for the technology level for each country, which is not an easy task. Finally, bringing the news shock to an open economy setup will help to answer questions of how the expectation of future technological improvements spillover to other countries and the role uncertainty plays in this transmission mechanism.

Appendix A

Chapter 3

A.1 Identification of news shocks

Taking a vector of endogenous variables $\mathbf{y}_t$, assuming that the utilization-adjusted TFP is ordered first, the moving average representation (in levels) is written as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \tag{A.1}$$

If there is a linear mapping of the innovations ($\mathbf{u}_t$) and the structural shocks ($\mathbf{s}_t$), this moving average representation can be rewritten as

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t \tag{A.2}$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \tag{A.3}$$

where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{A}_0$, $\mathbf{s}_t = \mathbf{A}_0^{-1}\mathbf{u}_t$, and $\mathbf{A}_0$ is the impact matrix that makes $\mathbf{A}_0\mathbf{A}_0^{'} = \mathbf{\Sigma}$ (variance-covariance matrix of innovations). It is possible to rewrite $\mathbf{A}_0$ as $\tilde{\mathbf{A}}_0\mathbf{D}$, where $\tilde{\mathbf{A}}_0$ is the lower triangular Cholesky factor of the covariance matrix of reduced form innovations (or any other orthogonalization), and $\mathbf{D}$ is any $k \times k$ matrix that satisfies $\mathbf{D}\mathbf{D}^{'} = \mathbf{I}$.

Considering that $\Omega_{i,j}(h)$ is the share of the forecast error variance of variable i of the structural shock j at horizon h, it follows that

$$\Omega_{1,1}(h)_{surprise} + \Omega_{1,2}(h)_{news} = 1 \forall h, \tag{A.4}$$

where $i = 1$ refers to utilization-adjusted TFP, $j = 1$ is the unexpected TFP shock, and $j = 2$ is the news shock. The share of the forecast error variance of the news shock is defined as

$$\Omega_{1,2}(h)_{news} = \frac{\mathbf{e}_1^{'}\left(\sum_{\tau=0}^{h}\mathbf{B}_\tau\tilde{\mathbf{A}}_0\mathbf{D}\mathbf{e}_2\mathbf{e}_2^{'}\mathbf{D}^{'}\ \tilde{\mathbf{A}}_0^{'}\mathbf{B}_\tau^{'}\right)\mathbf{e}_1}{\mathbf{e}_1^{'}\left(\sum_{\tau=0}^{h}\mathbf{B}_\tau\mathbf{\Sigma}\mathbf{B}_\tau^{'}\right)\mathbf{e}_1} = \frac{\sum_{\tau=0}^{h}\mathbf{B}_{1,\tau}\tilde{\mathbf{A}}_0\ \gamma\gamma^{'}\tilde{\mathbf{A}}_0^{'}\mathbf{B}_{1,\tau}^{'}}{\sum_{\tau=0}^{h}\mathbf{B}_{1,\tau}\mathbf{\Sigma}\mathbf{B}_{1,\tau}^{'}}, \tag{A.5}$$

where $\mathbf{e}_1$ is a selection vector with 1 in the position $i = 1$ and zeros elsewhere, $\mathbf{e}_2$ is a selection vector with 1 in the position $i = 2$ and zeros elsewhere, and $\mathbf{B}_\tau$ is the matrix of moving average coefficients measured at each period until τ. The combination of selection vectors with the proper column of $\mathbf{D}$ can be written as γ, which is an orthonormal vector that makes $\tilde{\mathbf{A}}_0\gamma$ the impact of a news shock over the variables.

The news shock is identified by solving the optimization problem

$$\gamma_2^{news} = argmax \sum_{h=0}^{H} \Omega_{1,2}(h)_{news}, \tag{A.6}$$

s.t.

$$\tilde{A}_0(1,j) = 0, \forall j > 1 \tag{A.7}$$

$$\gamma_2(1,1) = 0 \tag{A.8}$$

$$\gamma_2' \gamma_2 = 1, \tag{A.9}$$

where H is an truncation period, and the restrictions impose that the news shock does not have an effect on impact ($t = 0$) and that the γ vector is orthonormal.

Based on the γ_2^{news} vector, the structural unexpected TFP (s_t^{unexp}) and the news shock (s_t^{news}) are

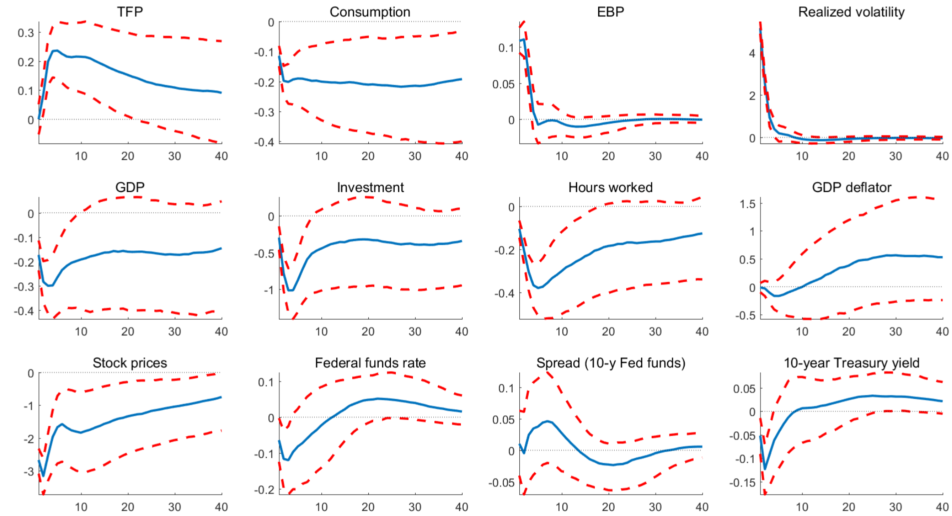
$$\begin{bmatrix} s_t^{unexp} \\ s_t^{news} \\ ... \end{bmatrix} = \tilde{\mathbf{A}}_0^{-1} \begin{bmatrix} \gamma_1^{unexp} & \gamma_2^{news} & ... \end{bmatrix}^{-1} \mathbf{u}_t', \tag{A.10}$$

assuming that

$$\gamma_1^{unexp} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ ... \end{bmatrix}. \tag{A.11}$$

A.2 Figures

Figure A.2.1: Responses to financial uncertainty (realized volatility) shocks in the baseline VAR model



Note: Dotted lines are 68% confidence bands computed with 1,000 posterior draws. The response of the 10-year rate is computed using the responses to the Fed funds and the spread. The baseline identification scheme for uncertainty shocks is described in section 3.2.2. The VAR model includes all variables in the first panel of Table 3.1 + realized volatility.

Figure A.2.2: Responses to financial uncertainty (LMN-fin-1) shocks in the baseline VAR model

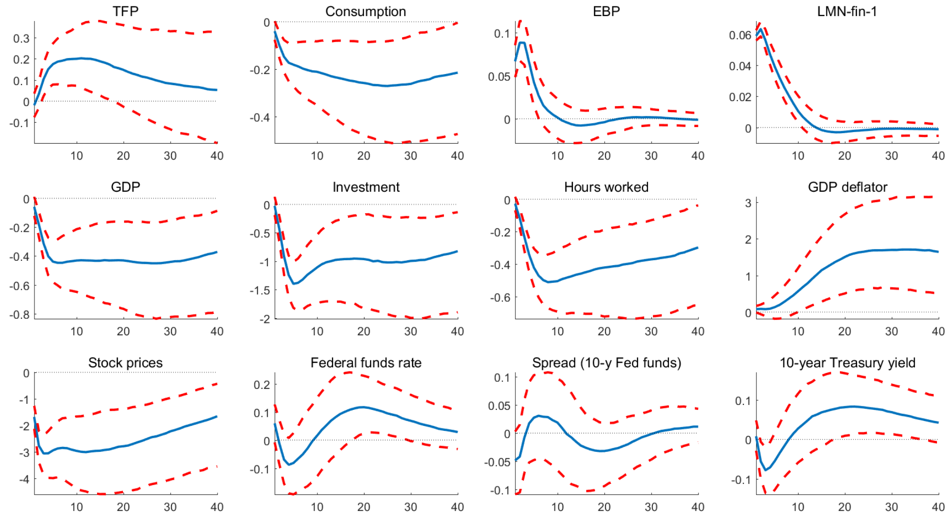
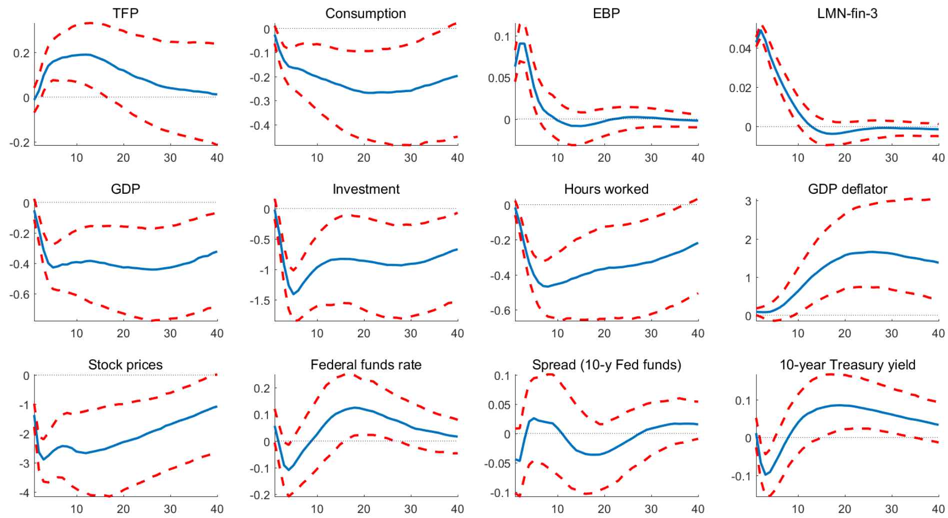


Figure A.2.3: Responses to financial uncertainty (LMN-fin-3) shocks in the baseline VAR model



Note: See note to Figure A.2.1. The VAR model includes all variables in the first panel of Table 3.1 + LMN-fin-1 (Figure A.2.2) or LMN-fin-3 (Figure A.2.3).

Figure A.2.4: Responses to financial uncertainty (LMN-fin-12) shocks in the baseline VAR model

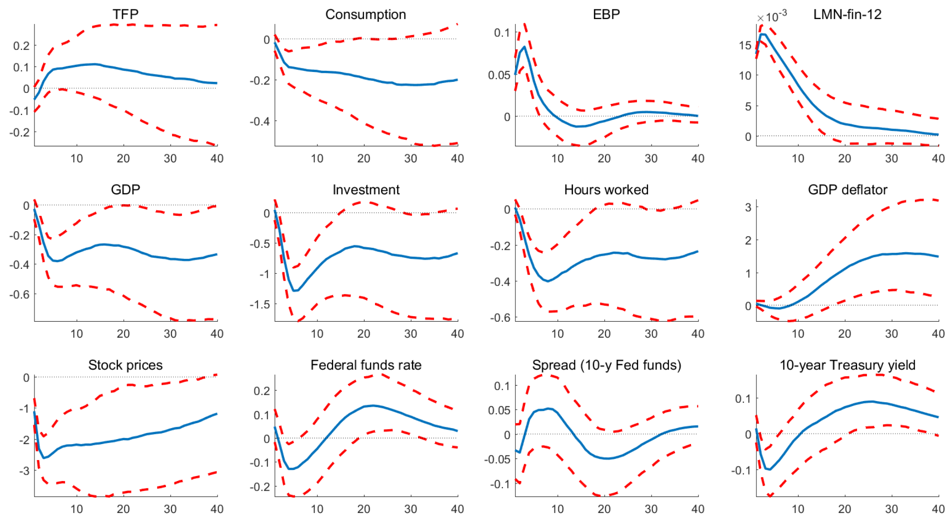
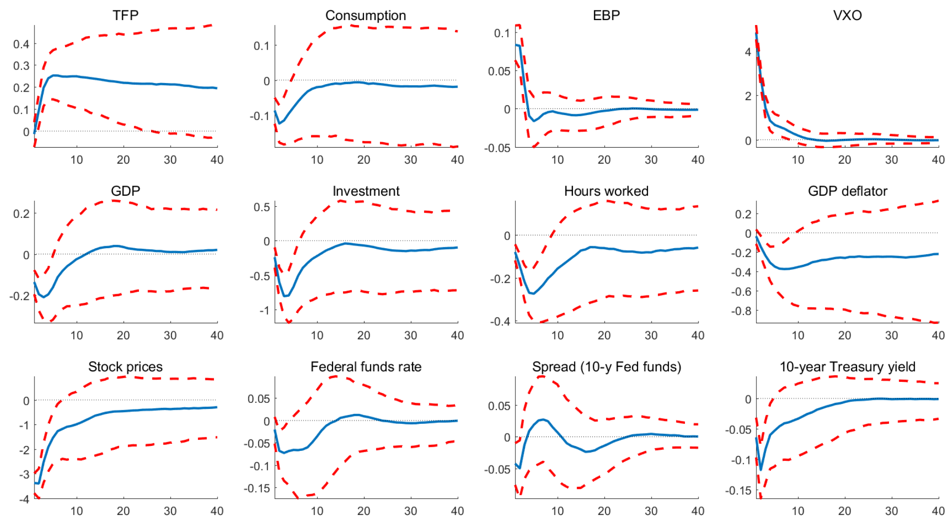


Figure A.2.5: Responses to financial uncertainty (VXO) shocks in the baseline VAR model



Note: See note to Figure A.2.1. The VAR model includes all variables in the first panel of Table 3.1 + LMN-fin-12 (Figure A.2.4) or VXO (Figure A.2.5).

