

# News and Uncertainty Shocks

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## Abstract

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 increases over the medium term. This leads to an attenuation of the effects on economic activity from technology 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.

Keywords: forecasting error variance, structural VAR, news shocks, uncertainty shocks.

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# 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, Motto, and Rostagno (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, Elstner, and Sims (2013), Jurado, Ludvigson, and Ng (2015), and Baker, Bloom, and Davis (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, Fuentes-Albero, Gilchrist, and Zakrajšek, 2016). We find that news and uncertainty shocks are positively correlated for a specific group of uncertainty measures. This set of measures coincides with the financial uncertainty measures in Ludvigson, Ma, and Ng (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).

The correlation between news and financial uncertainty shocks implies that 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. This correlation also implies that 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, Clark, and Marcellino (2016) 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, Schaal, and Taschereau-Dumouchel, 2016).

We survey the structural VAR literature on news and uncertainty shocks in Section 2, where we also provide the details of our baseline model and analysis of the responses to news and uncertainty shocks. Section 3 describes the identification strategy used to disentangle all sources of business cycle variation and our measure ‘good uncertainty’. Section 3 also presents the empirical results obtained with this new strategy and discusses implications for the DSGE literature on understanding the effects of uncertainty.

## **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.

## 2.1 Literature Review and Identification

The baseline model has news and uncertainty shocks identified as described in the literature. The identification schemes are applied to a structural vector autoregressive model. Relevant forward-looking variables are included among the endogenous variables<sup>1</sup>. 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 1. Quarterly data from 1975Q1 to 2012Q3 is employed.

News shocks are identified as in Barsky and Sims (2011). This approach differs from that of Beaudry and Portier (2006), who apply long-run restrictions. The underlying assumption is that news shocks have a zero effect on utilization-adjusted productivity at the impact ( $t = 0$ ), but it is the shock that best explains the forecast error variance of productivity after a sufficiently long timeframe. This identification scheme, following Barsky and Sims (2011), is closely related to Francis, Owyang, Roush, and DiCecio (2014) and Uhlig (2005)’s maximum forecast error variance approach. As part of the identification procedure, an unexpected productivity shock is identified as the one that affects productivity at all horizons. Details of the identification scheme are described in Appendix A. 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 fundamentality is not an issue affecting these empirical results, as

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<sup>1</sup>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).

suggested by Forni, Gambetti, and Sala (2014).

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. (2016) 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 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.

Uncertainty shocks are normally identified via Cholesky, exploiting the order of the endogenous variables and assuming that uncertainty is ordered first (Jurado et al., 2015;

Baker et al., 2016). Following Caldara et al. (2016), uncertainty shocks are identified by maximizing the forecast error variance of uncertainty after two quarters, with no restrictions at the impact. This approach is not very different from the short-run restrictions implied by the Cholesky decomposition but 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.

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, as suggested by Bańbura, Giannone, and Reichlin (2010) and Carriero, Clark, and Marcellino (2015)<sup>2</sup>. Confidence bands for the impulse response graphs are computed using 1,000 draws from the posterior distribution<sup>3</sup>.

## 2.2 Responses to News Shocks

Figure 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 1.9

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<sup>2</sup>We obtain the overall prior tightness of 0.2 by maximizing the log-likelihood over a discrete grid, as in Carriero et al. (2015).

<sup>3</sup>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.

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, Cova, Pisani, and Rebucci (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, Tsoukalas, and Zanetti (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.

## 2.3 Responses to Uncertainty shocks

Table 1 describes a list of 11 uncertainty measures considered in the literature. We apply the uncertainty shock identification scheme described in section 2.1 by including one uncertainty measure at a time in a VAR model with the 10 variables described in the top panel of Table 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 1 are in the Online Appendix B, Figures B.1 to B.11. The main differences are between financial and macroeconomic uncertainty measures. As a consequence, Figure 2 presents the responses for our baseline financial uncertainty variable – realized volatility – and Figure 3 shows the responses when uncertainty is measured by Ludvigson et al. (2016) 3-month-ahead macroeconomic 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 activity variables. The responses to macroeconomic uncertainty shocks (Figure 3) are stronger and



more persistent than the responses to financial uncertainty (Figure 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 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 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 and 5 with the macroeconomic uncertainty effects in Figures 2 and 4.

The persistent positive effect of financial uncertainty shocks on technology might be seen as counterintuitive. Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2014) and Bloom (2014) note that uncertainty 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 6 provides the impulse responses of TFP to financial uncertainty shocks, and Figure 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 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.

## 2.4 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 1. We recover the news and uncertainty structural shocks for the 1975-2012 period using the identification schemes discussed in section 2.1. We then calculate the correlations between news and each measure of uncertainty shocks. These values are presented in Table 2 and include the results of a test of the null hypothesis that the correlation is equal to zero.

The main result from Table 2 is that there is a positive and significant correlation between news and financial uncertainty 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 reinforces our previous results that uncertainty shocks may have positive medium-run effects on productivity and economic activity measures. They may also imply that the positive effects of technology news 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 Disentangling Uncertainty and News 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, is also a source of business cycle fluctuation.

#### **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 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 2) and measures changes in Knightian uncertainty (Ilut and Schneider, 2014)<sup>4</sup>. 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 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 ‘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  $\gamma_2^{news}$  and those obtained for identification of the financial  $\gamma_3^{finunc}$  and ambiguity  $\gamma_4^{amb}$  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  $\gamma_2^{news}$  (and  $\gamma_1^{unexp}$ ). Then, the financial uncertainty identification vector  $\gamma_3^{finunc}$  is obtained by maximizing the variance decomposition of financial uncertainty up to horizon 2. The third step obtains  $\gamma_4^{amb}$  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

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<sup>4</sup>For an alternative measure of ambiguity obtained by exploiting the SPF, see Rossi, Sekhposyan, and Soupre (2016).

QR decomposition<sup>5</sup> over the four  $\gamma$  vectors such that we obtain  $\gamma_2^{news*}$ ,  $\gamma_3^{finunc*}$  and  $\gamma_4^{amb*}$  from the orthonormal, ‘Q part’ of the decomposition. As  $\gamma_2^{news*}$  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.

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<sup>5</sup>The QR decomposition is an application of the Gram-Schmidt orthonormalization procedure. In our 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 computed by subtracting its projection over the previous three vectors.

### 3.2 Responses to ‘truly’ news and uncertainty shocks

Figures 8, 9 and 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 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. 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 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.

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 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 Explaining Business Cycle Variation

Table 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 2.1, 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) and 40 quarters (10 years).

There are two main results from Table 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 on the computation in Table 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.

