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News Shocks: Different Effects in Boom and Recession?

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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.

JEL classification: E32, C32, C51, O47.

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

In this paper we ask whether news about future changes in productivity affect the economy in a different way in booms than in recessions. We find that good news have a smaller effect on economic activity in a recession than in a boom. But what is more intriguing is that good news increase the probability of the economy escaping a recession by about five percentage points and this is a much stronger increase than in the probability of an economy continuing booming if the news comes in an expansion.

We build on the literature on news shocks initiated by Beaudry and Portier (2006). The idea of this literature is that mere news about technological improvements may lead to business cycle fluctuations. These news shocks are announcements of major innovations, such as telecoms, IT, or self-driving cars, that take time to diffuse or materialize and eventually increase aggregate productivity. Agents acknowledge the changes in future economic prospects when the news comes and adapt their behavior ahead of them. This can lead to a boom in both consumption and investment, which precedes the growth in productivity.

So far news shocks on future productivity have been analyzed only in linear settings, that is in models that were treating booms and recessions in the same way. By the properties of these linear models, the effect of a news shock is history independent, which means that the response of agents to news is the same if the economy is booming or in a recession. However, there is no reason to make this assumption. From a statistical point of view, this assumption has to be tested. From a theoretical perspective, the news literature often interprets this shock as a shock to agents' expectations that creates waves of optimism or pessimism concerning long-run economic outcomes. But this theory doesn't impose any prior restrictions regarding the independence of agents' psyche to the state they live in. In fact, it is more likely the case that pessimism and optimism are actually state-dependent. Moreover, there are also economic reasons to believe that responses to news can be different. For example firms are more likely to be financially constrained in recessions than in booms. By computing the first and second moments of the main economic indicators, conditional on the economy being in an expansion or a recession as indicated by the NBER based index, we find evidence in support of the fact that the macroeconomic environment is very different in the two states 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. In this paper we challenge 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 main contribution to the news literature is to open the possibility that news have different effects in booms and recessions. To perform our empirical analysis, we proceed as follows. We estimate a five-variable logistic smooth transition vector autoregressive (LSTVAR) model including total factor productivity (TFP), consumer expectations, output, inflation and stock prices (SP). Our model builds on Auerbach and Gorodnichenko (2012) and Teräsvirta et al. (2010) and allows for state-dependent dynamics through parameters and state-dependent impact effects through the variance-covariance matrix. We have a smooth transition from one regime to the other, given by a logistic function, which determines how the two regimes are combined at any given period in time. The

[1] Details are provided in Appendix A.1.

value of the transition function is dependent on the state of the economy indicated by output growth. We let the transition in the mean equation and the variance equation to be different, and estimate the parameters of the transition functions.

In a nonlinear vector autoregressive (VAR) context short-run restrictions are usually applied in order to identify structural shocks. In contrast, we choose to identify the news shock via a medium-run identification method. This is by now a standard approach in the empirical news literature,[2] but its implementation in a nonlinear model is a challenge. Our method takes into account the nonlinearity of the model and to the best of our knowledge, we are the first to apply this identification scheme in a nonlinear setting. Our identifying assumption is that a news shock about technological innovations is a shock with no impact effect on TFP but with maximal contribution to it after 10 years. 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 use a generalization of the forecast error variance decomposition. The reason is that 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 with an immediate effect on consumer expectations. As showed in Bolboaca and Fischer (2017), this shock has similar effects to the news. 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 indicate that there is significant state-dependency in the effects of the news, mainly in the short- and medium-run. 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. Positive news shocks coming in expansions reduce the probability of transitioning to a recession by 3 percentage points after approximately one year. When the positive news shock arrives in a recession, it increases the probability of a transition to an expansion by almost 5 percentage points. Thus we can interpret that positive news shocks are more effective in recessions than in booms. The impulse response to a news shock is in general larger in an expansion than in a recession. Our intuition for the difference in the responses across the two regimes relates to the heightened uncertainty of economic agents in a recession. By comparing the state-dependent results with those from the linear model, we find that the effects of news shocks are stronger in expansion than the linear model would indicate, and smaller in recession. Hence using the linear model would underestimate the effects of news in expansion and overestimate them in a recession. 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

[2] For an overview of the identification schemes employed in the empirical news literature see Bolboaca and Fischer (2017), while the most prominent approaches are those of Beaudry and Portier (2006), and Barsky and Sims (2011). For a topological view on the identification of linear and nonlinear structural vector autoregressions consider Neusser (2016a).

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. These results indicate that good news in boom are just some good news among many others, but good news in recession are more valuable. 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.

Our paper is related to several strands of literature. First of all, it contributes to the empirical literature on productivity related news shocks. The seminal paper on the effects of news about future changes in productivity is Beaudry and Portier (2006).[3] There is an ongoing debate about the effects of news shocks, and the conflicting evidence stems from the wide diversity in variable settings, productivity series used and identification schemes applied.[4] Moreover, our paper is methodologically related to the literature on state-dependent fiscal multipliers that uses STVAR models. Some examples are: Auerbach and Gorodnichenko (2012), Owyang et al. (2013), Caggiano et al. (2014), and Caggiano et al. (2015). Beyond the narrative, our paper contributes to the literature in the following ways. First from a methodological perspective, we contribute to the model estimation through the fact that we allow the transition in the mean equation and the variance equation to be different, and we estimate the parameters of both transition functions. Moreover, we apply a medium-run identification scheme to identify a structural shock in an STVAR model. From a theoretical point of view, the fact of having news increasing the probability of exiting a recession has implications for theory. Models should take into account that good news are more valuable in recessions.

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

We employ a five-dimensional LSTVAR model in levels.[5] We work with quarterly data for the U.S. economy from 1955Q1 to 2012Q4. Our benchmark system contains five variables in the following order: TFP adjusted for variations in factor utilization, University of Michigan index of consumer sentiment (ICS), real output, inflation and stock prices (details are provided in appendix A.2).

According to van Dijk et al. (2002), a smooth transition model can either be interpreted as a regime-switching model allowing for two extreme regimes associated with

[3] Extensive analyses of the empirical news literature are performed in Beaudry et al. (2011), and Beaudry and Portier (2014).

[4] For details, see Bolboaca and Fischer (2017).

[5] We acknowledge the fact that estimating a nonlinear model with non-stationary data has several drawbacks, but we aim at replicating the empirical results on news shocks available in the literature and these shocks have been investigated only in linear models with data in levels. We point in this paper whenever the inference based on our model is affected by the non-stationary of data.

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. 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:

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

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

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

where γ_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. Every period, the transition function attaches some probability to being in each regime given the value of the transition variable s_t. $\epsilon_t \sim N(0, \Sigma_t)$ is an m-dimensional reduced-form shock with mean zero and positive definite variance-covariance matrix, Σ_t. We allow the variance-covariance matrix to be regime-dependent:[6]

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

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 Π_1 and Π_2 but also for contemporaneous differences via the two covariance matrices, Σ_1 and Σ_2. This method is similar to the one employed in Auerbach and Gorodnichenko (2012),[7] but we depart from their approach by letting 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 VAR model when $\gamma_F = \gamma_G = 0$. The linear model is described by the following equation:

$$Y_t = \Pi' X_t + \epsilon_t, \quad (4)$$

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

[6] In Appendix B.4 we describe the test for the constancy of the error covariance matrix. In our case, the null hypothesis of a constant error covariance matrix is rejected. The results may be provided by the authors. The test applies to models using stationary data, and its results in our case may not be correct given that the distribution of the test statistic is not the same.

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

2.2 Transition Variable

The logistic transition function determines how the two regimes are combined at any given period in time. The value of the transition function is dependent on the state of the economy, which is given by the transition variable. As stated in Teräsvirta et al. (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'. This makes the identification of a recession a complex process based on weighing the behavior of various indicators of economic activity. One possibility is to use as transition variable the NBER based recession index,[8] which equals one if a quarter is defined by the NBER as recession, and zero otherwise. But having an exogenous variable as switching variable makes it impossible to investigate the effects of shocks on the transition from one state of the economy to the other. For this reason, we follow the common rule of thumb which defines a recession as two consecutive quarters of negative GDP growth, and use as transition variable a lagged three quarter moving average of the quarter-on-quarter real GDP. This choice 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 t. We depart from their approach in the sense that we do not assume the transition variable to be exogenous, but we define it as a function of a lagged endogenous variable, output. 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. By endogenizing the transition variable, we are able to analyze how shocks coming in a recession, for example, influence the chances of the economy to recover or to continue staying in that state.

The LSTVAR model is only indicated if linearity can be rejected. We tested linearity against the alternative of a nonlinear model, given the transition variable. We 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).[9]

2.3 Estimation

Once the transition variable and the form of the transition function are set, and under the assumption that the error terms are normally distributed, the parameters of the LSTVAR model are estimated using maximum likelihood estimation (MLE).

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

[8] `https://fred.stlouisfed.org/series/USREC`

[9] The test applies to models using stationary data, and its results in our case may not be correct given that the distribution of the test statistic is not the same.

