# News Shocks: Different Effects in Boom and Recession?*

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**Abstract**

This paper investigates the nonlinearity in the effects of news shocks about technological innovations. In a maximally flexible logistic smooth transition vector autoregressive model, state-dependent effects of news shocks are identified based on medium-run restrictions. We propose a novel approach to impose these restrictions in a nonlinear model using the generalized forecast error variance decomposition. We compute generalized impulse response functions that allow for regime transition and find evidence of state-dependency. The results also indicate that the probability of a regime switch is highly influenced by the news shocks.

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*Keywords*: smooth transition vector autoregressive model, nonlinear time-series model, news shock, generalized impulse responses, generalized forecast error variance decomposition.

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# 1 Introduction

News about technological innovations appear in the media constantly and market participants adjust their expectations and economic decisions accordingly. Because the diffusion of an innovation takes time, a positive news shock can initiate a boom absent of any concurrent technological change. We ask in this paper whether the economic environment at the time when the news arrives influences the responses to this shock. We find evidence of state-dependency mainly in the short-run, with the differences fading away in the long-run.

The idea of news is not novel in the macroeconomics literature, but has been reinvigorated in recent years following Beaudry and Portier (2006). In their seminal paper, they present evidence that today's news contains information about future technological prospects. In response to the anticipated future productivity improvements, economic agents start spending and, thus, consumption and investment increase. If everyone displays the same reaction to the news, this leads to a boom. In the medium-run, if agents' optimism proves to be justified, the economy follows productivity to a new long-run level; if it does not, a process of liquidation sets in and the economy returns to its original growth path.

So far news shocks on future productivity have been analyzed only in linear settings. In this paper we relax the linearity assumption and test whether the effect of the news is state-dependent, i.e. dependent on the state of the economy at the time it occurs. Our hypothesis is that even though new technologies are developed independently of the business cycle, conditional on whether the economy is in a recession or an expansion the responses to the news shock are different.

Our motivation is the following. Recessions, as defined by the NBER (National Bureau of Economic Research) quarterly index, are rare events. In the past fifty years they account only for about 18 percent of the time. By computing the first and second moments of the main economic indicators, conditional on the economy being in an expansion or a recession, we find evidence in support of the fact that the macroeconomic environment is very different in the two state of the economy[1]. In bad times, consumer confidence and business expectations are low, consumption and investment growth rates are below average while uncertainty is high. The opposite holds true in normal times. Then, why should firms and consumers react the same to news when the economic conditions are so different at the time the news is perceived?

Assessing the effects of the news shock in a nonlinear setting is our main contribution to the literature. To perform our empirical analysis, we proceed as follows. We estimate a five-variable logistic smooth transition vector autoregressive (LSTVAR) model including TFP, consumer expectations, output, inflation and

[1] Details are provided in Appendix A.

stock prices (SP). Our model builds on Auerbach and Gorodnichenko (2012) and Teräsvirta, Tjøstheim, and Granger (2010) and allows for state-dependent dynamics through parameters and state-dependent impact effects through the variance-covariance matrix. We permit the transition in the mean equation and the variance equation to be different. The transition is indicated by a three-quarter moving average of the output growth rate, introduced with a lag to avoid endogeneity problems. Instead of calibrating the parameters of the transition functions, as usually done in the literature, we estimate them.

The identification of news shocks has been intensively debated in the empirical news shock literature. The initial proposal of Beaudry and Portier (2006) was to impose either short-run or long-run restrictions. However, their long-run restriction scheme has been criticized by Kurmann and Mertens (2014) as inappropriate for models with more than two variables as it fails to determine productivity related news shocks in such multivariate systems. Their short-run identification relies on the assumption that the news shock affects stock prices but is orthogonal to total factor productivity (TFP) in the short-run. The most prominent identification scheme in the literature was brought up by Barsky and Sims (2011). They identify the news shock via medium-run restrictions based on the method of Uhlig (2004). The news shock is assumed to be orthogonal to TFP innovations and with maximum contribution to TFP over a specific horizon. While they initially found different results than Beaudry and Portier (2006), Beaudry and Portier (2014) show that the differences stemmed from the different variables included in the models. Once the same variables are used, the results become similar.

We choose to identify the news shock via a medium-run identification method. In a non-linear vector autoregressive (VAR) context short-run restrictions are usually applied. To the best of our knowledge, we are the first to employ a medium-run identification scheme in a LSTVAR model. The news shock is then defined as the shock with no impact effect on TFP but with maximal contribution to TFP at a specific horizon.

To analyze the effects of the news shock we compute generalized impulse responses that allow for endogenous regime transition by adjusting the transition functions in every simulation step. This approach accounts for the transition of the system from one regime to the other as a reaction to a shock and permits to measure the change in the probability of a regime transition after a news shock has occurred.

We further investigate the state-dependency in the contribution of the news shock to the variation in the variables of the model at different frequencies. We perform a generalization of the forecast error variance decomposition. A basic forecast error variance decomposition is inapplicable in a nonlinear setting because the shares do not sum to one.

We then perform several robustness checks. We compare the effects of the news shock to those of a confidence shock, obtained by applying short-run restrictions. The confidence shock is identified as the shock with no impact effect on TFP, but an immediate effect on consumer expectations. We also compare the results with those obtained by applying the same identification schemes within a linear VAR model that includes the same variables.

Our results, both in terms of impulse responses and relative contribution to the variance of the model's variables, indicate strong evidence of nonlinearity in the effects of the news shock mainly in the short-run. The generalized impulse responses show that the impact effect of the news shock is in general larger in an expansion than in a recession, while in the long-run the differences fade away. When analyzing the impact contribution of the news shock to the variation of all the variables in the model we observe that in an expansion the shares are similar to the ones in the linear model. In recessions, the news shock contributes more to the variance of the forward-looking variables, while the contribution to output's variance is almost nil. In the medium-run the shares converge to similar values in both regimes.

Furthermore, because we allow the model to transition from one regime to the other after a news shock has occurred, we find that news shocks significantly influence the probability of a regime change both in recessions and expansions.

When we compare the generalized impulse responses to the responses obtained in the linear model, even though they are qualitatively similar, it becomes evident that using the linear model to draw conclusions about the effects of the news shock in either of the regimes is flawed. The results from the linear model would lead to an underestimation of the effects in an expansion and an overestimation in a recession.

Comparing the effects of the news shock to those of the confidence shock, we find that, while in recessions the two deliver basically the same results, the impulse responses in expansions are stronger for the news shock and the contributions to the variance of the model's variables are different.

While there is evidence in favor of state-dependency, the same does not hold true for the asymmetry in the effects of news shocks. Our results indicate there is no significant difference between the effects of positive and negative shocks, no matter whether the shocks hit in an economic downturn or upturn.

The rest of the paper is organized as follows. In Section 2, we present the empirical approach and the estimation method employed. In Section 3, we describe the data. We discuss our results in Section 4, and offer some concluding remarks in Section 5.

# 2 Empirical approach

According to van Dijk, Teräsvirta, and Franses (2002), a smooth transition model can either be interpreted as a regime-switching model allowing for two extreme regimes associated with values of the transition function of 0 and 1 where the transition from one regime to the other is smooth, or as a regime-switching model with a "continuum" of regimes, each associated with a different value of the transition function.

For our research purpose, we employ a five-dimensional logistic smooth transition vector autoregressive (LSTVAR) model in levels. We model an economy with two extreme regimes (expansion, recession) between which the transition is smooth. By relaxing the assumption of linearity, we allow the model to capture different dynamics in two opposed regimes.

## 2.1 Model specification

Formally, the LSTVAR model of order $p$ reads:

$$Y_t = \Pi_1' X_t (1 - F(\gamma_F, c_F; s_{t-1})) + \Pi_2' X_t F(\gamma_F, c_F; s_{t-1}) + \epsilon_t \tag{1}$$

where $Y_t = (Y_{1,t}, ....Y_{m,t})'$ is an $m \times 1$ vector of endogenous variables, $X_t = (\mathbf{1}', Y_{t-1}', \ldots, Y_{t-p}')$ is a $(mp+1) \times 1$ vector of an intercept vector and endogenous variables, and $\Pi_l = (\Pi_{l,0}', \Pi_{l,1}', \ldots, \Pi_{l,p'})$ for regimes $l = 1, 2$ a $(mp+1) \times m$ matrix where $\Pi_{l,0}$ are $1 \times m$ intercept vectors and $\Pi_{l,j}$ with $j = 1, ..., p$ are $m \times m$ parameter matrices.

$F(\gamma_F, c_F; s_t)$ is the logistic transition function with transition variable $s_t$,

$$F(\gamma_F, c_F; s_t) = exp\left(-\gamma_F(s_t - c_F)\right) \; \left[1 + exp\left(-\gamma(s_t - c_F)\right)\right]^{-1}, \; \gamma > 0, \tag{2}$$

where $\gamma_F$ is called slope or smoothness parameter, and $c_F$ is a location parameter determining the middle point of the transition ($F(\gamma_F, c_F; c_F) = 1/2$). Therefore, it can be interpreted as the threshold between the two regimes as the logistic function changes monotonically from 0 to 1 when the transition variable decreases. At every period, the transition function attaches some probability of being in each regime given the value of the transition variable $s_t$. $\epsilon_t \sim N(0, \Sigma_t)$ is an $m$-dimensional vector reduced-form shock with mean zero and positive definite variance-covariance matrix, $\Sigma_t$. We allow the variance-covariance matrix to be regime-dependent but we test it for constancy.

$$\Sigma_t = (1 - G(\gamma_G, c_G; s_{t-1}))\Sigma_1 + G(\gamma_G, c_G; s_{t-1})\Sigma_2 \tag{3}$$

The transition between regimes in the second moment is also governed by a logistic transition function $G(\gamma_G, c_G; s_{t-1})$. We want to allow not only for dynamic differences in the propagation of structural shocks through $\Pi_1$ and $\Pi_2$ but also for contemporaneous differences via the two covariance matrices, $\Sigma_1$ and $\Sigma_2$. This method is similar to the one employed in Auerbach and Gorodnichenko (2012)[2], but we depart from their approach by permitting the parameters of the transition function in the variance equation to differ from the parameters in the mean equation.

The LSTVAR reduces to a linear vector autoregressive model when $\gamma_F = \gamma_G = 0$. The model is then given by:

$$Y_t = \Pi' X_t + \epsilon_t \tag{4}$$

where $\epsilon_t \sim N(0, \Sigma)$ is a vector of reduced-form residuals with mean zero and constant variance-covariance matrix, $\Sigma$.

## 2.2 Transition variable

The transition between regimes is defined through the logistic transition functions while the state of the economy is given by the transition variable. As stated in Teräsvirta, Tjøstheim, and Granger (2010), economic theory is not always fully explicit about the transition variable. There are several options. The transition variable can be an exogenous variable ($s_t = z_t$), a lagged endogenous variable ($s_t = Y_{i,t-d}$, for certain integer $d > 0$, and where the subscript $i$ is the position of this specific variable in the vector of endogenous variables), a function of lagged endogenous variables or a function of a linear time trend.

For our model, the transition variable needs to follow the business cycle and clearly identify expansionary and recessionary periods. The NBER defines a recession as 'a period of falling economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales', which makes the identification of a recession a complex process based on weighing the behavior of various indicators of economic activity. For this reason, we follow the common rule of thumb which defines a recession as two consecutive quarters of negative GDP growth. Consequently, we employ as transition variable $s_t$ a lagged three quarter moving average of the quarter-on-quarter real GDP.

This definition of the transition variable is close to the one used in Auerbach and Gorodnichenko (2012), as they set $s_t$ to be a seven quarter moving average of the realizations of the quarter-on-quarter real GDP growth rate, centered at time

[2] We thank Alan Auerbach, and Yuriy Gorodnichenko for making publicly available their codes for estimating a STVAR model.

$t$. We depart from their approach in the sense that we do not assume the transition variable to be an exogenous variable, but a function of a lagged endogenous variable. In order to avoid endogeneity problems, the transition functions $F$ and $G$ at date $t$ are based on $s_{t-1} = \frac{1}{3}(g^Y_{t-1} + g^Y_{t-2} + g^Y_{t-3})$, $g^Y_t$ being the growth rate of output.

The LSTVAR model is only indicated if linearity can be rejected. It is tested against the alternative of a nonlinear model, given the transition variable. We can reject the null hypothesis of linearity at all significance levels, regardless of the type of LM test we perform (for details, see Appendix B.1).

## 2.3 Estimation

Once the transition variable and the form of the transition function are set, the parameters of the LSTVAR model may be estimated using nonlinear least squares (NLS). With the assumption that the error terms are normally distributed, the NLS estimator is equivalent to the maximum likelihood estimator.

The conditional log-likelihood function of our model is given by:

$$log\ L = const + \frac{1}{2}\sum_{t=1}^{T} \log|\Sigma_t| - \frac{1}{2}\sum_{t=1}^{T} \epsilon_t' \Sigma_t^{-1} \epsilon_t, \tag{5}$$

where $\epsilon_t = Y_t - \Pi_1' X_t(1 - F(\gamma_F, c_F; s_{t-1})) - \Pi_2' X_t F(\gamma_F, c_F; s_{t-1})$.

The maximum likelihood estimator of the parameters $\Psi = \{\gamma_F, c_F, \gamma_G, c_G, \Sigma_1, \Sigma_2, \Pi_1, \Pi_2\}$ is given by:

$$\hat{\Psi} = \arg\min_{\Psi} \sum_{t=1}^{T} \epsilon_t' \Sigma_t^{-1} \epsilon_t \tag{6}$$

We then let $Z_t(\gamma_F, c_F) = [X_t'(1 - F(\gamma_F, c_F; s_{t-1})), X_t' F(\gamma_F, c_F; s_{t-1})]'$ be the extended vector of regressors, and $\Pi = [\Pi_1', \Pi_2']'$ such that equation (6) can be rewritten as:

$$\hat{\Psi} = \arg\min_{\Psi} \sum_{t=1}^{T} (Y_t - \Pi' Z_t(\gamma_F, c_F))' \Sigma_t^{-1} (Y_t - \Pi' Z_t(\gamma_F, c_F)) \tag{7}$$

It is important to note that conditional on $\{\gamma_F, c_F, \gamma_G, c_G, \Sigma_1, \Sigma_2\}$ the LSTVAR model is linear in the autoregressive parameters $\Pi_1$ and $\Pi_2$. Hence, for given $\gamma_F, c_F, \gamma_G, c_G$, $\Sigma_1$, and $\Sigma_2$, estimates of $\Pi$ can thus be obtained by weighted least squares (WLS), with weights given by $\Sigma_t^{-1}$. The conditional minimizer of the objective function can then be obtained by solving the first order condition (FOC) equation with respect to $\Pi$:

$$\sum_{t=1}^{T}(Z_t(\gamma_F, c_F)Y_t'\Sigma_t^{-1} - Z_t(\gamma_F, c_F)Z_t(\gamma_F, c_F)'\Pi\Sigma_t^{-1}) = 0 \tag{8}$$

The above equation leads to the following closed form of the WLS estimator of $\Pi$ conditional on $\{\gamma_F, c_F, \gamma_G, c_G, \Sigma_1, \Sigma_2\}$:

$$vec(\hat{\Pi}) = \left[\sum_{t=1}^{T}\left(\Sigma_t^{-1} \otimes Z_t(\gamma_F, c_F)Z_t(\gamma_F, c_F)'\right)\right]^{-1} vec\left[\sum_{t=1}^{T}\left(Z_t(\gamma_F, c_F)Y_t'\Sigma_t^{-1}\right)\right], \tag{9}$$

where *vec* denotes the stacking columns operator.

The procedure iterates on $\{\gamma_F, c_F, \gamma_G, c_G, \Sigma_1, \Sigma_2\}$, yielding $\Pi$ and the likelihood, until an optimum is reached. Therefore, it can be concluded that, when $\gamma_F, c_F, \gamma_G, c_G$, $\Sigma_1$, and $\Sigma_2$ are known, the solution for $\Pi$ is analytic. As explained in Hubrich and Teräsvirta (2013); Teräsvirta and Yang (2014b), this is key for simplifying the nonlinear optimization problem as, in general, finding the optimum in this setting may be numerically demanding. The reason is that the objective function can be rather flat in some directions and possess many local optima.

Therefore, we divide the set of parameters, $\Psi$, into two subsets: the 'nonlinear parameter set', $\Psi_n = \{\gamma_F, c_F, \gamma_G, c_G, \Sigma_1, \Sigma_2\}$ , and the 'linear parameter set', $\Psi_l = \{\Pi_1, \Pi_2\}$. To ensure that $\Sigma_1$, and $\Sigma_2$ are positive definite matrices, we redefine $\Psi_n$ as $\{\gamma_F, c_F, \gamma_G, c_G, chol(\Sigma_1), chol(\Sigma_2)\}$, where *chol* is the operator for the Cholesky decomposition.

