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Unraveling News: Reconciling Conflicting Evidence

Maria Bolboaca and Sarah Fischer

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Unraveling News: Reconciling Conflicting Evidence*

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Abstract

This paper addresses the lack of consensus in the empirical literature regarding the effects of technological diffusion news shocks. We attribute the conflicting evidence to the wide diversity in terms of variable settings, productivity series used and identification schemes applied. We analyze the different identification schemes that have been employed in this literature. More specifically, we impose short- and medium-run restrictions to identify a news shock. The focus is on the medium-run identification maximizing at and over different horizons. We show that the identified news shock depends critically on the applied identification scheme and on the maximization horizon. We also investigate the importance of the information content of the model and of the productivity measure used. We find that models which either contain a large set of macroeconomic variables or include variables that are strongly forward looking deliver more robust results. Moreover, we show that the productivity series used may influence results, but there is convergence of findings for newer total factor productivity series vintages. Our conclusion is that news shocks have expansionary properties.

JEL classification: E32, E23.

Keywords : productivity shock, news shock, structural vector autoregressive model, fundamentalness testing.

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1 Introduction

Macroeconomists have debated whether productivity improvements are expansionary or contractionary at business cycle frequencies for a long time. A consensus seems to have been reached on the fact that unanticipated productivity shocks increase output, consumption, and investment, while they decrease hours worked for several quarters.¹ However, the same cannot be said about the effect of expectations about future productivity improvements. While Beaudry and Portier (2006) find in their seminal paper that news about emerging technologies have expansionary properties on impact, the result is contradicted by Barsky and Sims (2011), and Kurmann and Sims (2017). Their findings indicate that news about technological improvements are initially contractionary.

In this paper we critically revisit the different approaches in the empirical news literature in order to examine whether news shocks are expansionary in the short- to medium-run.

Ever since the ideas of Pigou (1927) and Keynes (1936), economists have investigated ways to show that changes in expectations about future fundamentals may be an important source of economic fluctuations. One such approach was brought up by Beaudry and Portier (2004), and Beaudry and Portier (2006), henceforth BP, who proposed that news about emerging technologies that potentially increase future productivity have an effect on economic activity. Their influential papers founded the technological diffusion news literature. They investigate this conjecture by estimating a linear vector error correction model (VECM) with two variables, total factor productivity (TFP) and stock prices. Structural shocks are identified either with short-run or long-run restrictions. They find that the two identification schemes deliver highly cross-correlated news shocks, indicating that permanent changes in productivity are preceded by stock market booms. In two- to four-dimensional systems with consumption and output, hours worked, or investment, they find that a news shock leads to a temporary boom in consumption, output, hours, and investment that anticipates the permanent growth in TFP.

A growing literature questions or defends BP on their methodology and the effects of the news shock, but so far an agreement has not been reached. For example, Kurmann and Mertens (2014) criticize the long-run identification in their larger models. With more than two variables the identification scheme fails to determine TFP news.

Barsky and Sims (2011) (BS) propose a medium-run identification scheme² as an alternative method to identify the news shock. They estimate a four variables vector autoregressive (VAR) model in levels with TFP, consumption, output and hours worked,

¹See Basu et al. (2006), and Galí (1999), among others, for details on the estimation approach and results using total factor productivity in the first, and labor productivity in the latter.

²Throughout the paper we use two names interchangeably to define the same identification scheme, i.e. medium-run and maximum forecast error variance (max FEV).

or investment. They identify the news shock as the shock orthogonal to contemporaneous TFP movements that maximizes the sum of contributions to TFP's forecast error variance (FEV) over a finite horizon. Their results indicate that a positive news shock leads to an increase in consumption, and an impact decline in output, hours, and investment. Afterwards, aggregate variables largely track, but not anticipate, the movements in TFP. The news shock is thus not expansionary as in BP.

Beaudry and Portier (2014) show that the two identification schemes give similar results under the same information content, i.e. same variable setting. Most importantly, they point out that when consumption is replaced with stock prices in the four-variable model of BS, the results resemble very much those of BP.

Sims (2016), henceforth Sims, and Kurmann and Sims (2017), henceforth KS, find that the results also depend strongly on the TFP vintage series used. Furthermore, they introduce another identification scheme similar to BS where they omit the zero impact restriction and allow the identified shock to have an immediate effect on TFP. Their shock leads to an impact decrease in hours worked and, hence does not generate a boom in the economy. The response of hours worked to a news shock is currently the most debated point in the news literature. Almost the same identification scheme was used in Francis et al. (2014) to identify a technology shock instead of a news shock. While KS maximize the contribution at a finite horizon, Francis et al. (2014) maximize the contribution to the cumulated sum over that horizon. The authors argue that their identification scheme is similar to the long-run restrictions applied in Galí (1999) with the advantage of being applicable to data in levels. The max FEV method does not require precise assumptions about the number of common stochastic trends among the variables of interest in the model. The impact effect of the technology shock of Francis et al. (2014) and Galí (1999) on hours worked is negative. Hence, the negative response of hours worked found by KS is not surprising. It indicates that their identification scheme might not identify a news shock but rather a standard technology shock.

Most of the existing evidence on news shocks has been obtained using small-scale VAR or vector error correction (VECM) models. Forni et al. (2013) argue that this may be problematic, because when structural shocks have delayed effects on macroeconomic variables, VAR models used to estimate the effects of shocks may be affected by non-fundamentalness. Non-fundamentalness means that the variables used by the econometrician do not contain enough information to recover the structural shocks and the related impulse response functions. To circumvent the problem they estimate a FAVAR model which is designed to process large datasets and generally does not suffer from non-fundamentalness. In the case of news shocks, the FAVAR model suffers from another problem. As it requires stationarity of the dataset, it misses possible cointegrating relationships which determine the news shock. In stationary VARs and

VECMs, the non-fundamentalness test of Forni and Gambetti (2014) tests whether the identified shock is indeed structural. The results of Gambetti (2014-2015) applying the non-fundamentalness test indicate that forward-looking variables, such as consumer confidence, are an important source of information to identify structural news shocks. Sims (2012) reaches a similar conclusion and finds that news shocks can be identified once sufficient information is included in the model. Furthermore, even if non-fundamentalness prevails it may not be always a very severe problem as the non-fundamental representation could actually be very close to its fundamental presentation. Beaudry et al. (2016) derive a diagnostic that measures the potential severity of the non-fundamentalness problem.

Considering the wide diversity in terms of variable settings, productivity series used and identification schemes applied in this literature, our contribution is given by an overview of all the mentioned factors and a discussion of their role in generating the conflicting evidence.³ We further propose several key ingredients for the model to deliver robust results and show that a technology diffusion news shock leads indeed to an economic boom.

We estimate linear VAR models in levels with four lags for over 100 different variable settings, henceforth settings. In all these settings we keep the sample fixed to the period between 1955:Q1 and 2014:Q4, and include the same TFP series.⁴ As a first step, we analyze the cross-correlations of structural shocks, impulse response functions, and variance decompositions to investigate which settings seem to deliver reliable results. A reliable setting is necessary to compare differences in identification schemes. The analysis is conducted on short- and medium-run identification schemes identifying two structural shocks, an unanticipated productivity shock and a news shock. The analysis of settings is purely ad-hoc and is not based on a formal test. This means that we assume that models containing a large set of variables deliver more robust results. One reason is that larger models are less prone to non-fundamentalness problems. Another reason is that macroeconomic relationships which determine the medium-run effects of structural shocks are only modeled correctly if the necessary information is contained in the model. Furthermore, we assume that if the addition of a variable changes results strongly, then the variable is essential. Even though the analysis is not based on a test, we believe that our analysis shows differences between settings that are noteworthy. It becomes apparent that once certain variables are added to the model the informational content changes dramatically and this clearly affects results. There is a large pool of settings that deliver similar results and whose structural shocks are highly cross-correlated. We will call these settings robust or reliable throughout the paper.

³Similar but less extensive analyses of the literature were performed in Beaudry et al. (2011), Beaudry and Portier (2014), and Ramey (2016).

⁴We use the TFP16 vintage series which is described in the Data Section of the paper. Additionally, various TFP vintage series are compared.

Given a robust setting, we further consider various short- and medium-run identification schemes of news shocks that have been prominent in the literature. Short-run identification schemes need a variable containing a lot of information about future productivity and technology, such as stock prices or a measure of consumer confidence by construction. The shock is uncorrelated with contemporaneous productivity but still moves TFP in the long-run. The only two shocks affecting the informative variable on impact are the unanticipated productivity and the news shock. Medium-run identification schemes maximize the share of the forecast error variance (FEV) of TFP over or at a certain future horizon. The identification method does not rely on an informative variable. But to overcome an information deficiency problem it may still be a valuable addition. Furthermore, we verify robustness of results for different sample lengths and TFP vintage series.

Our results indicate that no matter which variables are added to TFP, the identified unanticipated productivity shocks are always highly cross-correlated. Nevertheless, the addition of a mixture of macroeconomic variables is necessary to obtain robust impulse responses and contributions. For the short-run identification of a news shock the observation is very similar. To identify the shock, TFP and the informative variable are needed, but the impulse responses are not robustly specified without more information. The shock depends entirely on the information content of the informative variable. The shocks identified through different expectation driven informative variables are only little cross-correlated. If the news shock is identified with a medium-run identification scheme, more information is necessary to identify a robust shock. The addition of strongly forward looking variables such as the index of consumer sentiment and stock prices deliver more robust results. If a large set of macroeconomic variables is included, stock prices do not seem to contain a lot of additional information. In the absence of these variables, as many macroeconomic variables as possible need to be added. A combination of two real macro variables such as output, consumption, and investment is essential to obtain reliable impulse responses. Inflation and interest rates capture the nominal side and have forward looking properties. The addition of the index of consumer sentiment affects the identified shock and makes it more robust as long as either nominal or real variables are included.

Once a robust set of variables is employed, different identification schemes of the news shock can be analyzed. Qualitatively, the results of short-run and medium-run identification schemes are very similar. We show that the positive responses to a news shock can be found for any identification scheme and sample. But if a medium-run identification scheme is employed, the response of hours worked clearly depends on the maximization horizon. The results stabilize if the maximization horizon becomes large and deliver a boom reaction akin to BP even for the identification schemes of BS or KS.

We confirm the result of Galí (1999), Basu et al. (2006), and Fève and Guay (2009) and find a negative impact reaction of hours worked to an unanticipated productivity shock.

Based on our extensive analysis we conclude that there exists a large set of variable settings that identify robust shocks and that deliver fairly robust impulse response functions and variance decomposition. The robust settings do not depend on the shock. This means that the same variable settings deliver robust impulse responses for the unanticipated productivity shock and the news shock. We find that the results clearly depend on the sample as well as the TFP series employed. While older TFP series vintages are more highly correlated with the Solow residual than newer ones, a part of the difference in results comes from the sample considered in these analyses.

The rest of the paper is organized as follows. In the next section we describe the model employed. In Section 3, we explain the different identification schemes. Section 4 then gives an overview of the data while Section 5 contains an extensive analysis of news shocks and unanticipated productivity shocks. In Section 6 we conclude.

2 Methodology

We estimate a linear vector autoregressive model in levels. The model is given by:

$$Y_t = c + \sum_{i=1}^p \Phi_i Y_{t-i} + \epsilon_t \quad (1)$$

where Y_t is a vector of k endogenous variables which we aim to model as the sum of an intercept c , p lags of the same endogenous variables and $\epsilon_t \sim WN(0, \Sigma)$, which is a vector of reduced-form residuals with mean zero and constant variance-covariance matrix, Σ . Φ_i are the matrices containing the VAR coefficients. Model (1) is a reduced form because all right-hand side variables are lagged and hence predetermined.

Most variables in Y_t are integrated. A cointegrating relationship is defined as a stationary linear combination of integrated variables. We assume that there exist cointegrating relationships between the variables which allow us to estimate a stable vector error correction model. As we analyze many different variable settings, the number and nature of the cointegrating relationships would vary from setting to setting. Since the number of cointegrating relationships is not always clearly indicated by economic theory or econometric tests, variability between settings may rather stem from errors in the model specification than the variable setting itself. Therefore, we find it more appropriate to work with a model in levels and do not specify the cointegrating relationships. As described in Kilian and Lütkepohl (2017), in VAR models with a lag order larger than one and including a constant, the least squares estimator of the parameters remains consistent even if the cointegration restrictions are not imposed in estimation and marginal

asymptotic distributions remain asymptotically normal even in the possible presence of a unit root or a near unit root. The reason is that the cointegration parameters and, hence, the cointegrating relationships are estimated superconsistently. However, in the presence of integrated variables, the covariance matrix of the asymptotic distribution is singular because some components of the estimator converge with rate T rather than \sqrt{T} . As a result, standard tests of hypotheses involving several VAR parameters jointly may be invalid asymptotically. Hence, Kilian and Lütkepohl (2017) advise to be cautious when conducting inference.⁵ In the case of no cointegrating relationships, the asymptotic distribution of the estimator is well-defined, but no longer Gaussian, and standard methods of inference do not apply. As it has been shown by Sims et al. (1990), an estimation in levels delivers reliable results if the model is cointegrated. Moreover, in several papers (e.g. Barsky and Sims (2011), Beaudry and Portier (2014)) it is shown that VAR and VEC models deliver similar results regarding news shocks.

It is assumed that the reduced-form residuals can be written as a linear combination of the structural shocks $\epsilon_t = Au_t$, assuming that A is nonsingular. Structural shocks are white noise distributed $u_t \sim WN(0, I_k)$ and the covariance matrix is normalized to the identity matrix. The structural shocks are completely determined by A . As there is no unambiguous relation between the reduced and structural form, it is impossible to infer the structural form from the observations alone. To identify the structural shocks from the reduced-form innovations, $k(k-1)/2$ additional restrictions on A are needed.⁶ In the following section we describe the identification schemes used in the empirical news literature.

3 Identification Schemes

In the news literature many different identification schemes have been employed to identify a news shock. The range goes from zero impact restrictions over zero long-run restrictions to maximizing the share of the forecast error variance decomposition given various criteria.

