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Forecast revisions as instruments for news shocks

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Abstract

Upon arrival of macroeconomic news, economic agents update their beliefs about the long-run fundamentals of the economy. I show that signals about the agents' long-run expectations, proxied by the economic outlook revisions of professional forecasters, convey sufficient information to identify the effects of expected future technological changes, or news shocks. A major advantage of this approach from the existing news shock literature is that it does not depend on an empirical measure for technology, or on assumptions about common trends and timing of the technological change. I show that technological news shocks cause a strong anticipation effect in investment and an increase in hours, while there is less evidence of consumption smoothing over time—in line with news-driven business cycle models featuring a key role of financial frictions.

Keywords: news shock, proxy SVAR, instrumental variable, professional forecasts

JEL codes: E32, E44

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1 Introduction

Agents react to the arrival of news about future technological changes. Theoretically, and absent of frictions, firms anticipating higher future productivity stemming from a permanent technological change, or a news shock, would invest now, and individuals would increase consumption to smooth their expected higher future income. Empirically, however, the aggregate evidence of such anticipation is blurry, and different identification assumptions lead to opposite conclusions. The economy either reacts strongly to news, reinforcing the comovement among GDP, investment, and consumption (Beaudry and Portier, 2006), or rather tracks the increase in productivity, and the importance of news shocks as a driver of business cycle is more subtle (Barsky and Sims, 2011). Moreover, empirical identification is conditional on strong premises, such as taking a stance on common trends or on the timing of the technological advance, and crucially depends on a measure that perfectly tracks aggregate technological changes. In this paper, I show that updated agents' expectations, proxied by professional forecast revisions, can be directly linked to the news-driven business cycle theory and convey information about technological news shocks that are sufficient to relax these strict identification conditions. After a news shock, investment and, consequently, GDP react strongly and immediately, indicating that firms indeed adapt their expansion plans when facing news about future productivity. Consumption, however, shows a delayed response and less evidence of anticipation, tracking the increase in productivity, indicating that individuals may be less prone to smoothing future income, or more financially constrained than firms.

Measuring the effect of news about future technological changes is a difficult task.[1] First, identifying a news shock implies separating technological shocks into unexpected and expected parts. Second, the effect of technological changes on productivity is not directly observed, and its proxies, such as utilization-adjusted total factor productivity (TFP), may be subject to measurement errors or substantial revisions (Cascaldi-Garcia, 2017 and Kurmann and Sims, 2021). And third, the news information may be

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

‘noisy,’ which would make a news shock identification infeasible (Blanchard, L’Huillier, and Lorenzoni, 2013 and Chahrour and Jurado, 2018). I circumvent these challenges by proposing an identification method that stems from a single assumption: if agents foresee higher future productivity, they should expect higher future economic growth. It follows that positive news about productivity should be (positively) correlated with news about future economic activity.

While news about future productivity are not directly observed, proxies for news about future economic growth 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. From the supply-side, three of these series are particularly relevant for technological news: GDP, investment, and industrial production. Positive news about future technology should be reflected as higher future GDP, investment, and industrial production. I propose a method of measuring revisions about the long-run trend of these variables by calculating differences between updates on forecasts and *now-casts*. This method, akin to a difference-in-differences procedure, allows the construction of a quarterly time series for forecast revisions about future GDP, investment, and industrial production.

I employ the proxy SVAR procedure introduced by Stock and Watson (2012) and Mertens and Ravn (2013) to the news shock case, using forecast revisions as instruments. This approach identifies structural shocks based on information external to the vector autoregression (VAR), through measures (namely, instruments) that are correlated to the targeted structural shock, and not correlated to other known structural shocks. The procedure consists of regressing these instruments against the residuals of a reduced-form VAR, and using this information to infer the contemporaneous impact of the structural shock on the macroeconomic variables. I show that, under certain assumptions, the constructed series of forecast revisions about future GDP, investment, and industrial production are instruments that provide empirical identification for the news shock.

The identification comes from revealed information about agents’ expectations, which is at the heart of the theoretical idea of business cycles driven by agents’ beliefs. This is an advantage compared to statistical procedures currently used for the news shock identification. In practice, two empirical identification strategies are available in the literature: based on a combination of short and long-run restrictions (Beaudry and Portier, 2006), or based on explaining the medium-run movements in technology (Barsky and Sims, 2011). The Beaudry and Portier (2006) methodology succeeds in generating contemporaneous positive comovement among macroeconomic variables. Utilization-adjusted TFP reacts to a news shock only in the medium-run, as would be expected with an anticipation of future news. However, this identification relies on strong assumptions about the order of integration of the variables and its cointegrating relationships.[2]

The partial identification approach of Barsky and Sims (2011) is less restrictive than Beaudry and Portier (2006), by assuming that a limited number of shocks generate movements in the technology level, proxied by utilization-adjusted TFP (Fernald, 2014). 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.[3] Utilization-adjusted TFP reacts almost immediately after impact, indicating that economic variables may be tracking TFP growth, rather than anticipating it. In addition, the identification procedure demands taking a stance over the timing of a news shock, or the forecast horizon over which the news shock's explanatory power for TFP is maximized.

The flexible identification proposed here reinforces the positive contemporaneous comovement, but highlights that most of the anticipation is manifested through higher investment, and not through consumption smoothing. After a (one standard deviation) news shock, utilization-adjusted TFP increases after around five quarters, reaching its highest level in 20 quarters, in line with the expected path of a slow diffusion of the tech-

[2]Barsky and Sims (2011) present a discussion about the issues of employing long-run restrictions for the news shock identification.

[3]See, for example, Barsky and Sims (2011), Kurmann and Otrok (2013), and Barsky, Basu, and Lee (2015). Cascaldi-Garcia and Galvão (2021) recover a positive comovement among GDP, consumption, investment, and hours worked by employing the Barsky and Sims (2011) approach in an identification strategy that imposes orthogonality between news and uncertainty shocks.

nological increment. GDP jumps around 0.3% on impact, driven mainly by the strong effect on investment (about 1.4%). The effect on consumption is zero on impact, showing no initial anticipation from individuals to the news shock. Over time, consumption grows to a higher level faster than utilization-adjusted TFP, evidencing some mild anticipation effect in the medium-run. Hours worked do not react on impact, but its response quickly becomes positive, reaching a peak of around 0.6% after two years. This result supports the economic intuition that the substitution effect from the higher future productivity is higher than the income effect, consistent with Christiano, Eichenbaum, and Vigfusson (2003). The distinct anticipation effect between investment and consumption is also evidenced by the overall importance of the news shock on explaining its unpredictable movements. While a news shock explains about 23% of the variance of investment on impact, its explanation power for consumption is of only about 2%. In the medium-run, however, the explanation power goes up to 33% for investment and 16% for consumption, evidencing that the news shock is indeed an important driver of both variables.

These results rationalize the theoretical findings of Görtz and Tsoukalas (2017), who extend the Schmitt-Grohe and Uribe (2012) DSGE model to accommodate financial frictions, which amplifies the news shock effect through a strong lending and investment phase. Putting it to data, the model favors a news shock transmission in which investment demand drives the cycle, with strong anticipation effect on investment and gradual increase in consumption. Also, nominal price and wage rigidities produce positive shifts in labor demand and labor supply, offsetting the income effect from the increased productivity, causing an increase in hours worked.

The use of exogenous variables as instruments for the structural shock of interest is a recent burgeoning literature in business cycles.[4] It has been applied to identify monetary policy shocks (Stock and Watson, 2012, Gertler and Karadi, 2015, Miranda-Agrippino and Ricco, 2021, and Caldara and Herbst, 2019), fiscal policy shocks (Mertens and Ravn, 2014 and Caldara and Kamps, 2017), uncertainty shocks (Carriero, Mumtaz, Theodoridis, and Theophilopoulou, 2015 and Piffer and Podstawski, 2018), and oil supply

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

shocks (Olea, Stock, and Watson, 2020). With respect to news shocks, extraneous data have been applied to news about future fiscal spending (Auerbach and Gorodnichenko, 2012), news about future oil supply (Arezki, Ramey, and Sheng, 2017 and Känzig, 2021), and technological news coming from patents (Miranda-Agrippino, Hoke, and Bluwstein, 2020 and Cascaldi-Garcia and Vukotić, 2022).

While the strategy of identifying a technological news shock through instruments based on expectations is innovative, the literature has already shown the predictive power of expectations on driving business cycles. Miyamoto and Nguyen (2020) argue that the precision of news shocks improves when forecast data is also considered in the information set. Levchenko and Pandalai-Nayar (2020) show that a non-technological expectation shock accounts for a large share of business cycle fluctuations in the short-run. Clements and Galvão (2021) show that data uncertainty influences the effect of expectation shocks.

In summary, this paper contributes to the extensive news shock literature[5] with novel evidence about the economic effects of expectation-driven business cycles (Pigou, 1927). The proposed identification procedure for technological news shocks relies on more pragmatic assumptions by bridging agents' expectations about future technology with observed revisions on economic forecasts. As such, a news shock identified with forecast revisions as instrumental variables is more likely to represent its true economic effects than what is identified with statistical methods found in the literature.

The outline of the paper is as follows. I show the relevance of forecast revisions for measuring news shocks in section 2. Section 3 presents the news shocks identification procedure with instrumental variables (proxy SVAR) and the discussion about the exogeneity of the proposed measures. Section 4 presents the results of the identified news shock with instrumental variables. Section 5 presents robustness checks, including the results of an alternative instrument constructed with the International Monetary Fund (IMF) forecasts.[6] Section 6 summarizes the findings and implications of this paper.

[5]See, among others, Beaudry and Portier (2006), Jaimovich and Rebelo (2009), Barsky and Sims (2011), Schmitt-Grohe and Uribe (2012), Kurmann and Mertens (2014), Forni, Gambetti, and Sala (2014), Crouzet and Oh (2016), Görtz and Tsoukalas (2017), Miranda-Agrippino et al. (2020), Görtz, Tsoukalas, and Zanetti (2020), Cascaldi-Garcia and Galvão (2021), and Cascaldi-Garcia and Vukotić (2022).

[6]Collected from historical World Economic Outlook publications.

2 Relevance of forecast revisions for measuring news

The process of identifying the effect of news about the future outcome of economic variables can be quite challenging. The alternative I propose is to look at professional forecast surveys, and measure the change in the forecasts between two consecutive periods. But how informative are these forecasts for the news shock driving the long-run growth of the economy? I tackle this question by presenting a simple model with three sources of exogenous shocks, as in Levchenko and Pandalai-Nayar (2020): 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, fiscal) explain short-run movements *around* this trend.

Suppose (log) real output follows a process with a deterministic trend as $\log y_t = \beta t + u_t$, where β is the slope of the long-run trend and u_t captures the short-run non-technological shocks that temporarily deviate $\log y_t$ from its long-run trend, following the process $u_t = \alpha u_{t-1} + \varrho_t$. Taking the long-run differences of $\log y_t$ leads to

$$\log y_{t+h} - \log y_t = \beta h + (u_{t+h} - u_t). \tag{1}$$

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. While estimating the slope of such a time trend demands 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

$$\tilde{\beta} = \frac{\log y_{t+h} - \log y_t}{(t+h) - t} \quad \text{or,} \quad \tilde{\beta} = \frac{\log y_{t+h} - \log y_t}{h}. \tag{2}$$

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

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

$$\tilde{\beta} = \frac{\beta(t+h) + u_{t+h} - (\beta t + u_t)}{h} \quad \text{or,} \quad \tilde{\beta} = \beta + \frac{(u_{t+h} - u_t)}{h}. \tag{3}$$

Figure 1 Long-run output level and trend

The approximate measure of the slope $\tilde{\beta}$ is defined as the true slope of long-run trend (β) plus the short-run deviations around the trend ($u_{t+h} - u_{k,t}$). By keeping h fixed, equation 2 is proportional to

$$\tilde{\beta} \propto \log y_{t+h} - \log y_t. \tag{4}$$

As such, the difference between the two observables ($\log y_{t+h} - \log y_t$) is proportional to a noisy measure of the slope of the 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, in logs, as in $\log y_t = \log A_t + \log f(K_t/L_t)$. The long-run differences can be defined as

$$\log y_{t+h} - \log y_t = (\log A_{t+h} - \log A_t) + (\log f(K_{t+h}/L_{t+h}) - \log f(K_t/L_t)). \tag{5}$$

If non-technological shocks cause the output to deviate from its long-run trend, technological shocks should produce permanent changes in the trend itself.[8] Linking

[8] Assuming that technology is the main driver of long-run growth, as in Smets and Wouters (2007).

with equation 1, this is equivalent to say that long-run changes changes in technology define the slope of the long-run trend, as in $\log A_{t+h} - \log A_t = \beta h$, and long-run changes in the production factors define the temporary deviations around the trend, as in $\log f(K_{t+h}/L_{t+h}) - \log f(K_t/L_t)) = u_{t+h} - u_t$.