Following Auerbach and Gorodnichenko (2012), we perform the estimation using a Markov Chain Monte Carlo (MCMC) method. More precisely, we employ a Metropolis- Hastings (MH) algorithm with quasi-posteriors, as defined in Chernozhukov and Hong (2003). The advantage of this method is that it delivers not only a global optimum but also distributions of parameter estimates. As we have seen previously, for any fixed pair of nonlinear parameters, one can easily compute the linear parameters and the likelihood. Therefore, we apply the MCMC method only to the nonlinear part of the parameter set, $\Psi_n$ (details are provided in Appendix B.3).

## 2.4 Starting values

From this nonlinear parameter set, we first estimate the starting values for the transition functions $\gamma_F$, $c_F$, $\gamma_G$, and $c_G$ using a logistic regression. The transition function defines the smooth transition between expansion and recession. Every period a positive probability is attached for being in either regime. This means that the dynamic behavior of the variables changes smoothly between the two extreme regimes and the estimation for each regime is based on a larger set of observations.

A common indicator of the business cycle is the NBER based recession indicator (a value of 1 is a recessionary period, while a value of 0 is an expansionary period). We believe that it is reasonable to assume that the transition variable should attach more probability to the recessionary regime when the NBER based recession indicator exhibits a value of one. We determine the initial parameter values of the transition functions by performing a logistic regression of the NBER business cycle on the transition variable (three quarter moving average of real GDP growth). Thus, our transition function is actually predicting the likelihood that the NBER based recession indicator is equal to 1 (rather than 0) given the transition variable $s_{t-1}$. Defining the NBER based recession indicator as $Rec$, then the probability of $Rec_t = 1$, given $s_{t-1}$, is:

$$P(Rec_t = 1 \mid s_{t-1}) = \frac{exp\,[-\gamma(s_{t-1} - c)]}{1 + exp\,[-\gamma(s_{t-1} - c)]} \tag{10}$$

The estimation delivers the starting values $\hat{\gamma}_F = \hat{\gamma}_G = 3.12$ and $\hat{c}_F = \hat{c}_G = -0.48$ (for details see Appendix B.2). Usually, in the macroeconomic literature, $\gamma$ is calibrated to match the duration of recessions in the US according to NBER business cycle dates (see Auerbach and Gorodnichenko (2012); Bachmann and Sims (2012); Caggiano, Castelnuovo, and Groshenny (2014)). The values assigned to $\gamma$ range from 1.5 to 3, but in all these settings, the location parameter, $c$, is imposed to equal zero, such that the middle point of the transition is given by the switching variable being zero. For comparison, we also estimate the logistic regression forcing the constant to be zero and obtain an estimate for $\gamma$ that equals 3.56. However, the Likelihood Ratio (LR) test[3] shows that the model with intercept provides a better fit. Moreover, the intercept is statistically different from zero so there is no econometric support for assuming it to be zero (see Appendix B.2).

The transition function with $\gamma = 3.12$ and $c = -0.48$, is shown in Figure 6. It is obvious that high values of the transition function are associated with the NBER identified recessions.

The choice of the other starting parameter values is presented in details in Appendix B.3.

[3]Perfoming the LR test for nested models we obtain that D=37.66 with p-value=0.000.

## 2.5 Evaluation

According to Teräsvirta and Yang (2014b), exponential stability of the model may be numerically investigated through simulation of counterfactuals. By generating paths of realizations from the estimated model with noise switched off, starting from a large number of initial points, it can be checked whether the paths of realizations converge. The convergence to a single stationary point is a necessary condition for exponential stability[4].

Yang (2014) proposes a test for the constancy of the error covariance matrix applicable to smooth transition vector autoregressive models. To test for constancy of the error covariance matrix, first, the model has to be estimated under the null hypothesis assuming the error covariance matrix to be constant over time. Similar to the linearity test for the dynamic parameters, the alternative hypothesis is approximated by a third-order Taylor approximation given the transition variable. In our case, the null hypothesis of a constant error covariance matrix is clearly rejected (for details, see Appendix B.4).

## 2.6 Identification of the news shock

### 2.6.1 Medium-run identification

The medium-run identification (MRI) scheme defines the news shock to be the shock that does not move TFP on impact and has maximal contribution to it at horizon $H$. It is based on the assumption that in the long-run TFP is only affected by anticipated (news) and unanticipated productivity shocks. This method, introduced by Beaudry, Nam, and Wang (2011) to identify news shocks, differs from the original one of Barsky and Sims (2011) because the latter aims at isolating the shock that maximizes its contribution to the forecast error variance of TFP not only at a given horizon, but to the cumulated forecast error variances over all horizons up to the truncation horizon. As Beaudry, Nam, and Wang (2011) argue, the difference is that the first identifies the shocks that have a permanent effect on TFP, while the second may confound shocks that have either permanent or temporary effects on TFP. Since the results obtained with the method of Barsky and Sims (2011) are proven to be sensitive to the choice of forecast horizon, we prefer to use the approach of Beaudry, Nam, and Wang (2011) instead.

This identification scheme imposes medium-run restrictions in the sense of Uhlig (2004)[5]. Innovations are orthogonalized, for example, by applying the Cholesky

[4] When $F(\gamma_F, c_F; s_{t-1})$ is a standard logistic function with a single transition variable, a naive approach for checking the model's stability is by investigating whether the roots of the lag polynomial of the two regimes lie outside the complex unit disk. However, this provides only a sufficient condition for stability.

[5]We thank Luca Benati for sharing with us his codes for performing a medium-run identifi-

decomposition to the covariance matrix of the residuals $\Sigma = \tilde{A}\tilde{A}'$, assuming there is a linear mapping between the innovations and the structural shocks. The unanticipated productivity shock is the only shock affecting TFP on impact. The news shock is then identified as the shock that has no impact effect on TFP and that, besides the unanticipated productivity shock, influences TFP the most in the medium-run, namely it is the shock with the highest share of the forecast error variance decomposition at some specified horizon $H$. In the benchmark setting, we set $H = 40$ quarters (10 years). We choose this specific horizon as we believe that shorter horizons are prone to ignore news on important and large technological innovations that need at least a decade to seriously influence total factor productivity. On the other hand, longer horizons might ignore shorter-run news as they only consider news shocks that turn out to be true in the long-run[6]. We define the entire space of permissible impact matrices as $\tilde{A}D$, where $D$ is a $k \times k$ orthonormal matrix ($DD' = I$)[7].

In the linear setting the $h$ step ahead forecast error is defined as the difference between the realization of $Y_{t+h}$ and the minimum mean squared error predictor for horizon $h$[8]:

$$Y_{t+h} - \mathbb{P}_{t-1}Y_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A} D u_{t+h-\tau} \tag{11}$$

The share of the forecast error variance of variable $j$ attributable to structural shock $i$ at horizon $h$ is then:

$$\Xi_{j,i}(h) = \frac{e_j'\left(\sum_{\tau=0}^{h} B_\tau \tilde{A} D e_i e_i' \tilde{A}' D B_\tau'\right) e_j}{e_j'\left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau'\right) e_j} = \frac{\sum_{\tau=0}^{h} B_{j,\tau} \tilde{A} \gamma \gamma' \tilde{A}' B_{j,\tau}'}{\sum_{\tau=0}^{h} B_{j,\tau} \Sigma B_{j,\tau}'} \tag{12}$$

where $e_i$ denote selection vectors with the $i$th place equal to 1 and zeros elsewhere. The selection vectors inside the parentheses in the numerator pick out the $i$th column of $D$, which will be denoted by $\gamma$. $\tilde{A}\gamma$ is a $m \times 1$ vector and is interpreted as an impulse vector. The selection vectors outside the parentheses in both numerator and denominator pick out the $j$th row of the matrix of moving average coefficients, which is denoted by $B_{j,\tau}$. Our identification scheme implies that the

cation in a linear framework.

[6]The results for the application of variations of the MRI scheme, i.e. maximizations at different horizons and up to different horizons, can be provided upon request.

[7]We use the fact that the model has a moving average (MA) representation $Y_t = B(L)\epsilon_t$, and assuming that there is a linear mapping between the innovations and the structural shocks of the form $\epsilon_t = Au_t$, the model has the following structural MA representation: $Y_t = C(L)u_t$.

[8]The minimum MSE predictor for forecast horizon $h$ at time $t-1$ is the conditional expectation.

productivity shock and the news shock account for almost all variation in TFP at horizon $H$. We identify the first shock as unanticipated productivity shock and the second shock as the news shock.

The application of the medium-run identification (MRI) to our nonlinear setting faces one big issue. The calculation of the forecast error variance decomposition depends on the estimation of the GIRFs which are history dependent and constructed as an average over simulated trajectories. If traditional methods are used, in general, the shares do not add to one which makes it unclear what is identified as the news shock. We use instead a method of estimating the generalized forecast error variance decomposition for which the shares sum to one by construction. Using this approach is the closest we can come to the application of the medium-run identification scheme. A detailed presentation of the procedure can be found in Appendix D.2.

### 2.6.2 Short-run identification

For robustness checks, we employ also a short-run identification (henceforth, SRI) to identify the news shock. The news shock is defined as the shock that has no impact effect on TFP, but is the only shock besides the unanticipated productivity shock that affects a forward-looking variable immediately.

The first SRI defines the news shock as the shock with no impact effect on TFP and the only shock which affects the index of consumer sentiment (ICS) on impact besides the unanticipated productivity shock. The news shock is then basically a confidence shock. We use the news view of confidence, introduced by Barsky and Sims (2012), which supposes that innovations in confidence summarize information about future changes in fundamentals.

The second short-run identification (SRI2) is the identification of Beaudry and Portier (2006) where the news shock is identified as the shock on stock prices instead of consumer confidence. In the literature it is often argued that the index of consumer sentiment captures better than stock prices agents' expectations about future developments in the economy (for details see Barsky and Sims (2012)).

In the linear framework, we identify this shock by imposing short-run restrictions on the moving-average representation of the model. The variance-covariance matrix of the reduced-form shocks is decomposed into two triangular matrices by applying the Cholesky decomposition $\Sigma = AA'$. Thereby, the innovations are orthogonalized and the first two shocks are identified as unanticipated productivity shock and news shock. The rest of the shocks are not economically interpreted.

The application of the SRI to the nonlinear setting is rather straight forward. We apply the Cholesky decomposition to the history-dependent impact matrix $\Sigma_t = \Sigma_1(1 - G(\gamma_G, c_G; s_{t-1})) + \Sigma_2 G(\gamma_G, c_G; s_{t-1})$ such that $\Sigma_t = A_t^G A_t^{G'}$.

The impact matrix $A_t^G$ is history-dependent and changes with $G(\gamma_G, c_G; s_{t-1})$.

The first shock is then identified as an unanticipated productivity shock whereas the second shock is the news shock. For more details, see Appendix D.1.

## 2.7 Sufficient information

Already mentioned in Barsky and Sims (2011), and further discussed in Sims (2012), the identification of news shocks may be confronted with the non-invertibility (or non-fundamentalness) problem. Non-invertibility arises when the economic agents have richer information sets than the econometrician, and therefore the observable variables included in the VAR do not contain sufficient information to perfectly recover the model's underlying structural shocks.

To be sure that our identified news shock is indeed a structural shock, we perform the test for sufficient information of Forni and Gambetti (2014) in our linear setting. The two authors show that when interested only in a single structural shock (or a subset of shocks), one can check whether the VAR is informationally sufficient by performing an orthogonality test[9]. For an estimated shock to be structural, a necessary condition is orthogonality to the past of the state variables.

We follow their procedure for testing orthogonality of the estimated shock (for details, see Appendix C.1).

The orthogonality test indicates whether the model contains sufficient information to identify a structural shock but it does not guarantee that this structural shock is indeed the desired news shock.

## 2.8 Generalized impulse responses

We analyze the dynamics of the model by estimating impulse response functions. The nonlinear nature of the LSTVAR does not allow to estimate traditional impulse response functions due to the fact that the reaction to a shock may be history-dependent.

In the literature, state-dependent impulse responses have often been used. In the LSTVAR, the transition function assigns every period some positive probability to each regime. To estimate state-dependent impulse response functions, an exogenous threshold is chosen that splits the periods into two groups depending on whether the values of the mean transition function are above or below that threshold. Given this threshold, the model is linear for a chosen regime which allows to estimate regime-specific IRFs. Nevertheless, state-dependent impulse response functions have several drawbacks. The imposed threshold is set exogenously, which arbitrarily assigns periods to either regime even though the model

[9]We thank Luca Gambetti for providing us his codes for performing the orthogonality test.

assigns some probability to both regimes at each period. Furthermore, the possibility of a regime-switch after a shock has occurred is completely ignored.

In order to cope with these issues, we estimate generalized impulse response functions (GIRFs) [10] instead as initially proposed by Koop, Pesaran, and Potter (1996). In addition, generalized impulse response functions have the advantage that they do not only allow for state-dependent impulse responses but also for asymmetric reactions. GIRFs may be different depending on the magnitude or sign of the occurring shock. A key point is that GIRFs allow to endogenize regime-switches if the transition function is a function of an endogenous variable of the LSTVAR. This allows us to see whether a shock affects the economy strong enough to move it from one regime to the other. In the literature, this point has usually been ignored.[11]

Hubrich and Teräsvirta (2013) define the generalized impulse response function as a random variable which is a function of both the size of the shock and the history. It is defined as follows:

$$GIRF(h, \epsilon_t, \Omega_{t-1}) = \mathbb{E}\left[Y_{t+h} \mid \epsilon_t^{\delta}, \Omega_{t-1}\right] - \mathbb{E}\left[Y_{t+h} \mid \Omega_{t-1}\right] \tag{13}$$

where $\epsilon_t^{\delta}$ is a vector of shocks, and $\Omega_{t-1}$ is the history the expectations are conditioned on and which contains the initial values used to start the simulation procedure.

The GIRFs are estimated by simulation. For each period $t$, $\mathbb{E}\left[Y_{t+h} \mid \Omega_{t-1}\right]$ is simulated based on the model and random shocks:

$$Y_{t+h}^{sim} = \Pi_1' X_{t+h}^{sim}(1 - F(\gamma_F, c_F; s_{t+h-1})) + \Pi_2' X_{t+h}^{sim} F(\gamma_F, c_F; s_{t+h-1}) + \epsilon_{t+h} \tag{14}$$

The transition functions, $F(\gamma_F, c_F; s_{t+h-1})$ and $G(\gamma_G, c_G; s_{t+h-1})$, being functions of an endogenous variable of the model, are allowed to adjust at every simulation step. Therefore, also the time-dependent covariance matrix $\Sigma_{t+h}$ changes in every simulation step, and this way the shocks are drawn independently at every horizon based on the history and the evolution of $\Sigma_{t+h}$:

$$\epsilon_{t+h} \sim \mathcal{N}(0, \Sigma_{t+h})$$

To simulate $\mathbb{E}\left[Y_{t+h} \mid \epsilon_t^{\delta}, \Omega_{t-1}\right]$, $\epsilon_t^{\delta}$ is set to a specific shock, where $\delta$ indexes the chosen identification scheme, magnitude and sign. For the rest of the horizon $\epsilon_{t+h} \sim \mathcal{N}(0, \Sigma_{t+h})$ for $h \geq 1$. By letting each of the transition functions update

[10] We thank Julia Schmidt for offering us her codes on computing GIRFs for a threshold VAR model.

[11] To our knowledge Caggiano et al. (2014) is the only paper to endogenize the transition function.

every simulation step a possible regime-transition in the aftermath of a shock is allowed.

For each period, the history $\Omega_{t-1}$ contains the starting values for the simulation. For every chosen period, we simulate $B$ expected values up to horizon $h$ given the model, the history and the vector of shocks. For every chosen period, we then average over the $B$ simulations.

To analyze the results, we sort the GIRFs according to some criteria such as regime, sign, or magnitude of the shocks and we scale them in order to be comparable. We define a period as being a recession if $F(\gamma_F, c_F; s_{t-1}) \geq 0.5$ and an expansion otherwise.[12] Then, to obtain the effect of a small positive shock in recession, we average over the chosen GIRFs fulfilling all these criteria. Details are provided in Appendix D.

## 2.9 Generalized forecast error variance decomposition

In a nonlinear environment, the shares of the forecast error variance decomposition generally do not sum to 1 which makes their interpretation rather difficult. Lanne and Nyberg (2014) propose a method of calculating the generalized forecast error variance decomposition such that this restriction is imposed.

