Essays on Productivity, Technological Change, and Economic Fluctuations

Maria Bolboaca

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To my mother, Elena, who always knew.

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Contents

Introduction

The real business cycle (RBC) theory of Kydland and Prescott (1982) initiated *a revolution in macroeconomics, a transformation in methodology that has reshaped how we conduct our science*.[1] The RBC revolutionary ideas[2] led to a major scientific debate within the field.[3] The controversial aspect of the RBC theory, which I address in this thesis, is the central role attributed to technology shocks in driving business fluctuations.

The technology shock of the RBC literature is defined as an unanticipated persistent shock on a measure of technological change, i.e. total factor productivity (TFP). The most popular estimate of TFP is the Solow residual, which is the difference between changes in output and changes in the production factors, weighted by the share of each factor in the production function. This measure, as explained by Solow (1957), does not capture only technologies, but includes *any kind of shift in the production function*. For this reason, the Solow residual received its moniker as 'measure of our ignorance'. 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. The macroeconomic literature considers this series more useful, and a more accurate measure of TFP than the Solow residual. Nevertheless, this corrected measure of TFP neither captures only technological change.

Moreover, studies that take a more microeconomic perspective of technological progress observe that there is a considerable time lag between the invention of new technologies, and their adoption in production at such a large scale that the diffusion is reflected in measures of aggregate productivity. For example, Eden and Nguyen (2016) show that in the US the adoption lag is about twenty years for technologies invented in the last two centuries. This implies that the technology shock defined in the RBC literature can be thought of as an unexpected improvement in productivity triggered by sudden changes in regulations or management practices that promote more production, but not by technological innovation. For this reason, throughout this thesis, this shock is named the unanticipated productivity shock.

The controversy related to the unanticipated productivity shock does not only concern its content, but also its effects on the economy. An important result of the RBC literature is that unanticipated productivity shocks are pro-cyclical, meaning that they lead to the comovement in macroeconomic aggregates observed in the data. However, empirical findings suggest that positive unanticipated productivity shocks lead to a fall in employment. Furthermore, they raise doubts about the central role attributed to these shocks in driving economic fluctuations.[4]

[1] For details, see Prescott (2006).

[2] See Rebelo (2005) for a discussion of the revolutionary ideas that the RBC theory introduced.

[3] See De Vroey (2016) for a discussion of the RBC controversies.

[4] See 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.

The unanticipated productivity shock seems neither a technology shock, nor an important driver of aggregate fluctuations. This opens the possibility of using other approaches to identify technology shocks, and to measure the impact of technological change on economic activity. One option is to apply identification schemes in structural autoregressive models to identify technology shocks from macroeconomic data. For example, Beaudry and Portier (2004), and Beaudry and Portier (2006) show that mere news about major innovations, such as information and communication technologies (ITC), may lead to business cycle fluctuations. The idea is that technologies need time to diffuse or materialize, and eventually increase aggregate productivity. However, agents acknowledge the changes in future economic prospects when the news arrives, and they adapt their behavior ahead of them. This can lead to a boom in both consumption and investment, which precedes the growth in productivity. The anticipated productivity (news) shock is usually defined in the literature as being a shock with no impact effect on productivity, which explains most of the variation in TFP after some years. This definition of the news shock is close to what is expected from a technology shock, i.e. to have no significant short-run effect on TFP given the slow diffusion of the technology, but to be a major source of fluctuations in productivity in the medium- and long-run. Beaudry and Portier (2006) find that news shocks lead to the comovement of macro aggregates, and are an important source of business cycle fluctuations. However, Barsky and Sims (2011), and Kurmann and Sims (2017) report contradictory results, as they show that news about technological improvements are contractionary on impact.

The second option to identify technology shocks is to use direct measures of technological change in the empirical analysis. Two recent proposals of such measures were made by Alexopoulos (2011), and Baron and Schmidt (2017). Alexopoulos (2011) uses new book titles in the category technology as proxy for the adoption of technological innovations. She finds that technology shocks identified using the book-based indicators are an important source of economic fluctuations. Moreover, she shows that TFP, investment, and labor increase following a technology shock. Baron and Schmidt (2017) use an indicator based on the counts of standards in the category ICT (and electronics). They claim that standardization precedes the implementation of new technologies and signals future productivity gains. This makes the technology shock identified using the standards-based indicator conceptually very similar to an anticipated productivity (news) shock. Baron and Schmidt (2017) find that TFP, output, and investment have an S-shaped response to a technology shock, which indicates that new technologies diffuse slowly, but have significant medium- and long-run effects on macroeconomic variables. They also show that forward looking variables respond on impact to technology shocks, which is in line with the predictions of the news literature.

The papers included in this thesis contribute to the macroeconomic literature by addressing several topical questions related to the causes and effects of fluctuations in productivity. In particular, they highlight the role played by technological change in shaping the economy, both directly through the diffusion of new technologies in production, and indirectly through the changes it triggers in agents' expectations about future economic outlook.

The first chapter of this thesis addresses the lack of consensus in the empirical literature regarding the effects of news shocks. In this paper, titled **"Unraveling News: Reconciling Conflicting Evidence"**, together with Sarah Fischer, we contribute to the debate with an extensive analysis of variable settings and identification schemes, and shed some light on the minimal information that is necessary for the identification of a news shock. We show that the news shock depends critically on the applied identification scheme. We compare the news shock to an unanticipated productivity shock, and find that some methods identify a news shock that is in fact a mixture of the two. 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 type of productivity series may influence results. Our conclusion is that robust news shocks have expansionary properties.

In the second chapter, titled **"The Impact of Technological Change"**, I combine the approaches presented before to show which of three shocks plays a more important role for driving macroeconomic fluctuations: the unanticipated productivity shock, the technology shock, or the news shock. My findings indicate that the two technological change indicators I described previously can be used interchangeably as they give similar results. Moreover, I show that news shocks play a more important role than technology shocks at business cycle frequencies, while in the medium- to long-run technology shocks take the lead. Unanticipated productivity shocks do not seem to be a significant source of aggregate fluctuations, regardless of the forecast horizon considered.

The third chapter, titled **"News as slow diffusing technology"**, joint work with Sarah Fischer, proposes a theoretical model to explain the evolution of productivity following unanticipated productivity and news shocks. The model predictions match the empirical results of both unanticipated productivity and news shocks qualitatively. The key ingredient for obtaining these results is the introduction of an endogenous technology adoption mechanism in a standard RBC model with real frictions. Intuitively, through this mechanism, we assume that the technology frontier evolves exogenously, but the production economy needs to engage in a costly adoption process in order to reap the benefits of using newly developed technologies.

The last chapter of my thesis, titled **"News shocks: Different Effects in Boom and Recession?"**, is an empirical paper written also with Sarah Fischer. In this paper we ask whether news about future changes in productivity affect the economy in a different way in booms than in recessions. We find that good news have a smaller effect on economic activity in a recession than in a boom. But what is more intriguing is that good news increase the probability of the economy escaping a recession by about five percentage points and this is a much stronger increase than in the probability of an economy continuing booming if the news comes in an expansion. This paper contributes to the literature in the following ways. First, there are several methodological contributions, in particular the introduction of the medium-run identification scheme into a nonlinear vector autoregressive model. From a theoretical point of view, the fact of having news increasing the probability of exiting a recession has implications for theory. In particular, models should take into account that good news are more effective in recession.

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Chapter 1

Unraveling News: Reconciling Conflicting Evidence

Maria Bolboaca and Sarah Fischer

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.

1.1 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 scheme[2] 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, 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

[1] See 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.

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

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 pe-

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

riod 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.

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

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

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 1.3, we explain the different identification schemes. Section 1.4 then gives an overview of the data while Section 1.5 contains an extensive analysis of news shocks and unanticipated productivity shocks. In Section 1.6 we conclude.

1.2 Methodology

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

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \epsilon_t \tag{1.1}$$

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 (1.1) 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.

1.3 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.

1.3.1 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

[5] Kilian 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.

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

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.

$$\begin{pmatrix} Unanticipated\ Productivity\ Shock_t \\ News\ Shock_t \end{pmatrix} = A^{-1}\epsilon_t = \begin{pmatrix} * & 0 \\ * & * \end{pmatrix} \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \tag{1.2}$$

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 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.

1.3.2 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.

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

$$Y_{t+h} - \mathbb{P}_{t-1} Y_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A} D u_{t+h-\tau} \tag{1.3}$$

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

$$\Xi_{j,i}(h) = \frac{e_j' \left(\sum_{\tau=0}^{h} B_\tau \tilde{A} D e_i e_i' \tilde{D}' A' B_\tau' \right) e_j}{e_j' \left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau' \right) e_j} = \frac{\sum_{\tau=0}^{h} B_{j,\tau} \tilde{A} \gamma_i \gamma_i' \tilde{A}' B_{j,\tau}'}{\sum_{\tau=0}^{h} B_{j,\tau} \Sigma B_{j,\tau}'} \tag{1.4}$$

where e_i denote selection vectors with the ith place equal to 1 and zeros elsewhere. The selection vectors inside the parentheses in the numerator pick out the ith column of D, which will be denoted by γ_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 jth 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:

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

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

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.

1.3.4 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.

1.3.5 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.

1.4 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 Reverse 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.

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

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 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.

1.4.1 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) 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.

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

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

TFP Vintages

In Table 1.1 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 Sims[11] 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 1.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 1.1: 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 1.1, 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 correlated with any of the series. But while its correlation coefficient is 0.75 with TFP07 and 0.59 with TFP13, the correlation dropps 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

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

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

[13] For 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).

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.

1.5 Discussion

1.5.1 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 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.

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

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

We look at four variable settings to which we add a combination of SP and cc. The variable combinations are: YCH, YCHInfli, IHInfli and Infli. 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 1.3, Appendix 1.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 YCHInfli(SP,cc), which is 0.98.

In Tables 1.4 and 1.5, Appendix 1.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 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 ccYCHInfli(SP). The strongest correlations are found between ccIHinfli(SP) and ccInfli(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 YCHInfli(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 Infli is almost zero. By adding stock prices to Infli, 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 ccYCHInfli(SP), with correlation coefficients of over 0.8. The correlation with the other settings is only about 0.6. The stronger

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

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.

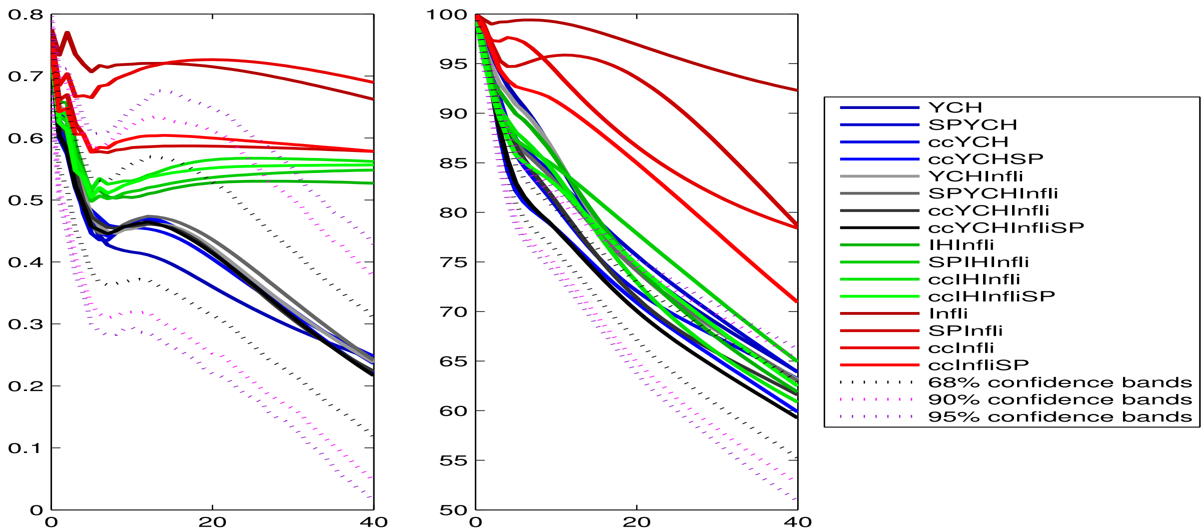

Figure 1.1: The left graph shows impulse response functions of TFP to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by an unanticipated productivity 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 1.1 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.

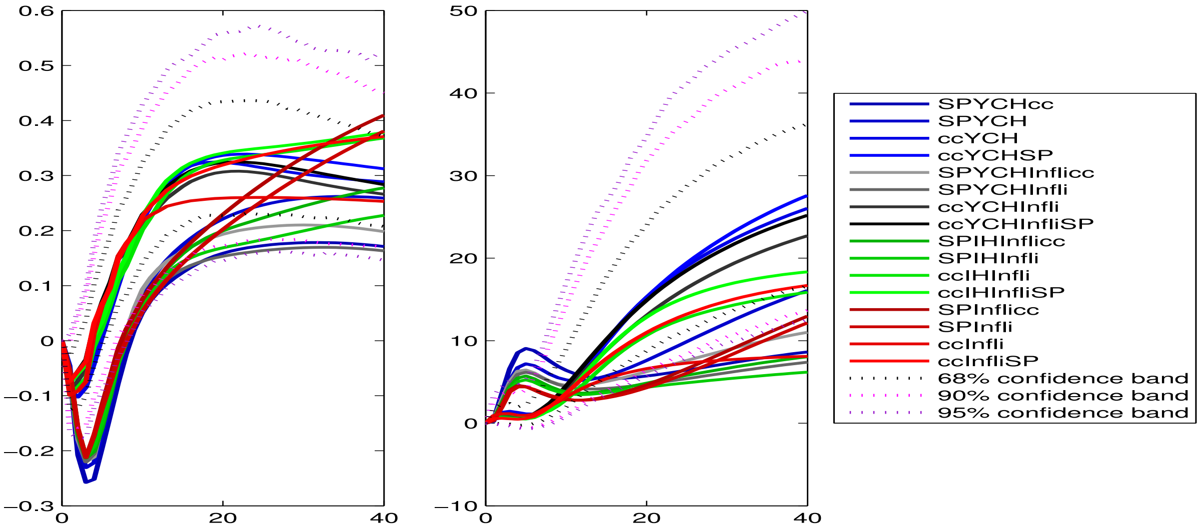

Figure 1.2: The left graph shows impulse response functions of TFP to a news shock identified with SRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified 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 1.2 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.

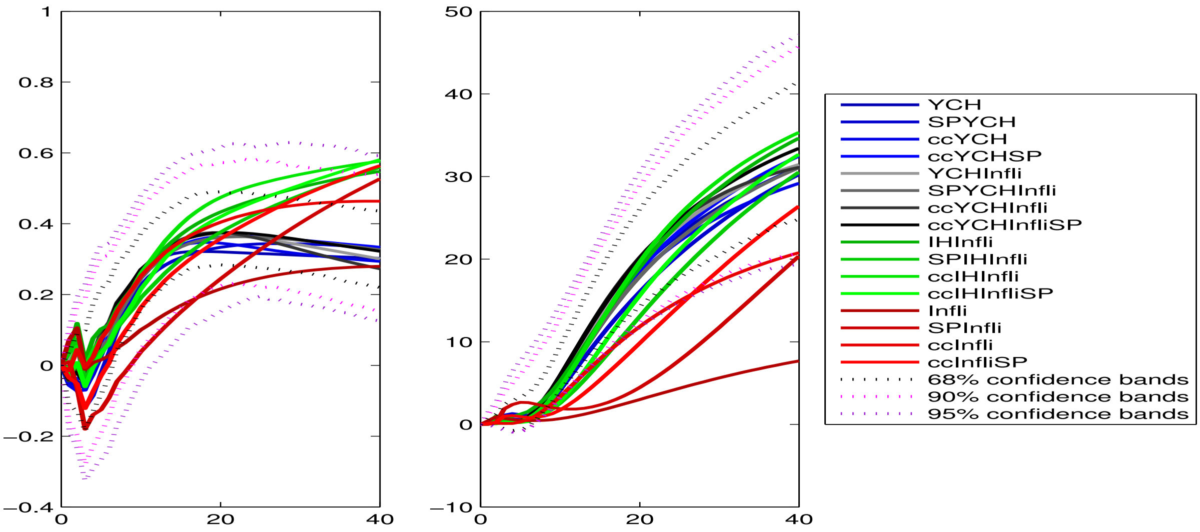

Figure 1.3: The left graph shows impulse response functions of TFP to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations.The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified with 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.

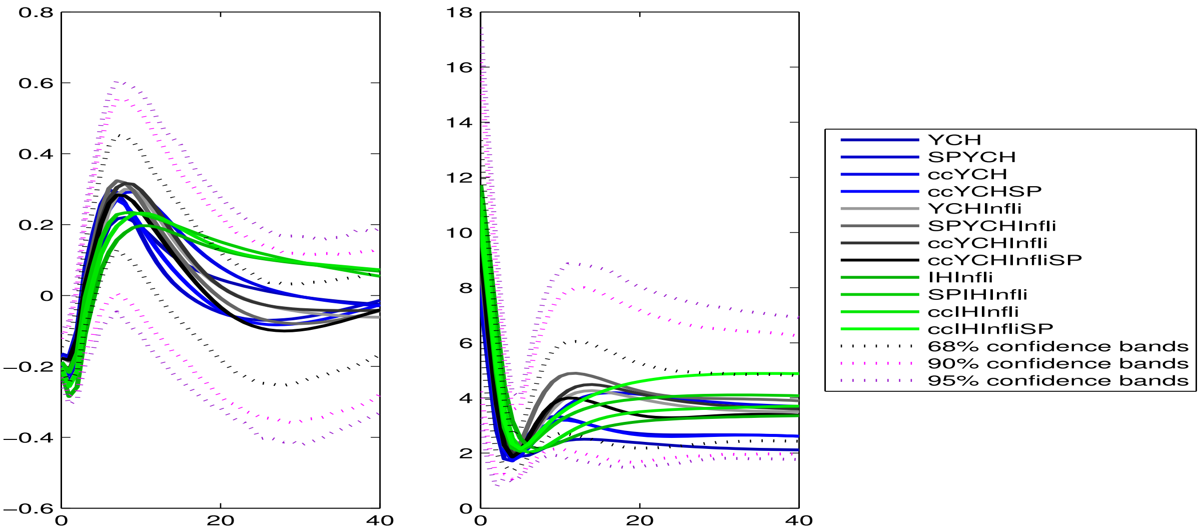

Figure 1.4: The left graph shows impulse response functions of hours worked to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations.The graph on the right shows the share of the forecast error variance of hours worked determined by an unanticipated 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.

As illustrated in Figure 1.3, 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.

In Figure 1.4 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.

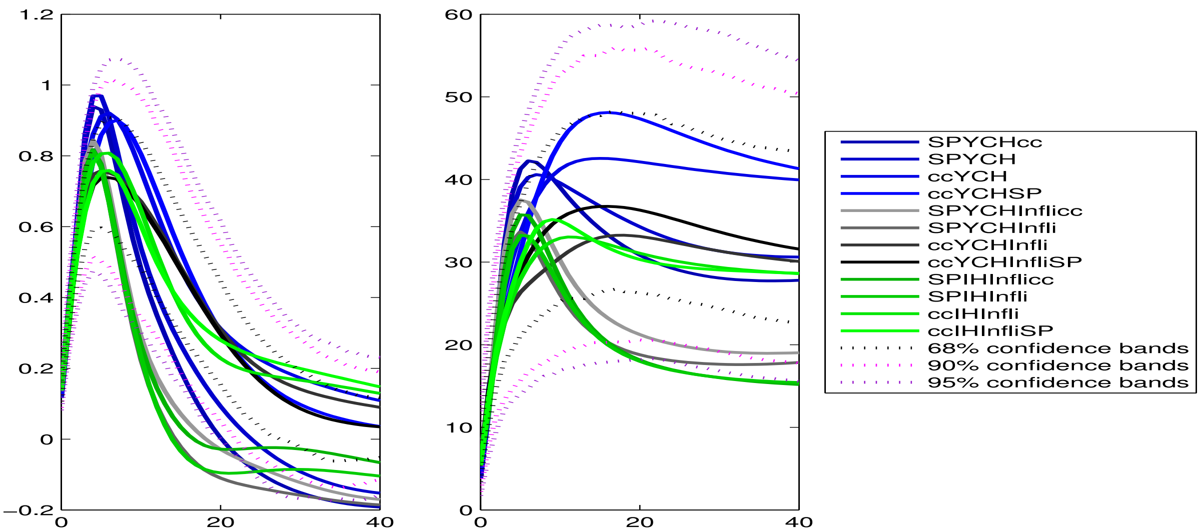

Figure 1.5: The left graph shows impulse response functions of hours worked to a news shock identified with SRI in different variable settings. The vertical axis refers to percentage deviations.The graph on the right shows the share of the forecast error variance of hours worked determined by a news 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 1.5 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.

In Figure 1.6 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.

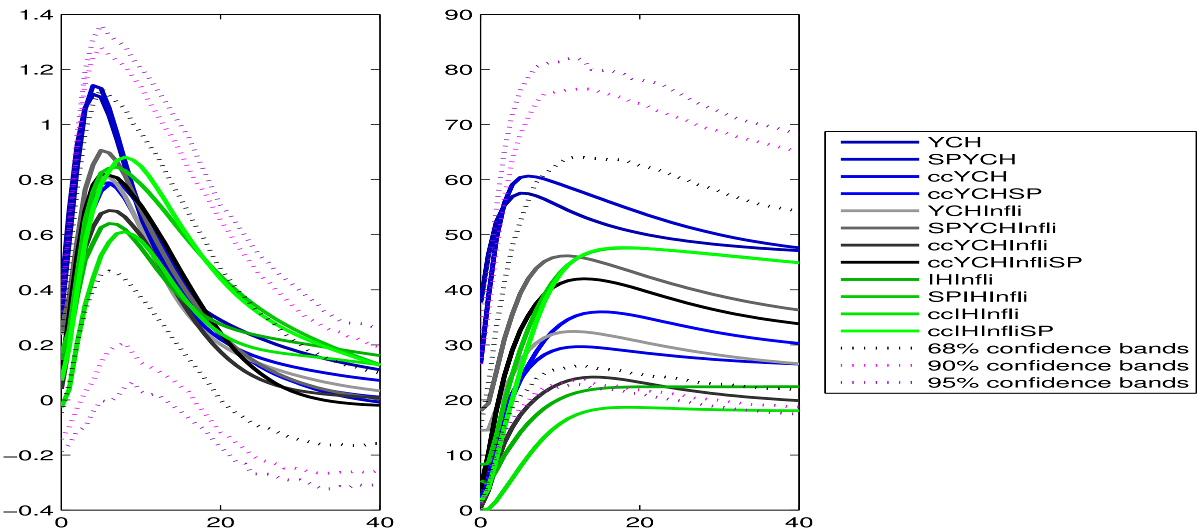

Figure 1.6: The left graph shows impulse response functions of hours worked to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of hours worked determined by a news 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 1.7. 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 1.8. 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.

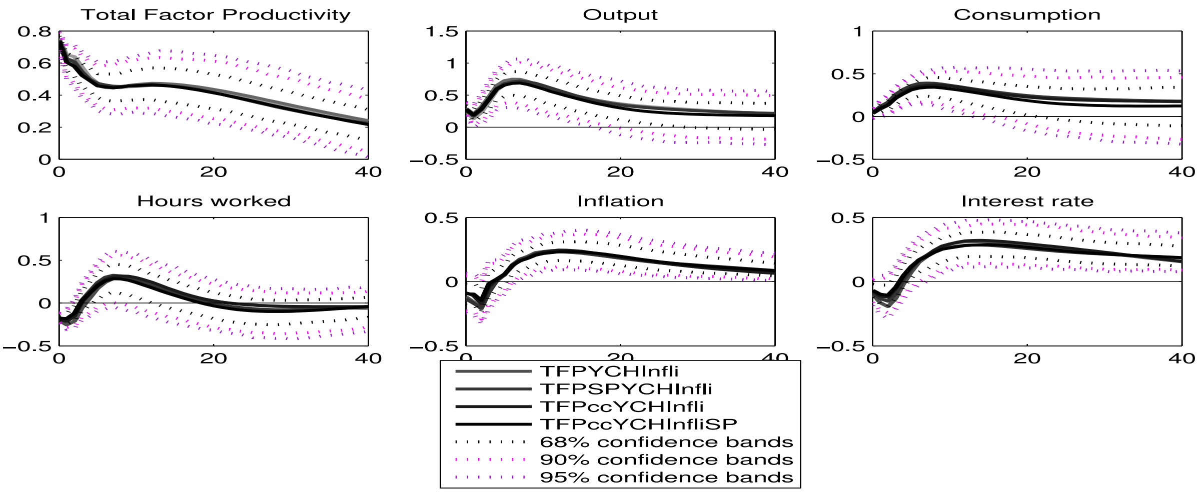

Figure 1.7: The graph shows impulse response functions of all variables to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

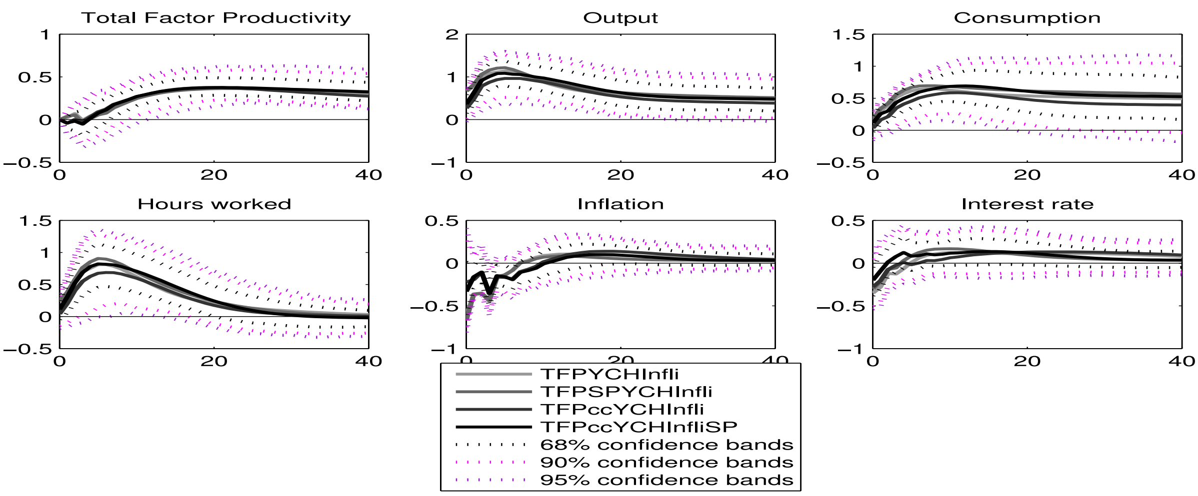

Figure 1.8: The graph shows impulse response functions of all variables to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The horizontal axes indicate the forecast horizons. The dotted lines correspond to the 68%, 90% and 95% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR of the baseline model, ccYCHInfliSP.

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 1.3. For a description of the various model settings consider Appendix 1.B.[17] We will abstract from the short-run identification as it does not deliver any further insights.

In Table 1.6, Appendix 1.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 1.7, Appendix 1.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.

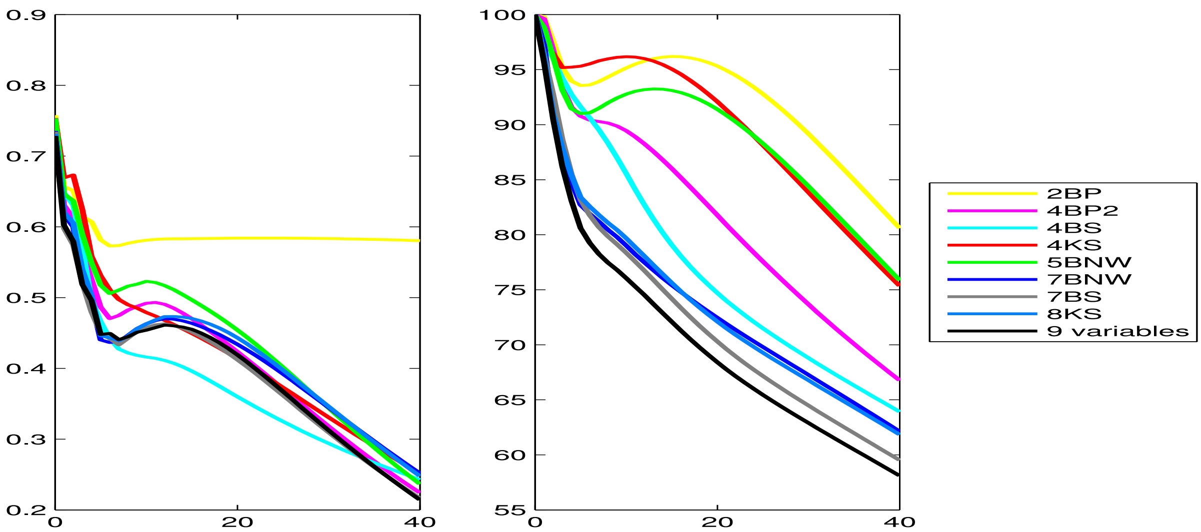

Figure 1.9: The left graph shows impulse response functions of TFP to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by an unanticipated productivity shock in different variable settings.The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons.

Figure 1.9 displays the impulse response functions on the left and the shares of the

[17]The 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 TFPccYCHIInfliSP.

FEV on the right for TFP to an unanticipated productivity shock. The impulse response 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.

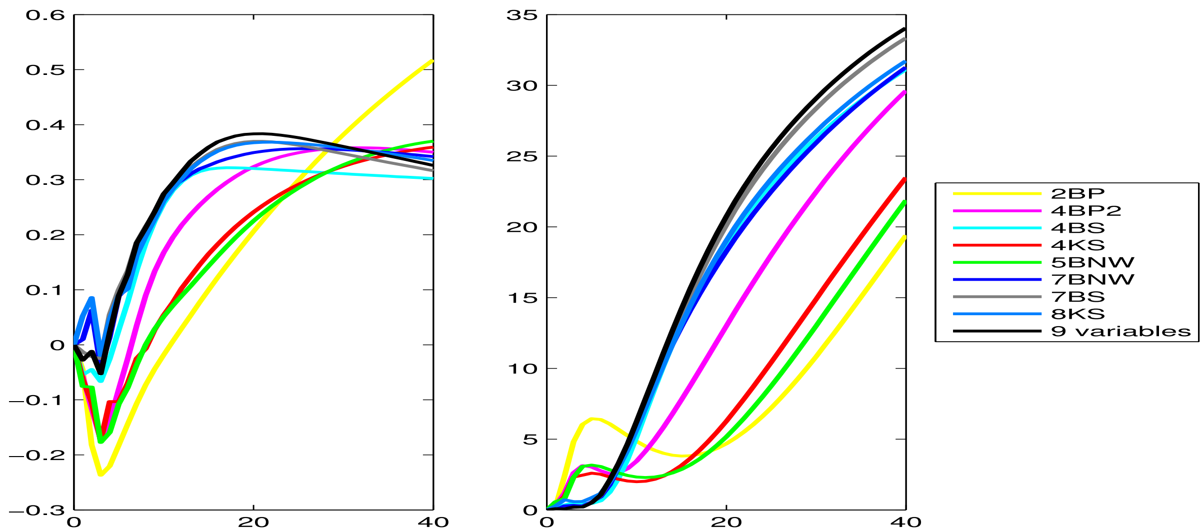

Figure 1.10: The left graph shows impulse response functions of TFP to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified with MRI in different variable settings.The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons.

In Figure 1.10 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.

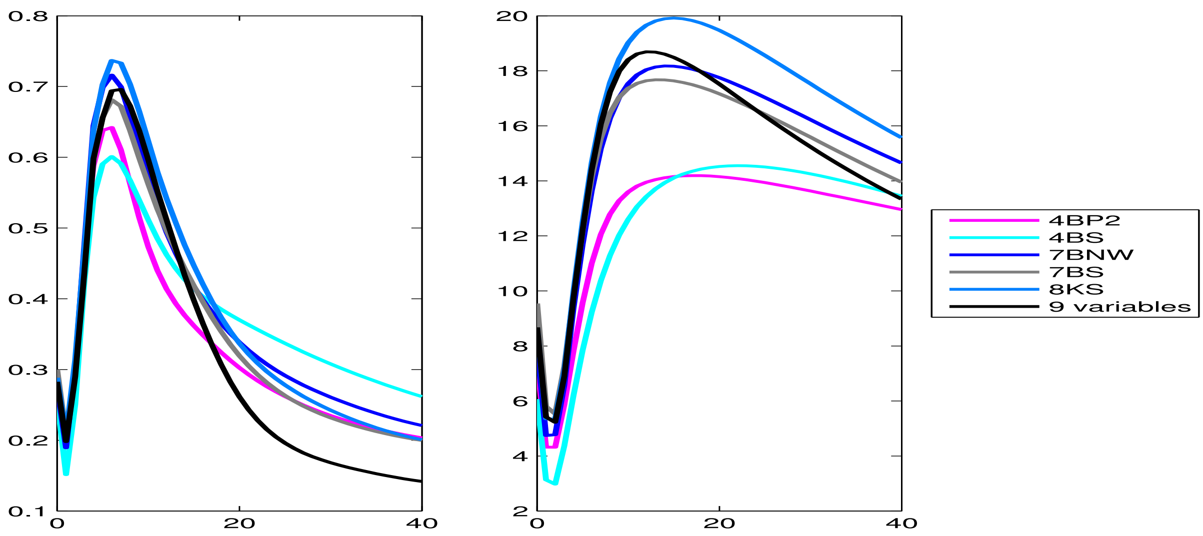

Figure 1.11: The left graph shows impulse response functions of output to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of output determined by an unanticipated productivity shock in different variable settings.The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons.

Figure 1.11 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 1.12 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.

The same exercise could be conducted for further identification schemes, for other

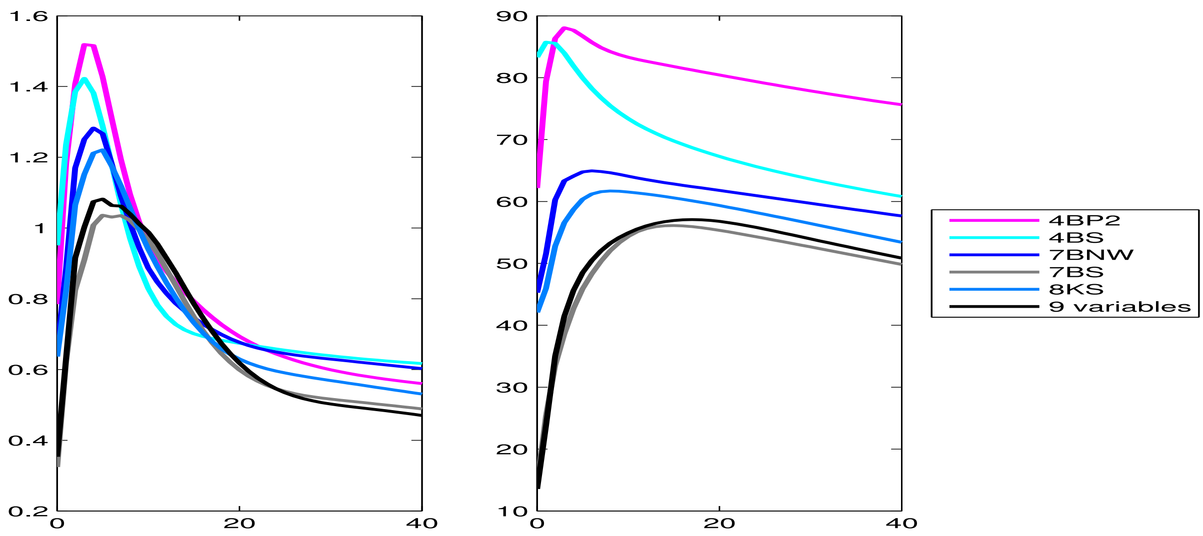

Figure 1.12: The left graph shows impulse response functions of output to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of output determined by a news shock identified with MRI in different variable settings.The vertical axis refers to percentage points. The horizontal axes indicate the forecast horizons.

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.

1.5.2 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 1.13 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.

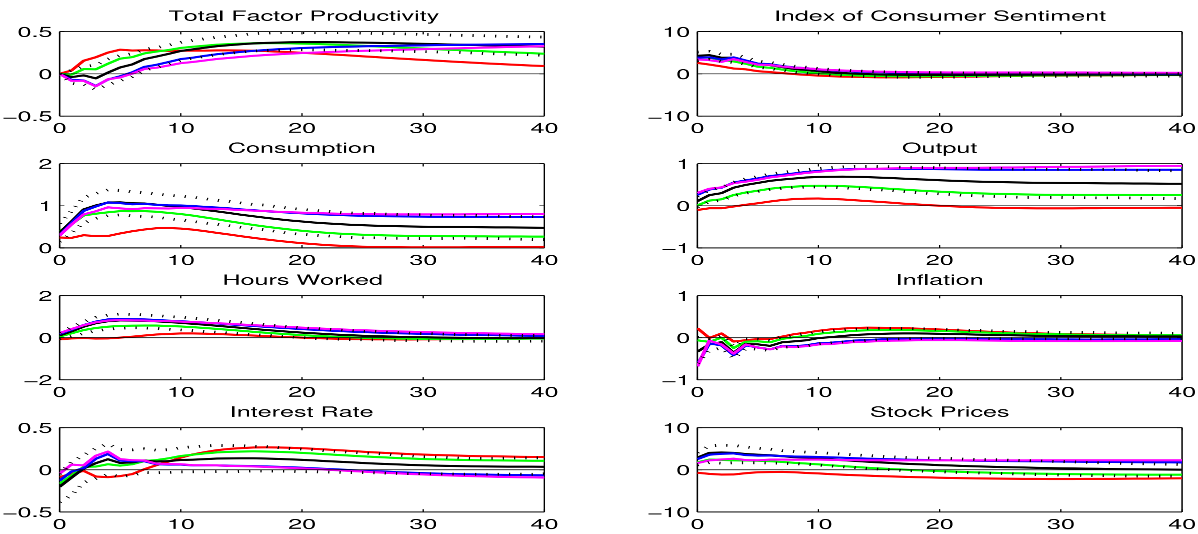

Figure 1.13: IRFs to a news shock identified with MRI maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal 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).

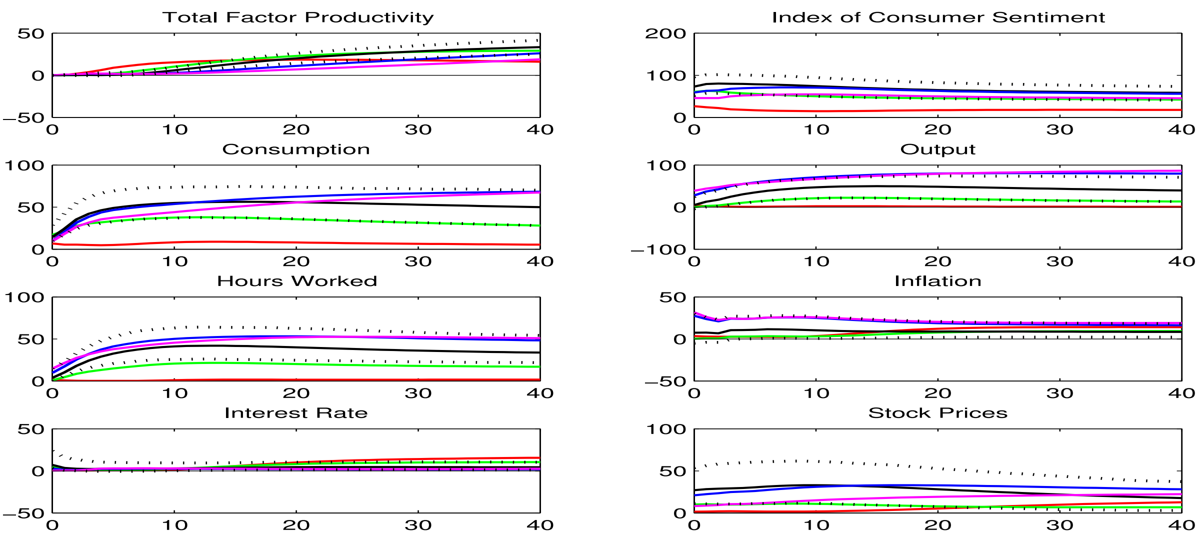

Figure 1.14: Contributions of a news shock identified with MRI maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond 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).

In Figure 1.14 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.

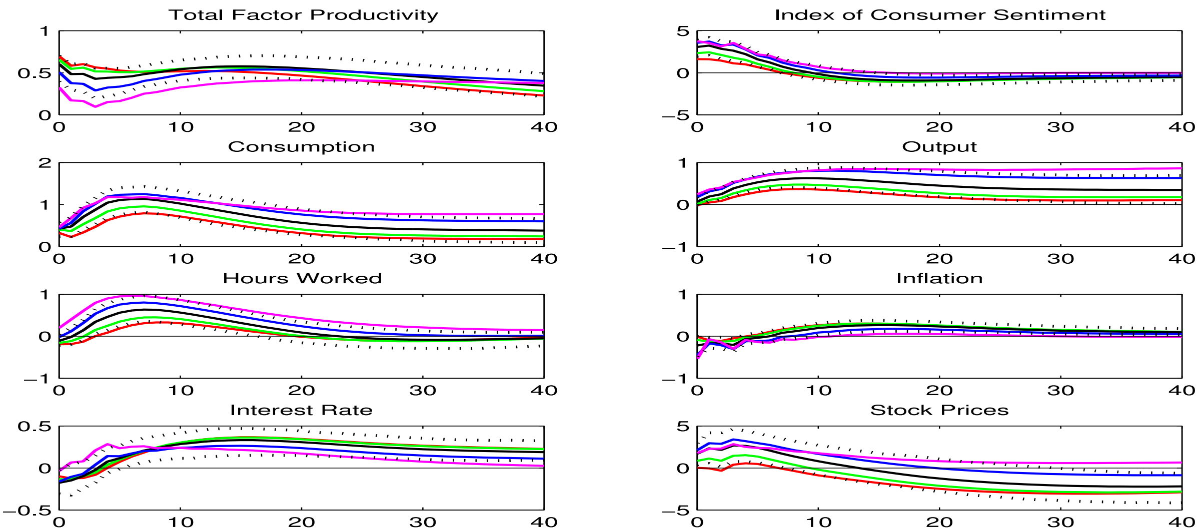

Figure 1.15: IRFs to a news shock identified with KS maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal 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 1.15 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.

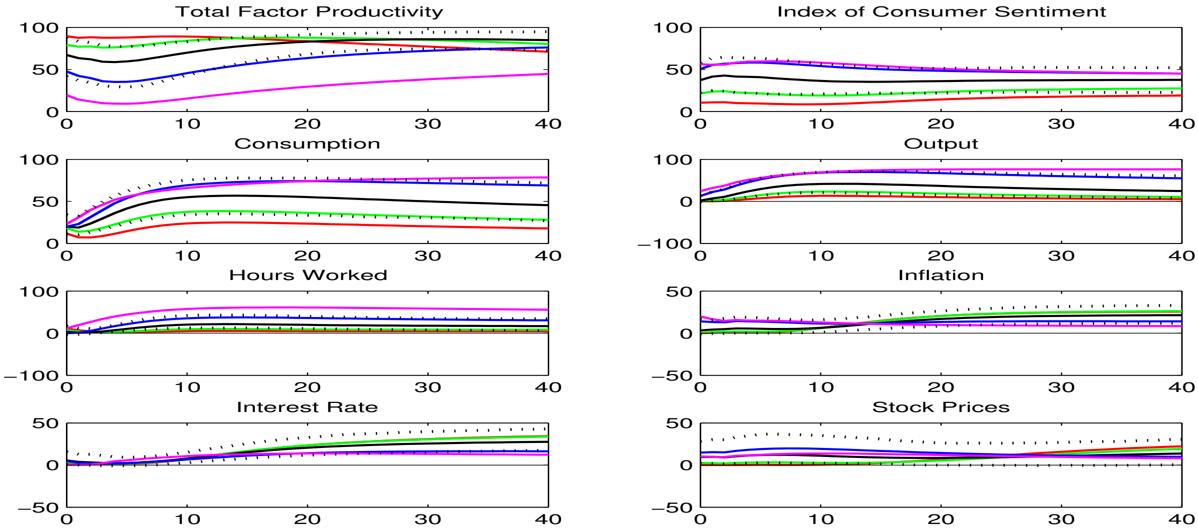

Figure 1.16: Contributions of a news shock identified with KS maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond 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).

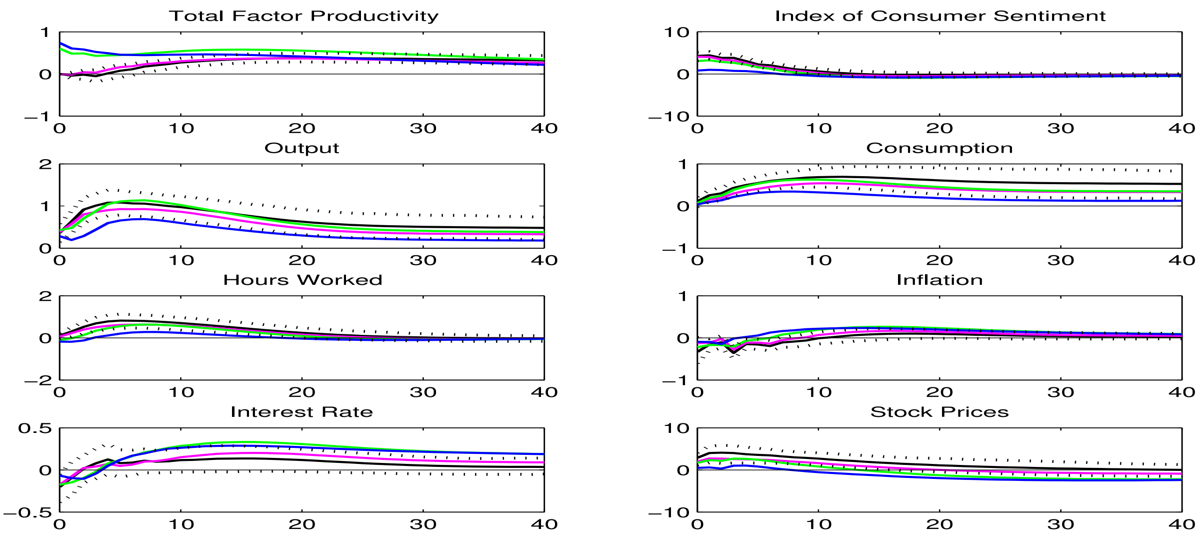

Figure 1.17: Impulse responses to a news shock identified with MRI-KS (green), MRI (black), MRI-BS (blue) with maximization horizon 40 quarters and a news shock obtained with SRI1 (magenta). The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for 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 1.16 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.

In Figure 1.17 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.

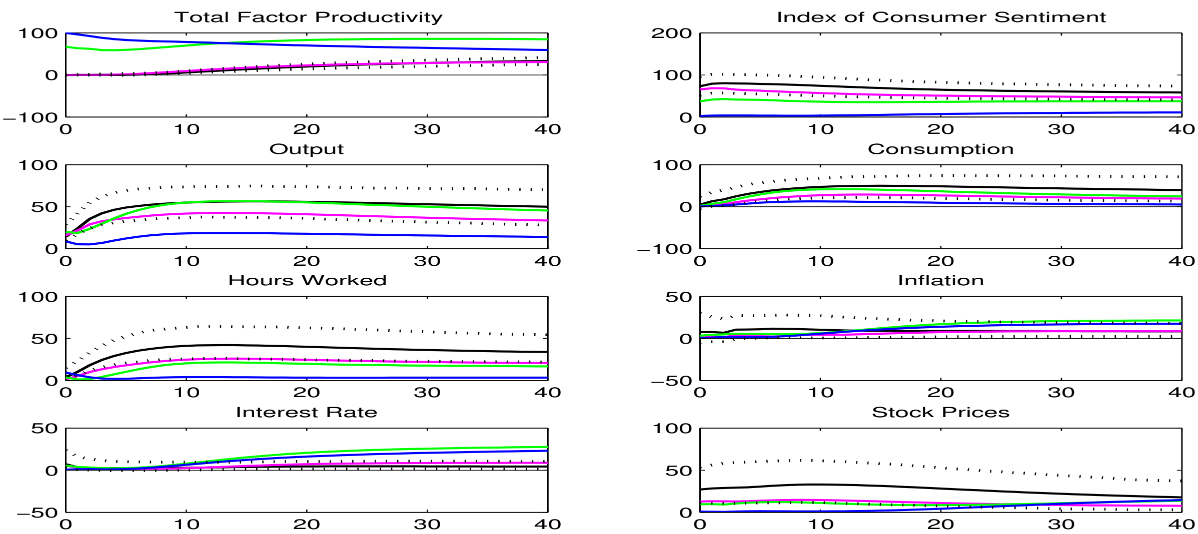

Figure 1.18: Contributions of a news shock identified with KS (green), MRI (black), BS (blue) with maximization horizon 40 quarters and a news shock obtained with SRI1 (magenta). The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines 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 1.18 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.

1.5.3 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.

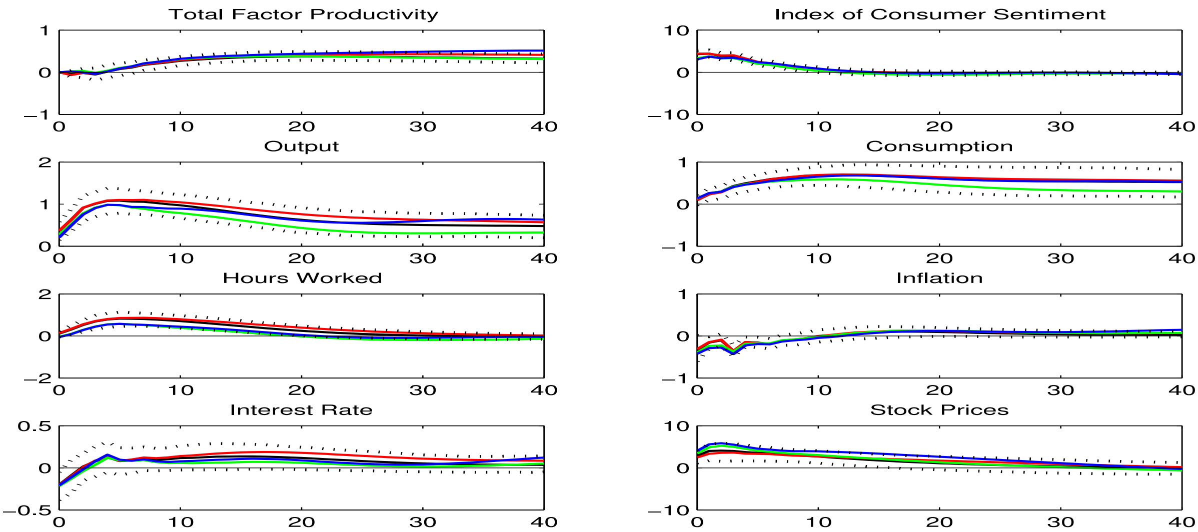

Figure 1.19: Impulse responses to a news shock identified with MRI maximized at 40 quarters, using TFP16 samples until 2000 (green), 2007 (red), 2011 (red), 2014 (black). The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. 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 1.19 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 1.20, 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.