Figure A.2.6: Responses to macroeconomic uncertainty (Policy uncertainty) shocks in the baseline VAR model

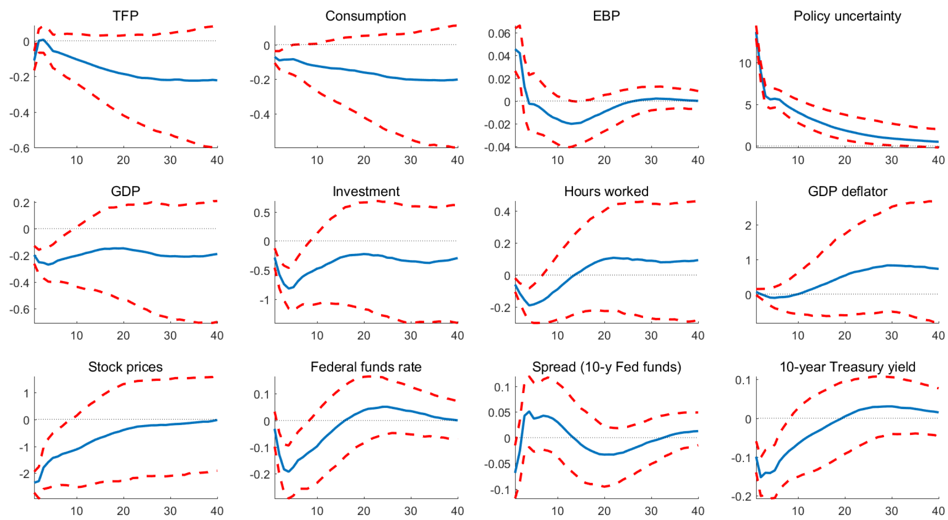
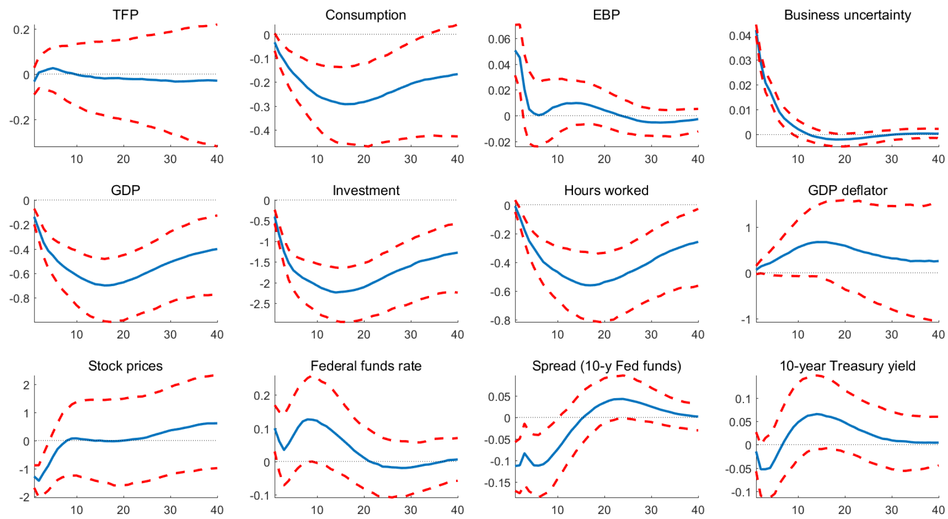


Figure A.2.7: Responses to macroeconomic uncertainty (Business uncertainty) shocks in the baseline VAR model



Note: See note to Figure A.2.1. The VAR model includes all variables in the first panel of Table 3.1 + Policy uncertainty (Figure A.2.6) or Business uncertainty (Figure A.2.7).

Figure A.2.8: Responses to macroeconomic uncertainty (SPF disagreement) shocks in the baseline VAR model

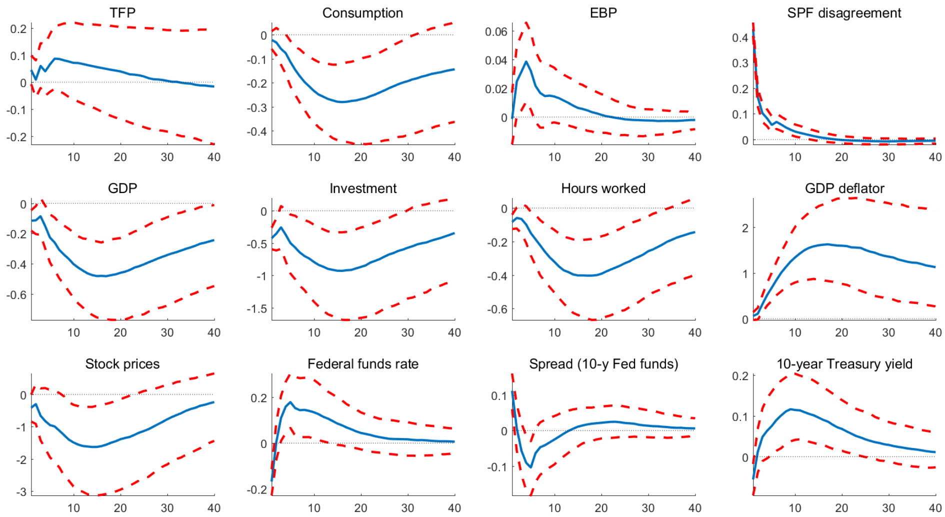
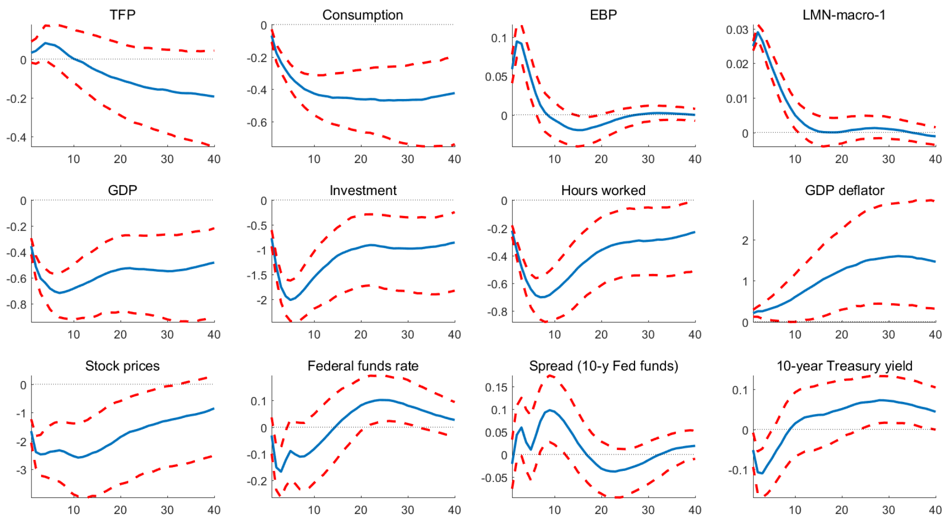


Figure A.2.9: Responses to macroeconomic uncertainty (LMN-macro-1) shocks in the baseline VAR model



Note: See note to Figure A.2.1. The VAR model includes all variables in the first panel of Table 3.1 + SPF disagreement (Figure A.2.8) or LMN-macro-1 (Figure A.2.9).

Figure A.2.10: Responses to macroeconomic uncertainty (LMN-macro-3) shocks in the baseline VAR model

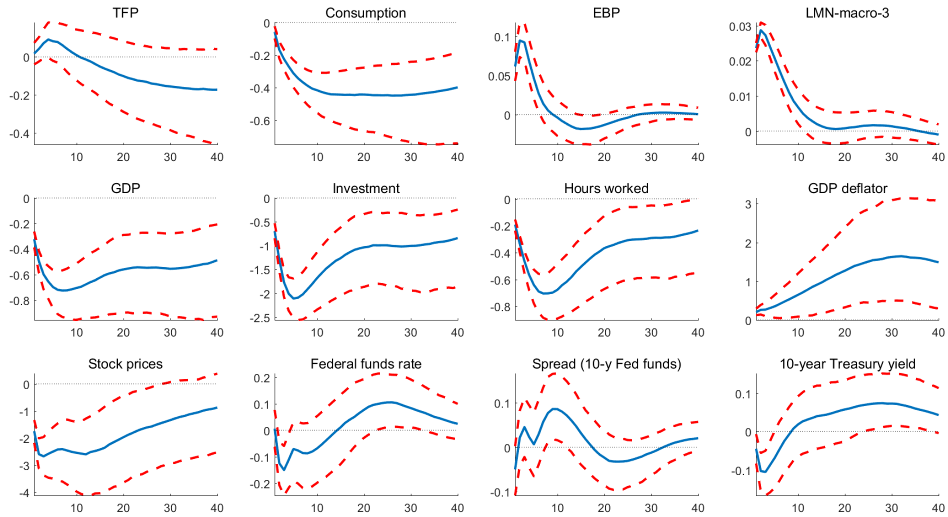
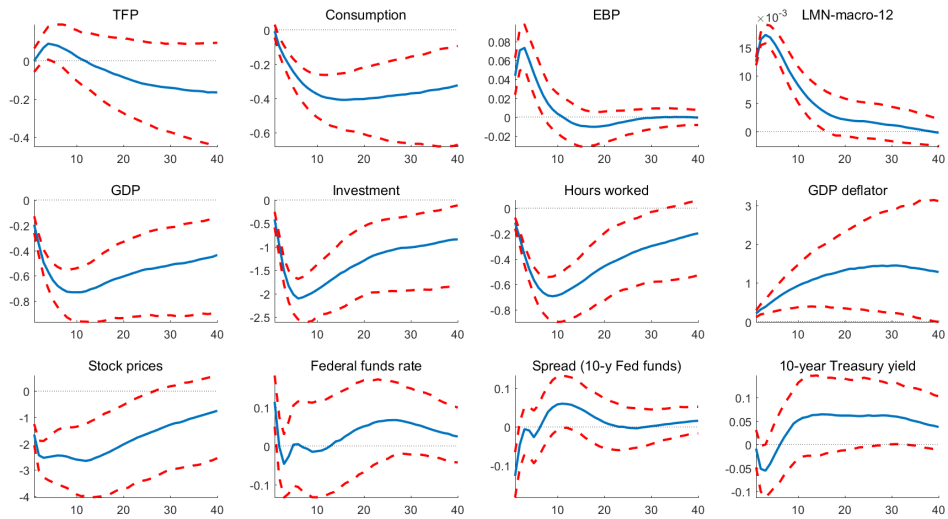


Figure A.2.11: Responses to macroeconomic uncertainty (LMN-macro-12) shocks in the baseline VAR model



Note: See note to Figure A.2.1. The VAR model includes all variables in the first panel of Table 3.1 + LMN-macro-3 (Figure A.2.10) or LMN-macro-12 (Figure A.2.11).

Appendix B

Chapter 4

B.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 4.1, but rewriting the reduced form residuals υ_t from equation 4.2 as

$$\begin{bmatrix} \upsilon_{1,t} \\ \upsilon_{2,t} \\ ... \\ \upsilon_{n,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & ... & 0 \\ a^*_{2,1} & 1 & ... & 0 \\ ... & ... & 1 & 0 \\ a^*_{n,1} & ... & a^*_{n,n-1} & 1 \end{bmatrix} \begin{bmatrix} \lambda^{1/2}_{1,t} & 0 & ... & 0 \\ 0 & \lambda^{1/2}_{2,t} & ... & 0 \\ ... & ... & ... & 0 \\ 0 & ... & 0 & \lambda^{1/2}_{n,t} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ ... \\ \epsilon_{n,t} \end{bmatrix}, \tag{B.1}$$

where $a^*_{j,i}$ are the elements of the matrix $\mathbf{A}_0^{-1}$. Under this structure, it is possible to rewrite each equation of the main VAR described in 4.1 and variable j as

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

where $A^{(i)}_{j,l}$ represents the coefficients of the matrices $\mathbf{A}_i$, and $B_{c,j}$ represents the coefficients of the matrices $\mathbf{B}_i$. 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

$$y^*_{t,j} = y_{t,j} - (a^*_{j,1}\lambda^{1/2}_{1,t}\epsilon_{1,t} + ... + a^*_{j,j-1}\lambda^{1/2}_{j-1,t}\epsilon_{j-1,t}) \tag{B.3}$$

it is possible to estimate equation B.2 as a standard generalized least squares (GLS) model.