They define the generalized forecast error variance decomposition of shock $i$, variable $j$, horizon $h$ and history $\Omega_{t-1}$ as:

$$\lambda_{j,i,\Omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(l, \delta_{it}, \Omega_{t-1})_j^2}{\sum_{i=1}^{K}\sum_{l=0}^{h} GIRF(l, \delta_{it}, \Omega_{t-1})_j^2} \quad (15)$$

The denominator measures the aggregate cumulative effect of all the shocks, while the numerator is the cumulative effect of the $i$th shock. By construction, $\lambda_{j,i,\Omega_{t-1}}(h)$ lies between 0 and 1, measuring the relative contribution of a shock to the $i$th equation to the total impact of all $K$ shocks after $h$ periods on the $j$th variable. According to the authors, the GIRF is readily generalized by averaging over the relevant shocks and histories. They recommend computing the GFEVD as the average of $\lambda_{j,i,\Omega_{t-1}}(h)$ over shocks and over all the histories. More details about the computation of the GFEVD can be found in Appendix D.4.

# 3 Data

We work with quarterly data for the U.S. economy from 1955Q1 to 2012Q4. This period contains nine recessions of different magnitudes which provide enough variation.

[12] At $F(\gamma_F, c_F; s_{t-1}) = 0.5$, the model attributes 50 percent probability to each regime

Our benchmark system contains five variables: TFP adjusted for variations in factor utilization, University of Michigan index of consumer sentiment, real output, inflation and stock prices. As advised in Beaudry, Portier, and Seymen (2013), we try to keep the number of variables as low as possible while assuring we have information sufficiency. Total factor productivity is a measure of productivity in the economy whereas stock prices represents a forward-looking variable which contains information about technological innovations. The consumer sentiment index is another forward-looking variable that contains information about the expectations of consumers and producers. Output includes information about the state of the economy. By including inflation we take care of the nominal side of the economy and add another forward-looking variable. By adding these three forward-looking variables, we believe that we encompass enough information to identify the news shock. For robustness checks, we additionally include consumption and hours worked.

We use the series of TFP adjusted for variations in factor utilization constructed with the method of Basu, Fernald, and Kimball (2006). They construct TFP controlling for non-technological effects in aggregate total factor productivity including varying utilization of capital and labor, nonconstant returns and imperfect competition, and aggregation effects. They identify aggregate technology by estimating a Hall-style regression equation with a proxy for utilization in each disaggregated industry. Aggregate technology change is then defined as an appropriately weighted sum of the residuals. The series of TFP annualized percent change adjusted for utilization for the nonfarm business sector is available on the homepage of the Federal Reverse Bank of San Francisco[13]. To obtain the log-level of TFP, the cumulated sum of dTFP was constructed. The S&P 500 stock market index is used as a measure of stock prices[14]. For output we use the log of the real gross value added for the nonfarm business sector available from the U.S. Department of Commerce: Bureau of Economic Analysis. For hours worked the measure hours of all persons for the nonfarm business sector available from the U.S. Department of Labor: Bureau of labor Statistics is employed. Everything is in logs and adjusted for population (US Population, all persons ages 15-64) and the price level for which we use the implicit price deflator for the nonfarm business sector both available from the U.S. Department of Labor: Bureau of Labor Statistics. The price deflator ($PD$) is also used to compute the annualized inflation rate adjusted for population $IR = 4^{*}(\log(PD_t) - \log(PD_{t-1}))$. It is sometimes argued that consumer confidence measures reflect more closely the expectations of firms and households about future technological innovations and economic behavior. We work with data from the surveys of consumers conducted by the University

[13] http://www.frbsf.org/economic-research/total-factor-productivity-tfp/

[14] http://data.okfn.org/data/core/s-and-p-500♯data

of Michigan. For the whole sample only the index of consumer expectations for six months is available.[15] As a measure of consumption we use the log of the sum of Personal Consumption Expenditures for Nondurable Goods and Personal Consumption Expenditures for Services (both available from the Department of Commerce: Bureau of Economic Analysis) divided by the price deflator and population. Hours worked are measured as the log of Nonfarm Business Sector: Hours of All Persons (available from the U.S. Department of Labor: Bureau of Labor Statistics) divided by population.

# 4 Results

## 4.1 Linear setting

We estimate a VAR in levels and do not assume a specific cointegrating relationship because this estimation is robust to cointegration of unknown form and gives consistent estimates of the impulse responses, as it is stated in Sims, Stock, and Watson (1990). Moreover, in several papers (e.g. Barsky and Sims (2011), Beaudry and Portier (2014)) it is shown that VAR and VEC models deliver similar results. Our system features four lags, as indicated by the Akaike Information Criterion. We keep the same number of lags for the nonlinear model.

We apply the three identification schemes to isolate structural shocks. To make sure that our benchmark model is not informationally deficient, hence, that the identification schemes we employ provide indeed structural shocks, the fundamentalness test of Forni and Gambetti (2014) is performed. In Table 4 from Appendix C.2, we report the results for the orthogonality test for the short-run identification schemes for the benchmark model (S3) and three other VAR specifications (S1,S2 and S4)[16]. In Table 5, the results of the test applied to the medium-run identification are reported.

It is obvious that specification S1, which is a bivariate model with TFP and SP instead of ICS (the basic framework of Beaudry and Portier (2006)), is informationally deficient. However, when replacing SP with ICS (S2), the model performs better in identifying the structural shock, orthogonality being rejected rarely and only at a 10% significance level. Our results for S1 are similar to those

[15]Consumer confidence reflects the current level of business activity and the level of activity that can be anticipated for the months ahead. Each month's report indicates consumers assessment of the present employment situation, and future job expectations. Confidence is reported for the nation's nine major regions, long before any geographical economic statistics become available. Confidence is also shown by age of household head and by income bracket. The public's expectations of inflation, interest rates, and stock market prices are also covered each month. The survey includes consumers buying intentions for cars, homes, and specific major appliances.

[16]The four specifications are described in Table 3 from Appendix C.2

obtained by Gambetti (2014-2015), although the $p$-values he reports are in general smaller than ours. A reason for the difference can be the fact that our samples cover different time spans (1960Q1-2010Q4 in Gambetti (2014-2015)) or that the dataset used in his analysis contains more time series (107 opposed to 87). The results for S2 suggest that a confidence indicator such as the index of consumer sentiment performs better than stock prices in providing the model with sufficient information to identify structural shocks, even in a bivariate model.

For our 5-variable benchmark model, the $p$-values in the two tables indicate that orthogonality is never rejected at the 5% significance level. This specification which contains the three forward looking variables mostly used in the literature, stock prices, inflation, and a measure of consumer confidence, passes the test of fundamentalness. A model with seven variables, by adding consumption and hours worked to the benchmark model, also contains enough information. Nevertheless, Gambetti (2014-2015) shows, using the fundamentalness test of Forni and Gambetti (2014), that a four variables model including TFP, SP (or output), consumption and hours worked does not have sufficient information to identify the news shock which indicates that consumption and hours worked are not a necessary addition to our benchmark system to identify the news shock.

In Figure 7 from Appendix E, a scatterplot of the news shock identified with MRI and the confidence shock obtained with SRI for our benchmark five-variable model is displayed. The two identification schemes identify very similar structural shocks. This result is further confirmed by the high correlation between the two shocks (0.76). Impulse responses displayed in Figure 8 from Appendix E show that both identified shocks trigger a strong positive co-movement of the real economy, while TFP only starts increasing after some quarters. This result also indicates that a confidence shock resembles very much a news shock.

Under the two identifications, TFP is not allowed to change on impact but it is important to note that there is neither a significant rise above zero for the first two years. After that, TFP starts rising in both cases until it stabilizes to a new permanent level which is slightly higher under MRI. This result is in line with those found in Beaudry and Portier (2006) and Beaudry, Nam, and Wang (2011), but partly contradict those of Barsky and Sims (2011). BS find a rapid and immediate rise in TFP following their news shock which is insignificant in their four-variable model. The reason why the impulse response of TFP to the identified shock under MRI is different from the ones obtained by Barsky and Sims (2011) might be the fact that BS isolate the shock that maximizes its contribution to the forecast error variance of TFP not only at a given horizon, but over all horizons up to $H$. As already argued before, this measure might include short-run movements in TFP. The information content of the two models could have been another reason, but our results stay the same even when we compare the 7-variable models.

The index of consumer sentiment rises significantly on impact in both settings. This finding is consistent with those of Beaudry, Nam, and Wang (2011) who use the same confidence indicator, and Barsky and Sims (2011) who include in their 7-variable model a component of the index (i.e. Business Conditions expected during the next 5 years).

Output also increases on impact, and continues to increase for about eight quarters until it stabilizes at a new permanent level. The effect on output of the news shock obtained with MRI is stronger. This contradicts the results of Barsky and Sims (2011), who, with a similar identification scheme, conclude there is no large increase in output as anticipation of a TFP increase, but, on the contrary, the news shock has a negative impact effect on output. However, Beaudry, Nam, and Wang (2011) obtain similar results under most of the identification schemes they employ.

Inflation falls significantly at impact, more under MRI, this response being very close to the one obtained by Barsky and Sims (2011). In this paper, the authors argue that this reaction to a positive news shock is consistent to the New Keynesian framework in which current inflation equals an expected present discounted value of future marginal costs. The impulse response of inflation under SRI is similar to the one obtained by Beaudry, Nam, and Wang (2011).

Stock prices rise on impact to the same level in both cases, but while under SRI the response resembles the one in Barsky and Sims (2011), under MRI stock prices continue increasing for a long time, reaching a peak after some twenty quarters.

In Figure 9 from Appendix E it can be seen that adding other variables does not significantly modify the results for the first five variables. Inflation diminishes faster, while the response of stock prices is almost identical under the two identification schemes. For the two new variables added, the responses are similar to those presented in Beaudry, Nam, and Wang (2011). Both consumption and hours worked rise on impact, and while the response of hours worked is hump-shaped, the effect on consumption is permanent. The response of consumption is slightly bigger under MRI, while the opposite holds for hours worked.

These findings confirm the initial results of Beaudry and Portier (2006) and partially contradict those of Barsky and Sims (2011). Under the two different identification schemes, we find extremely similar results. A shock on a measure of consumer confidence with no impact effect on TFP (news or optimism/pessimism shock) proved to be highly correlated with a shock with no impact effect on TFP but which precedes rises in TFP. This supports the conclusion of Beaudry, Nam, and Wang (2011) that all predictable and permanent increases in TFP are preceded by a boom period, and all positive news shocks are followed by an eventual rise in TFP. After the realization of a positive news shock we find an impact and then gradual increase in output, the survey measure of consumer confidence, stock prices, hours worked, and consumption, and a decline in inflation while TFP only follows some quarters later. According to Beaudry, Nam, and Wang (2011), the period until TFP starts increasing can be defined as a non-inflationary boom phase unaccompanied by an increase in productivity.

## 4.2 Nonlinear setting

In this section, we take the analysis one step ahead and examine whether the time when the news arrive matters. More precisely, we want to see whether the state of the economy (i.e. the economy being in an expansion or in a recession) influences the responses to the news shock. Will the boom effect of a positive news realization be the same in the two states? Will it matter whether it is good or bad news? Or is there a difference if the news are extreme or rather small?

To answer these questions, we estimate a smooth transition vector autoregressive model. We rely on the same setting as in the linear model containing five variables (TFP, ICS, output, inflation, SP) with four lags. As a contribution to the STVAR literature, our model comprises two instead of only one transition function, one for the mean equation and one for the variance equation. Moreover, we estimate both sets of parameters instead of simply calibrating them.

The results presented in Figure 10 from Appendix F show that the parameters in the transition function for the mean equation do not depart too much from the starting values (i.e. the initial estimates obtained using a logistic regression), while the value of $\gamma_G$ increases a lot after the MCMC iterations for the variance equation. This indicates that the transition behavior from recession to expansion is not the same for the mean and the variance of the economy. The transition in the mean is much more smooth than in the variance where it approaches a regime-switch.

We further evaluate the model to verify that it is not explosive and it delivers interpretable results. Because we estimate the model with level data that are potentially integrated or growing over time, it is clear that some of the roots will be very close to one.[17]We use the method indicated by Teräsvirta and Yang (2014b) to examine the stability of the system. The convergence to a single stationary point is a necessary condition for exponential stability, and therefore for our model not to be explosive. On these grounds, we simulate counterfactuals for our model with all the shocks switched off. In the long-run, the model converges to a stable path. By plotting the simulated paths in first differences we can show that they converge to zero (see Figure 11 in Appendix F). It is clear for each variable in our model that, independent of the history in the dataset chosen as initial values, the trajectories

[17]We prefer to estimate the model in levels to keep the information contained in long-run relationships. Sims, Stock, and Watson (1990) argue that a potential cointegrating relationship does not have to be specified to deliver reliable estimates. Moreover, Ashley (2009) shows that impulse response functions analysis can be more reliable if the model is estimated in levels.

converge to the same point. We can conclude that the stability assumption is not contradicted by these calculations, and therefore our model is not explosive.

Note that non-explosiveness of the model is necessary for the estimation of generalized impulse response functions and the generalized forecast error variance decomposition. Since our results for the nonlinear VAR are qualitatively similar to those obtained with the linear VAR, which are further in line with the literature, we are confident that the model is trustworthy.

### 4.2.1 Variance decomposition

In Table 1 we display the share of the (generalized) forecast error variance of the variables attributable to the news shock at different horizons in the two regimes of the STVAR model and in the linear VAR model. The numbers are percentage values. Not surprisingly, the contributions of the news shock are very close in expansions to those in the linear model since more than 85 percent of the periods contained in our sample are defined as normal times. These results are reassuring since they indicate that the two methods for computing the variance decomposition give similar results. The only bigger difference is the contribution of the news shock to the variance decomposition of TFP in expansions. In this case the news shock accounts for a bigger share of the forecast error variance of TFP both at high and lower frequencies.

In the linear model, the news shock explains little of the variation of TFP in the short-run, but almost 40 percent of it at a horizon of ten years. On impact, it accounts for almost half of the variance decomposition of the confidence index and inflation, and while the share stays almost constant in the case of inflation, for confidence it increases to more than 70 percent at frequencies up to ten years. The shock contributes less to the forecast error variance of output and stock prices on impact, about 20-25 percent, but the contribution increases significantly over time. It is more than 60 percent in the case of stock prices, and almost 80 percent for output at a horizon of ten years.

When making a comparison of the results for the two regimes of the nonlinear model, it becomes clear that the contribution of the news shock to the variance of all the variables in the model is state-dependent. The medium-run contribution to TFP is above 50 percent in both regimes. In expansion, the news shock influences all variables except for TFP on impact, but the contribution is below 50 percent, except for the case of inflation. On the other hand, in recession the news shock explains on impact a much bigger share of the variance in consumer confidence, inflation and stock prices while its contribution to the variance decomposition of output is almost nil. In the medium-run the contributions converge to similar values in the two regimes, with some slightly bigger values in the case of recessions for TFP, inflation and stock prices.

Table 1: Generalized Forecast Error Variance Decomposition for the news shock (MRI). The numbers indicate the percent of the forecast error variance of each variable at various forecast horizons explained by the news shock in expansions, recessions, and the linear model.

| | | Impact | One year | Two years | Ten years |
|---|---|---|---|---|---|
| TFP | Linear | 0 | 0.13 | 0.95 | 38.67 |
| | Expansion | 0 | 6.82 | 12.14 | 53.68 |
| | Recession | 0 | 42.66 | 42.65 | 67.54 |
| Confidence | Linear | 56.06 | 72.09 | 75.5 | 71.76 |
| | Expansion | 47.43 | 73.81 | 77.58 | 67.83 |
| | Recession | 86.79 | 70.14 | 70.61 | 61.77 |
| Output | Linear | 25.21 | 57.21 | 69.27 | 78.96 |
| | Expansion | 24.65 | 54.49 | 70.63 | 72.11 |
| | Recession | 1.25 | 39.9 | 64.57 | 71.48 |
| Inflation | Linear | 44.28 | 41.1 | 43.31 | 48.57 |
| | Expansion | 51.04 | 52.61 | 54.11 | 49.65 |
| | Recession | 84.86 | 72.68 | 70.92 | 66.55 |
| Stock Prices | Linear | 18.24 | 30.75 | 40.1 | 63.11 |
| | Expansion | 13.77 | 37.79 | 50.67 | 59.11 |
| | Recession | 69.62 | 79.2 | 79.12 | 72.14 |

We find the very big impact contributions of the news shock to the forecast error variance of all three forward-looking variables in the recession to be a particularly interesting result, mostly when the non-forward looking variable in the group, output, is almost unaffected. Another key finding is that, even though in a recession the news shock explains little of the variance decomposition of output on impact, the share increases significantly and fast, such that already in one year it is close to 40 percent. The same pattern is observed in the case of TFP, the news shock explaining more than 40 percent of its variance decomposition in recession at a horizon of one year.