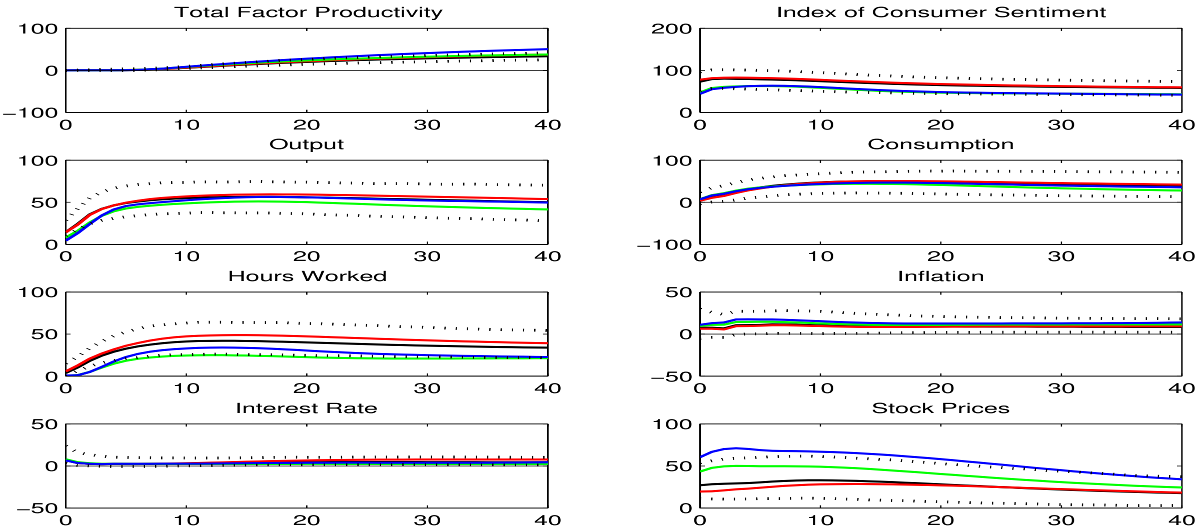

Figure 1.20: Contributions to the forecast error variance of a news shock identified with MRI maximized at 40 quarters, using TFP16 samples until 2000 (green), 2007 (red), 2011 (red), 2014 (black). The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. 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).

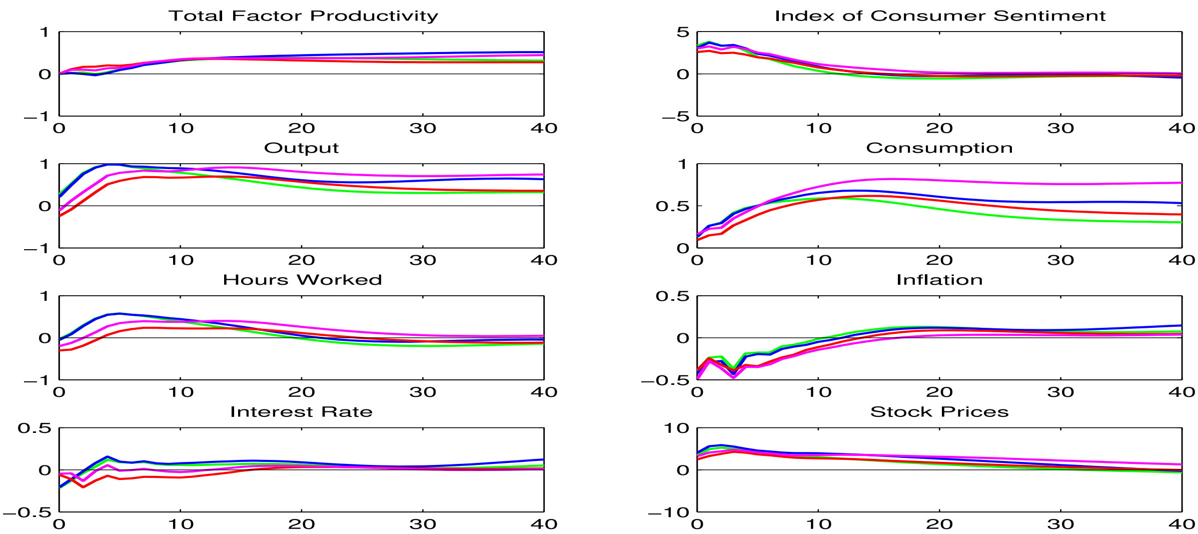

Figure 1.21: Impulse responses to a news shock identified with MRI maximized at horizon 40 quarters using different TFP vintage series and samples: TFP16/2000 (green), TFP16/2007 (red), TFP07/2000 (red), TFP07/2007 (black). The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal axes indicate the forecast horizons in quarters.

The biggest difference in the effects and contributions of a news shock comes from the TFP vintage series employed. In Figure 1.21 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 1.22, indicate that the vintage series definitely lead to the identification of different shocks.

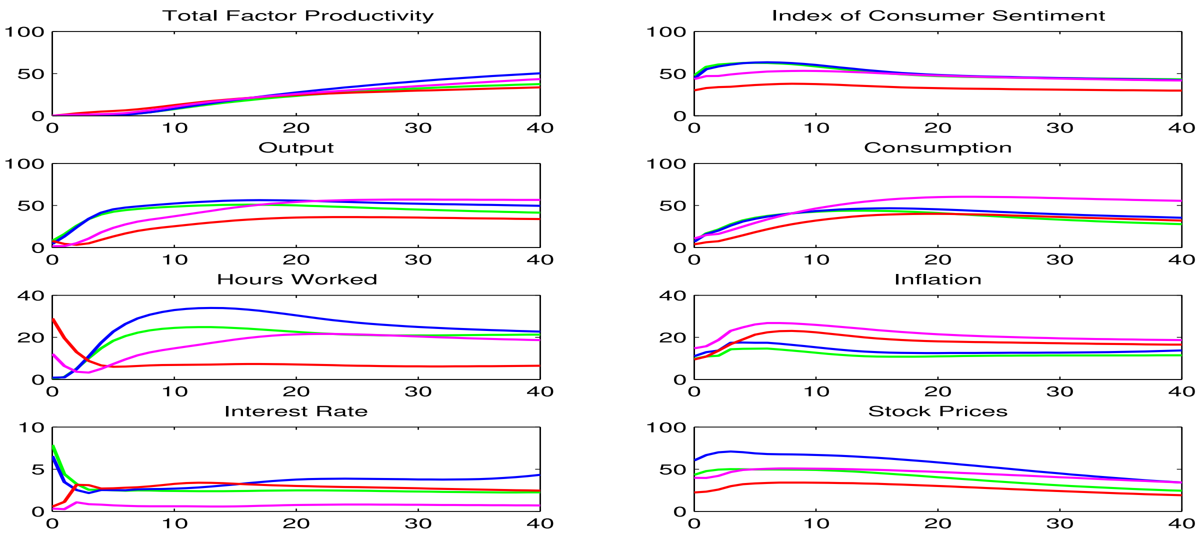

Figure 1.22: Contributions of a news shock identified with MRI maximized at horizon 40 quarters using different TFP vintage series and samples: TFP16/2000 (green), TFP16/2007 (red), TFP07/2000 (red), TFP07/2007 (black).The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters.

1.6 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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Appendix

1.A Data

TFP: log tfp adj. for capacity utilization (from Federal Reverse 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: Nondurable Goods, PCND, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis + Personal Consumption Expenditures: Services, PCESV, Q, sa, U.S. Department of Commerce: Bureau of Economic Analysis; divided by the price deflator and population)

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)

1.B Model Settings

Table 1.2: 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.

1.C Cross-Correlations between Shocks Obtained in Various Settings

Cross-correlations between unanticipated productivity shocks obtained in various settings

Table 1.3:

	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 1.4: 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 1.5: 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.

1.D Cross-Correlations between Shocks from Settings used in the Literature

Table 1.6: 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 1.7: 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.

Chapter 2

The Impact of Technological Change

Maria Bolboaca

Abstract

In this paper I introduce recent measures of technological change, based on counts of books in the field of technology and technological standardization, in an otherwise standard vector autoregressive model, to show the relative importance of unanticipated productivity shocks, technology shocks, and anticipated productivity (news) shocks, in driving macroeconomic fluctuations. The results indicate that news shocks play a more important role than technology shocks at business cycle frequencies, while in the medium- to long-run technology shocks take the lead. Unanticipated productivity shocks do not seem to be a significant source of aggregate fluctuations regardless of the forecast horizon.

2.1 Introduction

The aim of this paper is to contribute to the ongoing debate on the role played by different productivity shocks in driving macroeconomic fluctuations, and in particular to shed some light on the impact of technological change on economic activity.

The macroeconomic literature is far from reaching a consensus on which are the shocks that affect productivity and how important these shocks are for the rest of the economy. Following the reasoning proposed by the real business cycle (RBC) literature, aggregate productivity is affected immediately and permanently only by technology shocks, and these shocks are the main driving force of cyclical fluctuations.[1] However, studies that take a more microeconomic perspective of technological progress observe that there is a considerable time lag between the invention of new technologies and their adoption in production at such a large scale as the diffusion to be reflected in measures of aggregate productivity.[2] Hence, the shock defined in the RBC literature to be the only shock with impact effect on productivity cannot be a technology shock. For this reason, I prefer to further call it an unanticipated productivity shock. Moreover, empirical studies also question the RBC idea that this shock is the main source of macroeconomic fluctuations.[3]

With the unanticipated productivity shock being neither a technology shock, nor an important driver of aggregate fluctuations, other approaches have been taken to identify technology shocks, and to measure the impact of technological change on economic activity. One is to apply identification schemes to identify technology shocks from macroeconomic data. For example, Beaudry and Portier (2004), and Beaudry and Portier (2006), state that, while technologies need time to diffuse and increase aggregate productivity, economic agents receive news about them early on. This information about future potential productivity gains encourages them to respond immediately in order to be among the first to benefit from the adoption of the new technologies. The coordination of agents' actions may lead to an increase in consumption and investment, and consequently in output, in anticipation of the change in productivity determined by technological innovations. On these premises, Beaudry and Portier (2006) impose short-run restrictions in a vector autoregressive model to identify an anticipated productivity (news) shock. They define the news shock to be the shock with no impact effect on productivity, which has immediate effect on a forward looking variable. The idea is that forward looking variables, such as stock prices, or measures of consumer (business) confidence, capture the news about emerging technologies that potentially increase future productivity. They find that the news shock has no short-run effect on productivity, but afterwards it leads to a permanent increase in total factor productivity (TFP). In this respect, the news shock seems to match the slow diffusion of new technologies in productivity as indicated by micro studies. Moreover, Beaudry and Portier (2006) show that news shocks drive business cycle fluctuations. Barsky and Sims (2011), and Beaudry et al. (2011), propose the use of medium-run restrictions as an alternative method to identify news shocks. The definition of Beaudry et al. (2011) is that the news shock is the shock orthogonal to contemporaneous TFP movements that contributes the most to TFP's forecast error

[1] For details, see Kydland and Prescott (1982).

[2] Eden and Nguyen (2016) show that in the US the adoption lag is about twenty years for the technologies invented in the last two centuries, and that in the recent years technologies have been adopted faster than in the past.

[3] See 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.

variance (FEV) at a finite medium-run horizon. This definition of the news shock is even closer to what is expected from a technology shock, i.e. to have no significant short-run effect on TFP given the slow diffusion of the technology, but to be a major source of fluctuations in productivity in the medium- and long-run. The findings of Beaudry et al. (2011) are similar to those of Beaudry and Portier (2006).[4]

The results reported in the empirical news literature have the drawback of being highly dependent on the identification schemes employed. Consequently, another approach proposed is the use of direct measures of technological change in the empirical analysis. Some earlier proposals of indicators were the number of patents, or data on R&D expenditures. However, as shown in Baron and Schmidt (2017), these are proxies for inventive activities, which may or may not translate into new technologies. The reason is that at the time of invention it is hard to predict the future use, profitability, or commercialization date of products using the new technology. In the recent years, two new proxies were proposed. The first was made by Alexopoulos (2011), who uses new book titles in the category technology as proxy for the adoption of technological innovations. She finds that technology shocks identified using the book-based indicators are an important source of economic fluctuations. Moreover, she shows that TFP, investment, and labor increase following a technology shock. The second proposal belongs to Baron and Schmidt (2017), and is an indicator based on the counts of standards in the categories information and communication technologies (ICT), and electronics. Baron and Schmidt (2017) claim that standardization precedes the implementation of new technologies and signals future productivity gains. This makes the technology shock identified using the standards-based indicator conceptually very similar to an anticipated productivity (news) shock, as defined in the empirical news literature. Baron and Schmidt (2017) find that TFP, output, and investment have an S-shaped response to a technology shock, which indicates that new technologies diffuse slowly, but have significant medium- and long-run effects on macroeconomic variables. They also show that forward looking variables respond on impact to technology shocks, which is in line with the predictions of the news literature.

In this paper, I take an empirical approach to investigate which of these three shocks plays a more important role in driving macroeconomic fluctuations: the unanticipated productivity shock, the technology shock, or the anticipated productivity (news) shock. The unanticipated productivity shock is the only shock with impact effect on aggregate productivity. The technology shock is the shock on the measure of technological change that has no impact effect on TFP. The news shock is the shock on the index of consumer sentiment, which does not affect TFP, and the technological change indicator on impact.

My findings indicate that the two technological change indicators I employ, i.e. based on either book titles or standardization, give similar results. Following a technology shock, TFP does not respond for several years, but then it gradually increases until it stabilizes at a new long-run level. This goes against the idea that technology shocks should affect immediately productivity, but matches the slow diffusion of technologies in the economy, as indicated by studies of micro data. Macroeconomic aggregates are also unaffected by the technology shock on impact, but start responding positively to the shock soon afterwards, and increase for several quarters until they stabilize at higher new permanent levels. When comparing the technology shock with the other shocks, I observe that the technology shock has much stronger short- and medium-run effects on all

[4]For an analysis of this literature see Bolboaca and Fischer (2017a), Beaudry and Portier (2014), and Ramey (2016), among others.

macroeconomic variables than the unanticipated productivity shock. The unanticipated productivity shock has positive impact effects on almost all macroeconomic variables, with the exception of consumption on which the effect is almost nil, and hours worked for which the response is significantly negative, thus confirming the conclusion of Galí (1999) and Basu et al. (2006) that the unanticipated productivity shock is not expansionary.

An important comparison which, to the best of my knowledge, has not been done previously in the literature is between the technology and the news shock identified with short-run restrictions, when both shocks are identified in the same model. I find that the differences between the two shows are mostly apparent in the short-run. The impact effect of the news shock on investment, output, and hours worked is significantly higher than the one of the technology shock. With the exception of hours worked and the index of consumer sentiment, all variables stabilize at higher permanent levels following a news shock. However, these long-run levels are slightly lower than those reached after a technology shock hits the economy.

I also find that these three shocks have different roles in driving macroeconomic fluctuations, depending on the forecast horizon. The unanticipated productivity shock explains most of the fluctuations of TFP in the short-run, but does not seem to play an important role in driving macroeconomic fluctuations either in the short-run, or in the medium-run, as its contribution to the variation in macroeconomic variables is small at all forecast horizons. This once again contradicts the RBC literature that assigns a central role to the unanticipated productivity shock in driving economic fluctuations. When comparing the relative importance of the other two shocks, it is evident that the news shock plays a more important role than the technology shock at business cycle frequencies, while in the medium- to long-run the technology shock takes the lead.

Furthermore, I draw a parallel between a news shock identified with the medium-run identification scheme, the news shock obtained using short-run restrictions, and the technology shock. My findings indicate that the news shock obtained using medium-run restrictions is virtually a mixture of the technology shock and the news shock obtained with short-run restrictions.[5] However, depending on the truncation horizon, this shock may resemble more either the news shock obtained with short-run restrictions, or the technology shock.

This paper contributes to the empirical literature on productivity shocks[6] with the introduction of the technological change indicator in an otherwise standard linear vector autoregressive setting, and the identification of technology shocks along with the unanticipated and anticipated productivity shocks. Moreover, it contributes to the recent literature that develops direct measures of technological change (e.g. Alexopoulos (2011), Alexopoulos and Cohen (2011), and Baron and Schmidt (2017)) by making a comparison of several indicators, and evaluating their performance in a horse-race of potential important sources of macroeconomic fluctuations. Finally, with the results obtained in this paper, I aim to contribute to the theoretical literature that investigates the effect of technology shocks on economic activity. In particular, this paper provides empirical evidence in favor of theoretical models that depart from the exogeneity assumption on productivity, and which allow for a slow diffusion of technology into aggregate

[5] The news shock identified with the medium-run identification scheme is obtained along with the unanticipated productivity shock, but not with the other two shocks.

[6] Ramey (2016) offers a recent survey of the empirical literature on macroeconomic shocks, including the different types of productivity shocks.

productivity.[7]

The rest of the paper is organized as follows. In the next section I describe the direct measures of technological change employed. In section 2.3, I present the empirical approach, and the different identification schemes. Section 2.4 then gives an overview of the results, and section 2.5 concludes.

2.2 Measures of Technological Change

2.2.1 Book-Based Indicators

Following Alexopoulos (2011), the first measure of technological change I use is the book-based indicator obtained with data from the R.R. Bowker company, henceforth Bowker.[8] According to Peters (1992), Bowker provides statistics regarding the US publishing industry since 1880, but started reporting the number of new book titles and editions based on subject category only from 1950 onward (Nord and Miller (2009)). Alexopoulos (2011) employs the annual series for the categories technology, science, and history, for the sample period 1955-1997. My intuition for the reason why she did not consider more recent data is that until 1998 Bowker used the American Book Publishing Record database, which counted only the books categorized by the Library of Congress, while from then on they switched to the Books in Print database. This change of the procedure created a level shift in the series. In 2006, Bowker made another change of the methodology, but they restated the numbers for 2002-2005 data using the new approach in order to provide comparable prior year data.[9]

Using various sources,[10] I construct the annual series for the categories technology, and science, for the sample period 1955-2012. As previously discussed, the time series have two breaks, one in 1998 and the other in 2002.[11] In order to use this data for empirical analysis, one approach is to employ sub-samples of the unadjusted time series. Given the annual frequency of the data, the only subsample long enough to be considered is the one ranging from 1955 to 1997, as it is done in Alexopoulos (2011). For the comparability of my results with those obtained in the aforementioned paper, I call the indicator based on the new titles published on the subject technology, TECH97, and the one on the subject science, SCI97.[12] However, reducing the sample to the period prior to 1998 makes the indicators miss some important technological advances that occurred in the decade from 2000 to 2010. For example, on what concerns the technology indicator, there were major developments in ICT such as WI-FI, Internet search engines, GPS, smart phones, USB

[7]See, for example, Comin et al. (2009), and Bolboaca and Fischer (2017b), among others.

[8]Bowker is the world's leading provider of bibliographic information, which offers tools and resources, such as the Books In Print database and Identifier Services. Bowker is also the official ISBN (International Standard Book Number) Agency for the US. More information is available on the company's website: `http://www.bowker.com/`.

[9]Details on the changes implied by the latest methodology are presented in the ISBN Annual Output Reports available online on Bowker's website (`http://www.bowker.com/tools-resources/Bowker-Data.html`).

[10]Details concerning the data sources are presented in Appendix 2.A.

[11]The second break occurred in 2006, but given that the data has been adjusted for the period 2002-2005, the break is currently apparent in 2002.

[12]In Alexopoulos (2011) the indicators are named TECH, and SCI, respectively. Throughout this paper I add to these names the last two digits of the year corresponding to the last data point in the sample.

flash drives, and Bluetooth, among others, which are discarded by reducing the sample to the period prior to the 2000s. Another important information that is neglected is the tech bubble burst in 2000, the years of technology recession that followed, and the rebound from 2003 on. Hence, in order to use the data for the whole sample period, i.e. 1955-2012, I construct break-adjusted level data by fixing the level for the reference period to the latest available data point,[13] and recursively dividing by one-period growth rates to generate values for all other periods before the reference period.[14] The annual series for the categories technology, and science, both with level-breaks, and break-adjusted, are displayed in Figure 2.10, and Figure 2.11, in Appendix 2.B.

The book-based indicators obtained with data from Bowker have several drawbacks, some of them being signaled already by Alexopoulos (2011). One criticism is that the classification of titles in one of the twenty-three categories is done based on the Dewey Decimal Classification. According to Peters (1992), the Dewey Decimal numbers for each category are: Technology (600-609; 620-629; 660-669), and Science (500-599). This implies that category technology, for example, contains also dictionaries, and encyclopedias (603), or books on the history of technologies (609). Alexopoulos (2011) points also to the fact that, while these categories include some books which do not actually belong there, they also disregard some valuable materials such as company's product manuals, or books released by small publishers. To this list I would also add the non-traditional books.[15] By computing the ratio between the traditional and non-traditional annual title output as reported by Bowker (2017), in 2002 there were six times more traditional books printed, while in 2012 the figures indicate the opposite. The difference is arguably even bigger given that Bowker's figures are based on the number of ISBNs registered, and thus it does not include the non-traditional books without ISBNs (Bradley et al. (2011)). Besides the non-traditional prints, audiobooks and e-books are also excluded, which may downward bias the counts mainly for the more recent years. Given these limitations of Bowker's series, it seems reasonable to use also other proxies for technological change.

Alexopoulos (2011) proposes a second set of book-based indicators, which are constructed using catalog records from the Library of Congress, henceforth LC. LC claims to be the largest library in the world, with more than 164 million items at the level of 2016, and to have one of the world's most extensive and diverse collection of scientific and technical information.[16] In the US, LC is also involved in various cataloging and recording activities of bibliographical data, and in particular it provides libraries with MARC (machine-readable cataloging) records that contain information about bibliographic items. Alexopoulos and Cohen (2011) argue that the dataset of MARC records is *virtually a complete list of all major new titles copyrighted within the US across a vast range of topics.* Both Alexopoulos (2011), and Alexopoulos and Cohen (2011), use a technological change indicator based on the MARC records in the subgroup T, which

[13]The choice of the reference point is arbitrary, but in practice either the first or the latest available data point is chosen as reference period. In this particular case the choice of the latest available data point seems more reasonable since Bowker motivated the switch to the new methodology in 1998 by stating that the old approach undercounted the number of publications.

[14]For obtaining the values corresponding to the year 2001 and 1997, the growth rate used for the division is the average of the antecedent and subsequent one-period growth rates.

[15]According to Bowker's reports (e.g. Bowker (2017)), category non-traditional *consists of reprints (often public domain), other titles printed on-demand, and wiki-based material.* Bradley et al. (2011) state that non-traditional prints include also books whose authors choose to publish their own material (so-called self-published books).

[16]More information about LC can be found on `https://www.loc.gov/about/`.

corresponds to the field of technology, and another two more specific indicators for the categories telecommunications and computer software and hardware, respectively. In this paper, I only consider the indicator of total technological change, referred to as the TECH2 series in Alexopoulos (2011), mainly for testing the robustness of the Bowker's TECH97 series.[17]

The advantage of using MARC records-based indicators is that the MARC database contains more titles than the Bowker's counts, while its greater granularity allows the researcher to decide which subcategories to include in the indicators, and thus to create less noisy indices. On the other hand, these indicators also have their weaknesses. One of them is that more recent data cannot be used because of LC's large backlog of uncatalogued titles, which may create biases. This is the reason why Alexopoulos (2011), and Alexopoulos and Cohen (2011) use only the sample for the period 1955-1997, even though they had data up to 2004. Another issue is that, similarly to Bowker's indicators, these indices can only be constructed at annual frequency due to data availability. Moreover, depending on the LC's cataloging rules some titles may be disregarded, as it is the case of self-published materials that are not eligible for cataloging because they are not produced by a recognized publisher (Holley (2014)).

To address some of these issues related to the MARC records-based indicators, Alexopoulos and Cohen (2011) construct also a quarterly indicator for computer technologies based on the titles available on Amazon for the period 1980Q1-2008Q3. Amazon is the largest book retailer in the world, its virtual bookshelves containing more than 3.4 million books at any given time (Farfan (2017)). Amazon not only has the largest and diverse collection of titles (i.e. traditional and non-traditional books, prints and ebooks), but it also has an up-to-date database given that it cannot sell materials which are not recorded and cataloged. Using Amazon's database for making an indicator has several advantages. One is that the indicator can be constructed at quarterly frequency. Moreover, as opposed to the Bowker- or MARC records-based indices, this indicator has better chances of containing most of the titles published on a given topic, and hence best reflect the reality.[18] However, the Amazon-based indicator has also some limitations. Alexopoulos and Cohen (2011) mention the fact that classification of titles is done by Amazon's employees, and while there is no reason to assume there is something wrong with their classification, the grouping is not granular enough to allow the researcher to choose which subcategories to include in the index. For this reason, Alexopoulos and Cohen (2011) consider this index noisier than the MARC records-based indicator. Another drawback is the shorter timespan of this series. Because the backward reach of Amazon's titles is limited to 1980, it is not possible to use this series for the purpose of the present paper.

While having the potential of being valuable proxies for technological change, all the book-based indicators used so far in the literature have the drawback of being left to the discretion of either the cataloging institution, or the researcher. As seen in the discussion above, depending on the institutions' policies or researcher's preferences, the counts of titles on specific topics may be biased. For this reason, I believe it is important to use also a more objective proxy for technological change in the empirical analysis, and I consider the technological standardization-based indicator to be a good candidate for that.

[17] Details concerning the data source are presented in Appendix 2.A.

[18] Alexopoulos and Cohen (2011) do not explain how the Amazon-based indicator for computer technologies is constructed. In particular, they do not state if they excluded any titles depending on whether the books were self-published, or ebooks. Given that, I assume the indicator contains all titles available on Amazon on the chosen topic.

2.2.2 Technological standardization-based indicators

Baron and Schmidt (2014) were the first to use technology standards as an indicator of technological change for empirical research. Standardization is the process through which common rules for all producers and users of a technology are set such that compatibility is ensured. Because of that, standardization precedes the implementation of new technologies, and hence provides economic agents with information about future possible productivity gains.

Baron and Schmidt (2014) use data on standards documents from PERINORM to analyze the effect of the adoption of new technology standards on TFP, and economic activity. In the revised version of the paper, Baron and Schmidt (2017) replace the data from PERINORM with the one from the Searle Center Database. The reason is that the latter is a more comprehensive source of information on technology standards from a large sample of standard setting organizations, henceforth SSOs.[19] Standards are usually developed by SSOs (i.e. established organizations, informal consortia, or interest groups), while some firms can also adopt *de facto* standards. *De facto* standards emerge from public acceptance (e.g. MP3 audio format, HTML, PDF), but are often eventually adopted by established SSOs as formal (*de jure*) technology standards. The Searle Center database includes standards established by more than 600 SSOs (formal SSOs and informal standards consortia), but excludes *de facto* standards with the exception of those that have been eventually accredited as a *de jure* standard by one of the SSOs in the sample.

Baron and Schmidt (2017) explain that technology standards are a good proxy for technological change because standardization is an essential step in the implementation of new technologies due to its key role in harmonizing technological devices and ensuring compatibility. They focus their analysis on information and communication technologies (ICT) standards, arguing that ICT has been shown to be a general purpose technology (GPT), and has constituted the dominant GPT in recent decades. The series is constructed by counting the number of industry standards released per quarter in classes 33 ("Telecommunications. Audio and video engineering"), and 35 ("Information technology. Office machines") according to the international classification of standards (ICS) system. For robustness checks, Baron and Schmidt (2017) also create an indicator in which they include standards from the field of electronics.[20] Moreover, the information included in the Searle Center Database allows Baron and Schmidt (2017) to identify the national focus of standards, and hence create indicators based on standards released by US SSOs, as well as indices with standards released by both US and international SSOs that also apply to the US.

For the analysis in this paper, I use both technological standardization-based indicators (i.e. counts of standards on ICT, and ICT plus electronics, respectively) at quarterly and annual frequency. Nevertheless, the main indicator is the one based on counts of standards on ICT and electronics, as it includes more technologies, and thus I assume it to be closer to the indicator based on Bowker's book titles in the category technology (TECH). I perform most exercises with the indicators based on the standards released by US SSOs, but I consider for robustness checks also the series obtained using standards

[19]Baron and Spulber (2015) describes in details the Searle Center Database and the use of its content for empirical research.

[20]In this indicator, Baron and Schmidt (2017) add also the standards in the classes 31 ("Electronics") and 37 ("Image technology").

from international SSOs. I further check the results for the case when the indicators only include new standards, and no standards upgrades.[21] The data is available for the period 1949Q1-2014Q4.

The advantage of using the counts of technology standards adopted as proxy for technological change, as opposed to book titles counts, is that standardization is more regulated, and thus both the counting and classification are more objective, transparent, and consistent over time. Moreover, data is available at quarterly and annual frequency, which gives the possibility of performing more extensive analyses. However, there are some drawbacks of using this indicator. One issue is that the grouping of standards from various ICS classes is left to the discretion of the researcher. For example, Baron and Schmidt (2017) create the indicators using the counts of standards from classes 33-35, and 31-37, respectively, but one may think that some other technologies should be included in a general indicator of technological change (e.g. 71 ("Chemical technology"), or 75 ("Petroleum and related technologies")). Moreover, as Baron and Schmidt (2017) note, it might also be the case that there exists a longer time lag between standardization and adoption/commercialization of new technologies, than between the publication of new titles and adoption, which may affect the empirical results.

The other macroeconomic variables used in the estimations are: output in the business sector, hours of workers on non-farm payrolls, consumption, investment, TFP (adjusted for capacity utilization), and index of consumer sentiment from the University of Michigan. Macroeconomic aggregates are real, seasonally adjusted and in per capita terms, being divided by the population aged 16 and above. All data series are used in log levels in the empirical exercises. Quarterly data is available for the period 1955Q1-2014Q4. Annual data is available for all variables only from 1964, hence, in order to ensure comparability of results, the sample period used throughout this paper is 1964-2012. Details concerning the data construction and sources are presented in Appendix 2.A.

2.3 Comparison of Technological Change Indicators

Before introducing the technological change indicators presented in the previous section in the empirical analyses performed in the news literature, I consider it important to have a look at these series and investigate the relationship between them. In Figure 2.1, I present the annual series for the main two technological change indicators I use in this paper, the Bowker's book titles in the category technology (TECH), and the counts of standards on ICT and electronics that were released in the US (US ICT+ELEC Standards). While Bowker's series is available starting from 1955 and the counts of standards from 1949, I plot the series only from 1964 onwards since the empirical analysis is performed using annual data for the sample period 1964-2012, and hence the relationship between indicators is relevant only for this time frame. Only by eyeballing this figure one may observe that both series are upward trending. However, while the number of new titles displays a rather steady growth over time with a slight acceleration in the more recent years, the counts of standards grow more by leaps and bounds. Thus, it is hard to judge from this picture how correlated the two series are. The computation of cross correlations indicates a strong relationship between the series, but the trend in

[21] I am thankful to Julia Schmidt for providing me the dataset containing the various counts of standards that she uses in Baron and Schmidt (2017).

both series may give rise to this strong (maybe spurious) relation.[22] Therefore, I postpone the discussion of the importance of these two indicators, and whether we can use them interchangeably, to the results section in which I present impulse responses and forecast error variance decompositions for various settings.

Moreover, in this figure I highlight the year 1997 in order to indicate the end period for the sample used in Alexopoulos (2011). As it can be observed, both series display significant fluctuations in the period between 1998 and 2012 that deserve to be considered for the empirical analysis of the impact of technological change on economic activity. In the discussion of results, I explain the differences that arise from reducing the sample that covers the period 1964-2012 to the one that only covers the period 1964-1997.[23]

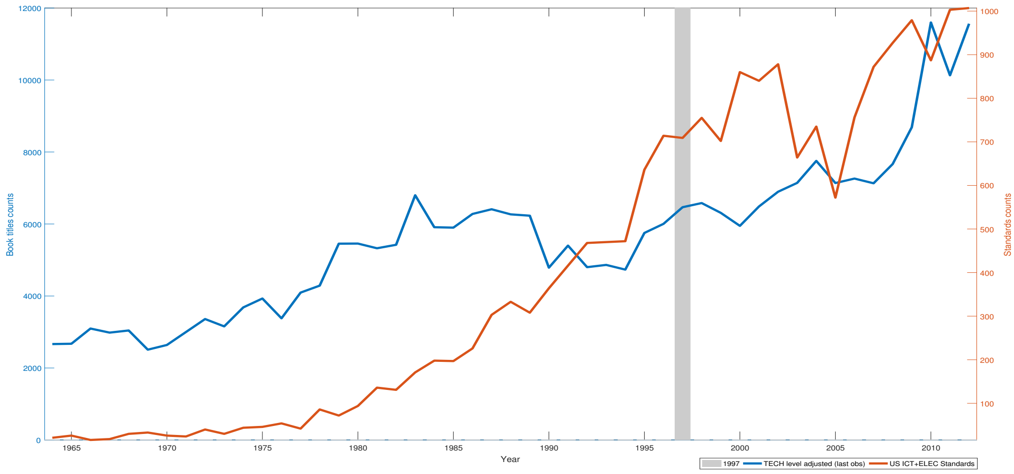

Figure 2.1: Comparison of the main technological change indicators for the sample period 1964-2012. The blue line represents the annual series for the Bowker's book titles in the category technology (TECH), break-adjusted level data obtained by fixing the level for the reference period to the latest available data point. The orange line defines the annual series for the counts of standards on ICT and electronics that were released in the US. The left-hand side axis corresponds to the number of book titles, while the right-hand side axis corresponds to the number of standards. The shaded area indicates the year 1997, which is the end period of the sample used in Alexopoulos (2011).

Figure 2.12, in Appendix 2.B, illustrates the two annual series for new titles in the category technology (TECH) for the sample period 1955-1997, which are used in Alexopoulos (2011). One is the indicator based on Bowker's book titles in the category technology (TECH97), while the other is the MARC records-based indicator for the field of technology (TECH2). Even though TECH2 is by construction a more exhaustive indicator of technological change than TECH97 because it includes more titles, the two series seem to follow a common growth path until the early 1980s, when they start to slightly diverge. For this reason, in the exercises performed with the shorter sample, I also check the robustness of results when TECH97 is replaced by TECH2.

[22]The cross correlations of growth rates or detrended series indicate only a weak relationship, which may be positive or negative depending on the leads or lags considered.

[23]Alexopoulos (2011) considers the sample 1955-1997, but not all data series in my sample are available starting from 1955.

In Appendix 2.C, I display the annual series for various technological standardization-based indicators.[24] In Figure 2.13, I plot the baseline series, which is the indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards), against the series that contains only the counts of new standards on ICT and electronics, and thus excludes any updated standards (US ICT+ELEC New Standards). Until late 1980s the series almost coincide, which implies that most of the standards developed were new ones. Afterwards, the gap between the series becomes larger, indicating that in the recent years many standards were not new, but updates of previously released standards. While I assume that a technology of the early 90s is not the same with the updated technology of today, and thus the original and the updated standards for this technology should not be considered the same, I also perform robustness checks with the indicator based only on new standards.

Figure 2.14, Appendix 2.C, illustrates the comparison between the baseline indicator (US ICT+ELEC Standards) and the indicator based only on counts of standards on ICT (US ICT Standards). Lastly, Figure 2.15 compares the indicators based on the counts of standards on ICT that were released in the US (US ICT Standards), and those released in the US and abroad (US+Int ICT Standards). Baron and Schmidt (2017) argue that the three series are positively correlated, with the relationship being stronger between the baseline indicator (US ICT+ELEC Standards) and the indicator based only on counts of standards on ICT (US ICT Standards).[25] Among these series, Baron and Schmidt (2017) choose the indicator based only on counts of standards on ICT released in the US (US ICT Standards) to be their baseline indicator, with the motivation that ICT is the most dominant general purpose technology (GPT) of the recent decades. In this paper, I prefer to use instead the indicator based on counts of all standards on ICT and electronics released in the US as baseline indicator because it is a more comprehensive index, but I use the other indicators for robustness checks.

2.4 Empirical Approach

I estimate a linear vector autoregressive (VAR) model, which is given by:

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

where Y_t is a vector of k endogenous variables modeled 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. As a general rule, the system with quarterly data features four lags, while the model with annual data has two lags.[26]

The variables in Y_t are log-levels, and most of them are also integrated. Nevertheless, I choose to estimate the VAR model in levels, and do not assume a specific cointegrating relationship between the variables. This is the approach taken in the empirical news literature with the motivation that by estimating the model in levels it is possible to

[24]The plots for the quarterly series look similar, and are not included in this paper. However, for the sample period 1975Q1-2011Q4, they are illustrated in Baron and Schmidt (2017).

[25]Based on my computations, results hold regardless of the sample size considered.

[26]For models with annual data, sometimes the Information Criteria indicate the use of more or less lags. I discuss these issues throughout the paper whenever it is the case.

keep the information contained in the long-run relationships. Moreover, this estimation is shown to be robust to cointegration of unknown form and gives consistent estimates of the impulse responses.[27] Given that the purpose of this paper is to compare the results obtained in models that comprise technological change indicators with those in the empirical news literature, I keep the modeling assumptions imposed in this literature.

The reduced-form residuals can be written as a linear combination of the structural shocks $\epsilon_t = Au_t$, assuming that A is nonsingular. Structural shocks are white noise distributed $u_t \sim WN(0, I_m)$ and the covariance matrix is normalized to the identity matrix. To identify the structural shocks from the reduced-form innovations, $k(k-1)/2$ additional restrictions on A are needed. Following the news literature, I consider two identification schemes. The first is based on short-run restrictions, while the other on medium-run restrictions. The goal is to identify two productivity shocks, an unanticipated productivity shock, and an anticipated (news) shock, along with a technology shock.

The short-run identification scheme is applied as it follows. The innovations are orthogonalized by decomposing the variance-covariance matrix Σ of the reduced-form shocks into the product of a lower triangular matrix A and its transpose A' ($\Sigma = AA'$). The first three shocks are defined as the unanticipated productivity shock, the technology shock, and the news shock. In systems with more than three variables, the other shocks cannot be economically interpreted without imposing additional restrictions.

Bolboaca and Fischer (2017a) argue that the unanticipated productivity shock can be thought of as an unexpected improvement in productivity due to sudden changes in policies or management practices that promote more production. This shock is identified with short-run zero restrictions under the assumption that TFP is on the first position in the system of variables, and the unanticipated productivity shock is the only shock having an impact effect on it. The second variable included in the system is the technological change indicator. The other shock on this variable, in addition to the unanticipated productivity shock, is defined to be the technology shock. The third variable has to be one that contains significant information about new technologies with great potential to increase productivity in the future. Beaudry and Portier (2006) were the first to introduce this concept, and used stock prices as the informative variable about future changes in productivity.[28] Bolboaca and Fischer (2017a) advise to use the index of consumer sentiment instead of stock prices as it contains more stable information about future productivity growth. Consequently, I put the index of consumer sentiment on the third position of the system. The shock on this variable, in addition to the unanticipated productivity shock, and the technology shock, is defined to be the news shock.

The second identification scheme imposes medium-run restrictions in the sense of Uhlig (2004).[29] As in the previous case, the unanticipated productivity shock is the only shock affecting TFP on impact. The news shock is then identified as the shock that has no impact effect on TFP and that, in adition to the unanticipated productivity shock,

[27] An extensive discussion of this issue is done in Bolboaca and Fischer (2017a).

[28] Barsky and Sims (2012), and Ramey (2016) argue that stock prices may not be the best variable to be used in this setting because they are very volatile and prone to react to many other forces.

[29] The first to apply medium-run restrictions to identify news shocks were Barsky and Sims (2011). The method I use in this paper to identify news shocks was introduced by Beaudry et al. (2011). This approach differs from the original one of Barsky and Sims (2011) because the latter aims at identifying a shock with no impact effect on TFP that maximizes the sum of contributions to TFP's FEV over all horizons up to the truncation horizon H. Bolboaca and Fischer (2017a) show that the news shock identified with the method of Barsky and Sims (2011) is contaminated with contemporaneous effects, being a mixture of shocks that have either permanent or temporary effects on TFP.

influences TFP the most in the medium-run. More precisely, it is the shock which explains the largest share of the TFP's forecast error variance (FEV) at some specified horizon h.

Innovations are orthogonalized by applying the Cholesky decomposition to the covariance matrix of the residuals, Σ. The entire space of permissible impact matrices can be written as $\tilde{A}D$, where D is a $k \times k$ orthonormal matrix ($DD' = I$). The h step ahead forecast error is defined as the difference between the realization of Y_{t+h} and the minimum mean squared error (MSE) predictor for horizon h:[30]

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

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

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

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

Note that TFP is on the first position in the system of variables, and let the unanticipated productivity shock be indexed by 1 and the news shock by 2. Having the unanticipated shock identified with the short-run zero restrictions, I identify the news shock by choosing the impact matrix to maximize contributions to $\Xi_{1,2}(h)$ at h=40 quarters, or h=80 quarters.

When I employ annual data, I investigate these shocks in settings which include, apart from TFP, the technological change indicator, and the index of consumer sentiment, either hours worked, consumption, output or investment as a fourth variable. In several applications, I also consider the three variables model. Given the limited number of observations in the sample with annual data, I do not consider larger settings. However, Bolboaca and Fischer (2017a) encourage the use of larger settings for the robustness of results, and for this reason, when using quarterly data, I work with a system that contains all seven variables.

With both identification schemes, I allow the unanticipated productivity shock to have an immediate effect on all variables. On the other hand, the technology shock has an immediate effect on the technological change indicator and the other variables of the model, but TFP responds with a lag. This approach is different from the one of Alexopoulos (2011), and Baron and Schmidt (2017), who place the technological change indicators on the last position of the system. The reason is that they want all macroeconomic variables to respond with a lag to a technology shock.[31] However, following the empirical news literature, I consider that a technology shock provides economic agents with information about the future potential productivity gains, which may encourage them to respond immediately in order to be among the first to benefit from the adoption

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

[31]Alexopoulos (2011) claims that the ordering of the variables do not influence her results.

of the new technologies. The coordination of agents' actions may lead to an increase in consumption and investment, and consequently in output, in anticipation of the change in productivity. This view opposes the one of Baron and Schmidt (2017) who consider that macroeconomic aggregates should respond with a lag to the technology shock because of the implementation lag and slow diffusion of technology into productivity. Finally, both TFP, and the technological change indicator respond with a lag to a news shock, but all other variables are allowed to react on impact.

2.5 Results

2.5.1 Results Obtained Using Bowker's Book-Based Indicators

The benchmark setting I use contains TFP adjusted for capacity utilization, the Bowker's book-based indicator for the category technology (TECH), and the index of consumer sentiment. The variables are introduced in the model in this precise order, and the structural shocks are obtained from the reduced from residuals by applying the short-run identification scheme. The first shock is the unanticipated productivity shock, and has an immediate effect on all three variables. The second shock, the technology shock has an impact effect on both the book-based indicator and the confidence index, but affects TFP with a lag. The third shock has an immediate effect on the index of consumer sentiment, but not on the others, which respond with a lag. The shock on the measure of consumer confidence, unrelated to current changes in productivity, has been shown in the empirical news literature to be highly correlated with the news shock.[32] While in the related literature, this shock is obtained in models that lack a direct measure of technological change, I choose to identify it also in this setting in order to investigate how the shock on the confidence measure, henceforth news shock, and the shock on the technological change indicator, i.e. technology shock, compare. Figure 2.2 displays the bias corrected mean impulse responses to a one standard deviation positive technology shock. These results are obtained in the three-variables VAR model, estimated with two lags.[33] While one lag is usually considered to be sufficient for estimating a VAR with annual data, I choose to employ two lags to ensure robustness of my results given that the system potentially contains unit root or near unit root variables.[34]

The impulse responses indicate that a positive technology shock leads to a permanent increase in TFP, the effect becoming apparent already in the second period. Consumer confidence also responds positively, but the effect is not significant for the first year. Interestingly, the positive effect is quite persistent, lasting for about ten years after the shock hits.

[32]Details can be found in Bolboaca and Fischer (2017a).

[33]The Akaike Information Criterion (AIC) indicates two lags, while the Bayesian Information Criterion (BIC) indicates one lag.

[34]See Kilian and Lütkepohl (2017) for details on the importance of lag augmentation in the particular case of VAR models with integrated variables.

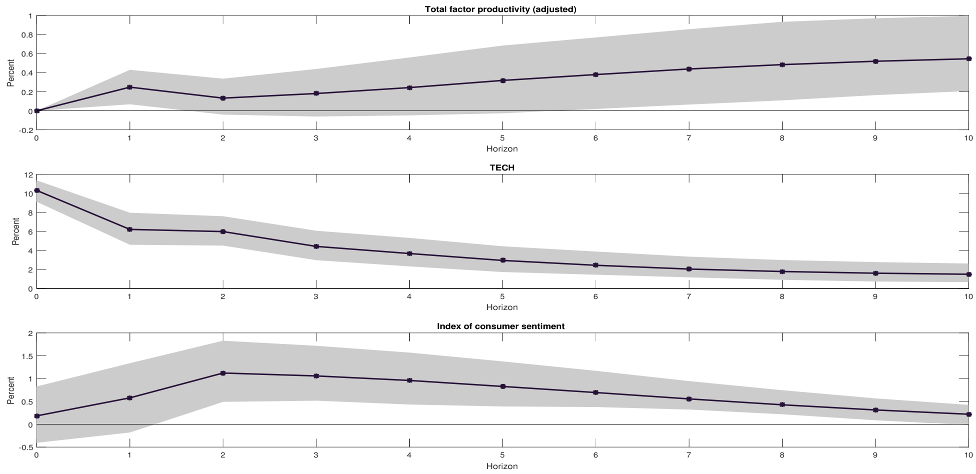

Figure 2.2: Impulse responses to a one standard deviation positive technology shock. The shaded area corresponds to the 68% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR. The horizontal axis indicates the forecast horizon (years) and the unit of the vertical axis is percentage points.

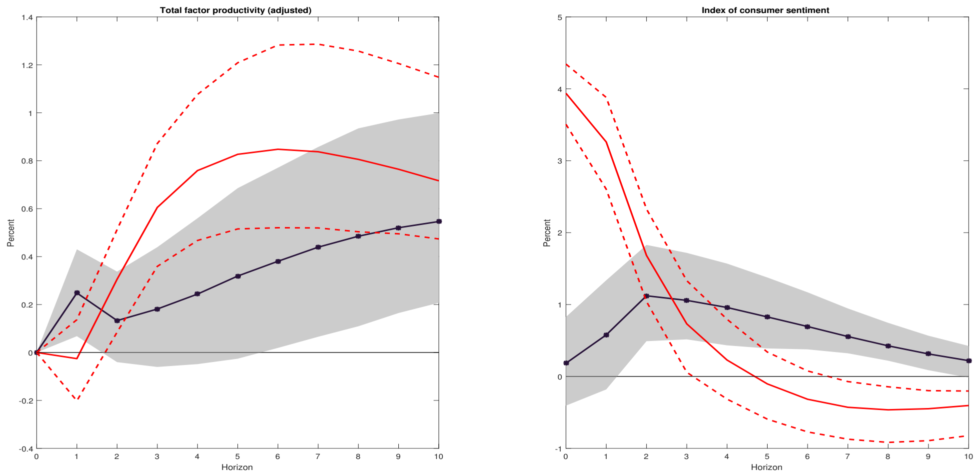

Figure 2.3: Comparison of the technology and news shocks. The black starred line corresponds to the impulse responses to a technology shock. The red solid line corresponds to the impulse responses to a news shock. The shaded area corresponds to the 68% confidence intervals for the responses to the technology shock, while the dotted red lines define the equivalent for the responses to the news shock. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

In Figure 2.3, I compare the effects of the technology shock to those of the news shock on TFP. It is evident that the responses to the two shocks are not significantly different from each other. While the news shock does not seem to affect productivity for the first two years after the shock hits, its effect becomes significantly positive afterwards and permanent. The mean impulse responses of TFP to the two shocks do not look similar.

However, the confidence bands overlap, which indicates that there are no significant differences between the two. In contrast, the effect of the news shock on the index of consumer sentiment is very different from the one of the technology shock. Consumer confidence increases immediately after the positive news shock hits, but the effect fades away fast.

The effects of both shocks on macroeconomic variables are presented in Figure 2.4. These impulse responses are obtained after estimating four-variables VAR models in which each of the variables is included as the forth.[35] The impulse responses indicate a positive impact effect of the technology shock on all variables. All four variables continue increasing after the shock hits, which indicates that they not only anticipate the increase in productivity but also track the diffusion of the new technologies. At a horizon of ten years, output, investment, and consumption seem to stabilize at a new permanent level, while the effect on hours worked starts diminishing. In contrast, the impulse responses to the news shock indicate significantly stronger positive impact effects of the news shock on the macroeconomic variables. All four responses display hump-shapes, and clearly indicate that the effects of the news shock are less persistent than those of the technology shock. The effects on most variables, with the exception of output, seem to fade away after ten years. To conclude, from the comparison of the impulse responses to these two shocks, I observe that both shocks have small or insignificant effects on TFP in the short-run, but lead to higher long-run levels of productivity. Both shocks lead also to a comovement of macro aggregates, with output, consumption, investment, and hours worked, increasing on impact. However, the dynamics of the macroeconomic variables are not the same following the two shocks.

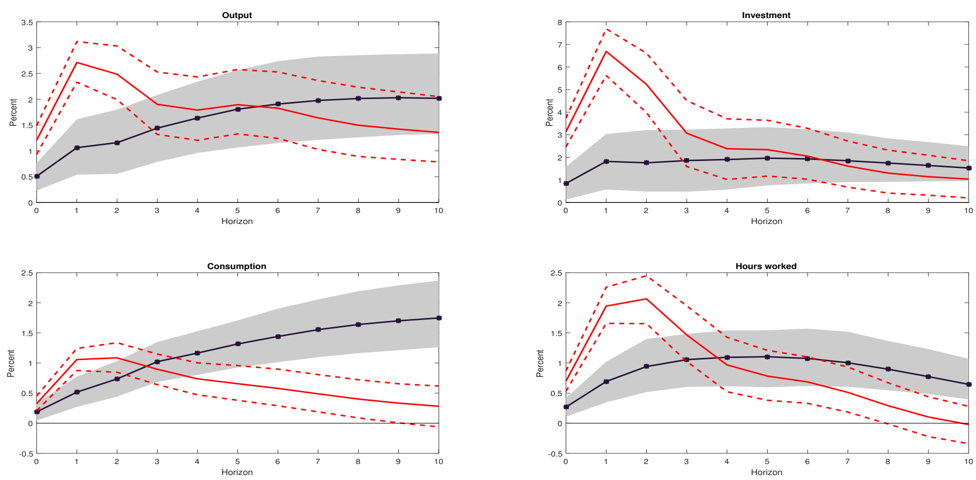

Figure 2.4: Comparison of the technology and news shocks. The black starred line corresponds to the impulse responses to a technology shock. The red solid line corresponds to the impulse responses to a news shock. The shaded area corresponds to the 68% confidence intervals for the responses to the technology shock, while the dotted red lines define the equivalent for the responses to the news shock. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

[35]The models are estimated with two lags. The AIC indicates two lags for the models with output, or consumption, as the forth variable, one for the model with investment, and four for the model with hours. There are no significant differences in the results when I change the number of lags to those indicated by AIC.

In Figure 2.16, Appendix 2.D, I present the impulse response functions to the unanticipated productivity shock. This shock is defined as the only shock with impact effect on TFP, while all the other variables of the model are allowed to respond on impact to it. For brevity, I do not make a discussion of all these impulses, and do not use them in the comparison of results. However, I consider some results worth mentioning. Firstly, the effect of the unanticipated productivity shock on TFP is persistent, but transitory. The impact effects on most macroeconomic variables are not significantly different from zero. In contrast, hours worked decrease on impact following the unanticipated productivity shock, which is in line with the results obtained in the related literature.[36] Moreover, the dynamics of most variables are also in accordance with the findings in the related literature, with the exception of consumption, for which the effect of the unanticipated productivity shock seems to be persistently negative in the long-run.