In the presence of stochastic technological shocks, the slope of the long-run trend will change depending on the shock realizations. A positive long-run technological shock should increase the long-run output growth, which is equivalent to making the time trend in Figure 1 steeper. Similarly, negative long-run technological shocks should make the curve flatter. 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 long-run changes in technology (technological shocks). Following the news shock literature, technology is characterized as a stochastic process driven by two shocks. The surprise technological shock ($\epsilon_{surprise,t}$) changes the level of technology on impact and the news shock ($\epsilon_{news,t-h}$) is observed h periods ahead and produces no change in the level of technology when observed. Say, for example, that technology follows a process as

$$\log A_t = \bar{\beta} + \log A_{t-1} + \epsilon_{surprise,t} + \epsilon_{news,t-h}, \tag{6}$$

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

$$\begin{aligned} \log A_{t+h} &= \bar{\beta} + \log A_{t+h-1} + \epsilon_{surprise,t+h} + \epsilon_{news,t}, \quad \text{or} \\ \log A_{t+h} &= (h+1)\bar{\beta} + \log A_{t-1} + \sum_{i=0}^{h} \epsilon_{surprise,t+i} + \sum_{i=0}^{h} \epsilon_{news,t-i}, \end{aligned} \tag{7}$$

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

$$\log A_{t+h} - \log A_t = h\bar{\beta} + \sum_{i=1}^{h} \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i}. \tag{8}$$

Suppose that $\log f(K_t/L_t)$ follows an AR(1) process as in

$$\log f(K_t/L_t) = \rho \log f(K_{t-1}/L_{t-1}) + \epsilon_{k,t}, \quad \text{and}$$
$$\log f(K_{t+h}/L_{t+h}) = \rho^{h+1} \log f(K_{t-1}/L_{t-1}) + \sum_{i=0}^{h} \rho^{h-i}\epsilon_{k,t+i}. \tag{9}$$

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

$$\begin{aligned} \log f(K_{t+h}/L_{t+h}) - \log f(K_t/L_t) =& ... \\ &...\rho(\rho^h - 1) \log f(K_{t-1}/L_{t-1}) + \sum_{i=1}^{h} \rho^{h-i}\epsilon_{k,t+i} + (\rho^h - 1)\epsilon_{k,t}. \end{aligned} \tag{10}$$

From equations 8 and 10, the long-run difference ($\log y_{t+h} - \log y_t$) is

$$\begin{aligned} \log y_{t+h} - \log y_t = h\bar{\beta} + \sum_{i=1}^{h} \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i} + ... \\ ... + \rho(\rho^h - 1) \log f(K_{t-1}/L_{t-1}) + \sum_{i=1}^{h} \rho^{h-i}\epsilon_{k,t+i} + (\rho^h - 1)\epsilon_{k,t}. \end{aligned} \tag{11}$$

By substituting equation 11 into equation 2, the noisy slope of the long-run trend $\tilde{\beta}_t$ will be composed by a constant term ($\bar{\beta}$), a technology process, and a production process, as in

$$\begin{aligned} \tilde{\beta}_t =& \bar{\beta} + \underbrace{\frac{1}{h}\left(\sum_{i=1}^{h} \epsilon_{surprise,t+i} + \sum_{i=0}^{h-1} \epsilon_{news,t-i}\right)}_{\text{Technology process}} + ... \\ & ... + \underbrace{\frac{1}{h}\left(\rho(\rho^h - 1) \log f(K_{t-1}/L_{t-1}) + \sum_{i=1}^{h} \rho^{h-i}\epsilon_{k,t+i} + (\rho^h - 1)\epsilon_{k,t}\right)}_{\text{Production process}}. \end{aligned} \tag{12}$$

Suppose that there is a professional forecaster that continuously forecasts output for the current period (*now-cast*, $\log y_t$) and for up to h periods ahead ($\log y_{t+h}$). If this agent is rational, this measure should bring information about her *current* perception about the level of technology h periods ahead, or, in this setup, information about the news shock in t ($\epsilon_{news,t}$). Define the forecast of current period t based on information up to $t-1$ as $\log y_{t|t-1}$.[9] 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

[9] I follow the definitions and similar notation as described in Clements (2015).

forecast of the slope of the long-run trend of output in $t-1$, as defined in equation 12, will be

$$\tilde{\beta}_{t|t-1} = \bar{\beta} + \frac{1}{h}\left(\sum_{i=1}^{h-1}\epsilon_{news,t-i}\right) + \frac{1}{h}\left(\rho(\rho^h - 1)\log f(K_{t-1}/L_{t-1})\right). \tag{13}$$

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 12) is

$$\tilde{\beta}_{t|t} = \bar{\beta} + \frac{1}{h}\left(\sum_{i=0}^{h-1}\epsilon_{news,t-i}\right) + \frac{1}{h}\left(\rho(\rho^h - 1)\log f(K_{t-1}/L_{t-1}) + (\rho^h - 1)\epsilon_{k,t}\right). \tag{14}$$

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

$$\Delta_{\tilde{\beta}} = \tilde{\beta}_{t|t} - \tilde{\beta}_{t|t-1}. \tag{15}$$

Substituting equations 13 and 14, this measure becomes

$$\begin{aligned}\Delta_{\tilde{\beta}} = &\left(\bar{\beta} + \frac{1}{h}\left(\sum_{i=0}^{h-1}\epsilon_{news,t-i}\right) + \frac{1}{h}\left(\rho(\rho^h - 1)\log f(K_{t-1}/L_{t-1}) + (\rho^h - 1)\epsilon_{k,t}\right)\right) - ...\\ &... - \left(\bar{\beta} + \frac{1}{h}\left(\sum_{i=1}^{h-1}\epsilon_{news,t-i}\right) + \frac{1}{h}\left(\rho(\rho^h - 1)\log f(K_{t-1}/L_{t-1})\right)\right)\end{aligned} \tag{16}$$

leading to

$$\Delta_{\tilde{\beta}} = \frac{1}{h}(\epsilon_{news,t} - (1-\rho^h)\epsilon_{k,t}), \tag{17}$$

which is proportional to

$$\Delta_{\tilde{\beta}} \propto \epsilon_{news,t} - (1-\rho^h)\epsilon_{k,t}. \tag{18}$$

It follows that a measure of the difference between forecasts of the slope of the long-run trend of output ($\Delta_{\tilde{\beta}}$) should be a noisy measure of the news shock $\epsilon_{news,t}$, observed today, that will change the level of technology only in $t+h$. Two implications stem from this relation. First, the capacity of the $\Delta_{\tilde{\beta}}$ measure to recover the structural news shocks relies on the degree of persistence of the short-run non-technological shocks. The higher is the persistence (ρ), the closer the measure $\Delta_{\tilde{\beta}}$ will be of the news shock $\epsilon_{news,t}$. In the limit, when $\rho \to 1$, $\Delta_{\tilde{\beta}} \to \epsilon_{news,t}$. Second, the $\Delta_{\tilde{\beta}}$ measure implies a trade-off between long-run signal and short-run non-technological noise. As the news shock is the information received today about technological changes h periods ahead, forecasts about longer forecast horizons bring more precise information about these permanent structural changes. However, the longer is the horizon h, the more contaminated the measure $\Delta_{\tilde{\beta}}$ will be of non-technological shocks. In the limit, when $h \to \infty$, $(1-\rho^h)\epsilon_{k,t} \to \epsilon_{k,t}$. Shorter horizons would imply less contamination from non-technological shocks, but also less information about long-run technological changes.

By employing the slope measure as in equation 4, the $\Delta_{\tilde{\beta}}$ measure can be easily computed using professional forecast updates as

$$\Delta_{\tilde{\beta}} \propto (\log y_{t+h|t} - \log y_{t|t}) - (\log y_{t+h|t-1} - \log y_{t|t-1}). \tag{19}$$

Finally, this implementation is akin to a difference-in-differences approach.[10] Equation 19 can be rearranged as

$$\Delta_{\tilde{\beta}} \propto (\log y_{t+h|t} - \log y_{t+h|t-1}) - (\log y_{t|t} - \log y_{t|t-1}), \tag{20}$$

or,

$$\begin{aligned}\Delta_{\tilde{\beta}} \propto &(\mathbb{E}[\log y_{t+h}|\mathbb{1}(\epsilon_{news,t})=1] - \mathbb{E}[\log y_{t+h}|\mathbb{1}(\epsilon_{news,t})=0]) - ... \\ &... - (\mathbb{E}[\log y_t|\mathbb{1}(\epsilon_{news,t})=1] - \mathbb{E}[\log y_t|\mathbb{1}(\epsilon_{news,t})=0]),\end{aligned} \tag{21}$$

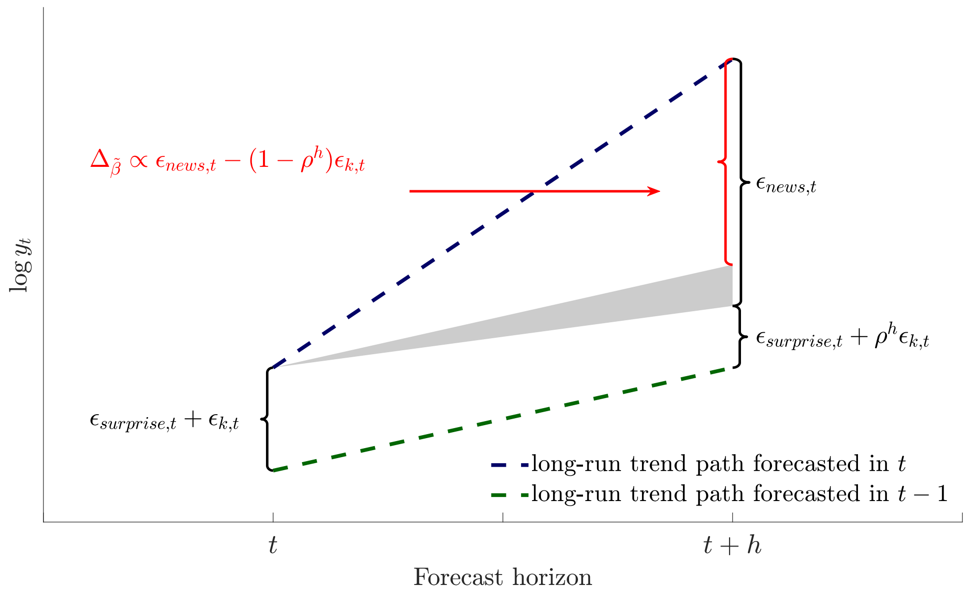
with the peculiarity that $\Delta_{\tilde{\beta}}$ is a noisy measure of the $\epsilon_{news,t}$ treatment effect, as opposed to its perfect measurement.

Figure 2 is a graphic representation of the procedure. The green line represents the implied output long-run trend path forecasted by a professional in time $t-1$, and the blue line represents her updated path in time t. The *now-cast* ($\log y_t$) revision is determined by the arrival of the surprise technological shock ($\epsilon_{surprise,t}$) and the non-technological

[10]See Meyer (1995) for a survey of the methodology and applications.

shock ($\epsilon_{k,t}$). The long-run ($\log y_{t+h}$) revision is determined by the surprise technological shock ($\epsilon_{surprise,t}$, which changes permanently the output level), the news shock ($\epsilon_{news,t}$), and the part of the non-technological shock that still persists in the long-run ($\rho^h \epsilon_{k,t}$). While the objective is to measure $\epsilon_{news,t}$, the difference-in-differences approach can only provide $\Delta_{\tilde{\beta}} \propto \epsilon_{news,t} - (1-\rho^h)\epsilon_{k,t}$. The size of the discrepancy between the structural $\epsilon_{news,t}$ and $\Delta_{\tilde{\beta}}$ is given by the gray area, which increases with h.

Figure 2 Difference-in-differences representation



The surprise technology shock $\epsilon_{surprise,t}$ shifts the forecast path upwards. Since the effect on the level is the same either in the current or in the future level of output, it is perfectly teased out by the procedure. That would also be the case if one considers a model with other permanent non-technological shocks (e.g., labor supply shocks, as in Shapiro and Watson, 1988).

The trade-off between more information with a longer forecast horizon (signal) and the discrepancy between the measure and the true structural shock (noise) raises the empirical questions of what is the minimum h to gather sufficient information about the technological news and if the discrepancy matters for the identification. In the following sections I bring empirical evidence that professional forecasters' data, even with relatively short forecast horizons, are indeed informative about the technological news, and that there are practical ways to deal with eventual contamination from non-technological shocks.

3 From forecast revisions to news shocks: identification through instrumental variables

In this section, I employ the methodology of calculating the forecast revisions about the slope of the long-run trend to construct instruments to identify technological news shocks. A news shock has the capacity of generating booms and busts based on agents' expectations about future technological improvements (Beaudry and Portier, 2006). 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 these variables. 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 such forecast revisions. For example, Bluedorn and Leigh (2018) show how forecast revisions in the current period output are accompanied by even higher forecast revisions on the ten-year-ahead output. It follows that professional forecasters are perceiving shocks today as causing a permanent long-run effect, as it is the case of a technological news shock. Under certain assumptions (discussed below), forecast revision measures can be used as external validity instruments for the identification of a news shock.

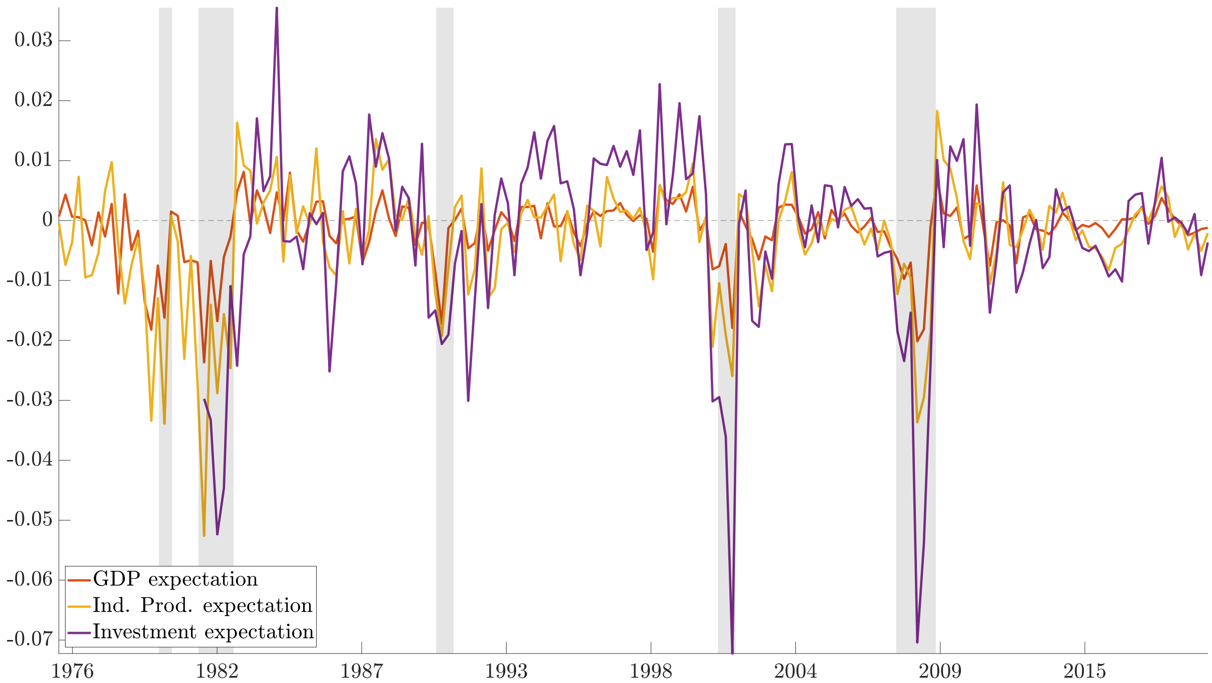
The proposed instruments are slope forecast revisions about the log of the future level of real GDP, of the log of nonresidential fixed investment, and of the log of industrial production, in the US, from the Survey of Professional Forecasters (Federal Reserve Bank of Philadelphia). This survey provides 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 19, following

$$\mathbf{Z}_t = (\mathbf{x}_{t+4|t} - \mathbf{x}_{t|t}) - (\mathbf{x}_{t+4|t-1} - \mathbf{x}_{t|t-1}), \tag{22}$$

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

These three series present similar patterns (Figure 3) and are highly correlated (Table 1); forecast revisions about future investment are more volatile than forecast revisions about future GDP and future industrial production. The most pronounced negative revisions match the recession periods identified by the National Bureau of Research Institute (NBER).