In Table 6 from Appendix F, we present the total contribution of the unanticipated productivity shock and the news shock to the forecast error variance of the variables. In the linear model, the two productivity related shocks combined explain almost 98 percent of the variation in TFP, about 93 percent of the variation in output at a horizon of ten years, and more than half of the variation in the other three variables. When we relax the linearity assumption, we observe the state-dependency in the combined contributions. Overall, we find much bigger contributions of these two shocks in recessions both at high and lower frequencies. The differences are particularly big on impact. In recessions, the two shocks explain together more than 95 percent of the impact variance decomposition of all the variables, while for TFP and inflation the shares are almost 100 percent. Since the two productivity shocks combined explain almost all the variation in recession, we have support for their high importance for driving economic fluctuations when they occur in downturns. They continue to play a major role also in normal times, but in that case there is more chance for other shocks to contribute to business cycle fluctuations.

When comparing the contributions of the news shock to those of the confidence shock (SRI) to the variance decomposition of the variables in the model, we find that in recessions there are some similarities between them. By looking at the results in Table 7 from Appendix F, it is clear that in recessions, besides the unanticipated productivity shock, the confidence shock has the largest influence on TFP (i.e. approximately 45 percent). Therefore, we can conclude that as long as there is sufficient information in the model also SRI isolates a shock that has a high medium-run impact on TFP. However, with the exception of the impact effect on consumer confidence, the confidence shock explains much less of the variance decomposition of the variables than the news shock, both at low and higher frequencies in the case of recessions. The differences between the contributions of the two shocks are even bigger when looking at expansions. The confidence shock contributes little on the short-run to TFP, output, inflation and stock prices, while on the medium-run the contribution increases, but it does not reach the level of the news shock. Again the only exception is the impact contribution of the confidence shock to the index of consumer sentiment which is twice as big as the one of the news shock.

These findings raise the question whether not only the reactions to the shocks is state-dependent, but actually different shocks are identified depending on the state of the economy. The contributions of the news shock to variables in recession resemble those of a confidence shock which is not the case in expansion. It is possible that the nature of the news shock as well as the unanticipated productivity shock are not exactly the same in different regimes which leads to a difference in the contributions to variables.

#### 4.2.2 Generalized impulse responses

The estimation of impulse response functions for a LSTVAR model is not straight forward. While Auerbach and Gorodnichenko (2012) estimate regime-dependent impulse response functions and Owyang, Ramey, and Zubairy (2013) opt for Jorda's method (Jorda (2005)), we decide to estimate generalized impulse response functions. Our way of estimating the GIRFs relaxes the assumption of staying in one regime once the shock hits the economy. A very important aspect is that the output is an endogenous variable of the model. When simulating the model for the computation of the GIRFs, this allows us to adjust the transition function every simulation step. In response to a shock, our method allows the model to change the regime. As a policy maker, it is of great interest whether news shocks can enforce regime changes. Moreover, we would actually expect that the reason for a regime change is a strong shock to the economy. By excluding this possibility a very interesting and important quality of the LSTVAR is ignored.

In Figure 1, the impulse responses of TFP and consumer confidence to a one standard deviation news shock obtained with the MRI scheme are displayed. Results are qualitatively very much in line with those obtained in the linear setting. A news shock about a technological innovation leads to an immediate increase in consumer confidence. However, the impact effect is bigger in expansions, and continues to be bigger for almost five years after the shock hits. In the case of TFP, there is no impact effect of the news shock in expansions, and also no significant change in the following two years. After that, TFP starts increasing, the change being of about one percentage point in ten years. There is also in this case a state-dependency evident in the short-run. The difference comes from the almost immediate reaction of TFP to the news shock when it hits in a recession. This indicates that there is not so much of an anticipation in this case.

The significance of the difference between the two regimes can be tested with confidence bands. Confidence bands indicate that the regime-dependence in the response to a news shock manifests itself in the short- and medium-run, while in the long-run the responses in the two regimes converge and the confidence bands overlap. This is not surprising as the same shock pushes the economy in a similar direction and every period some probability is attached to both regimes. When analyzing the confidence intervals for the two impulse responses, it is evident that those for recessions are much wider, mostly in the short-run, than those for expansions. The explanation is that we have more than eight times less starting values for the simulations in the case of recessions. Even though we simulate eight times more for each starting value belonging to this regime, it is clear that the much smaller number of recessionary periods in the sample matters[18].

In Figure 2, the impulse responses of the other three variables of the model, output, inflation and stock prices to a one standard deviation news shock obtained with the MRI scheme are displayed. Similarly to the responses of TFP and ICS, the responses are qualitatively similar, but there are quantitative differences. Inflation drops significantly in both states of the economy, more in recessions, but the state-dependency in responses fades away fast. Stock prices respond positively to the news shock. The reaction in recessions is bigger but the impact difference

[18]For details about the computation of GIRFs and their confidence bands, see Appendix D.

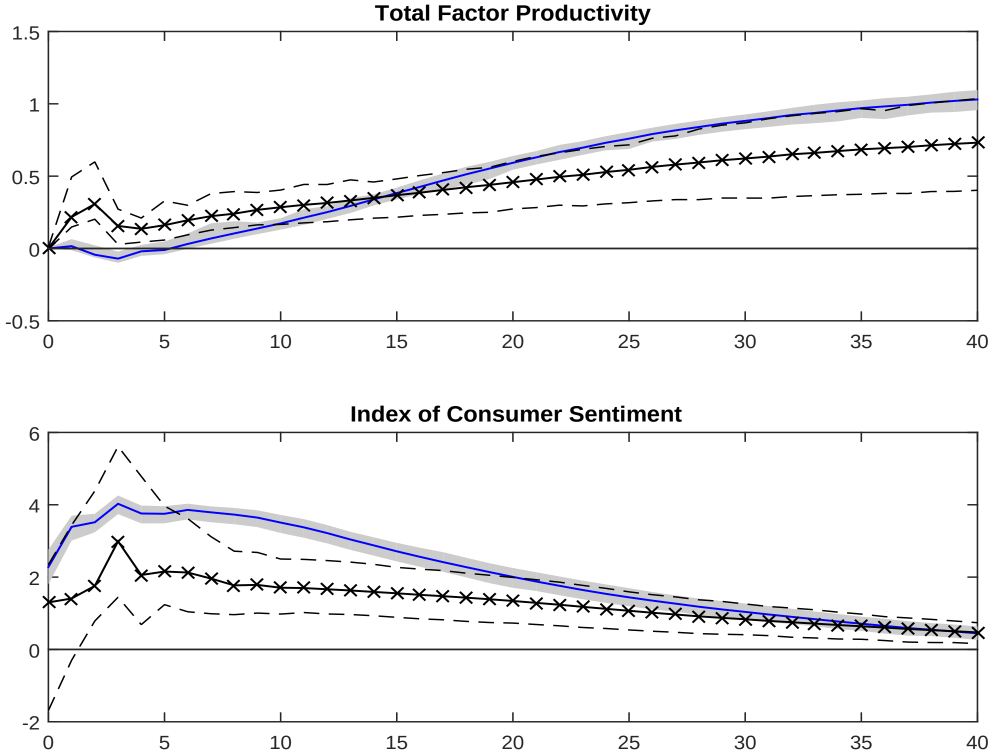


Figure 1: Generalized impulse response functions to a positive small news shock under MRI. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarters.

is not significant. At a horizon of two to five years, the effect of the news on stock prices seems to be larger in expansions. A key finding is the response of output to the news. In expansion, we have clear evidence of a positive effect of the news shock on output. On the other side, in a recession the impact effect is unclear, and not significantly different from zero for at least one year. After some time output starts increasing but the increase is much lower than the one occurring in an expansion.

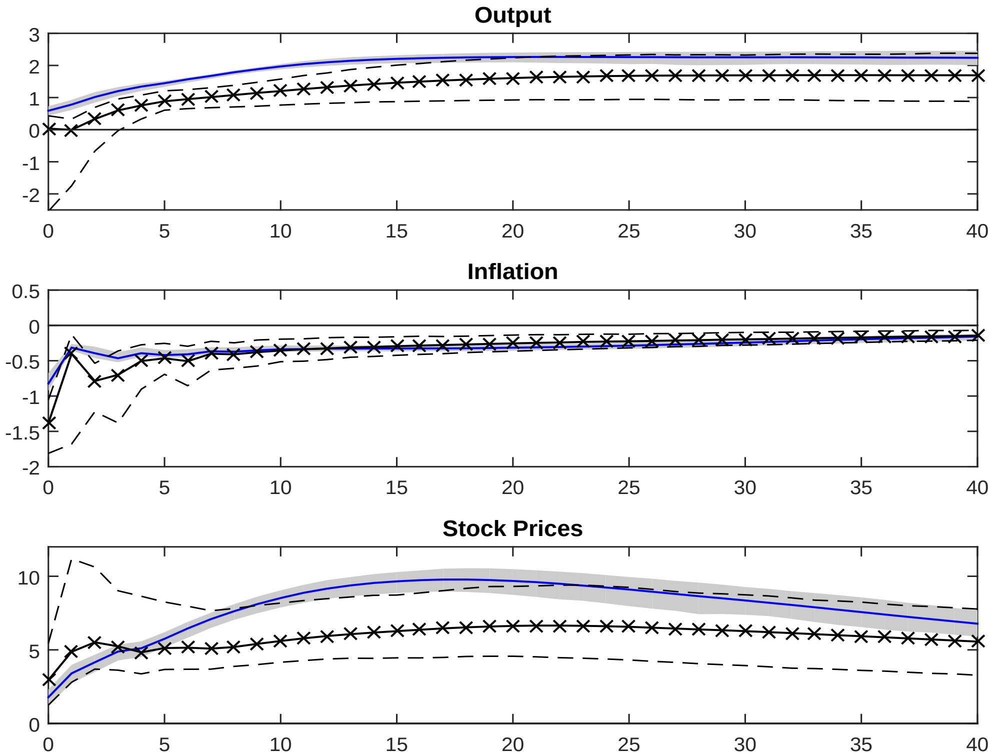


Figure 2: Generalized impulse response functions to a positive small news shock under MRI. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock, and the unit of the horizontal axis is quarters.

In Figure 14 from Appendix F, the responses to a small positive, a big positive, a small negative and a big negative news shock for both regimes are displayed. The big shock is three times the size of the small shock. The results are normalized to the same magnitude and sign to make them comparable. We find that the responses are qualitatively very similar. There are quantitative differences, though. It can be stated that the effect of a small negative shock in a recession seems to exhibit a stronger effect on output in the long-run. Thus, it is indicated that negative news depress the economy more in bad than in good times. Furthermore, small negative news shocks have stronger effects than the positive ones on consumer confidence and stock prices in the long-run, independent of the regime. Nevertheless, the magnitude and the sign of the shock do not seem to play an important role. Generally, it can be said that the reaction to a negative shock is slightly stronger and the reaction to a big shock increases by less than the increase in shock size. But the differences are not statistically significant.

As a next step, we compare the results obtained for the news shock with those for the confidence shock, under the SRI scheme (as showed in Figure 12 from Appendix F). We find that the results from the two identification schemes are qualitatively very similar to each other as well as to the linear case. If there are differences between the two identification methods they are of quantitative nature. The impulse responses for recession are actually almost the same for both identification schemes. This goes in line with the findings of the GFEVD which indicate that in recession the news shock is basically a confidence shock.

On the other hand, for the expansionary regime quantitative differences can be detected. While the effect of a news shock on total factor productivity is very much the same in the short run, TFP grows stronger under MRI even though the reaction of the index of consumer sentiment is almost the same. In expansion, a shock to consumer confidence does not reflect the entire news shock.

A possible explanation for the quantitative differences in expansion is the construction of MRI. With this identification method, it is possible that not exactly the same shock is identified in both regimes.The reason would be that not the same disturbances have the highest influence on medium-run TFP depending on whether they occur in expansionary or recessionary times. In recession, the highest influence on medium-run TFP seems to have a shock similar to the one identified with SRI. What influences TFP additionally when the shock occurs in expansion is not entirely clear.

When we make the comparison of the generalized impulse responses to the responses obtained in the linear setting, as it can be seen in Figure 3, we observe a strong similarity, apparent mainly in the short-run, between the responses in expansion and in the linear model. However, on the medium-run, it is evident that the responses to the news shock are stronger in expansions than on average. Therefore, using a linear model to show the effects of news shocks in normal times may underestimate their value. We see that the news shock has in expansion a much bigger effect on output than the linear model would predict, output stabilizing at a twice as big new permanent level in the expansionary regime. Similar conclusions can be drawn for TFP. Moreover, there is a temporary overreaction of stock prices to the news in expansion which the linear model misses.

On the contrary, using the impulse responses from a linear model to show the effects of a news shock in recessions may determine an overestimation of its value. As it can be seen in Figure 3, in a recession a news shock has on confidence half the impact effect implied by the linear model. Furthermore, output does not react for some quarters to a positive news shock in a recession, although the linear model indicates an immediate positive reaction.

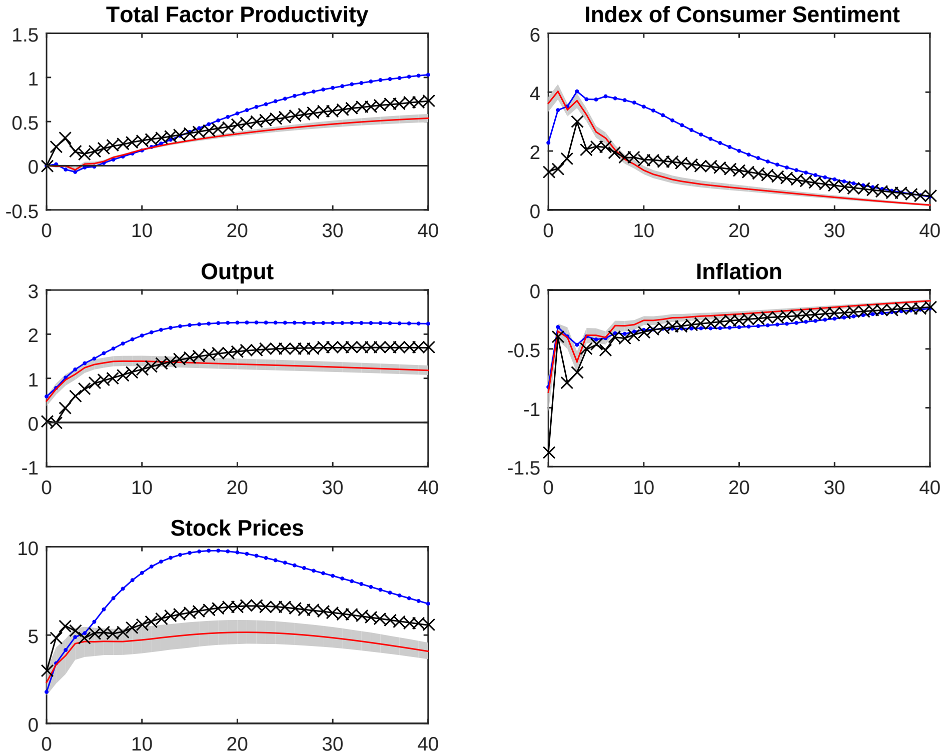


Figure 3: Comparison of the state-independent and the state-dependent effect of the news shock (under MRI). The figure displays the generalized impulse response functions to a positive small news shock in an expansion as the blue dotted line, the generalized impulse response functions to a positive small news shock in a recession as the starred black line, and the impulse responses to a news shock obtained by applying the same identification scheme in the linear model as the red line. The shaded light grey area represents the 95% bias-corrected confidence interval for the linear model. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

As a robustness check, we apply the identification scheme of Beaudry and Portier (2006) (SRI2). The news shock is then identified as the shock on stock prices instead of the index of consumer sentiment which has no impact effect on TFP. The impulse responses, displayed in Figure 13 from Appendix F, are qualitatively very similar but in absolute values smaller in both regimes than the impulse responses for the news shock obtained with the MRI and the confidence shock identified by applying the SRI. Thus, it is confirmed that stock prices do not capture the expectations of market participants as well as the index of consumer sentiment.

### 4.2.3 Regime transition

The probability of a change in regime is strongly influenced by news shocks.

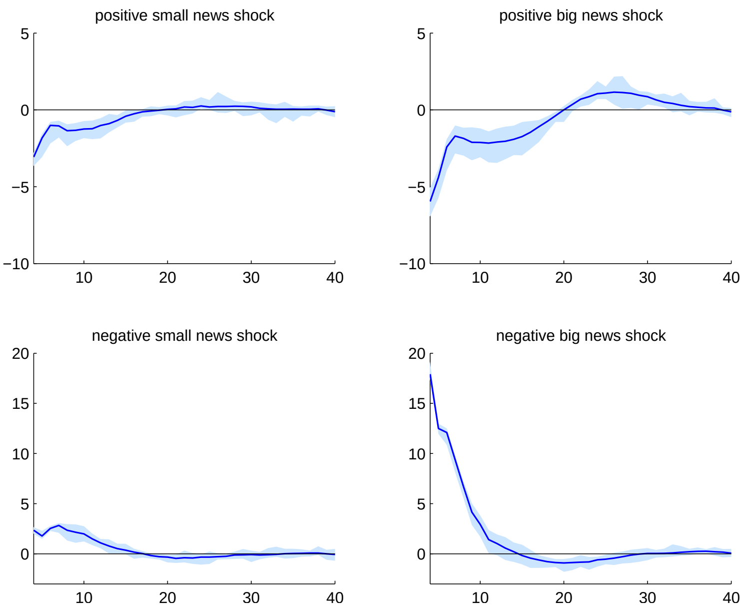


Figure 4: Regime transition probability change following a news shock. The four figures display the change in the probability of switching from an expansion to a recession starting one year after a news shock occured. The blue line shows the behavior following a news shock obtained with MRI, while the shaded light blue area represents the 95% bias-corrected confidence interval. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage points, and the unit of the horizontal axis is quarter.