Table 2.1: Forecast Error Variance Decomposition of TFP and ICS. The numbers indicate the percent of the FEV of TFP and ICS explained by the unanticipated productivity, technology and news shocks at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Total factor productivity (adjusted)					
TFP shock	97.38	70.78	62.86	46.84	43.05
TECH shock	1.82	6.49	10.66	26.62	31.98
News shock	0.06	21.56	24.35	21.81	19.89
Index of consumer sentiment					
TFP shock	8.15	14.48	14.57	14.57	14.59
TECH shock	1.69	15.68	16.65	16.76	16.79
News shock	89.52	66.88	65.76	65.50	65.44

In Table 2.1, I present the contribution of the unanticipated productivity shock, the technology shock and the news shock, to the FEV of TFP and the index of consumer sentiment.[37] As expected, the unanticipated productivity shock explains the biggest share of the variation in TFP at all forecast horizons. However, the news shock explains about 20 percent of the variation in TFP in the medium- and long-term. An interesting result is the percent of variation of TFP that can be attributed to the technology shock. The share is quite small in the short-run, but it starts increasing in the medium-run, being above 10 percent at a horizon of ten years, and almost 32 percent at a horizon of thirty years. What is even more intriguing is that, while the news shock contributes most to the variation of TFP at a horizon of ten years, the contribution of the technology shock continues to increase with the forecast horizon.

The contributions of the technology and news shocks to the variation in macroeconomic variables are displayed in Table 2.2. The technology shock explains a small percent of the variation in macroeconomic variables in the short-run, while the news shock explains more than 50 percent of the variation in most variables at a horizon of two years.

[36] See, for example, Galí (1999) and Basu et al. (2006).

[37] The shares displayed in the table are the average of the contributions obtained in the three-variables VAR model (TFP, TECH, index of consumer sentiment), and in the four-variables VAR models with output, consumption, investment, or hours worked as the forth variable. The shares obtained in each of these models can be provided by the author.

However, the roles are inversed when considering the lower frequencies. In the medium- to long-run, the technology shock explains more than 40 percent of the variation in output, about 34 percent of the variation in hours worked, and 17 percent of the variation in investment. A particular result is the high contribution that the technology shock has to the variation of consumption, which goes above 70 percent at a horizon of twenty years.

Table 2.2: Forecast Error Variance Decomposition of macro variables. The numbers indicate the percent of the FEV of output, consumption, investment, and hours worked explained by the technology shock and the news shock at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Output					
TECH shock	9.74	28.23	32.49	41.94	44.67
News shock	61.86	48.47	43.78	34.03	31.43
Consumption					
TECH shock	12.03	48.5	55.31	73.46	79.55
News shock	48.68	24.31	18.44	8.59	6.35
Investment					
TECH shock	4.51	12.28	14.06	16.79	17.36
News shock	61.33	53.37	51.13	45.54	43.36
Hours worked					
TECH shock	7.6	28.95	32.51	34.06	33.82
News shock	58.71	52.6	49.72	47.36	46.78

When replacing the book based indicator for category technology (TECH) with the indicator for category science (SCI), I do not obtain the same results. At first sight, most results hold qualitatively. In Figure 2.17, Appendix 2.D, I present the impulse responses to a one standard deviation positive technology shock (on variable SCI). These results are obtained in the three-variables VAR model, estimated with two lags, in which variable TECH is replaced by SCI. The impulse responses indicate that a positive technology shock leads to a permanent increase in TFP. In contrast to the shock on TECH, the response of consumer confidence is not significantly different from zero at all horizons. Moreover, in Figure 2.18, Appendix 2.D, it is evident that the effects on most macroeconomic variables are not significant, either on impact or at longer horizons. This indicates that the counts of new titles in category science cannot be used as an indicator for technological change instead of the counts of books in category technology.

As a final step in the analysis of results obtained using the book-based indicators, I wish to draw a parallel between these results and those obtained in Alexopoulos (2011). While the results I find in this paper are qualitatively in line with those of Alexopoulos (2011), there are several differences in our approaches. As I previously stated, we choose to place the indicator of technological change on different positions in the VAR. While I set it on the second position, Alexopoulos (2011) puts it last in the system of variables. This gives the difference in the impact responses of the variables in the model to the technology shock. With my approach, which follows the one in the empirical news literature, except for TFP, the other variables are allowed to respond on impact to the technology shock. In Alexopoulos (2011), all variables respond with a lag to this shock. My findings indicate that all macroeconomic variables respond significantly on impact to the technology shock, and hence I do not see a reason for imposing these ‘no impact response’ restrictions.

Another difference consists in the sample used for the empirical analysis. Alexopoulos (2011) uses data for the sample period 1955-1997, while the data employed in this paper covers the period 1964-2012. For comparison, I present in Figure 2.19, and Figure 2.20, in Appendix 2.D, the impulses responses to the technology shock when the Bowker’s book based indicator for category technology (TECH97) is used. For this analysis, I consider the subsample for the period 1964-1997.[38] Both Alexopoulos (2011) and I estimate a linear VAR model with data in log-levels. However, Alexopoulos (2011) includes one lag of the endogenous variables, and a linear time trend in the model.[39] In contrast, I choose a lag length of two. The choice is in several settings indicated by the AIC, the information criterion advised to be used in case of small sample size,[40] while in others I choose it for consistency and robustness.[41] The impulse responses displayed in Figure 2.19, and Figure 2.20, Appendix 2.D, indicate that using the shorter sample does not significantly influence the results. The technology shock leads to a permanent increase in TFP, and the comovement of macroeconomic variables. However, the confidence bands are wider, and this makes the persistence of the effects arguable. As the increase in the width of confidence bands may be the side-effect of estimating the VAR model with two lags, and using a shorter sample, I focus on the mean impulse responses to make my argument, and these are qualitatively similar to those obtained with the larger sample.

Moreover, in Figure 2.19, and Figure 2.20, in Appendix 2.D, I also present the impulse responses obtained when the Bowker’s book-based indicator is replaced by the MARC records-based indicator, both for the titles published in the category technology. The results indicate that the two technological change indicators can be used interchangeably as the effects of the two technology shocks are virtually the same on almost all variables, with the exception of consumption, on which the technology shock obtained using the MARC records-based indicator has a significantly smaller effect.

A last (possible) difference to the approach in Alexopoulos (2011) is that we might use different measures of productivity.[42] We both use the series constructed with the method of Fernald (2014) based on Basu et al. (2013) and Basu et al. (2006), but I perform the analysis using the TFP series that is adjusted for variations in capacity utilization. It is not clear to me whether the TFP series used by Alexopoulos (2011) is the same, or the one which is unadjusted for capacity utilization. I checked the robustness of results when the TFP series unadjusted for capacity utilization is used, and the differences are mostly quantitative. The impulse responses obtained with the unadjusted series usually indicate stronger effects of the technology shock, mainly in the short-run. However, the use of the TFP series that is unadjusted for capacity utilization is not recommended in this setting because capacity utilization may also respond to the technology shock, as firms

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[38] At annual frequency, not all time series in my sample are available starting from 1955. While I cannot use the exact sample period as in Alexopoulos (2011) for all estimations, I could perform the analysis for a bivariate model with only TFP and the technological change indicator, and the findings were very similar.

[39] Alexopoulos (2011) uses the BIC to decide upon the lag length, and includes a time trend to hopefully address the problem of estimating a model with level data, which may be (co-)integrated.

[40] See Liew (2004) for details on the choice of information criteria depending on the sample size.

[41] Kilian and Lütkepohl (2017) explain that the lag augmentation of VAR models with potentially integrated variables can ensure robustness of results, but may involve a loss of efficiency in estimation, reducing the power of tests and inflating the width of confidence intervals.

[42] Even if the measure is the same, we definitely use different vintages of the TFP series, as I employ the latest available vintage as of October 2017.

may decide to increase capacity until adopting the new technologies in order to smooth output production. Thus, the response of TFP to the technology shock may reflect the increase in capacity and not the diffusion of technologies in the short-run.

To conclude, using the the book-based indicators of Alexopoulos (2011) as a proxy for technological change I find that technology shocks lead to a comovement of macro aggregates, and explain a big share of the variation in these variables in the medium- to long-run. Technology shocks are more similar to news shocks than to unanticipated productivity shock. However, while the technology and news shocks have qualitatively similar effect on macroeconomic variables, there are significant quantitative differences. The effects of the news shock are stronger in the short-run, but they diminish in the medium- to long-run.

2.5.2 Results Obtained Using Standards-Based Indicators

In this section, I perform a similar analysis of technology shocks, but in this setting I use standards-based indicators as proxy for technological change. The benchmark setting I use contains TFP adjusted for capacity utilization, the counts of standards on ICT and electronics that were released in the US (US ICT+ELEC Standards), and the index of consumer sentiment. The variables are introduced in the model in this precise order, and the structural shocks are obtained from the reduced from residuals by applying the short-run identification scheme. As before, the first shock is the unanticipated productivity shock, the second is the technology shock, and the third is the news shock. The three-variables VAR model is estimated with two lags.[43]

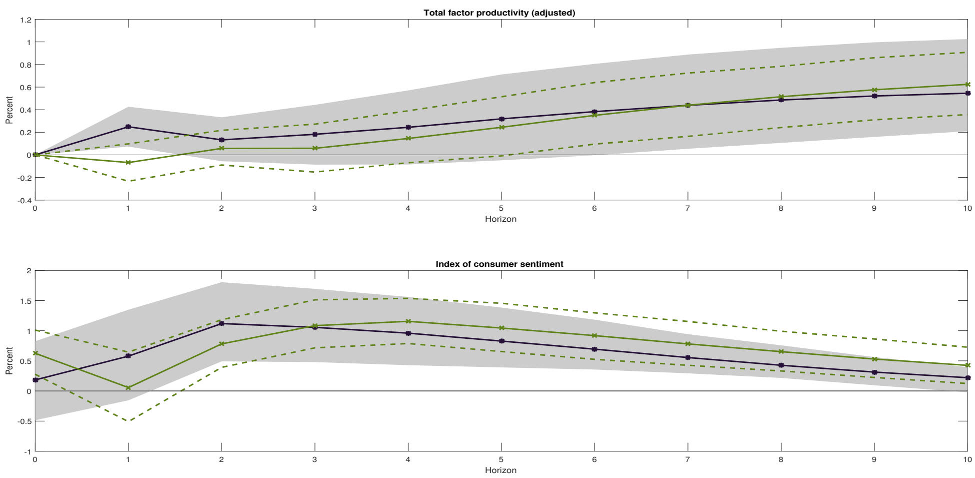

Figure 2.5: Comparison of technology shocks. The black starred line defines the impulse responses to a technology shock on variable TECH, and the shaded area is the corresponding 68% confidence interval. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the dotted green lines define the corresponding 68% confidence interval. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

Figure 2.5 displays the bias corrected mean impulse responses to one standard devi-

[43]The AIC indicates three lags, while the BIC indicates one lag.

ation positive technology shocks. I present the results for the technology shock obtained in this setting, in which I use the standards-based indicator US ICT-ELEC Standards as proxy for technological change, to those obtained in the previous analysis, in which I employed the book-based indicator TECH instead. The impulse responses indicate that a positive technology shock, on the standards-based indicator, leads to a permanent increase in TFP, but the effect is significant only after about five years. Consumer confidence responds positively already on impact, but the effect is not significant for the first year. Interestingly, I find the same persistent positive effect of both technology shocks on the confidence measure. Moreover, apart from the effect on TFP in the first year, the two shocks seem to lead to the same dynamics in TFP and the index of consumer sentiment, as the confidence bands overlap. The closeness in the effects of the two shocks is evident also in Figure 2.6, in which I compare the responses of macroeconomic variables to the two technology shocks. These impulse responses are obtained after estimating four-variables VAR models in which each of the variables is included as the forth.[44] The technology shock, on the standards-based indicator, has smaller impact and short-run effects on output and consumption. However, the confidence bands overlap, which indicates that there is no significant difference between these two technology shocks when judging from the perspective of impulse responses.

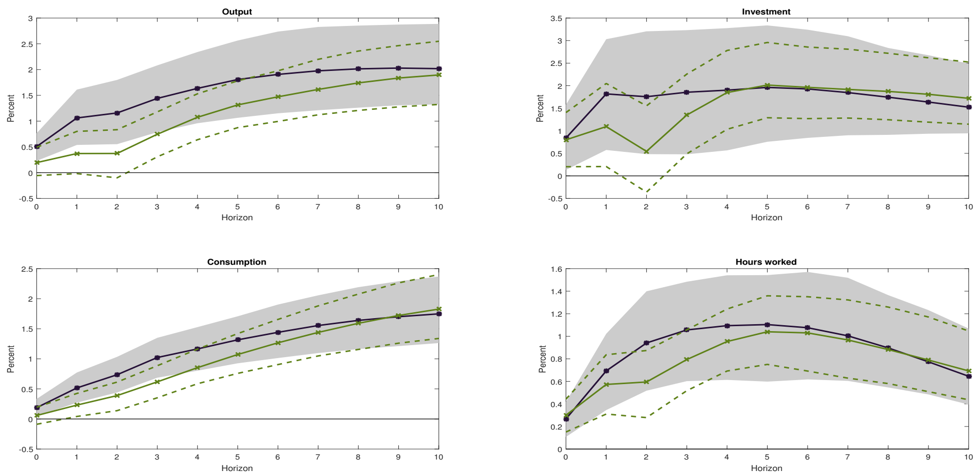

Figure 2.6: Comparison of technology shocks. The black starred line defines the impulse responses to a technology shock on variable TECH, and the shaded area is the corresponding 68% confidence interval. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the dotted green lines define the corresponding 68% confidence interval. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

To further investigate the relationship between the two technology shock, I present in Table 2.3 the contribution of each of them to the FEV of TFP and the index of consumer sentiment.[45] The contributions of the technology shocks to the variation of TFP

[44]The models are estimated with two lags.

[45]The shares displayed in the table are the average of the contributions obtained in the three-variables VAR model (TFP, technological change indicator, index of consumer sentiment), and in the four-variables VAR models with output, consumption, investment, or hours worked as the forth variable. The shares obtained in each of these models can be provided by the author.

at different forecast horizons follow the same pattern. The shares are rather small in the short-run, but start increasing in the medium- to long-run. An interesting result is that the technology shock on variable TECH explains a bigger share of the variation in TFP at business-cycle frequencies than the technology shock on variable US ICT+ELEC Standards, but the roles are reversed at lower frequencies. Baron and Schmidt (2017) explain that the difference stems from the fact that standardization occurs prior to the introduction of books and manuals describing the technology on the market. The intuition is that publishers launch the books close to the commercialization of products using the new technology in order to sell more. In contrast, standardization precedes the development of products that use the new technology. This is why the technology shock on the TECH variable more closely tracks the diffusion of the new technology into productivity, while the shock on standardization anticipates it. However, this argument does not clarify the reversal observed in the contributions in the medium-run. My explanation for this result is that the book-based indicator is a noisier proxy for technological change, and this may downward bias the effect of important technologies on economic activity. Lastly, it is important to note that when looking at the percent of variation of the confidence measure that can be attributed to the technology shocks, it is evident that the shares are close at all forecast horizons.

Table 2.3: Forecast Error Variance Decomposition of TFP and ICS. The numbers indicate the percent of the FEV of TFP and ICS explained by the technology shock on variable TECH, and the technology shock on variable US ICT+ELEC Standards, at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Total factor productivity (adjusted)					
TECH shock	1.82	6.49	10.66	26.62	31.98
US ICT+ELEC shock	0.50	2.41	5.49	34.12	48.57
Index of consumer sentiment					
TECH shock	1.69	15.68	16.65	16.76	16.79
US ICT+ELEC shock	1.99	17.04	18.89	20.09	20.12

The contributions of the technology shocks to the variation in macroeconomic variables are displayed in Table 2.4. As seen already in the case of TFP, both technology shocks explain a small percent of the variation in macroeconomic variables in the short-run, but at these high frequencies the technology shock on variable TECH has bigger contributions. On the other hand, in the medium- to long-run the technology shock on variable US ICT+ELEC Standards explains between 28 percent and 92 percent of the variation in macroeconomic variables, and thus seems to be a more important source of macroeconomic fluctuations.

In Table 2.6, Appendix 2.E, I present the contributions of the unanticipated productivity shock, the technology shock on variable US ICT+ELEC Standards, and the news shock, to the FEV of TFP and the index of consumer sentiment. The conclusions to be drawn are similar to those for the setting in which the book-based indicator was used as proxy for technological change. The only major difference consists in the contributions to the fluctuations of TFP. The unanticipated productivity shock explains the biggest share of the variation in TFP at business cycle frequencies. However, in the medium- to long-run, the technology shock becomes more important, as it explains more than 48 percent of the variation in TFP at a forecast horizon of thirty years, while the unanticipated shock explains less than 37 percent.

The contributions of the technology and news shocks to the variation in macroeconomic variables are displayed in Table 2.7, Appendix 2.E. Once more, the observations are very similar. The news shock explains about 50 percent of the variation in most variables at a horizon of two years, but the contributions drop at lower frequencies. In contrast, the technology shock explains a small percent of the variation in macroeconomic variables in the short-run, while in the medium- to long-run, it becomes a major source of macroeconomic fluctuations.

Table 2.4: Forecast Error Variance Decomposition of macro variables. The numbers indicate the percent of the FEV of output, consumption, investment, and hours worked explained by the technology shock on variable TECH, and the technology shock on variable US ICT+ELEC Standards, at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Output					
TECH shock	9.74	28.23	32.49	41.94	44.67
US ICT+ELEC shock	1.49	25.4	36.71	65.65	73.89
Consumption					
TECH shock	12.03	48.5	55.31	73.46	79.55
US ICT+ELEC shock	2.58	48.08	62.45	87.69	91.32
Investment					
TECH shock	4.51	12.28	14.06	16.79	17.36
US ICT+ELEC shock	2.48	15.01	18.96	27.87	31.46
Hours worked					
TECH shock	7.6	28.95	32.51	34.06	33.82
US ICT+ELEC shock	8.3	18.97	35.76	37.16	37.39

In the analysis presented so far I use the technological change indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards). As a robustness check, I perform the same empirical exercises, but I replace the baseline indicator with one of the following: the counts of new standards on ICT and electronics, excluding any updated standards (US ICT+ELEC New Standards), the counts of standards on ICT (US ICT Standards) only, and the counts of standards on ICT released in the US and abroad (US+Int ICT Standards). In Figure 2.21, Appendix 2.E, I present the impulse responses of TFP, the index of consumer sentiment, output, consumption, investment, and hours worked, to the various technology shocks. The results indicate that the baseline indicator and the indicator based on counts of only new standards on ICT and electronics can be used interchangeably as the mean impulse responses almost coincide. The impulse responses to the technology shock identified using the counts of standards on ICT (US ICT Standards) lie within the confidence bands of the baseline setting, with the exception of the short-run response of investment, which is not significantly different from zero in this case. A similar conclusion can be drawn for the technology shock obtained using the counts of standards on ICT released in the US and abroad. Most impulse responses to this shock lie also within the confidence bands of the baseline setting, with only the response of consumption being entirely outside the confidence interval and indicating an insignificant effect of the technology shock on this variable. To conclude, the baseline indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards) seems to give the most robust results among the standards-based indicators I investigated. Moreover, as seen in the comparison with the Bowker's book-based indicator for category technology, the two proxies for technological change deliver similar results in terms of impulse responses and shares of variation attributed to the technology shock they help identify. Based on these findings, I infer that the indicator based on counts of all standards on ICT and electronics (US ICT+ELEC Standards) is a robust proxy for technological change. Hence, I further use the quarterly series of this indicator constructed by Baron and Schmidt (2017) to perform several empirical exercises of the news literature.

I begin by estimating a seven-variables VAR model, which contains TFP adjusted for capacity utilization, the indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards), the index of consumer sentiment, investment, hours worked, output, and consumption. The variables are introduced in the model in this precise order, and the structural shocks are obtained from the reduced from residuals by applying short-run restrictions. The first shock is the unanticipated productivity shock, and has an immediate effect on all variables. The second shock, the technology shock has an impact effect on all variables, with the exception of TFP that responds with a lag. The third shock has an immediate effect on the index of consumer sentiment, and the other macroeconomic variables, but TFP and the standards-based indicator are affected with a lag. I consider the same sample period as in the exercises with annual data, i.e. 1964Q1-2012Q4, in order to have comparable results.[46] The model is estimated using quarterly data, with four lags. The choice of the lag length is motivated by the usual practice in the literature, and thus by obtaining results that can be compared with those in the empirical news literature. However, as it can be observed in Figure 2.22, Appendix 2.E, results do not change significantly if the estimation is performed with eight lags. The differences in impulse responses are evident only in the short-run. The results obtained in the model with eight lags indicate an insignificant effect of the technology shock on investment, output, and hours worked for the first two years, and on TFP for the first almost six years. In contrast, the effects obtained in the model with four lags become significantly positive at shorter horizons. Increasing the number of lags to twelve, as it is done in Baron and Schmidt (2017), leads to a higher uncertainty of the estimates, and makes the impulse responses statistically insignificant at longer horizons, but the results are still qualitatively similar.

In Figure 2.7, I compare the impulse responses to the technology shock with those to the unanticipated productivity shock. In response to a one standard deviation positive unanticipated productivity shock, TFP rises on impact, but the effect fades over time even though it is quite persistent. The shock has positive impact effects also on the index of consumer sentiment, investment, output, while on consumption it is almost nil. However, the impact effect on hours worked is significantly negative, which confirms the results of Galí (1999) and Basu et al. (2006). In the short-run, it is evident a hump-shaped pattern in the responses of the index of consumer sentiment, output, consumption, investment, and hours worked, but the effects wane after two to three years. Concerning the responses to the technology shock, TFP is restricted not to respond on impact, but in the first four to five years there is almost no change in its response. However, TFP starts increasing

[46] Quarterly data is available for the period 1955Q1-2014Q4, and results do not change considerably if the whole sample is used.

afterwards, and after about fifteen to twenty years it stabilizes at a new long-run level.[47] While I do not impose any restrictions for the impact effect on the other model variables as in Alexopoulos (2011), and Baron and Schmidt (2017), I do not find a significant impact effect of the technology shock on output, investment, consumption, and hours worked. Nevertheless, these variables start responding positively to the shock soon after the shock hits, and increase for several quarters until they stabilize at higher new permanent levels. The reactions of hours worked and investment display a hump-shaped pattern in the short-run. When comparing the two shocks through the impulse response functions, I observe that the technology shock has much stronger short- and medium-run effects on all macroeconomic variables than the unanticipated productivity shock.

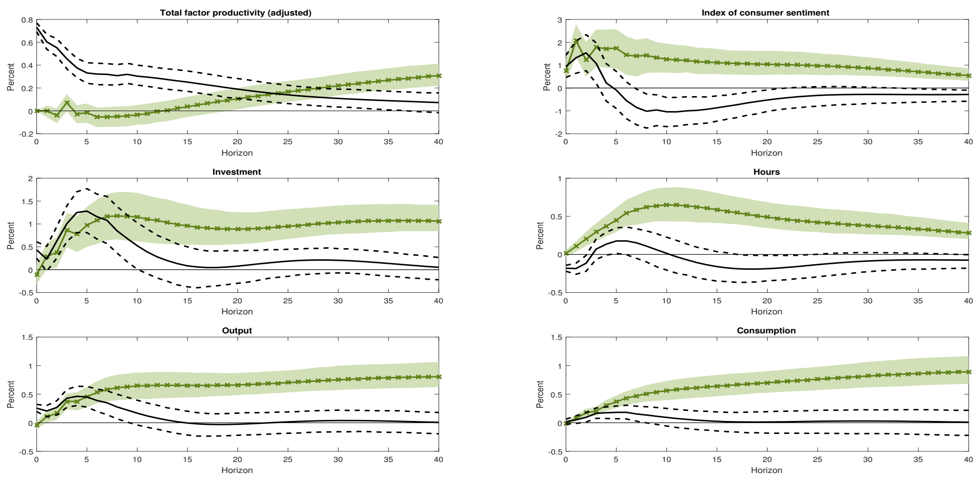

Figure 2.7: Comparison between the technology shock and the unanticipated productivity shock. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the shaded area is the corresponding 68% confidence interval. The black solid line represents the impulse responses to an unanticipated productivity shock, and the dotted black lines define the corresponding 68% confidence interval. The unit of the horizontal axis is quarters, and of the vertical axis is percentage points.

In Figure 2.8, I compare the effects of the technology shock to those of the news shock on the model variables. The results are very similar to those obtained in the models with annual data. The differences between the two are mostly apparent in the short-run. The impact effect of the news shock on investment, output, and hours worked is significantly higher than the one of the technology shock. Concerning the short-run dynamics, there is a hump-shaped pattern in the responses of output, consumption, investment, and hours worked to the news shock. With the exception of hours worked and the index of consumer sentiment, all variables stabilize at higher permanent levels following a news shock. However, these long-run levels are slightly lower than those reached after a technology shock hits the economy.[48]

[47]Figure 2.23, Appendix 2.E displays the impulse responses to the technology shock for forecast horizons up to 120 quarters.

[48]Figure 2.24, Appendix 2.E, displays the impulse responses to the technology shock, and to the news shock, for forecast horizons up to 120 quarters.

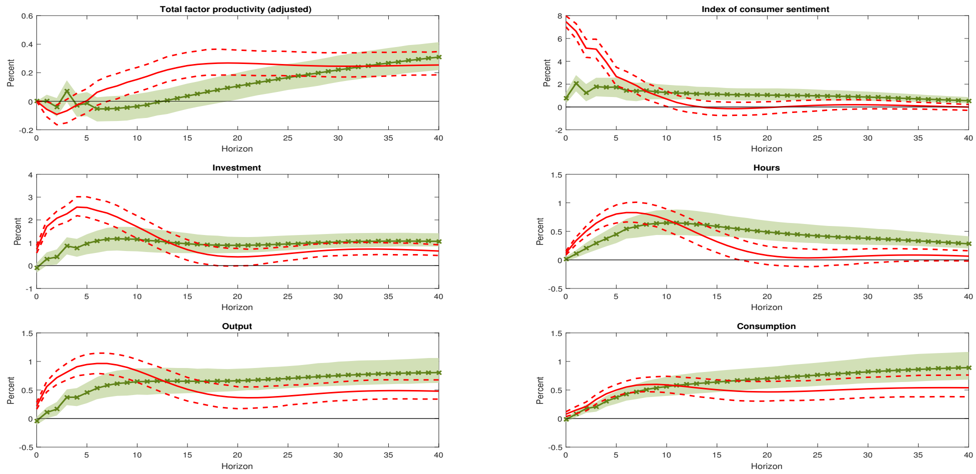

Figure 2.8: Comparison between the technology shock and the news shock. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the shaded area is the corresponding 68% confidence interval. The red solid line represents the impulse responses to a news shock, and the dotted red lines define the corresponding 68% confidence interval. The unit of the horizontal axis is quarters, and of the vertical axis is percentage points.

In order to further investigate the role played by these shocks in driving macroeconomic fluctuations, in Table 2.5 I present the contribution of each of them to the FEV of TFP, the index of consumer sentiment, investment, hours worked, output, and consumption. The contributions of the three shocks to the variation of the model variables at different forecast horizons follow the same pattern as observed previously in the models estimated with annual data. Undoubtedly, the shares do not coincide because of the different information content of the models, but the roles of these shocks are the same at various forecast horizons. The three shocks together explain more than 60 percent of the variation in TFP at all horizons considered. The unanticipated productivity shock explains most of the fluctuations of TFP in the short-run. However, this shock does not seem to play an important role in driving macroeconomic fluctuations either in the short-run, or in the medium-run, as its contribution to the variation in macroeconomic variables is small at all forecast horizons. This contradicts the real business cycle (RBC) literature that assigns a central role to the unanticipated productivity shock in driving economic fluctuations.[49] When comparing the relative importance of the other two shocks, it is evident that the news shock plays a more important role than the technology shock at business cycle frequencies, while in the medium- to long-run the technology shock takes the lead. The news shock explains between 25 and 42 percent of the variations in macroeconomic variables at business cycle frequencies, while the technology shock explains between 27 and 42 percent of the variations in the same variables at lower frequencies. The findings for the technology shock are in line with those of Alexopoulos (2011), and Baron and Schmidt (2017), who show that technology shocks explain a small percent of the variation in macroeconomic variables in the short-run, but have bigger contributions in the medium- to long-run.

[49] The unanticipated productivity shocks are known as technology shocks in the RBC literature where aggregate productivity is affected immediately and permanently only by technology.

Table 2.5: Forecast Error Variance Decomposition of model variables. The numbers indicate the percent of the FEV of the model's variables explained by the unanticipated productivity shock (TFP shock), the technology shock on variable US ICT+ELEC Standards, and the news shock, at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Total factor productivity (adjusted)					
TFP shock	69.65	41.77	35.5	14.74	9.42
US ICT+ELEC shock	0.49	5.73	11.71	32.3	36.6
News Shock	1.07	19.3	21.87	19.72	16.56
Index of consumer sentiment					
TFP shock	3.16	5.59	5.54	5.65	5.64
US ICT+ELEC shock	8.51	14.38	14.89	14.95	15.07
News Shock	79.84	56.86	54.41	52.37	52.25
Output					
TFP shock	8.92	3.29	2.56	1.23	0.92
US ICT+ELEC shock	9.65	32.32	35.22	40.42	41.37
News Shock	48.54	32.48	29.02	20.36	17.49
Consumption					
TFP shock	3.35	0.69	0.5	0.21	0.19
US ICT+ELEC shock	14.89	38.36	40.39	43.31	43.52
News Shock	32.31	23.71	21.92	16.76	14.78
Investment					
TFP shock	9.65	6.52	5.81	4.04	3.58
US ICT+ELEC shock	6.62	19.81	22.86	29.64	31.2
News Shock	43.21	40.33	37.75	29.32	26.59
Hours worked					
TFP shock	1.82	2.24	2.17	2.37	2.39
US ICT+ELEC shock	10.72	27.02	27.28	27.15	27.13
News Shock	26.45	23.08	21.09	19.14	19.16

The similarity of results to those of Baron and Schmidt (2017) extends beyond the shares of the FEV attributable to the technology shock, even though we take different empirical approaches.[50] The impulse responses to the technology shock reported by Baron and Schmidt (2017) are qualitatively similar to those I compute, with the only difference that in their paper the short-run responses of investment, and output, are insignificant for a longer period, and TFP initially decreases following the technology shock before picking up in the medium- and long-run. I do not find a significant decrease in TFP in response to the technology shock either in the baseline model or in the settings with more lags (i.e. 8, and 12 lags).

The last step of my analysis is to verify how a news shock identified with the medium-run identification scheme (MRI) compares with the news shock obtained using short-run restrictions, and the technology shock. The news shock identified with medium-run

[50] Baron and Schmidt (2017) estimate a linear VAR with quarterly data in log-levels, but include 12 lags in the model, and take a Bayesian approach for the estimation in order to use Bayesian shrinkage methods to tackle the problem of overparametrization. In contrast, I take a frequentist approach to estimate the model, and use a lag length of 4 quarters.

restrictions is defined to be the shock with no impact effect on productivity, which explains most of the variation of TFP in the medium-run. In Figure 2.9, I show that the news shock obtained using medium-run restrictions, with a truncation horizon of 10 years, is virtually a mixture of the technology shock and the news shock obtained with short-run restrictions. Note that this shock is identified in the same variable setting as before, but only together with the unanticipated productivity shock. The other two shocks obtained with short-run restrictions are not identified in this framework, and this allows the news shock obtained with medium-run restrictions to be a mixture of all shocks, with the exception of the unanticipated productivity shock. As it can be observed in Figure 2.9, the news shock identified with MRI is more similar to the news shock obtained with short-run restrictions than to the technology shock. This is confirmed also by computing the cross correlation coefficient between each pair of shocks. The correlation coefficient between the two news shocks is 0.69, while between the news shock obtained with MRI and the technology shock the coefficient equals 0.43. This is not a surprising result since in Table 2.5 it is evident that the news shock explains a bigger share of the FEV of TFP than the technology shock at a horizon of ten years.

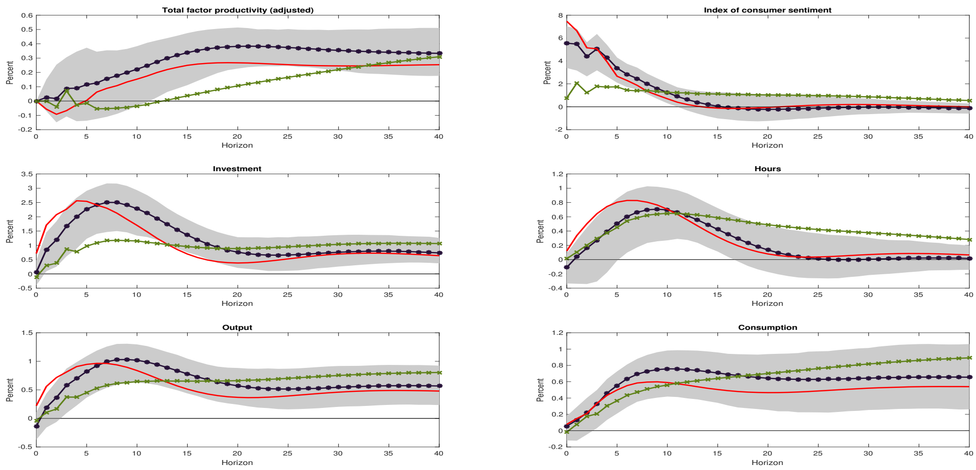

Figure 2.9: Comparison between the technology shock and the news shocks. The dark blue circled line defines the news shock obtained using medium-run restrictions, with a truncation horizon of 10 years. The shaded area is the corresponding 68% confidence interval. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the red solid line represents the impulse responses to a news shock, obtained with short-run restrictions. The unit of the horizontal axis is quarters, and of the vertical axis is percentage points.

However, when comparing the news shock obtained using medium-run restrictions, with a truncation horizon of 20 years, with the other shocks (see Figure 2.25, Appendix 2.E), I find that this news shock is more similar to the technology shock than to the news shock obtained with short-run restrictions. In this case, the correlation coefficient between the two news shocks is 0.45, while between the news shock obtained with MRI and the technology shock the coefficient equals 0.68. The results are reversed, which is also in line with the reversal of contributions of the two shocks to the variation of TFP at a forecast horizon of 20 years. This result confirms the conclusion of Bolboaca and Fischer (2017a) that the choice of the truncation horizon plays an important role in the identification of news shocks with MRI. With the choice of shorter truncation horizons, I find that MRI puts more emphasis on shocks that contribute more to TFP at business cycle frequencies, but with longer horizons, MRI isolates shocks that play a more important role in driving TFP fluctuations in the medium- and long-run. This is the reason why Bolboaca and Fischer (2017a) advise choosing longer truncation horizons, as this ensures obtaining more robust results.

2.6 Conclusions

Several approaches have been taken in the macroeconomic literature to measure the impact of technological change on economic activity. One is to apply identification schemes to identify technology shocks from macroeconomic data. The other is to use direct measures of technological change. Two recent proxies that were proposed are based on either counts of book in the field of technology, or technological standardization. The first was made by Alexopoulos (2011), who uses new book titles in the category technology as proxy for the adoption of technological innovations. The second belongs to Baron and Schmidt (2017) and is an indicator based on the counts of standards in the category ICT (and electronics). In this paper, I combine the two approaches to show which of three shocks plays a more important role for macroeconomic fluctuations: the unanticipated productivity shock, the technology shock, or the anticipated productivity (news) shock.

My findings indicate that the two technological change indicators can be used interchangeably as they give similar results. Regardless of the indicator employed, following a technology shock, TFP does not respond for several years, but then it gradually increases until it stabilizes at a new long-run level. Macroeconomic aggregates are also unaffected by the technology shock on impact, but start responding positively to the shock soon afterwards, and increase for several quarters until they stabilize at higher new permanent levels. When comparing the technology shocks with the other shocks, I observe that the technology shock has much stronger short- and medium-run effects on all macroeconomic variables than the unanticipated productivity shock. The unanticipated productivity shock has positive impact effects on almost all macroeconomic variables, with the exception of consumption on which the effect is almost nil, and hours worked for which the response is significantly negative. When comparing the technology with the news shock, I find that the differences between the two shows are mostly apparent in the short-run.

An important result is that these three shocks have different roles in driving macroeconomic fluctuations, depending on the forecast horizon. The unanticipated productivity shock does not seem to play an important role in driving macroeconomic fluctuations, as its contribution to the variation in macroeconomic variables is small at all forecast horizons. When comparing the relative importance of the other two shocks, I find that the news shock plays a more important role than the technology shock at business cycle frequencies, while in the medium- to long-run the roles are reversed. For this reason, I believe it is important for future research to find what is the information that the news shock captures, apart from the development of new technologies which have been now identified through the technology shock, that leads to much stronger fluctuations in macroeconomic aggregates in the short-run than the technology shock, and continues to explain a significant share of their variation also in the medium- and long-run.

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Appendix

2.A Data

The data I use in this paper is for the US economy. The Bowker book-based indicators are constructed using information from the Bowker annual reports on US print book production. The data is collected from the reports on US book titles (ISBN output) by category for the groups technology, science, and history. The dataset I construct for the sample period 1955-2012 contains data from three sources.[51] For the period 1955-1997, I use the dataset of Alexopoulos (2011), which is publicly available on the journal's website. For the period 1998-2001, I take the data from Greco et al. (2014). The data for the period 2002-2012 is obtained from Bowker's website (Bowker (2017)).

The MARC records-based indicator, TECH2, at annual frequency, is constructed by Alexopoulos (2011) for the period 1955-1997, and made publicly available on the journal's website.

The technological standardization-based indicators are created by Baron and Schmidt (2017) at quarterly frequency using the standards documents registered in the Searle Center database. The data is available for the period 1949Q1-2014Q4.[52] Using this data I construct also annual series, of which I use different subsamples depending on the timespan of the other annual series employed in the analysis.

I use the series of TFP adjusted for variations in factor utilization constructed with the method of Fernald (2014) based on Basu et al. (2013) and Basu et al. (2006).The series for the nonfarm business sector, annualized, and as percent change, is available on the homepage of the Federal Reverse Bank of San Francisco.[53]. The series is available both at quarterly and annual frequency. To obtain the log-level of TFP, I construct the cumulated sum of the original series, which is in log-differences.

Data for output, investment and consumption, both at quarterly and annual frequency, is from the Bureau of Economic Analysis. For output I use the real gross value added for the nonfarm business sector, while for consumption I use the sum of personal consumption expenditures for nondurable goods and personal consumption expenditures for services. Similarly, for investment I consider the sum of personal consumption expenditures on durable goods, and gross private domestic investment.

I obtain data on hours worked, both at quarterly and annual frequency, from the Bureau of Labor Statistics. As a measure of hours worked, I use the hours of all persons in the nonfarm business sector.

[51]There is no single source that provides publicly the series for the whole period except for Bowker, but when contacted via email a company's representative refused to offer me this data claiming that they do not share this information for academic purposes anymore.

[52]Baron and Schmidt (2017) employ the subsample 1975Q1-2011Q4.

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

Quarterly data on population, and price level is also from the Bureau of Labor Statistics. Population defines all persons with ages between 15 and 64 from the US, and the price level is the implicit price deflator for the nonfarm business sector. Annual data for the price level is from the Bureau of Economic Analysis and it is defined by the implicit price deflator for gross domestic product. Annual data for population is obtained from the Organization for Economic Co-operation and Development.

The index of consumer sentiment is from the University of Michigan. The University of Michigan conducts surveys of consumers and provides, among others, the index of consumer sentiment at monthly, quarterly, and annual frequency.[54]

Quarterly data is available for the sample period 1955Q1-2014Q4. Annual data for most variables covers also this sample period, with the exception of the index of consumer sentiment, and hours worked, which are only available starting from 1961, and 1964, respectively. Moreover, for some of them, the latest available data point is for 2012 (or 2012Q4). Hence, I restrict the sample period to cover the timespan between 1964 and 2012.

2.B Bowker's Book-Based Indicators

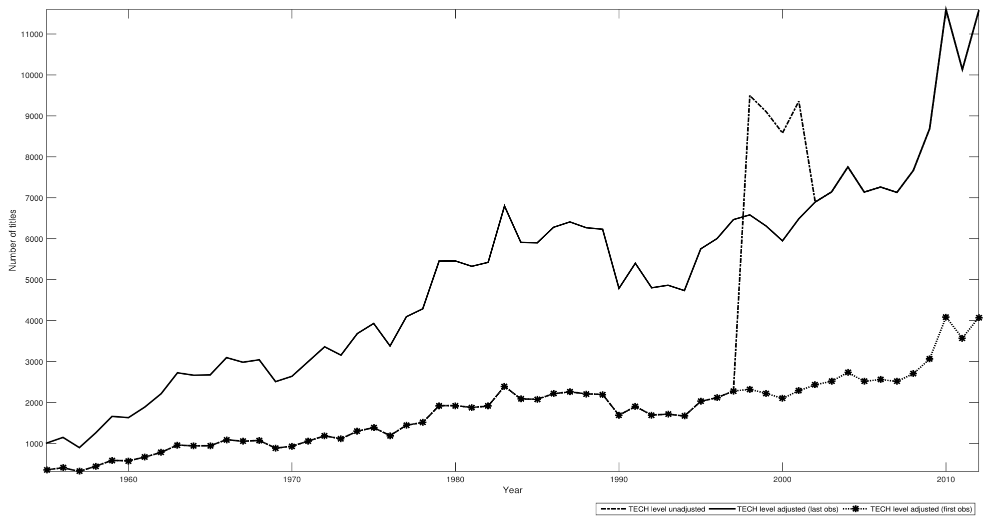

Figure 2.10: The annual series for the Bowker's book titles in the category technology (TECH) for the sample period 1955-2012. The dotted line corresponds to the original data with level breaks in 1998 and 2002. The solid line defines the break-adjusted level data obtained by fixing the level for the reference period to the latest available data point, while the starred line represents the break-adjusted level data obtained by fixing the level for the reference period to the first available data point.

The annual series for the Bowker's book titles in the categories technology, and science, for the sample period 1955-2012, have two breaks, one in 1998 and the other in 2002. Break-adjusted level data can be constructed by fixing the level for the reference period to either the latest or the first available data point. In the figures below I display the

[54]Details about the surveys, and computation of measures are available on `https://data.sca.isr.umich.edu/`.

original series along with the reconstructed series using both approaches, one with the reference period being the latest available data point, and the other with the reference period being the first observation.

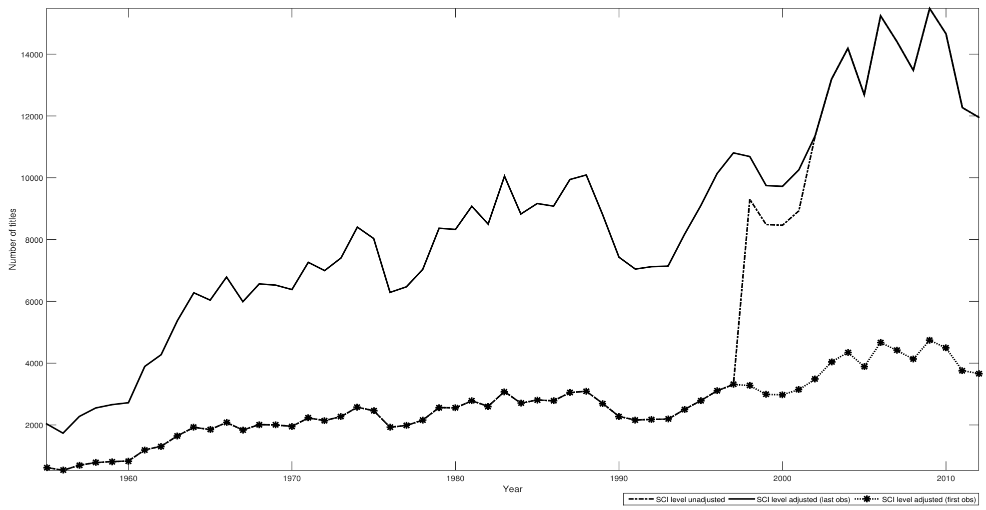

Figure 2.11: The annual series for the Bowker's book titles in the category science (SCI) for the sample period 1955-2012. The dotted line corresponds to the original data with level breaks in 1998 and 2002. The solid line defines the break-adjusted level data obtained by fixing the level for the reference period to the latest available data point, while the starred line represents the break-adjusted level data obtained by fixing the level for the reference period to the first available data point.

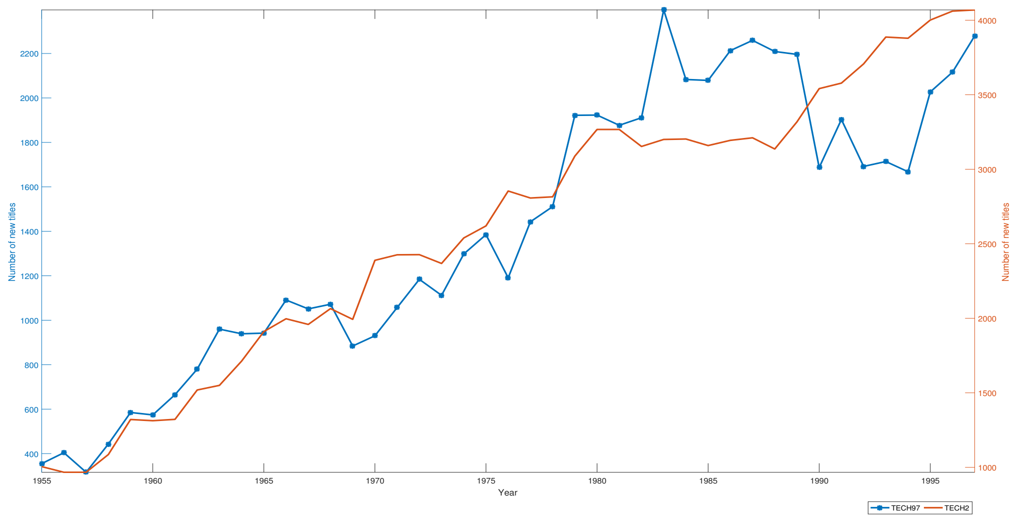

Figure 2.12: Comparison of the annual series for new titles in the category technology for the sample period 1955-1997, which are used in Alexopoulos (2011). The starred blue line corresponds to the indicator based on Bowker's book titles in the category technology (TECH97). The solid orange line defines the MARC records-based indicator for the field of technology (TECH2).

2.C Standards-Based Indicators

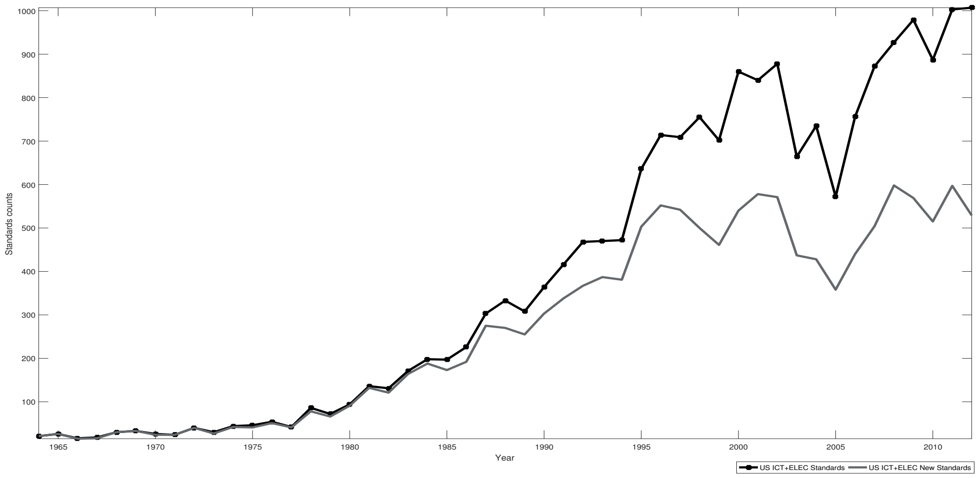

Figure 2.13: Comparison of the annual series for the counts of standards on ICT and electronics that were released in the US in the period 1964-2012. The black starred line corresponds to the total number of standards on ICT and electronics, while the gray solid line indicates the number only of new standards on ICT and electronics.

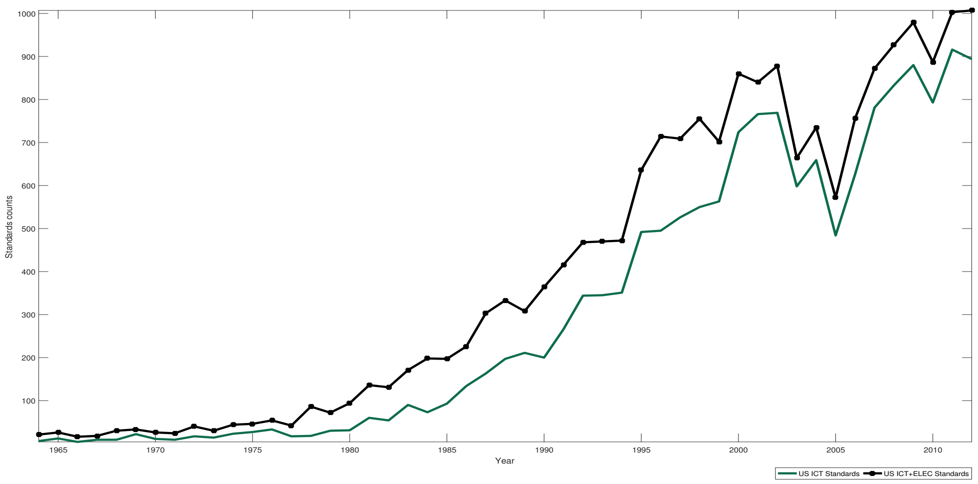

Figure 2.14: Comparison of the annual series for the counts of standards on ICT only, and on ICT along with electronics that were released in the US in the period 1964-2012. The black starred line corresponds to the total number of standards on ICT and electronics, while the green solid line indicates the number of standards only on ICT.

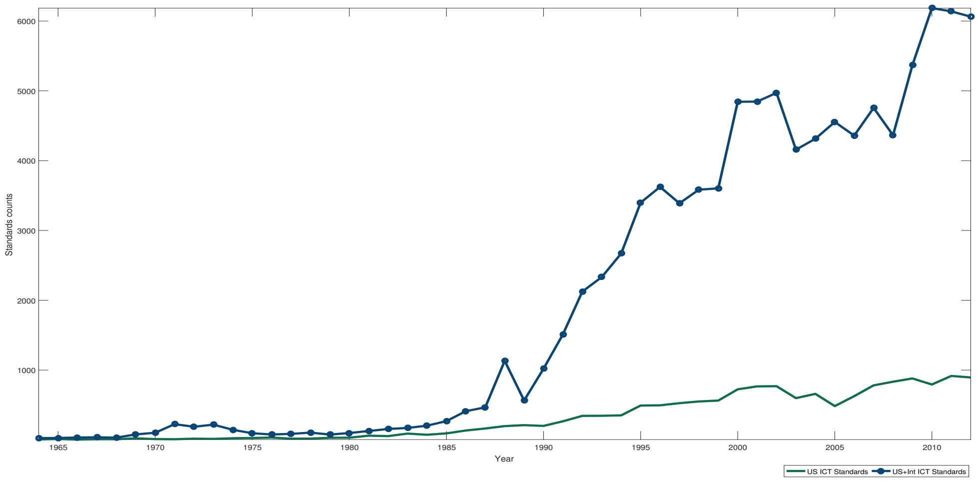

Figure 2.15: Comparison of the annual series for the counts of standards on ICT that were released in the US, and those released in the US and internationally in the period 1964-2012. The blue dotted line corresponds to the total number of standards on ICT released by US and international SSOs, while the green solid line indicates the number of standards on ICT released in the US.

