

Forecast revisions as instruments for news shocks

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Abstract

In this paper 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 technological 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 a news shock produces 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.

Keywords: news shock, proxy SVAR, instrumental variable, expectation.

JEL codes: E32, E44.

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1 Introduction

The literature on technological news shocks argues that the macroeconomy reacts 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, L’Huillier, and Lorenzoni, 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

¹See, for example, Beaudry and Portier (2006) and Barsky and Sims (2011).

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

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

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

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 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 (Piffer and Podstawski, 2017) and oil supply shocks (Montiel Olea, Stock, and Watson, 2016). With respect to news shocks, extraneous data has been applied to news about future fiscal spending (Auerbach and Gorodnichenko, 2012) and for news about future oil supply (Arezki, Ramey, and Sheng, 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

⁵See, for example, Barsky and Sims (2011), Kurmann and Otrok (2013) and Barsky, Basu, and Lee (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.

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

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) 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 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 (2017) 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 2. Section 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 4 summarizes the results of the identified news shock with instrumental variables. Section 5 concludes this paper.

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 (2015): 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

$$\log y_t = \beta t + \epsilon_{k,t}, \tag{1}$$

⁷See Stadler (1994) for an extensive review of the real business cycle literature.



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

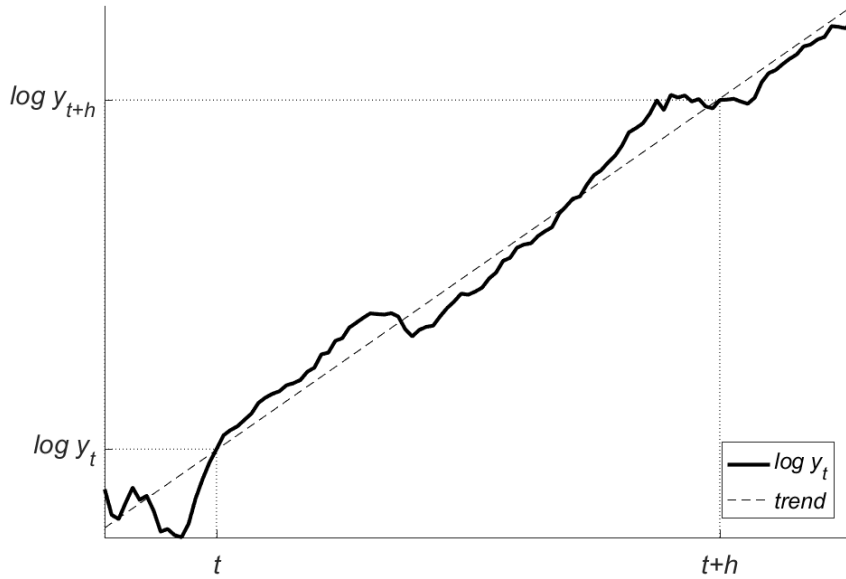
$$\epsilon_{k,t} = \epsilon_{k,t-1} + \varrho_t. \quad (2)$$

Taking the differences of $\log y_t$ leads to

$$\Delta \log y_t = \beta + \Delta \epsilon_{k,t}. \quad (3)$$

Figure 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 .

Figure 1 Long-run output level and trend



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 1, where $t + h$ is the long-run, it suffices to calculate

$$\begin{aligned} \tilde{\beta} &= \frac{\log y_{t+h} - \log y_t}{(t+h) - t} \\ \tilde{\beta} &= \frac{\log y_{t+h} - \log y_t}{h}. \end{aligned} \quad (4)$$

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

$$\begin{aligned}\tilde{\beta} &= \frac{\beta(t+h) + \epsilon_{k,t+h} - (\beta t + \epsilon_{k,t})}{h} \\ \tilde{\beta} &= \beta + \frac{(\epsilon_{k,t+h} - \epsilon_{k,t})}{h}.\end{aligned}\tag{5}$$

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 4 is proportional to

$$\tilde{\beta} \propto \log y_{t+h} - \log y_t.\tag{6}$$

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

$$y_t = A_t f(K_t/L_t),\tag{7}$$

or in logs

$$\log y_t = \log A_t + \log f(K_t/L_t),\tag{8}$$

and taking the differences

$$\Delta \log y_t = \Delta \log A_t + \Delta \log f(K_t/L_t).\tag{9}$$

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 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 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

$$\log A_t = \beta + \log A_{t-1} + \epsilon_{surprise,t} + \epsilon_{news,t-h}, \quad (10)$$

