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New 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 takes the analysis of news shocks from the linear to the nonlinear world. State-dependent and asymmetric effects of news shocks are obtained by applying a short-run and a medium-run identification scheme to a structural LSTVAR. We allow the model to be as flexible as possible and estimate generalized impulse response functions that grant the transition from one regime to the other. We introduce the medium-run identification into the nonlinear world using the generalized forecast error variance decomposition. The results reveal quantitative nonlinearities while they are in line with the literature for the linear world. We find that the probability of a regime switch is highly affected by the news shocks.

JEL classification: E32, E23, C32, C51, C52, O47.

Keywords: smooth transition VAR models, nonlinear time-series model, news shocks, asymmetry, generalized impulse responses, generalised forecast error variance decomposition, linearity testing, fundamentalness testing.

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1 Introduction

Consumer confidence is known to be a great predictor of the business cycle. In the recent crisis it became an important topic in economic research, politics and the media as consumer confidence remains low in many countries and hobbles the economic recovery. The reason is clear. As Petev and Pistaferri (2012) showed, in the case of the U.S. economy, growth in personal spending is closely linked to consumer confidence. When consumer confidence is low, people reduce their spending and borrow less. Faced with lower demand, businesses do not buy new equipment, or hire new people. This generates a vicious cycle and breaking it by boosting consumer confidence is a 'must' for policy makers.

Survey data shows that in recession consumer confidence is low while in expansion it is high. Positive news about the future development of the economy are known to increase confidence. But should we expect the same effect, independent of the state of the economy? We assume the reaction of confidence to news may also be state-dependent, as people could respond differently to them when the future looks gloomy than when it seems bright. This may further influence their decisions to spend or hoard, which will of course depend on how their expectations about the future changed.

In this paper, we estimate a nonlinear LSTVAR model and identify the news shock with a short-run and a medium-run identification scheme. We show that news about future productivity that boost consumer confidence have a quantitatively larger effect on the economy in expansions than in recessions. To obtain a similar effect on the economy in recession, the news shock must be larger.

Our paper is related to the literature on news-driven business cycles. The news-driven business cycle hypothesis sustains that business cycles are determined by changes in expectations about future fundamentals. The idea is not novel in the macroeconomics literature, as it can be traced back to Pigou (1927) and Keynes (1936), but has been reinvigorated in the recent years by Beaudry and Portier (2006). In this seminal paper, they show that news that are obtained today contain information about possible future technological change. In response, market participants start to accommodate to the future technological innovations already when the news arrives, which means before the technological change actually occurs. This creates an immediate boom, and also an eventual bust, if the productivity change is not at the level of expectations, without any significant change in fundamentals. A challenge of this literature is how to identify a news shock. One of the most prominent identification schemes is offered by Beaudry and Portier (2006) who propose identification either via short-run or long-run restrictions. On the other hand, Barsky and Sims (2011) identify the news shock via medium-run restrictions based on the method of Uhlig (2004). While they initially found contradictory results, Beaudry and Portier (2014) could show that this stemmed from the different information included in the models. Once the same variables were contained, the results did not differ.

So far news shocks on future technological innovation have been analyzed in linear settings. We argue that the linear world is too restrictive and that we need to allow for state-dependent reaction to news.

Data indicates that the transition from good times to recession is in general steep and fast while the recovery phase is much longer and more gradual. This implies that consumers' and investors' reactions to shocks might be state-dependent, too. Van Nieuwerburgh and Veldkamp (2006) propose a model with learning asymmetries over the business cycle. In good times, people are well informed and have precise estimates given the occurred shock while in bad times, uncertainty is higher and they are not sure what to expect. Their model explains very well the sharp down-turn of the economy which occurs fast as agents are well-informed and the prolonged recovery that stems from reluctance in uncertain times.

In the uncertainty literature, it has been shown that the response to shocks if uncertainty is high is more vague. Bloom (2009) explains this finding with a mentality of wait and see until uncertainty recedes. Conventional proxies of uncertainty such as stock market volatility are in general counter-cyclical indicating high uncertainty in bad times and low uncertainty in expansionary times. While in expansion a fast reaction to news is expected, the response in recession will occur only after some time.

To perform our empirical analysis, we proceed as follows. In the first stage, we estimate a linear baseline model where we verify sufficient information and that a structural news shock is identified by applying the test for sufficient information of Forni and Gambetti (2014). Our baseline model is a 5-variable VAR including total factor productivity (TFP), consumer expectations, output, inflation and stock prices. The news shock is identified with two different identification methods. Identification I relies on short-run restrictions where the news shock has no impact effect on TFP, but an immediate effect on consumer expectations. For Identification II we apply a medium-run identification method that identifies the news shock as the shock that contributes the most to TFP after ten years and has no impact effect on it. This identification stems from the assumption that only technology shocks and technology-based news shocks influence TFP in the medium-run. We show that the two identified news shocks are highly correlated. Moreover, we estimate impulse response functions and show that the two sets of impulse responses for Identification I and II are very close.

In the second stage, we employ a nonlinear five-variable logistic smooth transition vector autoregressive (LSTVAR) model to estimate state-dependent news shocks. Our model develops 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. The transition in the mean equation and the variance equation are modeled separately. The transition is indicated by a three-quarter moving average of the output growth rate lagged by two periods to avoid endogeneity problems. Instead of calibrating the parameters of the transition functions as usually done in the literature, we estimate them. The estimates for the two functions are significantly different, so using the same transition function may, at least in our case, distort the results. Also in the nonlinear world two identification schemes are employed. The news shock is identified via a short-run and a medium-run identification method. Short-run identifications in a non-linear VAR context are common in the literature. To the best of our knowledge, we are the first to employ a medium-run identification scheme in a LSTVAR model. In the nonlinear setting, the shares of the forecast error variance decomposition generally do not sum to one. We tackle this issue by using instead the approximation of the forecast error variance decomposition proposed by Lanne and Nyberg (2014) which sums to one by construction. The news shock is then identified as the shock with no impact effect on TFP and that has the highest impact after a certain horizon.

To analyze the effects of the news shock we compute generalized impulse responses that allow for endogenous regime transition by adjusting the transition functions every simulation step. To the best of our knowledge, we are the first to do so after Caggiano et al. (2014a) that employ this method to estimate fiscal multipliers. This approach enables the system to transition from one regime to the other as a reaction to a shock. We can then measure the change in the probability of a regime transition after a news shock has occurred.

Our results in the linear world support 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 (or bouts of optimism) are followed by an eventual rise in TFP. The impulse responses to the news shocks obtained with the two identification schemes are remarkably similar. They confirm the initial results of Beaudry and Portier (2006) and partially contradict those of Barsky and Sims (2011). 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.

When we take the analysis to the nonlinear world, we find qualitatively similar results using both identification. They indicate business cycle movements following a news shock. Quantitative state-dependencies can be detected while the asymmetry does not seem to play an important role. The response to the news shock is in general larger in an expansion than in a recession. Good news about the future has indeed the desired effect of increasing agents' confidence both in recessions and expansions, but the impact effect is twice as big in normal times. This further translates in a stronger increase in demand for consumption goods and therefore in output. In a recession, the effect seems to be delayed, as if the agents postpone the reaction to become more certain about the future. Only the stock market reacts faster and stronger, as stock prices increase in the short-run more in a recession than in an expansion.

Comparing the results obtained with the two identification schemes, we find that, while in recession Identification I and II deliver basically the same impulse responses, the impulse responses in expansion are higher for Identification II. With this identification method, it might be possible that not exactly the same shock is identified in both regimes. The reason might be that not the same disturbances have the highest influence on medium-run TFP depending on whether they occur in expansionary or recessionary times.

When we compare the generalized impulse responses to the responses obtained in the linear world, it becomes evident that using the linear model to draw conclusions about the effects of the news shock in either of the regimes is flawed. This would lead to an underestimation of the effects in an expansion and an overestimation in a recession.

We also show that the probability of a regime-transition is strongly influenced by the news shock. We find evidence that good news can boost the economy, independent of the state, but they are more effective in recessions than in expansions. An interesting finding is that, after a good news in normal times, there is a short-run boom followed by a bust in the medium-run. This is in line with the news-driven business cycles hypothesis. Our results also indicate that strong bad news can make a boom end, while similarly strong good news do not have the same power to take the economy out of a recession. However, even though negative news shocks increase the probability of staying in a recession, their effect is not as strong as when they hit in an expansion.

2 Empirical Approach

2.1 Linear vector autoregressive model

In the linear world, we estimate a linear vector autoregressive model in levels and identify structural shocks with two different identification schemes. The model is given by:

$$Y_t = \Pi' X_t + \epsilon_t \tag{1}$$

where Y_t is a vector of m endogenous variables which we aim to model and $X_t = (Y'_{t-1}, ..., Y'_{t-p}, \mathbf{1})'$ is a matrix of p lags of the same endogenous variables and a vector of ones. Π is a matrix containing the VAR coefficients and an intercept vector capturing the dynamics of the system. $\epsilon_t \sim N(0, \Sigma)$ is a vector of reduced-form residuals with mean zero and constant variance-covariance matrix, Σ.

2.2 Linear identification of the news shock

In the literature mainly two identification schemes are used. The most prominent identification scheme was brought up by Beaudry and Portier (2006) (BP). Their baseline model is a linear vector error correction model (VECM) with two variables, TFP and stock prices (SP). Structural shocks are identified either with short-run or long-run restrictions. They find that the two shocks are highly correlated, indicating that permanent changes in productivity growth are preceded by stock market booms. They also consider three- and four-dimensional systems where they add consumption, hours worked, and investment. The results are qualitatively similar for the first two variables in the model, and they also indicate a temporary boom in consumption, hours and investment that anticipates the permanent growth in TFP indicated by a positive news shock.

However, Kurmann and Mertens (2014) criticise their VECM with more than two variables for the fact that the long-run identification scheme fails to determine TFP news, while these higher dimension systems are crucial to quantify the business cycle effects of TFP news or to perform robustness checks. The authors argue that this identification problem is determined by the interplay between the cointegration assumption and the long-run restrictions.

Kurmann and Mertens (2014) plead instead for the approach of Barsky and Sims (2011) (BS) who employ a VAR model and identify TFP news as the shock orthogonal to contemporaneous TFP movements that maximizes the sum of contributions to TFP's forecast error variance over a finite horizon. They use similar data series to Beaudry and Portier (2006), but they obtain different results. After estimating a four variables VAR in levels with TFP, consumption, output and hours (or investment), they conclude that a good realization of the news shock is associated with an increase in consumption and impact declines in output, hours, and investment. After impact, aggregate variables largely track, and not anticipate, the movements in TFP. The news shock does not trigger the boom reaction as in Beaudry and Portier (2006).

Beaudry et al. (2013) compare these two identification methods of news shocks, providing reasons for the contradiction in results. Their approach to tackle this issue is by Monte Carlo simulations using artificial data that are generated with two different calibrated theoretical models serving as data generating process (DGP). The main insight is that when the same reduced-form model underlies the estimation, the two methods deliver quite similar results regardless of the properties of the underlying true DGP.

A similar conclusion is reached in Beaudry and Portier (2014). The authors use US data and estimate two- to four variable VARs with different combinations of variables. They show that the two identification schemes give similar results under the same information content. Most importantly, they point out that when one replaces consumption with stock prices in the four-variable model of Barsky and Sims (2011), the results resemble very much those of Beaudry and Portier (2006).

Therefore, it seems that an agreement has been reached in the literature that analysis the role played by news shocks in the linear world. Using the same observable variables in the model gives similar results, regardless of the identification scheme employed.

In what follows, we present the two slightly modified versions of BP's short-run and BS' medium-run identification schemes we use to isolate news shocks.

2.2.1 Identification I

Our short-run identification (henceforth, Identification I) departs from the one of Beaudry and Portier (2006) in the sense that we take the shock on the index of consumer sentiment to be the news shock, instead of the one on stock prices. Our choice is motivated by the common agreement in the literature that the index of consumer sentiment captures better than stock prices agents' expectations about future developments in the economy (for details see Barsky and Sims (2012)).

Therefore, the news shock is defined as the shock that has no impact effect on TFP, but is the only shock besides the technology shock that affects consumer sentiment immediately. We identify it by imposing short-run restrictions on the moving-average representation of the model.