2.D Results Obtained Using Bowker's Book-Based Indicators

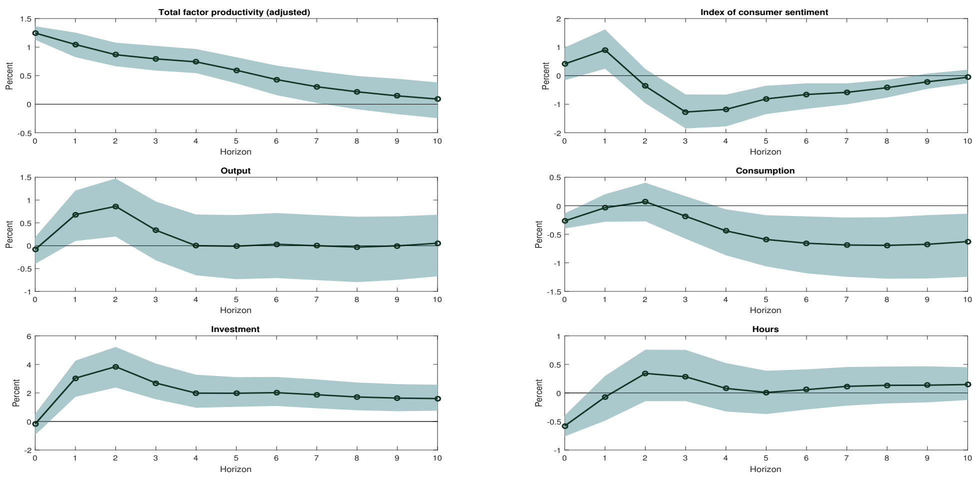

Figure 2.16: Impulse responses to the unanticipated productivity shock. The green circled line corresponds to the impulse responses to a one standard deviation unanticipated productivity shock. The shaded area corresponds to the 68% confidence intervals. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

The impulse responses in Figure 2.16 are obtained in four-variables VAR models, estimated with two lags. The first three were obtained in a model that contained TFP, TECH, index of consumer sentiment, and output. The last three were obtained in the same model by replacing output by one of the other three variables, consumption, investment, and hours worked, respectively. The unanticipated productivity shock is defined as the only shock with impact effect on TFP. All the other variables of the model are allowed to respond on impact to the unanticipated productivity shock.

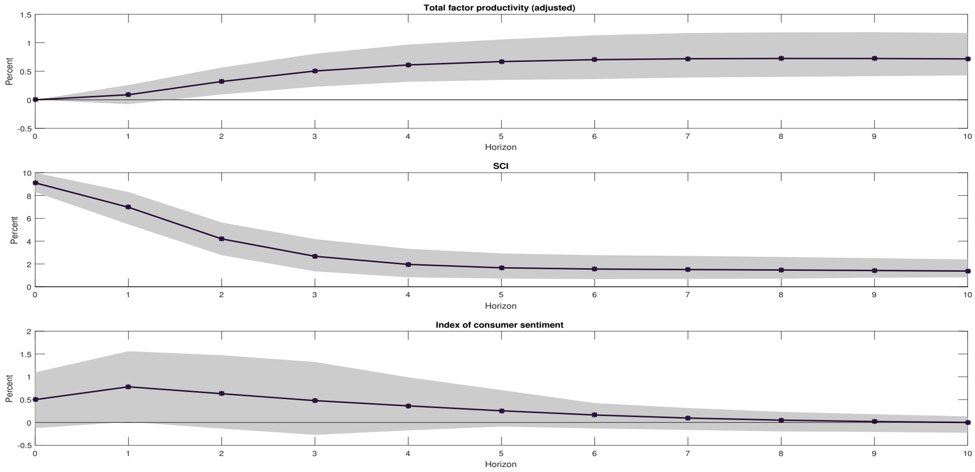

Figure 2.17: Impulse responses to a one standard deviation positive technology shock (SCI). The shaded area corresponds to the 68% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR. The horizontal axis indicates the forecast horizon (years) and the unit of the vertical axis is percentage points.

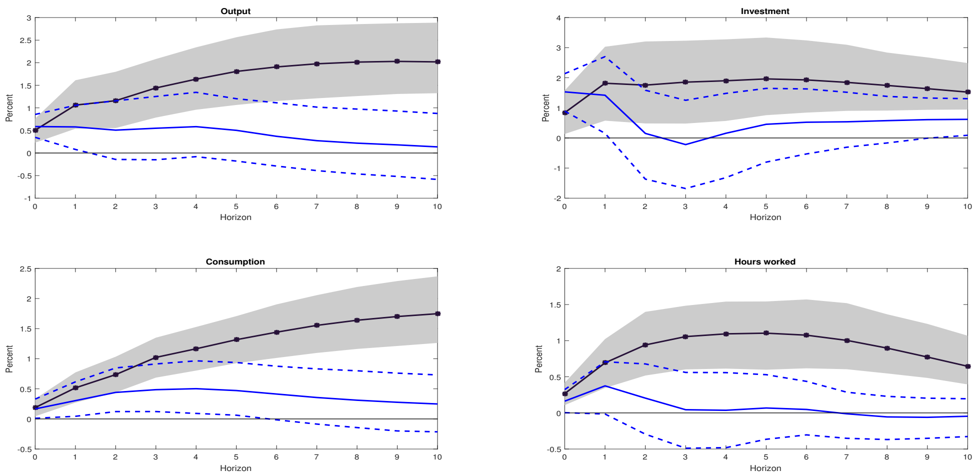

Figure 2.18: Comparison of technology shocks. The black starred line corresponds to the impulse responses to a technology shock, on variable TECH, and the shaded area defines the 68% confidence interval. The blue solid line corresponds to the impulse responses to a technology shock, on variable SCI, while the dotted blue lines delimit the 68% confidence interval. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

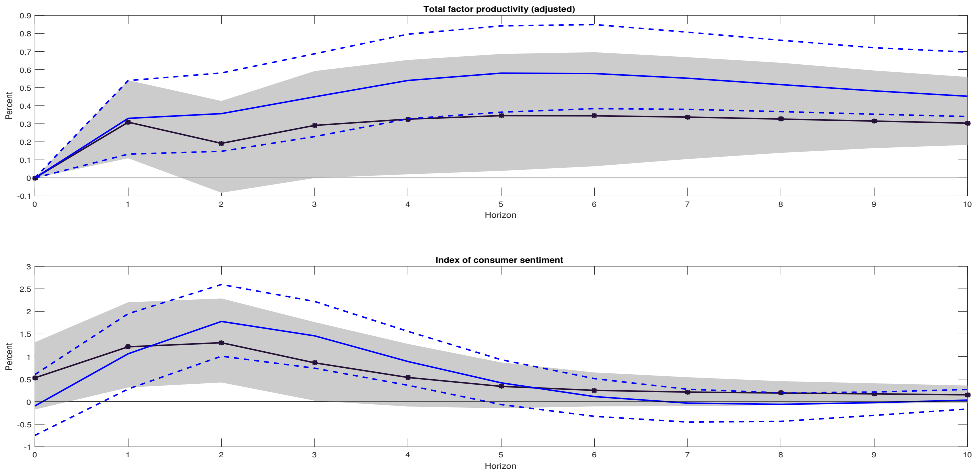

Figure 2.19: Comparison of technology shocks. The black starred line corresponds to the impulse responses to a technology shock, on variable TECH97, and the shaded area defines the 68% confidence interval. The blue solid line corresponds to the impulse responses to a technology shock, on variable TECH2, while the dotted blue lines delimit the 68% confidence interval. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

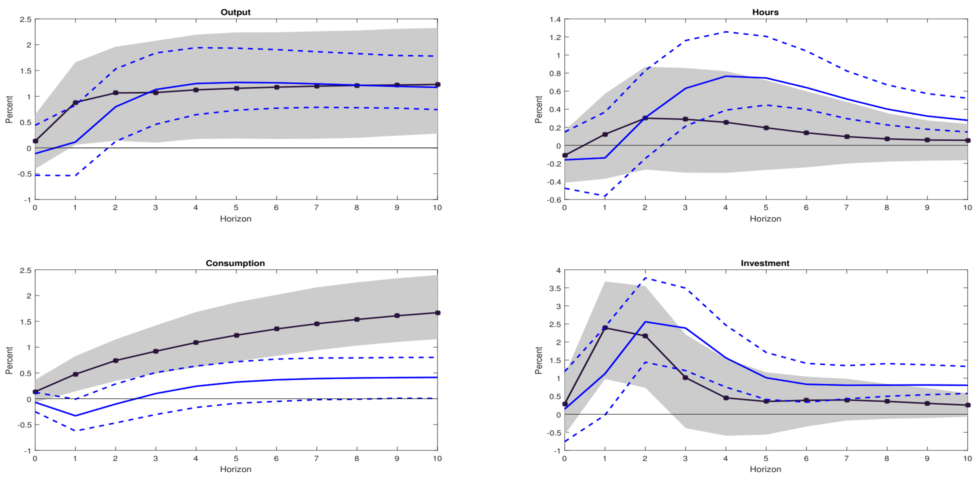

Figure 2.20: Comparison of technology shocks. The black starred line corresponds to the impulse responses to a technology shock, on variable TECH97, and the shaded area defines the 68% confidence interval. The blue solid line corresponds to the impulse responses to a technology shock, on variable TECH2, while the dotted blue lines delimit the 68% confidence interval. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

Figure 2.17 displays the bias corrected mean impulse responses to a one standard deviation positive technology shock (SCI). These results are obtained in the three-variables VAR model, estimated with two lags, but in which variable TECH was replaced by SCI. The impulse responses reported in Figure 2.18 are obtained after estimating four-variables

VAR models in which each of the variables is included as the forth. The first three variables are TFP, TECH or SCI (depending on the model), and the index of consumer sentiment. The forth variable is output, consumption, investment, or hours worked. The models are estimated with two lags. The impulse responses reported in Figure 2.19, and Figure 2.20 are obtained after estimating three-variables VAR models. The three variables are TFP, TECH97 or TECH2 (depending on the model), and the index of consumer sentiment, output, consumption, investment, or hours worked, as the third. The models are estimated with two lags. The sample period is 1964-1997.

2.E Results Obtained Using Standards-Based Indicators

Table 2.6: Forecast Error Variance Decomposition of TFP and ICS. The numbers indicate the percent of the FEV of TFP and ICS explained by the unanticipated productivity, technology and news shocks at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Total factor productivity (adjusted)					
TFP shock	98.93	78.26	72.41	47.70	36.65
US ICT+ELEC shock	0.50	2.41	5.49	34.12	48.57
News shock	0.08	17.42	19.37	14.44	10.99
Index of consumer sentiment					
TFP shock	11.05	26.75	27.74	27.75	27.82
US ICT+ELEC shock	1.99	17.04	18.89	20.09	20.12
News shock	85.85	53.85	50.79	48.86	48.75

The shares displayed in Table 2.6 are the average of the contributions obtained in the three-variables VAR model (TFP, US ICT+ELEC Standards, index of consumer sentiment), and in the four-variables VAR models with output, consumption, investment, or hours worked as the forth variable. The shares obtained in each of these models can be provided by the author.

The impulse responses for TFP, and the index of consumer sentiment, reported in Figure 2.21, are obtained after estimating a three-variables VAR model, which contains TFP, the indicator of technological change (US ICT+ELEC Standards, US ICT+ELEC New Standards, US ICT Standards, or US+Int ICT Standards), and the index of consumer sentiment. The other impulse responses are obtained after estimating a four-variables VAR models with output, consumption, investment, or hours worked, added as the forth. The models are estimated with two lags. The sample period is 1964-2012.

Table 2.7: Forecast Error Variance Decomposition of macro variables. The numbers indicate the percent of the FEV of output, consumption, investment, and hours worked explained by the technology shock on variable US ICT+ELEC Standard, and the news shock, at various forecast horizons (years).

	Horizon				
	2	**8**	**10**	**20**	**30**
Output					
US ICT+ELEC shock	1.49	25.4	36.71	65.65	73.89
News shock	56.08	48.08	40.63	21.64	16.37
Consumption					
US ICT+ELEC shock	2.58	48.08	62.45	87.69	91.32
News shock	42.63	36.25	18.27	5.78	3.63
Investment					
US ICT+ELEC shock	2.48	15.01	18.96	27.87	31.46
News shock	54.02	46.48	43.24	36.29	33.85
Hours worked					
US ICT+ELEC shock	8.3	18.97	35.76	37.16	37.39
News shock	46.17	31.83	28.36	27.43	27.22

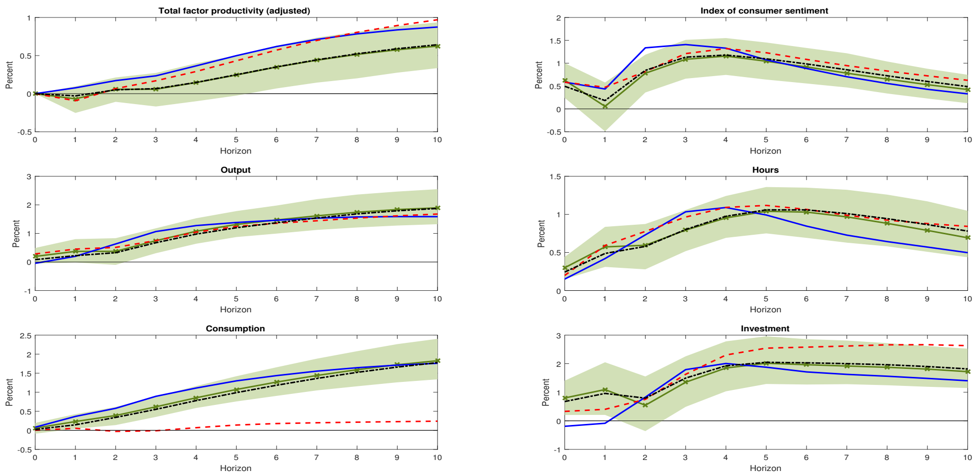

Figure 2.21: Comparison of technology shocks. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the shaded area is the corresponding 68% confidence interval. The black dotted line defines the impulse responses to a technology shock on variable US ICT+ELEC New Standards. The blue solid line gives the impulse responses to a technology shock on variable US ICT Standards, and the red dotted line is for the technology shock on variable US+Int ICT Standards. The unit of the horizontal axis is years, and of the vertical axis is percentage points.

The results reported in Figures 2.22 - 2.25 are obtained after estimating a seven-variables VAR model, which contains TFP adjusted for capacity utilization, the indicator based on counts of all standards on ICT and electronics released in the US (US ICT+ELEC Standards), the index of consumer sentiment, investment, hours worked, output, and consumption. The model is estimated with four lags using quarterly data covering the period 1964Q1-2012Q4.

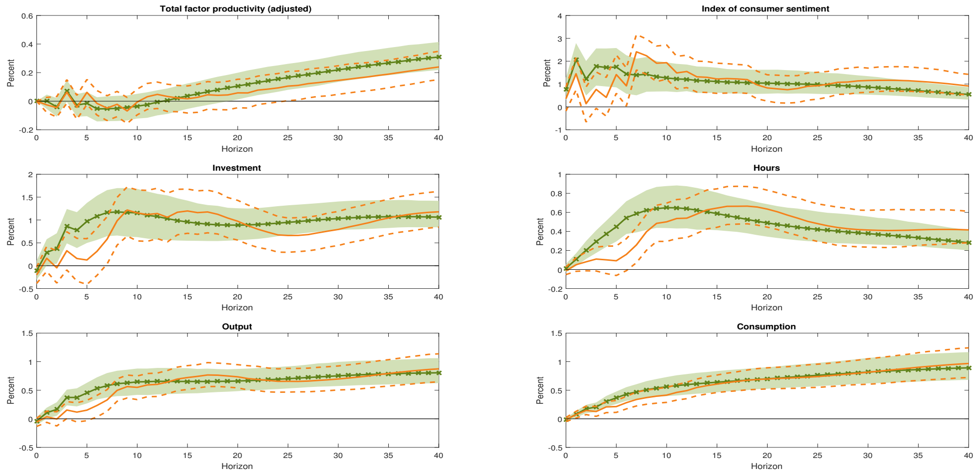

Figure 2.22: Comparison of technology shocks obtained in models estimated with different lag lengths. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards obtained in a model estimated with four lags, and the shaded area is the corresponding 68% confidence interval. The orange solid line represents the impulse responses to the same technology shock obtained in a model estimated with eight lags, and the dotted orange lines define the corresponding 68% confidence interval. The unit of the horizontal axis is quarters, and of the vertical axis is percentage points.

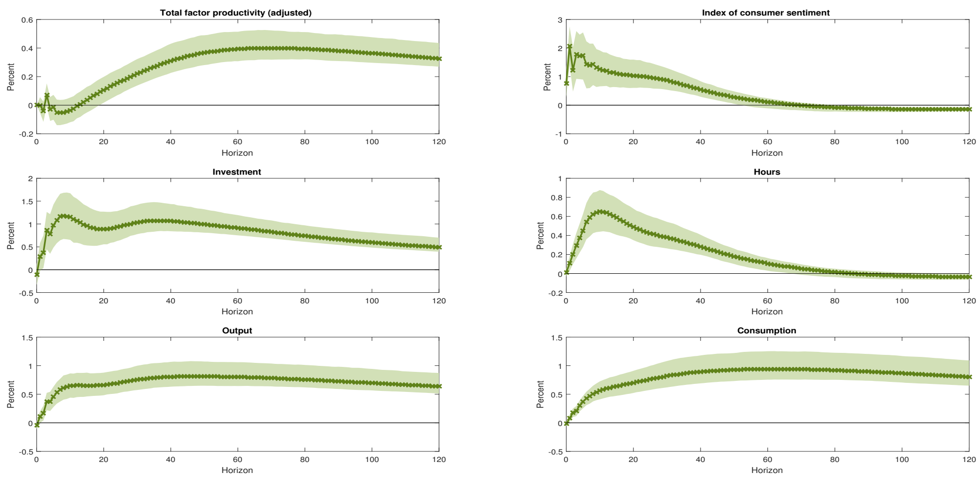

Figure 2.23: Impulse responses to the technology shock. The green crossed line represents the impulse responses to the technology shock on variable US ICT+ELEC Standards, obtained in the model estimated with four lags. The shaded area is the corresponding 68% confidence interval.The unit of the horizontal axis is quarters, and of the vertical axis is percentage points.

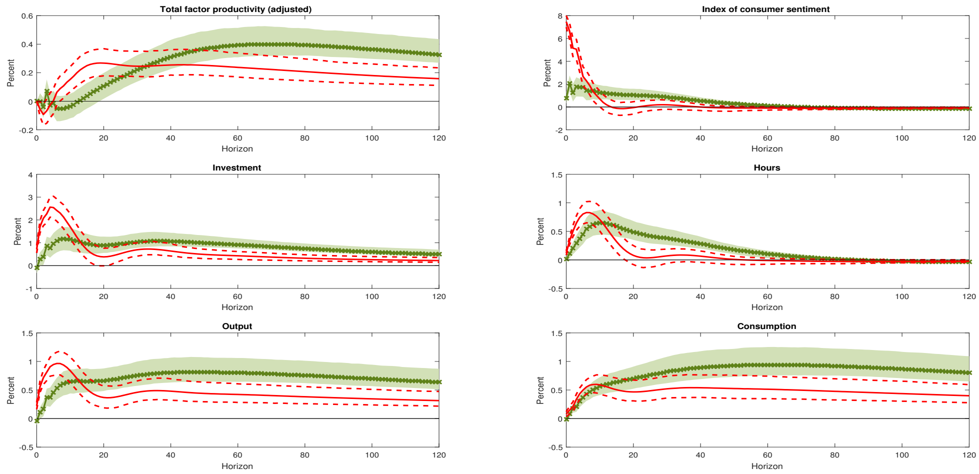

Figure 2.24: Comparison between the technology shock and the news shock. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the shaded area is the corresponding 68% confidence interval. The red solid line represents the impulse responses to a news shock, and the dotted red lines define the corresponding 68% confidence interval. The unit of the horizontal axis is quarters, and of the vertical axis is percentage points.

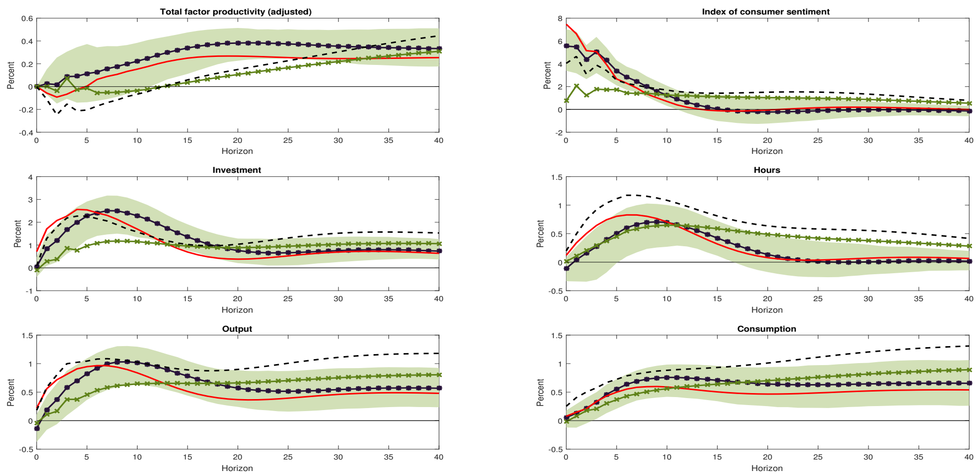

Figure 2.25: Comparison between the technology shock and the news shocks. The dark blue circled line defines the news shock obtained using medium-run restrictions, with a truncation horizon of 10 years. The shaded area is the corresponding 68% confidence interval. The black dotted line defines the news shock obtained using medium-run restrictions, with a truncation horizon of 20 years. The green crossed line represents the impulse responses to a technology shock on variable US ICT+ELEC Standards, and the red solid line represents the impulse responses to a news shock, obtained with short-run restrictions. The unit of the horizontal axis is quarters, and of the vertical axis is percentage points.

Chapter 3

News as Slow Diffusing Technology

Maria Bolboaca and Sarah Fischer

Abstract

In this paper we develop a medium scale dynamic stochastic general equilibrium model with real frictions that proposes an explanation for the evolution of productivity and delivers the comovement of macroeconomic aggregates in response to a technology diffusion news shock. An important feature of the model is that, even though the technology frontier evolves exogenously, the production economy needs to engage in a costly adoption process in order to reap the benefits of using newly developed technologies. The model predictions match the empirical results of both unanticipated productivity and technology diffusion news shocks qualitatively.

3.1 Introduction

The seminal paper of Kydland and Prescott (1982) initiated the real business cycle (RBC) literature that assigns a central role to real shocks, in particular to unanticipated productivity shocks,[1] in driving economic fluctuations. One of the key implications of the RBC theory is that unanticipated productivity shocks lead to the comovement in macro aggregates observed in the data. However, empirical findings suggest that positive unanticipated productivity shocks lead to a fall in employment (Basu et al. (2006)), while news about future changes in productivity has the expansionary effect on economic activity that was previously attributed to the unanticipated productivity shock (Beaudry and Portier (2006)).

In this paper we propose an endogenous technology adoption mechanism through which a simple RBC model generates predictions that mimic the effects of both empirical unanticipated productivity and news shocks. The model features a representative household, and one production sector in which a final good producing firm bundles the different goods produced by intermediate firms into a final output good. In this setting, news shocks are exogenous changes in the technologies for producing new intermediate goods. One might think that prototypes of new intermediate goods are created in research institutes and universities, while the private sector does not contribute to the invention process. Nevertheless, without the adoption of these prototypes, there is no technology transfer from the technological frontier to the economy. To be used a new technology must be successfully adopted, which involves a costly investment. Hence, technology diffusion is not instantaneous as it is usually assumed in the related literature.[2] The number of 'adopted' intermediate goods in the production of final output thus evolves endogenously, as it depends on the endogenous technology adoption, and represents the endogenous component of productivity. We add the exogenous component, which is the standard productivity measure in RBC models entirely determined by unanticipated productivity shocks.

We find that the model's predictions match the empirical results qualitatively. After an unanticipated productivity shock, there is an immediate increase in TFP but the effect, despite being quite persistent, fades over time. Investment also increases on impact, and continues increasing for some quarters. The effect of the unanticipated shock on investment is also transitory. The response of output follows a pattern similar to the one of investment, while the positive effect seems to be more persistent on consumption. Finally, the impact effect on hours worked is negative. It becomes positive after about one year but the effect is quite transitory and fades away much faster than in the case of the other variables. In response to a positive technology diffusion news shock, consumption, output, total investment, and hours worked increase on impact. TFP starts responding in the next period after the shock hits, and in one year and a half it almost reaches a permanently higher level. Apart from the different impact responses, the dynamics of the

[1] These shocks are known as technology shocks in the RBC literature where aggregate productivity is affected immediately and permanently only by technology.

[2] Comin et al. (2009) introduced this idea and mechanism to implement it in a complex two-sector model, but abandoned it in the newer version of the paper, Comin et al. (2016). Our model builds on their initial approach, but differs in several ways which we discuss in the next sections. Tsai (2012) uses also a costly technology adoption, following Comin et al. (2009), but he assumes that technological progress is embodied in new capital goods. Moreover he uses preferences that eliminate wealth effects, and this makes it impossible to get the negative effect of unanticipated productivity shocks on hours worked.

macroeconomic variables indicate that they basically track the movements in TFP. All variables experience a permanent increase, as they stabilize at higher levels in the long run.

The key feature of the model that allows us to generate the comovement of macro aggregates in response to the news shock, while obtaining the negative effect of the unanticipated productivity shock on hours worked, is the endogenous adoption mechanism. The model also incorporates two real rigidities, habit persistence and investment adjustment costs, that enhance the propagation of the shocks. As to the responses to the unanticipated technology shock, investment adjustment costs are essential for obtaining the negative response of hours worked. Regarding the effects of the news shock, the three elements play more important roles. The endogenous technology adoption mechanism triggers an increase in investment on impact because resources are immediately required to adopt the newly created technologies. This leads to an impact increase in the demand for output, and consequently in labor input. The demand for output overrides the supply, and this drives interest rates up. With higher interest rates, there is an intertemporal substitution of labor which offsets the wealth effect. This makes hours worked increase. Adjustment costs prevent agents from substituting investment in capital with investment in adoption when the new technologies become available. Habit formation leads households increase consumption when the news arrives, while otherwise they would allocate more resources to investment and less to consumption.

Our paper is related to several strands of literature. First of all, it builds on the empirical literature on productivity shocks. For the contractionary effects of unanticipated productivity shocks, the key references are Galí (1999)[3] and Basu et al. (2006), while the seminal paper on the effects of news about future changes in productivity is Beaudry and Portier (2006).[4] Ramey (2016) offers a recent survey of the empirical literature on macroeconomic shocks, including the different types of productivity shocks. There is an ongoing debate about the effects of productivity shocks independent of whether they are anticipated or not. These shocks are identified with structural vector autoregressive methods, and the conflicting evidence stems from the wide diversity in variable settings, productivity series used and identification schemes applied.[5] Nonetheless, under standard assumptions, the contractionary effects of unanticipated productivity shocks and the expansionary effects of news shocks prevail.

With this paper, we aim to contribute to the theoretical literature that reproduces these stylized facts. Hence, the paper is related to the theoretical literature that investigates the effect of unanticipated productivity shocks on hours worked. Frictionless models like the standard RBC of Kydland and Prescott (1982) indicate that employment increases after an unanticipated productivity shock. In contrast, models with nominal rigidities such as sticky prices and wages, as the one suggested by Galí (1999), or with real rigidities in the form of habit persistence and investment adjustment costs, as presented in Francis and Ramey (2005), generate a short-run decrease in hours worked following an unanticipated productivity improvement. Thus, standard models with frictions, either nominal or real, are capable of generating the decline in employment in response to an unanticipated productivity shock. On the other hand, replicating the effect of news about future changes in productivity is more challenging. The reason is that equilibrium in the

[3]See Galí and Rabanal (2005) for additional references.

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

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

labor market prevents news from triggering an aggregate expansion. News has a wealth effect on households, restraining labor supply. With capital and productivity unchanged, labor demand is unaltered. Hence, labor input decreases instead of increasing. This renders it impossible for both consumption and investment to rise since output decreases. The recent theoretical news literature proposes several approaches to produce the comovement of macro aggregates in response to news shocks.[6] For example, Beaudry and Portier (2004) obtain the comovement of macro aggregates in response to an anticipated productivity shock by using a multi-sector RBC model. Jaimovich and Rebelo (2009) obtain these results in a simpler one-sector RBC model, but only when augmented with real rigidities and a special class of preferences, which renders the positive effect of news on hours worked. Another approach is the one of Christiano et al. (2010), who use a model with both nominal and real rigidities to deliver the responses to the news shock. Lorenzoni (2011) provides an exhaustive overview of this literature. An important common assumption in these papers is that productivity evolves exogenously. Hence both the unanticipated productivity shock and the news shock are modeled as exogenous processes. In the case of the news shocks, today agents receive a signal that productivity will jump to a new permanent level in the near future, usually in 4 to 8 quarters. Therefore, our contribution to the literature is that we depart from the exogeneity assumption on productivity, and by doing so we let the modeled news shock mimic the slow diffusion of technology into aggregate productivity similarly to its empirical counterpart.

Moreover, we borrow the endogenous technology adoption mechanism used in the models of expanding varieties from the literature on economic growth. Romer (1990) introduced the model with an expanding variety of productive inputs in the literature on technological change and economic growth in order to endogenize R&D. Comin and Gertler (2006) use this mechanism in a two-sector RBC model, but allow for an endogenous rate of adoption of new technologies, along with the endogenous R&D. However, our approach is closer to the one of Comin and Hobijn (2010) and Anzoategui et al. (2017) because we work with a one-sector RBC model, and to Comin et al. (2009) in the sense that we keep technological change exogenous but have endogenous adoption of innovations. There is a slight resemblance of our model to the Schumpeterian models of creative destruction[7] in the fact that we allow for some varieties to become obsolete and be replaced by new ones in every period. Nevertheless, as opposed to the assumptions in the creative destruction models, this has no effect on growth.

Our paper is organized as follows: In the next section, we reproduce the empirical analysis of both unanticipated productivity shocks and news shocks in order to obtain the stylized facts which we aim to match with the theoretical model. In Section 3.3 we introduce a simple RBC model with exogenous technology diffusion and discuss the ingredients needed to generate the comovement of macro aggregates in response to a news shock. We conclude that, under reasonable parametrization, the model fails to match the empirical results. Therefore, in Section 3.4, we propose a model with endogenous technology diffusion as an alternative. This model is able to deliver the responses to both shocks. Moreover, it provides a more realistic interpretation of the technology diffusion news shock than the previously assumed idea of news about manna from heaven. Section

[6]Guo et al. (2015) enumerate the various features introduced in RBC models to produce the comovement of macro aggregates. These are: convex production possibility frontier, multiple production sectors, non-separable preferences, investment adjustment costs, knowledge capital, imperfect competition, countercyclical markups, sticky prices, and costly technology adoption, among others.

[7]See Aghion et al. (2014) for a summary of this literature.

3.5 concludes.

3.2 Empirical Evidence

This section reports evidence on the effects of identified unanticipated productivity shocks and technology diffusion news shocks on macro aggregates. We estimate a five variable vector autoregressive[8] (VAR) model in levels in which we include five variables in the following order: total factor productivity (TFP) adjusted for variations in factor utilization, real consumption, real investment, hours worked, and real output. We use U.S. quarterly data for the sample period 1960Q1-2014Q4,[9] and estimate the model using four lags as indicated by the Akaike criterion. In this setting we identify two productivity shocks. The first is defined as an unanticipated productivity shock and is the only shock that has impact effect on TFP. The second shock, which is usually defined in the empirical literature as the (technology diffusion) news shock, has no impact effect on productivity but contributes the most to the forecast error variance of TFP in the medium-run.[10] We take ten years as the horizon at which the shock should have maximum contribution to TFP, but the results are robust to different choices of horizon.[11]

Figure 3.1 reports the impulse response functions of total factor productivity, consumption, investment, hours worked, and output to a one standard deviation, positive unanticipated productivity shock as the black starred lines. The red lines are the impulse response functions of the same variables to a one standard deviation, positive news shock. The dotted lines correspond to the 68% confidence interval from 5000 bias-corrected bootstrap replications of the reduced form VAR.[12]

In response to a one standard deviation positive unanticipated productivity shock, total factor productivity rises on impact by 0.8%. The effect fades over time, but it is quite persistent. The shock has positive impact effects on investment, output, while on consumption it is almost nil. However, the impact effect on hours worked is significantly negative, which confirms the results of Galí (1999) and Basu et al. (2006). Concerning the short-run dynamics, we observe a hump-shaped pattern in the responses of output, consumption, investment, and hours worked. The effects of the unanticipated productivity shock wane in the medium-run. On the other hand, in response to a one standard deviation positive news shock, all variables rise on impact, except for total factor productivity.[13] Productivity is restricted not to respond on impact, but even in the short-run there is almost no change in its response. After about one year, productivity starts increasing and in almost five years it stabilizes at a new long-run level. The responses of the other variables display a hump-shaped pattern in the short-run, but afterwards they stabilize at higher permanent levels. When comparing the two sets of impulse responses, it becomes clear that the two shocks deliver significantly different responses. The effects of the news shock are much stronger and more persistent than of the unanticipated productivity shock. Moreover, the news shock has a significant positive effect on hours worked, while the effect of the unanticipated shock is significantly negative. In the fol-

[8]The model is described in Appendix 3.B.

[9]The data series are presented in Appendix 3.A.

[10]The identification scheme is presented in Appendix 3.C.

[11]For details about the variable settings see Bolboaca and Fischer (2017).

[12]The impulse responses with 68%, 90% and 95% confidence intervals for the unanticipated productivity shock are reported in Figure 3.11 and for the news shock in Figure 3.12, in Appendix 3.D.

[13]These results support the findings of Beaudry and Portier (2006) that news shocks are expansionary.

lowing sections we will investigate the ability of two theoretical models to account for these stylized facts.

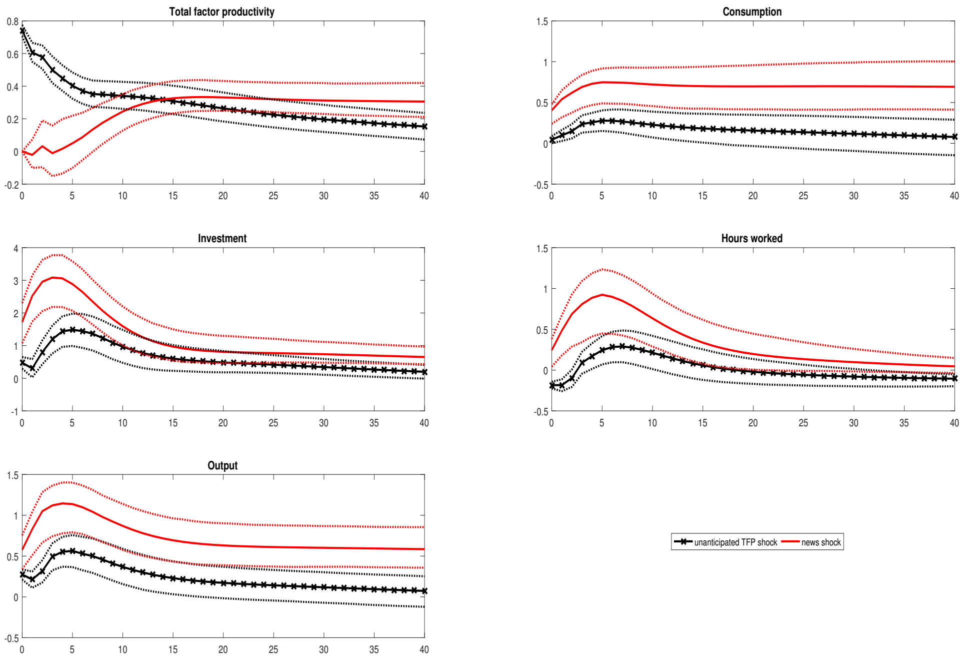

Figure 3.1: Impulse responses to an unanticipated productivity and to a technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The dotted lines correspond to the 68% confidence intervals. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

3.3 Model with Exogenous Technology Diffusion

In this section we use a simple dynamic stochastic general equilibrium (DSGE) model with exogenous technology diffusion to replicate our empirical results. We begin with the framework of the one-sector model of Jaimovich and Rebelo (2009). They introduce three elements into the neoclassical model to generate the comovement of macro aggregates in response to the news shock. The three elements are: variable capacity utilization, adjustment costs to investment, and a new class of preferences. These preferences are described by the following lifetime utility function:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t - \psi L_t^{\theta} X_t)^{1-\sigma} - 1}{1-\sigma},$$

where C_t denotes consumption, and X_t is defined by the following equation:

$$X_t = C_t^{\gamma} X_{t-1}^{1-\gamma}$$

X_t makes preferences non-time-separable in consumption and hours worked. We further refer to this class of preferences as JR preferences. When $\gamma = 1$ the preferences correspond to a class discussed in King et al. (1988), henceforth KPR, while when $\gamma = 0$ the preferences are of the type proposed by Greenwood et al. (1988), henceforth GHH. The assumptions on parameters are: $0 < \beta < 1, \theta > 1, \psi > 0, \sigma > 0$.

These preferences give a weak short-run wealth effect on labor supply and help generate a rise in hours worked in response to positive news. Very important implication of this approach is that these same elements generate also a comovement in response to unanticipated productivity shocks, and this contradicts the empirical results. Our aim is to modify this model in a way that allows us to have the comovement in the responses to a news shock, but not for a contemporaneous shock.

The model has the following structure. The economy is populated by households who consume, invest in physical capital, supply labor, and rent capital to firms. There is no heterogeneity in households and firms, so we can treat them as being one representative agent and one representative firm. The model equations and chosen calibration are presented in Appendix 3.E.1.[14]

The shock specifications are the same for neutral and investment-specific shocks. We only consider the neutral productivity shocks. The exogenous process for the natural logarithm of TFP ($ln(A_t) = a_t$) is:

$$a_t = \rho_a a_{t-1} + e_t, \text{ where } \rho_a = 1,$$

and the innovation in productivity, e_t, is the summation of two components,

$$e_t = \epsilon_t + \varepsilon_{t-4},$$

ϵ_t being the unanticipated component, and ε_t the anticipated or news component. The two components are independent white noises, which implies zero correlation between the news and unanticipated productivity shocks. The timing of the news shock is the following. At time zero the economy is in steady state and news arrives that there will be a one percent permanent increase in productivity, A_t, four quarters later.

Given the calibration of the parameters,[15] the model produces aggregate comovement in response to both unanticipated shocks to A_t and to news about future values of A_t.

As it can be seen in Figure 3.2, there is an immediate expansion in response to positive news about future changes in productivity. Consumption, investment, output, hours worked, and capital utilization, all rise after the news arrives, even though the improvement in productivity only occurs after some periods. The impact of news about A_t is less important than the realization of the unanticipated productivity shock. An unanticipated improvement in A_t has an immediate, direct impact on output. On the other hand, news of a future increase in A_t affects output only through changes in the supply of labor and in the amount of capital that is accumulated before the shock arrives. A future increase in A_t implies that investment will rise in the future. In the presence of investment adjustment costs, it is optimal to smooth investment over time, and so

[14] We keep the presentation of this model as succinct as possible. Details on the assumptions and parametrization can be found in Jaimovich and Rebelo (2009).

[15] Jaimovich and Rebelo (2009) show that there is a wide range of parameter values that generate aggregate comovement in response to news about future changes in A_t. Using the benchmark calibration and changing one parameter at a time: $\varphi''(1) > 0.4, \delta''(u)u/\delta'(u) < 2.5, \theta < 10, \gamma < 0.4$.

investment rises in period one. An increase in investment leads to a decline in the value of installed capital in units of consumption. Capital is less valuable because it is less costly to replace, so it is efficient to increase today's rate of capital utilization. The rise in utilization increases the marginal product of labor. This increase provides an incentive for hours worked to rise. As long as the wealth effect on the supply of labor is small enough, hours rise and we see an expansion in response to good news about future changes of A_t. In Appendix 3.E.2 we discuss the importance of each of the three elements (i.e.

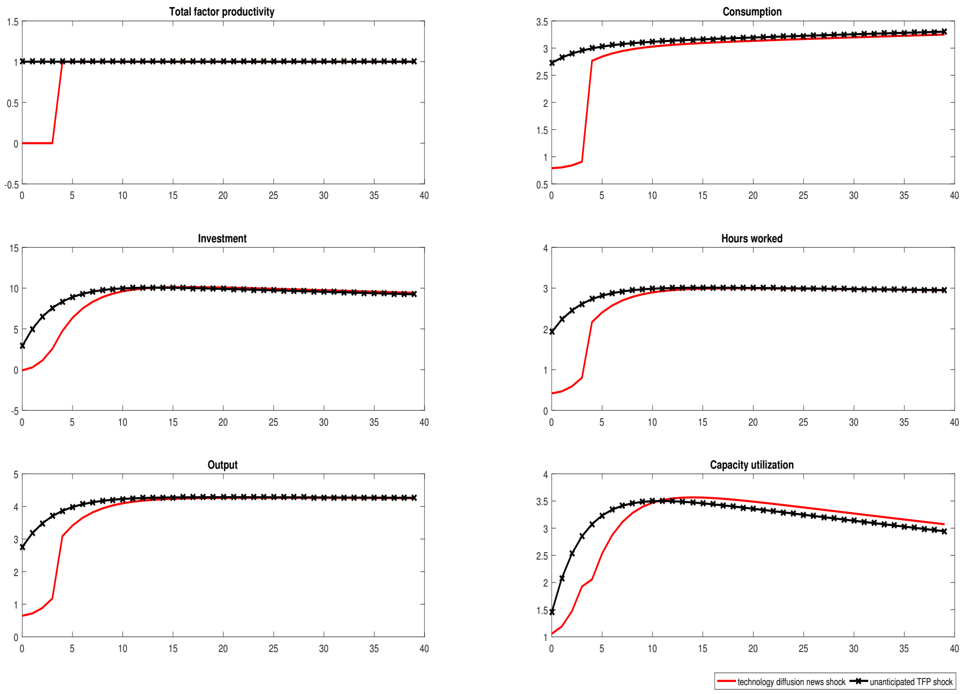

Figure 3.2: Impulse responses to a permanent unanticipated productivity shock and a news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

variable capacity utilization, adjustment cost to investment, and JR preferences) used by Jaimovich and Rebelo (2009) for obtaining the comovement of macro aggregates in response to the two productivity shocks.

When comparing the results presented in Figure 3.2 with the empirical evidence, we observe that there are some important differences. First of all, the impulse responses of TFP do not resemble. The empirical impulse response of TFP with regard to an unanticipated productivity shock is not permanent as its theoretical counterpart. Also the response of productivity with regard to the empirical news shock indicates a slow diffusion of technology after the news arrives, with aggregate productivity increasing slowly for several periods until reaching its new permanent level. Evidently, TFP does not remain unresponsive to the news shock for some periods and then jump to the new level as the theoretical response indicates. Moreover the impulse responses of hours worked with regard to the unanticipated productivity shock are contradictory. The empirical IRF indicates a negative impact effect of the shock, while the theoretical IRF gives the opposite. Lastly, the effect of the empirical news shock on investment is much stronger, while the theoretical results show almost no impact effect of this shock on investment.

We take two approaches to correct for these differences in responses. One is to model different exogenous processes for the two productivity shocks with the aim to bring closer the impulse responses of TFP. The other is to replace the JR preferences with more standard preferences that are time-separable in consumption and hours worked. We renounce at JR preferences in order to break the comovement of consumption and hours worked in response to any shock.

3.3.1 Different Shock Processes

We propose an ad-hoc shock specification that allows the unanticipated productivity shock to be persistent but not permanent, while the response of TFP to the news shock mimics technology diffusion similarly to the empirically found news shock.[16] By looking at Figure 3.3, we can observe that modeling the news shock as a technology diffusion shock mainly eliminates the jump when the announced productivity increase actually happens, as it allows for a slow diffusion of technology in the economy. However, it does not solve the problem of hours worked responding positively to the unanticipated productivity shock. Moreover, it affects the response of investment to the news shock. In this setting, investment drops after a positive news shock, which clearly contradicts the empirical evidence.

3.3.2 Habit Persistence

We replace JR preferences with a utility function that is time-separable in consumption and labor. We allow for intertemporal non-separability in consumption in the form of internal habit formation such that utility in consumption depends on consumption relative to own lagged consumption. There are two main reasons for introducing habit formation. One is to be able to mimic the "hump-shaped" responses of consumption to the productivity shocks that we see in the estimated impulse responses. The second is that habit persistence makes households anticipate the higher consumption when the news arrives. This leads to an increase in the marginal utility of consumption. Hence, also the marginal benefit from working today increases.

Preferences are described by the following utility function:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \left[\ln(C_t - \tau C_{t-1}) - \zeta \frac{L_t^{1+\eta}}{1+\eta} \right] \right\},$$

where τ controls for the degree of internal habit persistence. We calibrate $\tau = 0.6$ as in Christiano et al. (2010).

Lorenzoni (2011) shows, using the calibration $\tau = 0.6$, and $\varphi''(1) = 15$, that a news shock generates an immediate expansion in output, investment, consumption and hours worked in a simple RBC model with only habit persistence and investment adjustment costs. However, this holds only for the shock specification as in Jaimovich and Rebelo (2009) and for changes in productivity that occur soon after the news, preferably in less than one year. Moreover, the value used for the calibration of the investment adjustment

[16] The processes are described in Appendix 3.E.3.

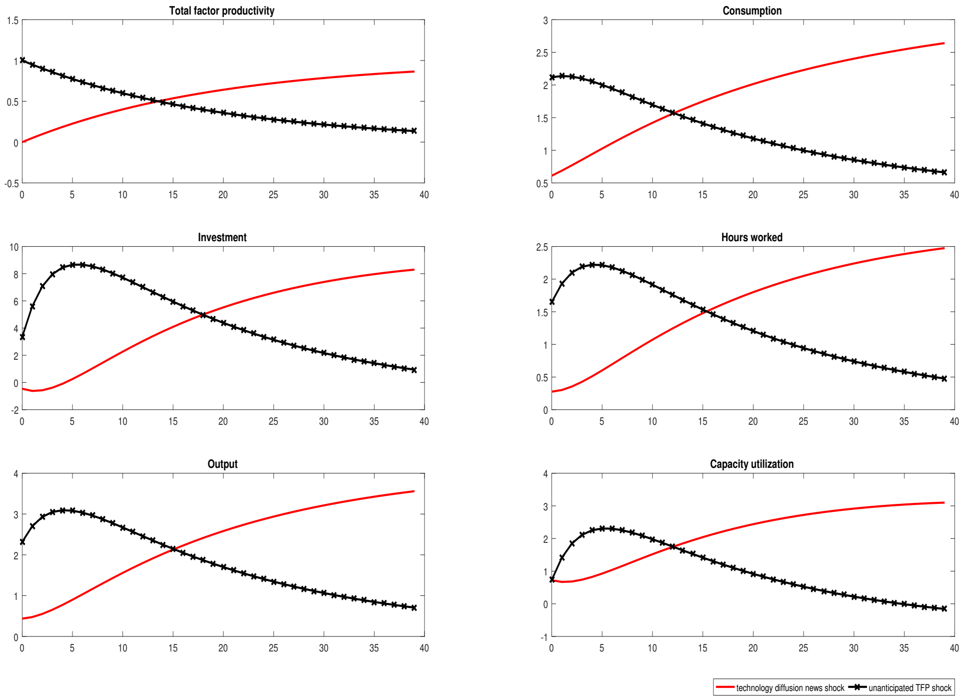

Figure 3.3: Impulse responses to a temporary unanticipated productivity shock and a technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

cost must also be quite big.[17] For example, Lorenzoni (2011) uses $\varphi''(1) = 15$, while the parameter equals 1.3 in Jaimovich and Rebelo (2009).

In Figure 3.4 we plot the impulse responses for the two shocks modeled to look more similar to the empirical productivity shocks. The impulse responses indicate that by making the utility function time-separable in labor and consumption and introducing habit persistence, we improve on the responses to an unanticipated productivity shock. We obtain the negative impact reaction of labor in response to an increase in productivity, along with the positive responses of output, consumption and investment.

Nevertheless, the results are worse in terms of impulse responses to the news shock. The news shock triggers a strong negative impact response of labor. The effect is negative also for investment, and almost nil for output.

Our conclusion after performing these exercises is that no matter the ingredients we add to the model, the empirical impact responses with regard to the news shock are hard to obtain as long as productivity is completely exogenous. The intuition is the following. If there is an announcement of potentially increased productivity in the future, no one needs to invest or contribute in any way for this to happen. Technology diffusion occurs exogenously and instantaneously at a certain time, while economic agents profit from this future productivity improvement no matter what they do. We consider this an unrealistic assumption. Our interpretation of a news shock is that it represents the public announcement of technological innovations that need time and further investment

[17] The complete list of results from this analysis are available from the authors.

to be developed and adopted in production at such a large scale that they reflect into increased productivity. Hence, we believe that we need an endogenous technology adoption mechanism in the model to boost investment, output and employment in response to a news shock. In the following section, we present our proposed model.

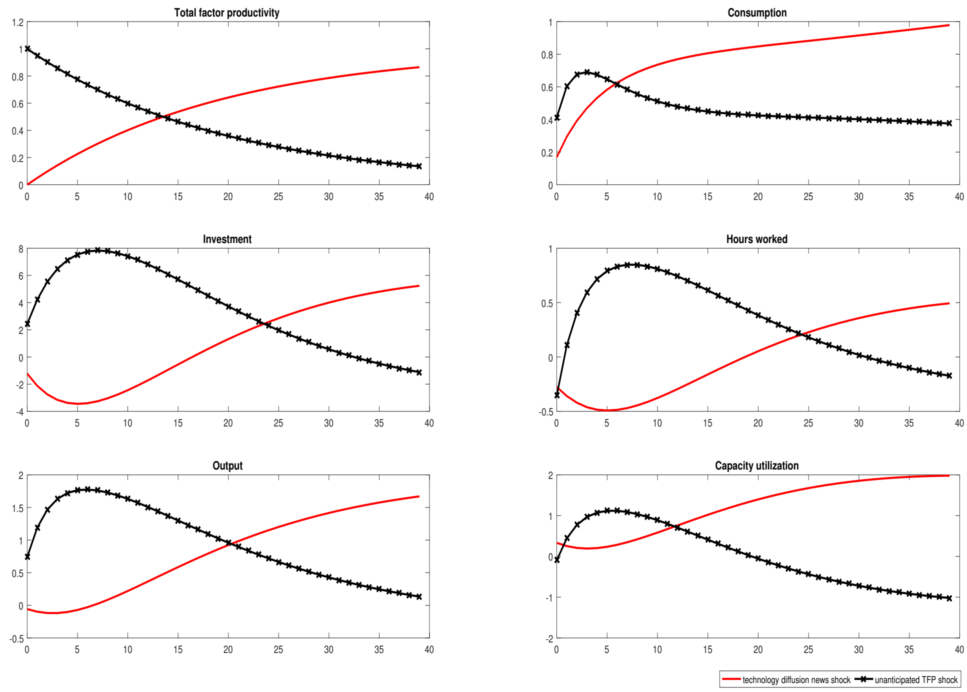

Figure 3.4: Impulse responses to a temporary unanticipated productivity shock and a technology diffusion news shock in a model with habit persistence. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

3.4 Model with Endogenous Technology Adoption

Our model is a medium scale DSGE model, which incorporates real frictions such as habit formation in consumption, and investment adjustment costs.

The model has the following structure. The economy is populated by households who consume, invest in physical capital and adoption of new technologies, supply labor, lease capital to firms, and accumulate bonds. There is no heterogeneity in households, so we treat them as being one representative agent. There exists a final good producing firm that bundles the different goods produced by intermediate firms into a final output good. The intermediate goods producers operate in an environment of monopolistic competition. They use capital and labor to produce heterogeneous output goods. Finally, there is a fiscal authority (i.e. government) whose spending requirement evolves exogenously. The fiscal authority finances this spending through lump sum taxes and debt.

