Technology Diffusion News Shocks

An Empirical and Theoretical Analysis of
Anticipated and Unanticipated Productivity Shocks

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Für Margrith Röösli-Hafner

Preface

This thesis focuses on the concept of news shocks about future productivity. The idea of this literature is that mere news about technological improvements may lead to business cycle fluctuations. Nowadays, an example of such a news shock would be self-driving vehicles. A few years ago they started to be present in the media with the first prototypes being tested. Today the first self-driving vehicles operate on public grounds but still have to be accompanied by a driver. At the same time the investment in fields such as radar technology or sensors increased substantially. One can only imagine by how much this technological improvement may increase productivity in the future and how many further innovations will be developed along with it.

Summary

The idea that productivity shocks which include news shocks are the main driving factor of economic growth has long been present in macroeconomic literature. The challenge is to understand the economic interrelatiohships and different effects of productivity shocks in the short- and long-run. The thesis is a collection of four papers focusing on news shocks and further productivity shocks. The papers are entiteled “Unraveling News: Reconciling Conflicting Evidence” (Chapter 1), “News as Slow Diffusing Technology” (Chapter 2), “News Shocks: Different Effects in Boom and Recession?” (Chapter 3), which are all co-authored by Maria Bolboaca, and the single-author paper “Questioning Productivity Shocks” (Chapter 4). The papers comprise an extensive empirical and theorectical analysis of news shocks. In the first paper, the empirical news literature is summarized and methods as well as results are compared. We give a broad overview over variable settings, identification schemes and results and show that most often the idea of a slow diffusing news shock leading to a boom is confirmed. In Chapter 2, we introduce endogenous technology adoption to a medium-scale dynamic stochastic general equilibrium model with real frictions. The model predictions match the empirical results of both unanticipated productivity and technology diffusion news shocks qualitatively. In Chapter 3, we go back to the empirical exploration of news shocks and estimate a smooth transition vector autoregressive model to identify differences in the effects of news shocks between boom and recession. Since the economic environment and atmoshpere are very distinct in boom and recession, we want to test whether it matters that the news shock is perceived in good or in bad economic times. Furthermore, we also contribute to the methodology of the estimation of smooth transition vector autoregressive models and introduce a new way of estimating impulse response functions in a nonlinear setting. The last Chapter is a project of my own, questioning assumptions in the literature on productivity shocks. I simultaneously identify three different productivity shocks and show that one of them may capture the long-run growth component of the economy.

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Bern, August 2017 Sarah Fischer

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Abstract

This thesis focuses on the concept of news shocks about future productivity. A news shock means that today we obtain information about a technological innovation or prototype which will increase future productivity. While the technological improvment is feasible today, it has not yet reached a wide distribution and usage in the whole economy. The new technology rather slowly diffuses in the economy and increases productivity over time. The concept of news shocks assumes that expectations about future economic prospects influence the economy. The technological innovation opens new markets and business opportunities which lead to increased investment and hours worked in fields associated with it. Investors, producers and service providers want to be able to comply with future demand. In anticipation of higher profits in the future consumption and output increase. Hence, a news shock causes a boom in the economy. Nowadays, an example of such a news shock would be self-driving vehicles. A few years ago they started to be present in the media with the first prototypes being tested. Today the first self-driving vehicles operate on public grounds but still have to be accompanied by a driver. At the same time the investment in fields such as radar technology or sensors increased substantially. One can only imagine by how much this technological improvement may increase productivity in the future and how many further innovations will be developed along with it.

The idea that productivity shocks which include news shocks are the main driving factor of economic growth has long been present in macroeconomic literature. The challenge is to understand the economic interrelatiohships and different effects of productivity shocks in the short- and in the long-run. The thesis is a collection of four papers focusing on news shocks and further productivity shocks. The papers are entiteled “Unraveling News: Reconciling Conflicting Evidence” (Chapter 1), “News as Slow Diffusing Technology” (Chapter 2), “News Shocks: Different Effects in Boom and Recession?” (Chapter 3), and “Questioning Productivity Shocks” (Chapter 4). Chapters 1 to 3 are all co-authored by Maria Bolboaca while Chapter 4 is a single-author paper. The papers comprise an extensive empirical and theorectical analysis of news shocks.

In the first paper, the empirical news literature is summarized and methods as well as results are compared. News shocks are generally analyzed in the context of structural vector autoregressive models. The news shock is identified in the model by making certain assumptions about its effects on macroeconomic variables. The models and identifying assumptions differ in the literature which can lead to conflicting results. We give a broad overview over variable settings, identification schemes and results. We thereby show that in the majority of cases the idea of a slow diffusing news shock leading to a boom is confirmed. In Chapter 2, we introduce endogenous technology adoption to a medium-scale dynamic stochastic general equilibrium model with real frictions. While so far a news shock was modelled as a jump increase in future productivity, our contribution is to model news as slow diffusing technology. The model predictions match the empirical results of both unanticipated productivity and technology diffusion news shocks

qualitatively. In Chapter 3, we go back to the empirical exploration of news shocks and estimate a smooth transition vector autoregressive model to identify differences in the effects of news shocks between boom and recession. Since the economic environment and atmoshpere are very distinct in boom and recession, we want to test whether it matters if the news shock is perceived in good or in bad economic times. We find that the effects are qualitatively similar, but that the news shock has a stronger impact in good times. Furthermore, we also contribute to the methodology of the estimation of smooth transition vector autoregressive models and of impulse response functions in a nonlinear setting. The last Chapter is a project of my own which questions assumptions in the literature on productivity shocks. I show that the assumptions imposed on the effects and contributions of productivity shocks, and especially news shocks, are crucial for the nature of the identified structural shock. They can lead to very different results and conclusions regarding productivity shocks. I identify three different productivity shocks simultaneously and show that one of them may capture the long-run growth component of the economy. Furthermore, I show that the total factor productivity news shock is almost identical to an investment-specific technology news shock identified with the same method. Overall, productivity shocks seem to be the drivers of the economy in the medium- and long-run. Further analysis is necessary to understand productivity shocks and the economic interrelationships.

The subsequent paragraphs summarize each chapter's motivation, research question, methodology, and main results.

Chapter 1 This paper addresses the lack of consensus in the empirical literature in regard to 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 show which macroeconomic variables are essential in a vector autoregressive model to identify robust productivity and news shocks and, furthermore, to obtain robust results. While there is less information necessary for the identification of the shock, only models including output, consumption and hours worked deliver reliable impulse responses to productivity shocks. Given a robust variable setting, we analyze the different identification schemes which 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. We show that the identified news shock depends critically on the applied identification scheme and on the maximization horizon.

Chapter 2 In this paper we develop a medium scale dynamic stochastic general equilibrium model with real frictions that both 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. Hours worked and output increase immediately, which is necessary to raise investment in technology adoption. In anticipation of higher future productivity consumption already increases today. Hence, a news shock leads to a slow and steady increase in productivity and a boom. The model predictions match the empirical results of both unanticipated productivity and technology diffusion news shocks qualitatively.

Chapter 3 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. We find that while the effects of a news shock are qualitatively similar, a news shock leads to a larger increase in productivity and, ultimately, output. A possible explanation may be that a good economic atmosphere fosters investment into technology adoption which leads to a faster and stronger increase. The results also indicate that the probability of a regime switch is highly influenced by the news shocks. Hence, a positive news shock may end a recession.

Chapter 4 In the last paper of the thesis, I revisit the identification of productivity shocks and consider identification schemes that have been extensively discussed in the literature. While the identifying assumptions are usually based on economic theory, the identified productivity shocks often fail to mimic their theoretical counterparts. The method in this paper is purely empirical. Instead of relating the identified shocks to theoretical counterparts, I question whether these shocks are indeed identifying what they have been designed for. My contribution is to question the nature of the identified shocks and the underlying assumptions. There are three key findings. Firstly, the identified news shock depends strongly on the identification scheme. Secondly, basically the same shock is identified, when a TFP news shock and an investment-specific technology news shock are identified separately. Thirdly, a certain identification scheme may capture the long-run growth component of the economy explaining most of the variation in the economy in the medium- and long-run. In a next step, the analysis should be extended to theoretical models.

Chapter 1

Unraveling News: Reconciling Conflicting Evidence

Maria Bolboaca and Sarah Fischer

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, Fernald, and Kimball (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, Gambetti, and Sala (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 evidences.[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, Nam, and Wang (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 identification schemes of BS or KS. We confirm the result of Galí (1999), Basu, Fernald, and Kimball (2006) and Fève and Guay (2009) and find a negative impact reaction of hours worked to an unanticipated productivity shock.

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

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

1.2 Linear Vector Autoregressive Model

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. For now, we constrain the coefficients and the variance-covariance matrix to be constant over time. This assumption is relaxed in Chapter 3. The 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 (forthcoming), 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, caution is required 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, Stock, and Watson (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

[5] Kilian and Lütkepohl (forthcoming) 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 (2016b).

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 as an unexpected improvement in productivity such as sudden changes in regulations or management practices that promote more production. The shock is identified as the only shock having an impact effect on TFP. BP argue that today's stock prices reveal important technological innovations which will materialize in the future. The news shock is, then, the only other shock having an impact effect on stock prices. We will call this identification scheme SRI2. In a two-variable model the news shock is just the remaining shock. The structural shocks are written as a linear combination of reduced form shocks (ϵ_{kt}) in a bi-variate system.

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

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, Fernald, and Kimball (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

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

to $\Xi_{1,2(h)}$ over h. This is equivalent to solving the following optimization problem:

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

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 Beaudry, Nam, and Wang (2011) – Short-Run Zero Restrictions and max FEV

Beaudry, Nam, and Wang (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, Fernald, and Kimball (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.

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 used the Solow residual as a measure of total factor productivity. A second measure they tried was 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, Fernald, and Kimball (2006) proposed 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 equa-

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

[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.

tion with a proxy for utilization in each disaggregated industry. Aggregate technology change is then defined as an appropriately weighted sum of the resulting residuals. In the literature this series has been considered 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, Fernald, and Kimball (2006) or later vintages of it. In follow-up papers, Basu et al. (2013) and Fernald (2014) improved 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.

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).

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 procedure becomes more constant.[14]

[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).

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

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

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 received.

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 evidences and to focus on the most important points. The settings in the following tables and graphs are named by their variable content.[15] TFP,

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

the first variable in the models is omitted due to lack of space. For brevity, we will also use confidence as a name for the index of consumer sentiment.

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

We look at four variable settings to which we add a combination of SP and cc. The variable combinations are: YCH, 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.C.1, 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.C.2 and 1.C.3, 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

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

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 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 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 often has been ignored in the literature

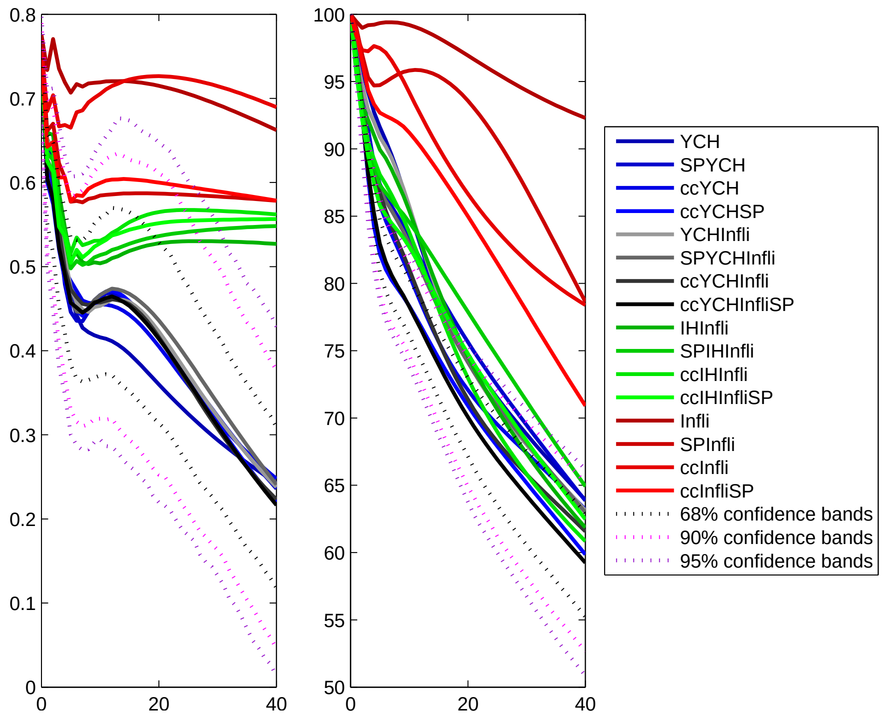

Figure 1.1: The left graph shows impulse response functions of TFP to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by an unanticipated productivity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

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.

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

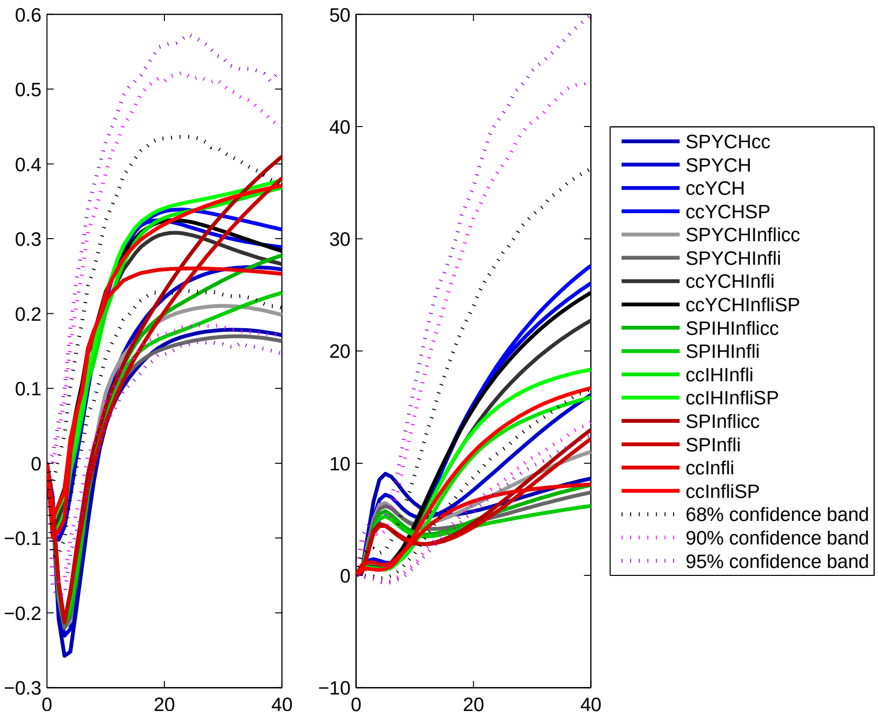

Figure 1.2: The left graph shows impulse response functions of TFP to a news shock identified with SRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified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

evolves. The shares of the forecast error variance are also very close in the short-run and disperse in the long-run. Since the results are coherent over all variable settings and the response of the baseline setting is significant at the 95% significance level, it can be concluded that the impact reaction of hours worked to an unanticipated productivity shock is negative.

In Figure 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.

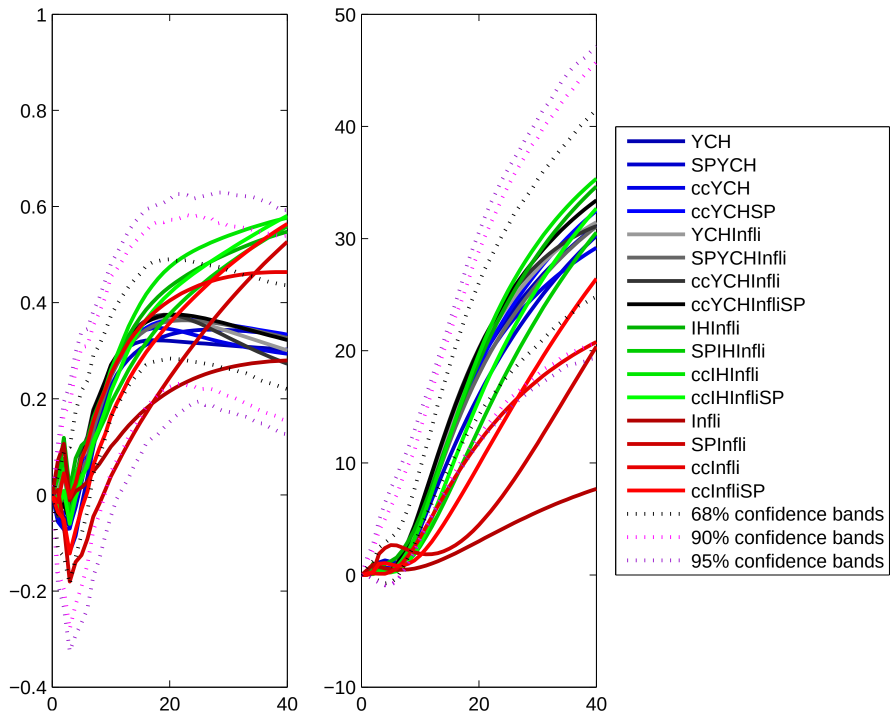

Figure 1.3: The left graph shows impulse response functions of TFP to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations.The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified with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

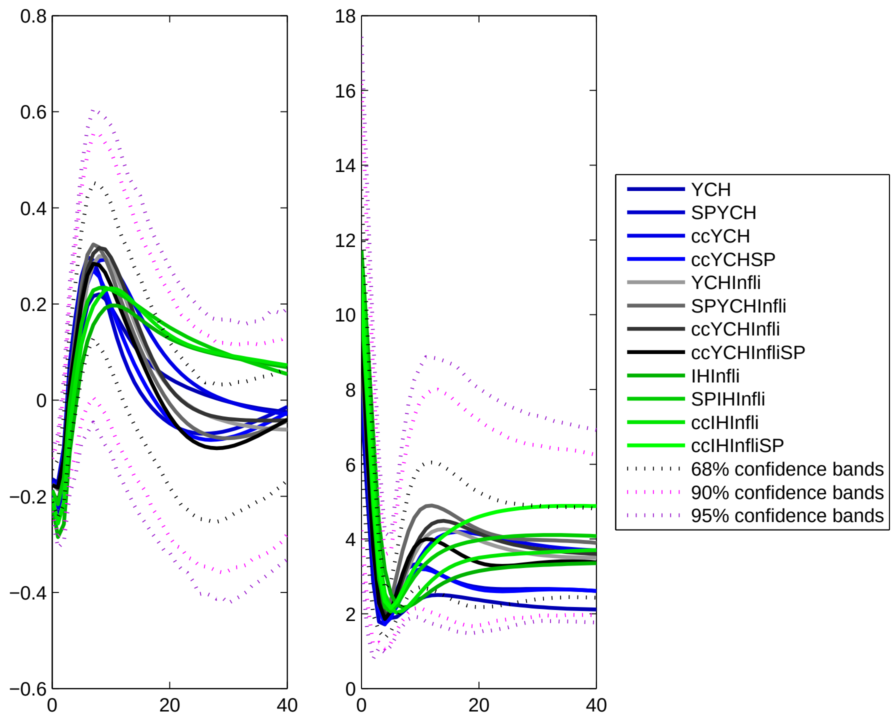

Figure 1.4: The left graph shows impulse response functions of hours worked to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations.The graph on the right shows the share of the forecast error variance of hours worked determined by an unanticipated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

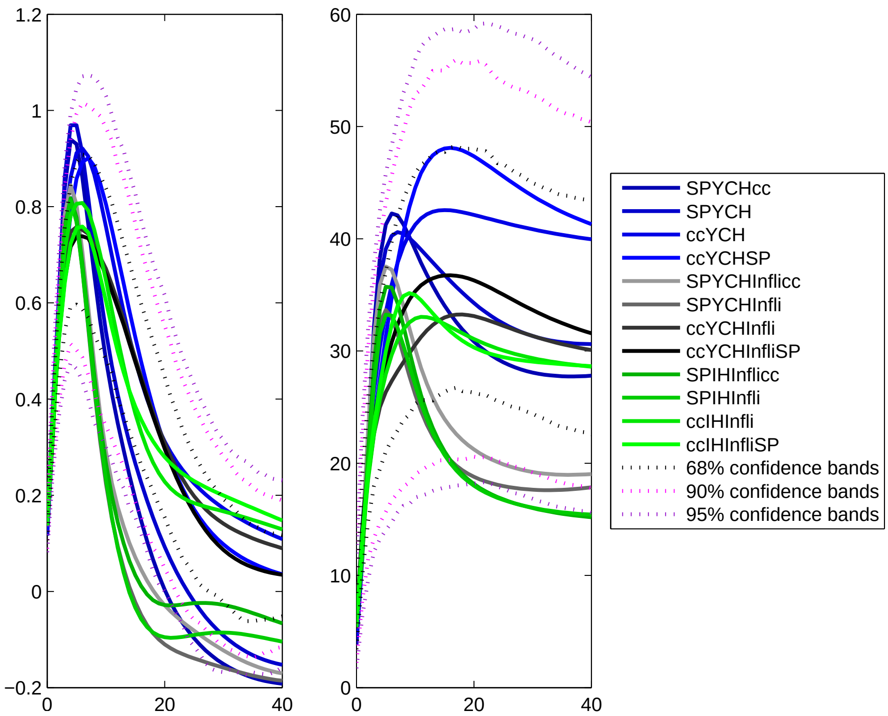

Figure 1.5: The left graph shows impulse response functions of hours worked to a news shock identified with SRI in different variable settings. The vertical axis refers to percentage deviations.The graph on the right shows the share of the forecast error variance of hours worked determined by a news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

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.

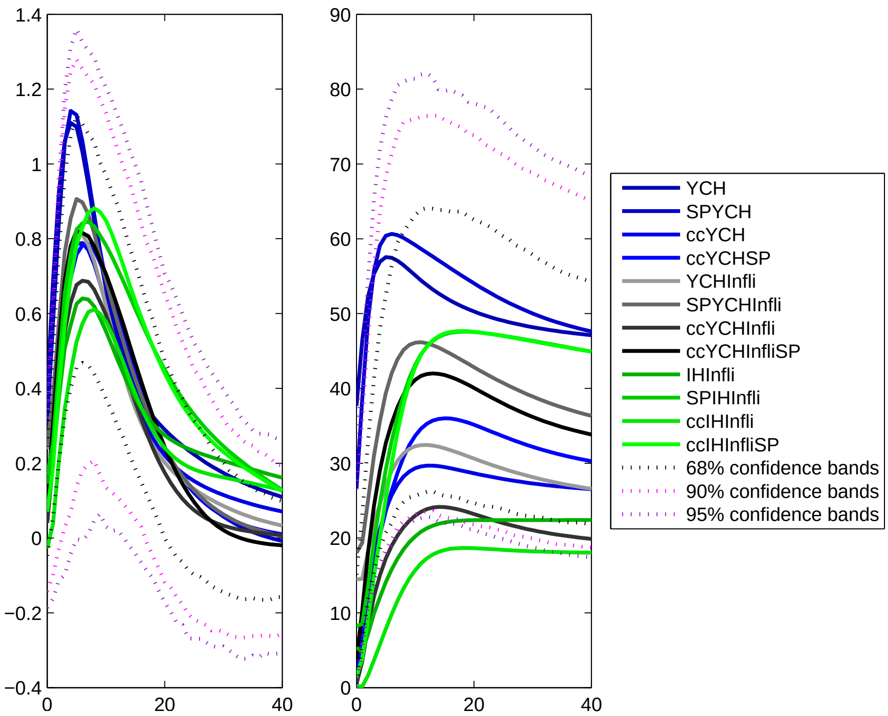

Figure 1.6: The left graph shows impulse response functions of hours worked to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of hours worked determined by a news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

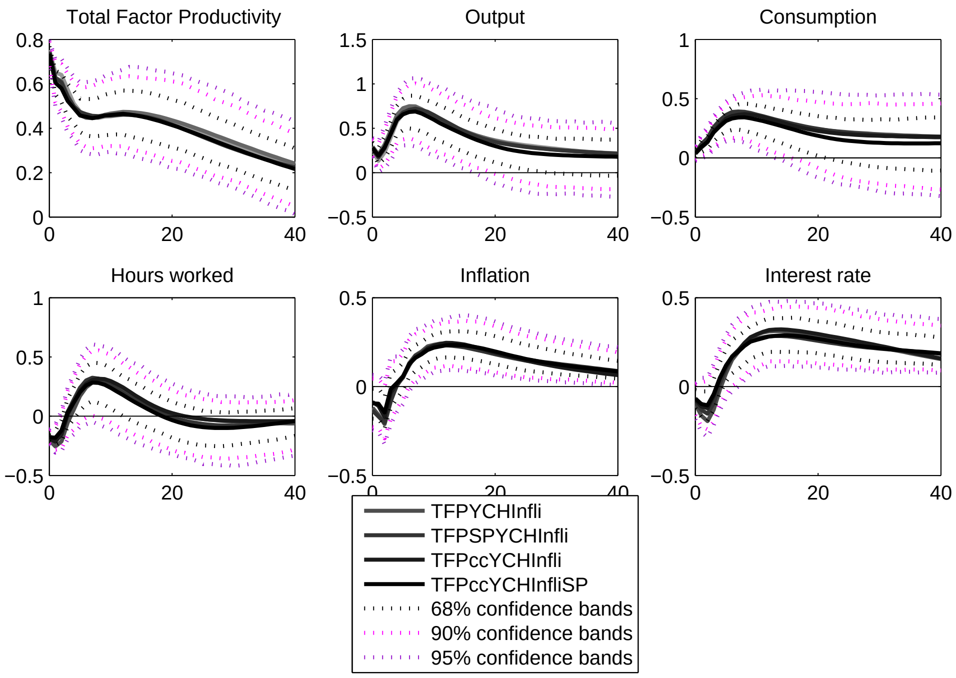

Figure 1.7: The left graph shows impulse response functions of all variables to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations.The graph on the right shows the share of the forecast error variance of all variables determined by a 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.

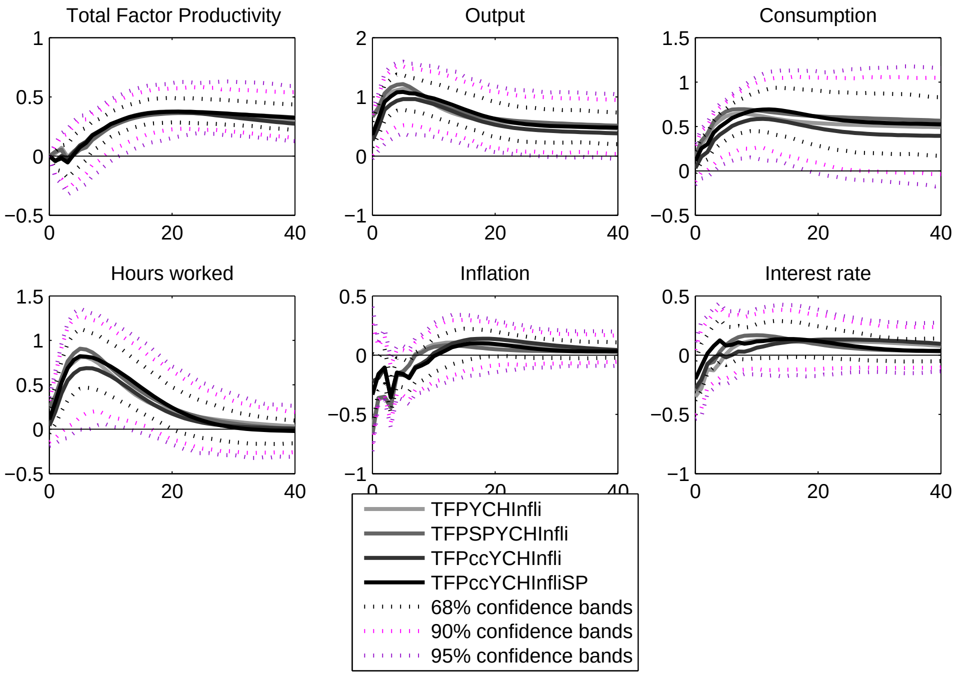

Figure 1.8: The left graph shows impulse response functions of all variables to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of all variables determined by a news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

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.

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.D.1, Appendix 1.D, we present the correlations between unanticipated productivity shocks of the variable settings. The results clearly indicate that the infor-

[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, Nam, and Wang (2011). KS stands for the variable settings in Kurmann and Sims (2017). 9 variables includes all variables TFPccYCHIInfliSP.

mation 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.D.2, 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.