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

where $\epsilon_t = Y_t - \Pi_1' X_t(1 - F(\gamma_F, c_F; s_{t-1})) - \Pi_2' X_t F(\gamma_F, c_F; s_{t-1})$.[10]

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 Π_1 and Π_2. Hence, for given $\gamma_F, c_F, \gamma_G, c_G$, Σ_1, and Σ_2, estimates of Π can be obtained by weighted least squares (WLS), with weights given by Σ_t^{-1}. The conditional minimizer of the objective function can then be obtained by solving the first order condition (FOC) equation with respect to Π:

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

The above equation leads to the following closed form of the WLS estimator of Π 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 Π and the likelihood, until an optimum is reached. Therefore, it can be concluded that, when $\gamma_F, c_F, \gamma_G, c_G$, Σ_1, and Σ_2 are known, the solution for Π is analytic. As explained in Hubrich and Teräsvirta (2013) and 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, Ψ, 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', $\Psi_l =$

[10] The conditional log-likelihood may be affected by the endogeneity of s_t.

$\{\Pi_1, \Pi_2\}$. To ensure that Σ_1, and Σ_2 are positive definite matrices, we redefine Ψ_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, Ψ_n (details are provided in Appendix B.3).[11]

2.4 Starting Values

From this nonlinear parameter set, we first estimate the starting values for the transition functions γ_F, c_F, γ_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:

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

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, γ 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), and Caggiano et al. (2014)). The values assigned to γ 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 γ that equals 3.56. However, the Likelihood Ratio (LR) test[12] shows that the model with intercept provides

[11] We follow the steps indicated in Auerbach and Gorodnichenko (2012), but the MCMC draws are very close one to other, and to the starting values which define a local optimum. Hence, in case the local optimum does not coincide with the global optimum, the parameter space is not well covered and the estimation does not achieve converge to the global optimum.

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

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.

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.[13]

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).[14]

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 orthogonal to contemporaneous movements in TFP that maximizes the contribution to TFP's forecast error variance (FEV) at horizon H. This method, introduced by Beaudry et al. (2011) to identify news shocks, differs from the original one of Barsky and Sims (2011) because the latter aims at identifying a shock with no impact effect on TFP that maximizes the sum of contributions to TFP's FEV over all horizons up to the truncation horizon H. In Bolboaca and Fischer (2017), we show that the news shock identified with the method of Barsky and Sims (2011) is contaminated with contemporaneous effects, being a mixture of shocks that have either permanent or temporary effects on TFP. Because of that, depending on the chosen truncation horizon, results may differ. On the other hand, MRI identifies a news shock that is robust to variations in the truncation horizon and for this reason it is going to be the identification scheme which we employ to identify the news shock in this model.

This identification scheme imposes medium-run restrictions in the sense of Uhlig

[13] 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.

[14] The test applies to models using stationary data, and its results in our case may not be correct given that the distribution of the test statistic is not the same.

(2004).[15] Innovations are orthogonalized, for example, by applying the Cholesky 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, in adition to the unanticipated productivity shock, influences TFP the most in the medium-run. More precisely, it is the shock which explains the largest share of the TFP's FEV at some specified horizon H. We set H equal to 40 quarters (i.e. 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.[16] We define the entire space of permissible impact matrices as $\tilde{A}D$, where D is a $m \times m$ orthonormal rotation matrix ($DD' = I$).[17]

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:[18]

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

The share of the FEV of variable j attributable to structural shock i at horizon h is then:

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

where e_i denote selection vectors with the ith place equal to 1 and zeros elsewhere. The selection vectors inside the parentheses in the numerator pick out the ith column of D, which will be denoted by γ. $\tilde{A}\gamma$ 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 jth row of the matrix of moving average coefficients, which is denoted by $B_{j,\tau}$. Note that TFP is on the first position in the system of variables, and let the unanticipated productivity shock be indexed by 1 and the news shock by 2. Having the unanticipated shock identified with short-run zero restrictions, we then identify the news shock by choosing the impact matrix to maximize contributions to $\Xi_{1,2}(H)$ at H=40 quarters. The other shocks cannot be economically interpreted without additional assumptions.

The use of the MRI to identify a news shock is by now a standard approach in the empirical news literature, but how to implement it in a nonlinear model is a challenge.

[15] We thank Luca Benati for sharing with us his codes for performing a medium-run identification in a linear framework.

[16] The results for the application of variations of the MRI scheme, i.e. maximizations at different horizons and up to different horizons, can be found in Bolboaca and Fischer (2017).

[17] The reduced-form residuals can be written as a linear combination of the structural shocks $\epsilon_t = Au_t$, assuming that A is nonsingular. Structural shocks are white noise distributed $u_t \sim WN(0, I_m)$ and the covariance matrix is normalized to the identity matrix. The structural shocks are completely determined by A. As there is no unambiguous relation between the reduced and structural form, it is impossible to infer the structural form from the observations alone. To identify the structural shocks from the reduced-form innovations, $m(m-1)/2$ additional restrictions on A are needed. A thorough treatment of the identification problem in linear vector autoregressive models can be found in Neusser (2016b).

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

The calculation of the FEV decomposition depends on the estimation of 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 (GFEV) for which the shares sum to one by construction. Using this approach is the closest we can get to the application of the medium-run identification scheme. A detailed presentation of the procedure can be found in Appendix C.2.

2.6.2 Short-Run Identification

For robustness checks, we employ also a short-run identification scheme (henceforth, SRI) to identify the news shock. This is the approach followed in Beaudry and Portier (2006), who use it to identify two different productivity shocks, an unanticipated productivity shock and a news shock in a bivariate system with TFP and stock prices. The unanticipated productivity shock is identified as the only shock having an impact effect on TFP. The news shock is, then, the only other shock having an impact effect on stock prices. We call this identification scheme SRI2.

It is argued in the literature[19] that measures of confidence in the economy of consumers and businesses contain more stable information about future productivity growth than stock prices. Hence, we use the identification scheme of BP also in a setting in which we replace stock prices by a confidence measure, and we call this method SRI1.

We identify these shocks in a linear framework by imposing short-run restrictions. The variance-covariance matrix Σ of the reduced-form shocks is decomposed into the product of a lower triangular matrix A with its transpose A' ($\Sigma = AA'$). This decomposition is known as the Cholesky-decomposition of a symmetric positive-definite matrix. Thereby, the innovations are orthogonalized and the first two shocks are identified as unanticipated productivity shock and news shock. The rest of the shocks cannot be interpreted economically without further assumptions.

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 $G(\gamma_G, c_G; s_{t-1})$. For more details, see Appendix C.1.

2.7 Generalized Impulse Responses

We analyze the dynamics of the model by estimating impulse response functions. The nonlinear nature of the LSTVAR does not allow us to estimate traditional impulse response functions due to the fact that the reaction to a shock is 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.[20] Given this threshold, the model is linear for a chosen regime which allows to estimate regime-specific IRFs.

[19] For details, see Barsky and Sims (2012), Ramey (2016), and Bolboaca and Fischer (2017).

[20] For example, Auerbach and Gorodnichenko (2012) use a threshold of 0.8, hence they define a period to be recessionary if $F(\gamma_F, c_F; s_t) > 0.8$.

Nevertheless, state-dependent impulse response functions have several drawbacks. The imposed threshold is set exogenously, which arbitrarily allocates periods to either regime even though the model assigns some probability to both regimes in 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) [21] as initially proposed by Koop et al. (1996). In addition, GIRFs 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 feature is that GIRFs allow to endogenize regime-switches if the transition is a function of an endogenous variable of the LSTVAR. This property of GIRFs lets us investigate whether news shocks have the potential to take the economy from one regime to the other. In the related empirical literature, this point has usually been ignored.[22]

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. The GIRF to shock i at horizon h is defined as the difference between the expected value of Y_{t+h} given the history Ω_{t-1}, and the shock i hitting at time t, and the expected value of Y_{t+h} given only the history:

$$GIRF(h, \xi_i, \Omega_{t-1}) = \mathbb{E}\left\{Y_{t+h} \mid e_{i,t} = \xi_i, \Omega_{t-1}\right\} - \mathbb{E}\left\{Y_{t+h} \mid e_t = \epsilon_t, \Omega_{t-1}\right\},$$

where e_t is a vector of shocks that may either have on position i the value ξ_i and 0 on the others, or may equal ϵ_t, which is a vector of randomly drawn shocks (i.e. $\epsilon_t \sim \mathcal{N}(0, \Sigma_t)$). Ω_{t-1} is the information up to time t that the expectations are conditioned on and which comprises the initial values used to start the simulation procedure. The GIRFs are computed by simulation. For each period t, $\mathbb{E}\left\{Y_{t+h} \mid e_t = \epsilon_t, \Omega_{t-1}\right\}$ is simulated based on the model and random shocks. On impact:

$$Y_t^{sim} = \Pi_1' X_t^{sim}(1 - F(\gamma_F, c_F; s_{t-1})) + \Pi_2' X_t^{sim} F(\gamma_F, c_F; s_{t-1}) + e_t, \tag{13}$$

and for $h \geq 1$:

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

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 in every simulation step. Therefore, also the time-dependent covariance matrix Σ_{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 Σ_{t+h}:

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

To simulate $\mathbb{E}\left\{Y_{t+h} \mid e_{i,t} = \xi_i, \Omega_{t-1}\right\}$, $e_{i,t}$ is set equal to a specific shock, ξ_i, depending on the chosen identification scheme, magnitude and sign, while the other impact shocks are zero. For the other horizons, $h \geq 1$, $\epsilon_{t+h} \sim \mathcal{N}(0, \Sigma_{t+h})$. By updating the transition functions at every simulation step, we allow for possible regime-transitions in the aftermath of a shock.