In the linear world, the variance-covariance matrix of the reduced-form shocks is decomposed into two lower triangular matrices by applying the Cholesky decomposition $\Sigma = AA'$. Thereby, the innovations are orthogonalized and the first two shocks are identified as technology shock and news shock. The rest of the shocks cannot be economically interpreted.

2.2.2 Identification II

The second scheme we employ (hereafter, Identification II) defines the news shock to be the shock that does not move TFP on impact and has maximal effect on TFP at horizon H. This method introduced by Beaudry et al. (2011) differs from the original one of Barsky and Sims (2011) because the latter aims at isolating the shock that maximises its contribution to the forecast error variance of TFP not only at a given horizon, but at all horizons up to the truncation horizon. Therefore, as Beaudry et al. (2011) argue, the difference is that the first identifies the shocks that have a permanent effect on TFP, while the second may confound shocks that have either permanent or temporary effects on TFP. Since the results obtained with the method of Barsky and Sims (2011) are proven to be sensitive to the choice of forecast horizon, we prefer to use the approach of Beaudry et al. (2011) instead.

Thus, this identification scheme imposes medium-run restrictions in the sense of Uhlig (2004). Innovations are orthogonalized, for example, by applying the Cholesky decomposition to the covariance matrix of the residuals. It is assumed that only the technology and the news shock influence TFP in the long-run. The news shock is then identified as the shock that has no impact effect on TFP and that besides the technology shock has the largest impact on TFP, namely the shock with the highest share of the forecast error variance decomposition at some specified horizon H. In the benchmark setting, we set H=40 quarters (10 years), but we perform robustness checks with different horizons.

In the linear setting the h step ahead forecast error is given defined as the difference between the realization of Y_{t+h} and the minimum mean squared error predictor for horizon h[1]:

$$Y_{t+h} - P_{t-1}Y_{t+h} = \sum_{\tau=0}^{h} B_\tau A u_{t+h-\tau} \tag{2}$$

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

$$\Xi_{j,i}(h) = \frac{e_j' \left(\sum_{\tau=0}^{h} B_\tau A e_i e_i' A' B_\tau'\right) e_j}{e_j' \left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau'\right) e_j} = \frac{\sum_{\tau=0}^{h} B_{j,\tau} A \gamma \gamma' A' B_{j,\tau}'}{\sum_{\tau=0}^{h} B_{j,\tau} \Sigma B_{j,\tau}'} \tag{3}$$

where e_i denote selection vectors with the ith place equal to 1 and zeros elsewhere. $A\gamma$ is a $m \times 1$ vector and has the interpretation 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 $B_{j,\tau}$.

Which identification scheme actually identifies the technology-related news shock is still an on-going debate. Therefore, we apply both identification schemes to our linear and non-linear settings to detect possible differences in the results and point to the factors that may determine them.

[1] We use the fact that the model has a moving average (MA) representation $Y_t = B(L)\epsilon_t$, and assuming that there is a linear mapping between the innovations and the structural shocks of the form $\epsilon_t = Au_t$, the model has the following structural MA representation: $Y_t = C(L)u_t$. The minimum MSE predictor for forecast horizon h at time $t-1$ is the conditional expectation.

2.3 Sufficient Information

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

Sims (2012) shows that the presence of news shocks introduces an incontestable missing state variable problem since the anticipation effects of the news shock make it both a shock and a state variable. Nevertheless, he argues that the possible non-invertibility problem is not severe in the case of news shocks as long as a large information set is used. Nonetheless, Beaudry et al. (2013) find that including too many variables in the VAR model leads to a wide dispersion of results such that statistical inference becomes impossible. Therefore, they advise to estimate VARs with few variables but including among them the ones with particularly strong forward-looking properties. This seems to be essential for successfully recovering the news shock.

Their results are further confirmed by Beaudry and Portier (2014), who also add that including a combination of stock prices and survey evidence in the model's set of variables may be more useful for identifying a news shock than only using one of the two. Furthermore, Gambetti (2014-2015), using the fundamentalness test of Forni and Gambetti (2014), shows that a four variables model including TFP, SP (or output), consumption and hours worked does not have sufficient information to identify the news shock, but adding to the model a component of the Michigan University consumer confidence index (i.e. Business Conditions expected during the next 5 years), output and inflation solves the non-fundamentalness problem.

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

We follow their procedure for testing orthogonality of the estimated shock (Details in Appendix B.1).

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

2.4 Smooth transition vector autoregression

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

2.4.1 Model specification

For our research purpose, we employ a generalization of the univariate LSTAR to the m-dimensional vector case (LSTVAR). We want to model an economy with two extreme regimes (expansion, recession) between which the transition is smooth. In our eyes the most appropriate model is the logistic smooth transition vector autoregressive model which allows a smooth transition between regimes.

Formally, the logistic smooth transition vector autoregressive model of order p reads:

$$Y_t = \left[\Pi'_{1,0} + \sum_{j=1}^{p} \Pi'_{1,j} Y_{t-j}\right] (1 - F(\gamma_F, c_F; s_{t-1})) + \left[\Pi'_{2,0} + \sum_{j=1}^{p} \Pi'_{2,j} Y_{t-j}\right] F(\gamma_F, c_F; s_{t-1}) + \epsilon_t \tag{4}$$

where $Y_t = (Y_{1,t}, ...Y_{m,t})'$ is an $m \times 1$ vector of endogenous variables, $\Pi_{1,0}$ and $\Pi_{2,0}$ are $1 \times m$ intercept vectors, $\Pi_{1,j}$ and $\Pi_{2,j}$, $j = 1, ..., p$ are $m \times m$ parameter matrices.

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

$$F(\gamma_F, c_F; s_t) = exp\left(-\gamma_F(s_t - c_F)\right) \ \left[1 + exp\left(-\gamma(s_t - c_F)\right)\right]^{-1}, \ \gamma > 0, \tag{5}$$

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

$$\Sigma_t = (1 - M(\gamma_M, c_M; s_{t-1}))\Sigma_1 + M(\gamma_M, c_M; s_{t-1})\Sigma_2 \tag{6}$$

The transition in the second moment between regimes is also governed by a logistic transition function $M(\gamma_M, c_M; s_t)$. 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 approach is similar to Auerbach and Gorodnichenko (2012), but we differ from it by allowing the parameters of the transition function in the variance equation to differ from the parameters in the mean equation.

2.4.2 Transition Variable

The transition between regimes is defined through the logistic transition functions. But the state of the economy is given by the transition variable. As stated in Teräsvirta et al. (2010), economic theory is not always fully explicit about the right transition variable for a model. In that case, the linearity test should be performed for each variable in the predetermined set of potential transition variables. If the null hypothesis is never rejected, then the linear model should be employed. Otherwise, if it is rejected for at least one of the models, then the model with the strongest rejection, measured by the p-value, should be chosen. There are several options for the transition variable. It 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 National Bureau of Economic Research (NBER) defines a recession as a period of falling economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales', which makes the identification of a recession a complex process based on weighing the behavior of various indicators of economic activity. For this reason, following the rule of thumb definition of a recession as two consecutive quarters of negative GDP growth, we employ as transition variable s_t a three quarter moving average of the quarter-on-quarter real GDP growth, centered at time $t-1$.

This definition of the transition variable is close to the one used in Auerbach and Gorodnichenko (2012), as they set s_t to be a seven quarter moving average of the realizations of the quarter-on-quarter real GDP growth rate, centered at time t. We depart from their approach in the sense that we do not assume the transition variable to be an exogenous variable, but a function of a lagged endogenous variable. In order to avoid endogeneity problems, the transition function $F(\gamma, c; s_{t-1})$ at date t is based on $s_{t-1} = \frac{1}{3}(g^Y_{t-1} + g^Y_{t-2} + g^Y_{t-3})$, g^Y_t being the growth rate of output.

The LSTVAR model is only indicated if linearity can be rejected given the alternative of an LSTVAR model and the transition variable.. We can reject the null hypothesis of linearity at all significance levels, regardless of the type of LM test we perform (see Details in A.1).

2.4.3 Estimation

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

$$log\ L = const + \frac{1}{2}\sum_{t=1}^{T}\log|\Sigma_t| - \frac{1}{2}\sum_{t=1}^{T}\epsilon_t'\Sigma_t^{-1}\epsilon_t, \tag{7}$$

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

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

$$\hat{\Psi} = \arg\min_{\Psi}\sum_{t=1}^{T}\epsilon_t'\Sigma_t^{-1}\epsilon_t \tag{8}$$

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 (17) can be rewritten as:

$$\hat{\Psi} = \arg\min_{\Psi}\sum_{t=1}^{T}(Y_t - \Pi' Z_t(\gamma_F, c_F))'\Sigma_t^{-1}(Y_t - \Pi' Z_t(\gamma_F, c_F)) \tag{9}$$

It is important to note that conditional on $\{\gamma_F, c_F, \gamma_M, c_M, \Sigma_1, \Sigma_2\}$ the LSTVAR model is linear in the autoregressive parameters Π_1 and Π_2. Hence, for given $\gamma_F, c_F, \gamma_M, c_M$, Σ_1, and Σ_2, estimates of Π can thus 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:

$$\sum_{t=1}^{T}(Z_t(\gamma_F, c_F)Y_t'\Sigma_t^{-1} - Z_t(\gamma_F, c_F)Z_t(\gamma_F, c_F)'\Pi\Sigma_t^{-1}) = 0 \tag{10}$$

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

$$vec(\hat{\Pi}) = \left[\sum_{t=1}^{T} \left(\Sigma_t^{-1} \otimes Z_t(\gamma_F, c_F) Z_t(\gamma_F, c_F)'\right)\right]^{-1} vec\left[\sum_{t=1}^{T} \left(Z_t(\gamma_F, c_F) Y_t' \Sigma_t^{-1}\right)\right], \tag{11}$$

where *vec* denotes the stacking columns operator.

The procedure iterates on $\{\gamma_F, c_F, \gamma_M, c_M, \Sigma_1, \Sigma_2\}$, yielding Π and the likelihood, until an optimum is reached. Therefore, it can be concluded that, when $\gamma_F, c_F, \gamma_M, c_M$, Σ_1, and Σ_2 are known, the solution for Π is analytic. As explained in Hubrich and Teräsvirta (2013), Teräsvirta and Yang (2014b) , this is key for simplifying the nonlinear optimization problem as, in general, finding the optimum in this setting may be numerically demanding. The reason is that the objective function can be rather flat in some directions and possess many local optima.

Therefore, we divide the set of parameters, Ψ, into two subsets: the 'nonlinear parameter set', $\Psi_n = \{\gamma_F, c_F, \gamma_M, c_M, \Sigma_1, \Sigma_2\}$, and the 'linear parameter set', $\Psi_l = \{\Pi_1, \Pi_2\}$. To ensure that Σ_1, and Σ_2 are positive definite matrices, we redefine Ψ_n as $\{\gamma_F, c_F, \gamma_M, c_M, chol(\Sigma_1), chol(\Sigma_2)\}$, 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 (see Details in Appendix A.3).

2.4.4 Starting Values

From this nonlinear parameter set, we first estimate the starting values for the transition functions γ_F, c_F, γ_M, and c_M 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. Thereby, 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 measure 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 estimating a logistic regressing 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. Defining the NBER based recession indicator as Rec, then the probability of $Rec_t = 1$, given s_t, is:

$$P(Rec_t = 1 \mid s_t) = \frac{exp\,[-\gamma(s_{t-1} - c)]}{1 + exp\,[-\gamma(s_{t-1} - c)]} \tag{12}$$

The estimation delivers the starting values $\hat{\gamma}_F = \hat{\gamma}_M = 3.12$ and $\hat{c}_F = \hat{c}_M = -0.48$ (for details see Appendix B). If we use a mean-adjusted switching variable, $\tilde{s_t} = s_t - \bar{s}$, as in Auerbach and Gorodnichenko (2012), the results are $\hat{\gamma}_F = \hat{\gamma}_M = 3.12$ and $\hat{c}_F = \hat{c}_M = -0.97$. The mean adjustment only changes the threshold by the mean $\bar{s} = 0.49$.

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), Caggiano et al. (2014b). 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 estimated the logit forcing the constant to be zero and obtained an estimate for γ that equals 3.56. In the setting with a mean-adjusted switching variable, γ equals 1.53, which is close to the value of 1.5 used by Auerbach and Gorodnichenko (2012). However, the Likelihood Ratio (LR) test[2] shows that the model with intercept provides a better fit. Moreover, the intercept is statistically different from 0 so there is no econometric support for assuming it to be zero (see Appendix B).