These features of the model are relatively standard for RBC models, with one particularity. As seen in the description of the model's structure, households invest not only in physical capital but also in the adoption of new technologies. This is the case because our model comprises an endogenous technology adoption mechanism, which we developed following Comin et al. (2009). Technologies for producing new intermediate goods arrive exogenously to the economy. One may think that they are created in research institutes and universities, while the private sector does not contribute to the invention process. Once created, these inventions are not immediately usable in production. In order to become usable, a new prototype must be successfully adopted. This involves a costly investment. Adopters receive funds from households for adopting these new technologies. However, there is an endogenous probability for an adopter to be successful in adoption. If the adopter fails this period, she may try again in the subsequent periods. Once she succeeds, she sells it on a competitive market to a firm that becomes the producer of a new intermediate good. This endogenous variety expansion determines the level of embodied productivity.

While we are mainly interested in the effects of two shocks, the disembodied productivity shock, and a shock on embodied technological change, we introduce another three shocks in order to estimate some of the parameters. These are shocks to marginal efficiency of investment, government spending, and intertemporal preference.

3.4.1 Production

There is only one production sector, and that is for output, Y_t. Within the sector there are two stages of production, for intermediate and final goods, respectively. The final goods sector is competitive, and the production technology is a constant elasticity of substitution (CES) bundling of intermediate goods. On the other hand, there is monopolistic competition in the intermediate goods sector, where a large number of firms produce differentiated products using capital and labor. The intermediate goods producers have market power, and charge the final goods producers a price above their marginal cost. Thus they earn a monopoly rent.

Producers of Final Goods

The final goods producers operate in a competitive market, so we can assume there exists only one representative firm. This firm does not use any factors of production but only "packs" the differentiated intermediate goods into one single final good. The composite Y_t is a CES aggregate of the output of a continuum, measure A_t, of differentiated intermediate goods producers. Let $Y_t(s)$ be the amount of output that intermediate goods firm s produces, then:

$$Y_t = \left(\int_0^{A_t} Y_t(s)^{\frac{1}{\vartheta}} ds \right)^{\vartheta},$$

where A_t is the total number of intermediate inputs adopted in production (i.e. the stock of adopted technologies). This implies that an expanding variety of intermediate goods increases the efficiency of producing final goods, which will be reflected in TFP. The evolution of A_t depends on endogenous technology adoption.

Final goods producers solve the following problem:

$$\max_{Y_t(s)} P_t \left(\int_0^{A_t} Y_t(s)^{\frac{1}{\vartheta}} ds \right)^{\vartheta} - \int_0^{A_t} Y_t(s) P_t(s) ds$$

whose first order condition (FOC) gives the final goods producers' demand functions:

$$Y_t(s) = \left[\frac{P_t(s)}{P_t}\right]^{\frac{\vartheta}{-(\vartheta-1)}} Y_t$$

and the price index:

$$P_t = \left(\int_0^{A_t} P_t(s)^{\frac{1}{-(\vartheta-1)}} ds\right)^{-(\vartheta-1)}$$

Producers of Intermediate Output Goods

There is a continuum of intermediate goods producers indexed by s. The mass of these firms is normalized to A_t. A typical intermediate firm produces a specialized output according to a constant returns to scale technology in labor and capital, with a common productivity shock, X_t.

$$Y_t(s) = X_t K_t(s)^{\alpha} L_t(s)^{1-\alpha},$$

where X_t is the level of disembodied productivity (i.e. the exogenous component of total factor productivity), and $K_t(s)$ and $L_t(s)$ are the amount of capital and labor that firm s rents.

The firm solves the following cost minimization problem, by taking the nominal rental rate R_t^k, and nominal wage W_t as given:

$$\begin{aligned} \min_{K_t(s), L_t(s)} \; & R_t^k K_t(s) + W_t L_t(s) \\ & s.t. \\ & Y_t(s) = X_t K_t(s)^{\alpha} L_t(s)^{1-\alpha} \end{aligned}$$

Let $\mu_t(s)$ be the marginal cost of production for the intermediate goods producer s. Then the factor demand equation for labor is:

$$L_t(s) = \mu_t(s)(1-\alpha)\frac{Y_t(s)}{W_t}$$

and similarly, the one for capital is:

$$K_t(s) = \mu_t(s)\alpha\frac{Y_t(s)}{R_t^k}$$

Afterwards, the firm solves the following maximization problem:

$$\begin{aligned} \max_{P_t(s)} \; & P_t(s)Y_t(s) - \mu_t(s)Y_t(s) \\ & s.t. \\ & Y_t(s) = \left[\frac{P_t(s)}{P_t}\right]^{\frac{\vartheta}{-(\vartheta-1)}} Y_t \end{aligned}$$

Normalizing the price of the final good $P_t = 1$, the FOC is:

$$P_t(s) = \vartheta \mu_t(s)$$

In a symmetric equilibrium, firms hire capital and labor in the same ratio, which in turn equals the average ratio (i.e. $K_t(s) = \bar{K}_t$, $L_t(s) = \bar{L}_t$, $\forall s$), because they face the same factor prices. Therefore, they have the same nominal marginal cost, $\mu_t(s) = \mu_t$. Going back to the pricing rule, having the same marginal cost, they also charge the same price. From the demand specification, if all firms charge the same price, they must produce the same amount of output. If firms are defined as existing over the unit interval, the output of any each firm would be equal to the aggregate output since this is the same as the average output. However, in this model we have that the number of intermediate firms is $A_t \neq 1$. Hence, the output of each firm is $1/A_t$ of the aggregate output of intermediate goods producers, and this defines the average output. Similarly, the average factor demand is $1/A_t$ of the aggregate. Using this information, we can write the average output of intermediate firms as:

$$\bar{Y}_t = Y_t(s) = X_t \bar{K}_t^{\alpha} \bar{L}_t^{1-\alpha} = X_t A_t^{-1} K_t^{\alpha} L_t^{1-\alpha}$$

Thus, aggregate output can be written as:

$$\begin{aligned} Y_t &= \left(\int_0^{A_t} Y_t(s)^{\frac{1}{\vartheta}} ds \right)^{\vartheta} = \left(\int_0^{A_t} \bar{Y}_t^{\frac{1}{\vartheta}} ds \right)^{\vartheta} \\ &= [X_t A_t^{\vartheta - 1}] K_t^{\alpha} L_t^{1-\alpha}, \end{aligned}$$

where the term in square brackets is identified with TFP. Given that TFP depends on X_t, and A_t, the model allows for both exogenous and endogenous movements in TFP.

Using these findings, we can rewrite the labor demand equation in aggregate terms as:

$$L_t = \frac{1}{\vartheta}(1-\alpha)\frac{Y_t}{w_t},$$

where w_t is the real wage.

Similarly, for capital we obtain that:

$$K_t = \frac{1}{\vartheta}\alpha\frac{Y_t}{r_t^k},$$

where r_t^k is the real rental rate of capital.

The last step at this stage is to compute the profits of the intermediate goods producers. The profit of producer s in nominal terms is:

$$\begin{aligned} F_t(s) &= P_t(s)Y_t(s) - \mu_t(s)Y_t(s) \\ &= \frac{(\vartheta - 1)}{\vartheta}\frac{P_t Y_t}{A_t} = F_t \end{aligned}$$

The profit of producer s in real terms is:

$$f_t = \frac{(\vartheta - 1)}{\vartheta}\frac{Y_t}{A_t}$$

Since there is a mass A_t of these firms, the total amount of profits made by intermediate firms equals $A_t F_t$ in nominal terms, and $A_t f_t$ in real terms.

3.4.2 Productivity

TFP has two components in this model. One is exogenous and is given by the disembodied productivity variable, X_t. The other, A_t, is endogenous, and is defined by the number of 'adopted' intermediate goods in the production of the final output. Next we present the processes that govern the evolution of these variables.

Evolution of disembodied productivity

We assume that the natural logarithm X_t follows an AR(1) process:

$$\ln X_t = \rho_x \ln X_{t-1} + s_x \epsilon_t^x,$$

where $0 < \rho_x < 1$, ϵ_t^x is i.i.d. and drawn from a standard normal distribution, and s_x is the standard deviation of the shock.

Innovation

In contrast with the assumption in the endogenous growth literature, innovation in this model is exogenous. Thus, growth is also exogenous. Let Z_t be the technological frontier at time t. Z_t comprises all technologies publicly available for producing intermediate goods. It contains both previously adopted technologies, which are already used in production, and 'not yet adopted' prototypes. The natural logarithm of Z_t follows a random walk with drift. This implies that $z_t \equiv (\frac{Z_t}{Z_{t-1}})$, the stochastic growth rate of the number of prototypes, is governed by the following process:

$$\ln z_t = \Delta_z + s_z \epsilon_t^z,$$

where Δ_z is calibrated to match the growth rate of the economy, ϵ_t^z is i.i.d. and drawn from a standard normal distribution, and s_z is the standard deviation of the shock.

In this setting, news about future economic prospects are captured by shocks to z_t. These changes in z_t govern the potential growth of new intermediate goods. However, without the adoption of the new technologies, there is no technology transfer from the technological frontier to the economy. Hence, the key difference between this model and the others in the related news literature is that technology diffusion is no longer instantaneous. In order to reap the benefits of using new technologies, firms need to become involved in a costly adoption process that is presented below.

Adoption of Innovations

The adoption sector is perfectly competitive, with free entry. Adopters are firms that try to make unexploited technologies usable. Households lend to these firms the resources they need to adopt the new inventions. Adopters succeed with an endogenously determined probability Ξ_t. Once an adopter makes a technology usable, she sells it to a firm that wants to enter the intermediate goods market by using the technology to produce a new variety of intermediate goods.

The adoption process works as follows. To try to make one prototype usable at time $t+1$, an adopting firm s invests $S_t(s)$ at time t. Its success probability $\Xi_t(s)$ is given by the following logistic function:[18]

$$\Xi_t(s) = \frac{2}{1 + exp(-\Gamma_t(s))} - 1,$$

with $\Gamma_t(s)$ being:

$$\Gamma_t(s) = \bar{\Gamma}\left[S_t(s)\frac{(Z_t - A_t)}{A_t}\right]^{\rho_\Gamma},$$

where $\bar{\Gamma} > 0$, $0 < \rho_\Gamma < 1$.[19]

We assume that the adoption probability increases in the amount of resources devoted to adoption at the firm level, $S_t(s)$, and in the distance between the current technological state of the economy, A_t, and the technological frontier, henceforth the technology gap. Empirical studies show that industries that are farther from the technological frontier converge faster[20] and we follow this line of logic in assuming that the adoption probability $\Xi_t(s)$, which is an indicator of the pace of technology adoption, is increasing in the technology gap.

In order to discuss the adopter's maximization problem, we need to clarify which is the cost of adopting a technology and the price she may charge the new intermediate goods producer when selling it. If there were no uncertainty regarding the successfulness of the adoption process, then the adopter's price would equal her cost, $S_t(s)$, given that she cannot make any profits while operating in a competitive market. The price charged to the intermediate goods producer would equal the present value of profits that the innovation would help generate, which would drive profits on the intermediate goods market to zero. The value an intermediate goods producer acquires after buying a new technology is given by the present value of profits from using the technology, $V_t(s)$. This firm makes profits, $f_t(s)$, due to her monopolistic power since she is the only producer of the new variety of intermediate goods. Given that the stochastic discount factor for returns between $t+1$ and t equals $\beta\frac{\lambda_{t+1}}{\lambda_t}$, we can express $V_t(s)$ as:

$$V_t(s) = f_t(s) + \mathbb{E}_t\left[\beta\frac{\lambda_{t+1}}{\lambda_t}\phi V_{t+1}(s)\right],$$

where ϕ is the survival rate of intermediate goods.[21]

Hence, the optimal level of investment in adoption would equal the present value of profits the technology generates, i.e. $S_t(s) = V_t(s)$. However, the adopter needs to take into account the fact that there is a probability of $1 - \Xi_t(s)$ that she is unsuccessful in making the technology usable in the current period. In this case, she may try again in

[18] $\Gamma_t(s)$ is used in the related literature as the function for the adoption probability, but we perform the transformation into $\Xi_t(s)$ in order to make sure that the probability lies between 0 and 1. We use the logistic function for the transformation because it allows us to mimic the diffusion of innovations. The initial stage of adoption is approximately exponential; then, as the economy converges to the technological frontier, adoption slows, and it finally stops when the technology gap is closed.

[19] $\bar{\Gamma}$ is a parameter which we calibrate to obtain a steady state value for $\Xi(s)$ of 0.025, which is the equivalent of a technology diffusion lag of 10 years, while ρ_Γ reflects decreasing returns to the adoption effort.

[20] Details on these empirical results ca be found in Griffith et al. (2002), Acemoglu et al. (2006), and Griffith et al. (2009), among others.

[21] As in the case of capital, we assume that adopted technologies also depreciate, and this is given by the fact that every period a fixed number $(1 - \phi)$ of intermediate goods become obsolete.

the following periods, but needs to consider this possibility when making her investment decision.

Let $J_t(s)$ be the value an adopter gets from acquiring an innovation that has not been adopted yet. $J_t(s)$ is given by:

$$J_t(s) = \max_{S_t(s)} -S_t(s) + \mathbb{E}_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t} \left[\Xi_t(s) \phi V_{t+1}(s) + (1 - \Xi_t(s)) J_{t+1}(s) \right] \right\}$$

Solving this maximization problem, we find that the choice of the optimal investment in adopting a new technology takes into consideration the effect it has on the probability of a successful adoption. This can be seen in the equation below:

$$0 = -1 + \mathbb{E}_t \left\{ \beta \frac{\lambda_{t+1}}{\lambda_t} (\phi V_{t+1}(s) - J_{t+1}(s)) \frac{\partial \Xi_t(s)}{\partial S_t(s)} \right\}$$

Note that the choice of $S_t(s)$ does not depend on any firm specific characteristics. Thus in equilibrium all adopting firms incur the same adoption costs, i.e. $S_t(s) = S_t$. This implies that the adoption probability is the same for all firms attempting adoption ($\Xi_t(s) = \Xi_t$), as are the value of using the new technology ($V_t(s) = V_t$) and the value of acquiring an innovation that has not been adopted yet ($J_t(s) = J_t$).

Evolution of Embodied Productivity

Embodied productivity, which is equivalent to the number of intermediate goods used in production, evolves according to the following equation:

$$\begin{aligned} A_{t+1} &= \Xi_t Z_t + (1 - \Xi_t) \phi A_t \\ &= \Xi_t (Z_t - \phi A_t) + \phi A_t, \end{aligned}$$

The level of embodied productivity depends on the old productivity level and the outcome of technology adoption activities. Note the similarity of this equation to the law of motion for capital, where the capital stock at the beginning of next period is given by the non-depreciated part of current period capital and contemporaneous investment. Since every period $(1 - \phi)$ of the intermediate goods become obsolete, if there is no technology adoption then A_{t+1} equals ϕA_t. This is the case if either the economy is at the technological frontier, and hence there is no technology gap (i.e. $A_t = Z_t$), or there is no investment in adoption, which makes the successful adoption probability zero. When the technology gap is wide, the economy tries to catch up through technology adoption. Given that the adoption market is competitive, every period adopting firms would want to try adoption. If all firms are successful, the technological frontier, Z_t, is reached. Ξ_t indicates how fast the technological convergence is. Hence, with probability Ξ_t, the technological frontier is reached, while with probability $(1 - \Xi_t)$ embodied productivity equals ϕA_t. By rearranging terms in the equation above, we can observe that the whole term $\Xi_t (Z_t - \phi A_t)$ gives the proportion by which productivity rises every period. From the evolution of embodied productivity we can infer that an increase in the productivity frontier, Z_t, is not instantaneously translated into a one-to-one increase in productivity. technology diffusion may be slower or faster depending on the pace of the adoption process implied by Ξ_t, but it is not immediate.

3.4.3 Households

There is one representative household whose preferences are additively separable in consumption and labor.[22] These preferences are characterized by the following lifetime utility function:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \iota_t \left[\ln(C_t - \tau C_{t-1}) - \zeta \frac{(L_t)^{1+\eta}}{1+\eta} \right] \right\},$$

where C_t is consumption, L_t labor supply, β is the discount factor, τ controls for the degree of internal habit persistence, η is the inverse of Frisch labor supply elasticity, and ζ is the labor disutility parameter. ι is an exogenous intertemporal preference shock. We allow for intertemporal non-separability in consumption in the form of internal habit formation such that utility in consumption depends on consumption relative to own lagged consumption.

In each and every period households consume, save, and supply labor. They save by either accumulating capital or lending to technology adopters. They make one period loans to adopters and also rent capital that has been accumulated directly to firms. Each household also has equity claims in the firms.

The capital accumulation equation is given by:

$$K_{t+1} = I_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}} \right) \right] b_t + [1-\delta] K_t,$$

where K_t is physical capital, I_t is the amount of final goods used by the households for investment in capital, $\varphi(\cdot)$ denotes adjustment costs to investment for which we assume that in the steady state $\varphi(\Delta_i) = \varphi'(\Delta_i) = 0$, where Δ_i is the growth rate of investment along the balanced growth path that we discuss later, and δ determines the capital depreciation rate. b_t is an exogenous marginal efficiency of investment shock.

The household's problem is to maximize utility subject to the budget constraint, evolution of embodied technology, and law of motion for capital:[23]

$$\max \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \iota_t \left[\ln(C_t - \tau C_{t-1}) - \zeta \frac{(L_t)^{1+\eta}}{1+\eta} \right] \right\}$$

$$s.t.$$

$$P_t C_t + P_t I_t + P_t S_t [A_{t+1} - A_t] + B_{t+1} = W_t L_t + R_{t-1} B_t + F_t A_t + R_t^k K_t - P_t T_t$$

$$A_{t+1} = \Xi_t \left(Z_t - \phi A_t \right) + \phi A_t$$

$$K_{t+1} = I_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}} \right) \right] b_t + [1-\delta] K_t$$

$$K_0,\ Z_0,\ A_0,\ B_0,\ I_{-1},\ C_{-1}\ given$$

In the budget constraint, $F_t A_t$ denotes the nominal profit of the intermediate goods production sector paid fully as dividends to households, P_t is the nominal price of goods, B_t is the amount of nominal government bonds that households acquire at $t-1$ and that pay at t a nominal gross interest rate R_{t-1}, and T_t is a real lump sum tax or transfer from

[22] The choice of this particular utility function with log utility in consumption is motivated by the fact that the marginal rate of substitution between consumption and leisure is linear in consumption and this ensures the existence of a balanced growth path with constant hours worked.

[23] The Lagrangian for this problem and the first order conditions are presented in Appendix 3.F.

the government. Note that we index the predetermined variables, K_t and A_t, by the time their level is used and not decided. Hence, having A_{t+1} decided at time t, the household allocates funds amounting to $P_t S_t[A_{t+1} - A_t]$ for technology adoption. Therefore, the household decides on labor supply, consumption, investment, capital and bond holding. These decisions that the household makes are quite standard in the macroeconomic literature, with the exception of the choice of investment in adoption. Knowing the evolution of embodied technology, the household chooses the optimal amount of resources to invest in the adoption of new technologies. This equation describes the supply of adoption investment.

The optimal choices of the household characterizing an interior solution are given in real terms by the following first order conditions:[24]

$$C_t : \iota_t(C_t - \tau C_{t-1})^{-1} - \beta\tau\mathbb{E}_t\iota_{t+1}(C_{t+1} - \tau C_t)^{-1} = \lambda_t \tag{3.1}$$

$$B_{t+1} : \lambda_t = \beta\mathbb{E}_t\left(\lambda_{t+1}R_t\frac{P_t}{P_{t+1}}\right) \tag{3.2}$$

$$I_t : 1 = q_t b_t\left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right) - \varphi'\left(\frac{I_t}{I_{t-1}}\right)\frac{I_t}{I_{t-1}}\right] + \beta\mathbb{E}_t\left[q_{t+1}b_{t+1}\frac{\lambda_{t+1}}{\lambda_t}\varphi'\left(\frac{I_{t+1}}{I_t}\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right] \tag{3.3}$$

$$K_{t+1} : q_t = \beta\mathbb{E}_t\left[\frac{\lambda_{t+1}}{\lambda_t}r^k_{t+1} + q_{t+1}(1-\delta)\right], \tag{3.4}$$

$$L_t : \iota_t\zeta L_t^\eta = \lambda_t w_t, \tag{3.5}$$

$$S_t : \lambda_t(A_{t+1} - A_t) = \Omega_t\frac{\partial\Xi_t}{\partial S_t}\left(Z_t - \phi A_t\right) \tag{3.6}$$

The transversality condition is:

$$\lim_{s\to\infty}\beta^s\mathbb{E}_t\lambda_{t+s}\left(K_{t+s} + B_{t+s}\right) = 0 \tag{3.7}$$

3.4.4 Government

The government consumes an exogenous share of output, $G_t = g_t Y_t$. The natural logarithm of the share of output allocated to government spending follows an AR(1) process with a non-stochastic mean equal to g_{ss}:

$$\ln g_t = (1 - \rho_G)\ln g_{ss} + \rho_G \ln g_{t-1} + s_G\epsilon_t^G,$$

[24] Λ_t is the Lagrange multiplier associated with the budget constraint, Ω_t is the Lagrange multiplier associated with the evolution of technology adoption, and Q_t is the Lagrange multiplier associated with the law of motion for capital. Note that we deflate the nominal variables using P_t as deflator, and define the Tobin's q as $q_t = \frac{Q_t}{\Lambda_t P_t}$, and $\lambda_t = \Lambda_t P_t$.

where $0 \leqslant \rho_G < 1$. The shock ϵ_t^G is i.i.d. and drawn from a standard normal distribution and s_G is the standard deviation of the shock. The government raises revenue via lump sum taxes and issues debt:

$$P_t g_t Y_t + R_{t-1} D_t \leqslant P_t T_t + D_{t+1},$$

D_t is the stock of nominal debt with which the government enters the period. The government pays back this debt with interest R_{t-1}. It raises revenue from lump sum taxes, and can issue new debt, D_{t+1}, to finance its nominal expenditures.

3.4.5 Stochastic Processes

To complete the presentation of the model, we add to the list of equations[25] the exogenous processes for marginal efficiency of investment (b_t), and intertemporal preference (ι).[26]

It is assumed that the natural logarithm of marginal efficiency of investment, (b_t), and intertemporal preference, ι, follow AR(1) processes with non-stochastic means normalized to unity (i.e. zero in logs):

$$\ln b_t = \rho_b \ln b_{t-1} + s_b \epsilon_t^b$$

$$\ln \iota_t = \rho_\iota \ln \iota_{t-1} + s_\iota \epsilon_t^\iota$$

The autoregressive parameters are assumed to lie between 0 and 1 and the shocks are i.i.d. and drawn from standard normal distributions, with s_b, and s_ι, being the standard deviation of each shock.

3.4.6 Calibration and Empirical Approach

In what follows we present our methodology for solving and evaluating the model. We solve the model numerically using a first order perturbation method. We use the solution to the log-linear approximation of the detrended model around its deterministic steady state to find the equilibrium values of all variables.[27] To apply this solution method we first need to assign values to the parameters of the model.[28] We partition the model parameters into two groups. The first group of parameters we calibrate, while the second group we estimate.

The group of parameters that we calibrate is composed of β (discount factor), η (inverse Frisch elasticity), δ (capital depreciation rate), κ (capital investment adjustment costs parameter), α (capital share in the production function), ϕ (survival rate of a technology), ϑ (steady state markups for intermediate goods), φ (labor disutility parameter),

[25] The complete list of equilibrium equations is presented in Appendix 3.F.

[26] Note that the exogenous processes for disembodied productivity (X_t), embodied technological change (z_t), and government spending (G_t) have been described before, and are not included in this section to avoid repetition.

[27] We solve the model in Matlab R2016a, using Dynare 4.4.3. toolbox. The codes are available from the authors upon request.

[28] We perform a quarterly calibration of the model for the US economy because we want to obtain results which may be comparable to those obtained from estimating a model with quarterly US data.

Δ_z (steady state growth of the economy), g_{ss} (ratio of steady state government spending to output) and $\bar{\Gamma}$ (parameter contained in the definition of Γ, and Ξ respectively).

In the steady state of this economy, the gross real interest rate equals the growth rate of prototypes times the inverse of the discount factor: $R = \Delta_z \beta^{-1}$. We calibrate the steady state growth rate of prototypes, Δ_z, to $1 + 0.02/4$ in order to match the roughly 2 percent annual growth rate of output in the US over the period 1960-2014.[29] We then calibrate the gross real interest rate to an annual rate of 5 percent, which we choose to be close to the mean after-tax return on capital over the same time span.[30] This implies that β equals $0.9926 = (1 + 0.02/4)/(1 + 0.05/4)$.

We set α equal to 0.37, which corresponds to a steady-state capital share of income of roughly 37 percent, that is the average value over the period 1960-2014.[31] We calibrate η, the inverse Frisch labor supply elasticity, to 1.[32]

Using estimates from Ramey and Francis (2009) for average weekly number of leisure hours,[33] and average weekly number of working hours[34] for the working-age population in the US from 1960 to 2005, we find that hours worked represent one third of available time. Hence, we calibrate φ, the labor disutility parameter, such that we have steady state hours worked equal to 1/3.

For the depreciation rate, δ, we set a value of 0.025, which implies an annual rate of depreciation on capital equal to 10 percent. This value of δ is in the range of values for the average of the investment to capital ratio for manufacturing machinery and equipment. The estimates reported in the literature, typically obtained using data from the NBER-CES Manufacturing Industry Database, vary depending on the industries considered in the analysis and sample period (e.g. 7.72 percent in Cooper and Priestley (2016), 11.7 percent in Albonico et al. (2014)). We calibrate ϕ, the quarterly survival rate of a technology, to $1 - 0.1/4$. This implies that we use the same rate of depreciation for technology as for capital, that is an annual obsolescence rate of 10 percent. Examples of calibrations chosen in the related literature are 3 percent per year (Comin and Gertler (2006)), 4 percent in Comin et al. (2009), and 8 percent in Anzoategui et al. (2017). Their motivation is that these values are contained in the range of estimates in the literature, with a minimum estimate of 4 percent in Caballero and Jaffe (1993) and a maximum

[29] We use data for real output per person in the non-farm business sector (percent change at annual rate, quarterly, seasonally adjusted) from the Federal Reserve Bank of St. Louis as provided on fred.stlouisfed.org to compute an average of 1.9 percent over 1960-2014.

[30] Gomme and Lkhagvasuren (2013) compute an average value of 4.9869 percent for the after-tax return to capital over 1954Q1 through 2009Q4. They use the approach of Gomme et al. (2011), that is to use NIPA data and compute the after-tax return to capital by dividing after-tax private market capital income by the corresponding capital stock. We choose a slightly higher value because from 2009 to 2014 the after-tax return to capital has been steadily increasing to almost 7 percent (for details see Gomme et al. (2015))

[31] We use data for the share of labor compensation in GDP at current national prices for the US (ratio, annual, not seasonally adjusted) from the Federal Reserve Bank of St. Louis as provided on fred.stlouisfed.org to compute the average share of labor over 1960-2014, and then approximate the average share of capital as being one minus the share of labor.

[32] The values used to calibrate the Frisch elasticity in general equilibrium models typically fall within the range from 1 to 4, with more recent estimates based on macro data indicating that the range should be reduced to the interval from 1 to 2 (for details see Fiorito and Zanella (2012), Keane and Rogerson (2012)), or even below 1 to get closer to the estimates obtained in the micro literature.

[33] Ramey and Francis (2009) define leisure hours as the total time available per week less hours used for sleep, meals, hygiene, commute, and household chores.

[34] According to Ramey and Francis (2009), working hours include paid hours in the private sector, hours worked for the government, and unpaid family labor

of 25 percent in Pakes and Schankerman (1987). However, in a more recent empirical analysis by Park et al. (2006), using a new method for estimating the depreciation rate of technological knowledge based on the analysis of technology cycle time applied to patent citation data, it is computed an average obsolescence rate of roughly 13.3 percent, with consistent upward trends being found over time.

We calibrate the steady state ratio of government spending to gross domestic product to 0.207, which equals the 20.7 percent average share of gross domestic product dedicated to government consumption expenditures and gross investment in the US for the period 1960-2014.[35]

We set the value of ϑ, the steady state gross markup for specialized intermediate goods, equal to 1.63. The range of estimates for markups in the US is large, results depending on the industries considered in the analysis, data, and methodology employed. The results presented in Hall (1988) indicate markup ratios close to, or above 100 percent, while in more recent studies, such as Oliveira Martins and Scarpetta (1996) and Høj et al. (2007), the estimates are in the range of zero to 30 percent for most industries and seldom over 50 percent. For the sectors with higher markups, the explanation is that they are due to innovation and monopoly rents. Given the specialized nature of the intermediate goods in this model, the related literature assumes that their markups should be in the high range, e.g. Comin and Gertler (2006) calibrate the markup to 1.6. However, there is also a practical need for our chosen calibration. The steady state gross markup for specialized intermediate goods is equal to $2 - \alpha$, which is required in order to ensure a balanced growth path.

For $\bar{\Gamma}$ we choose a value which gives a steady state value for Ξ of 0.025. Following Comin and Gertler (2006), we consider the average time for the adoption of an intermediate good to be $1/(4\Xi)$, that is equivalent to an average adoption lag of 10 years given our parametrization. Comin and Hobijn (2010) use technology measures[36] for 166 countries and 15 technologies for the period from 1820 to 2003 and find that on average countries need 45 years to adopt technologies after their invention. However, in the case of the US the adoption lag for these technologies reduces to 19.8 years (for details see Eden and Nguyen (2016)), and when we consider only the group of technologies that were invented after 1950 (e.g. cell phones, personal computers, internet usage, blast oxygen steel, magnetic resonance imaging), the average becomes 6.7 years. This implies that the US is more than 20 years ahead in adopting technologies than the average country, but also that recent technologies are adopted faster than in the past. Taking these results into account and given that we calibrate the model using information for the US from 1960 to 2014, choosing an average adoption lag of 10 years seems reasonable. This calibration also facilitates the comparison of a shock to the growth rate of prototypes to the empirical news (or slow-diffusing productivity) shock, which is defined as the shock with no impact effect on productivity that explains most of its forecast error variance in 10 years.

The group of parameters that we estimate contains τ (consumption habit), κ (capital investment adjustment costs parameter), ρ_Γ (expenditure elasticity of the adoption probability), persistence and standard deviation of shocks. We define the set of parameters

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[35] We use data for the shares of gross domestic product: government consumption expenditures and gross investment (percent, quarterly, not seasonally adjusted) from the Federal Reserve Bank of St. Louis as provided on fred.stlouisfed.org to compute the average over 1960-2014.

[36] Data is taken from the CHAT dataset, introduced by Comin and Hobijn (2004) and expanded by Comin et al. (2008).

to be estimated as: $\varpi = [\tau,\, \kappa,\, \rho_\Gamma,\, s_z,\, \rho_x,\, s_x,\, \rho_b,\, s_b,\, \rho_\iota,\, s_\iota,\, \rho_G,\, s_G]$.

In a first stage, we calibrate some of these parameters to standard values in the literature to investigate the theoretical impulse responses to the two productivity shocks. We switch off the other shocks as they are only needed for performing the estimation. Hence, we calibrate only the standard deviations of the unanticipated productivity shock and of the news shock (i.e. s_z and s_x) and the autocorrelation coefficient in the law of motion of X_t. We normalize the standard deviations of shocks to 0.01, and set the autocorrelation coefficient, ρ_x, to 0.95. The chosen value for the habit parameter, τ, is 0.75. This value is in the region between 0.6 and 0.9 in which the estimates for this parameter usually lie in the macroeconomic literature. For the parameter ρ_Γ that governs the elasticity of adoption with respect to adoption investments, we set the value equal to 0.9, which is close to the calibration in the related literature (e.g. 0.95 in Anzoategui et al. (2017), and 0.85 in Comin et al. (2016)). We calibrate κ, the capital investment adjustment costs parameter, equal to 1.3, which is the value used for calibration in Jaimovich and Rebelo (2009).[37]

In a second stage, we estimate all the parameters in the set ϖ. We use the approach of Christiano et al. (2005) to estimate these parameters. Specifically, we minimize a measure of the distance between model and empirical impulse response functions. We define as $\Psi(\varpi)$ the mapping from ϖ to the model impulse response functions, and as $\hat{\Psi}$ the corresponding empirical estimates.[38] Our estimator of ϖ is the solution to:

$$\hat{\varpi} = \min_{\varpi} \left[\hat{\Psi} - \Psi(\varpi)\right]' \Theta^{-1} \left[\hat{\Psi} - \Psi(\varpi)\right],$$

with Θ being a diagonal matrix with the sample variances of the $\hat{\Psi}$'s on the diagonal. These variances are the basis for the confidence intervals of the empirical impulse responses. Hence, with this choice of Θ, ϖ is effectively chosen such that $\Psi(\varpi)$ lies as much as possible inside these confidence intervals.

Regarding the starting parameter values, ϖ_s, we normalize the standard deviations of shocks to 0.01, and set all autocorrelation coefficients to 0.5. The starting value for the habit parameter, τ, is 0.75. For the parameter ρ_Γ we set the starting value equal to 0.75. This value is smaller than the 0.9 chosen for the calibration, but we wanted to have a starting value that is not very close to the upper bound. For κ we chose a starting value equal to 3.

To obtain $\hat{\Psi}$, we need the empirical impulse responses. From the impulse response functions to the two shocks for 40 quarters of the 5 variables included in the model, we include in $\hat{\Psi}$ only the first 10 elements, and the last 5 elements of the response functions of all variables to both shocks. This makes $\hat{\Psi}$ a $1 \times (5 * 15 * 2)$ vector.

We follow the same approach to compute $\Psi(\varpi)$, with the only difference that instead of real data we use data simulated from the model, starting with ϖ_s as calibration for the parameters to be estimated.

The diagonal matrix Θ is obtained by taking only the first 10, and the last 5 diagonal elements of the variance covariance matrix of the estimated impulse response functions to both shocks, and for each variable. This implies that the dimension of Θ is $(5 * 15 * 2) \times (5 * 15 * 2)$.

[37] The benchmark calibration is summarized in Table 3.2 from Appendix 3.G.

[38] There exists a vector of theoretical moments, Ψ, whose true value is denoted by Ψ_0 and which is substituted by an estimate $\hat{\Psi}$ in practice. It is assumed that $\sqrt{T}(\hat{\Psi} - \Psi_0) \sim N(0, \Sigma_\Psi)$, where T denotes the sample size.

To derive the standard deviations we use the fact that, under standard regularity conditions, $\sqrt{T}(\hat{\varpi} - \varpi_0) \sim N(0, \Sigma_\varpi)$, where ϖ_0 is the true value of ϖ and Σ_ϖ follows:[39]

$$\Sigma_\varpi = \left(\frac{\partial\Psi(\varpi)'}{\partial\varpi}\Theta^{-1}\frac{\partial\Psi(\varpi)'}{\partial\varpi}\right)^{-1}\frac{\partial\Psi(\varpi)'}{\partial\varpi}\Theta^{-1}\Sigma_\Psi\Theta^{-1}\frac{\partial\Psi(\varpi)'}{\partial\varpi}\left(\frac{\partial\Psi(\varpi)'}{\partial\varpi}\Theta^{-1}\frac{\partial\Psi(\varpi)'}{\partial\varpi}\right)^{-1}$$

3.4.7 Results

Theoretical Impulse Responses

Using the benchmark calibration presented in the previous section, and summarized in Table 3.2 from Appendix 3.G, we compute theoretical impulse responses to a one percent shock to disembodied productivity, X, and to exogenous embodied technology, Z. We consider these two shocks to be the model equivalent of the empirical technology diffusion (news) shock and unanticipated productivity shock we discussed in Section 3.2.

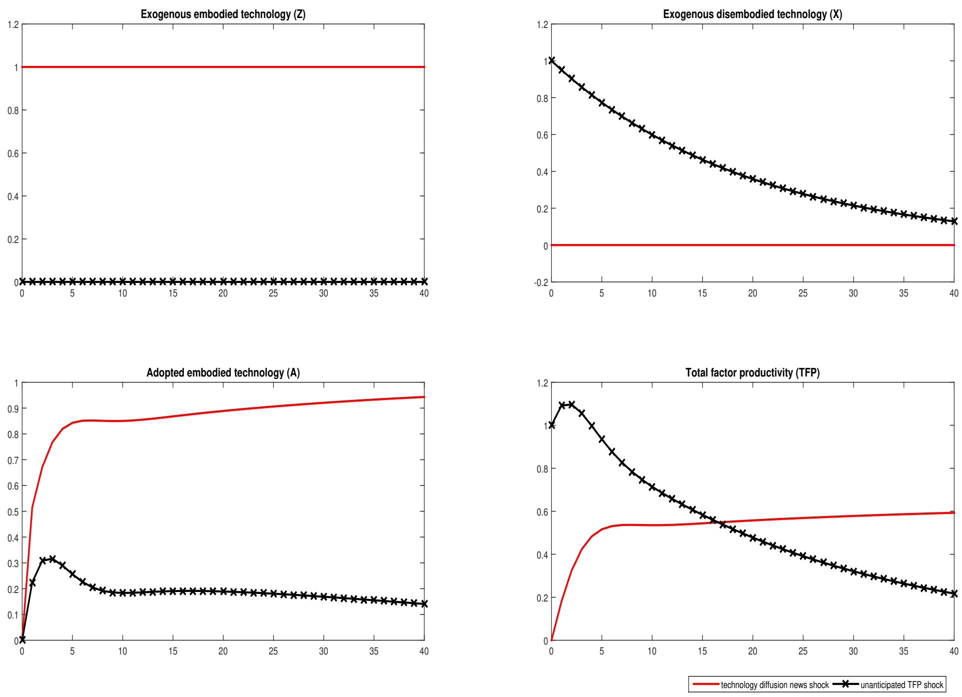

Figure 3.5: Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

In Figure 3.5 we see that the technology diffusion shock is a shock that takes on impact the technological frontier, Z, to a new permanent level. This shock however has no effect on the level of disembodied productivity, since X evolves purely exogenously. The level of adopted technologies, A and hence TFP, are not affected by the news shock on impact.

[39]For details see Fève et al. (2009).

There is a time lag between the period when the technology frontier improves until aggregate productivity changes because of the newer technology available. However, after the first period adoption occurs, and this triggers the fast increase in adopted technologies, and in TFP. In about one year and a half, the technology gap is almost closed, and both A and TFP seem to stabilize at a new higher permanent level. Therefore, whenever the technology gap is enlarged because of a change in the technology frontier, the economy responds immediately and uses resources to close it in order to reap the benefits of higher aggregate productivity. This mechanism is observed in Figure 3.6. After the news hits, there is an increase in funds allocated to adoption, which makes successful adoption more probable.

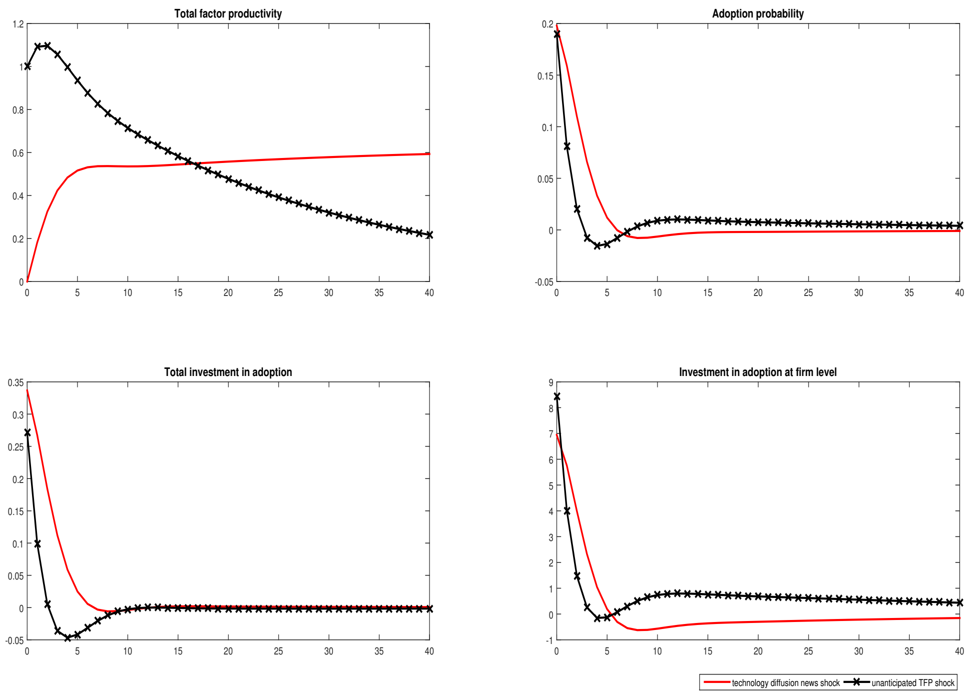

Figure 3.6: Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

Nevertheless, the economy may want to get closer to the frontier also when there is no change in the frontier itself, but only because it has the resources to make adoption investments. This is the case, for example, when there is a surprise productivity improvement. An increase in disembodied productivity, X, translates into a one-to-one increase in TFP, which leads to an increase in output. Having more resources available, households decide to spend some on adoption. As it can be seen in Figure 3.6, after an unanticipated productivity shock, there is an immediate increase in investment in adoption. But because there are not many technologies to be adopted given that the frontier is unchanged, investment is ceased much faster than after a news shock. This translates into fewer technologies adopted, and hence, into a smaller increase in A. However, this effect of an unanticipated productivity shock on adoption gives the hump-shape response of TFP in Figure 3.5. TFP continues to increase for some periods after the unanticipated productivity shock due to increased adoption. Because of this channel, the effect of the unanticipated productivity shock is more persistent on TFP than on X, and this makes the IRF of TFP look more similar to its empirical counterpart.

Comin et al. (2009) introduced this idea of endogenizing the adoption of technologies that are invented exogenously to provide a more realistic story for the technology diffusion news shock. However, our model differs significantly from theirs. They work with a complex two-sector model, for output and capital goods production, and have invention and adoption in both sectors. Moreover, we model both the evolution of the technology frontier and the adoption of new prototypes in different ways. Furthermore, their model predictions do not match the empirical evidence. More importantly is that in the newer version of the paper, Comin et al. (2016), the technology frontier does not evolve exogenously anymore. They endogenize also R&D, and both invention and adoption do not depend on investment anymore but on skilled capital employed in these sectors. Finally, given that there is no shock to the evolution of new technologies in this new framework, their news component is only the effect of an unanticipated productivity shock on adoption, which triggers the amplification of the response of TFP to the unanticipated shock. But as we illustrate in Figure 3.5, this is a much smaller effect than the one of a news shock, and hence cannot be used to explain the empirical evidence.

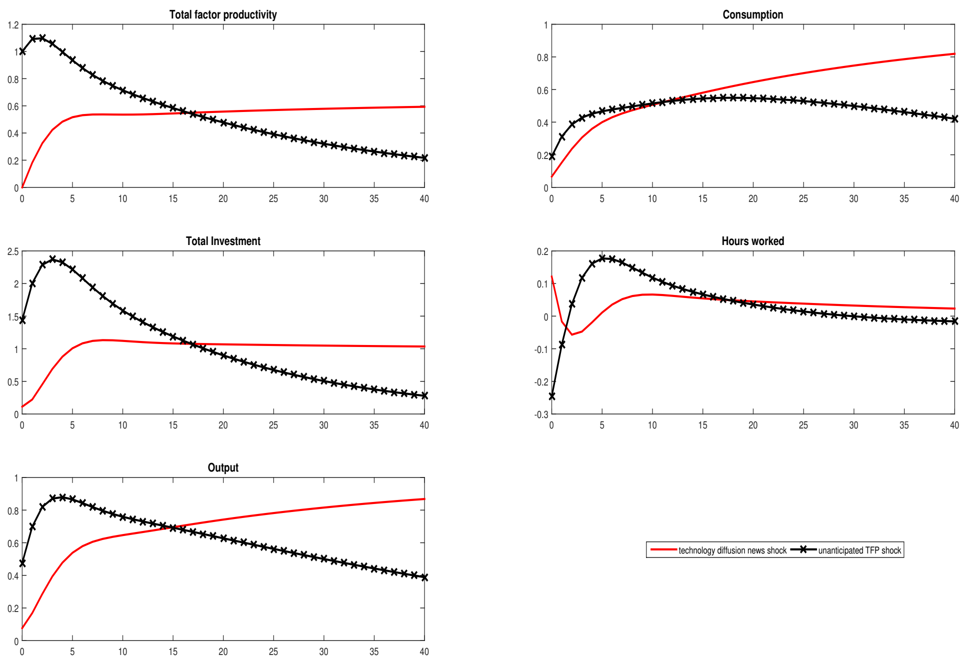

Figure 3.7: Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

In Figure 3.7 we report the impact effects and dynamics of the main macroeconomic variables in response to the two productivity shocks, as predicted by our theoretical model. These are the variables for which we provide empirical evidence in Figure 3.1. We find that the model's predictions match qualitatively the empirical results. After a surprise productivity shock, there is an immediate increase in TFP but the effect, even though it is quite persistent, is fading over time. Total investment, which comprises investment in both capital and adoption, also increases on impact, and continues increasing for some quarters. The effect of the unanticipated shock on investment is also transitory. The response of output follows a similar pattern to the one of total investment. However, the positive effect seems to be more persistent on consumption. Finally, the impact effect on hours worked is negative. It becomes positive after about one year but the effect is quite transitory and fades away much faster than in the case of the other variables. In response to a one standard deviation positive technology diffusion news shock, consumption, output, total investment, and hours worked increase on impact. As discussed previously, TFP starts responding in the next period after the shock hits, and after one year and a half it almost reaches a permanently higher level. Apart from the different impact responses, the dynamics of the macroeconomic variables indicate that they basically track the movements in TFP. All variables experience a permanent increase, as they stabilize at higher levels in the long run.

Discussion of the Key Elements of the Model

In this section we discuss the features of the model that allow us to generate the comovement of macro aggregates in response to the news shock, while obtaining the negative effect of the unanticipated productivity shock on hours worked.

In Figure 3.8 we plot the impulse responses to the two shocks of some of the other variables in the model, which are needed to stress the importance of the model's features. Concerning the responses to the unanticipated technology shock, investment adjustment costs are essential for obtaining the negative response of hours worked. Since there is a convex cost in the investment growth rate, agents want to adjust investment growth slowly. This gives the hump-shaped response of investment, which is partially reflected in output too. Because investment increases less on impact due to this friction, and given the rise in output, the resources that agents do not invest are then allocated to consumption. Hence, consumption responds more to the surprise productivity shock. This automatically translates into an increase in the marginal value of leisure, and thus to a fall in hours worked. Habit formation helps us to get the hump-shaped response of consumption, with the peak response occurring several quarters after the shock hits. The negative effect on hours worked is accentuated by stronger real rigidities. If agents find it costly to raise investment and consumption in response to the increased productivity, the only way to benefit from the shock is by enjoying more leisure. These two real frictions also give the decline in interest rate, that would have otherwise increased in response to the surprise productivity shock. This breaks the connection between the real interest rate and the marginal product of capital, with the rental rate increasing while the interest rate decreases. We obtain this negative effect on interest rates because the frictions lead to an increase in output supply that overrides the increase in demand for both consumption and investment.[40] The endogenous technology adoption mechanism only slightly amplifies the effects of the unanticipated technology shock.

[40]For details on the effect of investment adjustment costs and habit persistence on interest rates, see Beaudry and Guay (1996).

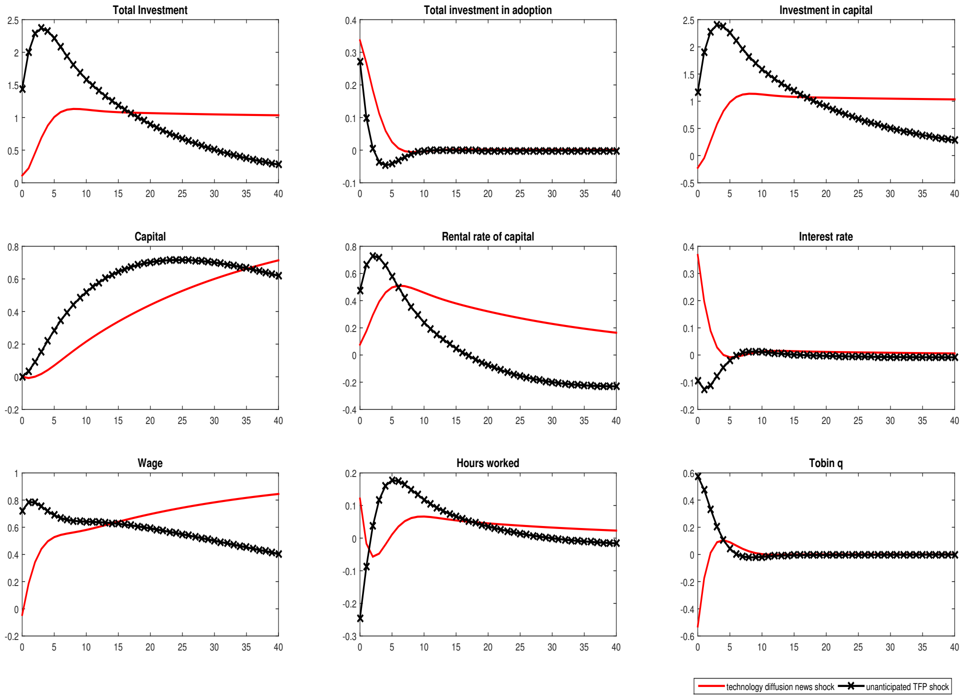

Figure 3.8: Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

With regard to the effects of the news shock, the three elements play more important roles. We do not discuss the case without endogenous technology adoption since this is the RBC with real frictions we discussed in Section 3.3. In that model there is no effect of the shock to the evolution of new technologies that we consider to be the model equivalent of the news shock. Hence, we discuss how the endogenous technology adoption helps us to achieve what was not possible in a standard RBC model. This mechanism triggers an increase in investment on impact because resources are immediately required to adopt the newly created technologies. This leads to an impact increase in the demand for output, and consequently in labor input. The demand for output overrides the supply, and this drives interest rates up. With higher interest rate there is an intertemporal substitution of labor which offsets the wealth effect. This makes hours worked increase.

Since there is no change in the marginal productivity of capital when the news comes, there is no encouragement to increase investment immediately. In fact, agents would rather substitute investment in capital with investment in adoption to adopt the newer technologies faster. This leads to an impact decrease in investment in capital. The investment adjustment costs play a role here. Because of them, investment in capital does not decrease much on impact. Hence, the effect of news on total investment is positive. Without adjustment costs (see Figure 3.17, Appendix 3.H), investment in capital would drop following a news shock, while consumption and investment in adoption would increase. The demand for output would be less than the supply. Thus, interest rates would increase. Agents would then prefer to enjoy more leisure. With labor supply decreasing, output also drops. Thus, the impact effects of the news shock in the model without investment adjustment costs would not match the empirical evidence.

It is obvious that investment adjustment costs are essential for this model to match the empirical evidence. However, they have the drawback of putting downward pressure on consumption. Since there is a high demand for investment and not much increase in output, in a model without habit persistence, consumption would drop (see Figure 3.18, Appendix 3.H). Without habit persistence, households do not have strong incentives to increase consumption. The rise in the interest rate means a decrease in the discounted price of future consumption, and agents would like to save more today. There are also no strong income effects since wage is not changing much on impact. In the absence of habit persistence, consumption would drop on impact, while output would increase only slightly since the increase in adoption investment is largely compensated by the drop of investment in capital. Employment would still increase on impact in order for output to increase, but by less than in the case with habit persistence. Habit formation makes households want to smooth consumption more, and this prevents the drop in consumption that we would observe otherwise.