We explain the differences and similarities in the most prominent identification schemes used in the literature. We look at theoretical properties as well as the implications for empirical results.

⁵Kilian and Lütkepohl (2017) argue that if Y_t consists of $I(0)$ and $I(1)$ variables only, it suffices to add an extra lag to the VAR process fitted to the data to obtain a nonsingular covariance matrix associated with the first p lags.

⁶A thorough treatment of the identification problem in linear vector autoregressive models can be found in Neusser (2016).

3.1 BP's Short-Run Zero Restrictions

Beaudry and Portier (2006) apply two different identification schemes. One is based on short-run restrictions, while the other is supposed to identify the same two shocks with long-run restrictions. Their basic model is a two-variable system containing total factor productivity and stock prices. As a measure of total factor productivity they construct the Solow residual either unadjusted or adjusted for capital utilization. Their goal is to identify two different productivity shocks, an unanticipated productivity shock and a news shock. The unanticipated productivity shock can be thought of as an unexpected improvement in productivity such as sudden changes in regulations or management practices that promote more production. The shock is identified as the only shock having an impact effect on TFP. BP argue that today's stock prices reveal important technological innovations which will materialize in the future. The news shock is, then, the only other shock having an impact effect on stock prices. We will call this identification scheme SRI2. In a two-variable model the news shock is just the remaining shock. The structural shocks are written as a linear combination of reduced form shocks (ϵ_{kt}) in a bi-variate system.

$$\begin{pmatrix} \text{Unanticipated Productivity Shock}_t \\ \text{News Shock}_t \end{pmatrix} = A^{-1}\epsilon_t = \begin{pmatrix} * & 0 \\ * & * \end{pmatrix} \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \quad (2)$$

Additional settings include consumption as a third variable and either hours worked, output or investment as a fourth variable. BP find that the unanticipated productivity shock has an immediate effect on all variables and that its effect on stock prices vanishes over time. On the other hand, the news shock has an immediate effect only on stock prices and real quantities, while TFP responds with a lag. Furthermore, the effect on real quantities and TFP is permanent. Thus, the news shock seems to introduce business cycle movements.

In several papers, such as Barsky and Sims (2012), and Ramey (2016), it is argued that stock prices may not be the best variable to be used in this model because they are very volatile and prone to react to many other forces. Confidence measures of consumers and producers about the economic outlook are considered to contain more stable information about future productivity growth. We call SRI1 the identification scheme of BP where stock prices are replaced by a confidence measure.

The two structural shocks are identified by imposing short-run restrictions. The variance-covariance matrix Σ of the reduced-form shocks is decomposed into the product of a lower triangular matrix A with its transpose A' ($\Sigma = AA'$). This decomposition is known as the Cholesky-decomposition of a symmetric positive-definite matrix. Thereby, the innovations are orthogonalized and the first two shocks are identified as

unanticipated productivity shock and news shock. The rest of the shocks cannot be economically interpreted without additional assumptions.

3.2 BP's Long-Run Zero Restrictions

The second identification scheme of BP assumes that the news shock is the only shock having a long-run effect on TFP and they show that this shock is highly correlated with the shock identified with short-run restrictions. On the one hand, these results suggest that the short-run news shock contains information about future TFP growth, which is instantaneously and positively reflected in stock prices. On the other hand, permanent changes in TFP are reflected in stock prices before they actually increase productive capacity. The similarity between the effects of these two shocks derives from the quasi-identity of the two shocks. Nevertheless, we are not applying the long-run identification scheme of BP as it has been shown by Kurmann and Mertens (2014) that the news shock is not identified for more than two variables. The authors argue that this identification problem is caused by the interplay between the cointegration assumption and the long-run restrictions. Kurmann and Mertens (2014) plead instead for a medium-run identification scheme in the style of BS.

3.3 BS' Short-Run Zero Restrictions and Max FEV

Barsky and Sims (2011) estimate a four- and a seven-variable VAR and apply a medium-run identification scheme to identify the news shock. We name this identification scheme based on the abbreviation for their paper, i.e. MRI-BS. The initial TFP vintage series from Basu et al. (2006) is used as TFP measure. They identify an unanticipated productivity shock by imposing the same restrictions as in BP, namely they define it as the only shock that affects TFP on impact. The news shock is then determined by a combination of the remaining shocks that maximizes the sum of the shares of the FEV of TFP over the first ten years (i.e. up to a horizon of 40 quarters). The method is based on the assumption that TFP is only affected by news and unanticipated productivity shocks. They contradict the business cycle view of BP as they find a negative impact reaction of output, hours worked and inflation to the news shock.

The identification scheme imposes medium-run restrictions in the sense of Uhlig (2004).⁷ Innovations are orthogonalized by applying the Cholesky decomposition to the covariance matrix of the residuals. The entire space of permissible impact matrices can be written as $\tilde{A}D$, where D is a $m \times m$ orthonormal matrix ($DD' = I$).

The h step ahead forecast error is defined as the difference between the realization of

⁷We thank Luca Benati for sharing with us his codes for performing a medium-run identification in a linear framework.

Y_{t+h} and the minimum mean squared error predictor for horizon h :

$$Y_{t+h} - \mathbb{P}_{t-1}Y_{t+h} = \sum_{\tau=0}^h B_{\tau} \tilde{A} D u_{t+h-\tau} \quad (3)$$

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

$$\Xi_{j,i}(h) = \frac{e'_j \left(\sum_{\tau=0}^h B_{\tau} \tilde{A} D e_i e'_i \tilde{D}' A' B'_{\tau} \right) e_j}{e'_j \left(\sum_{\tau=0}^h B_{\tau} \Sigma B'_{\tau} \right) e_j} = \frac{\sum_{\tau=0}^h B_{j,\tau} \tilde{A} \gamma_i \gamma'_i \tilde{A}' B'_{j,\tau}}{\sum_{\tau=0}^h B_{j,\tau} \Sigma B'_{j,\tau}} \quad (4)$$

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

Under the assumption that TFP is on the first position in the system of variables, and let the unanticipated productivity shock be indexed by 1 and the news shock by 2, then identifying the news shock implies choosing the impact matrix to maximize contributions to $\Xi_{1,2}(h)$ over h . This is equivalent to solving the following optimization problem:

$$\begin{aligned} \gamma_2^* = & \underset{\gamma_2}{\operatorname{argmax}} \sum_{h=0}^H \Xi_{1,2}(h) \\ & s.t. \\ & \tilde{A}(1, i) = 0, \forall i > 1 \\ & \gamma_2(1) = 0 \\ & \gamma_2' \gamma_2 = 1 \end{aligned}$$

The first two constraints impose that the news shock has no contemporaneous effect on TFP, while the third ensures that γ_2 is a column vector belonging to an orthonormal matrix.

3.4 BNW' Short-Run Zero Restrictions and Max FEV

Beaudry et al. (2011), henceforth BNW, use a very similar identification scheme as BS. But instead of maximizing the sum of the shares of the forecast error variance over a certain horizon, they maximize it simply at that horizon. By taking this approach, they omit information that is only valuable in the short-run and focus more on the medium-run and long-run effects of the news shock. By increasing the horizon to infinity, the

identification scheme approaches a long-run zero restriction framework, but the problem occurring with long-run zero restrictions and partial identification is avoided. This is our benchmark scheme, hence we name it simply MRI.

3.5 KS' Max FEV

Kurmann and Sims (2017) claim to have found a more robust identification scheme than BS that supposedly delivers robust results for any TFP vintage series. They only identify one shock which is no longer orthogonal to an unanticipated productivity shock. Their news shock is identified as the shock that maximizes the share of the forecast error variance in 20 years (horizon = 80 quarters). But they do not apply any zero restriction, thus the news shock can affect TFP on impact. We name this scheme MRI-KS. The authors confirm the results of BS and find a negative impact reaction of hours worked to the news shock. The main reason is that by omitting the zero impact restriction, the identified news shock becomes a mixture of an unanticipated productivity shock and a traditional news shock. Also the impulse responses appear to be a mixture of the reactions to an unanticipated technology and a news shock, which results in the negative impact reaction of hours worked.

4 Data

We work with quarterly data for the U.S. economy from 1955Q1 to 2014Q4.

We use the series of Total Factor Productivity adjusted for variations in factor utilization constructed with the method of Fernald (2014) based on Basu et al. (2013) and Basu et al. (2006). They construct TFP controlling for non-technological effects in aggregate total factor productivity including varying utilization of capital and labor and aggregation effects. They identify aggregate technology by estimating a Hall-style regression equation with a proxy for utilization in each disaggregated industry inspired by Hall (1990). Aggregate technology change is then defined as an appropriately weighted sum of the residuals. The series of TFP adjusted for utilization for the nonfarm business sector, annualized, and as percent change, is available on the homepage of the Federal Reserve Bank of San Francisco.⁸ We use the vintage series until October 2016 and downloaded in December 2016 (TFP16). To obtain the log-level of TFP, the cumulated sum of the original series, which is in log-differences, is constructed.

We use the S&P 500 stock market index as a measure of stock prices.⁹ We obtain data for output, consumption, investment, and the nominal interest rate from the Bureau of Economic Analysis. For output we use the real gross value added for the nonfarm

⁸<http://www.frbsf.org/economic-research/total-factor-productivity-tfp/>

⁹[http://data.okfn.org/data/core/s-and-p-500\\$/sharp\\$data](http://data.okfn.org/data/core/s-and-p-500$/sharp$data)

business sector. As a measure of consumption we use the sum of personal consumption expenditures for nondurable goods and personal consumption expenditures for services. Investment is measured as the sum of personal consumption expenditures on durable goods and gross private domestic investment. We obtain data on hours worked, population, and price level from the Bureau of Labor Statistics. As a measure of hours worked, we use the hours of all persons in the nonfarm business sector. Output, consumption, and stock prices are in logs and scaled by population (all persons with ages between 15 and 64) and the price level for which we use the implicit price deflator for the nonfarm business sector. Hours worked are in logs and scaled by population only. The price deflator (PD) is also used to compute the annualized inflation rate $IR = 4 * (\log(PD_t) - \log(PD_{t-1}))$. As a measure of the nominal interest rate we use the Effective Federal Funds Rate.

We use data from the surveys of consumers conducted by the University of Michigan for the measure of consumer confidence. For the whole sample only the index of consumer expectations for six months is available.¹⁰ We use the index in logs.

4.1 Total Factor Productivity

BP use the Solow residual as a measure of total factor productivity. A second measure they employ is the Solow residual corrected for capital utilization. As they indicate in the paper, the Solow residual has several caveats when used as a proxy for technology. The main point is that even though they try to capture capital utilization, they still miss the effort with which labor is employed. Thus, there is room for improvement in measuring TFP.

Basu et al. (2006) propose a model to correct the Solow residual for varying utilization of capital and labor, nonconstant returns, imperfect competition, and aggregation effects. Their fundamental identification comes from estimating sectoral production functions. They find that an increase in technology reduces factor inputs on impact. 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 resulting residuals. The literature considers this series more useful and a more accurate measure of TFP than the Solow residual. Therefore, the main body of the technological diffusion news literature has been working with the series of Basu et al. (2006) or later vintages of it. In follow-up papers, Basu et al. (2013) and Fernald (2014) improve the estimation model and method. As Sims (2016)

¹⁰Consumer 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.

shows, these changes lead to a quite different series which has a low correlation with the initial series and the series differ in their unconditional correlations with other variables. Moreover, Sims (2016) finds that the results of BS are not robust to the change of series.

4.1.1 TFP Vintages

In Table 1 we present the cross-correlation coefficients of various TFP vintages and the Solow residuals. For convenience we refer to cross-correlation simply as correlation. The series are taken either from the homepage of Eric Sims¹¹ or were downloaded at different points in time from the homepage of the Federal Reserve of San Francisco.¹² The Solow residual is constructed from the dataset in Appendix A. The TFP series are stored as the original series in log-differences and are indicated by the year in which they stop. The approach is similar to the one of KS. All series have been corrected for autocorrelation by regressing them on four lags of their own to avoid spurious correlation. For this comparison, the lengths of the series are all adjusted to match TFP07 and the sample we use for the model estimations (1955Q1-2007Q3).

Table 1: Cross-Correlations of TFP Vintages in Log-Differences

	Solow	TFP07	TFP11	TFP13	TFP14:1	TFP14:2	TFP15	TFP16
Solow	1	0.75	0.69	0.59	0.38	0.40	0.34	0.33
TFP07		1	0.95	0.83	0.54	0.58	0.56	0.56
TFP11			1	0.90	0.53	0.57	0.57	0.57
TFP13				1	0.60	0.63	0.63	0.62
TFP14:1					1	0.95	0.91	0.91
TFP14:2						1	0.96	0.96
TFP15							1	0.997
TFP16								1

As it can be seen in Table 1, there were two major changes in the composition of the TFP series. TFP07, TFP11 and TFP13 are highly correlated (> 0.83), while the correlation diminishes over time. The correlation coefficients with the rest of the vintages are all around 0.6. The major changes were made in 2014. The first vintage of 2014, entitled TFP14:1, is highly correlated with the more recent vintages with correlation coefficients of over 0.91. But there is an eminent second change in composition visible between the composition of TFP vintage 2014:1 and 2014:2. The three last vintages are all highly correlated with correlation coefficients of over 0.96, while the correlation between the two most recent vintages is almost one.¹³ Curiously, the Solow residual is not highly

¹¹https://www3.nd.edu/~esims1/tfp_vintage.html

¹²<http://www.frbsf.org/economic-research/total-factor-productivity-tfp/>

¹³For a more detailed analysis consider Sims (2016). The results are very close to Sims (2016) even though he works with a different sample (1947Q3:2007Q3).

correlated with any of the series. But while its correlation coefficient is 0.75 with TFP07 and 0.59 with TFP13, the correlation drops to 0.33 with the most recent vintages. This implies that the changes made in the methodology are taking the TFP series farther apart from the Solow residual. The first change that was made in Basu et al. (2013) is the switch to using updated utilization estimates and the assumption of constant returns to scale. The second change applied in Fernald (2014) involves new industry-level data to compute the aggregate utilization series. It seems that the changes in estimation and composition are major and possibly quite important for further empirical work performed with a TFP vintage series. It is reassuring that the procedure seems to be very coherent and becoming more and more stable from 2014Q2 on. The correlation between the two most recent vintages is extremely high which we interpret as a sign that the estimation procedure becomes more constant.¹⁴

Since Fernald (2014) argues that the newest estimation method is the most appropriate, it seems advisable to work with most recent vintages. Henceforth, we mainly work with TFP16 adjusted to a shorter sample size to avoid the problem of later data adjustments. Nevertheless, we compare some results to older vintage series.