The transition function with $\gamma = 3.12$ and $c = -0.48$, is shown in Figure 9. It is obvious that high values of the transition function are associated with the NBER identified recessions.

Starting values for two more parameters of the 'nonlinear parameter set' are needed, Σ_1 and Σ_2. The starting value for Σ_1 is given by the variance-covariance matrix of residuals from the auxiliary regression in equation (8). To obtain different starting values for Σ_2, the covariance matrix is altered by $\epsilon > 0$.

2.4.5 Evaluation

In Teräsvirta et al. (2010) it is stated that, when $F(\gamma, c; s_{t-1})$ is a standard logistic function with a single transition variable, the model is stable if and only if

[2] Perfoming the LR test for nested models, we obtain the following results: D=37.66 (p-value=0.000), or D=159.04 (p-value=0.000) if the switching variable is mean-adjusted

$$\left| I_m - \sum_{j=1}^{p} \Pi_{1,j} z^j \right| \neq 0 \text{ and } \left| I_m - \sum_{j=1}^{p} \Pi_{2,j} z^j \right| \neq 0 \quad \text{for} \quad |z| \leq 1. \tag{13}$$

When the roots of the lag polynomial of the regimes lie outside the complex unit disk, the sufficient and necessary condition for stability.

Stability is also checked by simulation of counterfactuals. By generating paths of realizations from the estimated model with noise switched of, starting from a large number of initial points, it can be checked whether the paths of realisations converge. According to Teräsvirta and Yang (2014b), this convergence to a single stationary point is a necessary condition for exponential stability.

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 (see Details in Appendix A.4).

2.5 Nonlinear identification of the news shock

2.5.1 Identification I

The application of Identification I to the nonlinear setting is rather straight forward. We apply the Cholesky decomposition to the history-dependent impact matrix $\Sigma_t = \Sigma_1(1 - M(\theta, \vartheta; s_{t-1})) + \Sigma_2 M(\theta, \vartheta; s_{t-1})$ such that $\Sigma_t = A_t^M A_t^{M\prime}$.

The impact matrix A_t^M is history-dependent and changes with $M(\theta, \vartheta; s_{t-1})$. The first shock is then identified as a technology shock whereas the second shock is the news shock.

2.5.2 Identification II

The application of Identification II to our nonlinear setting faces one big issue. The calculation of the forecast error variance decomposition depends on the estimation of the GIRFs which are history dependent and constructed as an average over iterations. 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.

Lanne and Nyberg (2014) have proposed a method of estimating the generalized forecast error variance decomposition that sums to one by construction. Using that is the closest we can come to the application of this method.

2.6 Generalized impulse responses

The coefficient estimates of a VAR model are in general difficult to interpret. Therefore, we analyze the dynamics of the model by estimating impulse response functions. The nonlinear nature of the LSTVAR does not allow to estimate traditional impulse response functions due to the fact that the reaction to a shock may be history dependent.

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

In order to cope with these issues, we estimate generalized impulse response functions (GIRFs) instead, which were initially proposed by Koop et al. (1996). On top of that, generalized impulse response functions have the advantage that they do not only allow for state-dependent impulse responses but also for asymmetric reactions. GIRFs may be different depending on the magnitude or sign of the occurring shock. A key point is that GIRFs allow to endogenize regime-switches if the transition function is a function of an endogenous variable of the LSTVAR. This allows us to see whether a shock affects the economy strong enough to move it from one regime to the other. In the literature, this point has usually been ignored.[3]

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

$$GIRF(h, \epsilon_t, \Omega_{t-1}) = E\left\{Y_{t+h} \mid \epsilon_t^{\delta}, \Omega_{t-1}\right\} - E\left\{Y_{t+h} \mid \Omega_{t-1}\right\} \tag{14}$$

where ϵ_t^{δ} is the vector of shocks, and Ω_{t-1} is the history the expectations are conditioned on. ϵ_t^{δ} is a vector of random shocks, and Ω_{t-1} is the history which contains the initial values used to start the simulation procedure.

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

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

$$Y^{sim}_{t+h} = \Pi'_1 X^{sim}_{t+h}(1 - F(\gamma, c; s_{t+h-1})) + \Pi'_2 X^{sim}_{t+h} F(\gamma, c; s_{t+h-1}) + \epsilon_{t+h} \tag{15}$$

The transition functions, $F(\gamma, c; s_{t+h-1})$ and $M(\theta, \vartheta; s_{t+h-1})$, being functions of an endogenous variable of the model, are allowed to adjust every simulation step. Therefore, also the time-dependent covariance matrix Σ_{t+h} changes 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 $E\left\{Y_{t+h} \mid \epsilon^{\delta}_t, \Omega_{t-1}\right\}$, ϵ^{δ}_t is set to a specific shock, where δ indicates the chosen identification scheme, magnitude and sign. For the rest of the horizon $\epsilon_{t+h} \sim \mathcal{N}(0, \Sigma_{t+h})$ for $h \geq 1$. By letting each of the transition functions update every simulation step a possible regime-transition in the aftermath of a shock is allowed.

For the simulation, we proceed in the following way. We define a period as being a recession if $F(\gamma, c; s_{t-1}) \geq 0.5$ and an expansion otherwise. 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. Then, to obtain the effect of a small positive shock in recession, we average over the chosen GIRFs fulfilling all these criteria.

2.7 Generalized forecast error variance decomposition

In a nonlinear environment, the shares of the forecast error variance decomposition generally do not sum to 1 which makes their interpretation rather difficult.

Lanne and Nyberg (2014) propose a method of calculating the generalized forecast error variance decomposition such that this restriction is imposed.

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

$$\lambda_{i,j,\Omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(l, \delta_{it}, \Omega_{t-1})^2_j}{\sum_{i=1}^{K} \sum_{l=0}^{h} GIRF(l, \delta_{it}, \Omega_{t-1})^2_j} \tag{16}$$

The denominator measures the aggregate cumulative effect of all the shocks, while the numerator is the cumulative effect of the ith shock. By construction,

$\lambda_{i,j,\Omega_{t-1}}(h)$ 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 the jth variable. According to the authors, the GIRF is readily generalized by averaging over the relevant shocks and histories. They recommend computing the GFEVD as the average of $\lambda_{i,j,\Omega_{t-1}}(h)$ over shocks and over all the histories.

3 Data

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

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

Nevertheless, Gambetti (2014-2015) shows, using the fundamentalness test of Forni and Gambetti (2014), that a four variables model including TFP, SP (or output), consumption and hours worked does not have sufficient information to identify the news shock, which indicates us that consumption and hours worked are not a valuable addition to our benchmark system.

We use the series of Total Factor Productivity adjusted for variations in factor utilization constructed with the method of Basu et al. (2006). They construct TFP controlling for non-technological effects in aggregate total factor productivity including varying utilization of capital and labor, nonconstant returns and imperfect competition, and aggregation effects. They identify aggregate technology by estimating a Hall-style regression equation with a proxy for utilization in each disaggregated industry. Aggregate technology change is then defined as an appropriately weighted sum of the residuals. The series of TFP annualized percent change adjusted for utilization for the nonfarm business sector is available on the homepage of the Federal Reverse Bank of San Francisco[4]. To obtain the log-level of TFP, the cumulated sum of dTFP was constructed. The S&P 500 stock market index is used as a measure of stock prices[5]. For output we use the log of the real gross value added for the nonfarm business sector available from the U.S. Department of Commerce: Bureau of Economic Analysis. For hours worked the measure hours of all persons for the nonfarm business sector available from the U.S. Department of Labor: Bureau of labor Statistics is employed. Everything is in logs and adjusted for population (US Population, all persons ages 15-64) and the price level for which we use the implicit price deflator for the nonfarm business sector both available from the U.S. Department of Labor: Bureau of Labor Statistics. The price deflator (PD) is also used to compute the annualized inflation rate adjusted for population $IR = 4^*(\log(PD_t) - \log(PD_{t-1}))$. It is sometimes argued that consumer confidence measures reflect more closely the expectations of firms and households about future technological innovations and economic behaviour. We work with data from the surveys of consumers conducted by the University of Michigan. For the whole sample only the index of consumer expectations for six months is available.[6] As a measure of consumption we use the log of the sum of Personal Consumption Expenditures for Nondurable Goods and Personal Consumption Expenditures for Services (both available from the Department of Commerce: Bureau of Economic Analysis) divided by the price deflator and population. Hours worked are measured as the log of Nonfarm Business Sector: Hours of All Persons (available from the U.S. Department of Labor: Bureau of Labor Statistics) divided by population.

4 Results

4.1 Linear world

We estimate a VAR in levels and do not assume a specific cointegrating relationship because this estimation is robust to cointegration of unknown form and gives consistent estimates of the impulse responses, as it is stated in Hamilton (1994). Moreover, in several papers (e.g. Barsky and Sims (2011), Beaudry and Portier

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

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

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

(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 two identification schemes to isolate a technology-based news shock. In Figure 10 from Appendix D, news shocks identified with Identification I and Identification II for our benchmark five-variable model are displayed. The two identification schemes identify very similar news shocks. This result is further confirmed by the high correlation between the two shocks (the coefficient of correlation equals 0.76).

To make sure that our benchmark model is not informationally deficient, hence, that the two identification schemes we employ provide indeed structural shocks, the fundamentalness test of Forni and Gambetti (2014) is performed. In Table 2 from Appendix B.2, we report the results for the orthogonality test for Identification I for the benchmark model (S3) and three other VAR specifications (S1,S2 and S4)[7]. In Table 3, the results of the test applied to Identification II are reported.

It is obvious that specification S1 which is a bivariate model with TFP and SP instead of ICS (the basic framework of Beaudry and Portier (2006)) is deficient. However, when replacing SP with ICS (S2), the model performs better in identifying the structural shock, orthogonality being rejected rarely and only at a 10% significance level. Our results for S1 are similar to those obtained by Gambetti (2014-2015), although the p-values he reports are in general smaller than ours. A reason for the difference can be the fact that our samples cover different time spans (1960Q1-2010Q4 in Gambetti (2014-2015)) or that the dataset used in his analysis contains more time series (107 opposed to 87). The results for S2 suggest that a confidence indicator such as the index of consumer sentiment performs better than stock prices in providing the model with sufficient information to identify structural shocks, even in a bivariate model.

For our 5-variable benchmark model, the p-values in the two tables indicate that orthogonality is never rejected at the 5% significance level. This specification which contains the three forward looking variables most used in the literature, stock prices, inflation, and a measure of consumer confidence, passes the test of fundamentalness. A model with seven variables, by adding consumption and hours worked to the benchmark model, also contains enough information.

Analyzing the impulse responses in Figure 10 from Appendix D indicates that the identified shock is not only a structural shock but a news shock, indeed. Moreover, this result is confirmed for both identification schemes.

Under the two identifications, TFP does not change on impact, which is due to the identifying restrictions in both settings, but it is important to note that there is no significant rise above zero also for the first two years. After that, TFP

[7]The four specifications are described in Table 1 from Appendix B.2

starts rising in both cases until it stabilizes to a new permanent level which is slightly higher under Identification II. This result is in line with those found in Beaudry and Portier (2006) and Beaudry et al. (2011), but partly contradict those of Barsky and Sims (2011). BS find a rapid and immediate rise in TFP following their news shock, but it is insignificant in their four-variable model. The reason why the impulse response of TFP to the identified shock under Identification II is different from the ones obtained by Barsky and Sims (2011) might be the fact that BS isolate the shock that maximizes its contribution to the forecast error variance of TFP not only at a given horizon, but at all horizons up to H. The information content of the two models could have been another reason, but our results stay different even when we compare the 7-variable models.

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

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

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

Stock prices rise on impact to the same level in both cases, but while under identification I, the response looks much alike the one in Barsky and Sims (2011), under Identification II, they continue increasing for a long time, reaching a peak after some twenty quarters.

In Figure 12 from Appendix D it can be seen that adding other variables does not significantly modify the results for the first five variables. Inflation diminishes faster, while the response of stock prices is almost identical under the two identification schemes. For the two new variables added, the responses are similar to those presented in Beaudry 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 Identification II, while the opposite holds for hours worked.