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

$$\log A_{t+h} = \beta + \log A_{t+h-1} + \epsilon_{surprise,t+h} + \epsilon_{news,t}, \quad (11)$$

or

$$\log A_{t+h} = (h+1)\beta + \log A_{t-1} + \sum_{i=0}^h \epsilon_{surprise,t+i} + \sum_{i=0}^h \epsilon_{news,t-i}. \quad (12)$$

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

$$\log A_{t+h} - \log A_t = h\beta + \sum_{i=1}^h \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i}. \quad (13)$$

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

$$\log f(K_{t+h}/L_{t+h}) - \log f(K_t/L_t) = \epsilon_{k,t+h} - \epsilon_{k,t}, \quad (14)$$

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

$$\log y_{t+h} - \log y_t = h\beta + \sum_{i=1}^h \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i} + (\epsilon_{k,t+h} - \epsilon_{k,t}). \quad (15)$$

By substituting equation 15 into equation 4, the noisy measure $\tilde{\beta}$ will be

$$\tilde{\beta} = \beta + \frac{1}{h} \left(\sum_{i=1}^h \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i} + (\epsilon_{k,t+h} - \epsilon_{k,t}) \right). \quad (16)$$

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 16, will be

$$\tilde{\beta}_{|t-1} = \beta + \frac{1}{h} \left(\sum_{i=1}^{h-1} \epsilon_{news,t-i} \right). \quad (17)$$

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 16) will be

$$\tilde{\beta}_{|t} = \beta + \frac{1}{h} \left(\sum_{i=0}^{h-1} \epsilon_{news,t-i} - \epsilon_{k,t} \right). \quad (18)$$

Now, the only difference between the forecast of the long-run trend evaluated at time

⁸I follow the definitions and similar notation as described in Clements (2015).

$t - 1$ 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

$$\Delta_{\tilde{\beta}} = \tilde{\beta}_{|t} - \tilde{\beta}_{|t-1}. \quad (19)$$

Substituting equations 17 and 18, this measure becomes

$$\Delta_{\tilde{\beta}} = \left(\beta + \frac{1}{h} \left(\sum_{i=0}^{h-1} \epsilon_{news,t-i} - \epsilon_{k,t} \right) \right) - \left(\beta + \frac{1}{h} \left(\sum_{i=1}^{h-1} \epsilon_{news,t-i} \right) \right) \quad (20)$$

leading to

$$\Delta_{\tilde{\beta}} = \frac{1}{h} (\epsilon_{news,t} - \epsilon_{k,t}), \quad (21)$$

which is proportional to

$$\Delta_{\tilde{\beta}} \propto \epsilon_{news,t} - \epsilon_{k,t}. \quad (22)$$

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, the differences between forecasts of the slope of the long-run trend of output can be computed as

$$\Delta_{\tilde{\beta}} \propto (\log y_{t+h|t} - \log y_{t|t}) - (\log y_{t+h|t-1} - \log y_{t|t-1}). \quad (23)$$

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 generat-

ing 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 23, following

$$\mathbf{Z}_t = (\mathbf{x}_{t+4|t} - \mathbf{x}_{t|t}) - (\mathbf{x}_{t+4|t-1} - \mathbf{x}_{t|t-1}), \quad (24)$$

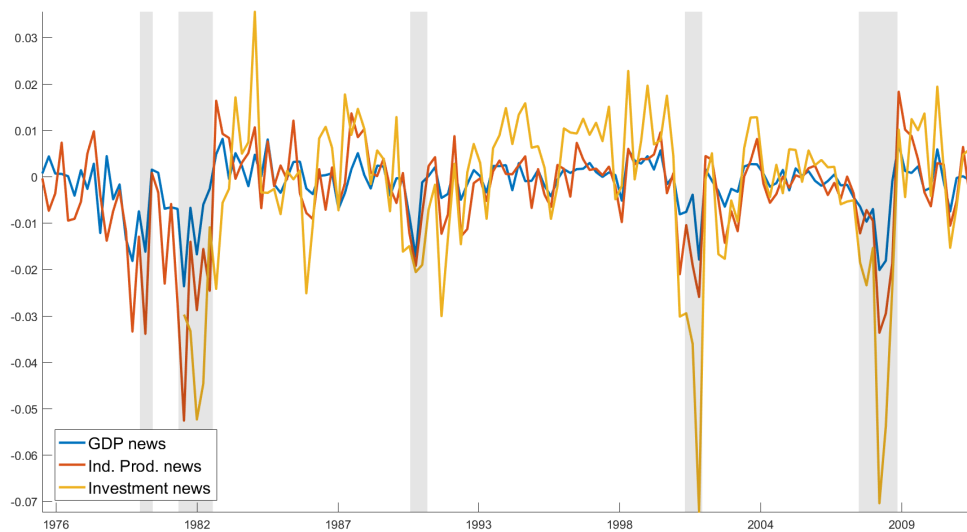
where \mathbf{Z}_t is a matrix collecting the three instruments (GDP, investment and industrial production forecast revisions).