B.2 Steps of the MCMC algorithm

The MCMC algorithm for this estimation follows the steps and notation proposed by Carriero et al. [2016a], which I describe here. The conditional posterior distributions for the draws described in this Section are detailed in Appendix B.5.

Step 1: *Draw of the idiosyncratic volatilities.*

Rescaling υ_t as $\tilde{\upsilon}_t = \mathbf{A}_0\upsilon_t$, combined with the linear factor model for the log-volatilities described by equation 4.3, it is possible to define the observation equations

$$\begin{cases} \ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{m,j} \ln m_t = \ln h_{j,t} + \ln \epsilon_{j,t}^2 & \text{if } j = 1, ..., n_m \\ \ln(\tilde{v}_{j,t}^2 + \bar{c}) - \beta_{f,j} \ln f_t = \ln h_{j,t} + \ln \epsilon_{j,t}^2 & \text{if } j = n_m + 1, ..., n \end{cases}, \tag{B.4}$$

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

$$h_{1:T} | \Theta, S_{1:T}, m_{1:T}, f_{1:T}, \tag{B.5}$$

using the Kim et al. [1998] algorithm, where $\mathbf{\Theta}$ collects the coefficients from the matrices $\mathbf{A}_i$, $\mathbf{B}_i$, δ, $\mathbf{D}_i$, the coefficients in the conditional mean of the idiosyncratic components $\gamma = (\gamma_{j,0}, \gamma_{j,1})$, the elements of the matrix $\mathbf{A}_0$, and the elements of the volatility matrices $\mathbf{\Phi}_v$ and $\mathbf{\Phi}_u$, as in

$$\mathbf{\Theta} = (\mathbf{A}_i, \mathbf{B}_i, \delta, \mathbf{D}_i, \gamma, \mathbf{A}_0, \mathbf{\Phi}_v, \mathbf{\Phi}_u). \tag{B.6}$$

Step 2: *Draw of the factor loadings.*

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

$$\beta_{m,j}, \beta_{f,j} | \mathbf{\Theta}, h_{1:T}, S_{1:T}, m_{1:T}, f_{1:T}. \tag{B.7}$$

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

$$\ln(\tilde{v}_{j,t}^2 + \bar{c}) - \ln h_{j,t} = \begin{cases} \beta_{m,j} \ln m_t + \ln \epsilon_{j,t}^2 & \text{if } j = 1, ..., n_m \\ \beta_{f,j} \ln f_t + \ln \epsilon_{j,t}^2 & \text{if } j = n_m + 1, ..., n \end{cases}. \tag{B.8}$$

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

The posterior coefficients and volatilities collected in $\mathbf{\Theta}$ are drawn as

$$\mathbf{\Theta} | \beta_{m,j}, \beta_{f,j}, h_{1:T}, S_{1:T}, m_{1:T}, f_{1:T}. \tag{B.9}$$

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

$$m_{1:T}, f_{1:T}|\mathbf{\Theta}, \beta_{m,j}, \beta_{f,j}, h_{1:T}, S_{1:T}, \tag{B.10}$$

by employing the particle Gibbs with ancestor sampling proposed by Andrieu et al. [2010] and Lindsten et al. [2014] described in Appendix B.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

$$S_{1:T}|\mathbf{\Theta}, \beta_{m,j}, \beta_{f,j}, h_{1:T}, m_{1:T}, f_{1:T}. \tag{B.11}$$

B.3 Particle Gibbs with ancestor sampling

Consider a state space model as in

$$\ln(\tilde{v}_t^2 + \bar{c}) - \ln h_t = \ln m_t + \ln \epsilon_t^2, \quad \ln \epsilon^2 \sim \chi^2(0, s_T) \tag{B.12}$$

$$\ln m_t = D_1 \ln m_{t-1} + \delta_m \Delta y_{t-1} + u_{m,t}, \quad u_t \sim IW(0, \phi) \tag{B.13}$$

where $\ln(\tilde{v}_t^2 + \bar{c})$ is a rescaled combination of the residuals from the VAR based on the loadings β_j, $\ln h_t$ is a rescaled combination of the idiosyncratic volatilities $\ln h_{j,t}$, and $\ln \epsilon_t^2$ has a variance which is a rescaled combination of the 10-state mixture of states draw $S_{1:T}$.

Step 1: *Draw of ϕ 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

$$u_{m,t} = \ln m_t^{i-1} - \left(D_1 \ln m_{t-1}^{i-1} + \delta_m \Delta y_{t-1}\right). \tag{B.14}$$

Draw $\tilde{\phi}$ as following

$$\phi \sim IW\left(d_\phi \underline{\phi} + \sum_{t=1}^{T} u_{m,t}^2, d_\phi + T\right). \tag{B.15}$$

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 Nth particle as the first observation of m_t^{i-1}, and zero for the other particles, as in

$$X_m(N,1) = \ln m_t^{i-1}(1,1), \qquad X_m(1:(N-1),1) = 0. \tag{B.16}$$

Compute $\ln \tilde{\epsilon}_1^{2,(j)}$ for each of the $j = 1 : N$ particles, as in

$$\ln \tilde{\epsilon}_1^{2,(j)} = (\ln(\tilde{v}_1^2 + \bar{c}) - \ln h_1) - X_m(j,1). \tag{B.17}$$

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

$$w(j,1) = \exp\left(-\frac{1}{2}\frac{\left(\ln \tilde{\epsilon}_1^{2,(j)}\right)^2}{S_{1:T}(1)}\right), \tag{B.18}$$

and normalizing

$$w(j,1) = \frac{w(j,1)}{\sum_{j=1}^{N} w(j,1)}. \tag{B.19}$$

Step 3: *Compute importance weights for $t = 2 : T$.*

Compute N predicted m_t based on the previous particles, as in

$$\ln \tilde{m}(j,t) = (D_1 X_m(j,t-1) + \delta \Delta y_{t-1}). \tag{B.20}$$

Draw an index vector $ind(N)$ that samples the particles from $P(ind(j) = j) \propto w(1:j, t-1)$, 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

$$X_n(j,t) = \ln \tilde{m}(ind(j),t) + \tilde{\phi}^{1/2} * randn(1,1), \tag{B.21}$$

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

$$X_m(N,t) = \ln m_t^{i-1}(1,t). \tag{B.22}$$

Compute $\ln \tilde{\epsilon}_1^{2,(j)}$ for each of the $j = 1 : N$ particles as before, following

$$\ln \tilde{\epsilon}_t^{2,(j)} = (\ln(\tilde{v}_t^2 + \bar{c}) - \ln h_t) - X_m(j,t), \tag{B.23}$$

the importance weights as

$$w(j,t) = \exp\left(-\frac{1}{2}\frac{\left(\ln \tilde{\epsilon}_t^{2,(j)}\right)^2}{S_{1:T}(t)}\right), \tag{B.24}$$

and normalizing

$$w(j,t) = \frac{w(j,t)}{\sum_{j=1}^{N} w(j,t)}. \tag{B.25}$$

The last part of this step is defining the Nth ancestor index. In a conventional Particle Gibbs, this is done by simply assigning $ind(N) = N$, 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 $ind(N)$ 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

$$w_{ind}(j,t) = w(j,t-1) * \exp\left(-\frac{1}{2}\frac{\left(m_t^{i-1}(1,t) - \tilde{m}(j,t)\right)^2}{\tilde{\phi}}\right), \tag{B.26}$$

normalizing

$$w_{ind}(j,t) = \frac{w_{ind}(j,t)}{\sum_{j=1}^{N} w_{ind}(j,t)}, \tag{B.27}$$

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

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 $\ln m_t^i = X_m(J, 1:T)$.

B.4 State-space representation

The model described by equations 4.1 and 4.5 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 ($\mathbf{D}_i$ lag order is $k = 1$) and on Δy_{t-1}. Equation 4.5 becomes

$$g_t = \mathbf{D}_1 g_{t-1} + \delta \Delta y_{t-1} + u_t, \tag{B.28}$$

or simply

$$g_t = \mathbf{D}_1 g_{t-1} + \delta y_{t-1} - \delta y_{t-2} + u_t. \tag{B.29}$$

Consider now that the main VAR (equation 4.1) has lag order of y_t of p, $l = 1$ lag of the macro and financial factors g_t, and $v_t = \mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\epsilon_t$. Rewrite equation 4.1 as

$$y_t = \mathbf{A}_1 y_{t-1} + ... + \mathbf{A}_p y_{t-p} + \mathbf{B}_0 g_t + \mathbf{B}_1 g_{t-1} + \mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\epsilon_t, \tag{B.30}$$

substituting g_t from equation B.29 in equation B.30, results in

$$\begin{aligned} y_t &= \mathbf{A}_1 y_{t-1} + ... + \mathbf{A}_p y_{t-p} + \mathbf{B}_0(\mathbf{D}_1 g_{t-1} + \delta y_{t-1} - \delta y_{t-2} + u_t) + ... \\ &... + \mathbf{B}_1 g_{t-1} + \mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\epsilon_t, \end{aligned} \tag{B.31}$$

which can be rearranged as

$$\begin{aligned} y_t &= (\mathbf{A}_1 + \mathbf{B}_0\delta) y_{t-1} + (\mathbf{A}_2 - \mathbf{B}_0\delta) y_{t-2} + ... + \mathbf{A}_p y_{t-p} + ... \\ &... + (\mathbf{B}_1 + \mathbf{B}_0\mathbf{D}_1) g_{t-1} + \mathbf{B}_0 u_t + \mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2}\epsilon_t. \end{aligned} \tag{B.32}$$

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

$$\begin{bmatrix} y_t \\ y_{t-1} \\ ... \\ y_{t-p} \\ g_t \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{F}_1 & \mathbf{F}_2 & ... & \mathbf{F}_3 & \mathbf{F}_4 \\ \mathbf{I}_n & 0 & ... & 0 & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & ... & \mathbf{I}_n & 0 \\ \delta & -\delta & ... & 0 & \mathbf{D}_1 \end{bmatrix}}_{\mathbf{F}} \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ ... \\ y_{t-p-1} \\ g_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2} & 0 & ... & 0 & \mathbf{B}_0 \\ 0 & 0 & 0 & 0 & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathbf{I}_2 \end{bmatrix} \begin{bmatrix} \epsilon_t \\ 0 \\ ... \\ 0 \\ u_t \end{bmatrix}, \tag{B.33}$$

where

$$\begin{aligned} \mathbf{F}_1 &= (\mathbf{A}_1 + \mathbf{B}_0\delta), \\ \mathbf{F}_2 &= (\mathbf{A}_2 - \mathbf{B}_0\delta), \\ \mathbf{F}_3 &= \mathbf{A}_p, \\ \mathbf{F}_4 &= (\mathbf{B}_1 + \mathbf{B}_0\mathbf{D}_1). \end{aligned} \tag{B.34}$$

The matrix $\mathbf{\Lambda}_t$ takes the form

$$\mathbf{\Lambda}_t = \begin{bmatrix} \lambda_{1,t} & 0 & ... & 0 \\ 0 & \lambda_{2,t} & ... & 0 \\ 0 & 0 & ... & \lambda_{n,t} \end{bmatrix}, \tag{B.35}$$

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

$$\lambda_{j,t} = \begin{cases} m_t^{\beta_{m,j}} h_{j,t} & \text{if } j = 1, ..., n_m \\ f_t^{\beta_{f,j}} h_{j,t} & \text{if } j = n_m + 1, ..., n \end{cases}, \tag{B.36}$$

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

$$\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1} + e_{j,t}, \quad j = 1, ..., n. \tag{B.37}$$