The results in Figure 4 and Figure 5 present the change in the probability of switching from one regime to the other starting one year after a news shock happened. We ignore the effect on the probability of switching for the first four quarters since the results are influenced by the starting values. Because our model features four lags, for the first four simulation periods the probability of switching depends on real data.

As shown in Figure 4, when the economy is in expansion, a positive small news shock reduces the probability of a transition to recession by approximately four percentage points after one year. The effect of a three times bigger shock is not increasing this probability much. When a big positive news shock hits the economy during normal times, the probability of going into a recession is reduced by almost six percentage points after one year. An interesting finding is the effect of the positive news shock on the transition probability after five years. Although in the short-run the news shock seems to keep the economy in expansion, in the medium-run, once the improvements in productivity become apparent (i.e. TFP starts increasing), they may acknowledge that they have overrated the future evolution of the economy and start behaving accordingly. This behavior then generates a bust, as the probability of moving from an expansion to a recession increases. This result confirms the findings of Beaudry and Portier (2006) that booms and busts can be caused by news shocks and no technological regress is needed for the economy to go in a recession.

Another important result is the effect of the negative news shock in an expansion. While the small news shock increases the probability of a transition to recession by approximately three percentage points after one year, a big negative shock increases the switching probability more than proportional to its size. The big negative news shock has an extremely large effect in expansion, when it increases the probability of a transition to recession by almost twenty percentage points. This shows that strong bad news can make a boom end, and the downturn is fast and sharp. A reason for this behavior is given by Van Nieuwerburgh and Veldkamp (2006) who explain that expansions are periods of higher precision information. Therefore, when the boom ends, precise estimates of the slowdown prompt strong reactions.

In Figure 5, we observe that, if the economy is in a recession, a small positive news shock increases the probability of a transition to an expansion by less than five percentage points after four quarters. If the shock is three times bigger, the probability of a regime switch increases by about eight percentage points after four quarters. Thus, the probability does not increase proportionally. Although the difference is not big, we can conclude that positive news shock are more effective in recessions than in expansions. It also does not seem to be a reversal in the medium-run, once TFP increases. Negative news shocks increase the probability of staying in a recession, but their effect is not as strong as when they hit in an expansion.

By comparing the two figures, we can conclude that negative news in an expansion increase more the probability of going in a recession than the one of going in an expansion of positive news in recession. The intuition for this result is also found in Van Nieuwerburgh and Veldkamp (2006). The authors argue that in a recession, uncertainty slows the recovery and make booms more gradual than downturns.

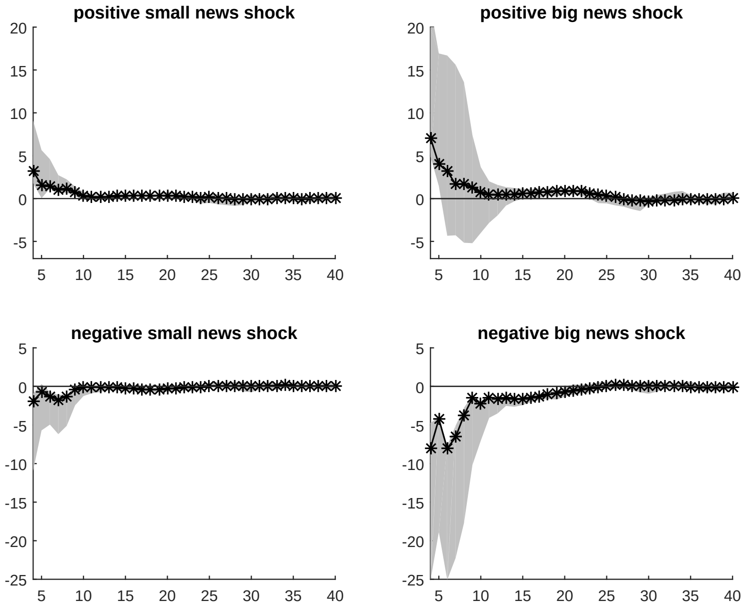


Figure 5: Regime transition probability change following a news shock. The four figures display the change in the probability of switching from a recession to an expansion starting one year after a news shock occured. The starred black line shows the behavior following a news shock obtained with MRI, while the shaded light grey area represents the 95% bias-corrected confidence interval. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage points, and the unit of the horizontal axis is quarter.

# 5 Conclusions

The Great Recession and the slow recovery of the following years have raised the question of what can turn the economy around back on the growth path. We confirm the view of the news literature that news shocks may trigger a boom and can initiate a transition from recession to expansion. But the response to a news shock hitting the economy in recession is delayed and smaller than when it occurs in normal times.

The type of news considered is about technological innovations. The idea is that technological innovations are permanent, but they diffuse slowly. After an innovation is conceived, it takes time for it to increase productivity in the economy. However, market participants react immediately, and this may lead to a boom, absent of any concurrent technological change.

To the best of our knowledge, the literature on news shocks has, so far, neglected nonlinearities. In this paper, we test whether the reactions to this technology related news shocks are state-dependent and/or asymmetric. By estimating a LSTVAR, we find evidence of quantitative state-dependencies, mainly in the short-and medium-run. The asymmetry between good and bad news does not seem to play an important role. The response to a news shock is in general larger in an expansion than in a recession. We also find that using a linear model to analyze the effects of news shocks one may underestimate their effect in an expansion while overestimating it in a recession.

A key finding is that the impact contribution of the news shock to the variation in all the variables of the model is state-dependent. While in expansion the results are close to those for the linear model, in recessions, the news shock contributes more on impact to the variance of the forward-looking variables, while the contribution to output's variance is almost nil. In the medium-run the shares converge to similar values in both regimes.

We show that the probability of a regime-transition is strongly influenced by the news shock. Our results indicate that strong bad news can make a boom end, while similarly strong good news do not have the same power to take the economy out of a recession.

Our intuition for the difference in the responses during the two regimes is the stronger uncertainty of the economic agents about what to expect in the future when they are in a recession. The result is that the same news shock leads to a lower business cycle effect when it hits the economy in a recession compared to occurring in expansion.

With this paper, we contribute to the empirical literature on STVAR models by introducing a medium-run identification scheme to isolate a structural shock and by estimating the parameters of two different transition functions of the model. Several checks of our results provide support in favor of their soundness. Another contribution is made to the empirical literature on news, by performing the analysis in a nonlinear setting.

We believe that future research in the news literature should try to develop a theoretical model, which can help explaining the mechanisms at work in this nonlinear setting.

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# Appendices

## A Data

We employ US Data from 1955:1-2012:4.

Table 2: Statistics

| | Expansion* | | Recession* | |
|---|---|---|---|---|
| | Mean | Variance | Mean | Variance |
| dTFP | 0.0028 | 0.0075 | 0.0039 | 0.0102 |
| ICS | 84.6619 | 12.7684 | 68.7171 | 14.8832 |
| dY | 0.0079 | 0.0093 | -0.0108 | 0.0119 |
| Infl | 0.0274 | 0.0208 | 0.0465 | 0.0420 |
| dSP | 0.0138 | 0.0524 | -0.0411 | 0.0932 |
| dC | 0.0070 | 0.0045 | -0.0004 | 0.0084 |
| dI | 0.0126 | 0.0255 | -0.0383 | 0.0355 |
| H | -7.5009 | 0.0501 | -7.5239 | 0.0389 |
| RR | 0.0224 | 0.0254 | 0.0223 | 0.0334 |
| NR | 0.0498 | 0.0309 | 0.0688 | 0.0479 |

* Defined according to the NBER business cycle indicator.

dTFP: difference of log tfp adj. for capacity utilization (from Federal Reverse Bank of San Francisco, following the method of Basu, Fernald, and Kimball (2006))

ICS: index of consumer sentiment (US consumer confidence - expectations sadj/US University of Michigan: consumer expectations voln, USCCONFEE, M, extracted from Datastream)

dY: difference of log real per capita output nonfarm (log of Real gross value added: GDP: Business: Nonfarm, A358RX1Q020SBEA, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis; adjusted for population: US population, working age, all persons (ages 15-64) voln, USMLFT32P, M, retrieved from Datastream)

Infl: inflation rate (4*log-difference of Nonfarm Business Sector: Implicit Price Deflator, IPDNBS, Q, sa, U.S. Department of Labor: Bureau of Labor Statistics)

dSP: difference of log real per capita stock stock prices (log of S&P 500, http://data.okfn.org/data/core//s-and-p-500♯data; divided by the price deflator and population)

dC: log real per capita consumption (log of Personal consumption expenditures: Nondurable goods, PCND, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis + Personal Consumption Expenditures: Services, PCESV, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis; divided by the price deflator and population)

dI: log real per capita investment (log of Personal consumption expenditures: Durable goods, PCDG, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis + Gross Private Domestic Investment, GPDI, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis; divided by the price deflator and population)

H: log per capita hours (log Nonfarm business sector: Hours of all persons, HOANBS, Q, sa, U.S. Department of Labor: Bureau of Labor Statistics; divided by population)

RR: real interest rate (nominal interest rate - annuylized inflation rate)

NR: nominal interest rate (Effective Federal Funds Rate, FEDFUNDS, M (averages of daily figures), nsa, Board of Governors of the Federal Reserve System)

# B Estimation of LSTVAR

## B.1 Linearity Test

For the test of linearity in the parameters we will first assume that the variance-covariance matrix $\Sigma_t = \Sigma$ is constant. Later we will test for constancy of the covariance matrix.

The null and alternative hypotheses of linearity can be expressed as the equality of the autoregressive parameters in the two regimes of the LSTVAR model in equation (1):

$$H_0 : \qquad \Pi_1 = \Pi_2, \tag{16}$$

$$H_1 : \qquad \Pi_{1,j} \neq \Pi_{2,j}, \text{ for at least one } j \in \{0, ..., p\}. \tag{17}$$

As explained in Teräsvirta, Tjøstheim, and Granger (2010) and van Dijk, Teräsvirta, and Franses (2002), the testing of linearity is affected by the presence of unidentified nuisance parameters under the null hypothesis, meaning that the null hypothesis does not restrict the parameters in the transition function ($\gamma_F$ and $c_F$), but, when this hypothesis holds true, the likelihood is unaffected by the values of $\gamma_F$ and $c_F$. As a consequence, the asymptotic null distributions of the classical likelihood ratio, Lagrange multiplier and Wald statistics remain unknown in the sense that they are non-standard distributions for which analytic expressions are most often not available.

Another way of stating the null hypothesis of linearity is $H_0' : \gamma_F = 0$. When $H_0'$ is true, the location parameter $c$ and the parameters $\Pi_1$ and $\Pi_2$ are unidentified.

The proposed solution to this problem, following Luukkonen, Saikkonen, and Teräsvirta (1988), is to replace the logistic transition function, $F(\gamma_F, c_F; s_{t-1})$, by a suitable $n$-order Taylor series approximation around the null hypothesis $\gamma_F = 0$.

The LSTVAR model in equation (2) can be rewritten as:

$$Y_t = \Pi_1' X_t + (\Pi_2 - \Pi_1)' X_t F_{t-1} + \epsilon_t, \tag{18}$$

where $X_t$ is the matrix of lagged endogenous variables and a constant.

Since our switching variable is a function of a lagged endogenous variable, for the LM statistic to have power, van Dijk, Teräsvirta, and Franses (2002) advise to approximate the logistic function by a third order Taylor expansion. This yields the auxiliary regression:

$$Y_t = \theta_0' X_t + \theta_1' X_t s_{t-1} + \theta_2' X_t s_{t-1}^2 + \theta_3' X_t s_{t-1}^3 + \epsilon_t^* \tag{19}$$

where $\epsilon_t^* = \epsilon_t + R(\gamma_F, c_F; s_{t-1})(\Pi_2 - \Pi_1)' X_t$, with $R(\gamma_F, c_F; s_{t-1})$ being the remainder of the Taylor expansion.

Since $\theta_i$, $i = 1, 2, 3$, are functions of the autoregressive parameters, $\gamma_F$ and $c_F$, the null hypothesis $H_0' : \gamma_F = 0$ corresponds to $H_0'' : \theta_1 = \theta_2 = \theta_3 = 0$. Under $H_0''$, the corresponding LM test statistic has an asymptotic $\chi^2$ distribution with $nm(mp + 1)$ degrees of freedom.

Denoting $Y = (Y_1, ...., Y_T)'$, $X = (X_1, ...., X_T)'$, $E = (\epsilon_1^*, ...., \epsilon_T^*)'$, $\Theta_n = (\theta_1', ...., \theta_n')'$, where $n = 3$ is the order of the Taylor expansion, and

$$Z_n = \begin{pmatrix} X_1' s_0 & X_1' s_0^2 & \cdots & X_1' s_0^n \\ X_2' s_1 & X_2' s_1^2 & \cdots & X_2' s_1^n \\ \vdots & \vdots & \ddots & \vdots \\ X_T' s_{T-1} & X_T' s_{T-1}^2 & \cdots & X_T' s_{T-1}^n \end{pmatrix}, \tag{20}$$

we can write equation (19) in matrix form:

$$Y = X\Theta_0 + Z_n \Theta_n + E. \tag{21}$$

The null hypothesis can be then also rewritten as: $H_0'' : \Theta_n = 0$. For the test we follow the steps described in Teräsvirta and Yang (2014a):

1. Estimate the model under the null hypothesis (the linear model) by regressing $Y$ on $X$. Compute the residuals $\tilde{E}$ and the matrix residual sum of squares, $SSR_0 = \tilde{E}' \tilde{E}$.

2. Estimate the auxiliary regression, by regressing $Y$ (or $\tilde{E}$) on $X$ and $Z_n$. Compute the residuals $\hat{E}$ and the matrix residual sum of squares, $SSR_1 = \hat{E}'\hat{E}$.

3. Compute the asymptotic $\chi^2$ test statistic:

$$LM_{\chi^2} = T(m - tr\left\{SSR_0^{-1}SSR_1\right\}) \tag{22}$$

or the F-version, in case of small samples:

$$LM_F = \frac{mT - K}{JmT} LM_{\chi^2}, \tag{23}$$

where $K$ is the number of parameters, and $J$ the number of restrictions.

Under $H_0''$, the F-version of the LM test is approximately $F(J, mT - K)$-distributed. We can reject the null hypothesis of linearity at all significance levels, regardless of the type of LM test we perform.

Having assumed a priori that the potential nonlinearity in the vector system is controlled by a single transition variable, we need to further test each equation separately using the selected transition variable in order to check whether there are any linear equations in the system. Under $H_0''$, the LM test statistic for each equation has an asymptotic $\chi^2$ distribution with $n(p+1)$ degrees of freedom while the F-version of the LM test is approximately $F(J, T - K)$-distributed, where $J = n(p+1)$ and $K = (n+1)(p+1)$.