These findings confirm the initial results of Beaudry and Portier (2006) and partially contradict those of Barsky and Sims (2011). Under the two different identification schemes, we find extremely similar results. A shock on a measure of consumer confidence with no impact effect on TFP (news or optimism/pessimism shock) proved to be highly correlated with a shock with no impact effect on TFP but which precedes rises in TFP. This supports the conclusion of Beaudry et al. (2011) that all predictable and permanent increases in TFP are preceded by a boom period, and all positive news shock 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 unaccompanied by an increase in productivity.

4.2 Nonlinear world

Beaudry and Portier (2006) found that the recognition of future developments in technology by the economic agents may trigger a boom in consumption and investment before any growth in productivity occurs. Beaudry et al. (2011) provided further support for the idea that bouts of optimism and pessimism drive much of the business cycle. Our results in the linear world confirmed their findings. In this section, we take their analysis one step ahead and examine whether the time when the news arrives matters. More precisely, we want to see whether the state of the economy (i.e. the economy being in an expansion or in a recession) influences the responses to the news shock. Will the boom effect of a positive news realization be the same in the two states? Will it matter whether it is good or bad news? Is there a difference if the news are extreme or rather small?

To answer these questions, we estimate a smooth transition vector autoregressive model. We rely on the same basic model as in the linear world containing five variables {Total Factor Productivity, Index of Consumer Sentiment, Output, Inflation, Stock Prices} with four lags. Compared to the literature, our model contains two instead of only one transition function, one for the mean equation and one for the variance equation. Moreover, we estimate both sets of parameters instead of simply calibrating them. The results presented in Figure 1 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 they change a lot after the MCMC iterations for the variance equation (i.e. the values increase). This indicates that the transition behavior from recession to expansion is not the same for the mean and the volatility of the economy. The transition in the mean is much more smooth than in the variance where it approaches a regime-switch. This finding shows how important it is to have transition functions for both the mean and variance equation in the model as otherwise the results might be distorted.

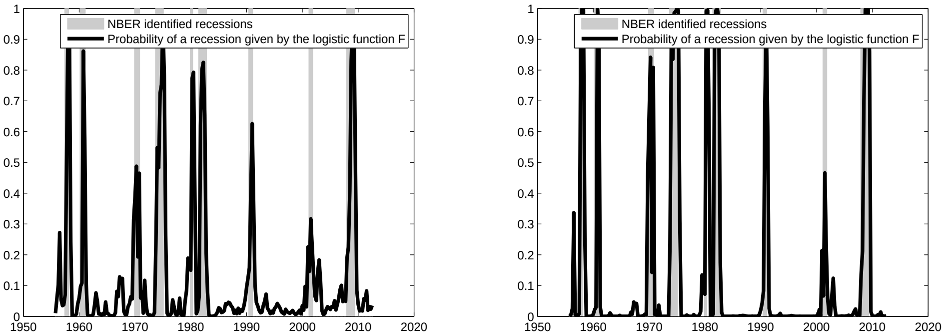

Figure 1: Comparison of the transition function for the mean equation (left) and the transition function for the variance equation (right) with average parameter values obtained from the MCMC iterations

We further test the model for stability to ensure that it delivers interpretable results.

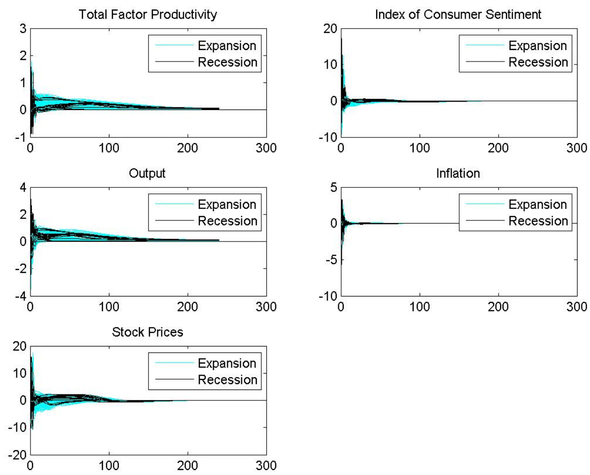

Figure 2: Stability check for the five processes. Each plot displays the paths of realizations from the estimated model with noise switched off, starting from a large number of initial points from both regimes.

We first analyze the roots of the lag polynomial of the two regimes, and since all lie outside the complex unit disk, the sufficient and necessary condition for stability is satisfied. Furthermore, by plotting the simulated paths after switching off the shocks we can show that our model converges to a stable point (see Figure 2). It is clear for each variable in our model that, independent of the history in the dataset chosen as initial value, the trajectories converge to the same stationary point.

4.2.1 Impulse Responses

As the coefficients of vector autoregressive models are generally hard to interpret, we compute impulse responses applying either the short-run or the medium-run identification method to isolate the news shock. To the best of our knowledge, we are the first to apply a maximum forecast error variance identification method (Identification II) in a nonlinear model.

The estimation of impulse response functions for a LSTVAR model is not so straight forward. While Auerbach and Gorodnichenko (2012) estimate regime-dependent impulse response functions and Owyang et al. (2013) opt for Jorda's method, we decide to estimate generalized impulse response functions. Whereas the methods of Auerbach and Gorodnichenko (2012) and Owyang et al. (2013) partly ignore the non-linearities and dynamics of the LSTVAR, our way of estimating the GIRFs does not only take them into account but goes in line with the nonlinear spirit of the model. A very important aspect is that the output is an endogenous variable of the model. When simulating the model for the estimation of the GIRFs, this allows us to adjust the transition function every simulation step. In response to a shock, our method allows the model to change the regime. This is not just a nice extra, but a crucial point. As 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 the most interesting and important quality of the LSTVAR is ignored.

We start by presenting results for Identification I with five variables which is our benchmark setting. In Figure 3, GIRFs to a one standard deviation news shock for Identification I are displayed. The significance between the two regimes can be tested with confidence bands. Results are qualitatively very much in line with the linear world. A news shock about future technological innovation leads to an immediate increase in consumer confidence and stock prices. As a result of higher expectations about future productivity output increases immediately through higher production which decreases pressure on prices and ultimately inflation.

Confidence bands indicate that the regime-dependence in the response to a news shock manifests itself in the short-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.

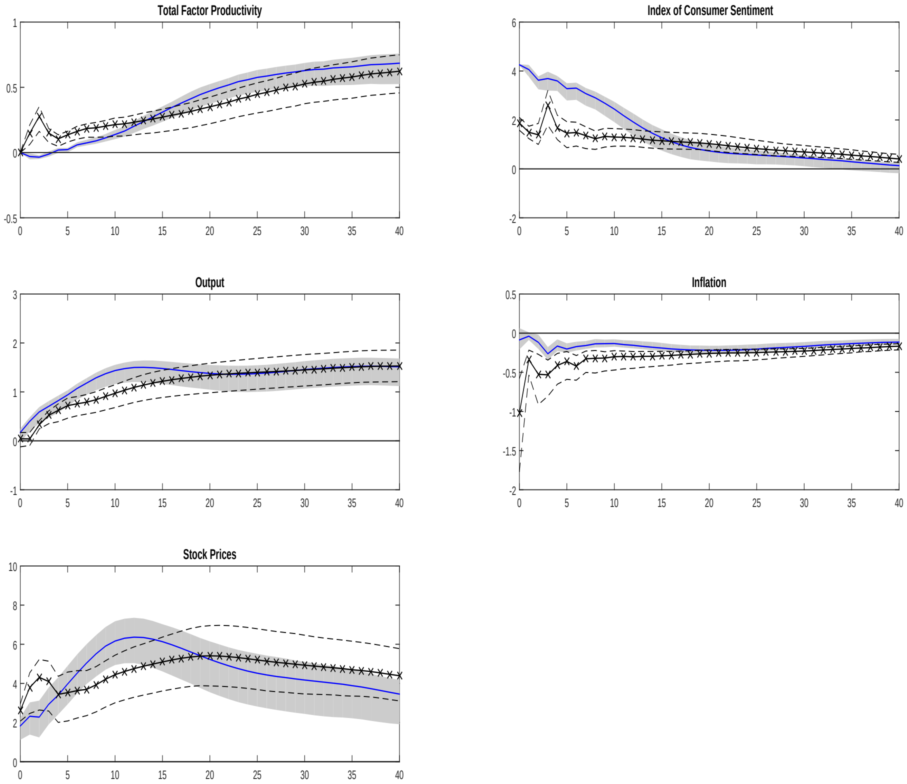

Figure 3: Generalized impulse response functions to a positive small news shock under Identification I. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light gray 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.

An important finding is the impact reaction of consumer confidence. It can be seen in Figure 3 that it is twice as big in expansion as it is in recession. This result reveals the importance of looking at the state-dependent effect of the same shock. Good news about the future have indeed the desired effect of increasing agents' confidence both in recessions and expansions, but the uncertainty present during the periods of economic slowdown impedes them to react as much as they do in normal times. More confident about the future which was already bright, consumers in an expansion demand right away more goods. However, the increase in confidence during a recession does not have the same effect on households. Consumers do not react immediately and are reluctant to open their wallets and start spending their savings. The envisioned economic recovery boosts their consumption demand only when they become more certain about it, but in the short-run they buy less goods than in normal times. This can be seen in the smaller increase in output during recessions. In the recessionary regime, output does not react on impact to the good news and only after some months firms start producing more. The postponed increase in production may be also attributed to the higher uncertainty that also firms face in recessions. They have hoarded labor and are reluctant to increase employment at the first sign of recovery. Even to incur the cost of overtime premiums paid to the employees for increasing their hours of work may be considered too risky as the possible increase in demand may not materialize. It seems they are still caught in a vicious circle and need more time to get out of it. Consumers do not start spending once they receive the news because they fear firms will not hire and they will not have more income to support higher permanent consumption, while companies do not employ more people since they fear there will not be more demand for their products. This is usually not the case in an expansion, as firms are more willing to pay the fixed costs of hiring and investing, being more confident that they will maintain the higher sales level.

This result is also supported by the short-run movement of TFP in response to a news shock. While in expansion the increase takes place after some quarters, in recession TFP starts to increase already one quarter after the news shock occurred. This could be explained by the way firms adjust their production to meet the economy's future needs. In an expansion, being confronted with the potential of higher sales, firms increase immediately production by acquiring more labor (i.e. increasing the number of hours worked) and capital, in the proportions governed by the technology in use. They can, therefore, meet the higher short-run demand and take their time to reorganize the business such that it accommodates the new technological innovation and produce more efficiently the permanent higher output that is being demanded. On the other side, the firms still present on the market in a recession are those which got rid of all the less productive inputs (e.g. inefficient machinery and unskilled workers), and in an attempt to be most efficiently operating, adopt fast new technologies. The diffusion of the innovation is, therefore, much faster in recessions than in expansions.

Investors know that the more effective production processes of the surviving firms during a recession will allow them to supply the increased consumer demand at high profit margins. Hence, they start investing in these companies' stocks. The buying pressure increases stock prices in the short-run more in a recession than in an expansion. The reason why the effect on stock prices is higher in recession even though the one on confidence is smaller, is investor's rush to be the first to benefit from the anticipation of future economic recovery and growing dividends.

The good news puts downward pressure on inflation in both states of the economy. Following the New-Keynesian reasoning that inflation dynamics are driven by the expected evolution of marginal costs, since firms anticipate lower future marginal costs due to the increase in productivity, inflation falls on impact. In expansion, firms need to supply immediately more goods to meet the increased demand of the consumers who want to smooth lifetime consumption. Therefore, they increase their demand for labor and capital, driving up production costs in the short-run. The effect of the short-run increase in marginal costs seems to be smaller than the one of the expected decrease in future marginal costs, and this way inflation drops. An explanation could be given by the presence of nominal rigidities. More precisely, the fact that real wage adjusts sluggishly in reaction to the good news, may explain the smaller change in current marginal costs. Nevertheless, because of this short-run upward pressure on marginal costs the decrease in inflation is smaller in expansion than in recession. The difference may be triggered by the smaller increase in production on the short-run during recessions.

The low inflation may also encourage a central bank with inflation-targeting policy to reduce the nominal interest rate, which may give a further explanation for the increase in stock prices in anticipation of a productivity improvement. The bigger decrease in inflation during a recession and the possible stronger reaction of the central bank can thus justify the stronger increase in stock prices in this state of the economy. The intervention of the central bank can act as an amplification mechanism of the anticipated technology shock.