Figure 3 Forecast revisions about future GDP, investment, and industrial production



Note: Forecast revisions constructed from expectations about the 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 2019:Q4, and for investment from 1981:Q3 to 2019:Q4. Shaded areas are the recession periods calculated by the NBER.

3.1 Proxy SVAR and identification procedure

Stock and Watson (2012), Mertens and Ravn (2013), and Gertler and Karadi (2015) show how structural shocks can be empirically recovered from one or more noisy measures that are informative about them. These measures are instruments for the targeted structural shock as long as they are relevant and not correlated with other structural shocks. Here I show how the instruments from forecast revisions can be used empirically to identify a news shock, starting with a standard reduced-form VAR. Consider a model with $\mathbf{y}_t$ as

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

	Real GDP revisions	Ind. prod. revisions	Investment revisions
Real GDP revisions	1.00	0.85	0.76
Ind. prod. revisions	0.85	1.00	0.73
Investment revisions	0.76	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 2019:Q4.

a $(n \times t)$ matrix that stacks the n endogenous variables (in levels), in which utilization-adjusted TFP is ordered first. Its reduced-form structure can be modeled as

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + ... + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{u}_t, \tag{23}$$

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

$$\mathbf{y}_t = \mathbf{B}(\mathbf{L})\mathbf{u}_t. \tag{24}$$

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

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{s}_t \tag{25}$$

and

$$\mathbf{y}_t = \mathbf{C}(\mathbf{L})\mathbf{s}_t, \tag{26}$$

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

$$\mathbb{E}[\mathbf{u}_t\mathbf{u}_t'] = \mathbb{E}[\mathbf{A}_0\mathbf{A}_0'] = \underset{n\times n}{\mathbf{\Sigma}}. \tag{27}$$

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

Let $\mathbf{Z}_t$ be a $(t \times k)$ matrix of proxies correlated to the $(1 \times t)$ structural shock $s_{news,t}$, and $\mathbf{s}_{2,t}$ an $(n-1 \times t)$ 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 two conditions:

$$\begin{aligned} &(i) \quad \mathbb{E}[z_t s'_{news,t}] = \underset{1\times 1}{\phi} \quad \text{(relevance)}, \\ &(ii) \quad \mathbb{E}[z_t \mathbf{s}'_{2,t}] = \underset{1\times(n-1)}{\mathbf{0}} \quad \text{(exogeneity)}, \end{aligned} \tag{28}$$

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 $\mathbf{Z}_t$ are correlated with the structural news shock $s_{news,t}$. 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

$$\mathbf{A}_0 = \begin{bmatrix} \underset{n\times 1}{\mathbf{\Lambda}_1} & \underset{n\times(n-1)}{\mathbf{\Lambda}_2} \end{bmatrix}, \quad \mathbf{\Lambda}_1 = \begin{bmatrix} \underset{1\times 1}{\lambda_{11}} \\ \underset{(n-1)\times 1}{\boldsymbol{\lambda}'_{21}} \end{bmatrix}, \quad \mathbf{\Lambda}_2 = \begin{bmatrix} \underset{1\times(n-1)}{\boldsymbol{\lambda}_{12}} \\ \underset{(n-1)\times(n-1)}{\boldsymbol{\lambda}_{22}} \end{bmatrix}, \tag{29}$$

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

$$\phi \underset{1\times n}{\mathbf{\Lambda}_1'} = \mathbb{E}[z_t \mathbf{u}_t']. \tag{30}$$

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

$$\mathbb{E}[z_t \mathbf{u}_t'] = \begin{bmatrix} \underset{1\times 1}{\mathbb{E}[z_t u_{1,t}']} & \underset{1\times(n-1)}{\mathbb{E}[z_t \mathbf{u}_{2,t}']} \end{bmatrix}, \tag{31}$$

where $\mathbf{u}_{2,t}$ collects all $(n-1)$ innovations other than the first $(u_{1,t})$, it is possible to rewrite equation 30 as

$$\frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}} = \left(\mathbb{E}[z_t u_{1,t}']^{-1}\mathbb{E}[z_t \mathbf{u}_{2,t}']\right)'. \tag{32}$$

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

$$\mathbf{u}_{2,t} = \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}} \hat{u}_{1,t} + \xi_t, \tag{33}$$

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

$$\mathbf{\Sigma} = \begin{bmatrix} \Sigma_{11} & \mathbf{\Sigma}_{12} \\ \mathbf{\Sigma}_{21} & \mathbf{\Sigma}_{22} \end{bmatrix}, \tag{34}$$

$\boldsymbol{\lambda}_{21}$ and λ_{11} can be identified by applying the restrictions from equation 27 following the closed form solution[11]

$$\lambda_{11}^2 = \Sigma_{11} - \boldsymbol{\lambda}_{12}\boldsymbol{\lambda}_{12}', \tag{35}$$

where

$$\begin{aligned} \boldsymbol{\lambda}_{12}\boldsymbol{\lambda}_{12}' &= \left(\mathbf{\Sigma}_{21} - \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\Sigma_{11}\right)' \mathbf{Q}^{-1} \left(\mathbf{\Sigma}_{21} - \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\Sigma_{11}\right), \\ \mathbf{Q} &= \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\Sigma_{11}\frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}' - \left(\mathbf{\Sigma}_{21}\frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}' + \frac{\boldsymbol{\lambda}_{21}}{\lambda_{11}}\mathbf{\Sigma}_{21}'\right) + \mathbf{\Sigma}_{22}. \end{aligned} \tag{36}$$

[11] As demonstrated by Mertens and Ravn (2013) and Gertler and Karadi (2015).

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. The restrictions described in equation 32 are sufficient for identification up to sign convention for the case of a single shock (Mertens and Ravn, 2013).

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

1. Estimate the reduced-form VAR;
2. Estimate $\mathbb{E}[z_t u'_{1,t}]^{-1}\mathbb{E}[z_t \mathbf{u}'_{2,t}]$ by the 2SLS regression of the VAR residuals on $\mathbf{Z}_t$;
3. Find the impact effects of a news shock by imposing the restrictions in equation 32.

3.2 Information set and Bayesian VAR estimation

As a common practice in the literature,[12] I take the utilization-adjusted TFP series constructed by Fernald (2014) as a proxy for the technological level of the U.S. 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 2019:Q4. It contains 14 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 (proxied by the stock market realized volatility), consumer confidence (measured by the Michigan Consumer Survey), price of investment, capacity utilization, 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 14 variables can be found in Table B.1 in the Appendix.

I estimate the model under a Bayesian VAR (BVAR) approach 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 them. I employ the Minnesota priors (Litterman,

[12] See, for example, Beaudry and Portier (2006), Barsky and Sims (2011), Kurmann and Otrok (2013), Cascaldi-Garcia and Galvão (2021), among others.

1986) to address the reasonably large number of endogenous variables. The estimation of the model and the prior hyper-parameters follow methodology proposed by Gianonne, Lenza, and Primiceri (2015), with 20,000 posterior draws. I compute the coverage bands for the impulse response graphs using 1,000 draws, storing every 20^{th} of the 20,000 total draws from the posterior distribution.[13]

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. 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 troublesome for other types of news, such as news about tax, government spending, or oil prices. Second, the forecast revision measures 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 extract signals about changes in the long-run trend of the economy.

Following Piffer and Podstawski (2018), 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 six different economic shocks: news about tax shocks, news about government defense spending, oil price shocks, monetary policy shocks, tax shocks,

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

and technological shocks.[14]

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 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 assumption is that technology is an exogenous variable that is driven by only two shocks: the news shock and the surprise technological shock, as in equation 6. 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

$$z_t^i = \mu_0 + \mu_{1,j} d_{j,t} + v_{j,t}, \tag{37}$$

where i indicates the instrument as 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 exogeneity tests, summarized in Table 2, show that the instrument measures pro-

[14] Apart from the technological shocks, all other economic shocks are 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.

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	0.65	0.39	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	-0.07	0.96	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	0.89	0.28	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.

posed 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 17 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 forecast revisions about investment only correlates with monetary policy.

In light of this evidence, I employ an agnostic approach of filtering the instruments from 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 from the effects of an economic activity factor to ensure that the forecast revision measures proposed only carry information acquired in time t. I proxy the economic activity by the first factor of the real activity dataset calculated by Stock and Watson (2016).[15]

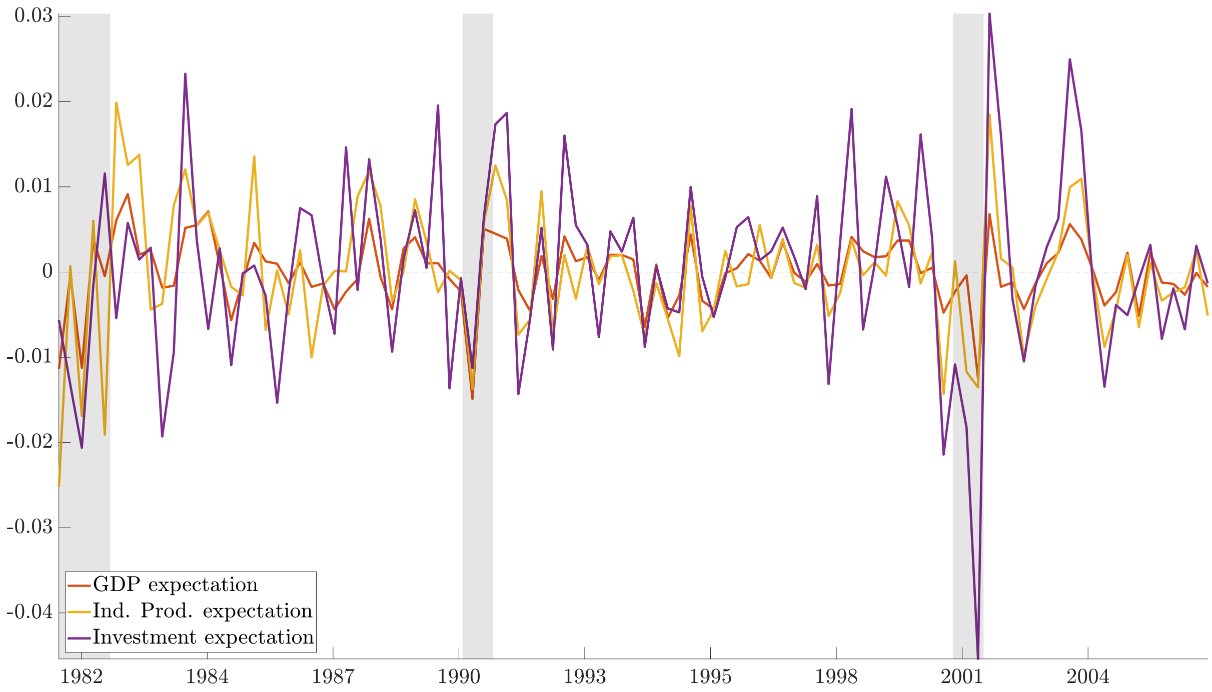
I construct a measure $\tilde{\mathbf{Z}}_t$ as the residual from projecting $\mathbf{Z}_t$ on $\mathbf{d}_t$, on $u_{1,t}$, and on five lags of the Stock and Watson (2016) economic activity factor F_t, as in

$$\mathbf{Z}_t = \mu_1 \mathbf{d}_t + \mu_2 u_{1,t} + \mathbf{M}(\mathbf{L}) F_t + \tilde{\mathbf{Z}}_t, \tag{38}$$

and use $\tilde{\mathbf{Z}}_t$ as 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 4 presents the three instruments after the filtering process, as the mean over 1,000 posterior draws. These filtered proxies are the benchmark employed to produce the results presented in the next section. In section 5.3 I present the results of an alternative instrument constructed with IMF forecasts, which do not require the filtering process described here.

[15]Dataset and replication files available at Mark Watson's website.

Figure 4 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.

Finally, the instruments are shorter than the information set due to data availability. I follow the same approach of Gertler and Karadi (2015) by performing the identification over the sub-sample where the instruments are available (1981:Q3 to 2006:Q3). As long as the instruments are indeed correlated with the targeted structural news shock, and not to other structural shocks, having instruments shorter than the estimation sample is not an issue, as the identification from the shorter sample can be applied to the whole sample. Following the steps described in section 3.1, I first estimate the reduced-form VAR over the whole sample (1975:Q1 to 2019:Q4), identify the news shock using the instruments and sub-sample of the reduced-form residuals $\mathbf{u}_t$ from 1981:Q3 to 2006:Q3, and then construct the impulse response functions from the estimated coefficients over the whole sample.

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 BVAR with 14 variables, testing the strength of the instruments and presenting the impulse responses of the identified news shock. Next, I compare the results from the BVAR with the results from the most standard identification procedure in the news shock literature, based on the maximization of the variance decomposition (Barsky and Sims, 2011).

4.1 Strength of the instruments

Following Gertler and Karadi (2015) and Piffer and Podstawski (2018), 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 28); 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 23. It follows that, if the instruments are correlated with the structural shock, they should also be correlated with $\mathbf{u}_t$.

The problem with such a test is that it only captures the contemporaneous relation between the instrument and the target variables. An instrument for monetary policy shock, for example, should have a contemporaneous effect on short-term interest rates, and the instrument can be tested if it helps explaining the residuals of this target variable. Testing for the strength of technological news shocks, however, is more complicated than other contemporaneous shocks, as the main target variable (utilization-adjusted TFP) is expected to *not* react on impact. I follow an alternative procedure by testing the strength on selected forward looking variables that can potentially react contemporaneously to the news shock (e.g, confidence, stock prices, and GDP).[16]

The idea of the test is to take each of the reduced-form innovations $u_{i,t}$ from $\mathbf{u}_t$ and

[16] The test for all the variables in the information set is presented in Table B.2 in the Appendix.

regress them against the filtered instruments $\tilde{\mathbf{Z}}_t = [\tilde{z}_t^{gdp}, \tilde{z}_t^{ip}, \tilde{z}_t^{inv}]$, as in

$$u_{i,t} = \alpha + \theta_i \tilde{\mathbf{Z}}_t + \eta_i, \quad i = 2, ..., n, \tag{39}$$

where θ_i collects the coefficients for the instruments. I test if the coefficients θ_i are individually (or 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 confidence, stock prices, and GDP. The predictive power of the instruments over these variables is also relevant, varying between 10% and 27%. Taking individually, the instrument of forecast revisions about GDP is significant for all three variables, the forecast revisions about industrial production is significant for confidence and GDP, and the forecast revisions about investment is significant for confidence and stock prices.