### **3.4 Robustness Check**

The results in section 2.4 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 using business uncertainty as a proxy for 'ambiguity'. The results presented in Table 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.

### **3.5 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, 2015), 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 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, Shaliastovich, and Yaron (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 and 4) is normally higher than that explained by financial uncertainty, in particular over long horizons. As a consequence, our results support Carriero et al. (2016) 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. (2016) .

## 4 Conclusion

Financial uncertainty and news shocks are correlated. 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 different 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 supports 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., 2016) as sources of business cycles.

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## A Appendix: 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

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

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

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t \quad (2)$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \quad (3)$$

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

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

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

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

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  $\tau$ . The combination of selection vectors with the proper column of  $\mathbf{D}$  can be written as  $\gamma$ , 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

$$\gamma_2^{news} = \underset{\gamma}{\operatorname{argmax}} \sum_{h=0}^H \Omega_{1,2}(h)_{news}, \quad (6)$$

s.t.

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

$$\gamma_2(1, 1) = 0 \quad (8)$$

$$\gamma_2' \gamma_2 = 1, \quad (9)$$

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  $\gamma$  vector is orthonormal.

Based on the  $\gamma_2^{news}$  vector, the structural unexpected TFP ( $s_t^{unexp}$ ) and the news shock ( $s_t^{news}$ ) are

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

assuming that

$$\gamma_1^{unexp} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \dots \end{bmatrix}. \quad (11)$$



Table 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
<b>Financial Uncertainty Measures</b>		
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 LMN-fin-1	Financial forecasting uncertainty computed by	Ludvigson's
4 LMN-fin-3	Ludvigson et al. (2016). -1 is one-month-ahead, -3 is	website
5 LMN-fin-12	three-months and -12 is one-year ahead.	(Feb/2016)
<b>Macroeconomic Uncertainty Measures</b>		
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 LMN-macro-1	Macro forecasting uncertainty computed by Ludvigson	Ludvigson's
5 LMN-macro-3	et al. (2016). -1 is one-month-ahead, -3 is three-months	website
6 LMN-macro-12	and -12 is one-year ahead.	(Feb/2016)

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

Table 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 1 + one measure of uncertainty at time, as indicated. For details on data and availability, see Table 1.*

Table 3 Variance Decomposition of Output, Consumption, Investment and Hours to News, Financial Uncertainty and Ambiguity Shocks

(a) Output

	News Shocks			Financial Uncertainty			Good Unc.	SPF Disagreement		
h	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

	News Shocks			Financial Uncertainty			Good Unc.	SPF Disagreement		
h	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	0.01	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

	News Shocks			Financial Uncertainty			Good Unc.	SPF Disagreement		
h	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

	News Shocks			Financial Uncertainty			Good Unc.	SPF Disagreement		
h	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 2.1, and the ‘truly news’ and ‘truly uncertainty’ schemes in section 3.1. In all cases, the VAR model includes all 10 variables in the first panel of Table 1 + realized volatility + SPF disagreement.*

Table 4 Variance Decomposition of Output, Consumption, Investment and Hours to News, Financial Uncertainty and Business Uncertainty Shocks

(a) Output

	News Shocks			Financial Uncertainty			Good Unc.	Business Uncertainty		
h	Base- line	Truly News	Truly Unc.	Base- line	Truly News	Truly Unc.		Base- line	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

	News Shocks			Financial Uncertainty			Good Unc.	Business Uncertainty		
h	Base- line	Truly News	Truly Unc.	Base- line	Truly News	Truly Unc.		Base- line	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

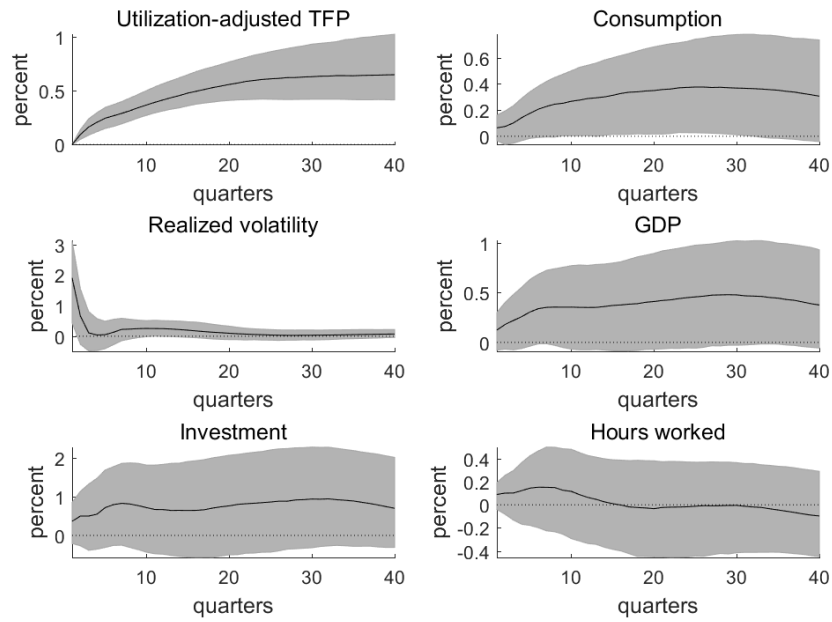
	News Shocks			Financial Uncertainty			Good Unc.	Business Uncertainty		
h	Base- line	Truly News	Truly Unc.	Base- line	Truly News	Truly Unc.		Base- line	Truly News	Truly Unc.
0	9.8	17.7	9.8	2.1	2.1	9.3	7.2	4.1	3.5	4.1
8	9.2	22.6	9.2	7.5	7.5	19.0	11.5	29.2	26.8	28.6
16	7.2	16.6	7.2	4.1	4.1	11.6	7.5	42.6	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

	News Shocks			Financial Uncertainty			Good Unc.	Business Uncertainty		
h	Base- line	Truly News	Truly Unc.	Base- line	Truly News	Truly Unc.		Base- line	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