In a setting with no real rigidities (see Figure 3.19, Appendix 3.H) the increase in consumption is smaller than in the case without investment adjustment costs only, and the decrease in output and investment in capital is slightly higher. Hence, we conclude that both types of real rigidities are needed, while investment adjustment costs play a more important role than habit persistence. In contrast to Jaimovich and Rebelo (2009), we do not include variable capacity utilization. The addition of this third real rigidity is not needed to replicate the empirical evidence, and its inclusion would in fact worsen our results. It would make investment in capital drop even more in response to the news shock, and this way it would reduce the positive effect on total investment.[41]

VAR Results with Real and Simulated Data

For this exercise, we perform the estimation of some of the parameters, as described in Section 3.4.6.

The parameters that we estimate are $\varpi = [\tau,\ \kappa,\ \rho_\Gamma,\ s_z,\ \rho_x,\ s_x,\ \rho_b,\ s_b,\ \rho_\iota,\ s_\iota,\ \rho_G,\ s_G]$.

From the results presented in Table 3.1, we can infer that some model parameters have to be adjusted in order for the impulse responses obtained with real data and those obtained with simulated data from our model to get closer. For example, the habit persistence parameter needs to have a higher value. In our benchmark calibration, it equals 0.75, and the estimation gives a value of almost 0.83. The value of the parameter in the investment adjustment cost function is also higher than in our benchmark calibration (i.e. 1.9 as opposed to 1.3), but since we started the estimation from a high value, it still indicates that the model does not need as big adjustment costs as a standard RBC to deliver the comovement of macro aggregates in response to the news shock. Another parameter whose value is higher than in our benchmark calibration is the investment elasticity of adoption. While we calibrated the parameter to 0.9, after the estimation we obtain a value of almost 0.96 even though we started the estimation from 0.75. This clearly indicates that the model needs a number that is close to 1 for this elasticity. Concerning the standard deviations and autocorrelation coefficients of shocks, we obtain the most important results for the news shock and the surprise productivity shock. We observe that to minimize the distance between impulse responses, we need the news shock

[41] Results can be provided by the authors upon request.

to have a bigger standard deviation (i.e. 0.016 as opposed to 0.01 in the benchmark calibration), while the unanticipated productivity shock should have a smaller standard deviation (i.e. 0.006), and autocorrelation coefficient (i.e. 0.68 as opposed to 0.95 in the benchmark calibration).

Table 3.1: Estimation results

Parameter	Description	Starting Value	Estimated Value
τ	habit persistence	0.75	0.825 (0.09)
κ	investment adjustment costs	3	1.916 (0.10)
ρ_Γ	investment elasticity of adoption	0.75	0.958 (0.02)
s_z	s.d. of news shock	0.01	0.016 (0.01)
ρ_x	autocorrelation coefficient of surprise productivity shock	0.5	0.678 (0.24)
s_x	s.d. of surprise productivity shock	0.01	0.006 (0.00)
ρ_b	autocorrelation coefficient of of marginal efficiency of investment shock	0.5	0.391 (0.18)
s_b	s.d. of marginal efficiency of investment shock	0.01	0.009 (0.03)
ρ_ι	autocorrelation coefficient of intertemporal preference shock	0.5	0.540 (0.15)
s_ι	s.d. of intertemporal preference shock	0.01	0.011 (0.02)
ρ_G	autocorrelation coefficient of government spending shock	0.5	0.396 (0.17)
s_G	s.d. of government spending shock	0.01	0.009 (0.02)

After we replace the calibrated values of the parameters with the estimation results, we simulate data from the model for total factor productivity, consumption, investment, hours worked, and output. The correlation coefficients between the simulated series and the real series are: 0.96 (TFP), 0.99 (consumption), 0.89 (investment), -0.06 (hours worked), 0.98 (output). Hence the variables that are trending in the model are strongly correlated with the real data, while the model does not have enough information to match the movement in real hours worked. We then perform the estimation of the five variable VAR model in levels with four lags as we did in Section 3.2. The only difference is that we use the simulated data from the model instead of the U.S. quarterly data.

In this setting, we impose the short- and medium-run restrictions to identify the two productivity shocks. The first is defined as an unanticipated productivity shock and is the only shock that has impact effect on TFP. The second shock is the (technology diffusion) news shock, which has no impact effect on productivity but contributes the most to the forecast error variance of TFP in the medium-run.[42] We take ten years as the horizon at which the shock should have the maximum contribution to TFP.

The results reported in Figure 3.9 indicate that the impulse responses to an unanticipated productivity shock obtained with data simulated from the model lie within the 95% confidence interval of the empirical responses, with only the impact effect of the shock on investment being above the upper limit of the confidence interval. Thus, the theoretical model can statistically account for all the empirical impulse response functions with regard to the unanticipated productivity shock.

[42]The identification scheme is presented in Appendix 3.C.

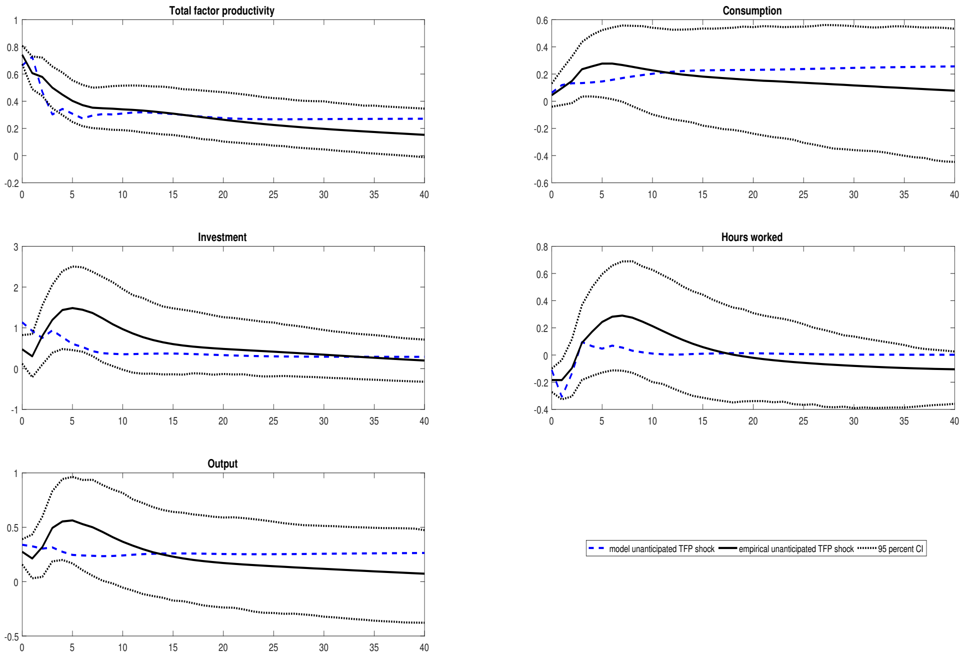

Figure 3.9: Impulse responses to an unanticipated productivity shock. The black line shows the responses to the unanticipated productivity shock in a VAR with real data, , while the dotted black lines correspond to the 95% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR. The blue dashed line gives the responses to the unanticipated productivity shock in a VAR with data simulated from the theoretical model. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

In Figure 3.10 we observe that the model can also statistically account for the empirical impulse response functions of consumption, investment, output, and hours worked with regard to the news shock. These impulse responses obtained with data simulated from the model lie within the 95% confidence interval of the empirical responses. However, when looking at the effect of the news shock on total factor productivity we observe that the impulse response obtained in the model with simulated data is not contained in the confidence interval of the empirical response. This implies that in order to deliver similar effects of the news shock on macro aggregates, the theoretical model needs a news shock that diffuses almost immediately in aggregate productivity and has a much stronger effect on total factor productivity than the empirical news shock. To us this in an indicator that by modeling the diffusion of new technologies into aggregate productivity we do get closer to replicating the empirical results, but there are still some apparent quantitative differences. In order to improve our results, we believe that it is essential to introduce a mechanism through which we may capture the effect of news about newly created prototypes on the demand side of the economy.

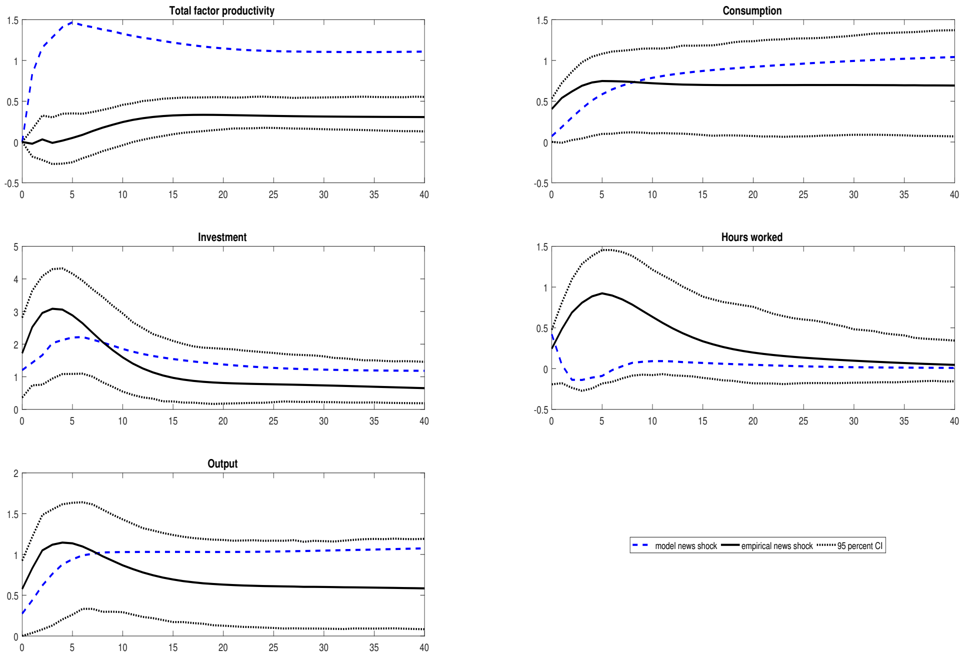

Figure 3.10: Impulse responses to a news shock. The black line shows the responses to the news shock in a VAR with real data, while the dotted black lines correspond to the 95% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR. The blue dashed line gives the responses to the news shock in a VAR with data simulated from the theoretical model. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

3.5 Conclusions

In this paper we propose a theoretical model that generates the comovement of macroeconomic aggregates in response to technology diffusion news shocks, while delivering the usual responses to unanticipated productivity shocks. The key ingredient for obtaining these results is the introduction of an endogenous technology adoption mechanism in a standard RBC model with real frictions. Our results indicate that consumption, investment, output, and hours worked increase on impact following a news shock, while TFP starts responding in the next period after the shock hits. All variables experience a permanent increase, as they stabilize at higher levels in the long run. On the other hand, an unanticipated productivity shock leads to an immediate increase in TFP, but the effect fades over time. The responses of investment, consumption, and output to the unanticipated productivity shock track the movements in TFP. What is important is that the impact effect on hours worked is negative. These model predictions match the empirical results of news shocks qualitatively. However, some quantitative differences are still apparent. We believe that these differences stem from the fact that the model does not entirely capture the effect of news about newly created prototypes on the demand side of the economy. We think that introducing a mechanism that would make consumers more responsive to the news shock is an important next step.

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Appendix

3.A Data

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

Output: 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)

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

Investment: 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)

Hours worked: 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)

3.B Linear Vector Autoregressive Model

The model we estimate is given by:

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

where Y_t is a vector of m 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 are the matrices containing the VAR coefficients.

It is assumed that the reduced-form residuals can be written as a linear combination of the structural shocks $\epsilon_t = Au_t$, where $\Sigma = A'A$. To identify the structural shocks from the reduced-form shocks, $n(n-1)/2$ additional restrictions on A are needed. In the following section we describe the identification schemes used in the empirical news literature.

3.C Identification Scheme

The identification scheme imposes medium-run restrictions in the sense of Uhlig (2004).[43] Innovations are orthogonalized by applying the Cholesky decomposition to the covariance matrix of the residuals, Σ. The entire space of permissible impact matrices can be written as $\tilde{A}D$, where D is a $k \times k$ orthonormal matrix ($DD' = I$).

The h step ahead forecast error is defined as the difference between the realization of Y_{t+h} and the minimum mean squared error predictor for horizon h:[44]

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

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

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

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

Note that TFP is on the first position in the system of variables, and let the unanticipated productivity shock be indexed by 1 and the news shock by 2. Having the unanticipated shock identified with the short-run zero restrictions, we then identify the news shock by choosing the impact matrix to maximize contributions to $\Xi_{1,2}(h)$ at h=40 quarters.

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

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

3.D Empirical Evidence

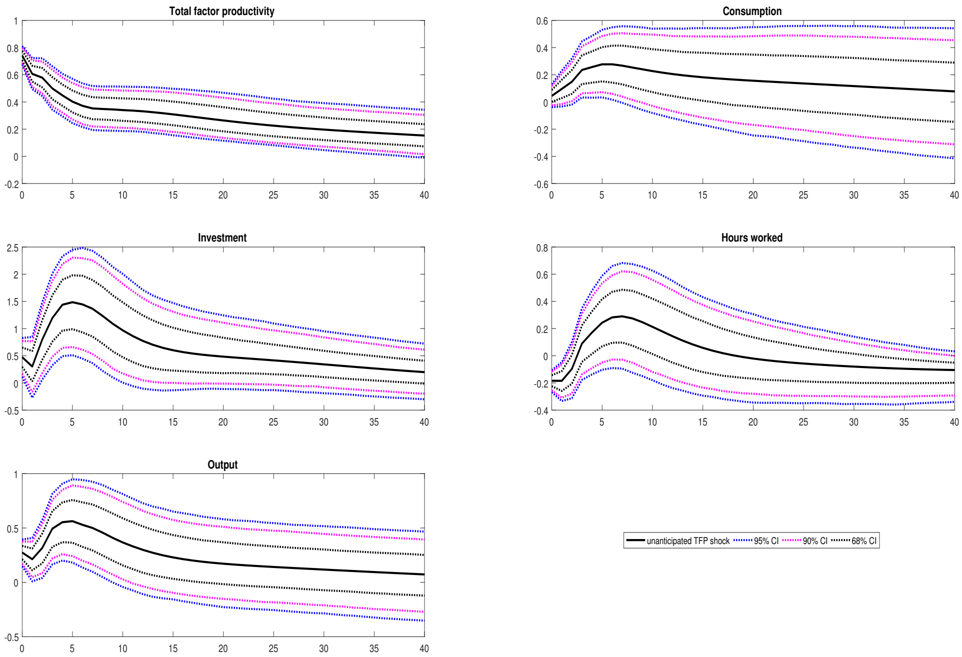

Figure 3.11: Impulse responses to an unanticipated productivity shock. The black line shows the responses to the unanticipated productivity shock. The dotted lines correspond to the 68%, 90%, and 95% confidence intervals. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

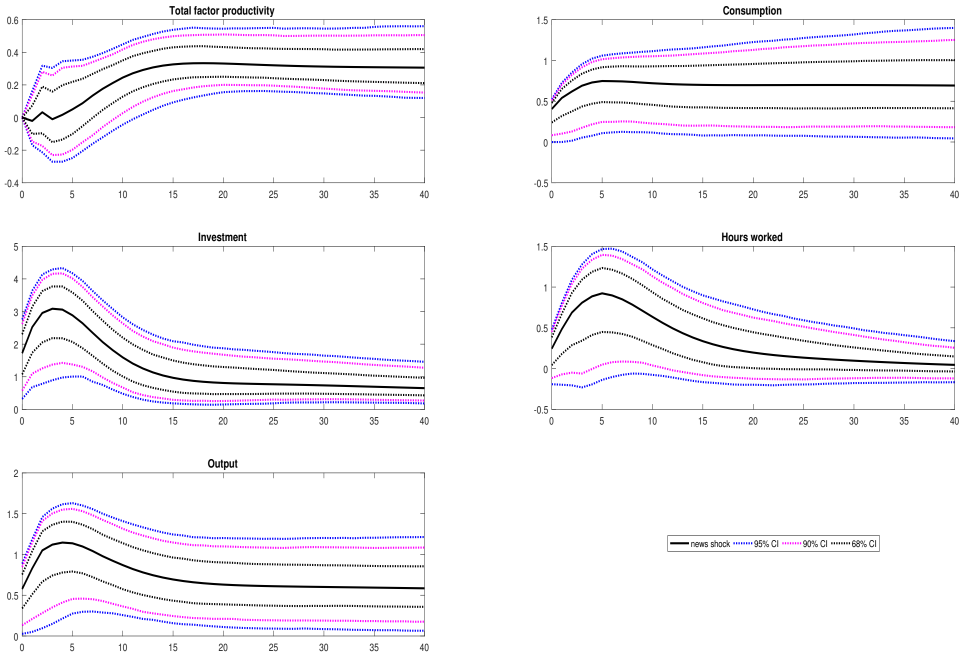

Figure 3.12: Impulse responses to a news shock. The black line shows the responses to the news shock. The dotted lines correspond to the 68%, 90%, and 95% confidence intervals. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

3.E Model with Exogenous Technology Diffusion

3.E.1 Model Equations

Production of Output

Output is produced using the following Cobb-Douglas production function:

$$Y_t = A_t(u_t K_t)^{1-\alpha} L_t^{\alpha}, \tag{3.8}$$

where A_t is the level of TFP, K_t is the capital stock, u_t is the utilization rate, and L_t hours worked.

Households' Problem

Agents maximize lifetime utility:

$$U = E_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t - \psi L_t^{\theta} X_t)^{1-\sigma} - 1}{1-\sigma},$$

where C_t denotes consumption, and X_t is defined by the following equation:

$$X_t = C_t^{\gamma} X_{t-1}^{1-\gamma}$$

X_t makes preferences non-time-separable in consumption and hours worked. We further refer to this class of preferences as JR preferences. When $\gamma = 1$ the preferences correspond to a class discussed in King et al. (1988), henceforth KPR, while when $\gamma = 0$ the preferences are of the type proposed by Greenwood et al. (1988), henceforth GHH. The assumptions on parameters are: $0 < \beta < 1, \theta > 1, \psi > 0, \sigma > 0$.

Output can be used for consumption and investment:

$$Y_t = C_t + I_t/b_t, \tag{3.9}$$

where b_t is the current state of technology for producing capital. An increase in b_t results from investment-specific technological progress.

The combination of equations (3.8) and (3.9) gives the resource constraint:

$$C_t + I_t/b_t = A_t(u_t K_t)^{1-\alpha} L_t^{\alpha} \tag{3.10}$$

The law of motion for capital is given by the following equation:

$$K_{t+1} = I_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right)\right] + \left[1 - \delta(u_t)\right] K_t,$$

where $\varphi(\cdot)$ denotes adjustment costs to investment. In steady state $\varphi(1) = \varphi'(1) = 0$. $\delta(u_t)$ determines capital depreciation and is convex in u_t, with $\delta'(u_t) > 0, \delta''(u_t) \geq 0$.

The households' problem is to maximize utility subject to the resource constraint, and law of motion for capital, as it follows:

$$\begin{aligned}
&\max \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \frac{(C_t - \psi L_t^{\theta} X_t)^{1-\sigma} - 1}{1-\sigma} \\
&s.t. \\
&C_t + I_t/b_t = A_t(u_t K_t)^{1-\alpha} L_t^{\alpha} \\
&X_t = C_t^{\gamma} X_{t-1}^{1-\gamma} \\
&K_{t+1} = I_t[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right)] + [1 - \delta(u_t)]K_t \\
&K_0,\ I_{-1},\ X_{-1}\, given
\end{aligned}$$

The Lagrangian for this problem is:

$$\begin{aligned}
&\mathcal{L}_t = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{(C_t - \psi L_t^{\theta} X_t)^{1-\sigma} - 1}{1-\sigma} \right. \\
&-\lambda_t \left[C_t + I_t/b_t - A_t(u_t K_t)^{1-\alpha} L_t^{\alpha}\right] \\
&-\mu_t \left(X_t - C_t^{\gamma} X_{t-1}^{1-\gamma}\right) \\
&\left. -\eta_t \left\{K_{t+1} - I_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right)\right] - \left[(1 - \delta(u_t)\right] K_t \right\} \right\},
\end{aligned}$$

where λ_t , μ_t, and η_t are Lagrange multipliers associated with each of the constraints.

The first order conditions characterizing an interior solution are:

$$C_t: \quad \beta^t (C_t - \psi L_t^{\theta} X_t)^{-\sigma} - \lambda_t \beta^t + \beta^t \mu_t \gamma C_t^{\gamma-1} X_{t-1}^{1-\gamma} = 0$$

$$\Rightarrow \quad (C_t - \psi L_t^\theta X_t)^{-\sigma} + \mu_t \gamma C_t^{\gamma-1} X_{t-1}^{1-\gamma} = \lambda_t$$

$$X_t: \quad -\beta^t \psi L_t^\theta (C_t - \psi L_t^\theta X_t)^{-\sigma} - \mu_t \beta^t + E_t[\beta^{t+1} \mu_{t+1}(1-\gamma) C_{t+1}^{\gamma} X_t^{-\gamma}] = 0$$

$$\Rightarrow \quad (C_t - \psi L_t^\theta X_t)^{-\sigma} \psi L_t^\theta + \mu_t = \beta E_t[\mu_{t+1}(1-\gamma) C_{t+1}^{\gamma} X_t^{-\gamma}]$$

$$L_t: \quad -\beta^t \psi \theta X_t L_t^{\theta-1} (C_t - \psi L_t^\theta X_t)^{-\sigma} + \beta^t \lambda_t \alpha A_t (u_t K_t)^{1-\alpha} L_t^{\alpha-1} = 0$$

$$\Rightarrow \quad (C_t - \psi L_t^\theta X_t)^{-\sigma} \theta \psi L_t^{\theta-1} X_t = \lambda_t \alpha A_t (u_t K_t)^{1-\alpha} L_t^{\alpha-1}$$

$$u_t: \quad \beta^t \lambda_t (1-\alpha) A_t u_t^{-\alpha} K_t^{1-\alpha} L_t^\alpha - \beta^t \eta_t \delta'(u_t) K_t = 0$$

$$\Rightarrow \quad \lambda_t (1-\alpha) A_t u_t^{-\alpha} K_t^{1-\alpha} L_t^\alpha = \eta_t \delta'(u_t) K_t$$

$$K_{t+1}: \quad -\beta^t \eta_t + E_t \left\{ \beta^{t+1} \eta_{t+1} [1 - \delta(u_{t+1})] + \beta^{t+1} \lambda_{t+1} (1-\alpha) A_{t+1} u_{t+1}^{1-\alpha} K_{t+1}^{-\alpha} L_{t+1}^\alpha \right\} = 0$$

$$\Rightarrow \quad \eta_t = \beta E_t \left\{ \lambda_{t+1} (1-\alpha) A_{t+1} u_{t+1}^{1-\alpha} K_{t+1}^{-\alpha} L_{t+1}^\alpha + \eta_{t+1} [1 - \delta(u_{t+1})] \right\}$$

$$\begin{aligned} I_t: \quad & \beta^t \eta_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right) - \frac{I_t}{I_{t-1}} \varphi'\left(\frac{I_t}{I_{t-1}}\right) \right] + \\ & E_t \left[\beta^{t+1} \eta_{t+1} \left(\frac{I_{t+1}}{I_t}\right)^2 \varphi'\left(\frac{I_{t+1}}{I_t}\right) \right] - \lambda_t / b_t = 0 \end{aligned}$$

$$\Rightarrow \quad \lambda_t / b_t = 1 - \varphi\left(\frac{I_t}{I_{t-1}}\right) - \varphi'\left(\frac{I_t}{I_{t-1}}\right) \frac{I_t}{I_{t-1}} + \beta E_t \left[\eta_{t+1} \varphi'\left(\frac{I_{t+1}}{I_t}\right) \left(\frac{I_{t+1}}{I_t}\right)^2 \right]$$

Benchmark Calibration

The calibration chosen in Jaimovich and Rebelo (2009) is the following: $\sigma \to 1$ (equivalent to log-utility), $\beta = 0.985, \alpha = 0.64, \gamma = 0.001, \varphi''(1) = 1.3, \delta''(u)u/\delta'(u) = 0.15$.

3.E.2 Discussion of the Key Elements of the Model with Exogenous Technology Diffusion

Variable Capacity Utilization

A model with constant capacity utilization (i.e. $u_t = 1, \delta(u_t) = \delta$) eliminates the first order condition with respect to u_t. As displayed in Figure 3.13, in a model without variable capacity utilization, only investment is smoothed by the investment adjustment costs. In response to a news shock, output does not react until productivity changes. Investment and consumption decrease on impact. When the productivity improvement occurs, all variables jump to the new permanent level. Investment is smoothed which makes consumption slightly decline immediately after the increase in productivity. Once the technology is implemented, the responses of the model's variables mirror the reactions to an unanticipated productivity shock.

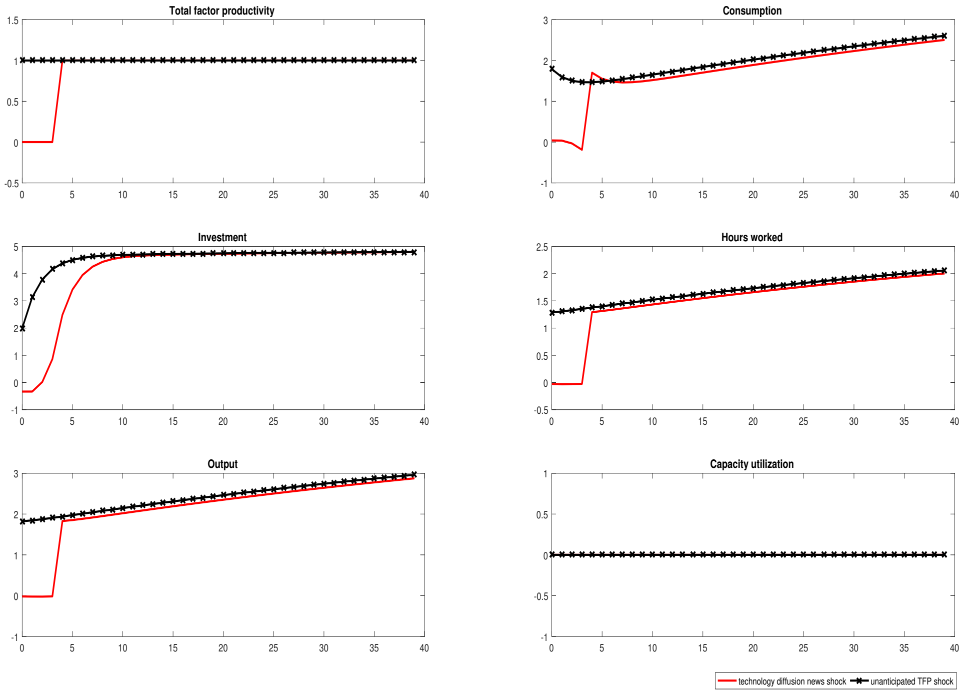

Figure 3.13: Impulse responses to a permanent unanticipated productivity shock and a news shock in a model with constant capacity utilization. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock.

Preferences

The strongest response of L_t occurs with GHH preferences ($\gamma = 0$). However, in this case hours worked are not stationary as they increase permanently (see Figure 3.15). With KPR preferences ($\gamma = 1$), L_t converges back to the steady state after the shock, but its short-run response is very weak. When γ is equal to 0.001 or 0.25, the short-run impact of a wage increase on L_t is in between that obtained with GHH and KPR preferences. Lower values of γ produce short-run responses that are closer to those obtained with GHH preferences. As long as $0 < \gamma \leq 1$, hours worked converge to the steady state.

The wealth effect is zero for GHH preferences and negative for KPR. In both cases the wealth effect is constant over time. When $0 < \gamma < 1$, the wealth effect varies over time. In the long-run, this effect is similar to that with KPR preferences. In the short-run, the effect is actually positive, leading to an increase in labor supply. This positive wealth effect results from the fact that the disutility from working is high when X_t is high. Since consumption rises over time, X_t also increases over time, and the disutility from working is higher in the future than in the present.

If γ is set to one, thus with KPR preferences, the effects of the unanticipated productivity shock and the news shock are less pronounced on all the variables (see Figure 3.14). Moreover, there are qualitatively different responses of hours worked and investment with regard to a news shock. Thus, a news shock leads to an initial decline in hours worked and investment. Interestingly, once productivity actually improves, output and consumption jump. But since hours worked and investment are now increasing substantially, consumption declines after the jump to converge from below to the new long-run level. This means that as soon as we allow the utility function to be time-separable in hours worked and consumption, hours worked and investment strongly decline in response to a news shock, while consumption increases more.

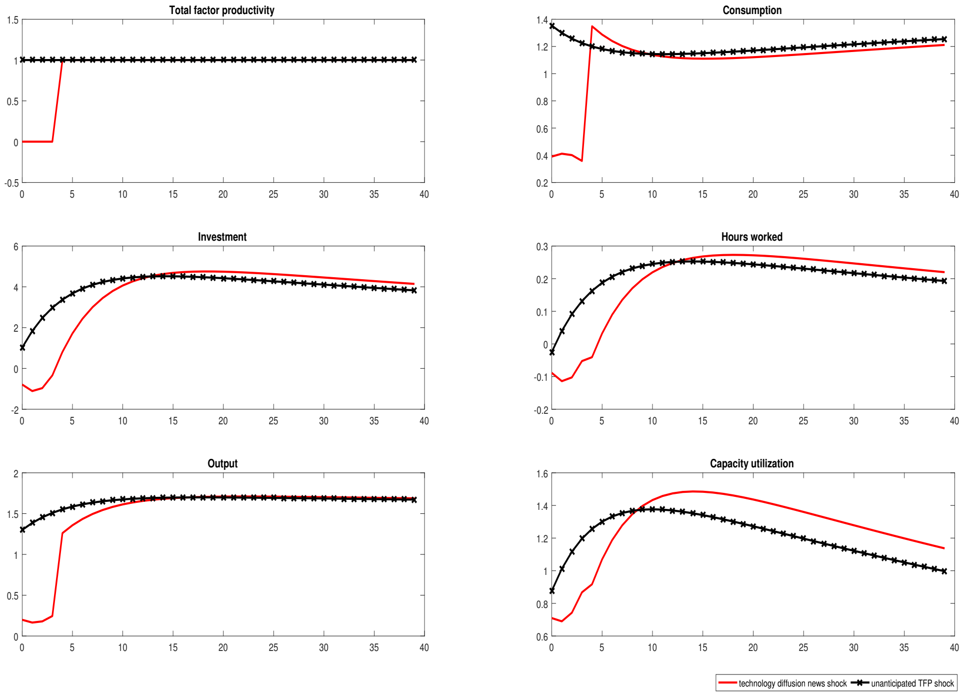

Figure 3.14: Impulse responses to a permanent unanticipated productivity shock and a news shock in a model with KPR preferences. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

Investment Adjustment Costs

As it can be observed in Figure 3.16, in a setting without investment adjustment costs there is no investment smoothing and the economy reacts immediately to the news. Investment, capital utilization, hours worked, and output decrease on impact, and then jump to the new saddle path once productivity changes. In response to an unanticipated productivity shock, all variables jump immediately to the new saddle path and then slowly converge along it. Output reaches its new steady state immediately.

3.E.3 Different Shock Processes

We propose the following ad-hoc shock specification in which a_t is the sum of two components:

$$a_t = a_{1,t} + a_{2,t},$$

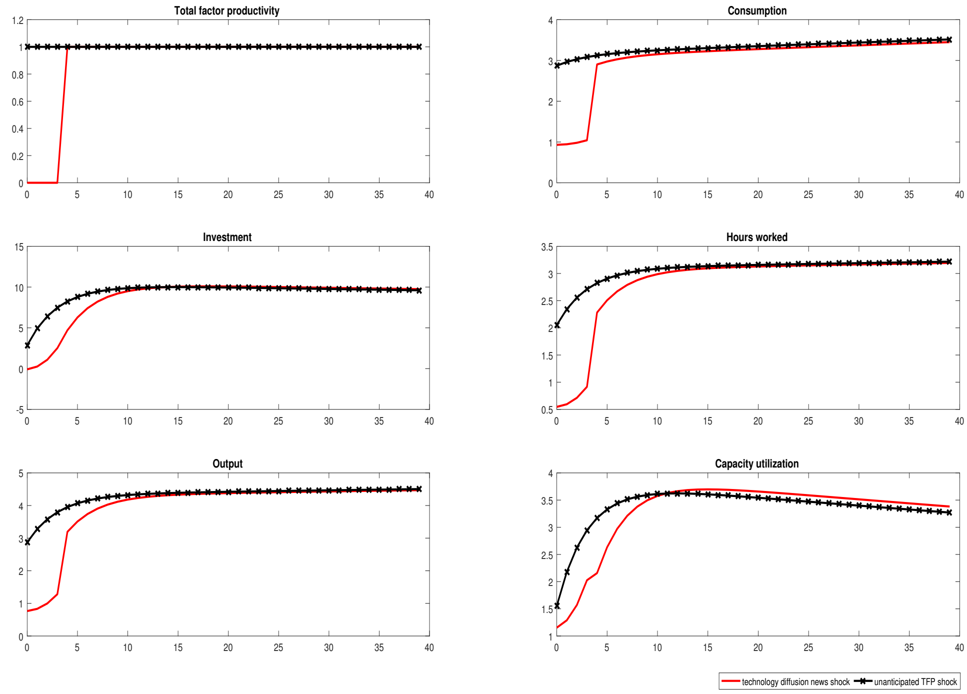

Figure 3.15: Impulse responses to a permanent unanticipated productivity shock and a news shock in a model with GHH preferences. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

where $a_{2,t}$ is the temporary component, and follows the following process:

$$a_{2,t} = \rho_2 a_{2,t-1} + \epsilon_t, \text{ where } \rho_2 = 0.95$$

ϵ_t, the unanticipated productivity shock, is an i.i.d standard normal shock. The process of the temporary component allows the unanticipated productivity shock to be persistent but not permanent. For the other component, $a_{1,t}$, we model a process for which the response of TFP to the news shock mimics technology diffusion similarly to the empirically found news shock:

$$a_{1,t} = \rho_1 a_{1,t-1} + (1-\rho_1) a_{3,t-1}, \text{ where } \rho_1 = 0.95,$$

and $a_{3,t}$ evolves as:

$$a_{3,t} = \rho_3 a_{3,t-1} + \varepsilon_t, \text{ where } \rho_3 = 1$$

and ε_t, the news shock, is an i.i.d standard normal shock.

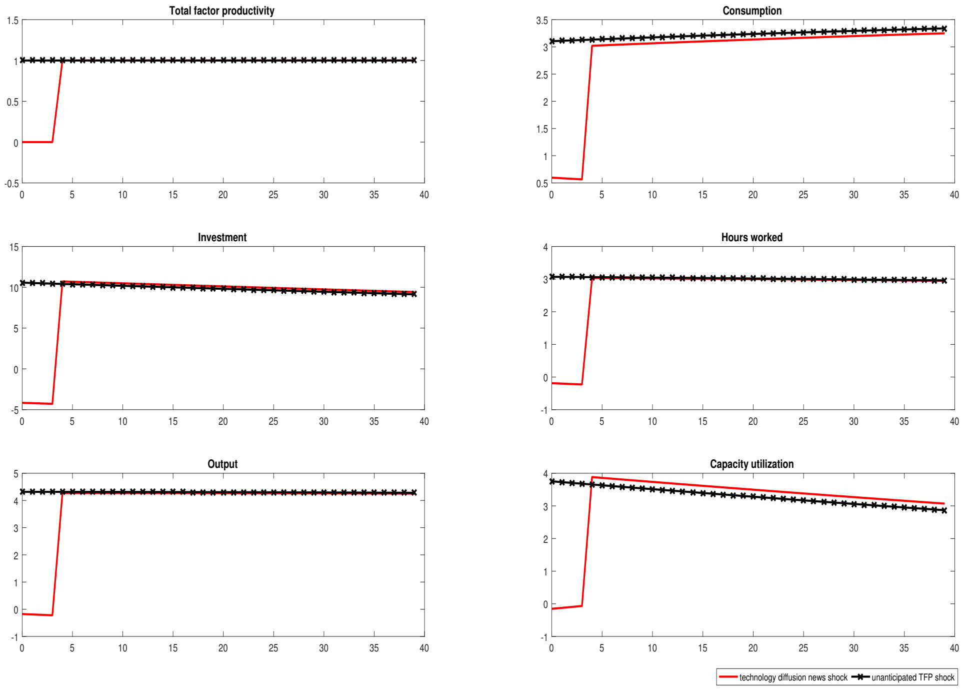

Figure 3.16: Impulse responses to a permanent unanticipated productivity shock and a news shock in a model without investment adjustment costs. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

3.F Model with Endogenous Technology Adoption

3.F.1 Household's problem

The Lagrangian for the household's problem is:

$$\begin{aligned}\mathcal{L}_t = \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \Bigg\{ & \iota_t \left[\ln(C_t - \tau C_{t-1}) - \zeta \frac{L_t^{1+\eta}}{1+\eta} \right] \\ & + \Lambda_t [W_t L_t + R_{t-1} B_t + F_t A_t + R_t^k K_t - P_t C_t - \\ & P_t I_t - P_t S_t (A_{t+1} - A_t) - B_{t+1} - P_t T_t] \\ & + \Omega_t \left[\Xi_t \left(Z_t - \phi A_t \right) + \phi A_t - A_{t+1} \right] \\ & + Q_t \left\{ I_t \left[1 - \varphi \left(\frac{I_t}{I_{t-1}} \right) \right] b_t + (1-\delta) K_t - K_{t+1} \right\} \Bigg\},\end{aligned}$$

where Λ_t is the Lagrange multiplier associated with the budget constraint, Ω_t is the Lagrange multiplier associated with the evolution of technology adoption, and Q_t is the Lagrange multiplier associated with the law of motion for capital.

The first order conditions are:

$$C_t : \ \iota_t (C_t - \tau C_{t-1})^{-1} - \beta \tau \mathbb{E}_t \iota_{t+1} (C_{t+1} - \tau C_t)^{-1} = \Lambda_t P_t$$

$$B_{t+1}: \Lambda_t = \beta \mathbb{E}_t(\Lambda_{t+1} R_t)$$

$$I_t: \Lambda_t P_t = Q_t b_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right) - \varphi'\left(\frac{I_t}{I_{t-1}}\right)\frac{I_t}{I_{t-1}}\right] + \beta \mathbb{E}_t \left[Q_{t+1} b_{t+1} \varphi'\left(\frac{I_{t+1}}{I_t}\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right]$$

$$K_{t+1}: \beta \mathbb{E}_t \Lambda_{t+1} R^k_{t+1} = Q_t - \beta \mathbb{E}_t Q_{t+1}(1-\delta)$$

$$L_t: \iota_t \zeta L_t^\eta = \Lambda_t W_t$$

$$S_t: \Lambda_t P_t (A_{t+1} - A_t) = \Omega_t \frac{\partial \Xi_t}{\partial S_t} (Z_t - \phi A_t)$$

3.F.2 Equilibrium

A competitive and symmetric equilibrium of the economy consists of a distribution of profits, allocations for output producing firms, for technology adopting firms, and for the representative household, and a price path, such that, taking $K_0, A_0, B_0, Z_0, C_{-1}, I_{-1}$ and the stochastic processes for the exogenous variables as given, household's allocation satisfies the optimal choices in equations (3.1) - (3.6); firms' allocations maximize profits; the capital, labor, and bonds markets clear in every period, budget constraints hold with equality, and the transversality condition holds.

For bond market-clearing, we require that $B_t = D_t$ and $B_{t+1} = D_{t+1}$ which means that households hold the government bonds. Using the government's budget constraint we can solve for $P_t T_t$:

$$P_t T_t = P_t g_t Y_t + R_{t-1} D_t - D_{t+1}$$

Using this, we can rewrite the budget constraint as follows:

$$P_t C_t + P_t I_t + P_t S_t [A_{t+1} - A_t] = W_t L_t + F_t A_t + R^k_t K_t - (P_t g_t Y_t + R_{t-1} D_t - D_{t+1}) - B_{t+1} + R_{t-1} B_t$$

which is equivalent to:

$$P_t C_t + P_t I_t + P_t S_t [A_{t+1} - A_t] = W_t L_t + F_t A_t + R^k_t K_t - P_t g_t Y_t$$

and in real terms is:

$$C_t + I_t + S_t[A_{t+1} - A_t] = \frac{W_t}{P_t} L_t + \frac{F_t A_t}{P_t} + r^k_t K_t - g_t Y_t$$

Real dividends received by the household are just the sum of real profits from the intermediate good firms:

$$\frac{F_t A_t}{P_t} = \bar{Y}_t A_t \frac{P_t(s)}{P_t} - r^k_t K_t - w_t L_t$$

We introduce this in the integrated household budget constraint:

$$C_t + I_t + S_t[A_{t+1} - A_t] + g_t Y_t = \bar{Y}_t A_t \frac{P_t(s)}{P_t} - r^k_t K_t - w_t L_t + w_t L_t + r^k_t K_t$$

After some manipulations and having normalized P_t to one, we obtain the resource constraint of the economy:

$$\begin{aligned} C_t + I_t + S_t[A_{t+1} - A_t] + g_t Y_t &= \left[\frac{P_t(s)}{P_t(s) A_t^{-(\vartheta-1)}}\right]^{\frac{\vartheta}{-(\vartheta-1)}} Y_t A_t \frac{P_t(s)}{P_t} \\ &= \left[A_t^{(\vartheta-1)}\right]^{1+\frac{\vartheta}{-(\vartheta-1)}} Y_t A_t = Y_t \end{aligned}$$

We have previously derived the factor demand functions in real terms as:

$$L_t = \frac{(1-\alpha)}{\vartheta} \frac{Y_t}{w_t}$$

$$K_t = \frac{\alpha}{\vartheta} \frac{Y_t}{r_t^k}$$

In order to get the final set of equilibrium conditions we need to eliminate the price level from the equations. We use the fact that $\frac{P_t}{P_{t-1}} = \Pi_t$, and assume that $\Pi_t = 1$, $\forall t$, to write the Euler equation as:

$$\lambda_t = \beta \mathbb{E}_t \lambda_{t+1} R_t$$

The full set of equilibrium conditions is:

$$C_t + I_t + S_t[A_{t+1} - A_t] = Y_t(1 - g_t)$$

$$Y_t = [X_t A_t^{\vartheta-1}] K_t^{\alpha} L_t^{1-\alpha}$$

$$L_t = \frac{(1-\alpha)}{\vartheta} \frac{Y_t}{w_t}$$

$$K_t = \frac{\alpha}{\vartheta} \frac{Y_t}{r_t^k}$$

$$\lambda_t = \beta \mathbb{E}_t \lambda_{t+1} R_t$$

$$\iota_t (C_t - \tau C_{t-1})^{-1} - \beta \tau \mathbb{E}_t \iota_{t+1} (C_{t+1} - \tau C_t)^{-1} = \lambda_t$$

$$q_t = \beta \mathbb{E}_t \left[\frac{\lambda_{t+1}}{\lambda_t} r_{t+1}^k + q_{t+1}(1-\delta)\right]$$

$$1 = q_t b_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right) - \varphi'\left(\frac{I_t}{I_{t-1}}\right)\frac{I_t}{I_{t-1}}\right] + \beta \mathbb{E}_t \left[q_{t+1} b_{t+1} \frac{\lambda_{t+1}}{\lambda_t} \varphi'\left(\frac{I_{t+1}}{I_t}\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right]$$

$$\iota_t \zeta L_t^{\eta} = \lambda_t w_t$$

$$\lambda_t (A_{t+1} - A_t) = \Omega_t \frac{\partial \Xi_t}{\partial S_t} (Z_t - \phi A_t)$$

$$K_{t+1} = I_t b_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right)\right] + [1 - \delta] K_t$$

$$A_{t+1} = \Xi_t (Z_t - \phi A_t) + \phi A_t$$

$$\Xi_t = \frac{2}{1 + exp(-\Gamma_t)} - 1$$

$$\Gamma_t = \bar{\Gamma}\left[S_t \frac{(Z_t - A_t)}{A_t}\right]^{\rho_\Gamma}$$

$$f_t = \frac{(\vartheta - 1)}{\vartheta} \frac{Y_t}{A_t}$$

$$V_t = f_t + \phi \mathbb{E}_t \left[\beta \frac{\lambda_{t+1}}{\lambda_t} V_{t+1}\right]$$

$$J_t = \max_{S_t} -S_t + \mathbb{E}_t \left\{\beta \frac{\lambda_{t+1}}{\lambda_t} [\Xi_t \phi V_{t+1} + (1 - \Xi_t) J_{t+1}]\right\}$$

$$0 = -1 + \mathbb{E}_t \left[\beta \frac{\lambda_{t+1}}{\lambda_t} (\phi V_{t+1} - J_{t+1}) \frac{\partial \Xi_t}{\partial S_t}\right]$$

These are 18 equations for 18 endogenous variables: $K_{t+1}, L_t, Y_t, A_{t+1}, S_t, J_t, V_t, \Xi_t, \Gamma_t, \lambda_t, C_t, I_t, q_t, w_t, f_t, \Omega_t, r_t^k, R_t$.

3.F.3 Stationary Equilibrium

Exogenous technological innovations induce growth in the model. The growth rate of the economy is given by z_t. In order to solve the model, we first discuss the balanced growth path and then we deflate the variables which are growing.

In the steady state, the growth rate of the number of prototypes is constant, given by Δ_z. Hence, the technology frontier grows at the constant rate Δ_z. Since there is no population growth, from the set of equilibrium conditions we can infer that A_t, Y_t, K_t, I_t, C_t, and w_t grow at the same constant rate Δ_z. λ_t decreases at this rate, while the other endogenous variables are constant along the balanced growth path.

To derive the set of equations that describe the stationary equilibrium, we deflate the model by the growth component, Z_t. Note that the predetermined variables, such as A_t and K_t, which are used at time t but have been decided at $t-1$, are deflated by the growth component at $t-1$.

The adoption success probability is constant in the steady state:

$$\Xi_t = \frac{2}{1+exp(-\Gamma_t)} - 1$$

$$\Gamma_t = \bar{\Gamma}\left[S_t\left(\frac{\frac{Z_t}{Z_t}Z_t}{\frac{A_t}{Z_{t-1}}Z_{t-1}} - 1\right)\right]^{\rho_\Gamma} = \bar{\Gamma}\left[S_t\left(\frac{z_t}{\tilde{A}_t} - 1\right)\right]^{\rho_\Gamma}$$

The evolution of embodied technology can be rewritten as:

$$\begin{aligned}
&\frac{A_{t+1}}{Z_t}Z_t = \Xi_t\left(\frac{Z_t}{Z_t}Z_t - \phi\frac{A_t}{Z_{t-1}}Z_{t-1}\right) + \phi\frac{A_t}{Z_{t-1}}Z_{t-1}\\
&\Leftrightarrow \tilde{A}_{t+1}z_t = \Xi_t\left(z_t - \phi\tilde{A}_t\right) + \phi\tilde{A}_t
\end{aligned}$$

The resource constraint can be stationarized as it follows:

$$\begin{aligned}
&\frac{C_t}{Z_t}Z_t + \frac{I_t}{Z_t}Z_t + S_t\left(\frac{A_{t+1}}{Z_t}Z_t - \frac{A_t}{Z_{t-1}}Z_{t-1}\right) = \frac{Y_t}{Z_t}Z_t(1-g_t)\\
&\Leftrightarrow \tilde{C}_t + \tilde{I}_t + S_t\left(\tilde{A}_{t+1} - \frac{\tilde{A}_t}{z_t}\right) = \tilde{Y}_t(1-g_t)
\end{aligned}$$

For the production function, we have:

$$\begin{aligned}
&\frac{Y_t}{Z_t}Z_t = \left[X_t\left(\frac{A_t}{Z_{t-1}}Z_{t-1}\right)^{(\vartheta-1)}\right]\left(\frac{K_t}{Z_{t-1}}Z_{t-1}\right)^{\alpha}L_t^{1-\alpha}\\
&\Leftrightarrow \tilde{Y}_t z_t = \left[X_t\tilde{A}_t^{(\vartheta-1)}\right](\tilde{K}_t)^{\alpha}L_t^{1-\alpha}
\end{aligned}$$

which is the case iff $\vartheta = 2-\alpha$.