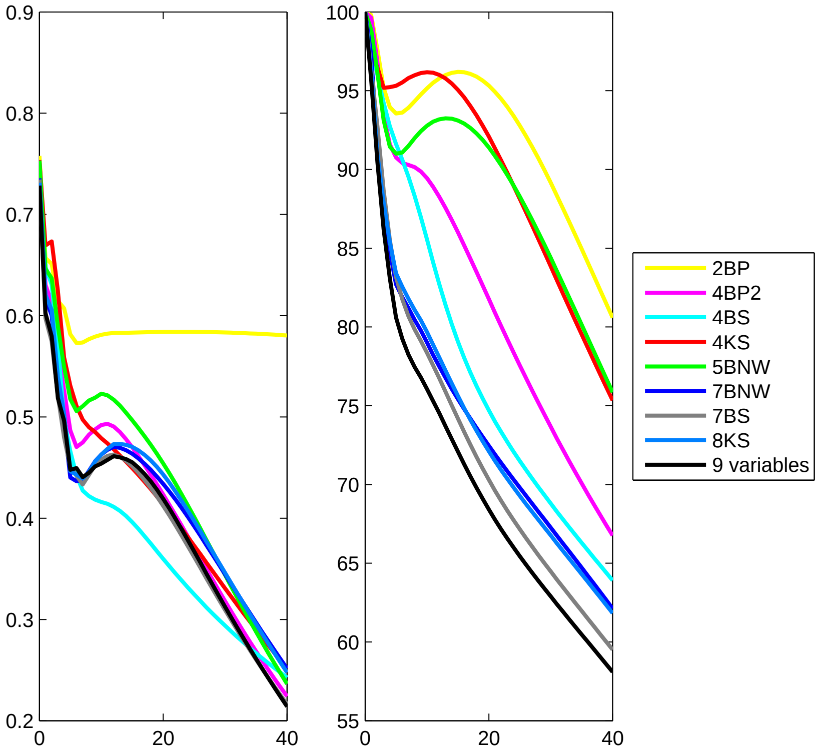

Figure 1.9: The left graph shows impulse response functions of TFP to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by an unanticipated productivity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

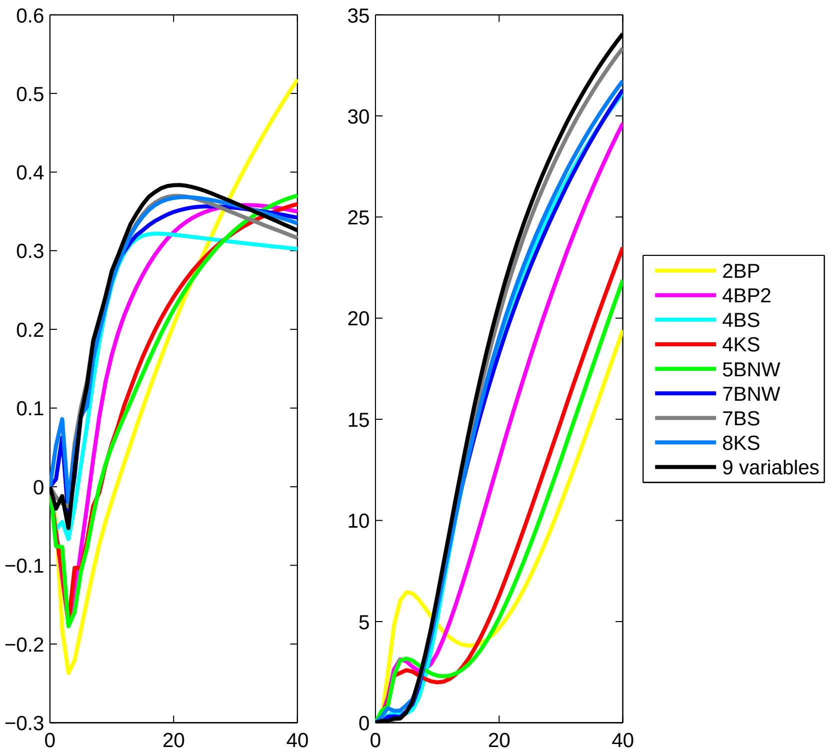

Figure 1.10: The left graph shows impulse response functions of TFP to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of TFP determined by a news shock identified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

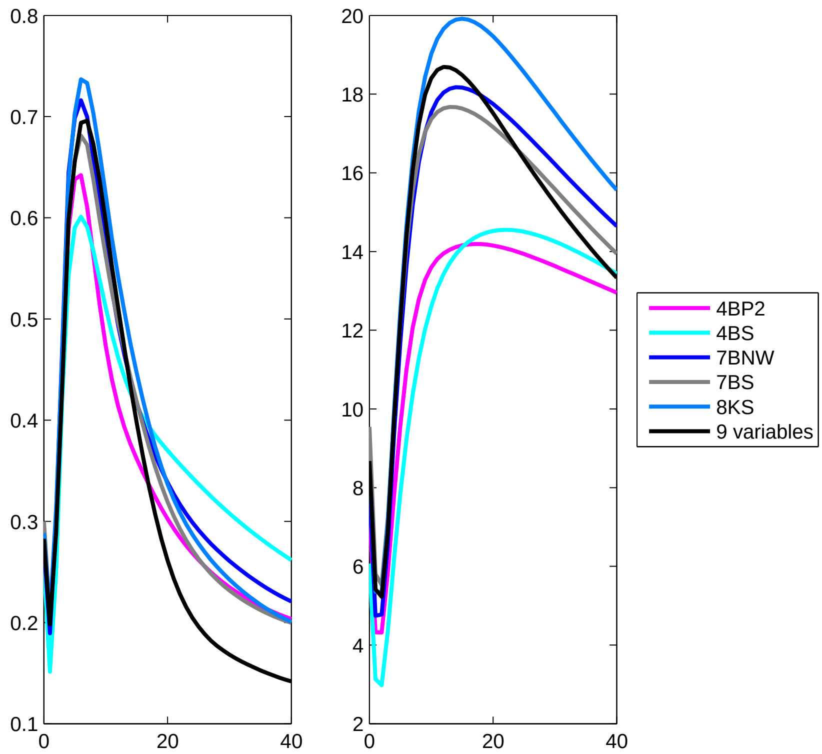

Figure 1.11: The left graph shows impulse response functions of output to an unanticipated productivity shock in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of output determined by an unanticipated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

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

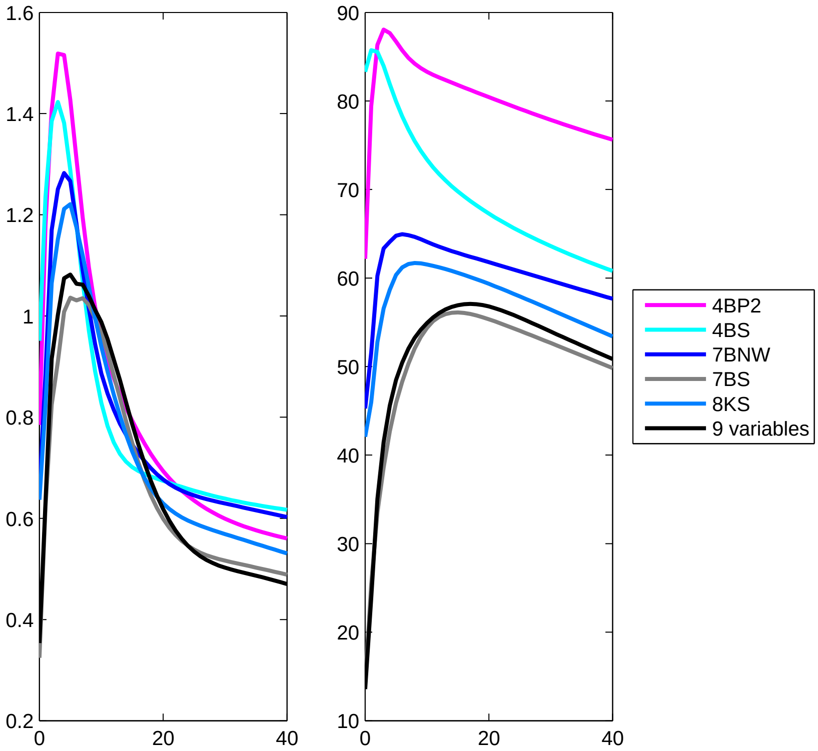

Figure 1.12: The left graph shows impulse response functions of output to a news shock identified with MRI in different variable settings. The vertical axis refers to percentage deviations. The graph on the right shows the share of the forecast error variance of output determined by a news shock identified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

effects well.

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

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, Nam, and Wang (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.

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.

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 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.

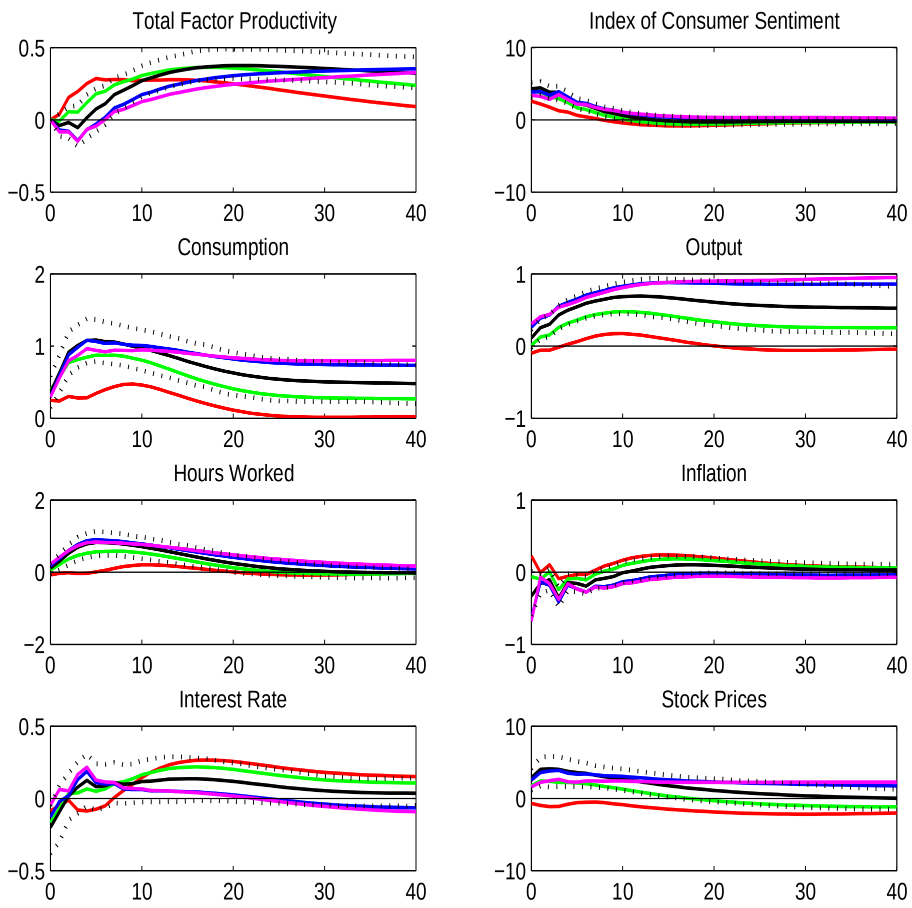

Figure 1.13: IRFs to a news shock identified with MRI maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal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

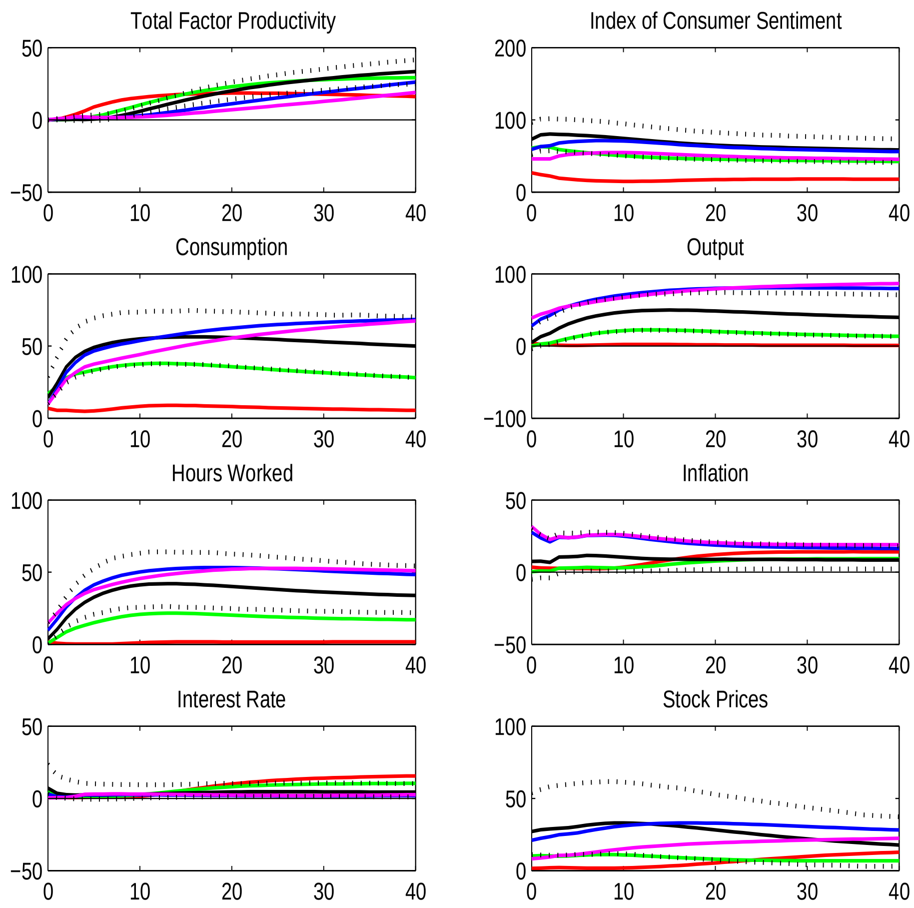

Figure 1.14: Contributions of a news shock identified with MRI maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond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

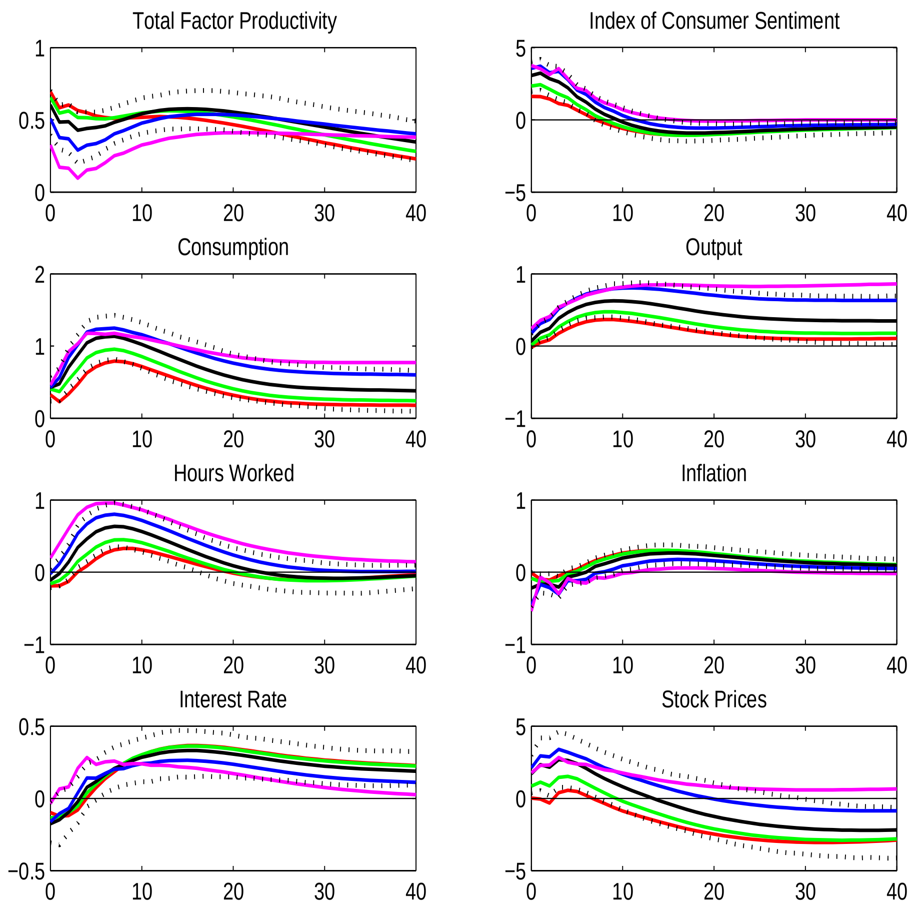

Figure 1.15: IRFs to a news shock identified with KS maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points. The horizontal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

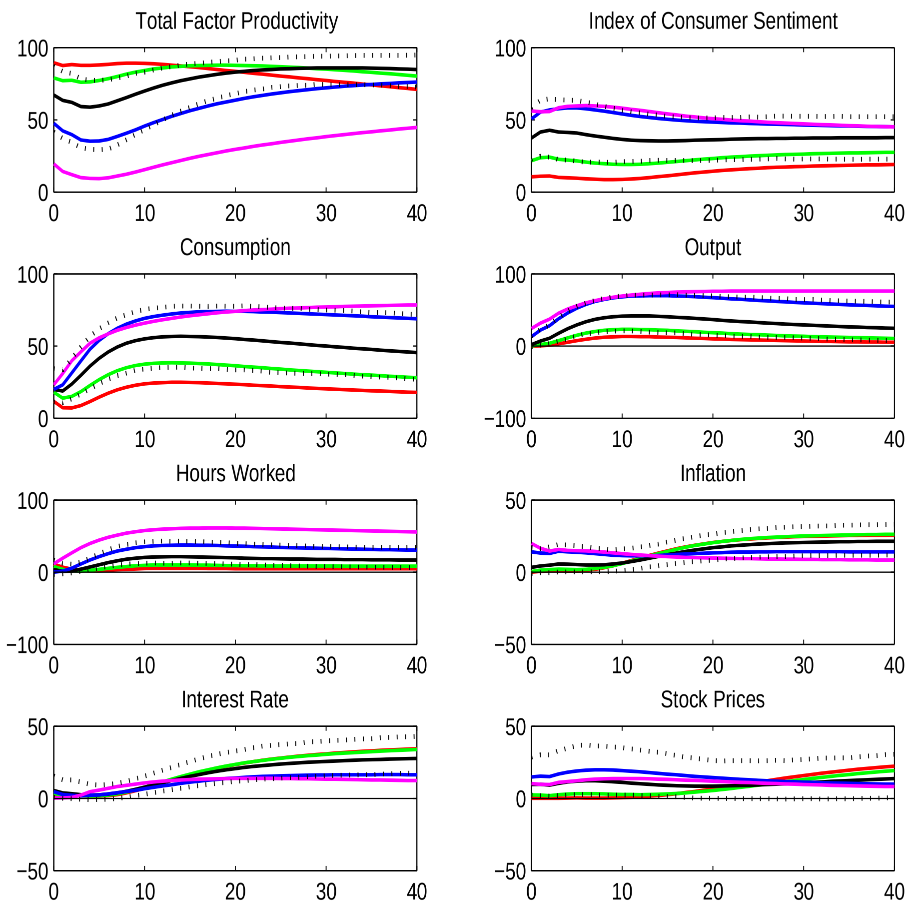

Figure 1.16: Contributions of a news shock identified with KS maximizing at different horizons 12 (green), 20 (red), 40 (black), 80 (blue), 120 (magenta) quarters. The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond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

We have shown that no matter the identification scheme, we can find a positive impact effect on hours worked. But results differ considerably with the maximization horizon.

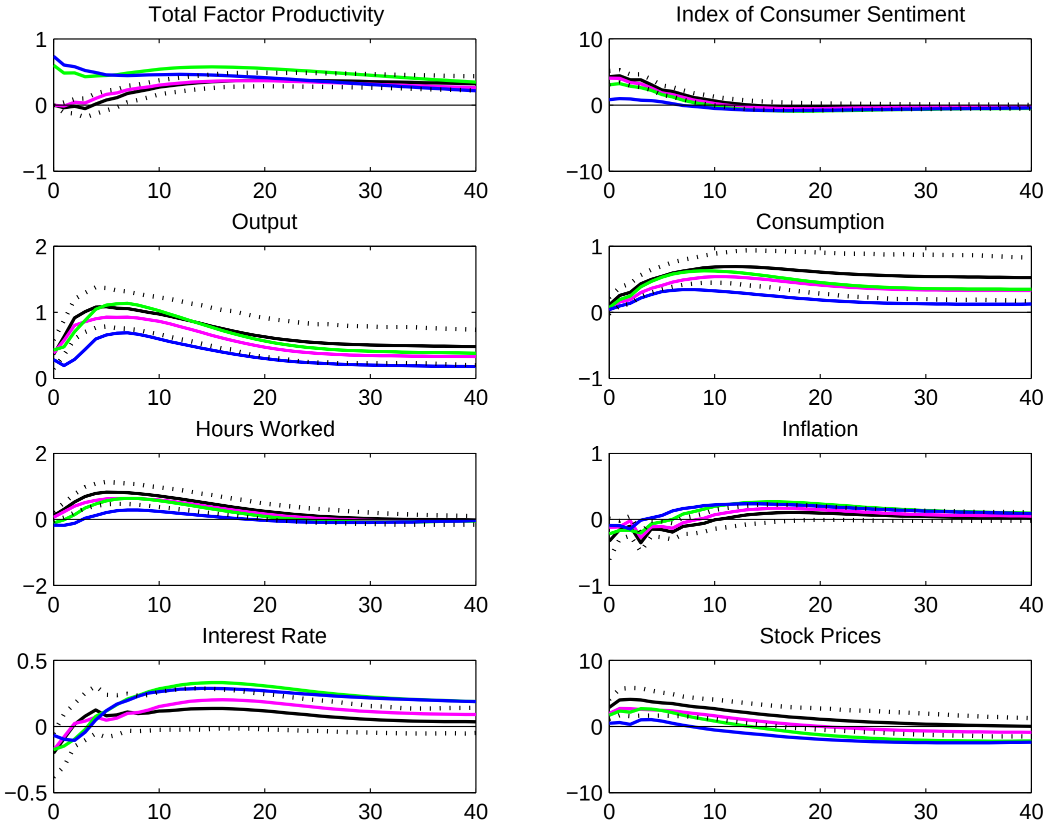

Figure 1.17: Impulse responses to a news shock identified with MRI-KS (green), MRI (black), MRI-BS (blue) with maximization horizon 40 quarters and a news shock obtained with SRI1 (magenta). The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for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

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.

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.

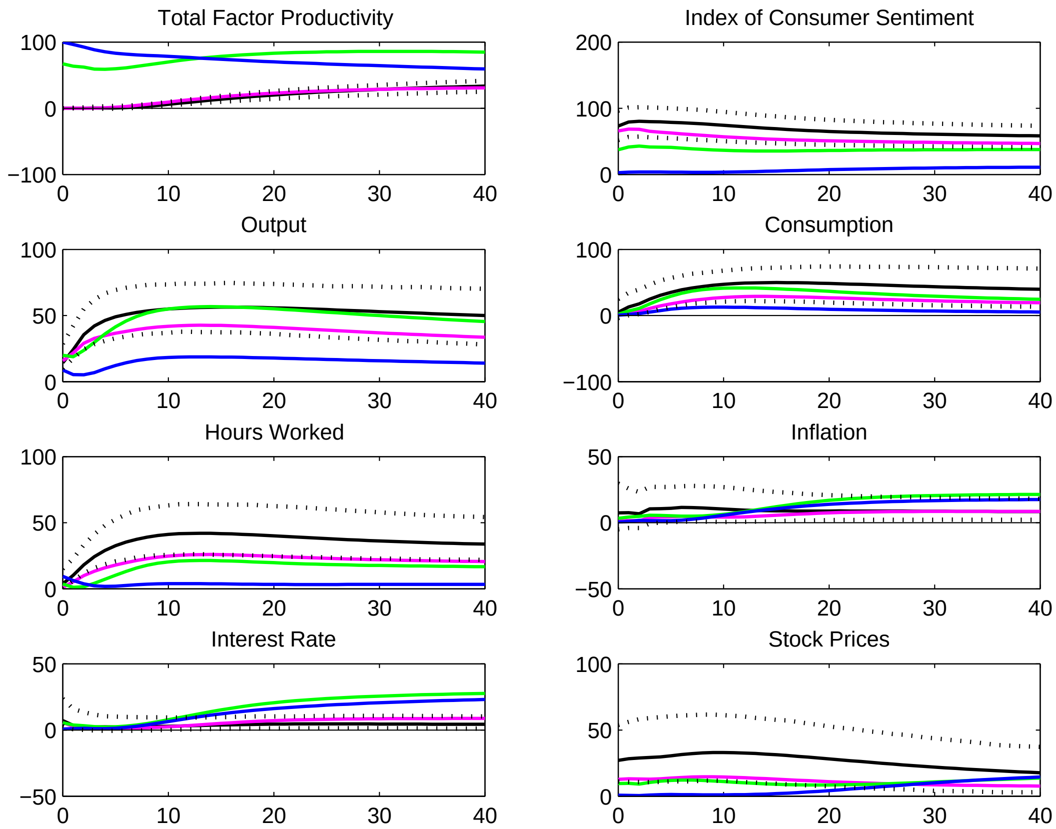

Figure 1.18: Contributions of a news shock identified with KS (green), MRI (black), BS (blue) with maximization horizon 40 quarters and a news shock obtained with SRI1 (magenta). The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters. The dotted lines correspond to the 68% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR of the model with MRI (black).

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.

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.

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.

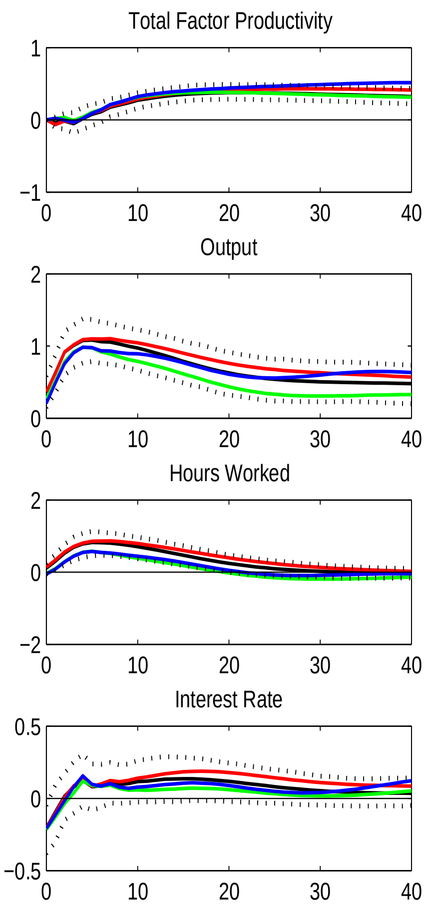

Figure 1.19: Impulse responses to a news shock identified with MRI maximized at 40 quarters, using TFP16 samples until 2000 (green), 2007 (red), 2011 (red), 2014 (black). The unit of the vertical axes is percentage deviation, with the exception of the index of consumer sentiment for which it is points.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

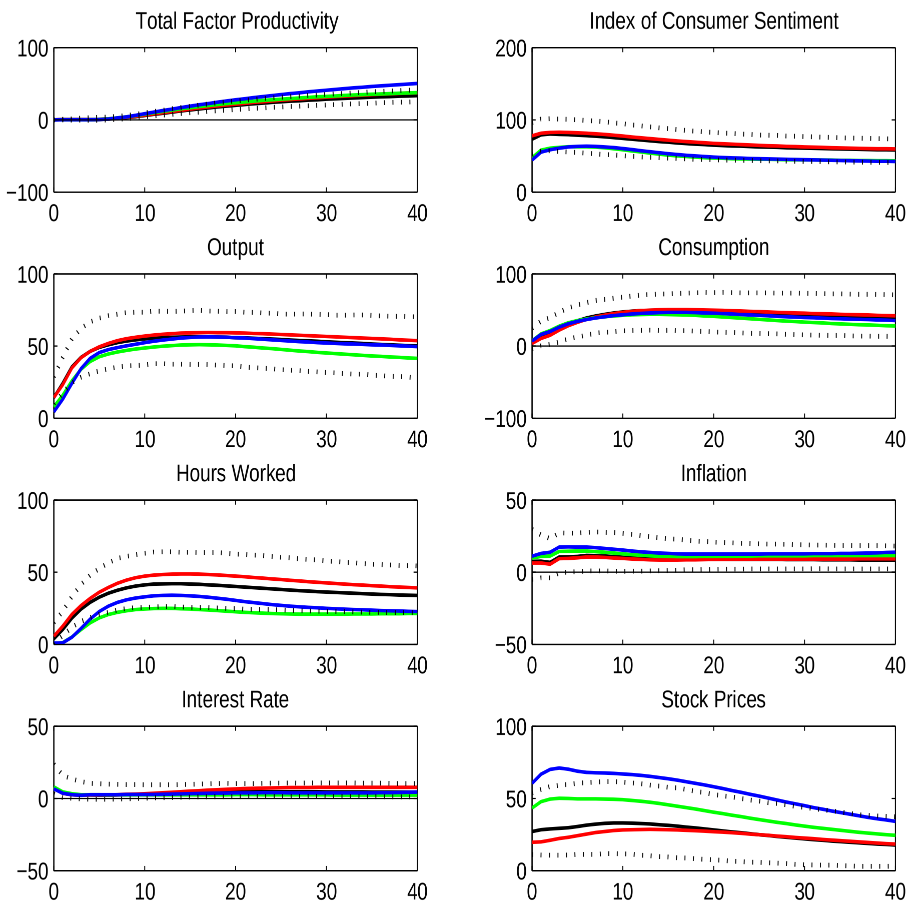

Figure 1.20: Contributions to the forecast error variance of a news shock identified with MRI maximized at 40 quarters, using TFP16 samples until 2000 (green), 2007 (red), 2011 (red), 2014 (black). The unit of the vertical axes is percentages. The horizontal axes indicate the forecast horizons in quarters.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

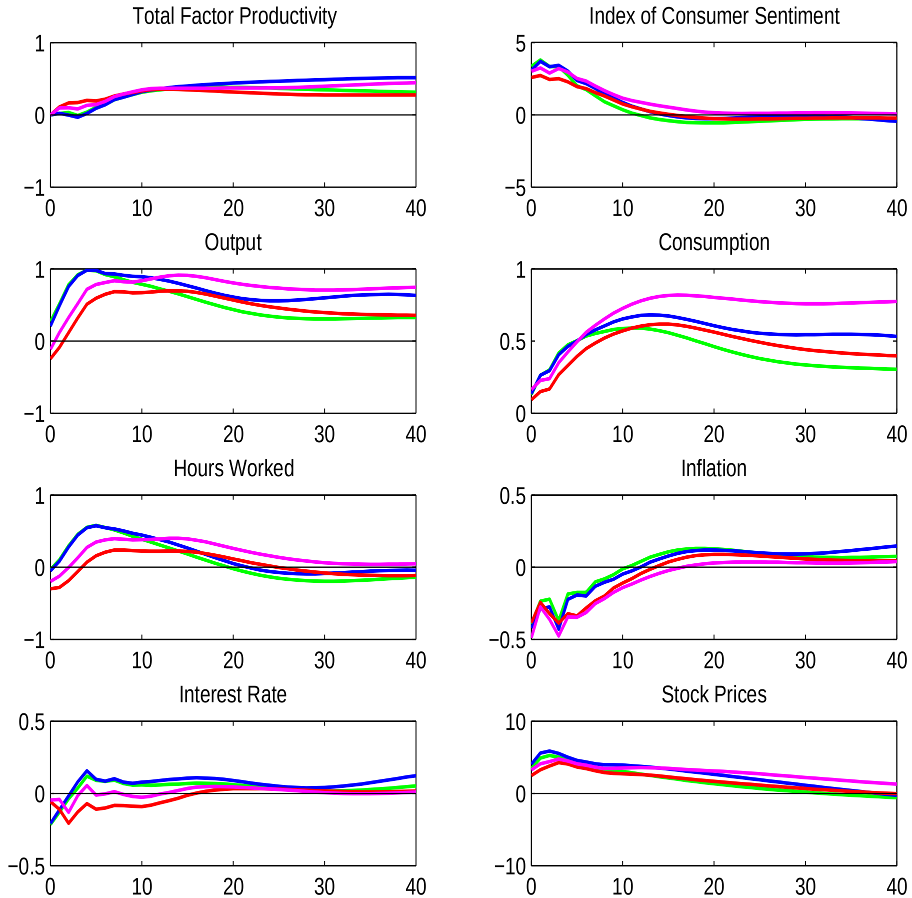

Figure 1.21: Impulse responses to a news shock identified with MRI maximized at horizon 40 quarters using different TFP vintage series and samples: TFP16/2000 (green), TFP16/2007 (red), TFP07/2000 (red), TFP07/2007 (black). The unit of the vertical axes is percentage deviation, with the exception of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

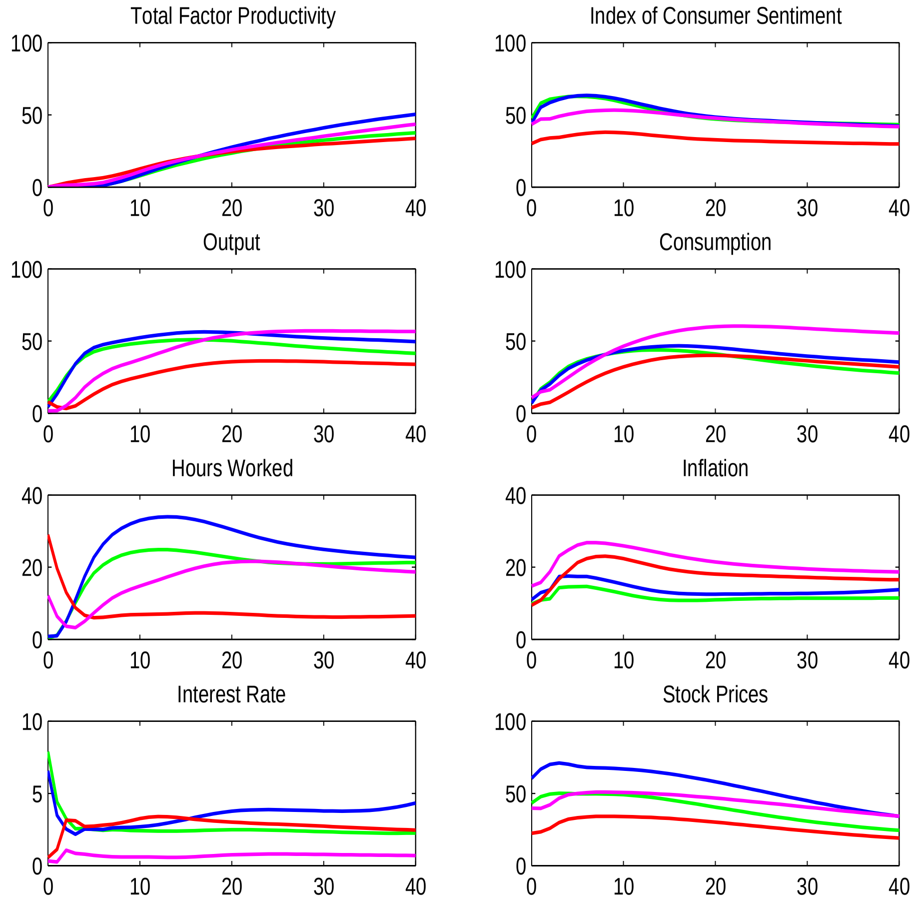

Figure 1.22: Contributions of a news shock identified with MRI maximized at horizon 40 quarters using different TFP vintage series and samples: TFP16/2000 (green), TFP16/2007 (red), TFP07/2000 (red), TFP07/2007 (black).The unit of the vertical axes is percentages. The horizontal axes indicate the forecast 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 neither the unanticipated productivity shock nor 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, Fernald, and Kimball (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.B.1: 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, Nam, and Wang (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

Table 1.C.1: Cross-Correlations Between Unanticipated Productivity Shocks.