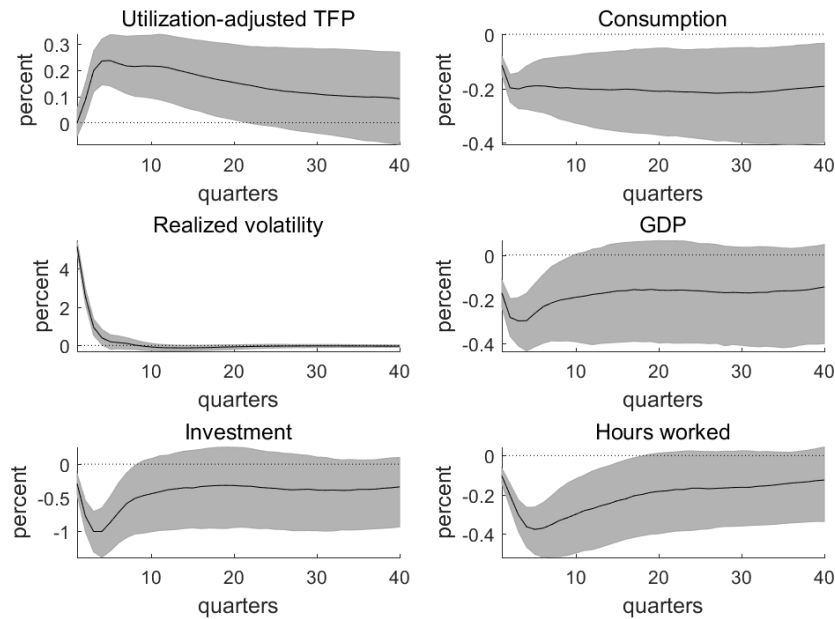
*Note: See notes to Table 3. The VAR model includes all 10 variables in the first panel of Table 1 + realized volatility + business uncertainty.*

Figure 1 Responses to news shocks in the baseline VAR model



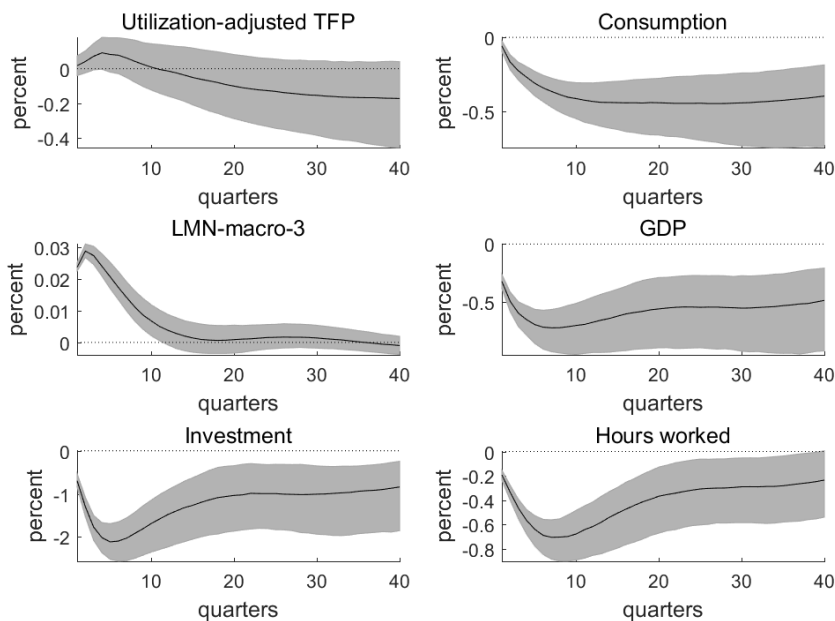
*Note:* Shaded areas are 68% confidence bands computed with 1,000 posterior draws. The baseline identification scheme for news shocks is described in section 2.1, and appendix A. The VAR model includes all variables in the first panel of Table 1 + realized volatility.

Figure 2 Responses to financial uncertainty (realized volatility) shocks in the baseline VAR model



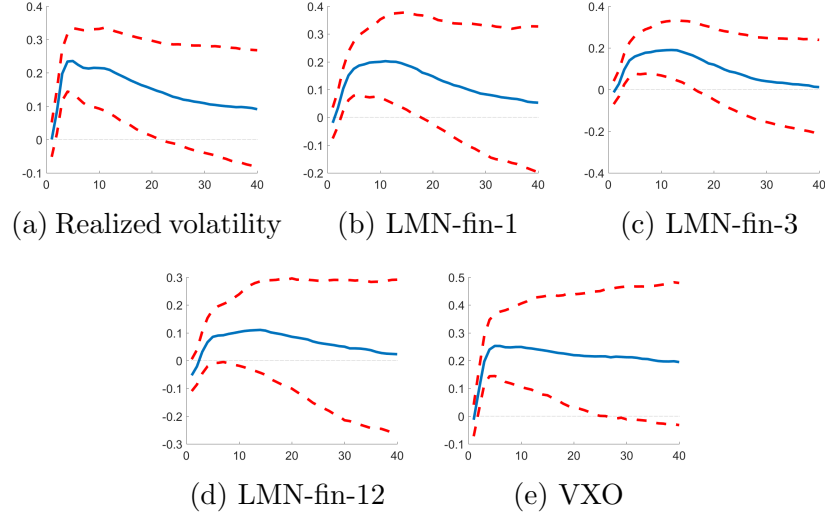
*Note: Shaded areas are 68% confidence bands computed with 1,000 posterior draws. The baseline identification scheme for uncertainty shocks is described in section 2.1. The VAR model includes all variables in the first panel of Table 1 + realized volatility.*

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



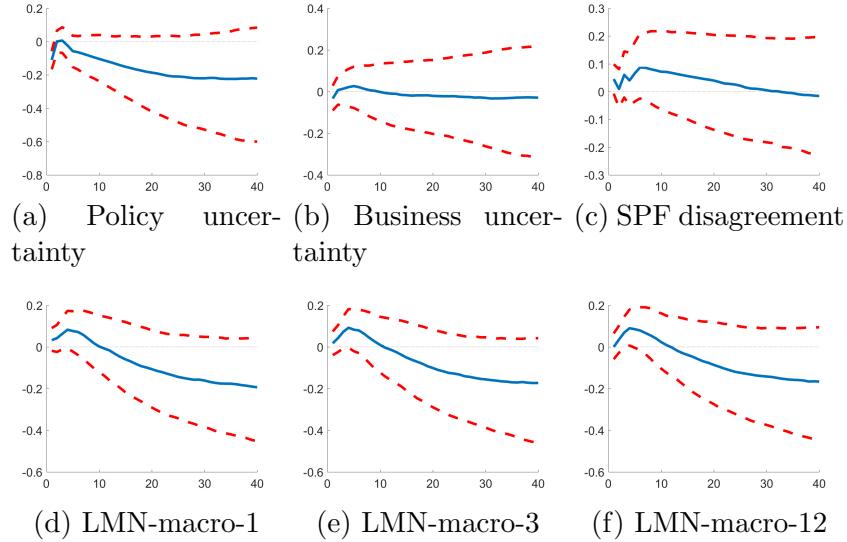
*Note: See notes to Figure 2. The VAR model includes all variables in the first panel of Table 1 + macroeconomic uncertainty (LMN-macro-3).*