We simulate GIRFs for every period in our sample and do not draw periods randomly, because we want to make sure that our results are not determined by extreme periods

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

[22] To our knowledge Caggiano et al. (2015) is the only paper to endogenize the transition function.

that are drawn too often. For each period, the history Ω_{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.[23] With this definition, the economy spends roughly 15% of the time in recession which corresponds closely to the value indicated by the NBER index. Then, to obtain, for example, the effect of a small positive news shock in recession, we take all the GIRFs to a small positive news shock for which $F(\gamma_F, c_F; s_{t-1}) \geq 0.5$ and compute their average. Details are provided in Appendix C.

2.8 Generalized Forecast Error Variance Decomposition

In a nonlinear environment, the shares of the FEV decomposition generally do not sum to one which makes their interpretation rather difficult. Lanne and Nyberg (2016) propose a method of calculating the generalized forecast error variance decomposition (GFEVD) such that this restriction is imposed. They define the GFEVD of shock i, variable j, horizon h, and history Ω_{t-1} as:

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

The denominator measures the squared aggregate cumulative effect of all the shocks, while the numerator is the squared cumulative effect of shock i. By construction, $\lambda_{j,i,\Omega_{t-1}}(h)$ lies between 0 and 1, measuring the relative contribution of a shock to the ith equation to the total impact of all K shocks after h periods on variable j. More details about the computation of the GFEVD can be found in Appendix C.4.

3 Results

3.1 Linear Setting

We estimate a linear 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. [24] Moreover, in papers revelant to our context (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. In Figure 7, Appendix D, a scatterplot of the news shock identified with MRI and the confidence shock

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

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

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, Appendix D, show that both identified shocks trigger a strong positive comovement 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 identification schemes, 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 increasing in both cases until it stabilizes at 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 et al. (2011). The index of consumer sentiment rises significantly on impact in both settings. This finding is consistent with those of Beaudry et al. (2011) who use the same confidence indicator. 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. Inflation falls significantly on 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 the negative reaction to a positive news shock is consistent with the New Keynesian framework in which current inflation represents the expected present discounted value of future marginal costs. The impulse response of inflation under SRI is similar to the one obtained by Beaudry et al. (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 about twenty quarters.

In Figure 9, Appendix D, we show that adding other variables does not significantly modify the results for the first five variables. Inflation decreases 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 et al. (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. Under the two different identification schemes, we find similar results. A shock on a measure of consumer confidence with no impact effect on TFP (news or optimism shock) proves to be highly correlated with a shock with no impact effect on TFP but which precedes increases in TFP. This supports the conclusion of Beaudry et al. (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 et al. (2011), the period until TFP starts increasing can be defined as a non-inflationary boom phase without an increase in productivity.

3.2 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 verify 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 effect of a positive news shock be the same in the two states? Will it matter whether it is good or bad news? Or is there a difference between extreme or rather small news shocks?

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 in the transition functions (i.e. smoothness and threshold parameters) instead of simply calibrating them.

The results presented in Figure 10, Appendix E, 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 γ_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 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.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 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 E). It is clear for each variable in our model that, independent of the history in the dataset chosen as initial values, the trajectories 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. The non-explosiveness of the model is necessary for the estimation of GIRFs and the GFEVD.

3.2.1 Variance Decomposition

In Table 1 we display for each variable the share of the (generalized) FEV 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 in the FEV of TFP both at high and lower frequencies.

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

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

When comparing the results between the two regimes of the nonlinear model, it becomes clear that the contribution of the news shock to the FEV 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 contributes less than 50 percent to the FEV in all variables, except TFP on impact and the inflation rate. 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.

We find intriguing the fact that, even though in a recession the news shock explains little of output variance on impact, the share increases significantly and fast, such that after 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 in recession at a horizon of one year.

In Table 3, Appendix E, we present the total contribution of the unanticipated productivity shock and the news shock to the FEV of the variables. In the linear model, the two productivity related shocks combined explain almost 98 percent of variation in TFP, about 93 percent of 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 larger contributions of these two shocks in recessions both in the short- and the medium-run. The differences are particularly large on impact. In recessions, the two shocks explain together more than 95 percent of the impact variance of all variables, for TFP and inflation the shares being almost 100 percent. Since the two productivity shocks combined explain almost all the variation in recession, we have support for their high importance in 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 4, Appendix E, 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 FEV of variables than the news shock in recessions. The differences between the contributions of the two shocks are even bigger when looking at expansions. The confidence shock contributes little in the short-run to TFP, output, inflation and stock prices, while in 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.

3.2.2 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 et al. (2013) opt for Jorda's method (Jorda (2005)), we decide to estimate generalized impulse response functions. Our approach for 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. Simulating the model for the computation of the GIRFs gives the possibility to adjust the transition function in every period. 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 we present the impulse responses of TFP and consumer confidence to a one standard deviation news shock obtained with the MRI scheme. 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 in both states. However, the impact effect is bigger in expansions, and the gap between the two stays large 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 an evident state-dependency 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 technology diffusion is much faster in this case.

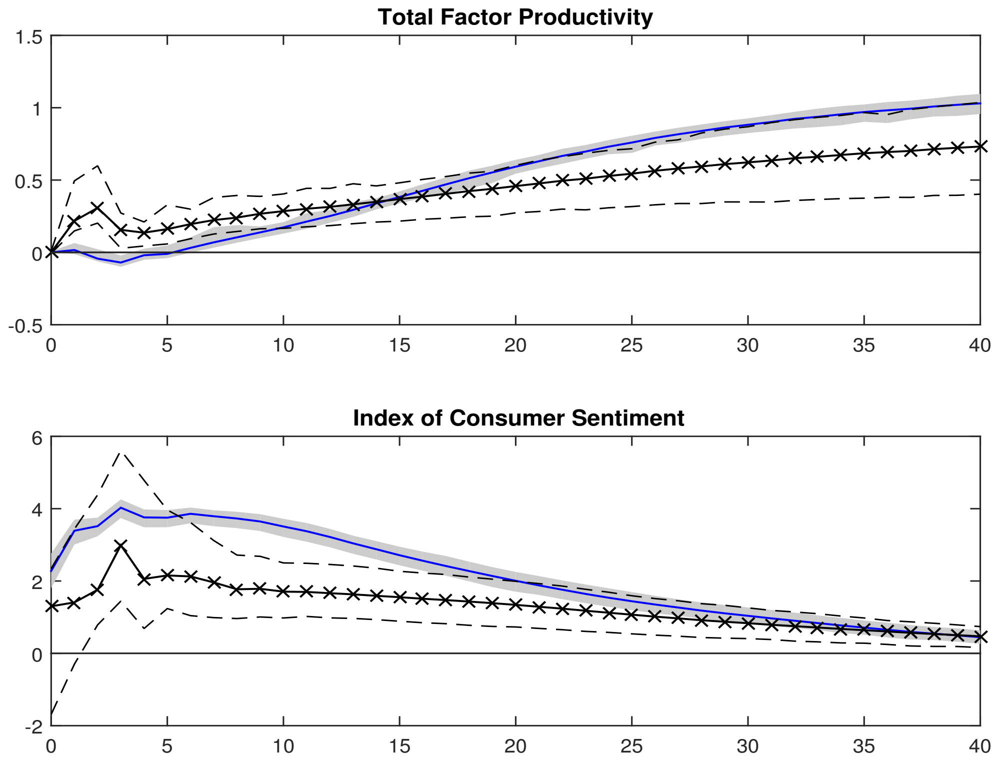

Figure 1: Generalized impulse response functions to a positive small news shock under MRI. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while 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.

The regime-dependence in the response to a news shock is significant 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.[25] 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 in Figure 2. 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 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 peculiar 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 stabilizes at a lower permanent level than following a news shock occurring in an expansion.