	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.C.2: Cross-Correlations Between News Shocks.

	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.C.3: Cross-Correlations Between News Shocks.

	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 Related Literature

Table 1.D.1: Cross-Correlations Between Unanticipated Productivity Shocks.

	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.D.2: Cross-Correlations Between News Shocks (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

News as Slow Diffusing Technology

Maria Bolboaca and Sarah Fischer

2.1 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, while news about future changes in productivity has the expansionary effect on economic activity that was previously attributed to the unanticipated productivity shock.

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 are created in research institutes and universities, while the private sector does not contribute to the invention process. Nevertheless, without the adoption of new technologies, there is no technology transfer from the technological frontier to the economy. To be used a prototype must be successfully adopted, which involves a costly investment. Hence, technology diffusion is not instantaneous as it is usually assumed in the related literature, even though it may be slower or faster depending on the adoption process.[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 macroeconomic variables indicate that they basically track the movements in TFP. All

[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, Gertler, and Santacreu (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, Gertler, and Santacreu (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.

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, the most important element are investment adjustment costs. This friction is 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, Fernald, and Kimball (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, Nam, and Wang (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, Gertler, and Santacreu (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 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 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 diffusion technology news shock than the previously assumed idea of news about manna from heaven. Section 5 concludes.

[6] Guo, Sirbu, and Weder (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, Akcigit, and Howitt (2014) for a summary of this literature.

2.2 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 2.1 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, Fernald, and Kimball (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 following sections we will investigate the ability of two theoretical models to account for these stylized facts.

[8] The model is described in Appendix 2.B.

[9] The data series are presented in Appendix 2.A.

[10] The identification scheme is presented in Appendix 2.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 2.D.1 and for the news shock in Figure 2.D.2, in Appendix 2.D.

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

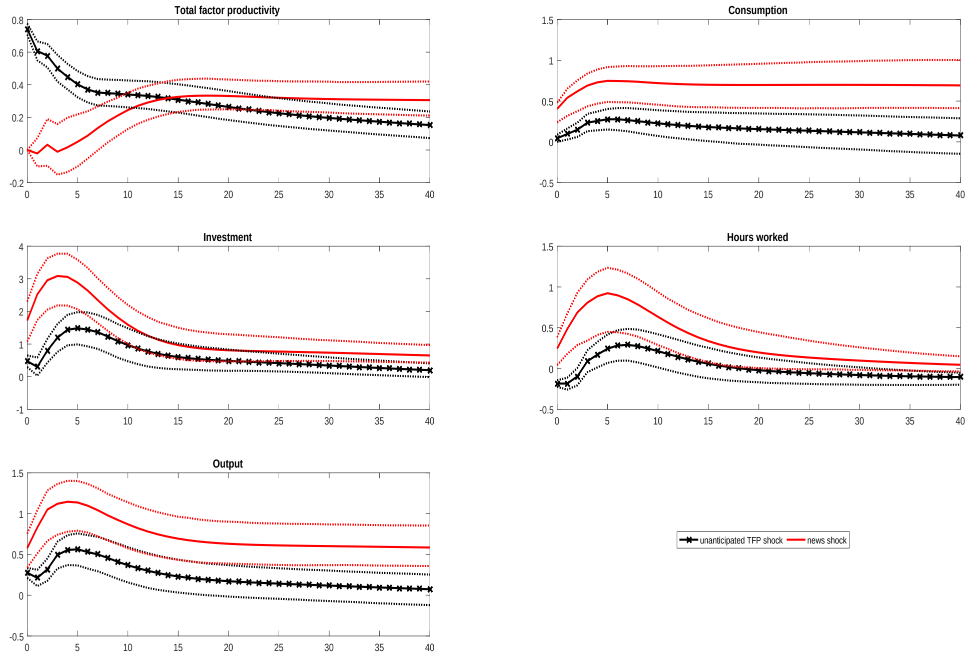

Figure 2.1: Impulse responses to an unanticipated productivity and to a technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The dotted lines correspond to the 68% confidence intervals. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

2.3 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, Plosser, and Rebelo (1988), henceforth KPR, while when $\gamma = 0$ the preferences are of the type proposed by Greenwood, Hercowitz, and Huffman

(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 2.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 2.1, 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 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

[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: $\varphi''(1) > 0.4, \delta''(u)u/\delta'(u) < 2.5, \theta < 10, \gamma < 0.4$.

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.

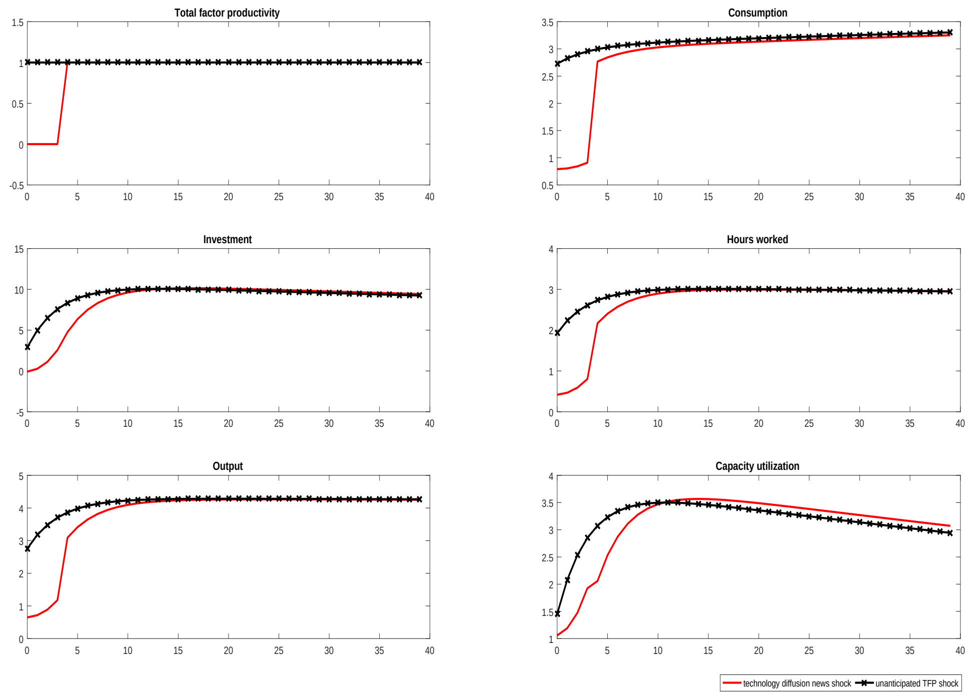

Figure 2.1: Impulse responses to a permanent unanticipated productivity shock and a news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

In Appendix 2.E.2 we discuss the importance of each of the three elements (i.e. 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 2.1 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.

2.3.1 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 2.2, we can observe that modeling the news shock as a diffusion technology 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.

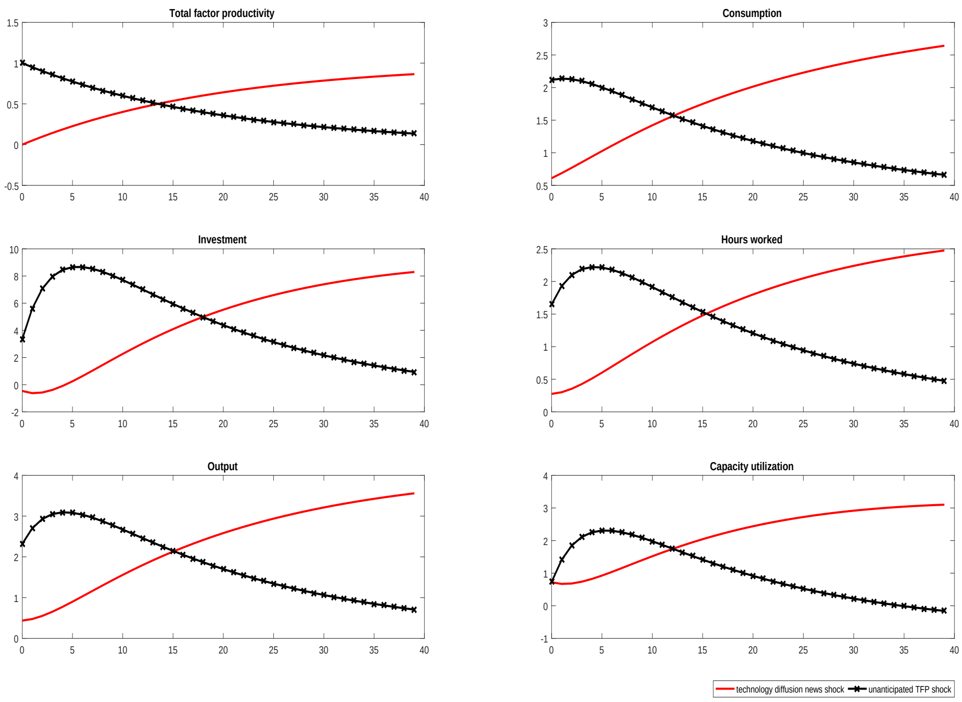

Figure 2.2: Impulse responses to a temporary unanticipated productivity shock and a technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

[16] The processes are described in Appendix 2.E.3.

2.3.2 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 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 2.3 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 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

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

to a news shock. In the following section, we present our proposed model.

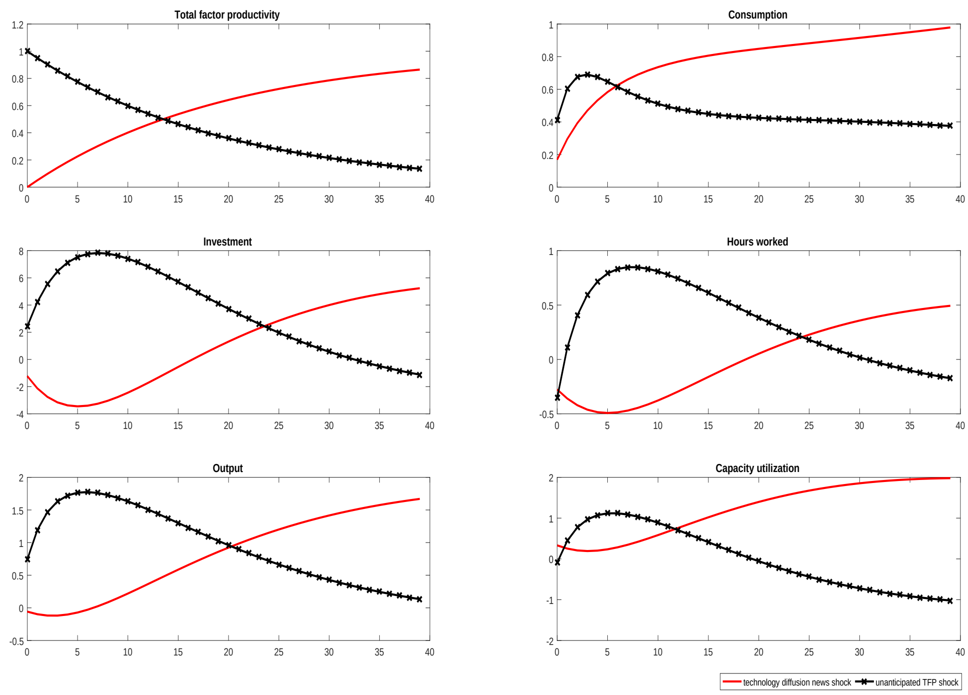

Figure 2.3: Impulse responses to a temporary unanticipated productivity shock and a technology diffusion news shock in a model with habit persistence. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

2.4 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, Gertler, and Santacreu (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.

2.4.1 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.

2.4.2 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

Contrary to 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]

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

[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 mimick 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.

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 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

[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, Redding, and Simpson (2002), Acemoglu, Aghion, and Zilibotti (2006), and Griffith, Redding, and Simpson (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.

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:

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

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 $\Xi_t \left(Z_t - \phi A_t \right)$ 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. Technological diffusion may be slower or faster depending on the pace of the adoption process implied by Ξ_t, but it is not immediate.

2.4.3 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:

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

[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.

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 will 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]

$$\begin{aligned}
&\max \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \iota_t \left[\ln(C_t - \tau C_{t-1}) - \zeta \frac{(L_t)^{1+\eta}}{1+\eta} \right] \right\} \\
&s.t. \\
&P_t C_t + P_t I_t + P_t S_t [A_{t+1} - A_t] + B_{t+1} = W_t L_t + R_{t-1} B_t + F_t A_t + R_t^k K_t - P_t T_t \\
&A_{t+1} = \Xi_t (Z_t - \phi A_t) + \phi A_t \\
&K_{t+1} = I_t \left[1 - \varphi\left(\frac{I_t}{I_{t-1}}\right)\right] b_t + [1-\delta] K_t \\
&K_0,\ Z_0,\ A_0,\ B_0,\ I_{-1},\ C_{-1}\ given
\end{aligned}$$

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 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.

[23] The Lagrangian for this problem and the first order conditions are presented in Appendix 2.F.

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

$$C_t:\ \iota_t(C_t-\tau C_{t-1})^{-1}-\beta\tau\mathbb{E}_t\iota_{t+1}(C_{t+1}-\tau C_t)^{-1}=\lambda_t \tag{2.1}$$

$$B_{t+1}:\ \lambda_t=\beta\mathbb{E}_t\left(\lambda_{t+1}R_t\frac{P_t}{P_{t+1}}\right) \tag{2.2}$$

$$I_t:\ 1=q_tb_t\left[1-\varphi\left(\frac{I_t}{I_{t-1}}\right)-\varphi'\left(\frac{I_t}{I_{t-1}}\right)\frac{I_t}{I_{t-1}}\right]+\beta\mathbb{E}_t\left[q_{t+1}b_{t+1}\frac{\lambda_{t+1}}{\lambda_t}\varphi'\left(\frac{I_{t+1}}{I_t}\right)\left(\frac{I_{t+1}}{I_t}\right)^2\right] \tag{2.3}$$

$$K_{t+1}:\ q_t=\beta\mathbb{E}_t\left[\frac{\lambda_{t+1}}{\lambda_t}r^k_{t+1}+q_{t+1}(1-\delta)\right], \tag{2.4}$$

$$L_t:\ \iota_t\zeta L_t^\eta=\lambda_tw_t, \tag{2.5}$$

$$S_t:\ \lambda_t(A_{t+1}-A_t)=\Omega_t\frac{\partial\Xi_t}{\partial S_t}\left(Z_t-\phi A_t\right) \tag{2.6}$$

The transversality condition is:

$$\lim_{s\to\infty}\beta^s\mathbb{E}_t\lambda_{t+s}\left(K_{t+s}+B_{t+s}\right)=0 \tag{2.7}$$

2.4.4 Government

The government consumes an exogenous share of output, $G_t=g_tY_t$. 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}:

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

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:

$$P_tg_tY_t+R_{t-1}D_t\leqslant P_tT_t+D_{t+1},$$

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.

[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 $q_t=\frac{Q_t}{\Lambda_tP_t}$, and $\lambda_t=\Lambda_tP_t$.

2.4.5 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.

2.4.6 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), 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

[25] The complete list of equilibrium equations is presented in Appendix 2.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.

[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.

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, Kalyvitis, and Pappa (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, Gertler, and Santacreu (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 of 25 percent in Pakes and Schankerman (1987). However, in a more recent empirical analysis by Park, Park, and Shin (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]

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[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, Ravikumar, and Rupert (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, Ravikumar, and Rupert (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

[35] We use data for the shares of gross domestic product: government consumption expenditures and

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 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 surprise 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

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, Hobijn, and Rovito (2008).

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, Eichenbaum, and Evans (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 $(5 * 15 * 2) \times (5 * 15 * 2)$.

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]

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

[37] The benchmark calibration is summarized in Table 2.G.1 from Appendix 2.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.

[39] For details see Fève, Matheron, and Sahuc (2009).

2.4.7 Results

Theoretical Impulse Responses

Using the benchmark calibration presented in the previous section, and summarized in Table 2.G.1 from Appendix 2.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 diffusion technology shock and surprise productivity shock we discussed in Section 2.

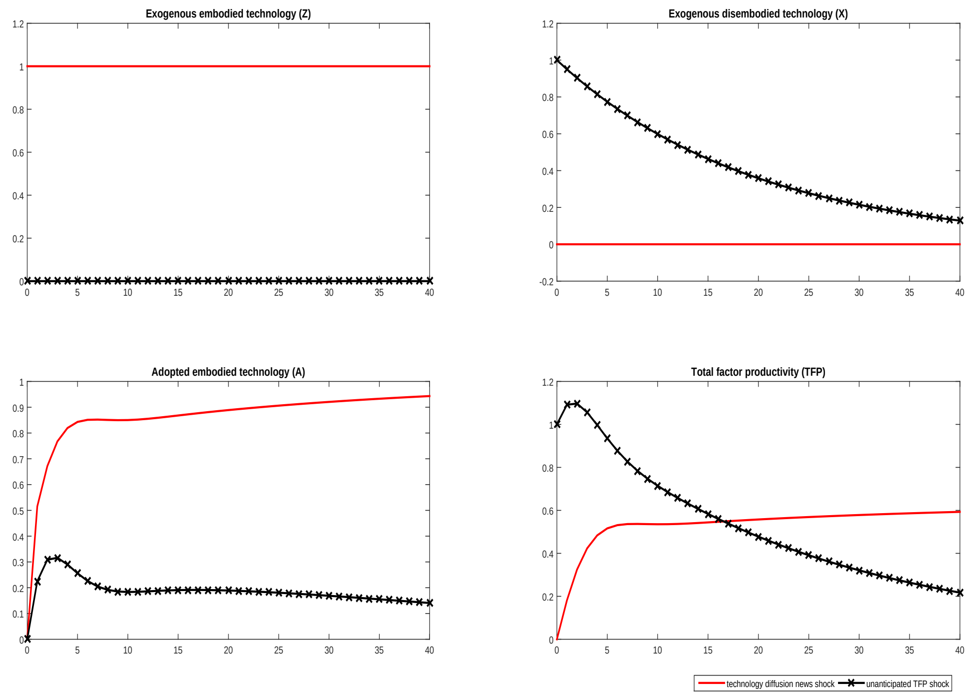

Figure 2.1: Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

In Figure 2.1 we see that the diffusion technology 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. 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 2.2. After the news hits, there is an increase in funds allocated to adoption, which makes successful adoption more probable.

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 2.2, after a surprise 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 a surprise productivity shock on adoption gives the hump-shape response of TFP in Figure 2.1. TFP continues to increase for some periods after the surprise productivity shock due to increased adoption. Because of this channel, the effect of the surprise productivity shock is more persistent on TFP than on X, and this makes the IRF of TFP look more similar to its empirical counterpart.

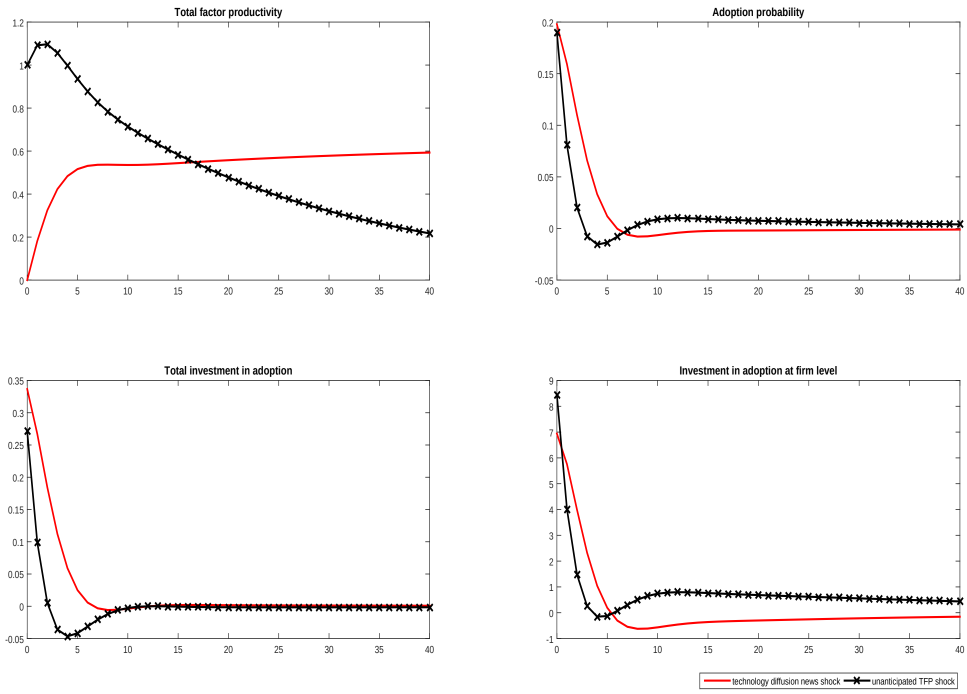

Figure 2.2: Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

Comin, Gertler, and Santacreu (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 a surprise productivity shock on adoption, which triggers the amplification of the response of TFP to the unanticipated shock. But as we illustrate in Figure 2.1, this is a much smaller effect than the one of a news shock, and hence cannot be used to explain the empirical evidence.

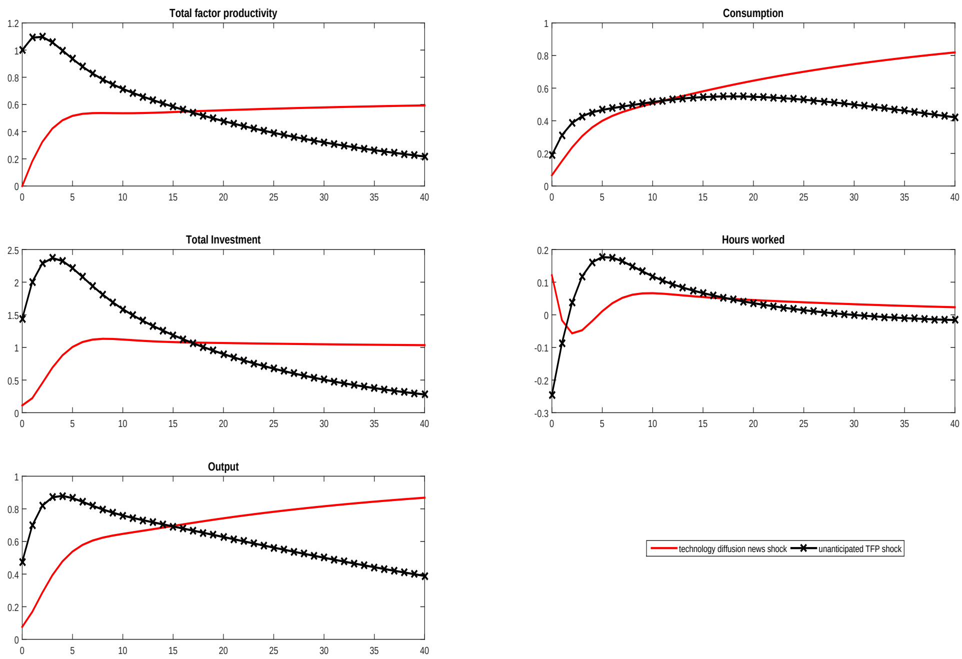

Figure 2.3: Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

In Figure 2.3 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 2.1. 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 surprise productivity shock on hours worked.

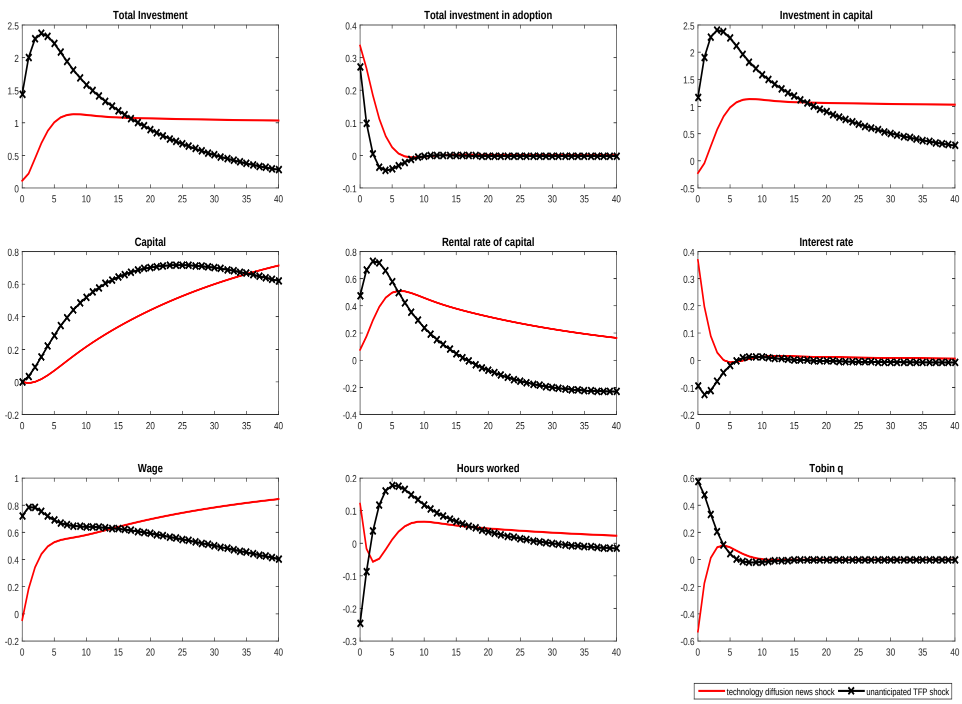

Figure 2.4: Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

In Figure 2.4 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.

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 2.3. 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 2.H.1, Appendix 2.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 2.H.2, Appendix 2.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

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

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 2.H.3, Appendix 2.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 4.6. The parameters that we estimate are $\varpi = [\tau,\ \kappa,\ \rho_\Gamma,\ s_z,\ \rho_x,\ s_x,\ \rho_b,\ s_b,\ \rho_\iota,\ s_\iota,\ \rho_G,\ s_G]$. The results of the estimation are presented in Table 2.1:

Table 2.1: 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)

From the results presented in Table 2.1, we can infer that some model parameters have to be adjusted in order for the impulse responses obtained with real data and those obtained

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

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 to have a bigger standard deviation (i.e. 0.016 as opposed to 0.01 in the benchmark calibration), while the surprise 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).

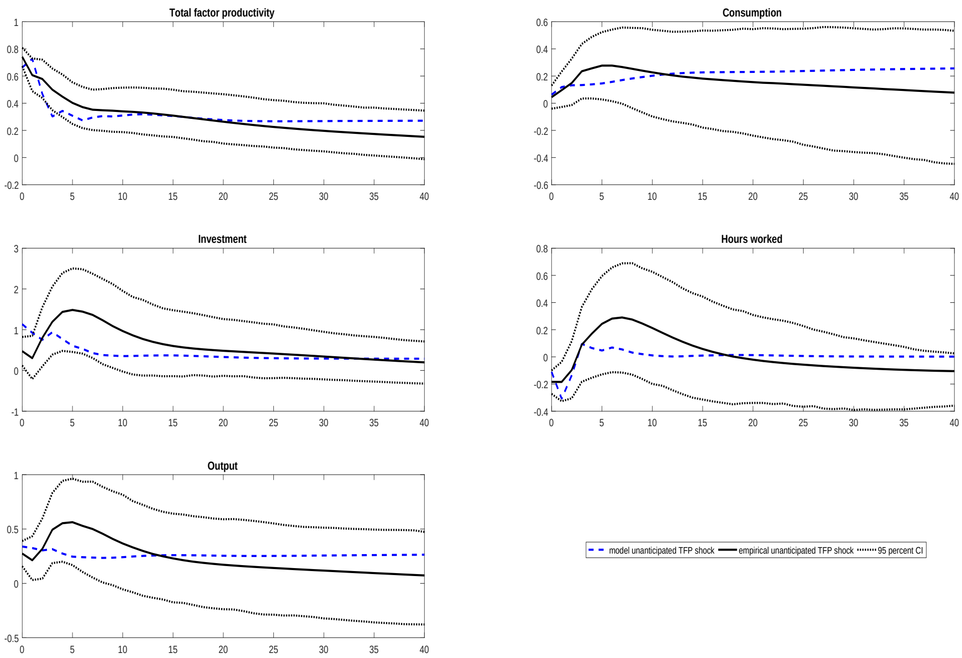

Figure 2.5: Impulse responses to an unanticipated productivity shock. The black line shows the responses to the unanticipated productivity shock in a VAR with real data, , while the dotted black lines correspond to the 95% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR. The blue dashed line gives the responses to the surprise 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.

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 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 a surprise 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.

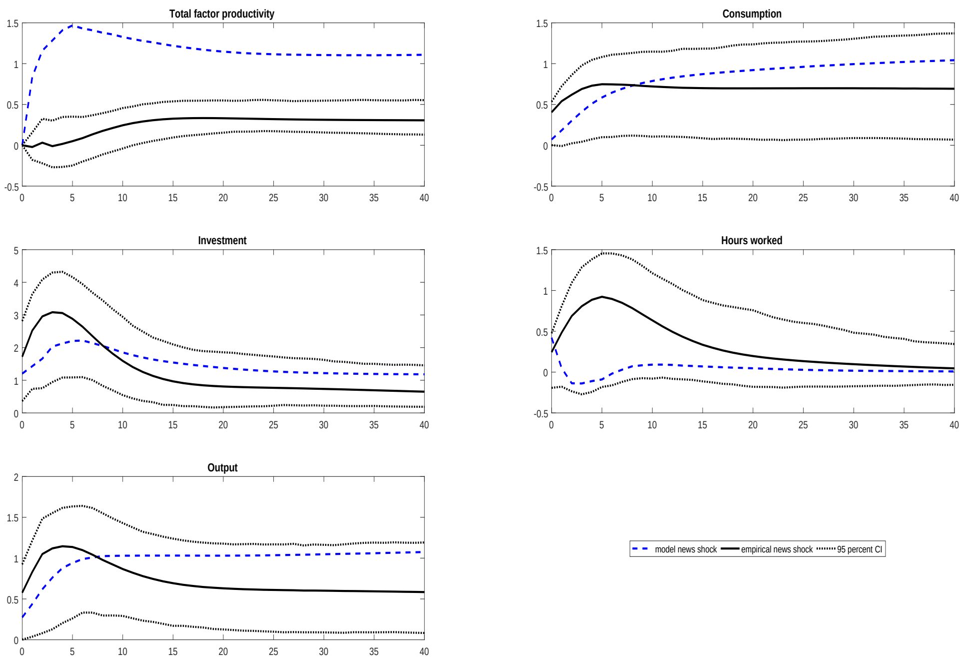

Figure 2.6: Impulse responses to a news shock. The black line shows the responses to the news shock in a VAR with real data, while the dotted black lines correspond to the 95% confidence interval from 1000 bias-corrected bootstrap replications of the reduced form VAR. The blue dashed line gives the responses 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.

The results reported in Figure 2.5 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

[42] The identification scheme is presented in Appendix 2.C.

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.

In Figure 2.6 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.

2.5 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

2.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, Fernald, and Kimball (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)

2.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 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 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, $k(k-1)/2$ additional restrictions on A are needed. In the following section we describe the identification schemes used in the empirical news literature.