5 Discussion

5.1 Discussion of Variable Settings

Before we compare the responses to shocks identified with different identification schemes, we first determine which variables are essential to identify a robust news shock and an unanticipated productivity shock. The information content of the model is in general very important to identify structural shocks in VAR models, but it is even more important in this particular case since the variables included in the model have to capture the news that agents receive.

Many different combinations of variables have been used in the literature without further analysis about the actual information content. We conduct an extensive analysis of impulse responses, forecast error variance decompositions for two short-run (SRI1, SRI2) and a medium-run identification scheme (MRI). We identify two structural shocks, the first is an unanticipated productivity shock that is identified as the only shock affecting TFP on impact. The second shock is a technological diffusion news shock, henceforth news shock, identified according to the three mentioned identification schemes. We assume that similar results obtained from many different variable settings indicate robustness and that the information content is extensive enough to identify true and reliable shocks. Results stabilize as more information is included. Furthermore, the conclusion

¹⁴A detailed analysis of the TFP vintage series is given in Sims (2016) and Kurmann and Sims (2017).

about qualified models and the variables' important information do neither depend on the identified shock nor on the identification scheme.

We estimate a VAR in levels with four lags. We use data for the sample period 1955Q1-2014Q4. In all models we include the same TFP vintage series, namely TFP16. This is the first variable in every model setting. We have looked at over 100 different variable combinations, but we only present very specific variable combinations and examples in order to demonstrate clear evidence and to focus on the most important points. The settings in the following tables and graphs are named by their variable content.¹⁵ TFP, the first variable in the models is omitted due to lack of space. For brevity, we will also use confidence as a name for the index of consumer sentiment.

We find that a certain minimum amount of information needs to be included in order to identify robust shocks and to obtain reasonable impulse responses. The most important variables are TFP, output and consumption. A strong forward looking variable, such as a measure of consumer confidence or stock prices, contains valuable information. Additional variables such as hours worked, inflation or interest rates are necessary to correctly identify the news shock but only change the results slightly. Interestingly, measures of stock prices lose their worth if a lot of macroeconomic information is included in the model.

We look at four variable settings to which we add a combination of SP and cc. The variable combinations are: YCH, YCHInfl, IHInfl and Infl. Thus, the models either only contain real macro variables, or only nominal variables, or a combination of them. First, we look at cross-correlations between various shocks. Autocorrelation can be clearly rejected for all identified shocks by an F-test of regressing the shocks on two of their own lags.¹⁶ Therefore, we do not correct for autocorrelation and work with the direct cross-correlations between the shocks.

Table 3, Appendix C, displays the cross-correlations, henceforth correlations, between unanticipated productivity shocks of different variable settings. The identification method is always the same. The unanticipated productivity shock is assumed to be the only shock affecting TFP on impact. All correlation coefficients are above 0.9. This indicates that the main ingredient to identify an unanticipated productivity shock is TFP itself. Given the variable settings, the inclusion of stock prices or confidence does not alter the result. The highest correlation between different settings can be found for YCH(SP,cc) and YCHInfl(SP,cc), which is 0.98.

In Tables 4 and 5, Appendix C, we report the correlations between news shocks of different variable settings and identification schemes MRI, SRI1 and SRI2. A general observation for MRI is that the news shock for a certain variable combination is strongly

¹⁵Y: output, C: consumption, H: hours worked, I: investment, Infl: inflation rate, i: interest rate, cc: index of consumer sentiment, SP: stock prices.

¹⁶Consider Neusser (2016) for the analysis of time series.

influenced by the addition of confidence. For example the correlation between YCH and SPYCH is 0.82 and between ccYCH and ccYCHSP is even 0.97. On the other hand, between ccYCHSP and SPYCH the correlation is only 0.54. If confidence is included, the news shocks of the different variable settings are all highly correlated (> 0.8) except for ccYCH(SP), whose shock is highly correlated only to the one of ccYCHInfl(SP). The strongest correlations are found between ccIHInfl(SP) and ccInfl(SP), which indicates that hours worked and investment do not change the identified news shock. On the other hand, if we only consider settings without cc, we find the highest correlation between YCHInfl(SP) and IHInfl(SP) of over 0.8. The reason seems to be that both models contain a reasonable amount of real and nominal information. The addition of stock prices does not change the result. But the correlation between YCH and Infl is almost zero. By adding stock prices to Infl, the correlation increases from basically zero to 0.27. If stock prices are added to both settings the correlation of the news shocks is about 0.55. Stock prices surely add valuable real information to small models. Given all other variable settings we have looked at, we can conclude that for the identification of a robust news shock especially the inflation rate, interest rates and confidence are important ingredients.

The short-run identification schemes identify the news shock either based on stock prices or based on confidence. The news shocks based on the same informative variable are all highly correlated with correlation coefficients of over 0.94. The strongest correlations can be found between models containing the inflation rate and interest rates. On the other hand, shocks identified with SP and shocks identified with cc only have a correlation coefficient of approximately 0.4. It does not play a role whether the other informative variable is also included in the model. Hence, the main information to identify a robust shock with a short-run identification scheme are TFP and the informative variable (SP or cc). But the two shocks are quite different.

Surprisingly, the news shock identified with SRI1 is highly correlated with the MRI news shock of the settings ccYCH(SP) and ccYCHInfl(SP), with correlation coefficients of over 0.8. The correlation with the other settings is only about 0.6. The stronger correlation between SRI2 and a MRI news shock can be found for SPYCH and it is around 0.66. If neither SP nor cc are included in the model setting of MRI, the correlation to SRI news shocks is low. We conclude that, once confidence is included in the model, it does not matter immensely whether the news shock is identified with MRI or SRI1. Overall, it seems that confidence contains a lot of information about future TFP which cannot be found in any other variable considered.

In the following graphs we show impulse response functions and variance decompositions for all variable settings. Models including the same variables with and without cc or SP are displayed in shades of the same basis color. The settings (cc)YCH(SP) which

are only including real variables are shown in shades of blue whereas the settings only containing nominal variables (cc)Infli(SP) are shown in red. The green lines correspond to the variable settings (cc)IHInfli(SP) containing a mixture of nominal and real variables. In black shades we show our baseline settings (cc)YCHInfli(SP) that is delivering the most robust results. The groupings will be called 'real', 'nominal', 'mixture' and 'baseline'. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP. The left graph shows impulse responses while the right graph shows the corresponding forecast error variances explained by the specific shock.

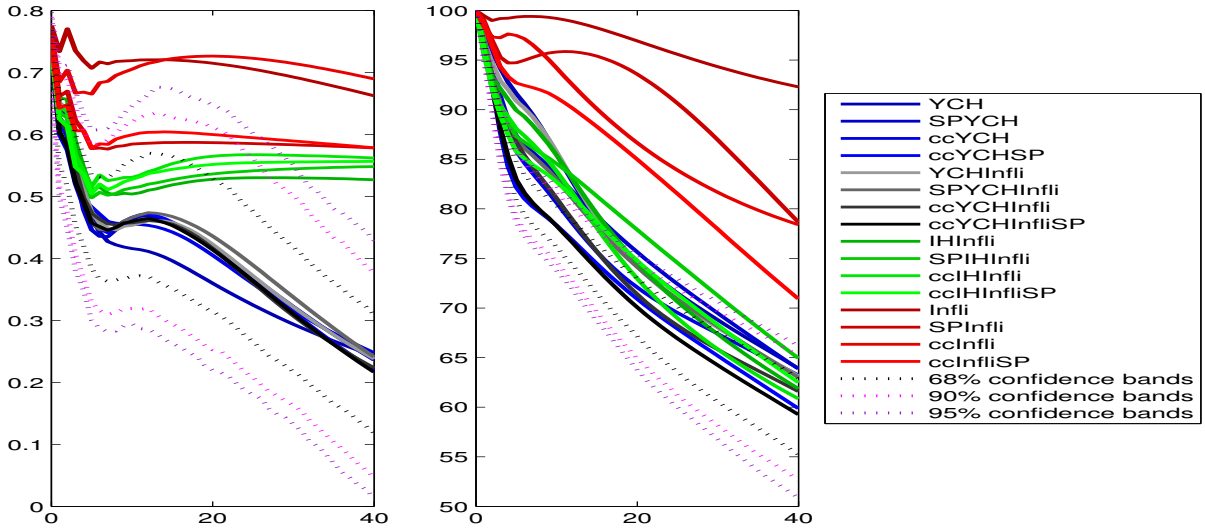


Figure 1: The left graph shows impulse response functions of TFP to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

Figure 1 displays the impulse responses and forecast error variances of TFP explained by an unanticipated productivity shock. While all models seem to identify a very similar shock, the effects and contributions of the shocks are quite different overall. The results of settings 'real' are very similar to 'baseline', which additionally include inflation and the nominal interest rate. The only exception is the plain model YCH, excluding confidence and stock prices. The confidence bands of the baseline setting indicate significant differences in effects and contributions in the medium- and long-run. Given the extensive analysis of models, we conclude that the true impulse response of TFP to an unanticipated productivity shock is in line with 'baseline' and most of 'real'. The cross-correlation analysis of shocks shows that the unanticipated productivity shocks of 'mixture' and even some of 'nominal' are highly correlated with the shock of 'baseline', but the impulse responses follow a qualitatively different path and estimate a more than 0.2 percentage

points higher long-run effect. Looking at the contribution of the unanticipated productivity shock to TFP, all four 'nominal' settings estimate a much higher contribution, especially in the long-run. Thus, even though mainly TFP itself is necessary to identify an unanticipated productivity shock, to estimate the correct effect and contribution more information is needed. Specifically, real macroeconomic variables such as output, consumption and hours worked are necessary to model macroeconomic relationships. This last point is not surprising, but is important to be noted since it has often been ignored in the literature.

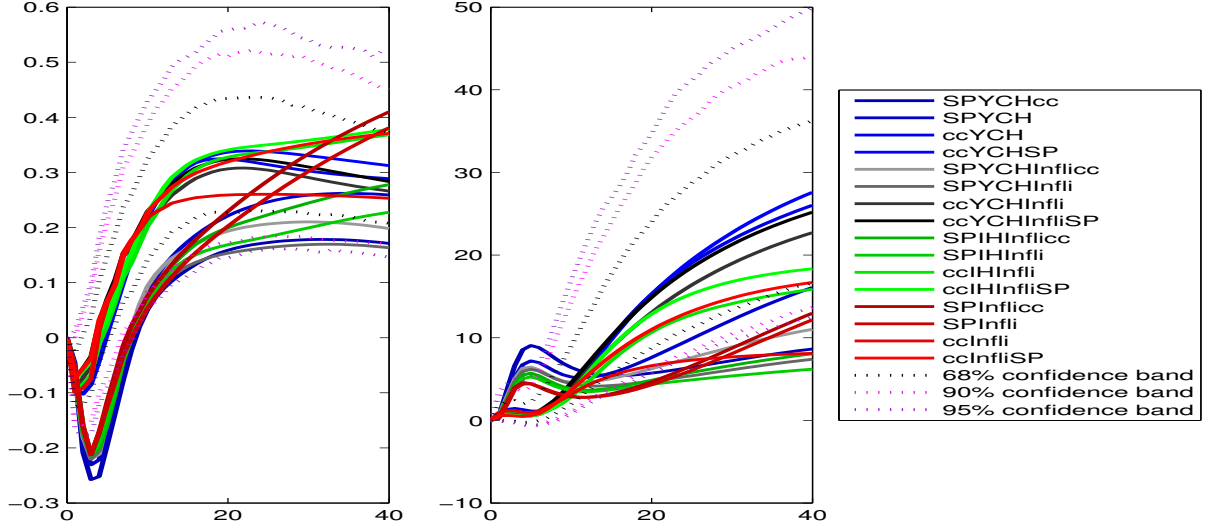


Figure 2: The left graph shows impulse response functions of TFP to a news shock identified with SRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified with SRI in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

Next, we look at the identification schemes SRI1 and SRI2. The news shock is identified as the second shock after an unanticipated productivity shock affecting either confidence or stock prices on impact. Figure 2 contains the impulse responses and forecast error variances of TFP. Also, the impulse responses indicate that the two identification schemes do not identify the same shock. Nevertheless, the impulse responses are qualitatively very similar. In the short-run the results only depend on the identification scheme but not at all on the variable settings. Thus, the effect of the shock is purely determined by TFP and the informative variable. In the long-run SRI1 appears to deliver more stable results.

As illustrated in Figure 3, the implications of the results for the news shock identified with MRI are similar to those of the cross-correlation analysis. The 'real' and especially the 'baseline' settings seem more robust, while the 'mixture' settings overestimate the long-run effect. For the 'nominal' settings, it matters a lot whether consumer confidence is added. Even though MRI news shocks of 'nominal' including cc are highly correlated

with those of 'baseline', there is a large difference in results. It seems that the 'nominal' settings do not model macroeconomic relationships sufficiently well, which is due to the lack of real variables.