## B.2 Estimation results of logistic model

| Dependent variable: *rec* (=1 for a recessionary period, =0 otherwise) | |
|---|---|
| Independent variables: | |
| Switching variable | -3.1245***<br>(0.4806) |
| Intercept | -1.5038***<br>(0.2721) |
| No. of observations: 228<br>Log Likelihood: -48.977<br>LR $\chi^2_{(1)}$: 104.25***<br>Pseudo $R^2$: 0.5156 | |

Significance levels : *10% **5% ***1%

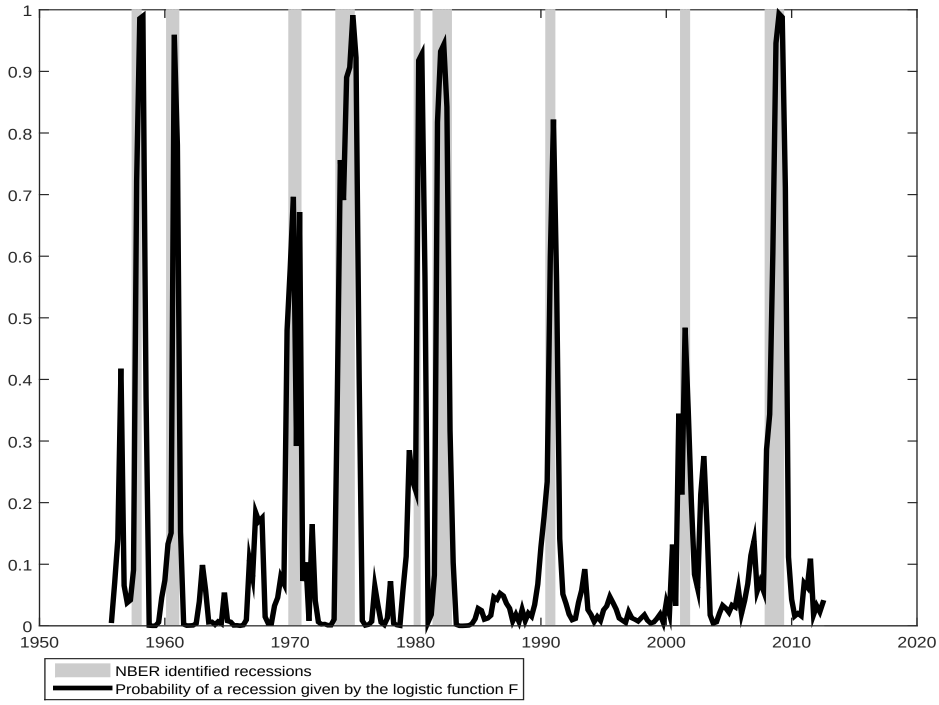


Figure 6: Initial transition function with estimated parameters obtained from a logistic regression

## B.3 MCMC procedure - MH algorithm

Our approach is, given the quasi-posterior densitiy $p(\Psi_n) \propto e^{L(\Psi_n)}$, known up to a constant, and a pre-specified candidate-generating (or proposal) density $q(\Psi'_n \mid \Psi_n)$, to construct chains of length $N$, $(\Psi_n^0, ..., \Psi_n^N)$. We follow the forthcoming steps:

1. Choose intial parameter value $\Psi_n^0$.
2. For $j = 1, ..., N$:
    (a) Generate $\Psi'_n$ from $q(\Psi'_n \mid \Psi_n^j)$ and $u$ from $U[0,1]$.
    (b) Compute the probability of move, $\alpha(\Psi_n^j, \Psi'_n)$:

$$\alpha(\Psi_n^j, \Psi'_n) = \min\left\{\frac{p(\Psi'_n)q(\Psi'_n \mid \Psi_n^j)}{p(\Psi_n^j)q(\Psi_n^j \mid \Psi'_n)}, 1\right\} \tag{24}$$

(c) Update $\Psi_n^{j+1}$ from $\Psi_n^j$, using:

$$\Psi_n^{j+1} = \begin{cases} \Psi'_n & \text{if } u \leq \alpha(\Psi_n^j, \Psi'_n); \\ \Psi_n^j & \text{otherwise.} \end{cases} \tag{25}$$

3. Return the values $(\Psi_n^0, ..., \Psi_n^N)$.

To implement the MH algorithm, it is essential to choose suitable starting parameter values, $\Psi_n^0$, and candidate-generating density, $q(\Psi'_n \mid \Psi_n)$.

The importance of the starting parameter values is given by the fact that in case $\Psi_n^0$ is far in the tails of the posterior, $p(\Psi_n)$, MCMC may require extended time to converge to the stationary distribution. This problem may be avoided by choosing a starting value based on economic theory or other factors.

The starting values for the transition function parameters are obtained by a logistic regression of the NBER business cycle on the transition variable. The starting values for the covariance matrices $(\Sigma_1, \Sigma_2)$ are obtained from the auxiliary regression 19 in Appendix B.1, where it is altered by $\varepsilon > 0$ for the second.

The choice of the candidate-generating density, $q(\Psi'_n \mid \Psi_n)$, is also important because the success of the MCMC updating and convergence depends on it. Although the theory on how this choice should be made is not yet complete (Chib and Greenberg (1995)), it is usually advised to choose a proposal density that approximates the posterior density of the parameter. However, this approach is hard to implement when the parameter set contains many elements, so in practice ad- hoc initial approximations, such as a $N(0,1)$ proposal density may be used and subsequently improved on using the MCMC acceptance rates. Therefore, this being the case in our setting, we use a candidate-generating density, $q(\Psi'_n \mid \Psi_n) = f(|\Psi'_n - \Psi_n|)$, with $f$ being a symmetric distribution, such that:

$$\Psi'_n = \Psi_n + \psi, \ \psi \sim f \tag{26}$$

Since the candidate is equal to the current value plus noise, this case is known in the literature as the random walk MH chain. We choose $f$ to be a multivariate normal density, $N(0, \sigma_\psi^2)$, with $\sigma_\psi^2$ being a diagonal matrix.

Note that since $f$ is symmetric, $q(\Psi'_n \mid \Psi_n) = q(\Psi_n \mid \Psi'_n)$ and the probability of move only contains the ratio $\frac{p(\Psi'_n)}{p(\Psi_n^j)} = \frac{e^{L(\Psi'_n)}}{e^{L(\Psi_n^j)}}$.

What remains to be done at this stage is to specify a value for the standard deviation, $\sigma_\psi$. Since $\sigma_\psi$ determines the size of the potential jump from the current to the future value, one has to be careful because if it is too large it is possible that the chain makes big moves and gets far away from the center of the distribution while if it is too small the chain will tend to make small moves and take long time to cover the support of the target distribution. To avoid such situations, we calibrate it to one percent of the initial parameter value, as adviced in Auerbach and Gorodnichenko (2012).

For the normal proposal density, the acceptance rate depends heavely on $\sigma_\psi$. Hence, in order to make sure we obtain an acceptance rate between 25% and 45%, as indicated in Roberts, Gelman, and Gilks (1997), we adjust the variance of the proposal density every 500 draws for the first 20,000 iterations.

We use N=120,000, out of which the first 20,000 draws are discarded, while the remaining are used for the computation of estimates and confidence intervals.

## B.4 Constancy of the Error Covariance Matrix

Yang (2014) proposes a test for the constancy of the error covariance matrix applicable to smooth transition vector autoregressive models. It is based on the assumption that the time-varying conditional covariance matrix $\Sigma_t$ can be decomposed as follows:

$$\Sigma_t = P\Lambda_t P', \tag{27}$$

where the time-invariant matrix $P$ satisfies $PP' = I_m$, $I_m$ being an identity matrix, and $\Lambda_t = diag(\lambda_{1t}, \dots, \lambda_{mt})$ which elements are all positive.

Under this assumption, the log-likelihood function for observation $t =, \dots, T$ based on vector Gaussian distributed errors is:

$$\begin{aligned}\log L_t &= c - \frac{1}{2}\log|\Sigma_t| - \frac{1}{2}u_t\Sigma_t^{-1}u_t' \\ &= c - \frac{1}{2}\log|\Lambda_t| - \frac{1}{2}w_t\Lambda_t^{-1}w_t' \\ &= c - \frac{1}{2}\sum_{i=1}^{m}(\log\lambda_{it} + w_{it}^2\lambda_{it}^{-1})\end{aligned}$$

where $w_t = u_t P$.

The null hypothesis to be tested is then:

$$H_0 : \lambda_{it} = \lambda_i, \quad i = 1, \dots, m \tag{28}$$

The LM test given in Yang (2014) is based on the statistic:

$$LM = \frac{1}{2}\sum_{i=1}^{m}\left[\left(\sum_{t=1}^{T}\tilde{g}_{it}\tilde{z}_{it}'\right)\left(\sum_{t=1}^{T}\tilde{z}_{it}\tilde{z}_{it}'\right)^{-1}\left(\sum_{t=1}^{T}\tilde{g}_{it}\tilde{z}_{it}\right)\right]. \tag{29}$$

To test for constancy of the error covariance matrix, first, the model has to be estimated under the null hypothesis assuming the error covariance matrix to be constant over time. The residuals of this model $\tilde{u}_t$ are collected and the empirical covariance matrix $\tilde{\Sigma}_t$ is computed and decomposed into $\tilde{\Sigma}_t = \tilde{P}\tilde{\Lambda}_t\tilde{P}'$. In a next step, the transformed residuals $\tilde{w}_t = \tilde{u}_t\tilde{P}$ and $\tilde{g}_{it} = \tilde{w}_{it}^2/\tilde{\lambda}_i - 1$ are computed. For each equation, an auxiliary regression of $\tilde{g}_{it}$ on $\tilde{z}_{it}$ is run. $\tilde{z}_{it}$ is chosen to be a first or higher order approximation of the transition function. In the case of the logistic smooth transition VAR and a first order approximation $\tilde{z}_{it}$ may be a function of time $z_{it} = [t/T1]$ or the switching variable. The LM statistic is then computed as follows:

$$LM = \sum_{i=1}^{m} T\frac{SSG_i - RSS_i}{SSG_i}, \tag{30}$$

where $SSG_i$ is the sum of squared $\tilde{g}_{it}$, and the $RSS_i$ the corresponding residual sum of squares in the auxiliary regression. Under regularity conditions, the LM statistic is asymptotically $\chi^2$ distributed with degrees of freedom equal to the number of restrictions.

Yang (2014) shows that this test exhibits high power and size even if the assumption from equation (27) does not hold and performs especially well in the case of smooth transition VARs.

In our case, the null hypothesis of a constant error covariance matrix is clearly rejected.

# C Fundamentalness Test

## C.1 Procedure

1. Take a large dataset $Q_t$, capturing all of the relevant macroeconomic information.We use a dataset which contains 87 quarterly macroeconomic series for the U.S. from 1955Q1 to 2012Q4.

2. Set a maximum number of factors $p$ and compute the first $p$ principal components of $Q_t$. The authors suggest to choose $p$ between 4 and 10. We set the maximum number of factors $p = 10$ and compute the first $p$ principal components of the dataset. We use the principal components to obtain the unobserved factors.

3. Test whether the estimated shock is orthogonal to the past of the principal components, $p$ (we use lags 1, 4, and 6), by regressing the critical structural shock (news shock) on the past of the principal components and performing an F-test of the null hypothesis that the coefficients are jointly zero.

## C.2 Results

Table 3: Linear model specifications

| | TFP | ICS | Output | Inflation | SP | Consumption | Hours |
|---|---|---|---|---|---|---|---|
| S1 | × | × | | | | | |
| S2 | × | | | | × | | |
| S3 | × | × | × | × | × | | |
| S4 | × | × | × | × | × | × | × |

Table 4: Results of the fundamentalness test for SRI

| | | Principal components | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Specification | lags | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| S1 | 1 | 0.45 | 0.03 | 0.07 | 0.11 | 0.13 | 0.05 | 0.09 | 0.13 | 0.13 | 0.10 |
| | 4 | 0.96 | 0.35 | 0.65 | 0.73 | 0.75 | 0.58 | 0.50 | 0.70 | 0.45 | 0.19 |
| | 6 | 0.97 | 0.40 | 0.51 | 0.47 | 0.33 | 0.25 | 0.20 | 0.05 | 0.06 | 0.05 |
| S2 | 1 | 0.58 | 0.08 | 0.16 | 0.25 | 0.32 | 0.33 | 0.34 | 0.28 | 0.37 | 0.38 |
| | 4 | 0.76 | 0.61 | 0.67 | 0.60 | 0.73 | 0.78 | 0.83 | 0.60 | 0.64 | 0.68 |
| | 6 | 0.47 | 0.58 | 0.83 | 0.81 | 0.93 | 0.94 | 0.92 | 0.60 | 0.65 | 0.76 |
| S3 | 1 | 0.77 | 0.95 | 0.85 | 0.88 | 0.91 | 0.93 | 0.92 | 0.91 | 0.94 | 0.94 |
| | 4 | 0.95 | 0.99 | 0.96 | 0.87 | 0.95 | 0.97 | 0.96 | 0.75 | 0.71 | 0.71 |
| | 6 | 0.54 | 0.91 | 0.98 | 0.91 | 0.98 | 0.98 | 0.96 | 0.67 | 0.67 | 0.79 |
| S4 | 1 | 0.83 | 0.91 | 0.79 | 0.87 | 0.93 | 0.94 | 0.94 | 0.90 | 0.93 | 0.96 |
| | 4 | 0.93 | 0.99 | 0.97 | 0.90 | 0.96 | 0.97 | 0.97 | 0.81 | 0.75 | 0.78 |
| | 6 | 0.61 | 0.94 | 0.98 | 0.93 | 0.98 | 0.98 | 0.97 | 0.69 | 0.70 | 0.83 |

Each value from the table reports a p-value of the F-test obtained from the regression of the news shock estimated using specifications S1 to S4 on 1,4 and 6 lags of the first difference of the first 10 principal components. The news shock is identified as the shock on the second variable (SP for S1 and ICS for S2-S4) that does not move TFP on impact.

Table 5: Results of the fundamentalness test for MRI

| | | Principal components | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Specification | lags | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| S1 | 1 | 0.42 | 0.02 | 0.06 | 0.10 | 0.11 | 0.05 | 0.09 | 0.13 | 0.13 | 0.12 |
| | 4 | 0.92 | 0.31 | 0.62 | 0.74 | 0.78 | 0.63 | 0.50 | 0.69 | 0.45 | 0.22 |
| | 6 | 0.92 | 0.37 | 0.44 | 0.44 | 0.28 | 0.27 | 0.19 | 0.06 | 0.06 | 0.05 |
| S2 | 1 | 0.75 | 0.08 | 0.15 | 0.23 | 0.25 | 0.25 | 0.29 | 0.22 | 0.29 | 0.31 |
| | 4 | 0.78 | 0.62 | 0.53 | 0.52 | 0.68 | 0.70 | 0.71 | 0.43 | 0.52 | 0.58 |
| | 6 | 0.43 | 0.57 | 0.76 | 0.77 | 0.90 | 0.92 | 0.89 | 0.55 | 0.64 | 0.76 |
| S3 | 1 | 0.74 | 0.89 | 0.76 | 0.73 | 0.80 | 0.85 | 0.82 | 0.76 | 0.82 | 0.87 |
| | 4 | 0.81 | 0.98 | 0.97 | 0.62 | 0.81 | 0.88 | 0.64 | 0.16 | 0.12 | 0.15 |
| | 6 | 0.21 | 0.69 | 0.91 | 0.58 | 0.73 | 0.82 | 0.55 | 0.16 | 0.15 | 0.27 |
| S4 | 1 | 0.79 | 0.95 | 0.79 | 0.90 | 0.92 | 0.90 | 0.88 | 0.74 | 0.80 | 0.81 |
| | 4 | 0.82 | 0.98 | 0.98 | 0.64 | 0.81 | 0.71 | 0.52 | 0.18 | 0.13 | 0.21 |
| | 6 | 0.65 | 0.94 | 0.98 | 0.73 | 0.86 | 0.79 | 0.57 | 0.19 | 0.18 | 0.29 |

Each value from the table reports a p-value of the F-test obtained from the regression of the news shock estimated using specifications S1 to S4 on 1,4 and 6 lags of the first difference of the first 10 principal components. The news shock is identified as the shock that does not move TFP on impact and has maximal effect on TFP at horizon 40.

# D Estimation of GIRF and GFEVD

## D.1 Estimation of GIRF with SRI

The GIRFs are estimated by simulation for eight different cases:

| case | regime | magnitude | sign |
|---|---|---|---|
| 1 | Expansion | $\sigma$ | + |
| 2 | Expansion | $3\sigma$ | + |
| 3 | Expansion | $\sigma$ | - |
| 4 | Expansion | $3\sigma$ | - |
| 5 | Recession | $\sigma$ | + |
| 6 | Recession | $3\sigma$ | + |
| 7 | Recession | $\sigma$ | - |
| 8 | Recession | $3\sigma$ | - |

$\sigma$ denotes the standard deviation of the news shock.

The simulation for a case starts by choosing a period $t$ and its corresponding history $\Omega_{t-1}$ from the sample that satisfies the regime criterium of that case. We define a period as being a recession if $F(\gamma_F, c_F; s_{t-1}) \geq 0.5$ and an expansion otherwise.

The simulation of the GIRF

$$GIRF(h, \epsilon_t, \Omega_{t-1}) = \mathbb{E}\left[Y_{t+h} \mid \epsilon_t^\delta, \Omega_{t-1}\right] - \mathbb{E}\left[Y_{t+h} \mid \Omega_{t-1}\right] \tag{31}$$

is performed in two steps by simulating $\mathbb{E}\left[Y_{t+h} \mid \epsilon_t^\delta, \Omega_{t-1}\right]$ and $\mathbb{E}\left[Y_{t+h} \mid \Omega_{t-1}\right]$ individually and then taking the difference.