2.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]

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

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

$$\Xi_{j,i}(h) = \frac{e_j' \left(\sum_{\tau=0}^{h} B_\tau \tilde{A} D e_i e_i' \tilde{D}' A' B_\tau' \right) e_j}{e_j' \left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau' \right) e_j} = \frac{\sum_{\tau=0}^{h} B_{j,\tau} \tilde{A} \gamma_2 \gamma_2' \tilde{A}' B_{j,\tau}'}{\sum_{\tau=0}^{h} B_{j,\tau} \Sigma B_{j,\tau}'}$$

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_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:

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

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.

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.

2.D Empirical Evidence

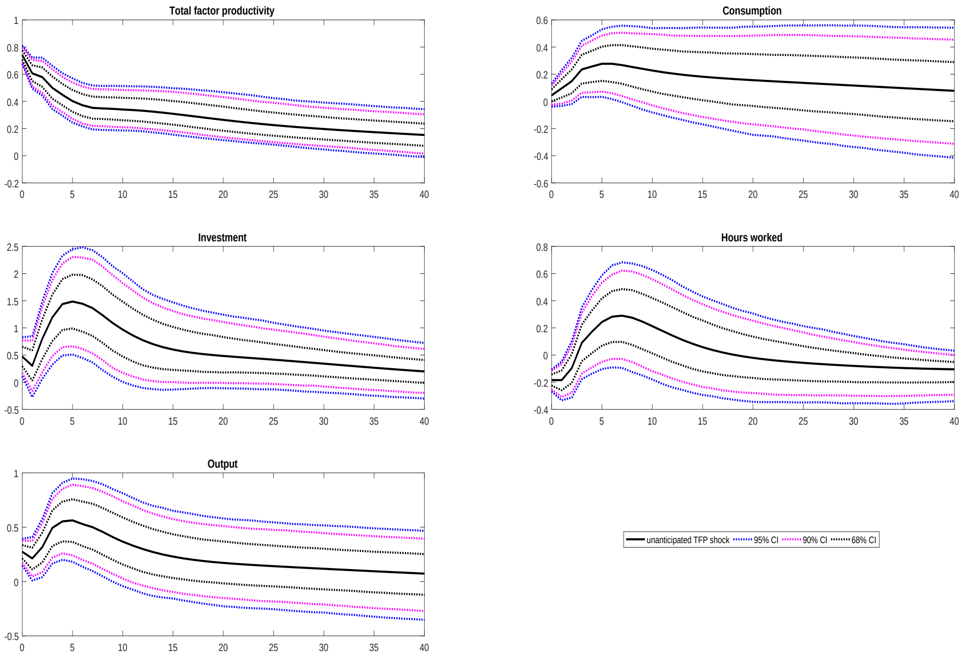

Figure 2.D.1: Impulse responses to an unanticipated productivity shock. The black line shows the responses to the unanticipated productivity shock. The dotted lines correspond to the 68%, 90%, and 95% confidence intervals. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

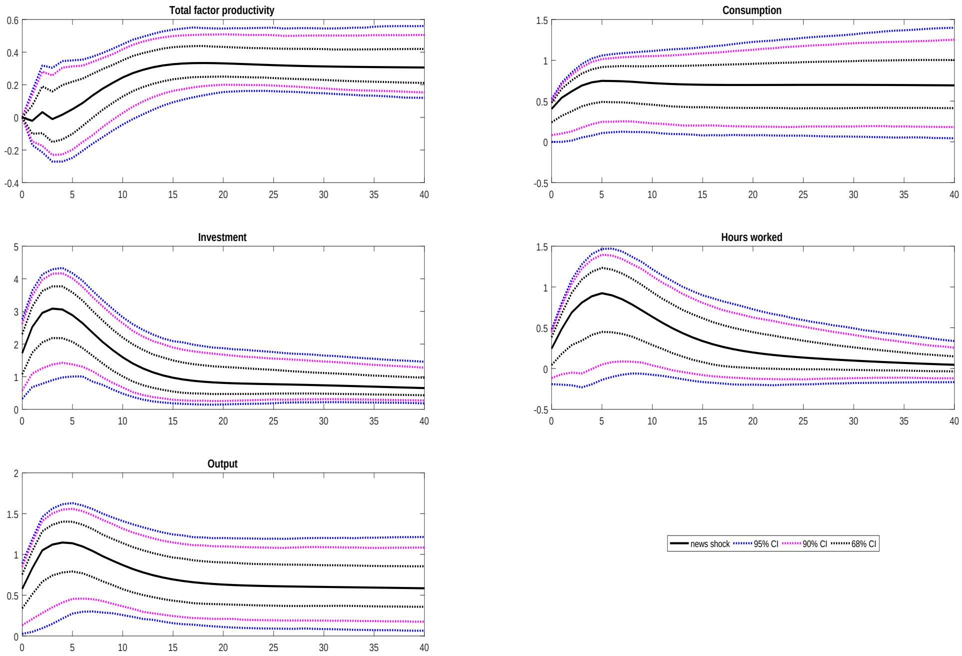

Figure 2.D.2: Impulse responses to a news shock. The black line shows the responses to the news shock. The dotted lines correspond to the 68%, 90%, and 95% confidence intervals. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

2.E Model with Exogenous Technology Diffusion

2.E.1 Model Equations

Production of Output

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

$$Y_t = A_t(u_t K_t)^{1-\alpha} L_t^{\alpha}, \tag{2.8}$$

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, Plosser, and Rebelo (1988), henceforth KPR, while when $\gamma = 0$ the preferences are of the type proposed by Greenwood, Hercowitz, and Huffman (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:

$$Y_t = C_t + I_t/b_t, \tag{2.9}$$

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 (2.8) and (2.9) gives the resource constraint:

$$C_t + I_t/b_t = A_t(u_t K_t)^{1-\alpha} L_t^{\alpha} \tag{2.10}$$

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), $\beta = 0.985, \alpha = 0.64, \gamma = 0.001, \varphi''(1) = 1.3, \delta''(u)u/\delta'(u) = 0.15$.

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

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 2.E.1, 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.

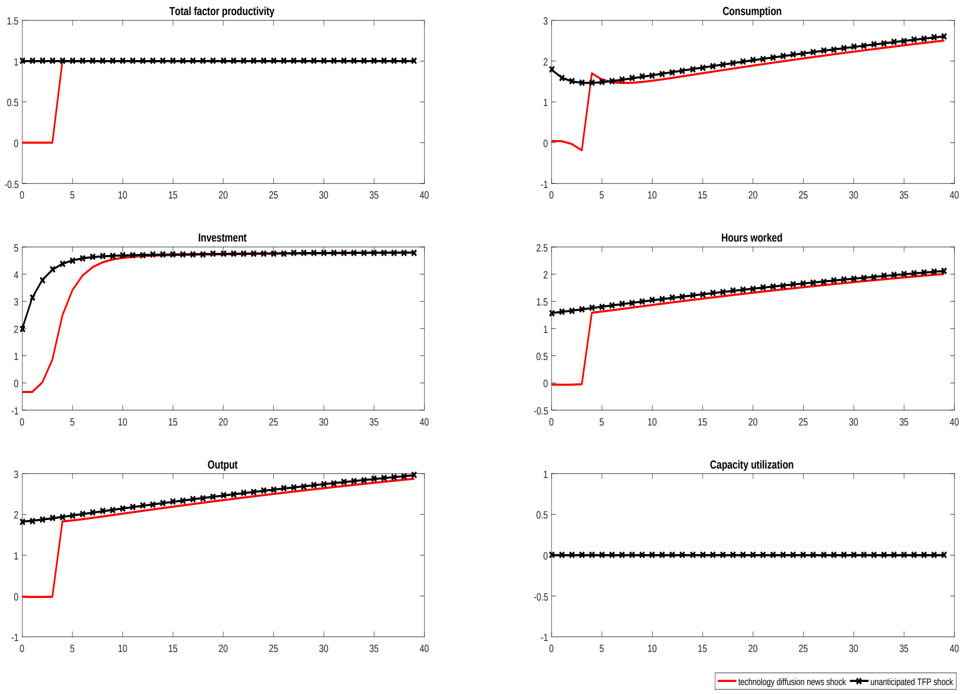

Figure 2.E.1: Impulse responses to a permanent unanticipated productivity shock and a news shock in a model with constant capacity utilization. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock.

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 2.E.3). 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.

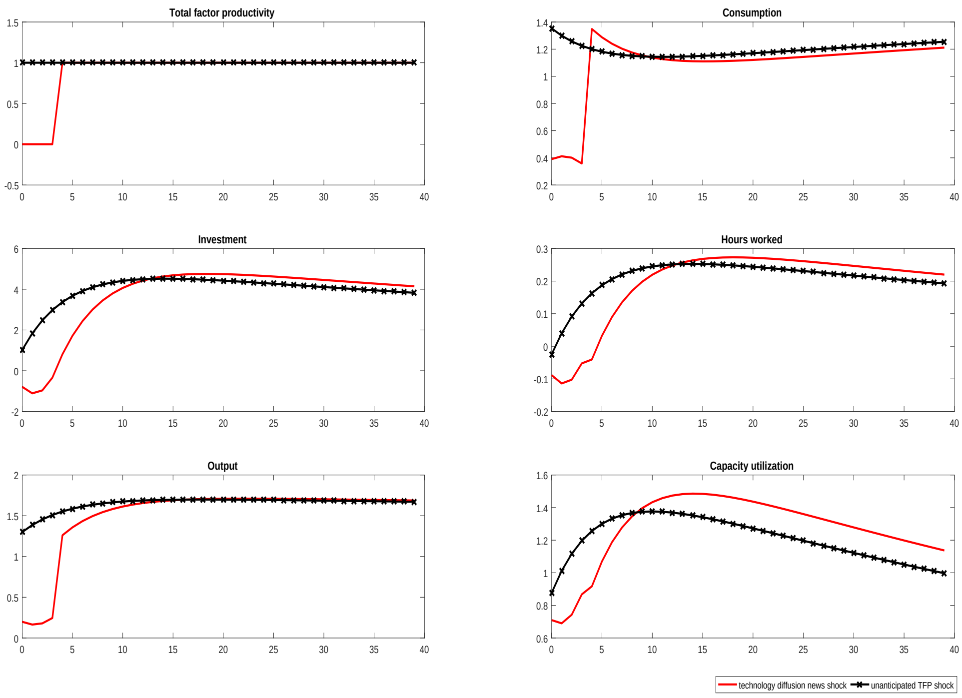

Figure 2.E.2: Impulse responses to a permanent unanticipated productivity shock and a news shock in a model with KPR preferences. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

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 2.E.2). 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.

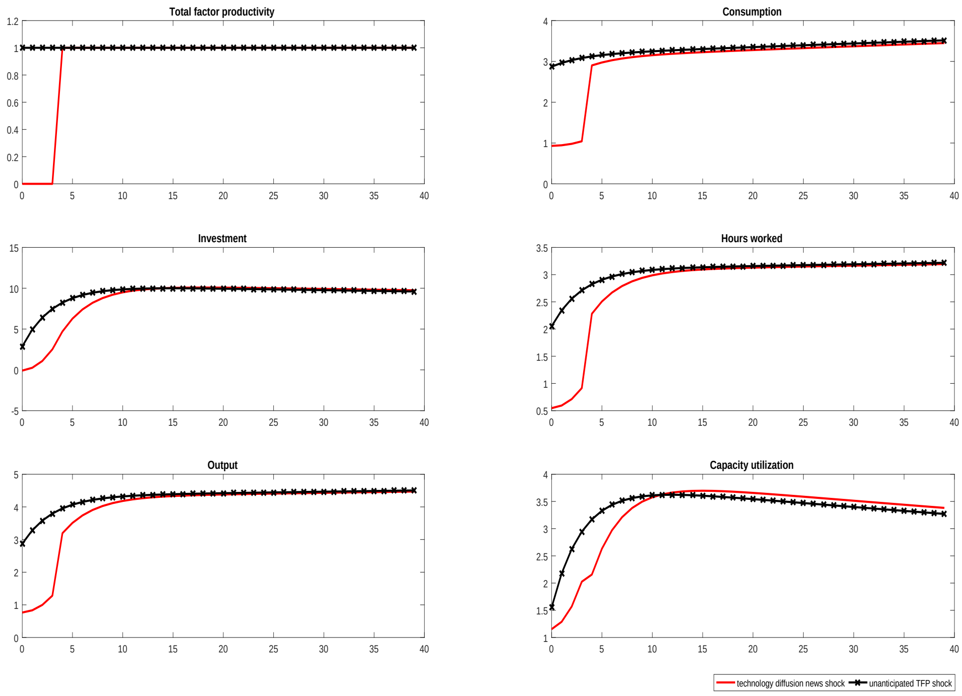

Figure 2.E.3: Impulse responses to a permanent unanticipated productivity shock and a news shock in a model with GHH preferences. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

Investment Adjustment Costs

As it can be observed in Figure 2.E.4, 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.

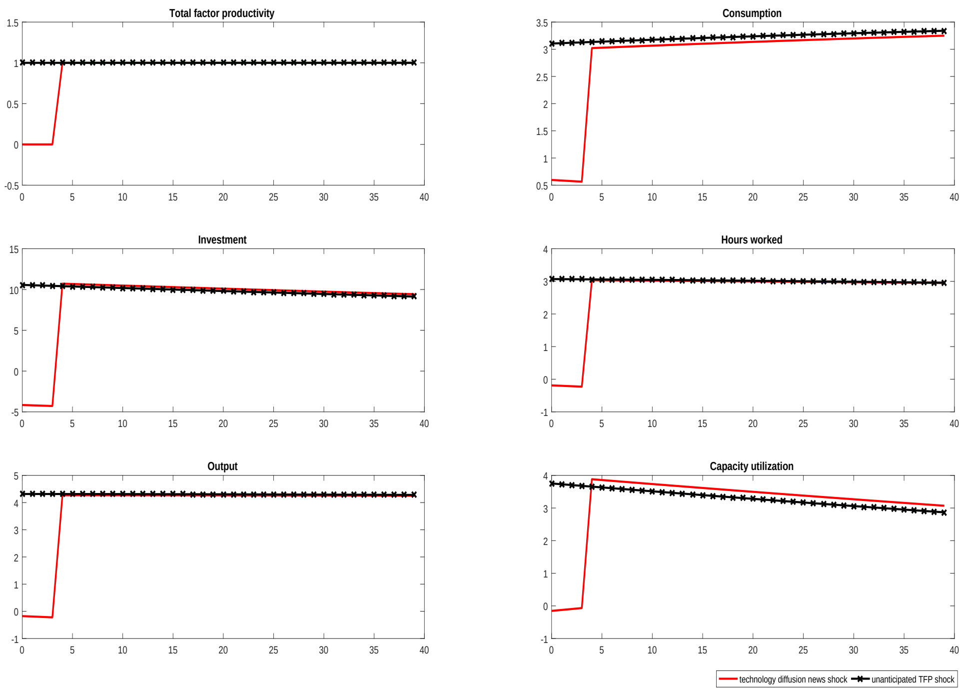

Figure 2.E.4: Impulse responses to a permanent unanticipated productivity shock and a news shock in a model without investment adjustment costs. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

2.E.3 Different Shock Processes

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

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

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 is the unanticipated productivity shock, and ε_t the news shock. Both are i.i.d standard normal shocks. 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:

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

2.F Model with Endogenous Technology Adoption

2.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:

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

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

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

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

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

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

2.F.2 Equilibrium

A competitive and symmetric equilibrium of the economy consists of a distribution of profits $\{f_t A_t\}_{t=0}^{\infty}$, allocations for output producing firms $\left\{K_t^d, L_t^d, Y_t\right\}_{t=0}^{\infty}$, for technology adopting firms $\left\{S_t^d\right\}_{t=0}^{\infty}$ and for the representative household $\left\{C_t, I_t, S_t^s, B_{t+1}, K_{t+1}^s, L_t^s\right\}_{t=0}^{\infty}$, and a price path $\left\{R_t, r_t^k, w_t\right\}_{t=0}^{\infty}$ 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 2.1 - 2.6; 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:

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

which is equivalent to:

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

and in real terms is:

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

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

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

We introduce this in the integrated household budget constraint:

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

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:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

2.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:

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

The resource constraint can be stationarized as it follows:

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

For the production function, we have:

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

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)

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

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}

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

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

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

Households' FOC wrt S_t

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

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

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

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

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

[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 $\varphi = \frac{\kappa}{2}\left(\frac{\tilde{I}_t}{\tilde{I}_{t-1}}z_t - \Delta_z\right)^2$.

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

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

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

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

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

2.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

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

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

Table 2.G.1: 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

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

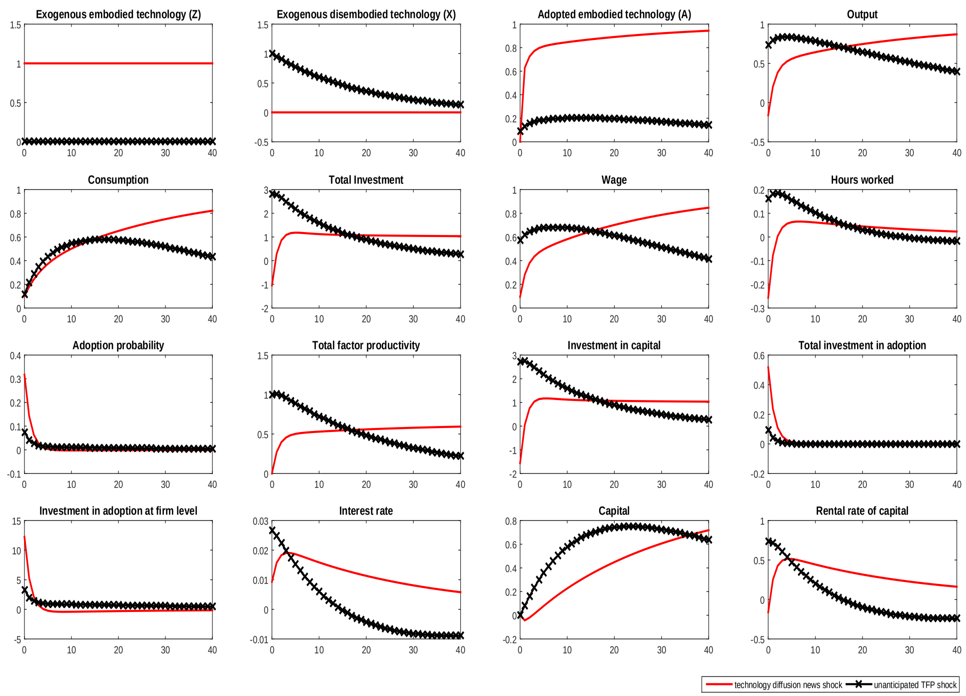

Figure 2.H.1: Model without investment adjustment costs. Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

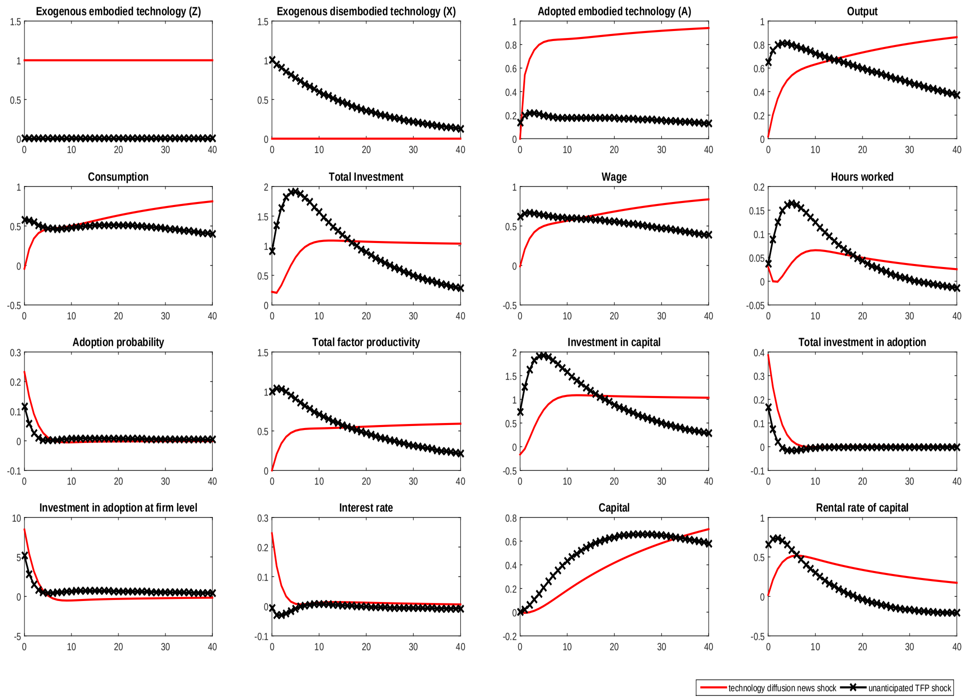

Figure 2.H.2: Model without habit persistence. Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

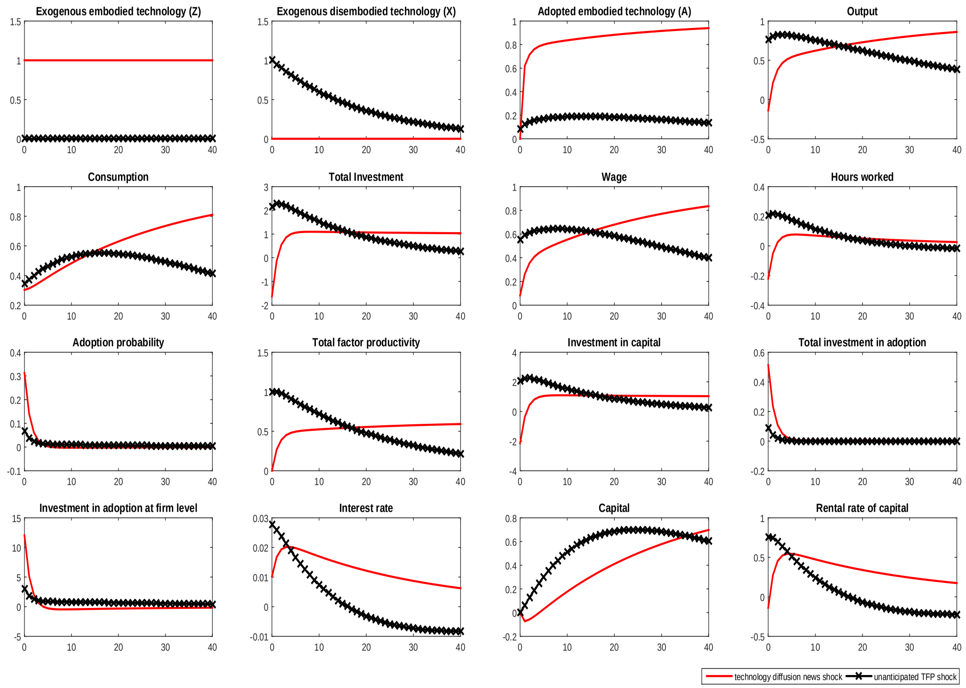

Figure 2.H.3: Model with no investment adjustment costs and no habit persistence. Impulse responses to an unanticipated productivity and technology diffusion news shock. The black starred line shows the responses to the unanticipated productivity shock, while the red line shows the responses to the news shock. The horizontal axes indicate the forecast horizons and the units of the vertical axes are percentage deviations.

Chapter 3

News Shocks: Different Effects in Boom and Recession?

Maria Bolboaca and Sarah Fischer

3.1 Introduction

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

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

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

Our main contribution to the news literature is to open the possibility that news have different effects in booms and recessions. To perform our empirical analysis, we proceed as follows. We estimate a five-variable logistic smooth transition vector autoregressive (LSTVAR) model including total factor productivity (TFP), consumer expectations, output, inflation and stock prices (SP). Our model builds on Auerbach and Gorodnichenko (2012) and Teräsvirta, Tjøstheim, and Granger (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

[1] Details are provided in Appendix 3.A.1.

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

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

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

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

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

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

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

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

3.2 Empirical Approach

We employ a five-dimensional LSTVAR model in levels.[5] We work with quarterly data for the U.S. economy from 1955Q1 to 2012Q4. Our benchmark system contains five variables in the following order: TFP adjusted for variations in factor utilization, University of Michigan index of consumer sentiment (ICS), real output, inflation and stock prices (details are provided in appendix 3.A.2).

According to van Dijk, Teräsvirta, and Franses (2002), a smooth transition model

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

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

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

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.

3.2.1 Model Specification

Formally, the LSTVAR model of order p reads:

$$Y_t = \Pi_1' X_t (1 - F(\gamma_F, c_F; s_{t-1})) + \Pi_2' X_t F(\gamma_F, c_F; s_{t-1}) + \epsilon_t, \tag{3.1}$$

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,

$$F(\gamma_F, c_F; s_t) = exp\left(-\gamma_F(s_t - c_F)\right) \left[1 + exp\left(-\gamma_F(s_t - c_F)\right)\right]^{-1}, \ \gamma_F > 0, \tag{3.2}$$

where γ_F is called slope or smoothness parameter, and c_F is a location parameter determining the middle point of the transition ($F(\gamma_F, c_F; c_F) = 1/2$). Therefore, it can be interpreted as the threshold between the two regimes as the logistic function changes monotonically from 0 to 1 when the transition variable decreases. Every period, the transition function attaches some probability to being in each regime given the value of the transition variable s_t. $\epsilon_t \sim N(0, \Sigma_t)$ is an m-dimensional reduced-form shock with mean zero and positive definite variance-covariance matrix, Σ_t. We allow the variance-covariance matrix to be regime-dependent:[6]

$$\Sigma_t = (1 - G(\gamma_G, c_G; s_{t-1}))\Sigma_1 + G(\gamma_G, c_G; s_{t-1})\Sigma_2 \tag{3.3}$$

The transition between regimes in the second moment is also governed by a logistic transition function $G(\gamma_G, c_G; s_{t-1})$. We want to allow not only for dynamic differences in the propagation of structural shocks through Π_1 and Π_2 but also for contemporaneous differences via the two covariance matrices, Σ_1 and Σ_2. This method is similar to the one employed in Auerbach and Gorodnichenko (2012),[7] but we depart from their approach by letting the parameters of the transition function in the variance equation to differ from the parameters in the mean equation.

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

$$Y_t = \Pi' X_t + \epsilon_t, \tag{3.4}$$

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

[6] In Appendix 3.B.4 we describe the test for the constancy of the error covariance matrix. In our case, the null hypothesis of a constant error covariance matrix is rejected. The results may be provided by the authors. The test applies to models using stationary data, and its results in our case may not be correct given that the distribution of the test statistic is not the same.

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

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

For our model, the transition variable needs to follow the business cycle and clearly identify expansionary and recessionary periods. The NBER defines a recession as 'a period of falling economic activity spread across the economy, lasting more than a few months, normally visible in real GDP, real income, employment, industrial production, and wholesale-retail sales'. This makes the identification of a recession a complex process based on weighing the behavior of various indicators of economic activity. One possibility is to use as transition variable the NBER based recession index,[8] which equals one if a quarter is defined by the NBER as recession, and zero otherwise. But having an exogenous variable as switching variable makes it impossible to investigate the effects of shocks on the transition from one state of the economy to the other. For this reason, we follow the common rule of thumb which defines a recession as two consecutive quarters of negative GDP growth, and use as transition variable a lagged three quarter moving average of the quarter-on-quarter real GDP. This choice of the transition variable is close to the one used in Auerbach and Gorodnichenko (2012), as they set s_t to be a seven quarter moving average of the realizations of the quarter-on-quarter real GDP growth rate, centered at time t. We depart from their approach in the sense that we do not assume the transition variable to be exogenous, but we define it as a function of a lagged endogenous variable, output. In order to avoid endogeneity problems, the transition functions F and G at date t are based on $s_{t-1} = \frac{1}{3}(g^Y_{t-1} + g^Y_{t-2} + g^Y_{t-3})$, g^Y_t being the growth rate of output. By endogenizing the transition variable, we are able to analyze how shocks coming in a recession, for example, influence the chances of the economy to recover or to continue staying in that state.

The LSTVAR model is only indicated if linearity can be rejected. We tested linearity against the alternative of a nonlinear model, given the transition variable. We reject the null hypothesis of linearity at all significance levels, regardless of the type of LM test we perform (for details, see Appendix 3.B.1).[9]

3.2.3 Estimation

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

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

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

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

$$log\ L = const + \frac{1}{2}\sum_{t=1}^{T}\log|\Sigma_t| - \frac{1}{2}\sum_{t=1}^{T}\epsilon_t'\Sigma_t^{-1}\epsilon_t, \tag{3.5}$$

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

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

$$\hat{\Psi} = \arg\min_{\Psi}\sum_{t=1}^{T}\epsilon_t'\Sigma_t^{-1}\epsilon_t \tag{3.6}$$

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 (3.6) can be rewritten as:

$$\hat{\Psi} = \arg\min_{\Psi}\sum_{t=1}^{T}(Y_t - \Pi' Z_t(\gamma_F, c_F))'\Sigma_t^{-1}(Y_t - \Pi' Z_t(\gamma_F, c_F)) \tag{3.7}$$

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:

$$\sum_{t=1}^{T}(Z_t(\gamma_F, c_F)Y_t'\Sigma_t^{-1} - Z_t(\gamma_F, c_F)Z_t(\gamma_F, c_F)'\Pi\Sigma_t^{-1}) = 0 \tag{3.8}$$

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

$$vec(\hat{\Pi}) = \left[\sum_{t=1}^{T}\left(\Sigma_t^{-1}\otimes Z_t(\gamma_F, c_F)Z_t(\gamma_F, c_F)'\right)\right]^{-1} vec\left[\sum_{t=1}^{T}\left(Z_t(\gamma_F, c_F)Y_t'\Sigma_t^{-1}\right)\right], \tag{3.9}$$

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', $\Psi_l =$

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

$\{\Pi_1, \Pi_2\}$. To ensure that Σ_1, and Σ_2 are positive definite matrices, we redefine Ψ_n as $\{\gamma_F, c_F, \gamma_G, c_G, chol(\Sigma_1), chol(\Sigma_2)\}$, where *chol* is the operator for the Cholesky decomposition.

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

3.2.4 Starting Values

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

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

$$P(Rec_t = 1 \mid s_{t-1}) = \frac{exp\left[-\gamma(s_{t-1} - c)\right]}{1 + exp\left[-\gamma(s_{t-1} - c)\right]} \tag{3.10}$$

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 3.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, Castelnuovo, and Groshenny (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

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

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

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 3.B.2).

The transition function with $\gamma = 3.12$ and $c = -0.48$, is shown in Figure 3.B.1. 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 3.B.3.

3.2.5 Evaluation

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

Yang (2014) proposes a test for the constancy of the error covariance matrix applicable to smooth transition vector autoregressive models. To test for constancy of the error covariance matrix, first, the model has to be estimated under the null hypothesis assuming the error covariance matrix to be constant over time. Similar to the linearity test for the dynamic parameters, the alternative hypothesis is approximated by a third-order Taylor approximation given the transition variable. In our case, the null hypothesis of a constant error covariance matrix is clearly rejected (for details, see Appendix 3.B.4).[14]

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

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

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

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

(2004).[15] Innovations are orthogonalized, for example, by applying the Cholesky decomposition to the covariance matrix of the residuals $\Sigma = \tilde{A}\tilde{A}'$, assuming there is a linear mapping between the innovations and the structural shocks. The unanticipated productivity shock is the only shock affecting TFP on impact. The news shock is then identified as the shock that has no impact effect on TFP and that, in adition to the unanticipated productivity shock, influences TFP the most in the medium-run. More precisely, it is the shock which explains the largest share of the TFP's FEV at some specified horizon H. We set H equal to 40 quarters (i.e. 10 years). We choose this specific horizon as we believe that shorter horizons are prone to ignore news on important and large technological innovations that need at least a decade to seriously influence total factor productivity. On the other hand, longer horizons might ignore shorter-run news as they only consider news shocks that turn out to be true in the long-run.[16] We define the entire space of permissible impact matrices as $\tilde{A}D$, where D is a $m \times m$ orthonormal rotation matrix ($DD' = I$).[17]

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

$$Y_{t+h} - \mathbb{P}_{t-1}Y_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A} D u_{t+h-\tau} \tag{3.11}$$

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

$$\Xi_{j,i}(h) = \frac{e_j'\left(\sum_{\tau=0}^{h} B_\tau \tilde{A} D e_i e_i' \tilde{D}' A' B_\tau'\right) e_j}{e_j'\left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau'\right) e_j} = \frac{\sum_{\tau=0}^{h} B_{j,\tau} \tilde{A} \gamma \gamma' \tilde{A}' B_{j,\tau}'}{\sum_{\tau=0}^{h} B_{j,\tau} \Sigma B_{j,\tau}'} \tag{3.12}$$

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

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

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

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

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

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

The calculation of the FEV decomposition depends on the estimation of GIRFs, which are history dependent and constructed as an average over simulated trajectories. If traditional methods are used, in general, the shares do not add to one which makes it unclear what is identified as the news shock. We use instead a method of estimating the generalized forecast error variance decomposition (GFEV) for which the shares sum to one by construction. Using this approach is the closest we can get to the application of the medium-run identification scheme. A detailed presentation of the procedure can be found in Appendix 3.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 3.C.1.