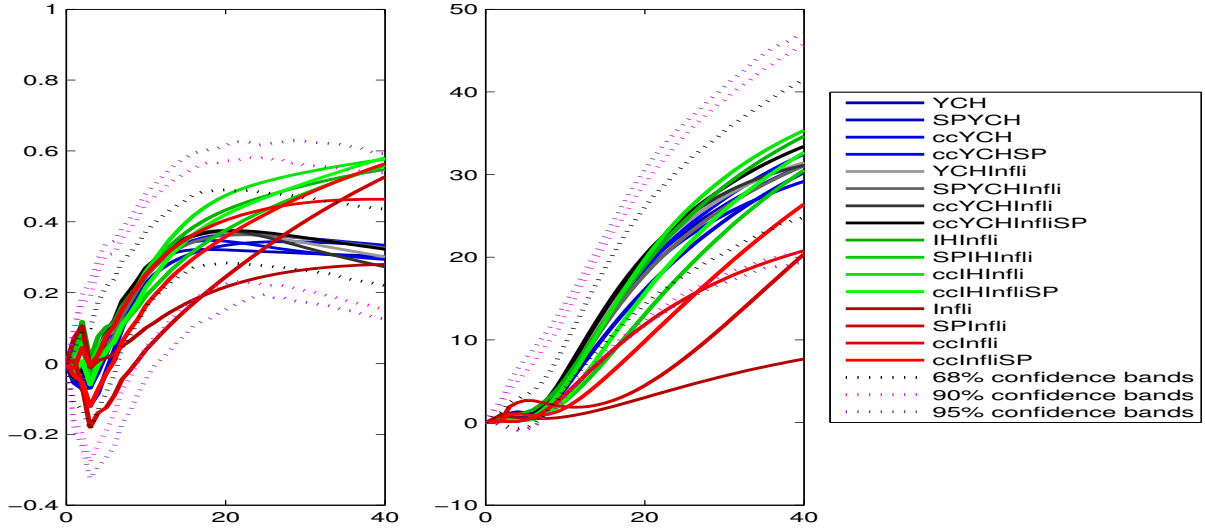


Figure 3: The left graph shows impulse response functions of TFP to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified with MRI in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

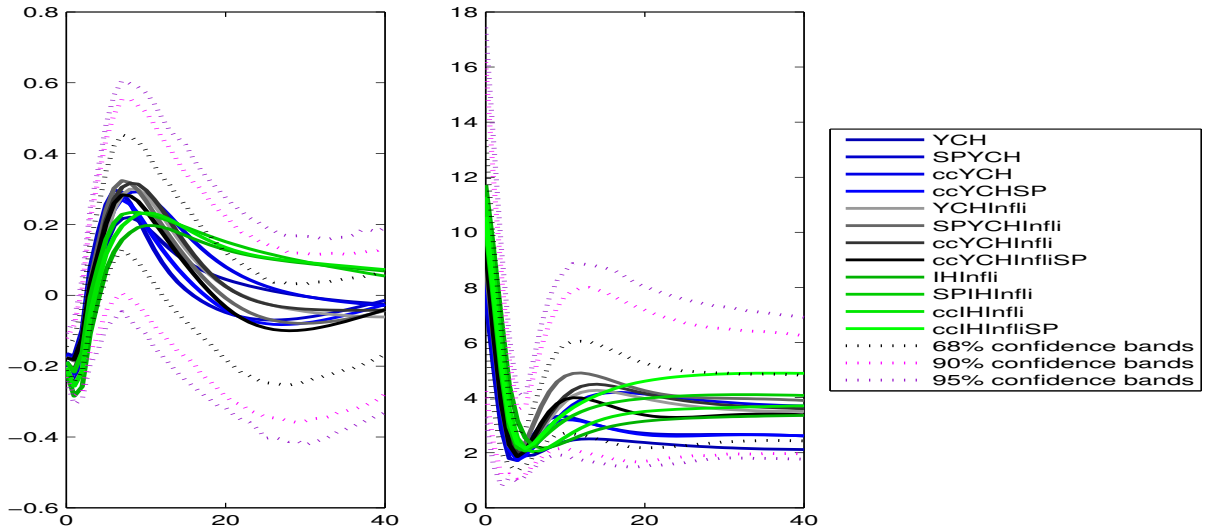


Figure 4: The left graph shows impulse response functions of hours worked to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of hours worked determined by an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

In Figure 4 we show the effect and contribution of an unanticipated productivity shock on hours worked. In contrast to TFP, the impulse responses are qualitatively

and quantitatively closer which is also indicated by the confidence bands of the baseline setting. In the short-run all settings deliver very similar results that drift apart as time evolves. The shares of the forecast error variance are also very close in the short-run and disperse in the long-run. Since the results are coherent over all variable settings and the response of the baseline setting is significant at the 95% significance level, it can be concluded that the impact reaction of hours worked to an unanticipated productivity shock is negative.

In Figure 5 the news shock is either identified with SRI1 or SRI2, hence, the informative variable on position two is either confidence or stock prices. We further consider settings where the other informative variable is also added to verify whether the additional information changes the results. The impulse responses indicate that the inclusion of confidence leads to a higher long-run effect and contribution for most settings. Even though all shocks are highly correlated, merely the short-run results are close.

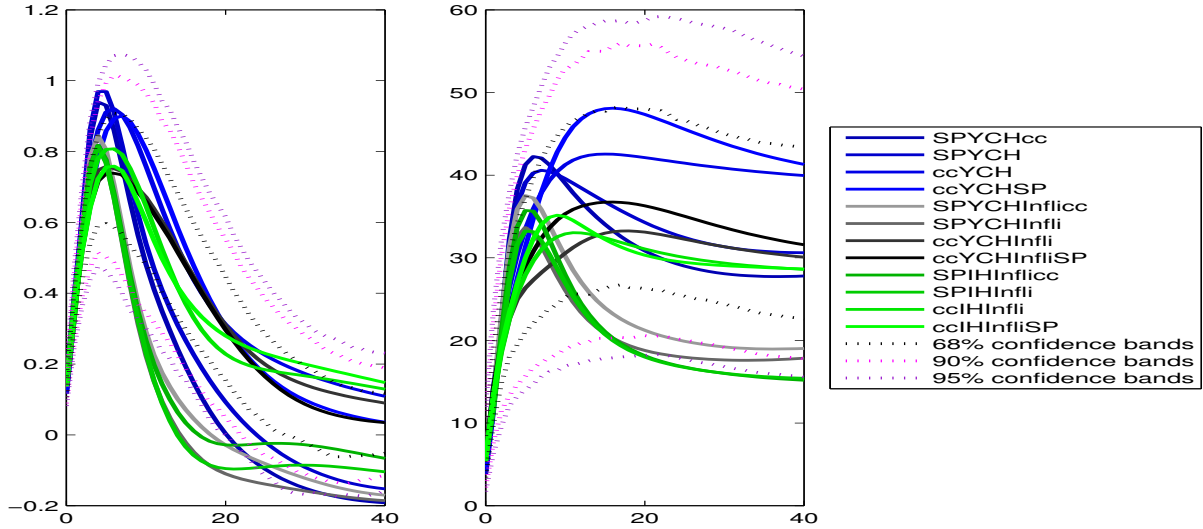


Figure 5: The left graph shows impulse response functions of hours worked to a news shock identified with SRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of hours worked determined by a news shock identified with SRI in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

In Figure 6 we present the impulse responses of hours worked to a news shock identified with MRI and the corresponding shares of the forecast error variance. 'Baseline' seems to be the most robust setting again. The impulse responses display qualitatively very similar results. The same is true for the contributions, but they spread over 30 percentage points in the long-run. While it matters less for TFP, the inclusion of confidence seems to play a more important role in this case. The models including cc are more highly correlated and also deliver more similar results.

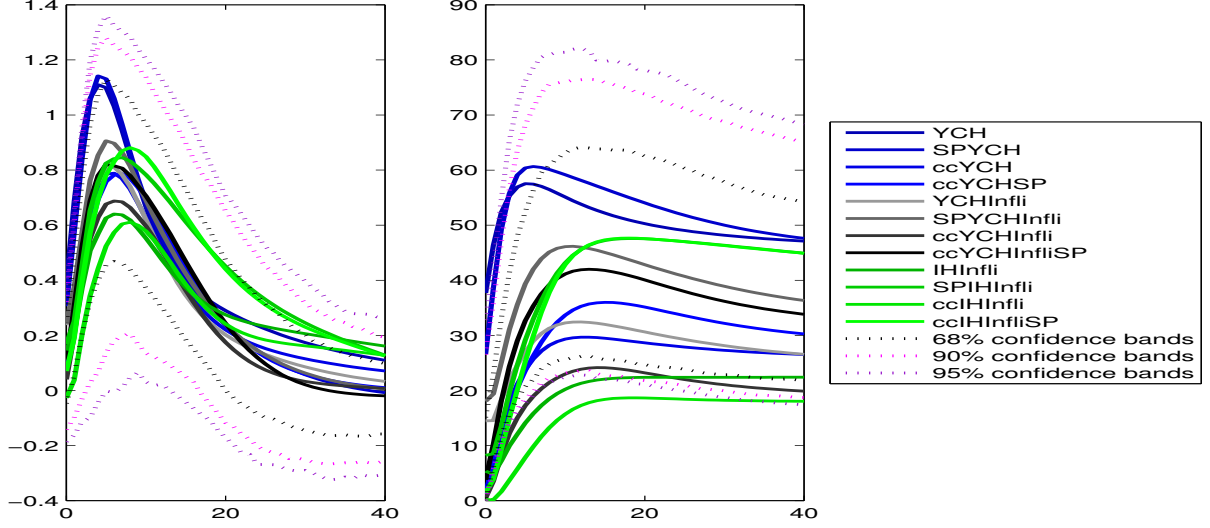


Figure 6: The left graph shows impulse response functions of hours worked to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of hours worked determined by a news shock identified with MRI in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

While it matters for other variable settings, the addition of confidence or stock prices does not affect the results of the 'baseline' settings (TFP, Y, C, H, Infl, i(cc),(SP)) strongly. The impulse responses of the 'baseline' settings to an unanticipated productivity shock are displayed in Figure 7. In the short-run, the inclusion of stock prices mainly affects the inflation rate. In general it reduces the long-run effect. There is more variation in the results to a MRI news shock, which we show in 8. All variables display a different short-run reaction depending on the inclusion of confidence. Most prominent is the impact response of inflation, which is doubled. For output, consumption, hours worked and the interest rate, it also matters whether stock prices are added. The addition of stock prices increases the effects. We conclude that the variable setting is quite robust to the addition of stock prices or confidence. And even though the correlation between the news shock of TFPYCHInfli and TFPccYCHInfliSP is only 0.54, results are very close. All impulse responses and contributions clearly lie within the confidence bands of ccYCHInfliSP. While consumer confidence seems to include important information on TFP and determines to a great extent the identified shock, the combination of real and nominal variables as in the 'baseline' settings is key to obtain robust impulse responses. TFP, inflation, interest rates and confidence are the main ingredients needed to identify robust unanticipated productivity and news shocks. But to obtain robust results for the long-run effect and the contribution to each variable, more or different information is needed. A robust model contains a combination of real macroeconomic variables (i.e. Y, C, I). The most encompassing combination is output and consumption. The further addition of investment does not influence results much. Hours worked is another important

addition including information on the labor market, which affects mainly the magnitudes of results.

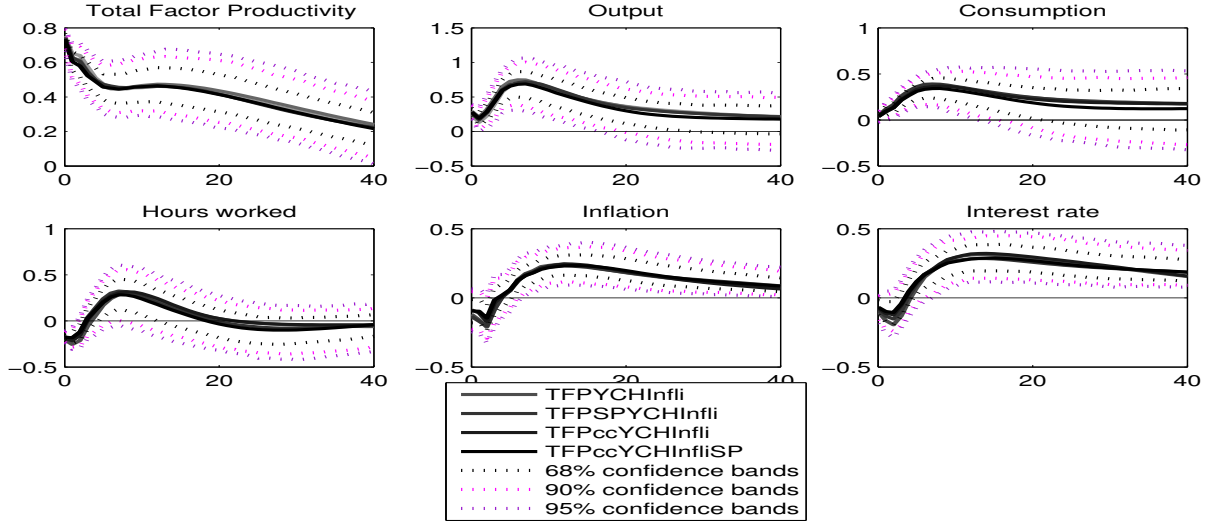


Figure 7: The graph shows impulse response functions of all variables to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

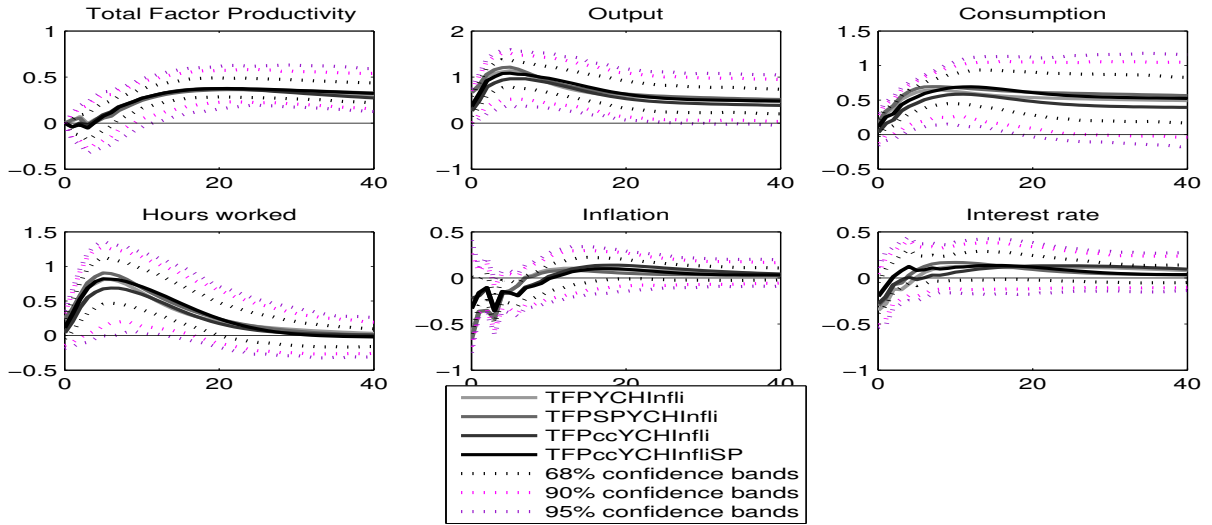


Figure 8: The graph shows impulse response functions of all variables to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

5.1.1 Variable Settings Used in the Literature

In what follows we perform the same analysis but with variable settings that have been used in the related empirical news literature. A discussion of the applied identification

schemes in the respective papers is given in Section 3. For a description of the various model settings consider Appendix B.¹⁷ We will abstract from the short-run identification as it does not deliver any further insights.