Table 3 Instrument relevance tests

	$\tilde{z}_t^{gdp}$		$\tilde{z}_t^{ip}$		$\tilde{z}_t^{inv}$		$\tilde{\mathbf{Z}}_t$ jointly	
	F-stat.	R^2	F-stat.	R^2	F-stat.	R^2	F-stat.	R^2
Confidence	34.4	0.26	17.8	0.15	19.1	0.16	11.9	0.27
	(0.00)		(0.00)		(0.00)		(0.00)	
Stock Prices	9.9	0.09	0.8	0.01	6.8	0.06	6.0	0.16
	(0.00)		(0.37)		(0.01)		(0.00)	
GDP	6.9	0.06	10.3	0.09	0.8	0.01	3.8	0.10
	(0.01)		(0.00)		(0.36)		(0.01)	

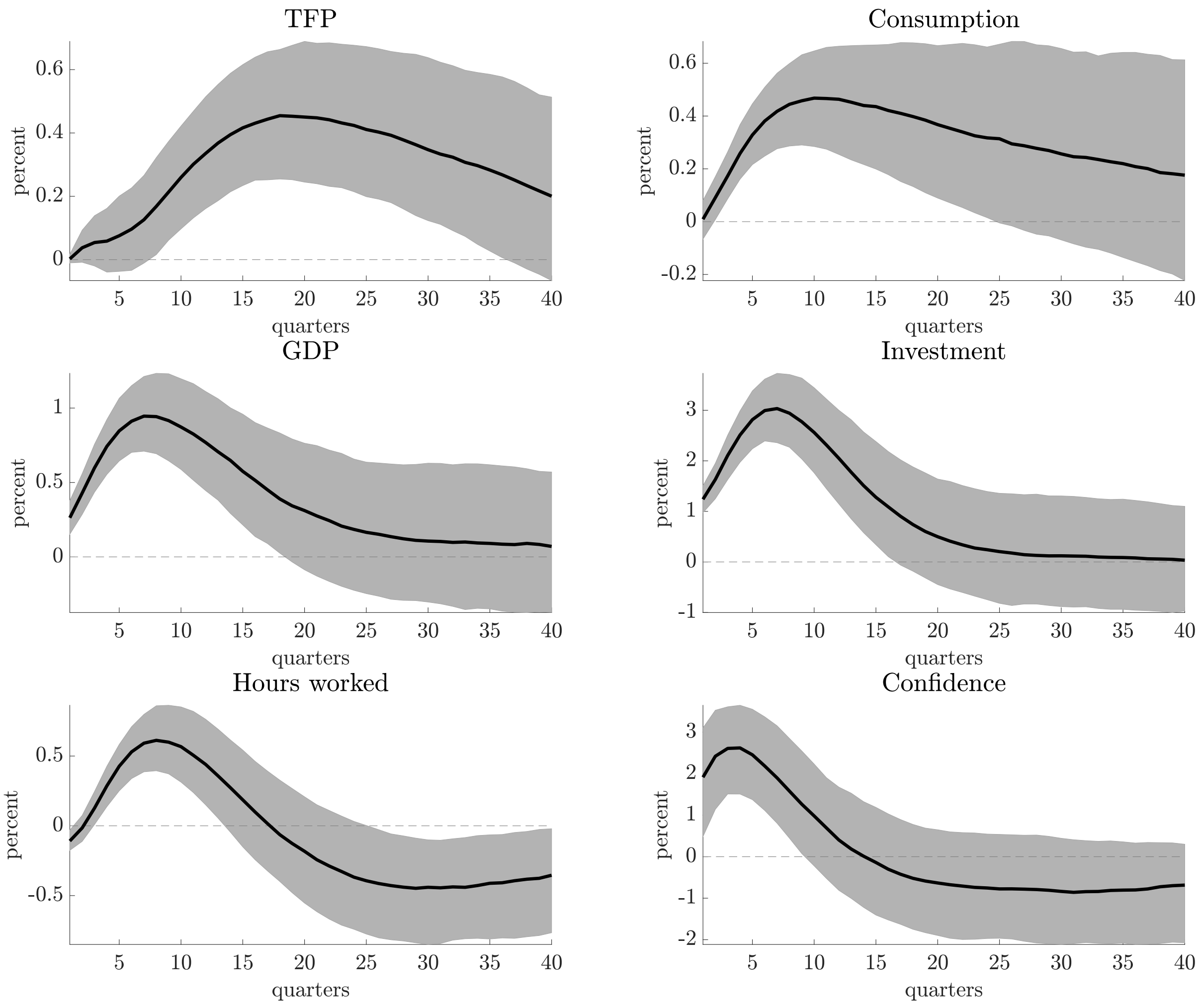
Note: F-statistics calculated by testing if the coefficients of the (filtered) forecast revisions about GDP, industrial production, and investment are individually or jointly significant in explaining the residuals from the VAR corresponding to each variable in the first column, as in equation 39. Numbers in parentheses are p-values. 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 includes all variables in Table B.1 in the Appendix.

The strong relation of the instruments with confidence 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 and increased consumer confidence, indicating that agents foresee information about future technological opportunities.

4.2 Economic responses to a news shock identified with instrumental variables

Figures 5 and 6 present the impulse responses after a news shock identified with instrumental variables. The gray area defines the 68% coverage bands computed with 1,000 posterior draws, and incorporates parameter uncertainty.[17]

Figure 5 Impulse responses to a news shock under an instrumental variable approach (main variables)



Note: Impulse responses for selected variables of a news shock computed by employing instrumental variables, estimated with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The gray area defines the 68% coverage bands computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

[17] For every posterior draw, the instruments are filtered taking into consideration the new residual $u_{1,t}$ (as described by equation 38). The resulting filtered instruments are then used for the identification on that specific draw.

The first important result from Figure 5 is the effect of the identified shock on utilization-adjusted TFP, a proxy for the technological level of the economy. Considering that technology follows an exogenous process, 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 38). This imposition is equivalent to the short-run restriction employed by Beaudry and Portier (2006) and Barsky and Sims (2011). Figure C.1 in the Appendix presents the impulse responses of a news shock relaxing this restriction.[18] After around five quarters, utilization-adjusted TFP becomes significantly positive, reaching its highest level after around 20 quarters. The effect diminishes in the long-run, but remains positive.

The utilization-adjusted TFP response is in line with the expected path that news shocks should cause on the technological level of the economy (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 other macroeconomic variables that there is a positive and significant reaction on impact. GDP jumps around 0.3% on impact, driven mainly by the strong effect on investment (about 1.4% on impact). Consumer confidence increases by about 2%, in line with the idea that positive news makes the consumers more optimistic.[19]

The effect on consumption is zero on impact, showing no initial anticipation from the consumers to the news shock. Over time, consumption grows to a new higher level faster than utilization-adjusted TFP. While utilization-adjusted only reaches its peak after around 18 quarters, consumption reaches its maximum effect earlier, after around 10 quarters. This difference in timing evidences some mild anticipation effect in the medium-run.

Hours worked does not react on impact. The response quickly becomes positive,

[18]While utilization-adjusted TFP jumps on impact, the responses to consumption, GDP, investment, hours worked, GDP deflator, stock prices, and confidence are qualitatively similar to the ones presented in Figures 5 and 6. This result indicates that the instruments proposed here also carry information about the surprise technology shock, but the economic effects of this extra information is small.

[19]See, for example, Beaudry and Portier (2006), Barsky and Sims (2011), Milani (2017), Angeletos, Collard, and Dellas (2018), Fève and Guay (2019), and Levchenko and Pandalai-Nayar (2020).

reaching a peak of almost 0.6% after two years. There is a debate on the literature about what is the expected effect of a news shock on hours worked. Beaudry and Portier (2006) show that a news shock generates a positive and significant effect on hours (consistent with the results from Christiano et al., 2003), while Barsky and Sims (2011) present a negative effect of news on hours (in line with the technological shock from Galí, 1999). The positive effect in hours worked 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).

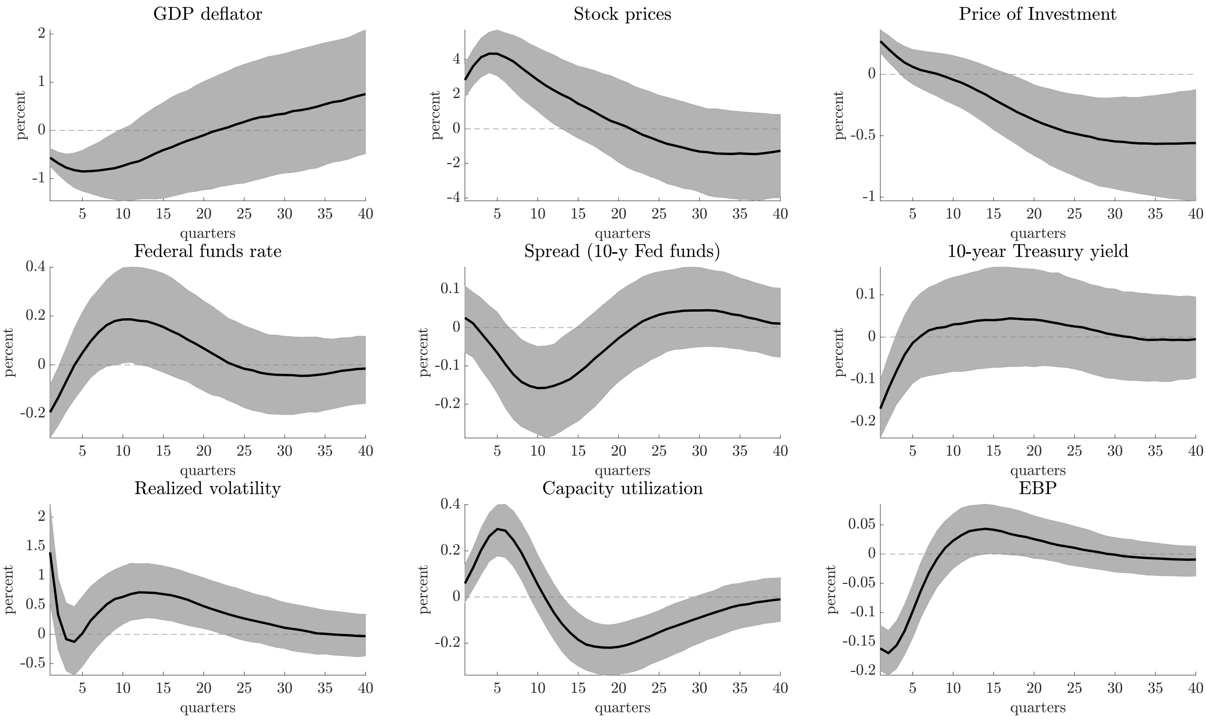
The strong reaction on investment, slow increase in consumption, and positive effect on hours worked corroborate the findings of Görtz and Tsoukalas (2017), who extend the Schmitt-Grohe and Uribe (2012) DSGE model to accommodate financial frictions, which amplifies the news shock effect through a strong lending and investment phase. As in the empirical results presented here, their model favors a news shock transmission in which investment demand drives the cycle. The positive effects on hours is explained by nominal price and wage rigidities, which produce positive shifts in labor demand and labor supply, offsetting the income effect from the increased productivity.

Figure 6 presents the economic responses to a news shock on the other variables in the BVAR. 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 the GDP deflator is also in line with the characterization of a news shock as a 'supply shock,' ruling out the possibility that the identification is capturing pressures from the demand side. The Federal funds rate falls by about 0.2 p.p as a response to the deflationary effect, while there is virtually no effect on the slope of the term structure. This result is consistent with the mild effects on the spread of the term structure after a news shock presented by Cascaldi-Garcia (2017), and contributes to the literature that discusses the effectiveness of the monetary policy on reacting to news shocks.[20]

The effect on stock prices is positive of around 3% on impact, showing a strong

[20]See Kurmann and Otrok (2013) and Gambetti, Görtz, Korobilis, Tsoukalas, and Zanetti (2021).

Figure 6 Impulse responses to a news shock under an instrumental variable approach (additional variables)



Note: Impulse responses for selected variables of a news shock computed by employing instrumental variables, estimated with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The gray area defines the 68% coverage bands computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

reaction from the market to the news about future technology. The effect converges back to zero in the medium-run, consistent with the efficiency of the stock market. The price of investment reaction on impact is close to zero, in line with a neutral technological shock.[21] Financial uncertainty is proxied by the realized volatility, and it increases in the short-run. Cascaldi-Garcia and Galvão (2021) find similar results for news shocks identified with information sets augmented by several measures of financial uncertainty, one at a time. Capacity utilization shows some positive adjustment in the short-run, and negative in the medium-run. Excess bond premium falls on impact, representing a reduction on the overall cost of credit.

Table 4 presents the variance decompositions after a news shock for selected variables. Proxy VAR setups impose an extra complication for variance decomposition calculations.

[21] Fisher (2006) presents the theoretical implications of neutral and investment-specific technological shocks and its effects on the relative price of investments.

The correlation between the instruments and the true structural shock is not known, which may cause scale issues.[22] In the light of this potential problem, Table 4 presents the median and the 16% and 84% coverage bands of the variance decomposition over the BVAR posterior draws. 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	Output			Consumption			Investment			Hours worked		
	16%	50%	84%	16%	50%	84%	16%	50%	84%	16%	50%	84%
0	5.1	11.0	18.4	0.2	1.7	5.5	14.0	23.1	32.4	0.0	0.5	2.2
8	15.7	25.8	37.7	7.1	15.8	26.5	21.8	33.4	46.3	4.5	10.4	18.8
16	10.2	20.6	32.3	5.8	15.5	27.4	14.8	24.8	37.0	3.5	7.5	15.0
24	8.2	16.5	27.6	4.3	12.9	25.5	11.7	20.6	31.7	4.4	8.9	15.4
36	6.3	13.7	23.9	3.4	10.6	22.2	9.5	17.9	28.7	5.0	10.6	19.2

Note: Variance decomposition of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975:Q1 to 2019:Q4. h denotes the forecast horizon. The 68% coverage bands computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

GDP and investment react to the news shock instantaneously. The news shock explains 11.0% (median) of the unpredictable movements of GDP on impact, but the coverage bands are wide (from 5.1% to 18.4%). This share is of 23.1% for investment on impact, with coverage bands of 14.0% to 32.4%. The immediate effect of the news shock on consumption and hours worked is around zero, in line with the low explained part of the shock on impact (median of 1.7% for consumption and 0.5% for hours worked). After two years the explanation power of the news shock for these variables rises to 15.8% for consumption and 10.4% for hours worked. The explanation power for output and investment also peaks after two years: 25.8% and 33.4%, respectively.

[22] On one hand, Plagborg-Møller and Wolf (2021) argue that existing methods for identification through instrumental variables do not answer the question of how important the shocks are in driving business cycles without recoverability assumptions. On the other hand, Stock and Watson (2018) say that variance decompositions can be calculated as long as the VAR is invertible.