3.2.7 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,

[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 $F(\gamma_F, c_F; s_t) > 0.8$.

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 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, Pesaran, and Potter (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:

$$Y_t^{sim} = \Pi_1' X_t^{sim}(1 - F(\gamma_F, c_F; s_{t-1})) + \Pi_2' X_t^{sim} F(\gamma_F, c_F; s_{t-1}) + e_t, \tag{3.13}$$

and for $h \geq 1$:

$$Y_{t+h}^{sim} = \Pi_1' X_{t+h}^{sim}(1 - F(\gamma_F, c_F; s_{t+h-1})) + \Pi_2' X_{t+h}^{sim} F(\gamma_F, c_F; s_{t+h-1}) + \epsilon_{t+h} \tag{3.14}$$

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.

[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. (2014) is the only paper to endogenize the transition function.

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 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 3.C.

3.2.8 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 (2014) 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:

$$\lambda_{j,i,\Omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})_j^2}{\sum_{i=1}^{K}\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})_j^2} \tag{3.15}$$

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 3.C.4.

3.3 Results

3.3.1 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.

[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, Stock, and Watson (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.

We apply the three identification schemes to isolate structural shocks. In Figure 3.D.1, Appendix 3.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 in Figure 3.D.2, Appendix 3.D, show that both identified shocks trigger a strong positive comovement of the real economy, while TFP only starts increasing after some quarters. This result also indicates that a confidence shock resembles very much a news shock.

Under the two identification schemes, TFP is not allowed to change on impact but it is important to note that there is neither a significant rise above zero for the first two years. After that, TFP starts increasing in both cases until it stabilizes at a new permanent level, which is slightly higher under MRI. This result is in line with those found in Beaudry and Portier (2006) and Beaudry, Nam, and Wang (2011). The index of consumer sentiment rises significantly on impact in both settings. This finding is consistent with those of Beaudry, Nam, and Wang (2011) who use the same confidence indicator. 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, Nam, and Wang (2011). Stock prices rise on impact to the same level in both cases, but while under SRI the response resembles the one in Barsky and Sims (2011), under MRI stock prices continue increasing for a long time, reaching a peak after about twenty quarters.

In Figure 3.D.3, Appendix 3.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, Nam, and Wang (2011). Both consumption and hours worked rise on impact, and while the response of hours worked is hump-shaped, the effect on consumption is permanent. The response of consumption is slightly bigger under MRI, while the opposite holds for hours worked. 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, Nam, and Wang (2011) that all predictable and permanent increases in TFP are preceded by a boom period, and all positive news shocks are followed by an eventual rise in TFP. After the realization of a positive news shock we find an impact and then gradual increase in output, the survey measure of consumer confidence, stock prices, hours worked, and consumption, and a decline in inflation while TFP only follows some quarters later. According to Beaudry, Nam, and Wang (2011), the period until TFP starts increasing can be defined as a non-inflationary boom phase without an increase in productivity.

3.3.2 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 3.E.1, Appendix 3.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 3.E.2 in Appendix 3.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 3.1 we display for each variable the share of the (generalized) FEV attributable to the news shock at different horizons in the two regimes of the STVAR model and in the linear VAR model. The numbers are percentage values. Not surprisingly, the contributions of the news shock are very close in expansions to those in the linear model since more than 85 percent of the periods contained in our sample are defined as normal times. These results are reassuring since they indicate that the two methods for computing the variance decomposition give similar results. The only bigger difference is the contribution of the news shock to the variance decomposition of TFP in expansions. In this case the news shock accounts for a bigger share in the FEV of TFP both at high and lower frequencies.

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

Table 3.1: Generalized Forecast Error Variance Decomposition for the news shock (MRI). The numbers indicate the percent of the forecast error variance of each variable at various forecast horizons explained by the news shock in expansions, recessions, and the linear model.

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

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

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

In Table 3.E.1, Appendix 3.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 3.E.2, Appendix 3.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, Ramey, and Zubairy (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 3.1 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 belonging to this regime, it is clear that the much smaller number of recessionary periods in the sample matters.[25]

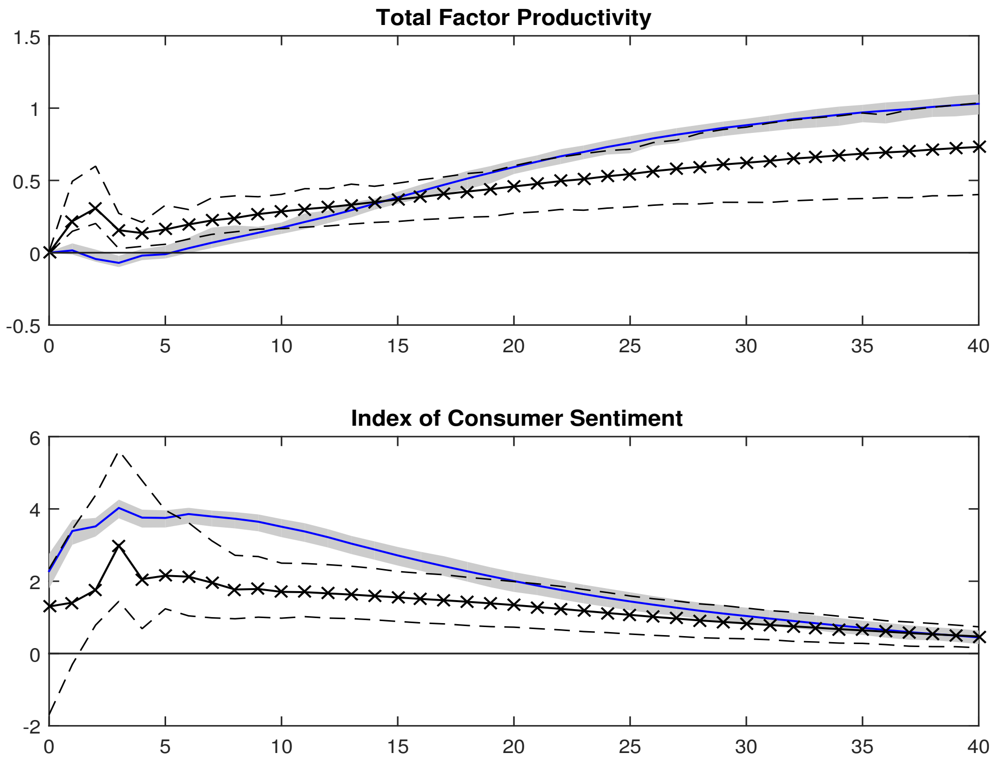

Figure 3.1: Generalized impulse response functions to a positive small news shock under MRI. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while 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.

[25] For details about the computation of GIRFs and their confidence bands, see Appendix 3.C.

The impulse responses of the other three variables of the model, output, inflation and stock prices to a one standard deviation news shock obtained with the MRI scheme are displayed in Figure 3.2. Similarly to the responses of TFP and ICS, the responses are qualitatively similar, but there are quantitative differences. Inflation drops significantly in both states of the economy, more in recessions, but the state-dependency in responses fades away fast. Stock prices respond positively to the news shock. The reaction in recessions is bigger but the impact difference is not significant. At a horizon of two to five years, the effect of the news on stock prices seems to be larger in expansions. A peculiar finding is the response of output to the news. In expansion, we have clear evidence of a positive effect of the news shock on output. On the other side, in a recession the impact effect is unclear, and not significantly different from zero for at least one year. After some time output starts increasing but stabilizes at a lower permanent level than following a news shock occurring in an expansion.

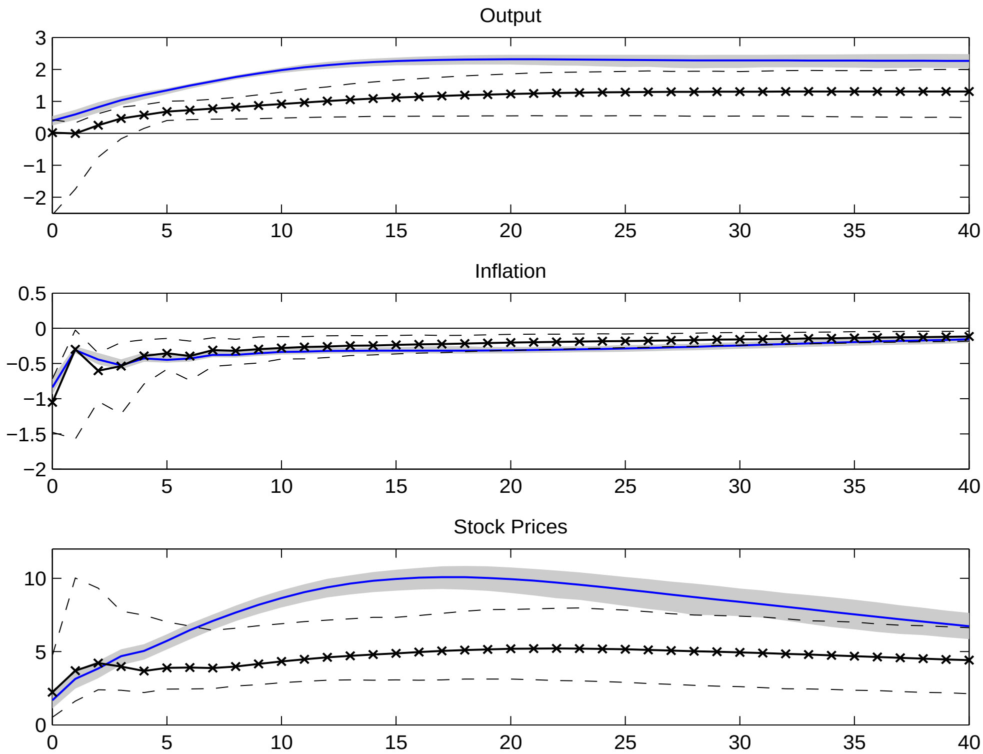

Figure 3.2: Generalized impulse response functions to a positive small news shock under MRI. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage deviation from the case without the shock, and the unit of the horizontal axis is quarters.

In Figure 3.E.5, Appendix 3.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 statistically significant.

As a next step, we compare the results obtained for the news shock with those for the confidence shock, under the SRI scheme (as showed in Figure 3.E.3 from Appendix 3.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 news shock.

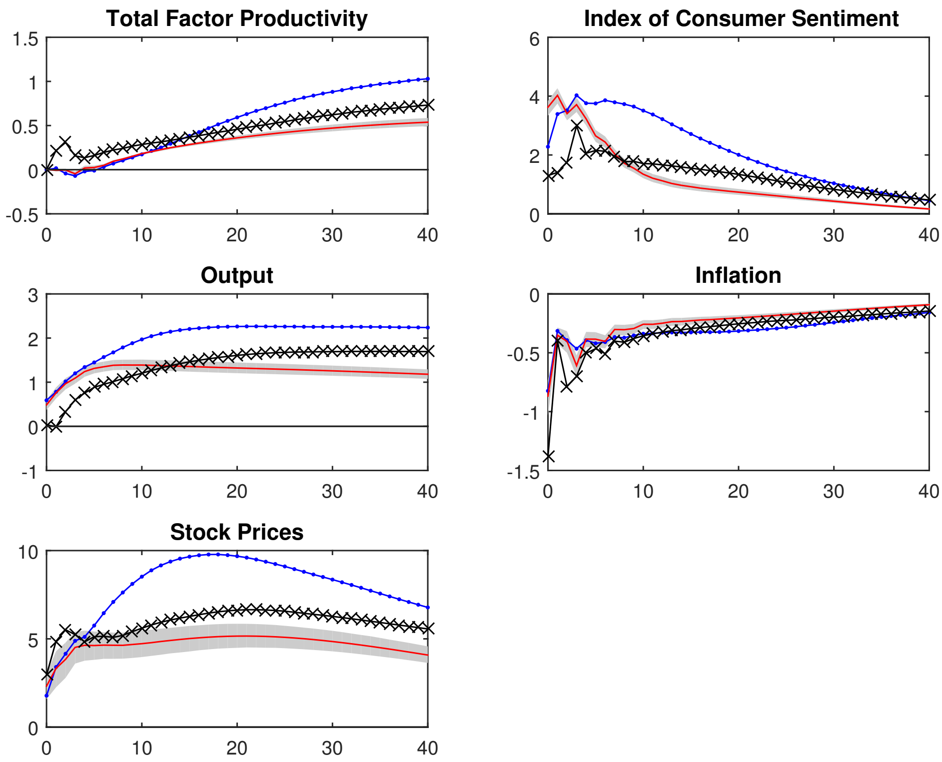

Figure 3.3: Comparison of the state-independent and the state-dependent effect of the news shock (under MRI). The figure displays the generalized impulse response functions to a positive small news shock in an expansion as the blue dotted line, the generalized impulse response functions to a positive 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.

When comparing the GIRFs to the responses obtained in the linear setting, as displayed in Figure 3.3, we observe a strong similarity, apparent mainly in the short-run, between the responses in expansion and in the linear model. However, on the medium-run, it is evident that the responses to the news shock are stronger in expansions. Therefore, using a linear model to show the effects of news shocks in normal times may underestimate their value. We find that the news shock has in expansion a much bigger effect on output than the linear model would predict, output stabilizing at a twice as high new permanent level in the expansionary regime. Similar conclusions can be drawn for TFP. Moreover, there is a temporary overreaction of stock prices to the news in expansion, which the linear model misses.

On the contrary, using the impulse responses from a linear model to show the effects of a news shock in recessions may determine an overestimation of its value. As it can be seen in Figure 3.3, 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 3.E.4, Appendix 3.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.

The results in Figure 3.4 and Figure 3.5 present the change in the probability of switching from one regime to the other starting one year after a news shock happened. We ignore the effect on the probability of switching for the first four quarters since the results are influenced by the starting values. Because our model features four lags, for the first four simulation periods the probability of switching depends on real data.

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

As shown in Figure 3.4, when the economy is in expansion, a positive small news shock reduces the probability of a transition to recession by approximately four percentage points after one year. A shock three times larger is not increasing this probability by much. When a big positive news shock hits the economy during normal times, the probability of going into a recession is reduced by almost six percentage points after one year. An interesting finding is the effect of the positive news shock on the transition probability after five years. Although in the short-run the news shock seems to keep the economy booming, in the medium-run, once the improvements in productivity become apparent (i.e. TFP starts increasing), agents may acknowledge that they have overrated the future evolution of the economy and start behaving accordingly. This behavior then generates a bust, as the probability of moving from an expansion to a recession increases. This result confirms the findings of Beaudry and Portier (2006) that booms and busts can be caused by news shocks and no technological regress is needed for the economy to fall into a recession.

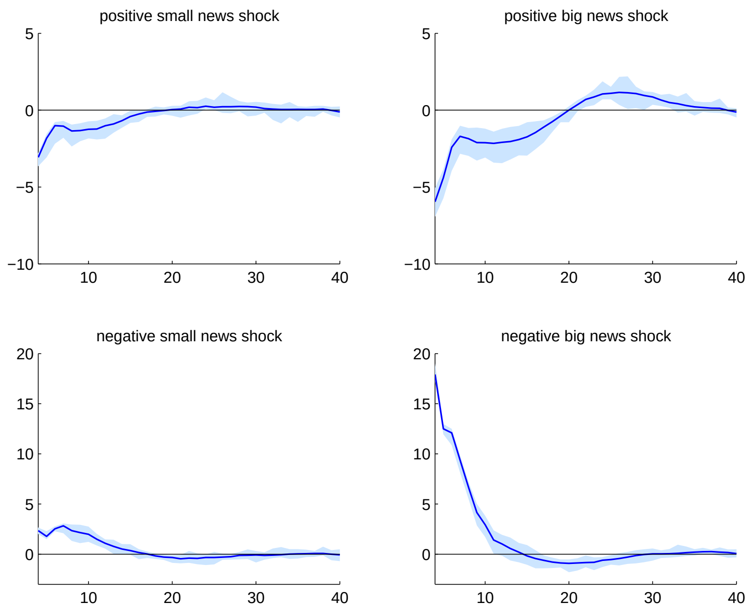

Figure 3.4: Regime transition probability change following a news shock. The four figures display the change in the probability of switching from an expansion to a recession starting one year after a news shock occurred. The blue line shows the behavior following a news shock obtained with MRI, while the shaded light blue area represents the 95% bias-corrected confidence interval. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage points, and the unit of the horizontal axis is quarter.

In Figure 3.5, we observe that, if the economy is in a recession, a small positive news shock increases the probability of transitioning into an expansion by almost five percentage points after four quarters. If the shock is three times bigger, the probability of a regime switch increases by about eight percentage points after four quarters. It does not seem to be a reversal in the medium-run, once TFP increases, as it was the case in booms. Negative news shocks increase the probability of staying in a recession, but their effect is not as strong as when they hit in an expansion.

By comparing the two figures, we conclude that positive news shock are more effective in recessions than in expansions, leading to a twice as large increase in the probability of regime transition. On the other hand, negative news in booms ncrease more the probability of going in a recession than the one of going in an expansion of positive news in recession. The intuition for this result is found in Van Nieuwerburgh and Veldkamp (2006). The authors argue that in a recession, uncertainty delays the recovery and makes booms more gradual than downturns.

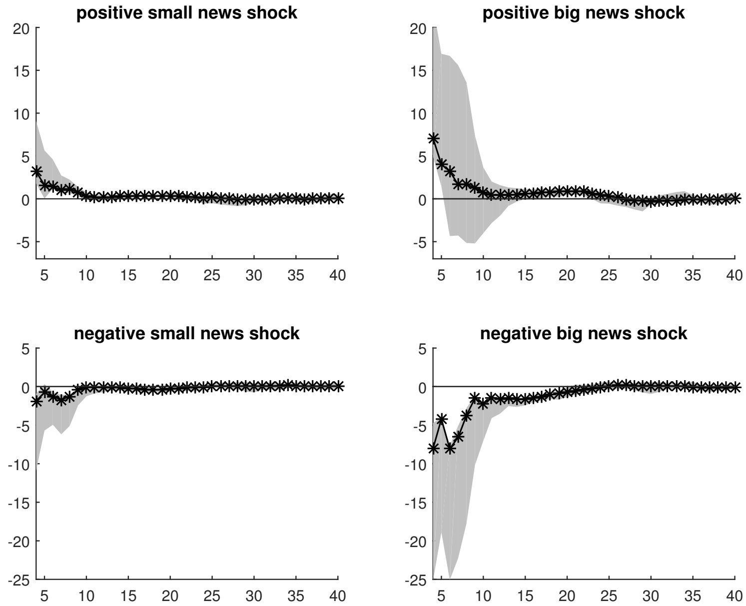

Figure 3.5: Regime transition probability change following a news shock. The four figures display the change in the probability of switching from a recession to an expansion starting one year after a news shock occurred. The starred black line shows the behavior following a news shock obtained with MRI, while the shaded light grey area represents the 95% bias-corrected confidence interval. The confidence bands indicate the 5th and the 95th percentile of 1,000 MCMC draws. The unit of the vertical axis is percentage points, and the unit of the horizontal axis is quarter.

3.4 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

3.A Data

3.A.1 Descriptive Statistics

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

Table 3.A.1: 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)

3.A.2 Details on Data Used in Benchmark Model

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

Our benchmark system contains five variables: TFP adjusted for variations in factor utilization, index of consumer sentiment, real output, inflation and stock prices. Total factor productivity is a measure of productivity in the economy whereas stock prices represents a forward-looking variable which contains information about technological innovations. The consumer sentiment index is another forward-looking variable that contains information about the expectations of consumers and producers. Output includes information about the state of the economy. By including inflation we take care of the nominal side of the economy and add another forward-looking variable. By adding these three forward-looking variables, we believe that we encompass enough information to identify the news shock. For robustness checks in the linear setting, we additionally include consumption and hours worked.

We use the series of TFP adjusted for variations in factor utilization constructed with the method of Fernald (2014) based on Basu et al. (2013) and Basu, Fernald, and Kimball (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$\sharp$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.

3.B Estimation of LSTVAR

3.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 (3.1):

$$H_0 : \qquad \Pi_1 = \Pi_2, \tag{3.16}$$

$$H_1 : \qquad \Pi_{1,j} \neq \Pi_{2,j}, \text{ for at least one } j \in \{0, ..., p\}. \tag{3.17}$$

As explained in Teräsvirta, Tjøstheim, and Granger (2010) and van Dijk, Teräsvirta, and Franses (2002), the testing of linearity is affected by the presence of unidentified nuisance parameters under the null hypothesis, meaning that the null hypothesis does not restrict the parameters in the transition function (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, Saikkonen, and Teräsvirta (1988), is to replace the logistic transition function, $F(\gamma_F, c_F; s_{t-1})$, by a suitable n-order Taylor series approximation around the null hypothesis $\gamma_F = 0$.

The LSTVAR model in equation (3.2) can be rewritten as:

$$Y_t = \Pi_1' X_t + (\Pi_2 - \Pi_1)' X_t F_{t-1} + \epsilon_t, \tag{3.18}$$

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

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

[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.

$$Y_t = \theta_0' X_t + \theta_1' X_t s_{t-1} + \theta_2' X_t s_{t-1}^2 + \theta_3' X_t s_{t-1}^3 + \epsilon_t^* \tag{3.19}$$

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

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

Denoting $Y = (Y_1, ..., Y_T)'$, $X = (X_1, ..., X_T)'$, $E = (\epsilon_1^*, ..., \epsilon_T^*)'$, $\Theta_n = (\theta_1', ..., \theta_n')'$, and

$$Z_n = \begin{pmatrix} X_1' s_0 & X_1' s_0^2 & \cdots & X_1' s_0^n \\ X_2' s_1 & X_2' s_1^2 & \cdots & X_2' s_1^n \\ \vdots & \vdots & \ddots & \vdots \\ X_T' s_{T-1} & X_T' s_{T-1}^2 & \cdots & X_T' s_{T-1}^n \end{pmatrix}, \tag{3.20}$$

we can write equation (3.19) in matrix form:

$$Y = X\theta_0 + Z_n \Theta_n + E. \tag{3.21}$$

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:

$$LM_{\chi^2} = T(m - tr\left\{SSR_0^{-1} SSR_1\right\}) \tag{3.22}$$

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

$$LM_F = \frac{mT - K}{JmT} LM_{\chi^2}, \tag{3.23}$$

   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 $K = (n+1)(p+1)$.

3.B.2 Estimation Results of Logistic Model

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

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

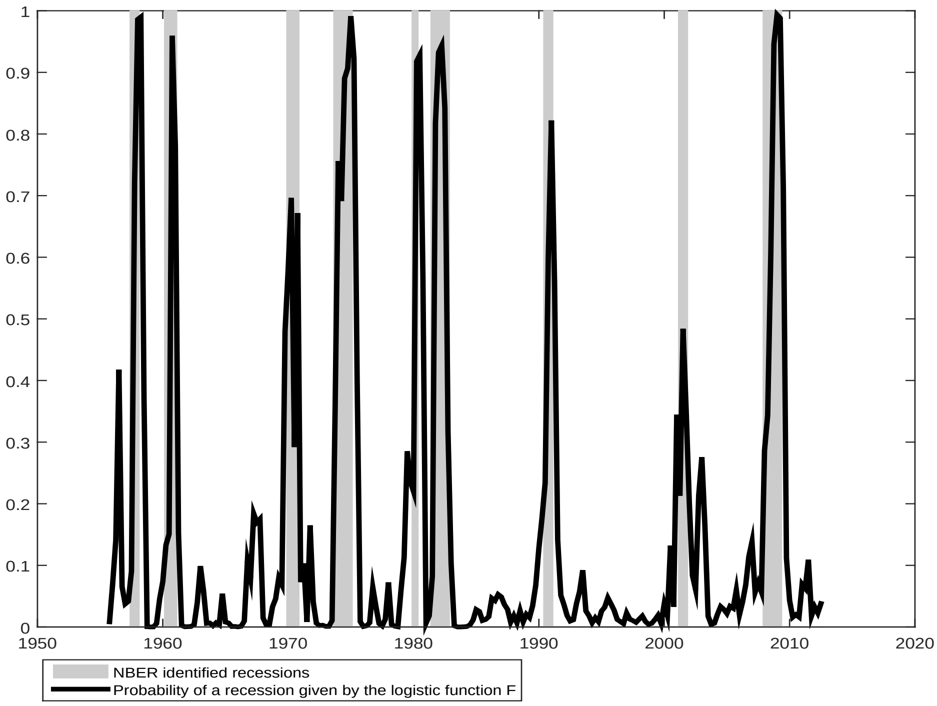

Figure 3.B.1: Initial transition function with estimated parameters obtained from a logistic regression

3.B.3 MCMC Procedure - MH Algorithm

Our approach is, given the quasi-posterior densitiy $p(\Psi_n) \propto e^{L(\Psi_n)}$,[29] known up to a constant, and a pre-specified candidate-generating (or proposal) density $q(\Psi'_n \mid \Psi_n)$, to construct chains of length N, $(\Psi_n^0, ..., \Psi_n^N)$. We follow the steps:

1. Choose intial parameter value Ψ_n^0.

2. For $j = 1, ..., N$:

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

(a) Generate Ψ'_n from $q(\Psi'_n \mid \Psi^j_n)$ and u from $U[0,1]$.

(b) Compute the probability of move, $\alpha(\Psi'_n, \Psi^j_n)$:

$$\alpha(\Psi'_n, \Psi^j_n) = \min\left\{\frac{p(\Psi'_n)q(\Psi^j_n \mid \Psi'_n)}{p(\Psi^j_n)q(\Psi'_n \mid \Psi^j_n)}, 1\right\} \tag{3.24}$$

(c) Update Ψ^{j+1}_n from Ψ^j_n, using:

$$\Psi^{j+1}_n = \begin{cases} \Psi'_n & \text{if } u \leq \alpha(\Psi'_n, \Psi^j_n); \\ \Psi^j_n & \text{otherwise.} \end{cases} \tag{3.25}$$

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 3.19 in Appendix 3.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:

$$\Psi'_n = \Psi_n + \psi,\ \psi \sim f \tag{3.26}$$

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, Gelman, and Gilks (1997), we adjust the variance of the proposal density every 500 draws for the first 20,000 iterations.

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

3.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:

$$\Sigma_t = P\Lambda_t P', \tag{3.27}$$

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:

$$H_0 : \lambda_{it} = \lambda_i, \quad i = 1, \ldots, m \tag{3.28}$$

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

$$LM = \frac{1}{2}\sum_{i=1}^{m}\left[\left(\sum_{t=1}^{T}\tilde{g}_{it}\tilde{z}_{it}'\right)\left(\sum_{t=1}^{T}\tilde{z}_{it}\tilde{z}_{it}'\right)^{-1}\left(\sum_{t=1}^{T}\tilde{g}_{it}\tilde{z}_{it}\right)\right]. \tag{3.29}$$

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:

$$LM = \sum_{i=1}^{m} T\frac{SSG_i - RSS_i}{SSG_i}, \tag{3.30}$$

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 (3.27) does not hold and performs especially well in the case of smooth transition VARs.

3.C Estimation of GIRF and GFEVD

3.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: $\sigma/\ 3\sigma$). 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.

3.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 3.C.1. The only difference is that the orthogonalization of the history-dependent covariance matrix is approximated by

$$A^G_{t+h} = G(\gamma_G, c_G; s_{t+h-1})A_1 + (1 - G(\gamma_G, c_G; s_{t+h-1}))A_2 \tag{3.31}$$

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.

3.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.

3.C.4 Generalized Forecast Error Variance Decomposition

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

$$\lambda_{j,i,\Omega_{t-1}}(h) = \frac{\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})_j^2}{\sum_{i=1}^{K}\sum_{l=0}^{h} GIRF(h, \xi_i, \Omega_{t-1})_j^2} \tag{3.32}$$

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.

3.D Results in the Linear Setting

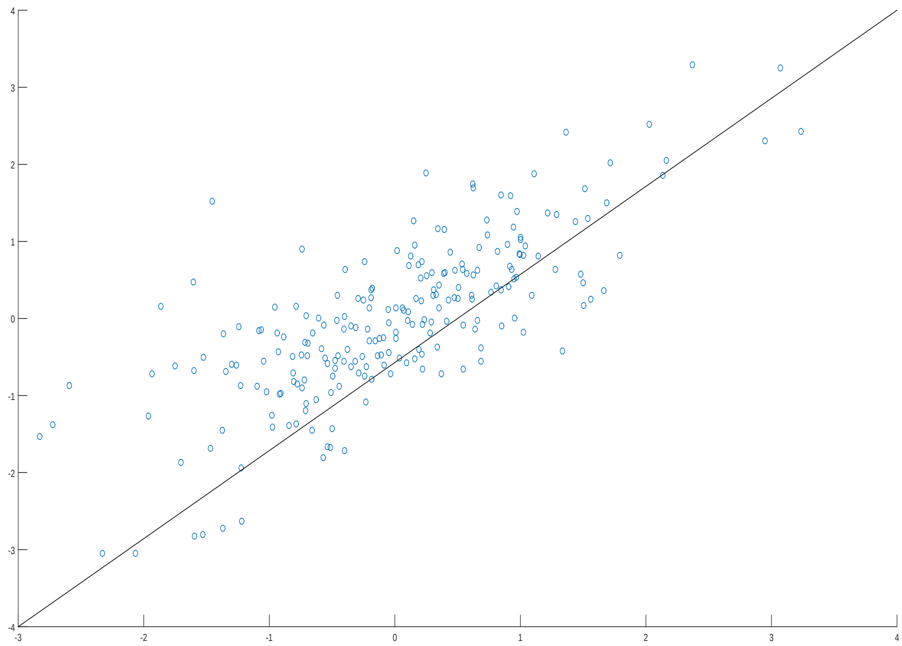

Figure 3.D.1: Comparison of the news and the confidence shocks using a scatterplot. The confidence shock is identified using a SRI which assumes that the confidence shock affects ICS on impact but not TFP. Under a MRI, the news shock is defined as the shock that does not move TFP on impact but has maximal effect on it at $H = 40$.