Figure 4 Responses of utilization-adjusted TFP to different measures of financial uncertainty shocks in the baseline model



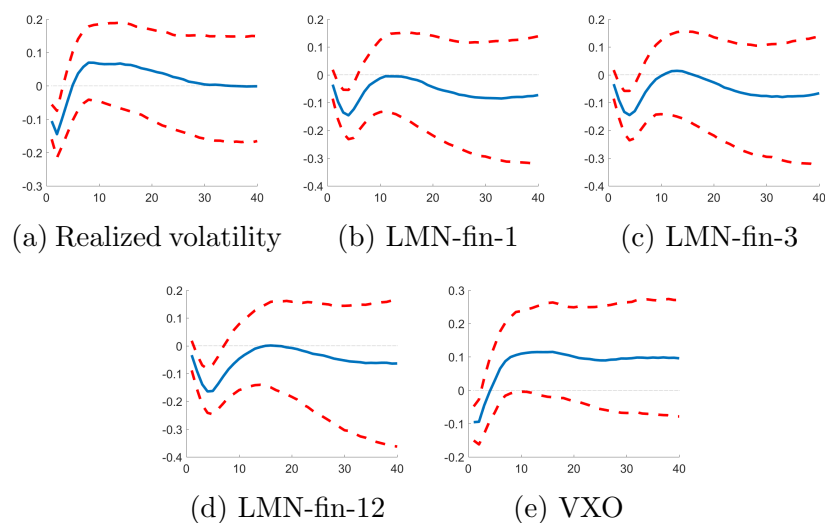
*Note:* See Table 1 for description of uncertainty measures. Dotted lines are 68% confidence bands computed with 1,000 posterior draws. These responses are computed for one financial uncertainty variable at a time in a VAR that also includes the 10 variables in the top panel of Table 1. Identification scheme as described in section 2.1.

Figure 5 Responses of utilization-adjusted TFP to different measures of macroeconomic uncertainty shocks in the baseline model



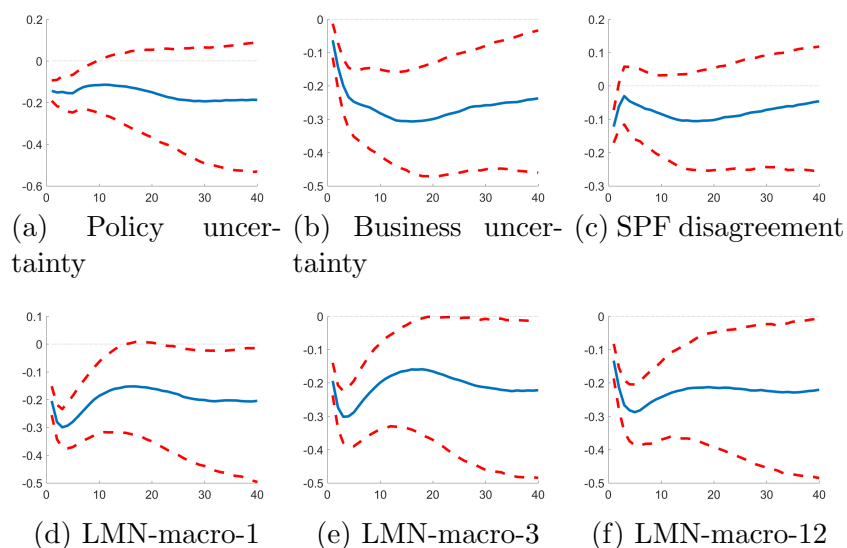
*Note:* See notes to Figure 4. These responses are computed for one macroeconomic uncertainty variable at a time in a VAR that also includes the 10 variables in the top panel of Table 1. Identification scheme as described in section 2.1.

Figure 6 Responses of non-adjusted TFP to different measures of financial uncertainty shocks in the baseline model



*Note: See notes to Figure 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 1. The difference between these results and Figure 4 is that here TFP is not adjusted for utilization. Identification scheme as described in section 2.1.*

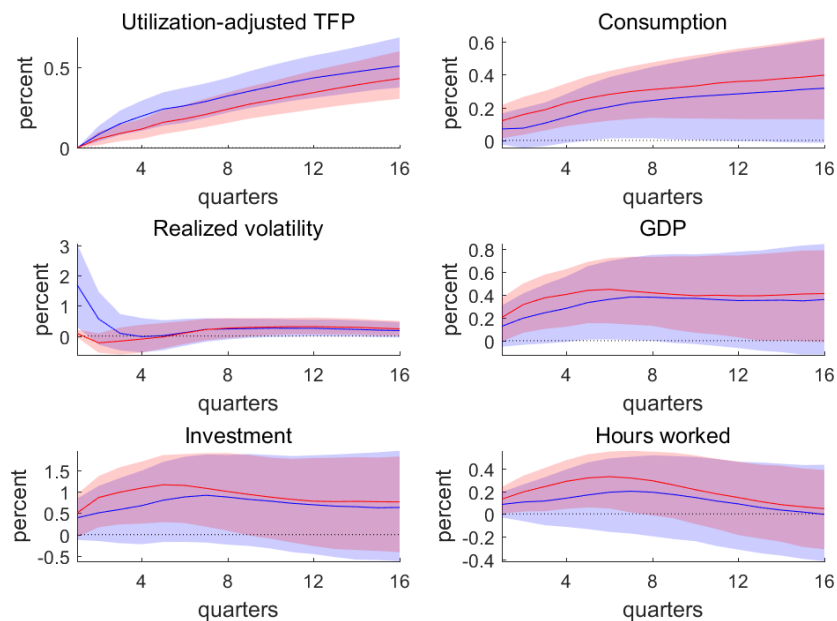
Figure 7 Responses of non-adjusted TFP to different measures of macroeconomic uncertainty shocks in the baseline model



*Note: See notes to Figure 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 1. The difference between these results and Figure 5 is that here TFP is not adjusted for utilization. Identification scheme as described in section 2.1.*