In Figure 13 from Appendix E, the responses to a small positive, a big positive, a small negative and a big negative news shock for both regimes are displayed. The big shock is three times the size of the small shock. The results are normalized to the same magnitude and sign to make them comparable. We find that the responses are qualitatively very similar. There are quantitative differences, though. It can be stated that the effect of a small negative shock in a recession seems to exhibit a stronger effect on output in the long-run. Thus, it is indicated that negative news depress the economy more in bad than in good times. Furthermore, small negative news shocks have stronger effects than the positive ones on consumer confidence and stock prices in the long-run, independent of the regime. Nevertheless, the magnitude and the sign of the shock do not seem to play an important role. Generally, it can be said that the reaction to a negative shock is slightly stronger and the reaction to a big shock increases by less than the increase in shock size. But the differences are not statistically significant.

As a next step, we compare in Figure 4 the results obtained using the two identification schemes. 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 which is also an indication that the same shock is identified.

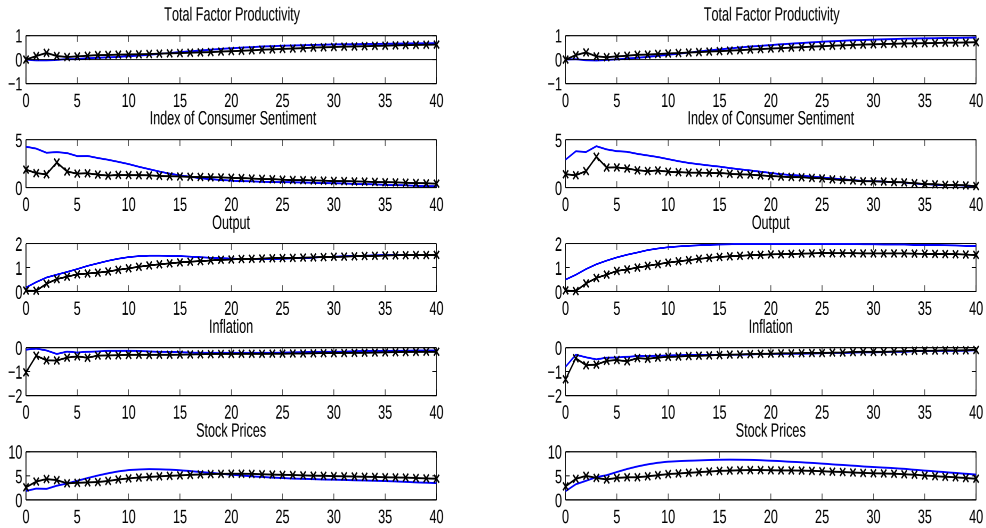

Figure 4: Comparison of the generalized impulse response functions to a positive small news shock under Identification I (left) and Identification II (right). Identification I assumes that news shocks affect ICS on impact but not TFP. Identification II defines the news shock to be the shock that does not move TFP on impact but has maximal effect on it at $H = 40$. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in 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.

On the other hand, for the expansionary regime quantitative differences can be detected. While the effect of a news shock on total factor productivity is very much the same in the short run, TFP grows stronger under Identification II even though the reaction of the index of consumer sentiment is almost the same. The stronger effect on TFP leads then to an even larger effect on output which increases more than under Identification I. Another interesting point is that for Identification II inflation decreases much more than for Identification I which would also fuel output. Finally, the stronger reaction under Identification II is also found in stock prices.

A possible explanation for the quantitative differences in expansion is the construction of Identification II. With this identification method, it might be possible that not exactly the same shock is identified in both regimes. The responses in the recessionary regime are very close under the two identification schemes. However, they are slightly different in the expansionary regime. The reason would be that not the same disturbances have the highest influence on medium-run TFP depending on whether they occur in expansionary or recessionary times. In recession, the highest influence on medium-run TFP seems to have a news (confidence) shock similar to the one identified with Identification I. What influences TFP additionally when the shock occurs in expansion is not yet clear. We address this issue in the next section by using the similarity of the responses in the expansionary regime to the ones in the linear world (see Figure 5) to analyze the share of the forecast error variance decomposition attributable to the news shock identified with the two schemes.

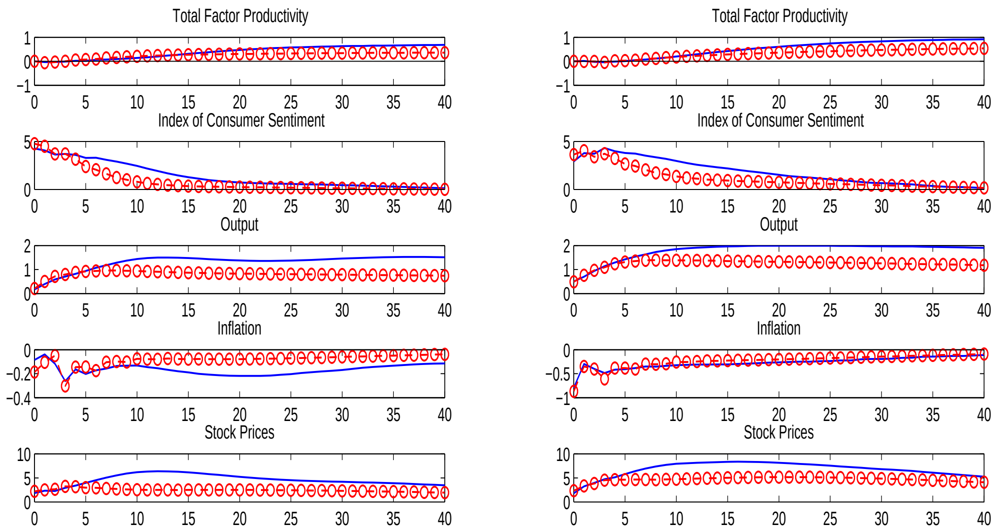

Figure 5: Comparison of Identification I and Identification II. The left panel displays the generalized impulse response functions to a positive small news shock under Identification I in an expansion as the blue line and the impulse responses to a news shock obtained by applying the same identification in the linear model as the red line with circles. The right panel displays the generalized impulse response functions to a positive small news shock under Identification II in an expansion as the blue line and the impulse responses to a news shock obtained by applying the same identification in the linear model as the red line with circles. 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.

Before moving to the discussion of the results for the variance decomposition, we present some findings from the comparison of the generalized impulse responses to the responses obtained in the linear world. In Figure 5 we observe a strong similarity, apparent mainly in the short-run, between the responses in expansion and in the linear model. This is no surprise since more than 85 percent of the periods contained in our sample are defined as normal times. However, on the medium-run, it is evident that the responses to the news shock are stronger in expansions than on average. Therefore, using a linear model to show the effects of news shocks in normal times may underestimate their value. Under both identifications, we see that the news shock has in expansion a much bigger effect on output than the linear model would predict, output stabilizing at a twice as big new permanent level in the expansionary regime. Similar conclusions can be drawn for TFP. Moreover, there is a temporary overreaction of stock prices to the news in expansion which the linear model misses.

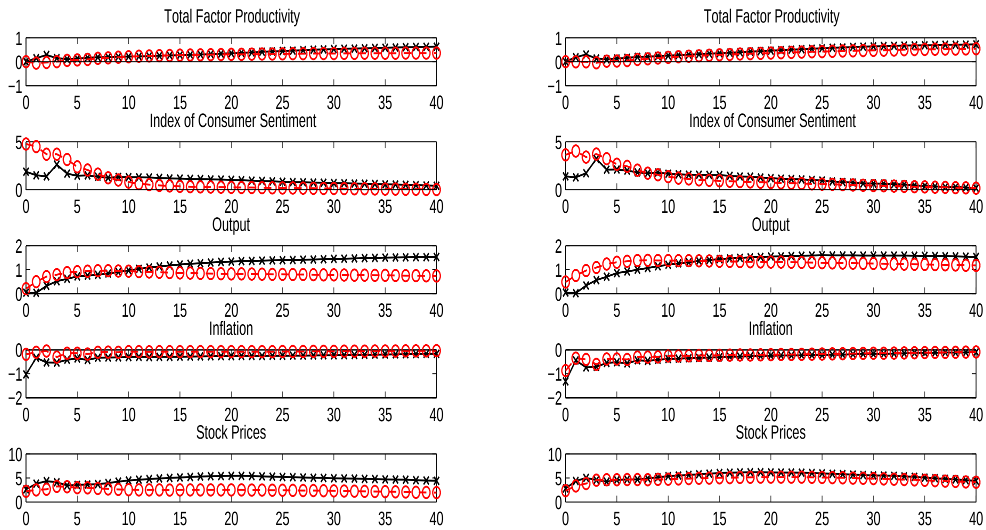

Figure 6: Comparison of Identification I and Identification II. The left panel displays the generalized impulse response functions to a positive small news shock under Identification I in a recession as the starred black line and the impulse responses to a news shock obtained by applying the same identification in the linear model as the red line with circles. The right panel displays the generalized impulse response functions to a positive small news shock under Identification II in a recession as as the starred black line and the impulse responses to a news shock obtained by applying the same identification in the linear model as the red line with circles. 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 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 6, in a recession a news shock has on confidence half the impact effect implied by the linear model. Furthermore, output does not react for some quarters to a positive news shock in a recession, although the linear model indicates an immediate positive reaction.

4.2.2 Variance Decomposition

The problem in nonlinear models is generally that the shares of the forecast error variance decomposition do not add up to one. We estimate the GFEVD according to Lanne and Nyberg (2014) which by construction does respect this criterion.

In this section, we rely mainly on Identification I. While under Identification II, the news shock exhibits a high share of the generalized forecast error variance decomposition by construction, this is not so clear for Identification I. Moreover, whether this is also the case for Identification I has actually often been doubted in the literature.

In recessions, it became obvious in the previous section that the two schemes identify the same shock. By looking at the results in Table 5 from Appendix E, it is clear that in recessions besides the technology shock the news shock obtained under Identification I has the largest influence on TFP. Therefore, we can conclude that as long as sufficient information is used also Identification I isolates a shock that has a high medium-run impact on TFP. The news shock contributes between 30% to 50% to the variance of all variables. In recession, the technology shock and the news shock account together for more than 60% of total variance of TFP in the long-run. Moreover, the news shock accounts for almost 45% of total variance of output.

Nevertheless, there are some differences between regimes. For total factor productivity, output, inflation and stock prices the influence in recession of the news shock is larger than in expansion. This is a further indication that in expansion another factor must influence medium-run TFP. Nevertheless, the news shock obtained with Identification I influences the economy in the long-run to a large extent.

As indicated in the previous section, we take advantage of the similarity between the responses to the news shock identified in the linear world and those from the expansionary regime to further investigate the differences given by the two identification schemes employed. By comparing the shares of the generalized forecast error variance decomposition attributable to the news shock under Identification I in expansion with those attributable to the same news shock in the linear world (see Table 4 from Appendix D), we remark that the results are quite similar. However, when we compare the contributions to the variance of TFP at horizon 40 of the two news shocks identified with different schemes, we see that under Identification II the contribution is higher. This provides further evidence in favor of the idea that, in expansion, there are other factors that contribute in the medium-run to the variance of TFP apart from the shock on confidence.

4.2.3 Regime Transition

The probability of a change in regime given a certain shock is very similar for both identification schemes and is strongly influenced by the news shocks.