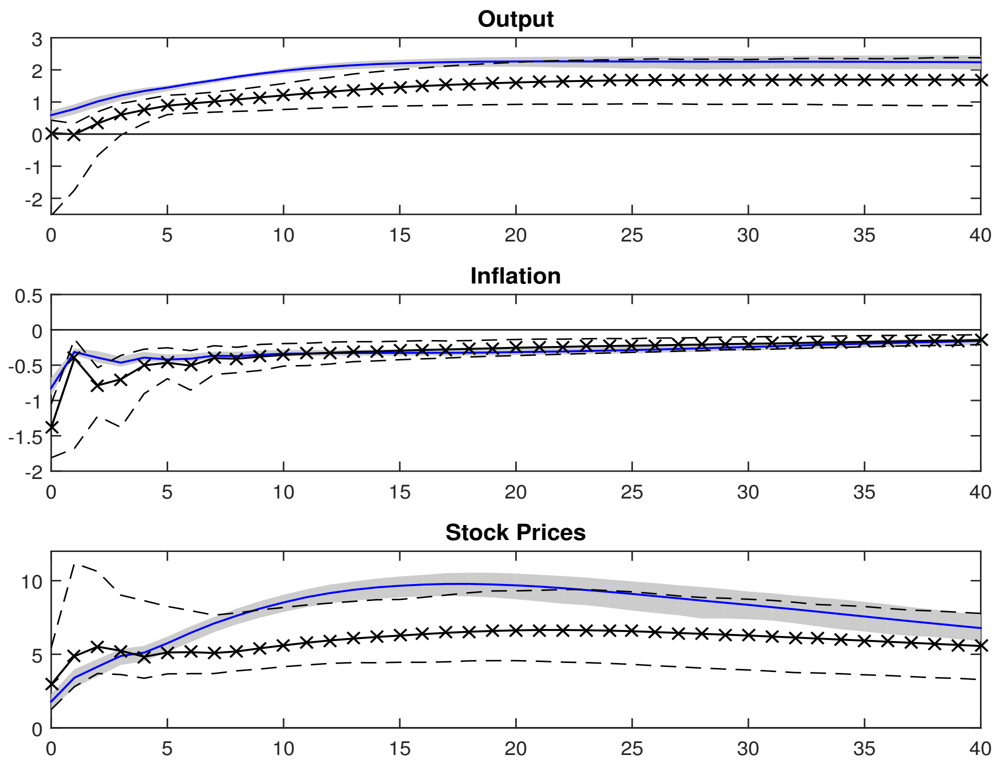

Figure 2: Generalized impulse response functions to a positive small news shock under MRI. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while 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, Appendix E, we present the responses to a small positive, a big positive, a small negative and a big negative news shock for both regimes. 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. The effect of a small negative shock in a

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

recession seems to exhibit a stronger effect on output in the long-run. This indicates 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. Regarding the magnitude of the news shock, we find that the response to a big shock is not proportionate with the shock size. Nevertheless, the magnitude and the sign of the shock do not seem to play an important role as 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 E). 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.

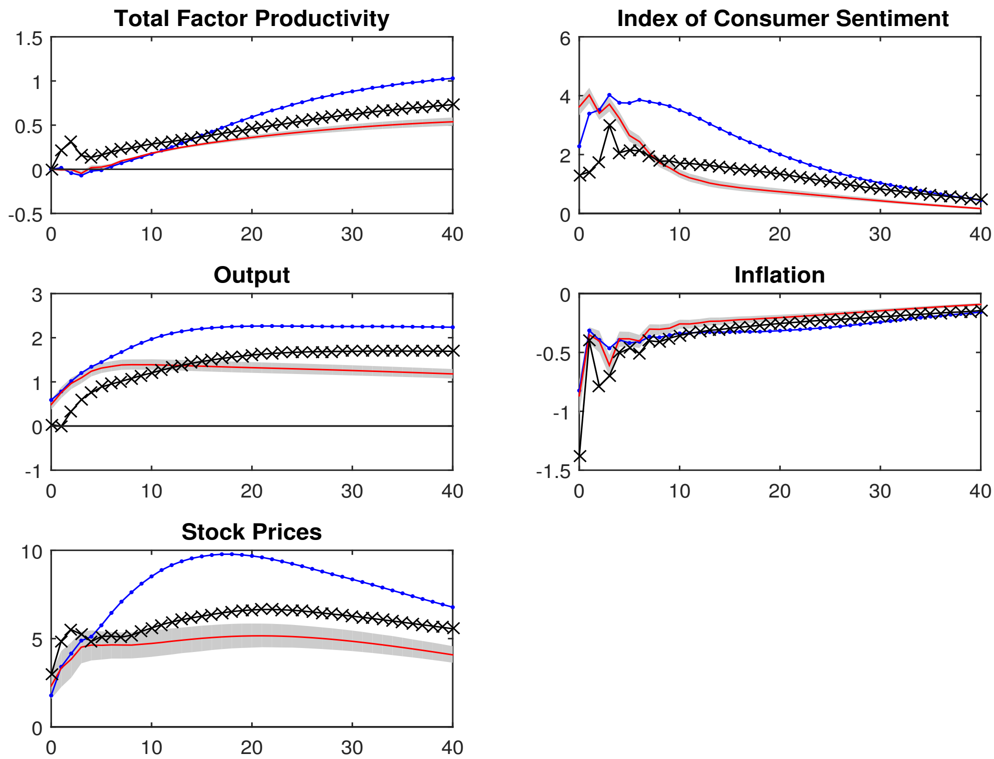

Figure 3: Comparison of the state-independent and the state-dependent effect of the news shock (under MRI). The figure displays the generalized impulse response functions to a positive small news shock in an expansion as the blue dotted line, the generalized impulse response functions to a positive small 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.

On the other hand, we find quantitative differences in the expansionary regime. While the effect of a news shock on TFP 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. When comparing the GIRFs to the responses obtained in the linear setting, as displayed 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. Therefore, using a linear model to show the effects of news shocks in normal times may underestimate their value. We find 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 high 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 half the impact effect implied by the linear model on confidence. 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.

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 with no impact effect on TFP. The impulse responses, displayed in Figure 13, Appendix E, are qualitatively very similar but smaller in absolute values in both regimes than the impulse responses for the news shock obtained with the MRI and the confidence shock identified by applying the SRI. This confirms that stock prices do not capture the expectations of market participants as well as the index of consumer sentiment.

3.2.3 Regime Transition

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

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.

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 end a boom, and lead the economy into a downturn 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.

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. A shock three times larger is not increasing this probability by 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 booming, in the medium-run, once the improvements in productivity become apparent (i.e. TFP starts increasing), agents 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 fall into a recession.

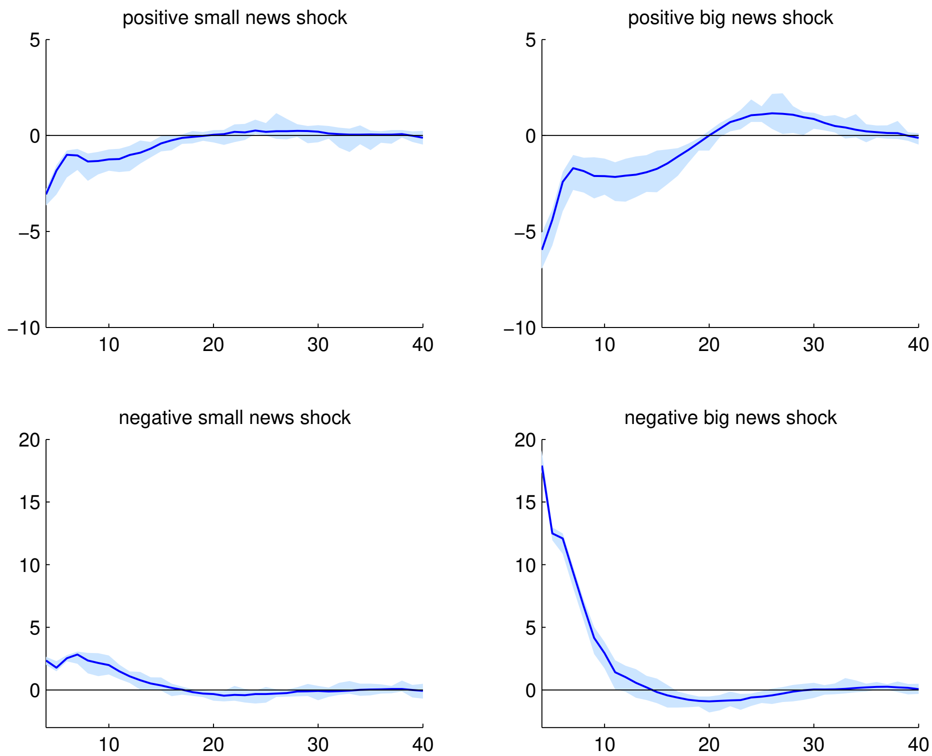

Figure 4: Regime transition probability change following a news shock. The four figures display the change in the probability of switching from an expansion to a recession starting one year after a news shock occurred. The blue line shows the behavior following a news shock obtained with MRI, while the 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.

In Figure 5, we observe that, if the economy is in a recession, a small positive news shock increases the probability of transitioning into an expansion by almost 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. It does not seem to be a reversal in the medium-run, once TFP increases, as it was the case in booms. 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 conclude that positive news shock are more effective in recessions than in expansions, leading to a twice as large increase in the probability of regime transition. On the other hand, negative news in booms ncrease 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 found in Van Nieuwerburgh and Veldkamp (2006). The authors argue that in a recession, uncertainty delays the recovery and makes booms more gradual than downturns.