4.3 Instrumental variables *versus* maximization of the 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 Barsky and Sims (2011)' identification for news shocks is to find the orthogonalization among the innovations that best explains unpredictable movements of utilization-adjusted TFP over a predefined medium-run forecast horizon, conditional on being orthogonal to surprise changes on the same variable. The procedure was built upon Faust (1998), Uhlig (2005), and Francis, Owyang, Roush, and DiCecio (2014), and has been employed by several papers in the news shock literature.[23] The full identification procedure is described in Appendix A.

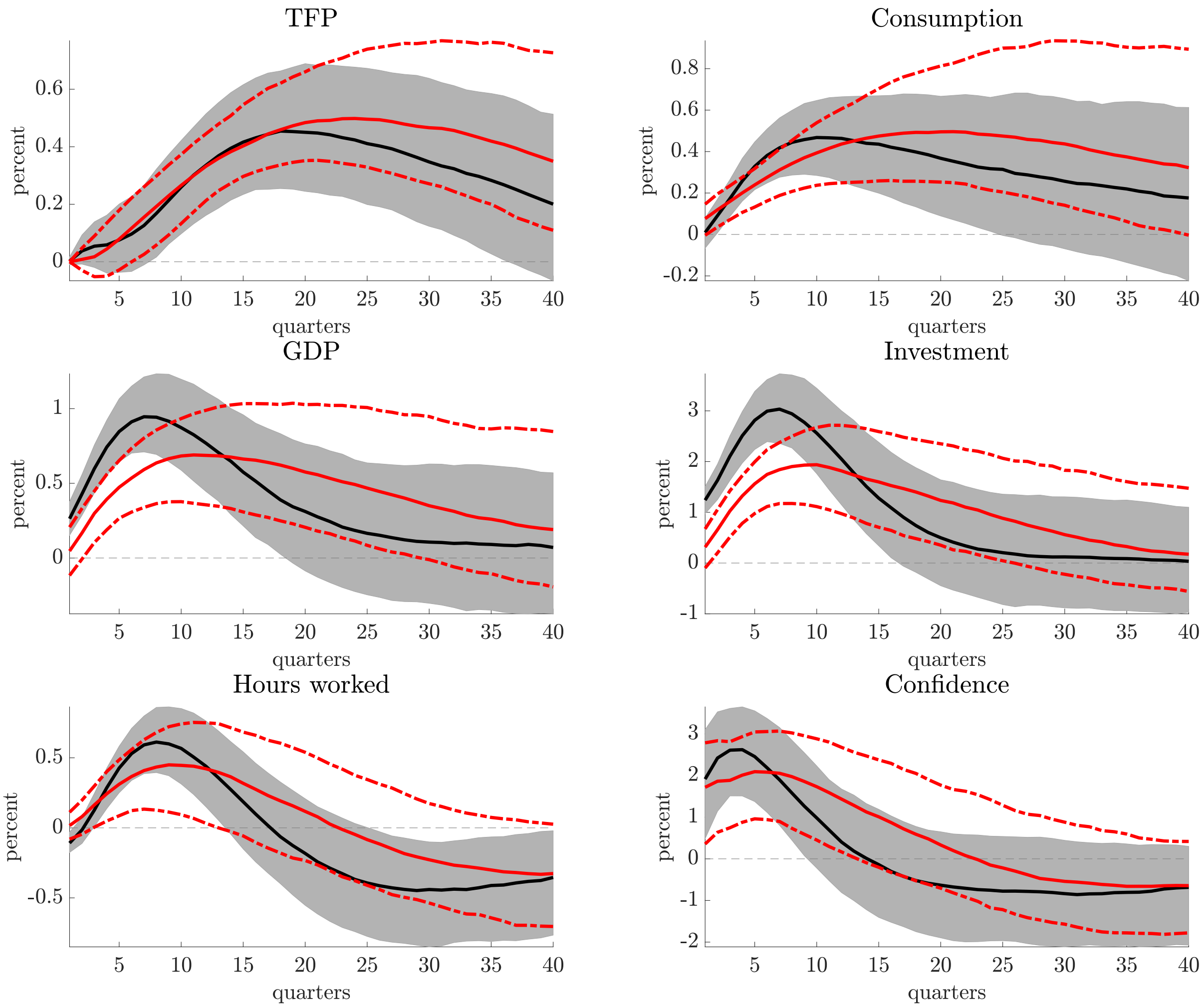
I compare the results from the identification with instrumental variables by employing the same database, period, and BVAR estimation described in subsection 3.2, but identifying the news shock as in Barsky and Sims (2011). Figure 7 compares the impulse response functions of selected variables for the identification based on the instrumental variables approach (in black) and on maximizing the variance decomposition (in red). The impulse response functions for the other variables in the BVAR can be found in Figure C.3 in the Appendix.

The impulse responses evidence that both identification procedures produce qualitatively similar results. However, the coverage bands of the identification using the Barsky and Sims (2011) approach are wider than the ones from the instrumental variables approach, particularly in the short-run.[24] The economic effects on investment and, consequently, on GDP are higher with the instrumental variables procedure. The effects on utilization-adjusted TFP and on consumption are very similar on impact, but more intense in the long run using the Barsky and Sims (2011) identification.

[23] See, for example, Kurmann and Otrok (2013), Beaudry and Portier (2014), Levchenko and Pandalai-Nayar (2020), Cascaldi-Garcia and Galvão (2021), Angeletos, Collard, and Dellas (2020), Görtz et al. (2020), Clements and Galvão (2021), among others.

[24] I employ the same posterior draws for each procedure, and identify the news shock both with instrumental variables and with the Barsky and Sims (2011) approach for every draw.

Figure 7 Impulse responses to a news shock identified with the instrumental variables (black) and the Barsky and Sims (2011) (red) approaches (main variables)



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), estimated with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification of the instrumental variables procedure conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The dotted red lines define the 68% coverage bands for the Barsky and Sims (2011) approach, the gray area the coverage bands for the instrumental variables approach, all computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

The effect on hours worked on impact is essentially zero for both approaches. In the medium-run, the instrumental variables approach presents a significantly positive effect, while Barsky and Sims (2011) coverage bands are 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). The effect on confidence is positive with both identification strategies, but it is more persistent with the Barsky and Sims (2011) approach.

Figure 8 helps to better understand the different effects of anticipation from the economic agents to future technological developments. The figure presents histograms of the effect on impact (h=0) to a news shock identified with the instrumental variables (in blue) and the Barsky and Sims (2011) (in red) approaches. On impact, the effect on utilization-adjusted TFP is zero with both identification strategies, and the effect on other economic variables represent the anticipation to the future increase in TFP.

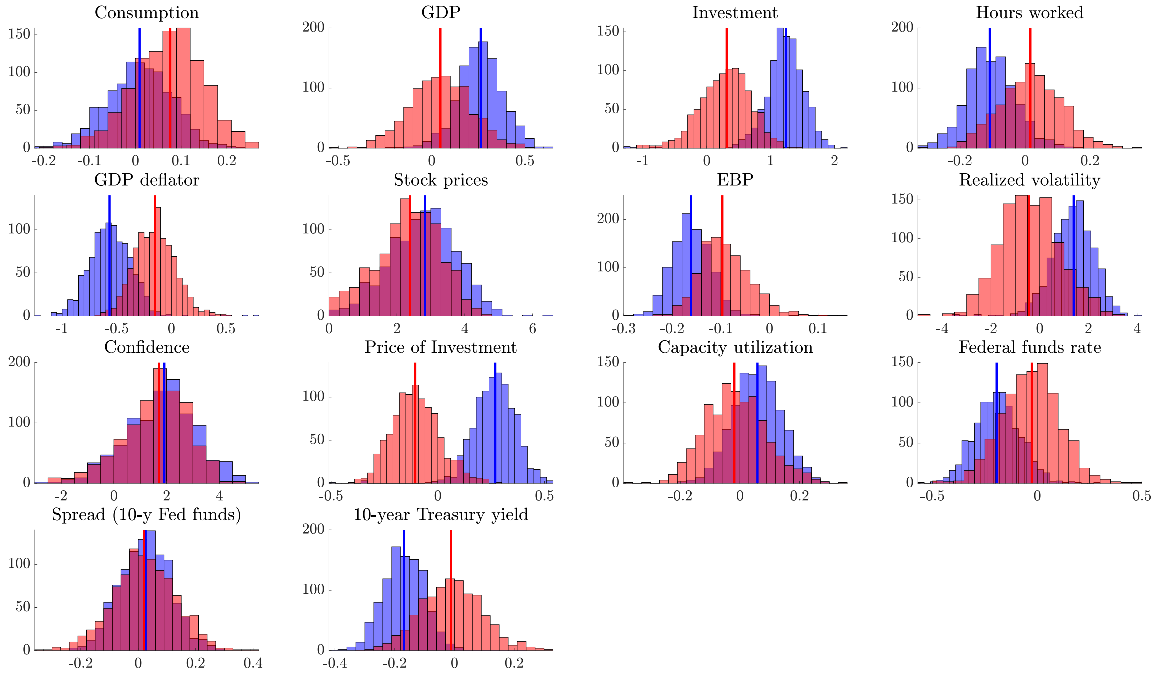
Some key comparisons are worth highlighting. The effect on consumption on impact is very similar with both approaches, and the coverage bands do not rule out a zero effect. However, the anticipation effect on GDP and investment is substantially stronger (and significant) with the instrumental variables approach. The effect on the GDP deflator is more deflationary with the instrumental variables, which justifies the stronger loosening on the Federal funds rate. Both procedures show a zero effect on impact on the spread of the term structure.

I also compare the reconstructed historical path of the news shock from the instrumental variables approach and from the Barsky and Sims (2011) approach, presented in Figure 9. The movements of both shocks are very similar. The series with the instrumental variables is somewhat less volatile, with a standard deviation of 0.49 in comparison to the 0.65 of the Barsky and Sims (2011) series. The two series share a correlation of 0.59 which, together with the similarity of the impulse responses, confirms the power of the instrumental variables on empirically recovering what is understood by the literature as a technological news shock.

5 Robustness checks

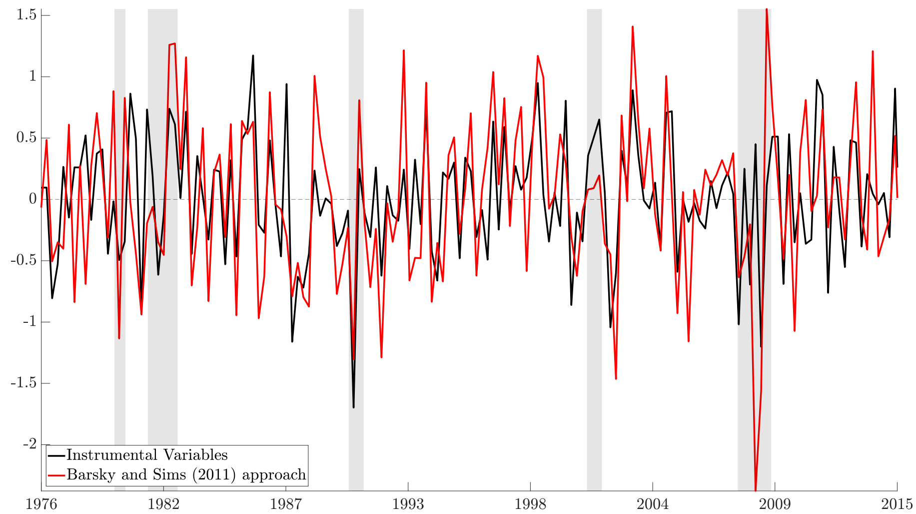
In this section I present three robustness checks. First, I show that the SPF instruments are able to qualitatively recover the theoretical news shock even in a small-scale VAR with three variables. Second, I present an identification with placebo instruments, showing that the SPF instruments indeed matter for the proper identification of the news shock.

Figure 8 Distribution of impact effects to a news shock identified with the instrumental variables (blue) and the Barsky and Sims (2011) (red) approaches



Note: Distribution of impact effects computed by employing the identification procedure of maximizing the variance decomposition (red) described in Appendix A, and by employing the instrumental variables approach (blue), estimated with quarterly data ranging from 1975:Q1 to 2019:Q4. Impact effects on utilization-adjusted TFP not shown here because it is zero by construction. Identification of the instrumental variables procedure conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. Histograms constructed over all 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

Figure 9 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), estimated with quarterly data ranging from 1975:Q1 to 2019:Q4. The series are the median across 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

Finally, I present an alternative instrument constructed with forecasts provided by the IMF. The advantage of this series is that the forecast horizon is longer than the SPF, and the results are qualitatively similar to the ones obtained with the SPF instruments.

5.1 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, investment, hours worked, or consumption.[25] The models are estimated as a vector error correction model (VECM) with four lags and two cointegration relationships. Figure 10 presents the impulse responses for each model, with confidence, investment, hours worked, and consumption as the third variable.

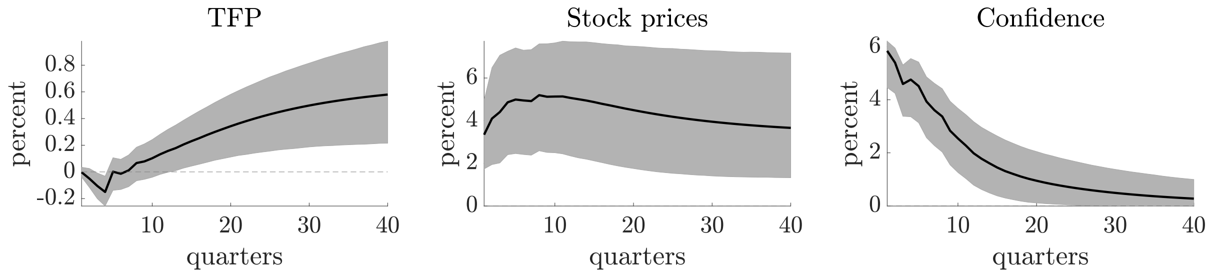
As before, the effect of the news shock identified with instrumental variables on utilization-adjusted TFP is zero on impact. Utilization-adjusted TFP grows to a new higher level in the long-run, regardless of which of the four models is considered. The effect on utilization-adjusted TFP only becomes 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 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 model for consumption, but there is no clear reversion for the other three models. These results indicate that the identification of the news shock is considerably sensitive to model specification.