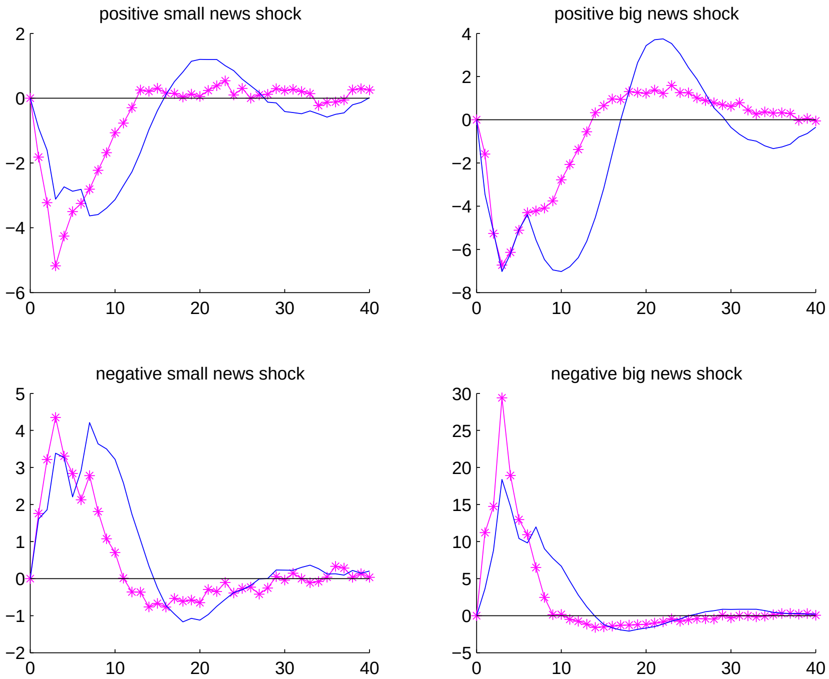

Figure 7: Regime Transition Probability under Identification I and II. The four figures display the change in the probability of switching from an expansion to a recession following a news shock. The solid blue line shows the behavior following a news shock obtained with Identification I, while the purple line with circles shows the behavior following a news shock obtained with Identification II. The unit of the vertical axis is percentage points, and the unit of the horizontal axis is quarter.

As shown in Figure 7, when the economy is in expansion, a positive small news shock reduces the probability of a transition to recession by approximately five percentage points after one year. The effect of a three times bigger shock is not influencing too much this probability. When a big positive news shock hits the economy during normal times, the probability of going into a recession is reduced by almost eight percentage points after one year. An interesting finding is the effect of the positive news shock on the switching probability after five years. Although in the short-run the news shock seems to create a boom due to the reaction of the economic agents to the innovations, in the medium-run, once the improvements in productivity become apparent (i.e. TFP starts increasing), they may acknowledge that they have overrated the future evolution of the economy and start behaving accordingly. This behavior then generates a bust, as the probability of moving from an expansion to a recession increases. This result confirms the findings of Beaudry and Portier (2006) that booms and busts can be caused by news shocks and no technological regress is needed for the economy to go in a recession.

Another important result is the effect of the negative news shock in an expansion. While the small news shock increases the probability of a transition to recession by approximately four 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, even more under Identification II when it increases the probability of a transition to recession by almost 30 percentage points. This shows that strong bad news can make a boom end, and the downturn is fast and sharp. A reason for this behavior is given by Van Nieuwerburgh and Veldkamp (2006) who explain that expansions are periods of higher precision information. Therefore, when the boom ends, precise estimates of the slowdown prompt strong reactions.

The two identification methods give slightly different results in expansions. It is quite important in the case of the big negative news shock. This shock increases the probability of a transition to recession by almost 30 percentage points after one year while it only rises by less than 20 percentage points for Identification I. This indicates again that the shock in expansion obtained with Identification II is driven by further factors.

In Figure 8, we observe that, if the economy is in a recession, a small positive news shock obtained with Identification II increases the probability of a transition to an expansion by less than five percentage points after four quarters. If the shock is three times bigger, the probability of a regime switch increases by fifteen percentage points after four quarters. Thus, the probability does not increase proportionally. Even though under Identification I, the effect of the shock is smaller, we can conclude that positive news shock are more effective in recessions than in expansions. It also does not seem to be a reversal in the medium-run, once TFP increases. Negative news shocks increase the probability of staying in a recession, but their effect is not as strong as when they hit in an expansion.

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

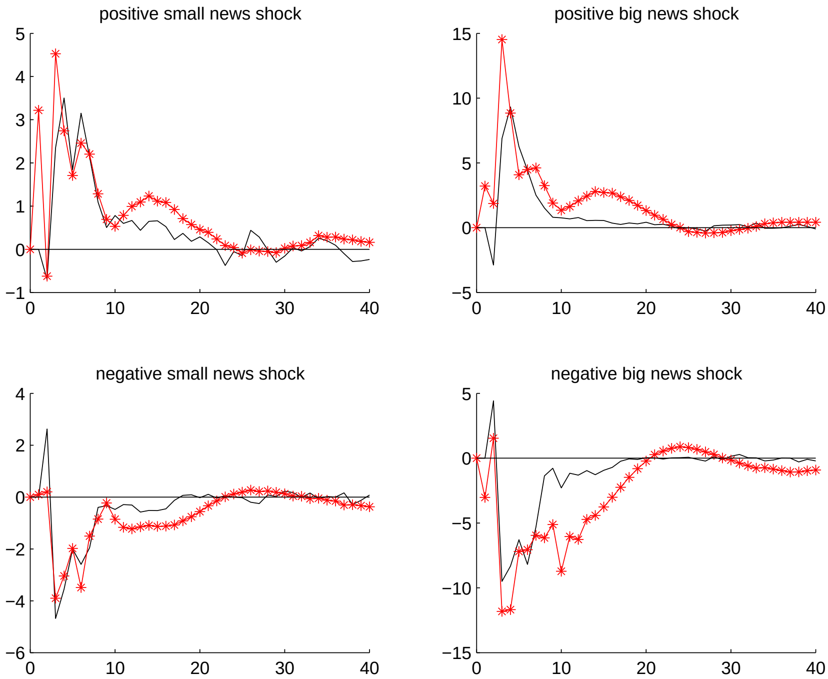

Figure 8: Regime Transition Probability under Identification I and II. The four figures display the change in the probability of switching from a recession to an expansion following a news shock. The solid back line shows the behavior following a news shock obtained with Identification I, while the red line with circles shows the behavior following a news shock obtained with Identification II. The unit of the vertical axis is percentage points, and the unit of the horizontal axis is quarter.

5 Conclusions

The Great Recession has seen dramatic drops in consumer confidence to such low levels that can only be rivaled by those from the recession of the early 1980s. As Petev and Pistaferri (2012) showed, in the case of the U.S. economy, growth in personal spending is closely linked to consumer confidence. When consumer confidence is low, people reduce their spendings and borrow less. Faced with lower demand, businesses do not buy new equipment, or hire new people. This generates a vicious cycle and breaking it by boosting consumer confidence became a 'must' for policy makers during the last years.

Although theoretical and empirical work has analyzed the importance of confidence shocks in the economy, to the best of our knowledge, research has only been conducted using linear models. Nonetheless, nothing guarantees that the responses to a bout of optimism (or a good news as we define a positive shock on the index of consumer sentiment) are the same regardless of the state of the economy.

We use the news view of confidence, introduced by Barsky and Sims (2012), which supposes that innovations in confidence summarize information about future changes in fundamentals. We show that two common methods to identify a news shock deliver similar results in qualitative as well as in quantitative aspects given the same information is included. Interestingly, in the nonlinear case, results indicate that the medium-run identification method might capture different dynamics when identifying the news shock for two regimes which is manifested in quantitative differences.

By estimating a LSTVAR, we find evidence of quantitative state-dependencies, mainly in the short-run, while the asymmetry between good and bad news does not seem to play an important role. The response to a news shock is in general larger in an expansion than in a recession. We also find that using a linear model to analyze the effects of news shocks in different states of the economy, one may underestimate their value in an expansion, while overestimating it in a recession.

We show that the probability of a regime-transition is strongly influenced by the news shock. Our results indicate that strong bad news can make a boom end, while similarly strong good news do not have the same power to take the economy out of a recession. We also find evidence that after a good news in normal times, there is a short-run boom followed by a bust in the medium-run. This is in line with the news-driven business cycles hypothesis.

Our intuition for the difference in the responses during the two regimes is the stronger uncertainty of the economic agents about what to expect in the future when they are in a recession. According to Bray (2009), many years of psychological research shows that humans have a difficult time dealing with it and a sense of being out of control in their lives. When faced with uncertainty, they get into survival mode and start constricting their spending even though their business or personal income is doing well.

Future research should try to empirically investigate this state-dependent relation, but it may be a challenging task in a STVAR. The reason is that the estimation of this type of nonlinear models is complex and demanding on the information included.

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Appendices

A Estimation of LSTVAR

A.1 Linearity Test

For the test of linearity in the parameters we will 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:

$$H_0 : \qquad \Pi_1 = \Pi_2, \tag{17}$$

$$H_1 : \qquad \Pi_{1,j} \neq \Pi_{2,j}, \text{ for at least one } j \in \{0, ..., p\}. \tag{18}$$

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 (5) can be rewritten as:

$$Y_t = \Pi_1' X_t + (\Pi_2 - \Pi_1)' X_t F_{t-1} + \epsilon_t, \tag{19}$$

where X_t is matrix of lagged endogenous variables.

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:

$$Y_t = \theta_0' X_t + \theta_1' X_t s_{t-1} + \theta_2' X_t s_{t-1}^2 + \theta_3' X_t s_{t-1}^3 + \epsilon_t^* \tag{20}$$

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.

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

$$Z_n = \begin{pmatrix} X_1' s_0 & X_1' s_0^2 & \cdots & X_1' s_0^n \\ X_2' s_1 & X_2' s_1^2 & \cdots & X_2' s_1^n \\ \vdots & \vdots & \ddots & \vdots \\ X_T' s_{T-1} & X_T' s_{T-1}^2 & \cdots & X_T' s_{T-1}^n \end{pmatrix}, \tag{21}$$

we can write equation (20) in matrix form:

$$Y = X\Theta_0 + Z_n \Theta_n + E. \tag{22}$$

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:

$$LM_{\chi^2} = T(m - tr\left\{SSR_0^{-1} SSR_1\right\}) \tag{23}$$

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

$$LM_F = \frac{mT - K}{GmT} LM_{\chi^2}, \tag{24}$$

   where K is the number of parameters, and G the number of restrictions.

Under H_0'', the F-version of the LM test is approximately $F(G, mT - K)$-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 $F(G, T-K)$-distributed, where $G = n(p+1)$ and $K = (n+1)(p+1)$.

A.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%

Dependent variable: *rec* (=1 for a recessionary period, =0 otherwise)	
Independent variables:	
Switching variable	-3.5644*** (0.4619)
No. of observations: 228 Log Likelihood: -67.8045 Wald $\chi^2_{(1)}$: 59.55***	

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

Dependent variable: *rec* (=1 for a recessionary period, =0 otherwise)	
Independent variables:	
Mean-adjusted switching variable	-3.1245 *** (0.4806)
Intercept	-3.0314 *** (0.3976)
No. of observations: 228 Log Likelihood: -48.977 LR $\chi^2_{(1)}$: 104.25*** Pseudo R^2: 0.5156	

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

Dependent variable: rec (=1 for a recessionary period, =0 otherwise)	
Independent variables:	
Mean-adjusted switching variable	-1.5328*** (0.2494)
No. of observations: 228 Log Likelihood: -128.4993 Wald $\chi^2_{(1)}$: 37.78***	

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

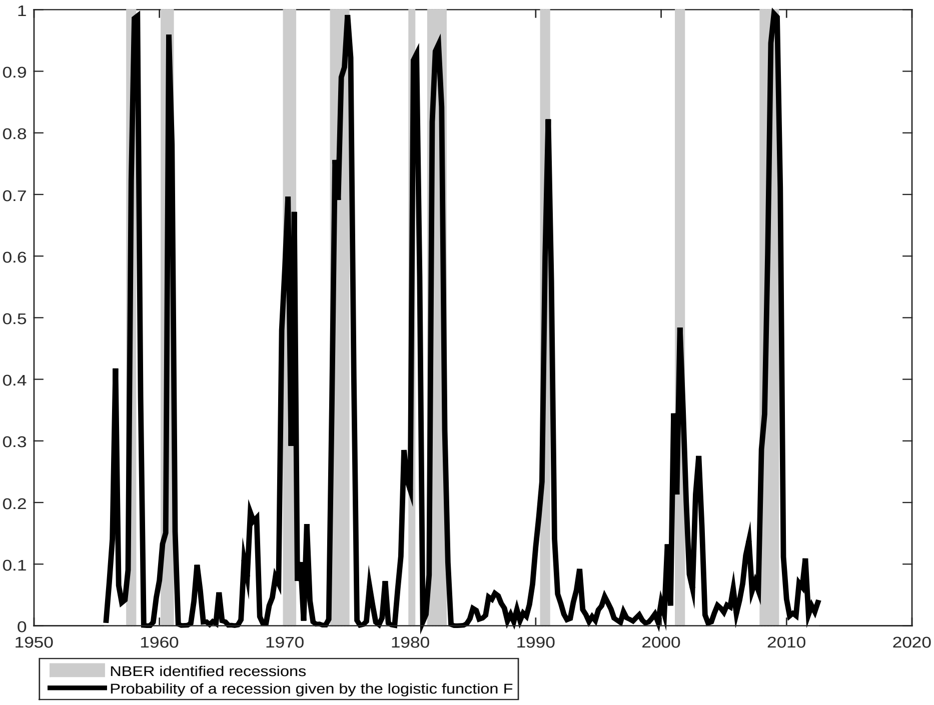

Figure 9: Initial transition function with estimated parameters obtained from a logistic regression

A.3 MCMC procedure

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

1. Choose intial parameter value 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, $\alpha(\Psi_n^j, \Psi_n')$:

$$\alpha(\Psi_n^j, \Psi_n') = \min\left\{\frac{p(\Psi_n')q(\Psi_n' \mid \Psi_n^j)}{p(\Psi_n^j)q(\Psi_n^j \mid \Psi_n')}, 1\right\} \tag{25}$$

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

$$\Psi_n^{j+1} = \begin{cases} \Psi_n' & \text{if } u \leq \alpha(\Psi_n^j, \Psi_n'); \\ \Psi_n^j & \text{otherwise.} \end{cases} \tag{26}$$

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, $q(\Psi_n' \mid \Psi_n)$.