B.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 B.2. I follow the proposed priors and notation from Carriero et al. [2016a], with priors defined as

$$vec(\mathbf{A}_i; \mathbf{B}_i) \sim N(vec(\underline{\mu}_A), \underline{\mathbf{\Omega}}_A), \quad i = 1, ..., p, \tag{B.38}$$

$$a_j \sim N(\underline{\mu}_{a,j}, \underline{\mathbf{\Omega}}_{a,j}), \quad j = 2, ..., n, \tag{B.39}$$

$$\beta_j \sim N(\underline{\mu}_\beta, \underline{\mathbf{\Omega}}_\beta), \quad j = 2, ..., n_m, n_{m+2}, ..., n, \tag{B.40}$$

$$\gamma_j \sim N(\underline{\mu}_\gamma, \underline{\mathbf{\Omega}}_\gamma), \quad j = 1, ..., n, \tag{B.41}$$

$$\delta \sim N(\underline{\mu}_\delta, \underline{\mathbf{\Omega}}_\delta), \tag{B.42}$$

$$\phi_j \sim IG(d_\phi \underline{\phi}, d_\phi), \quad j = 1, ..., n, \tag{B.43}$$

$$\mathbf{\Phi}_u \sim IW(d_{\Phi_u} \underline{\mathbf{\Phi}}_u, d_{\Phi_u}). \tag{B.44}$$

Under these priors, the posterior conditional distributions follow

$$vec(\mathbf{A}_i; \mathbf{B}_i) | \mathbf{A}_0, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} \sim N(vec(\bar{\mu}_A), \bar{\mathbf{\Omega}}_A), \quad i = 1, ..., p, \tag{B.45}$$

$$a_j | \mathbf{A}_i, \mathbf{B}_i, \beta, m_{1:T}, f_{1:T}, h_{1:T}, y_{1:T} \sim N(\bar{\mu}_{a,j}, \bar{\mathbf{\Omega}}_{a,j}), \quad j = 2, ..., n, \tag{B.46}$$

$$1\beta_j|\mathbf{A}_i,\mathbf{A}_0,\mathbf{B}_i,\gamma,\boldsymbol{\Phi},\beta,m_{1:T},f_{1:T},S_{1:T},y_{1:T}\sim N(\underline{\mu}_\beta,\underline{\boldsymbol{\Omega}}_\beta),\quad j=2,...,n_m,n_{m+2},...,n, \tag{B.47}$$

$$\gamma_j|\mathbf{A}_i,\mathbf{A}_0,\mathbf{B}_i,\boldsymbol{\Phi},\beta,m_{1:T},f_{1:T},h_{1:T},y_{1:T}\sim N(\underline{\mu}_\gamma,\underline{\boldsymbol{\Omega}}_\gamma),\quad j=1,...,n, \tag{B.48}$$

$$\delta|\mathbf{A}_i,\mathbf{A}_0,\mathbf{B}_i,\boldsymbol{\Phi},\gamma,\beta,m_{1:T},f_{1:T},h_{1:T},y_{1:T}\sim N(\underline{\mu}_\delta,\underline{\boldsymbol{\Omega}}_\delta), \tag{B.49}$$

$$\phi_j|\mathbf{A}_i,\mathbf{A}_0,\mathbf{B}_i,\gamma,\beta,m_{1:T},f_{1:T},h_{1:T},y_{1:T}\sim IG(d_\phi\underline{\phi},d_\phi),\quad j=1,...,n, \tag{B.50}$$

$$\Phi_u|\mathbf{A}_i,\mathbf{A}_0,\mathbf{B}_i,\gamma,\beta,\delta,m_{1:T},f_{1:T},h_{1:T},y_{1:T}\sim IW(d_{\Phi_u}\underline{\boldsymbol{\Phi}}_u,d_{\Phi_u}). \tag{B.51}$$

The posterior $\bar{\mu}_A$ is drawn equation-by-equation through the triangularization method described in Section B.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 β are drawn following a GLS-based form depending on the mixture states drawn for the volatilities, as in Carriero et al. [2016a].

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 $\underline{\boldsymbol{\Omega}}_A$ is diagonal, with standard Minnesota shrinkage form, as in

$$\underline{\boldsymbol{\Omega}}_A=var[\underline{A}_k^{ij}]=\begin{cases}\left(\frac{\theta_1^2}{l^2}\right) & \text{if } i=j,\\ \left(\frac{\theta_1\theta_2}{l}\frac{\sigma_i}{\sigma_j}\right)^2, & \text{if } i=j,\\ (\theta_0\sigma_i)^2, & \text{if intercept or } g_t.\end{cases} \tag{B.52}$$

where l is the lag. The overall prior tightness θ_1 is set here as 0.05, the cross-shrinkage parameter θ_2 is set to 0.5 and the intercept shrinkage parameter θ_0 is set to 1,000. I follow Carriero et al. [2016a] by also setting a prior variance for the uncertainty factors $\ln m_t$ and $\ln f_t$ equal to the intercept. The variance parameters σ_i 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 B.1.

There is discussion in the literature on the impact of the prior on the components a_j of matrix $\mathbf{A}_0$. 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. [2016a] 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

Table B.1: Mean and variance priors

	Mean	Variance	Degree of freedom
a_j	0	10	-
$(\gamma_{i,0}, \gamma_{i,1})$	$(\ln \sigma_i^2, 0)$	$(2, 0.4^2)$	-
β_j, for $j = 2, ..., n_m$, and $j = n_{m+2}, ...n$	1	0.4^2	-
$\mathbf{D}_i$	0.8, for first own lag, 0 otherwise	0.2^2	-
δ	0	0.1^2	-
ϕ_j	0.03	-	10
$\mathbf{\Phi}_u$	$0.01 I_n$		10
$\ln m_0$ and $\ln f_0$	0	-	-
$\ln h_{i,0}$	$\ln \sigma_i^2$	2	-

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 B.33, where the coefficients δ are also part of $\mathbf{F}_1$ and $\mathbf{F}_2$. I follow strategy similar to Mumtaz and Theodoridis [2015] by imposing additional shrinkage to the variance of δ, which I set to $\left(\frac{\theta_1^2}{l^2}\right)$.

B.6 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 $v_t = \mathbf{A}_0^{-1} \mathbf{\Lambda}_t^{1/2} \epsilon_t$ 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, τ_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 ϵ_t. The generalized impulse response (GI) of a r set of randomly drawn $\omega^r_{j,t}$ is given by

$$GI^r(k, \tau_j, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}) = \mathbb{E}[y^r_{t+k}|\tau_j, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}] - \mathbb{E}[y^r_{t+k}|\omega_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}], \tag{B.53}$$

where k is the forecast point in time, $\mathbf{Z}_t$ is the information set containing all the known history up to time t defined as $\mathbf{Z}_t = (y_{t-p}, ..., y_t; g_{t-p}, .., g_t)$,[1] $\mathbf{\Pi}$ collects the coefficient matrices as $\mathbf{\Pi} = [\mathbf{A}_i, \mathbf{B}_i, \mathbf{D}_i, \beta_j, \gamma_j, \delta]$, $\mathbb{E}[y^r_{t+k}|\tau_j, \omega^r_{j,t}, \mathbf{Z}_t]$ is the shocked path of y_t and $\mathbb{E}[y^r_{t+k}|\omega^r_{j,t}, \mathbf{Z}_t]$ is the baseline path of the baseline path of y_t.

Repeat the procedure of equation B.53 R times, and take the averages over R of these paths. Koop et al. [1996] show that as $R \to \infty$, by the Law of Large Numbers these averages will converge the conditional expectations $\mathbb{E}[y_{t+k}|\tau_j, \mathbf{Z}_t, \mathbf{\Pi}]$ and $\mathbb{E}[y_{t+k}|\mathbf{Z}_t, \mathbf{\Pi}]$, and the generalized impulse response can be constructed as

$$GI(k, \tau_j, \mathbf{Z}_t, \mathbf{\Pi}) = \mathbb{E}[y_{t+k}|\tau_j, \mathbf{Z}_t, \mathbf{\Pi}] - \mathbb{E}[y_{t+k}|\mathbf{Z}_t, \mathbf{\Pi}]. \tag{B.54}$$

B.6.1 Generalized impulse responses for a news shock

For the news shock case, I start with the state-space procedure presented in equations B.33 and B.36 (Appendix B.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 ϵ_t. By construction, ϵ_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 ϵ_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 B.33 and B.36, respectively, as

$$\begin{bmatrix} y_t \\ y_{t-1} \\ ... \\ y_{t-p} \\ g_t \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{F}_1 & \mathbf{F}_2 & ... & \mathbf{F}_3 & \mathbf{F}_4 \\ \mathbf{I}_n & 0 & ... & 0 & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & ... & \mathbf{I}_n & 0 \\ \delta & -\delta & ... & 0 & \mathbf{D}_1 \end{bmatrix}}_{\mathbf{F}} \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ ... \\ y_{t-p-1} \\ g_{t-1} \end{bmatrix} + \begin{bmatrix} \mathbf{A}_0^{-1}\mathbf{\Lambda}_t^{1/2} & 0 & ... & 0 & \mathbf{B}_0 \\ 0 & 0 & 0 & 0 & 0 \\ ... & ... & ... & ... & ... \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \mathbf{I}_2 \end{bmatrix} \begin{bmatrix} \epsilon_t \\ 0 \\ ... \\ 0 \\ 0 \end{bmatrix}, \tag{B.55}$$

[1]Where $g_t = (\ln m_t; \ln f_t)$.

and

$$\ln h_{j,t} = \gamma_{j,0} + \gamma_{j,1} \ln h_{j,t-1}, \quad j = 1, ..., n. \tag{B.56}$$

Now that the model has only a single set of innovations ϵ_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 $\omega^r_{j,t}$ and K being the forecast period, construct by simulation a baseline path from $t+1$ to $t+K$ for the idiosyncratic innovations $\ln h^r_{j,t}$ using equation B.56, and for $y^r_{t,base}$, $g^r_{t,base}$[2] and $\mathbf{\Lambda}^r_{t,base}$ using equation B.55.

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

Take the same draw r from Step 1, and the idiosyncratic innovations $\ln h^r_{j,t}$. For $t+1$, construct a one standard deviation shock on utilization-adjusted TFP by adding to $\omega^r_{j,t+1}$ the shock τ^r_{TFP}, 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 $y^r_{TFP,t}$, $g^r_{TFP,t}$[3] and $\mathbf{\Lambda}^r_{TFP,t}$ using equation B.55.

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

Following equation B.53, 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

$$\begin{aligned} GI^r_{TFP,t}(k, \tau^r_{TFP}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}) = {} & \mathbb{E}[y^r_{t+k,TFP}, g^r_{t+k,TFP} | \tau^r_{TFP}, \mathbf{\Lambda}^r_{t+k,TFP}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}] \\ & - \mathbb{E}[y^r_{t+k,base}, g^r_{t+k,base} | \mathbf{\Lambda}^r_{t+k,base}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}]. \end{aligned} \tag{B.57}$$

Step 4: *Identify the news shock.*

Identify the news shock for the draw r as the orthogonalization on ϵ_t that maximizes the variance decomposition of utilization-adjusted TFP over a predefined K forecast period.[4] The idea of identifying the news shock for every r draw is in line with the

[2]Where $g_{t,base} = (\ln m_{t,base}; \ln f_{t,base})$.
[3]Where $g_{t,TFP} = (\ln m_{t,TFP}; \ln f_{t,TFP})$.
[4]For this paper, I follow Barsky and Sims [2011] and set $K = 40$ quarters ahead.

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 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 4.3.1, the news shock $\tau^r_{t,news}$ can be identified as

$$\tau^r_{t,news} = \arg\max \frac{\sum_{k=0}^{K} GI^r_{TFP,t}(k, \tau^r_{TFP}, \omega^r_{j,t}, \mathbf{Z}_t, , \mathbf{\Pi}, \tau) GI^r_{TFP,t}(k, \tau^r_{TFP}, \omega^r_{j,t}, \mathbf{Z}_t, , \mathbf{\Pi}, \tau)'}{\sum_{k=0}^{K} \mathbf{B}_1 A^{-1} \Lambda^{1/2}_{t+k,TFP} (A^{-1} \Lambda^{1/2}_{t+k,TFP})' \mathbf{B}_1'}, \tag{B.58}$$

subject to

$$\begin{aligned} & A^{-1}(1, j) = 0, \quad \forall j > 1, \\ & \tau(1,1) = 0, \\ & \tau'\tau = 1, \end{aligned} \tag{B.59}$$

where $\mathbf{B}_1$ is the line correspondent to the utilization-adjusted TFP coefficients in the state-space representation described in equation B.33 (Appendix B.4).

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

Take the same draw r from Step 1, and the idiosyncratic innovations $\ln h^r_{j,t}$. For $t+1$, construct a TFP news shock by adding the shock $\tau^r_{t,news}$ to $\omega^r_{j,t+1}$. Construct by simulation a news shocked path from $t+1$ to $t+K$ for $y^r_{t,news}$, $g^r_{t,news}$[5] and $\mathbf{\Lambda}^r_{t,news}$ using equation B.55.