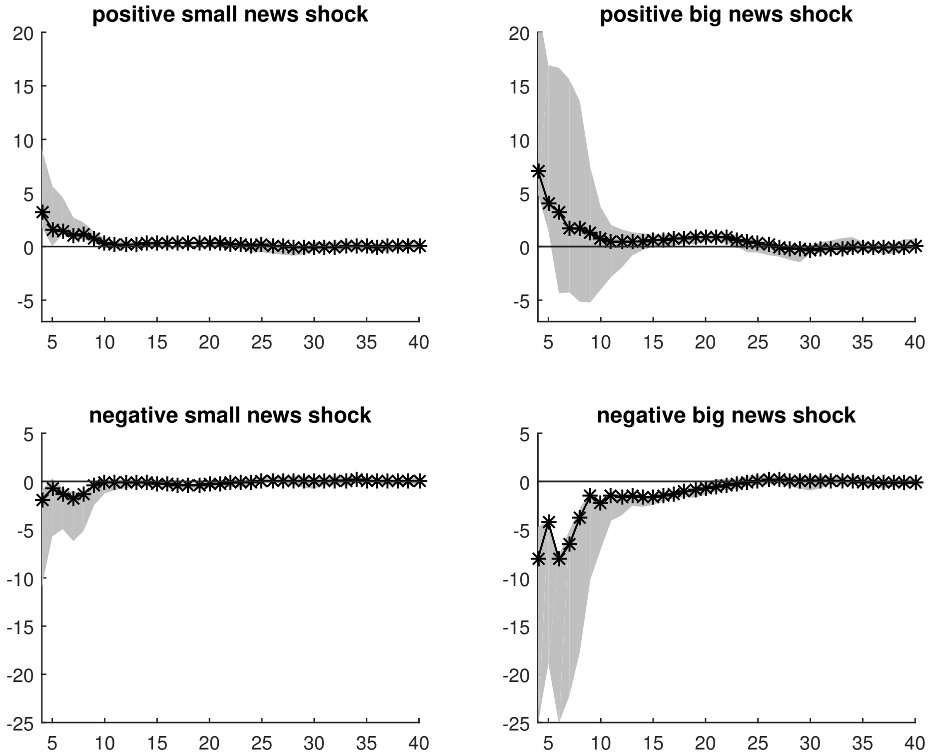

Figure 5: Regime transition probability change following a news shock. The four figures display the change in the probability of switching from a recession to an expansion starting one year after a news shock occurred. The starred black line shows the behavior following a news shock obtained with MRI, 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.

4 Conclusions

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

The type of news considered is about technological innovations. The idea is that technological innovations have a permanent effect, 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 response to a news shock is in general larger in an expansion than in a recession. Our intuition for the difference in the responses between 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. 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.

The impact contribution of the news shock to the variation in all the variables of the model is also 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 good news increase the probability of the economy escaping a recession by about five percentage points and this is a much stronger increase than in the probability of an economy continuing booming if the news comes in an 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 robustness 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

A.1 Descriptive Statistics

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, 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 - annualized 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)

A.2 Details on Data Used in Benchmark Model

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.

Our benchmark system contains five variables: TFP adjusted for variations in factor utilization, index of consumer sentiment, real output, inflation and stock prices. 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 in the linear setting, we additionally include consumption and hours worked.

We use the series of TFP adjusted for variations in factor utilization constructed with the method of Fernald (2014) based on Basu et al. (2013) and Basu et al. (2006). They construct TFP controlling for non-technological effects in aggregate total factor productivity including varying utilization of capital and labor and aggregation effects. They identify aggregate technology by estimating a Hall-style regression equation with a proxy for utilization in each disaggregated industry inspired by Hall (1990). Aggregate technology change is then defined as an appropriately weighted sum of the residuals. The series of TFP adjusted for utilization for the nonfarm business sector, annualized, and as percent change, is available on the homepage of the Federal Reverse Bank of San Francisco.[26] To obtain the log-level of TFP, we construct the cumulated sum of the original series, which is in log-differences.

We use the S&P 500 stock market index as a measure of stock prices.[27] Data for output and consumption we obtain from the Bureau of Economic Analysis. For output we use the real gross value added for the nonfarm business sector. As a measure of consumption we use the sum of personal consumption expenditures for nondurable goods and personal consumption expenditures for services. We obtain data on hours worked, population, and price level from the Bureau of Labor Statistics. As a measure of hours worked, we use the hours of all persons in the nonfarm business sector. Output, consumption, and stock prices are in logs and scaled by population (all persons with ages between 15 and 64) and the price level for which we use the implicit price deflator for the nonfarm business sector. Hours worked are in logs and scaled by population only. The price deflator (PD) is also used to compute the annualized inflation rate $IR = 4^{*}(\log(PD_t) - \log(PD_{t-1}))$.

We use data from the surveys of consumers conducted by the University of Michigan for the measure of consumer confidence. For the whole sample only the index of consumer expectations for six months is available.[28] We use the index in logs.

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

[27] `http://data.okfn.org/data/core/s-and-p-500$\sharp$data`

[28] 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

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 et al. (2010) and van Dijk et al. (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 (γ_F and c_F), but, when this hypothesis holds true, the likelihood is unaffected by the values of γ_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 Π_1 and Π_2 are unidentified.

The proposed solution to this problem, following Luukkonen et al. (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 et al. (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 θ_i, $i = 1, 2, 3$, are functions of the autoregressive parameters, γ_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 χ^2 distribution with $nm(mp+1)$ degrees of freedom, where $n = 3$ is the order of the Taylor expansion.

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.

Denoting $Y = (Y_1, ..., Y_T)'$, $X = (X_1, ..., X_T)'$, $E = (\epsilon_1^*, ..., \epsilon_T^*)'$, $\Theta_n = (\theta_1', ..., \theta_n')'$, 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 χ^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 χ^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*** (0.4806)
Intercept	-1.5038*** (0.2721)
No. of observations: 228 Log Likelihood: -48.977 LR $\chi^2_{(1)}$: 104.25*** Pseudo R^2: 0.5156	

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

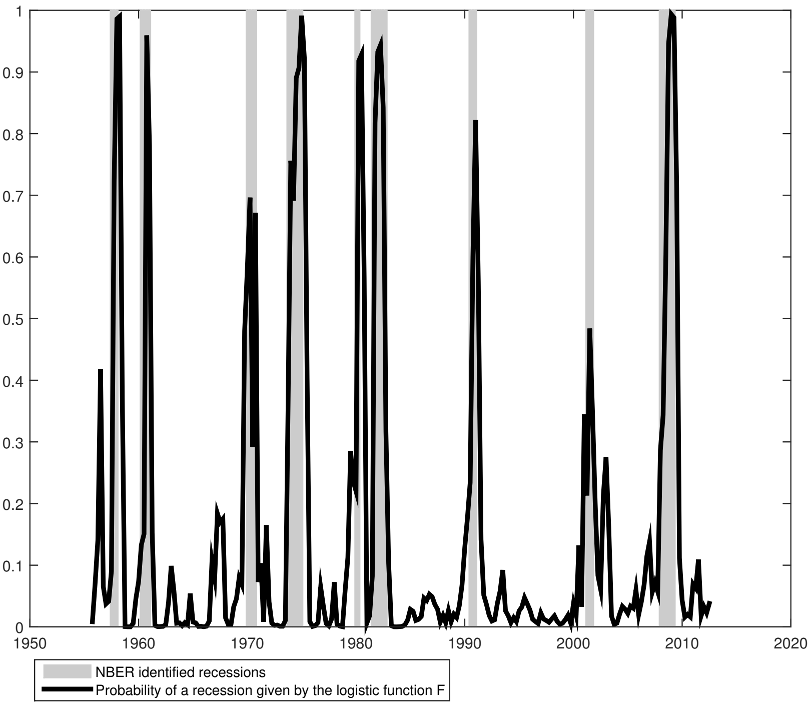

Figure 6: Initial transition function with estimated parameters obtained from a logistic regression

B.3 MCMC Procedure - MH Algorithm

Our approach is, given the quasi-posterior densitiy $p(\Psi_n) \propto e^{L(\Psi_n)}$,[29] 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 steps:

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

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

   (c) Update Ψ_n^{j+1} from Ψ_n^j, using:

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

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

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

[29] $L(\Psi_n)$ is the likelihood function.

The importance of the starting parameter values is given by the fact that in case Ψ_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 (Σ_1, Σ_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 σ_ψ^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, σ_ψ. Since σ_ψ 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 σ_ψ. Hence, in order to make sure we obtain an acceptance rate between 25% and 45%, as indicated in Roberts et al. (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 Σ_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 $\Lambda_t = diag(\lambda_{1t}, \ldots, \lambda_{mt})$ 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 $w_t = u_tP$.

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 χ^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.