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, 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:

$$\Psi_n' = \Psi_n + \psi,\ \psi \sim f \tag{27}$$

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.

A.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:

$$\Sigma_t = P \Lambda_t P', \tag{28}$$

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

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

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

where $w_t = u_t P$.

The null hypothesis to be tested is then:

$$H_0 : \lambda_{it} = \lambda_i, \quad i = 1, \ldots, p \tag{29}$$

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

$$LM = \frac{1}{2} \sum_{i=1}^{p} \left[\left(\sum_{t=1}^{T} \tilde{g}_{it} \tilde{z}'_{it} \right) \left(\sum_{t=1}^{T} \tilde{z}_{it} \tilde{z}'_{it} \right)^{-1} \left(\sum_{t=1}^{T} \tilde{g}_{it} \tilde{z}_{it} \right) \right]. \tag{30}$$

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:

$$LM = \sum_{i=1}^{p} T \frac{SSG_i - RSS_i}{SSG_i}, \tag{31}$$

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. The degrees of freedom of the LM test is p.

Yang (2014) shows that this test exhibits high power and size even if the assumption from equation (28) does not hold and performs especially well in the case of smooth transition VARs.

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

B Fundamentalness Test

B.1 Procedure

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

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

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

B.2 Results

Table 1: Linear world specifications

2-variable model							
S1	TFP	SP					
S2	TFP	ICS					
5-variable model							
S3	TFP	ICS	Output	Inflation	SP		
7-variable model							
S4	TFP	ICS	Output	Inflation	SP	Consumption	Hours

Table 2: Results of the fundamentalness test for identification I

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

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

Table 3: Results of the fundamentalness test for identification II

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

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

C Estimation of GIRF and GFEVD

C.1 Estimation of GIRF

The GIRFs are estimated by simulation for eight different cases:

case	regime	magnitude	sign
1	1	1	1
2	1	2	1
3	1	1	2
4	1	2	2
5	2	1	1
6	2	2	1
7	2	1	2
8	2	2	2

Regime is 1 if the starting period is defined as an expansion, and 2 if it is a recession. Magnitude is 1 if one standard deviation innovations are considered, while magnitude is 2 if three times larger innovations are used instead. Sign is 1 if positive shocks are analyzed, and 2 if the shocks are negative.

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 $F(\gamma, c; s_{t-1}) \geq 0.5$ and an expansion otherwise.

The simulation of the GIRF

$$GIRF(h, \epsilon_t, \Omega_{t-1}) = E\left\{Y_{t+h} \mid \epsilon_t^{\delta}, \Omega_{t-1}\right\} - E\left\{Y_{t+h} \mid \Omega_{t-1}\right\} \tag{32}$$

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

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

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

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

The shocks are drawn from a normal distribution with variance $\Sigma_{t+h} = M(\theta, \vartheta; s_{t+h-1})\Sigma_1 + (1 - M(\theta, \vartheta; s_{t+h-1}))\Sigma_2$. The variance is history-dependent through the switching variable and adjusts every simulation horizon.

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

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

For each period we perform B simulations and then average over them. Since among the periods, we have about six times more defined expansionary than recessionary periods, for each recession, we simulate $B = 6350$ expected values up to horizon h given the model, the history and the vector of shocks, while for an expansionary history we simulate for $B = 1000$.

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

C.2 Confidence Bands

To estimate confidence bands, we draw $D = 50$ positions from the results of the MCMC routines. For each position we estimate GIRFs according to the identification scheme. The confidence bands are then the respective quantiles of the set of estimated GIRFs from the draws.

C.3 Generalized Forecast Error Variance Decomposition

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

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

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

C.4 GIRF for Identification II

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

Step 1:
The news shock is identified as the shock that has no impact effect on TFP, but maximizes the generalized forecast error variance decomposition at horizon 40. The rotation matrix is found by minimizing the negative of the GFEVD at horizon 40 within a grid search. 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 above. The only difference is that the orthogonalization of the history-dependent covariance matrix is approximated by

$$\Sigma_{t+h} = A^{M}_{t+h} A^{M'}_{t+h}$$

$$A^{M}_{t+h} = M(\theta, \vartheta; s_{t+h-1})A_1 + (1 - M(\theta, \vartheta; s_{t+h-1}))A_2 \tag{34}$$

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

The specific shock $\epsilon^{\delta}_{t} = A^{M}_{t+h} e_i$ where A^{M}_{t+h} is the orthogonalization of Σ_{t+h} according to the identification scheme. e_i is a vector of zeros with the ith position being determined by the case (Sign: positive/negative, Magnitude: 1/3). Under Identification II, the news shock is identified as the first shock.

D Results in the linear world

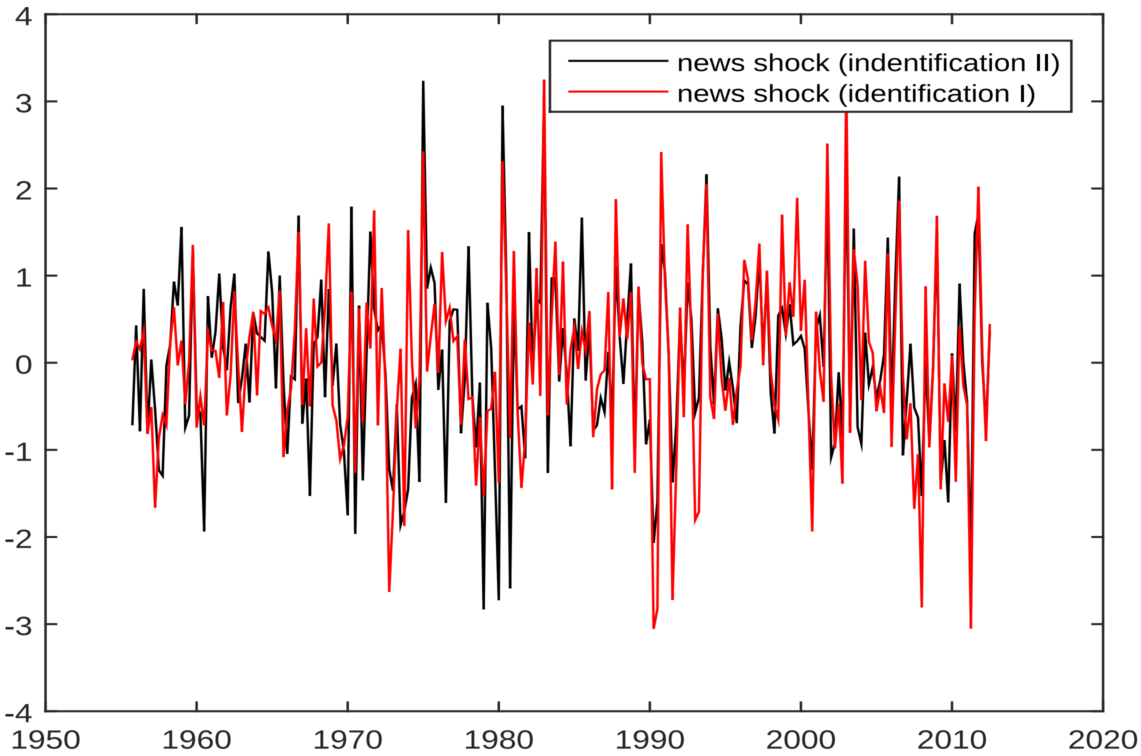

Figure 10: Comparison of the news shock. Identification I assumes that the news shock affects ICS on impact but not TFP. Identification II defines the news shock to be the shock that does not move TFP on impact but has maximal effect on it at $H = 40$.

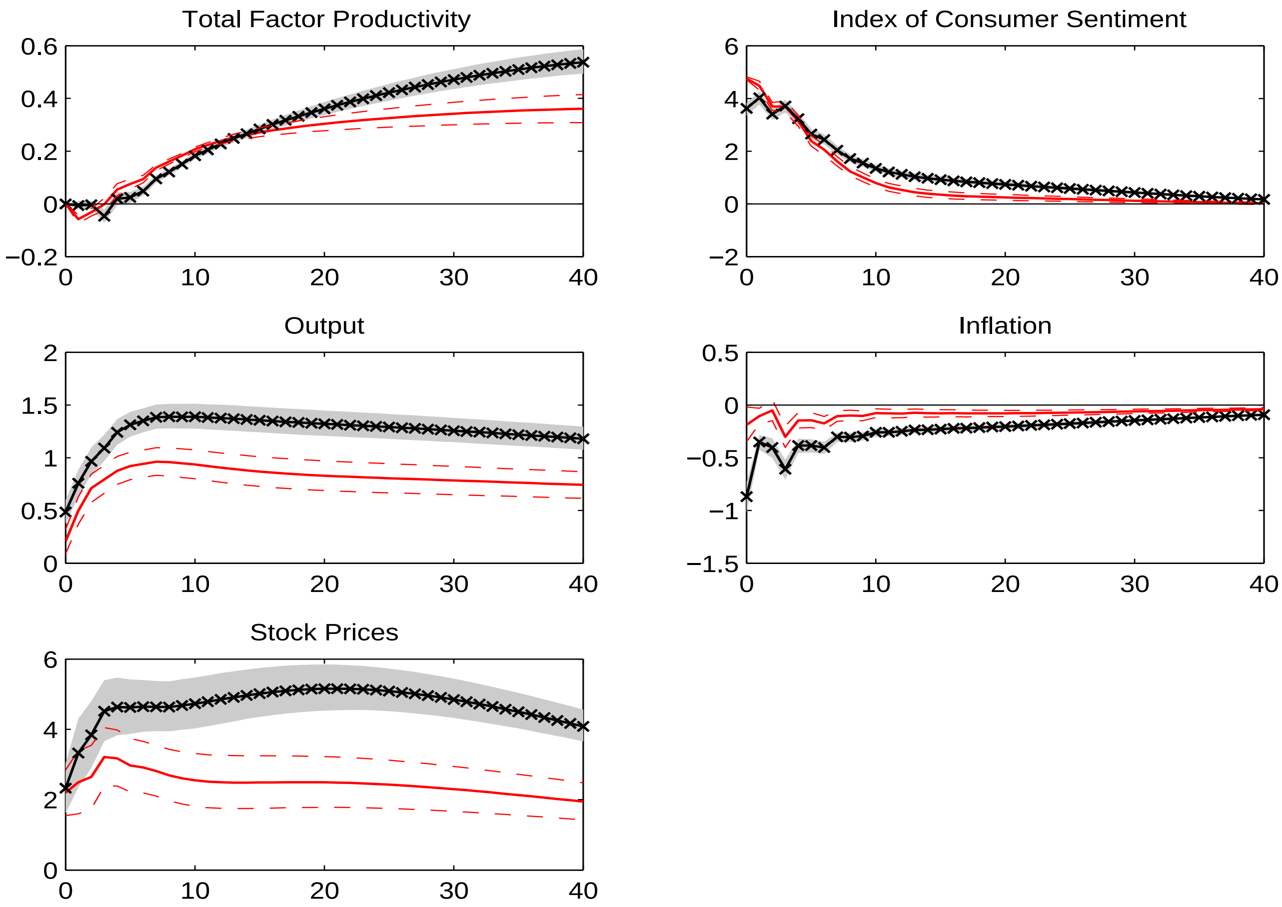

Figure 11: Impulse responses to a news shock. Comparison of Identification I and Identification II in a linear model.The red solid line shows the response for Identification I, while the black starred line the response for Identification II. The shaded region is the 95 confidence interval for Identification II, and the dotted lines are the 97.5th and 2.5th quantiles for Identification I. 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.