Figure 2 shows the three measures constructed here. These series present similar patterns and are highly correlated (Table 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

⁹See, for example, Beaudry and Portier (2006), Barsky and Sims (2011), Cascardi-Garcia and Galvao (2017), among others.

identified by the National Bureau of Research Institute (NBER).

Figure 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 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 1 Correlations between forecast revisions about future GDP, investment and industrial production

	Real GDP news	Ind. prod. news	Investment news
Real GDP news	1.00	0.86	0.77
Ind. prod. news	0.86	1.00	0.73
Investment news	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 2. Correlations calculated from 1981:Q3 to 2012:Q3.

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

$$\mathbf{y}_t = \mathbf{A}_1 \mathbf{y}_{t-1} + \dots + \mathbf{A}_p \mathbf{y}_{t-p} + \mathbf{u}_t, \quad (25)$$

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

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L}) \mathbf{u}_t. \quad (26)$$

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

$$\mathbf{u}_t = \mathbf{A}_0 \mathbf{s}_t \quad (27)$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L}) \mathbf{s}_t, \quad (28)$$

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

$$\mathbb{E}[\mathbf{u}_t \mathbf{u}_t'] = \mathbb{E}[\mathbf{A}_0 \mathbf{A}_0'] = \underset{n \times n}{\boldsymbol{\Sigma}}. \quad (29)$$

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{A}_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:

$$\begin{aligned} (i) \quad \mathbb{E}[z_t s'_{news,t}] &= \phi_{1 \times 1} \quad (\text{relevance}), \\ (ii) \quad \mathbb{E}[z_t \mathbf{s}'_{2,t}] &= \mathbf{0}_{1 \times (n-1)} \quad (\text{exogeneity}), \end{aligned} \tag{30}$$

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 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 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

$$\mathbf{A}_0 = \begin{bmatrix} \mathbf{\Lambda}_1 & \mathbf{\Lambda}_2 \\ n \times 1 & n \times (n-1) \end{bmatrix}, \quad \mathbf{\Lambda}_1 = \begin{bmatrix} \lambda_{11} \\ 1 \times 1 \\ \lambda'_{21} \\ (n-1) \times 1 \end{bmatrix}, \quad \mathbf{\Lambda}_2 = \begin{bmatrix} \lambda_{12} \\ 1 \times (n-1) \\ \lambda_{22} \\ (n-1) \times (n-1) \end{bmatrix}, \tag{31}$$

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

$$\phi \mathbf{\Lambda}'_1 = \mathbb{E}[z_t \mathbf{u}'_t]_{1 \times n}. \tag{32}$$

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

$$\mathbb{E}[z_t \mathbf{u}'_t] = \begin{bmatrix} \mathbb{E}[z_t u'_{1,t}] & \mathbb{E}[z_t \mathbf{u}'_{2,t}] \\ 1 \times 1 & 1 \times (n-1) \end{bmatrix}, \tag{33}$$

where $\mathbf{u}_{2,t}$ collects all $(n-1)$ innovations other than the first $(u_{1,t})$, it is possible to rewrite equation 32 as

$$\frac{\lambda_{21}}{\lambda_{11}} = (\mathbb{E}[z_t u'_{1,t}]^{-1} \mathbb{E}[z_t \mathbf{u}'_{2,t}])'. \quad (34)$$

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

$$\mathbf{u}_{2,t} = \frac{\lambda_{21}}{\lambda_{11}} \hat{u}_{1,t} + \xi_t, \quad (35)$$

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

$$\Sigma = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}, \quad (36)$$

λ_{21} and λ_{11} can be identified by applying the restrictions from equation 29 following the closed form solution¹⁰

$$\lambda_{11}^2 = \Sigma_{11} - \lambda_{12} \lambda'_{12}, \quad (37)$$

where

$$\begin{aligned} \lambda_{12} \lambda'_{12} &= \left(\Sigma_{21} - \frac{\lambda_{21}}{\lambda_{11}} \Sigma_{11} \right)' \mathbf{Q}^{-1} \left(\Sigma_{21} - \frac{\lambda_{21}}{\lambda_{11}} \Sigma_{11} \right), \\ \mathbf{Q} &= \frac{\lambda_{21}}{\lambda_{11}} \Sigma_{11} \frac{\lambda_{21}'}{\lambda_{11}} - \left(\Sigma_{21} \frac{\lambda_{21}'}{\lambda_{11}} + \frac{\lambda_{21}}{\lambda_{11}} \Sigma'_{21} \right) + \Sigma_{22}. \end{aligned} \quad (38)$$

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 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 ;

¹⁰As demonstrated by Mertens and Ravn (2013) and Gertler and Karadi (2015).