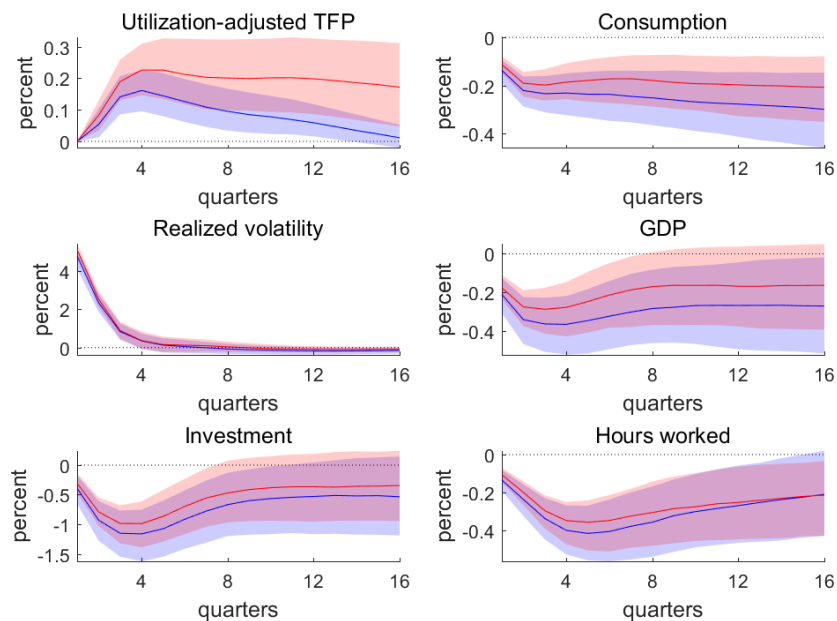


Figure 8 Responses to news shocks with the ‘truly news’ (red lines) and the ‘truly uncertainty’ (blue lines) identification schemes



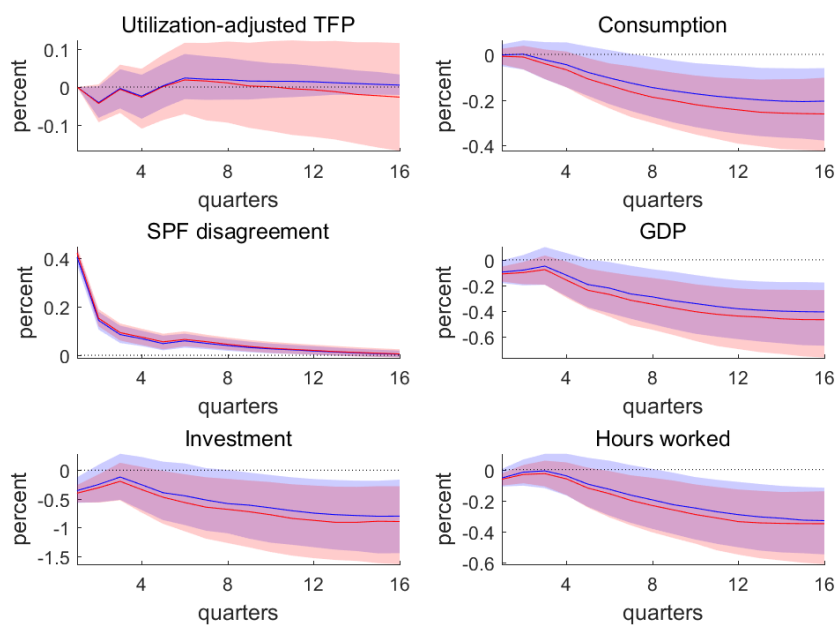
*Note: Shaded areas are 68% confidence bands computed with 1,000 posterior draws. The ‘truly news’ and ‘truly uncertainty’ identification schemes are described in section 3.1. The VAR model includes all 10 variables in the first panel of Table 1 + realized volatility + business uncertainty.*

Figure 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 8.*

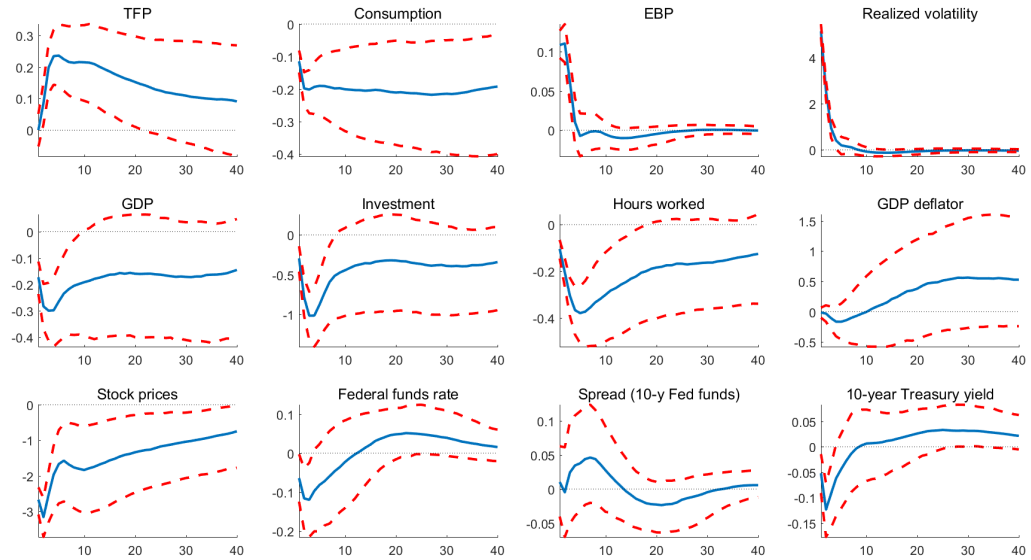
Figure 10 Responses to ambiguity shocks with the ‘truly news’ (red lines) and the ‘truly uncertainty’ (blue lines) identification schemes



*Note: See notes to Figure 8.*

## B For Online Publication – Appendix: Figures

Figure B.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 2.1. The VAR model includes all variables in the first panel of Table 1 + realized volatility.*

Figure B.2 Responses to financial uncertainty (LMN-fin-1) shocks in the baseline VAR model