In Table 6, Appendix D, we present the correlations between unanticipated productivity shocks of the variable settings. The results clearly indicate that the information content of the model is not very important to identify this shock. Between all settings the correlation is above 0.9. This confirms our previous result that to identify an unanticipated productivity shock mainly a measure of technology is needed.

The correlations between news shocks identified with MRI are displayed in Table 7, Appendix D. Again we find that models with SP are strongly correlated with each other and the same for cc. As the setting 9 contains both measures, the high correlation with 7BS of over 0.8 and the lower correlation of 0.63 with 8KS suggests that cc plays an important role and affects the news shock. The news shocks of 7BNW and 8KS have a high correlation coefficient of 0.93 indicating that investment does not add a lot of necessary information. The news shocks from the smaller models 2BP, 4BP2, 4BS and 4KS are less correlated with the shocks from larger models. This points to an information deficiency of the smaller models.

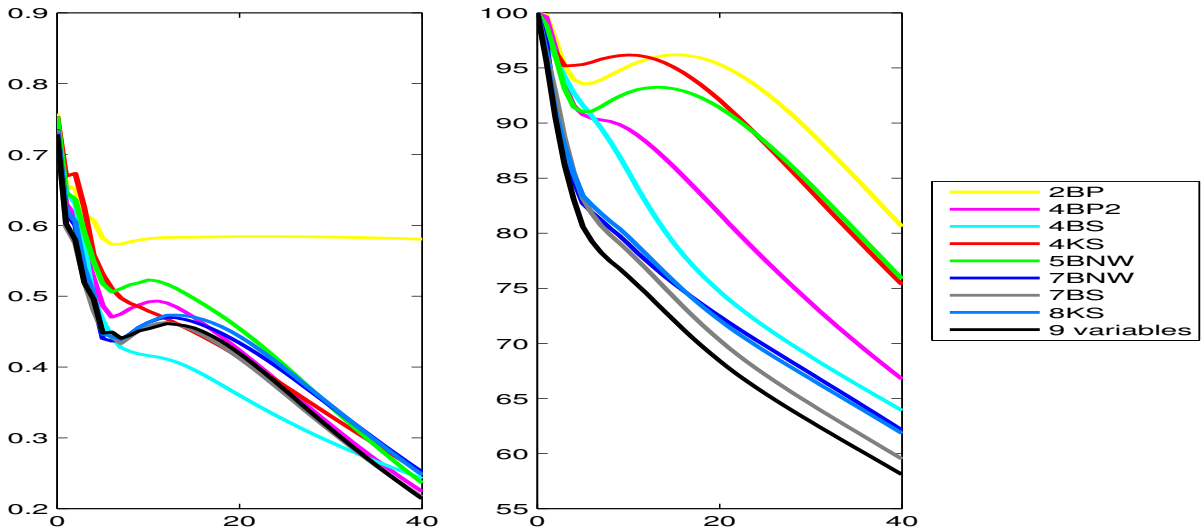


Figure 9: The left graph shows impulse response functions of TFP to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons.

Figure 9 displays the impulse response functions on the left and the shares of the FEV on the right for TFP to an unanticipated productivity shock. The impulse response

¹⁷The numbers used in the naming of settings indicate the number of variables included in the model setting. BP stands for the variable settings in Beaudry and Portier (2006). BS stands for the variable settings in Barsky and Sims (2011). BNW stands for the variable settings in Beaudry et al. (2011). KS stands for the variable settings in Kurmann and Sims (2017). 9 variables includes all variables TFPccYCHIInfiSP.

function of TFP to an unanticipated productivity shock is similar for most models. There is one setting with an obviously different response and that is 2BP. This model only includes minimal information, namely TFP and stock prices. There are other models such as 4BS and 4KS, whose responses do not move adequately and are off in the medium- or long-run. The larger models follow a similar pattern and their long-run responses are very close. It is evident that the models that perform badly in terms of IRFs do not show a consistent pattern in the variance decomposition either. For the other models the contribution lies within a range of 0.1 percentage points after one year, indicating a clear pattern. It seems that even though small models are able to identify an unanticipated productivity shock as indicated by the high correlation coefficients between shocks, there is not enough information in the models to obtain coherent impulse response functions.

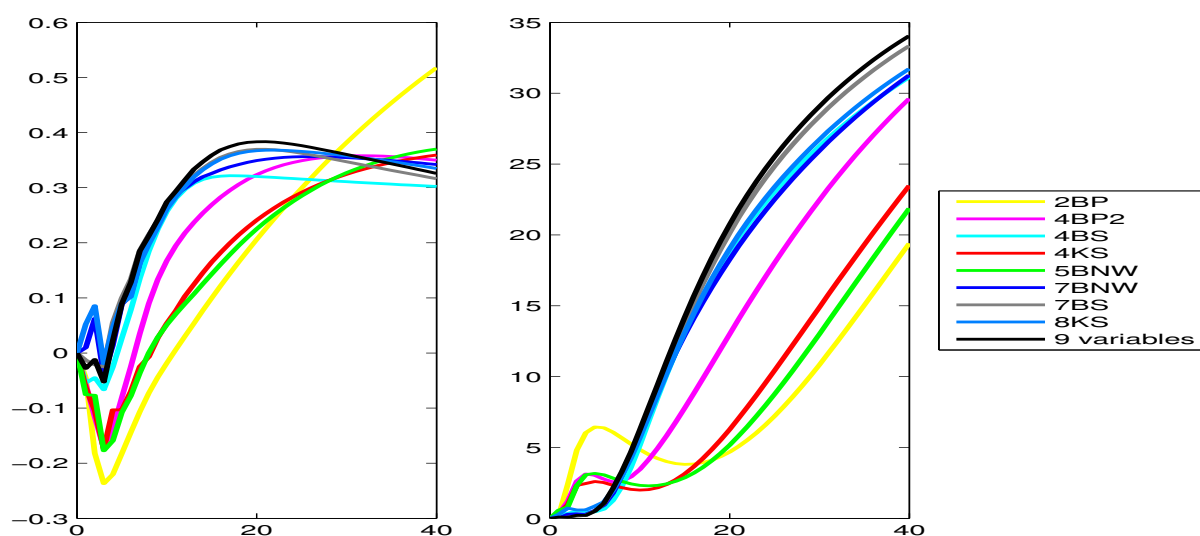


Figure 10: The left graph shows impulse response functions of TFP to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified with MRI in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons.

In Figure 10 we present the impulse responses of TFP to a news shock identified with MRI and the contribution of this shock to TFP's variance. The picture for this identification is more scattered. In the very short-run the impulse response of TFP increases in only three models, while it remains below zero for all other models for at least one year. The models with the positive short-run effect are 7BNW and 8KS which are both models that include a lot of macroeconomic information excluding confidence. Considering the small negative responses of 7BS and 9, the effect in the first year is probably around zero. After one year all model settings indicate a strong increase in TFP that reaches its peak between 18 and 30 quarters. Smaller models display a more negative short-run response which leads to a slower evolution of TFP. 2BP seems to overestimate the long-run effect of the news shock on TFP. A similar conclusion can be reached concerning the contribution of the shocks. 2BP, 4KS and 5BNW, which are all

models lacking cc and output, clearly underestimate the long-run contribution.

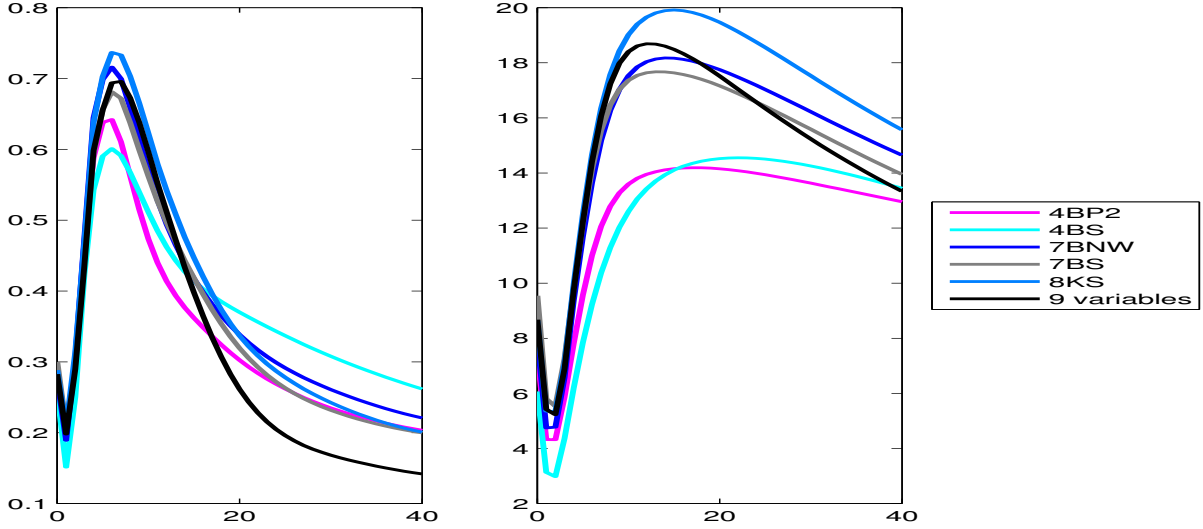


Figure 11: The left graph shows impulse response functions of output to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of output determined by an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons.

Figure 11 illustrates the effects of an unanticipated productivity shock in terms of impulse responses of output and contribution to the FEV of output at different horizons. Only model settings including output can be considered for this exercise. The impulse response functions of most model settings seem to be very similar, especially in the short-run. 4BS displays a slightly higher long-run effect and, similar to 4BP2, it has a slightly different evolution from the rest. 4BP2 and 4BS seem to underestimate the contribution in the medium- and long-run.

In Figure 12 we consider the response of output to a news shock identified with MRI and the share of the FEV of output explained by this shock. In the medium-run the effect and contribution of the news shock seems to be overestimated by smaller models. The analysis so far gives a clear picture of better and worse parameter settings. First of all, there are model settings that are undoubtedly not advisable. For example, 2BP or (TFP,cc) always display different patterns than the rest of the models. 4BS and 4KS are two other models that lack sufficient information to deliver robust results. Nevertheless, they suffice to grasp the idea of news shocks due to the inclusion of consumption and hours worked. They either lack sufficient real or nominal information and do not include any informative variable (SP,cc). Our analysis of further models indicates that hours worked, interest rates, and inflation are important to determine the magnitude of the effect. The necessity of including consumption becomes even more obvious if further variable settings are considered. It seems advisable to work with models that either include many real and nominal variables or at least add confidence as a partial substitute. In smaller models the combination of variables is key and the inclusion of stock prices and confidence becomes

more important. Apparently, confidence contains additional information on TFP which is not present in the other eight macroeconomic variables, including stock prices. Overall, it can be said that most larger variable settings capture the structural shocks and their effects well.

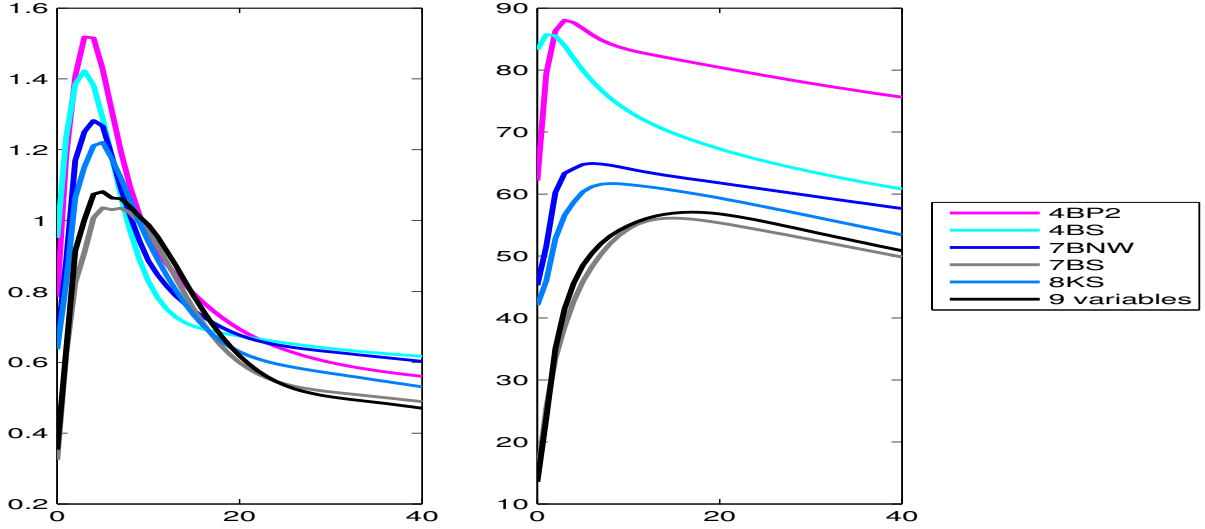


Figure 12: The left graph shows impulse response functions of output to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of output determined by a news shock identified with MRI in different variable settings. The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons.

