Examining news shocks

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Contents

List of Tables

List of Figures

Abstract

A fundamental discrepancy surrounds news shocks, that is, a-priori information agents receive about developments in the economy. Whereas news shocks appear relevant empirically, in theoretical real-business-cycle models news about future total factor productivity generates counterfactual predictions. In standard real-business-cycle models these predictions emerge on top of the failures in this class of models, already known in the literature.

This coincidence of empirical evidence and theoretical failure motivates the search for a structure of real-business-cycle models that makes news shocks work. In these models, when good news is indicated, agents anticipate today the positive income effect of tomorrow. When news prove correct and total factor productivity eventually increases, a strong substitution effect occurs. The sequence of these two effects is what causes the adverse consequences of news shocks. The analysis indicates that the main feature responsible for the failure of standard models is the high substitutability of consumption and investment.

However, evaluating a non-standard three-sector real-business-cycle model shows that a low substitutability of consumption and investment is not the only element needed to fix the adverse consequences of news shocks. The results are robust with respect to assumptions that vary the exact means of how new information enters the model. In light of the former results, this robustness suggests that the real structure of the models, as opposed to the informational structure, is the crucial part determining success and failure of news shocks.

This thesis shows that there is no easy way of formalizing news shocks. Nevertheless, it provides a discussion of elements and their combination that appear relevant for guiding future research. Appropriate frictions in the factor markets in combination with a multiple sector model appear promising. Furthermore, one suggestion originally proposed in Cochrane (1994) and refreshed here is to construct models that disseminate news about candidates of shocks inducing wealth effects, but no intertemporal substitution.

Chapter 1

Introduction

> *Thus the "fortune-teller" is trying to foresee something that is really quite unforeseeable. This is characteristic of all forms of foreseeing. And precisely because what they "see" is so vague, it is hard to repudiate fortune-tellers' claims.*[1]

News about the future is both valuable and vague.[2] In ancient times, merchants, commanders, and emperors made their way to the oracle of Delphi to make inference about the future and to make sure to take the right decisions. Nowadays, the budget of the German government is negotiated based on profound forecasts about future tax income. The business world orientates its investment decisions on economic leading indicators such as consumer confidence and total book orders. Alternatively, research institutions composite indicators out of economic variables and opinion polls, e.g. the Business Climate Index of the Ifo Institute for Economic Research and a business cycle barometer regularly disseminated by the German Institute for Economic Research, to anticipate today economic up- and downturns of tomorrow. Certainly, the most prominent example of the economic compilation of news is the immediate adjustment of stock prices following new information on the prospect of a share. However, even though in these days the means of projection are (most of the time) more transparent, the basic challenge has not change in the course of centuries − uncertainty as a matter of daily life.

That uncertainty matters in the economy is well-established and reflected, for example, in the widely-used modelling assumption of rational expectations. That news matters was recognized already by early economists. Despite of this, the popularity of explicitly modelling the arrival of new information to explain business cycle fluctuations in economic models is modest compared to the obvious evidence.

In this thesis, I examine news shocks, that is, new information agents receive today about developments in the economy tomorrow. Naturally, news about the future is uncertain.[3] From a modelling perspective, news has no direct impact on the economy as is the case, say, if a shock to total factor productivity changes marginal productivity; news of today affects today's expectations, and thus leads to contemporaneous adjustments.[4]

A fundamental discrepancy surrounds news shocks. The empirical literature aiming at identifying the major sources of macroeconomic fluctuations assigns a potential role to news shocks. At the same time, theoretical real-business-cycle models featuring news shocks produce counterfactual predictions in addition to those failures in this class of models already well-known in the literature. In real-business-cycle models news about the future often takes the form of some a-priori knowledge about future total factor productivity.[5] Therefore, when good news is indicated, agents anticipate today the positive income effect of tomorrow. This leads to contemporaneous increases in consumption and leisure. In the case, total factor productivity eventually increases, a strong substitution effect between consumption and leisure occurs. The sequence of these two effects is responsible for the adverse consequences of news shocks.

Hairault, Langot, and Portier (1997) and Beaudry and Portier (2000) are two references that formalize news shocks in real-business-cycle models. Whereas the former studies the impact of news on the leading property of consumption with respect to output, the latter describes a three-sector economy capable of producing expectation-led business cycles.

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[3]In addition to this natural uncertainty, the literature provides several explanations for the uncertainty of information, i.e. prohibitive high cost of full information, limited monitoring capacity, measurement errors, data revisions, or phenomena like expected inflation, business cycles, or preferences that factually are unobservable, to name only a few.

[4]News shocks should be carefully discriminated from sunspots. Sunspots formalize the idea of self-fulfilling prophecies. News shocks are different in that they carry over a piece of substantial but uncertain information. Agents take the information and its uncertainty into account to adjust their intertemporal decisions. News shocks do not induce self-fulfilling elements. For example, Harrison and Weder (2001) use sunspots to explain the Great Depression. Farmer (1999) provides a comprehensive treatment of sunspots.

[5]The theoretical literature has worked out a number of different channels to make information matter for business cycle fluctuations. See, among others, Caplin and Leahy (1993), Zeira (1994), or Van Nieuwerburgh and Veldtkamp (2003). I briefly review these contributions in section 2.2.

As a starting point, I follow Hairault, Langot, and Portier (1997) and incorporate news shocks into a real-business-cycle model that may be considered standard. The results point to the adverse consequences of news shocks in such a model and motivate the focus of this thesis, the search for *a model structure that makes news shocks work.* For this purpose, I identify the high elasticity of substituting consumption and investment as the main element driving the adverse results in the standard model, and derive three important dimensions to evaluate the performance of a model with news shocks. Then I turn to investigating the three-sector model originally proposed by Beaudry and Portier (2000) that by construction exhibits a low elasticity of substituting consumption and investment. However, it turns out that the structure of this model still induces counterfactual predictions. I account for the robustness of these results by varying the specific way of how news shocks are introduced into the models.

The analysis in this thesis strongly suggests that there is no straightforward way of formalizing news shocks. Furthermore, the robustness of results with respect to informational variations suggest that the informational structure is of minor importance.[6] Predominantly relevant appears the real structure of the model.

The remainder of this thesis looks as follows. Chapter 2 reviews the empirical and theoretical literature that relate to news shocks and, more general, to the arrival of new information in economic models. Chapter 3 analysis the real-business-cycle model along the lines of Hairault, Langot, and Portier (1997). The model is similar the one in Cooley and Prescott (1995) but augmented with a news shock. In chapter 4, I review the three-sector economy in Beaudry and Portier (2000) featuring a low short-term elasticity of substituting consumption and investment in conjunction with news shocks. I analyze this model in detail throughout chapter 5 and evaluate its performance with respect to news shocks in chapter 6. Chapter 7 derives augmentations of this model and of the one in Hairault, Langot, and Portier (1997) with an explicit major on the formulation of news shocks. Results are summarized and discussed in chapter 8 and chapter 9 concludes.

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[6] In the following, I discriminate the *real* and the *information* structure of the models applied. Under the heading *real* I subsume elements like technology, preferences, endowment, or the number of sectors in the model. Since the models to come are real models in the sense that exchange takes place in consumption units and not with the help of nominal means of payment there is no grounds for confusion. Assumptions determining the shape of new information, its informational content, and the way how agents form beliefs is summarized by the term *informational* structure.

Chapter 2

News shocks in the literature

Prescott and Hayashi examine Japan's economic downturn in the 1990s. With respect to the extraordinary growth of Japan's economy in the late 1980s and early 1990s they express the view that "the unusual pickup in economic activity, particularly investment, was due to an anticipation of higher productivity growth that never materialized" (Prescott and Hayashi (2002, p. 229)). This appears reasonable in the light of the accompanying "bubble" periods at the stock markets. But is there more than anecdotal evidence and pure intuition that justifies the examination of news shocks?

2.1 Evidence on news shocks

Searching for the major forces driving movements in real GNP, Uhlig (2003a) reports empirical findings with respect to news shocks when aiming at identification of a medium and a short run shock. Results are based on a seven-variable BVAR estimated with quarterly data from 1964 to 2001. Impulse response function for the medium run shock suggest that one potential interpretation is a productivity shock as applied in RBC theories, even though the response of GNP happens gradually and not, as theory would suggest, instantaneously. As is noted, the short run shock causes an adjustment pattern in the variables in line with a "misjudged productivity signal". GNP increases substantially in the first two quarters to revert its path and turn negative after three years. The same pattern is observed in the response of private investment and hours worked whereas real nondurable consumption takes up the initial boom, but leaves aside the subsequent downturn. Adjustments in the nominal variables suggest the following course of events: the anticipated increase in productivity increases wages. Anticipating inflationary pressure, the central bank counteracts by increasing interest rates. Eventually, the absence of the anticipated productivity increase leads, in conjunction with higher interest rates, to an economic downturn. Variance decompositions show that the fraction of variation in the data explained by

the short run shock is in the range of 50% for real GNP, private investment, and hours worked in the first two quarters. The corresponding fraction of variation in real nondurable consumption is much smaller with about 15%. Taking both shocks together, they easily explain 80% of data variation in real GNP, private investment and nondurable consumption within the first five years.

Assessing which types of shocks drive economic fluctuations, Cochrane (1994) investigates monetary shocks, technology shocks, shocks to oil prices, and credit shocks. He concludes that there is little profound evidence for the relevance of any of these shocks, and turns to examining news shocks. Intuitively, every consumer should have idiosyncratic information about his individual prospects and, taking this information seriously, is likely to adjust consumption accordingly. News about future developments could then lead to adjustments in today's consumption − an endogenous shock to consumption.[1] Cochrane follows this idea and implements a RBC model where agents receive a-priori information about future productivity. According to Rotemberg (1994, p. 367), Cochrane is the first to pursue theoretically the combination of a technology process with news shocks. Estimates of a consumption-output VAR based on data simulated with the model mimics impulse response functions that come out of a similar analysis with real data. Identification of the VAR uses the Blanchard-Quah decomposition (Blanchard and Quah (1989,1993)); transitory shocks have no permanent effect on output, whereas permanent shocks possibly shift the long-run levels of output and consumption. Variance decompositions show that transitory shocks explain the major bulk of fluctuations in output whereas for consumption the permanent shock is prevalent. Both, impulse response functions and the variance decomposition are in line with what can be observed in real data.

It appears suggestive that these two contributions, both providing a broad atheoretical assessment of the evidence about what shocks drive economic fluctuations, assign a potentially important role to news shocks.

2.2   Theoretical literature on news shocks and new information

The theoretical literature on news and the arrival of new information spreads over quite different areas of economic research and utilizes different information channels. Endogenous arrival of information is formalized in Zeira (1994) where agents learn about economic conditions. In the model,

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[1] This argument does not explain in detail how idiosyncratic information leads to coordinated behavior or conformity on an aggregate level which is necessary for producing a more or less sudden change in aggregate consumption. One potential explanation could be the one of informational cascades as spelled out in Bikhchandani, Hirshleifer, and Welch (1992).

increasing investment delivers information about factual market conditions because the production potential of a new technology and the maximum demand for a new product is unknown a-priori. Then "informational" cycles in output and investment are the outcome of two counteracting forces. The cost of over-investment slows market entry, whereas entry is encouraged by the creation of new investment opportunities, i.e. increasing demand. The relative size of forces changes and causes informational cycles.

Similarly, Caplin and Leahy (1993) show macroeconomic consequences of sectoral informational cycles. In their model, the path of investment reveals information about investment profitability which is only imperfectly observable. At the same time, investment is irreversible making the collection of information profitable.

A different way to formalize the endogenous arrival of new information is to build models that integrate filtering algorithms, like the Kalman filter, and extract signals out of a noisy environment. In Andersen and Beier (2000) agents filter market exchange rates to discriminate permanent vs. transitory shifts in exchange rates. The noisy evolution of exchange rates implies non-neutral effects of monetary shocks and enriches adjustment dynamics in the model. Whereas the updating scheme in Andersen and Beier (2000) draws on new exchange rate observations, Coenen, Levin, and Wieland (2001) show that money provides information about output additional to that contained in the historic output path, when the output series is subject to measurement errors and revisions. This is due to the fact that money reacts to the true movements in output. Van Nieuwerburgh and Veldtkamp (2003) investigate the asymmetry of business cycles in a model where the technology shock is unobservable and output is measured with noise. When investment is high, the filtering of information is more accurate and leads to immediate and decisive reactions of agents.

2.3   News shocks in the real-business-cycle literature.

The analyzes of news shocks are rare in conjunction with real-business-cycle (RBC) models. This may be due to the fact that news shocks appear to introduce demand-induced variation in models entirely directed to explain business-cycle fluctuations by relying on variation that originates in the production side of the economy.[2]

Despite of this, Hairault, Langot, and Portier (1997) (HLP) incorporate a news shock into a standard RBC model.[3] The authors point towards episodes mirrored in macroeconomic data that require initiating movements

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[2] I do not review the general literature on RBC models in this thesis and refer the reader instead to the volume edited by Cooley (1995) and references therein.

[3] See the next chapter for more details on the term "standard".

in consumption to account for. In their model, the household receives in advance some information about a future innovation in total factor productivity (TFP). This new information leads to adjustments in the sphere of the household and surfaces as an autonomous movement of consumption in relation to its other determinants, which may appear to the econometrician as a shock in consumption. Additionally, in this model these consumption movements determine a leading property of consumption with respect to output. The model does describe what news is indicated in advance. However, it does not deliver explanation on why this news emerge.

A similar approach is followed in Beaudry and Portier (2000) (BP). Business cycle fluctuations in their model are the result of erroneous anticipations on which agents base their investment decisions. Depending on the type of forecast error, agents unintentionally and ignorantly are either excessively optimistic or pessimistic regarding the future development of the economy. As will become clear in the next chapter, a standard RBC model is not capable of producing expectation-led business cycles. To this end, BP describe a three-sector economy, whose structure enables expectation-led business cycles to occur, and then proceed to assess the ability of such a model to replicate the pattern of U.S. recessions without relying on technological regress. Again, households receive a signal some periods in advance about future innovations in TFP and take measures to adjust accordingly. These measures trigger substantial dynamics, even though they are not accompanied by any fundamental change in the economy.

In their influential paper, Kydland and Prescott (1982) in turn apply a setting where consumers cannot observe productivity but instead observe a noisy measured indicator. In the model, consumers form optimal beliefs about TFP in the current period. Shocks to TFP have either permanent or transitory effects. Agents infer news when new observations of TFP add to their knowledge about the type of shock observed. The arrival of news therefore has a structural explanation which stands in contrast to the contributions of HLP and BP.

Brief outline. In this analysis, I take as a starting point the innovative combination of news shocks signalling future shocks to TFP, as pursued in Cochrane (1994), and provide a treatment of the puzzling predictions which news shocks produce in standard RBC models. I essentially reach the same conclusion as in Cochrane (1994) in that news shocks induce counterintuitive dynamic adjustments that result in a severe failure of standard RBC models when compared to stylized facts of business cycles.[4] These failures are on top of the shortcomings in the class of models so far documented in the

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[4]A comparison of the different consequences induced by news shocks in contrast to more "traditional" shocks like preference shocks, government spending shocks, capital dividend tax shocks, shocks associated with labor hoarding or a varying degree of capital utilization is a potentially interesting exercise, but beyond the scope of this analysis.

literature. Drawing on BP (2000), this analysis proceeds by investigating if a different model structure is capable of recovering results more in line with what is reported on business cycles.

Chapter 3

News facts in real-business-cycle models

It is well known that standard RBC models fail on a number of dimensions.[1] Inelastic labor supply implies strongly procyclical real wages, a phenomenon not apparent in the data. Furthermore, the models have severe problems to generate reasonable statistics for data on real wages, interest rates, and returns to capital and fail to replicate a negative correlation of consumption and leisure. In general the internal propagation of shocks is weak. On a more fundamental basis, objections are raised against some features this class of models builds on, e.g. perfect market clearing, technology shocks as the one and only source of fluctuation, and issues surrounding the endogeneity of technology.

However, without sharing a fundamentalistic view one might regard RBC models as a reasonable starting point on the way to more elaborated (realistic) models. Based on a certain degree of microfoundation, already simple representatives of the RBC class are capable of reproducing relative standard deviation in economic variables as can be observed in data on business cycle frequency.[2]

Bearing this in mind, in this chapter I investigate in some detail the consequences of news shocks in a standard RBC model. It turns out that RBC models featuring news shocks produce a number of counterfactual predic-

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[1] The term *standard RBC models* should be understood merely as a name for a certain class of RBC models that are often used as a benchmark nowadays: one sector models with utility that is separable across time and arguments, Cobb-Douglas technology, and usually abstracting from a governmental sector. Examples are the model described in Hansen (1985) or the one in Cooley and Prescott (1995).

[2] Uhlig (2003) provides a recent confrontation of an RBC model including a government and population growth with real data. The sequence of excitement, disillusionment, and response as given by the articles of Edward Prescott's "Theory ahead of Business Cycle Measurement", Lawrence Summer's "Some sceptical Observations on Real Business Cycle Theory", and E. Prescott's "Response to a Skeptic" leads directly into the center of the debate surrounding RBC models. The latter three articles are printed in Cooley (1995).

tions in addition to those briefly outlined so far. In section 3.1, I start with solving a RBC model similar to Cooley and Prescott (1995) featuring news shocks. The focus of section 3.2 is how to implement a model with this specific information structure into the Toolkit, a code for analyzing nonlinear dynamic stochastic models easily. In section 3.3, I document the counterfactual consequences which news shocks with a varying degree of informational content drag behind. The last section 3.4 identifies the constraint leading to these counterfactual predictions and motivates the modelling approach followed in the remainder of this analysis.

3.1 A real-business-cycle model with news shocks

In this section I set up and solve a standard RBC model featuring news shocks. The analysis follows the one in HLP (1997) where news shocks are introduced into the model of Cooley and Prescott (1995) to achieve a leading property of consumption with respect to output. I follow the convention that variables known at time t are subscripted t. Apart from this, I adopt the notation of Cooley and Prescott (1995).

Setting up the model. The HLP economy is populated by a representative household, living infinitely long, and a representative firm. The household suffers if forced to work and derives utility from consumption. Preferences are separable across time and among arguments.

$$U(C_t, L_t) = (1 - \alpha)\frac{C_t^{1-\rho} - 1}{1 - \rho} + \alpha \log(1 - L_t)$$

The parameter $\rho \neq 1$ steers the relative risk aversion of the household — high ρ implies strong effort to smooth consumption over time.[3] C_t is consumption, L_t are labor hours, and α determines the relative weight of both variables. In each period the household is endowed with a time contingent normalized to unity. Furthermore, it owns the accumulated capital stock in the economy.

The representative firm produces according to a Cobb-Douglas technology with constant returns to scale. Production factors are labor L_t and the capital stock K_{t-1},

$$Y_t = e^{z_t}K_{t-1}^{\theta}L_t^{1-\theta}, \quad 0 < \theta < 1.$$

Here θ is the capital share of income and z_t denotes the exogenous process driving movements in total factor productivity (TFP). Y_t is the only good

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[3]Cooley and Prescott (1995) use the special case of $\rho = 1$. In the limit $\frac{C_t^{1-\rho}-1}{1-\rho}$ then becomes $\log C_t$. In addition to this change I set the growth factors γ and η equal to zero.

in the economy and can be either reinvested or consumed. The capital stock depreciates with time at a rate δ and accumulates if the household invests,

$$K_{t+1} = D_{t+1} - (1 - \delta)K_t \ ,$$

where D_t stands for aggregate investment.

The information structure. Consider how news shocks can be introduced into the economy. HLP (1997) argue that in every period a certain pool of inventions emerges. Moreover, they assume *(i)* that it takes time to convert these inventions into innovations relevant for production and *(ii)* that compiling inventions into innovations in some cases might be unsuccessful. In period t the household has knowledge about the deterministic time lag n needed to convert inventions into relevant innovations and about inventions $S_t^{(t+n)}$ made in the current period. However, the fraction of successfully compiled inventions is uncertain and reveals only in period $t + n$. With these assumptions one can write the evolution of the TFP process as follows.

$$z_{t+n} = \lambda z_{t+n-1} + \epsilon_{t+n} \ , \tag{3.1}$$

$$S_t^{(t+n)} = \epsilon_{t+n} + \nu_{t+n} \ , \tag{3.2}$$

where ϵ and ν are random variables independent of each other and identically $\mathcal{N}(0, \sigma_i), i = \{\epsilon, \nu\}, |\lambda| < 1$, and n is a positive integer.

How do agents use the a-priori information about ϵ_{t+n}? In this setup the best forecast of ϵ_{t+n} is given by solving a signal extraction problem, where ϵ_{t+n} is the signal and ν_{t+n} is noise. Conditional on the realization of inventions the agents expect an innovation to TFP of size

$$E\left[\epsilon_{t+n} | S_t^{(t+n)}\right] = \chi S_t^{(t+n)} \ , \quad \text{where} \quad \chi = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_\nu^2} \ . \tag{3.3}$$

Put differently, agents expect $\chi\%$ of the observed inventions to become innovations n periods ahead. In the following I refer to $S_t^{(t+n)}$ as the signal. This is sensible from an economic point of view. From an statistical point of view, however, ϵ is the signal.

Solving the model. Since the economy displays no (information) externalities the decentralized solution has a social planner counterpart according to the First Welfare Theorem. This is true if the social planner's objective is to maximize the constrained utility of the representative household. The dynamic problem then is summarized by stating the Lagrangian,

$$\Theta(C_t, L_t, K_t, \mu_t) = E_0[\sum_{t=0}^{\infty} \beta^t ((1 - \alpha)\frac{C_t^{1-\rho} - 1}{1 - \rho} + \alpha \log(1 - L_t)$$

$$- \mu_t \left(C_t + K_t - e^{z_t} K_{t-1}^\theta L_t^{1-\theta} - (1 - \delta)K_{t-1}\right))] \ . \tag{3.4}$$

Deriving first order necessary conditions (FONCs), computing the steady state of the economy, and log-linearizing equations is fairly standard in this model setup. I define $\alpha_1 = \frac{(1-\theta)(1-\alpha)\bar{Y}}{\alpha\bar{C}^\rho}$ and $\alpha_2 = \frac{\bar{L}}{1-\bar{L}}\left(\frac{1+\alpha_1}{\alpha_1}\right)$. Then log-linearized equations for the model without news shocks are

$$0 = \bar{C}\hat{C}_t + \bar{D}\hat{D}_t - \bar{Y}\hat{Y}_t \tag{3.5}$$

$$0 = \bar{D}\hat{D}_t + (1-\delta)\bar{K}\hat{K}_{t-1} - \bar{K}\hat{K}_t \tag{3.6}$$

$$0 = z_t + \theta\hat{K}_{t-1} + (1-\theta)\hat{L}_t - \hat{Y}_t \tag{3.7}$$

$$0 = -\rho\hat{C}_t + \hat{Y}_t - \alpha_2\hat{L}_t \tag{3.8}$$

$$0 = \theta\frac{\bar{Y}}{\bar{K}}\hat{Y}_t - \theta\frac{\bar{Y}}{\bar{K}}\hat{K}_{t-1} - \bar{R}\hat{R}_t \tag{3.9}$$

$$0 = E_t\left[\rho\hat{C}_t - \rho\hat{C}_{t+1} + \hat{R}_{t+1}\right] \ . \tag{3.10}$$

For the exact definition of the model equilibrium, for details on the solution of the model, and for issues surrounding calibration I refer the reader to Cooley and Prescott (1995). Instead, I delve into an exposition how to take into account news shocks in the solution procedure.

How to make news matter? In the current framework news are a-priori information about future TFP innovations. In a statistical sense, the best way of using this information is to produce a forecast of ϵ_{t+n} that is different from zero. Forecasting ϵ_{t+n} as zero is what implicitly is done in models without news: the best forecast of ϵ_{t+n} is its unconditional mean. However, observing the signal $S_t^{(t+n)}$, the best forecast of ϵ_{t+n} is given by the signal extraction formula (3.3).

In every period there are n signals "active" in the economy. Define the sequence of active signals as $\Omega_t = [S_{t-n+1}^{(t+1)}, \ldots, S_t^{(t+n)}]$. To produce a best forecast of z_{t+n} it is necessary to exploit the information of each individual signal. Therefore

$$E\left[z_{t+n}|\Omega_t\right] = \lambda^n z_t + \sum_{i=0}^{n-1} \lambda^i \chi S_{t-i}^{(t+n-i)} \ . \tag{3.11}$$

Because the forecast of z_{t+n} helps to reduce uncertainty about future developments in the economy it should sensibly be taken into account in the Euler equation (3.10), the formula weighting contemporaneous versus future consumption.

The fact that each signal bears only information about the TFP innovation in period $t+n$ implies a convenient simplification of the forecasting scheme. Signalling the autocorrelated z_{t+n} instead would induce the signal to bear information on realizations of z_{t+k} for $k = 1, 2, \ldots, n-1$. For producing a best forecast these intertemporal dependencies would need to be taken into account.

Consider the case for n equal to 1, and define $\Phi = \theta \frac{\bar{Y}}{\bar{K}\bar{R}}$ and $\alpha_3 = \Phi\theta - \theta - \Phi + 1 - \alpha_2$. Then shifting equations (3.8) and (3.9) forward by one period, substituting out $\rho\hat{C}_{t+1}$ and $\hat{R}_{t+1}$ in (3.10), and using (3.7) to replace $\hat{Y}_{t+1}$ delivers an Euler equation explicitly showing TFP.

$$0 = E_t \left[\rho\hat{C}_t + (\Phi\theta - \theta - \Phi)\hat{K}_t - \alpha_3\hat{L}_{t+1} + (\Phi - 1)z_{t+1}|\Omega_t \right]$$

The expectation is conditional on the information transmitted by the sequence of signals. The only variable for which the conditional expectation differs from the unconditional one is z_{t+1}. Substituting out $E\left[z_{t+1}|\Omega_t\right]$ delivers the unconditional Euler equation, [4]

$$0 = E_t \left[\rho\hat{C}_t + (\Phi\theta - \theta - \Phi)\hat{K}_t - \alpha_3\hat{L}_{t+1} + (\Phi - 1)\lambda z_t + (\Phi - 1)\chi S_t^{(t+1)} \right] .$$
(3.12)

Note that if χ converges to zero the informational content of the signal vanishes and the framework degenerates to the original model without a-priori information, regardless of the implementation lag assumed. The next step towards a quantitative evaluation of news shocks is implementing the model into the Toolkit.

3.2 Implementation into the Toolkit.

I implement the economy as described so far with an implementation lag n equal to 1. See Uhlig (1999) for the notation used here and a detailed description of the computations for the recursive law of motion. Define the vectors $\mathbf{x_t}, \mathbf{y_t}$ and $\mathbf{z_t}$ as

$$\mathbf{x_t} = \hat{K}_t, \quad \mathbf{y_t} = \left[\begin{array}{ccccc} \hat{Y}_t & \hat{C}_t & \hat{L}_t & \hat{D}_t & \hat{R}_t \end{array} \right]', \quad \mathbf{z_t} = \left[\begin{array}{cc} z_t & S_t^{(t+1)} \end{array} \right]'$$

and cast equations (3.5) to (3.9) and (3.12) into the form given by the matrix equations (3.19) and (3.20) in Uhlig (1999).