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

Following equation B.53, 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

$$\begin{aligned} GI^r_{t,news}(k, \tau^r_{t,news}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}) = {} & \mathbb{E}[y^r_{t+k,news}, g^r_{t+k,news} | \tau^r_{t,news}, \mathbf{\Lambda}^r_{t+k,news}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}] \\ & - \mathbb{E}[y^r_{t+k,base}, g^r_{t+k,base} | \mathbf{\Lambda}^r_{t+k,base}, \omega_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}]. \end{aligned} \tag{B.60}$$

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

[5]Where $g_{t,news} = (\ln m_{t,news}; \ln f_{t,news})$.

news and baseline paths across all R draws of ω_{j,t^r} as

$$\begin{aligned}
\bar{y}_{t+k,news}(k,\tau_{t,news},\mathbf{Z}_t,\mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} y^r_{t+k,news}(\tau^r_{t,news},\mathbf{\Lambda}^r_{t+k,news},\omega^r_{j,t},\mathbf{Z}_t,\mathbf{\Pi}),\\
\bar{g}_{t+k,news}(k,\tau_{t,news},\mathbf{Z}_t,\mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} g^r_{t+k,news}(\tau^r_{t,news},\mathbf{\Lambda}^r_{t+k,news},\omega^r_{j,t},\mathbf{Z}_t,\mathbf{\Pi}),\\
\bar{y}_{t+k,base}(k,\mathbf{Z}_t,\mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} y^r_{t+k,base}(\mathbf{\Lambda}^r_{t+k,base},\omega^r_{j,t},\mathbf{Z}_t,\mathbf{\Pi}),\\
\bar{g}_{t+k,base}(k,\mathbf{Z}_t,\mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} g^r_{t+k,base}(\mathbf{\Lambda}^r_{t+k,base},\omega^r_{j,t},\mathbf{Z}_t,\mathbf{\Pi}).
\end{aligned} \tag{B.61}$$

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

$$\begin{aligned}
GI_{t,news}(k,\tau_{t,news},\mathbf{Z}_t,\mathbf{\Pi}) = {}&[\bar{y}_{t+k,news}(k,\tau_{t,news},\mathbf{Z}_t,\mathbf{\Pi}),\bar{g}_{t+k,news}(k,\tau_{t,news},\mathbf{Z}_t,\mathbf{\Pi})]\\
&-[\bar{y}_{t+k,base}(k,\mathbf{Z}_t,\mathbf{\Pi}),\bar{g}_{t+k,base}(k,\mathbf{Z}_t,\mathbf{\Pi})].
\end{aligned} \tag{B.62}$$

After testing different R sizes, I set $R = 1,000$ for this paper. Since changing from $R = 1,000$ to $R = 5,000$ did not present any noticeable difference, $R = 1,000$ is sufficiently large to achieve the difference between conditional expectations expressed in equation B.54.

B.6.2 Generalized impulse responses for uncertainty shocks

Here I describe the procedure for constructing the generalized impulse responses to macro and financial uncertainty shocks.

Step 1: *Construct a baseline path.*

Considering one draw r of the random innovations $\omega^r_{j,t}$ and K being the forecast period, construct by simulation a baseline path from $T+1$ to $T+K$ for the idiosyncratic innovations $\ln h^r_{j,t}$ using equation B.56, and for $y^r_{t,base}$, $g^r_{t,base}$ and $\mathbf{\Lambda}^r_{t,base}$ using equation B.55.

Step 2: *Construct a shocked path for each of the uncertainty shocks.*

Take the same draw r from Step 1, and the idiosyncratic innovations $\ln h^r_{j,t}$. Construct the macro and financial shocks through a lower triangular Cholesky decomposition as

$$\begin{aligned} \tau^r_{macro} &= chol(\mathbf{\Phi}_u, \text{`lower'}) * q_i^{macro}, \\ \tau^r_{fin} &= chol(\mathbf{\Phi}_u, \text{`lower'}) * q_i^{fin}, \end{aligned} \tag{B.63}$$

where q_i^{macro} is a 2×1 vector with 1 in the first position and zero in the second, and q_i^{fin} is a 2×1 vector with zero in the first position and 1 in the second. For $T+1$, construct a one standard deviation shock on macro uncertainty by substituting $(u_{m,t}, u_{f,t})'$ in equation B.33 for τ^r_{macro}. Construct by simulation a macro shocked path from $T+1$ to $T+K$ for $y^r_{t,macro}$, $g^r_{t,macro}$ and $\mathbf{\Lambda}^r_{t,macro}$ using equation B.33. Repeat the process for the financial uncertainty by using τ^r_{fin} to construct paths for $y^r_{t,fin}$, $g^r_{t,fin}$ and $\mathbf{\Lambda}^r_{t,fin}$.

Step 3: *Construct the impulse responses for the uncertainty shocks.*

Following equation B.53, construct the impulse responses for the macro and financial shocks as the differences between the shocked and the baseline paths for the draw r as

$$\begin{aligned} GI^r_{macro}(k, \tau^r_{macro}, \omega^r_{j,t}, \mathbf{Z}_T, \mathbf{\Pi}) &= \mathbb{E}[y^r_{T+k,macro}, g^r_{T+k,macro} | \tau^r_{macro}, \mathbf{\Lambda}^r_{T+k,macro}, \omega^r_{j,t}, \mathbf{Z}_T, \mathbf{\Pi}] \\ &\quad - \mathbb{E}[y^r_{T+k,base}, g^r_{T+k,base} | \mathbf{\Lambda}^r_{T+k,base}, \omega^r_{j,t}, \mathbf{Z}_T, \mathbf{\Pi}], \\ GI^r_{fin}(k, \tau^r_{fin}, \omega^r_{j,t}, \mathbf{Z}_T, \mathbf{\Pi}) &= \mathbb{E}[y^r_{T+k,fin}, g^r_{T+k,fin} | \tau^r_{fin}, \mathbf{\Lambda}^r_{T+k,fin}, \omega^r_{j,t}, \mathbf{Z}_T, \mathbf{\Pi}] \\ &\quad - \mathbb{E}[y^r_{T+k,base}, g^r_{T+k,base} | \mathbf{\Lambda}^r_{T+k,base}, \omega^r_{j,t}, \mathbf{Z}_T, \mathbf{\Pi}]. \end{aligned} \tag{B.64}$$

Step 4: *Construct the average impulse responses for the uncertainty shocks.*

Repeat Steps 1 to 3 for R number of times and form the averages of the shocked and baseline paths across all R draws of ω_{j,t^r} as

$$
\begin{aligned}
\bar{y}_{t+k,macro}(k, \tau_{t,macro}, \mathbf{Z}_t, \mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} y^r_{t+k,macro}(\tau^r_{t,macro}, \mathbf{\Lambda}^r_{t+k,macro}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}),\\
\bar{y}_{t+k,fin}(k, \tau_{t,fin}, \mathbf{Z}_t, \mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} y^r_{t+k,fin}(\tau^r_{t,fin}, \mathbf{\Lambda}^r_{t+k,fin}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}),\\
\bar{g}_{t+k,macro}(k, \tau_{t,macro}, \mathbf{Z}_t, \mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} g^r_{t+k,macro}(\tau^r_{t,macro}, \mathbf{\Lambda}^r_{t+k,macro}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}),\\
\bar{g}_{t+k,fin}(k, \tau_{t,fin}, \mathbf{Z}_t, \mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} g^r_{t+k,fin}(\tau^r_{t,fin}, \mathbf{\Lambda}^r_{t+k,fin}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}),\\
\bar{y}_{t+k,base}(k, \mathbf{Z}_t, \mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} y^r_{t+k,base}(\mathbf{\Lambda}^r_{t+k,base}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}),\\
\bar{g}_{t+k,base}(k, \mathbf{Z}_t, \mathbf{\Pi}) &= \frac{1}{R}\sum_{r=1}^{R} g^r_{t+k,base}(\mathbf{\Lambda}^r_{t+k,base}, \omega^r_{j,t}, \mathbf{Z}_t, \mathbf{\Pi}).
\end{aligned}
\tag{B.65}
$$

Lastly, construct the final generalized impulse responses for the macro and financial shocks as the differences between these averages, as in

$$
\begin{aligned}
GI_{t,macro}(k, \tau_{t,macro}, \mathbf{Z}_t, \mathbf{\Pi}) &= [\bar{y}_{t+k,macro}(k, \tau_{t,macro}, \mathbf{Z}_t, \mathbf{\Pi}), \bar{g}_{t+k,macro}(k, \tau_{t,macro}, \mathbf{Z}_t, \mathbf{\Pi})]\\
&\quad - [\bar{y}_{t+k,base}(k, \mathbf{Z}_t, \mathbf{\Pi}), \bar{g}_{t+k,base}(k, \mathbf{Z}_t, \mathbf{\Pi})],\\
GI_{t,fin}(k, \tau_{t,fin}, \mathbf{Z}_t, \mathbf{\Pi}) &= [\bar{y}_{t+k,fin}(k, \tau_{t,fin}, \mathbf{Z}_t, \mathbf{\Pi}), \bar{g}_{t+k,fin}(k, \tau_{t,fin}, \mathbf{Z}_t, \mathbf{\Pi})]\\
&\quad - [\bar{y}_{t+k,base}(k, \mathbf{Z}_t, \mathbf{\Pi}), \bar{g}_{t+k,base}(k, \mathbf{Z}_t, \mathbf{\Pi})].
\end{aligned}
\tag{B.66}
$$

As it is the case for the news shock, I set $R = 1,000$ for the uncertainty shocks, which is enough to achieve the difference between conditional expectations expressed in equation B.54.

B.7 Data description

Table B.2: Description of macroeconomic variables

	Name	Description	Source
1	Utilization-adjusted TFP	Utilization-adjusted TFP in log levels. Computed by Fernald [2014].	Fernald's website (Nov/2015)
2	Consumption	Real per capita consumption in log levels. Computed using PCE (nondurable goods + services), price deflator and population.	Fred
3	Output	Real per capita GDP in log levels. Computed using the real GDP (business, nonfarm) and population.	Fred
4	Investment	Real per capita investment in log levels. Computed using PCE durable goods + gross private domestic investment, price deflator and population.	Fred
5	Hours	Per capita hours in log levels. Computed with Total hours in nonfarm business sector and population values.	Fred
6	Prices	Price deflator, computed with the implicit price deflator for nonfarm business sector.	Fred
7	FFR	Fed funds rate.	Fred
8	Payroll	Total nonfarm payroll: All employees in log levels.	Fred
9	IP	Industrial production index in log levels.	Fred
10	Help to unemp.	Help wanted to unemployment ratio.	Fred
11	Pers. income	Real personal income in log levels.	Fred
12	M&T sales	Real manufacturing and trad sales in log levels.	Fred
13	Earnings	Average of hourly earnings (goods producing) in log levels.	Fred
14	PPI	Producer price index (finished goods) in log levels.	Fred

Note: All for the 1975Q1-2012Q3 period. Monthly series converted to quarterly by averaging over the quarter.

Table B.3: Description of financial variables

	Name	Description	Source
1	Spread	Difference between the 10-year Treasury rate and the FFR.	Fred
2	S&P500	S&P500 stock index in logs levels.	Fred
3	S&P dividend yield	S&P dividend yield, in log and annualized.	Fred
4	EBP	Excess bond premium as computed by Gilchrist and Zakrajšek [2012].	Gilchrist's website (Mar/2015)
5	Excess returns	CRSP excess returns, in log and annualized.	French's website (Jul/2016)
6	SMB	Small minus big risk factor, in log and annualized.	French's website (Jul/2016)
7	HML	High minus low risk factor, in log and annualized.	French's website (Jul/2016)
8	Momentum	Momentum, in log and annualized.	French's website (Jul/2016)
9	R15-R11	Small stock value spread, in log and annualized.	French's website (Jul/2016)
10	Ind. 1	Consumer industry sector-level return, in log and annualized.	French's website (Jul/2016)
11	Ind. 2	Manufacturing industry sector-level return, in log and annualized.	French's website (Jul/2016)
12	Ind. 3	High technology industry sector-level return, in log and annualized.	French's website (Jul/2016)
13	Ind. 4	Health industry sector-level return, in log and annualized.	French's website (Jul/2016)
14	Ind. 5	Other industries sector-level return, in log and annualized.	French's website (Jul/2016)

Note: All for the 1975Q1-2012Q3. Monthly series converted to quarterly by averaging over the quarter.