The same exercise could be conducted for further identification schemes, for other samples and different horizons in the MRI. The results appear to be very robust and the essential variables remain the same. This is the reason why we believe that these results are noteworthy and important for future research.

5.2 The Role of the Horizon in the Medium-Run Identification Scheme

Even though we have presented the several medium-run identification schemes used in the literature, we briefly summarize the approaches again. Barsky and Sims (2011) maximize the share of the forecast error variance over a certain horizon (BS-MRI) whereas Beaudry et al. (2011) maximize it at a certain horizon (MRI) and both their news shocks remains orthogonal to an unanticipated productivity shock. Kurmann and Sims (2017) maximize at a certain horizon but give up on the orthogonality condition (KS-MRI). In the following we compare the three medium-run identification schemes and show how different horizons influence results. As our baseline model we use the variable setting including total factor productivity, confidence, output, consumption, hours worked, inflation, interest rates and stock prices.

Figure 13 displays the impulse responses to a news shock identified with MRI. The news shock is identified as the shock with maximum contribution to TFP at horizons three, five, ten or twenty years. We find that results are very sensitive to the choice of horizon. For horizons 12 and 20, TFP increases almost immediately which indicates that we are not really looking at a news shock. Probably more transitory productivity effects are included. With maximization horizon 12, the impact response of hours worked is negative. Moreover, stock prices seem not to react at all. Otherwise, the results are qualitatively very similar, but the response of output, consumption and hours to a news shock increase with the identifying horizon. Furthermore, the results seem to stabilize for higher maximization horizons. Very similar results are obtained with the identification scheme MRI-BS. In general the effects are slightly smaller resulting from the fact that short-run effects are always included.

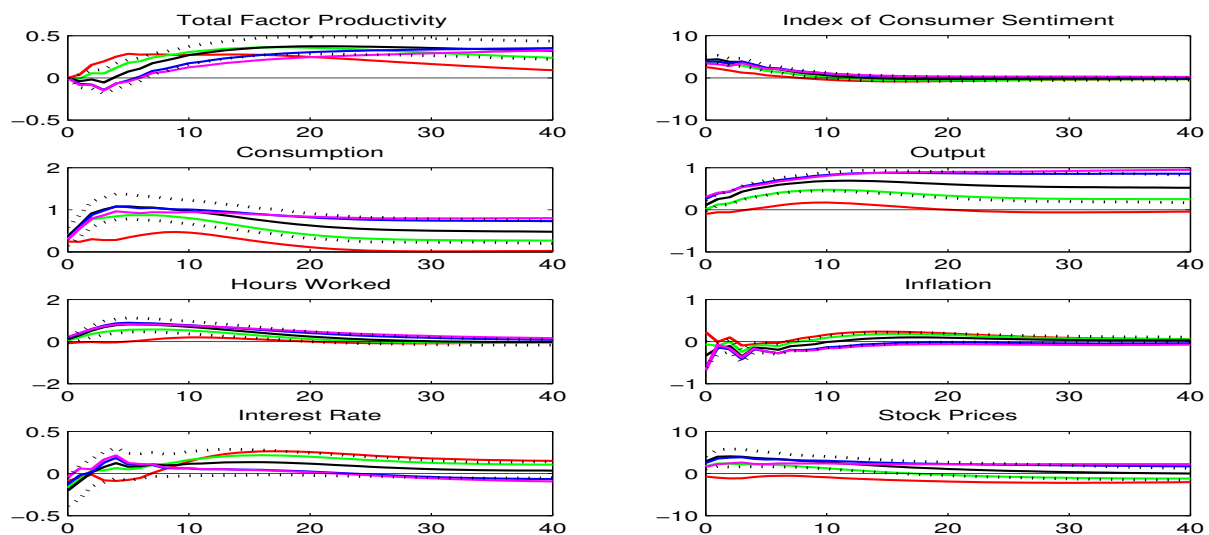


Figure 13: IRFs to a news shock identified with MRI maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model with MRI maximizing at horizon 40 (black).

In Figure 14 we present the contributions of a news shock identified with MRI at different maximization horizons to the FEV of all variables. The differences between the horizons become even more apparent. The identification scheme maximizing at horizon 12 seems to identify a shock that contributes fast to TFP reaching the maximum after two years while higher horizons maximize the contribution in the long-run which is higher. As a result the shock does not contribute to the forecast error variance of output, inflation, consumption and hours worked at any horizon and also the contribution to confidence and stock prices is low. The contribution generally increases with the horizon. The exceptions are confidence and stock prices for which the highest contribution is obtained with 40 quarters (10 years). This last observation may signify that economic agents

mainly form expectations about technological innovations that have a considerable effect on productivity in at least ten years.

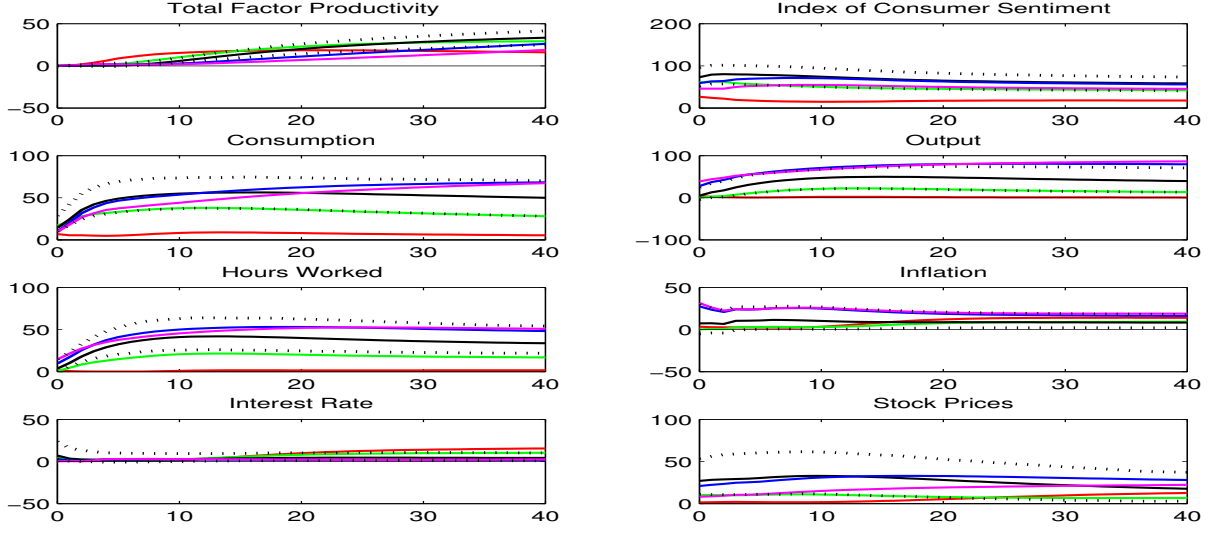


Figure 14: Contributions of a news shock identified with MRI maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model with MRI maximizing at horizon 40 (black).

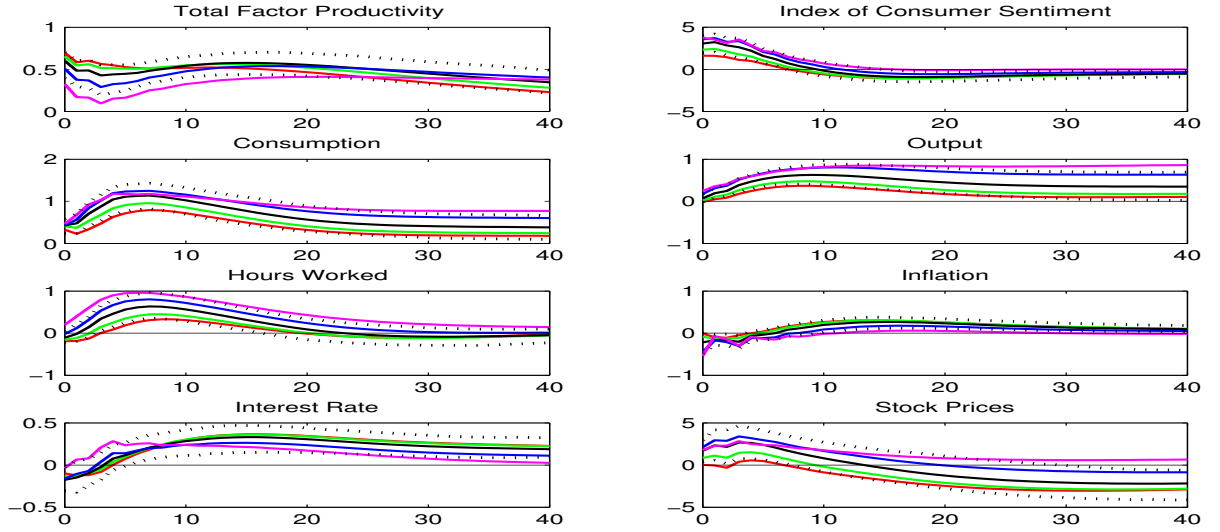


Figure 15: IRFs to a news shock identified with KS maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model with MRI maximizing at horizon 40 (black).

In Figure 15 we show the impulse responses to a news shock identified with MRI-KS for horizons 12, 20, 40, 80 and 120 quarters. Qualitatively, the impulse responses depend less on the maximization horizon. The impulse responses to MRI-KS12 and MRI-KS20 look very similar to the responses to an unanticipated productivity shock. Thus, we conclude

that the omission of the orthogonality assumption between contemporaneous TFP and the news shock creates a shock that mixes these two innovations. In general, the effect becomes larger as the horizon increases, while the short-run effect on TFP decreases. We contradict Kurmann and Sims (2017) by showing that the reaction of hours worked becomes positive on impact once the horizon is high. We use a slightly different variable setting than they do and exchange investment for confidence. If their variable setting were used, the effect on hours worked would already be positive for horizon 80 quarters which is exactly the setting in their paper.

Figure 16 illustrates the contribution of the news shock identified with MRI-KS for horizons 12, 20, 40, 80 and 120 quarters. If shorter horizons are applied, the identified shock seems to explain approximately 80 percent of the variation in TFP, which is close to the sum of the contribution of an unanticipated productivity shock and a news shock identified with MRI. We conclude that as long as shorter maximization horizons are considered, the identified shock seems to be a mixture of unanticipated productivity and a news shock. Identification schemes with shorter maximization horizons identify a shock that does not contribute to inflation, consumption or stock prices on impact, meanwhile longer maximization horizon schemes contribute up to thirty percent on impact. We have shown that no matter the identification scheme, we can find a positive impact effect on hours worked. But results differ considerably with the maximization horizon.

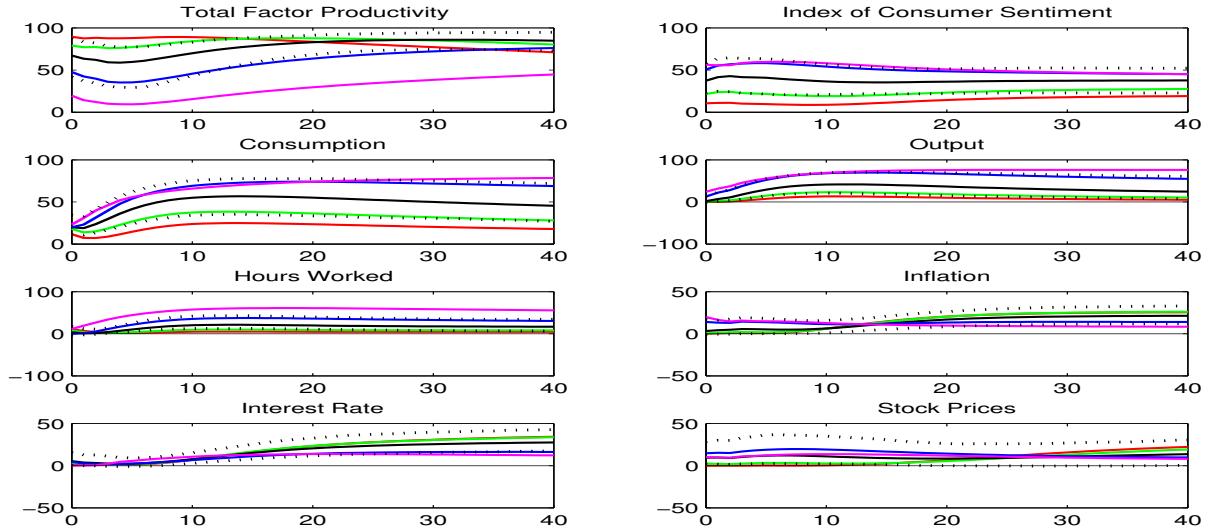


Figure 16: Contributions of a news shock identified with KS maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model with MRI maximizing at horizon 40 (black).

In Figure 17 we present the impulse responses of TFP to a news shock identified with either MRI, MRI-BS or MRI-KS, and to an unanticipated productivity shock. It seems that the three identification schemes deliver very similar results given the same maximization horizon is used. The response to a MRI-BS shock is always smaller than to

a MRI shock since more short-run effects are considered. Even though a MRI-KS shock affects TFP strongly on impact, the responses of the remaining variables are very similar to those obtained with the other identification schemes. The most important difference is hours worked. It seems that the MRI-KS news shock is a mixture of a MRI news shock and an unanticipated productivity shock, which explains the negative reaction of hours worked.