3. Find the impact effects of a news shock by imposing the restrictions in equation 34.

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, Ma, and Ng, 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 B.1 in the Appendix.

I estimate the model under a Bayesian VAR (BVAR) approach. The idea of identifying shocks with instrumental variables and estimating the model with a BVAR is also employed by Caldara and Kamps (2017). 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 hyperparameters follows methodology proposed by Gianonne, Lenza, and Primiceri (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.¹²

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

¹²To 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) .

3.3 Exogeneity of the instruments

I show in Section 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 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 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.¹³

The measure for news about tax shocks is the proxy calculated by Leeper, Walker, and Yang (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

¹³Apart 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 3.2).

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 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 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

$$z_t^i = \mu_0 + \mu_{1,j}d_{j,t} + v_{j,t}, \quad (39)$$

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 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 21 shows that the slope measure can be contaminated by other non-technological shocks. This is particularly 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

Table 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 3.2). All shocks divided by 10^3 for presentation reasons.

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 .

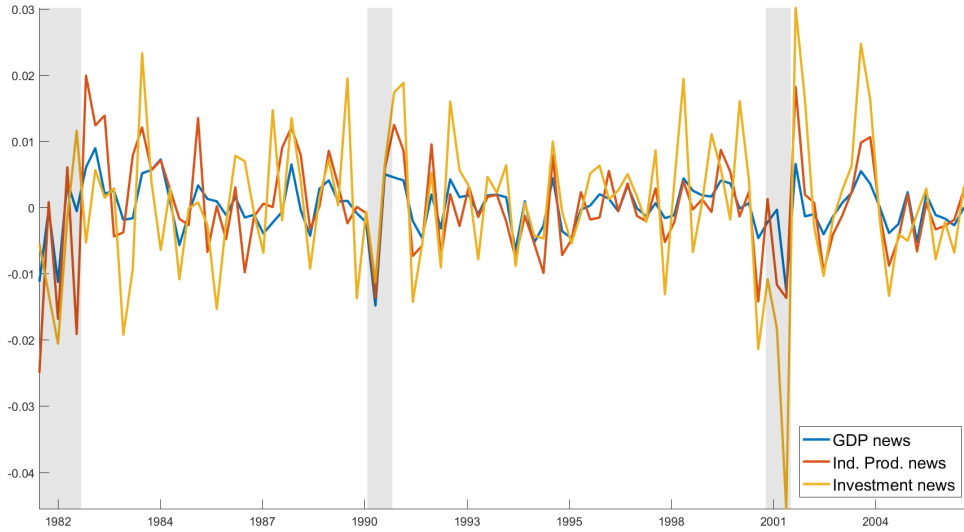
I proxy the economic activity by the first factor of the real activity dataset calculated by Stock and Watson (2016).¹⁴

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

$$\mathbf{Z}_t = \mu_1 \mathbf{d}_t + \mu_2 u_{1,t} + \mathbf{M}(\mathbf{L})F_t + \tilde{\mathbf{Z}}_t, \quad (40)$$

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 3 presents the three instruments after the filtering process, as the mean over 1,000 posterior draws.

Figure 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 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 3.3. Time period from 1981:Q4 to 2006:Q3 due to data availability. Shaded areas are the recession periods calculated by the NBER.

¹⁴The dataset and replication files are available at Mark Watson's website.

4 Results

In this section I present the results for a news shock identified using the instruments and the procedure described in Section 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.

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 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 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

$$u_{i,t} = \alpha + \theta_i \tilde{\mathbf{Z}}_t + \eta_i, \quad i = 2, \dots, n, \quad (41)$$

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 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 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 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 41. The residuals are calculated as the median across 1,000 posterior draws (as described in subsection 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 B.1 in the Appendix.