The specification of the exogenous process requires some attention. First, it is important to take into account that a signal once issued remains n periods unchanged in the economy. This can be ensured by letting the same signal bounce for n periods through the exogenous matrix process. Secondly, the specific structure of the signal as the sum of ϵ_t and ν_t is most

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[4]The case for general n works similarly. Generate a sequence of Euler equations where the expectation of $\hat{C}_{t+k-1}$ is (intertemporally) substituted by the expectations of $\hat{C}_{t+k}$ and $\hat{R}_{t+k}$ for $k = 1, \ldots, n$. Shift equations (3.8) and (3.9) forward by n periods and substitute out $\rho\hat{C}_{t+n}$ and $\hat{R}_{t+n}$ in the remaining Euler equation. Using (3.11) delivers

$$0 = E_t \left[\rho\hat{C}_t + (\Phi\theta - \theta - \Phi)\hat{K}_{t+n-1} - \alpha_3\hat{L}_{t+n} + (\Phi - 1)\lambda^n z_t + (\Phi - 1)\sum_{i=0}^{n-1} \lambda^i \chi S_{t-i}^{(t+n-i)} \right] .$$

easily constructed outside the model. This is done in the function hlp.m that replaces the random generator in the file simul.m of the Toolkit. See the appendix B.1 for the code and some explanations. For $n = 1$ the first remark is superfluous and $\mathbf{z_t}$ evolves according to

$$\mathbf{z_t} = \begin{bmatrix} \lambda & 0 \\ 0 & 0 \end{bmatrix} \mathbf{z_{t-1}} + \boldsymbol{\epsilon_t} \ . \tag{3.13}$$

For $n > 1$ a slightly different specification of the exogenous process is conve- nient. Consider for example the case for $n = 2$. Define $\mathbf{z_t}$ as $\begin{bmatrix} z_t & S_t^{(t+2)} & S_{t-1}^{(t+1)} \end{bmatrix}'$ and let the exogenous process be

$$\mathbf{z_t} = \begin{bmatrix} \lambda & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \mathbf{z_{t-1}} + \boldsymbol{\epsilon_t} \ . \tag{3.14}$$

Here the signal is fed into the economy in the second row of $\mathbf{z_t}$ to remain in the exogenous matrix process for another period. The extension for $n > 2$ is straightforward. The code for solving this model using the Toolkit program is provided in appendix B.1.

Calibration. Table 3.1 summarizes the parameters that calibrate the model. HLP estimate χ equal to 0.718 indicating that 71.8% of all inventions find a useful application in production. However, I close down growth in tech-

Table 3.1: CALIBRATION OF THE HLP ECONOMY

$\bar{L}$	0.31	steady state employment
θ	0.377	capital share
δ	0.0267	depreciation rate
$\bar{R}$	1.0107	real interest per quarter
ρ	1	relative risk aversion
λ	1	autocorrelation of TFP
α	0.6692	relative utility weight of leisure
χ	0.5	fraction of the signal anticipated to innovate technology
σ_ϵ	0.75	standard deviation of TFP shock in %
σ_ν	0.75	standard deviation of noise in %

Notes: All parameter values, except ρ and the standard deviation of ν, σ_ν, are chosen according to HLP (1997). Growth factors, denoted in the original source by γ and η, are neglected here.

nology and population. A value for χ equal to 0.5 then delivers a somewhat more pronounced leading property of consumption, $\text{Corr}(Y_t, C_{t-1}) = 0.78$ and $\text{Corr}(Y_t, C_t) = 0.53$, whereas HLP (1997) report for the same quantities

14

the values 0.73 and 0.66, respectively. The remaining parameters are well established in the RBC literature and therefore not discussed any further.

3.3 The consequences of news shocks

The focus of this section is the impact, news shocks have on the behavior of the HLP economy. I discuss dynamic adjustments following shocks in ϵ_{t+1} and ν_{t+1}. I investigate what impact the information content of the signal has on the interdependencies of variables. With these results in hands, I briefly turn to the robustness of the failure of news shocks and review possible roads to reconcile news shocks easily. In this context, I review a suggestion of Cochrane (1994).

Dynamic adjustments. Panel *(a)* of figure 3.1 shows the dynamic adjustment of the HLP economy following a shock ϵ_{t+1}. A positive realization of the TFP shock in period $t+1$ initiates the dissemination of a signal $S_t^{(t+1)}$ in period t. Based on this a-priori information the household expects a TFP innovation of size $\chi S_t^{(t+n)}$ to materialize in the subsequent period.

The anticipation of a technology-induced boom coincides with the expectation of a future positive wealth effect. Given certainty equivalence, the household adjusts as if part of this expected positive wealth effect is certain already at once. Therefore and due to a set of preferences for which the wealth effect dominates the substitution effect the household increases both consumption and leisure. Output decreases since the workforce shrinks. Nevertheless, most of the decrease in investment is due to higher consumption. Note that the immediate adjustment in consumption is more hesitant than in the case of a risk-loving household.

One period beyond the signal the TFP innovation arrives. Now the response of the HLP economy is qualitatively similar to one generated by a standard RBC model.[5] TFP increases and causes strong substitution of leisure for consumption that dominates the wealth effect. Investment sharply increases and tappers off subsequently. The capital stock accumulates slowly up to the point when depreciation starts dominating investment.

In panel *(b)* of figure 3.1 the dynamic adjustment is depicted that follows a shock ν_{t+1}, i.e. a situation where the signal is entirely void of information. In the first period the household adjusts exactly in the same way as it did to a shock ϵ_{t+1}. This is natural since the signal is qualitatively not different from the one in panel *(a)*. However, in the next period the household learns that the signal does not imply fundamental changes and immediately

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[5]Responses are not identical in quantitative terms due to the fact that *(i)* in this experiment $S_t^{(t+1)}$ entirely consists of ϵ_{t+1} but agents associate only $\chi\%$ of $S_t^{(t+1)}$ with ϵ_{t+1} and *(ii)* the economy rests no longer in the steady state at the point the TFP shock arrives.

cuts off consumption and leisure below their steady-state levels. As a result, investment increases slightly above steady state and regenerates some of the capital stock and output jumps back to steady state. For both shocks the initial response in the economy is the stronger the higher the information content of the signal is, i.e. the smaller the variance of the noise term accompanying the signal.

Good news trigger economic downturns. What is puzzling in the response pattern in panel *(a)* of figure 3.1 is that good news trigger an economic downturn, i.e. decreases in output and investment. The decrease in output is the result of the isolated wealth effect in the first period. So is the decrease in investment − it compensates the decrease in output and the increase in consumption. As is the case for the majority of standard RBC models, in the HLP economy investment functions as a residual between GNP and consumption following the tight command of the accounting identity.

To be more specific, the response pattern of output and investment in conjunction with the one of consumption that manifests the anticipation of the future wealth effect is puzzling concerning two dimensions. The first puzzle is an economic one: intuition suggests that households increase consumption *and* investment in response to good news about the future; the former to enjoy the positive wealth effect at once and the latter to position the capital stock for the productive times to come. Fama (1992) analysis the co-movement of consumption, output and investment. Controlling for additional leads and lags the co-movement in the growth rates of consumption and investment is significantly positive which supports, contrary to the HLP economy, economic intuition.[6]

The impact of the information content of the signal. The second puzzle surfaces if one compares simulated time series for GNP, consumption and investment with real data. One stylized fact of business cycles is a positive autocorrelation of output growth at the first few orders. It is already visible in the plots of figure 3.1 that news shocks work counter this notion: the deviation of output from steady state implies increasing negative first order autocorrelation of output growth. Panel*(a)* in figure 3.2 documents that this consequence of news shock aggravates if the informational content of the signal χ increases. A corresponding plot of investment (not shown here) looks quite similar.[7] Whereas for low values of χ the autocorrelation of output growth is not significantly different from zero, it turns

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[6]See in Fama (1992) table 1 on page 474.

[7]It is evident that news shocks cause changes in moments of simulated data for hours worked, the interest rate, and the capital stock. However, I consider it sufficient to document time-series implications for GNP, consumption and investment.

strongly negative and ends up below -0.15 review for χ close to one. It is a well-documented fact that standard RBC models are incapable of producing significant positive autocorrelation of output growth, see Cogley and Nason (1995). However, apparently news shocks aggravate the performance of standard RBC models severely.

Panel *(b)* in figure 3.2 plots the first order autocorrelation of the GNP-level series and correlations between the level of consumption, investment and output. Corresponding to the impulse response pattern in figure 3.1, $\mathrm{corr}(Y_t, D_t)$ remains close to one. Most strikingly, $\mathrm{Corr}(Y_t, C_t)$ decreases from above 0.8 to below 0.2 when χ hikes through the unity interval. Taking these two observations together one can infer a decrease in the correlation of consumption and investment $-$ a side-effect of the news shock. A clear downward trend is observable for the autocorrelation of output and the correlation of output with leading investment. The leading property of consumption is reflected in the increasing correlation of output and leading consumption.

Robustness analysis and alternative specification of news. Is the impulse response pattern of figure 3.1 sensitive to parameterization, to straightforward modifications of the model, or to the exact specification of the news shock?

Concerning parameterization the two parameters that are most likely to influence the intertemporal rational of the household accordingly are ρ, the elasticity of substituting consumption across time, and β, the household's discount rate. Reducing the intertemporal elasticity of substitution generates a household putting more weight on a smooth consumption path across time as opposed to the consumption level. Even though the decrease in the initial response of consumption gradually affects the response of investment there appears to be no hope for a qualitative change. Tuning the discount rate of the household towards 1 coincides with increasing the weight of expected utility. One could argue that a household with higher weight on future utility follows what I have labelled economic intuition. It turns out that even for β equal to 1 the effect of higher weighted future utility on investment is minor in size, not to mention the direction.

According to Cochrane (1994) modifications like adjustment costs of capital, varying labor effort, and a varying degree of capital utilization do not reconcile the working of news shocks. However, Cochrane experiments with a different mechanism of feeding new information into the model $-$ smooth news. Additional to a random walk technology shock he includes a process of the following form.

$$\begin{bmatrix} a_t \\ z_t \end{bmatrix} = \begin{bmatrix} 1 & \theta(L) \\ 0 & \rho \end{bmatrix} \begin{bmatrix} a_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_t \\ \delta_t \end{bmatrix}$$

Here a_t denotes technology, z_t are news, $\theta(L) = 1 + L + L^2 \cdots + L^{12}$, ρ

is close to 1, $\sigma_\epsilon = 1$, σ_δ is small, and ϵ_t and δ_t are independent of each other. A news shock δ_t propagates instantaneously and completely into the model, whereas technology smoothly approaches the path of news mainly within the first 12 periods. The result is a smooth version of the impulse response pattern in figure 3.1. Fitting a VAR to data simulated with a model featuring a shock as described, Cochrane shows that smooth news approximate impulse responses of a VAR estimated with real data. He concludes with the following comment:

> "The proportional news shock in the real business-cycle model is carefully crafted to give a wealth effect, raising consumption, and a transitorily higher wage, to induce higher labor supply. It is not necessary that news be of such a variable; in fact, as we have seen, it hurts the model to be so." (Cochrane (1994, p. 356)). [8]

Apparently, some fundamental modifications are required to make news shocks work. BP (2000) follow a different approach for reconciling news shocks. In a three-sector economy they abandon the real structure of the model such that news lead to expectation-driven booms and recessions.

3.4   How to resuscitate news shocks?

BP note that the impulse response pattern following a news shock is not an inherent property of news shocks as such. Furthermore, they argue that the observed pattern is neither connected to the working assumption of rational expectations nor to forward looking behavior in general. The main reason why news shocks fail is that consumption and investment are inescapably tied together by means of the accounting identity, $Y_t = C_t + D_t$; if GNP remains unchanged consumption and investment move in opposite directions. This restriction originates in the real structure of the model and thereby constrains the set of possible equilibria. It is not inherent to news shocks.

To overcome the counterfactual consequences of news shocks in standard RBC models, BP propose a three-sector economy in which "current consumption decisions [...] are decoupled from current investment decisions" (BP (2000, p. 19.)). In the BP economy the production of investment and consumption takes place in separate sectors. Investment is produced with labor and a fixed factor both supplied by a representative household. The

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[8] Cochrane suggests to experiment with news shocks about government spending shocks instead. However, I do not extend my analysis to a government sector. Rotemberg (1994) comments on this approach and points to a "unfortunate" consequence: smooth news as specified in Cochrane (1994) substantially increase the relative standard deviation of transitory changes in technology with respect to the standard deviation of permanent changes.

production of consumption in turn requires services and capital stock as factors. The capital stock accumulates according to investment made. Services are produced in the third sector with a technology using again labor and a fixed factor. Labor is perfectly mobile across the service- and the investment-sector. With the decision where to shift workforce the household influences the level of output, i.e. the sum of investment and consumption, and the relation of consumption and investment. However, since the technology in the consumption-sector severely constrains the substitution of services with the capital stock and vice versa this relation is fairly fixed in the short run. According to BP this setup describes sensibly short-term substitutability constraints prevalent in modern economies. However, the main difference to a standard one-sector RBC model is the fact that investment is created out of a resource that is non-consumable − labor.

In the remainder of this analysis, I replicate the modestly documented analysis in BP (2000) and assess if the three-sector economy can reconcile the appropriate working of news shocks and, if so, to what extent. In the next chapter I review the model setup and explain the real and the informational structure of the BP economy. In chapter 5 I provide a detailed solution of the model. In particular, I discuss the intertemporal rational of the household, delve into solving for the steady state and log-linearize the non-linear system of equations describing optimality conditions of the model economy. I spend some time on the details of how to incorporate news shocks into the economy, and describe the implementation of the model with the help of the Toolkit program.[9] Chapter 5 ends with a discussion surrounding the calibration of the model. In chapter 6, I investigate the model along several dimensions: I report results based on simulations and review the impulse response pattern as induced by the three-sector structure and the information structure of the model. Separate sections are devoted to the discussion of the short-term substitutability constraint and to the assessment of the time-series properties of consumption and output. The chapter closes with providing a first answer to the question motivating this research: what model structure makes news shocks work? Chapter 7 works out a variation of the BP economy with respect to the informational setting and links to the HLP economy discussed in the previous pages. A review of arguments and a discussion is contained in chapter 8 and chapter 9 summarizes and concludes.

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[9]See Uhlig (1999).
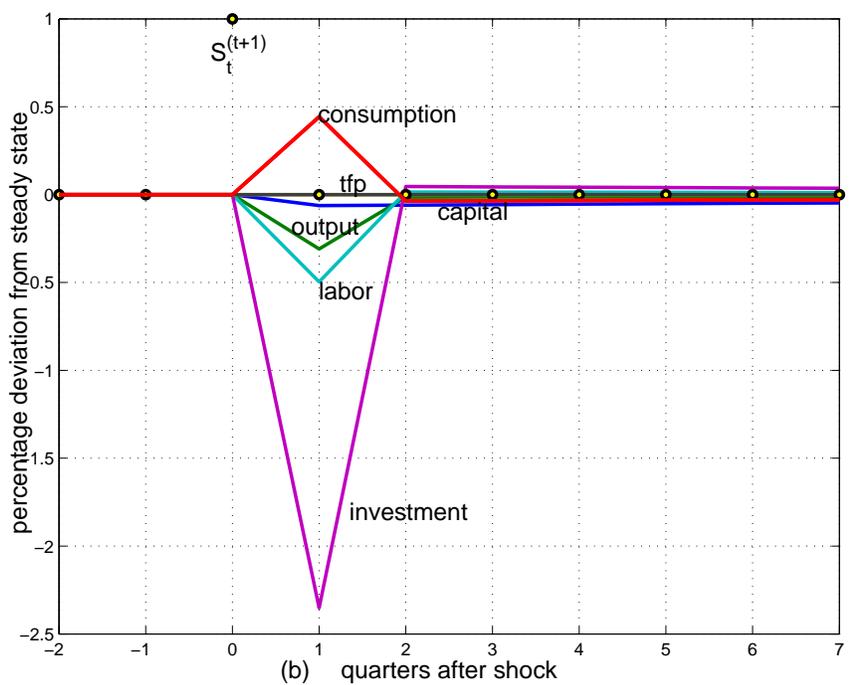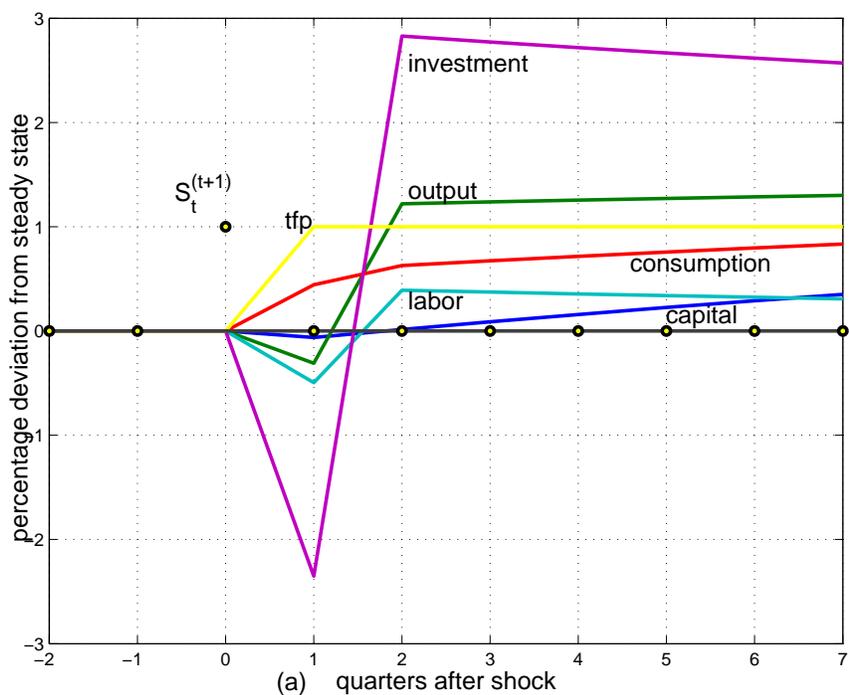
Figure 3.1: IRFs in the HLP model.

According to the specification of the model the signal lead TFP innovations by one period. Panel *(a)* shows impulse response function after a shock in ϵ_{t+1}. Panel *(b)* plots impulse response function for a shock in ν_{t+1}.
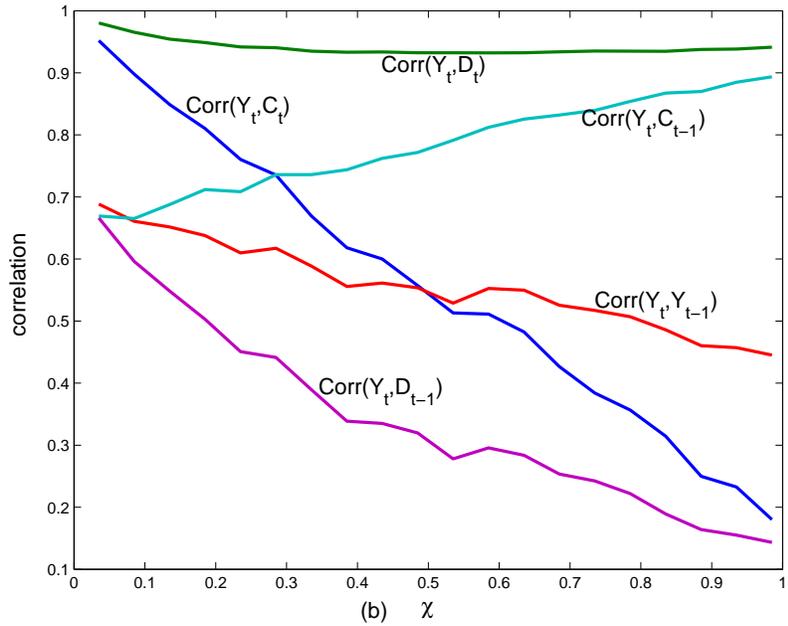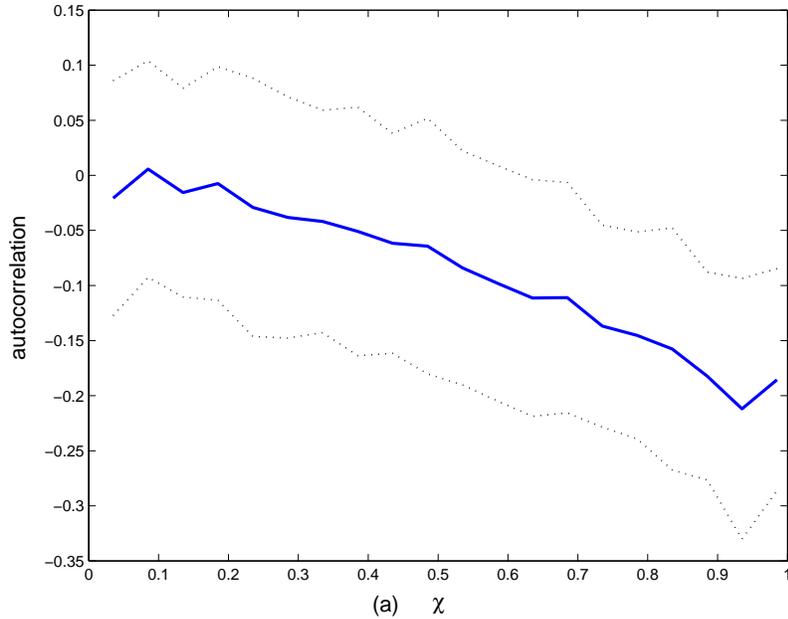
Figure 3.2: CORRELATION OF OUTPUT, CONSUMPTION, AND INVESTMENT.

Panel *(a)* shows first order autocorrelation of output growth. A low value of χ corresponds to a small signal to noise ratio. The signal leads TFP innovations by one period. Quantities are averages based on 100 simulation with sample length 100 each. The trending level GNP series is constructed as the sum of unfiltered raw data plus an exponential trend with a growth factor of 0.008. Panel *(b)* depicts correlations of output level, consumption and investment for varying χ. Quantities are computed based on a similar procedure and the same parameters as the quantities in panel *(a)*. Small sample standard errors are in the range 0.08 up to 0.11.

Chapter 4

A three-sector economy

In this chapter the three-sector model of BP (2000) featuring news shocks is reviewed. The basic setup of the model is explained, followed by a detailed description of the real structure of the economy in section 4.1. One focus is the informational situation in the model. It is explained comprehensively in section 4.3. The chapter closes by summarizing the situation of a representative household in the economy.

4.1 The model

BP investigate a three-sector real economy.[1] The economy is populated by a representative household, one firm producing a non-durable good, a firm producing investment goods, and a firm producing a final consumption good. Production of the durable investment good can be imagined as plant and housing infrastructure, whereas the equivalent of the production of the non-durable would be trading and/or the provision of services. The firm producing the consumption good uses both the durable and the non-durable good as production inputs. The model economy abstracts from a government sector as well as from nominal means of payment. Consumption is used as numéraire.

Capital is accumulated by producing the durable good. The household owns the entire stock of capital since it buys every output unit produced in the durable good sector at a price p_t. It rents capital at the rate r_t to the final good producing firm. The service sector, i.e. the one in which the non-durable good is produced, can be thought of as directly accompanying the sector in which the consumption good is finalized.

In every period the household receives a signal about future total factor productivity – the news shock. The signal correctly indicates TFP with a certain probability. However, in some cases it is entirely void of information.

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[1] I have significantly altered (and hopefully simplified) the notation of the original. See table 9.1 in the appendix for a notation key.

The specification of the signal suggests to think of it as the forecasting technology of agents.

4.2   The real structure

Production in the durable good or construction sector is organized according to a Cobb-Douglas technology using labor $L_{d,t}$ and a fixed factor F_d as inputs.[2]

$$D_t = \Delta_t L_{d,t}^\gamma F_d^{1-\gamma} , \quad 0 < \gamma < 1$$

Δ_t is TFP and γ is labor income as a share of total durable output. Both inputs are supplied by the household and the firm again resells its total output D_t at the price of p_t consumption units to the household.

The household stores the durable good and faces a rate of depreciation δ that deteriorates its capital stock. Therefore the evolution of the capital stock K_t follows

$$K_t = D_t + (1 - \delta)K_{t-1} .$$

The provision of services again follows a Cobb-Douglas technology that uses labor $L_{m,t}$ and the sector-specific factor F_m, both supplied by the household, as inputs.

$$N_t = \eta_t L_{m,t}^\alpha F_m^{1-\alpha} , \quad 0 < \alpha < 1$$

η_t is TFP in the service sector and α is the income share of labor. Services N_t are instantaneously put into the production of the consumption good.

The consumption good is produced as a constant-elasticity-of-substitution (CES) composite of the durable and the non-durable good.

$$C_t = [aN_t^\nu + (1-a)K_{t-1}^\nu]^{\frac{1}{\nu}}$$

Here a belongs to the unit interval and denotes the relative weight of each input. The elasticity of substitution between the durable and the non-durable input is given by ϑ with $\nu = (\vartheta - 1)/\vartheta$. BP assume $0 < \vartheta < 1$. As ϑ approaches infinity the durable good can entirely be replaced with the non-durable input. With ϑ close to zero the CES technology converges to a Leontieff technology where inputs are related via fixed coefficients and substitution of one input with the other is impossible. The CES technology characterizes inflexibility in the production process. Once the firm has committed itself to an amount of capital it is restricted to top up production with the respective amount of N_t to reach a certain level of output.

In each period the household derives utility from consumption and leisure according to a utility function that is separable in its arguments and across time.

$$U(C_t, L_{m,t}, L_{d,t}) = log(C_t) + A\left(\bar{L}_n + \bar{L}_d - L_{m,t} - L_{d,t}\right)$$

---

[2] A natural interpretation of a fixed factor in production is land.

The household's per period endowment consists of time, the two sector-specific fixed factors and the accumulated stock of capital based on some initial value K_0. Total time is denoted by $\bar{L}_d + \bar{L}_m$ and can be spent either working $L_{m,t}$ hours in the service sector, working $L_{d,t}$ hours in the construction sector or enjoying leisure time. A is a constant scaling factor.

BP assume that across sectors firms realize zero profits. Because the two sector-specific fixed factors are essential for both intermediate firms, in each period the household sells fixed factors entirely and receives returns $\Phi_{d,t}$ and $\Phi_{m,t}$ equal to the marginal product of the respective factor. Apart from this the household derives labor income $\omega_{n,t}L_{m,t}$ and $\omega_{d,t}L_{d,t}$ from work in both intermediate sectors and earns the rental rate of capital r_t for lending its capital stock from period $t-1$ to t.

$$C_t + p_t D_t = \omega_{n,t}L_{m,t} + \omega_{d,t}L_{d,t} + r_t K_{t-1} + \Phi_{m,t}F_m + \Phi_{x,t}F_d \ .$$

The household's income matches expenses, i.e. the cost of consumption and the cost of continuing the capital stock.