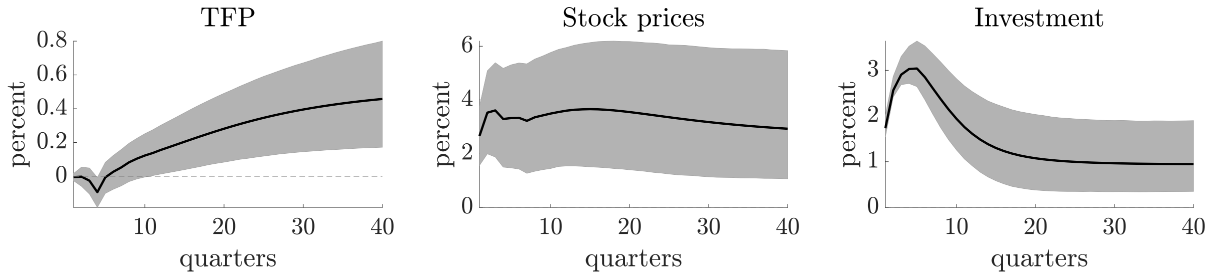
Consumer confidence jumps on impact with the news shock, converging back to zero in the long-run. Investment shows a positive effect on impact, achieving its highest effect after around six quarters, and converging to a new higher level in the long-run. The

[25] Series constructed as described in Table B.1 in the Appendix.

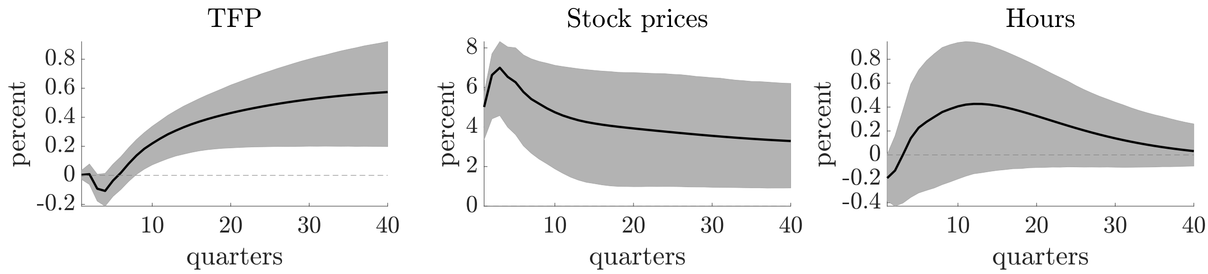
Figure 10 Impulse responses for a news shock identified with instrumental variables in a three-variables model



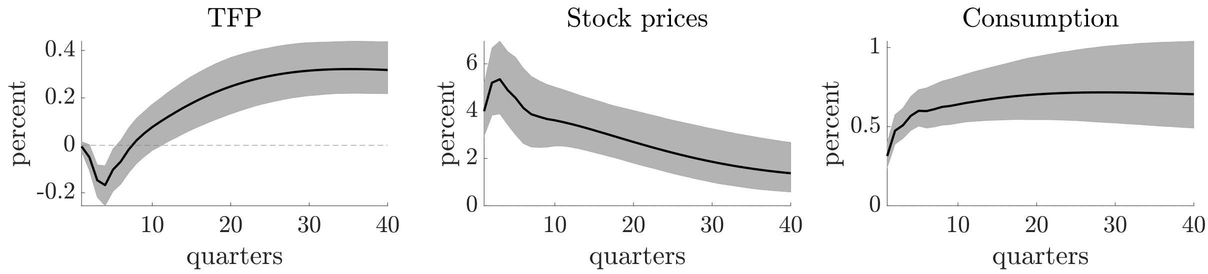
(a) TFP, Stock prices and Confidence



(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 VECM with three variables, with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The gray area defines the 68% coverage bands computed with Bayesian simulated distribution by Monte-Carlo integration with 10,000 draws. The models are estimated with four lags, as a VAR in levels.

effect on hours worked is positive after around 12 quarters and reverts back to zero in the long-run, but the coverage bands do not rule out a zero effect. 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 10 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.

5.2 Placebo instruments

In this subsection I evaluate whether the impulse responses observed in Figures 5 and 6 are indeed driven by the instruments, and not by some statistical anomaly from the identification procedure. Here, I identify the news shock with placebo instruments, constructed by randomly scrambling the data of the three instruments over time, and identifying the news shock for each set of placebos following the exact same procedure described in section 3. I repeat the scrambling and identification procedure 100 times, and present the results of the distribution over all these identifications.

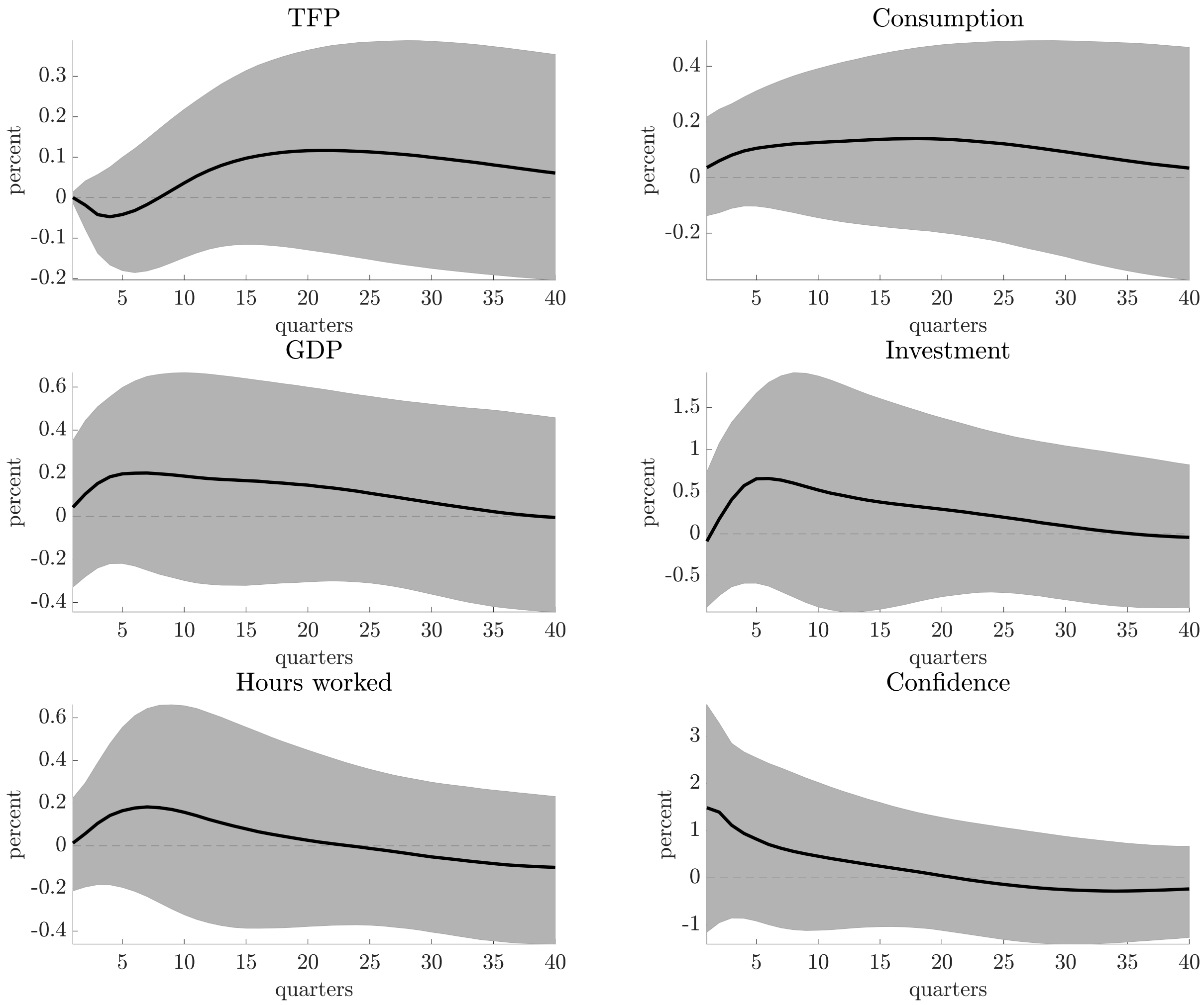
Figure 11 presents the impulse responses for selected variables of the news shock identified with placebos.[26] As expected, a news shock identified with placebo instruments produce no economic results. The coverage bands are large, and include a zero effect for the whole forecast horizon for all variables. It follows that the instruments proposed here do carry important information about the expectation of the future level of technology.

5.3 IMF forecasts with longer horizon

As discussed in section 3.3, one potential problem of the SPF forecasts is that they may not be long enough to carry substantial information about long-run structural changes. In this subsection I produce a robustness check with an alternative measure with forecasts of a longer horizon. The International Monetary Fund (IMF) provides forecasts for a

[26]The full impulse response functions for the placebo identification can be found in Figure C.4 in the Appendix.

Figure 11 Impulse responses to a news shock identified with placebo instruments (main variables)



Note: Impulse responses for selected variables of a news shock computed by employing placebo instrumental variables, with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The gray area defines the 68% coverage bands computed with 1,000 posterior draws and 100 different randomly scrambled placebos. The VAR includes all variables in Table B.1 in the Appendix.

series of economic indicators, including GDP, up to five years ahead. The forecasts are produced twice a year, since 1990, at the Spring and Fall editions (usually April and October) of the World Economic Outlook (WEO) report.[27] I construct the instrument with the same procedure described in section 3, but now taking the five years ahead annual forecasts of the (log) level of GDP.

[27] Since July/2007, the IMF started releasing WEO updates in June/July and January, and an additional update in November/2008. However, the WEO updates only release short-run forecasts (current and next year), so there is no information about the long-run assumptions. This limitation makes it infeasible to use the WEO updates for news shock identification purposes.

While this series has the advantage of a longer forecast horizon than the SPF (five years, instead of four quarters), it also has two shortcomings. First, it is constructed based on only one forecaster (IMF), while the SPF compiles data over several forecasters.[28] The forecast may be biased towards more optimistic, pessimistic, or judgmental evaluations from the forecaster. Taking the mean of the forecasts produced by the SPF minimizes those biases, favoring SPF data over forecasts from only one source.

Second, the fact that IMF forecasts are only released on the second and fourth quarters of the year implies that news acquired at the first and third quarters will only show up on the subsequent forecast. If this is the case, the agents (and so the econometrician) already had information about the economy one period before the identification of the shock, and expectations may be confounded with realizations. I deal with this shortcoming with two alternatives: by smoothing the information between the current and previous period, implying that half of the information acquired in the second quarter was already known in the first quarter; and by considering a value zero for the quarters with no information. While I employ the smoothed series as a benchmark here, I present the results for the un-smoothed version in the Appendix. Figure 12 shows the smoothed (benchmark) and un-smoothed versions of the instrument constructed with the IMF forecasts.

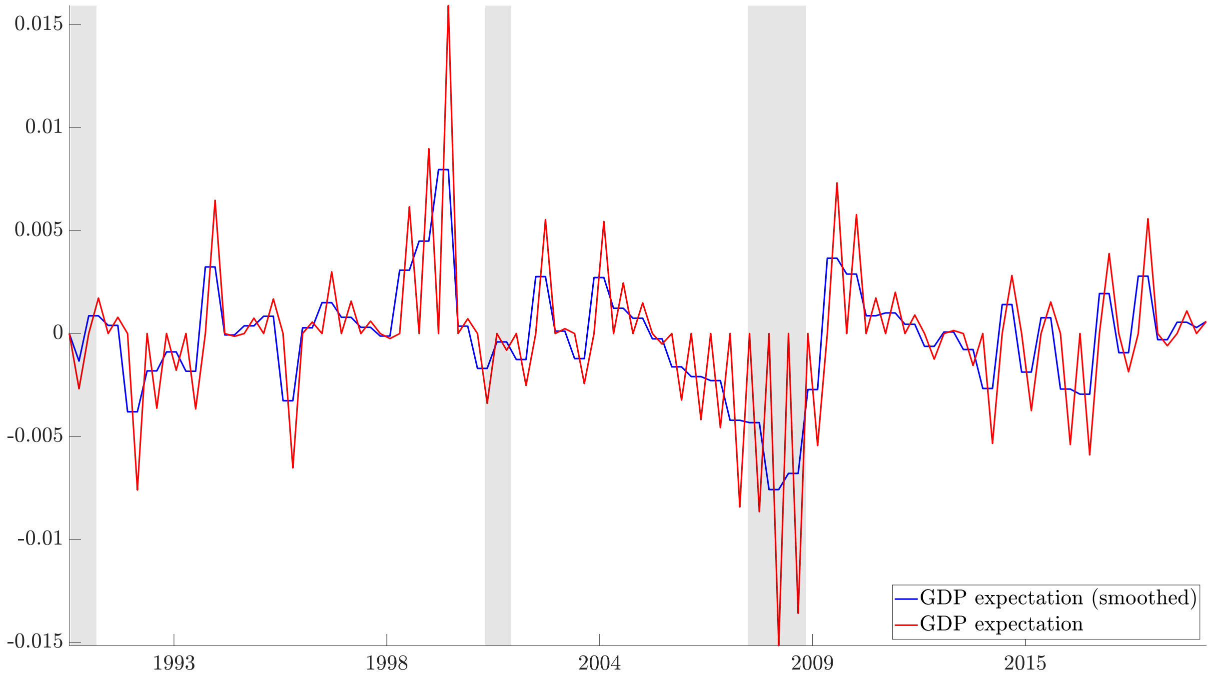
Table 5 presents the exogeneity tests of the smoothed series against the same identified shocks from the literature employed in section 3.3. The series is not correlated with any of the selected shocks. This result is a good indicative that longer forecast horizons make the signal from the news shock sufficiently large to compensate for the noise from non-technological short-term shocks. It follows that the IMF series can be directly employed as an instrument for the news shock, without the filtering step described by equation 38.

Figure 13 presents the impulse responses after a news shock identified with the instrumental variable from the IMF forecasts for the main economic variables. The gray area defines the 68% coverage bands computed with 1,000 posterior draws.[29] The results are qualitatively similar to the ones presented in Figure 5, when SPF forecasts are employed.

[28] The survey for the first quarter of 2021, for example, compiled data from 39 different forecasters.

[29] The full impulse responses can be found in Figure C.5 in the Appendix. Table B.3 in the Appendix presents the results for the instrument relevance tests. The full impulse responses for the un-smoothed version can be found in Figure C.6 in the Appendix.

Figure 12 Forecast revisions about future GDP from the World Economic Outlook (IMF)



Note: Forecast revisions constructed from expectations about future GDP, constructed from the International Monetary Fund (IMF) – World Economic Outlook, following the procedure described in section 2. Data from 1990:Q3 to 2019:Q4. Shaded areas are the recession periods calculated by the NBER.