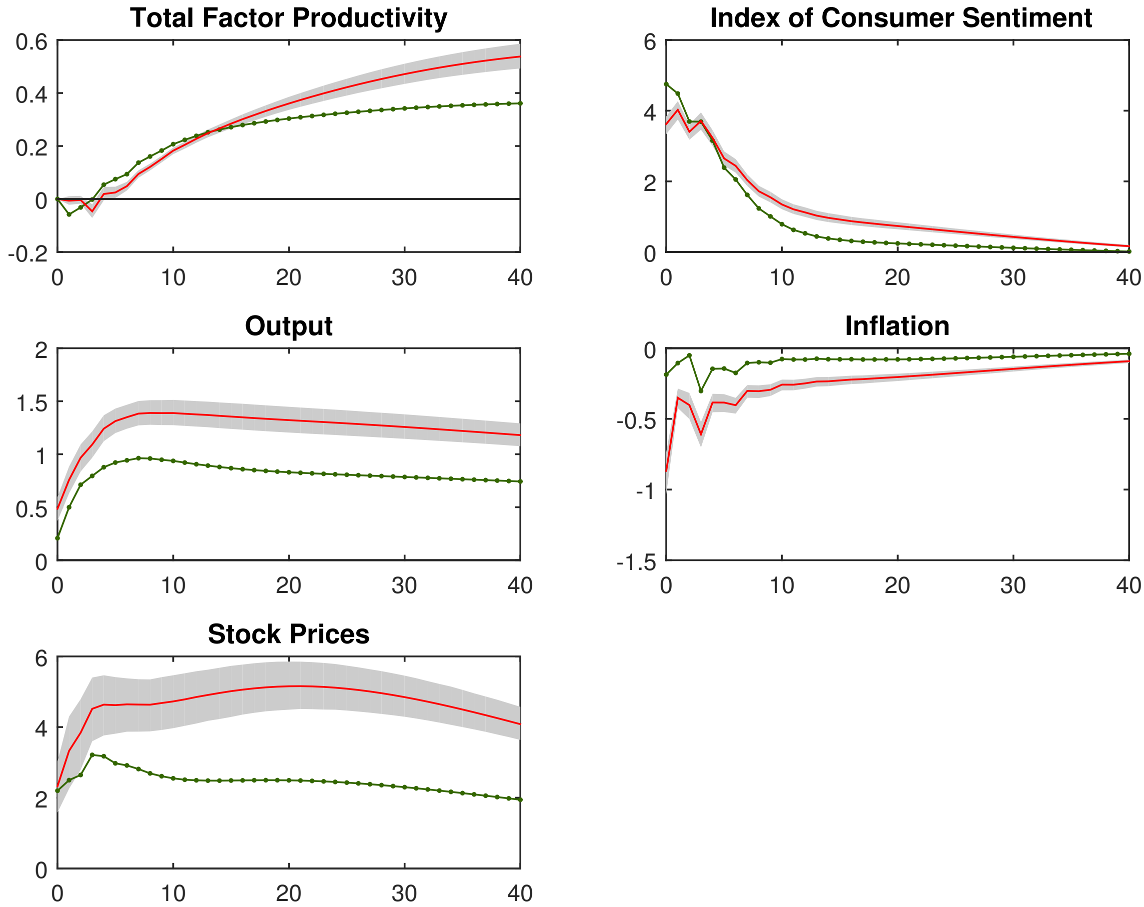

Figure 3.D.2: Comparison of news shock and confidence shock in a linear model.The red solid line shows the response to the news shock, while the green dotted line is the response to the confidence shock. The shaded region is the 95 percent confidence interval for the news shock. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

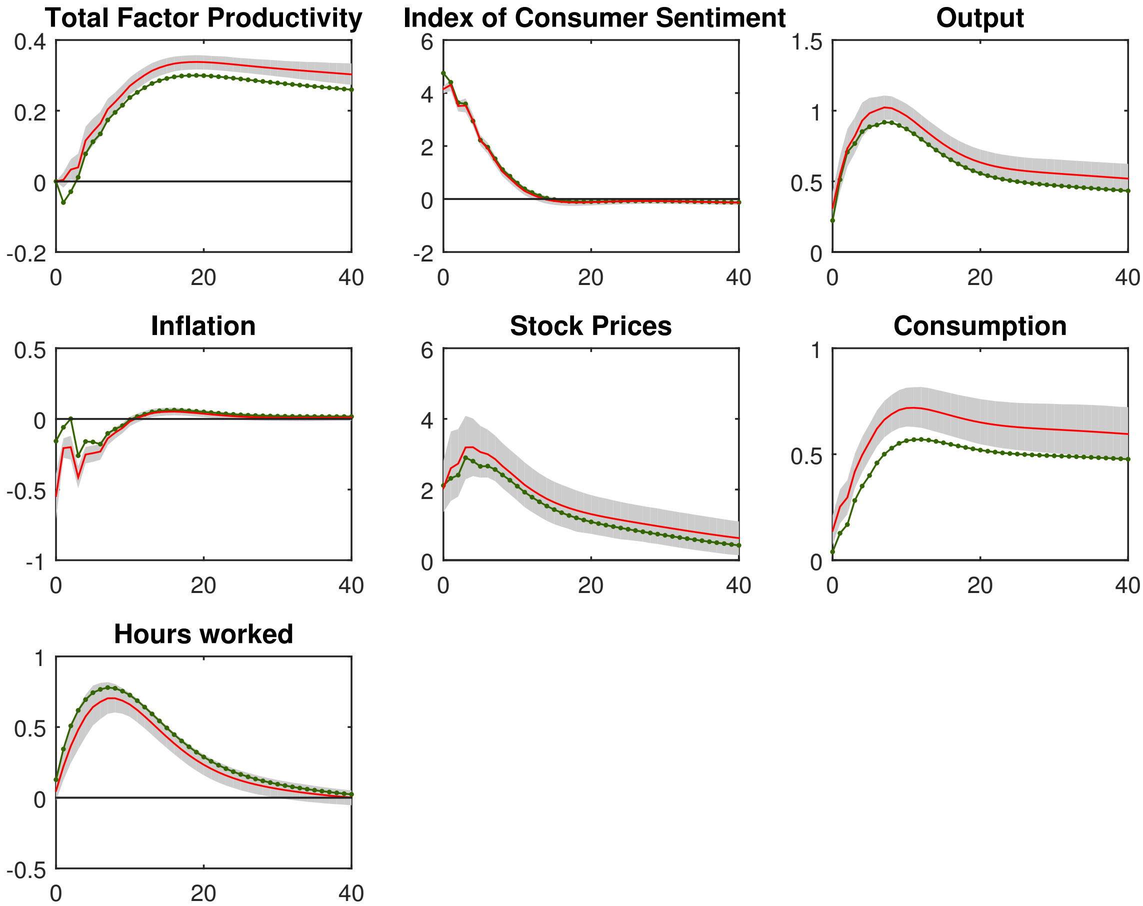

Figure 3.D.3: Comparison of news shock and confidence shock in a linear seven variables model. The red solid line shows the response to the news shock, while the green dotted line is the response to the confidence shock. The shaded region is the 95 percent confidence interval for the news shock. The 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,

3.E Results in the Nonlinear Setting

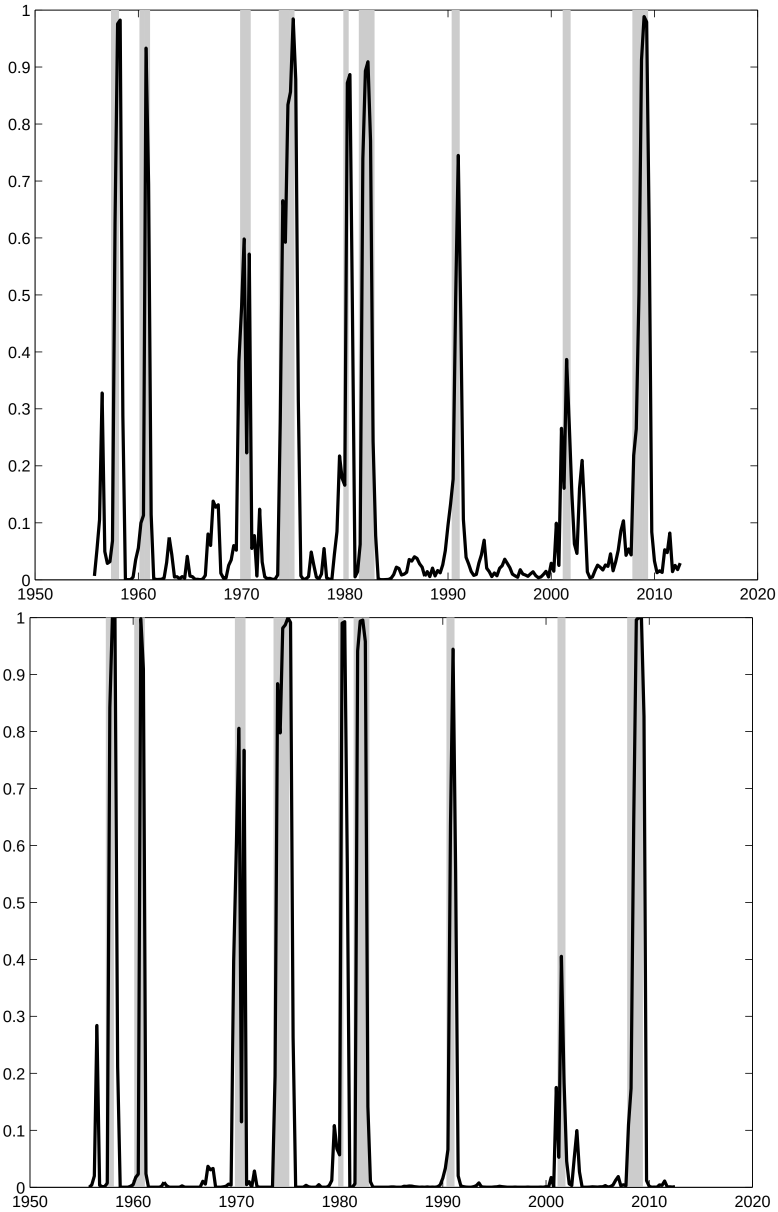

Figure 3.E.1: Comparison of the transition function for the mean equation - F (top), and the transition function for the variance equation - G (bottom), with average parameter values obtained from the MCMC iterations ($\gamma_F = 3.00$, $c_F = -0.61$, $\gamma_G = 6.31$, $c_G = -0.52$). The black line 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.

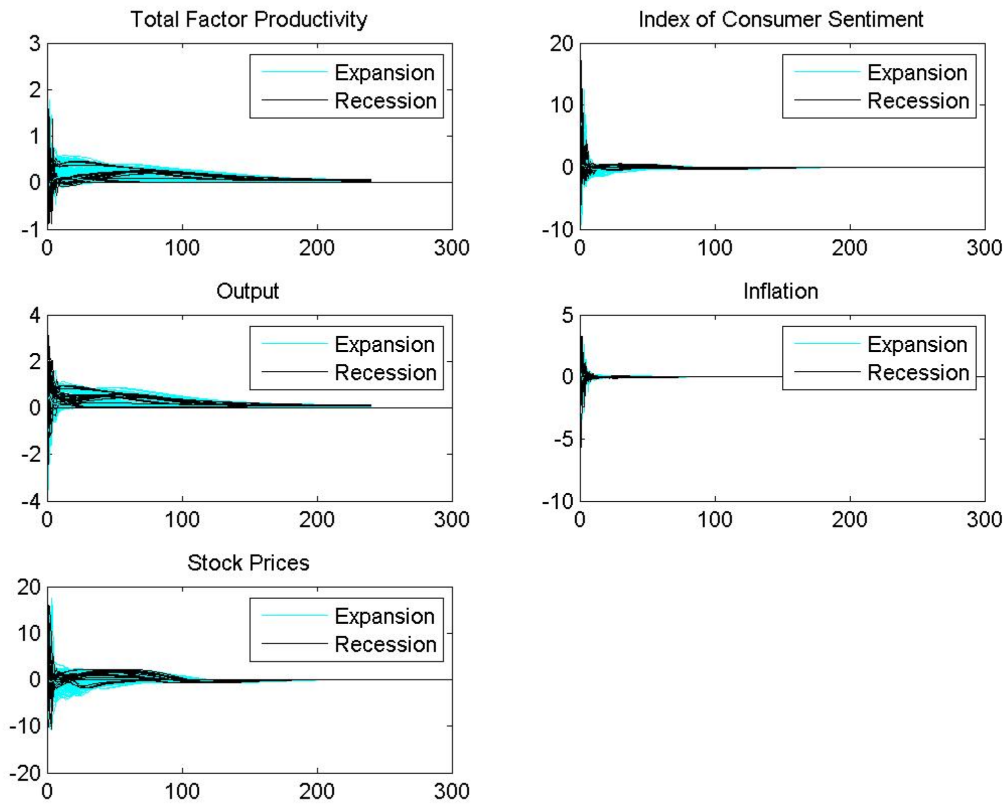

Figure 3.E.2: Stability check for the five processes. Each plot displays the paths of realizations (in first differences) from the estimated model with noise switched off, starting from a large number of initial points from both regimes.

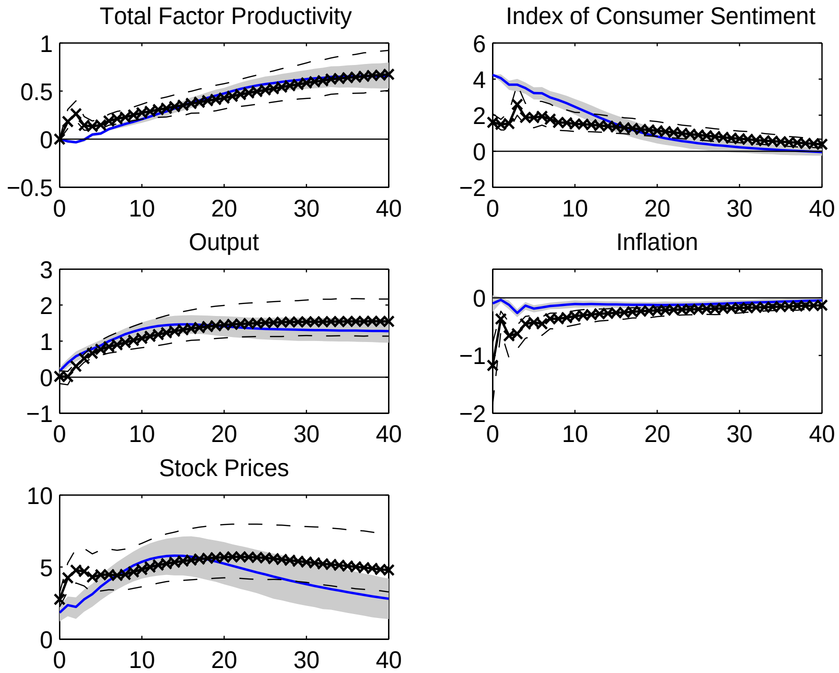

Figure 3.E.3: Generalized impulse response functions to a positive small confidence shock under SRI. SRI assumes that the confidence shock affects ICS on impact but not TFP. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed 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.

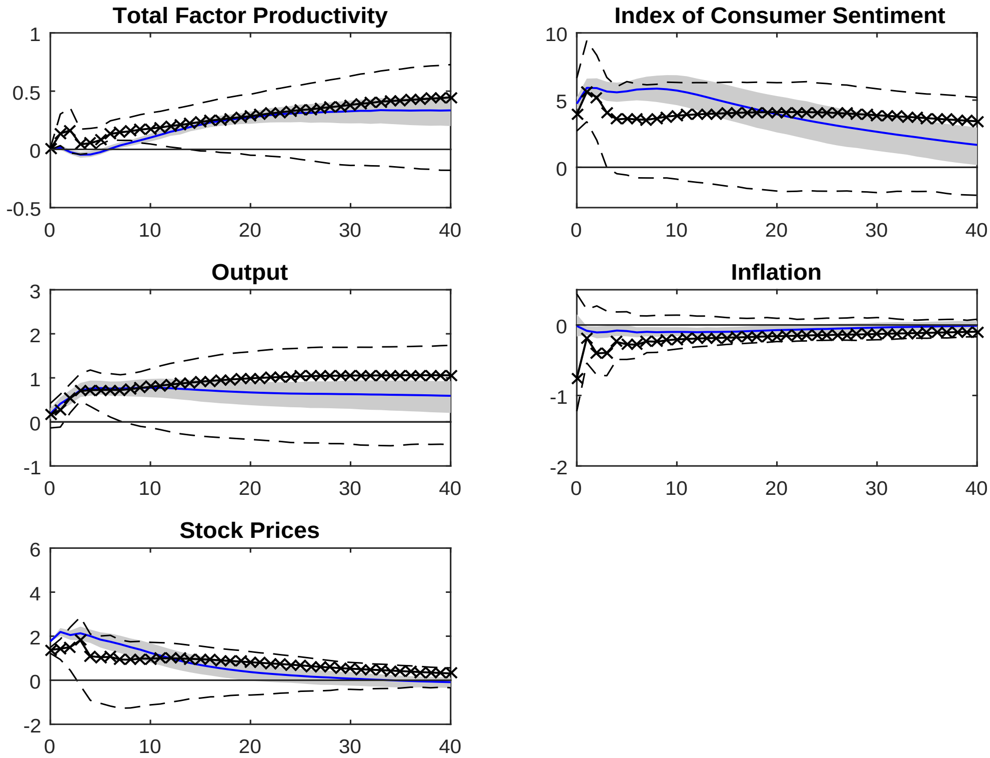

Figure 3.E.4: Generalized impulse response functions to a positive small news shock under SRI2. SRI2 assumes that the news shock affects SP on impact but not TFP. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines 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.

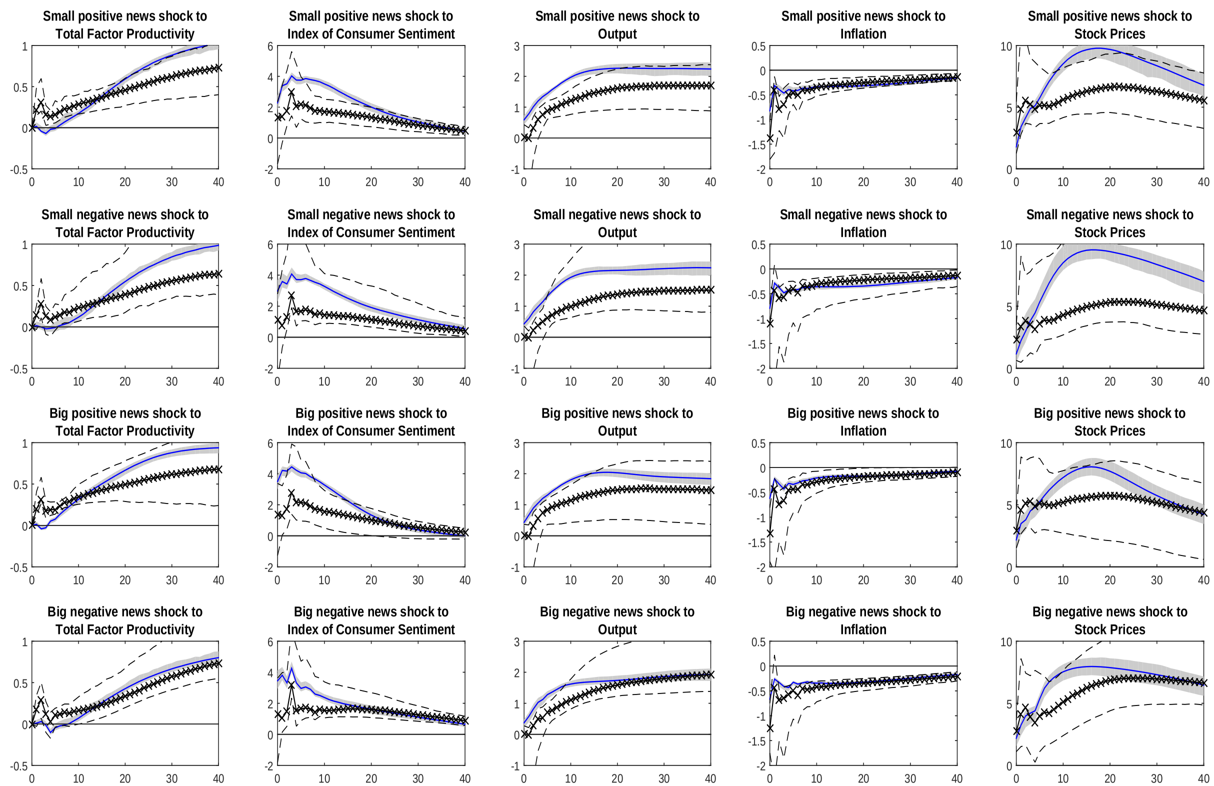

Figure 3.E.5: Generalized impulse response functions to news shocks of different signs and magnitudes. The starred black line is the point estimate in recession, and the solid blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, 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.

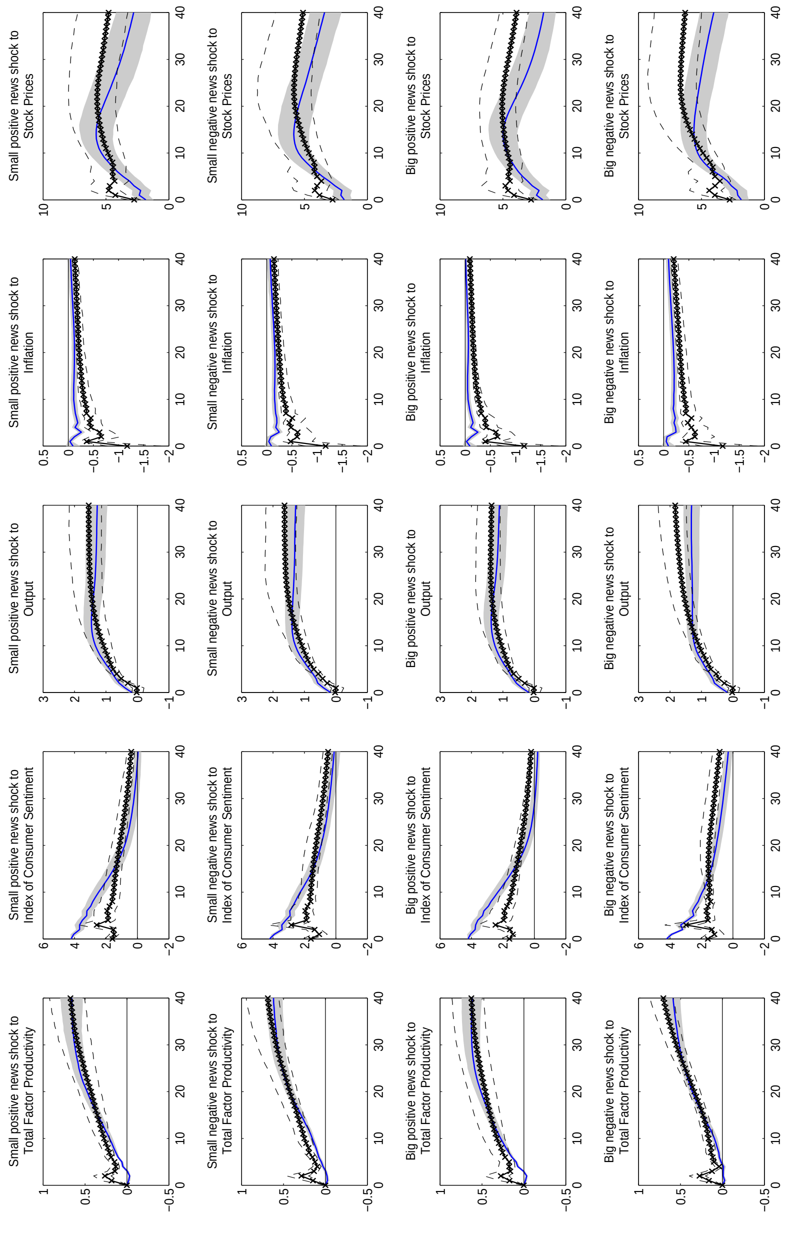

Figure 3.E.6: Generalized impulse response functions to confidence shocks of different signs and magnitudes. The starred black line is the point estimate in recession, and the blue line is the point estimate in expansion. The dashed black lines define the 95% bias-corrected confidence interval for recession, while the shaded light grey area represents the 95% bias-corrected confidence interval for expansion. The unit of the vertical axis is percentage deviation from the case without the shock (for ICS it is points), and the unit of the horizontal axis is quarter.

Table 3.E.1: 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 3.E.2: 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

Chapter 4

Questioning Productivity Shocks

Sarah Fischer

4.1 Introduction

In the literature many different and sometimes contradicting assumptions have been imposed to identify productivity shocks, in particular news shocks. While the identifying assumptions are usually based on economic theory, the identified productivity shocks often fail to mimic their theoretical counterparts. In this paper, I question the nature of the identified shocks and the underlying assumptions. I show that the identified shocks and the following conclusions about productivity shocks strongly depend on the identifying assumptions. The results implies that future research needs to be careful in relating theoretical and empirical productivity shocks.

In empirical macroeconomic literature there are three different productivity shocks identified. An unanticipated productivity shock, a news shock and a general productivity shock. Productivity may also be replaced by technology. At the same time, these three empirical shocks are often related to an exogenous unanticipated productivity shock and an exogenous anticipated productivity shock in DSGE models. There is no consensus about the interrelationship of empirical and theoretical productivity shocks. I revisit the identification of productivity shocks and consider identification schemes that have been extensively discussed in the literature.[1] While the identifying assumptions are usually based on economic theory, the identified productivity shocks often fail to mimic their theoretical counterparts. The method in this paper is purely empirical. Instead of clearly relating the identified shocks to theoretical counterparts, I question what these shocks are indeed identifying. I specifically question the nature of the identified shocks and the underlying assumptions. I simultaneously identify up to three productivity shocks and show how each of the shocks is affected. Furthermore, I add several other macroeconomic shocks to study a possible interference with identification schemes of productivity shocks. It also allows to test whether the measure of total factor productivity and investment-specific technology are only affected by productivity shocks. There are three key findings. Firstly, the identified news shock depends strongly on the identification scheme. Secondly, basically the same shock is identified when a TFP news shock and an investment-specific technology news shock are identified separately. Thirdly, a certain identification scheme may capture the long-run growth component of the economy explaining most of the variation in the economy in the medium- and long-run.

Future research needs to address several issues in regard to productivity shocks. It seems important that it is clear whether the researcher wants to identify a completely unanticipated shock or a shock with large medium- or long-run contribution or a mixture of all. Furthermore, the correspondence between the different identification methods of productivity shocks and theoretical shocks need to be stated more clearly. At the moment it seems as if any identification method has been used to characterize an unanticipated exogenous technology shock in a DSGE model. Obviously, the deductions are very different and depend critically on the stated assumptions such as orthogonality and maximization horizon. Finally, the interrelationship between TFP and investment-specific technology and the economy needs to be further discussed. The exogeneity assumption imposed in most DSGE models may not be appropriate and models with endogenous technology adoption as introduced in Chatper 2 may be helpful.

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 impor-

[1] A discussion of productivity shocks in theoretical and empirical models is given in Chapter 2 of this thesis.

tant source of economic fluctuations. One such approach was brought up by Beaudry and Portier (2004), and Beaudry and Portier (2006), 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. The unanticipated productivity shock is identified as the only shock affecting TFP on impact. The news shock is identified as the innovation in stock prices orthogonal to the unanticipated technology shock. In the news literature, news shocks are either identified via short-run restrictions or a medium-run identification scheme. The short-run restrictions rely on the information contained in a strongly forward-looking variable such as a measure of consumer sentiment (confidence) or stock prices (SP). Such a measure is not imperative for a medium-run identification scheme. There the news shock is identified as the shock maximizing the contribution to the forecast error variance of TFP at a finite horizon[2]. Various identification schemes of news shocks are discussed in detail in Chapter 1 of this thesis.[3] Most of the time, the orthogonality assumption between the news shock and an unanticipated technology shock is kept. An exception is Kurmann and Sims (2017) who allow for immediate effects of news shocks on TFP. All identification schemes share the assumption that TFP is only affected by unanticipated and anticipated productivity shocks at any horizon.[4] In Chapter 1, it is shown that an unanticipated productivity shock increases economic activity but decreases hours worked on impact while depending on the maximization horizon any of the identification schemes finds that news shocks lead to business cycle effects.

Recently, investment-specific technology shocks have gained more attention in the empirical literature. Investment-specific technical change makes new equipment either less expensive or better than the old equipment. Investment-specific technology shocks have been considered in the analysis of growth and business cycles by Greenwood, Hercowitz, and Huffman (1988) and Greenwood, Hercowitz, and Krusell (2000) and investment-specific technology news shocks have been introduced in the DSGE literature by Jaimovich and Rebelo (2009). Generally, TFP and investment-specific technology are assumed to be independent. Unanticipated investment-specific technology shocks were first analyzed in a VAR setting by Fisher (2006) who identifies investment-specific technology shocks and neutral technology shocks with long-run restrictions. His main assumption is that the relative price of investment is only affected by the investment-specific technology shock in the long-run. Ben Zeev and Khan (2015) also consider investment-specific news shocks which they identify with a max FEV method. They further introduce a new method that allows the simultaneous identification of a news shock and an investment-specific news shock. A similar method is employed by Benati (2014b). They find that investment-specific technology shocks are a more important source for business cycles than TFP news shocks.

In this paper, I explore unanticipated and anticipated productivity shocks based on identification schemes used in the literature and add further macroeconomic shocks. I estimate a vector autoregressive model in levels for the sample 1955Q1-2014Q4 and employ a robust variable setting deduced in Chapter 1 including TFP, confidence, real output,

[2] This identification scheme may also be referred to as the max FEV method.

[3] A thorough discussion of news shocks can also be found in Beaudry and Portier (2014).

[4] In the literature productivity shocks are also often referred to as technology shocks. Unanticipated productivity shocks may also be called surprise technology shocks.

real consumption, hours worked, inflation and the nominal interest rate. I start with identifying four different shocks to TFP. If three of them are identified simultaneously, they explain most of the variation in TFP and quantities[5] at business cycle frequencies[6] and in the long-run.The first shock is an unanticipated productivity shock (UPS) following the standard identification in the literature. The second shock is a news shock identified as the innovation in confidence orthogonal to the unanticipated productivity shock, henceforth SRI1. This identification scheme is similar to Beaudry and Portier (2006). The third and fourth shock then are news shocks identified as the shock that maximizes the contribution to the forecast error variance of TFP at horizon 10 years or 30 years, henceforth MRI40 and MRI120. Similar news shocks were identified in Beaudry, Nam, and Wang (2011). In the news literature SRI1, MRI40 and MRI120 have been used to identify the same structural shock, a technological diffusion news shock. I start by only identifying two shocks simultaneously, the unanticipated productivity shock and a news shock. While the news shock MRI40 is highly cross-correlated with SRI1, the cross-correlation is much lower for MRI120 and SRI1. Based on the notion that MRI40/SRI1 and MRI120 may be partially capturing different innovations I identify an unanticipated productivity shock together with SRI1 and MRI120, adding the restriction of MRI120 being orthogonal to SRI1.

As a measure of investment-specific technology I use the inverse of the relative price of investment by DiCecio (2009).[7] I add the relative price of investment (RPI) to the model and position it after TFP as in Ben Zeev and Khan (2015). I identify an unanticipated investment-specific technology shock (IST), and an investment-specific technology news shock. The results are robust to the order of TFP and RPI. For the identification of the shocks I need to make two more assumptions. Firstly, RPI is only affected by UPS and IST on impact. Secondly, the investment-specific technology news shock maximizes the share of the forecast error variance after 30 years (IST120). In contrast to Ben Zeev and Khan (2015), I consider the TFP news shock and the investment-specific technology news shock only separately.

Furthermore, I add a monetary policy shock and an oil price shock. The monetary policy shock is identified as the innovation in interest rates that affects the rest of the economy with a lag. The identifying assumptions are standard in the macroeconomic literature. A thorough discussion of monetary policy shocks and their identification can be found in Christiano, Eichenbaum, and Evans (1999) and Ramey (2016). For the identification of the oil price shock, I assume that on impact the oil price is only affected by the oil price shock. This has been the standard linear identification assumption in the literature of oil price shocks since Hamilton (1983).

I consider various combinations of all mentioned shocks. It would be interesting to consider further macroeconomic shocks. I did not consider fiscal shocks as they explain only little of business cycle variations which is discussed in Ramey (2016). Recently, credit shocks, labor supply shocks or uncertainty shocks have gained more attention.

The exploration of productivity shocks and further macroeconomic shocks leads to several interesting conclusions. 1) The identified news shock and its effects on the econ-

[5] Quantities refer to the real variables, output, consumption and hours worked, in the model.