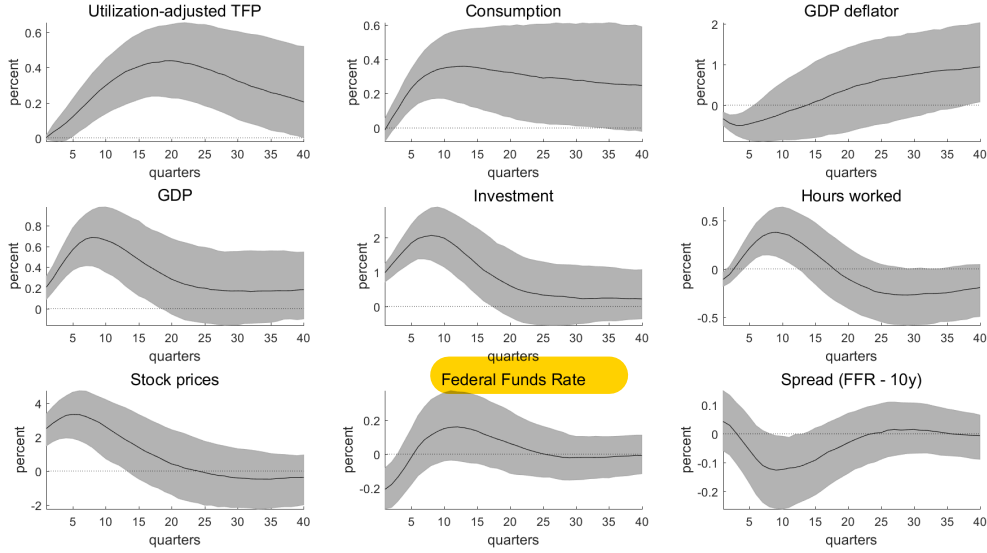
The strong relation of the instruments and stock prices is a positive indication of the connection between the instruments and the news shock. Beaudry and Portier (2006) show that permanent changes in productivity growth are preceded by stock market booms, indicating that agents foresee information about 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.¹⁵ 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.

¹⁵See, for example, Kurmann and Otrok (2013), Cascarini-Garcia (2017) and Gambetti, Korobilis, Tsoukalas, and Zanetti (2017).

4.2 Economic responses to a news shock identified with instrumental variables

Figure 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.¹⁶ The full impulse responses can be found in Figure C.1 in the Appendix.

Figure 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 B.1 in the Appendix.

The first important result from Figure 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 40). This imposition is equivalent to the short-run

¹⁶For every posterior draw, the instruments are filtered taking into consideration the new residual $u_{1,t}$ (as described by equation 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.

restriction employed both by Beaudry and Portier (2006) and 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 Cascarini-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, Eichenbaum, and Vigfusson, 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 4 presents the variance decomposition after a news shock for selected variables. Figure C.2 in the Appendix presents the variance decomposition graphs for all variables included in the BVAR.

Table 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 B.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.

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.¹⁷ The full identification procedure is described in Appendix A.

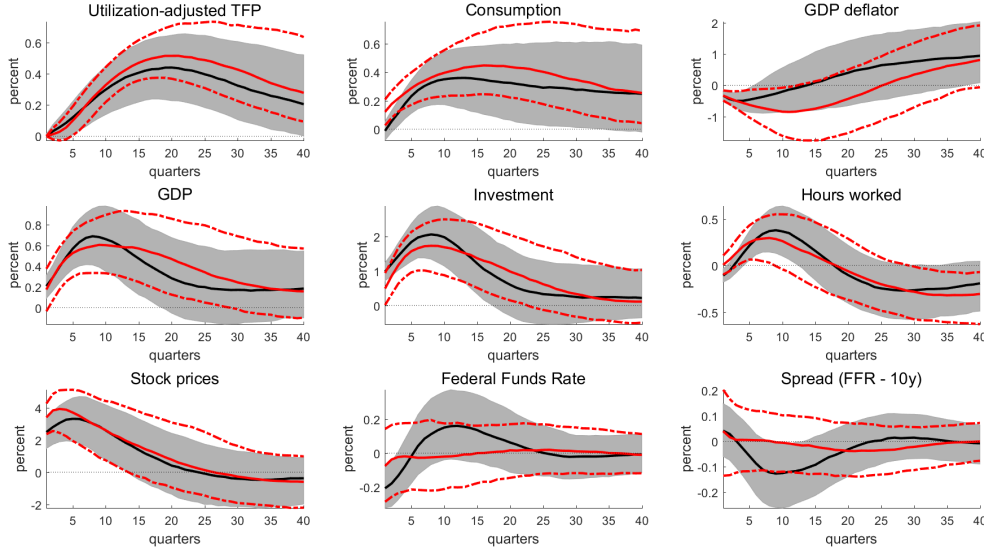
I compare the results from the identification with instrumental variables by employing the same database, period and BVAR estimation described in subsection 3.2, but identifying the news shock as in BS. Figure 5 compares the impulse response functions of selected variables for the identification based 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 C.3 in the Appendix.