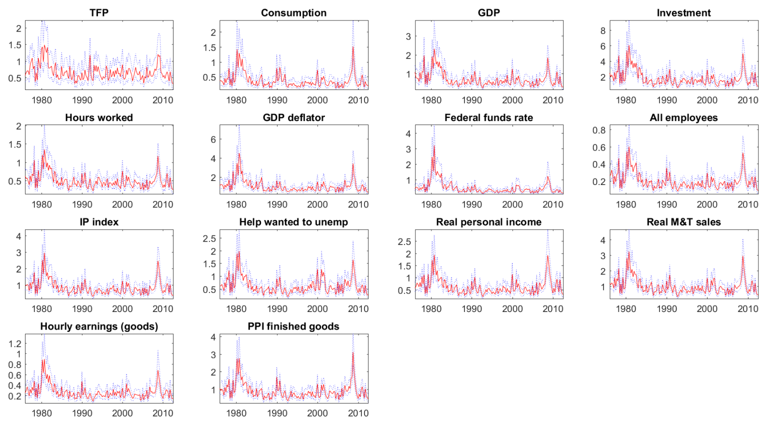
Table B.4: Macroeconomic and financial uncertainties

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

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

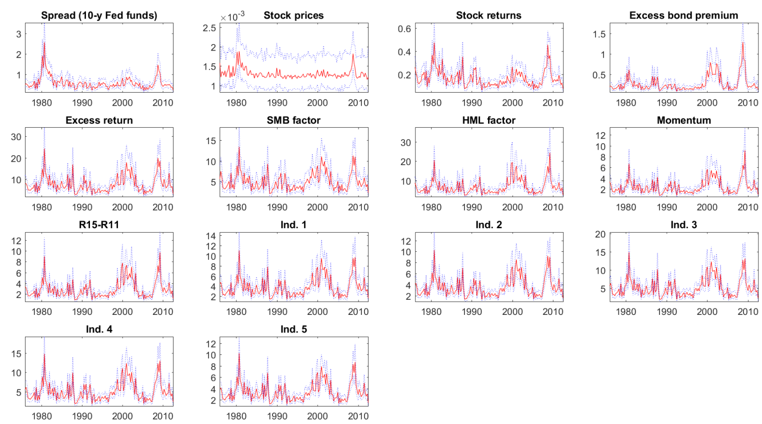
B.8 Volatilities

Figure B.8.1: 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 B.2.

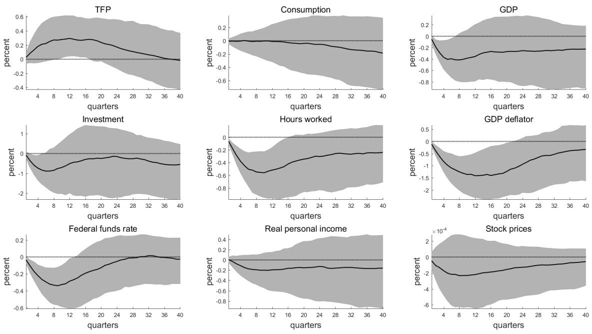
Figure B.8.2: Volatilities of financial variables



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 B.3.

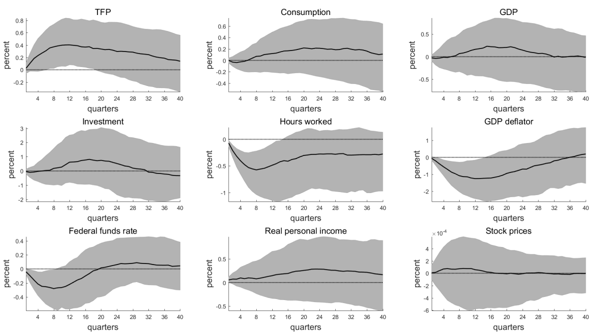
B.9 Alternative ordering of uncertainty shocks

Figure B.9.3: Impulse responses to a financial uncertainty shock with financial uncertainty ordered first



The uncertainty shocks with alternative ordering are identified through Cholesky decomposition with financial uncertainty ordered first, and macroeconomic uncertainty ordered last, as described in Section 4.3.3. The generalized impulse responses of the uncertainty shock are the average of 1,000 simulated random innovations, as described in Appendix B.6. The shaded areas define the 68% confidence bands computed with 200 posterior draws.

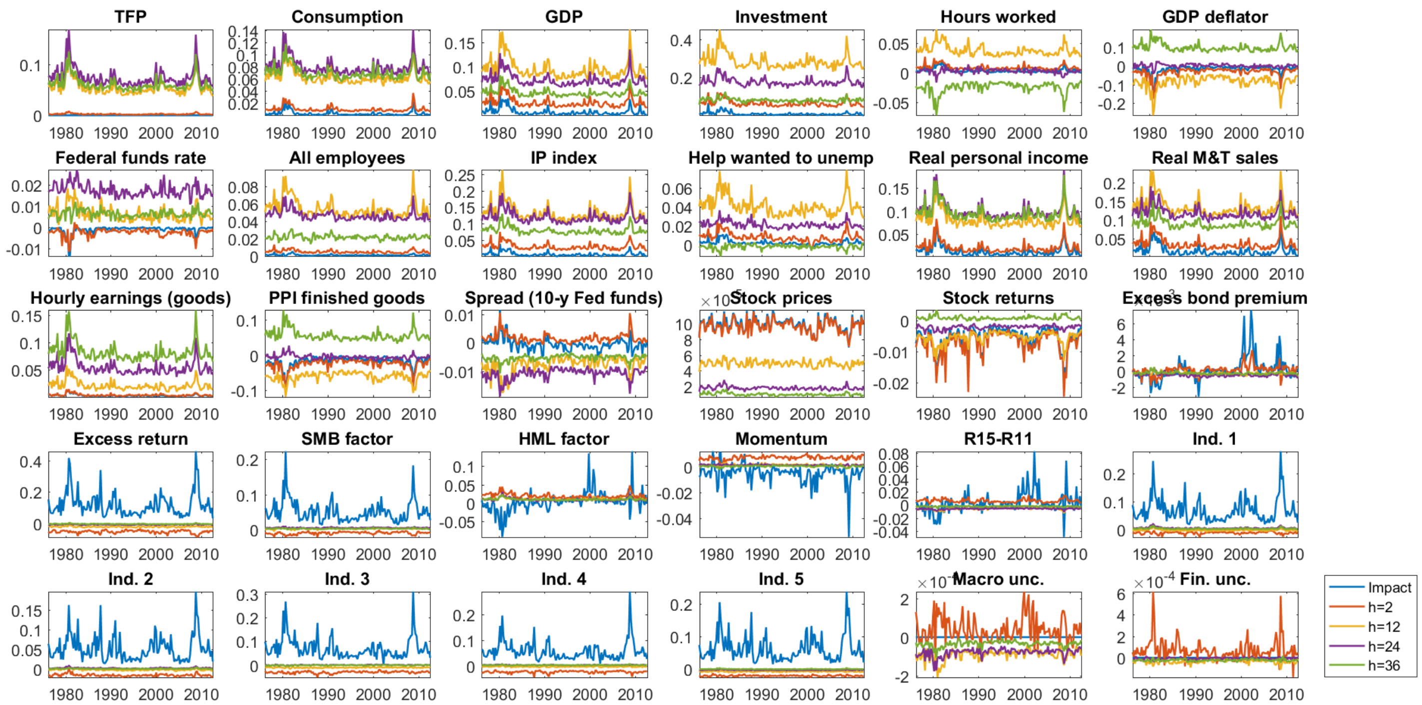
Figure B.9.4: Impulse responses to a macroeconomic uncertainty shock with financial uncertainty ordered first



Note: The uncertainty shocks with alternative ordering are identified through Cholesky decomposition with financial uncertainty ordered first, and macroeconomic uncertainty ordered last, as described in Section 4.3.3. The generalized impulse responses of the uncertainty shock are the average of 1,000 simulated random innovations, as described in Appendix B.6. The shaded areas define the 68% confidence bands computed with 200 posterior draws.

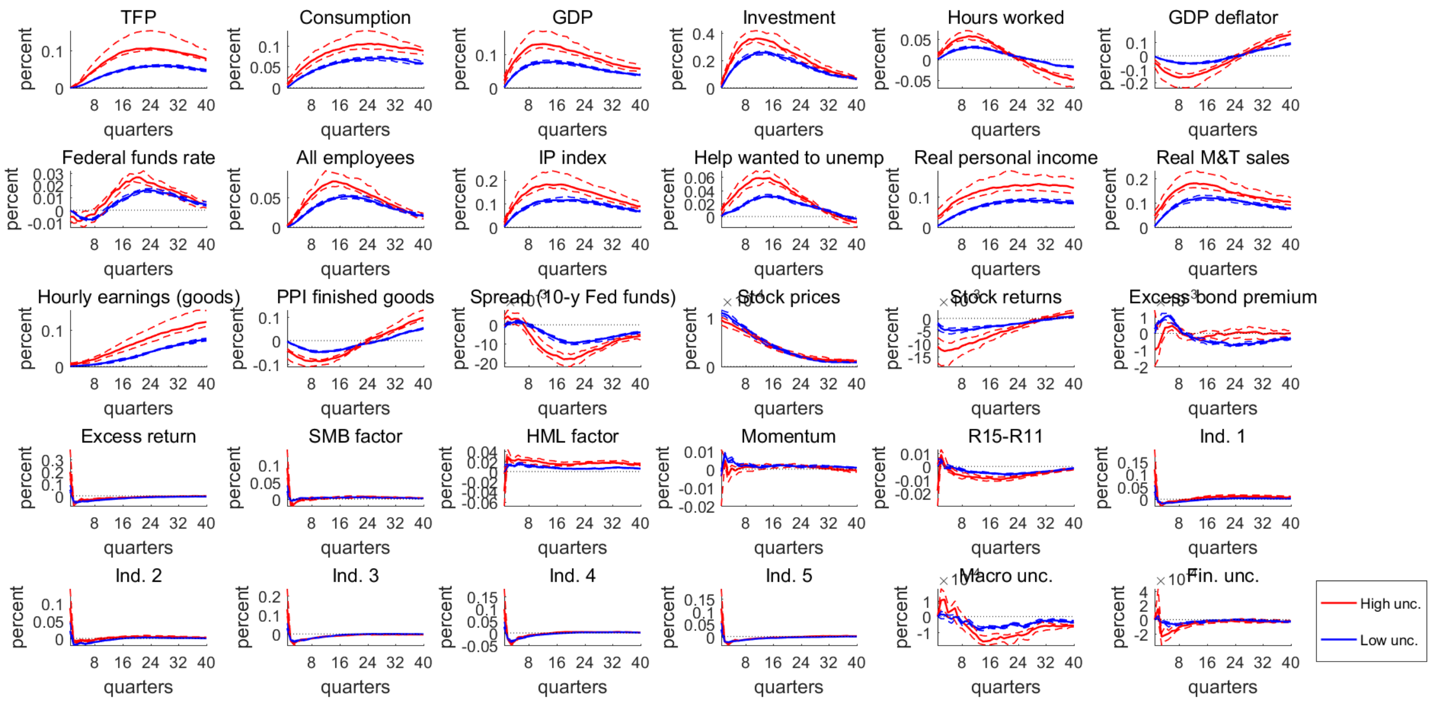
B.10 Full generalized impulse responses

Figure B.10.5: Time-varying effects of news shocks over different forecast horizons



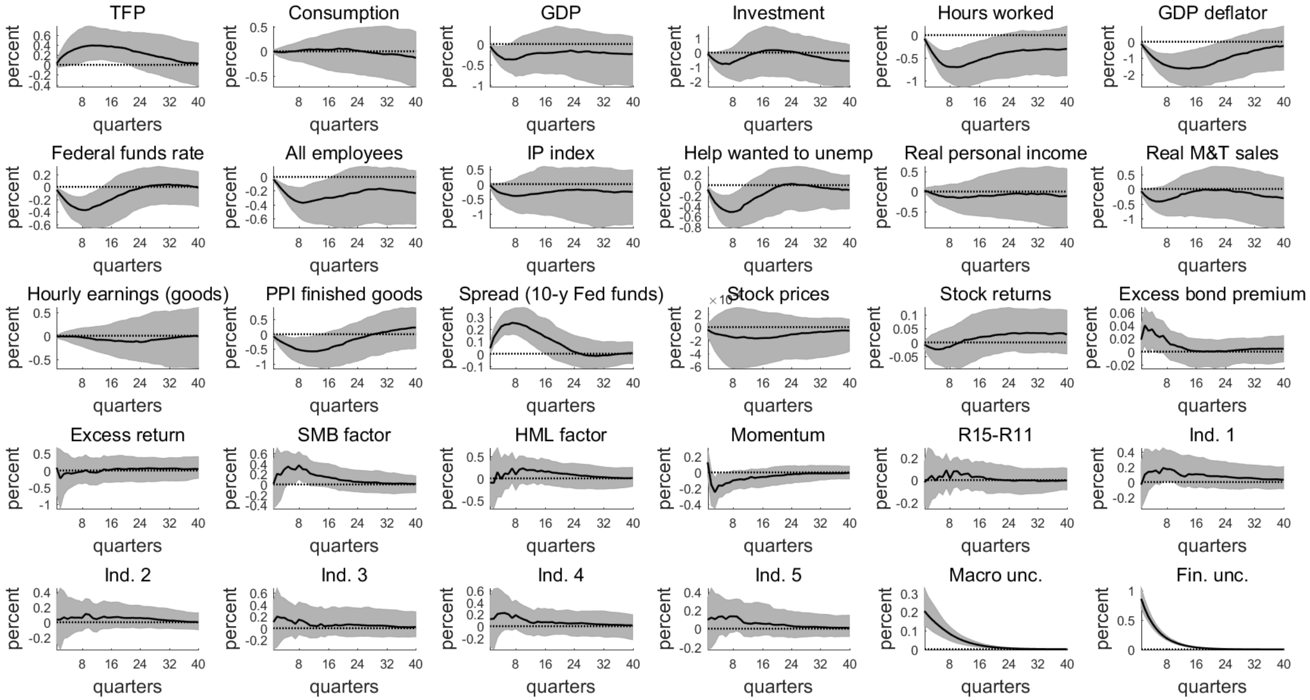
Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.1. The generalized impulse responses for each period are the average of 1,000 simulated random innovations, as described in Appendix B.6. Each line corresponds to the effect of the news shock h-quarters ahead from the point in time.