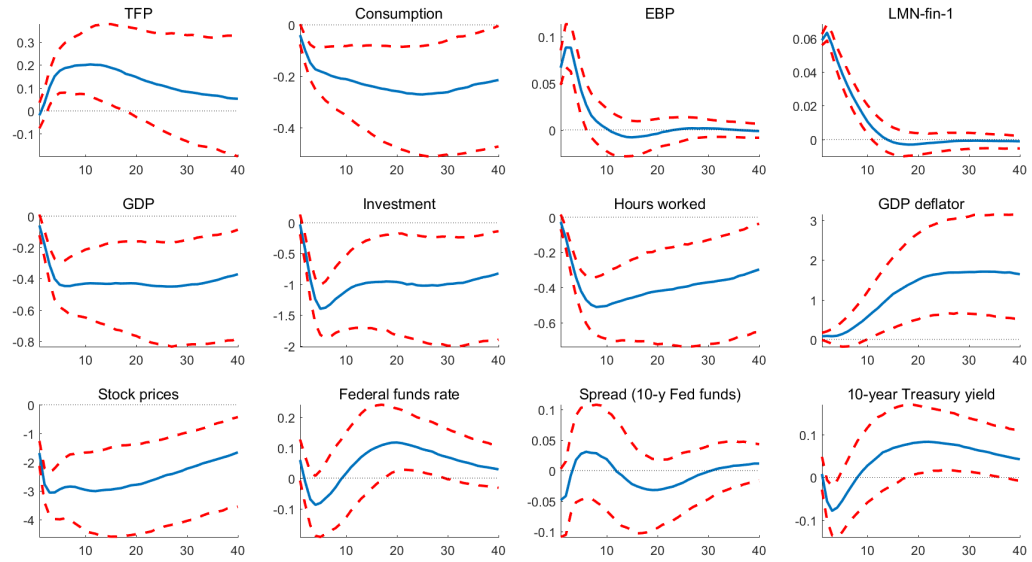
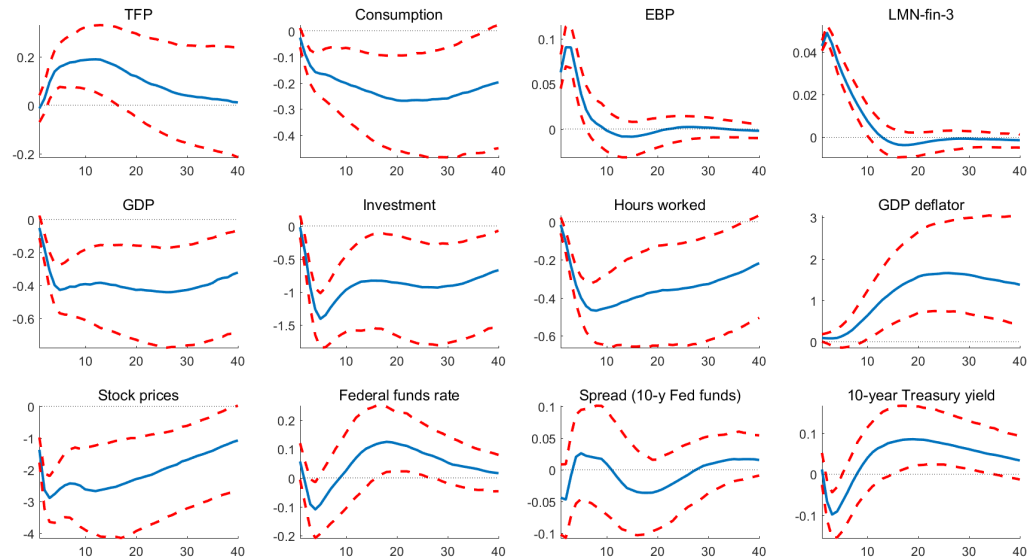


Figure B.3 Responses to financial uncertainty (LMN-fin-3) shocks in the baseline VAR model



*Note: See note to Figure B.1. The VAR model includes all variables in the first panel of Table 1 + LMN-fin-1 (Figure B.2) or LMN-fin-3 (Figure B.3).*

Figure B.4 Responses to financial uncertainty (LMN-fin-12) shocks in the baseline VAR model

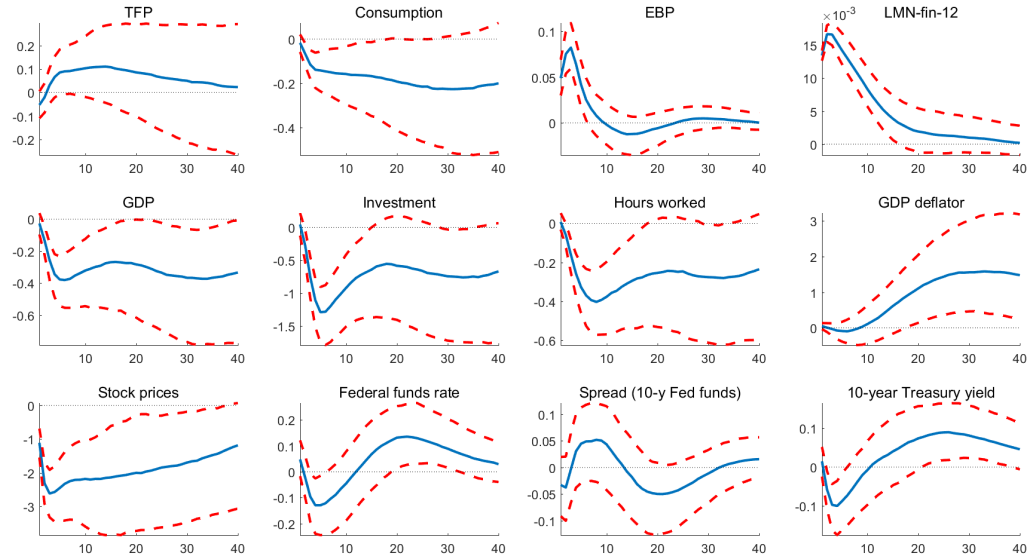
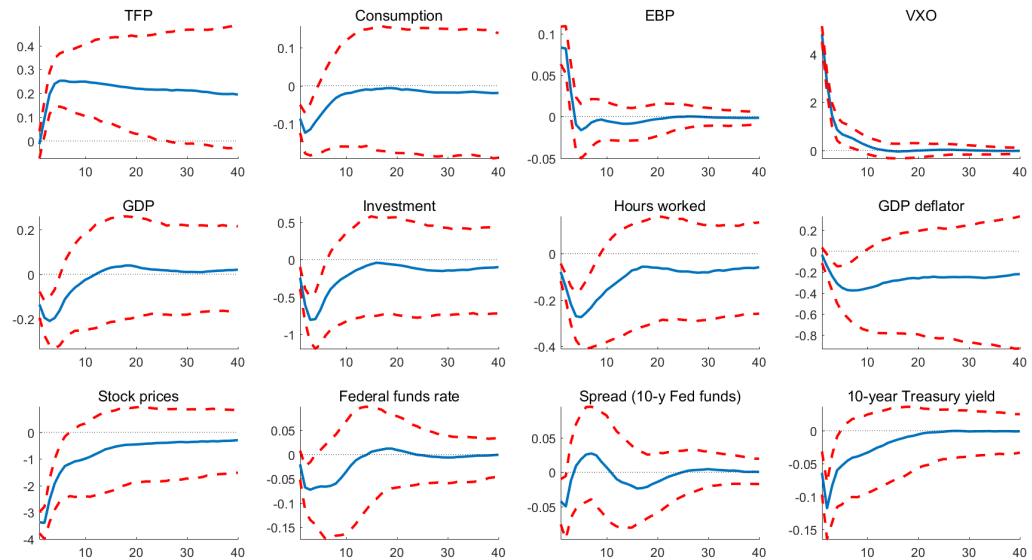