First, by comparing the impulse responses it is possible to notice that both identifications procedures present the same qualitative results. However, the coverage bands of the identification using the BS approach are substantially wider than when using the instrumental variables, particularly in the short-run.¹⁸ The economic effects on utilization-adjusted TFP and on consumption are more intense using the BS approach through all

¹⁷See, for example, Kurmann and Otrók (2013), Beaudry and Portier (2014), Cascarini-Garcia and Galvao (2017), Levchenko and Pandalai-Nayar (2017), Clements and Galvao (2018), among others.

¹⁸I 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.

Figure 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 A, 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 B.1 in the Appendix.

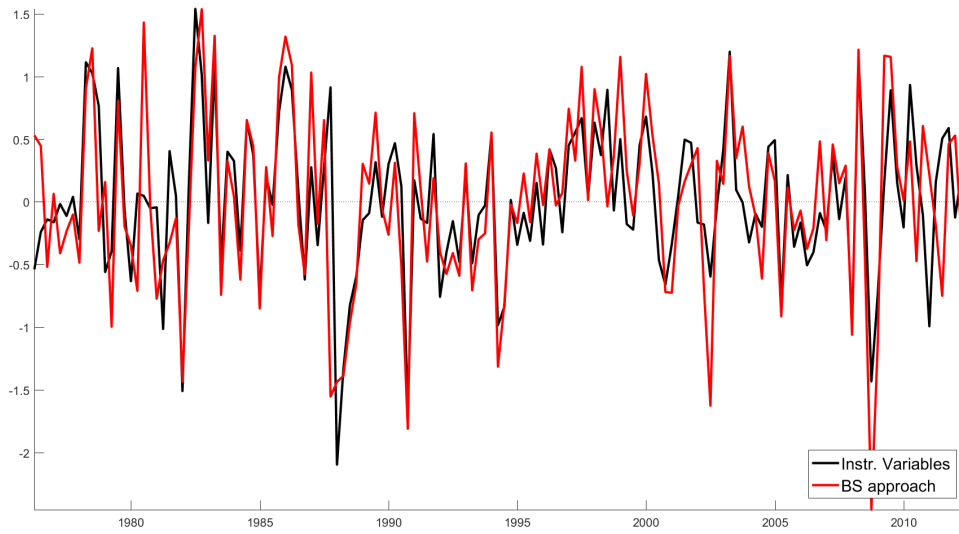
forecast horizons. The effect on impact on GDP is basically the same when using either of the procedures, but the coverage bands of the BS approach rule out a zero effect. Investment rises more using the instrumental variable; also, the BS coverage bands also do not rule out a zero effect. The effect 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. 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.

Figure 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 A, 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 B.1 in the Appendix.

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 Michi-

gan Consumer Survey), investment, hours worked or consumption.¹⁹ The models are estimated with four lags, as vector error correction models (VECM) with two cointegration relations. Figure 7 presents the impulse responses for each model, with confidence, investment, hours worked and consumption as the third variable.

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.

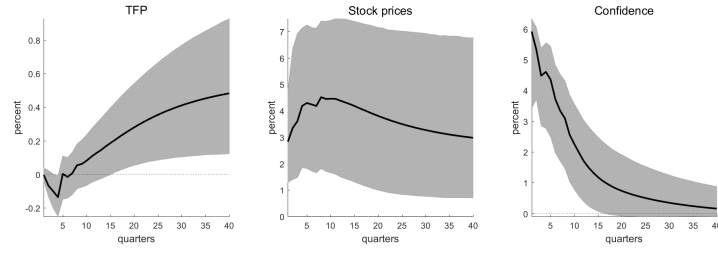
The effect on stock prices is positive and significant on impact for all four models. However, the size of the impact and the path over time is quite distinct depending on which variable is chosen as the third in the system. The path of stock prices seems to converge back to zero in the long-run in the 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, 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.