Figure B.10.6: Impulse responses to news shocks in periods of high and low macro uncertainty



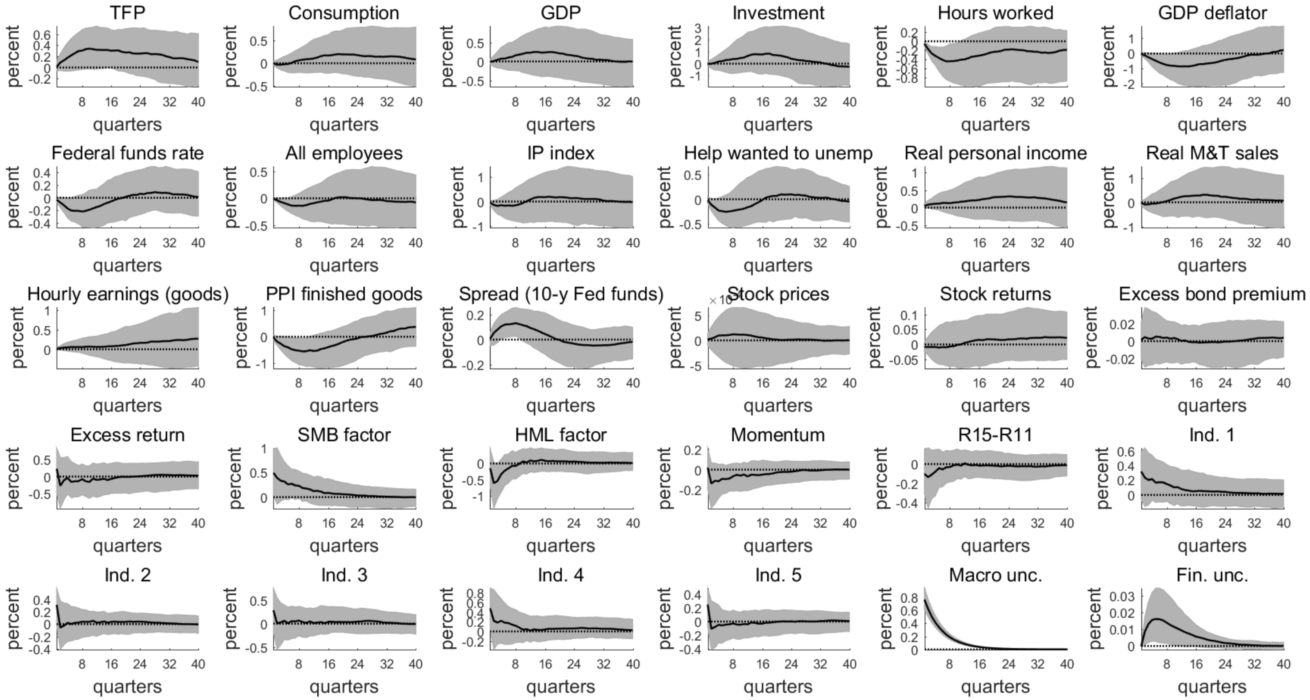
Note: The news shock is identified for each period in time under the procedure proposed in Section 4.3.1. Red and blue lines correspond to the average of generalized impulse responses on periods of high and low uncertainty, respectively. High and low uncertainty are the periods with the higher and lower 10% values for the macroeconomic uncertainty, respectively. Each impulse response is evaluated at the posterior mean. Dashed lines correspond to 68% distribution of the impulse responses in the high and low periods.

Figure B.10.7: Impulse responses to a financial uncertainty shock



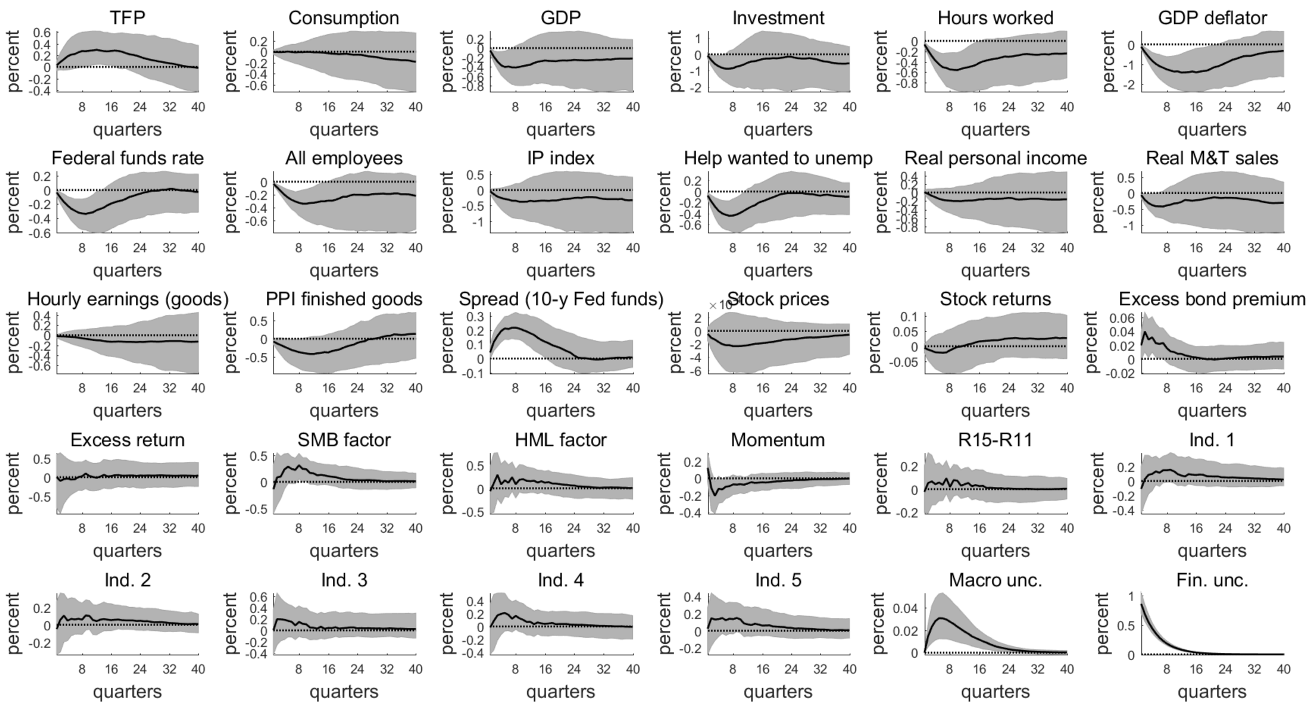
Note: The uncertainty shocks are identified through Cholesky decomposition with macroeconomic uncertainty ordered first, and financial uncertainty ordered last, as described in Section 4.3.3. The generalized impulse responses of the uncertainty shock are the average of 1,000 simulated random innovations, as described in Appendix B.6. The shaded areas define the 68% confidence bands computed with 200 posterior draws.

Figure B.10.8: Impulse responses to a macroeconomic uncertainty shock



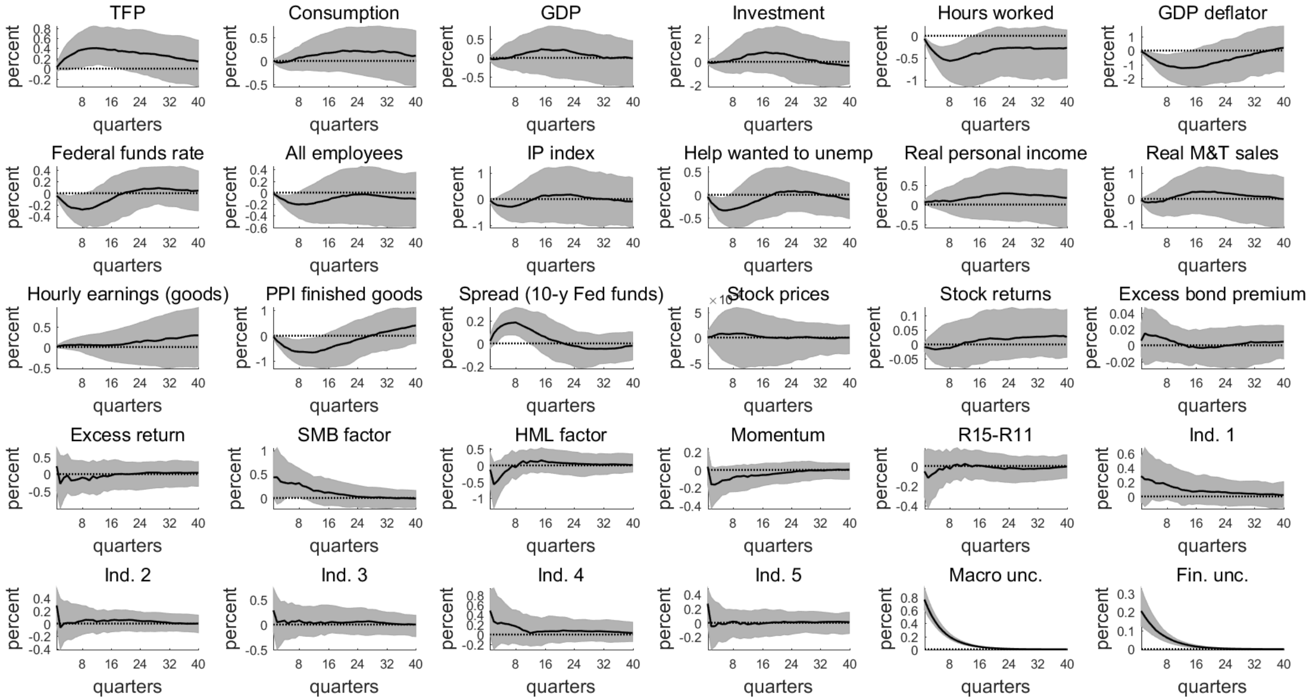
Note: The uncertainty shocks are identified through Cholesky decomposition with macroeconomic uncertainty ordered first, and financial uncertainty ordered last, as described in Section 4.3.3. The generalized impulse responses of the uncertainty shock are the average of 1,000 simulated random innovations, as described in Appendix B.6. The shaded areas define the 68% confidence bands computed with 200 posterior draws.

Figure B.10.9: Impulse responses to a financial uncertainty shock with financial uncertainty ordered first



The uncertainty shocks with alternative ordering are identified through Cholesky decomposition with financial uncertainty ordered first, and macroeconomic uncertainty ordered last, as described in Section 4.3.3. The generalized impulse responses of the uncertainty shock are the average of 1,000 simulated random innovations, as described in Appendix B.6. The shaded areas define the 68% confidence bands computed with 200 posterior draws.