Concerning the FOCs for the households' problem, we have:
Households' FOC wrt B_{t+1} (Euler equation)

$$\begin{aligned}
&\lambda_t Z_t = \beta\mathbb{E}_t\lambda_{t+1}Z_{t+1}\frac{1}{z_{t+1}}R_t\\
&\Leftrightarrow \tilde{\lambda}_t = \beta\mathbb{E}_t\tilde{\lambda}_{t+1}\frac{1}{z_{t+1}}R_t
\end{aligned}$$

Households' FOC wrt C_t

$$\iota_t\left(\frac{C_t}{Z_t}Z_t-\tau\frac{C_{t-1}}{Z_{t-1}}Z_{t-1}\right)^{-1}-\beta\tau\mathbb{E}_t\iota_{t+1}\left(\frac{C_{t+1}}{Z_{t+1}}Z_{t+1}-\tau\frac{C_t}{Z_t}Z_t\right)^{-1}=\frac{\lambda_t Z_t}{Z_t}$$
$$\Leftrightarrow \iota_t\left(\tilde{C}_t-\tau\tilde{C}_{t-1}\frac{1}{z_t}\right)^{-1}-\beta\tau\mathbb{E}_t\iota_{t+1}\left(\tilde{C}_{t+1}z_{t+1}-\tau\tilde{C}_t\right)^{-1}=\tilde{\lambda}_t$$

Households' FOC wrt K_{t+1}

$$q_t=\beta\mathbb{E}_t\frac{\lambda_{t+1}Z_{t+1}}{\lambda_t Z_t}\frac{Z_t}{Z_{t+1}}\left[r^k_{t+1}+q_{t+1}(1-\delta)\right]$$
$$\Leftrightarrow q_t=\beta\mathbb{E}_t\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t}\frac{1}{z_{t+1}}\left[r^k_{t+1}+q_{t+1}(1-\delta)\right]$$

Households' FOC wrt I_t[45]

$$\begin{aligned}1=&q_t b_t\left[1-\varphi\left(\frac{\frac{I_t}{Z_t}}{\frac{I_{t-1}}{Z_{t-1}}}\frac{Z_t}{Z_{t-1}}\right)-\varphi'\left(\frac{\frac{I_t}{Z_t}}{\frac{I_{t-1}}{Z_{t-1}}}\frac{Z_t}{Z_{t-1}}\right)\frac{\frac{I_t}{Z_t}}{\frac{I_{t-1}}{Z_{t-1}}}\frac{Z_t}{Z_{t-1}}\right]\\&+\beta\mathbb{E}_t\left[q_{t+1}b_{t+1}\frac{\lambda_{t+1}Z_{t+1}}{\lambda_t Z_t}\frac{Z_t}{Z_{t+1}}\varphi'\left(\frac{\frac{I_{t+1}}{Z_{t+1}}}{\frac{I_t}{Z_t}}\frac{Z_{t+1}}{Z_t}\right)\left(\frac{\frac{I_{t+1}}{Z_{t+1}}}{\frac{I_t}{Z_t}}\frac{Z_{t+1}}{Z_t}\right)^2\right]\\&\Leftrightarrow\\1=&q_t b_t\left[1-\varphi\left(\frac{\tilde{I}_t}{\tilde{I}_{t-1}}z_t\right)-\varphi'\left(\frac{\tilde{I}_t}{\tilde{I}_{t-1}}z_t\right)\frac{\tilde{I}_t}{\tilde{I}_{t-1}}z_t\right]\\&+\beta\mathbb{E}_t\left[q_{t+1}b_{t+1}\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t}\frac{1}{z_{t+1}}\varphi'\left(\frac{\tilde{I}_{t+1}}{\tilde{I}_t}z_{t+1}\right)\left(\frac{\tilde{I}_{t+1}}{\tilde{I}_t}z_{t+1}\right)^2\right]\end{aligned}$$

Households' FOC wrt L_t

$$\iota_t\zeta L_t^\eta=\frac{\lambda_t Z_t}{Z_t}\frac{w_t}{Z_t}Z_t$$
$$\Leftrightarrow \iota_t\zeta L_t^\eta=\tilde{\lambda}_t\tilde{w}_t$$

Households' FOC wrt S_t

$$\lambda_t Z_t\left(\frac{A_{t+1}}{Z_t}Z_t-\frac{A_t}{Z_{t-1}}Z_{t-1}\right)=\Omega_t\frac{\partial\Xi_t}{\partial S_t}\left(\frac{Z_t}{Z_t}Z_t-\phi\frac{A_t}{Z_{t-1}}Z_{t-1}\right)$$
$$\Leftrightarrow \tilde{\lambda}_t\left(\tilde{A}_{t+1}-\frac{\tilde{A}_t}{z_t}\right)=\tilde{\Omega}_t\frac{\partial\Xi_t}{\partial S_t}\left(z_t-\phi\tilde{A}_t\right)$$

For the law of motion for capital and the factor demand equations, we find:

$$\frac{K_{t+1}}{Z_t}Z_t=\frac{I_t}{Z_t}Z_t\left[1-\varphi\left(\frac{\frac{I_t}{Z_t}}{\frac{I_{t-1}}{Z_{t-1}}}\frac{Z_t}{Z_{t-1}}\right)\right]b_t+(1-\delta)\frac{K_t}{Z_{t-1}}Z_{t-1}$$
$$\Leftrightarrow \tilde{K}_{t+1}=\tilde{I}_t\left[1-\varphi\left(\frac{\tilde{I}_t}{\tilde{I}_{t-1}}z_t\right)\right]b_t+(1-\delta)\frac{\tilde{K}_t}{z_t}$$

[45]The adjustment cost function is defined as $\varphi=\frac{\kappa}{2}\left(\frac{I_t}{I_{t-1}}-\Delta_i\right)^2$ which is equivalent to $\varphi=\frac{\kappa}{2}\left(\frac{\tilde{I}_t}{\tilde{I}_{t-1}}z_t-\Delta_z\right)^2$.

$$L_t = \frac{(1-\alpha)}{\vartheta}\frac{\tilde{Y}_t}{\tilde{w}_t}$$

$$\tilde{K}_t = \frac{\alpha}{\vartheta}\frac{\tilde{Y}_t}{r_t^k} z_t$$

The last step is to stationarize the equations related to technology adoption:

$$f_t = \frac{(\vartheta-1)}{\vartheta}\frac{\frac{Y_t}{Z_t}Z_t}{\frac{A_t}{Z_{t-1}}Z_{t-1}}$$
$$\Leftrightarrow f_t = \frac{(\vartheta-1)}{\vartheta}\frac{\tilde{Y}_t}{\tilde{A}_t} z_t$$

$$V_t = f_t + \phi \mathbb{E}_t \left[\beta \frac{\lambda_{t+1} Z_{t+1}}{\lambda_t Z_t}\frac{Z_t}{Z_{t+1}} V_{t+1}\right]$$
$$\Leftrightarrow V_t = f_t + \phi \mathbb{E}_t \left[\beta \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t z_{t+1}} V_{t+1}\right]$$

$$J_t = \max_{S_t} -S_t + \mathbb{E}_t \left\{\beta \frac{\lambda_{t+1} Z_{t+1}}{\lambda_t Z_t}\frac{Z_t}{Z_{t+1}}\left[\Xi_t \phi V_{t+1} + (1-\Xi_t) J_{t+1}\right]\right\}$$
$$\Leftrightarrow J_t = \max_{S_t} -S_t + \mathbb{E}_t \left\{\beta \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t z_{t+1}}\left[\Xi_t \phi V_{t+1} + (1-\Xi_t) J_{t+1}\right]\right\}$$

$$0 = -1 + \mathbb{E}_t \left[\beta \frac{\lambda_{t+1} Z_{t+1}}{\lambda_t Z_t}\frac{Z_t}{Z_{t+1}}(\phi V_{t+1} - J_{t+1})\frac{\partial \Xi_t}{\partial S_t}\right]$$
$$\Leftrightarrow 0 = -1 + \mathbb{E}_t \left[\beta \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t z_{t+1}}(\phi V_{t+1} - J_{t+1})\frac{\partial \Xi_t}{\partial S_t}\right]$$

3.F.4 Set of Equilibrium Conditions with Stationary Variables

Having deflated by the growth component, Z_t, all the variables that were growing, we can summarize the set of model equations that describe the stationary equilibrium.

1. Success probability of adoption

$$\Xi_t = \frac{2}{1 + exp(-\Gamma_t)} - 1$$

2. Definition of Γ

$$\Gamma_t = \bar{\Gamma}\left[S_t\left(\frac{z_t}{\tilde{A}_t} - 1\right)\right]^{\rho_\Gamma}$$

3. Evolution of technology adoption

$$\tilde{A}_{t+1} z_t = \Xi_t \left(z_t - \phi \tilde{A}_t \right) + \phi \tilde{A}_t$$

4. Resource constraint

$$\tilde{C}_t + \tilde{I}_t + S_t \left(\tilde{A}_{t+1} - \frac{\tilde{A}_t}{z_t} \right) = \tilde{Y}_t (1 - g_t)$$

5. Production function

$$\tilde{Y}_t z_t = \left[X_t \tilde{A}_t^{(\vartheta-1)} \right] (\tilde{K}_t)^{\alpha} L_t^{1-\alpha}$$

6. Households' FOC wrt B_{t+1} (Euler equation)

$$\tilde{\lambda}_t = \beta \mathbb{E}_t \tilde{\lambda}_{t+1} \frac{1}{z_{t+1}} R_t$$

7. Households' FOC wrt C_t

$$\iota_t \left(\tilde{C}_t - \tau \tilde{C}_{t-1} \frac{1}{z_t} \right)^{-1} - \beta \tau \mathbb{E}_t \iota_{t+1} \left(\tilde{C}_{t+1} z_{t+1} - \tau \tilde{C}_t \right)^{-1} = \tilde{\lambda}_t$$

8. Households' FOC wrt K_{t+1}

$$q_t = \beta \mathbb{E}_t \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t} \frac{1}{z_{t+1}} \left[r_{t+1}^k + q_{t+1}(1-\delta) \right]$$

9. Households' FOC wrt I_t

$$\begin{aligned} 1 = & q_t b_t \left[1 - \varphi \left(\frac{\tilde{I}_t}{\tilde{I}_{t-1}} z_t \right) - \varphi' \left(\frac{\tilde{I}_t}{\tilde{I}_{t-1}} z_t \right) \frac{\tilde{I}_t}{\tilde{I}_{t-1}} z_t \right] \\ & + \beta \mathbb{E}_t \left[q_{t+1} b_{t+1} \frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t} \frac{1}{z_{t+1}} \varphi' \left(\frac{\tilde{I}_{t+1}}{\tilde{I}_t} z_{t+1} \right) \left(\frac{\tilde{I}_{t+1}}{\tilde{I}_t} z_{t+1} \right)^2 \right] \end{aligned}$$

10. Households' FOC wrt S_t

$$\tilde{\lambda}_t \left(\tilde{A}_{t+1} - \frac{\tilde{A}_t}{z_t} \right) = \tilde{\Omega}_t \frac{\partial \Xi_t}{\partial S_t} \left(z_t - \phi \tilde{A}_t \right)$$

11. Households' FOC wrt L_t

$$\iota_t \zeta L_t^{\eta} = \tilde{\lambda}_t \tilde{w}_t$$

12. Law of motion for capital

$$\tilde{K}_{t+1} = \tilde{I}_t \left[1 - \varphi \left(\frac{\tilde{I}_t}{\tilde{I}_{t-1}} z_t \right) \right] b_t + (1-\delta) \frac{\tilde{K}_t}{z_t}$$

13. Factor demand equation for labor

$$L_t = \frac{(1-\alpha)}{\vartheta}\frac{\tilde{Y}_t}{\tilde{w}_t}$$

14. Factor demand equation for capital

$$\tilde{K}_t = \frac{\alpha}{\vartheta}\frac{\tilde{Y}_t}{r_t^k}z_t$$

15. Profits

$$f_t = \frac{(\vartheta-1)}{\vartheta}\frac{\tilde{Y}_t}{\tilde{A}_t}z_t$$

16. Value of an adopted intermediate good

$$V_t = f_t + \phi\mathbb{E}_t\left[\beta\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t z_{t+1}}V_{t+1}\right]$$

17. Value of acquiring an innovation that has not been adopted yet

$$J_t = \max_{S_t} -S_t + \mathbb{E}_t\left\{\beta\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t z_{t+1}}\left[\Xi_t\phi V_{t+1} + (1-\Xi_t)J_{t+1}\right]\right\}$$

18. Optimal choice of investment in adoption

$$0 = -1 + \mathbb{E}_t\left[\beta\frac{\tilde{\lambda}_{t+1}}{\tilde{\lambda}_t z_{t+1}}(\phi V_{t+1} - J_{t+1})\frac{\partial\Xi_t}{\partial S_t}\right]$$

3.G Benchmark Calibration of the Model with Endogenous Technology Adoption

Table 3.2: Benchmark calibration of model with endogenous technology adoption

Parameter	Description	Value
τ	consumption habit	0.75
β	discount factor	0.9926
η	inverse Frisch elasticity	1
δ	capital depreciation rate	0.025
α	capital share in the production function	0.37
$\bar{\Gamma}$	ss adoption lag	0.10/4
ϕ	survival rate of a technology	1-0.1/4
ϑ	steady state markups for intermediate goods	1.63
φ	labor disutility parameter	ss L is 1/3
δ_z	ss growth of the economy	2%
g_{ss}	ss government spending share of output	20.7%
ρ_Γ	adoption elasticity	0.9
κ	capital investment adjustment costs parameter	1.3
ρ_x	autocorrelation disembodied productivity shock	0.95
s_x	standard deviation of unanticipated productivity shock	0.01
s_z	standard deviation of technology diffusion news shock	0.01

3.H Discussion of the Key Elements of the Model with Endogenous Technology Adoption

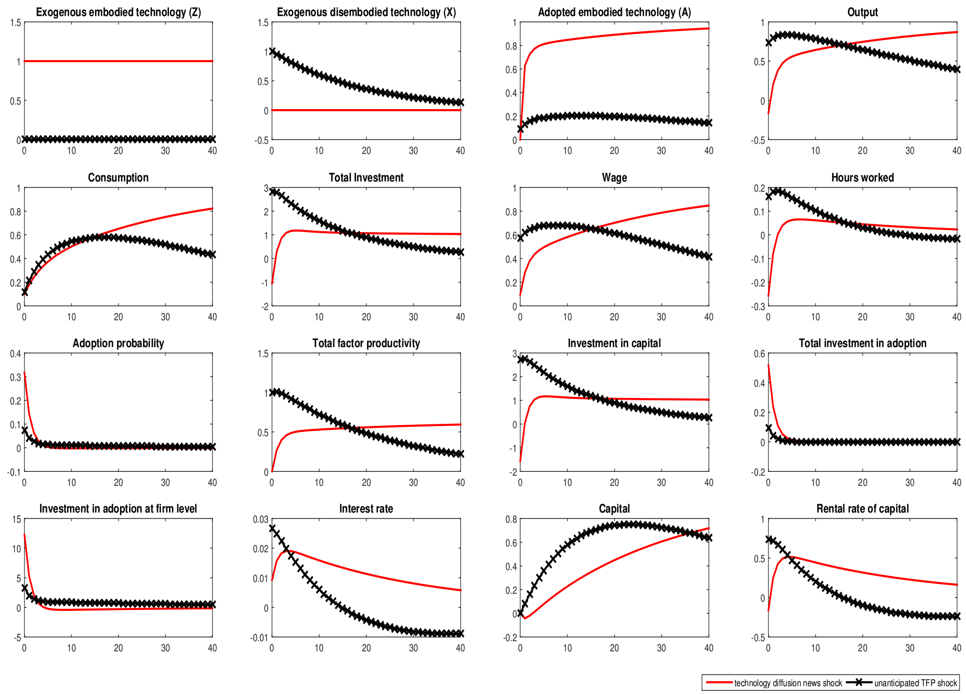

Figure 3.17: Model with no investment adjustment costs. Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

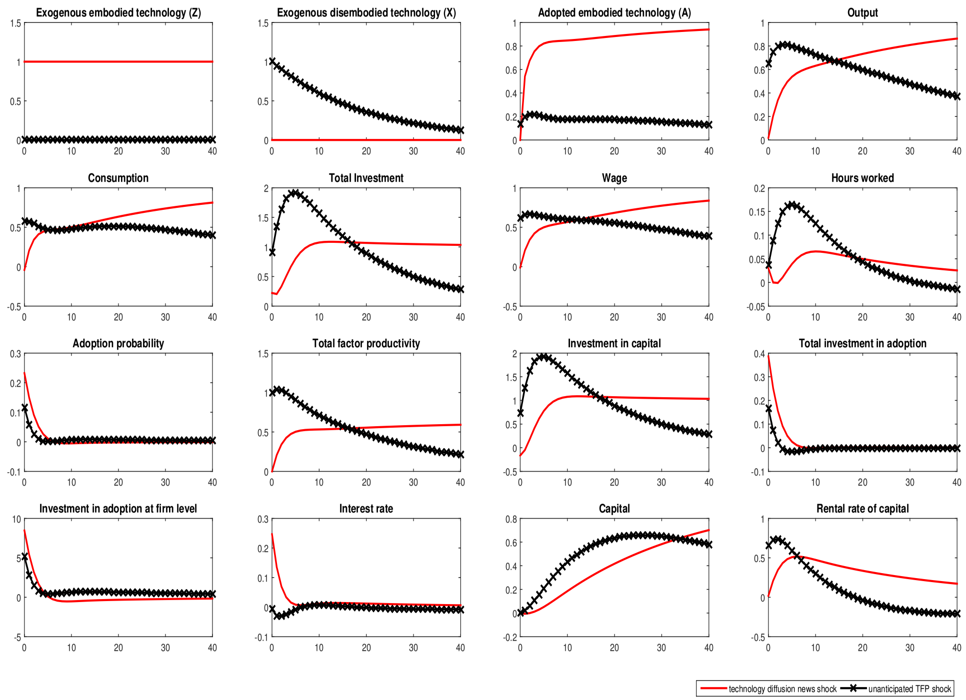

Figure 3.18: Model with no habit persistence. Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

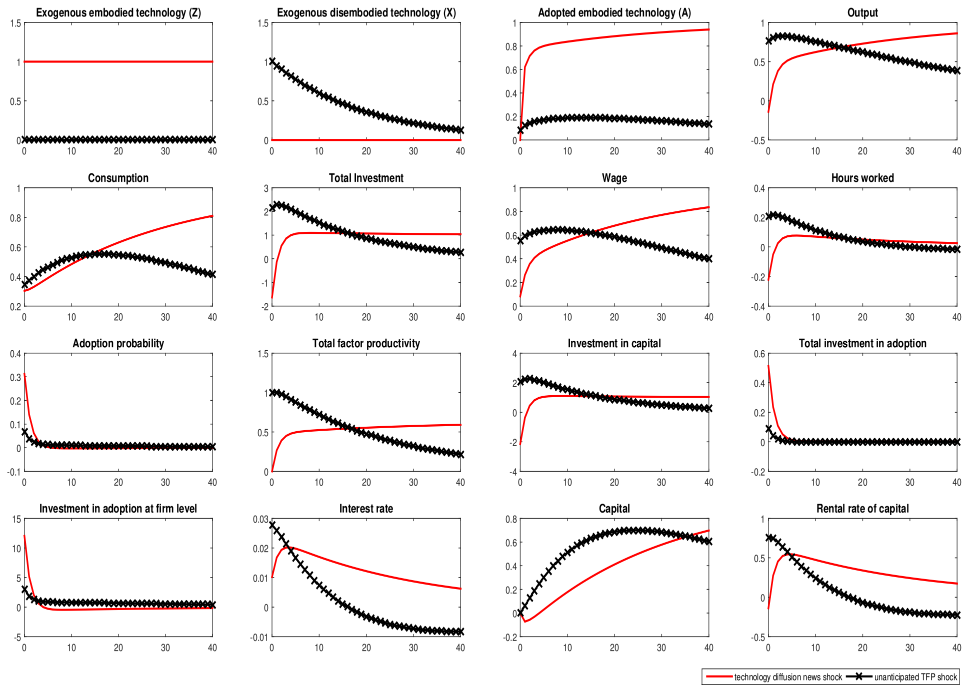

Figure 3.19: Model with no investment adjustment costs and no habit persistence. Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

Chapter 4

News Shocks: Different Effects in Boom and Recession?

Maria Bolboaca and Sarah Fischer

Abstract

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

4.1 Introduction

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

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

So far news shocks on future productivity have been analyzed only in linear settings, that is in models that treat booms and recessions in the same way. By the properties of these linear models, the effect of a news shock is history independent, which means that the response of agents to news is the same if the economy is booming or in a recession. However, there is no reason to make this assumption. From a statistical point of view, this assumption has to be tested. From a theoretical perspective, the news literature often interprets this shock as a shock to agents' expectations that creates waves of optimism or pessimism concerning long run economic outcomes. But theory does not impose any prior restrictions regarding the independence of agents' psyche to the state they live in. In fact, it is more probable that pessimism and optimism are actually state-dependent. Moreover, there are also economic reasons to believe that responses to news can be different. For example, firms are more likely to be financially constrained in recessions than in booms. By computing the first and second moments of the main economic indicators, conditional on the economy being in an expansion or a recession as indicated by the NBER based index, we find evidence in support of the previous arguments.[1] In bad times, consumer confidence and business expectations are low, consumption and investment growth rates are below average, while uncertainty is high. The opposite holds true in normal times. On these premises, in this paper we challenge the linearity assumption in the literature and test whether the effects of news are state-dependent, i.e. dependent on the state of the economy at the time news arrives.

Our main contribution to the news literature is to open the possibility that news have different effects in booms and recessions. To perform our empirical analysis, we proceed as follows. We estimate a five-variable logistic smooth transition vector autoregressive (LSTVAR) model including total factor productivity (TFP), consumer expectations, output, inflation and stock prices (SP). Our model builds on Auerbach and Gorodnichenko (2012) and Teräsvirta et al. (2010), and allows for state-dependent dynamics through parameters and state-dependent impact effects through the variance-covariance matrix. We have a smooth transition from one regime to the other, given by a logistic function, which determines how the two regimes are combined at any given period in time. The value of the transition function is dependent on the state of the economy indicated by

[1] Details are provided in Appendix 4.A.1.

output growth. We let the transition in the mean equation and the variance equation to be different, and estimate the parameters of the transition functions.

In a nonlinear vector autoregressive (VAR) context short-run restrictions are usually applied in order to identify structural shocks. In contrast, we choose to identify the news shock via a medium-run identification method. This is by now a standard approach in the empirical news literature,[2] but its implementation in a nonlinear model is a challenge. Our method takes into account the nonlinearity of the model and to the best of our knowledge, we are the first to apply this identification scheme in a nonlinear setting. Our identifying assumption is that a news shock about technological innovations is a shock with no impact effect on TFP but with maximal contribution to it after 10 years. To analyze the effects of the news shock we compute generalized impulse responses that allow for endogenous regime transition by adjusting the transition functions in every simulation step. This approach accounts for the transition of the system from one regime to the other as a reaction to a shock and permits to measure the change in the probability of a regime transition after a news shock has occurred. We further investigate the state-dependency in the contribution of the news shock to the variation in the variables of the model at different frequencies. We use a generalization of the forecast error variance decomposition. The reason is that a basic forecast error variance decomposition is inapplicable in a nonlinear setting because the shares do not sum to one.

We then perform several robustness checks. We compare the effects of the news shock to those of a confidence shock, obtained by applying short-run restrictions. The confidence shock is identified as the shock with no impact effect on TFP, but with an immediate effect on consumer expectations. As showed in Bolboaca and Fischer (2017), this shock has similar effects to the news shock.[3] We also compare the results with those obtained by applying the same identification schemes within a linear VAR model that includes the same variables.

Our results indicate that there is significant state-dependency in the effects of the news, mainly in the short- and medium-run. Because we allow the model to transition from one regime to the other after a news shock has occurred, we find that news shocks significantly influence the probability of a regime change both in recessions and expansions. Positive news shocks coming in expansions reduce the probability of transitioning to a recession by 3 percentage points after approximately one year. When the positive news shock arrives in a recession, it increases the probability of a transition to an expansion by almost 5 percentage points. Thus we can interpret that positive news shocks are more effective in recessions than in booms. The impulse response to a news shock is in general larger in an expansion than in a recession. Our intuition for the difference in the responses across the two regimes relates to the heightened uncertainty of economic agents in a recession. By comparing the state-dependent results with those from the linear model, we find that the effects of news shocks are stronger in expansion than the linear model would indicate, and smaller in recession. Hence using the linear model would underestimate the effects of news in expansion and overestimate them in a recession. When analyzing the impact contribution of the news shock to the variation

[2] For an overview of the identification schemes employed in the empirical news literature see Bolboaca and Fischer (2017), while the most prominent approaches are those of Beaudry and Portier (2006), and Barsky and Sims (2011).

[3] The confidence shock is also referred to in the related literature as a news shock obtained with short-run restrictions. We prefer to name it a confidence shock in this paper to make a clear distinction between this shock and the other news shock obtained with the medium-run identification scheme.

of all the variables in the model we observe that in an expansion the shares are similar to the ones in the linear model. In recessions, the news shock contributes more to the variance of the forward-looking variables, while the contribution to output's variance is almost nil. In the medium-run the shares converge to similar values in both regimes. These results indicate that good news in boom are just some good news among many others, but good news in recession are more valuable. Comparing the effects of the news shock to those of the confidence shock, we find that, while in recessions the two deliver basically the same results, the impulse responses in expansions are stronger for the news shock and the contributions to the variance of the model's variables are different. While there is evidence in favor of state-dependency, the same does not hold true for the asymmetry in the effects of news shocks. Our results indicate there is no significant difference between the effects of positive and negative shocks, no matter whether the shocks hit in an economic downturn or upturn.

Our paper is related to several strands of literature. First of all, it contributes to the empirical literature on productivity related news shocks. The seminal paper on the effects of news about future changes in productivity is Beaudry and Portier (2006).[4] There is an ongoing debate about the effects of news shocks, and the conflicting evidence stems from the wide diversity in variable settings, productivity series used and identification schemes applied.[5] Moreover, our paper is methodologically related to the literature on state-dependent fiscal multipliers that uses STVAR models. Some examples are: Auerbach and Gorodnichenko (2012), Owyang et al. (2013), Caggiano et al. (2014), and Caggiano et al. (2015). Our paper contributes to the literature in the following ways. First, from a methodological perspective, we contribute to the model estimation through the fact that we allow the transition in the mean equation and the variance equation to be different, and we estimate the parameters of both transition functions. Moreover, we apply a medium-run identification scheme to identify a structural shock in an STVAR model. From a theoretical point of view, the fact of having news increasing the probability of exiting a recession has implications for theory. Models should take into account that good news are more effective in recessions.

The rest of the paper is organized as follows. In Section 4.2, we present the empirical approach and the estimation method employed. In Section 4.3, we describe the data. We discuss our results in Section 4.4, and offer some concluding remarks in Section 4.5.

4.2 Empirical Approach

We employ a five-dimensional LSTVAR model in levels.[6] We work with quarterly data for the U.S. economy from 1955Q1 to 2012Q4. Our benchmark system contains five variables in the following order: TFP adjusted for variations in factor utilization, University of Michigan index of consumer sentiment (ICS), real output, inflation and stock prices (details are provided in appendix 4.A.2).

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

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

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

According to van Dijk et al. (2002), a smooth transition model can either be interpreted as a regime-switching model allowing for two extreme regimes associated with values of the transition function of 0 and 1 where the transition from one regime to the other is smooth, or as a regime-switching model with a "continuum" of regimes, each associated with a different value of the transition function. We model an economy with two extreme regimes (expansion, recession) between which the transition is smooth. By relaxing the assumption of linearity, we allow the model to capture different dynamics in two opposed regimes.

4.2.1 Model Specification

Formally, the LSTVAR model of order p reads:

$$Y_t = \Pi_1' X_t (1 - F(\gamma_F, c_F; s_{t-1})) + \Pi_2' X_t F(\gamma_F, c_F; s_{t-1}) + \epsilon_t, \tag{4.1}$$

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

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

$$F(\gamma_F, c_F; s_t) = exp\left(-\gamma_F(s_t - c_F)\right) \; \left[1 + exp\left(-\gamma_F(s_t - c_F)\right)\right]^{-1}, \; \gamma_F > 0, \tag{4.2}$$

where γ_F is called slope or smoothness parameter, and c_F is a location parameter determining the middle point of the transition ($F(\gamma_F, c_F; c_F) = 1/2$). Therefore, it can be interpreted as the threshold between the two regimes as the logistic function changes monotonically from 0 to 1 when the transition variable decreases. Every period, the transition function attaches some probability to being in each regime given the value of the transition variable s_t. $\epsilon_t \sim N(0, \Sigma_t)$ is an m-dimensional reduced-form shock with mean zero and positive definite variance-covariance matrix, Σ_t. We allow the variance-covariance matrix to be regime-dependent:[7]

$$\Sigma_t = (1 - G(\gamma_G, c_G; s_{t-1}))\Sigma_1 + G(\gamma_G, c_G; s_{t-1})\Sigma_2 \tag{4.3}$$

The transition between regimes in the second moment is also governed by a logistic transition function $G(\gamma_G, c_G; s_{t-1})$. We want to allow not only for dynamic differences in the propagation of structural shocks through Π_1 and Π_2 but also for contemporaneous differences via the two covariance matrices, Σ_1 and Σ_2. This method is similar to the one employed in Auerbach and Gorodnichenko (2012),[8] but we depart from their approach by letting the parameters of the transition function in the variance equation to differ from the parameters in the mean equation.

The LSTVAR reduces to a linear VAR model when $\gamma_F = \gamma_G = 0$. The linear model is described by the following equation:

$$Y_t = \Pi' X_t + \epsilon_t, \tag{4.4}$$

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

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

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

4.2.2 Transition Variable

The logistic transition function determines how the two regimes are combined at any given period in time. The value of the transition function is dependent on the state of the economy, which is given by the transition variable. As stated in Teräsvirta et al. (2010), economic theory is not always fully explicit about the transition variable. There are several options. The transition variable can be an exogenous variable ($s_t = z_t$), a lagged endogenous variable ($s_t = Y_{i,t-d}$, for certain integer $d > 0$, and where the subscript i is the position of this specific variable in the vector of endogenous variables), a function of lagged endogenous variables or a function of a linear time trend.

For our model, the transition variable needs to follow the business cycle and clearly identify expansionary and recessionary periods. The NBER defines a recession as 'a period of falling economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales'. This makes the identification of a recession a complex process based on weighing the behavior of various indicators of economic activity. One possibility is to use as transition variable the NBER based recession index,[9] which equals one if a quarter is defined by the NBER as recession, and zero otherwise. But having an exogenous variable as switching variable makes it impossible to investigate the effects of shocks on the transition from one state of the economy to the other. For this reason, we follow the common rule of thumb which defines a recession as two consecutive quarters of negative GDP growth, and use as transition variable a lagged three quarter moving average of the quarter-on-quarter real GDP. This choice of the transition variable is close to the one used in Auerbach and Gorodnichenko (2012), as they set s_t to be a seven quarter moving average of the realizations of the quarter-on-quarter real GDP growth rate, centered at time t. We depart from their approach in the sense that we do not assume the transition variable to be exogenous, but we define it as a function of a lagged endogenous variable, output. In order to avoid endogeneity problems, the transition functions F and G at date t are based on $s_{t-1} = \frac{1}{3}(g^Y_{t-1} + g^Y_{t-2} + g^Y_{t-3})$, g^Y_t being the growth rate of output. By endogenizing the transition variable, we are able to analyze how shocks coming in a recession, for example, influence the chances of the economy to recover or to continue staying in that state.

The LSTVAR model is only indicated if linearity can be rejected. We tested linearity against the alternative of a nonlinear model, given the transition variable. We reject the null hypothesis of linearity at all significance levels, regardless of the type of LM test we perform (for details, see Appendix 4.B.1).[10]

4.2.3 Estimation

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

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

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

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

$$log\ L = const + \frac{1}{2}\sum_{t=1}^{T}\log|\Sigma_t| - \frac{1}{2}\sum_{t=1}^{T}\epsilon_t'\Sigma_t^{-1}\epsilon_t, \tag{4.5}$$

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

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

$$\hat{\Psi} = \arg\min_{\Psi}\sum_{t=1}^{T}\epsilon_t'\Sigma_t^{-1}\epsilon_t \tag{4.6}$$

We then let $Z_t(\gamma_F, c_F) = [X_t'(1 - F(\gamma_F, c_F; s_{t-1})), X_t' F(\gamma_F, c_F; s_{t-1})]'$ be the extended vector of regressors, and $\Pi = [\Pi_1', \Pi_2']'$ such that equation (4.6) can be rewritten as:

$$\hat{\Psi} = \arg\min_{\Psi}\sum_{t=1}^{T}(Y_t - \Pi' Z_t(\gamma_F, c_F))'\Sigma_t^{-1}(Y_t - \Pi' Z_t(\gamma_F, c_F)) \tag{4.7}$$

It is important to note that conditional on $\{\gamma_F, c_F, \gamma_G, c_G, \Sigma_1, \Sigma_2\}$ the LSTVAR model is linear in the autoregressive parameters Π_1 and Π_2. Hence, for given $\gamma_F, c_F, \gamma_G, c_G$, Σ_1, and Σ_2, estimates of Π can be obtained by weighted least squares (WLS), with weights given by Σ_t^{-1}. The conditional minimizer of the objective function can then be obtained by solving the first order condition (FOC) equation with respect to Π:

$$\sum_{t=1}^{T}(Z_t(\gamma_F, c_F)Y_t'\Sigma_t^{-1} - Z_t(\gamma_F, c_F)Z_t(\gamma_F, c_F)'\Pi\Sigma_t^{-1}) = 0 \tag{4.8}$$

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

$$vec(\hat{\Pi}) = \left[\sum_{t=1}^{T}\left(\Sigma_t^{-1}\otimes Z_t(\gamma_F, c_F)Z_t(\gamma_F, c_F)'\right)\right]^{-1} vec\left[\sum_{t=1}^{T}\left(Z_t(\gamma_F, c_F)Y_t'\Sigma_t^{-1}\right)\right], \tag{4.9}$$

where *vec* denotes the stacking columns operator.

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

Therefore, we divide the set of parameters, Ψ, into two subsets: the 'nonlinear parameter set', $\Psi_n = \{\gamma_F, c_F, \gamma_G, c_G, \Sigma_1, \Sigma_2\}$, and the 'linear parameter set', $\Psi_l = \{\Pi_1, \Pi_2\}$. To ensure that Σ_1, and Σ_2 are positive definite matrices, we redefine Ψ_n as $\{\gamma_F, c_F, \gamma_G, c_G, chol(\Sigma_1), chol(\Sigma_2)\}$, where *chol* is the operator for the Cholesky decomposition.

Following Auerbach and Gorodnichenko (2012), we perform the estimation using a Markov Chain Monte Carlo (MCMC) method. More precisely, we employ a Metropolis-Hastings (MH) algorithm with quasi-posteriors, as defined in Chernozhukov and Hong (2003). The advantage of this method is that it delivers not only a global optimum but also distributions of parameter estimates. As we have seen previously, for any fixed pair of nonlinear parameters, one can easily compute the linear parameters and the likelihood. Therefore, we apply the MCMC method only to the nonlinear part of the parameter set, Ψ_n (details are provided in Appendix 4.B.3).[11]

4.2.4 Starting Values

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

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

$$P(Rec_t = 1 \mid s_{t-1}) = \frac{exp\,[-\gamma(s_{t-1} - c)]}{1 + exp\,[-\gamma(s_{t-1} - c)]} \tag{4.10}$$

The estimation delivers the starting values $\hat{\gamma}_F = \hat{\gamma}_G = 3.12$ and $\hat{c}_F = \hat{c}_G = -0.48$ (for details see Appendix 4.B.2). Usually, in the macroeconomic literature, γ is calibrated to match the duration of recessions in the US according to NBER business cycle dates (see Auerbach and Gorodnichenko (2012); Bachmann and Sims (2012); Caggiano et al. (2014)). The values assigned to γ range from 1.5 to 3, but in all these settings, the location parameter, c, is imposed to equal zero, such that the middle point of the transition is given by the switching variable being zero. For comparison, we also estimate the logistic regression forcing the constant to be zero and obtain an estimate for γ that equals 3.56. However, the Likelihood Ratio (LR) test[12] shows that the model with intercept provides a better fit. Moreover, the intercept is statistically different from zero so there is no econometric support for assuming it to be zero (see Appendix 4.B.2).

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

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

The transition function with $\gamma = 3.12$ and $c = -0.48$, is shown in Figure 4.6. It is obvious that high values of the transition function are associated with the NBER identified recessions.

The choice of the other starting parameter values is presented in details in Appendix 4.B.3.

4.2.5 Evaluation

According to Teräsvirta and Yang (2014b), exponential stability of the model may be numerically investigated through simulation of counterfactuals. By generating paths of realizations from the estimated model with noise switched off, starting from a large number of initial points, it can be checked whether the paths of realizations converge. The convergence to a single stationary point is a necessary condition for exponential stability.[13]

Yang (2014) proposes a test for the constancy of the error covariance matrix applicable to smooth transition vector autoregressive models. To test for constancy of the error covariance matrix, first, the model has to be estimated under the null hypothesis assuming the error covariance matrix to be constant over time. Similar to the linearity test for the dynamic parameters, the alternative hypothesis is approximated by a third-order Taylor approximation given the transition variable. In our case, the null hypothesis of a constant error covariance matrix is clearly rejected (for details, see Appendix 4.B.4).[14]

4.2.6 Identification of the News Shock

Medium-Run Identification

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

This identification scheme imposes medium-run restrictions in the sense of Uhlig (2004).[15] Innovations are orthogonalized, for example, by applying the Cholesky de-

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

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

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

composition to the covariance matrix of the residuals $\Sigma = \tilde{A}\tilde{A}'$, assuming there is a linear mapping between the innovations and the structural shocks. The unanticipated productivity shock is the only shock affecting TFP on impact. The news shock is then identified as the shock that has no impact effect on TFP and that, in adition to the unanticipated productivity shock, influences TFP the most in the medium-run. More precisely, it is the shock which explains the largest share of the TFP's FEV at some specified horizon H. We set H equal to 40 quarters (i.e. 10 years). We choose this specific horizon as we believe that shorter horizons are prone to ignore news on important and large technological innovations that need at least a decade to seriously influence total factor productivity. On the other hand, longer horizons might ignore shorter-run news as they only consider news shocks that turn out to be true in the long-run.[16] We define the entire space of permissible impact matrices as $\tilde{A}D$, where D is a $k \times k$ orthonormal rotation matrix ($DD' = I$).[17]

In the linear setting the h step ahead forecast error is defined as the difference between the realization of Y_{t+h} and the minimum mean squared error predictor for horizon h:[18]

$$Y_{t+h} - \mathbb{P}_{t-1}Y_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A} D u_{t+h-\tau} \tag{4.11}$$

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

$$\Xi_{j,i}(h) = \frac{e_j' \left(\sum_{\tau=0}^{h} B_\tau \tilde{A} D e_i e_i' \tilde{A}' D B_\tau' \right) e_j}{e_j' \left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau' \right) e_j} = \frac{\sum_{\tau=0}^{h} B_{j,\tau} \tilde{A} \gamma \gamma' \tilde{A}' B_{j,\tau}'}{\sum_{\tau=0}^{h} B_{j,\tau} \Sigma B_{j,\tau}'} \tag{4.12}$$

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

The use of the MRI to identify a news shock is by now a standard approach in the empirical news literature, but how to implement it in a nonlinear model is a challenge. The calculation of the FEV decomposition depends on the estimation of GIRFs, which are history dependent and constructed as an average over simulated trajectories. If traditional methods are used, in general, the shares do not add to one which makes it unclear

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

[17] The reduced-form residuals can be written as a linear combination of the structural shocks $\epsilon_t = Au_t$, assuming that A is nonsingular. Structural shocks are white noise distributed $u_t \sim WN(0, I)$ 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. A thorough treatment of the identification problem in linear vector autoregressive models can be found in Neusser (2016).

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

what is identified as the news shock. We use instead a method of estimating the generalized forecast error variance decomposition (GFEV) for which the shares sum to one by construction. Using this approach is the closest we can get to the application of the medium-run identification scheme. A detailed presentation of the procedure can be found in Appendix 4.C.2.

Short-Run Identification

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

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

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

The application of the SRI to the nonlinear setting is rather straight forward. We apply the Cholesky decomposition to the history-dependent impact matrix $\Sigma_t = \Sigma_1(1 - G(\gamma_G, c_G; s_{t-1})) + \Sigma_2 G(\gamma_G, c_G; s_{t-1})$ such that $\Sigma_t = A_t^G A_t^{G'}$. The impact matrix A_t^G is history-dependent and changes with $G(\gamma_G, c_G; s_{t-1})$. For more details, see Appendix 4.C.1.

4.2.7 Generalized Impulse Responses

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

In the literature, state-dependent impulse responses have often been used. In the LSTVAR, the transition function assigns every period some positive probability to each regime. To estimate state-dependent impulse response functions, an exogenous threshold is chosen that splits the periods into two groups depending on whether the values of the mean transition function are above or below that threshold.[20] Given this threshold, the model is linear for a chosen regime which allows to estimate regime-specific IRFs. Nevertheless, state-dependent impulse response functions have several drawbacks. The imposed threshold is set exogenously, which arbitrarily allocates periods to either regime

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

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

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

In order to cope with these issues, we estimate generalized impulse response functions (GIRFs) [21] as initially proposed by Koop et al. (1996). In addition, GIRFs have the advantage that they do not only allow for state-dependent impulse responses but also for asymmetric reactions. GIRFs may be different depending on the magnitude or sign of the occurring shock. A key feature is that GIRFs allow to endogenize regime-switches if the transition is a function of an endogenous variable of the LSTVAR. This property of GIRFs lets us investigate whether news shocks have the potential to take the economy from one regime to the other. In the related empirical literature, this point has usually been ignored.[22]

Hubrich and Teräsvirta (2013) define the generalized impulse response function as a random variable which is a function of both the size of the shock and the history. The GIRF to shock i at horizon h is defined as the difference between the expected value of Y_{t+h} given the history Ω_{t-1}, and the shock i hitting at time t, and the expected value of Y_{t+h} given only the history:

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

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

$$Y_t^{sim} = \Pi_1' X_t^{sim}(1 - F(\gamma_F, c_F; s_{t-1})) + \Pi_2' X_t^{sim} F(\gamma_F, c_F; s_{t-1}) + e_t, \tag{4.13}$$

and for $h \geq 1$:

$$Y_{t+h}^{sim} = \Pi_1' X_{t+h}^{sim}(1 - F(\gamma_F, c_F; s_{t+h-1})) + \Pi_2' X_{t+h}^{sim} F(\gamma_F, c_F; s_{t+h-1}) + \epsilon_{t+h} \tag{4.14}$$

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

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

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

We simulate GIRFs for every period in our sample and do not draw periods randomly, because we want to make sure that our results are not determined by extreme periods that are drawn too often. For each period, the history Ω_{t-1} contains the starting values for the simulation. For every chosen period, we simulate B expected values up to horizon

[21] We thank Julia Schmidt for offering us her codes on computing GIRFs for a threshold VAR model.
[22] To our knowledge Caggiano et al. (2015) is the only paper to endogenize the transition function.

h given the model, the history and the vector of shocks. For every chosen period, we then average over the B simulations.

To analyze the results, we sort the GIRFs according to some criteria such as regime, sign, or magnitude of the shocks and we scale them in order to be comparable. We define a period as being a recession if $F(\gamma_F, c_F; s_{t-1}) \geq 0.5$ and an expansion otherwise.[23] With this definition, the economy spends roughly 15% of the time in recession which corresponds closely to the value indicated by the NBER index. Then, to obtain, for example, the effect of a small positive news shock in recession, we take all the GIRFs to a small positive news shock for which $F(\gamma_F, c_F; s_{t-1}) \geq 0.5$ and compute their average. Details are provided in Appendix 4.C.

4.2.8 Generalized Forecast Error Variance Decomposition

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

$$\lambda_{j,i,\Omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})_j^2}{\sum_{i=1}^{K}\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})_j^2} \tag{4.15}$$

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

4.3 Results

4.3.1 Linear Setting

We estimate a linear VAR in levels and do not assume a specific cointegrating relationship because this estimation is robust to cointegration of unknown form and gives consistent estimates of the impulse responses. [24] Moreover, in papers revelant to our context (e.g. Barsky and Sims (2011), Beaudry and Portier (2014)) it is shown that VAR and VEC models deliver similar results. Our system features four lags, as indicated by the Akaike Information Criterion. We keep the same number of lags for the nonlinear model.

We apply the three identification schemes to isolate structural shocks. In Figure 4.7, Appendix 4.D, a scatterplot of the news shock identified with MRI and the confidence shock obtained with SRI for our benchmark five-variable model is displayed. The two identification schemes identify very similar structural shocks. This result is further confirmed by the high correlation between the two shocks (0.76). Impulse responses displayed

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

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

in Figure 4.8, Appendix 4.D, show that both identified shocks trigger a strong positive co-movement of the real economy, while TFP only starts increasing after some quarters. This result also indicates that a confidence shock resembles very much a news shock.

Under the two identification schemes, TFP is not allowed to change on impact but it is important to note that there is neither a significant rise above zero for the first two years. After that, TFP starts increasing in both cases until it stabilizes at a new permanent level, which is slightly higher under MRI. This result is in line with those found in Beaudry and Portier (2006) and Beaudry et al. (2011). The index of consumer sentiment rises significantly on impact in both settings. This finding is consistent with those of Beaudry et al. (2011) who use the same confidence indicator. Output also increases on impact, and continues to increase for about eight quarters until it stabilizes at a new permanent level. The effect on output of the news shock obtained with MRI is stronger. Inflation falls significantly on impact, more under MRI, this response being very close to the one obtained by Barsky and Sims (2011). In this paper, the authors argue that the negative reaction to a positive news shock is consistent with the New Keynesian framework in which current inflation represents the expected present discounted value of future marginal costs. The impulse response of inflation under SRI is similar to the one obtained by Beaudry et al. (2011). Stock prices rise on impact to the same level in both cases, but while under SRI the response resembles the one in Barsky and Sims (2011), under MRI stock prices continue increasing for a long time, reaching a peak after about twenty quarters.

In Figure 4.9, Appendix 4.D, we show that adding other variables does not significantly modify the results for the first five variables. Inflation decreases faster, while the response of stock prices is almost identical under the two identification schemes. For the two new variables added, the responses are similar to those presented in Beaudry et al. (2011). Both consumption and hours worked rise on impact, and while the response of hours worked is hump-shaped, the effect on consumption is permanent. The response of consumption is slightly bigger under MRI, while the opposite holds for hours worked. Under the two different identification schemes, we find similar results. A shock on a measure of consumer confidence with no impact effect on TFP (news or optimism shock) proves to be highly correlated with a shock with no impact effect on TFP but which precedes increases in TFP. This supports the conclusion of Beaudry et al. (2011) that all predictable and permanent increases in TFP are preceded by a boom period, and all positive news shocks are followed by an eventual rise in TFP. After the realization of a positive news shock we find an impact and then gradual increase in output, the survey measure of consumer confidence, stock prices, hours worked, and consumption, and a decline in inflation while TFP only follows some quarters later. According to Beaudry et al. (2011), the period until TFP starts increasing can be defined as a non-inflationary boom phase without an increase in productivity.

4.3.2 Nonlinear Setting

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

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

The results presented in Figure 4.10, Appendix 4.E, show that the parameters in the transition function for the mean equation do not depart too much from the starting values (i.e. the initial estimates obtained using a logistic regression), while the value of γ_G increases a lot after the MCMC iterations for the variance equation. This indicates that the transition behavior from recession to expansion is not the same for the mean and the variance of the economy. The transition in the mean is much more smooth than in the variance where it approaches a regime-switch.

We further evaluate the model to verify that it is not explosive and delivers interpretable results. Because we estimate the model with level data that are potentially integrated or growing over time, it is clear that some of the roots will be very close to one.We use the method indicated by Teräsvirta and Yang (2014b) to examine the stability of the system. The convergence to a single stationary point is a necessary condition for exponential stability, and therefore for our model not to be explosive. On these grounds, we simulate counterfactuals for our model with all shocks switched off. In the long-run, the model converges to a stable path. By plotting the simulated paths in first differences we can show that they converge to zero (see Figure 4.11 in Appendix 4.E). It is clear for each variable in our model that, independent of the history in the dataset chosen as initial values, the trajectories converge to the same point. We can conclude that the stability assumption is not contradicted by these calculations, and therefore our model is not explosive. The non-explosiveness of the model is necessary for the estimation of GIRFs and the GFEVD.

Variance Decomposition

In Table 4.1 we display for each variable the share of the (generalized) FEV attributable to the news shock at different horizons in the two regimes of the STVAR model and in the linear VAR model. The numbers are percentage values. Not surprisingly, the contributions of the news shock are very close in expansions to those in the linear model since more than 85 percent of the periods contained in our sample are defined as normal times. These results are reassuring since they indicate that the two methods for computing the variance decomposition give similar results. The only bigger difference is the contribution of the news shock to the variance decomposition of TFP in expansions. In this case the news shock accounts for a bigger share in the FEV of TFP both at high and lower frequencies.

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

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

We find intriguing the fact that, even though in a recession the news shock explains little of output variance on impact, the share increases significantly and fast, such that after one year it is close to 40 percent. The same pattern is observed in the case of TFP, the news shock explaining more than 40 percent of its variance in recession at a horizon of one year.

Table 4.1: Generalized Forecast Error Variance Decomposition for the news shock (MRI). The numbers indicate the percent of the forecast error variance of each variable at various forecast horizons explained by the news shock in expansions, recessions, and the linear model.

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

In Table 4.3, Appendix 4.E, we present the total contribution of the unanticipated productivity shock and the news shock to the FEV of the variables. In the linear model, the two productivity related shocks combined explain almost 98 percent of variation in TFP, about 93 percent of variation in output at a horizon of ten years, and more than half of the variation in the other three variables. When we relax the linearity assumption, we observe the state-dependency in the combined contributions. Overall, we find much larger contributions of these two shocks in recessions both in the short- and the medium-run. The differences are particularly large on impact. In recessions, the two shocks explain together more than 95 percent of the impact variance of all variables, for TFP and inflation the shares being almost 100 percent. Since the two productivity shocks combined explain almost all the variation in recession, we have support for their high importance in driving economic fluctuations when they occur in downturns. They continue to play a major role also in normal times, but in that case there is more chance for other shocks to contribute to business cycle fluctuations.

When comparing the contributions of the news shock to those of the confidence shock (SRI) to the variance decomposition of the variables in the model, we find that in recessions there are some similarities between them. By looking at the results in Table 4.4, Appendix 4.E, it is clear that in recessions, besides the unanticipated productivity shock, the confidence shock has the largest influence on TFP (i.e. approximately 45 percent). Therefore, we can conclude that as long as there is sufficient information in the model also SRI isolates a shock that has a high medium-run impact on TFP. However, with the exception of the impact effect on consumer confidence, the confidence shock explains much less of the FEV of variables than the news shock in recessions. The differences between the contributions of the two shocks are even bigger when looking at expansions. The confidence shock contributes little in the short-run to TFP, output, inflation and stock prices, while in the medium-run the contribution increases, but it does not reach the level of the news shock. Again, the only exception is the impact contribution of the confidence shock to the index of consumer sentiment which is twice as big as the one of the news shock.

Generalized Impulse Responses

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

In Figure 4.1 we present the impulse responses of TFP and consumer confidence to a one standard deviation news shock obtained with the MRI scheme. Results are qualitatively very much in line with those obtained in the linear setting. A news shock about a technological innovation leads to an immediate increase in consumer confidence in both states. However, the impact effect is bigger in expansions, and the gap between the two stays large for almost five years after the shock hits. In the case of TFP, there is no impact effect of the news shock in expansions, and also no significant change in the following two years. After that, TFP starts increasing, the change being of about one percentage point in ten years. There is also an evident state-dependency in the short-run. The difference comes from the almost immediate reaction of TFP to the news shock when it hits in a recession. This indicates that technology diffusion is much faster in this case.

The regime-dependence in the response to a news shock is significant in the short- and medium-run, while in the long-run the responses in the two regimes converge and the confidence bands overlap. This is not surprising as the same shock pushes the economy in a similar direction and every period some probability is attached to both regimes. When analyzing the confidence intervals for the two impulse responses, it is evident that those for recessions are much wider, mostly in the short-run, than those for expansions. The explanation is that we have more than eight times less starting values for the simulations in the case of recessions. Even though we simulate eight times more for each starting value belongir
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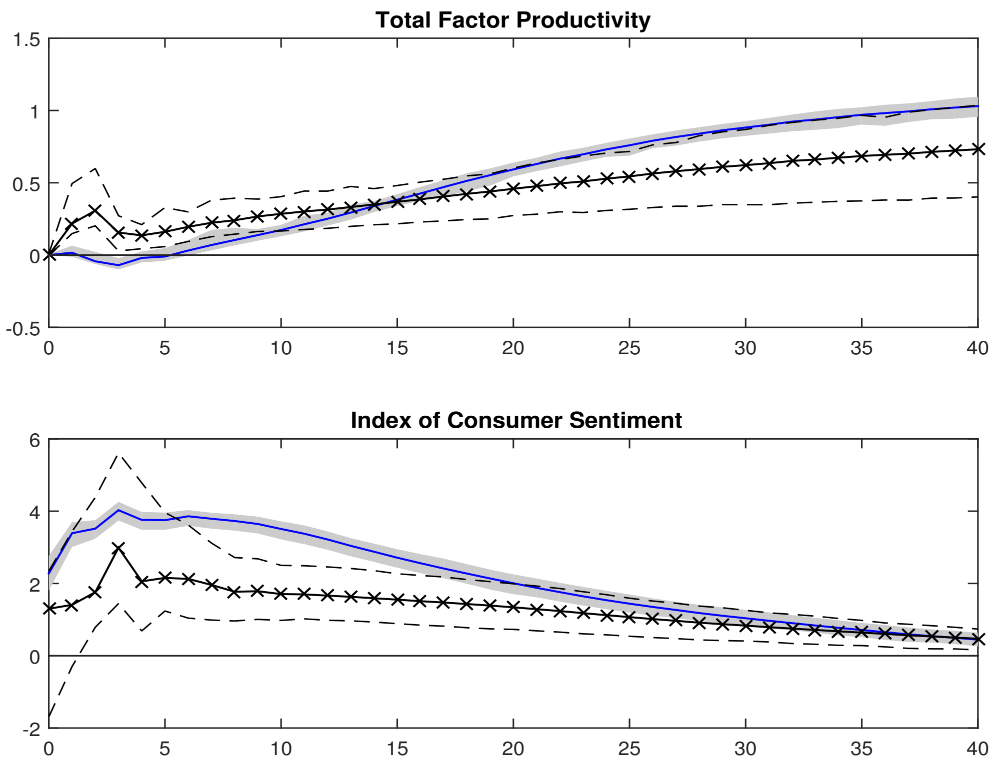

Figure 4.1: Generalized impulse response functions to a positive small news shock under MRI. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarters.

output, inflation and stock prices to a one standard deviation news shock obtained with the MRI scheme are displayed in Figure 4.2. Similarly to the responses of TFP and ICS, the responses are qualitatively similar, but there are quantitative differences. Inflation drops significantly in both states of the economy, more in recessions, but the state-dependency in responses fades away fast. Stock prices respond positively to the news shock. The reaction in recessions is bigger but the impact difference is not significant. At a horizon of two to five years, the effect of the news on stock prices seems to be larger in expansions. A peculiar finding is the response of output to the news. In expansion,

[25] For details about the computation of GIRFs and their confidence bands, see Appendix 4.C.

we have clear evidence of a positive effect of the news shock on output. On the other side, in a recession the impact effect is unclear, and not significantly different from zero for at least one year. After some time output starts increasing but stabilizes at a lower permanent level than following a news shock occurring in an expansion.