Step 1: Simulation of $\mathbb{E}\left[Y_{t+h} \mid \Omega_{t-1}\right]$

For a chosen period and history, conditional expected values of $Y_{t+h}$ are simulated up to horizon $h$ given the model. For the first $p$ simulations also data contained in the history is used. Every period the model is shocked randomly by

$$\epsilon_{t+h} \sim \mathcal{N}(0, \Sigma_{t+h}).$$

The shocks are drawn from a normal distribution with variance

$$\Sigma_{t+h} = G(\gamma_G, c_G; s_{t+h-1})\Sigma_1 + (1 - G(\gamma_G, c_G; s_{t+h-1}))\Sigma_2.$$

The variance is history-dependent through the switching variable and adjusts every simulation horizon.

Step 2: Simulation of $\mathbb{E}\left[Y_{t+h} \mid \epsilon_t^\delta, \Omega_{t-1}\right]$

In the first period, only a specific shock affects the model. $\epsilon_t^\delta = A_{t+h}^G e_i$ where $A_{t+h}^G$ is the orthogonalization of $\Sigma_{t+h}$ according to the identification scheme. $e_i$ is a vector of zeros with the $i$th position being determined by the case (Sign: positive/negative, Magnitude: $\sigma$/ $3\sigma$). In the case of SRI, the news shock is identified as the second shock. For the rest of the horizon $h \geq 1$, the model is shocked with randomly drawn shocks $\epsilon_{t+h} \sim \mathcal{N}(0, \Sigma_{t+h})$ according to Step 1 .

For each period we perform $B$ simulations and then average over them. Since among the periods, we have about eight times more defined expansionary than recessionary periods, for each recession, we simulate $B = 8000$ expected values up to horizon $h$ given the model, the history and the vector of shocks, while for an expansionary history we simulate for $B = 1000$.

To analyze the results, we sort the GIRFs according to some criteria such as regime, sign, or magnitude of the shocks and we scale them in order to be comparable. Then, to obtain, for example, the effect of a small positive shock in recession, we average over the chosen GIRFs fulfilling all these criteria.

## D.2 Estimation of GIRF with MRI

For the estimation of GIRF with the MRI, first, the rotation matrix that maximizes the generalized forecast error variance decomposition at horizon 40 has to be identified and, second, the GIRF have to be estimated given the rotation matrix.

Step 1:
The news shock is identified as the shock that has no impact effect on TFP, but maximizes the generalized forecast error variance decomposition at horizon 40. The rotation matrix is found by minimizing the negative of the GFEVD at horizon 40. The estimated covariance matrices for both regimes are used as starting values. They are rotated to set the restriction that the news shock has no impact effect.

Step 2:
The GIRF are estimated as described in Appendix D.1. The only difference is that the orthogonalization of the history-dependent covariance matrix is approximated by

$$\Sigma_{t+h} = A_{t+h}^{G} A_{t+h}^{G\prime}$$

$$A_{t+h}^{G} = G(\gamma_G, c_G; s_{t+h-1})A_1 + (1 - G(\gamma_G, c_G; s_{t+h-1}))A_2 \quad (32)$$

where $\Sigma_1 = A_1 A_1'$ and $\Sigma_2 = A_2 A_2'$.

The specific shock $\epsilon_t^{\delta} = A_{t+h}^{G} e_i$ where $A_{t+h}^{G}$ is the orthogonalization of $\Sigma_{t+h}$ according to the identification scheme. $e_i$ is a vector of zeros with the $i$th position being determined by the case (Sign: positive/negative, Magnitude: $\sigma$/ $3\sigma$). Under MRI, the unanticipated productivity shock can be identified as the first shock and then the news shock as any other shock.

## D.3 Confidence Bands

To estimate confidence bands, we draw $D = 1000$ positions from the results of the MCMC routines. For each position we estimate GIRFs according to the identification scheme. The confidence bands are then the respective quantiles of the set of estimated GIRFs from the draws.

## D.4 Generalized Forecast Error Variance Decomposition

The estimation of the GFEVD is based on the estimation of generalized impulse response functions.

$$\lambda_{j,i,\Omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(l, \delta_{it}, \Omega_{t-1})_j^2}{\sum_{i=1}^{K} \sum_{l=0}^{h} GIRF(l, \delta_{it}, \Omega_{t-1})_j^2} \tag{33}$$

We perform simulations to obtain GIRFs for all six shocks by adjusting $\epsilon_t^\delta$ for a given horizon, shock and variable. To obtain the numerator of $\lambda_{j,i,\Omega_{t-1}}(h)$, the squared GIRF just have to be summed up to horizon $h$. For the denominator the squared GIRF are in addition summed over all shocks $K$.

# E Results in the linear setting

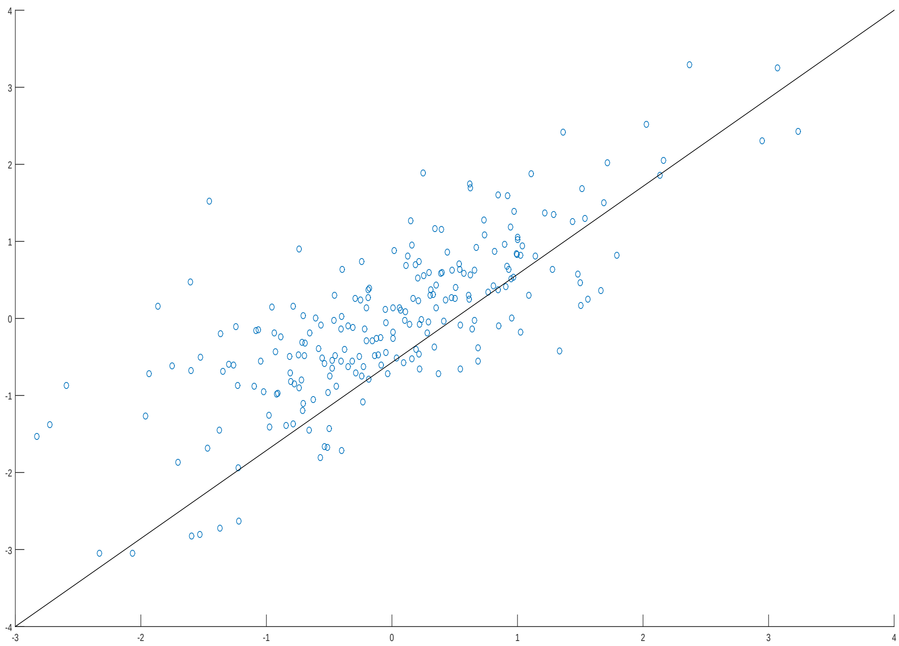


Figure 7: Comparison of the news and the confidence shocks using a scatterplot. The confidence shock is identified using a SRI which assumes that the confidence shock affects ICS on impact but not TFP. Under a MRI, the news shock is defined as the shock that does not move TFP on impact but has maximal effect on it at $H = 40$.

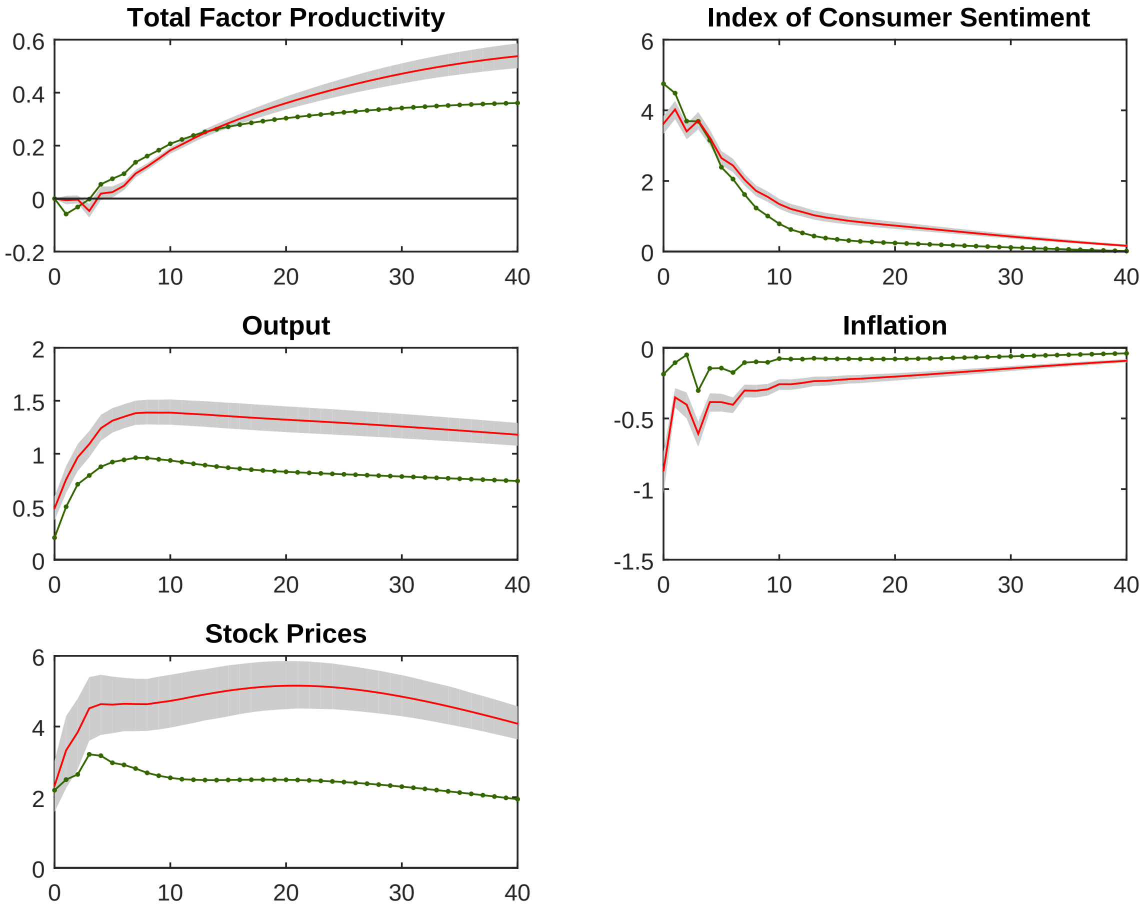


Figure 8: Comparison of news shock and confidence shock in a linear model.The red solid line shows the response to the news shock, while the green dotted line is the response to the confidence shock. The shaded region is the 95 percent confidence interval for the news shock. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

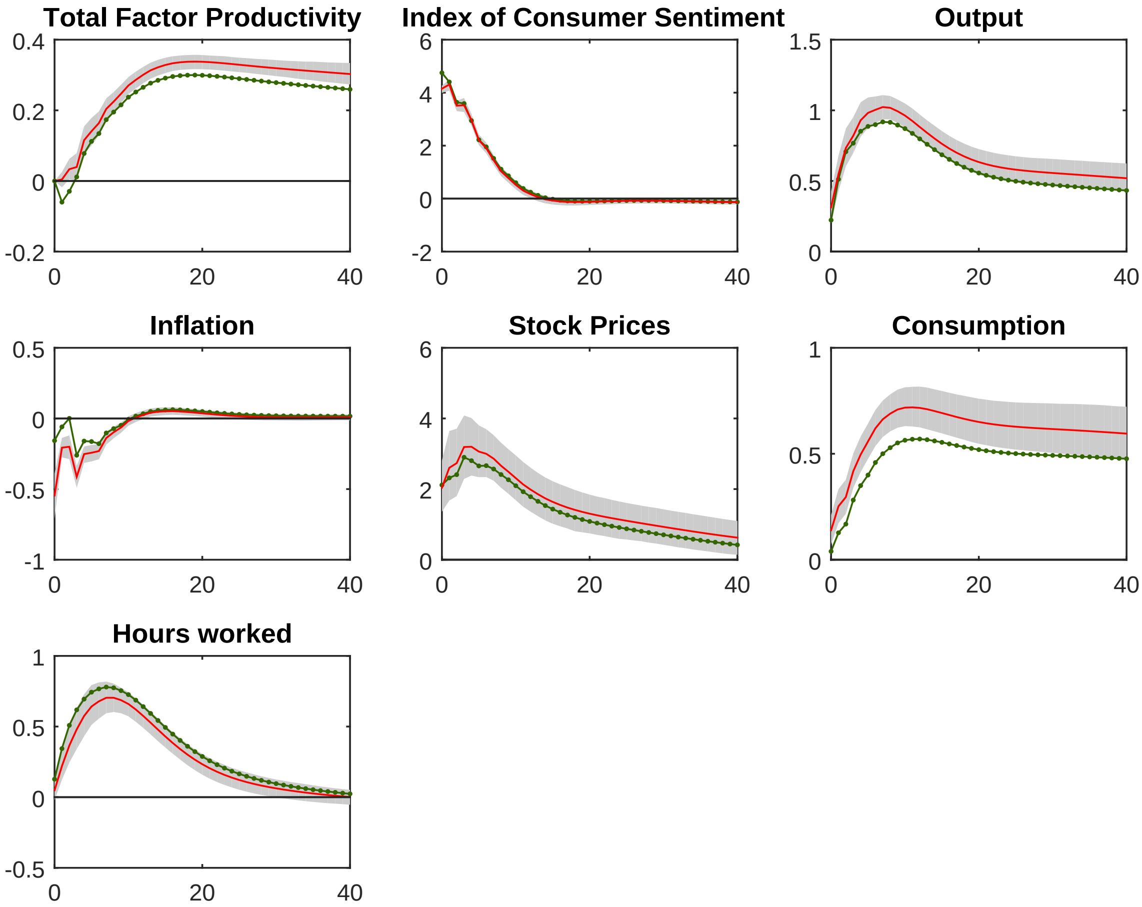


Figure 9: Comparison of news shock and confidence shock in a linear seven variables model. The red solid line shows the response to the news shock, while the green dotted line is the response to the confidence shock. The shaded region is the 95 percent confidence interval for the news shock. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter,

# F Results in the nonlinear setting

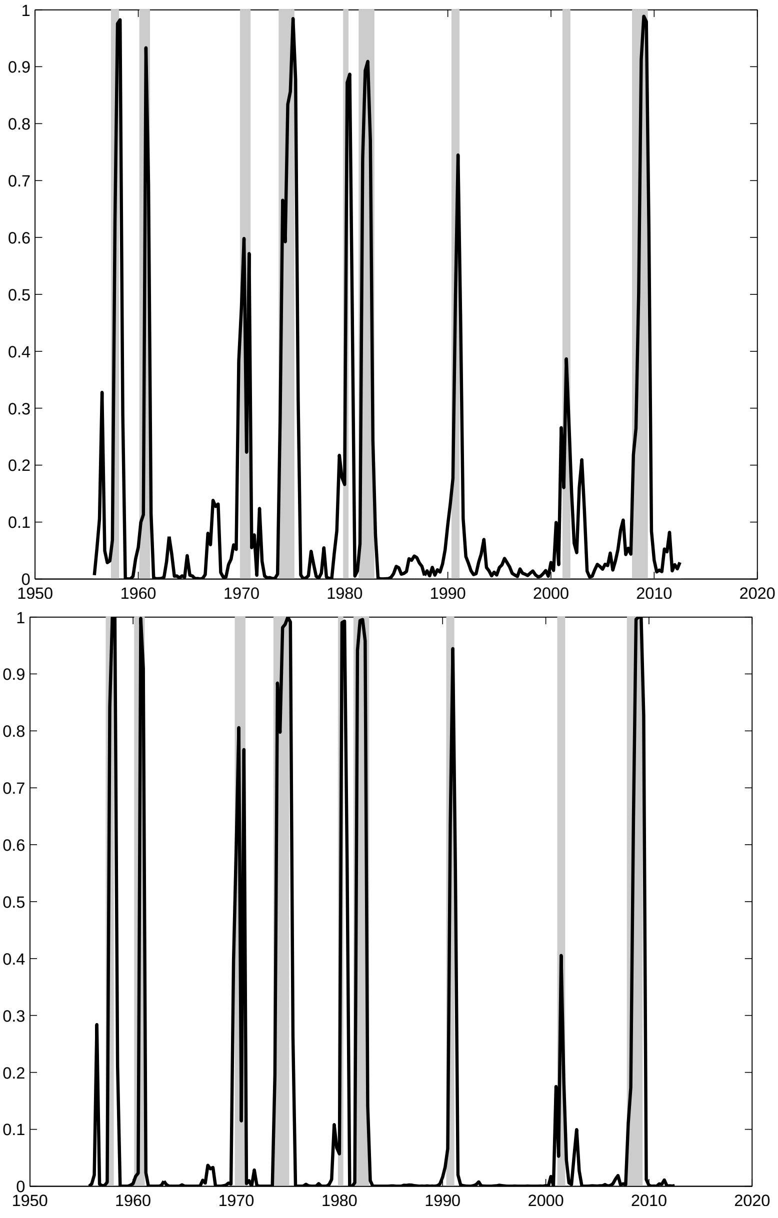


Figure 10: Comparison of the transition function for the mean equation - F (top), and the transition function for the variance equation - G (bottom), with average parameter values obtained from the MCMC iterations ($\gamma_F = 3.00$, $c_F = -0.61$, $\gamma_G = 6.31$, $c_G = -0.52$). The black line is the probability of a recession given by the logistic function, while the grey bars define the NBER identified recessions. The unit of the horizontal axis is quarters, while the unit of the vertical axis is percent in decimal form.