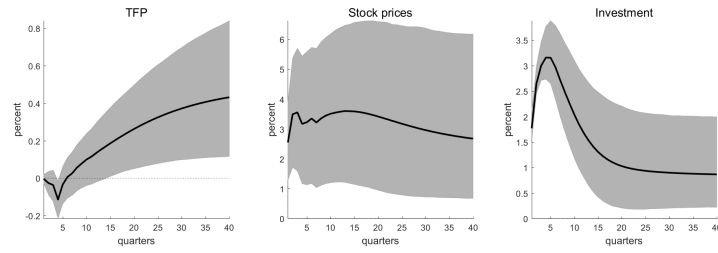
In summary, the results from Figure 7 provide qualitative evidence of the power of the instrumental variables on recovering the theoretical economic effects of a technological news shock, even in a small-scale VAR.

¹⁹The 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 constructed as described in Table B.1 in the Appendix.

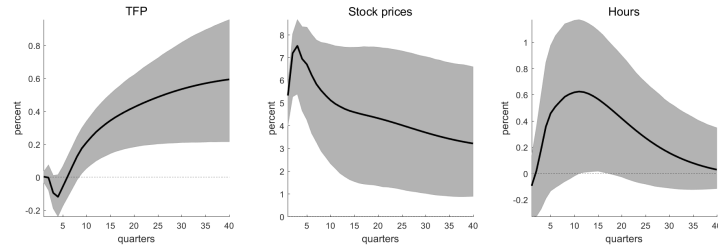
Figure 7 Impulse responses for a news shock identified with instrumental variables in a three-variables model



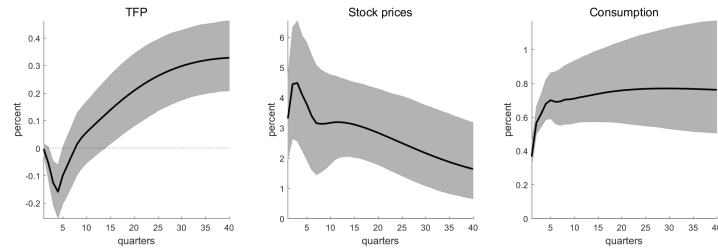
(a) TFP, Stock prices and Confidence



(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.

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.

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A Appendix: 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

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \quad (42)$$

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

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t \quad (43)$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \quad (44)$$

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

$$\Omega_{1,1}(h)_{surprise} + \Omega_{1,2}(h)_{news} = 1\forall h, \quad (45)$$

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

$$\Omega_{1,2}(h)_{news} = \frac{\mathbf{e}_1' \left(\sum_{\tau=0}^h \mathbf{B}_\tau \tilde{\mathbf{A}}_0 \mathbf{D} \mathbf{e}_2 \mathbf{e}_2' \mathbf{D}' \tilde{\mathbf{A}}_0' \mathbf{B}_\tau' \right) \mathbf{e}_1}{\mathbf{e}_1' \left(\sum_{\tau=0}^h \mathbf{B}_\tau \mathbf{\Sigma} \mathbf{B}_\tau' \right) \mathbf{e}_1} = \frac{\sum_{\tau=0}^h \mathbf{B}_{1,\tau} \tilde{\mathbf{A}}_0 \gamma \gamma' \tilde{\mathbf{A}}_0' \mathbf{B}_{1,\tau}'}{\sum_{\tau=0}^h \mathbf{B}_{1,\tau} \mathbf{\Sigma} \mathbf{B}_{1,\tau}'}, \quad (46)$$

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}_τ 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

$$\begin{aligned} \gamma_2^{news} = \underset{\gamma}{\operatorname{argmax}} \quad & \sum_{h=0}^H \Omega_{1,2}(h)_{news}, \\ \text{s.t.} \quad & \end{aligned} \quad (47)$$

$$\tilde{A}_0(1, j) = 0, \forall j > 1 \quad (48)$$

$$\gamma_2(1, 1) = 0 \quad (49)$$

$$\gamma_2' \gamma_2 = 1, \quad (50)$$

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

$$\begin{bmatrix} s_t^{surprise} \\ s_t^{news} \\ \dots \end{bmatrix} = \tilde{\mathbf{A}}_0^{-1} \begin{bmatrix} \gamma_1^{surprise} & \gamma_2^{news} & \dots \end{bmatrix}^{-1} \mathbf{u}'_t, \quad (51)$$

assuming that

$$\gamma_1^{surprise} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \dots \end{bmatrix}. \quad (52)$$

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) .