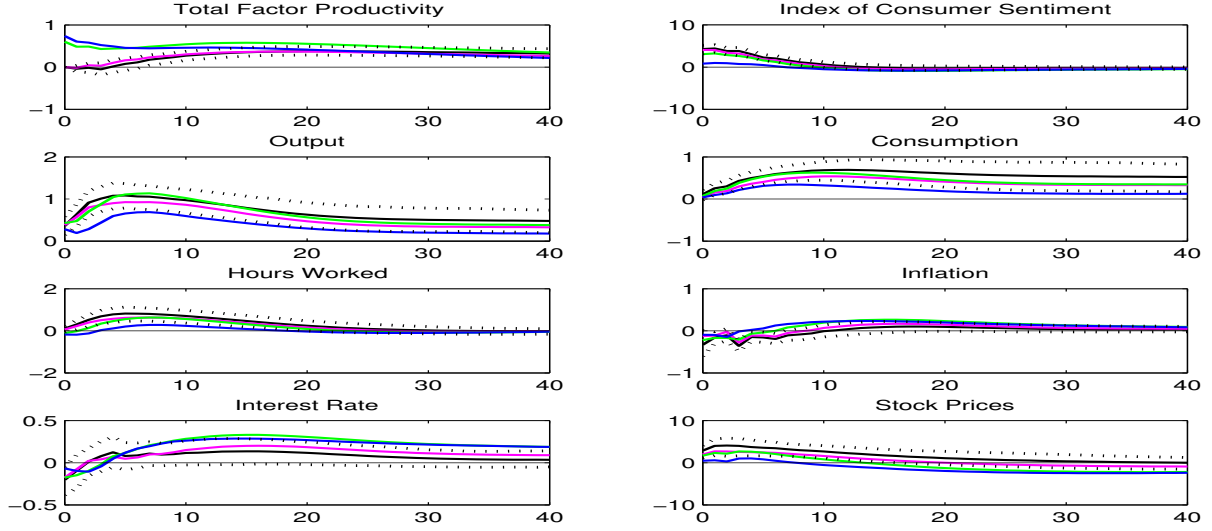


Figure 17: Impulse responses to a news shock identified with MRI-KS (green), MRI (black), MRI-BS (blue) with maximization horizon 40 quarters and a news shock obtained with SRI1 (magenta). The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model with MRI (black).

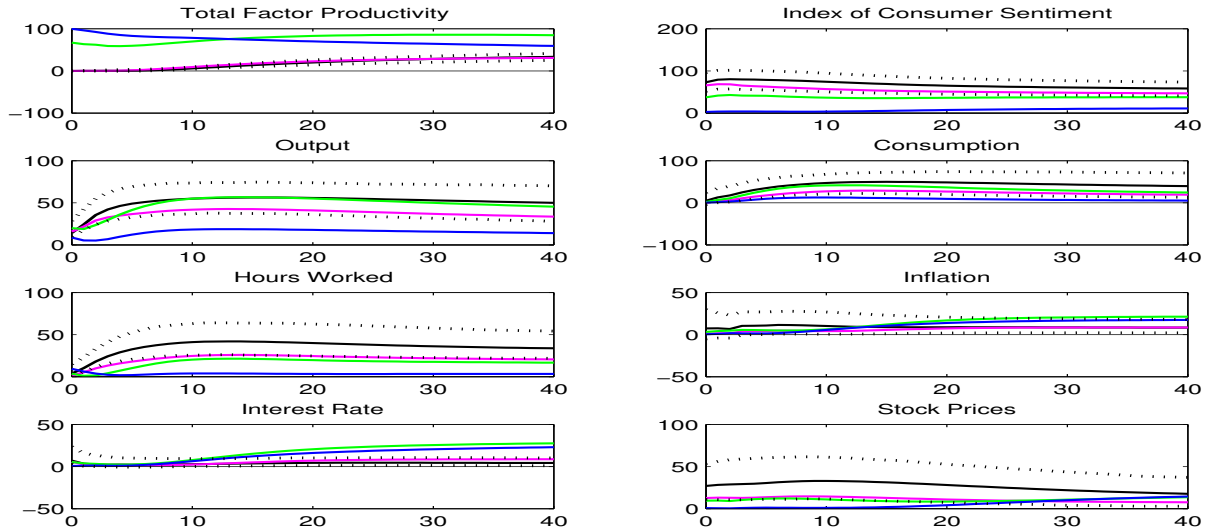


Figure 18: Contributions of a news shock identified with KS (green), MRI (black), BS (blue) with maximization horizon 40 quarters and a news shock obtained with SRI1 (magenta). The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model with MRI (black).

The contributions of the shocks displayed in Figure 18 provide more support in favor of the fact that the KS shock is a mixture of an unanticipated productivity shock and a MRI shock. The contribution of the MRI shock is in general much larger than that of the MRI-BS shock. As the horizon increases, the impulses and contributions for these two methods converge also quantitatively. In our opinion, it is evident from this analysis that the identification scheme of MRI-KS does not identify a news shock but rather a mixture of a news shock and a persistent unanticipated productivity shock. Even conceptually, the strong impact reaction of TFP they find seems counterintuitive considering that a new technology, which is not yet in use, needs time to diffuse or materialize and hence to have an effect on aggregate productivity. Nevertheless, it may be interesting to separate a transitory from a permanent unanticipated productivity shock.

We believe that this analysis has clearly indicated for all medium-run identification methods that news shocks identified with shorter horizons are dominated by transitory shocks that do not correspond to the news shock we are looking for. If we sum the contributions up to a certain horizon, the smaller maximization horizons contaminate the news shock with contemporaneous effects.

5.3 The Role of the Sample and TFP Vintage Series

In the news literature different samples as well as different TFP vintage series have been employed. In this section we show in what way this affects the identified news shock based on MRI maximized at horizon 40 quarters.

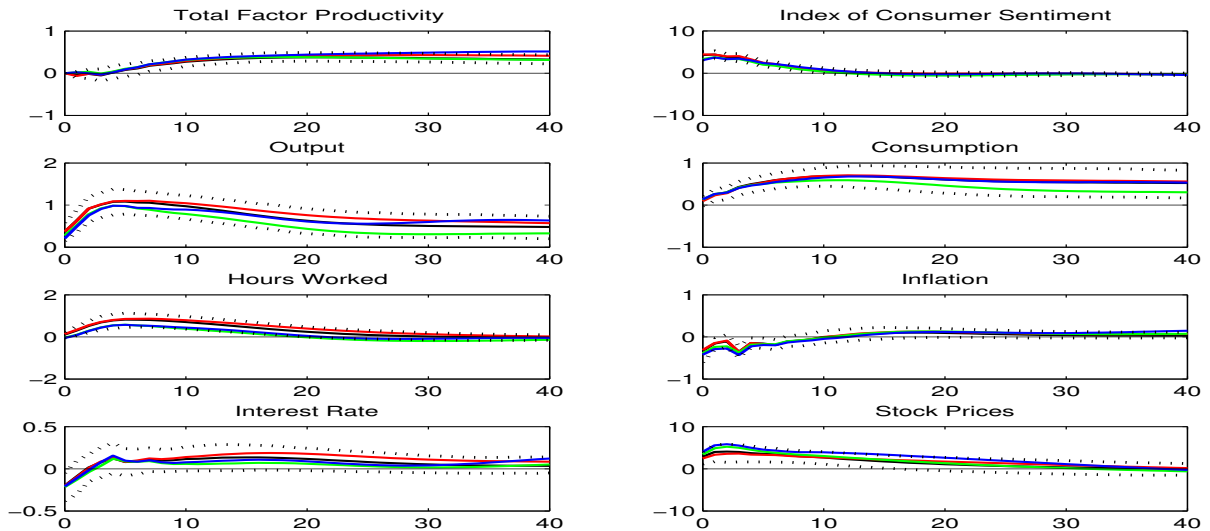


Figure 19: Impulse responses to a news shock identified with MRI maximized at 40 quarters, using TFP16 samples until 2000 (green), 2007 (red), 2011 (red), 2014 (black). The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model using TFP16 samples until 2014 (black).

In Figure 19 we display impulse responses to a news shock for the samples up to 2000, 2007, 2011, 2014. In general, the results are very similar both qualitatively and quantitatively. The main difference and debating point is the impact reaction of hours worked. While it is slightly negative and close to zero for shorter samples, it has become positive later on. This result was shown in Kurmann and Sims (2017) and indicates that the identification scheme may not be robust over time. But if the maximization horizon were increased, the impact effect of hours worked would become positive also for shorter samples.

The forecast error variance decomposition, shown in Figure 20, also indicates that generally the same shock is identified. Again the biggest difference can be found for hours worked where the impact contribution is larger in shorter samples but afterwards the contributions of the news shocks from later samples become much stronger. While the shock seemed more related to stock prices in the sample until 2000, confidence reacts much stronger in the two most recent samples.

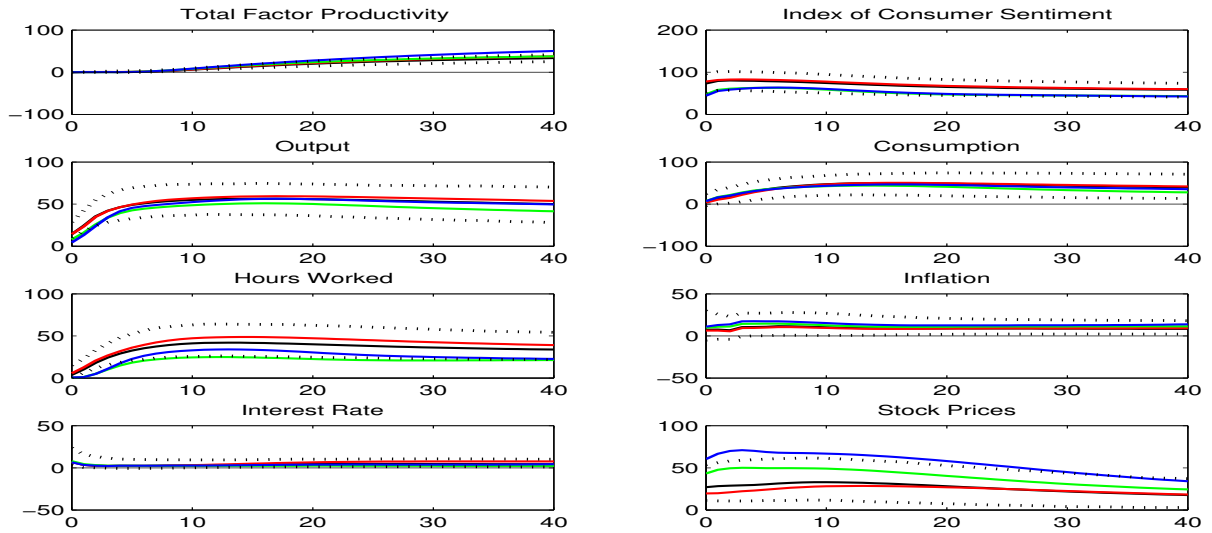


Figure 20: Contributions to the forecast error variance of a news shock identified with MRI maximized at 40 quarters, using TFP16 samples until 2000 (green), 2007 (red), 2011 (red), 2014 (black). The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model using TFP16 samples until 2014 (black).

The biggest difference in the effects and contributions of a news shock comes from the TFP vintage series employed. In Figure 21 we show the impulse responses to a news shock estimated with TFP07 and TFP16 for samples until 2000 and 2007. The results with TFP07 were also found by Barsky and Sims (2011) indicating a contractionary effect of news shocks. Furthermore, the increase of TFP is fast and strong. These results cannot be recovered with newer TFP vintage series after the revision in 2014. The reaction of output and consumption is now always positive. The effect on hours worked depends on the maximization horizon and the sample. As has been shown before using TFP16 and a sample until 2000 or 2007 leads to a slightly negative effect on hours worked. Undoubtedly,

this effect is much smaller than the one found with earlier vintages. Also the contributions of the shocks using different samples and TFP vintage series, as displayed in Figure 22, indicate that the vintage series definitely lead to the identification of different shocks.

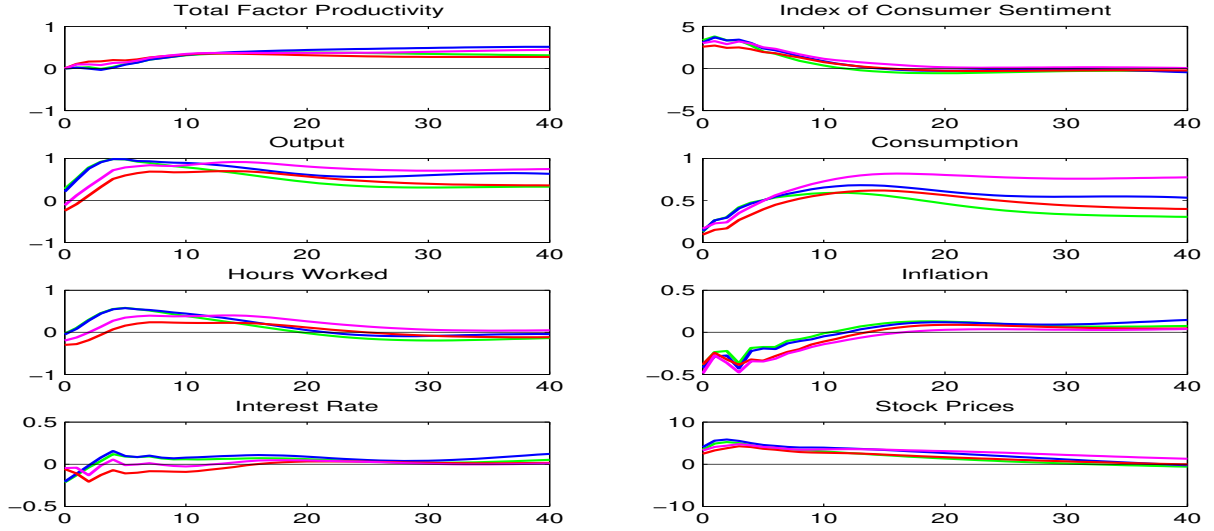


Figure 21: Impulse responses to a news shock identified with MRI maximized at horizon 40 quarters using different TFP vintage series and samples: TFP16/2000 (green), TFP16/2007 (red), TFP07/2000 (red), TFP07/2007 (black). The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal axes indicate the forecast horizons in quarters.