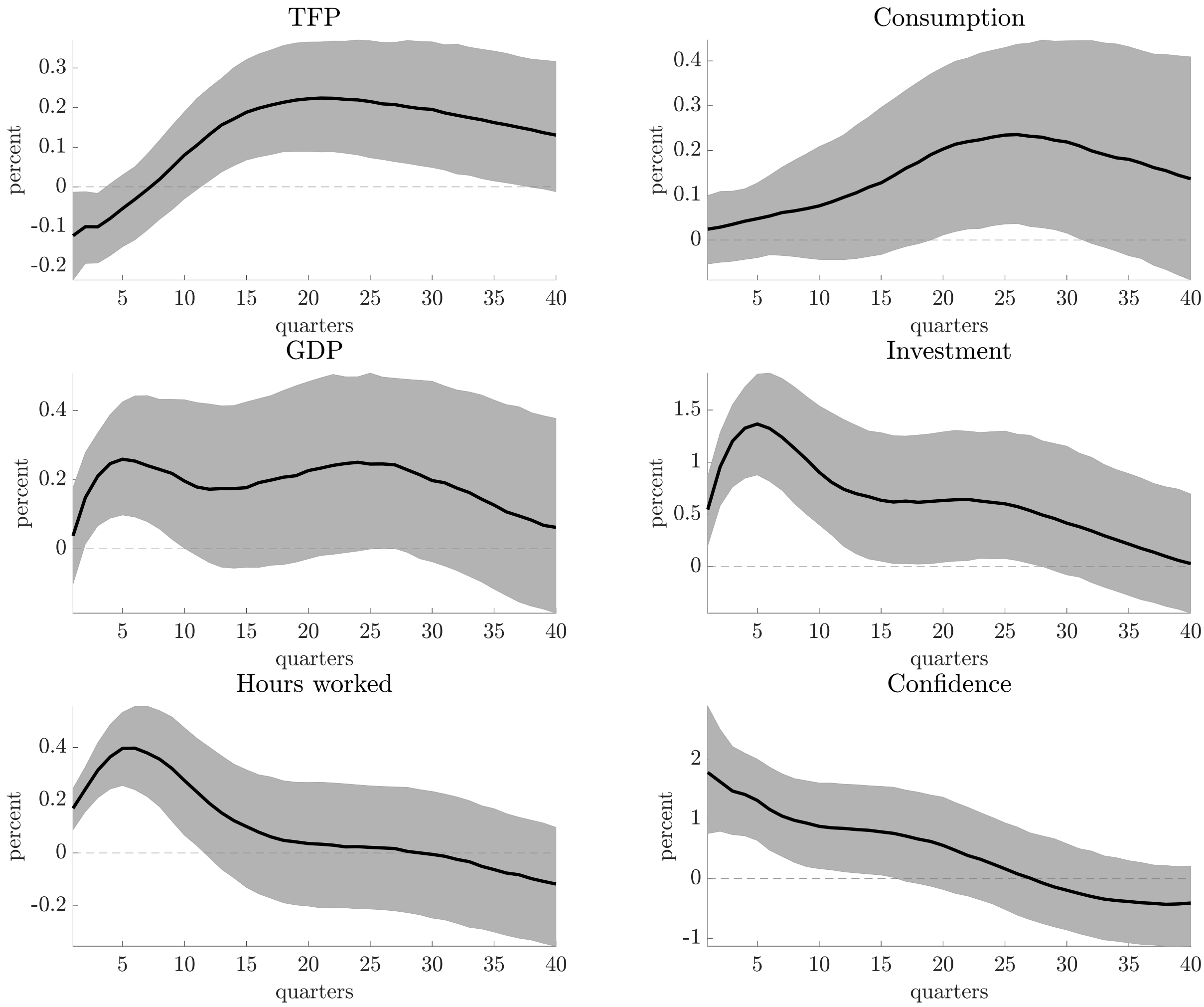
Table 5 Exogeneity tests for the forecast revisions from the IMF

Forecast revision about GDP				
Shock	Source	μ_1	P-value	Obs
News about tax	Leeper et al. (2013)	4.64	0.28	66
News about govt. spending	Ramey (2011)	-49.27	0.32	66
Oil price	Hamilton (2003)	0.06	0.17	66
Monetary policy	Romer and Romer (2004)	1.61	0.12	66
Tax	Mertens and Ravn (2011)	0.65	0.70	66
Technology	First residual from the BVAR	-0.32	0.45	66

Note: Coefficient μ_1 estimated from individual regressions of the forecast revision about GDP against the structural shocks. Data for the regressions range from 1990:Q3 to 2006:Q3. 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.

Utilization-adjusted TFP is not restricted to zero on impact in this case. Nevertheless, the effect is only marginally negative, becoming positive after around 12 quarters. GDP and investment react positively on impact, with a stronger effect on investment, as it was the case with the SPF instruments. The effect on impact on consumption is indistinguishable from zero, also similar to the previous results. Hours worked and confidence grow on impact, converging back to zero in the long run for both cases.

Figure 13 Impulse responses to a news shock under an instrumental variable approach with IMF forecasts (main variables)



Note: Impulse responses for selected variables of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1990:Q3 to 2019:Q4 due to data availability of the instruments. The gray area defines the 68% coverage bands computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

6 Conclusion

Forecast revisions carry valuable information about the future path of the technology level, and can be used as instruments to identify news shocks. The results from this paper contribute to the news shock literature by highlighting new evidence concerning the economic effects of news shocks through a novel identification method, which relies solely on updated information about agents' expectations.

If technology is the main driver of the economy in business cycle frequencies, forecast revisions about the outlook 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 important instruments for recovering the underlying technological news shock.

The news shock identified with instruments produces the theoretical comovement among real macroeconomic variables as initially proposed by Beaudry and Portier (2006). However, most of the anticipation effect comes from investment, and not through consumption. After a news shock, investment strongly reacts, hours worked increase, but there is less evidence of consumption smoothing over time—in line with theoretical models with financial frictions.

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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

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

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

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

and

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

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

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

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

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

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

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

The news shock is identified by solving the optimization problem

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

s.t.

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

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

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

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

Based on the γ_2^{news} vector, the structural surprise technological shock ($s_t^{surprise}$) and the news shock (s_t^{news}) are

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

assuming that

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

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

B Appendix: Additional tables

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 (Apr/2021)
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 log levels.	Fred
8	EBP	Excess bond premium as computed by Gilchrist and Zakrajšek (2012).	Favara, Gilchrist, Lewis, and Zakrajšek (2016) (Apr/2021)
9	Realized Volatility	Realized volatility computed using daily returns using the robust estimator by Rousseeuw and Croux (1993).	CRSP
10	Consumer Confidence	Consumer confidence in log levels. Computed by the Survey of Consumers of the University of Michigan.	U-Michigan's website (Apr/2021)
11	Price of Investment	Relative price of investment constructed as the ratio between investment and consumption deflators.	Fred
12	Capacity Utilization	Capacity utilization in log levels. Computed by Fernald (2014).	Fernald's website (Apr/2021)
13	FFR	Fed funds rate.	Fred
14	Spread	Difference between the 10-year Treasury rate and the FFR.	Fred

Note: All for the 1975:Q1-2019:Q4 period. Monthly series converted to quarterly by averaging over the quarter.

Table B.2 Instrument relevance tests

	z_t^{gdp}		z_t^{ip}		z_t^{inv}		$\tilde{\mathbf{Z}}_t$ jointly	
	F-stat.	R^2	F-stat.	R^2	F-stat.	R^2	F-stat.	R^2
Consumption	1.7	0.02	2.6	0.03	0.7	0.01	0.8	0.03
	(0.19)		(0.11)		(0.41)		(0.47)	
GDP	6.9	0.07	10.3	0.09	0.8	0.01	3.8	0.11
	(0.01)		(0.00)		(0.37)		(0.01)	
Investment	6.0	0.06	6.2	0.06	0.2	0.00	3.1	0.09
	(0.02)		(0.01)		(0.69)		(0.03)	
Hours worked	0.0	0.00	1.2	0.01	0.0	0.00	1.0	0.03
	(0.97)		(0.28)		(0.96)		(0.41)	
GDP deflator	0.0	0.00	0.2	0.00	0.8	0.01	0.6	0.02
	(1.00)		(0.68)		(0.37)		(0.65)	
Stock prices	9.9	0.09	0.8	0.01	6.8	0.07	6.0	0.16
	(0.00)		(0.37)		(0.01)		(0.00)	
EBP	0.0	0.00	0.1	0.00	0.9	0.01	0.8	0.02
	(0.86)		(0.74)		(0.35)		(0.51)	
Financial uncertainty	0.0	0.00	0.0	0.00	0.7	0.01	0.3	0.01
	(0.94)		(1.00)		(0.41)		(0.79)	
Confidence	34.4	0.26	17.8	0.15	19.1	0.16	11.9	0.27
	(0.00)		(0.00)		(0.00)		(0.00)	
Price of investment	0.2	0.00	1.2	0.01	1.0	0.01	0.8	0.02
	(0.65)		(0.27)		(0.32)		(0.51)	
Capacity utilization	6.1	0.06	8.1	0.08	2.4	0.02	2.7	0.08
	(0.02)		(0.01)		(0.13)		(0.05)	
Federal funds rate	0.2	0.00	4.6	0.05	0.0	0.00	3.0	0.09
	(0.67)		(0.03)		(0.94)		(0.03)	
Spread (10y - Fed funds)	0.1	0.00	0.1	0.00	0.0	0.00	0.0	0.00
	(0.80)		(0.72)		(0.96)		(0.99)	

Note: F-statistics calculated by testing if the coefficients of the (filtered) forecast revisions about GDP, industrial production, and investment are individually or jointly significant in explaining the residuals from the VAR corresponding to each variable in the first column, as in equation 39. Numbers in parentheses are p-values. 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 38). 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 includes all variables in Table B.1 in the Appendix.

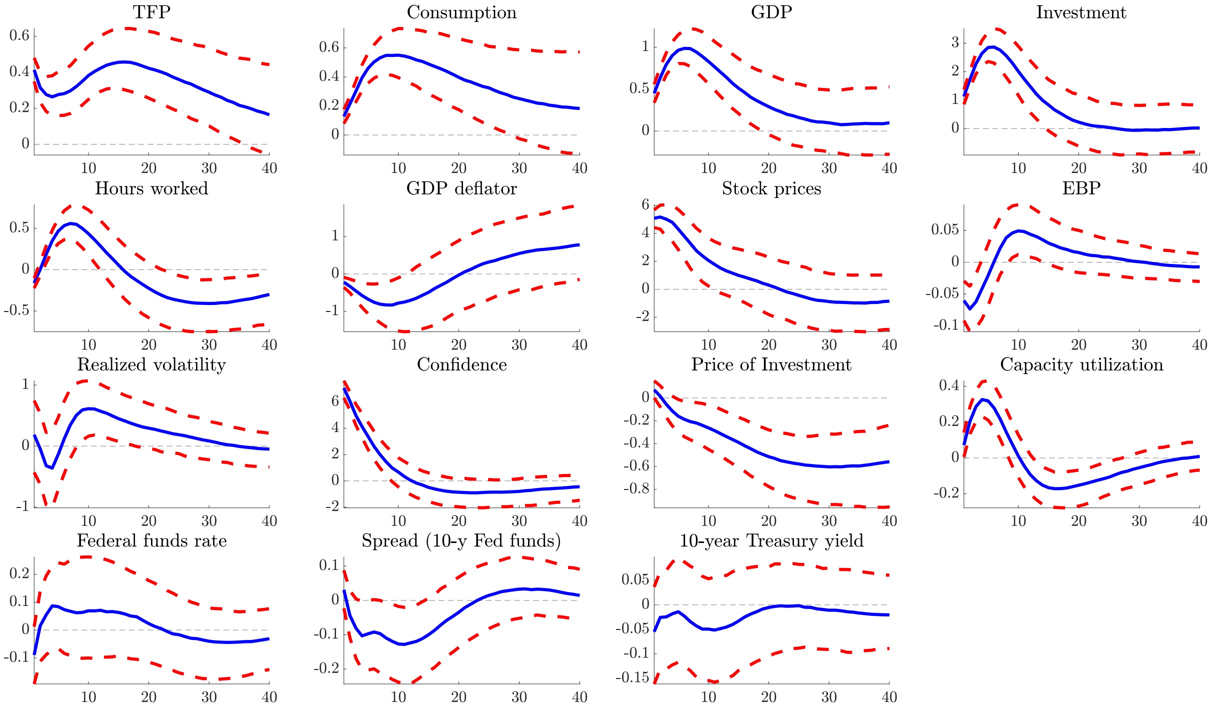
Table B.3 Instrument relevance tests for the IMF forecast instrument

Innovation variable	F-stat	P-value	R^2
Consumption	0.01	0.91	0.00
GDP	0.43	0.52	0.00
Investment	3.05	0.08	0.03
Hours worked	1.54	0.22	0.02
GDP deflator	1.89	0.17	0.02
Stock prices	3.87	0.05	0.04
EBP	1.40	0.24	0.01
Financial uncertainty	0.00	0.97	0.00
Confidence	1.15	0.29	0.01
Price of investment	1.06	0.31	0.01
Capacity utilization	1.63	0.20	0.02
Federal funds rate	4.35	0.04	0.04
Spread (10y - Fed funds)	1.00	0.32	0.01

Note: F-statistics calculated by testing if the coefficients of the forecast revision about GDP (smoothed series) is significant in explaining the residuals from the VAR corresponding to each variable in the first column, as in equation 39. The residuals are calculated as the median across 1,000 posterior draws (as described in subsection 3.2). Time period is from 1990:Q3 to 2019:Q4 due to data availability (167 observations). The VAR includes all variables in Table B.1 in the Appendix.