Figure B.5 Responses to financial uncertainty (VXO) shocks in the baseline VAR model



*Note: See note to Figure B.1. The VAR model includes all variables in the first panel of Table 1 + LMN-fin-12 (Figure B.4) or VXO (Figure B.5).*

Figure B.6 Responses to macroeconomic uncertainty (Policy uncertainty) shocks in the baseline VAR model

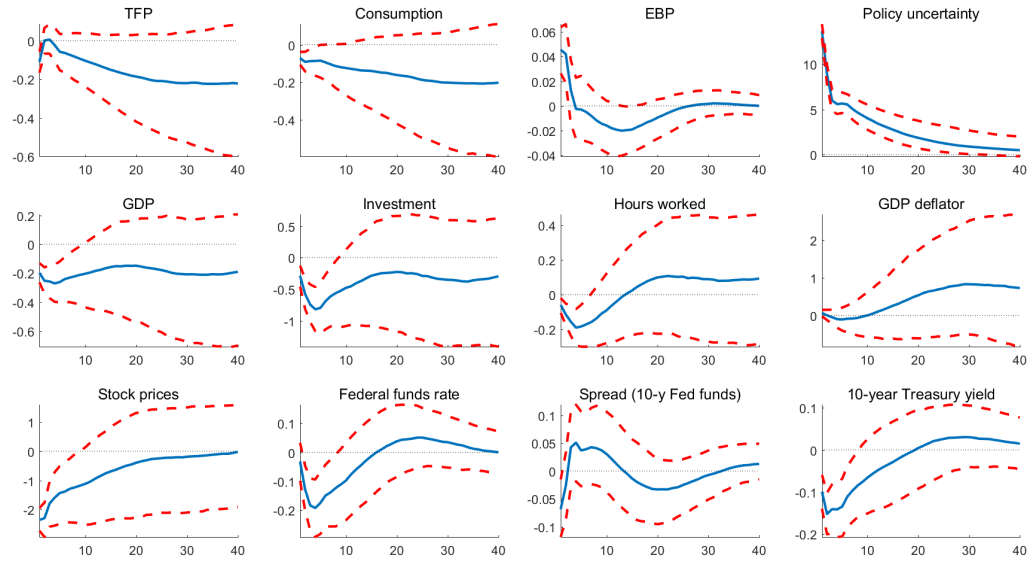
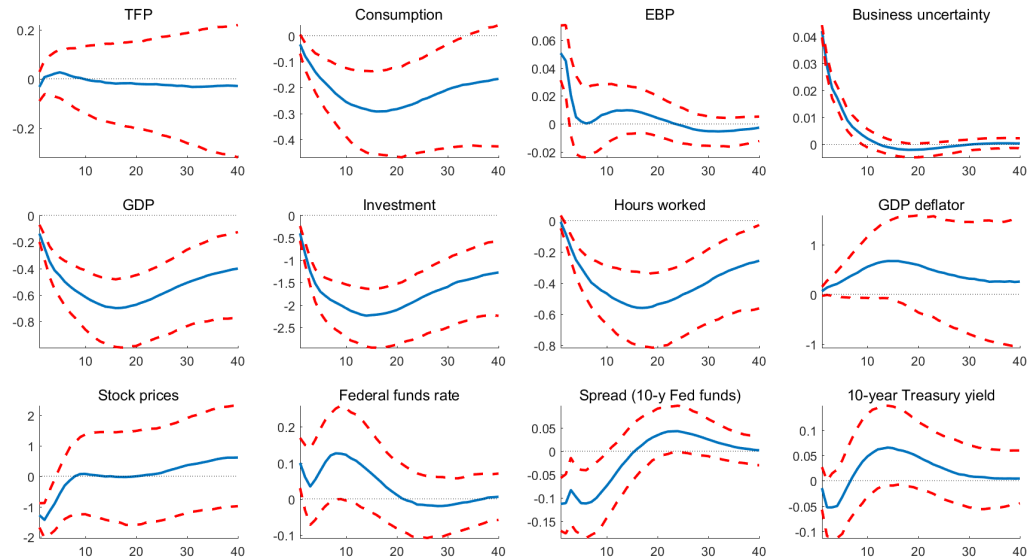


Figure B.7 Responses to macroeconomic uncertainty (Business uncertainty) shocks in the baseline VAR model



*Note: See note to Figure B.1. The VAR model includes all variables in the first panel of Table 1 + Policy uncertainty (Figure B.6) or Business uncertainty (Figure B.7).*

Figure B.8 Responses to macroeconomic uncertainty (SPF disagreement) shocks in the baseline VAR model