[6] As business cycle frequencies I consider wider frequencies of 4 to 40 quarters. The results are only mildly affected if the upper horizon is lowered.

[7] As shown in Greenwood, Hercowitz, and Krusell (2000), this inverse relatiohship between investment-specific technology and the real price of investment can be derived in either a one-sector model or a two-sector model with consumption and investment sectors.

omy strongly depend on the identification scheme. While the news shock MRI40 is highly cross-correlated with SRI1, the cross-correlation is much lower for MRI120 and SRI1. SRI1 and MRI40 mainly contribute at business cycle frequencies but only up to 30% to output, consumption or hours. Most of the variation of TFP at business cycle frequencies is explained, but in the long-run the contribution declines. The contribution of MRI120 to real quantities is high in the medium-run and even stronger in the long-run. For example, it explains 47% of the variation in consumption on impact but 92% in the long-run. An identification scheme identifying UPS and MRI120 leaves up to 20% of the variation in TFP at business cycle frequencies unexplained but explains most of it in the long-run. The results indicate, on the one hand, that MRI40 and SRI1 capture similar innovations. Yet, on the other hand, MRI40 and MRI120 seem to partially capture different innovations describing differing effects on the economy. I also compare the shocks to the identification scheme MRI-KS and can show that this identification scheme captures a mixture of an unanticipated productivity shock and a news shock identified with MRI. The shock also depends strongly on the maximization horizon. For example Mansfield(1989) shows that it takes 5-15 years for a new technological innovation to diffuse in the economy. Thus, one would expect that MRI40 and MRI120 identify basically the same shock, which is not the case.

2) Identifying an unanticipated productivity shock and SRI1 and MRI120 simultaneously increases the explained variation in TFP and consumer confidence in comparison to an identification of only two productivity shocks. These three shocks together explain over 90% of the variation in TFP at any horizon. The contribution to the rest of the variables is almost identical to a model including only MRI120 and UPS. They contribute 19-94% to the forecast error variance of output, 65-98% to consumption, 33-72% to hours and up to 45% to inflation. MRI120 is the only contributor to the variation in inflation. I conclude that consumer confidence seems to capture something that does affect the whole economy including TFP at business cycle frequencies. This shock is clearly different from a news shock explaining most of TFP in the long-run.

3) The shock investment-specific technology news shock is basically the same as the TFP news shock. I find that the unanticipated productivity shock and the unanticipated investment-specific technology shock do not contribute much to business cycle variations. In contrast, the contribution of IST120 is practically the same as for MRI120. This holds for all variables and at all horizons. Hence, IST120 has a large contribution to the variation of quantities at business cycle frequencies and in the long-run. Furthermore, it contributes up to 40% to the forecast error variance of TFP and up to 60% to the forecast error variance of RPI after 30 years. I conclude that it is irrelevant which technology measure is used to identify a shock that contributes most to the variation in TFP and RPI in the long-run. My results are supported by findings of Schmitt-Grohé and Uribe (2011). They show that TFP and RPI are actually cointegrated, which means they are driven by a common stochastic trend. This would mean that these measures are not independent but closely related instead. Benati (2014a) explores several reasons that could lead to this result. I would further argue, that the news shock I identify may capture the long-run growth component of the economy in the sense of King et al. (1991). The reason is that this shock explains a large fraction of the variation in the economy at business cycle frequencies.

4) Both, the monetary policy shock and the oil price shock contribute to the variation in TFP and RPI. Moreover, I find significant effects of these two shocks on TFP and RPI. This means that either TFP and investment-specific technology are also affected by

other shocks than productivity shocks. Or that the measures are somehow flawed. The result is especially interesting as it is obtained for both, TFP and RPI.

5) The identification schemes using shorter maximization horizons such as MRI40 is substantially affected by the addition of further macroeconomic shocks. The negative effect of the interest rate to a news shock identified with MRI40 turns positive one a monetary policy shock is added.

The rest of the paper is organized as follows: In Section 2 the empirical model is described. Section 3 discusses three TFP productivity shocks that together explain most of the variation in real variables at business cycle frequency. In section 4 investment-specific technology shocks and a monetary policy shock and oil price shock are added to the analysis. Section 5 concludes.

4.2 Model

I identify the structural shocks by estimating a linear vector autoregressive model in levels. The shocks are then identified by implementing alternative identification schemes. The model is given by:

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \epsilon_t \tag{4.1}$$

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. I constrain the coefficients and the variance-covariance matrix to be constant over time. This assumption is relaxed in Chapter 3. The model (4.1) 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. I assume that there exist cointegrating relationships between the variables which would allow me to estimate a stable vector error correction model. As I 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, I find it more appropriate to work with a model in levels and do not specify the cointegrating relationships. As described in Kilian and Lütkepohl (forthcoming), 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, caution is called for in conducting inference.[8] In

[8] In the presence of integrated variables, the covariance matrix of the asymptotic distribution of least

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, Stock, and Watson (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 $u_t \sim WN(0, I_m)$ and the covariance matrix is normalized to the identity matrix. The structural shocks are completely determined by A. As there is no unambiguous relation between the reduced and structural form, it is impossible to infer the structural form from the observations alone. To identify the structural shocks from the reduced-form innovations, $k(k-1)/2$ additional restrictions on A are needed.[9]

4.3 Productivity Shocks

4.3.1 Identification

I will start by identifying two different productivity shocks in a 7-variable model and, hence, only partially identify the model. The chosen model encompasses enough information to identify robust productivity shocks and deliver reliable impulse response functions given the identification scheme.[10] The first shock is an unanticipated productivity shock which is the only shock affecting TFP on impact (UPS). The second shock is a news shock. I apply three different identification schemes to identify the news shock and compare all four productivity shocks. The first news shock is identified with short-run restrictions. It is the innovation in consumer confidence that is orthogonal to contemporaneous TFP. The identification of these two shocks can be obtained via short-run zero restrictions and setting TFP and consumer confidence as the first two variables.

$$\tilde{A} = \begin{pmatrix} \star & 0 & 0 & 0 & 0 & 0 & 0 \\ \star & \star & 0 & 0 & 0 & 0 & 0 \\ \star & \star & \star & \star & \star & \star & \star \\ \star & \star & \star & \star & \star & \star & \star \\ \star & \star & \star & \star & \star & \star & \star \\ \star & \star & \star & \star & \star & \star & \star \\ \star & \star & \star & \star & \star & \star & \star \end{pmatrix}$$

Furthermore, I consider medium-run restrictions in the sense of Uhlig (2004)[11] that were used in Beaudry, Nam, and Wang (2011) or Barsky and Sims (2011) to identify

squares estimator 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.Kilian and Lütkepohl (forthcoming) 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.

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

[10] An analysis of robust variable settings is given in Chapter 1.

[11] I thank Luca Benati for sharing with me his codes for performing a medium-run identification in a linear framework.

news shocks. According to Francis et al. (2014), medium-run identification schemes have the advantage over long-run restrictions that they can be used in systems with integrated level data. Innovations are orthogonalized by applying the Cholesky decomposition to the covariance matrix of the residuals ($\Sigma = \tilde{A}\tilde{A}'$). The news shock is then identified as the shock that has no impact effect on TFP and maximizes the contribution to the variation of TFP in the medium-run (MRI). Specifically, the news shock is the shock with the highest share of the forecast error variance decomposition at some specific horizon H. 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 $\mathbb{P}_{t-1}Y_{t+h}$ for horizon h:

$$Y_{t+h} - \mathbb{P}_{t-1}Y_{t+h} = \sum_{\tau=0}^{h} B_\tau \tilde{A} D u_{t+h-\tau} \tag{4.2}$$

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

$$\Xi_{j,i}(h) = \frac{e_j'\left(\sum_{\tau=0}^{h} B_\tau \tilde{A} D e_i e_i' \tilde{D}' A' B_\tau'\right) e_j}{e_j'\left(\sum_{\tau=0}^{h} B_\tau \Sigma B_\tau'\right) e_j} = \frac{\sum_{\tau=0}^{h} B_{j,\tau} \tilde{A} \gamma_i \gamma_i' \tilde{A}' B_{j,\tau}'}{\sum_{\tau=0}^{h} B_{j,\tau} \Sigma B_{j,\tau}'} \tag{4.3}$$

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 $B_{j,\tau}$. Identifying the news shock which is indexed by 3 implies choosing the impact matrix to maximize contributions to $\Xi_{1,3(h)}$ over h. This is equivalent to solving the following optimization problem:

$$\begin{aligned}
\gamma^* =& argmax \Xi_{1,3}(h) \\
& s.t. \\
& \tilde{A}(1,i) = 0, \forall i > 1 \\
& \gamma(1) = 0 \\
& \gamma_3'\gamma_3 = 1
\end{aligned}$$

The first two constraints impose that the news shock has no contemporaneous effect on TFP, while the third ensures that γ_3 is a column vector belonging to an orthonormal matrix. The identification scheme then implies that the news shock (MRI) and the unanticipated productivity shock (UPS) account for most of the variation in TFP at horizon H.

The third variation of identifying news shocks is to apply the same medium-run identification scheme but to omit the orthogonality condition to contemporaneous TFP (MRI-KS). This method was applied by Kurmann and Sims (2017) to identify news shocks. Before that a variation of MRI-KS was used by Francis et al. (2014) among others to identify neutral productivity shocks in the sense of Galí (1999). Hence, it is not clear what kind of productivity shock is identified with MRI-KS.

4.3.2 Results

In the following, I compare six different productivity shocks. I estimate a VAR in levels including total factor productivity, consumer confidence, output, consumption, hours, inflation and interest rates. Data is discussed in Appendix 4.A. I consider an unanticipated productivity shock (UPS), a news shock identified with short-run restrictions (SRI1), two news shocks identified with medium-run restrictions orthogonal to UPS and maximization horizons 10 and 30 years (MRI40 and MRI120) and two news shocks identified with medium-run restrictions not orthogonal to contemporaneous TFP and maximization horizons 10 and 30 years (MRI-KS40 and MRI-KS120). In Mansfield (1989) and Rogers (2003) it is argued that the adoption rate of new technologies depends on the type of innovation, but that on average it takes 5-15 years for a technological innovation to diffuse in the economy. Based on that, I would expect that dentification schemes with maximization horizons of 40 and larger would capture a similar shock, which is not the case. Table 4.1 shows cross-correlations, henceforth correlation, between different productivity shocks. Autocorrelation can be rejected for all shocks. By construction the correlation between the unanticipated productivity shock is orthogonal to SRI1, MRI40 and MRI120. MRI40 identifies a very similar shock as SRI1 indicated by a correlation coefficient of 0.85. MRI120 is less correlated with SRI1 and MRI40 with correlation coefficients around 0.5. This indicates that increasing the maximization horizon changes the identified shock. The result is robust to higher horizons of MRI120. The identification scheme MRI-KS omits the orthogonality condition and, therefore, may include short-run innovations to TFP. The correlations indicate as such since the correlation coefficient between UPS and MRI-KS40 is quite high with 0.83. MRI-KS120 is only mildly correlated with UPS and also the correlation with SRI1, MRI40 and MRI-KS40 is modest with a correlation coefficient of around 0.6. But it is highly correlated with MRI120. The increase of the maximization horizon seems to change the captured innovations in TFP. To sum up, the identified news shock depends to a great extent on the identification scheme and the horizon at which the forecast error variance of TFP is maximized. Nevertheless, SRI1, MRI40, MRI120 and MRI-KS120 are all correlated with coefficients over 52% indicating that they capture partially similar innovations.

Table 4.1: Cross-Correlations Between Different Productivity Shocks.

Shock	UPS	SRI1	MRI40	MRI120	MRI-KS40	MRI-KS120
UPS	1					
SRI1	-2E-15	1				
MRI40	-4E-13	0.85	1			
MRI120	1E-12	0.62	0.52	1		
MRI-KS40	0.83	0.45	0.54	0.21	1	
MRI-KS120	0.48	0.62	0.55	0.87	0.64	1

While the impulse response functions to the news shocks from different identification schemes mainly differ in the magnitude of the effects with the exception of hours worked[12], the variance decompositions confirm the notion that different maximization horizons pick

[12] Impulse responses for various identification schemes and maximization horizons are displayed in Chapter 1.

up different TFP innovations which changes the effects on the whole economy. All identification schemes have the assumption in common that only productivity shocks affect TFP. Hence, the unanticipated productivity shock plus the news shock should explain TFP at all horizons. Table 4.2 contains the forecast error variance decomposition for an unanticipated productivity shock and a news shock identified with either SRI1, MRI40, MRI120, MRI-KS40 or MRI-KS120. On impact, the systems identifying an unanticipated productivity shock do clearly best since 100% of the forecast error of TFP is explained. And up to ten years the UPS explains the majority of the forecast error variance of TFP while SRI1, MRI40 or MRI120 only contribute between 12 and 31%. In the long-run, SRI1 and MRI40 explain less than 30% of the variation in TFP leaving more than 40% unexplained. MRI-KS40 explains 70% of the forecast error variance of TFP on impact and even 85% after five and ten years, but its contribution declines in the long-run. For a horizon of thirty years, MRI120 and MRI-KS120 explain with 57% and 67% clearly the most. While MRI-KS120 leaves more than 60% of the variation in TFP unexplained, UPS and MRI120 can explain over 85%. The identification scheme MRI-KS seems to capture a mixture of UPS and MRI[13]. The unanticipated productivity shock barely explains anything of consumer confidence, even at a horizon of thirty years the contribution measures only 10%. SRI1 is identified as the innovation to consumer confidence orthogonal to the unanticipated productivity shock and is the main determinant of variation in confidence. Confirming the notion obtained from the cross-correlations, MRI40 seems to capture mainly the innovation of confidence and explains a similar amount of TFP and confidence as SRI1, especially at longer horizons. Furthermore, the contributions of the two shocks to other variables are very similar. MRI120, MRI-KS40 and MRI-KS120 only contribute between 35 to 45% to confidence at all horizons. The news shocks vary the most in the contributions to quantities. The unanticipated productivity shock is in general not contributing much. Only to the variation in output at a horizon of five years it contributes 20%. SRI1, MRI40 and MRI-KS40 contribute only little on impact but between 26-46% to output, between 11-31% to consumption and between 4-33% to hours at business cycle frequencies. Contrary, MRI120 and MRI-KS120 contribute more to quantities at any horizon. While the impact contribution to output is only 11% and 19% it increases to 69% an 84% after ten years. The contribution to consumption increases from 35-47% on impact to 86-89% at horizon ten. MRI120 and MRI-KS120 also contribute approximately 60% to hours worked.

[13]Ben Zeev and Khan (2015) come to a similar conclusion regarding the identification schemes but consider investment-specific technology shocks.

Table 4.2: Share of forecast error variance decomposition attributable to the unanticipated productivity shock and the news shock identified with either short-run restrictions or medium-run restrictions at horizon 40 or 120.

Variable	**Shock**	**Horizon**				
		Impact	One year	Five years	Ten years	Thirty years
TFP	UPS	1	0.89	0.71	0.62	0.30
	SRI1	0	0.01	0.13	0.23	0.27
	MRI40	0	0.00	0.20	0.31	0.24
	MRI120	0	0.05	0.04	0.12	0.57
	MRI-KS40	0.70	0.64	0.85	0.85	0.45
	MRI-KS120	0.23	0.10	0.23	0.40	0.67
Confidence	UPS	0.03	0.04	0.07	0.09	0.10
	SRI1	0.97	0.83	0.65	0.56	0.54
	MRI40	0.71	0.78	0.62	0.55	0.53
	MRI120	0.37	0.43	0.45	0.43	0.42
	MRI-KS40	0.34	0.39	0.34	0.35	0.35
	MRI-KS120	0.47	0.55	0.47	0.40	0.39
Output	UPS	0.08	0.09	0.20	0.15	0.08
	SRI1	0.07	0.29	0.40	0.37	0.30
	MRI40	0.07	0.31	0.42	0.35	0.21
	MRI120	0.11	0.43	0.55	0.69	0.84
	MRI-KS40	0.13	0.26	0.46	0.36	0.18
	MRI-KS120	0.19	0.55	0.79	0.84	0.82
Consumption	UPS	0.01	0.07	0.11	0.06	0.04
	SRI1	0.01	0.11	0.31	0.28	0.25
	MRI40	0.00	0.17	0.31	0.22	0.14
	MRI120	0.47	0.66	0.81	0.89	0.92
	MRI-KS40	0.00	0.15	0.27	0.16	0.08
	MRI-KS120	0.35	0.68	0.90	0.86	0.82
Hours	UPS	0.10	0.02	0.04	0.04	0.03
	SRI1	0.05	0.25	0.33	0.30	0.29
	MRI40	0.00	0.15	0.23	0.20	0.19
	MRI120	0.21	0.49	0.64	0.65	0.65
	MRI-KS40	0.08	0.04	0.13	0.11	0.10
	MRI-KS120	0.05	0.35	0.60	0.58	0.56
Inflation	UPS	0.01	0.02	0.15	0.16	0.15
	SRI1	0.01	0.03	0.04	0.04	0.04
	MRI40	0.03	0.09	0.09	0.10	0.09
	MRI120	0.38	0.26	0.24	0.25	0.27
	MRI-KS40	0.02	0.06	0.19	0.24	0.23
	MRI-KS120	0.31	0.24	0.14	0.12	0.13
Interest Rate	UPS	0.01	0.01	0.18	0.25	0.23
	SRI1	0.01	0.07	0.08	0.07	0.07
	MRI40	0.14	0.04	0.04	0.06	0.06
	MRI120	0.00	0.09	0.09	0.09	0.15
	MRI-KS40	0.08	0.04	0.19	0.30	0.29
	MRI-KS120	0.01	0.05	0.13	0.10	0.12

None of these identification schemes can explain 100% of the variation in TFP at all horizons even though they are based on that assumption. Moreover, SRI1 and MRI120 rather seem to capture partially different innovations. Therefore, I assume that by combining an unanticipated productivity shock, a SRI1 news shock and a MRI120 news shock, it should be possible to explain the forecast error variance of TFP to almost 100% at any horizon. Moreover, a large fraction of the rest of the system will be explained by these three shocks. Hence, I add the assumption that the news shock MRI120 is not only orthogonal to contemporaneous TFP but also to contemporaneous consumer confidence and identify three productivity shocks. The following two conditions are added to the optimization problem:

$$\tilde{A}(2,i) = 0, \forall i > 2, \tag{4.4}$$

$$\gamma_3(2) = 0 \tag{4.5}$$

Table 4.3 contains the results of the variance decomposition for the three shocks. The sum of explained variation in TFP and confidence is higher than for any of the before mentioned identification schemes. MRI120 explains very little of the variation in these two variables at shorter horizons but 38% of TFP after 30 years. In comparison to a model with UPS and MRI120, the contributions to the rest of the variables have not changed much by identifying the two news shocks simultaneously. This indicates that without the orthogonality assumption MRI120 is capturing SRI1 to a great extent. But also that MRI120 captures partially different innovations. By identifying three shocks I explain over 90% of TFP and over 85% of confidence at any horizon. Furthermore, I explain between 53-86% of output, between 75-95% of consumption, 52-71% of hours, 33-57% of inflation and 14-47% of interest rates at business cycle frequencies. SRI1 and MRI120 are the main contributors to output, consumption and hours worked. While SRI1 explains more of output at business cycle frequencies, the contribution of MRI120 is larger to consumption. MRI120 is the only contributor to the variation in inflation at any horizon. After 30 years, the combination of shocks explains over 90% of TFP, confidence, output and consumption, 72% of hours and over 50% of inflation and interest rates. A large fraction of the forecast error variance at horizon zero of output, hours, and inflation and especially the interest rate remains unexplained. These results lead to several questions. For example, what is identified with SRI1? Does it take more than 10 years for productivity to increase after a new technological innovation occurs? Or why does a shock that is not captured by consumer confidence and only affects TFP in the long-run explain over 98% of the variation in consumption at any horizon?

Table 4.3: Share of forecast error variance decomposition attributable to an unanticipated productivity shock and a news shock identified with short-run restrictions (SRI1) and a news shock identified with medium-run restrictions maximized at horizon 120 and orthogonal to SRI1 (MRI120). TOTAL sums the contributions of all shocks.

Variable	**Shock**	**Horizon**				
		Impact	One year	Five years	Ten years	Thirty years
TFP	UPS	1	0.89	0.71	0.62	0.30
	SRI1	0	0.01	0.13	0.23	0.27
	MRI120	0	0.07	0.07	0.06	0.38
	TOTAL	1	0.96	0.91	0.90	0.95
Confidence	UPS	0.03	0.04	0.07	0.09	0.10
	SRI1	0.97	0.83	0.65	0.56	0.54
	MRI120	0	0.02	0.13	0.19	0.21
	TOTAL	1	0.89	0.85	0.85	0.85
Output	UPS	0.08	0.09	0.20	0.15	0.08
	SRI1	0.07	0.29	0.40	0.37	0.30
	MRI120	0.04	0.15	0.18	0.33	0.57
	TOTAL	0.19	0.53	0.78	0.86	0.94
Consumption	UPS	0.01	0.07	0.11	0.06	0.04
	SRI1	0.01	0.11	0.31	0.28	0.25
	MRI120	0.64	0.57	0.48	0.61	0.70
	TOTAL	0.65	0.75	0.89	0.95	0.98
Hours	UPS	0.10	0.02	0.04	0.04	0.03
	SRI1	0.05	0.25	0.33	0.30	0.29
	MRI120	0.18	0.25	0.32	0.38	0.40
	TOTAL	0.33	0.52	0.69	0.71	0.72
Inflation	UPS	0.01	0.02	0.15	0.16	0.15
	SRI1	0.01	0.03	0.04	0.04	0.04
	MRI120	0.45	0.28	0.31	0.37	0.40
	TOTAL	0.47	0.33	0.50	0.57	0.59
Interest Rate	UPS	0.01	0.01	0.18	0.25	0.23
	SRI1	0.01	0.07	0.08	0.07	0.07
	MRI120	0.00	0.05	0.07	0.15	0.24
	TOTlAL	0.02	0.14	0.33	0.47	0.54

As Blanchard and Quah (1989) argue, supply disturbances are likely to affect the trend as well as the business cycle while demand shocks probably only have a minor effect on the long-run trend. Hence, both SRI1 and MRI120 seem to capture productivity shocks, but not the same. Another possibility may be that news shocks are contaminated by other macroeconomic shocks that are omitted. But if that were the case it may question the assumption that TFP is only affected by productivity shocks. Furthermore, it would clearly pose a problem for the analysis of news shocks.

The impulse response functions to several productivity shocks – MRI40, SRI1, MRI120 and MRI120-cc which is the shock orthogonal to SRI1 – are shown in graph 4.1. As already discussed in Chapter 1, the effect of MRI120 is in general larger than of SRI1 and

MRI40, but qualitatively similar. The most notable difference is the negative impact reaction of the nominal interest rate to MRI40. It becomes apparent that MRI120 captures a mixture of SRI1 and MRI120-cc. In Figure 4.B.1, Appendix 4.B, the confidence interval of MRI40 is added. While the impulse responses to SRI1 are contained in the confidence interval, this is not the case for MRI120 and MRI120-cc.

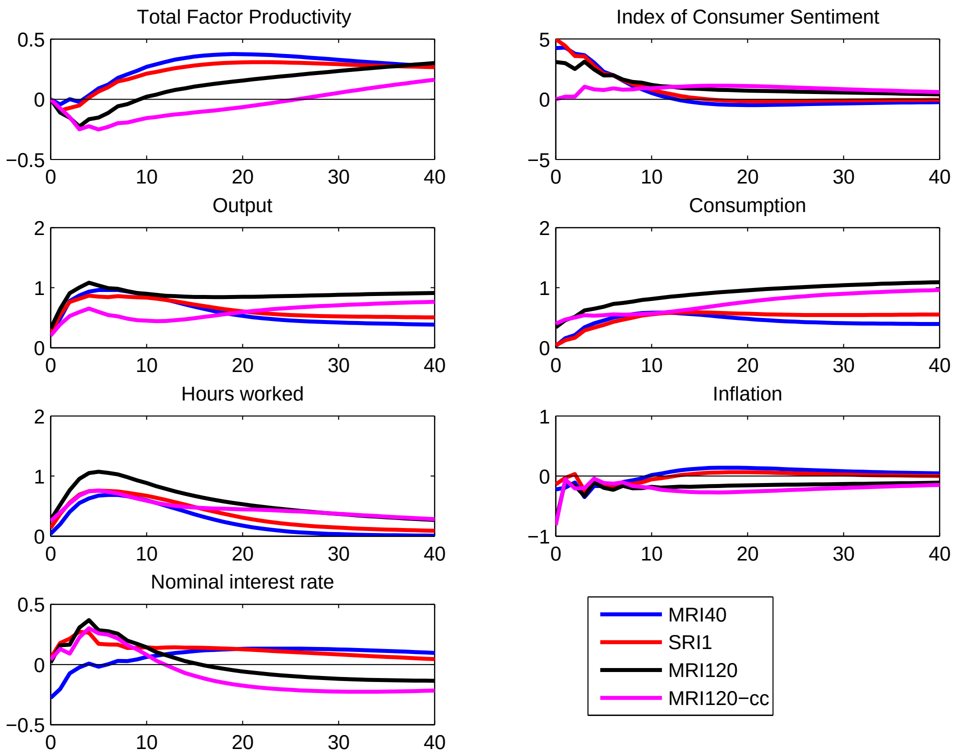

Figure 4.1: The graph shows impulse response functions to a news shock identified with SRI1 (red), a news shock identified with MRI maximized at horizon 40 (black), a news shock identified with MRI maximized at horizon 120 (black) and a news shock maximized at horizon 120 orthogonal to SRI1 (magenta). The vertical axis refers to percentage points. The horizontal axis indicates the forecast horizons.

In the following, I will add several other macroeconomic shocks to the identification scheme to see whether news shocks may partially capture other macroeconomic shocks. It must be added that also the rest of the shocks and their identifying assumptions can be debated. But they have been extensively used and analyzed in the macroeconomic literature.

4.4 Adding Further Macroeconomic Shocks

I add an unanticipated and news investment-specific technology shock, an oil price shock (OPS) and a monetary policy shock (MP) to the model. I need to add two more variables, the inverse of the relative price of investment (RPI) as a measure of investment-specific technology and the oil price. As a measure for the oil price I do not use the standard measure, the U.S. crude oil imported acquisition cost by refiners because it is only available from 1974 on. Instead I use the spot crude oil price: west texas intermediate. The two measures have a cross-correlation coefficient of 0.9 after correcting for autocorrelation. Furthermore, the results are robust to the choice of variable. I use the logged measure of investment-specific technology introduced by DiCecio (2009) which is the investment deflator divided by the consumption deflator[14]. A reduction in the relative price of investment is a positive investment-specific technology shock. The investment-specific technology shock (IST) was introduced in a SVAR model by Fisher (2006) where he identifies it by assuming that it is the only shock affecting the relative price of investment in the long-run. The news investment-specific technology shock (ISTN) was introduced by Ben Zeev and Khan (2015) where it is identified with a medium-run identification scheme maximizing the sum of contributions to the forecast error variance of RPI over 15 years. Their results are robust for other measures of the relative price of investment. Latter also introduce a new method to identify a neutral and an investment-specific news shock simultaneously.

4.4.1 Identification

The variables are ordered as follows: real oil price, total factor productivity, relative price of investment, consumer confidence, real output, real consumption, hours worked, inflation, nominal interest rates. The data is further discussed in Appendix 4.A. The oil price shock, the unanticipated productivity shock, the unanticipated investment-specific technology shock and the news shock with SRI1 are the first four shocks. They are identified as the innovations of the respective variables orthogonal with respect to current values of the preceding variables. The ordering of the unanticipated productivity shock and the investment-specific technology shock are set as in Ben Zeev and Khan (2015) and the results are robust to changing the order. The oil price is put first as generally done in the literature where it is assumed that the oil price is only affected by oil price shocks on impact. The oil price affects TFP and RPI in the short- as well as the long-run but is itself unaffected by most of the shocks. If the ordering is changed and the oil price is put on position three, the short-run effect on TFP and RPI is zero by construction but the medium-run effect remains positive. Therefore, I choose the baseline ordering with the oil price set first. The shock on position nine is a monetary policy shock which is the innovation in interest rates and only affects the rest of the economy with a lag. The identification of this shock is standard in the literature. Ramey (2016) points out that so far this is the most convincing and robust identification scheme, but that it leads to a price puzzle in more recent samples. All five shocks can be identified with a Cholesky decomposition of the covariance matrix of reduced-form innovations.

[14] As shown in Greenwood, Hercowitz, and Krusell (2000), this inverse relationship between investment-specific technology and the real price of investment can be derived in either a one-sector model or a two-sector model with consumptions and investment sectors. The series can be retrieved from https://fred.stlouisfed.org/series/PIRIC

$$\tilde{A} = \begin{pmatrix} \star & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \star & \star & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \star & \star & \star & 0 & 0 & 0 & 0 & 0 & 0 \\ \star & \star & \star & \star & 0 & 0 & 0 & 0 & 0 \\ \star & \star & \star & \star & \star & \star & \star & \star & 0 \\ \star & \star & \star & \star & \star & \star & \star & \star & 0 \\ \star & \star & \star & \star & \star & \star & \star & \star & 0 \\ \star & \star & \star & \star & \star & \star & \star & \star & 0 \\ \star & \star & \star & \star & \star & \star & \star & \star & 0 \\ \star & \star & \star & \star & \star & \star & \star & \star & \star \end{pmatrix}$$

Additionally, I identify either a standard news shock or an investment-specific technology news shock with a medium-run identification scheme. Identifying the news shocks MRI120 or IST120 requires finding the γ that maximizes the contribution to the forecast error variance of TFP or RPI at horizon H orthogonal to the rest of the shocks. In contrast to Ben Zeev and Khan (2015), I do not sum the contributions over the whole horizon.

The news shock is indexed by 5. Identifying the news shock implies choosing the impact matrix to maximize contributions to $\Xi_{2,5(h)}$ over h. This is equivalent to solving the following optimization problem:

$$\begin{aligned} \gamma^* = & argmax \Xi_{2,5}(h) \\ & s.t. \\ & \tilde{A}(1,i) = 0, \forall i > 1 \\ & \gamma_5(1) = 0 \\ & \tilde{A}(2,i) = 0, \forall i > 2 \\ & \gamma_5(2) = 0 \\ & \tilde{A}(3,i) = 0, \forall i > 3 \\ & \gamma_5(3) = 0 \\ & \tilde{A}(4,i) = 0, \forall i > 4 \\ & \gamma_5(4) = 0 \\ & \gamma_5' \gamma_5 = 1 \end{aligned}$$

The first eight constraints impose that the news shock has no contemporaneous effect on the oil price, TFP, RPI and consumer confidence while the ninth ensures that γ is a column vector belonging to an orthonormal matrix.

4.4.2 Results

I have considered all possible mixtures of shocks, but only present an excerpt of results. The addition of the monetary policy shock does only mildly affect contributions of productivity shocks but changes the effect of MRI40 (not orthogonal to SRI1) on interest rates. Figure 4.1 shows impulse responses to news shocks MRI40, SRI1, MRI40-MP (which is the news shock identified at horizon 10 years orthogonal to a monetary policy shock) and a monetary policy shock (MP) where MRI40 and MRI40-MP are not orthogonal to SRI1.

The addition of the monetary policy shock only slightly reduces the effect of MRI40 for most variables. But the impact response of the nominal interest rate completely changes once the monetary policy shock is added. It is now positive and very close to the response of SRI1. If the maximization horizon were increased to 48, the impulse responses of SRI1 and MRI48-MP would be practically identical. Hence, MRI40 is not robust to adding further macroeconomic shocks. The expansionary monetary policy shock affects the economy with a lag and leads to qualitatively similar effects on the economy as news shocks. Output, consumption and hours worked response is in a hump-shape with a peak after six to eight quarters. The main difference is the strong decline in interest rates. A monetary policy shock clearly seems to increase total factor productivity at business cycle frequencies.