C Estimation of GIRF and GFEVD

C.1 Estimation of GIRF with SRI

The GIRFs are estimated by simulation for eight different cases:

case	regime	magnitude	sign
1	Expansion	σ	+
2	Expansion	3σ	+
3	Expansion	σ	-
4	Expansion	3σ	-
5	Recession	σ	+
6	Recession	3σ	+
7	Recession	σ	-
8	Recession	3σ	-

σ denotes the standard deviation of the news shock.

The simulation for a case starts by choosing a period t and its corresponding history Ω_{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

$$GIRF(h, \xi_i, \Omega_{t-1}) = \mathbb{E}\{Y_{t+h} \mid e_{i,t} = \xi_i, \Omega_{t-1}\} - \mathbb{E}\{Y_{t+h} \mid e_t = \epsilon_t, \Omega_{t-1}\}$$

is performed in two steps by simulating $\mathbb{E}\{Y_{t+h} \mid e_{i,t} = \xi_i, \Omega_{t-1}\}$ and $\mathbb{E}\{Y_{t+h} \mid e_t = \epsilon_t, \Omega_{t-1}\}$ individually and then taking the difference.

Step 1: Simulation of $\mathbb{E}\{Y_{t+h} \mid e_t = \epsilon_t, \Omega_{t-1}\}$

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 forecast horizon.

Step 2: Simulation of $\mathbb{E}\{Y_{t+h} \mid e_{i,t} = \xi_i, \Omega_{t-1}\}$

In the first period, only a specific shock affects the model. $e_{i,t} = \xi_i = A_t^G e_i$ where A_t^G is the Cholesky factor of Σ_t. e_i is a vector of zeros with the expection of position i on which we put a value determined by the criteria imposed to the shock (sign: positive/negative, magnitude: σ/ 3σ). In the case of SRI, the news shock is identified as the second shock, while the first shock is an unanticipated productivity shock. The other shocks do not have an economic interpretation without imposing further assumptions. For the other horizons, $h \geq 1$, the model is shocked with randomly drawn shocks $\epsilon_{t+h} \sim \mathcal{N}(0, \Sigma_{t+h})$ as in Step 1.

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

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.

C.2 Estimation of GIRF with MRI

For the estimation of GIRF with the MRI, first, the rotation matrix that maximizes the generalized FEV 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 GFEVD 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 C.1. The only difference is that the orthogonalization of the history-dependent covariance matrix is approximated by

$$A^G_{t+h} = G(\gamma_G, c_G; s_{t+h-1})A_1 + (1 - G(\gamma_G, c_G; s_{t+h-1}))A_2 \tag{31}$$

where A_1 and A_2 are obtained using the MRI identification scheme. We use as initial values the Cholesky decomposition of the covariance matrices of the residuals in each state, Σ_1 and Σ_2, and then we search the matrices which, through their mixture, give a covariance matrix A^G_t that delivers the news shock with maximum contribution to TFP's GFEV at horizon 40.

As in the case of SRI, the news shock is identified as the second shock, while the first shock is an unanticipated productivity shock. The other shocks do not have an economic interpretation without imposing further assumptions.

C.3 Confidence Bands

To estimate confidence bands, we use $D = 1000$ MCMC draws. 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.

C.4 Generalized Forecast Error Variance Decomposition

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

$$\lambda_{j,i,\Omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})^2_j}{\sum_{i=1}^{K}\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})^2_j} \tag{32}$$

We perform simulations to obtain GIRFs for all six news shocks (according to regime, size, and sign) by adjusting e_{t+h} 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 GIRFs are in addition summed over all shocks K.

D Results in the Linear Setting

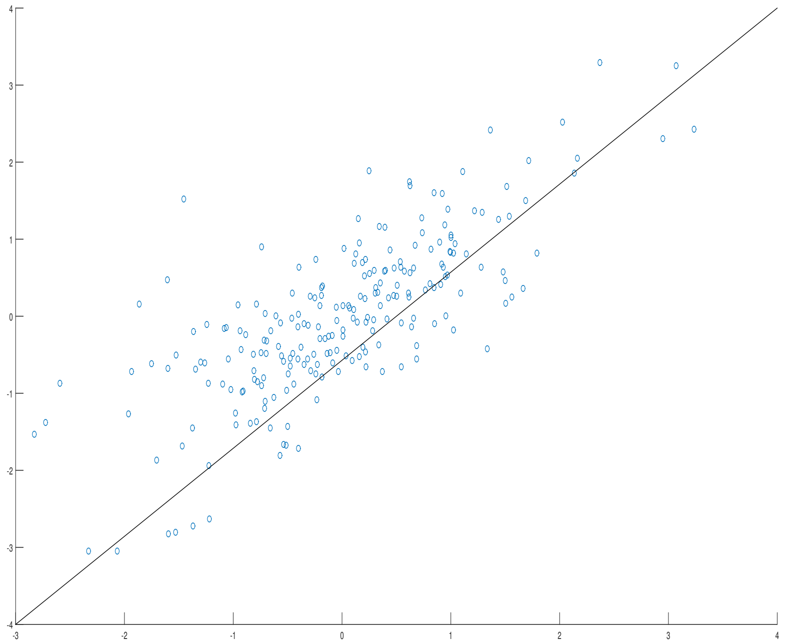

Figure 7: Comparison of the news and the confidence shocks using a scatterplot. The confidence shock is identified using a SRI which assumes that the confidence shock affects ICS on impact but not TFP. Under a MRI, the news shock is defined as the shock that does not move TFP on impact but has maximal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

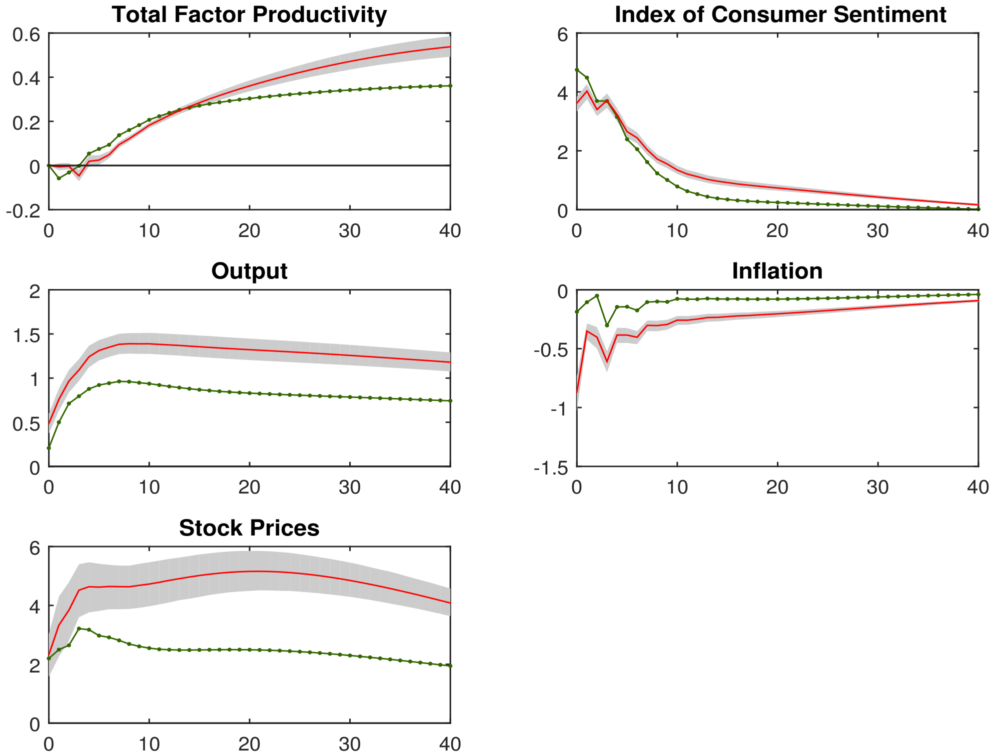

Figure 8: Comparison of news shock and confidence shock in a linear model.The red solid line shows the response to the news shock, while the green dotted line is the response to the confidence shock. The shaded region is the 95 percent confidence interval for the news shock. The unit of the vertical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