In Figure 4.14, Appendix 4.E, we present the responses to a small positive, a big positive, a small negative and a big negative news shock for both regimes. The big shock is three times the size of the small shock. The results are normalized to the same magnitude and sign to make them comparable. We find that the responses are qualitatively very similar. There are quantitative differences, though. The effect of a small negative shock in a recession seems to exhibit a stronger effect on output in the long-run. This indicates that negative news depress the economy more in bad than in good times. Furthermore, small negative news shocks have stronger effects than the positive ones on consumer confidence and stock prices in the long-run, independent of the regime. Regarding the magnitude of the news shock, we find that the response to a big shock is not proportionate with the shock size. Nevertheless, the magnitude and the sign of the shock do not seem to play an important role as the differences are not statistic

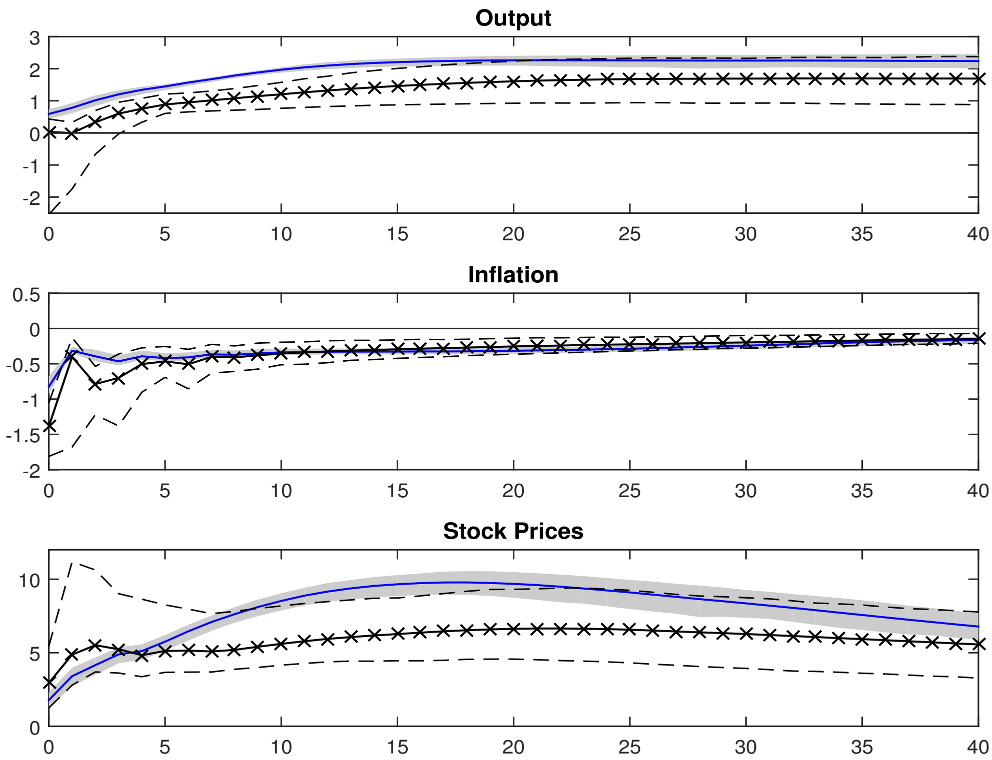

Figure 4.2: Generalized impulse response functions to a positive small news shock under MRI. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock, and the unit of the horizontal axis is quarters.

As a next step, we compare the results obtained for the news shock with those for the confidence shock, under the SRI scheme (as showed in Figure 4.12 from Appendix

4.E). We find that the results from the two identification schemes are qualitatively very similar to each other as well as to the linear case. If there are differences between the two identification methods they are of quantitative nature. The impulse responses for recession are actually almost the same for both identification schemes. This goes in line with the findings of the GFEVD which indicate that in recession the news shock is basically a confidence shock.

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

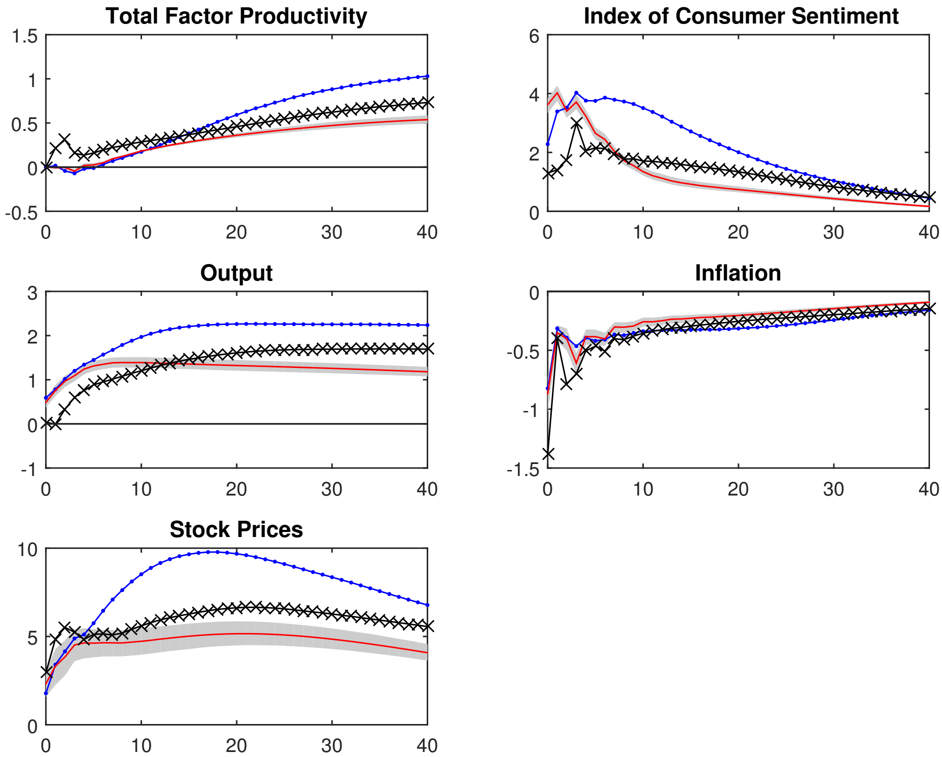

Figure 4.3: Comparison of the state-independent and the state-dependent effect of the news shock (under MRI). The figure displays the generalized impulse response functions to a positive small news shock in an expansion as the blue dotted line, the generalized impulse response functions to a positive small news shock in a recession as the starred black line, and the impulse responses to a news shock obtained by applying the same identification scheme in the linear model as the red line. The shaded light grey area represents the 95% bias-corrected confidence interval for the linear model. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

setting, as displayed in Figure 4.3, we observe a strong similarity, apparent mainly in the short-run, between the responses in expansion and in the linear model. However, on the medium-run, it is evident that the responses to the news shock are stronger in expansions. Therefore, using a linear model to show the effects of news shocks in normal times may underestimate their value. We find that the news shock has in expansion a much bigger effect on output than the linear model would predict, output stabilizing at a twice as high new permanent level in the expansionary regime. Similar conclusions can be drawn for TFP. Moreover, there is a temporary overreaction of stock prices to the news in expansion, which the linear model misses.

On the contrary, using the impulse responses from a linear model to show the effects of a news shock in recessions may determine an overestimation of its value. As it can be seen in Figure 4.3, in a recession a news shock has half the impact effect implied by the linear model on confidence. Furthermore, output does not react for some quarters to a positive news shock in a recession, although the linear model indicates an immediate positive reaction.

As a robustness check, we apply the identification scheme of Beaudry and Portier (2006) (SRI2). The news shock is then identified as the shock on stock prices instead of the index of consumer sentiment with no impact effect on TFP. The impulse responses, displayed in Figure 4.13, Appendix 4.E, are qualitatively very similar but smaller in absolute values in both regimes than the impulse responses for the news shock obtained with the MRI and the confidence shock identified by applying the SRI. This confirms that stock prices do not capture the expectations of market participants as well as the index of consumer sentiment.

Regime Transition

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

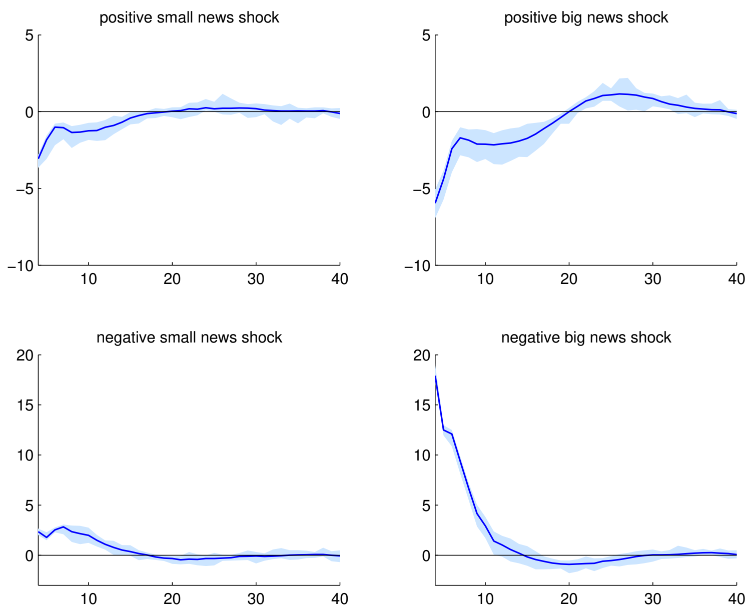

Figure 4.4: Regime transition probability change following a news shock. The four figures display the change in the probability of switching from an expansion to a recession starting one year after a news shock occured. The blue line shows the behavior following a news shock obtained with MRI, while the shaded light blue area represents the 95% bias-corrected confidence interval. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage points, and the unit of the horizontal axis is quarter.

The results in Figure 4.4 and Figure 4.5 present the change in the probability of switching from one regime to the other starting one year after a news shock happened. We ignore the effect on the probability of switching for the first four quarters since the results are influenced by the starting values. Because our model features four lags, for the first four simulation periods the probability of switching depends on real data.

As shown in Figure 4.4, when the economy is in expansion, a positive small news shock reduces the probability of a transition to recession by approximately four percentage points after one year. A shock three times larger is not increasing this probability by much. When a big positive news shock hits the economy during normal times, the probability of going into a recession is reduced by almost six percentage points after one year. An interesting finding is the effect of the positive news shock on the transition probability after five years. Although in the short-run the news shock seems to keep the economy booming, in the medium-run, once the improvements in productivity become apparent (i.e. TFP starts increasing), agents may acknowledge that they have overrated the future evolution of the economy and start behaving accordingly. This behavior then generates a bust, as the probability of moving from an expansion to a recession increases. This result confirms the findings of Beaudry and Portier (2006) that booms and busts can be caused by news shocks and no technological regress is needed for the economy to fall into a recession.

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

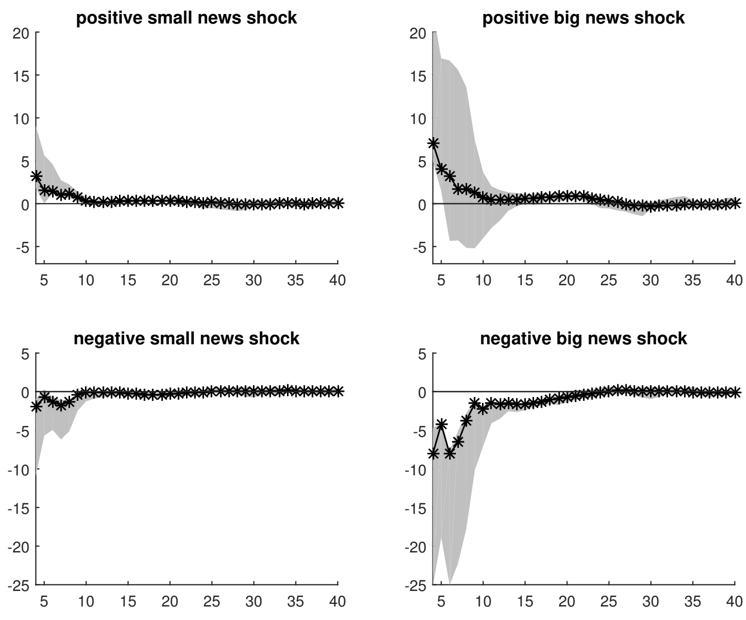

Figure 4.5: Regime transition probability change following a news shock. The four figures display the change in the probability of switching from a recession to an expansion starting one year after a news shock occured. The starred black line shows the behavior following a news shock obtained with MRI, while the shaded light grey area represents the 95% bias-corrected confidence interval. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage points, and the unit of the horizontal axis is quarter.

a recession, a small positive news shock increases the probability of transitioning into an expansion by almost five percentage points after four quarters. If the shock is three times bigger, the probability of a regime switch increases by about eight percentage points after four quarters. It does not seem to be a reversal in the medium-run, once TFP increases, as it was the case in booms. Negative news shocks increase the probability of staying in a recession, but their effect is not as strong as when they hit in an expansion.

By comparing the two figures, we conclude that positive news shock are more effective in recessions than in expansions, leading to a twice as large increase in the probability of regime transition. On the other hand, negative news in booms ncrease more the probability of going in a recession than the one of going in an expansion of positive news in recession. The intuition for this result is found in Van Nieuwerburgh and Veldkamp (2006). The authors argue that in a recession, uncertainty delays the recovery and makes booms more gradual than downturns.

4.4 Conclusions

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

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

To the best of our knowledge, the literature on news shocks has, so far, neglected nonlinearities. In this paper, we test whether the reactions to this technology related news shocks are state-dependent and/or asymmetric. By estimating a LSTVAR, we find evidence of quantitative state-dependencies, mainly in the short- and medium-run.

The response to a news shock is in general larger in an expansion than in a recession. Our intuition for the difference in the responses between the two regimes is the stronger uncertainty of the economic agents about what to expect in the future when they are in a recession. The result is that the same news shock leads to a lower business cycle effect when it hits the economy in a recession compared to occurring in expansion. We also find that using a linear model to analyze the effects of news shocks one may underestimate their effect in an expansion while overestimating it in a recession.

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

We show that the probability of a regime-transition is strongly influenced by the news shock. Our results indicate that good news increase the probability of the economy escaping a recession by about five percentage points and this is a much stronger increase than in the probability of an economy continuing booming if the news comes in an expansion.

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

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

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Appendix

4.A Data

4.A.1 Descriptive Statistics

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

Table 4.2: Statistics

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

* Defined according to the NBER business cycle indicator.

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

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

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

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

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

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

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

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

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

4.A.2 Details on Data Used in the Benchmark Model

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

Our benchmark system contains five variables: TFP adjusted for variations in factor utilization, index of consumer sentiment, real output, inflation and stock prices. Total factor productivity is a measure of productivity in the economy whereas stock prices represents a forward-looking variable which contains information about technological innovations. The consumer sentiment index is another forward-looking variable that contains information about the expectations of consumers and producers. Output includes information about the state of the economy. By including inflation we take care of the nominal side of the economy and add another forward-looking variable. By adding these three forward-looking variables, we believe that we encompass enough information to identify the news shock. For robustness checks in the linear setting, we additionally include consumption and hours worked.

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

We use the S&P 500 stock market index as a measure of stock prices.[27] Data for output and consumption we obtain from the Bureau of Economic Analysis. For output we use the real gross value added for the nonfarm business sector. As a measure of consumption we use the sum of personal consumption expenditures for nondurable goods and personal consumption expenditures for services. We obtain data on hours worked, population, and price level from the Bureau of Labor Statistics. As a measure of hours worked, we use the hours of all persons in the nonfarm business sector. Output, consumption, and stock prices are in logs and scaled by population (all persons with ages between 15 and 64) and the price level for which we use the implicit price deflator for the nonfarm business

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

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

sector. Hours worked are in logs and scaled by population only. The price deflator (PD) is also used to compute the annualized inflation rate $IR = 4^*(\log(PD_t) - \log(PD_{t-1}))$.

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

4.B Estimation of LSTVAR

4.B.1 Linearity Test

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

The null and alternative hypotheses of linearity can be expressed as the equality of the autoregressive parameters in the two regimes of the LSTVAR model in equation (4.1):

$$H_0: \quad \Pi_1 = \Pi_2, \tag{4.16}$$

$$H_1: \quad \Pi_{1,j} \neq \Pi_{2,j}, \text{ for at least one } j \in \{0, ..., p\}. \tag{4.17}$$

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

Another way of stating the null hypothesis of linearity is $H_0' : \gamma_F = 0$. When H_0' is true, the location parameter c and the parameters Π_1 and Π_2 are unidentified.

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

The LSTVAR model in equation (4.2) can be rewritten as:

$$Y_t = \Pi_1' X_t + (\Pi_2 - \Pi_1)' X_t F_{t-1} + \epsilon_t, \tag{4.18}$$

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

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

$$Y_t = \theta_0' X_t + \theta_1' X_t s_{t-1} + \theta_2' X_t s_{t-1}^2 + \theta_3' X_t s_{t-1}^3 + \epsilon_t^* \tag{4.19}$$

[28] Consumer confidence reflects the current level of business activity and the level of activity that can be anticipated for the months ahead. Each month's report indicates consumers assessment of the present 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.

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

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

Denoting $Y = (Y_1, ..., Y_T)'$, $X = (X_1, ..., X_T)'$, $E = (\epsilon_1^*, ..., \epsilon_T^*)'$, $\Theta_n = (\theta_1', ..., \theta_n')'$, and

$$Z_n = \begin{pmatrix} X_1' s_0 & X_1' s_0^2 & \cdots & X_1' s_0^n \\ X_2' s_1 & X_2' s_1^2 & \cdots & X_2' s_1^n \\ \vdots & \vdots & \ddots & \vdots \\ X_T' s_{T-1} & X_T' s_{T-1}^2 & \cdots & X_T' s_{T-1}^n \end{pmatrix}, \tag{4.20}$$

we can write equation (4.19) in matrix form:

$$Y = X\theta_0 + Z_n\Theta_n + E. \tag{4.21}$$

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

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

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

3. Compute the asymptotic χ^2 test statistic:

$$LM_{\chi^2} = T(m - tr\left\{SSR_0^{-1} SSR_1\right\}) \tag{4.22}$$

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

$$LM_F = \frac{mT - K}{JmT} LM_{\chi^2}, \tag{4.23}$$

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

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

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

4.B.2 Estimation Results of Logistic Regression Model

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

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

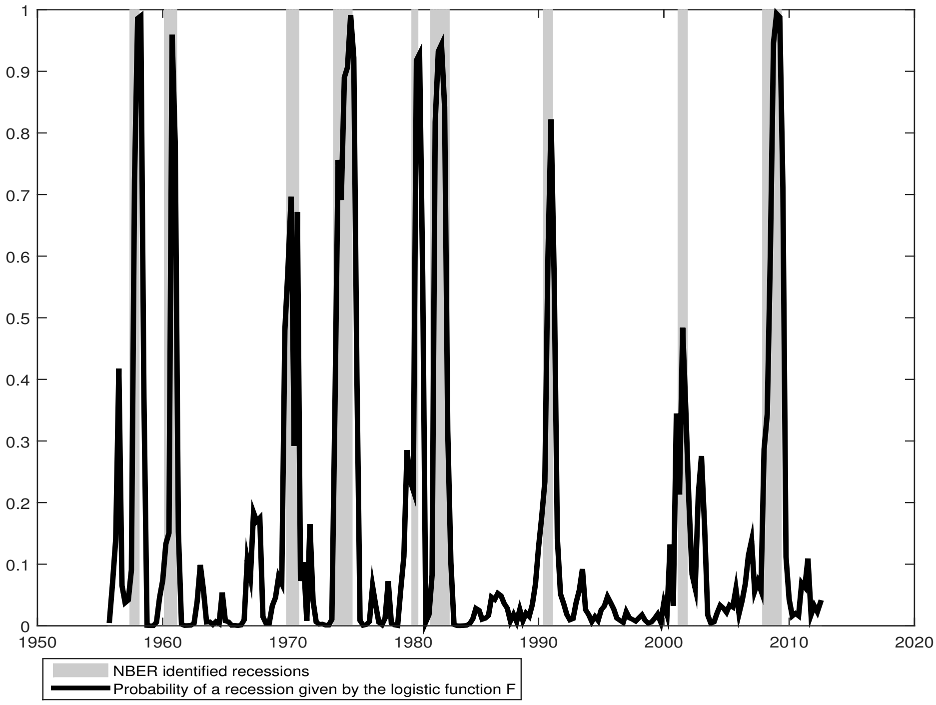

Figure 4.6: Initial transition function with estimated parameters obtained from a logistic regression

4.B.3 MCMC Procedure - MH algorithm

Our approach is, given the quasi-posterior densitiy $p(\Psi_n) \propto e^{L(\Psi_n)}$,[29] known up to a constant, and a pre-specified candidate-generating (or proposal) density $q(\Psi'_n \mid \Psi_n)$, to construct chains of length N, $(\Psi_n^0, ..., \Psi_n^N)$. We follow the steps:

1. Choose intial parameter value Ψ_n^0.

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

2. For $j = 1, ..., N$:

   (a) Generate Ψ'_n from $q(\Psi'_n \mid \Psi^j_n)$ and u from $U[0,1]$.

   (b) Compute the probability of move, $\alpha(\Psi'_n, \Psi^j_n)$:

$$\alpha(\Psi'_n, \Psi^j_n) = \min\left\{\frac{p(\Psi'_n)q(\Psi^j_n \mid \Psi'_n)}{p(\Psi^j_n)q(\Psi'_n \mid \Psi^j_n)}, 1\right\} \tag{4.24}$$

   (c) Update Ψ^{j+1}_n from Ψ^j_n, using:

$$\Psi^{j+1}_n = \begin{cases} \Psi'_n & \text{if } u \leq \alpha(\Psi'_n, \Psi^j_n); \\ \Psi^j_n & \text{otherwise.} \end{cases} \tag{4.25}$$

3. Return the values $(\Psi^0_n, ..., \Psi^N_n)$.

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

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

The starting values for the transition function parameters are obtained by a logistic regression of the NBER business cycle on the transition variable. The starting values for the covariance matrices (Σ_1, Σ_2) are obtained from the auxiliary regression 4.19 in Appendix 4.B.1, where it is altered by $\varepsilon > 0$ for the second.

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

$$\Psi'_n = \Psi_n + \psi,\ \psi \sim f \tag{4.26}$$

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

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

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

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

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

4.B.4 Constancy of the Error Covariance Matrix

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

$$\Sigma_t = P\Lambda_t P', \tag{4.27}$$

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

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

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

where $w_t = u_t P$.

The null hypothesis to be tested is then:

$$H_0 : \lambda_{it} = \lambda_i, \quad i = 1, \ldots, m \tag{4.28}$$

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

$$LM = \frac{1}{2}\sum_{i=1}^{m}\left[\left(\sum_{t=1}^{T}\tilde{g}_{it}\tilde{z}_{it}'\right)\left(\sum_{t=1}^{T}\tilde{z}_{it}\tilde{z}_{it}'\right)^{-1}\left(\sum_{t=1}^{T}\tilde{g}_{it}\tilde{z}_{it}\right)\right]. \tag{4.29}$$

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

$$LM = \sum_{i=1}^{m} T\frac{SSG_i - RSS_i}{SSG_i}, \tag{4.30}$$

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

Yang (2014) shows that this test exhibits high power and size even if the assumption from equation (4.27) does not hold and performs especially well in the case of smooth transition VARs.

4.C Estimation of GIRF and GFEVD

4.C.1 Estimation of GIRF with SRI

The GIRFs are estimated by simulation for eight different cases:

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

σ denotes the standard deviation of the news shock.

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

The simulation of the GIRF

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

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

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

For a chosen period and history, conditional expected values of Y_{t+h} are simulated up to horizon h given the model. For the first p simulations also data contained in the history is used. Every period the model is shocked randomly by $\epsilon_{t+h} \sim \mathcal{N}(0, \Sigma_{t+h})$. The shocks are drawn from a normal distribution with variance

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

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

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

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

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

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

4.C.2 Estimation of GIRF with MRI

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

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

Step 2:
The GIRF are estimated as described in Appendix 4.C.1. The only difference is that the orthogonalization of the history-dependent covariance matrix is approximated by

$$A^G_{t+h} = G(\gamma_G, c_G; s_{t+h-1})A_1 + (1 - G(\gamma_G, c_G; s_{t+h-1}))A_2 \tag{4.31}$$

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

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

4.C.3 Confidence Bands

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

4.C.4 Generalized Forecast Error Variance Decomposition

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

$$\lambda_{j,i,\Omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})_j^2}{\sum_{i=1}^{K} \sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})_j^2} \tag{4.32}$$

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

4.D Results in the Linear Setting

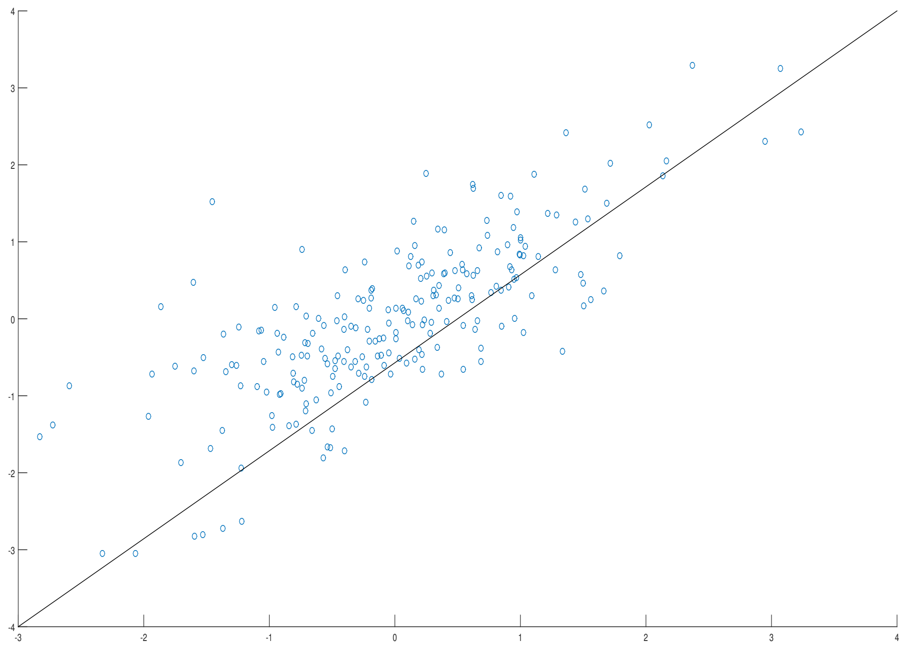

Figure 4.7: Comparison of the news and the confidence shocks using a scatterplot. The confidence shock is identified using a SRI which assumes that the confidence shock affects ICS on impact but not TFP. Under a MRI, the news shock is defined as the shock that does not move TFP on impact but has maximal effect on it at $H = 40$.

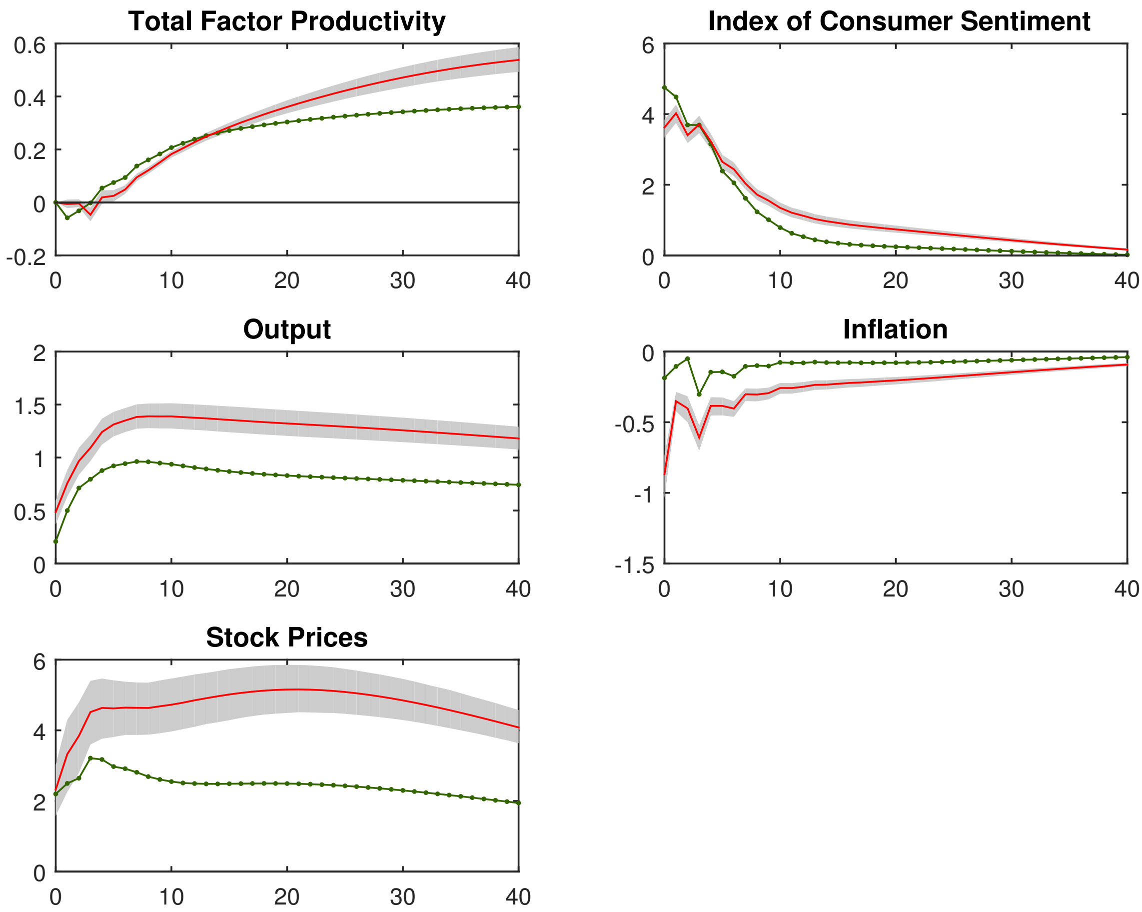

Figure 4.8: Comparison of news shock and confidence shock in a linear model.The red solid line shows the response to the news shock, while the green dotted line is the response to the confidence shock. The shaded region is the 95 percent confidence interval for the news shock. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

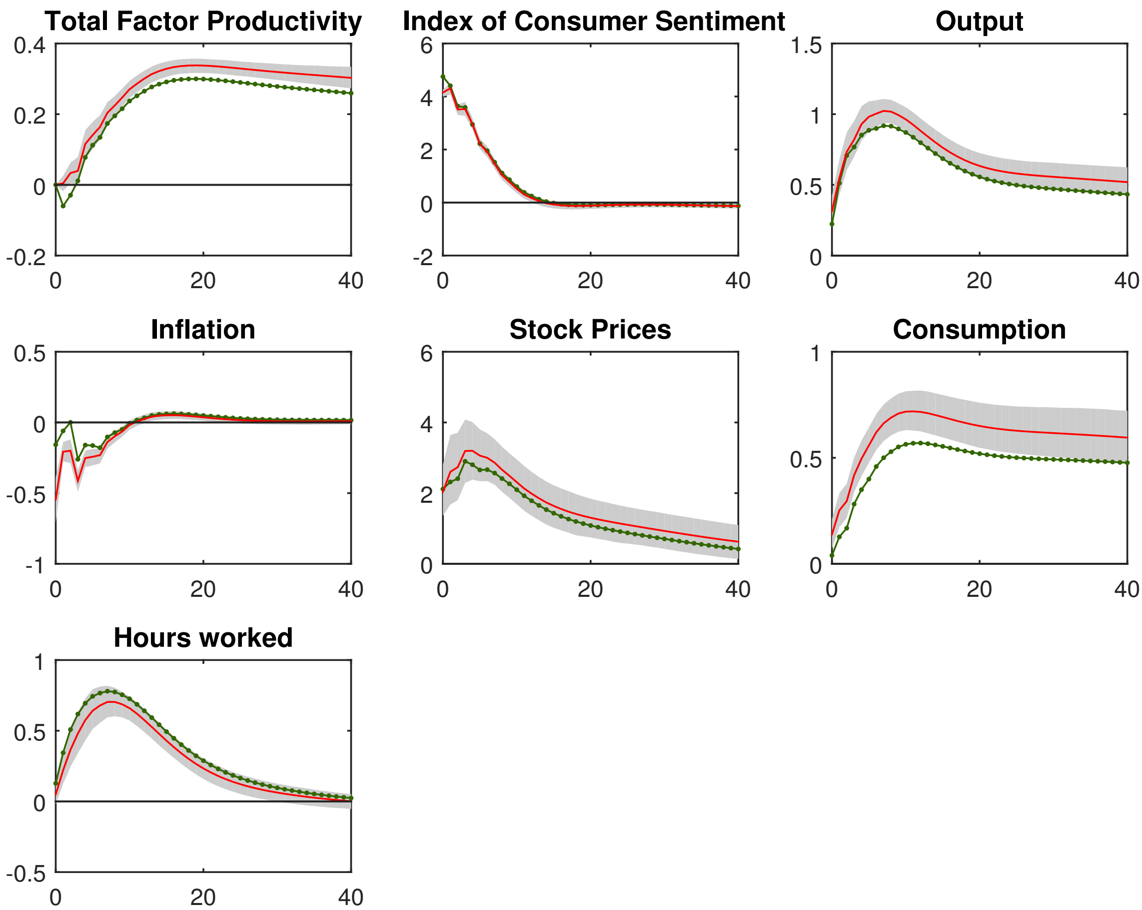

Figure 4.9: Comparison of news shock and confidence shock in a linear seven variables model. The red solid line shows the response to the news shock, while the green dotted line is the response to the confidence shock. The shaded region is the 95 percent confidence interval for the news shock. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter,

4.E Results in the Nonlinear Setting

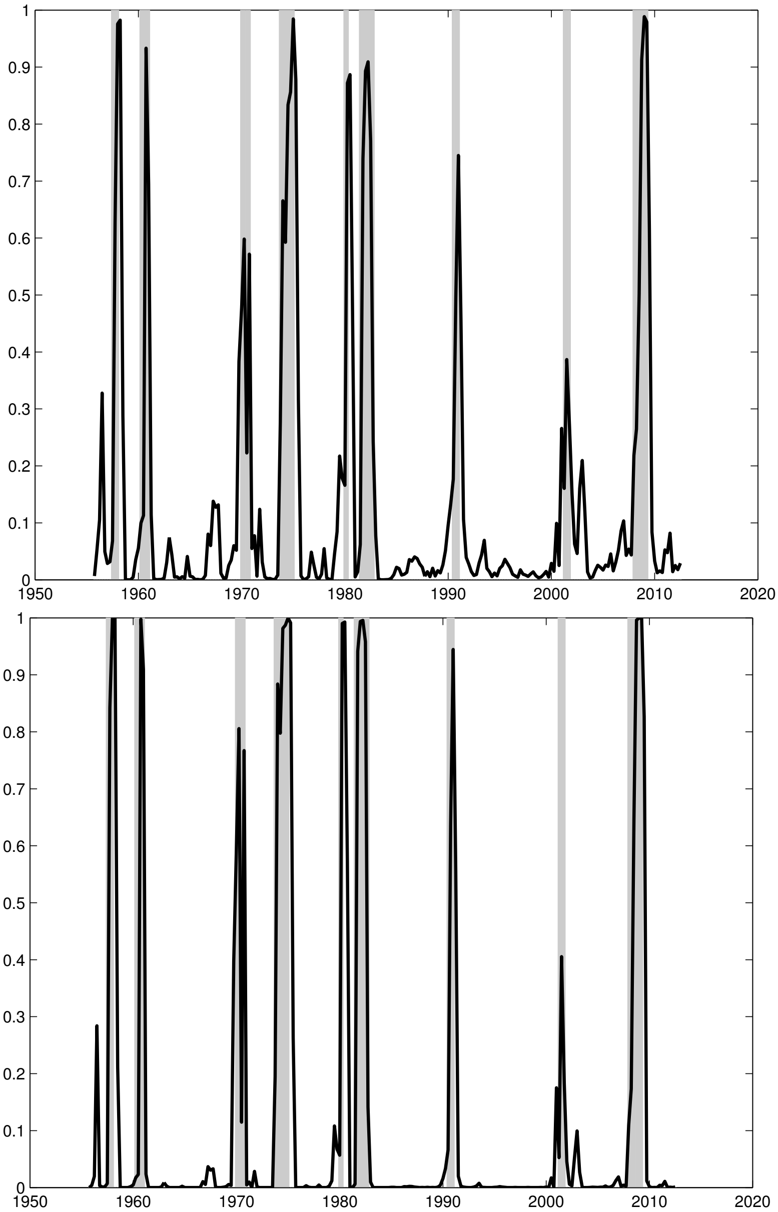

Figure 4.10: Comparison of the transition function for the mean equation - F (top), and the transition function for the variance equation - G (bottom), with average parameter values obtained from the MCMC iterations ($\gamma_F = 3.00$, $c_F = -0.61$, $\gamma_G = 6.31$, $c_G = -0.52$). The black line is the probability of a recession given by the logistic function, while the grey bars define the NBER identified recessions. The unit of the horizontal axis is quarters, while the unit of the vertical axis is percent in decimal form.

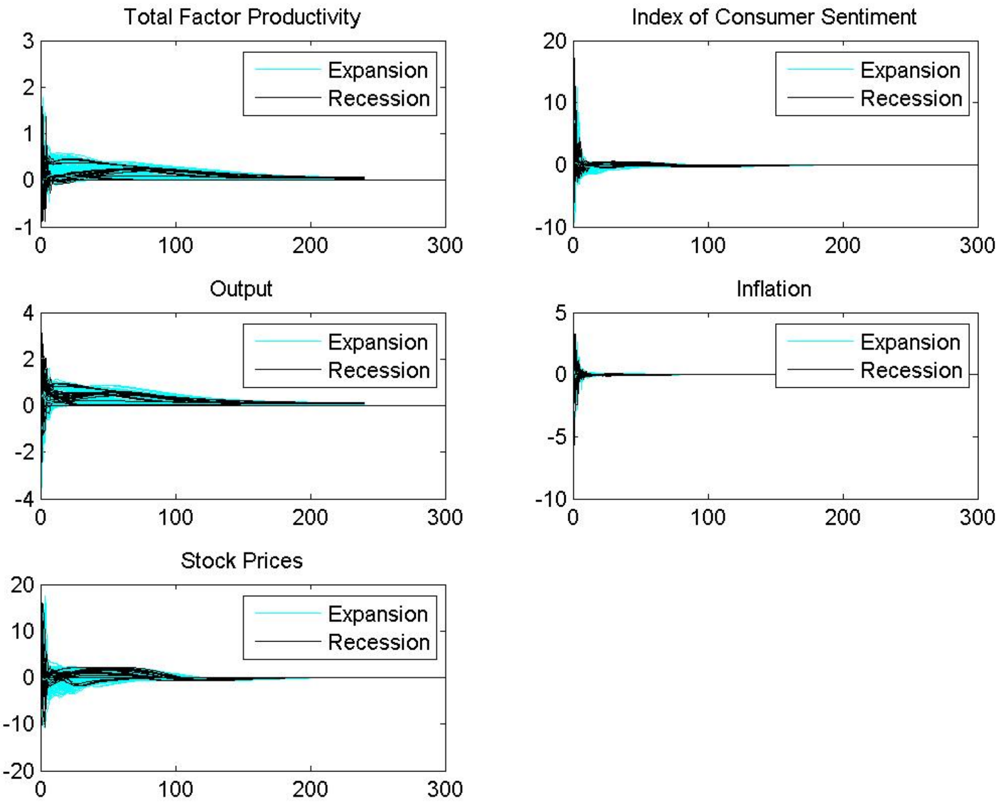

Figure 4.11: Stability check for the five processes. Each plot displays the paths of realizations (in first differences) from the estimated model with noise switched off, starting from a large number of initial points from both regimes.

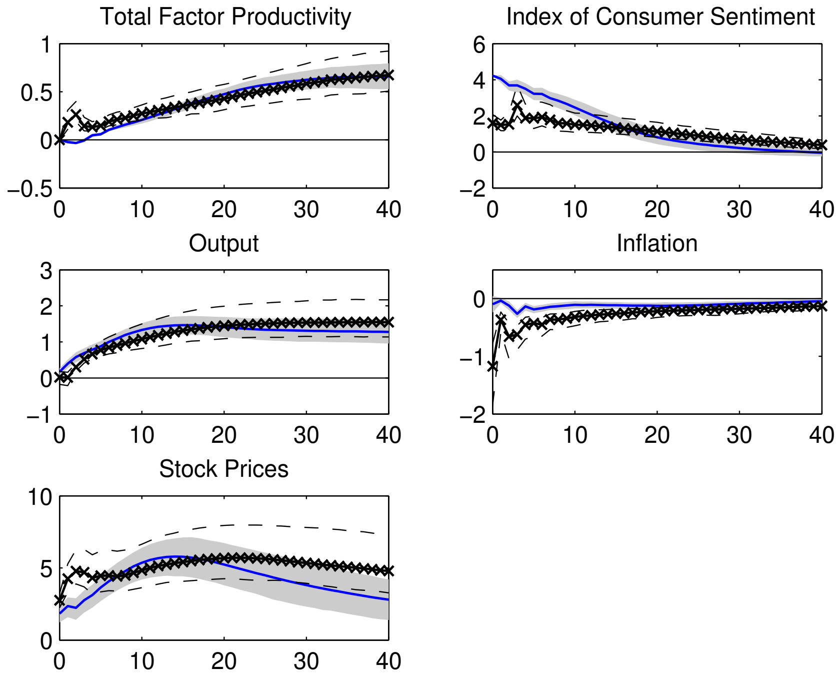

Figure 4.12: Generalized impulse response functions to a positive small confidence shock under SRI. SRI assumes that the confidence shock affects ICS on impact but not TFP. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarters.

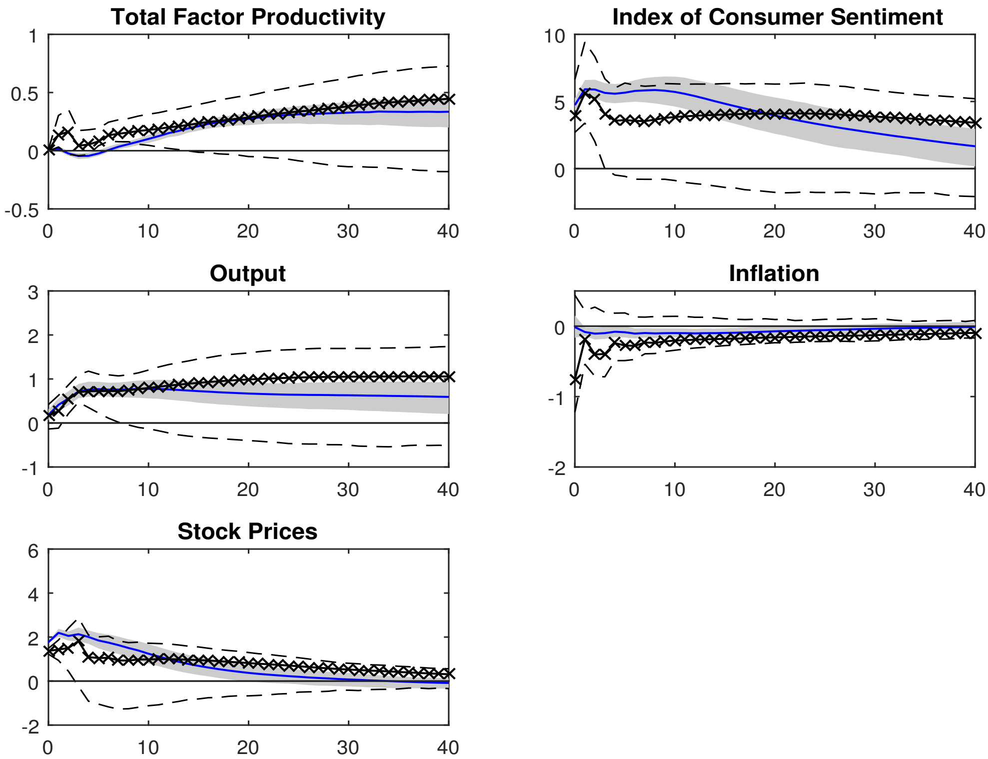

Figure 4.13: Generalized impulse response functions to a positive small news shock under SRI2. SRI2 assumes that the news shock affects SP on impact but not TFP. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

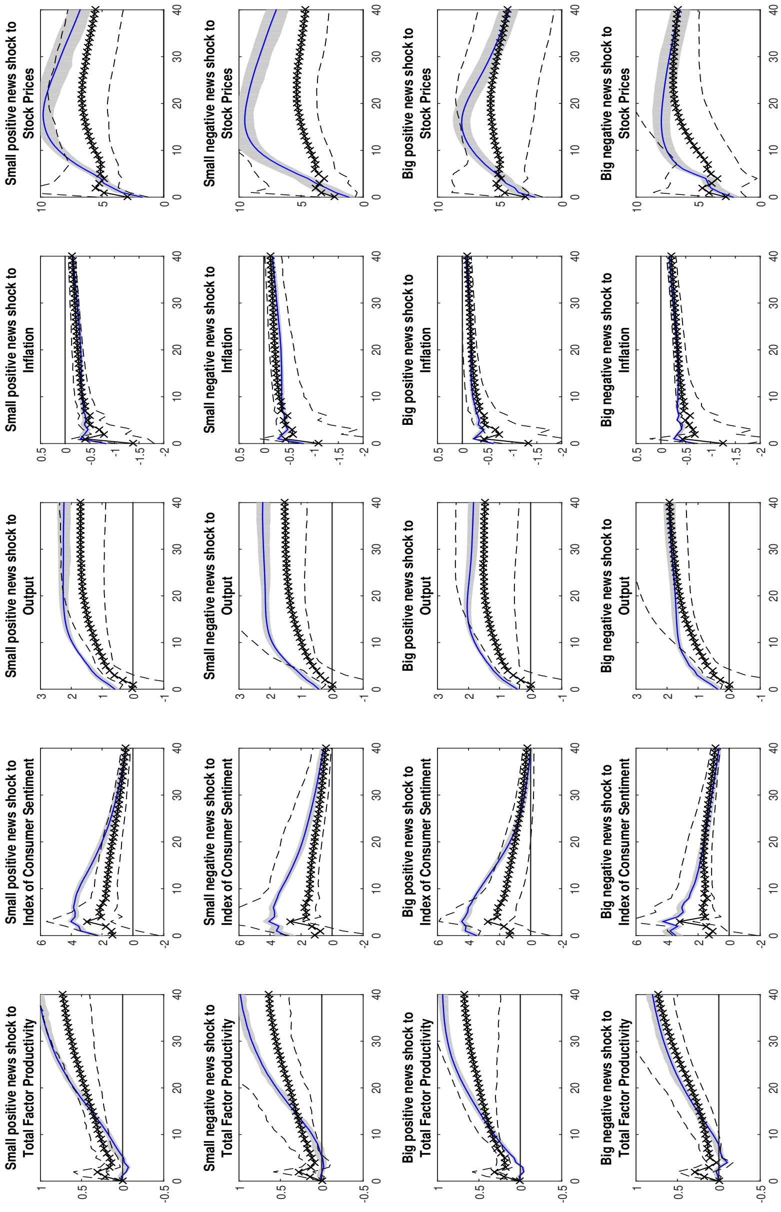

Figure 4.14: Generalized impulse response functions to news shocks of different signs and magnitudes. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

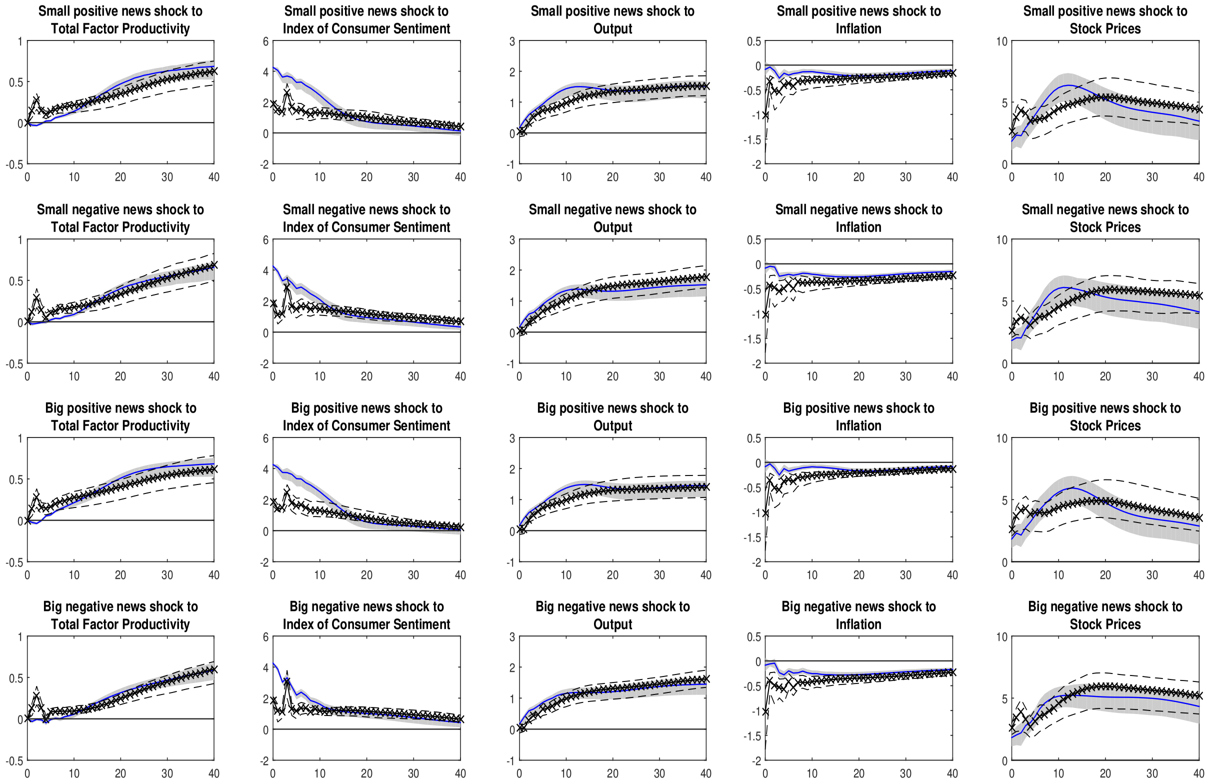

Figure 4.15: Generalized impulse response functions to confidence shocks of different signs and magnitudes. The starred black line is the point estimate in recession, and the blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

Table 4.3: Generalized Forecast Error Variance Decomposition. The numbers indicate the percent of the forecast error variance of each variable at various forecast horizons explained by the unanticipated TFP shock together with the anticipated (news) TFP shock identified with the MRI scheme, in expansions, recessions, and the linear model.

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

Table 4.4: Generalized Forecast Error Variance Decomposition for the confidence shock (SRI). The numbers indicate the percent of the forecast error variance of each variable at various forecast horizons explained by the confidence shock in expansions, recessions, and the linear model.

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

Declaration of Consent

I declare herewith that this thesis is my own work and that I have not used any sources other than those stated. I have indicated the coauthorship and adoption of quotations as well as thoughts taken from other authors as such in the thesis. I am aware that the Senate pursuant to Article 36 para. 1 lit. r of the University Act of 5 September, 1996 is authorised to revoke the title awarded on the basis of this thesis. I allow herewith inspection in this thesis.

Bern, 21 November 2017

Maria Bolboaca