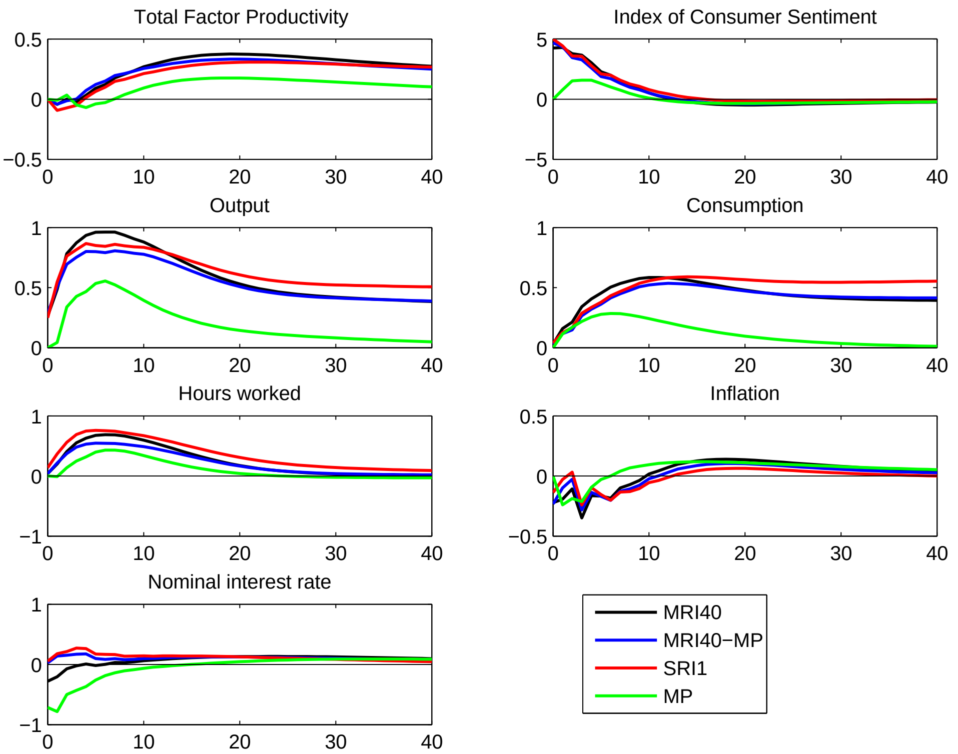

Figure 4.1: The graph shows impulse response functions to a news shock identified with SRI1 (red), a news shock identified with MRI maximized at horizon 40 (black), a news shock identified with MRI maximized at horizon 40 orthogonal to a monetary policy shock (blue) and a monetary policy shock (green). The vertical axis refers to percentage points. The horizontal axis indicates the forecast horizons.

Table 4.1 shows the forecast error variance decomposition adding further macroeconomic shocks. I find that the oil price shock and the monetary policy shock affect the relative price of investment and, to similar extent, TFP. The results are robust to the ordering of the oil price, TFP and RPI. The only notable discrepancy can be found for the impact contribution of the oil price shock to RPI which measures 19% if the variables are kept in this order. This means that either total factor productivity and the relative price of investment are indeed affected by other macroeconomic shocks. Or that the measures of TFP and RPI may be flawed. Nevertheless, the fact that this result is found for TFP and RPI is interesting. Table 4.B.1, in Appendix, contains the forecast error variance decomposition if MRI120 is not orthogonal to SRI1 and shows that the results is independent of the orthogonality assumption between SRI1 and MRI120.

An even mores significant result is that the neutral technology news shock and the investment-specific news shock are highly cross-correlated with a correlation coefficient of 0.97. In Table 4.B.2 Appendix 4.B, results to an investment-specific technology news shock are shown. The two shocks have an almost identical contribution and effects on variables. Thus, it can be argued that basically the same shock is identified and it is not clear which sort of shock it is. A hint may be the fact that the news shock contributes 20% to RPI already at a horizon of 20 while the contribution to TFP is basically nil until horizon ten years. This would confirm the result of Ben Zeev and Khan (2015) that it is mainly investment-specific news shocks contributing to the business cycle. Nevertheless, this shock can also be identified without the relative price of investment. This result is independent of the maximization horizon and also holds if we abstract from orthogonality to confidence. Furthermore, the contributions of most shocks to the variation in TFP and RPI are of very similar sizes. There seems to be a close connection between RPI and TFP. This raises new questions. Namely, what is measured by TFP series? Are they mainly capturing investment-specific technology? Or is investment-specific technology strongly influencing TFP? Through which channels would an a IST news or a TFP news shock trigger such a strong response of consumption? And ultimately, are we really identifying a news shock?

A possible explanation is that this shock identifies the long-run growth component of the economy. This component seems to be the most important factor at business cycle frequencies and especially in the long-run. Furthermore, the difference to SRI1 is not clear. More research is necessary in that direction combining empirical and theoretical insights. I think that a model including endogenous technology adoption as introduced in Chapter 2 may be a valuable starting point.

Figure 4.2 displays impulse responses to an oil price shock, news shocks SRI1 and MRI120 and a monetary policy shock in a 9-variable model identifying all shocks simultaneously. News shock MRI120 is orthogonal to all identified shocks including SRI1 and MP. The responses to an unanticipated productivity shock and an unanticipated investment-specific technology shock are not shown as they have only minor effects on most variables. A positive oil price shock leads to a hump-shaped decrease in economic activity with a lag which manifest mostly in output and hours. The trough is reached after six to eight quarters. Furthermore, it leads to a temporary increase in inflation, a decrease in the relative price of investment and a persistent decrease in total factor productivity. The responses to the rest of the shocks are not strongly affected by the addition of further shocks. The exception is the effect of MRI120 on the interest rate during the first year which has declined to almost zero. A positive TFP news shock or IST news shock actually reduces the rel. price of investment in the long-run. It can be seen that RPI reacts slowlier to SRI1 but faster to MRI120 than TFP. MRI120 decreases RPI by almost 0.8%. This may be an indication that SRI1 is capturing more of a news shock while MRI120 is capturing more of a IST news shock. But I do not know enough about the two shocks to disentangle the TFP news and IST news parts. The oil price shock also decreases RPI in the long-run while an expansionary monetary policy shock increases it. The results are robust to replacing MRI120 with IST120.

Table 4.1: Share of forecast error variance decomposition attributable to an oil price shock (OPS), an unanticipated productivity shock (UPS), a news shock identified with short-run restrictions (SRI1), a news shock identified with max FEV and maximization horizon 120 (MRI120) and a monetary policy shock (MP).

Variable	**Shock**	**Horizon**				
		Impact	One year	Five years	Ten years	Thirty years
Oil Price	OPS	1	0.89	0.69	0.54	0.52
	UPS	0	0.00	0.01	0.04	0.05
	IST	0	0.00	0.02	0.03	0.03
	SRI1	0	0.00	0.01	0.01	0.02
	MRI120	0	0.05	0.18	0.26	0.26
	MP	0	0.04	0.03	0.05	0.06
	TOTAL	1	0.98	0.94	0.93	0.94
TFP	OPS	0.02	0.07	0.11	0.13	0.06
	UPS	0.98	0.81	0.64	0.52	0.24
	IST	0	0.01	0.01	0.02	0.02
	SRI1	0	0.01	0.10	0.17	0.22
	MRI120	0	0.05	0.06	0.09	0.42
	MP	0	0.00	0.03	0.03	0.02
	TOTAL	1	0.96	0.94	0.96	0.98
RPI	OPS	0.19	0.11	0.06	0.09	0.05
	UPS	0.01	0.03	0.04	0.03	0.06
	IST	0.80	0.73	0.35	0.20	0.06
	SRI1	0	0.00	0.04	0.11	0.23
	MRI120	0	0.02	0.20	0.38	0.53
	MP	0	0.00	0.02	0.04	0.02
	TOTAL	1	0.90	0.71	0.84	0.95
Confidence	OPS	0.01	0.03	0.03	0.05	0.07
	UPS	0.03	0.04	0.04	0.05	0.06
	IST	0.01	0.00	0.01	0.01	0.01
	SRI1	0.96	0.79	0.62	0.55	0.54
	MRI120	0	0.04	0.15	0.18	0.18
	MP	0	0.08	0.08	0.09	0.09
	TOTAL	1	0.98	0.94	0.94	0.94

Variable	**Shock**	**Horizon**				
		Impact	One year	Five years	Ten years	Thirty years
Output	OPS	0.00	0.03	0.08	0.05	0.03
	UPS	0.07	0.06	0.12	0.10	0.07
	IST	0.01	0.01	0.01	0.01	0.00
	SRI1	0.08	0.32	0.36	0.33	0.29
	MRI120	0.05	0.13	0.23	0.38	0.54
	MP	0	0.05	0.06	0.04	0.03
	TOTAL	0.21	0.60	0.86	0.91	0.96
Consumption	OPS	0.05	0.02	0.02	0.01	0.01
	UPS	0.01	0.06	0.10	0.08	0.06
	IST	0.06	0.02	0.01	0.00	0.00
	SRI1	0.02	0.14	0.30	0.29	0.28
	MRI120	0.46	0.45	0.49	0.58	0.62
	MP	0	0.06	0.03	0.02	0.01
	TOTAL	0.59	0.75	0.94	0.97	0.99
Hours	OPS	0.01	0.01	0.05	0.05	0.04
	UPS	0.12	0.03	0.01	0.01	0.01
	IST	0.01	0.01	0.02	0.02	0.02
	SRI1	0.08	0.31	0.32	0.32	0.27
	MRI120	0.16	0.20	0.30	0.30	0.37
	MP	0	0.02	0.05	0.05	0.04
	TOTAL	0.38	0.57	0.76	0.76	0.77
Inflation	OPS	0.01	0.10	0.13	0.16	0.16
	UPS	0.00	0.01	0.03	0.04	0.04
	IST	0.01	0.03	0.03	0.03	0.03
	SRI1	0.01	0.02	0.04	0.03	0.04
	MRI120	0.58	0.40	0.38	0.39	0.38
	MP	0	0.05	0.09	0.09	0.09
	TOTAL	0.61	0.61	0.70	0.74	0.75
Interest Rate	OPS	0.01	0.02	0.09	0.16	0.18
	UPS	0.01	0.01	0.07	0.09	0.09
	IST	0.01	0.02	0.04	0.03	0.03
	SRI1	0.01	0.10	0.11	0.09	0.09
	MRI120	0.00	0.02	0.05	0.10	0.13
	MP	0.91	0.55	0.30	0.25	0.23
	TOTAL	0.94	0.73	0.65	0.72	0.74

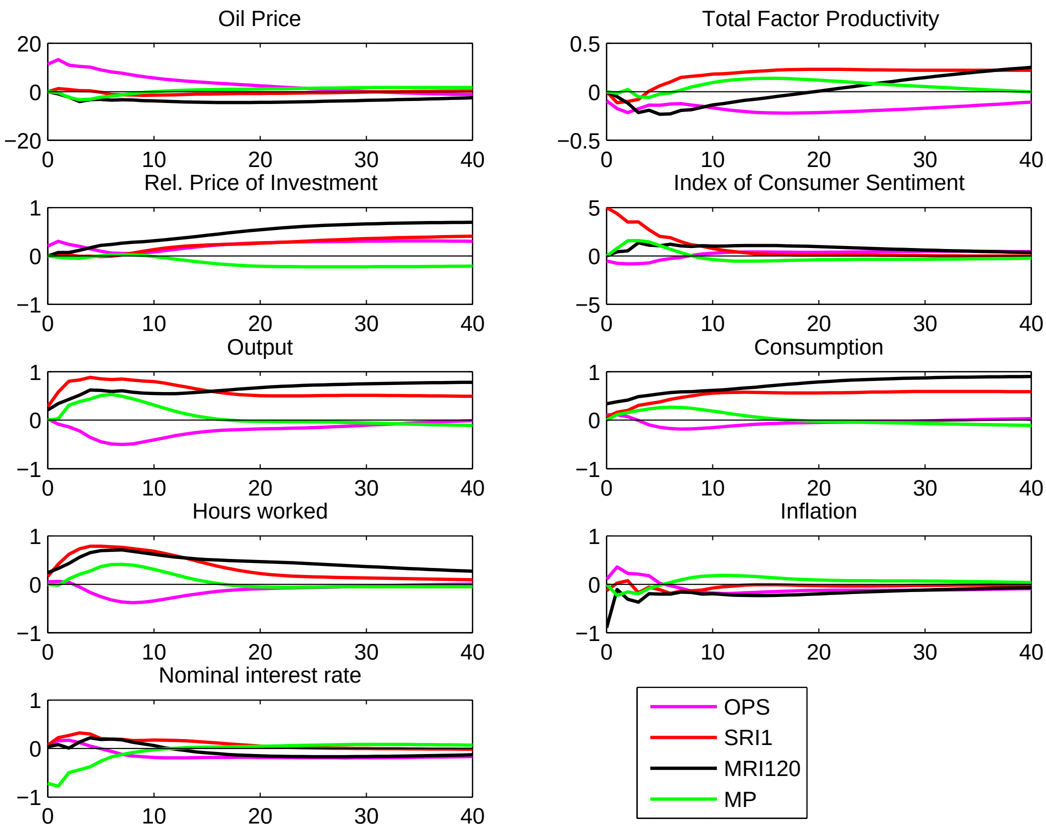

Figure 4.2: The graph shows impulse response functions to an oil price shock (magenta), a news shock identified with SRI1 (red), a news shock identified with MRI maximized at horizon 120 orthogonal to all other shocks (black), and a monetary policy shock (blue) and a monetary policy shock (green). The vertical axis refers to percentage points. The horizontal axis indicates the forecast horizons.

4.5 Conclusions

I revisit the identification of productivity shocks and consider identification schemes that have been extensively discussed in the literature. My contribution is to question the nature of the identified shocks and the underlying assumptions. In empirical analysis news shocks have generally been isolated from other macroeconomic shocks except for unanticipated productivity shocks. I add a monetary policy shock, an oil price shock and an unanticipated investment-specific technology shock to the model. Furthermore, I simultaneously identify a news shock with short-run restrictions and with medium-run restrictions with a large maximization horizon. The news shock identified with medium-run restrictions is either a TFP news shock or an IST news shock. I can show that depending on the maximization horizon, the max FEV method either identifies a shock almost identical to SRI1 or a shock that explains most of the variation in the economy. Thus, two different shocks affect total factor productivity and the whole economy at business cycle frequencies and in the long-run. There are three key findings. Firstly, the identified news shock depends strongly on the identification scheme. This is true for productivity shocks in general. Secondly, basically the same shock is identified when a TFP news shock and an investment-specific technology news shock are identified separately. Thirdly, a certain identification scheme may capture the long-run growth component of the economy explaining most of the variation in the economy in the medium- and long-run.

Future research needs to address several issues in regard to productivity shocks. It seems important that it is clear whether the researcher wants to identify a completely unanticipated shock or a shock with large medium- or long-run contribution or a mixture of all. Furthermore, the correspondence between the different identification methods of productivity shocks and theoretical shocks need to be stated more clearly. At the moment it seems as if any identification method has been used to characterize an unanticipated exogenous technology shock in a DSGE model. Obviously, the deductions are very different and depend critically on the stated assumptions such as orthogonality and maximization horizon. Finally, the interrelationship between TFP and investment-specific technology and the economy needs to be further discussed. The exogeneity assumption imposed in most DSGE models may not be appropriate and models with endogenous technology adoption as introduced in Chatper 2 may be helpful.

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Appendix

4.A Data

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

I 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, Fernald, and Kimball (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.[15] We use the vintage series until October 2016 and downloaded in December 2016 (TFP16). To obtain the log-level of TFP I construct the cumulated sum of the original series, which is in log-differences.

I use the S&P 500 stock market index as a measure of stock prices.[16] I obtain data for output, consumption, investment, the nominal interest rate, the relative price of investment and the oil price from the Bureau of Economic Analysis. For output I use the real gross value added for the nonfarm business sector. As a measure of consumption I 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. I obtain data on hours worked, population, and price level from the Bureau of Labor Statistics. As a measure of hours worked, I 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 I use the Effective Federal Funds Rate. As a measure for the relative price of investment I use the log of the ratio of the investment deflator and the consumption deflator. I use the log of the spot crude oil price: west texas intermediate scaled by the price deflator as a measure for the real oil price.

I 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

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

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

expectations for six months is available.[17] We use the index in logs.

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, Fernald, and Kimball (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)

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)

RPI: relative price of investment (log of DiCecio, Riccardo, Relative Price of Investment Goods [PIRIC], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PIRIC, August 16, 2017)

oil price: (log of Federal Reserve Bank of St. Louis, Spot Crude Oil Price: West Texas Intermediate (WTI) [WTISPLC], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/WTISPLC, August 17, 2017 / divided by the price deflator)

[17] 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.

4.B Results

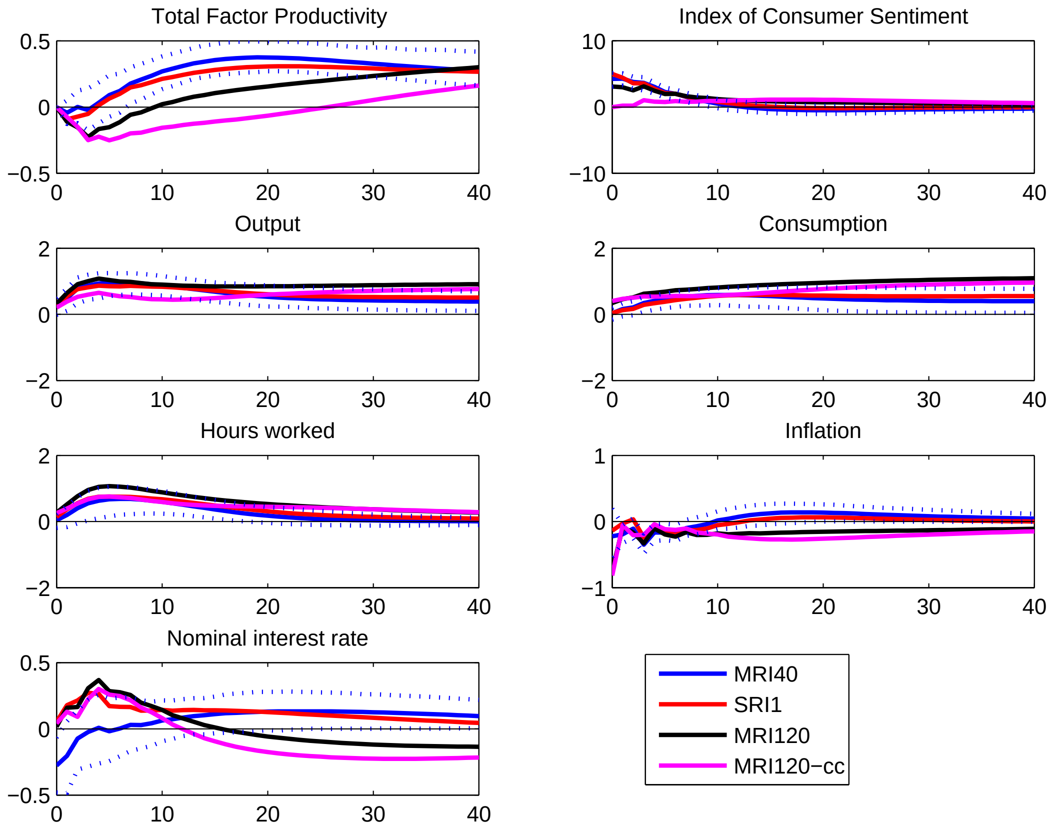

Figure 4.B.1: The graph shows impulse response functions to a news shock identified with SRI1 (red), a news shock identified with MRI maximized at horizon 40 (black), a news shock identified with MRI maximized at horizon 120 (black) and a news shock maximized at horizon 120 orthogonal to SRI1 (magenta). The dotted lines correspond to the 68% confidence intervals from 1000 bias-corrected bootstrap replications of the reduced form VAR. The vertical axis refers to percentage points. The horizontal axis indicates the forecast horizons.

Table 4.B.1: Share of forecast error variance decomposition attributable to an oil price shock (OPS), an unanticipated productivity shock (UPS), a news shock identified with max FEV and maximization horizon 120 (MRI120) and a monetary policy shock (MP).

Variable	**Shock**	**Horizon**				
		Impact	One year	Five years	Ten years	Thirty years
Oil Price	OPS	1	0.89	0.69	0.54	0.52
	UPS	0	0.00	0.01	0.04	0.05
	IST	0	0.00	0.02	0.03	0.03
	MRI120	0	0.02	0.16	0.21	0.20
	MP	0	0.04	0.03	0.05	0.06
	TOTAL	1	0.96	0.90	0.87	0.86
TFP	OPS	0.02	0.07	0.11	0.13	0.06
	UPS	0.98	0.81	0.64	0.52	0.24
	IST	0	0.01	0.01	0.02	0.02
	MRI120	0	0.05	0.04	0.16	0.60
	MP	0	0.00	0.03	0.03	0.02
	TOTAL	1	0.96	0.82	0.86	0.94
RPI	OPS	0.19	0.11	0.06	0.09	0.05
	UPS	0.01	0.03	0.04	0.03	0.06
	IST	0.80	0.73	0.35	0.20	0.06
	MRI120	0	0.02	0.24	0.48	0.76
	MP	0	0.00	0.02	0.04	0.02
	TOTAL	1	0.89	0.71	0.84	0.95
Confidence	OPS	0.01	0.03	0.03	0.05	0.07
	UPS	0.03	0.04	0.04	0.05	0.06
	IST	0.01	0.00	0.01	0.01	0.01
	MRI120	0.31	0.39	0.44	0.43	0.42
	MP	0	0.08	0.08	0.09	0.09
	TOTAL	0.35	0.55	0.61	0.64	0.65

Variable	**Shock**	**Horizon**				
		Impact	One year	Five years	Ten years	Thirty years
Output	OPS	0.00	0.03	0.08	0.05	0.03
	UPS	0.07	0.06	0.12	0.10	0.07
	IST	0.01	0.01	0.01	0.01	0.00
	MRI120	0.12	0.39	0.54	0.68	0.82
	MP	0	0.05	0.06	0.04	0.03
	TOTAL	0.20	0.53	0.81	0.88	0.95
Consumption	OPS	0.05	0.02	0.02	0.01	0.01
	UPS	0.01	0.06	0.10	0.08	0.06
	IST	0.06	0.02	0.01	0.00	0.00
	MRI120	0.41	0.58	0.78	0.86	0.90
	MP	0	0.06	0.03	0.02	0.01
	TOTAL	0.52	0.75	0.94	0.97	0.98
Hours	OPS	0.01	0.01	0.05	0.05	0.04
	UPS	0.12	0.03	0.01	0.01	0.01
	IST	0.01	0.01	0.02	0.02	0.02
	MRI120	0.24	0.46	0.59	0.59	0.60
	MP	0	0.02	0.05	0.05	0.04
	TOTAL	0.38	0.57	0.76	0.76	0.77
Inflation	OPS	0.01	0.10	0.13	0.16	0.16
	UPS	0.00	0.01	0.03	0.04	0.04
	IST	0.01	0.03	0.03	0.03	0.03
	MRI120	0.49	0.34	0.34	0.35	0.35
	MP	0	0.05	0.09	0.09	0.09
	TOTAL	0.51	0.53	0.63	0.66	0.68
Interest Rate	OPS	0.01	0.02	0.09	0.16	0.18
	UPS	0.01	0.01	0.07	0.09	0.09
	IST	0.01	0.02	0.04	0.03	0.03
	MRI120	0.01	0.09	0.10	0.12	0.16
	MP	0.91	0.55	0.30	0.25	0.23
	TOTAL	0.94	0.69	0.59	0.65	0.68

Table 4.B.2: Share of forecast error variance decomposition attributable to an oil price shock (OPS), an unanticipated productivity shock (UPS), a news shock identified with short-run restrictions (SRI1), a investment-specific technology news shock identified with max FEV and maximization horizon 120 (IST120) and a monetary policy shock (MP).

Variable	**Shock**	**Horizon**				
		Impact	One year	Five years	Ten years	Thirty years
Oil Price	OPS	1	0.89	0.69	0.54	0.52
	UPS	0	0.00	0.01	0.04	0.05
	IST	0	0.00	0.02	0.03	0.03
	SRI1	0	0.00	0.01	0.01	0.02
	IST120	0	0.05	0.16	0.24	0.24
	MP	0	0.04	0.03	0.05	0.06
	TOTAL	1	0.98	0.92	0.91	0.91
TFP	OPS	0.02	0.07	0.11	0.13	0.06
	UPS	0.98	0.81	0.64	0.52	0.24
	IST	0	0.01	0.01	0.02	0.02
	SRI1	0	0.01	0.10	0.17	0.22
	IST120	0	0.04	0.05	0.09	0.41
	MP	0	0.00	0.03	0.03	0.02
	TOTAL	1	0.95	0.93	0.95	0.98
RPI	OPS	0.19	0.11	0.06	0.09	0.05
	UPS	0.01	0.03	0.04	0.03	0.06
	IST	0.80	0.73	0.35	0.20	0.06
	SRI1	0	0.00	0.04	0.11	0.23
	IST120	0	0.03	0.24	0.41	0.54
	MP	0	0.00	0.02	0.04	0.02
	TOTAL	1	0.91	0.75	0.88	0.96
Confidence	OPS	0.01	0.03	0.03	0.05	0.07
	UPS	0.03	0.04	0.04	0.05	0.06
	IST	0.01	0.00	0.01	0.01	0.01
	SRI1	0.96	0.79	0.62	0.55	0.54
	IST120	0	0.03	0.13	0.16	0.16
	MP	0	0.08	0.08	0.09	0.09
	TOTAL	1	0.98	0.93	0.93	0.93

Variable	**Shock**	**Horizon**				
		Impact	One year	Five years	Ten years	Thirty years
Output	OPS	0.00	0.03	0.08	0.05	0.03
	UPS	0.07	0.06	0.12	0.10	0.07
	IST	0.01	0.01	0.01	0.01	0.00
	SRI1	0.08	0.32	0.36	0.33	0.29
	IST120	0.04	0.12	0.22	0.37	0.53
	MP	0	0.05	0.06	0.04	0.03
	TOTAL	0.21	0.59	0.85	0.90	0.95
Consumption	OPS	0.05	0.02	0.02	0.01	0.01
	UPS	0.01	0.06	0.10	0.08	0.06
	IST	0.06	0.02	0.01	0.00	0.00
	SRI1	0.02	0.14	0.30	0.29	0.28
	IST120	0.46	0.46	0.49	0.57	0.61
	MP	0	0.06	0.03	0.02	0.01
	TOTAL	0.59	0.76	0.94	0.96	0.97
Hours	OPS	0.01	0.01	0.05	0.05	0.04
	UPS	0.12	0.03	0.01	0.01	0.01
	IST	0.01	0.01	0.02	0.02	0.02
	SRI1	0.08	0.31	0.32	0.32	0.27
	IST120	0.11	0.15	0.26	0.26	0.32
	MP	0	0.02	0.05	0.05	0.04
	TOTAL	0.33	0.53	0.71	0.71	0.72
Inflation	OPS	0.01	0.10	0.13	0.16	0.16
	UPS	0.00	0.01	0.03	0.04	0.04
	IST	0.01	0.03	0.03	0.03	0.03
	SRI1	0.01	0.02	0.04	0.03	0.04
	IST120	0.67	0.46	0.41	0.41	0.40
	MP	0	0.05	0.09	0.09	0.09
	TOTAL	0.70	0.67	0.73	0.76	0.77
Interest Rate	OPS	0.01	0.02	0.09	0.16	0.18
	UPS	0.01	0.01	0.07	0.09	0.09
	IST	0.01	0.02	0.04	0.03	0.03
	SRI1	0.01	0.10	0.11	0.09	0.09
	IST120	0.00	0.02	0.04	0.10	0.12
	MP	0.91	0.55	0.30	0.25	0.23
	TOTAL	0.94	0.72	0.65	0.71	0.74

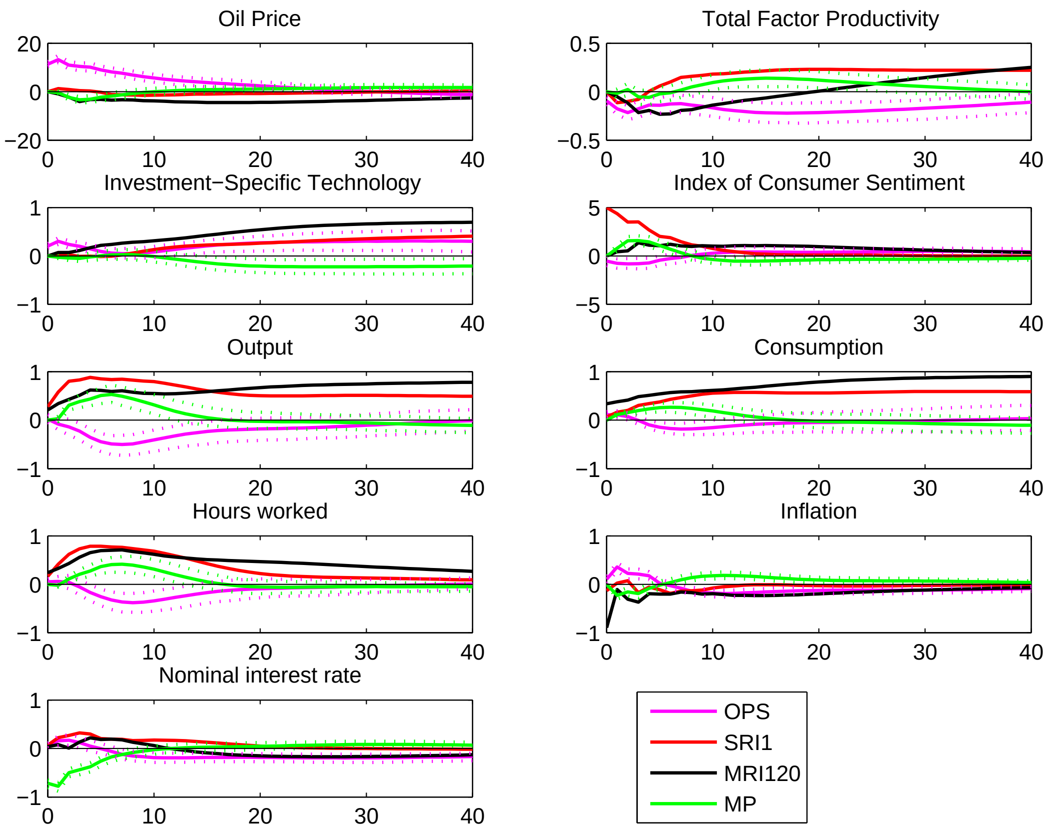

Figure 4.B.2: The graph shows impulse response functions to an oil price shock (magenta), a news shock identified with SRI1 (red), a news shock identified with MRI maximized at horizon 120 orthogonal to all other shocks (black), and a monetary policy shock (blue) and a monetary policy shock (green). The dotted lines correspond to the 68% confidence interval from 500 bias-corrected bootstrap replications of the reduced form VAR of the model. The vertical axis refers to percentage points. The horizontal axis indicates the forecast horizons.

Selbständigkeitserklärung

Ich erkläre hiermit, dass ich diese Arbeit selbständig verfasst und keine anderen als die angegebenen Quellen benutzt habe. Alle Koautorenschaften sowie alle Stellen, die wörtlich oder sinngemäss aus Quellen entnommen wurden, habe ich als solche gekennzeichnet. Mir ist bekannt, dass andernfalls der Senat gemäss Artikel 36 Absatz 1 Buchstabe o des Gesetzes vom 5. September 1996 über die Universität zum Entzug des aufgrund dieser Arbeit verliehenen Titels berechtigt ist.

Bern, 30. August 2017

Sarah Fischer