B Appendix: Data description

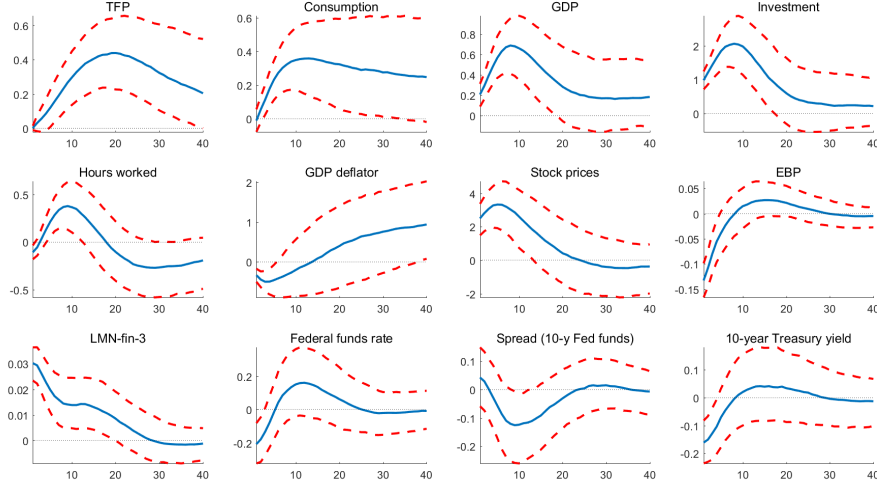
Table B.1 Description of variables

	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.

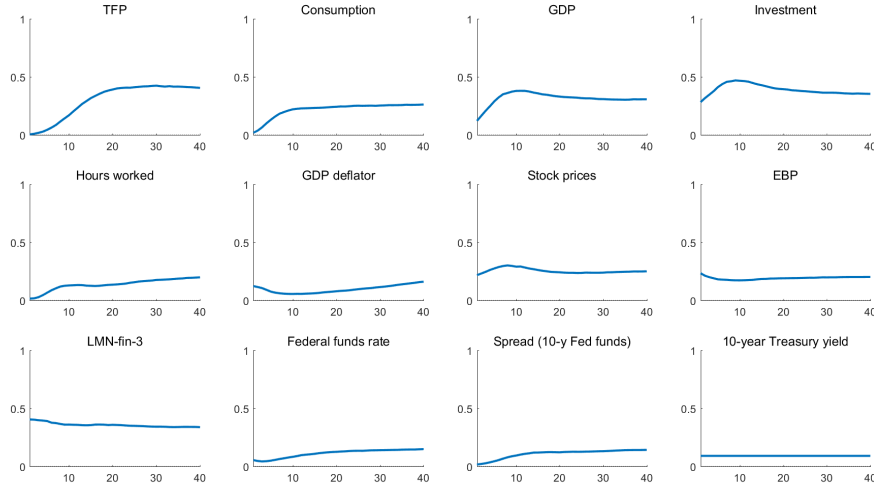
C Additional figures

Figure C.1 Impulse responses to a news shock under an instrumental variable approach



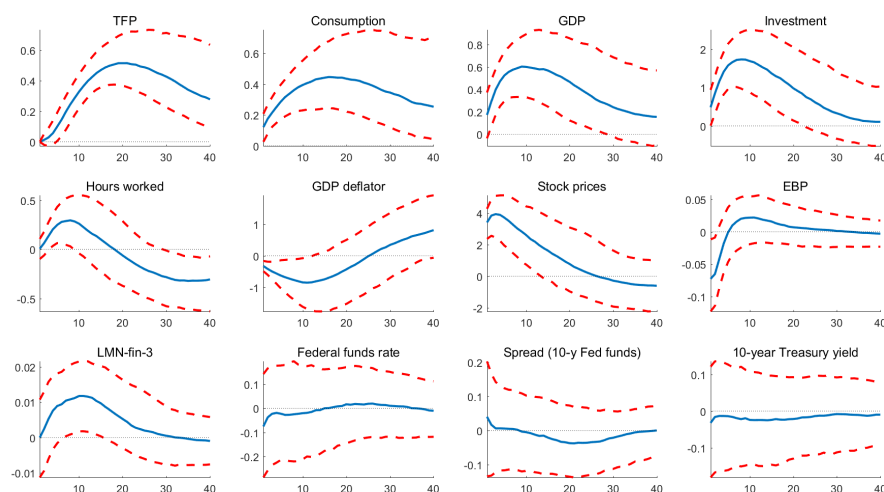
Note: Impulse responses of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975Q1 to 2012Q3. The dashed lines define the 68% confidence bands computed with 1,000 posterior draws. The VAR model includes all variables in Table B.1.

Figure C.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 B.1.

Figure C.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 A, 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 B.1.