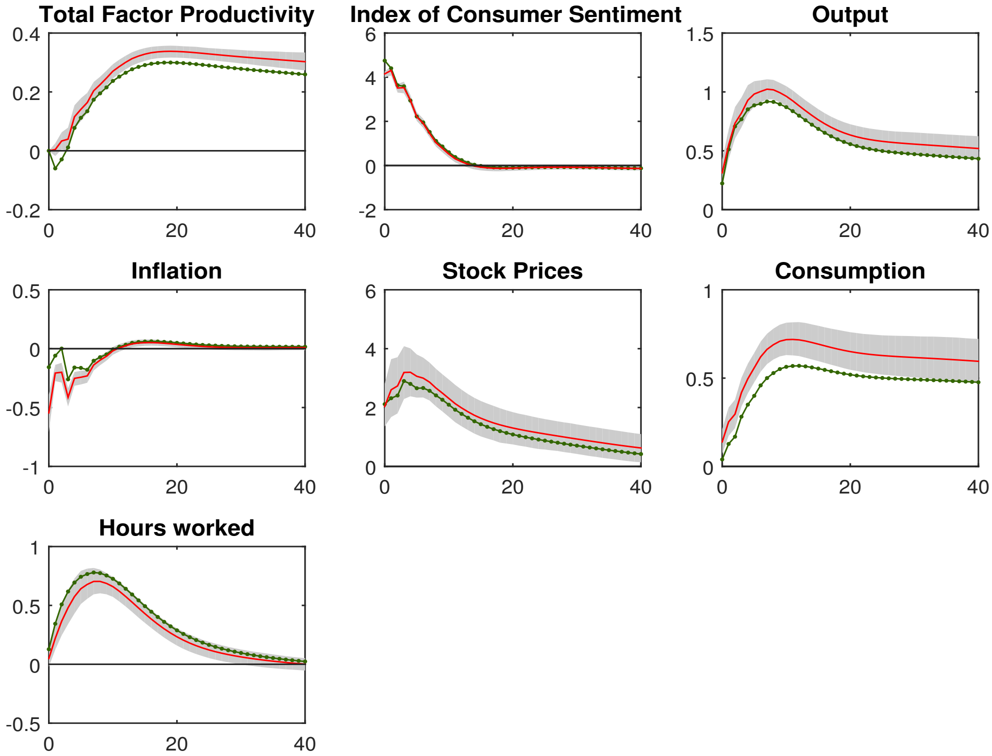

Figure 9: Comparison of news shock and confidence shock in a linear seven variables model. The red solid line shows the response to the news shock, while the green dotted line is the response to the confidence shock. The shaded region is the 95 percent confidence interval for the news shock. The unit 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,

E Results in the Nonlinear Setting

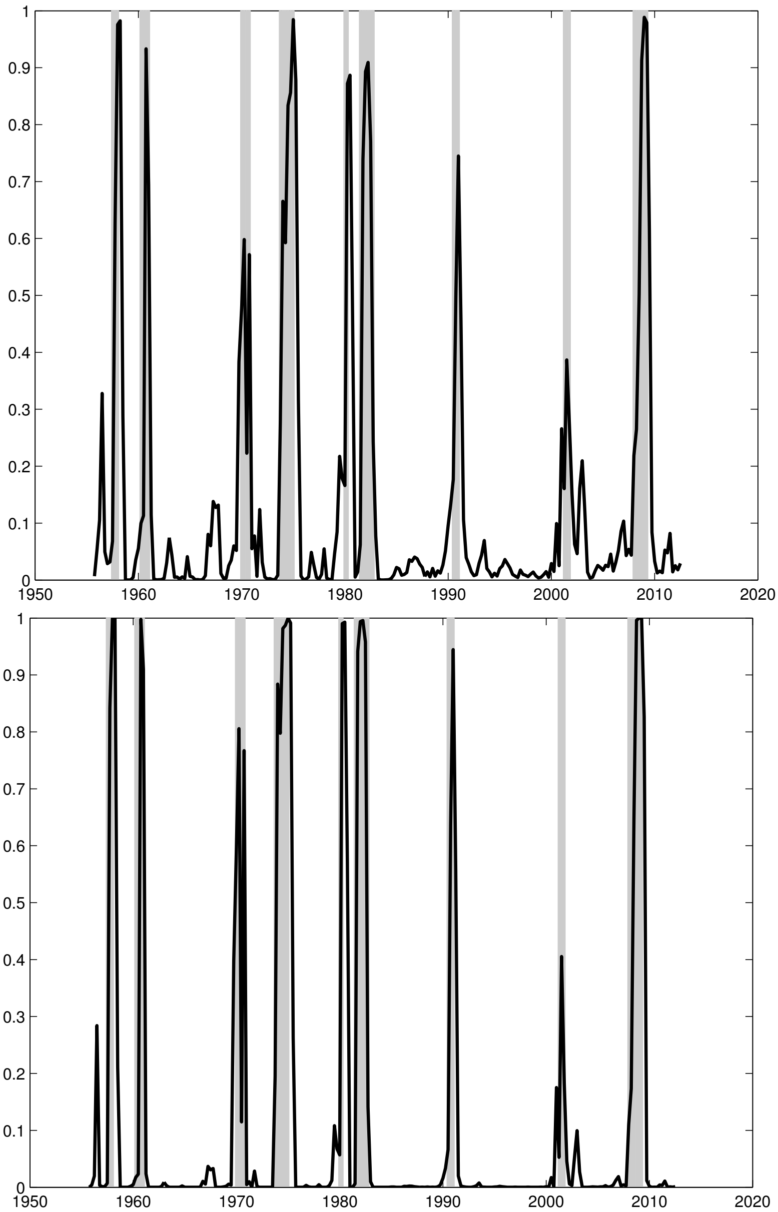

Figure 10: Comparison of the transition function for the mean equation - F (top), and the transition function for the variance equation - G (bottom), with average parameter values obtained from the MCMC iterations ($\gamma_F = 3.00$, $c_F = -0.61$, $\gamma_G = 6.31$, $c_G = -0.52$). The black line is 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.

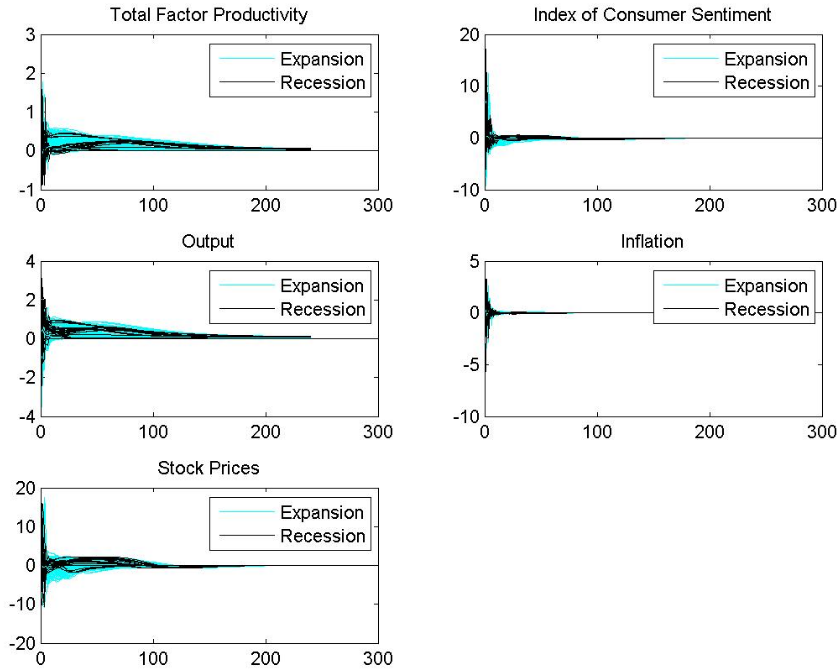

Figure 11: Stability check for the five processes. Each plot displays the paths of realizations (in first differences) from the estimated model with noise switched off, starting from a large number of initial points from both regimes.

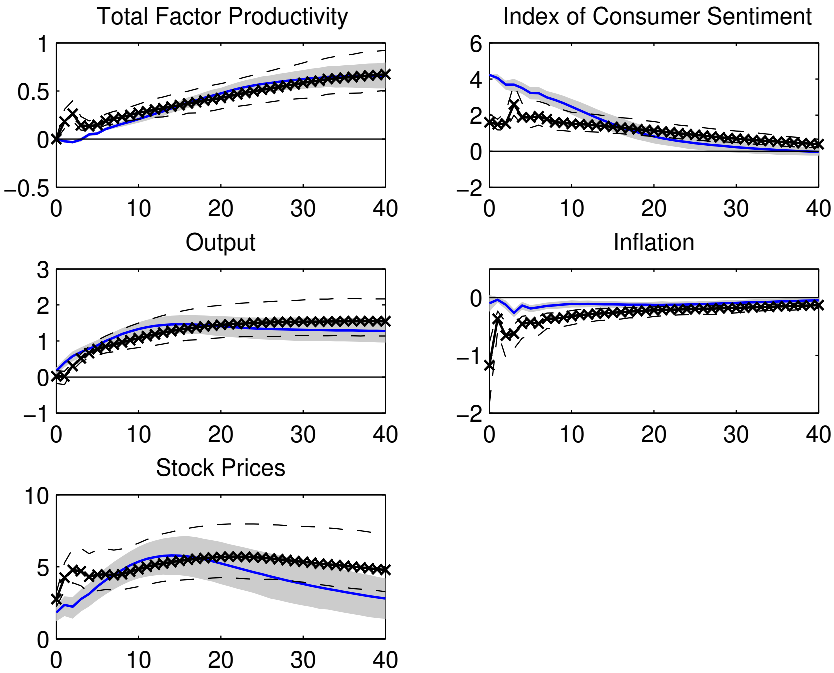

Figure 12: Generalized impulse response functions to a positive small confidence shock under SRI. SRI assumes that the confidence shock affects ICS on impact but not TFP. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed 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.