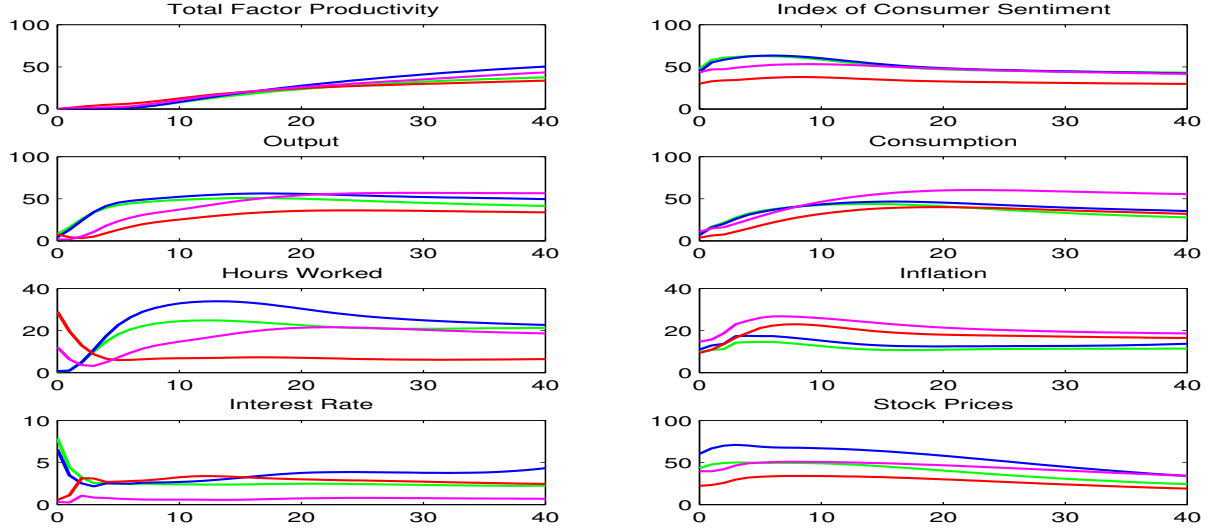


Figure 22: Contributions of a news shock identified with MRI maximized at horizon 40 quarters using different TFP vintage series and samples: TFP16/2000 (green), TFP16/2007 (red), TFP07/2000 (red), TFP07/2007 (black). The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters.

6 Conclusions

In the news literature various identification schemes in many different variable settings have been employed to identify a technology diffusion news shock and to discuss its effects

on economic activity. The literature still has not come to an agreement on what is the optimal variable setting and identification scheme to be used. More importantly, there is no consensus on whether the news shock is expansionary or contractionary. Our paper contributes to the debate with an extensive analysis of variable settings and identification schemes, and sheds some light on the minimal information that is necessary for the identification of a news shock. Small-scale models are not giving satisfactory results for either the unanticipated productivity shock or the news shock. Furthermore, we show how different samples or identification schemes may change some effects of the news shock on the economy. Depending on the variable setting, identification scheme, maximization horizon, TFP vintage series and sample that is chosen, the results may differ.

In our opinion and close to the definition of Beaudry and Portier (2006), a news shock is a technological innovation or change in the technical environment that is known today, but its full potential will only develop in the future and over time. An example are self-driving cars that are now known to be feasible, as there are working prototypes and some are already in use. However, there is no present change in aggregate productivity due to their invention as their full potential of productivity improvement will only become visible in TFP measures in the next years or decades. Having this example in mind, we believe that a medium-run identification scheme with zero impact effect of the news and a longer maximization horizon may be more appropriate than others. Based on that, we conclude that news shocks do have an expansionary effect.

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Appendices

A Data

TFP: log tfp adj. for capacity utilization (from Federal Reserve Bank of San Francisco, following the method of Fernald (2014), Basu et al. (2013) and Basu et al. (2006))

cc: index of consumer sentiment (US CONSUMER CONFIDENCE - EXPECTATIONS SADJ/US UNIVERSITY OF MICHIGAN: CONSUMER EXPECTATIONS VOLN, USCCONFEE, M, extracted from Datastream)

Y: log real per capita output nonfarm (log of Real gross value added: GDP: Business: Nonfarm, A358RX1Q020SBEA, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis; adjusted for population: US POPULATION, WORKING AGE, ALL PERSONS (AGES 15-64) VOLN, USMLFT32P, M, retrieved from Datastream)

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

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

C: log real per capita consumption (log of Personal Consumption Expenditures: Non-durable Goods, PCND, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis + Personal Consumption Expenditures: Services, PCESV, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis; divided by the price deflator and population)

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

H: log per capita hours (log Nonfarm Business Sector: Hours of All Persons, HOANBS, Q, sa, U.S. Department of Labor: Bureau of Labor Statistics; divided by population)

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

Solow residual: $(\log(tfp) = \log(Y/(H^{av(ls)}KS^{1-av(ls)}))$; ls:Share of Labour Compensation in GDP at Current National Prices for United States, LABSHPUSA156NRUG, annual, nsa, University of Groningen, University of California, Davis; KS: US CBO FCST SURVEY-INDEX OF CAPITAL SERVICES(NONFARM BUS SECT), USFCICSN, annual/linearly interpolated, US CBO)

B Model Settings

Table 2: Model settings

	variables								
	TFP	SP	Y	C	I	H	Infl	i	ICS
2BP	×	×							
4BP1	×	×		×		×			
4BP2	×	×	×	×					
4BP3	×	×		×	×				
5BNW	×	×		×		×		×	
7BNW	×	×	×	×		×	×	×	
4KS	×			×		×	×		
8KS	×	×	×	×	×	×	×	×	
4BS	×		×	×		×			
7BS	×	×	×	×		×	×		×
9	×	×	×	×	×	×	×	×	×

The numbers indicate the number of variables included in the model setting. BP stands for the variable settings in Beaudry and Portier (2006). BS stands for the variable settings in Barsky and Sims (2011). BNW stands for the variable settings in Beaudry et al. (2011). Sims stands for the variable settings in Sims (2016). The pure number 9 is a model containing all variables.

C Cross-Correlations between Shocks Obtained in Various Settings

Table 3: Cross-correlations between unanticipated productivity shocks obtained in various settings

	Model Settings							
SPS	YCH	SPYCH	ccYCH	ccYCHSP	YCHInfli	SPYCHInfli	ccYCHInfli	ccYCHInfliSP
YCH	1							
SPYCH	0.98	1						
ccYCH	0.98	0.97	1					
ccYCHSP	0.96	0.98	0.98	1				
YCHInfli	0.98	0.96	0.97	0.95	1			
SPYCHInfli	0.96	0.98	0.95	0.96	0.98	1		
ccYCHInfli	0.96	0.95	0.98	0.96	0.98	0.97	1	
ccYCHInfliSP	0.94	0.96	0.96	0.98	0.96	0.98	0.98	1
IHInfli	0.95	0.94	0.95	0.93	0.97	0.95	0.96	0.94
SPIHInfli	0.93	0.95	0.93	0.94	0.95	0.97	0.95	0.96
ccIHInfli	0.94	0.93	0.96	0.94	0.96	0.94	0.98	0.96
ccIHInfliSP	0.92	0.94	0.94	0.95	0.94	0.95	0.96	0.97
Infli	0.92	0.91	0.91	0.89	0.94	0.93	0.93	0.91
SPInfli	0.92	0.95	0.93	0.93	0.95	0.96	0.94	0.94
ccInfli	0.91	0.90	0.93	0.91	0.94	0.92	0.95	0.93
ccInfliSP	0.91	0.93	0.93	0.94	0.93	0.94	0.95	0.96
	IHInfli	SPIHInfli	ccIHInfli	ccIHInfliSP	Infli	SPInfli	ccInfli	ccInfliSP
IHInfli	1							
SPIHInfli	0.98	1						
ccIHInfli	0.99	0.97	1					
ccIHInfliSP	0.97	0.99	0.98	1				
Infli	0.94	0.93	0.93	0.91	1			
SPInfli	0.94	0.96	0.94	0.95	0.96	1		
ccInfli	0.94	0.93	0.96	0.94	0.97	0.96	1	
ccInfliSP	0.93	0.95	0.95	0.96	0.95	0.98	0.97	1

Each value from the table reports the cross-correlation between an unanticipated productivity shock from a specific model setting.

Table 4: Cross-correlations between news shocks obtained in various model settings.

	Model Settings							
MRI	YCH	SPYCH	ccYCH	ccYCHSP	YCHInfli	SPYCHInfli	ccYCHInfli	ccYCHInfliSP
YCH	1							
SPYCH	0.82	1						
ccYCH	0.39	0.47	1					
ccYCHSP	0.40	0.54	0.97	1				
YCHInfli	0.65	0.58	0.26	0.27	1			
SPYCHInfli	0.65	0.73	0.32	0.36	0.95	1		
ccYCHInfli	0.28	0.40	0.85	0.82	0.52	0.54	1	
ccYCHInfliSP	0.38	0.55	0.85	0.87	0.54	0.62	0.96	1
IHInfli	0.35	0.32	0.17	0.17	0.87	0.80	0.50	0.48
SPIHInfli	0.37	0.49	0.24	0.26	0.84	0.87	0.54	0.57
ccIHInfli	0.03	0.17	0.61	0.58	0.52	0.50	0.89	0.82
ccIHInfliSP	0.13	0.32	0.64	0.64	0.55	0.59	0.89	0.88
Infli	-0.03	0.03	0.01	0.02	0.59	0.56	0.35	0.32
SPInfli	0.27	0.55	0.32	0.34	0.53	0.66	0.46	0.55
ccInfli	0.00	0.15	0.55	0.53	0.49	0.48	0.85	0.78
ccInfliSP	0.20	0.46	0.69	0.69	0.48	0.58	0.84	0.88
SRI								
SPYCH	0.25	0.69	0.41	0.42	0.21	0.40	0.40	0.49
ccYCH	0.25	0.36	0.94	0.90	0.16	0.22	0.82	0.82
SPYCHInfli	0.24	0.66	0.40	0.40	0.23	0.43	0.43	0.52
ccYCHInfli	0.20	0.32	0.89	0.85	0.18	0.24	0.85	0.85
SPIHInfli	0.25	0.66	0.39	0.40	0.23	0.42	0.43	0.51
ccIHInfli	0.19	0.31	0.87	0.83	0.17	0.24	0.84	0.84
SPInfli	0.24	0.66	0.38	0.39	0.22	0.42	0.42	0.51
ccInfli	0.18	0.30	0.88	0.83	0.16	0.22	0.83	0.83

Each value from the table reports the cross-correlation between a news shock from a specific model setting and identification scheme.

Table 5: Cross-correlations between news shocks obtained in various model settings.

	Model Settings							
MRI	IHInfli	SPIHInfli	ccIHInfli	ccIHInfliSP	Infli	SPInfli	ccInfli	ccInfliSP
IHInfli	1							
SPIHInfli	0.95	1						
ccIHInfli	0.67	0.69	1					
ccIHInfliSP	0.67	0.74	0.97	1				
Infli	0.76	0.76	0.60	0.58	1			
SPInfli	0.54	0.74	0.50	0.62	0.64	1		
ccInfli	0.63	0.66	0.96	0.93	0.66	0.52	1	
ccInfliSP	0.53	0.68	0.83	0.92	0.51	0.80	0.84	1
SRI								
SPYCH	0.14	0.38	0.29	0.41	0.07	0.69	0.30	0.62
ccYCH	0.13	0.21	0.63	0.69	-0.02	0.30	0.59	0.73
SPYCHInfli	0.17	0.41	0.34	0.46	0.11	0.74	0.35	0.67
ccYCHInfli	0.17	0.25	0.66	0.73	0.01	0.33	0.64	0.76
SPIHInfli	0.17	0.42	0.34	0.46	0.11	0.75	0.35	0.67
ccIHInfli	0.16	0.24	0.67	0.73	-0.02	0.32	0.63	0.76
SPInfli	0.16	0.41	0.33	0.46	0.12	0.77	0.35	0.68
ccInfli	0.14	0.22	0.66	0.72	-0.03	0.32	0.61	0.77
SRI	SPYCH	ccYCH	SPYCHInfli	ccYCHInfli	SPIHInfli	ccIHInfli	SPInfli	ccInfli
SPYCH	1							
ccYCH	0.42	1						
SPYCHInfli	0.94	0.41	1					
ccYCHInfli	0.39	0.96	0.43	1				
SPIHInfli	0.94	0.41	0.99	0.43	1			
ccIHInfli	0.39	0.94	0.42	0.99	0.43	1		
SPInfli	0.94	0.40	0.98	0.42	0.99	0.42	1	
ccInfli	0.38	0.94	0.42	0.97	0.42	0.98	0.42	1

Each value from the table reports the cross-correlation between a news shock from a specific model setting and identification scheme.

D Cross-Correlations between Shocks from Settings Used in the Literature

Table 6: Cross-correlations between unanticipated productivity shocks identified in the literature.

	Model Settings								
	2BP	4BP2	4BS	4KS	5BNW	7BNW	7BS	8KS	9
2BP	1.00								
4BP2	0.97	1.00							
4BS	0.93	0.96	1.00						
4KS	0.93	0.96	0.97	1.00					
5BNW	0.97	0.98	0.96	0.97	1.00				
7BNW	0.93	0.95	0.95	0.92	0.96	1.00			
7BS	0.93	0.95	0.95	0.95	0.94	0.94	1.00		
8KS	0.91	0.94	0.93	0.93	0.94	0.98	0.95	1.00	
9	0.90	0.92	0.92	0.92	0.93	0.97	0.97	0.99	1

Each value from the table reports the cross-correlation between an unanticipated productivity shock from a specific model setting.

Table 7: Cross-correlations between news shocks identified in the literature (MRI).

	Model Settings								
	2BP	4BP2	4BS	4KS	5BNW	7BNW	7BS	8KS	9
2BP	1								
4BP2	0.68	1							
4BS	0.22	0.79	1						
4KS	0.20	0.59	0.64	1					
5BNW	0.46	0.67	0.46	0.51	1				
7BNW	0.46	0.72	0.65	0.41	0.78	1			
7BS	0.44	0.49	0.40	0.30	0.19	0.41	1		
8KS	0.41	0.67	0.61	0.57	0.69	0.93	0.46	1	
9	0.47	0.49	0.35	0.26	0.46	0.63	0.88	0.63	1

Each value from the table reports the cross-correlation between a news shock from a specific model setting identified with the medium-run identification scheme.