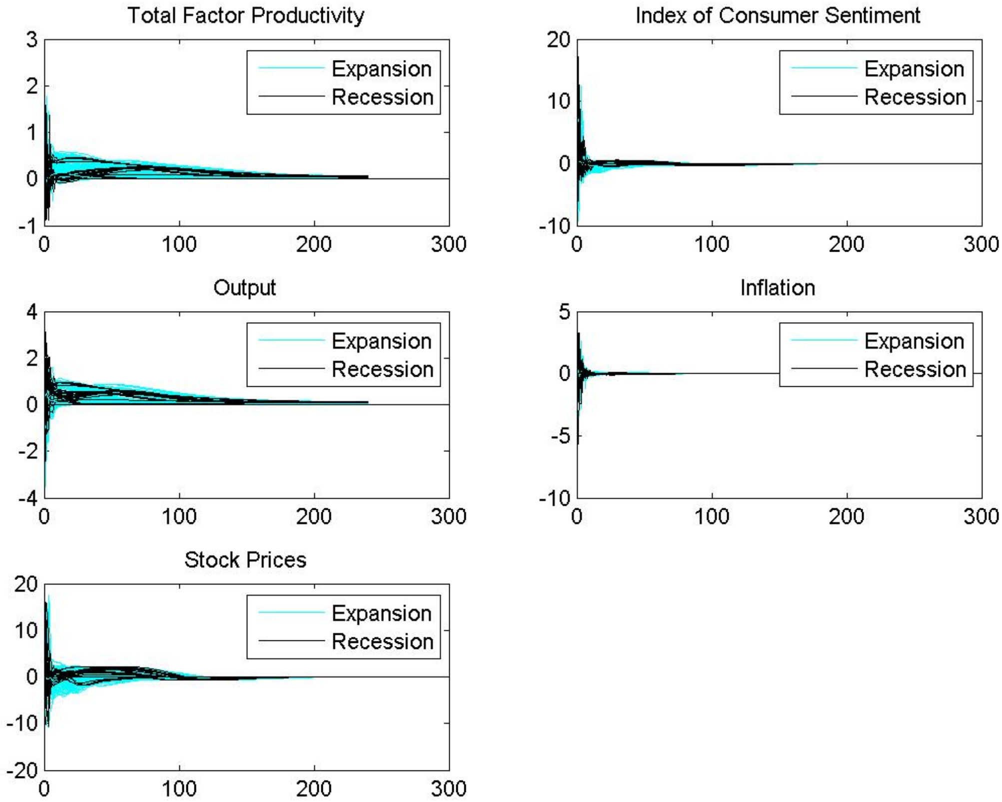


Figure 11: Stability check for the five processes. Each plot displays the paths of realizations (in first differences) from the estimated model with noise switched off, starting from a large number of initial points from both regimes.

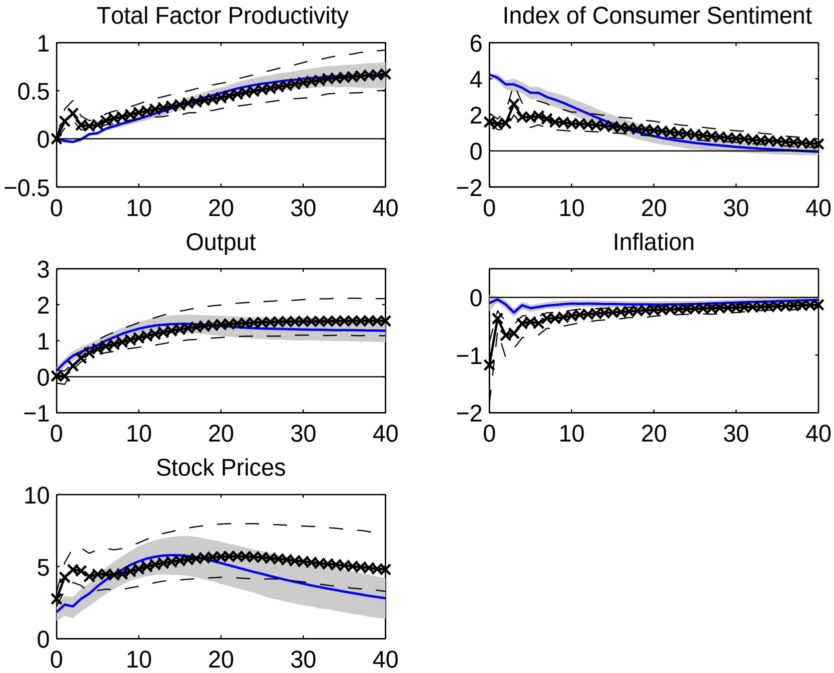


Figure 12: Generalized impulse response functions to a positive small confidence shock under SRI. SRI assumes that the confidence shock affects ICS on impact but not TFP. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarters.

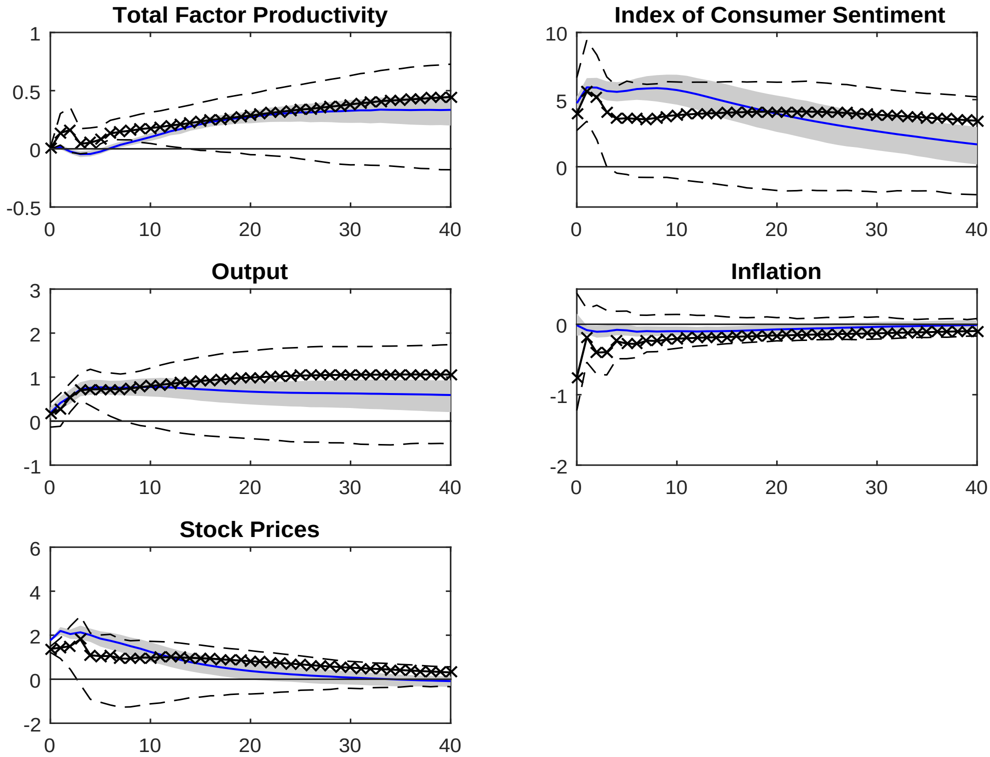


Figure 13: Generalized impulse response functions to a positive small news shock under SRI2. SRI2 assumes that the news shock affects SP on impact but not TFP. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

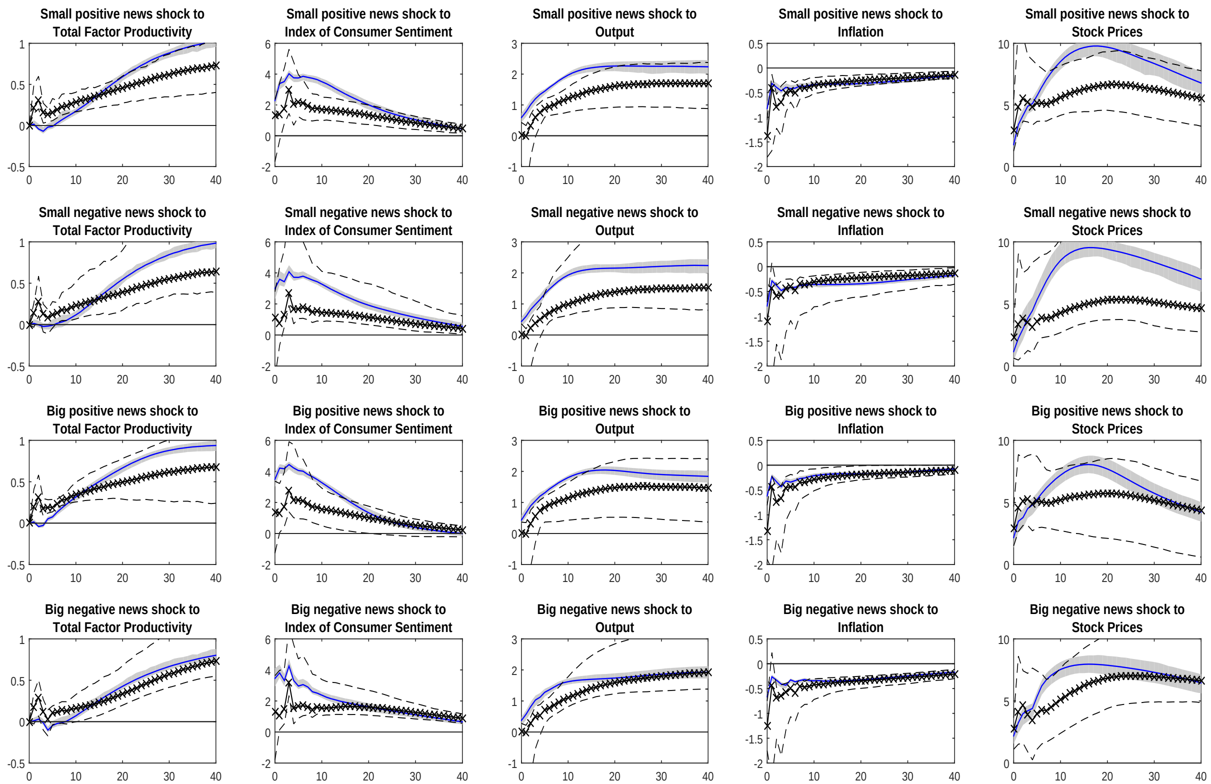


Figure 14: Generalized impulse response functions to news shocks of different signs and magnitudes. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

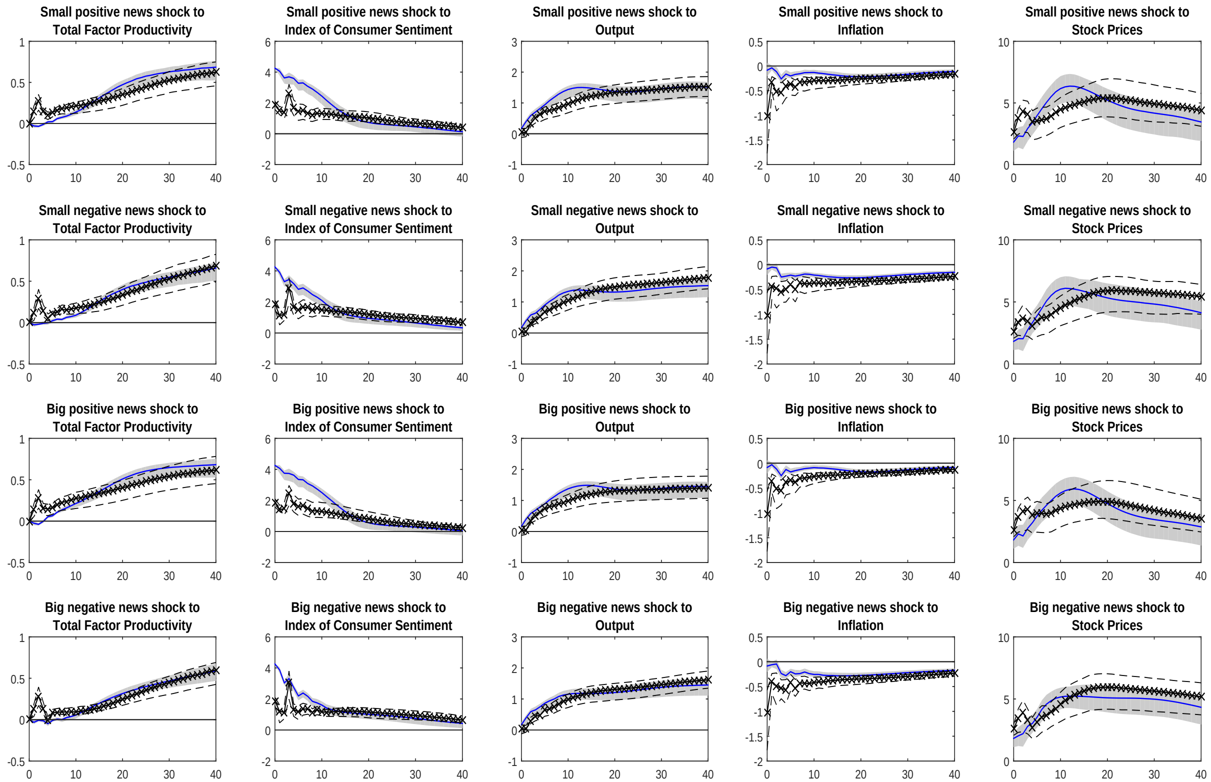


Figure 15: Generalized impulse response functions to confidence shocks of different signs and magnitudes. The starred black line is the point estimate in recession, and the blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

Table 6: Generalized Forecast Error Variance Decomposition. The numbers indicate the percent of the forecast error variance of each variable at various forecast horizons explained by the unanticipated TFP shock together with the anticipated (news) TFP shock identified with the MRI scheme, in expansions, recessions, and the linear model.

| | | Impact | One year | Two years | Ten years |
|---|---|---|---|---|---|
| Total TFP | Linear | 100.00 | 95.17 | 94.40 | 97.75 |
| | Expansion | 96.58 | 82.88 | 77.64 | 74.09 |
| | Recession | 99.69 | 91.79 | 86.27 | 86.32 |
| Total confidence | Linear | 59.60 | 75.30 | 78.31 | 78.50 |
| | Expansion | 48.70 | 75.33 | 80.04 | 75.46 |
| | Recession | 94.60 | 95.50 | 95.59 | 91.77 |
| Total output | Linear | 33.83 | 67.37 | 84.12 | 93.09 |
| | Expansion | 33.27 | 60.59 | 78.22 | 79.13 |
| | Recession | 96.16 | 96.46 | 95.64 | 90.44 |
| Total inflation | Linear | 45.69 | 42.49 | 45.01 | 52.24 |
| | Expansion | 55.51 | 56.75 | 59.32 | 59.30 |
| | Recession | 99.10 | 97.36 | 96.94 | 94.02 |
| Total stock prices | Linear | 19.81 | 33.41 | 42.16 | 64.68 |
| | Expansion | 14.67 | 39.62 | 53.87 | 67.51 |
| | Recession | 96.64 | 96.81 | 96.10 | 91.95 |

Table 7: Generalized Forecast Error Variance Decomposition for the confidence shock (SRI). The numbers indicate the percent of the forecast error variance of each variable at various forecast horizons explained by the confidence shock in expansions, recessions, and the linear model.

| | | Impact | One year | Two years | Ten years |
|---|---|---|---|---|---|
| TFP | Linear | 0 | 0.38 | 2.16 | 23 |
| | Expansion | 0 | 4.62 | 8.76 | 27.98 |
| | Recession | 0 | 23.56 | 25.77 | 46.7 |
| Confidence | Linear | 96.46 | 88.46 | 83.29 | 68.38 |
| | Expansion | 98.59 | 76.35 | 65.31 | 44.29 |
| | Recession | 92.51 | 54.46 | 51.88 | 43.29 |
| Output | Linear | 4.61 | 28.14 | 33.79 | 33.1 |
| | Expansion | 3.29 | 20.83 | 29.43 | 28.14 |
| | Recession | 0.63 | 24.83 | 43.48 | 47.73 |
| Inflation | Linear | 2.05 | 4.26 | 4.93 | 5.92 |
| | Expansion | 0.64 | 5.5 | 7.61 | 13.3 |
| | Recession | 52.28 | 45.78 | 45.06 | 43.58 |
| Stock Prices | Linear | 16.32 | 16.18 | 17.89 | 17.32 |
| | Expansion | 14.76 | 16.29 | 20.68 | 20 |
| | Recession | 49.48 | 52.12 | 52.83 | 48.17 |