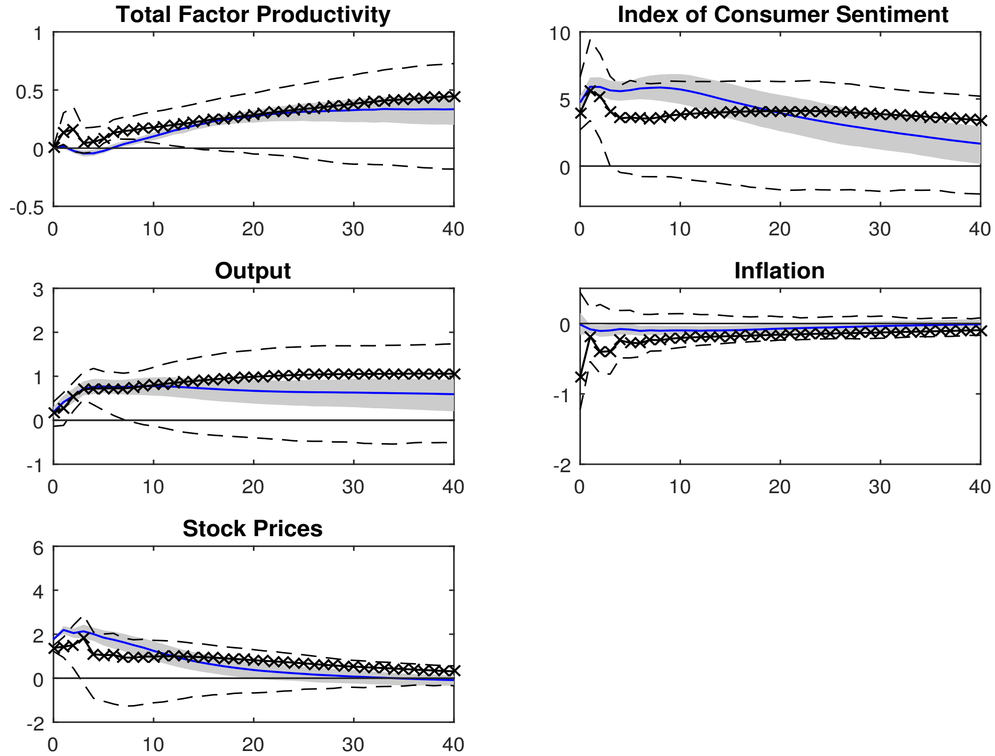

Figure 13: Generalized impulse response functions to a positive small news shock under SRI2. SRI2 assumes that the news shock affects SP on impact but not TFP. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines 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.

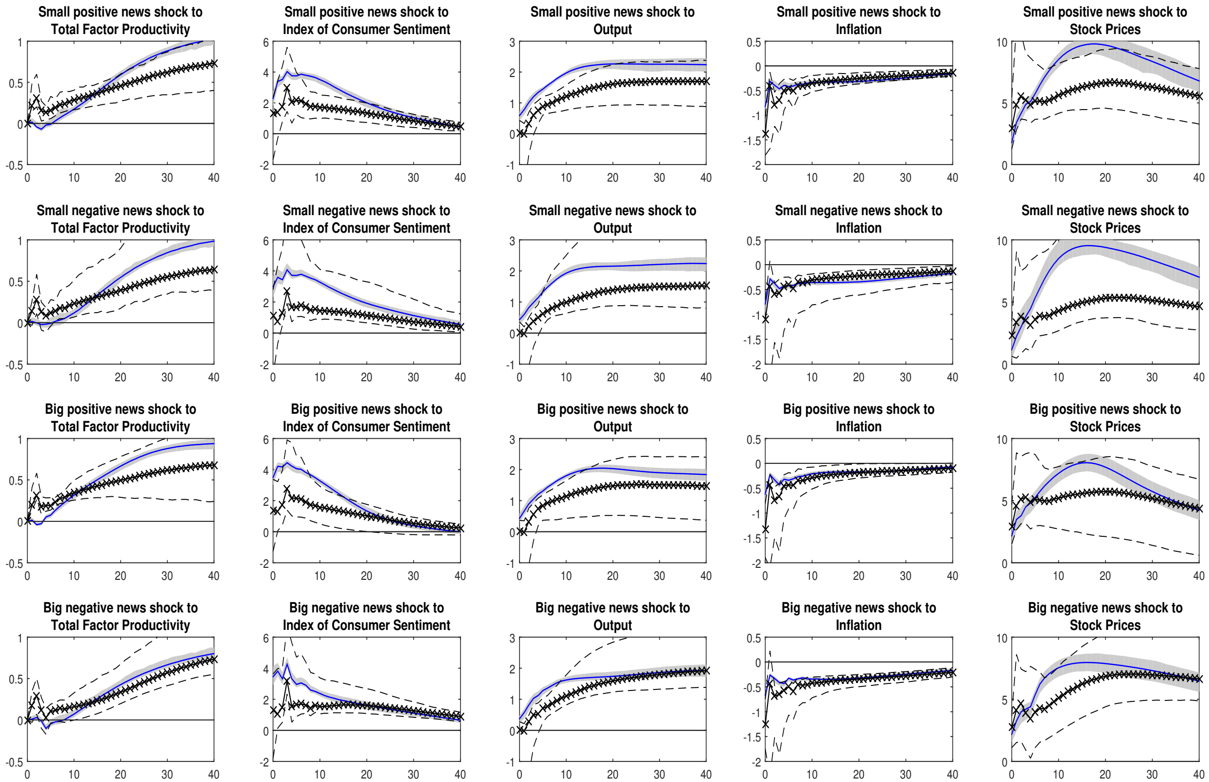

Figure 14: Generalized impulse response functions to news shocks of different signs and magnitudes. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, 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.

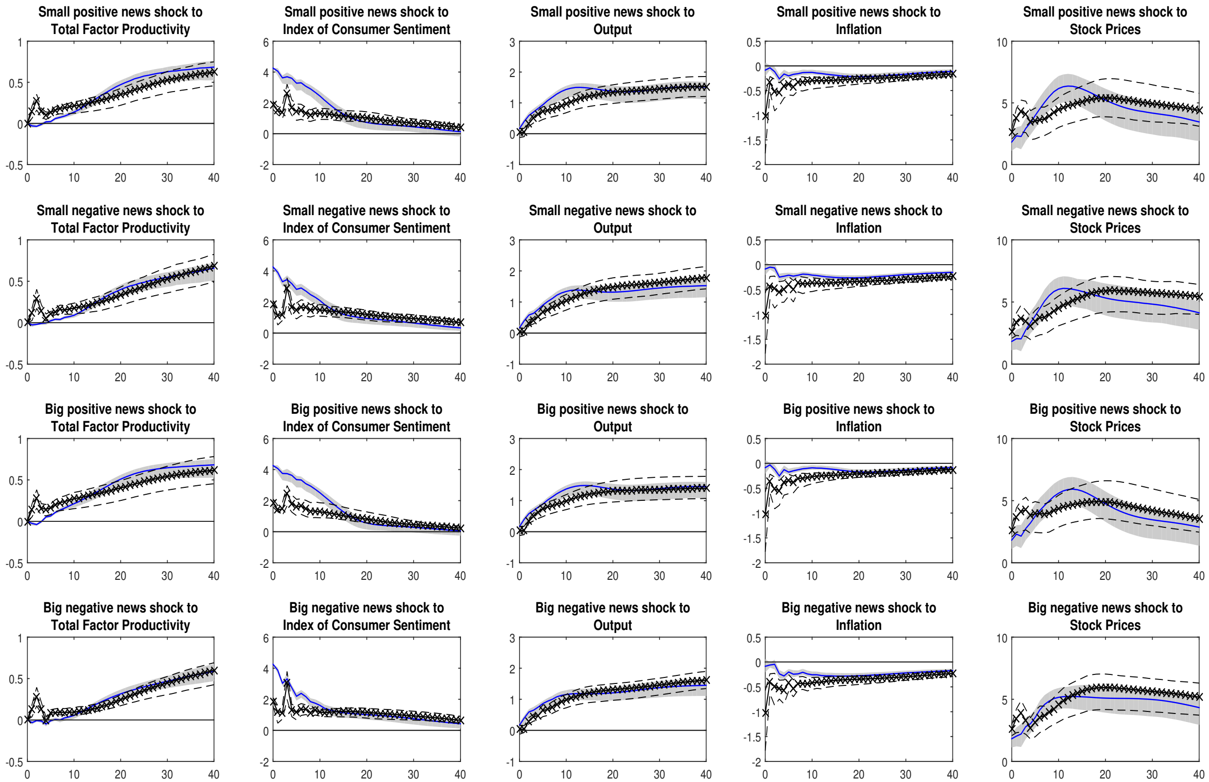

Figure 15: Generalized impulse response functions to confidence shocks of different signs and magnitudes. The starred black line is the point estimate in recession, and the blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, 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 3: 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 4: 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