Figure B.10.10: Impulse responses to a macroeconomic uncertainty shock with financial uncertainty ordered first



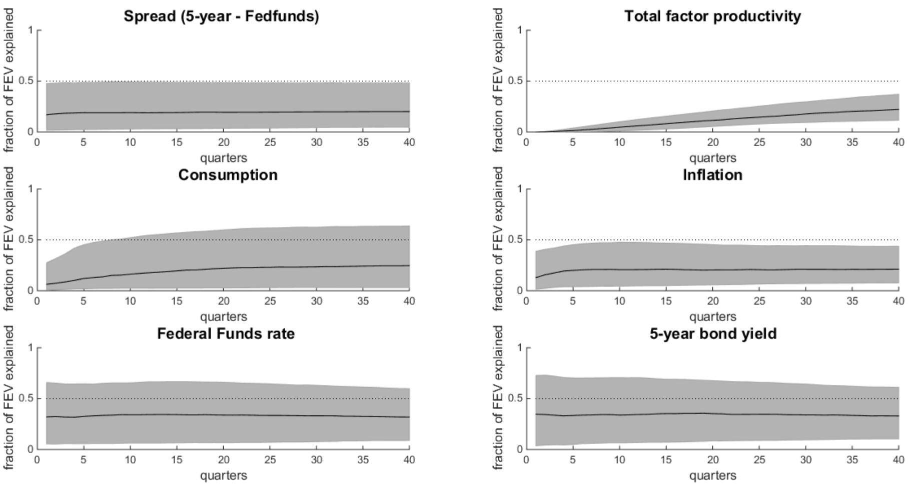
Note: The uncertainty shocks with alternative ordering are identified through Cholesky decomposition with financial uncertainty ordered first, and macroeconomic uncertainty ordered last, as described in Section 4.3.3. The generalized impulse responses of the uncertainty shock are the average of 1,000 simulated random innovations, as described in Appendix B.6. The shaded areas define the 68% confidence bands computed with 200 posterior draws.

Appendix C

Chapter 5

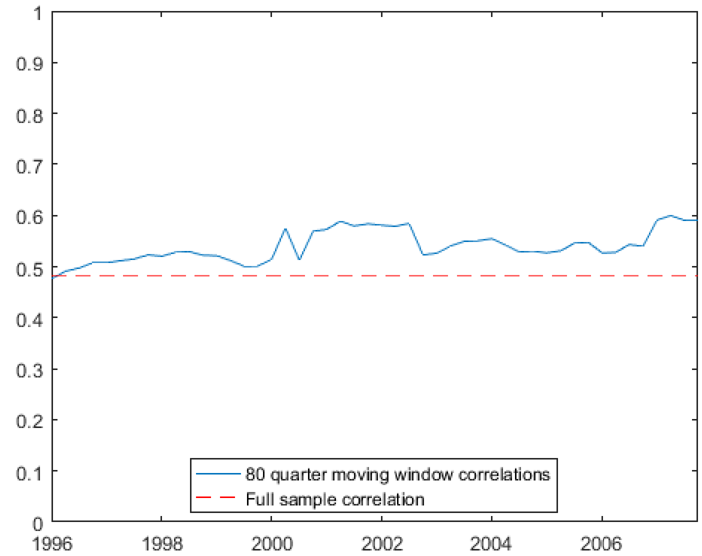
C.1 Figures

Figure C.1.1: Fraction of forecast error variance explained by a news shock with the new version of the utilization-adjusted TFP under the Kurmann and Otrok [2013] model



The grey area corresponds to the 16%-84% coverage bands of the model considering the new TFP series.

Figure C.1.2: Correlations between news and slope shocks on an 80 quarter moving window from an alternative VAR model augmented by financial variables and considering the old utilization-adjusted TFP series



Calculation of correlations between the recovered news and slope shocks over an 80 quarter moving window under the original identification of Kurmann and Otrok [2013]. Correlation over the full sample (from 1975:I to 2007:IV) is 0.48. The date in the horizontal axis corresponds to the final observation of the 80 quarter moving window.

Appendix D

Chapter 6

D.1 Barsky and Sims [2011] identification

Taking a vector of endogenous variables $\mathbf{y}_t$, assuming that the utilization-adjusted TFP is ordered first, the moving average representation (in levels) is written as

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \tag{D.1}$$

If there is a linear mapping of the innovations ($\mathbf{u}_t$) and the structural shocks ($\mathbf{s}_t$), this moving average representation can be rewritten as

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t \tag{D.2}$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \tag{D.3}$$

where $\mathbf{C}(\mathbf{L}) = \mathbf{B}(\mathbf{L})\mathbf{A}_0$, $\mathbf{s}_t = \mathbf{A}_0^{-1}\mathbf{u}_t$, and $\mathbf{A}_0$ is the impact matrix that makes $\mathbf{A}_0\mathbf{A}_0^{'} = \mathbf{\Sigma}$ (variance-covariance matrix of innovations). It is possible to rewrite $\mathbf{A}_0$ as $\tilde{\mathbf{A}}_0\mathbf{D}$, where $\tilde{\mathbf{A}}_0$ is the lower triangular Cholesky factor of the covariance matrix of reduced form innovations (or any other orthogonalization), and $\mathbf{D}$ is any $k \times k$ matrix that satisfies $\mathbf{D}\mathbf{D}^{'} = \mathbf{I}$.

Considering that $\Omega_{i,j}(h)$ is the share of the forecast error variance of variable i of the structural shock j at horizon h, it follows that

$$\Omega_{1,1}(h)_{surprise} + \Omega_{1,2}(h)_{news} = 1 \forall h, \tag{D.4}$$

where $i = 1$ refers to utilization-adjusted TFP, $j = 1$ is the surprise technological shock, and $j = 2$ is the news shock. The share of the forecast error variance of the news shock is defined as

$$\Omega_{1,2}(h)_{news} = \frac{\mathbf{e}_1^{'}\left(\sum_{\tau=0}^{h}\mathbf{B}_\tau\tilde{\mathbf{A}}_0\mathbf{D}\mathbf{e}_2\mathbf{e}_2^{'}\mathbf{D}^{'}\ \tilde{\mathbf{A}}_0^{'}\mathbf{B}_\tau^{'}\right)\mathbf{e}_1}{\mathbf{e}_1^{'}\left(\sum_{\tau=0}^{h}\mathbf{B}_\tau\mathbf{\Sigma}\mathbf{B}_\tau^{'}\right)\mathbf{e}_1} = \frac{\sum_{\tau=0}^{h}\mathbf{B}_{1,\tau}\tilde{\mathbf{A}}_0\ \gamma\gamma^{'}\tilde{\mathbf{A}}_0^{'}\mathbf{B}_{1,\tau}^{'}}{\sum_{\tau=0}^{h}\mathbf{B}_{1,\tau}\mathbf{\Sigma}\mathbf{B}_{1,\tau}^{'}}, \tag{D.5}$$

where $\mathbf{e}_1$ is a selection vector with 1 in the position $i = 1$ and zero elsewhere, $\mathbf{e}_2$ is a selection vector with 1 in the position $i = 2$ and zero elsewhere, and $\mathbf{B}_\tau$ is the matrix of moving average coefficients measured at each period until τ. The combination of selection vectors with the proper column of $\mathbf{D}$ can be written as γ, which is an orthonormal vector that makes $\tilde{\mathbf{A}}_0\gamma$ the impact of a news shock over the variables.

The news shock is identified by solving the optimization problem

$$\gamma_2^{news} = argmax \sum_{h=0}^{H} \Omega_{1,2}(h)_{news}, \tag{D.6}$$

s.t.

$$\tilde{A}_0(1,j) = 0, \forall j > 1 \tag{D.7}$$

$$\gamma_2(1,1) = 0 \tag{D.8}$$

$$\gamma_2' \gamma_2 = 1, \tag{D.9}$$

where H is an truncation period, and the restrictions impose that the news shock does not have an effect on impact ($t = 0$) and that the γ vector is orthonormal.

Based on the γ_2^{news} vector, the structural surprise technological shock ($s_t^{surprise}$) and the news shock (s_t^{news}) are

$$\begin{bmatrix} s_t^{surprise} \\ s_t^{news} \\ ... \end{bmatrix} = \tilde{\mathbf{A}}_0^{-1} \begin{bmatrix} \gamma_1^{surprise} & \gamma_2^{news} & ... \end{bmatrix}^{-1} \mathbf{u}_t', \tag{D.10}$$

assuming that

$$\gamma_1^{surprise} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ ... \end{bmatrix}. \tag{D.11}$$

To ensure a positive news shock, I check whether the response of stock prices is positive on impact. If the response is negative, all computed responses are multiplied by (-1).

D.2 Data description

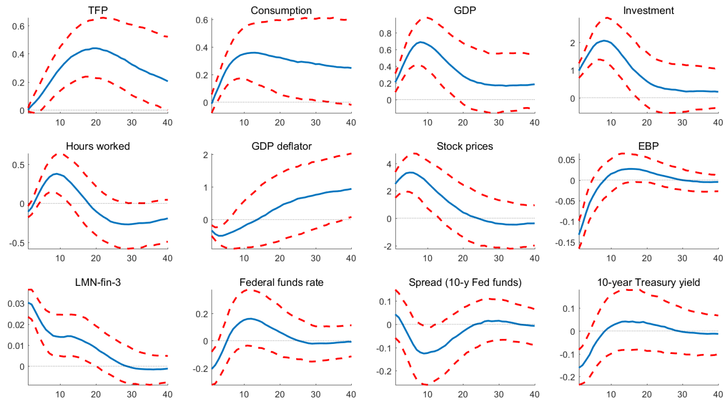
Table D.1: Description of variables

	Name	Description	Source
1	Utilization-adjusted TFP	Utilization-adjusted TFP in log levels. Computed by Fernald [2014].	Fernald's website (Nov/2015)
2	Consumption	Real per capita consumption in log levels. Computed using PCE (nondurable goods + services), price deflator and population.	Fred
3	Investment	Real per capita investment in log levels. Computed using PCE durable goods + gross private domestic investment, price deflator and population.	Fred
4	Output	Real per capita GDP in log levels. Computed using the real GDP (business, nonfarm) and population.	Fred
5	Hours	Per capita hours in log levels. Computed with Total hours in nonfarm business sector and population values.	Fred
6	Prices	Price deflator, computed with the implicit price deflator for nonfarm business sector.	Fred
7	SP500	SP500 stock index in logs levels.	Fred
8	EBP	Excess bond premium as computed by Gilchrist and Zakrajšek [2012].	Gilchrist's website (Mar/2015)
9	LMN-fin-3	Financial forecasting uncertainty three-months computed by Ludvigson et al. [2016].	Ludvigson's website (Feb/2016)
10	FFR	Fed funds rate.	Fred
11	Spread	Difference between the 10-year Treasury rate and the FFR.	Fred

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

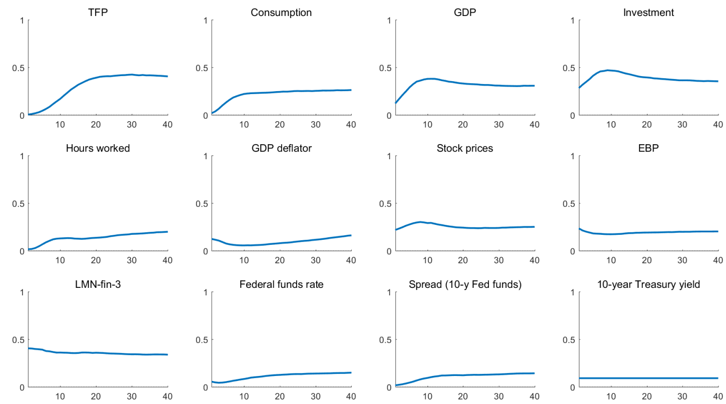
D.3 Additional figures

Figure D.3.1: Impulse responses to a news shock under an instrumental variable approach



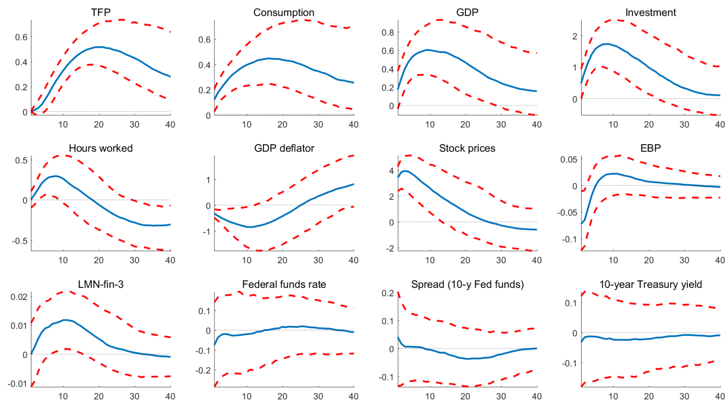
Note: Impulse responses of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975Q1 to 2012Q3. The dashed lines define the 68% confidence bands computed with 1,000 posterior draws. The VAR model includes all variables in Table D.1.

Figure D.3.2: Variance decomposition of news shock under an instrumental variable approach



Note: Variance decomposition of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975Q1 to 2012Q3. The dashed lines define the 68% confidence bands computed with 1,000 posterior draws. The VAR model includes all variables in Table D.1.

Figure D.3.3: Impulse responses to a news shock identified with the Barsky and Sims [2011] approach



Note: Impulse responses of a news shock computed by employing the identification procedure of maximizing the variance decomposition described in Appendix D.1, with quarterly data ranging from 1975Q1 to 2012Q3. The dashed lines define the 68% confidence bands computed with 1,000 posterior draws. The VAR model includes all variables in Table D.1.

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