The authors note that in principle each sector-production should draw on a separate capital stocks. However, introduction of fixed factors ensures decreasing returns to scale with respect to labor and at the same time circumvents the inconvenience of treating several capital stocks in the model. The disadvantage of the fixed-factor-shortcut is that additional dynamic elements are cut off the model. It is not clear a-priori how they affect the rationale of the household. Without further investigation it is therefore difficult to judge if the assumption is a reasonable one.

4.3   The information structure

The information structure lays out what agents at which point in time know and what kind of uncertainty agents face. Since the processes driving TFP in the model are part of the stochastic environment and since it appears natural to specify the news shock such that it provides new information about future TFP innovations, I include the discussion of the TFP processes in this section.

TFP in the investment sector.   Total factor productivity Δ_t in the durable good sector is non-stochastic and evolves according to

$$\Delta_t = \Delta_0 e^{gt} \ .$$

BP justify the assumption of no stochastic variation in the durable good sector along several lines. First, it seems unreasonable to study the model with shocks perfectly correlated among sectors. Secondly, expectations about future increases of TFP that concern the durable good sector do not appear

relevant to the evolution of business cycles. Finally, innovations to TFP in the non-durable good sector bear the advantage of being easily interpreted as a higher degree of goods-differentiation when agents derive utility from variety of goods. Expectations about a higher variety of goods and the accompanying adjustments in the durable good sector would then precede a business cycle.

TFP in the service sector. Technology in the non-durable good sector η_t follows a process that grows at deterministic rate g,

$$\eta_t = \eta_0 \tilde{\eta}_t e^{gt} \quad \text{and} \quad \tilde{\eta}_t = \tilde{\eta}_{t-1}^{\lambda} e^{\epsilon_t} \quad ,$$

where $|\lambda| < 1$, η_0 is the initial value, and ϵ_t is a draw from a *iid* binomial random variable with zero mean and variance σ_ϵ. ϵ_t takes a value that shifts TFP in period t either above or below the average growth rate g, i.e. either ϵ^H or ϵ^L.

BP direct their analysis to the question if news shocks can generate real business cycles even though TFP never regresses. To this end they restrict the realization of ϵ in a situation of regress to be larger than $-g$. Since my analysis does not focus on recessions but on the general structure in which news shocks show consistency with basic real business cycle observations, I omit this particular restriction. For given p I chose values for ϵ^H and ϵ^L such that they are consistent with a zero mean and a standard deviation σ_ϵ.[3]

$$\epsilon_t = \begin{cases} \epsilon^H = \sqrt{\frac{p}{1-p}}\sigma_\epsilon & \text{with probability} \quad 1-p \ , \\ \epsilon^L = -\sqrt{\frac{1-p}{p}}\sigma_\epsilon & \text{with probability} \quad p \ . \end{cases} \tag{4.1}$$

The news shock. In every period the household receives a signal about a future innovation to TFP. I denote the signal indicating in period t the nature of the n-period-ahead-innovation ϵ_{t+n} as $S_t^{(t+n)}$. The signal announces TFP correctly with probability q. A right signal takes the same value as ϵ_{t+n}. A wrong signal takes a value that steams from the same distribution, ϵ belongs to, but is different from the realization ϵ_{t+n},

$$S_t^{(t+n)} = \begin{cases} \epsilon_{t+n} & \text{with probability} \quad q \ , \\ \neg\epsilon_{t+n} & \text{with probability} \quad 1-q \ . \end{cases} \tag{4.2}$$

---

[3]This involves the solution of a two equation system,

$$p\epsilon^L + (1-p)\epsilon^H = 0$$
$$p(\epsilon^L)^2 + (1-p)(\epsilon^H)^2 = \sigma_\epsilon^2 \ ,$$

which delivers $\epsilon^L = -\sqrt{\frac{1-p}{p}}\sigma_\epsilon$ and $\epsilon^H = \sqrt{\frac{p}{1-p}}\sigma_\epsilon$. BP find for given p, the restriction $\min(\epsilon) > -g$, and a zero mean for the high state a value $\epsilon^H = \frac{pg}{1-p}$.

Based on this structure in each period one out of four states of the economy occurs as summarized in table 4.1. In a scenario in which the economy grows

Table 4.1: THE FOUR STATES OF THE ECONOMY

probability	state signalled rightly	state signalled wrongly
state: above trend	$q(1-p)$	$(1-q)(1-p)$
state: below trend	qp	$(1-q)p$

above-average a correct signal occurs with probability $q(1-p)$, whereas the signal is entirely void of information with probability $(1-q)(1-p)$. In a below-average growth state of the economy a right signal appears with probability qp and with probability $(1-q)p$ the signal is wrong.

Two comments are in order at this point. First, note that the goal BP follow with this specific setup is to capture the notion that "forecasts [...] can sometimes be substantially wrong" (BP (2000, p. 23)). However, it is important to note that the signal itself does not represent a statistical forecast of TFP. Consider the case where the signal takes either a value of 1 if the TFP innovation is high or a value of 0 in the case of a low TFP innovation. These values are by no means connected to ϵ^H and ϵ^L but serve the same purpose as the actual specification of the signal does if only the household knows how to decode the signal. To this end it is more appropriate to think of the signal as the course of action suggested by a statistical forecast.

Secondly, the signal does not improve as time goes by. One should expect that over time additional information would provide better guidance. But consider the case with, say, $n = 2$. Then in every period two signals are at work in the economy. The one disseminated in period $t-1$ signals the $t+1$ innovation of TFP. The one issued in t indicates the innovation for period $t+2$. However, due to the specification the signal emerging in $t-1$ does not improve in t.

The household's problem. The chapter closes by summarizing the household's situation. The household maximizes utility with arguments C, L_m and L_d subject to the constraints imposed by production of the consumption and the investment good.

$$\max \ U(C_t, L_{m,t}, L_{d,t}) = log(C_t) + A(\tilde{L}_n + \tilde{L}_d - L_{m,t} - L_{d,t})$$

subject to

$$C_t = [a\left(\eta_t L_{m,t}^\alpha F_m^{1-\alpha}\right)^\nu + (1-a)K_{t-1}^\nu]^{\frac{1}{\nu}} \qquad (4.3)$$

$$K_t = \Delta_t L_{d,t}^\gamma F_d^{1-\gamma} + (1-\delta)K_{t-1}$$

The budget constraint is redundant in this problem since prices and perfect competition ensure it to hold in every period. The period endowment consists of the two fixed factors and the accumulated capital stock. In every period the household receives a signal about that state of future TFP. Apart from this, his informational knowledge includes the historic pathes of all variables in the model. I approximate the solution of this model economy using log-linearization in the following chapter.

Chapter 5

Analyzing the model

In this chapter the model of BP (2000) is analyzed. Having described the model with respect to its real and informational structure in 4.1, I start here with the setup of the social planner problem and the derivation of the first order necessary conditions (FONCs). Section 5.2 deals with the interpretation of the FONCs and derives an explicit expression for the return to consumption which considerably enhances the understanding of the intertwined intertemporal rationale of the household. For the model's steady state is solved in section 5.3 and log-linearization is briefly described in 5.4. In section 5.5, the incorporation of news shocks and quantitative implications of the model are treated. The last section deals with the calibration of the model.

5.1 Equilibrium and first order conditions

The competitive model equilibrium is determined by a sequence of quantities $\{K_t, C_t, L_{m,t}, L_{d,t}\}_{t=0}^{\infty}$ and prices $\{p_t, r_t, \omega_{n,t}, \omega_{d,t}\}_{t=0}^{\infty}$ such that

- good markets clear, i.e. $Y_t = C_t + p_t D_t$,

- labor markets clear, i.e. labor supply equals labor demand,

- the problem (4.3) is solved.

Starting conditions K_{-1}, η_0 and Δ_0 are assumed to exist and the time paths of η_t and Δ_t are exogenous.

In the following F_m and F_d are normalized to unity and interior solutions for $L_{m,t}$ and $L_{d,t}$ are assumed. In this model the household's problem and the social planner problem coincide.[1] I proceed by solving the social planner

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[1]This is the case since the model does not allow feedback between the formation of beliefs and the choices of K, C, L_n and L_d. With feedback active experimentation of the social planner would deliver additional information at some inefficiency costs. As Nieuwerburgh and Veldtkamp (2003, p. 10) note, "a planner economy with active experimentation

problem of which the objective function is given by

$$
\Theta(C_t, L_{m,t}, L_{d,t}, K_t, \lambda_t, \mu_t) = E_0 [\sum_{t=0}^{\infty} \beta^t \{ log(C_t) + A(\tilde{L}_n + \tilde{L}_d - L_{m,t} - L_{d,t})
$$
$$
- \lambda_t \{ C_t - [a(\eta_t L_{m,t}^\alpha F_m^{1-\alpha})^\nu + (1-a)K_{t-1}^\nu]^{\frac{1}{\nu}} \}
$$
$$
- \mu_t \{ K_t - \Delta_t L_{d,t}^\gamma F_d^{1-\gamma} - (1-\delta)K_{t-1} \} \}] .
$$
$$(5.1)$$

Defining an auxiliary variable $H_t = \partial C_t / \partial K_{t-1}$, FONCs plus accompanying definitions can be written as follows.

$$
\lambda_t = \frac{1}{C_t} \tag{5.2}
$$

$$
A = \lambda_t \frac{a \alpha N_t^\nu}{L_{m,t}} \left[a N_t^\nu + (1-a)K_{t-1}^\nu \right]^{\frac{1-\nu}{\nu}} \tag{5.3}
$$

$$
\mu_t = A \frac{L_{d,t}}{\gamma D_t} \tag{5.4}
$$

$$
\mu_t = \beta E \left[\lambda_{t+1} H_{t+1} + (1-\delta)\mu_{t+1} \right] \tag{5.5}
$$

$$
C_t = \left[a N_t^\nu + (1-a)K_{t-1}^\nu \right]^{\frac{1}{\nu}}
$$

$$
K_t = D_t + (1-\delta)K_{t-1} .
$$

$$
N_t = \eta_t L_{m,t}^\alpha F_m^{1-\alpha}
$$

$$
D_t = \Delta_t L_{d,t}^\gamma F_d^{1-\gamma} .
$$

$$
H_t = (1-a)K_{t-1}^{(\nu-1)} \left[a N_t^\nu + (1-a)K_{t-1}^\nu \right]^{\frac{1-\nu}{\nu}}
$$

What is left is an expression for the price of the durable good, p_t, which is needed for computing aggregated output, and an equation determining the return to investment, r_t. Since the model implicitly is solved for a pareto efficient market equilibrium the price of investment can be inferred from the shadow prices. This is because in a Walrasian economy the marginal rate of substitution between consumption and investment equals the relative price

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has no decentralized counterpart because information externalities invalidate the welfare theorems."

which in turn is equal to the ratio of shadow prices. Normalizing the price of consumption to unity gives

$$p_t = \frac{\mu_t}{\lambda_t} \ .$$

The expression for the return to investment is rather intuitive.[2]

$$r_t = \frac{\partial C_t / \partial K_{t-1} + (1 - \delta) p_t}{p_{t-1}} - 1$$

One additional unit investment p_t measured in consumption units and invested from period t to $t+1$ increases next-periods consumption marginally and remains depreciating in the capital stock.

5.2 Interpreting first order conditions

This section interprets the FONCs. Three of the four FONCs are fairly standard, whereas the Euler-type condition requires some additional investigation in order to provide an intuitive interpretation. This is done both verbally and formally.

The first derivative (5.2) equates λ_t with the marginal utility of consumption, i.e. λ_t is the shadow price of a consumption unit at the margin. Condition (5.3) is again standard and states that the disutility of labor and the utility of consumption produced with this labor equate at the margin and contemporaneously.

The effect of a change in L_d is trickier since labor in the durable good sector is due to the three-sector structure of the model intertwined with the recursive law of motion of capital and thereby induces intertemporal adjustments which are non-standard. First, consider the Lagrangian parameter μ_t that equals the marginal disutility of labor normalized by the additional investment units one could produce with this labor, i.e. μ_t is the shadow price for investment. Secondly, the Euler-type equation (5.5) formalizes the intertemporal adjustments. The disutility of working for an additional investment unit equates to the (discounted and expected) utility of increased consumption due to the additional investment unit. The second term on the right hand comes from the fact that (accumulated but depreciating) capital takes over some of the consumption production that otherwise would have to be done by hand.

However, since it is slightly confusing that some utility is due to additional consumption and some of it is due to additional leisure I derive an Euler equation based on a situation in which *(i)* the household decides to

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[2]Return to investment and return to capital are identical in the model due to $\partial K_t / \partial D_t = 1$.

postpone a small amount of consumption by one period, *(ii)* aggregate labor remains constant over time, and *(iii)* one ends up with a capital stock not different compared to a situation of a passive household. As a by-product of this derivation one gets the consumption return to forgone consumption. Derivation starts verbally and ends formally.

The household decreases consumption in period t by, say, a small amount ΔC_t. Since from the perspective of period t the capital stock is fixed, supply adjustment of C_t must take place via a decrease of the labor effort ΔL_m in the service sector. Due to perfect labor mobility across sectors abandoned labor shifts to production in the investment good sector which in turn triggers an increase of the capital stock ΔK_t. At the eve of period t the initial blip in consumption resulted into an increase of the capital stock caused by a movement of labor between sectors.

What is happening now in period $t + 1$? Discriminate a direct and an indirect effect of ΔK_t. Directly the higher capital stock contributes to higher period $t+1$ consumption. But in order to end up with a capital stock not different compared to a situation of a passive behavior, the household now retrenches the capital it painfully generated in the previous period by shifting labor from the investment to the service sector. More labor in the service sector again produces higher consumption output. This is the indirect effect.

Formally these thoughts can be expressed using total differentials. Using $\Delta K_{t-1} = 0$ and the total differential of the CES production function,

$$-\Delta C_t = -\frac{\partial C_t}{\partial L_{m,t}}\Delta L_{m,t} \quad \Longleftrightarrow \quad |\Delta L_{m,t}| = \frac{\Delta C_t}{\frac{\partial C_t}{\partial L_{m,t}}} = \Delta L_{d,t} \ ,$$

one gets for the change in the capital stock the marginal product of labor times the amount of labor abandoned in the service sector, $\Delta K_t = \frac{\partial D_t}{\partial L_{d,t}}\Delta L_{d,t}$. From *(iii)* the condition

$$\Delta K_{t+1} = \frac{\partial D_{t+1}}{\partial L_{d,t+1}}\Delta L_{d,t+1} + (1-\delta)\Delta K_t = 0$$

follows. Solving for $\Delta L_{d,t+1}$ and taking into account that labor is perfectly mobile between sectors, $|\Delta L_{d,t+1}| = \Delta L_{n,t+1}$ gives

$$\Delta L_{n,t+1} = \frac{(1-\delta)\Delta K_t}{\frac{\partial D_{t+1}}{\partial L_{d,t+1}}} = \frac{(1-\delta)}{\frac{\partial D_{t+1}}{\partial L_{d,t+1}}}\frac{\partial D_t}{\partial L_{d,t}}\frac{\Delta C_t}{\frac{\partial C_t}{\partial L_{m,t}}} \ .$$

Forming the total differential of C_{t+1} and plugging in the change in labor and in the capital stock delivers

$$\Delta C_{t+1} = \frac{\partial C_{t+1}}{\partial L_{n,t+1}}\frac{(1-\delta)}{\frac{\partial D_{t+1}}{\partial L_{d,t+1}}}\frac{\partial D_t}{\partial L_{d,t}}\frac{\Delta C_t}{\frac{\partial C_t}{\partial L_{m,t}}} + \frac{\partial C_{t+1}}{\partial K_t}\frac{\partial D_t}{\partial L_{d,t}}\frac{\Delta C_t}{\frac{\partial C_t}{\partial L_{m,t}}} \ .$$

Defining $R_{t+1} = \frac{\Delta C_{t+1}}{\Delta C_t}$ one can write

$$R_{t+1} = \underbrace{\frac{\partial C_{t+1}}{\partial L_{n,t+1}} \underbrace{\frac{(1-\delta)}{\frac{\partial D_{t+1}}{\partial L_{d,t+1}}} \frac{\partial D_t}{\partial L_{d,t}} \underbrace{\frac{1}{\frac{\partial C_t}{\partial L_{m,t}}}}_{|\Delta L_{m,t}|}}_{\Delta K_t} + \frac{\partial C_{t+1}}{\partial K_t} \frac{\partial D_t}{\partial L_{d,t}} \underbrace{\frac{1}{\frac{\partial C_t}{\partial L_{m,t}}}}_{\frac{|\Delta L_{m,t}|}{\Delta K_t}}}_{\Delta L_{n,t+1}} ,$$

which, admittedly, looks not necessarily intuitive but has the advantage of explicitly showing all intertemporal effects in terms of consumption-based utility changes. One could now reconcile the standard Euler equation given by

$$\frac{\partial U}{\partial C_t} = \beta E \left[\frac{\partial U}{\partial C_{t+1}} R_{t+1} \right] .$$

5.3 Solving for the steady state

The next step towards a solution of the model is the computation of the steady state. Note, however, that at this stage the news shock does not alter the derivation of the model. This is due to the fact that the steady state is a non-stochastic environment and, additionally, the news shock is specified such that it does not exhibit any externalities. The steady state value of a variable is indicated by a $\overline{bar}$. In principle one searches values for the variables $\bar{C}, \bar{L}_n, \bar{L}_d, \bar{K}, \bar{\mu}, \bar{N}, \bar{D}, \bar{H}$, having assigned appropriate values to parameters $a, \nu, \alpha, \beta, \gamma, \delta, \eta_0, \Delta_0$. As it turns out, it is hard to infer values for a and the ratio $\frac{\eta_0}{\Delta_0}$ from economic data. To this end BP chose these parameters consistent with assumptions regarding the labor income share and the consumption share of output. I follow this approach here and choose $a = 0.5$ and $\frac{\eta_0}{\Delta_0} = 10.$[3] A number of additional requirements are assumed to hold in steady state as summarized in table 5.1.

Table 5.1: STEADY STATE REQUIREMENTS

A	1	scale of the utility of leisure
$\tilde{L}_n + \tilde{L}_d$	2	total time amount of household
$L_n + L_d$	$(\tilde{L}_n + \tilde{L}_d)/3$	working time in steady state
$(\omega_n L_n + \omega_d L_d)/Y$	66%	labor share of total output
C/Y	75%	consumption share of total output

Defining the steady state of TFP as the detrended values one gets for

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[3] I have followed a trial and error procedure. Therefore these values imply a labor share of 0.6606 and a consumption share of 0.7712.

the non-durable good sector

$$\bar{\eta} = \frac{\eta_0 \tilde{\bar{\eta}} e^{gt}}{e^{gt}} = \eta_0 \quad \text{since} \quad \tilde{\bar{\eta}} = 1 \ .$$

Proceeding in the same way for the durable good sector delivers $\bar{\Delta} = \Delta_0$ where Δ_0 is arbitrarily normalized to unity.

I approach two ways for solving the non-linear system of equations determining the steady state, see the appendix A.1. The first one reduces the system to one equation in $\bar{L}_d$,

$$0 = \frac{a}{1-a} \left(\frac{\eta_0}{\Delta_0} \right)^\nu \frac{\alpha \delta^{\nu-1}(1 - \beta(1-\delta))}{\beta \gamma} \bar{L}_d^{1-\nu\gamma} - \left(\tfrac{2}{3} - \bar{L}_d \right)^{1-\nu\alpha} \ . \qquad (5.6)$$

However, unless the parameters in the exponents of L_d take convenient values it is not possible to solve this equation analytically. For a given parameter vector, I search a value for $\bar{L}_d$ so that it solves (5.6) and do this by running the Matlab function fzero.m. It is informative to get an impression of how $\bar{L}_d$ changes as the vector $(a \ \frac{\eta_0}{\Delta_0})$ takes different values. For different ratios $\frac{\eta_0}{\Delta_0}$ and a in the unity interval the value $\bar{L}_d$ is plotted in figure (5.1). L_d lies in the range between 18% and 68% of aggregate labor. The value for $\bar{L}_d$ resulting for $(a \ \frac{\eta_0}{\Delta_0})' = (0.5 \ \ 10)'$ makes approximately 45% of aggregate labor which seems reasonable, taking into account that in the steady state the household exclusively invests to restore depreciated capital but facing at the same time a relatively low steady state value of TFP. Having the variability of L_d in mind, one can in principle compute steady state values for the remaining variables using equations (A.1) to (A.8) in appendix A.1. As it turns out, however, approximating one variable but solving analytically for the remaining variables puts heavy weight in terms of the remaining residual on one equation and thereby distorts all follow-up computations. To circumvent this unfavorable side effect I approximate the solution of the entire system integrally by using the Matlab function fsolve.m. Convergence is achieved for different starting vectors almost immediately, the sum of residuals is smaller by a large factor and individual residuals per equation are much more evenly distributed. Therefore the following computations are based on steady state values achieved numerically for the entire system.

5.4 Log-linearization of the system

The solution strategy is to overcome the non-linear structure of the system by rewriting equations (5.2) to (5.5) plus accompanying definitions in log-linearized form. I add one equation defining the price of investment, one for aggregate output Y_t, and one determining aggregate labor $\bar{L}_t$. Log-linearized variables are indicated by a $\widehat{hat}$.
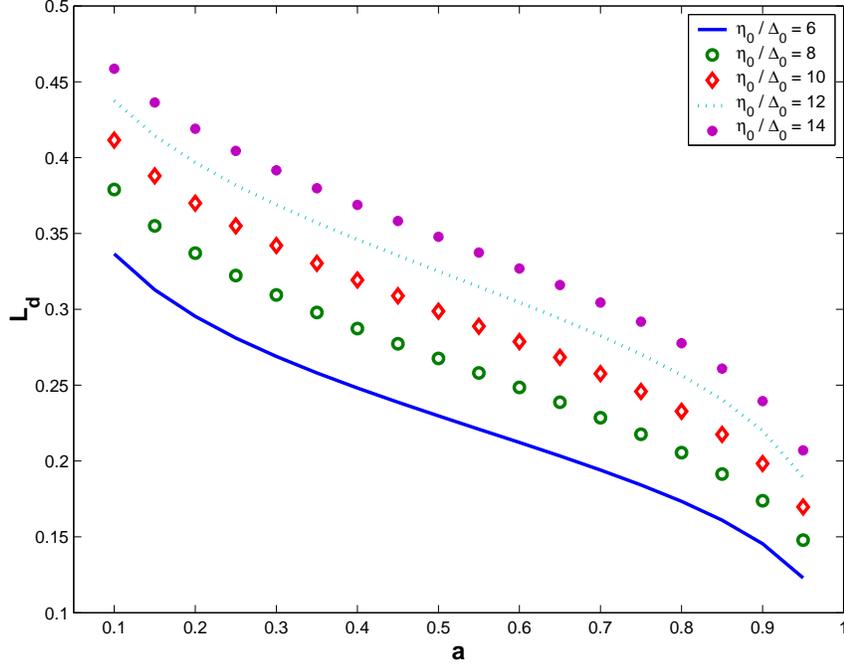
Figure 5.1: STEADY STATE ROBUSTNESS ANALYSIS.

To achieve stationarity for log-linearized variables in the model I let $\hat{\eta}_t$ be the percentage deviation from trend,

$$\hat{\eta}_t = \frac{\eta_t - \eta_0 e^{gt}}{\eta_0 e^{gt}} = \tilde{\eta}_t - 1 \ .$$

Using the fact that $\tilde{\eta}_t - 1 \approx \log \tilde{\eta}_t$ is a reasonable approximation for small numbers one can write

$$\hat{\eta}_t \approx \log \tilde{\eta}_t = \lambda \log \tilde{\eta}_{t-1} + \epsilon_t \ .$$

The process for technology in the durable goods sector is assumed non-stochastic as

$$\Delta_t = \Delta_0 e^{gt} \ .$$

Proceeding similarly as for the non-durable goods sector delivers $\hat{\Delta}_t = 0.$[4] Log-linearized equations are given in appendix A.2. A detailed description of how to incorporate news shocks into the log-linearized model follows now.

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[4]See section 4.3 for a justification of this assumption.

5.5 News shocks made operational

The model carries two stochastic elements, the TFP process in the service sector and the news shock. In contrast to a TFP innovation pure news as such do not trigger any adjustment in the economy. However, news become relevant if the piece of new information affects the future prospect of the household which indeed is the case if news regard future TFP innovations. But how to make operational the idea of news? It requires identifying the part of the model governing the intertemporal decision making and needs an explicit formulation of how agents form beliefs. Intertemporal decisions are weighed in the Euler equation. The formulation of agent's beliefs is treated in the following.

Observing a signal agents will infer what kind and what size of future TFP is likely to come up. Based on the probability of each state of the economy and conditional on the observed signalization, I compute the conditional expectation agents form with respect to future shocks to TFP. $\epsilon^H, \epsilon^L, p$ and q are defined in equation 4.1 and 4.2.

$$\theta^H \equiv E\left[\epsilon_{t+n}|S_t^{(t+n)} = \epsilon^H\right] = \frac{q(1-p)^2\epsilon^H + (1-q)p^2\epsilon^L}{q(1-p)^2 + (1-q)p^2}$$

$$\theta^L \equiv E\left[\epsilon_{t+n}|S_t^{(t+n)} = \epsilon^L\right] = \frac{(1-q)(1-p)^2\epsilon^H + qp^2\epsilon^L}{(1-q)(1-p)^2 + qp^2}$$

The next step is to use the new information forming a forecast of the TFP innovations n periods ahead. Here it turns out that having a signal about the innovation of TFP instead of one signalling TFP itself simplifies forecasting considerably.[5] Because certain values for p and q might well imply an asymmetric distribution of ϵ and $S^{(t+n)}$ it simplifies implementation into the Toolkit to explicitly specify one conditional expectation for each state of the world. Define the sequence of signals active in the economy at time t as $\Omega_t = [S_{t-n+1}^{(t+1)}, \ldots, S_t^{(t+n)}]$.

$$E\left[\log \tilde{\eta}_{t+n}|\Omega_t\right] = \lambda^n \log \tilde{\eta}_t \hspace{3cm} (5.7)$$

$$+ \sum_{i=0}^{n-1} \lambda^i [\theta^H \left(\frac{S_{t-i}^{(t+n-i)} - \epsilon^L}{\epsilon^H - \epsilon^L}\right) + \theta^L \left(\frac{S_{t-i}^{(t+n-i)} - \epsilon^H}{\epsilon^L - \epsilon^H}\right)]$$

$$= \lambda^n \log \tilde{\eta}_t + \sum_{i=0}^{n-1} \lambda^i \Psi(S_{t-i}^{(t+n-i)})$$

The two multiplicative terms in round brackets are "switching" terms; depending on the realization of $S_t^{(t+n)}$ they switch on the appropriate condi-

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[5]Signalling TFP implies taking into account cross-correlations of the signal and TFP across time and the information contained in the autocorrelation of TFP.

tional expectation and at the same time switch off the other.[6]

The aim is now to embed this conditional expectation, linear as it is, into the log-linearized Euler equation. After plugging in expressions for $\hat{C}_{t+1}$ (A.11) and $\hat{H}_{t+1}$ (A.17) the Euler equation looks as follows.

$$\bar{\mu}\hat{\mu}_t = \beta E \left[\frac{\bar{H}}{\bar{C}} \left((\nu - 1)\hat{K}_t + (1 - \nu\alpha)\hat{L}_{m,t+1} - \nu \log \tilde{\eta}_{t+1} \right) + (1 - \delta)\bar{\mu}\hat{\mu}_{t+1} | \Omega_t \right] .$$
$$(5.9)$$

To make it explicit, I plug in the expression for $E \left[\log \tilde{\eta}_{t+n} | \Omega_t \right]$ for the case of $n = 1$, i.e. the signal shows up one period before of the actual TFP innovation. This gives the new Euler equation

$$0 = E \left[\frac{\beta \bar{H}(\nu - 1)}{\bar{C}} \hat{K}_t + \frac{\beta \bar{H}(1 - \nu\alpha)}{\bar{C}} \hat{L}_{m,t+1} - \frac{\beta \bar{H}\nu\lambda}{\bar{C}} \log \tilde{\eta}_t \right.$$
$$\left. - \frac{\beta \bar{H}\nu}{\bar{C}} \left\{ \frac{\theta^H(1 - \epsilon^L) + \theta^L(\epsilon^H - 1)}{\epsilon^H - \epsilon^L} \right\} S_t^{(t+1)} + \beta(1 - \delta)\bar{\mu}\hat{\mu}_{t+1} \right] - \bar{\mu}\hat{\mu}_t .$$
$$(5.10)$$

The cases for $n = 2$ and $n = 3$ are a bit more tedious and therefore outsourced to the appendix A.2. The general procedure is to shift (5.9) forward by one period which delivers an expression for $\bar{\mu}\hat{\mu}_{t+1}$. If $n > 2$ it is necessary to generate a sequence of such equations. Substituting $\bar{\mu}\hat{\mu}_{t+1}$ into (5.10) and taking into account that the evolution of $\log \tilde{\eta}_t$ is recursive one gets a Euler equation for n arbitrarily large. However, note that the signal will have diminishing influence the farther it points into the future. This, for example, is reflected by the coefficient of the most recent signal $S_t^{(t+n)}$, $(1 - \delta)^{(n-1)}\beta^{(n-1)}\frac{\bar{H}\nu}{\bar{C}}$.