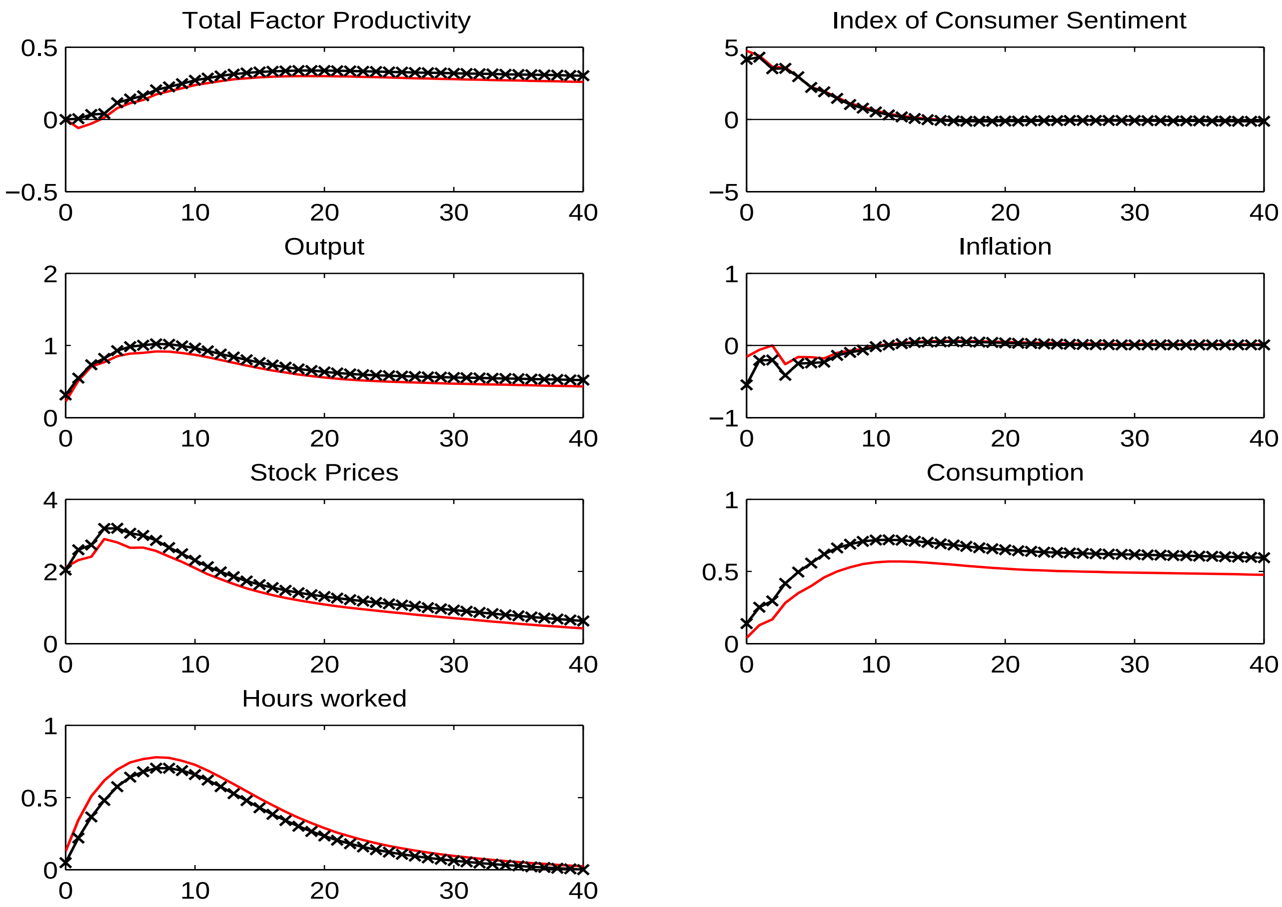

Figure 12: Impulse responses to a news shock. Comparison of Identification I and Identification II in a linear seven variables model. The red solid line shows the response for Identification I, while the black starred line the response for Identification II.The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

Table 4: Share of forecast error variance decomposition attributable to the news shock obtained with two different identification schemes

Identification I					
	h=0	h=4	h=8	h=16	h=40
TFP	0.0	0.4	2.2	9.6	23.0
ICS	96.5	88.5	83.3	75.5	68.4
Output	4.6	28.1	33.8	34.8	33.1
Inflation	2.1	4.3	4.9	5.1	5.9
SP	16.3	16.2	17.9	17.3	17.3
Identification II					
	h=0	h=4	h=8	h=16	h=40
TFP	0.0	0.1	1.0	8.7	38.7
ICS	56.1	72.1	75.5	74.6	71.8
Output	25.2	57.2	69.3	76.1	79.0
Inflation	44.3	41.1	43.3	45.6	48.6
SP	18.2	30.8	40.1	49.6	63.1

E Results in the nonlinear world

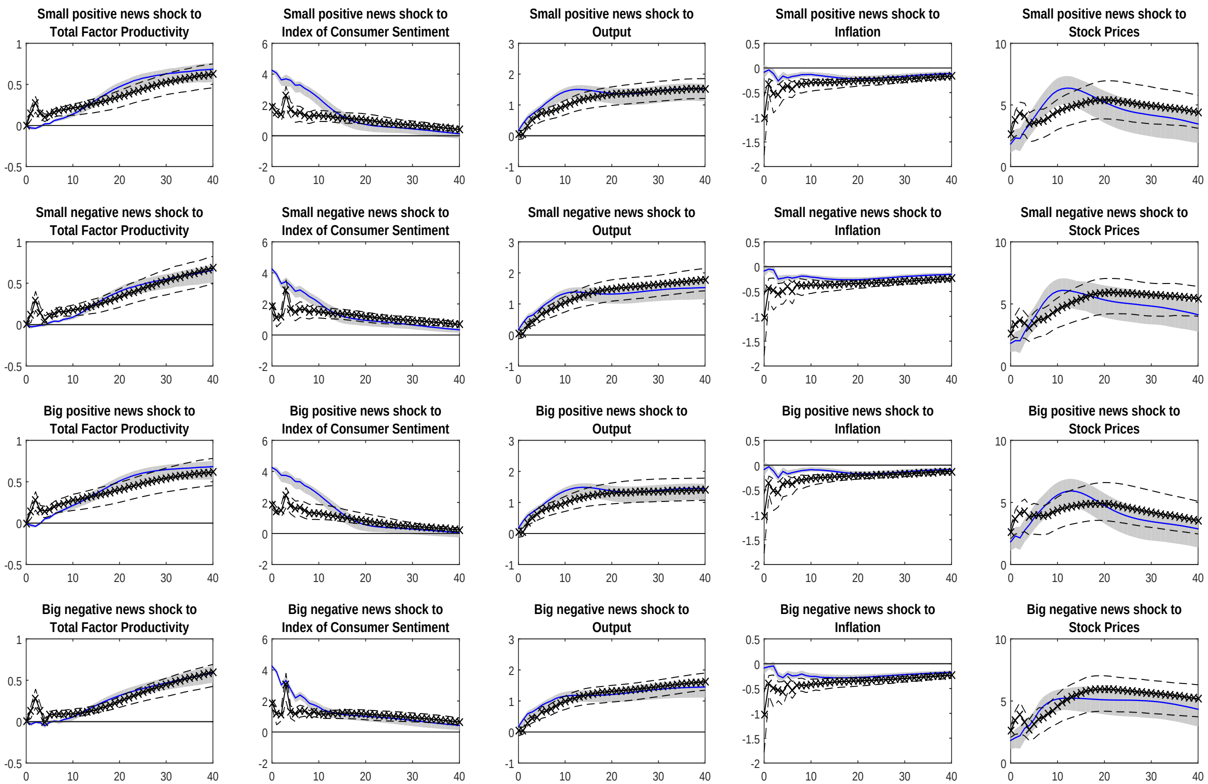

Figure 13: Generalized impulse response functions to news shocks of different signs and magnitudes under Identification I. The solid black line is the point estimate in recession, and the dash-dot blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence 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 5: Generalized Forecast Error Variance Decomposition under Identification I

Expansion						Recession					
Technology Shock											
	h=0	h=4	h=8	h=16	h=40		h=0	h=4	h=8	h=16	h=40
TFP	96.1	72.6	59.0	43.0	19.1	TFP	99.3	50.6	44.6	37.5	23.2
ICS	1.7	2.7	3.9	6.3	9.3	ICS	5.7	30.3	29.3	29.4	32.5
Y	9.5	8.2	9.5	9.1	8.6	Y	74.5	53.6	33.5	22.8	23.2
Infl	4.4	5.0	8.2	10.6	11.8	Infl	10.6	26.1	26.9	27.6	28.6
SP	0.7	3.7	5.2	6.8	9.7	SP	22.6	27.1	24.4	21.2	24.2
News Shock											
	h=0	h=4	h=8	h=16	h=40		h=0	h=4	h=8	h=16	h=40
TFP	0.0	5.4	9.4	16.1	28.2	TFP	0.2	29.3	31.9	34.7	44.4
ICS	98.3	71.5	59.9	49.7	40.5	ICS	94.2	45.2	42.3	38.9	34.4
Y	3.2	20.1	28.6	32.8	28.7	Y	0.9	23.0	38.2	45.3	43.0
Infl	0.5	7.2	10.2	13.7	18.7	Infl	52.5	38.7	38.3	37.8	35.8
SP	13.8	15.5	20.8	24.6	23.7	SP	49.1	44.7	45.4	45.5	40.8
3rd Shock											
	h=0	h=4	h=8	h=16	h=40		h=0	h=4	h=8	h=16	h=40
TFP	0.0	11.6	14.0	16.3	20.6	TFP	0.2	6.5	7.7	8.7	10.5
ICS	0.0	13.6	14.8	15.2	16.4	ICS	0.0	6.3	8.4	10.1	11.1
Y	87.1	62.7	39.5	25.6	24.0	Y	24.3	11.7	9.6	10.4	11.8
Infl	2.9	11.6	13.1	17.9	19.2	Infl	1.4	9.4	9.7	10.0	10.8
SP	0.5	14.9	15.6	16.4	18.3	SP	1.3	6.1	7.7	9.8	11.0
4th Shock											
	h=0	h=4	h=8	h=16	h=40		h=0	h=4	h=8	h=16	h=40
TFP	0.0	5.6	9.6	14.8	23.4	TFP	0.2	10.4	11.0	13.1	16.9
ICS	0.0	9.3	17.0	23.7	27.3	ICS	0.0	13.7	14.9	16.5	16.4
Y	0.0	4.0	16.1	27.3	32.1	Y	0.1	6.2	12.3	17.6	18.0
Infl	92.2	73.9	64.0	51.6	42.5	Infl	35.4	23.4	22.7	22.0	21.0
SP	0.1	10.3	20.8	29.3	35.6	SP	6.4	9.9	12.4	17.1	18.7
5th Shock											
	h=0	h=4	h=8	h=16	h=40		h=0	h=4	h=8	h=16	h=40
TFP	0.0	4.8	8.0	9.9	8.7	TFP	0.2	3.3	4.8	6.0	5.0
ICS	0.0	2.9	4.5	5.1	6.5	ICS	0.0	4.5	5.1	5.2	5.6
Y	0.0	5.1	6.2	5.3	6.6	Y	0.1	5.5	6.3	3.9	3.9
Infl	0.0	2.4	4.5	6.2	7.8	Infl	0.0	2.3	2.4	2.7	3.8
SP	84.9	55.6	37.7	22.9	12.7	SP	20.6	12.2	10.2	6.5	5.3