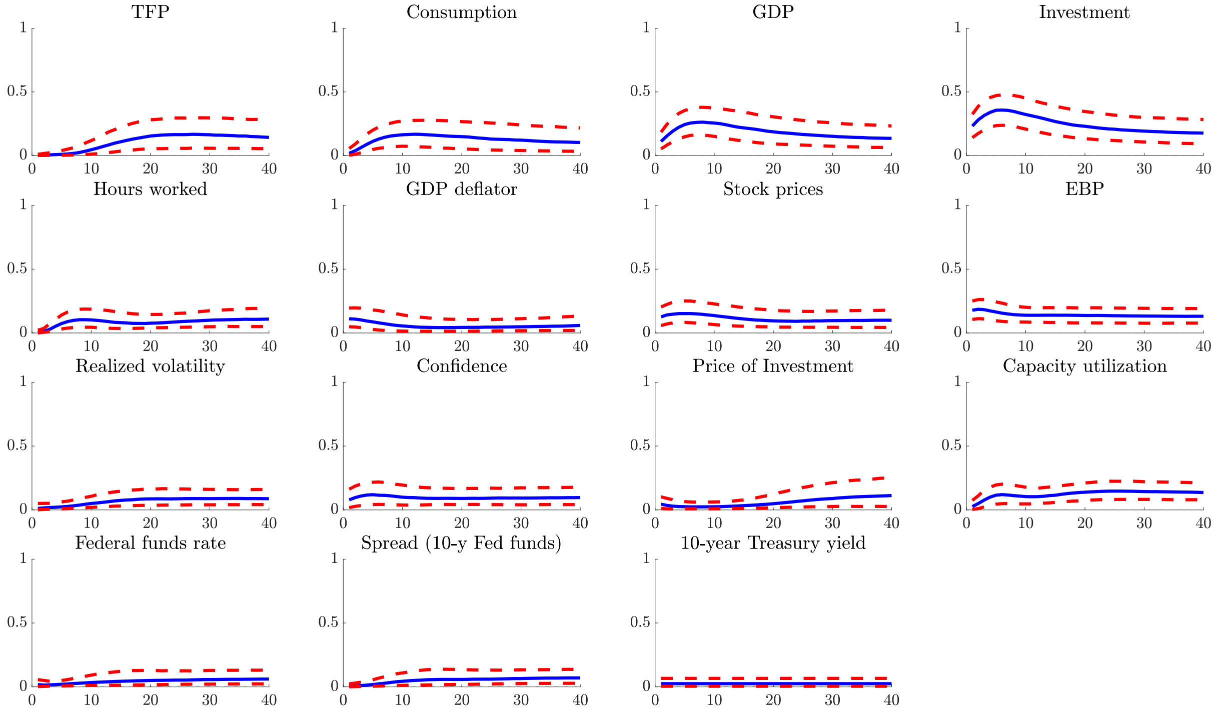
C Additional figures

Figure C.1 Impulse responses to a news shock under an instrumental variable approach (without controlling for surprise TFP shocks)



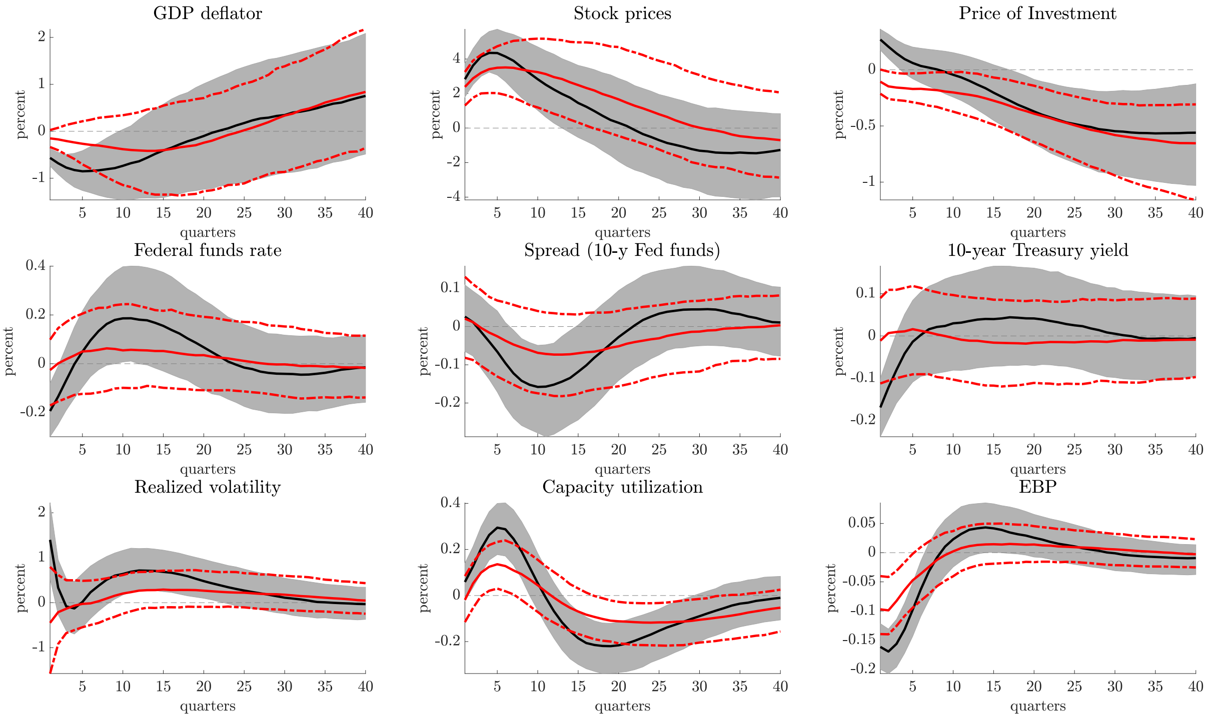
Note: Impulse responses of a news shock computed by employing instrumental variables, estimated with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The dashed lines define the 68% coverage bands computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

Figure C.2 Variance decomposition of news shock under an instrumental variable approach



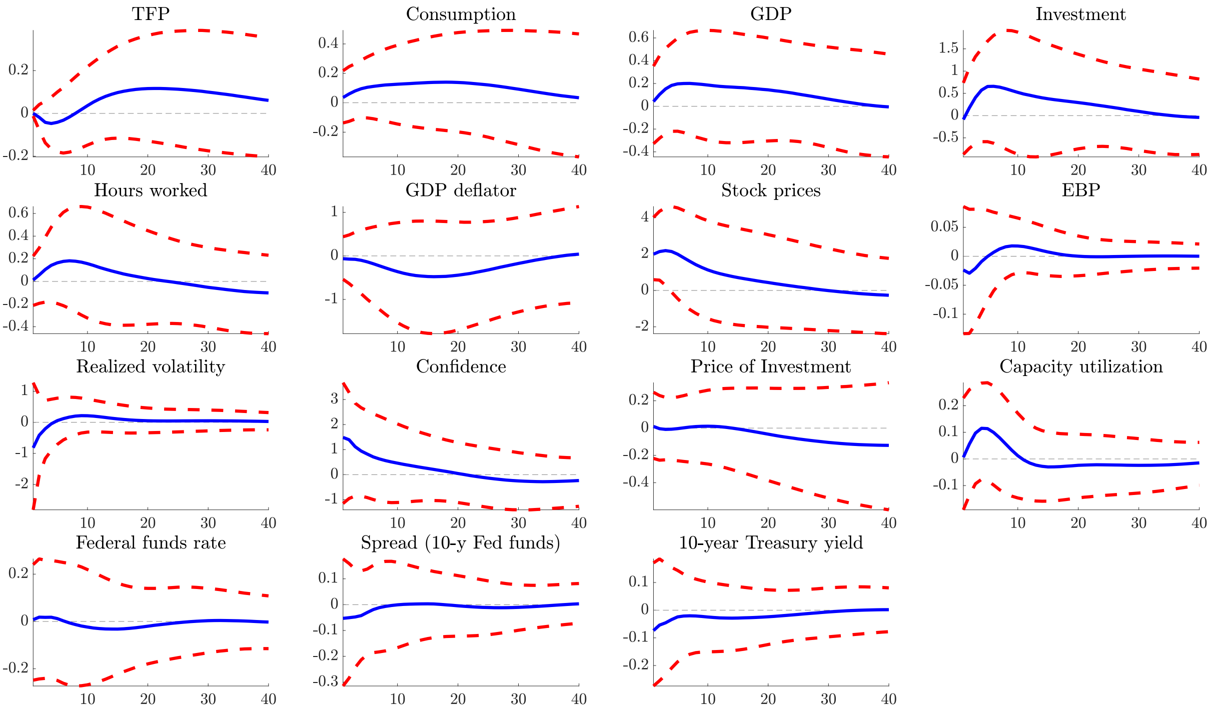
Note: Variance decomposition of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The dashed lines define the 68% coverage bands computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

Figure C.3 Impulse responses to a news shock identified with the instrumental variables (black) and the Barsky and Sims (2011) (red) approaches (additional variables)



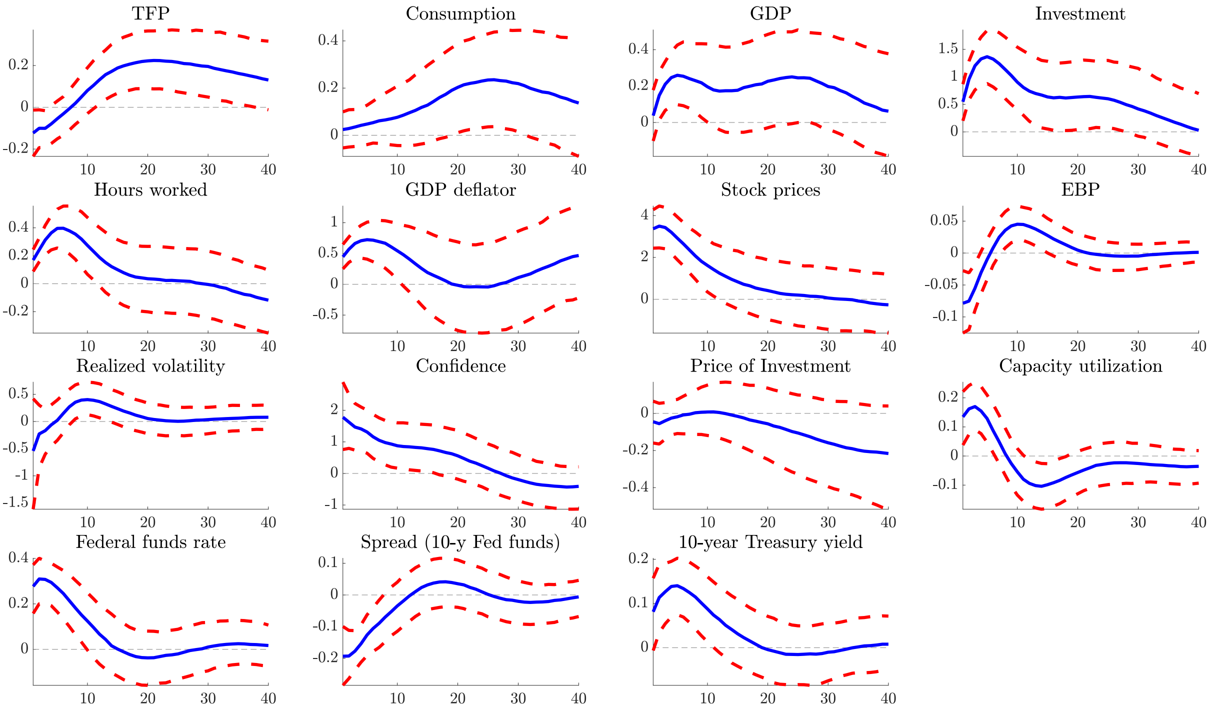
Note: Impulse responses for selected variables of a news shock computed by employing the identification procedure of maximizing the variance decomposition (red) described in Appendix A, and by employing the instrumental variables approach (black), estimated with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification of the instrumental variables procedure conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The dotted red lines define the 68% coverage bands for the Barsky and Sims (2011) approach, the gray area the coverage bands for the instrumental variables approach, all computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

Figure C.4 Impulse responses to a news shock identified with placebo instruments



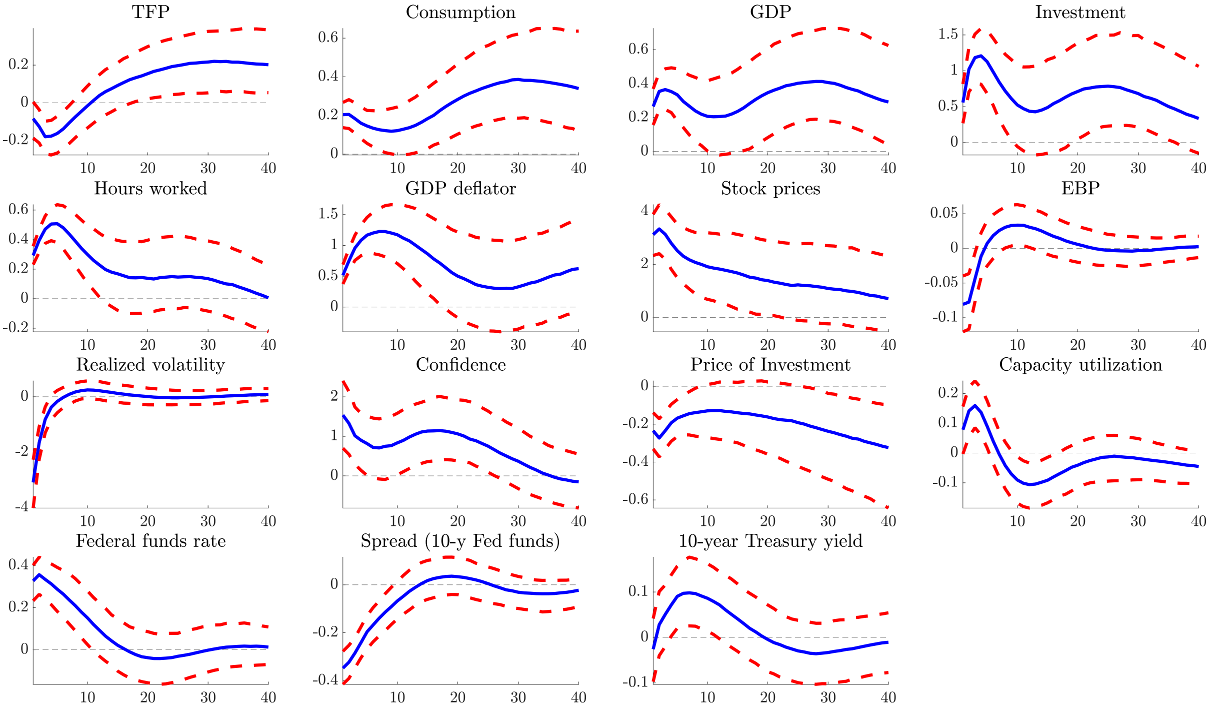
Note: Impulse responses of a news shock computed by employing placebo instrumental variables, with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1981:Q3 to 2006:Q3 due to data availability of the instruments. The dashed lines define the 68% coverage bands computed with 1,000 posterior draws and 100 different randomly scrambled placebos. The VAR includes all variables in Table B.1 in the Appendix.

Figure C.5 Impulse responses to a news shock under an instrumental variable approach with IMF forecasts



Note: Impulse responses of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1990:Q3 to 2019:Q4 due to data availability of the instruments. The dashed lines define the 68% confidence bands computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.

Figure C.6 Impulse responses to a news shock under an instrumental variable approach with IMF forecasts (un-smoothed)



Note: Impulse responses of a news shock computed by employing instrumental variables, with quarterly data ranging from 1975:Q1 to 2019:Q4. Identification conducted over the sub-sample 1990:Q3 to 2019:Q4 due to data availability of the instruments. The dashed lines define the 68% confidence bands computed with 1,000 posterior draws. The VAR includes all variables in Table B.1 in the Appendix.