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[6] Reshuffling equation (5.7) to isolate $S_{t-i}^{(t+n-i)}$ produces a constant terms which conflicts with the assumptions of the Toolkit program. I solve this problem by assuming that the constant term equates to the unconditional mean of the distribution of $S_t^{(t+n)}$. For $n = 1$ the equation then changes to

$$E \left[\log \tilde{\eta}_{t+n} | \Omega_t \right] = \lambda \log \tilde{\eta}_t + \frac{\theta^H - \theta^L}{\epsilon^H - \epsilon^L} S_t^{(t+1)} + \frac{\theta^L \epsilon^H - \theta^H \epsilon^L}{\epsilon^H - \epsilon^L} \qquad (5.8)$$

$$\stackrel{\text{by asspt.}}{=} \lambda \log \tilde{\eta}_t + \left\{ \frac{\theta^H - \theta^L}{\epsilon^H - \epsilon^L} + \frac{\theta^L \epsilon^H - \theta^H \epsilon^L}{\epsilon^H - \epsilon^L} \right\} S_t^{(t+1)}$$

$$= \lambda \log \tilde{\eta}_t + \left\{ \frac{\theta^H(1 - \epsilon^L) + \theta^L(\epsilon^H - 1)}{\epsilon^H - \epsilon^L} \right\} S_t^{(t+1)}$$

This is a crude assumption, since it implies a non-zero mean for ϵ and therefore in principle alters ϵ^H and ϵ^L. How much of inconsistency results, depends on the values attached to p, q, and σ_ϵ. If $p = 0.535$, $q = 0.875$, and $\sigma_\epsilon = 1.5\%$, the constant is -0.0657. One alternative is to drop the constant completely. However, it is not clear a-priori which assumption distorts the analysis less and for the values used the first seems appropriate.

5.6 Implementation into the Toolkit

I implement the model so that the code allows for $n = 1, 2, 3$. See Uhlig (1999) for the notation used here and a detailed description of the computations.[7] I abstain from including the return to capital since this would additionally increase the state vector by shifting $\hat{p}_t$ out of $\mathbf{y_t}$ into $\mathbf{x_t}$. Define the vectors $\mathbf{x_t}, \mathbf{y_t}$ and $\mathbf{z_t}$ as

$$\mathbf{x_t} = \left[\begin{array}{cccccc} \hat{K}_t & \hat{L}_{m,t}^{(1)} & \hat{\mu}_t^{(1)} & \hat{K}_t^{(1)} & \hat{L}_{m,t}^{(2)} & \hat{\mu}_t^{(2)} \end{array} \right]'$$

$$\mathbf{y_t} = \left[\begin{array}{ccccccccc} \hat{Y}_t & \hat{C}_t & \hat{D}_t & \hat{N}_t & \hat{L}_{d,t} & \hat{L}_{m,t} & \hat{H}_t & \hat{p}_t & \hat{L}_t & \hat{\mu}_t \end{array} \right]',$$

$$\mathbf{z_t} = \left[\begin{array}{cccc} \log \tilde{\eta}_t & S_t^{(t+n)} & S_{t-1}^{(t+n-1)} & S_{t-2}^{(t+n-2)} \end{array} \right]'$$

and add those equations that define the five auxiliary variables to the expectational matrix equation (3.20) in the above reference. These equations are

$$0 = E\left[\mathbf{A_{t+1}} - \mathbf{B_t}\right] \text{ ,with}$$

$$\mathbf{A_{t+1}} = [\hat{L}_{m,t+1} \ \hat{\mu}_{t+1} \ \hat{K}_{t+1} \ \hat{L}_{n,t+1}^{(1)} \ \hat{\mu}_{t+1}^{(1)}]' \text{ and } \mathbf{B_t} = [\hat{L}_{m,t}^{(1)} \ \hat{\mu}_t^{(1)} \ \hat{K}_t^{(1)} \ \hat{L}_{m,t}^{(2)} \ \hat{\mu}_t^{(2)}]'.$$

The signal once issued remains unchanged in the economy until it reaches its destination date. Technically speaking, this ensures the amplification of the effects the signal has on state and endogenous variables as for example visible in figure (6.2). I ensure this by letting the exogenous process be

$$\mathbf{z_t} = \left[\begin{array}{cccc} \lambda & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{array} \right] \mathbf{z_{t-1}} + \boldsymbol{\epsilon_t} \ . \tag{5.11}$$

The signal is fed into the economy in the second row of $\mathbf{z_t}$, bounces for another n periods through the exogenous process and is therefore available until it drops out after $max(n)$ periods.

The assumptions regarding the distribution of the innovation in TFP and the one of the signal and the particular specification of the exogenous process require some recoding of the original Toolkit program. The TFP innovation ϵ_t and the signal $S_t^{(t+n)}$ are both binomial random variables and additionally intertwined. This is coded in the function bin.m which replaces the command randn(.) in the file simul.m. The new file is named simul_BP.m.

Input arguments of bin.m are the variables SIM_LENGTH, k_exog, ϵ^H, ϵ^L, p, q, and n. The output of bin(.) is a matrix of size(k_exog, SIM_LENGTH)

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[7]If you are about to become a toolkid you might want to take part in and enrich the discussions of the Toolkit newsgroup. Check http://groups.yahoo.com/group/toolkitprogram/. However, there is a warning: no constants possible!

having in rows $\epsilon_t, S_t^{(t+n)}, S_t^{(t+n)}, \ldots, S_t^{(t+n)}$, i.e. the signal $S_t^{(t+n)}$ is just replicated (k_exog-1) times. The respective column of this matrix is assigned to the vector $\boldsymbol{\epsilon_t}$ in simul_BP.m. Having this specification of $\mathbf{z_t}$, it is necessary to set the standard deviations of entries in rows 3 to 5 in the vector $\boldsymbol{\epsilon_t}$ to a very small but positive number. This is done in the file defining all the matrices like AA, BB, ... in the matrix Sigma. Since the first n realizations of ϵ_t are not announced by any signal it is reasonable to discard the first few simulated observations. See the appendix B.2 for the code of bin.m and a few additional remarks.

5.7 Calibration

In this section the calibration of the model is described. I start by discussing the choice of labor shares, the standard deviation of the TFP innovation and the parameters governing the informational structure in the model. Then I focus on how the model is put in line with some central empirical moments by means of a grid search.

BP note that semiannual calibration of the model seems to be more in line in a model without any adjustment costs and additionally bears the advantage that in their setting recessions can be associated with declining output. Calibrating the model to quarterly data would have enhanced considerably the comparability since this frequency is standard in the real business cycle literature. Nevertheless, I suspect that model properties change only marginally $-$ γ and α would not change at all, g is likely to change only slightly if so and a higher value for β and a lower value for δ mainly take into account adjustment to the higher frequency $-$ and following BP enables a direct comparison with their results, which I prefer at this point.

Table 5.2: CALIBRATION OF THE BP ECONOMY

β	0.98	discount rate of the household
δ	0.05	depreciation rate of capital
γ	0.97	labor share durable good sector
α	0.60	labor share non-durable good sector
g	0.017	estimated growth factor of TFP
σ_ϵ	1.5%	standard deviation of TFP shock in %
p	0.535*	probability of a below-trend innovation
q	0.875*	probability of a correct signal
ϑ	0.251*	ela. of subst. of services and capital

Notes: Data source given in BP (2000) is U.S. NIPA from 1959:I up to 1997:II. Parameter values calibrate the model at semiannual frequency. A $\star$ indicates that parameters are found by means of a grid search.

The values assigned to the respective parameters are given in table 5.2. For the case here interesting parameters are γ, α, the parameters governing the innovation to TFP and the shape of the signal, p, q, and σ_ϵ, and finally ϑ. I discuss each in turn.

Labor shares. γ and α governing the labor share of income in the durable and the non-durable good sector. BP draw on Burnside, Eichenbaum and Rebelo (1995) to conclude that the labor share is close to the short-term return to labor.[8] This would imply values for γ and α around 0.60. Additionally BP cite Allen (1985) who derives an estimate slightly below 1.0 for the labor share in the construction industry. Allen's estimation is based on a pooled sample among US states for two years, 1972 and 1977. BP take into account these two investigations and chose γ equal to 0.97 and α as 0.60.

However, the respective literature supplies a number of different choices. First, it is not clear if the results in Burnside, Eichenbaum and Rebelo (1995) that are derived for production with capital and labor map one to one to a production environment using a fixed factor instead of capital. Second, Boldrin, Christiano and Fisher (2001) study asset returns in a two sector model with imperfect factor mobility between sectors and habit persistence. They follow Christiano and Eichenbaum (1992) in choosing the labor share equal to 0.64 and assume equal shares in the investment and the consumption good sector. Finally, Long and Plosser (1983) work in a model with six sectors with a labor share in the construction industry of about 0.36 based on *Historical statistics of the United States*.[9] Again for purpose of comparison, I follow the specification of BP keeping in mind that the choice of γ and α is likely to influence the relative movements of labor in the durable and non-durable good sector and, thereby, the behavior of aggregate labor.

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[8]The contribution of Burnside, Eichenbaum and Rebelo is placed in the center of an interesting discussion among competing fields of the literature. They discuss in length the property of returns to scale in production. This topic affects the literature on self-fulfilling beliefs or the *animal spirit* hypothesis, e.g. Farmer (1999). Increasing returns to scale are utilized to achieve sunspot solutions in dynamic models. Another body of research that draws on increasing returns is the group of researchers working on the propagation of demand shocks in microfounded models, e.g. Mankiw and Romer (1991). Here increasing returns to scale ensure procyclical movements in productivity. Last but not least, the contribution affects the fundamental RBC paradigm advocated by, among others, Kydland and Prescott (1982) and King, Plosser and Rebelo (1988) in that it claims that RBC models with aggregate technology shocks that have to rely on a large volatility of these shocks and additionally predict a high correlation between output growth and the aggregated technology shock are empirically implausible. The alternative explanation derived by Burnside, Eichenbaum and Rebelo (1995) is to combine cyclical movements in the capital utilization rate with labor hoarding. However, conclusions are subjected to measurement errors in particular with respect to capital, to data frequency, estimation method, and model specification.

[9]See the reference in the article of Long and Plosser, p. 56.

Standard deviation of TFP. The value of the TFP standard deviation σ_ϵ used in the analysis of BP is 2.55%.[10] Since the distribution of the signal builds on the one of the TFP innovation, the standard deviation of the signal increases slightly to about 2.84%. Note that because the signal as specified in BP (2000) does not coincide with the notion of a statistical forecast it is not appropriate to compare the standard deviation of the signal with the uncertainty surrounding e.g. GDP forecasts as produced by EUROSTAT.[11]

The focus of the analysis of BP is on explaining recessions by drawing on a TFP that never regresses. This is the assumption driving the standard deviation of the signal to this remarkably size. Abandoning this focus I find that a standard deviation for the TFP innovation σ_ϵ equal to 1.5% delivers standard deviations of output, investment and consumption roughly in line with what can be observed in real data. The standard deviation of the signal then computes to 1.584% which is, compared to the number BP use, smaller by a factor 2 but still sizeable.[12]

A fraction of the large standard deviation σ_ϵ is likely to be devoted to the highly stylized evolution of the innovation to TFP. However, the RBC literature usually reports values for σ_ϵ in the range 0.712% in Hansen (1985) up to 0.763% in Prescott (1986). As is argued in Burnside, Eichenbaum and Rebelo (1995), even these values are still implausibly large if compared to estimated standard deviations of technology shocks.

Parameters governing the informational structure. Abstracting from the uncertainty that remains with respect to the choices of γ, α, and σ_ϵ three parameters are core in the model. They are p, the probability of a below-trend innovation in TFP; q, the probability of the signal indicating the right state of the economy; and ϑ, the elasticity of substitution between capital and the non-durable good in the final production CES function.

As is obvious, it is not straightforward to infer estimates for these three parameters based on economic data. To this end BP conduct a Simulated Method of Moments (SMM) estimation. In contrast I abstain from using rigorous methods for estimation of these parameters as there are the Simulated Method of Moments estimator, as described in Duffie and Singleton (1993), the Generalized Methods of Moment (GMM) estimator used in Christiano and Eichenbaum (1992), or Maximum Likelihood (ML) estimation as applied in Leeper and Sims (1994). Here the focus are qualitative features of the model under the necessary condition that the quantitative properties of

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[10]It can be computed using the fact that the growth signal amounts to 4.17% and at the same time is equal to $pg/(1-p)$. This delivers a value for g equal to 0.017 that can be used to compute $\sigma_\epsilon = \sqrt{\frac{2-p}{1-p}}pg$. The standard deviation of the signal $S_t^{(t+n)}$ computes based on the values for ϵ^H, ϵ^L, p, and q.

[11] For further discussion of this issue the reader is referred to section 7.1.

[12]See the next chapter for details on matching empirical moments.

the model are roughly in line with what is considered stylized fact. To show consistency between the model's core quantities and empirical moments handled in the literature, I perform an informal grid search over the parameters space (p, q, ϑ) with σ_ϵ equal to 1.5%.[13] The value of n is fixed equal to 2 since this is the value the model of BP performs best. The empirical quantities to be matched are the standard deviation of output, the standard deviation of investment, the one of consumption, and contemporaneous correlations of investment and consumption with output. I do not use any formal criterion for choosing a specific vector (p, q, ϑ).

One severe drawback of a grid search is the lack of any parameter uncertainty. Additionally there is no guarantee of choosing a parameter vector such that objective functions in the named alternative methods would reach local or even global maxima. SMM, GMM or alternatively ML estimation would ensure this by guidance of the gradient. However, none of these methods guarantees for a global maximum. To this end a certain degree of uncertainty is common among a basic grid search and each of the above cited methods. The advantage of grid-searching lies in its rather intuitive and simple-to-implement nature. Having this and the purpose at hand in mind, this method is regarded as appropriate for finding a reasonable parameter vector (p, q, ϑ). Searching the interval $[0.200, 0.667]$ for ϑ and the unity interval for p and q, a reasonable matching of the empirical moments occurs at $(53.5, 87.5, 0.251)$. Based on these parameter values the models' simulation properties and internal adjustment paths are evaluated in the following chapter.

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[13]The approach of calibrating the model by means of a grid search follows the analysis in Kydland and Prescott (1982).

Chapter 6

Evaluating the model

Evaluating the economy developed on the previous pages is the focus of this chapter. I discuss simulation results and relate them to what is found in BP (2000) and in the corresponding literature in section 6.1. In section 6.2, I discuss the impulse response patterns following different combinations of news and TFP shocks and compare them to the standard RBC model of chapter 3. The implication of the CES-production technology and the properties of the output series and are investigated in section 6.3 and 6.4, respectively. The last section provides a first answer to the question motivating this research.

6.1 Results based on simulation

In this section, I interpret the parameter values used as degrees of freedom to fit the model to some widely-applied empirical moments and put them in relation to what is reported in BP (2000). Studying the quantitative properties of the model shows that the model is capable of reproducing basic stylized facts of real business cycles. Time series of the core variables and a sequence of the signal accompanied by the simulated path of TFP clarify the high degree of stylization induced by the binomial distribution for the TFP innovation.

Results of the grid search. The resulting vector of the grid search (p, q, ϑ) takes values $(53.5, 87.5, 0.251)$ at a reasonable match of the data. It implies that in about 87% of the cases agents are well informed about TFP innovations forthcoming in one year. The probability of either a high or a low state of the economy is almost symmetric; about 54% of all periods experience an above-trend TFP innovation. The grid search delivers an elasticity of substitution between capital and the non-durable good of about 0.25. This suggests that for matching the data a fair amount of complementarity between the two goods is needed, a property which a Cobb-Douglas

production function with its unit elasticity of substitution does not own.

These results are in line with what is reported in BP (2000). Regarding the informational content of the signal they report almost the same value q equal to 0.82, if so with a large standard error of 0.31. The calibrated value for p is 0.71 with a standard error of 0.04. As is explained in section 4.1, BP assume a rightward-skewed distribution for the TFP innovation. Since the analysis herein follows a different focus, this assumption is replaced by assuming a symmetric distribution for ϵ. Targeting the same empirical moments the grid search delivers a higher relative frequency $(1 - p)$ of the high state realization.

BP report a value for ν equal to -3.78 with a standard error of 1.21. This implies an elasticity of substitution of about 0.2. Even though this value implies slightly less substitutability between capital and the non-durable good, there is no substantial difference to the value reported here. Respective simulated moments of the model as it is described here and those extracted by BP are tabulated in 6.1.

Table 6.1: EMPIRICAL AND SIMULATED MOMENTS

quantity	simulated moments		empirical moments		moments sim. by BP	
stdev(Y_t)	2.38	(0.24)	2.16	(0.22)	1.85	(0.27)
stdev(D_t)	8.44	(0.65)	6.87	(0.67)	5.84	(0.80)
stdev(C_t)	1.34	(0.16)	1.06	(0.09)	1.07	(0.18)
corr(Y_t, Y_{t-1})	0.62	(0.07)	0.79	(0.08)	0.67	(0.09)
corr(Y_t, D_t)	0.83	(0.03)	0.95	(0.01)	0.91	(0.01)
corr(Y_t, C_t)	0.54	(0.07)	0.64	(0.08)	0.63	(0.06)

Notes: Standard errors in parenthesis. Simulated moments are based on the model calibrated for semiannual frequency. In particular, the parameter vector (p, q, ϑ) takes values $(0.535, 0.875, 0.251)$ and $n = 2$. Quantities are averages based on 70 simulations of 100 semesters, discarding the first 30 observations in each simulation. Series are detrended using $\lambda_{HP} = 800$ for semiannual data frequency. Moments simulated by BP (2000), table 4, derive from a model slightly different regarding the assumption about the skewness of the TFP residual (see section 4.1) and are HP-detrended for semiannual frequency. HP-filtered empirical moments are taken from BP (2000), table 4. Data source therein is U.S. NIPA from 1959:I up to 1997:II.

Comparing column one and two indicates that the model slightly overstates the standard deviations of output, investment, and consumption and, at the same time, produces correlations that lie somewhat below the respective empirical moments. Even though, the model calibrated in BP (2000) performs somewhat better in general, it still exhibits a clear deviation regarding the autocorrelation of output. Focusing on the relative size of standard deviations, it appears that the model captures real data rather convincingly. Overall, given that the evaluation of the model is based on an informal

grid searching procedure the matching of empirical moments is surprisingly good.

Simulations. Panel *(a)* in figure 6.1 displays series for output, investment, and consumption as coming out of a model simulation with a signal leading the factual TFP innovation by two periods. The variation of investment is by far largest, followed by the one in output; consumption evolves smoothest. This order mirrors relative variation in real data. The impression that output leads consumption finds strong support in the correlation statistics where $\text{corr}(Y_t, C_{t-2})$ is the largest. Investment and output move together strongest contemporaneously.

Panel *(b)* displays the path of the two stochastic elements driving the economy, TFP in the non-durable good sector and its signal. The sequence of signals makes evident the even and symmetric distribution of $S_t^{(t+n)}$. The path of TFP is the product of a number of highly stylizing assumptions. Additionally, and due to the binomial nature of its residual, TFP substantially deviates from the long-run growth trend.

Overall, the model simulates moments of output, consumption, and investment reasonably close to what is observed in real data. However, eye analysis or, alternatively, spectral density analysis easily clarify the highly stylized evolution of the respective series.

6.2 Dynamic adjustment and economic intuition

For purpose of comparison, I reproduce here a central plot in BP (2000). I investigate the dynamic adjustment of the model to various combinations of TFP shock and a-priori indication and its economic intuition. A confrontation with the impulse response functions of the standard RBC model, chapter 3, highlights crucial differences. In section 6.4, I work towards a first answer to the question motivating this research, i.e. what model structure makes news shocks work?

Reproducing BP. Impulse response functions summarize the dynamic properties of the model and thereby give important insight into the ability of the model to cope with news shocks. Figure 6.2 reproduces figure 6 in BP (2000) by showing the IRFs to a isolated signal. Adjustments in the paths of output, consumption and investment are triggered solely due to a signal in period 0. (The signal is not visible in this plot.) The economy experiences an expectation-led boom − output, investment and consumption increase in the light of a future increase of TFP − to drive into recession 18 month later when it becomes public that the expected TFP innovation fails to materialize. Initially, investment increases, thereby accumulating

44

the capital stock, to make way for a situation where productivity in the service sector is high but the capital stock is low. With one period delay, consumption builds up smoothly to revert its direction towards steady state one period after the signal's plausibility fails. Aggregate output is close in shape to the response of investment; after an amplified boom it drastically falls back into a pronounced recession.

> "In our view, these dynamics capture the idea, suggested by Pigou and others, that forecast errors may be key in understanding recessions." (BP (2000, p. 18))

Even though this figure appears to show the essence of the idea that expectations potentially create business cycles, it is only weakly related to the model at hand. This is because the joint specification of the signal and the innovation in TFP does not include the case of an isolated signal, i.e. a signal not followed by a subsequent TFP innovation. Response patterns like the one in figure 6.2 are consistent with the model only if one allows for a non-zero probability for scenarios where spurious signals appear. This is done in section 7.2, where I combine the three-sector structure with the informational structure proposed by HLP.

Correctly signalled TFP shock. I turn to analyzing the response of the economy to a TFP innovation indicated a year in advance, a situation consistent with the model at this stage. Panel *(a)* in figure 6.3 shows the case of a correctly signalled positive TFP innovation. The signal indicates in period 0 a positive TFP innovation in period 2. This initiates massive production in the investment sector and, accordingly, increases in output and the capital stock. Since investment adds to the capital stock, which enters the production of consumption with delay, and since the household shifts all its additional workforce to the investment sector, consumption increases with a one-period lag. It appears that the household accepts a temporal decrease in utility to position for the good times ahead making way for a situation where productivity is high but the capital stock is low. This originates in the limited substitutability between capital and services, induced by the CES-production technology in the consumption sector. Note that the initial increase in output is entirely devoted to investment. In period 1 consumption starts moving, boosted by the build-up in the capital stock and a slight increase in service-sector labor to enable a balanced production.

When the TFP shock arrives, service-sector labor decreases substantially − an indication that capital is the limited input in the production of consumption, not services. Nevertheless, due to the accumulated capital stock consumption jumps up and amplifies the response of output. Investment-sector labor decreases and indicates that the household is not willing to enforce the accumulation of capital after the TFP shock.

Comparing IRFs here with those of the standard RBC model. A point to be stressed is the quite different behavior of the household here and in the standard RBC model after a correctly signalled positive TFP innovation, see figure 3.1. Here the wealth effect is dominated by the priority of accumulating capital, i.e. investment-sector labor increases. This is core for the immediate boom in investment as apposed to the investment blip in the standard model. The investment response externalizes to output and affects the properties of this series. A second important difference is the lagged response of consumption. It seems that if the household is able to maintain its status quo with respect to consumption, it prefers to postpone consumption for putting timely effort into capital accumulation instead. Abstracting from the fact that, when the TFP innovation appears the economy is already deviating from steady state, the subsequent substitution effect looks quite similar to the one in the standard model. Output, investment, and aggregate labor are above steady state and capital and consumption behave hump-shaped.

Wrongly signalled TFP shock. Consider in figure 6.4 what happens after a wrongly signalled negative TFP innovation. Evidently, up to period 2 the response pattern is identical to the one following a correctly signalled positive TFP shock. When in period 2 agents learn that the TFP innovation takes the opposite state, strong adjustments occur: aggregate labor decreases sharply below steady state and labor is shifted from the investment sector to the service sector dampening the low level of productivity there and, at the same time, retrenching the capital stock. Despite the large movement of labor into the service sector the drop in services is still sizeable. Consumption and capital smoothly decrease and fall below steady state to revert after some long periods. The path of capital provides information about changes in the capital stock. After the huge initial accumulation and despite of the sharp decrease in the investment-sector labor, depreciation is the element eventually driving the capital stock back to steady state.

Response of prices. Panel *(a)* in figure 6.5 depicts the IRFs of the investment price p_t, summarizing the difficulty of substituting consumption and investment, and the return to capital. In the case of a correctly signalled TFP innovation, expectations of consumption gains guide the household to build up capital. Meeting these expectations, the price of investment moves upwards. At the point, when the TFP shock arrives the price increases even more indicating that now services can be achieved at much less work. As the productivity in the service sector dies out, p_t decreases slowly. The return to capital indicates the conditions for shifting consumption between periods. Postponed consumption in the first two periods is paid a high yield, whereas after the TFP innovation foregone consumption is no longer valued highly

since the TFP shock dies out in the course of time. Further postponement of consumption then would correspond to letting productive times pass by unused.

In Panel *(b)* the investment price and the return to capital respond to a wrongly signalled negative TFP innovation. Again, there is no difference to panel *(a)* up to period 2. Observing the negative TFP innovation in period 2 makes the household recognize the oversupply of capital and, accordingly, the investment price decreases sharply. Furthermore, the return to capital jumps below steady state to ensure that accumulation of capital stops.

The discussion in this section clarifies that IRFs of the three-sector model differ substantially from those in the standard RBC model. In particular, investment responds positively to a news shock. This effect externalizes to aggregate output. The core property that generates such kind of dynamic behavior in the model is the limited substitutability of services and capital, further investigated next. A drawback, however, is the observation that consumption lags output, or, put differently, that output leads consumption. I provide more details on this in section 6.4.