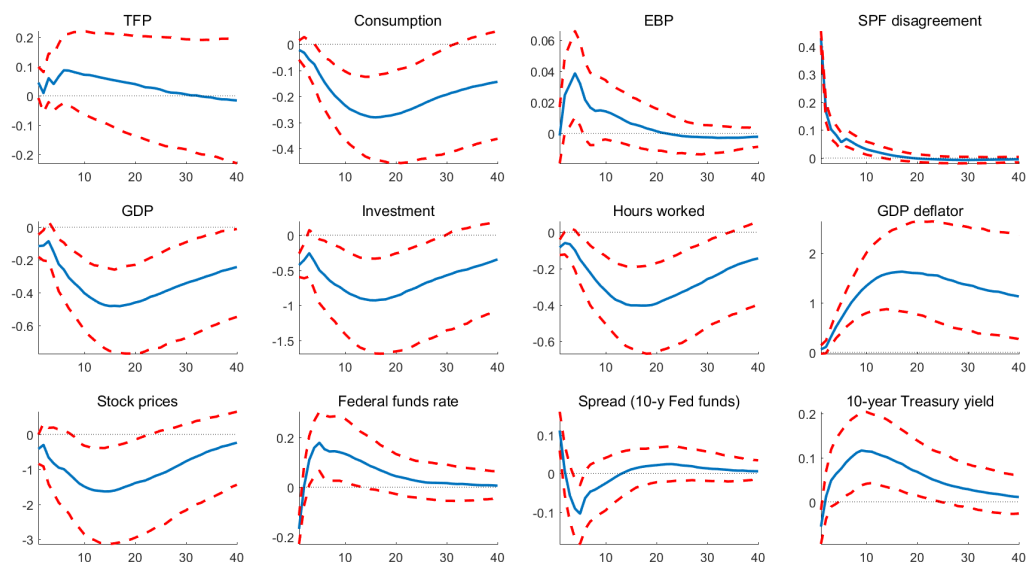
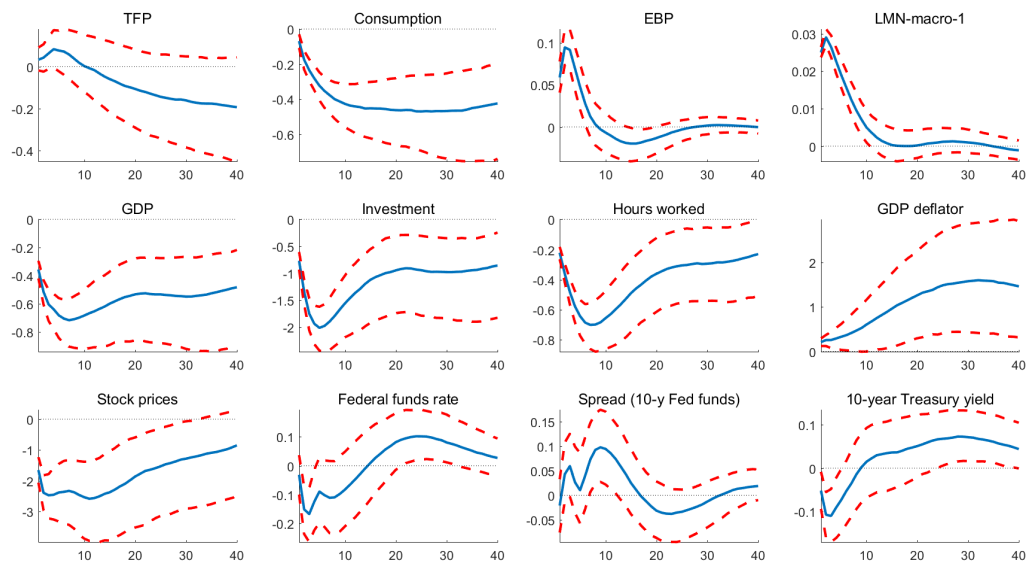


Figure B.9 Responses to macroeconomic uncertainty (LMN-macro-1) shocks in the baseline VAR model



*Note: See note to Figure B.1. The VAR model includes all variables in the first panel of Table 1 + SPF disagreement (Figure B.8) or LMN-macro-1 (Figure B.9).*

Figure B.10 Responses to macroeconomic uncertainty (LMN-macro-3) shocks in the baseline VAR model

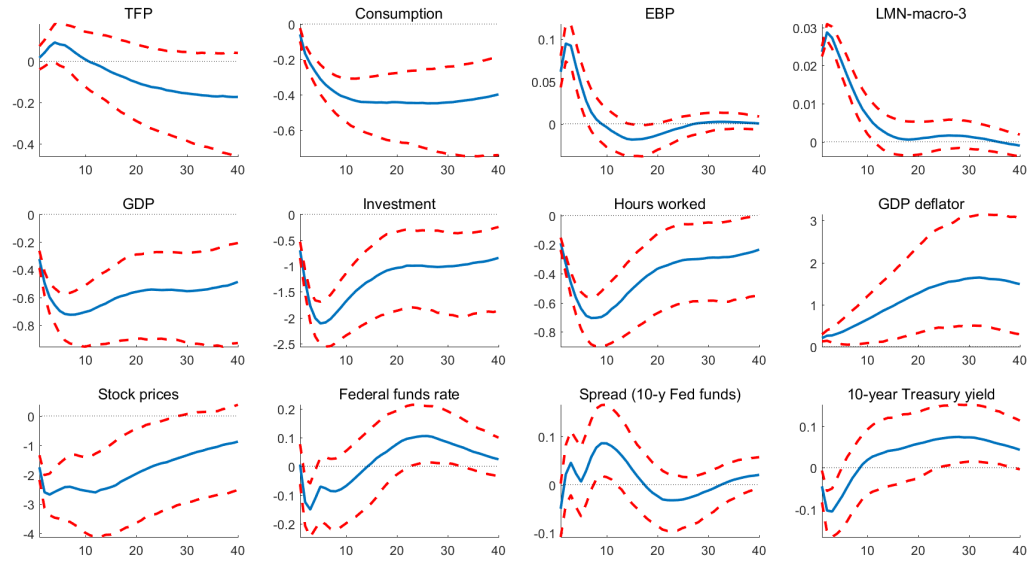
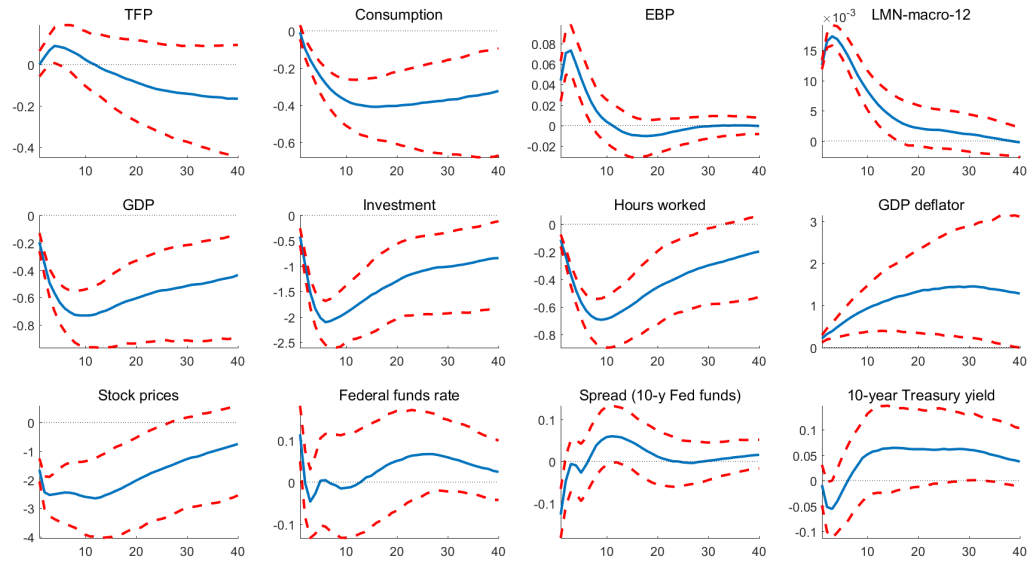


Figure B.11 Responses to macroeconomic uncertainty (LMN-macro-12) shocks in the baseline VAR model



*Note: See note to Figure B.1. The VAR model includes all variables in the first panel of Table 1 + LMN-macro-3 (Figure B.10) or LMN-macro-12 (Figure B.11).*