6.3 Short-term substitutability of consumption and investment

The core element generating IRFs presented in the previous section is a low short-term substitutability between consumption and investment. Here I use comparative statics to isolate the effect of the CES-technology that is crucial for generating this limited substitutability.

BP note that the limited substitutability appears to be a "sensible description of short-term substitutability constraints in a modern economy" (BP (2000, p. 19)). On a similar basis, Boldrin et alt. (2001) argue in favor of inflexibilities in the factor markets. They assume that capital once installed in one sector is fixed forever. Moreover, they extend inflexibilities to the labor market. This friction is absent in the BP-economy where labor is perfectly mobile across sectors. In the light of the results established in Cogley and Nason (1995), especially the inflexibility with respect to the intersectoral movement of labor appears fruitful. Cogley and Nason show positive autocorrelation of output growth in a model with labor adjustment costs.

Whereas Boldrin et alt. (2001) exclude any short-term substitution between consumption and investment a-priori, BP let the data quantify the degree of substitutability producing the best match with real data. One advantage of the setup in BP (2000) is that it allows to quantify the size of the restriction implicitly induced by the limited substitutability between

47

services and capital. Evaluating the tightness of the restriction is possible by using as benchmark a Cobb-Douglas (CD) technology, the special case of a CES-technology with an elasticity of substitution equal to unity.

Comparative statics. Consider the situation where *(i)* the household decides a one percentage increase in steady state investment keeping overall workforce constant and *(ii)* the economy is in steady state. How much does this increase in investment lower consumption contemporaneously? The additional investment requires 0.3% of steady-state working hours shifting from the service sector to the investment sector. This labor movement triggers a decrease of steady-state service-sector output of 2.7%. But and not surprisingly, this has almost no effect on consumption using the calibrated elasticity of substitution between services and capital ϑ close to 0.25.

What happens now if one tunes ϑ up to unity, the Cobb-Douglas case? The change in services then triggers a 0.15% loss of steady-state consumption.[1] Put differently, the elasticity of substitution between consumption and investment in steady state is a small figure in the BP economy, whereas the same quantity in the case of a CD-technology amounts to approximately 2.64%.

It is interesting to check the sensitivity of this result with respect to the parameters governing the labor share of income in the investment and the service good sector, α and γ .[2] Exchanging the values attached to both parameters, i.e. α is set to 0.97 and γ becomes 0.6, delivers values for the elasticity of substitution between consumption and investment of 2.95% in the Cobb-Douglas case and still a tiny number in the BP economy. Results seem fairly robust along this dimension.

I have shown here that the tightly calibrated CES-technology in the BP model is the element responsible for the low short-term substitutability of consumption and investment and, thereby, for the increase of investment in response to good news. In the next section, I analyze if this short-term substitutability constraint of the BP economy is capable of producing substantial internal propagation of TFP innovations and news shocks.

6.4 Investigating output and consumption

As is discussed at length in Cogley and Nason (1995), in RBC models that rely entirely on intertemporal substitution, capital accumulation, and capital adjustment costs, "output dynamics are nearly the same as impulse dynamics" (Cogley and Nason (1995, p. 509)). Accordingly, these models are not capable of reproducing the positive autocorrelation that can be

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[1] I chose a labor share of income equal to 0.6.

[2] These parameters were discussed in section 5.7.

observed in output growth at the first few lags. I have shown in chapter 3 that introducing news shocks into standard RBC models aggravates the existing failure of this class of models. To verify, if a three-sector economy is able to improve upon the shortcoming of standard models I investigate the properties of the simulated output series.[3] It turns out that the auto-correlation function of this series is close to one in a standard RBC models *without* a news shock. In a second step towards a comprehensive evaluation of the three-sector economy, I analyze the reason and the reasonability of the lagging property of consumption.

Investigating output. Aggregate output is plotted in figure 6.6. At first glance, the two series do not look much different from real-data GNP. Business cycles occur at reasonable horizons, say, between five to ten years. Furthermore, it is hard to fix the effect of news shocks, e.g. an episode where agents fail to anticipate future TFP innovations correctly, by just scanning plots. First order autocorrelation of the HP-filtered level series is in the range of 0.62, somewhat understating the number of real-data GNP.

There is at least some indication that the adverse effect of news shocks on output growth documented in chapter 3 vanishes when investment is no longer determined as a residual − the IRFs display much richer dynamics compared to those implied by standard models.

Autocorrelation functions of output growth at different leading horizons of the signal are shown in figure 6.7 for a signal leading TFP between 1 period in panel *(a)* and 3 periods in panel *(c)*. Indeed, the three-sector structure improves the size of internal propagation when compared to the standard RBC model *with* news shocks. But the BP model remains behind standard RBC models *without* news.[4]

Except the very first data point in panel *(a)* and the second one of panel *(b)* the autocorrelation of output growth is at no horizon significantly different from zero. These blips, however, appear to be related to the length of the leading horizon of the signal. They could well mirror the effect of a wrongly signalled TFP innovation that triggers severe adjustments in the economy at the point when agents learn about the falsity of their information.[5] It is not to be noted that these downturns in output growth at the

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[3]There are different ways of evaluating the size of internal propagation. Uhlig (2003) suggests to compare the model under consideration to a "primitive" re-scaling procedure of total factor productivity. Cochrane (1994) discusses the pros and cons of various amplification factors, i.e. variability of output that is not due to variability in TFP. I choose the criterion of output growth since it is well established in the literature, since it has a clear-cut empirical counterpart, and since it seems to be a criterion difficult to undermine.

[4]BP (2000) plot in figure 7 a histogram based on averaged relative frequencies. Their output series is rightward-skewed distributed. However, due to their assumption of no technological regress, realizations of ϵ^H have a size of 4.17% whereas realizations of ϵ^L have size -1.7%. This asymmetry appears to transmit to the output series.

[5]See the next paragraph for a reason why for $n = 3$ the blip is much smaller than in

first lags are undesirable.

Even though, the BP model is calibrated with a substantial degree of friction as regards the short-term substitutability between consumption and investment, this still seems to be insufficient to beat the standard models by showing stronger internal propagation.

Investigating consumption. As already mentioned in section 6.1, in the three-sector economy considered here consumption lags output. This is problematic from different perspectives.

First, there is evidence that consumption leads output rather than output consumption. To support this notion, I provide figures derived in Cooley and Prescott (1995) in table 6.2. If this table supports any property of consumption different from contemporaneous co-movement, it is certainly a leading property.

Table 6.2: The consumption dynamics in the US cycle (1954-91)

i	-4	-3	-2	-1	0	1	2	3	4
$\mathrm{Corr}(Y_t, C_{t+i})$	0.42	0.57	0.72	0.82	0.83	0.67	0.46	0.22	-0.01

Notes: Source of these figures is table 1 in Cooley and Prescott (1995).

The lagging property of consumption in the simulated data is inherently related to the leading horizon of the signal. Consider table 6.3; if the signal is redundant information, as is the case in the first row, the co-movement of output and consumption is strongest contemporaneously. In the case, the signal leads TFP innovations by one or two periods, output does so with respect to consumption. For $n = 3$ this pattern is no longer obvious. This feature of the data is related to the fact that the initial movement in output following a news shock is entirely devoted to a boom in investment since consumption moves with a lag only.[6] If, however, n is larger than 2 this effect diminishes due to the build-up in the capital stock now enabling additional production of consumption.

Secondly, economic intuition and, in particular, the idea of news shocking the information set of agents suggest that consumption is leading output rather than vice versa. Cochrane (1994) argues that every consumer has idiosyncratic information about her or his own prospect. Taking this information seriously the agent is likely to adjust personal consumption accordingly − idiosyncratic information influences individual consumption. If this is the case, then in the aggregate consumption is likely to reveal information about future aggregate output.

the cases $n < 3$.

[6]See the discussion of the IRFs in section 6.2.

Table 6.3: CORRELATION OF OUTPUT AND CONSUMPTION

n	$\text{Corr}(C_t, Y_t)$	$\text{Corr}(C_{t-1}, Y_t)$	$\text{Corr}(C_{t-2}, Y_t)$	$\text{Corr}(C_{t-3}, Y_t)$
0	0.94	0.75	0.55	0.37
1	0.50	0.86	0.64	0.41
2	0.51	0.74	0.82	0.57
3	0.63	0.77	0.73	0.60

Notes: Correlations are averages based on simulating the model for a sample of 100 observations 70 times and n displays the leading horizon of the signal.

Even though the model incorporates a news shock it is not able to replicate a leading property of consumption. This contrasts results in HLP (1997) where the leading property of consumption is the main motivation for introducing a news shock into the optimal growth model. Instead, news in the BP model make output lead consumption. Moreover, the length of output's lead depends on the leading horizon of the signal.

6.5 Do three-sectors recover news shocks?

This research is motivated by the question, what underlying model structure makes news shocks work?

To answer this question, I have identified one important reason for the severe failures of standard RBC models due to news shocks − the unit elasticity of contemporaneously substituting consumption and investment. Consecutively, I have analyzed a three-sector economy, originally proposed in BP (2000), that drives the elasticity of substituting consumption and investment in the short run close to zero. Moreover, the BP economy features a highly stylized informational structure − news emerges either as entirely correct signal or as signal completely void of information.

The analysis shows, that in principle news shocks can generate expectation-led business cycles in the BP model; i.e. output, investment, and consumption respond positively to good news. As was the case for the standard RBC model, however, important and counterintuitive consequences of news shocks surface in the BP model when digging deeper. Instead of leading output, which would be intuitively appealing, consumption appears to limp behind output, and the lag of consumption is related to the lead of news. Furthermore, despite the fact that the BP economy is calibrated with a substantial degree of friction, the model fails on generating sizeable internal propagation. A model that makes news shocks work therefore certainly needs a structure supporting low short-term substitutability of consumption and investment. However, as the BP model shows, this alone is not

sufficient.

It appears that the analysis of BP cures one leg and does so at the expense of the other. In a standard RBC model, good news trigger a positive response of consumption but, at the same time, a decrease in investment. The BP economy reacts to good news by increasing investment, but depresses the contemporaneous response of consumption. This, in turn, implies the lagging property of consumption.

However, at this point, it is not clear if and to what extent the adverse consequences in the BP model and in the standard RBC model hinge exclusively on the real structure of the models, or if a potential remedy is hidden in the type of assumptions made to formulate news shocks. To shed light on this issue, in both models I modify the assumptions determining the news shock.
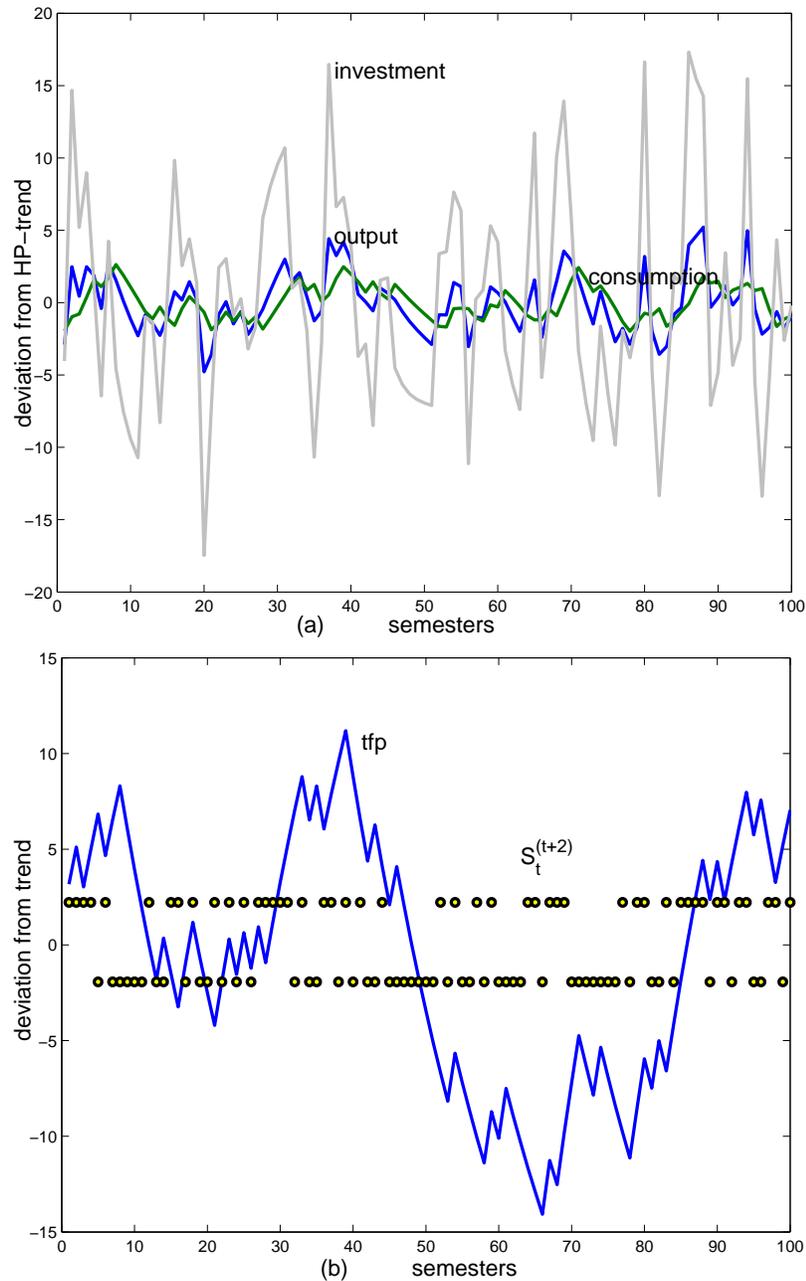
Figure 6.1: SIMULATED TIME SERIES.

Panel *(a)* shows simulated series for output, investment and consumption. The model is simulated assuming a signal that leads the factual realization of TFP by two periods. All series are filtered using the HP-filter with $\lambda_{HP} = 800$. Panel *(b)* displays the sequence of the signal accompanied by a simulated path of TFP. Again the signal appears two periods in advance. For purpose of clarity the TFP series is not HP-filtered but displays (by construction) deviation from the long-run growth path.
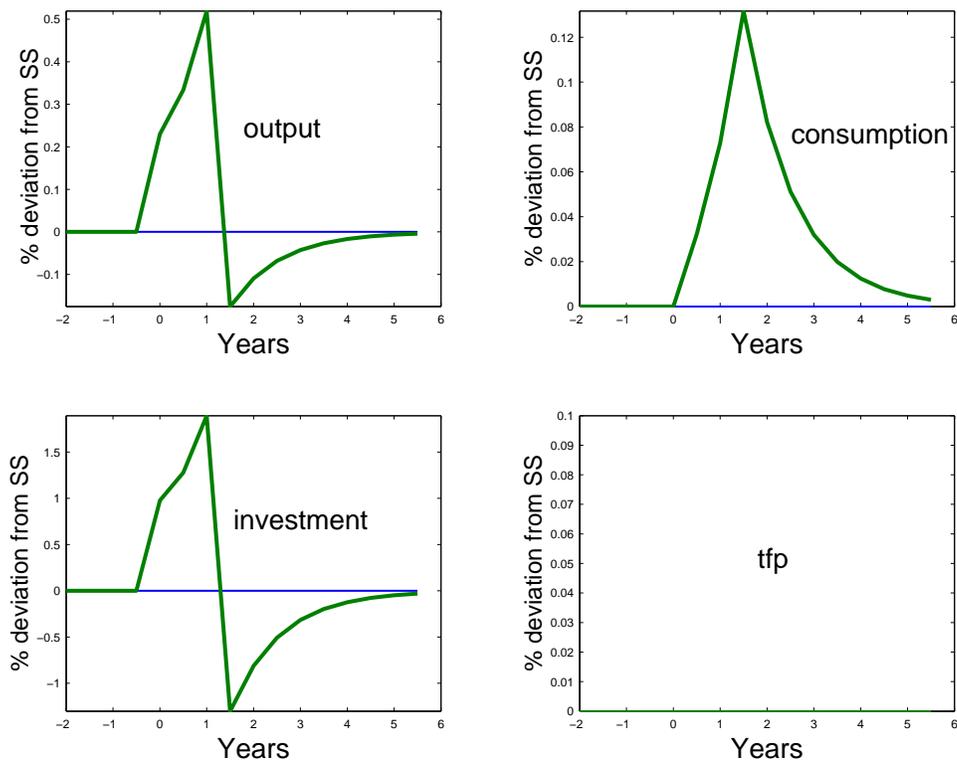
Figure 6.2: Reproduction of figure 6 in BP (2000).

Impulse responses to an innovation in TFP that is signalled three periods in advance but never occurs. BP compute impulse response functions to a signal of size 4.17% whereas here the economy is shocked with a signal of size 1%. This explains the difference in scales.
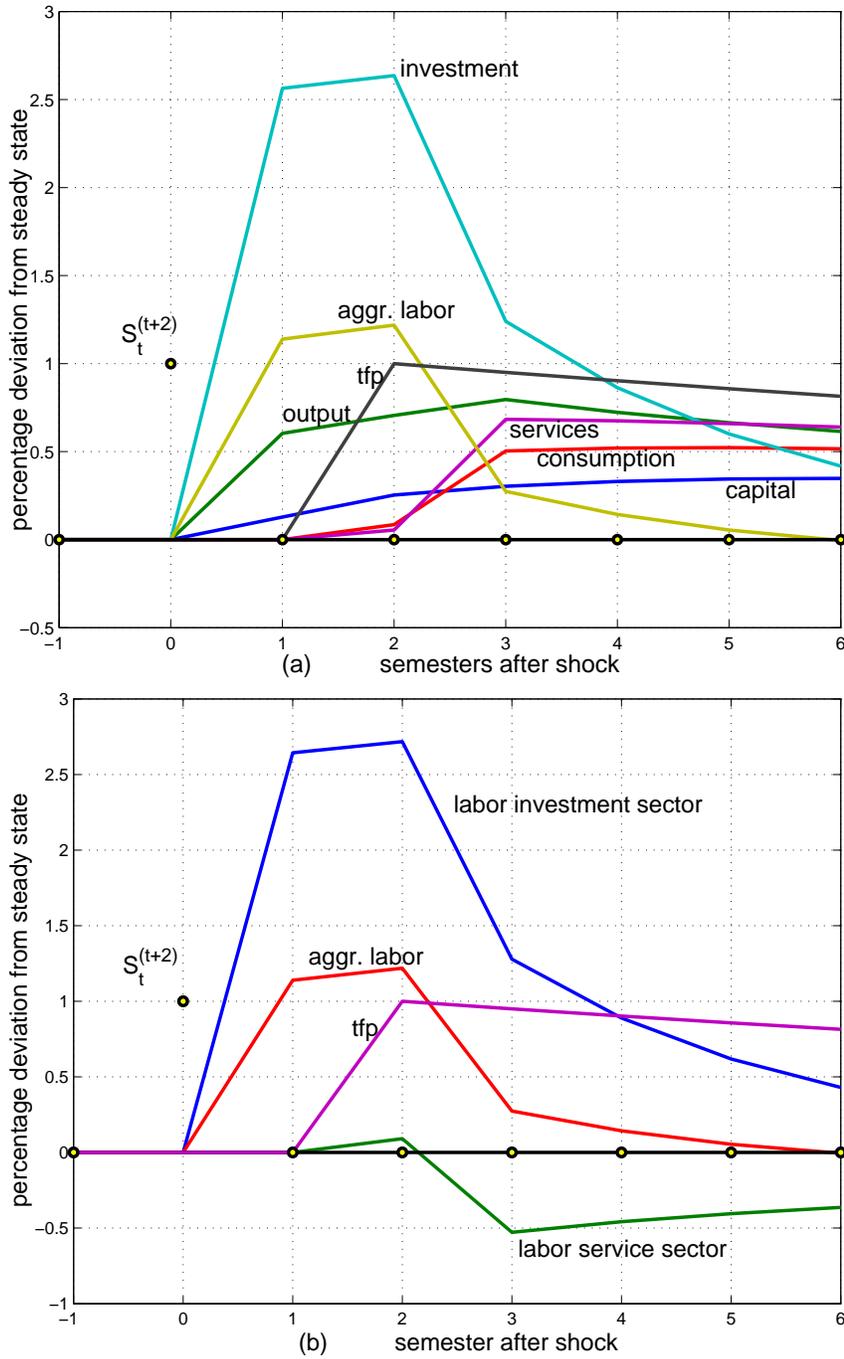
Figure 6.3: IRFs to a correctly signalled TFP shock.

Impulse response functions for a signal leading TFP innovations by two periods. Here the signal correctly indicates the TFP shock to occur. Panel *(a)* shows responses of output, consumption, investment, capital, aggregate labor, services and the path of TFP, whereas panel *(b)* shows the intersectoral movement of labor.
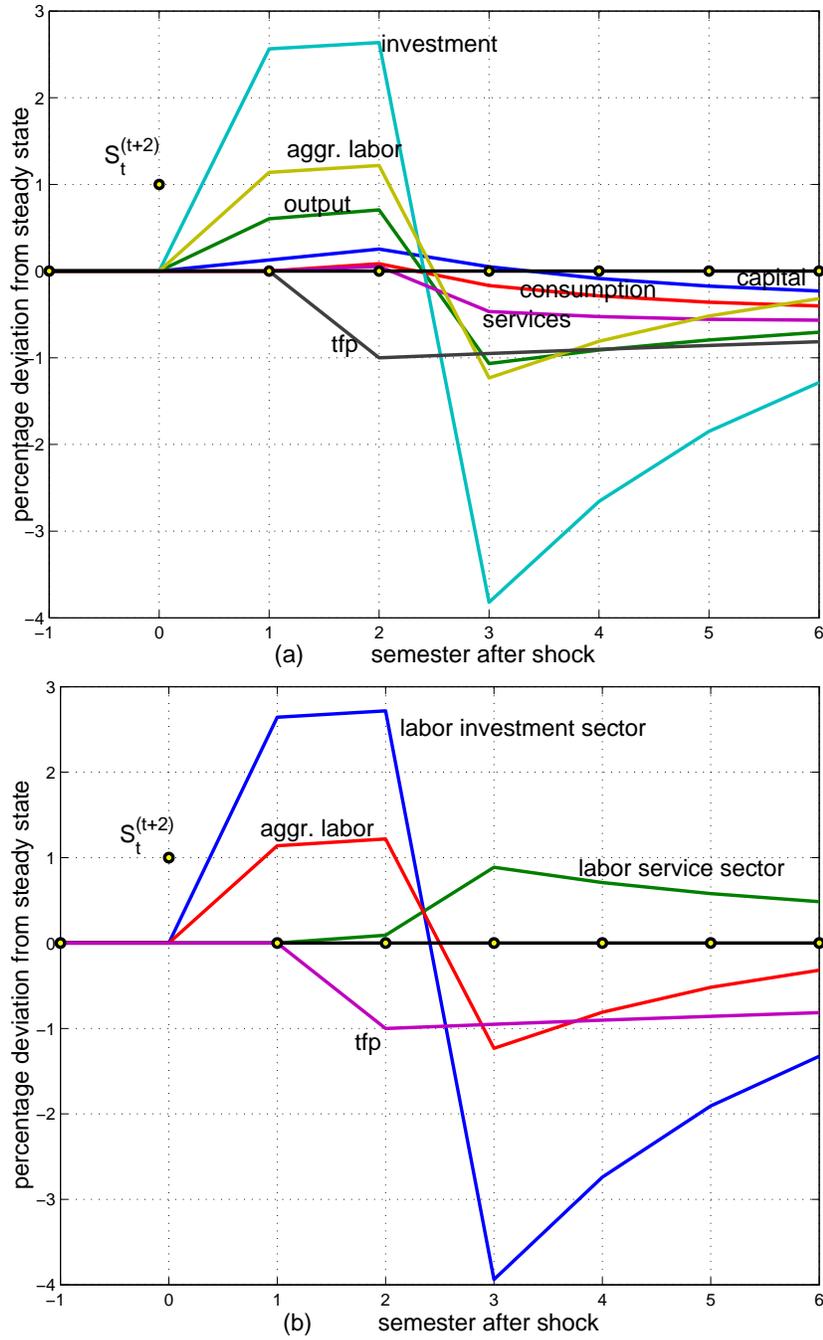
Figure 6.4: IRFs to a wrongly signalled TFP shocks.

Impulse responses functions for a signal leading TFP innovations by two periods. Here the signal gives the wrong indication by signalling a positive shock to TFP whereas The actual realization of the TFP innovation is negative. Panel *(a)* shows responses of output, consumption, investment, capital, aggregate labor, services and the path of TFP, whereas panel *(b)* shows the intersectoral movement of labor.
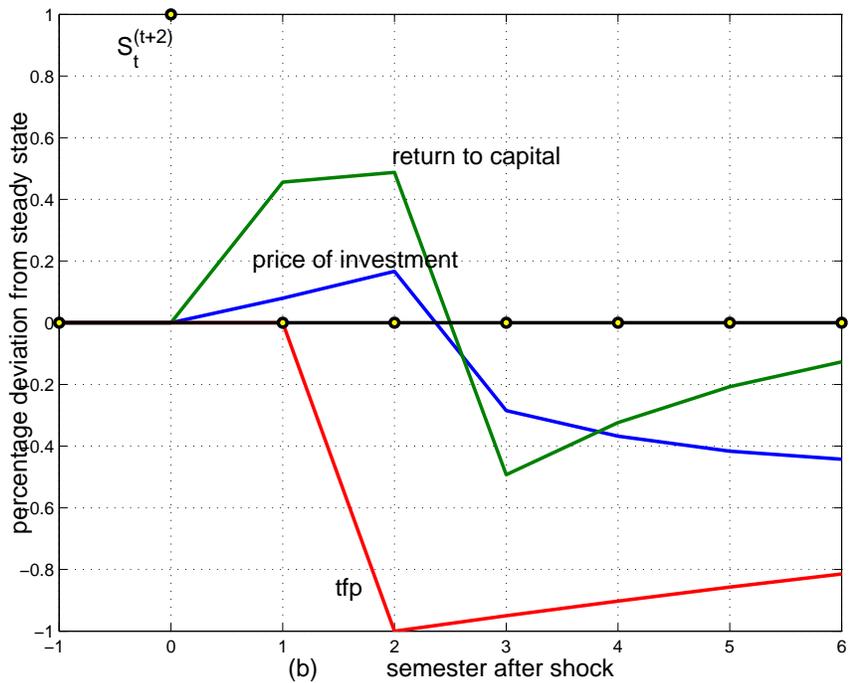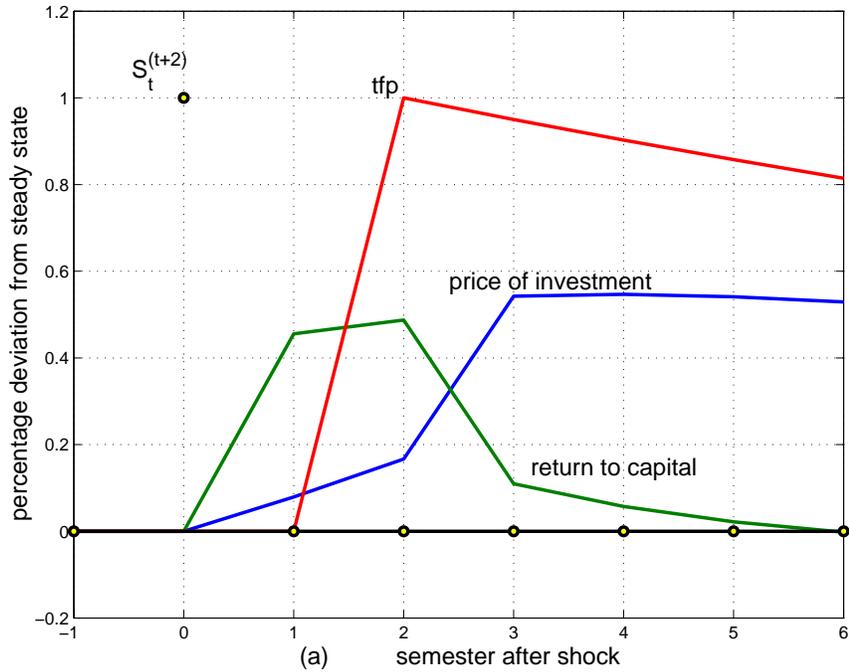
Figure 6.5: IRFs of prices to signalled TFP shocks.

Impulse responses functions for the price of investment (re-scaled) and the return to capital. The leading horizon of the signal is two periods. Panel *(a)* shows the behavior of prices after a correctly signalled TFP shock. Panel *(b)* depicts the adjustment following a wrongly signalled TFP shock.
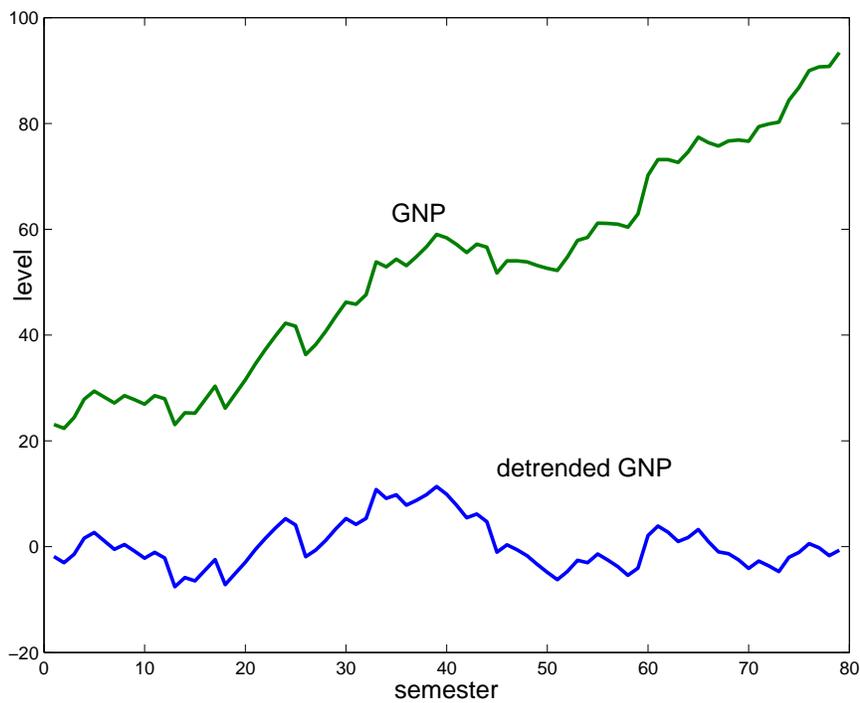
Figure 6.6: LEVEL SERIES OF GNP.

Detrended (and unfiltered) GNP is what comes out of a model simulation. The trending series is constructed using the unfiltered GNP series and adding an exponential trend with growth factor g equal to 0.017.
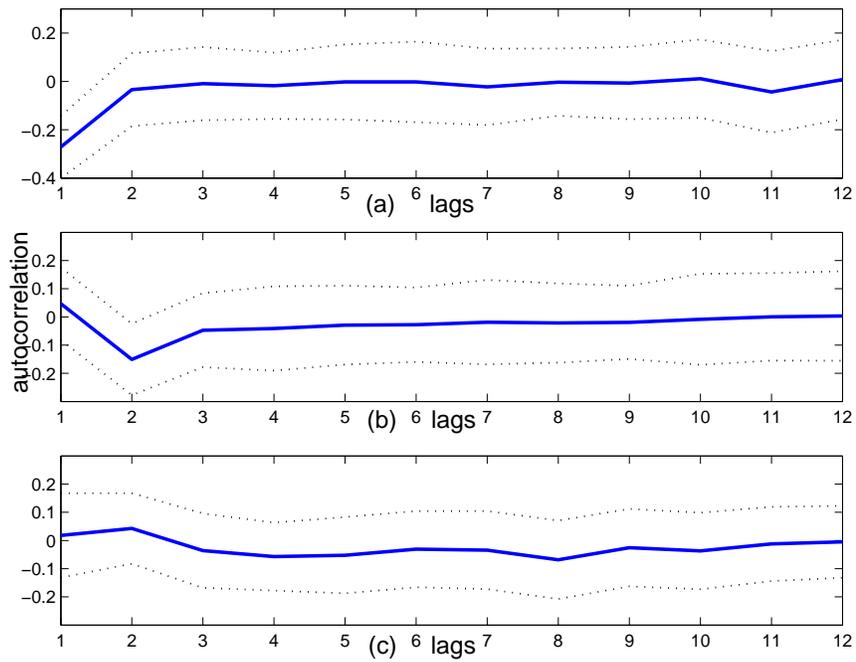
Figure 6.7: AUTOCORRELATION FUNCTIONS OF OUTPUT GROWTH.

Panel *(a)* depicts the autocorrelation function for lag 1 to 12 of output growth for a signal leading the TFP innovation by one period, panel *(b)* shows the autocorrelation function for a leading horizon of the signal of two periods, and panel *(c)* plots the autocorrelation function when the signal leads three periods. The growth rate is the first difference of the log of the trending output series. All autocorrelation functions are averages of 100 simulations, each simulation generating a sample of 80 observations. Thin lines are error bands of width one standard deviation.

59

Chapter 7

News shocks put differently: Variations

In this chapter, I study the reasonability of the information structure in the BP and the standard RBC model and test the sensitivity of results, so far established, when varying the information structure of both models. To this end, in section 7.1, I compute forecasts of TFP innovations given that agents observe the signal and compare these forecasts to real-world equivalents. The high degree of stylization in the BP model that becomes apparent at this point suggests a modification of its information structure. Consecutively, in section 7.2, instead of pursuing the extreme assumption that the signal indicates a future TFP innovation either correctly or incorrectly, I analyze the implication of signals that are noisy measures of future TFP innovations. This corresponds to the setup applied in the standard RBC model in chapter 3. In section 7.3, the information structure of the standard RBC model is modified. One possible way to approach the counterfactual predictions of the standard RBC model with news is to postulate a structural explanation for the arrival of news. When TFP is subject to two qualitatively different shocks, confusion about the factual type of shock leads to suboptimal adjustments. In the course of time, agents can infer the type of the shock from subsequent TFP realizations and confusion subsides.

7.1   Implicit forecasts in the two models

In order to link the information structure in BP (2000) with the one in HLP (1997) I compare projections of TFP innovations implicit in both frameworks. Additionally, I conduct a comparison with real-world projections of nominal GDP, available from the Survey of Professional Forecasters.[1] Obviously, this latter comparison needs to be conducted with some

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[1]This source is available in the web, www.phil.frb.org/econ/liv/index.html.

care, because TFP and GDP differ in characteristics and measurement. But the Survey of Professional Forecasters provides mean forecasts of nominal GDP based on a large number of forecasting institutions, whereas there is no hope to find forecasts of similar quality for TFP. Additionally, Cogley and Nason (1995) document that in standard RBC models input dynamics essentially coincide with (literally) output dynamics, because internal propagation is weak. The same holds true for the model of BP as documented most strikingly in figure 6.7. To circumvent measurement problems I compare the fraction of total variability in each variable that is explained by its forecast. Consider the following OLS-regression,

$$\epsilon_t = \varrho S_{t-n}^{(t)} + \mu_t \ . \tag{7.1}$$

Here ϵ_t is the TFP innovation, $S_{t-n}^{(t)}$ is some indication at time $t - n$ about the TFP innovation at time t, the leading horizon of the signal n is set equal to 1, and μ_t is the residual. The distribution of the signal is conditional on the respective setup. In HLP (1997) $S_{t-n}^{(t)}$ is normally distributed with zero mean and variance $(\sigma_\epsilon^2 + \sigma_\nu^2)$. In the BP model, $S_{t-n}^{(t)}$ follows a binomial distribution; for details see equation 4.2.

For an initial sample $t = 1, \ldots, \tilde{T}$ with $\tilde{T} \leq T$ I compute an estimate of ϱ. Based on this estimate $\hat{\varrho}$ I then derive the n-step-ahead forecast error. I repeat this procedure for increasing $\tilde{T}$ until $\tilde{T} = T$ to compute the mean squared forecast error,

$$\text{MSFE} = E[(\epsilon_t - \hat{\epsilon}_{t|t-n})^2] \quad , \text{where } \hat{\epsilon}_{t|t-n} = \hat{\varrho} S_{t-n}^{(t)} \ .$$

Based on the entire sample $t = 1, \ldots, T$ I compute the fraction of total variability explained by the respective projection.

$$\text{R}^2 = 1 - \frac{\hat{\mu}' \hat{\mu}}{\hat{\epsilon}' \hat{\epsilon}}$$

As a comparison I provide results for a similar regression of nominal GDP,

$$\log Y_t^{detr} = \alpha_0 + \alpha_1 \log \widehat{Y}_t^{detr} + \mu_t \ . \tag{7.2}$$

Here $\log Y_t^{detr}$ is the deviation from HP-trend for quarterly data of logarithmic nominal GDP, $\log \widehat{Y}_t^{detr}$ is the deviation from HP-trend of the logarithmic mean forecast for GDP in the quarter t, and α_0 is a constant. Forecasts are provided quarterly from 1968:04 to 2003:01. I do not compute the MSFE in this regression due to measurement considerations. Results are shown in table 7.1.

The R^2 in the HLP and the BP model are close to the one in a similar regression of nominal GDP. Therefore, in the two models uncertainty surrounding implicit forecasts is comparable to their real-world equivalent.

61

Table 7.1: Implicit forecasts in the BP and the HLP model

statistics	HLP model		BP model		Nominal GDP
R^2	0.50	(0.08)	0.57	(0.11)	0.60
MSFE	0.25	(0.05)	1.01	(0.32)	.
stdev(dep.var.)	0.70	.	1.50	.	1.16
stdev(indep.var.)	0.70	.	1.58	.	1.53

Notes: Statistics for the HLP and the BP model are derived from the regression (7.1) and are based on an iterative procedure. Recursion starts from an initial sample of size $\tilde{T}$ equal to 30 increasing to total sample size $T = 80$. The R^2 summarizes total sample information. This procedure is repeated 1000 times which delivers standard errors reported in parenthesis. Standard deviations are in percentages. Corresponding figures for nominal GDP come from the regression 7.2. A dot stands for *not applicable.*

Comparing the two models with each other, however, the MSFE implied by the assumptions in BP (2000) is larger by a factor 4 when compared to the corresponding quantity in HLP (1997). This mirrors the substantial degree of stylization induced by the binomial distributions of the TFP innovation and the signal.[2] Despite of this, results suggests that the information structure in both models is a reasonable approximation of real world.

7.2 Modifying the three-sector model

Even though it is illuminating to study BP's radical assumption about the distribution of the signal and the TFP innovation, the fact that it results into extreme stylization makes it hard to accept. To this end, I integrate the information assumption, made in HLP (1997) and reviewed in section 3.1, in the BP economy as it is described in chapter 4. This corresponds to using equation (3.11), here reproduced for convenience, instead of equation (5.7) for deriving the Euler equation that incorporates news shocks.[3]

$$E\left[\log \tilde{\eta}_{t+n} | \Omega_t \right] = \lambda^n \log \tilde{\eta}_{t+n} + \sum_{i=0}^{n-1} \lambda^i \chi S_{t-i}^{(t+n-i)} \ .$$

The quantity $\log \tilde{\eta}_t$ is time t TFP in the non-durable sector. With the informational structure of HLP, figure 6.2 that shows the dynamic adjustment after an isolated signal becomes validate part of the model dynamics.[4] An

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[2]Note that HLP derive estimates for stdev(dep.var.) $= \sigma_\epsilon = .75$ and stdev(indep.var.) $= \sigma_\nu = .47$ delivering a R^2 equal to .718 and a MSFE of size .16. Their value for χ corresponds exactly to the R^2 here which sheds light on the role of the R^2 in this setting.

[3]See section 5.5 on how derivation takes place.

[4]See the discussion in section 6.2 on this.

isolated signal $S_t^{(t+n)}$ corresponds to a realization of $\epsilon_{t+n} = 0$ and a realization of $\nu_{t+n} = 1$. Furthermore, dynamic adjustments plotted in figure 6.3 now correspond to a realization of $\epsilon_{t+n} = 1$ and a realization of $\nu_{t+n} = 0$, whereas impulse response functions shown in figure 6.4 correspond to a realization of $\epsilon_{t+n} = -1$ and a realization of $\nu_{t+n} = 2$.[5]

Calibration and grid search. I calibrate the model with the same parameters (if relevant) as chosen in the analysis of BP, see table 5.2. The standard deviation of the TFP innovation, σ_ϵ, is in the analysis of BP implicitly determined by making assumptions about the binomial distribution of ϵ. It turns out that here σ_ϵ as large as 2.0 matches empirical standard deviations reasonably well. Again a grid search is conducted on the parameter space (n, χ, ϑ) delivering for $n = 2$ a value of χ equal to 0.435 and a elasticity of substitution between services and capital $\vartheta = 0.26$.

Results. Table 7.2 provides simulated moments of the BP model when the information structure is modified, empirical moments as derived by BP (2000), and moments simulated by BP. Simulated moments show that

Table 7.2: Simulated Moments in the modified BP model

quantity	simulated moments		empirical moments		moments simulated by BP	
stdev(Y_t)	2.10	(0.23)	2.16	(0.22)	1.85	(0.27)
stdev(D_t)	7.26	(0.68)	6.87	(0.67)	5.84	(0.80)
stdev(C_t)	1.15	(0.18)	1.06	(0.09)	1.07	(0.18)
corr(Y_t, Y_{t-1})	0.60	(0.08)	0.79	(0.08)	0.67	(0.09)
corr(Y_t, D_t)	0.84	(0.03)	0.95	(0.01)	0.91	(0.01)
corr(Y_t, C_t)	0.57	(0.07)	0.64	(0.08)	0.63	(0.06)

Notes: Standard errors in parenthesis. Simulated moments are based on the model calibrated for semiannual frequency. The search vector takes values $(2, .435, -2.8)$. For further details see text and notes of table 6.1.

the model is capable of roughly reproducing empirical standard deviations. However, as is the case for the version of the BP model described in chapter 4, correlations are underestimated (see table 6.1). Along these lines, the different information structure does not seem to have a large impact.

The implications of the different informational structure with respect to the autocorrelation of output growth again are negligible. Simulations essentially repeat results shown in figure 6.7. The only visible difference is a

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[5]Note that figure 6.2 assumes a leading horizon of the signal of three periods, whereas figures 6.3 and 6.4 are computed based on a leading horizon of two periods. This is due to the context in section 6.2.

slightly more negative autocorrelation for $n = 3$ at the first few lags. Moreover, the leading property of output with respect to consumption is still in place. The correlation between consumption and output contemporaneously amounts to 0.57 and increases to its maximum 0.77 when consumption lags output by two periods.

Adding up, this section documents robustness of the results derived in chapter 6 with respect to the way how news shocks are incorporated into the BP model. I conclude that, to a large extent, the real structure is the driving force determining the performance of the BP model.

7.3 Modifying the standard real-business-cycle model

Does the performance of the standard RBC model improve once it is confronted with a different information structure? To study this question, I augment the standard model with a structural explanation for news shocks that is, in some respects, close to the setup in Kydland and Prescott (1982). News with structural foundation contrast the exposition in HLP (1997) and in BP (2000); even though the arrival of a-priori information in each case is motivated by a plausible story, from a rigorous modelling point of view news shocks as specified there remain rather ad hoc. In the following, I motivate the exact specification, set up a respective model, and detail on how to solve for the dynamics of the model. Implementation into the Toolkit is described briefly to spend some space on hiking through results.

Confusion generates endogenous news. One way of formalizing the idea of a structural explanation for news is to introduce a TFP process that is subject to two qualitatively different types of shocks. Observing a TFP realization, agents face uncertainty regarding the type of shock. In the course of time agents can update their beliefs with new TFP observations and confusion subsides.[6]

In the standard RBC model as described in chapter 3, agents derive utility from consumption and leisure, preferences are separable across time and among arguments, a Cobb-Douglas technology converts labor and capital into a single good that can be either invested or consumed, and the household is endowed with some initial capital stock and, in every period, a fixed contingent of time. Usually, in such a setting TFP is specified as an AR(1) process,

$$z_t = \lambda z_{t-1} + \epsilon_t \quad \text{where} \quad \epsilon_t \sim iid.\mathcal{N}(0, \sigma_\epsilon) \quad \text{and} \quad |\lambda| < 1 \ .$$

However, consider the case in which TFP evolves as the sum of a transitory

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[6]Evans and Honkapohja (2000) provides a good introduction into this area of research.

and a permanent component,

$$z_t = \xi_t^{(1)} + \xi_t^{(2)} \tag{7.3}$$
$$\xi_t^{(1)} = \rho_1 \xi_{t-1}^{(1)} + \epsilon_t, \quad |\rho_1| \leq 1$$
$$\xi_t^{(2)} = \rho_2 \xi_{t-1}^{(2)} + \mu_t, \quad |\rho_2| < 1 .$$

Furthermore, $\xi^{(i)}$ is assumed unobservable and ϵ and μ are independent of each other and iid. $\mathcal{N}(0, \sigma_i)$, $i = 1, 2$.[7] This form of TFP is supported by the empirical literature documenting transitory and permanent effects in GNP, among others Blanchard and Quah (1989) and Quah (1992). Another justification is given in Van Nieuwerburgh and Veldtkamp (2003). The authors study a model in which output is the outcome of production plus an additive noise term. Their interpretation of the noise term is that it captures the effect of intangibles on output, e.g. senior management, branding and marketing, or research and development. Once log-linearized, their setting corresponds to the one employed here.[8]

The influential contribution of Kydland and Prescott (1982) applies a slightly augmented setting in that consumers do not observe twofold TFP but instead observe a noisy measured indicator of (7.3). According to the authors, the noise component may be due to "the fact that there are errors in the best or consensus forecast of what productivity will be for the period" (Kydland and Prescott (1982, p. 1352)). It turns out, however, that the variance of the indicator shock needs to remain small since otherwise the shock implies business fluctuations of employment smaller than those of TFP. Moreover, the paper does not explicitly delve into the consequences specific to such a setting.

Note that the augmentation differs from the version in chapter 3 in that no a-priori information emerges; here the new information derives from learning about the quality of TFP at a time when TFP is already relevant for production. This circumvents the initial counter-movements in consumption and investment documented for the standard RBC model with a-priori information in chapter 3.

Disentangling confusion with the Kalman filter. When agents observe current TFP, which from their perspective allows no unique interpre-

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[7]It is informative to mention that if ρ_1 is equal to unity then after a shock in $\xi^{(1)}$ some of the variables in the economic model converge to a new steady state and thereby diverge from the evaluation point of the approximation.

[8] Note that this process is a linear counterpart of another interesting process for TFP,

$$z_t = \rho_t z_{t-1} + \epsilon_t$$
$$\rho_t = \lambda \rho_{t-1} + \mu_t, \quad \text{with} \quad |\lambda| < 1 .$$

TFP evolves according to a persistence that in itself is random. This was pointed out to me by Bartosz Mackowiak.

tation regarding the initiating shock, they form rational beliefs. This corresponds to incorporating Kalman filtering of the process z into the standard RBC model. Since this substantially augments the application of beliefs in previous chapters, I provide an exposition with some details. However, for studying the Kalman filter I refer the reader to chapter 13 in Hamilton (1994). With respect to the Kalman filter, I follow the notation in Hamilton's book; apart from this the notation corresponds to the one in chapter 3.

The reasoning why Kalman filtered z_t's fulfill the notion of rational beliefs draws on the fact that the Kalman filter delivers forecasts optimal among *any* function over the sequence $\{z\}_{t=0}^{T}$ if innovations are normally distributed. Define Ω_t as the household's information set including all variables in the model dated t and their historic pathes and define the expectations of $\xi^{(i)}$ given information of time t as

$$\hat{\xi}_{t+1|t}^{(i)} = E[\xi_{t+1}^{(i)}|\Omega_t] \quad , \text{where} \quad i = 1, 2 \; .$$

The general state space representation is determined by the state and the observation equation.

$$\xi_{t+1} = F\xi_t + \nu_{t+1}$$
$$y_t = A'x_t + H'\xi_t + w_t$$

y_t is a $(n \times 1)$ vector of variables observed at time t, ξ_t is the $(r \times 1)$ state vector of unobservable variables with components $\xi^{(i)}, i = 1, \dots, r$, and x_t is a $(k \times 1)$ vector of predetermined or exogenous variables.[9] The matrices $F_{(r \times r)}$, $A'_{(n \times k)}$ and $H'_{(n \times r)}$ contain the parameters of the process. Each vector of white noise ν_t and w_t is specified as

$$E[\nu_t \nu_\tau\prime] = \begin{cases} Q & \text{for} \quad t = \tau \\ 0 & \text{otherwise,} \end{cases} \quad \text{and} \quad E[w_t w_\tau\prime] = \begin{cases} R & \text{for} \quad t = \tau \\ 0 & \text{otherwise,} \end{cases}$$

with $Q_{(r \times r)}$ and $R_{(n \times n)}$ being positive semi-definite. Additionally, both vectors are assumed uncorrelated at all leads and lags, $E[\nu_t w_\tau'] = 0, \forall t, \tau$. It is assumed that the initial state vector ξ_1 is uncorrelated with ν_t and $w_t, t = 1, 2, \dots, T$.[10] The system matrices A', H', F, Q and R are assumed to be known and deterministic. For the problem at hand, the Kalman filter is ultimately used to achieve a forecast of the state vector using information as of time t, $\hat{\xi}_{t+1|t}$. Implicitly, however, an estimate of the state vector at

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[9] That is, x_t contains no information about ξ_{t+s} and $w_{t+s}, s = 0, 1, 2, \dots$ that is not yet contained in $y_{t-1}, y_{t-2}, \dots, y_1$ and can therefore consist of lagged y_t's.

[10] This implies a number of results. Since ξ_t can be written as a linear function of $\{\xi_1, \nu_2, \nu_3, \dots, \nu_t\}$, it holds that $E[\nu_t \xi_\tau\prime] = 0, \tau < t$. Based on this, derivation of $E[w_t \xi_\tau\prime] = 0, \forall \tau$ and $E[w_t y_\tau\prime] = E[\nu_t y_\tau\prime] = 0, \tau < t$ is straightforward.

time t based on information of time t, $\hat{\xi}_{t|t}$ is computed first. The equation for updating the state vector is given by

$$\hat{\xi}_{t|t} = \hat{\xi}_{t|t-1} + P_{t|t-1}H(H'P_{t|t-1}H + R)^{-1} \times (y_t - A'x_t + H'\hat{\xi}_{t|t-1}) \ ,$$

and a forecast of the state vector takes the form $\hat{\xi}_{t+1|t} = F\hat{\xi}_{t|t}$.

Casting the process z into state space representation delivers system matrices $A = 0, F = \mathrm{diag}(\rho_1, \rho_2), H' = [1 \quad 1], Q = \mathrm{diag}(\sigma_1, \sigma_2)$ and $R = 0$. The state equation when separated into univariate equations becomes for $i = 1, 2$

$$\hat{\xi}^{(i)}_{t+1|t} = \rho_i \left[\hat{\xi}^{(i)}_{t|t-1} + \kappa_i(z_t - \hat{\xi}^{(i)}_{t|t-1} - \hat{\xi}^{(i)}_{t|t-1}) \right] \ . \tag{7.4}$$

Here $\bar{K}_{2\times1} = PH(H'P)^{-1} = [\kappa_1 \quad \kappa_2]'$ indicates the "steady state" gain matrix of the Kalman filter.[11] The expression in squared brackets computes the updated belief of the respective component. Intuitively, since it holds that $\kappa_1 + \kappa_2 = 1$, the forecast error of period t is completely distributed between the two components of z. The explicit use of the ρ_i's clarifies that agents exploit their knowledge about the structure of the process z.[12]

Equations (7.4) are what is needed to make agents form rational beliefs about the fraction of z devoted to a specific shock. The difference to the formation of beliefs in previous chapters is the recursive forecasting/updating scheme. However, the general procedure is the same: explicitly take into account how agents form conditional expectations,

$$E[z_{t+1}|\Omega_t] = E[\xi^{(1)}_{t+1} + \xi^{(2)}_{t+1}|\Omega_t] = \hat{\xi}^{(1)}_{t+1|t} + \hat{\xi}^{(2)}_{t+1|t} \ ,$$

and augment the Euler equation accordingly. Substituting this expression into the Euler equation (3.10) and defining $\Phi = \theta\frac{\bar{Y}}{KR}$ and $\alpha_3 = \Phi\theta - \theta - \Phi + 1 - \alpha_2$ results in

$$0 = E_t \left[\rho\hat{C}_t + (\Phi\theta - \theta - \Phi)\hat{K}_t - \alpha_3\hat{L}_{t+1} + (\Phi - 1)\left[\hat{\xi}^{(1)}_{t+1|t} + \hat{\xi}^{(2)}_{t+1|t} \right] \right] \ . \tag{7.5}$$

In the case of no (information) externalities, the equilibrium of the model can be deducted from the welfare maximizing social planner.

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[11]Due to the fact that $\xi^{(1)}$ is allowed to follow a random walk in which case its unconditional mean and variance are not defined, the distribution of the innovations is chosen to be the prior distribution for the initial state vector. This enables the use of $\xi^{(i)}_{1|0} = 0$ and the respective elements of P_1 equal to $\sigma_i, i = 1, 2$.

[12]Writing the Kalman filter in this form reveals the assumption that z_t is the only new information in the complete economic model arising in period t. This needs not necessarily be the case. For example, Coenen, Levin and Wieland (2001) solve a fully-fledged monetary model where GNP is uncertain due to the "real-time" data problem. But since money reacts to the true GNP movements and therefore contains additional information independent of the revised data point of GNP delivered by the statistical agencies, the appropriate setup is to additionally incorporate money as information variable into the updating scheme.

Implementation into the Toolkit and Calibration. Adding the forecasting equations (7.4) as well as $z_t = \xi_t^{(1)} + \xi_t^{(2)}$ to the log-linearized FONCs as given by equation (3.5) up to (3.9) and using the Euler equation (7.5) is now sufficient to solve for the recursive law of motion. Note that since the forecasting scheme is recursive, the two components of the Kalman state vector become members of the Toolkit state vector.

For calibration of parameters I stick to table 3.1 regarding the "traditional" parameters. The parameters $\sigma_1, \sigma_2, \rho_1$ and ρ_2 need additional treatment. Kydland and Prescott (1982) chose σ_1 equal to 0.9%, σ_2 equal to 0.18%, ρ_1 close to but smaller than one, and ρ_2 equal to zero. Van Nieuwerburgh and Veldtkamp (2003) chose σ_1 equal to 0.7% , σ_2 as large as 2.0%, ρ_1 equal to 0.95 and ρ_2 equal to zero. I chose σ_1 equal to 0.7% and ρ_1 equal to 0.95. For the parameters of the temporary component I vary σ_2 in the interval 0.18% up to 2.0% and set ρ_2 equal to zero.

Results in the RBC model with confusion. Important results can be read out of figure 7.1. Following a shock ϵ_t in panel *(a)*, the path of $\hat{\xi}_t^{(1)}$ shows the impact of the Kalman filter. TFP jumps up initially and beliefs converge slowly to the decaying path of the persistent TFP component. This triggers the overshooting of output when compared to perfect information. The pattern suggests that persistence in output growth does not improve due to the confusion assumption. Both investment and consumption jump up initially which should be expected if the effect of confusion does not dominate the wealth and substitution effects. Comparing the adjustment of output with the one of consumption shows that consumption is no leading indicator for output. This impression is confirmed through correlations between the two variables; contemporaneously they correlate with about 0.8, whereas correlation for leading consumption is close to zero and for lagging consumption is around 0.6. The shock μ_t in panel *(b)* produces a picture reminding of figure 6.2. Output jumps up to fall drastically below steady state in the next period. The same holds true for labor and investment (not shown) whereas consumption here in contrast to the BP model moves contemporaneously. These patterns are robust to the choice of σ_2. I conclude that confusion and its resolution imply initial co-movement of investment and consumption of the same direction but do not establish a leading property of consumption and persistence in output growth.

This last section shows that a different information structure, i.e. confusion about the type of TFP innovation, cannot reestablish news shocks in the standard model. Taking results in this chapter together points towards the minor role of the information structure and, therefore, implicitly assigns an important role to the real structure of the model featuring news shocks.
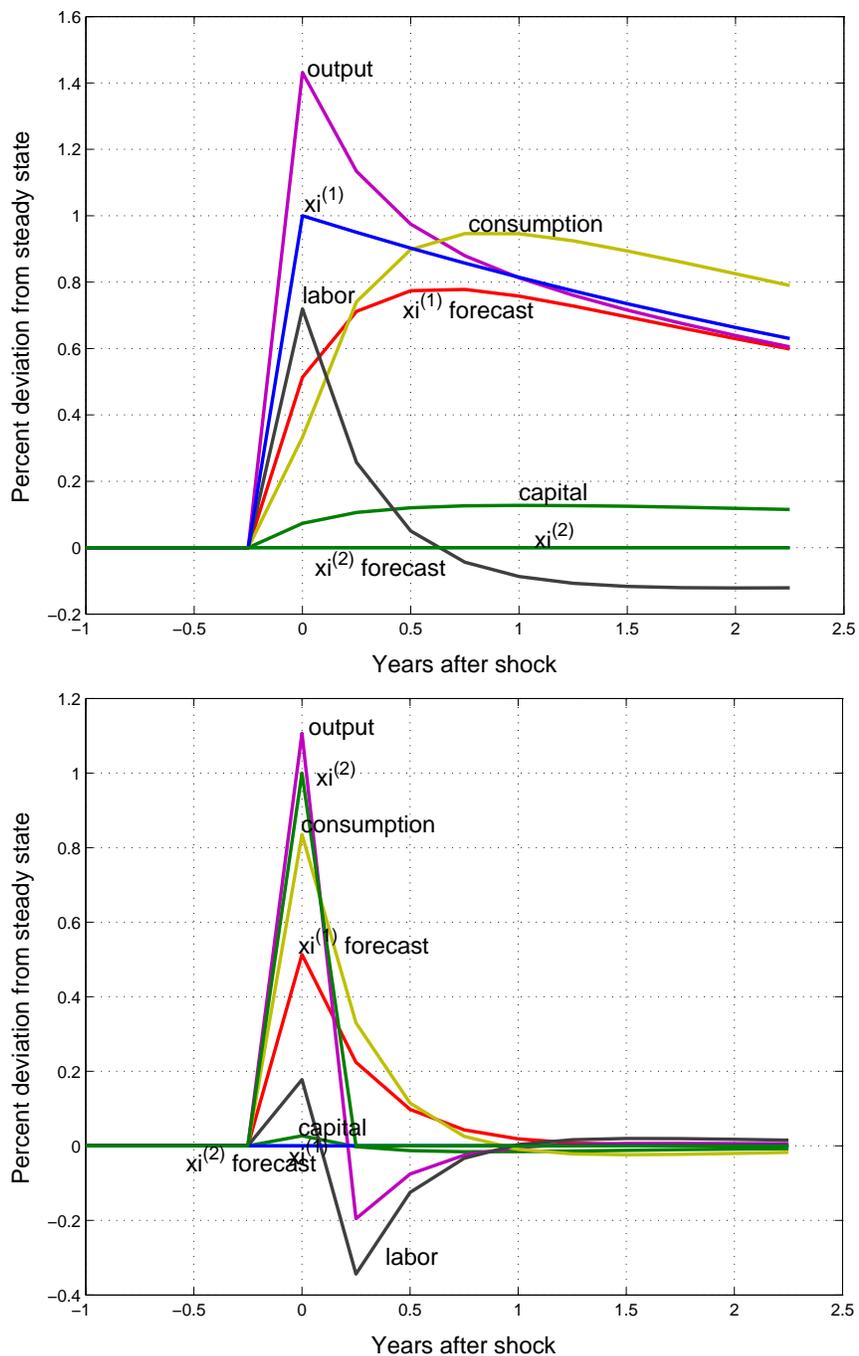
Figure 7.1: IRFs in the standard RBC model with confusion.

Panel *(a)* shows impulse response functions after a shock ϵ_t. Panel *(b)* plots the economy's response to a shock μ_t. In both panels, investment qualitatively follows the path of output but is omitted here. The underlying standard deviation of the transitory component of z_t takes a value $\sigma_2 = 0.75\%$.

69

Chapter 8

Summary of results and discussion

In section 8.1, I review the line of arguments pursued on the previous pages, the results that have been established and the conclusions derived. I discuss additional aspects left aside up to now, and indicate limitations of the analysis in section 8.2.

8.1   Review of arguments and results

The empirical literature that studys the major forces of business cycle fluctuations suggests the relevance of news shocks at the short horizon. Whereas Cochrane (1994) finds little evidence for the relevance of traditional candidates of shocks and sounds the depth for a mechanism to generate consumption shocks, Uhlig (2003a) indicates a role for economic adjustments that follow wrong anticipations about future productivity to explain short-run variation in the data.

Even though news shocks seem to matter empirically it proves difficult to formalize the notion of news shocks in theoretical models. In the RBC literature, modelling efforts that imply an extension of the information set of agents beyond the *historic* path of economic variables are rare. Two articles that explicitly formalize news shocks are HLP (1997) and BP (2000). In a standard RBC model, HLP (1997) study the impact of news on the leading property of consumption with respect to output. BP (2000) develop a three-sector model that, in principle, produces expectation-led business cycles. However, the analysis in both articles produces counterintuitive and, along some dimensions, counterfactual predictions. This motivates the search for a model structure that makes news shocks work.

To this end, I review a standard RBC model with news along the lines of HLP (1997) and report the failure of the model along three dimensions that appear predominant, namely, the counterintuitive initial adjustments of con-

sumption and investment following a news shock, the adverse consequences of news with respect to the persistence of output growth, and the unfavorable co-movement of output and consumption induced by a-priori information. These failures are on top of the shortcomings of this class of models that are already well-known in the literature. Among others, Cochrane (1994) identifies the unit elasticity of contemporaneously substituting consumption and investment as one important reason for the shortcoming of standard models.

As a second step, I review the three-sector economy of BP (2000) and analyze the model along the three dimensions identified relevant. The three-sector economy is interesting because it features a short-term substitutability of consumption and investment close to zero. As it turns out, however, the structure of the BP model cures the counterintuitive initial adjustments of investment and consumption but fails on restoring results along the other two dimensions, i.e. the persistence of output growth and the leading indicator property of consumption with respect to output.

At this stage, two possible roads lend themselves to proceed. One is a comprehensive investigation of the real structure. The other one is analyzing the role of the information structure. I chose the latter and investigate the reasonability of the assumptions determining news shocks in the analysis of BP (2000) and HLP (1997). Overall, results let the informational assumptions appear reasonable, even though there is some indication that the high degree of stylization in BP (2000) matters. I explore the robustness of results derived for the BP and the HLP model by studying a modified version of each model. Variations are restricted to the informational structure and strongly suggest that the real structure of the models is the driving force of results. Even though a low short-run substitutability is, to some extent, important, it is not sufficient for reconciling news shocks along all three dimensions.

In this thesis, I have not been able to identify a model structure that makes news shocks work. However, I have established a number of results that possibly are important for guiding future research on this topic.

8.2   Discussing the analysis

There are aspect, I left aside on the previous pages for one or the other reason. Most fruitful appears the extension of the analysis to the real structure of the models featuring news shocks. Initially, I have been passing by this junction with a preference for assessing the informational structure. Now, with the robustness analysis regarding the informational structure in hand, this road gains appeal. Results in Cogley and Nason (1995) and in Boldrin et al. (2001) suggest that the lack of persistence in output growth can be overcome by introducing some frictions to the adjustment of labor. There

are other articles levelling grounds for respective assumptions, e.g. Phelan and Trejos (2000) document a number of factors impeding the intersectoral movements of labor and Ramey and Shapiro (2000) show potentially large costs if capital is shifted across sectors. Finding a setup that produces a reasonable response pattern in investment *and* consumption appears more difficult. Here, too, labor appears to be important since it is the only resource that can be extended to boost the economy in the case of pure news.

Certainly, it is of interest to compare news shocks to more traditional shocks, e.g. preferences shocks, capital dividend tax shocks, labor hoarding, variable capital utilization, or government spending shocks. But I think this exercise becomes much more high-yielded once an appropriate news shock model is found. In the light of results in Uhlig (2003a) and according to basic intuition, it appears to be the case that news shocks are relevant merely on the short to medium time horizon. This, however, would make it interesting to search for an appropriate companion among the traditional shocks accompanying news shocks and capable of explaining medium to long run variation in the data.

Furthermore, I have constantly ignored the impact of news on the co-movement between output and capital, aggregate labor, interest rates, real wages, TFP, and on the correlation between leisure and consumption. It is not clear if there are only favorable effects of news like, for example, reducing the correlation of output and TFP due to the additional stochastic element. Again, I consider this a second step on the way towards a good model of news shocks.

In section 4.3, I point to the counterintuitive fact that the signal in the BP model does not improve over time. Even though, in the light of results established in chapter 7, this is likely to influence the properties of the model only at the margin, it would be a first step towards a structural explanation of what kind of news emerge and why they do. For example, one such explanation is provided in Kydland and Prescott (1982). Note, however, that experimentation in the standard RBC model with an information structure that explains the arrival of news due to agents constantly resolving confusion about two qualitatively different shocks to TFP, has not been successful yet (see section 7.3). Nevertheless, there may be grounds for extending confusion further − according to the real time data problem contemporaneous GNP is unknown in the real world and respective figures emerge with considerable delay and are subject to revisions. This is documented in Coenen, Levin, and Wieland (2001) and suggests to extend the analysis in the standard RBC model to an informational setup where agents cannot observe contemporaneous output and, instead, base their decisions on beliefs.

One obvious limitation of the analysis in this thesis is the calibration of the models. Some of the parameter choices are, despite of the fact that they are in line with corresponding values reported in the literature, rather ad

hoc. Furthermore, the informal grid search is appealing only with respect to its convenience. It is simple to implement and may be justified due to the focus of the analysis. Using objective methods certainly would increase confidence into results and would provide additional information in form of parameter uncertainty. Nevertheless, I am confident that results derived here are fairly robust with respect to different methods. To this end, I am convinced by the main conclusion of this analysis: the real structure, as opposed to the information structure, is the major determinant of the consequences of news shocks.

Chapter 9

Conclusion

The coincidence of empirical observations and theoretical failures motivates the search for a model structure that makes news shocks work. Empirical literature documents a lack of consensus explanation of business cycle fluctuations − traditional candidates of shocks do not appear to match the evidence satisfactorily. News shocks are assigned a potential role to overcome this gap. When introduced into theoretical models, however, news shocks produce predictions not in line either with economic intuition or with stylized facts of business cycles.

In the standard RBC model, news shocks fail along three dimensions; the counterintuitive IRFs of consumption and investment following a news shock, the reduction of internal propagation, and the unfavorable comovement of output and consumption due to news. One important reason is the high substitutability of consumption and investment. However, a three-sector economy, similar to the model in BP (2000), with a low substitutability of consumption and investment still fails along two of the three dimensions. Modifications of both models point to the minor importance of the exact informational assumptions determining news shocks. Moreover, robustness of the failure of the models applied against variations in these assumptions assigns an outstanding role to the real structure in determining success or failure of model-economies featuring news shocks.

This thesis clarifies that there is no straightforward way of formalizing the idea of news shocks. Nevertheless, it provides a discussion of elements and their combination that appear relevant for guiding future research. Appropriate frictions in the factor markets in combination with a multiple sector model appear promising. Furthermore, a suggestion originally proposed in Cochrane (1994) and refreshed here is to construct models that disseminate news about candidates of shocks inducing wealth effects but no intertemporal substitution.

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Table 9.1: NOTATION KEY

Beaudry&Portier	Weber	
Non-durable good sector		
X_t	N_t	non-durable good
$\theta_{x,t}$	η_t	TFP
$l_{x,t}$	$L_{m,t}$	hours worked
$\tilde{l}_x$	F_m	sector-specific fixed factor
α_x	α	income share of labor
$\bar{l}_x$	$\bar{L}_m$	total time available for work in
		the production of non-durables
Durable good sector		
I_t	D_t	durable good
$\theta_{k,t}$	Δ_t	TFP
$l_{k,t}$	$L_{d,t}$	hours worked
$\tilde{l}_k$	F_d	sector-specific fixed factor
α_k	γ	income share of labor
$\bar{l}_k$	$\bar{L}_d$	total amount of time available for
		work in the production of durables
Final good sector		
C_t	C_t	consumption per capita
K_t	K_t	capital per capita
ν	ν	parameter governing the elasticity
		of substitution between N_t and K_t
Utility and the budget constraint		
ν_0	A	fixed scaling constant
p_t	p_t	price of the durable good
$\omega_{x,t}$	$\omega_{n,t}$	wage rate in non-durable good sector
$\omega_{k,t}$	$\omega_{d,t}$	wage rate in durable good sector
r_t	r_t	rental rate of capital
$\Pi_{x,t}$	$\Phi_{m,t}$	compensation of the fixed factor
		in the non-durable good sector
$\Pi_{k,t}$	$\Phi_{d,t}$	compensation of the fixed factor
		in the durable good sector

Notes: The dating convention is changed according to the notion that variables dated t are observed in t. This concerns the law of motion for K_t, which in BP (2000) is given by $K_{t+1} = I_t + (1 - \delta)K_t$. Subsequently, in my analysis the appearance of K changes in the budget constraint and in the final good production function.

Appendix A

Mathematics of the three-sector model

A.1 Steady state equations

Dropping time subscripts and substituting out the Lagrangian λ delivers the following system of equations.

$$C = \frac{a\alpha\bar{N}^{\nu}}{\bar{L}_n}\left[a\bar{N}^{\nu} + (1-a)\bar{K}^{\nu}\right]^{\frac{1-\nu}{\nu}} \tag{A.1}$$

$$\bar{\mu} = \frac{\bar{L}_d}{\gamma\bar{D}}\; . \tag{A.2}$$

$$\bar{\mu} = \beta\left[\frac{\bar{H}}{\bar{C}} + \bar{\mu}(1-\delta)\right] \tag{A.3}$$

$$\bar{C} = \left[a\bar{N}^{\nu} + (1-a)\bar{K}^{\nu}\right]^{\frac{1}{\nu}} \tag{A.4}$$

$$\bar{K} = \frac{\bar{D}}{\delta} \tag{A.5}$$

$$\bar{N} = \eta_0\bar{L}_n^{\alpha} \tag{A.6}$$

$$\bar{D} = \Delta_0\bar{L}_d^{\gamma} \tag{A.7}$$

$$\bar{H} = (1-a)\bar{K}^{(\nu-1)}\left[a\bar{N}^{\nu} + (1-a)\bar{K}^{\nu}\right]^{\frac{1-\nu}{\nu}} \tag{A.8}$$

Steady state equations for the determination of the investment price and for the return to investment are $\bar{p} = \bar{\mu}\bar{C}$ and $\bar{r} = \frac{\bar{H}}{\bar{p}} - \delta$.

Solution by reducing the system to one equation in L_d: Assuming that the household spends one third of its total time working, one gets $\bar{L}_m + \bar{L}_d = \frac{2}{3}$. Using equation (A.2) and (A.3) and substituting out $\bar{D}$ delivers

$$\bar{L}_d^{1-\gamma} \frac{(1 - \beta(1 - \delta))}{\beta\gamma\Delta_0} = \frac{\bar{H}}{\bar{C}} \tag{A.9}$$

Using equation (A.1) and (A.8) one can compute an expression for $\frac{\bar{H}}{\bar{C}}$.

$$\frac{\bar{H}}{\bar{C}} = \frac{1-a}{a\alpha\eta_0^\nu} \left(\frac{\Delta_0}{\delta}\right)^{\nu-1} \bar{L}_d^{\gamma\nu-\gamma} \left(\tfrac{2}{3} - \bar{L}_d\right)^{1-\nu\alpha}$$

Substituting out $\frac{\bar{H}}{\bar{C}}$ in (A.9) and summarizing terms yields

$$0 = \frac{a}{1-a} \left(\frac{\eta_0}{\Delta_0}\right)^\nu \frac{\alpha\delta^{\nu-1}(1 - \beta(1 - \delta))}{\beta\gamma} \bar{L}_d^{1-\nu\gamma} - \left(\tfrac{2}{3} - \bar{L}_d\right)^{1-\nu\alpha} \ . \tag{A.10}$$

A.2 Linearized equations with and without news shocks

I set $\bar{a}_k = \frac{(1-a)\bar{K}^\nu}{a\bar{N}^\nu+(1-a)\bar{K}^\nu}$ and $\bar{a}_n = \frac{a\bar{N}^\nu}{a\bar{N}^\nu+(1-a)\bar{K}^\nu}$. This delivers the following log-linearized equations.

$$0 = \nu\hat{N}_t - \hat{L}_{m,t} + (1-\nu)\left[\bar{a}_n\hat{N}_t + \bar{a}_k\hat{K}_{t-1}\right] - \hat{C}_t \tag{A.11}$$

$$0 = \hat{L}_{d,t} - \hat{D}_t - \hat{\mu}_t \tag{A.12}$$

$$0 = \left[\bar{a}_n\hat{N}_t + \bar{a}_k\hat{K}_{t-1}\right] - \hat{C}_t \tag{A.13}$$

$$0 = \bar{D}\hat{D}_t + (1-\delta)\bar{K}\hat{K}_{t-1} - \bar{K}\hat{K}_t \tag{A.14}$$

$$0 = \log\tilde{\eta}_t + \alpha\hat{L}_{m,t} - \hat{N}_t \tag{A.15}$$

$$0 = \gamma\hat{L}_{d,t} - \hat{D}_t \tag{A.16}$$

$$0 = (\nu-1)\hat{K}_{t-1} + (1-\nu)\left[\bar{a}_n\hat{N}_t + \bar{a}_k\hat{K}_{t-1}\right] - \hat{H}_t \tag{A.17}$$

$$0 = \bar{C}\hat{C}_t + \bar{p}\bar{D}\hat{p}_t + \bar{p}\bar{D}\hat{D}_t - \bar{Y}\hat{Y}_t \tag{A.18}$$

$$0 = \bar{L}_m \hat{L}_{m,t} + \bar{L}_d \hat{L}_{d,t} - \bar{L} \hat{L}_t \qquad (A.19)$$

$$0 = \hat{\mu}_t + \hat{c}_t - \hat{p}_t \qquad (A.20)$$

$$0 = \beta E\left[\frac{\bar{H}}{\bar{C}}\left(\hat{H}_{t+1} - \hat{C}_{t+1}\right) + (1-\delta)\bar{\mu}\hat{\mu}_{t+1}\right] - \bar{\mu}\hat{\mu}_t \qquad (A.21)$$

The return to investment in log-linearized form is

$$0 = \frac{\bar{H}}{\bar{p}}\hat{H}_t + (1-\delta)\hat{p}_t - (1+\bar{r})\hat{p}_{t-1} - \bar{r}\hat{r}_t \ . \qquad (A.22)$$

Equations that replace the Euler equation in case of news shocks.
The case for $n = 2$:

$$
\begin{aligned}
0 = E[&\frac{\beta\bar{H}(\nu-1)}{\bar{C}}\hat{K}_t + \frac{\beta\bar{H}(1-\nu\alpha)}{\bar{C}}\hat{L}_{m,t+1} - \frac{\beta\bar{H}\nu\lambda}{\bar{C}}\left(1 + (1-\delta)\beta\lambda\right)\log\tilde{\eta}_t \\
&- \bar{\mu}\hat{\mu}_t - \frac{\beta\bar{H}\nu}{\bar{C}}\left\{\frac{\theta^H(1-\epsilon^L) + \theta^L(\epsilon^H-1)}{\epsilon^H - \epsilon^L}\right\}S_{t-1}^{(t+1)} \\
&+ \frac{(1-\delta)\beta^2\bar{H}(\nu-1)}{\bar{C}}\hat{K}_{t+1} + \frac{(1-\delta)\beta^2\bar{H}(1-\nu\alpha)}{\bar{C}}\hat{L}_{m,t+2} \\
&- \frac{(1-\delta)\beta\bar{H}\nu}{\bar{C}}\left\{\frac{\theta^H(1-\epsilon^L) + \theta^L(\epsilon^H-1)}{\epsilon^H - \epsilon^L}\right\}S_t^{(t+2)} + \beta(1-\delta)^2\bar{\mu}\hat{\mu}_{t+2}] \ .
\end{aligned}
$$
$$(A.23)$$

The case of $n = 3$:

$$
\begin{aligned}
0 = E[&\frac{\beta\bar{H}(\nu-1)}{\bar{C}}\hat{K}_t + \frac{\beta\bar{H}(1-\nu\alpha)}{\bar{C}}\hat{L}_{m,t+1} \\
&- \frac{\beta\bar{H}\nu\lambda}{\bar{C}}\left(1 + (1-\delta)\beta\lambda + (1-\delta)^2\beta^2\lambda^2\right)\log\tilde{\eta}_t \\
&- \bar{\mu}\hat{\mu}_t - \frac{\beta\bar{H}\nu}{\bar{C}}\left\{\frac{\theta^H(1-\epsilon^L) + \theta^L(\epsilon^H-1)}{\epsilon^H - \epsilon^L}\right\}S_{t-2}^{(t+1)} \\
&+ \frac{(1-\delta)\beta^2\bar{H}(\nu-1)}{\bar{C}}\hat{K}_{t+1} + \frac{(1-\delta)\beta^2\bar{H}(1-\nu\alpha)}{\bar{C}}\hat{L}_{m,t+2} \\
&- \frac{(1-\delta)\beta^2\bar{H}\nu}{\bar{C}}\left\{\frac{\theta^H(1-\epsilon^L) + \theta^L(\epsilon^H-1)}{\epsilon^H - \epsilon^L}\right\}S_{t-1}^{(t+2)} \\
&+ \frac{(1-\delta)^2\beta^3\bar{H}(\nu-1)}{\bar{C}}\hat{K}_{t+2} + \frac{(1-\delta)^2\beta^3\bar{H}(1-\nu\alpha)}{\bar{C}}\hat{L}_{m,t+3} \\
- \frac{(1-\delta)^2\beta^3\bar{H}\nu}{\bar{C}}&\left\{\frac{\theta^H(1-\epsilon^L) + \theta^L(\epsilon^H-1)}{\epsilon^H - \epsilon^L}\right\}S_t^{(t+3)} + \beta^3(1-\delta)^3\bar{\mu}\hat{\mu}_{t+3}] \ .
\end{aligned}
$$
$$(A.24)$$

Appendix B

Toolkit codes

B.1 A standard real-business-cycle model with news shocks

The construction of the signal takes place in the function hlp.m. The function replaces the command randn(.) in the Toolkit file simul.m, see B.2 for corresponding details for the implementation of the model of Beaudry and Portier (2000). The function looks as follows.

```
function [mat] = hlp(n, sigma_eps, sigma_nu, SIM_LENGTH, k_exog);
%function [mat] = hlp(n, sigma_eps, sigma_nu, SIM_LENGTH, k_exog);

simul = SIM_LENGTH;
eps = sigma_eps*randn(simul+n, 1);                  % TFP innovation
nu  =  sigma_nu*randn(simul+n, 1);                  % noise
sig = eps + nu;                                     % signal
sig = kron(ones(1,k_exog-1) , sig);
mat = horzcat(eps(1:simul,:) , sig(n+1:simul+n,:) ); % shift both in relation
mat = mat';
```

The Toolkit code for the model as such is printed below. Note that I have renamed the corrected simul.m file as simul_HLP.m. This file is then called by do_it_HLP.m instead of do_it.m. For the equations determining the model see the main text.

```
% Cooley and Prescott's RBC model (1995) with a-priori information about future TFP.
% ...
% Thomas F. Cooley and Edward C. Prescott (1995). "Economic Growth
% and Business Cycles." In Frontiers of Business Cycle
% Research, edited by Thomas F. Cooley, Princeton, Princeton
% University Press.
% ...
% The signalling mechanism is out of Hairault, Langot and Portier's RBC model
% as described in:
% "Time to implement and aggregate fluctuation", Journal of Economic Dynamics
% and Control, 22, (1997), 109-121.
```

```
signal = 1 ;                    % If signal = 1, a signal is included.
                                % If signal = 0, no signal is included.

n = 1;      % Periods the signal occurs in advance:
            % needed in hlp.m, the function constructing the signal.

%===============================================
%========        Setting parameters      =========
%===============================================
L_bar     = .31;              % Steady state employment, a third of total time
theta     = .377;             % Capital share
delta     = .0267;            % Depreciation rate for capital
R_bar     = 1.0107;           % One percent real interest per quarter
rho       = 1;                % Constant of relative risk aversion
lambda    = 1;                % Autocorrelation of technology shock
gamma     = 1;                % growth factor of technological progress
alfa      = 0.6692;           % relative weight of leisure and consumption

%===============================================
%======== Calculating the steady state  =========
%===============================================
 betta = 1.0/R_bar;
 YK_bar= (R_bar + delta - 1)/theta;
 K_bar = (YK_bar)^(1.0/(theta-1)) * L_bar;
 D_bar = delta * K_bar;
 Y_bar = YK_bar * K_bar;
 C_bar = Y_bar - delta*K_bar;

%===============================================
%======   Specifying signal extraction   =========
%===============================================
sigma_eps = .75;              % Standard deviation of technology shock in %
sigma_nu  = .75;              % Standard deviation of noise in %
chhi      = sigma_eps^2/(sigma_eps^2+sigma_nu^2);
                              % percentage of epsilon anticipated to innovate technology

% Shortcut
 Phi = theta*Y_bar/(K_bar*R_bar);
 alfa1 = (1-theta)*(1-alfa) /alfa*Y_bar*C_bar^(-rho);
 alfa2 = L_bar/(1-L_bar)*(1/alfa1+1);

%=======================================
%======= Declaring the matrices: =======
%=======================================

VARNAMES = ['capital        ',  %1
            'output         ',  %2
            'consumption    ',  %3
            'labor          ',  %4
            'investment     ',  %5
            'interest       ',  %6
            'technology     ',  %7
            'S_t^{(t+1)}    ']; %8

AA = [ 0
       -K_bar*gamma
```

```
                0
                0
                0];


BB = [ 0
       (1-delta)*K_bar
       theta
       0
       - theta * YK_bar];


       % output   consumption    labor      investment     R
CC = [ -Y_bar,      C_bar,        0,          D_bar,       0         %Equ.1)
           0,          0,         0,          D_bar,       0         %Equ.2)
          -1,          0,     (1-theta),          0,       0         %Equ.3)
           1,       -rho,       -alfa2,           0,       0         %Equ.4)
   theta*YK_bar,       0,         0,              0, - R_bar];       %Equ.5)


DD = [ zeros(2,2)
       1 ,   0
       zeros(2,2)];


NN = [ lambda, 0
         0,    0 ];


%========================================
%====== The economy with a signal ========
%========================================

if signal ==1;

    Sigma = diag([  1,   1 ]);

    FF = [ 0 ];

    GG = [ Phi*theta - theta - Phi ];

    HH = [ 0 ];

    JJ = [ 0, 0, -(Phi*theta - theta - Phi + 1 - alfa2) , 0, 0 ];

    KK = [ 0,  rho, 0, 0, 0 ];

    LL = [ 0, 0 ];

    MM = [ (Phi-1)*lambda, (Phi-1)*chhi ];



%========================================
%====== The economy without any signal ===
%========================================

elseif signal == 0;

    Sigma = diag([ sigma_eps^2, sigma_eps^2 + sigma_nu^2 ]);

    FF = [ 0 ];
```

```
        GG = [ 0 ];

        HH = [ 0 ];

        JJ = [ 0, -rho, 0, 0, 1 ];

        KK = [ 0,  rho, 0, 0, 0 ];

        LL = [ 0, 0 ];

        MM = [ 0, 0 ];


    else disp('Specify the variable "signal" either as 0 or as 1! TRY
    AGAIN.'); break; end;




    %================================
    %===== Setting the options: ======
    %================================

    [l_equ,m_states] = size(AA); [l_equ,n_endog ] = size(CC);
    [l_equ,k_exog  ] = size(DD);


    PERIOD     = 4;                 % number of periods per year
    GNP_INDEX  = 2;                 % Index of output among the variables
    IMP_SELECT = [1:8];             % indices of the variables to be plotted
    DO_SIMUL   = 1;                 % Calculates simulations

     SIM_LENGTH = 80;
     SIM_MODE   = 2;
     SIM_N_SERIES = 70;
     SIM_DISCARD = 30;
     HORIZON = 20;

    DO_MOMENTS = 1;                 % moments based on frequency-domain
    HP_SELECT  = 1:(m_states+n_endog+k_exog);
                                    % Selecting the variables for the HP Filter calcs.
    DO_COLOR_PRINT = 0;
    DISPLAY_IMMEDIATELY = 1;
    DO_PLOTS = 1;
    DO_IMPRESP = 1;
    DO_HP_GRAPH = 0;
    SIM_GRAPH = 1;

    IMP_SUBPLOT=1;

    % Starting the calculations:

     do_it_HLP;



      disp('==================================================================================');
      disp(' NOTE: since you have used do_it_HLP.m which calls simul_BP.m instead of simul_HLP.m,%');
      disp('       the realization of the shocks is intertwined with the one of the signal.     %');
      disp('       See simul_HLP.m for details.                                                  %');
      disp('==================================================================================');
```

B.2 A three-sector model with news shocks

In simul.m I replace every occurrence of randn(SIM_LENGTH, k_exog) by bin(SIM_LENGTH, k_exog, epsH, epsL, p, q, n). Talking in line numbers of the original simul.m, randn(.) occurs twice, once in line 151 and then again in line 172. I do not use the Matlab function binom.m since it is not available for the student version of Matlab. The output of bin(.) is a matrix of size(k_exog, SIM_LENGTH) having in rows $\epsilon_t, S_t^{(t+n)}, S_t^{(t+n)}, \ldots, S_t^{(t+n)}$, i.e. $S_t^{(t+n)}$ is just replicated (k_exog-1) times. To call the new simul_BP.m - file change the respective entry in do_it.m.

```
function [ out ] = bin( SIM_LENGTH, k_exog, epsH, epsL, p, q, n )
% function [ out ] = bin( SIM_LENGTH, k_exog, epsH, epsL, p, q, n )
% bin.m sets up a random vector epsilon following a bernoulli distribution
% with parameters (p,sim). Since matlab students version does not allow binomrnd(.),
% computations are based on the function rand(.). In a second step bin
% creates a signal indicating epsilon rightly with probability q.
%
% The  output of this function is a matrix of size(k_exog, SIM_LENGTH) having
% in rows
% epsilon(t)
% signal_t^(t+n)      (the signal arising in t, signalling the state in t+n)
% signal_t^(t+n)
% ...


simul = SIM_LENGTH + n;            % length of epsilon vector
eps = zeros(simul,1);              % epsilon
s   = zeros(simul, k_exog-1);      % signal matrix


% Generate a random vector drawn form a uniform[0,1] distribution
a = 0; b = 1; uni = a + (b-a) * rand(simul,1);


% Generate epsilon
for i = 1:max(size(eps));
    if uni(i,:) > p        % 1-p realizations
        eps(i,:) = epsH;
    else
        eps(i,:) = epsL;
    end
end


% Generate a NEW random vector drawn form a uniform[0,1] distribution
a = 0; b = 1; uni = a + (b-a) * rand(simul,1);

% Generate the signal: one with prob. q
for i = 1:length(eps);
        if uni(i,:) < q
            s(i,:) = 1;   %right signals have value one
        else
            s(i,:) = 0;
        end
end
```

```
% Attach the appropriate value to the signal
for i = 1:length(eps);
        if s(i,:) == 1;
            s(i,:) = eps(i,:);
        elseif s(i,:) == 0 & eps(i,:) == epsH;
               s(i,:) = epsL;
        elseif s(i,:) == 0 & eps(i,:) == epsL;
               s(i,:) = epsH;
        end
end


% shift epsilon and the signal according to n
out = horzcat(eps(1:end-n,:), s(n+1:end,:))';
```

The actual Matlab code of the model is given below. The computation of the steady state by solving a system of non-linear equations needs the Matlab function fsolve.m. It is not available for the student version of Matlab. However, see the appendix A.1 and there equation A.10. This equation can be solved using the Matlab function fzero.m that is available for students. However, differences are visible when comparing the solution of fzero.m with folve.m.

```
% Paul Beaudry and Franck Portier (2000).
% "An exploration into Pigou's Theory of Cycles", working paper.
% ...
% A three-sector model featuring news shocks. In period t a TFP
% shock is signalled that arises n periods later with a probability of q.


%=============================
% Setting Parameters         %
%=============================

n = 2;                      % n be of [0,1,2,3].  number of periods the signal
                            % arises before the realization of tfp it signals.
alpha     = .6;             % labor share intermediate goods production
beta      = .98;            % discount rate of household
gamma     = .97;            % labor share in durable goods production
delta     = .05;            % depreciation rate
A         = 1;              % parameter scaling the utility of leisure vs. consumption
lambda    = 0.95;           % autocorrelation of the tfp in the intermediate goods sector
Del       = 1;              % steady state level of TFP in the durable good sector
eta       = 10*Del;         % steady state level of TFP in the non-durable good sector
a         = 0.5;            % relative weight of capital and non-durable good
nu        = -2.95;          % parameter governing the substitutability of N and K
sigma_eps = 1.4;            % standard dev. of the total factor productivity shock in percent


%=============================
% Specifying the signal eps %
%=============================

p = 0.535;                           % probability of a "below g" epsilon state
q = 0.875;                           % probability of a right signal

epsH =   sqrt(p/(1-p)) * sigma_eps;  % value epsilon takes in the "above g" state
epsL = - sqrt((1-p)/p) * sigma_eps;  % value epsilon takes in the "below g" state
```

```
ThetaH = 1/(q*(1-p)^2 + (1-q)*p^2) * (q*(1-p)^2*epsH + (1-q)*p^2*epsL); % E[eps(t+n)|S_t^(t+n) = epsH]
ThetaL = 1/((1-q)*(1-p)^2 + q*p^2) * ((1-q)*(1-p)^2*epsH + q*p^2*epsL); % E[eps(t+n)|S_t^(t+n) = epsL]

sg    = ( ThetaH * (1-epsL) + ThetaL * (epsH-1) ) /(epsH-epsL) ;        %coefficient of the signal
const = ( ThetaL*epsH - ThetaH*epsL ) / ( epsH - epsL );
        % To get rid of the constant term that comes out of the signal specification
        % this expression (i.e. 'sg') assumes that the constant equals the unconditional
        % mean of the distribution of eps. This is a reasonable approximation for those
        % values of p and q that drive (ThetaL*epsH - ThetaH*epsL)/(epsH - epsL) close to zero.
sigma_s = sqrt(q*epsH^2 + (1-q)*epsL^2);


%============================
% Steady State computation  %
%============================
% For using fsolve.m use the lines below.
% The system of nonlinear equations
% is defined in the function bp.m.
%
% x0 = [C_bar, Ln_bar, Ld_bar, K_bar, Mu_bar, N_bar, D_bar, H_bar]';

% initial guess:
x0 = [2.6183
    0.5127
    0.1003
    2.1483
    0.9622
    2.6790
    0.1074
    0.1774];

x = fsolve(@bp, x0, optimset('fsolve'), alpha, beta, gamma, ...
          delta, nu, a, Del, eta);
% x = [5.6088 0.3498 0.2873 5.9646 0.9931 5.3244 0.2982 0.3922]';
% solution vector for the above parameterization.

 C_bar   = x(1,:);
 Ln_bar  = x(2,:);
 Ld_bar  = x(3,:);
 K_bar   = x(4,:);
 Mu_bar  = x(5,:);
 N_bar   = x(6,:);
 D_bar   = x(7,:);
 H_bar   = x(8,:);

P_bar = Mu_bar*C_bar;                                      % price of capital
R_bar = H_bar/P_bar - delta;                               % return to capital
Y_bar = C_bar + P_bar*D_bar;                               % output
La_bar = 2/3;                                              % aggregated labor
consu_share = C_bar/Y_bar ;                                % consumption share
labor_share = ( P_bar*gamma*D_bar + alpha*N_bar ) / Y_bar; % labor share of output


%Shorthands
 an_bar = a*N_bar^nu / ( a*N_bar^nu + (1-a)*K_bar^nu );
 ak_bar = (1-a)*K_bar^nu / ( a*N_bar^nu + (1-a)*K_bar^nu );
 betarc = beta*H_bar/C_bar;

%============================
% Declaring the matrices    %
%============================
```

```
VARNAMES = ['capital              ', %1
            'Ln(1)                ', %2
            'mu(1)                ', %3
            'capital(1)           ', %4
            'Ln(2)                ', %5
            'mu(2)                ', %6
            'output               ', %7
            'consumption          ', %8
            'durable              ', %9
            'nondurable           ', %10
            'Ld                   ', %11
            'Ln                   ', %12
            'H(elp)               ', %13
            'price of D           ', %14
            'aggr. labor          ', %15
            'mu                   ', %16
            'tfp nondurable       ', %18
            'signal^{(t+n)}_t     ', %19
            'signal^{(t+n-1)}_{(t-1)}', %20
            'signal^{(t+n-2)}_{(t-2)}']; %21

AA = [ 0,    0,   0,   0,   0,   0
       0,    0,   0,   0,   0,   0
       0,    0,   0,   0,   0,   0
    - K_bar, 0,   0,   0,   0,   0
       0,    0,   0,   0,   0,   0
       0,    0,   0,   0,   0,   0
       0,    0,   0,   0,   0,   0
       0,    0,   0,   0,   0,   0
       0,    0,   0,   0,   0,   0
       0,    0,   0,   0,   0,   0];


BB = [ (1-nu)*ak_bar,      0, 0, 0, 0, 0
                  0,       0, 0, 0, 0, 0
             ak_bar,       0, 0, 0, 0, 0
       (1-delta)*K_bar,    0, 0, 0, 0, 0
                  0,       0, 0, 0, 0, 0
                  0,       0, 0, 0, 0, 0
   (nu-1)+(1-nu)*ak_bar,   0, 0, 0, 0, 0
                  0,       0, 0, 0, 0, 0
                  0,       0, 0, 0, 0, 0
                  0,       0, 0, 0, 0, 0];

%Order:  output   consumption  D         N          Ld      Ln      r      p      aggr. L  mu
CC = [    0,          -1,       0,    nu+(1-nu)*an_bar, 0,    -1,     0,     0,      0,  0    % Equ. 1)
          0,           0,      -1,         0,           1,     0,     0,     0,      0, -1    % Equ. 2)
          0,          -1,       0,      an_bar,         0,     0,     0,     0,      0,  0    % Equ. 3)
          0,           0,     D_bar,       0,           0,     0,     0,     0,      0,  0    % Equ. 4)
          0,           0,       0,        -1,           0,   alpha,   0,     0,      0,  0    % Equ. 5)
          0,           0,      -1,         0,         gamma,   0,     0,     0,      0,  0    % Equ. 6)
          0,           0,       0,  (1-nu)*an_bar,      0,     0,    -1,     0,      0,  0    % Equ. 7)
       -Y_bar,      C_bar,  P_bar*D_bar,   0,           0,     0,     0,P_bar*D_bar, 0,  0    % Equ. 8)
          0,           0,       0,         0,         Ld_bar, Ln_bar, 0,     0,   -La_bar,0   % Equ. 9)
          0,           1,       0,         0,           0,     0,     0,    -1,      0,  1];  % Equ. 10)


DD = zeros(10,4); DD(5,1) = 1;


   GG = [betarc*(nu-1), betarc*(1-alpha*nu), 0,  0,  0,  0
```

90

```
          0, -1,  0,  0,  0,  0
          0,  0, -1,  0,  0,  0
          0,  0,  0, -1,  0,  0
          0,  0,  0,  0, -1,  0
          0,  0,  0,  0,  0, -1];

    HH = [ zeros(6,6)];

    JJ = [ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0
           0,  0,  0,  0,  0,  1,  0,  0,  0,  0
           0,  0,  0,  0,  0,  0,  0,  0,  0,  1
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0
           0,  0,  0,  0,  0,  0,  0,  0,  0,  0 ];

    KK = zeros(6,10);
    KK(1,10) = -Mu_bar;

    LL = zeros(6,4);

    NN = [lambda,  0,  0,  0
               0,  0,  0,  0
               0,  1,  0,  0
               0,  0,  1,  0];

    Sigma = diag([ sigma_eps^2 ,  sigma_s^2, .00000001, .00000001 ]);


if n==3;
      %===========================
      %       case for n = 3      %
      %===========================
  FF = [ beta*betarc*(1-delta)*(nu-1),  beta*betarc*(1-delta)*(1-nu*alpha),  0,...
             beta^2*betarc*(1-delta)^2*(nu-1),  beta^2*betarc*(1-delta)^2*(1-nu*alpha),...
               beta^3*(1-delta)^3*Mu_bar
        zeros(2,6)
        1, 0, 0, 0, 0, 0
        0, 1, 0, 0, 0, 0
        0, 0, 1, 0, 0, 0];

  MM = [ - betarc*nu*lambda*( 1 + beta*(1-delta)*lambda + beta^2*(1-delta)^2*lambda^2),...
                 - beta^2*(1-delta)^2*betarc*nu*sg, - beta*(1-delta)*betarc*nu*sg , - betarc*nu*sg
         zeros(5,4)];


  elseif n==2;
        %===========================
        %       case for n = 2      %
        %===========================
      FF = [ beta*betarc*(1-delta)*(nu-1),  beta*betarc*(1-delta)*(1-nu*alpha),  0,  0, 0, 0
               zeros(2,6)
             1, 0, 0, 0, 0, 0
             0, 1, 0, 0, 0, 0
             0, 0, 1, 0, 0, 0];

    MM = [ - betarc*nu*lambda*( 1 + beta*(1-delta)*lambda),...
               - beta*(1-delta)*betarc*nu*sg, - betarc*nu*sg, 0
           zeros(5,4)];
```

```
elseif n==1;
        %==========================
        %       case for n = 1      %
        %==========================
      FF = [  zeros(3,6)
            1, 0, 0, 0, 0, 0
            0, 1, 0, 0, 0, 0
            0, 0, 1, 0, 0, 0];

        MM = [ - betarc*nu*lambda,  - betarc*nu*sg, 0, 0
           zeros(5,4)];

elseif n==0;
        %==========================
        %       case for n = 0      %
        %==========================


    FF = [  zeros(3,6)
          1, 0, 0, 0, 0, 0
          0, 1, 0, 0, 0, 0
          0, 0, 1, 0, 0, 0];

    MM = [ - betarc*nu*lambda,  0, 0, 0
                          zeros(5,4)];

else disp(' n should be 0,1,2,3 !! Try again. '); break; end;


% Setting the options:

[l_equ,m_states] = size(AA); [l_equ,n_endog ] = size(CC);
[l_equ,k_exog  ] = size(DD);



PERIOD      = 2;               % number of periods per year
GNP_INDEX   = 7;               % Index of output among the variables
IMP_SELECT = [7:9,11:12, 15, 17];%  the indices of the variables to be plotted
DO_SHOCK_RESP = 1;             % = 1, if impulse responses to shocks shall be calculated.
SELECT_SHOCKS = [1:2];         %:k_exog, select the impulse responses shocks
DO_STATE_RESP = 1;             % = 1, if impulse responses to deviations of state variables
SELECT_STATES = [1] ;          % : m_states; select the states to which impulse responses
HORIZON = 12;

N_LEADS_LAGS = 6;
DO_SIMUL   = 1;                % Calculates simulations
SIM_MODE = 2;                  % ENSURE Computation of N Series.
SIM_LENGTH = 100;
SIM_DISCARD = 30;
SIM_N_SERIES = 70;


DO_MOMENTS = 1;                           % Calculates moments based on the frequency-domain
HP_SELECT  = 1:(m_states+n_endog+k_exog); % Selecting the variables for the HP Filter calcs.
HP_LAMBDA = 800;

 SIM_GRAPH   = 0;
 IMP_SUBPLOT=1;
 IMP_SINGLE=0;
 DO_HP_GRAPH = 0;
```

```
DISPLAY_IMMEDIATELY = 1;

% Starting the calculations:
do_it_BP;

        disp('=================================================================================');
        disp(' NOTE: since you have used do_it_BP.m which calls simul_BP.m instead of simul.m,');
        disp('       the distribution of the shocks is bivariate. See simul_BP.m for details. ');
        disp('=================================================================================');
```

The function for computing the steady state of the model is reproduced
here. I have named it bp.m.

```
function [ f ] = bp( x , alpha, beta, gamma, delta, nu, a, Del,
eta );
% THIS is the code for evaluating the steady state of BP2000.
% x(1) = C
% x(2) = Ln
% x(3) = Ld
% x(4) = K
% x(5) = mu
% x(6) = N
% x(7) = D
% x(8) = r

 f = [   (a*alpha*x(6)^nu)/x(2) * (a*x(6)^nu + (1-a)*x(4)^nu)^((1-nu)/nu) - x(1);
          x(3)/(gamma*x(7)) - x(5);
          beta*( x(8)/x(1) + (1-delta)*x(5) ) - x(5);
         (a*x(6)^nu + (1-a)*x(4)^nu)^(1/nu) - x(1);
          x(7)/delta - x(4);
          eta*x(2)^alpha - x(6);
          Del*x(3)^gamma - x(7);
         (1-a)*x(4)^(nu-1) * (a*x(6)^nu + (1-a)*x(4)^nu)^((1-nu)/nu) - x(8) ];
```

B.3   A standard real-business-cycle model with confusion

```
% Cooley and Prescott's RBC model (1995), augmented with an technology process that has a transitory
% and a permanent component.

%================================================
%========      Setting parameters      =========
%================================================
L_bar     = .31;                  % Steady state employment is a third of total time endowment
theta     = .4;                 % Capital share
delta     = .012;               % Depreciation rate for capital
R_bar     = 1.0132;               % One percent real interest per quarter
rho       = 1;                  % Constant of relative risk aversion
rho_1     = 0.95; % Autocorrelation of the permanent technology component
rho_2     = 0.000001;  % autocorrelation of the transitory technology shock
sigma_1 = .75; % Standard deviation of technology shock.  Units: Percent.
sigma_2  = .75; % Standard deviation of technology shock.  Units: Percent.
```

```
%=================================================
%======== Calculating the steady state  =========
%=================================================
betta    = 1.0/R_bar; YK_bar  = (R_bar + delta - 1)/theta; K_bar =
(YK_bar)^(1.0/(theta-1)) * L_bar; D_bar    = delta * K_bar; Y_bar =
YK_bar * K_bar; C_bar   = Y_bar - delta*K_bar; alfa =
fzero(inline('x/(1-x) - 1.78'),0.5);


% Shortcut
Phi = theta*Y_bar/(K_bar*R_bar); alfa1 = (1-theta)*(1-alfa) / alfa
*Y_bar*C_bar^(-rho); alfa2 = L_bar/(1-L_bar)*(1/alfa1+1);


%=========================================================================
%============ Computation of the gain matrix K in steady state ===========
%=========================================================================

% Notation:   P_for = P(t|t-1).

% System matrices:
F = diag([rho_1, rho_2]); H = [ 1
      1 ];
R = 0;                              % Var.Cov.matrix of the innovation of the observational equ.
Q = diag([sigma_1 , sigma_2]);   % Var.Cov.matrix of the innovation of the state equ.


P_for = diag([sigma_1 / (1 - rho_1) , sigma_2 / (1 - rho_2)]); % Unconditional variances of xi and nu.
% P_for = diag([sigma_1, sigma_2]); % Uncond. Variance, if rho_1 = 1 and if assuming that
% the prior of the first draw of xi is the same as the distribution of the residuals.

P_for1 = eye(size(P_for));       % Part of the stopping rule.
m = [];                          % This vector governs the path of K.
i = 1;

while abs(sum(diag( P_for1 - P_for ))) > 0.00001
    P_for1 = P_for;

    K = P_for * H * inv(H'*P_for*H + R);
    P_for  = F *(P_for - K * H' * P_for)*F' + Q ;
    m = vertcat(m,K');%diag(P_for)');
    i = i+1;
    i
end

disp('The convergence path of K:'); m

kap1 = K(1,:);     % size(K) =  2    1
kap2 = K(2,:);     % size(K) =  2    1
% ============== DONE ============


%==============================
%=== Declaring the matrices. ==
%==============================

VARNAMES = ['capital            ',  %1
            'xi^{(1)} forecast',  %2
            'xi^{(2)} forecast',  %3
```

```
                   'output           ',  %4
                   'consumption      ',  %5
                   'labor            ',  %6
                   'investment       ',  %7
                   'interest         ',  %8
                   'z                ',  %9
                   'xi^{(1)}         ',  %10
                   'xi^{(2)}         ']; %11


          % for k(t):
AA = [ 0,         0,       0
      - K_bar,    0,       0
       0,         0,       0
       0,         0,       0
       0,         0,       0
       0,        -1,       0
       0,         0,      -1
       0,         0,       0];

% for k(t-1):
BB = [ 0,                 0,            0
      (1-delta)*K_bar, 0,               0
      theta,             0,             0
       0,                0,             0
      - theta * YK_bar, 0,              0
       0,            rho_1*(1-kap1), -rho_1*kap1
       0,            -rho_2*kap2,     rho_2*(1-kap2)
       0,                0,            0];

%Order:   output      consumption  labor       investment interest      z
CC = [    -Y_bar,      C_bar,       0,          D_bar,      0,            0       % Equ. 1)
           0,          0,           0,          D_bar,      0,            0       % Equ. 2)
          -1,          0,          (1-theta),   0,          0,            1       % Equ. 3)
           1,         -rho,        -alfa2,      0,          0,            0       % Equ. 4)
          theta*YK_bar, 0,         0,           0,        - R_bar,        0       % Equ. 5)
           0,          0,           0,          0,          0,      rho_1*kap1 % Equ. 6)
           0,          0,           0,          0,          0,      rho_2*kap2 % Equ. 7)
           0,          0,           0,          0,          0,         -1  ]; % Equ. 8)

DD = [ 0, 0
       0, 0
       0, 0
       0, 0
       0, 0
       0, 0
       0, 0
       1, 1];

FF = [ Phi*theta - theta - Phi, 0, 0 ];

GG = [ Phi*theta - theta - Phi,  Phi-1 ,  (Phi-1) ];

HH = [ 0, 0, 0 ];

JJ = [ 0, 0, -(Phi*theta - theta - Phi + 1 - alfa2),  0,  0,  0];

KK = [ 0,  rho,  0,  0,  0,  0 ];

LL = [ 0, 0 ];

MM = [ 0, 0 ];
```

```
NN = [rho_1, 0
      0, rho_2];

Sigma = [ sigma_1^2,      0
             0,         sigma_1^2 ];

% Setting the options:

[l_equ,m_states] = size(AA); [l_equ,n_endog ] = size(CC);
[l_equ,k_exog  ] = size(DD);


PERIOD    = 4;              % number of periods per year, i.e. 12 for monthly, 4 for quarterly
GNP_INDEX = 4;              % Index of output among the variables selected for HP filter
IMP_SELECT = [1:11];        % a vector containing the indices of the variables to be plotted
DO_SIMUL  = 1;              % Calculates simulations
DO_MOMENTS = 0;             % Calculates moments based on frequency-domain methods

SIM_LENGTH = 100; SIM_MODE = 2; SIM_N_SERIES = 70;
HP_SELECT  = 1:(m_states+n_endog+k_exog); % Selecting the variables for the HP Filter calcs.
HORIZON = 10;

DO_PLOTS = 1; DO_IMPRESP = 1; DO_HP_GRAPH = 0; SIM_GRAPH = 0;
IMP_SUBPLOT=0;

DISPLAY_IMMEDIATELY = 0;

do_it;
```

Erklärung zur Urheberschaft

Hiermit erkläre ich, dass ich die vorliegende Arbeit allein und nur unter Verwendung der aufgeführten Quellen und Hilfsmittel angefertigt habe.

Henning Weber

Berlin, 29. Dezember 2003